Arab Academy for Science, Technology and Maritime Transport

College of Engineering and Technology

CONSTRUCTION AND BUILDING ENGINEERING DEPARTMENT

PRICE ESTIMATING OF LOW RISE STEEL BUILDING BASED ON NEURAL NETWORK SYSTEM

A Thesis
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بسم الله الرحمن الرحيم

﴿ قَالُواْ سُبْحَانَكَ لاَ عِلْمَ لَنَا إِلاَّ مَا

عَلَّمْتَنَا إِنَّكَ أَنتَ الْعَلِيمُ الْحَكِيمُ ﴾

صدق الله العظيم.

سورة البقرة آية رقم (32)

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((وما توفيقي إلا بالله))

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ABSTRACT

The importance of accurate cost estimate during the early stages of construction project has been widely recognized for many years. Early project cost estimate often become the basis for project's funding, choosing the appropriate project delivery system, tender evaluation, bidding decision and many others. Many studies showed that the construction materials bear a significant impact on the project cost. Materials costs represent above 50 percent of the cost profile of most construction projects. Any inaccuracy in material cost estimate is likely to affect the total cost of the project. The objective of this research was to develop an artificial neural network (ANN) model that could predict the weight of the steel structures in low rise steel buildings with a reasonable accuracy during the early stages of the project. The weight of steel structures is the basis for the preliminary cost estimating of low rise steel buildings. A back-propagation network consisting of one input layer of 6 neurons corresponding to the six inputs parameters, one hidden layer of 6 neurons, and one output layer of one neuron was developed. The model is based on the findings of formal interviews based on written questionnaire to identify the key parameters that influence the weight of steel structure of low rise steel buildings. Data from 80 low rise steel buildings projects in Egypt were used in training, and testing the proposed model. A random selection of data from 65 projects was used as training data set for the ANN model and the remainder (data from 15 projects) were used as testing set in which the performance of the ANN model was tested. The mean absolute percentage error calculated for the neural network model over the entire testing data set was 5.4%, i.e. an average accuracy of estimating the material weight of steel structure of 94.6% was achieved. This demonstrates a reasonable accuracy of the proposed model. To facilitate the use of this NN on estimating the cost/price of new projects, a user-friendly interface was developed using spreadsheet to simplify user inputs and automat cost/price prediction.

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CHAPTER 1

Introduction

1.1 General

Cost is one of the most important criteria in decision making during the early stages of developing a construction project. To estimate the cost, decision makers, designers and cost estimators use a number of cost estimating techniques and intuitive judgments by utilizing both their experience and data from previous projects. Several cost estimating methods for the different phases of a project can be observed in the literature, including; conceptual and preliminary cost estimates; detailed cost estimates; and definitive cost estimates (Barrie and Paulson 1992; Halpin and Woodhead 1998; Peurifoy and Oberlender 2002; Abdel-Razek 2004).

Conceptual and preliminary cost estimates are generally made in the early phases of a project, normally before the drawings and specifications are available. Conceptual cost estimates are needed by the owner, contractor, designer, or lending organization for several purposes, including studying the economical feasibility of a project, financial evaluation of alternatives, and establishment of an initial budget. Conceptual cost estimates are not expected to be precise because the project itself is not yet defined in terms of the plans and specifications upon which computations of quantities are based.

As a developing country, Egypt experiences rapid population and economical growth, and parallel to this an increasing demand for residential and building projects, including light manufacturing plant. From 1982 to 2001, 2723 factories have been built in Egypt, with an average of 136 factories per year while in 2002, 220 factories have been constructed which indicates that the investments in this field are booming within the next years (ESIS 2007). With these considerations, the cost of low rise steel building (LRSB) becomes an increasingly important issue in developing countries such as Egypt.

Current practice shows that the building materials bear a significant impact on the cost of a building. The importance of the materials costs is that they represent above 50 percent of the cost profile of most construction projects (Abdel-Razek and McCaffer 1986; Abdel-Razek and McCaffer 1987; Harris and McCaffer 1995).

A small percentage cut in materials costs could result in sizeable decrease in project cost. The estimating of material cost is, therefore, an important element and any inaccuracy in their estimates is likely to affect the total cost of the project (Abdel-Razek and McCaffer 1986; Abdel-Razek and McCaffer 1987; Harris and McCaffer 1995). The material cost of LRSB consists of several items including the cost of steel structural system and the cost sheeting area. The weight of steel structure is the basis for the material cost estimating of LRSBs.

The importance of decisions made at the initial design stage is significant since succeeding design tasks, analysis and detailed design generally aim at satisfying the constraints imposed during this formative stage. Furthermore, it is accepted that the ability to influence cost is greatest at the earlier stages of a project's life (Barrie and Paulson 1992). The weight of the steel structure is impacted significantly by decisions made at the concept and design phase. A basic concept in being able to reliably estimate steel structure weight during the early stages is to relate this weight to its influential drivers. Typically, regression analysis can be used to establish this relationship but recent applications include the use of artificial neural network and neurofuzzy models (Elhag and Boussebaine 1998; Hegazy and Ayed 1998). These relational models are different to the trend models since they only assume that the relation between material weight and the influential factors will remain constant and not that past trends are unchanging. According to Günaydin and Doğan (2004), linear regression analysis shows little or no success at all when early design parameters are used. The linear relationship in linear regression imposes a functional relationship which may not always be appropriate (Wilmot and Mei 2005). While this may be at least partially addressed through transformation of variables, the assumption of a specific mathematical formulation limits the ability of the model to fit the data on which it is estimated. In contrast, neural network (NN) models have no implicit functional form and therefore have greater freedom to fit the data than regression models (Wilmot and Mei 2005). Methods involving the new technology yield results that are both more realistic and accurate (Günaydin and Doğan 2004).

1.2 Problem Statement

The inspiration for artificial neural networks originated from the study of processes in the human brain. The network acquires knowledge through a learning process. The inter-neuron connection strengths known as synaptic weights are used to store the knowledge (Haykin 1994). This learning ability of neural networks gives an advantage in solving complex problems whose analytic or numerical solutions are hard to obtain (Rafiq et al. 2001). Material weight prediction during the early phases of a construction project is one of those problems. Various researchers have used neural networks as a tool for prediction and optimization of various project performance indicators. But in the area of cost and material weight estimating there exist only few applications.

In Egypt, some researchers applied ANNs technique in cost estimating. George (1997) used ANNs for estimating the quantities and costs of pre-stressed concrete bridge. Mohamed (2001) developed ANN model for estimating the preliminary cost of gravity sewage networks. Mohamed (2002) developed a neural network-based model for estimating the construction budget for academic building. Sherif (2004) used ANNs for predicting price per square meter of concrete building projects. Georgy and Barsoum (2005) used ANNs for estimating the construction budget of school construction projects. Elfaitury (2008) and Elfaitury et al. (2008) used ANN for predicting conceptual cost of Libyan highway projects. The results of the study were compared with the results of two earlier studies (Khorshid and Abdel-Razek 1991; Abdel-Razek 1992) that investigated and quantified the estimating inaccuracy in Egypt. Similarities between the studies' results were concluded.

Lack of a model for estimating the weight of structural steel framing of LRSB utilizing ANN during the early stages of developing such buildings, and taking into account the construction environment in Egypt, motivated the author to develop an ANN based model to estimate the weight of steel structure of LRSB.

1.3 Objectives of the Study

The objective of this thesis is to develop and test a model of estimating the material weight of steel structure of LRSB in the early design phase via the application of ANN. An ANN model can help the designers and cost estimators to make informed decisions at the early phases of the project. It should be pointed out that with an ANN model, it is possible to obtain a fairly accurate prediction, even when adequate information is not available in the early stages of the project (Rafiq et al. 2001).

In more details, the objectives of this study can be summarized in the following points:

1. Identifying the most effective factors affect the weight of steel structure of LRSB.
2. Developing a ANN model by using BrainMaker Professional version 3.73 (2001) and Hegazy and Ayed (1998) model to improve the estimate accuracy of the LRSB steel structure weight.
3. Developing a user-friendly interface to simplify user inputs and automat cost/price prediction.

1.4 Methodology

In order to achieve the above-mentioned objectives, a four-step research methodology was developed. In the first stage, other ANN based cost and material weight estimating models were investigated. In the second stage, the main parameters affecting the material weight of steel structure of LRSB were identified from literature review. These parameters formed the basis of a questionnaire, which was developed to sample the opinions of construction participants (engineers working in specialty steel fabrication companies and consultants) on the degree of importance of each of the parameters. In the third stage, an ANN model was designed for estimating the material weight of structural steel framing of LRSB by using data for 80 projects collected from major steel company. Then the model was tested for obtaining the best possible network configuration. In the fourth stage, to facilitate the use of this NN on estimating the cost/price of new projects, a user-friendly interface was developed using spreadsheet to simplify user inputs and automat cost/price.

The study methodology is shown in Fig 1.1 as following flow chart:

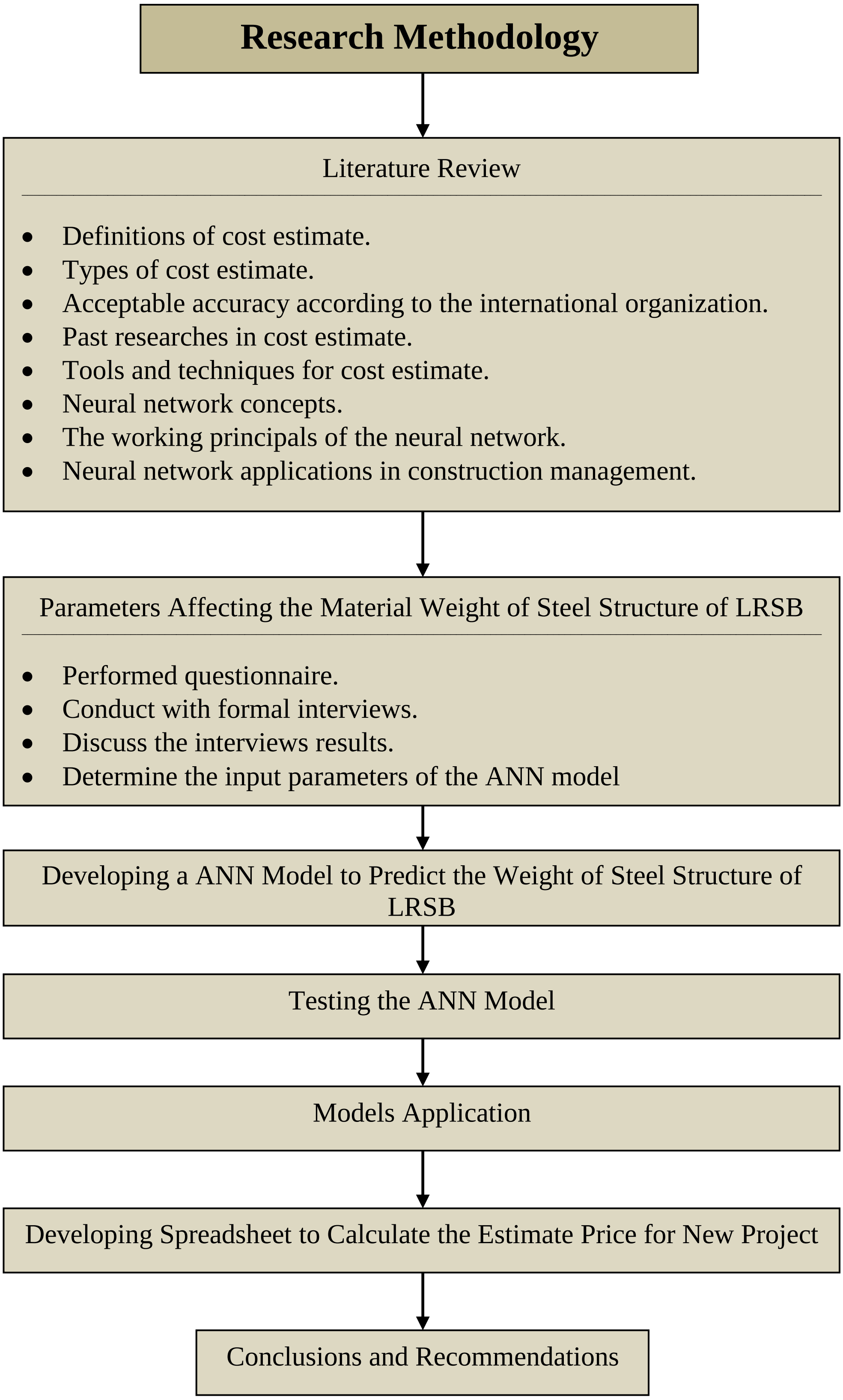


Fig 1.1: Illustration of Study Methodology

1.5 Scope of Research

The weights of steel structure of LRSB are variance according to the design requirements, the building accessories and the building end use. Following consideration are taken into account in this study to develop a useful model to estimate the weight of steel structure of LRSB in Egypt.

The study concentrated on:

1- Low rise steel building, Fig 1.2 (multi-story building is not allowed).
2- The Egyptian codes for design of such building is the governing codes.
3- The type of steel grade used is ST .52.
4- Wall and roof bracing is X-bracing (other bracing types are not allowed to be used) as shown in Fig 1.2.
5- Own weight is only applied on the design (other loads are not allowed such as: crane, mezzanine, roof curb).
6- Type of framing is a rigid frame (trusses is not allowed) as shown in Fig 1.2, 1.3.
7- No jack beams are used to increase the bay spacing.
8- No intermediate columns are permitted in the building except end wall columns as shown in Figs 1.2 and 1.3.

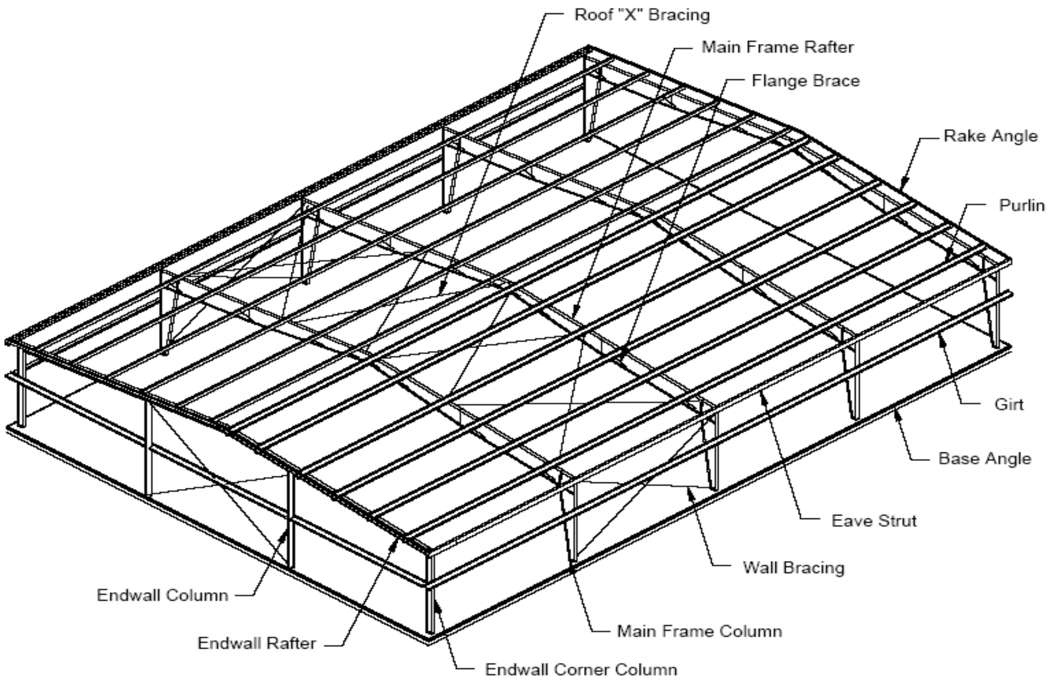


Fig 1.2: Isometric shape of the low rise steel building

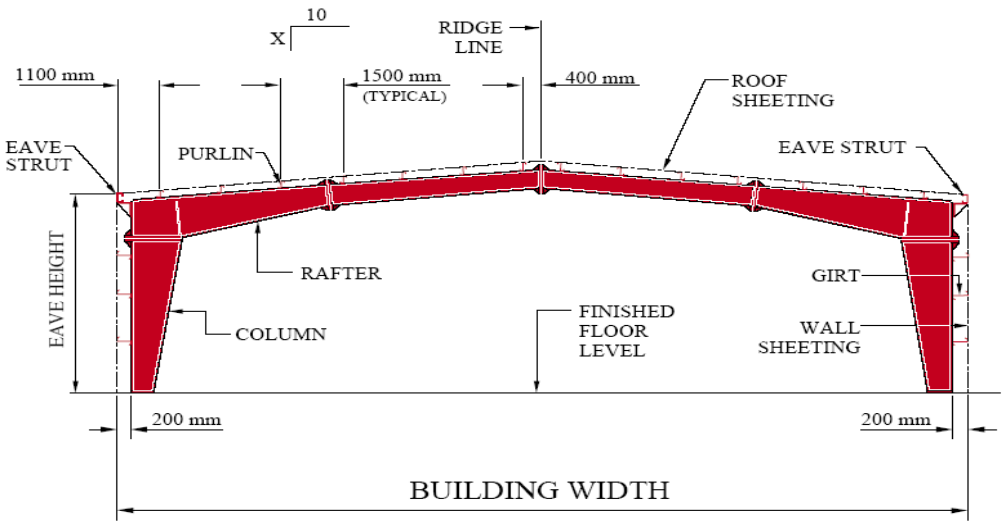


Fig 1.3: Elevation view

1.6 Thesis Guideline

The thesis is organized in contains 6 chapters.

1- Chapter 1 presented an introduction. It included the main objectives of this thesis and the methodology which used to achieve the objectives.
2- Chapter 2 discussed a cost estimate. It included the types of cost estimates, tools and techniques and the acceptable accuracy according to the international organizations.
3- Chapter 3 described an artificial neural network. It included the definition of the artificial neural network, types of ANN, concepts in neural computing, structures of neural networks, architecture and training of ANNs and applications of ANNs in construction management.
4- Chapter 4 explained a parameters affecting the material weight of steel structure of LRSB. It included the performed questionnaire contains, interviews result and the most effective parameters affecting the material weight of steel structure of LRSB..
5- Chapter 5 outlined a steps of design the artificial neural networks model by using the spreadsheet which developed by Hegazy and Ayed (1998) and BrainMaker professional software version 3.73 (2001) to predict the weight of steel structure of LRSB.
6- Chapter 6 is the thesis conclusions and recommendations for future work.

CHAPTER 2

Cost Estimate

Early estimates are critical to the initial decision-making process for the construction of capital projects. As such, the importance of early estimates to owners and their project teams cannot be overemphasized. Early estimates are typically plagued by limited scope definition (and thus high potential for scope change) and are often prepared under stiff time constraints. Furthermore, reliable cost data are often difficult to obtain during the conceptual stages of a project, particularly if basic design and geographic issues remain unresolved. Early estimates, even when grossly inaccurate, often become the basis upon which all future estimates are judged (with future estimates sometimes being ‘‘corrected’’ to be consistent with early estimates).

According to Halpin and Woodhead (1998), the owner’s estimate is used to:

1. Ensure that the design produced is within the owner’s financial resources to construct (i.e., that the architect/engineer has not designed a gold-plated project).
2. Establish a reference point in evaluating the bids submitted by the competing contractors.

Many of international organizations listed the type of cost estimate with the acceptable accuracy depend on its point of view. Most of these types will be described in this chapter.

2.1 Definition of Cost Estimate

The Society of Cost Estimating and Analysis (SCEA 2008) defined the cost estimate as, the art of approximating the probable cost or value of something based on information available at the time.

The Project Management Institute (PMBOK 2004) defined the cost estimate as, a quantitative assessment of the likely costs of the resources required to complete schedule activities.

According to Abdel-Razek (2004), the CIOB (1983) defined the cost estimate as, the technical process of predicting costs of construction.

2.2 Type of Cost Estimate

Cost estimating methods vary in accordance with the level of design detail that is available to the estimator at the time of estimate. As the level of design detail increases, the designer typically maintains estimates of cost to keep the client informed of the general level of costs to be expected. The production of the plans and specifications usually proceeds in two steps. The first step is called preliminary design and offers the owner a pause in which to review construction before detail design commences (Halpin and Woodhead 1998). The second step is called the detailed design and engineering after the project proceeds from concept through preliminary design and the bidding phase, the level of detail increase and allowing the development of a more accurate estimate.

The Department of Energy in USA (DOE 2008) have a four basic types of cost estimates that are developed and used by DOE and these estimates are:

1. Planning/feasibility study estimates

   Planning/feasibility study estimates are normally prepared by the operating consultant for a proposed project prior to completing conceptual design. Planning estimates are used for scoping studies.

   The basis for the planning estimate must describe the purpose of the project, general design criteria, significant features and components, proposed methods of accomplishment, proposed construction schedule, and any known research and development requirements. Planning estimates are based on past cost experience with similar type facilities, where available. Engineering costs in this type of estimate generally are based on a percentage of estimated construction costs, and consideration will be given to the complexity of the project in establishing the percentage to be used. Similarly, an allowance for contingency will be included in the total project estimate using a percentage of total engineering and construction costs established on the basis of complexity and uncertainties of the component parts of the project.

2. Budget or Conceptual Design Estimates

   The fundamental purposes of a budget or conceptual design estimate are:

   - To ensure project feasibility and attainable performance levels;
   - To develop a reliable project cost estimate consistent with realistic schedules;
   - To use it to establish baseline project definitions, schedules, and costs.

   The completed conceptual design estimate normally serves as the basis for preparation of a construction project data sheet.

   The basis for a budget or conceptual design estimate shall include as many of the detailed requirements, all general criteria and design parameters, applicable codes and standards, quality assurance requirements, space allocations for required functions, types of construction, significant features and components, building and facility utility services, site work, process equipment requirements and schedules.

3. Title I Design Estimate

   The Title I design estimate is an intermediate estimate used to verify that the Title I design details still remain within the project funding. The Title I design details are written in the Title I design phase; this is the initial work accomplished under an approved project. Estimates of this type are completed in conjunction with the Title I preliminary design phase.

   The basis for the Title I estimates shall include all drawings, outline specifications, data sheets, bills of material, schedule refinements, definitions of scope, methods of performance, and changes in codes, standards, and specifications.

4. Title II Design Estimates

   The purpose of the Title II estimate is to estimate construction costs as accurately as possible, prior to the commencement of competitive bidding and construction activities. As Title II design specifications and drawings are developed, the Title II estimate is completed.

   The basis for the Title II cost estimate must include all the approved engineering data, methods of performance, final project definition and parameters, project schedule, and final exact detailed requirements. This will include a complete list of all engineering data used (i.e., drawing data sheets, specifications, bills of material, job instructions, proposed schedules, etc.) Since the Title II definitive design results in working drawings and specifications for construction work, including procurement and shop fabrication, the Title II estimates are prepared in accordance with the approved Title II drawings and specifications.

According to Halpin and Woodhead (1998), there are four levels of estimates and the ones most commonly encountered. To recapitulate, the four types of estimates are:

1. Conceptual estimate.
2. Preliminary estimate.
3. Engineer’s estimate.
4. Bid estimate.

These four levels of precision reflect the fact that as the project proceeds from concept through preliminary design and the bidding phase, the level of detail increase, allowing the development of a more accurate estimate.

Estimating continues during the construction phase to establish whether the actual costs agree with bid estimate.

The Association for the Advancement of Cost Engineering (AACE 2008) identified a progression of five types of estimates of construction costs:

1. Concept Screening (Class 5)

   Class 5 estimates are generally prepared based on very limited information, and subsequently have wide accuracy ranges. As such, some companies and organizations have elected to determine that due to the inherent inaccuracies, such estimates cannot be classified in a conventional and systemic manner. Class 5 estimates, due to the requirements of end use, may be prepared within a very limited amount of time and with little effort expended sometimes requiring less than an hour to prepare.

2. Study or Feasibility (Class 4)

   Class 4 estimates are generally prepared based on limited information and subsequently have fairly wide accuracy ranges. They are typically used for project screening, determination of feasibility, concept evaluation, and preliminary budget approval. Typically, engineering is from 1% to 15% complete.

3. Budget or Control (Class 3)

   Class 3 estimates are generally prepared to form the basis for budget authorization, appropriation, and/or funding. As such, they typically form the initial control estimate against which all actual costs and resources will be monitored. Typically, engineering is from 10% to 40% complete.

4. Control or Bid/Tender (Class 2)

   Class 2 estimates are generally prepared to form a detailed control baseline against which all project work is monitored in terms of cost and progress control. For contractors, this class of estimate is often used as the "bid" estimate to establish contract value. Typically, engineering is from 30% to 70% complete.

5. Check Estimate or Bid (Class 1)

   Class 1 estimates are generally prepared for discrete parts or sections of the total project rather than generating this level of detail for the entire project. The parts of the project estimated at this level of detail will typically be used by subcontractors for bids, or by owners for check estimates. The updated estimate is often referred to as the current control estimate and becomes the new baseline for cost/schedule control of the project. Class 1 estimates may be prepared for parts of the project to comprise a fair price estimate or bid check estimate to compare against a contractor's bid estimate. Typically, engineering is from 50% to 100% complete.

According to Abdel-Razek (2001), there are several methods for estimating the cost of construction project. The method adopted depends on the level of information available, the needs of the recipient of the estimate and the time available to prepare the estimate. The methods are shown in Fig 2.1.

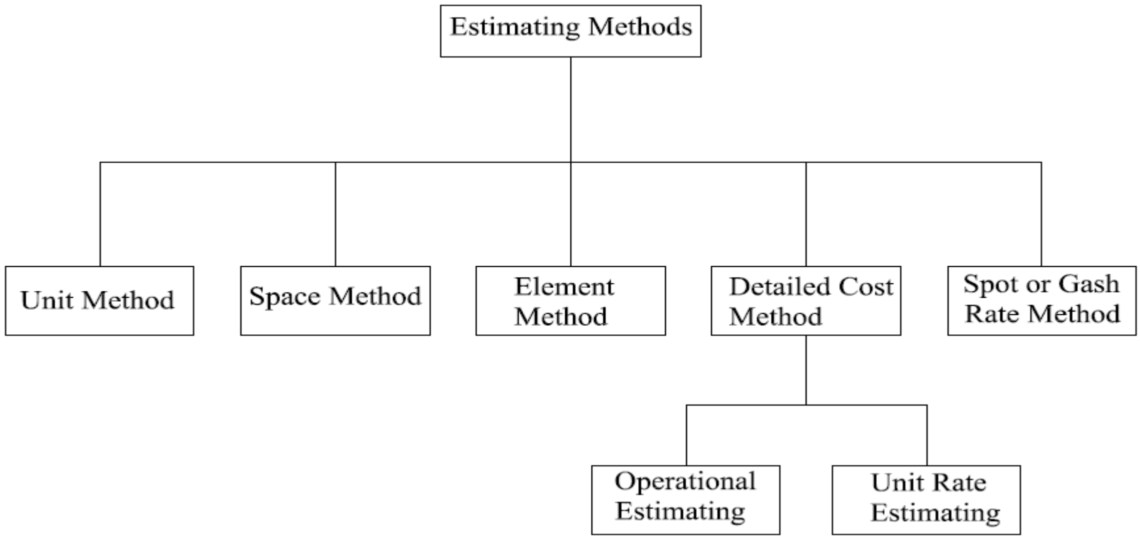


Fig 2.1: Cost estimating methods (source: Abdel-Razek 2001)

According to all above description, this study will focus on estimates prepared at a pre-design stage (conceptual phase) , when the level of the LRSB projects definition within 10 to 40 % (according to the available information about the building parameters).

2.3 Accuracy of Cost Estimate

The importance of accurate estimates during the early stages of capital projects has been widely recognized for many years. Early project estimates represent a key ingredient in business unit decisions and often become the basis for a project's ultimate funding.

According to DOE (2008), The AACE defines accuracy as the degree of conformity of a measured or calculated value to some recognized standard or specified value.

Accuracy depends on the amount of quality information available as well as the judgment and experience of the estimator. Consequently, as the amount of information and specific details increase, so does the degree of accuracy.

Degree of acceptable estimates accuracy are classified according to the DOE (2008) is illustrated in Table 2.1

Table 2.1: Degree of accuracy according to the DOE according to (DOE G 430.1-1)

Degrees of Accuracy		
Type	Purposes	Accuracy Range
Planning/Feasibility	Scoping Studies. Preliminary budget estimates of Total Project Cost.	± 40%
Budget/Conceptual Design Estimate	Ensure project feasibility. Develop reliable project cost estimate. Establish baseline project definitions, schedules, and costs. (Design 10% to 15% Complete)	± 30%
Title I Estimate	Verify that Title I design details still remain within the project funding. (Design 25% to 35% complete)	± 20%
Title II or Definitive Estimate (Detailed)	Estimate construction costs as accurately as possible, prior to the commencement of competitive bidding and construction activities. (Design 60% to 100% Complete)	- 5% to + 15%

According to all above description, the study will focus on estimates prepared at a pre-design stage (Conceptual phase), when the level of the LRSB projects definition within 10 to 15 %. The expected accuracy range for this study will be between ± 30 %.

Degree of acceptable estimates accuracy are classified according to the estimate class of the AACE (2008) is illustrated in Table 2.2

Table 2.2: Degree of accuracy according to the AACE International Cost Estimation Classifications (18R-97)

Estimate Class	Level of Project Definition (%)	End Usage (Typical Purpose)	Expected Accuracy Range (%)
Class 5	0 to 2	Concept Screening	-50 to +100
Class 4	1 to 5	Study or Feasibility	-30 to +50
Class 3	10 to 40	Budget or Control	-20 to +30
Class 2	30 to 70	Control or Bid/Tender	-15 to +20
Class 1	50 to 100	Check Estimate or Bid	-10 to +15

According to all above description, this study will focus on estimates prepared at a pre-design stage (Class 3) , when the level of the LRSB projects definition within 10 to 40 %. The expected accuracy range for this study will be between -20 to +30 %.

The Construction Industry Institute's (CII 1998) defines accuracy as, any cost estimate is assigned a range of accuracy (percentage). These ranges narrow as the quantity and quality of information increase through the life of project. This infers that estimate accuracy is a function of available information (scope definition), a generally accepted fact in engineering and construction. Good estimating practice and experienced personnel are also found to have considerable impact on estimate accuracy, especially on conceptual estimates, since at this stage the level of scope definition is low and often poorly defined.

The CII's study (1998) highlights the following as major factors impacting estimates' accuracy:

- Quality and amount of information available for preparing the estimate.
- Time allocated to prepare the estimate.
- Proficiency of the estimator and the estimating team.
- Tools and techniques used in preparing the estimate.

Degree of acceptable estimates accuracy are classified according to the CII (1998) is illustrated in Table 2.3

Table 2.3: Degree of accuracy according to the CII Cost Estimate Definitions (CII SD-6)

Estimate Class	Percentage Range	Description/Methodology
Order of Magnitude	± 30 to 50	Feasibility Study: cost/capacity curves
Factored Estimate	± 25 to 30	Major equipment: cost/factors
Control Estimate	± 10 to 15	Quantities: mech./elec./civil drawings.
Detailed or Definitive	± <10	Based on detailed drawings

According to all above description, the study will focus on estimates prepared at a pre-design stage (Factored estimate). The expected accuracy range for this study will be between ±25 to 30 %.

2.4 Past Researches in Cost Estimate

Many researchers have been conducted to measure prediction cost estimate for the new construction projects such as:

Kouskoulas and Koehn (1974 in Ayed 1997) used location, construction year, building type, number of floors, quality, and building technology as the independent variables to explain the variations in the project cost.

Karshenas (1984 in Ayed 1997) argued that because the type of building has an important effect on the project cost, different types of buildings should be studied separately. Karshenas focused on conceptual cost modeling for multistory steel-framed office buildings and used published data for modeling. The model developed by Karshenas included nonlinear terms to express project cost in terms of typical floor area and building height. Karshenas, along with Kouskoulas and Koehn, performed a residual analysis to check model predictions. Neither of the models was validated by a technique such as cross validation, however.

Uhlik (1984) developed a combined stochastic and deterministic model for highway projects to optimize cost estimation in uncertain situations. His developments accounted for the uncertainties associated with quantity of rock in cut areas to estimate fleet production and determine the optimum distribution of material in cut and fill areas.

Akeel (1989) developed a database tool for statistically based construction cost estimating

Ellis (1989) analysis was performed to produce a predictive model for construction production rates and examine their variability.

Lopez (1993) conducted a study on forecasting construction costs in hyper-inflated economies. In this study, Mexican economic indicators were compared with those from the United States. As a result a new Mexican cost index was developed using Box and Jenkins models.

Pantzeter (1993) Multiple regression analysis has also been used to develop a methodology for modeling the cost and duration of concrete highway bridges. In this research, different projects were divided into five work categories and the cost of each category was modeled by applying statistical techniques.

Touran (1993) suggested using the Monte Carlo simulation technique with subjective correlations for probabilistic cost estimating. Published data on low-rise building projects were used to show the application of the suggested procedure.

Al-Bani (1994) developed a concrete cost estimate model for small residential buildings. The research studied the inter-relationships between the different physical elements of a concrete structure such as footings and columns using mathematical expressions and formulas.

Hegazy and Ayed (1998) utilized neural networks for conceptual cost estimation of highway projects. Hegazy and Ayed used 14 projects for training and four projects for testing the neural network models. Three neural networks models with 10 input variables were developed by different methods. The techniques involving regression analysis, simulation, and neural networks each have certain advantages and disadvantages for conceptual cost estimation

Al-Tabtabai et al. (1999) also 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. They used environmental, company and project specific factors. Their model measured the combined effect of these factors on the percentage change in expected cost. The network generated outputs reaching a mean absolute percentage error of 8.1%.

Siqueira (1999) presented an automated cost estimating system for low-rise structural steel buildings by utilizing design variables such as area, perimeter, height, load, etc. His model was developed by the cost of seventy five projects collected from major structural steel fabricator in Québec between 1994 and 1997. He used commercial software of ANN and showed that the neural network model outperformed regression. The mean absolute percentage error calculated for the neural network model was 11% for the cost estimating of structural steel framing.

Isidore and Back (2002) discussed the importance of quantifying the risk of an estimate by using probabilistic range estimating. Isidore and Back developed an integrated range estimation and probabilistic scheduling technique called MSAT and used a construction project to demonstrate the technique.

Sheryl et al. (2003) Understanding how the building design influences construction costs is a challenging task for construction cost estimators. Estimators must determine what design conditions are important (i.e., incur a cost), when they are important, and how they affect construction costs when creating cost estimates. Estimators have different preferences for what design conditions they consider and when and how they adjust the project's activities, resources, and resource productivity rates that form the basis of a cost estimate for a particular design.

Wilmot and Mei (2005) utilized neural networks for conceptual cost estimation and described in terms of a highway construction cost index, to the cost of construction material, labor, and equipment, the characteristics of the contract and the contracting environment prevailing at the time the contract

2.5 Tools and Techniques for Cost Estimate

In construction, deterministic cost estimation models (referred to as parametric models) have traditionally been in wide use by many researchers due to their simple formulations. In these techniques, historical data are used to develop cost relationships based solely on statistical analysis. They have been used to estimate one characteristic of a system, usually its cost, from other performance characteristics of the system. The term "Parametric Estimating". however, may mean different things to different researchers (Black 1982). For instance. it may mean the determination of the life cycle cost of a system from a mathematical model containing a number of parameters and based on case histories of similar projects. On the other hand, it could mean the cost estimation of any system, made up of aggregated components. by means of mathematical models containing parameters (Ayed 1997).

In parametric analysis, the main parametric equation has to be defined with its associated independent variables before any analysis can be performed. The variables in the parametric equation could be identified by highlighting those characteristics of the system under study that are most directly related to its cost. Then, a mathematical relationship for correlating data could be used to express this relationship. The most popular mathematical models are linearized forms of the arithmetic, logarithmic and semi-logarithmic equations (Black 1982). In the parametric cost estimating technique, there is one dependent variable which is the cost and two or more independent variables like size. location, capacity, time .... etc. The equations generally take one of the following three forms:

1) Linear relationships:

$$Cost=a+bX_1+cX_2+ \ldots\ldots\ldots$$

2) Logarithmic relationships:

$$Log(Cost)=a+b \log X_1 + c \log X_2+\ldots\ldots\ldots$$

3) Exponential relationships:

$$Cost=a+ b X_1^{c} + d X_2^{e} +.:\ldots\ldots\ldots$$

Where a, b, c, d and e are constant and X_1, X_2 , X_3 , X. .... X, are the performance characteristics of a system.

The best criterion for choosing a form of the cost estimating relationship is a good understanding of how costs vary with changes in the independent parameters. This is a difficult task that is based on the experience of the estimators involved and. as such, has been performed mainly on a trial and error basis (Ayed 1997)..

A major disadvantage of the traditional techniques for parametric estimating is that the mathematical form has to be defined before any analysis can be performed to determine the actual cost function that best fits the historical data (Creese and Li 1995).

Also, modeling the cost of a system as a function of a member of independent variables is not an easy task. This is due to the large number of variables present in the system under evaluation and the numerous interactions among them. Another drawback is the use of a single cost estimation relationship to all cost variables involved which often have different mathematical correlation with the cost of that system. These problems may explain the low accuracy and limited use of parametric estimating techniques based on mathematical analysis in the construction industry and the need for a more accurate technique to solve the cost estimation problem (Ayed 1997).

According to the PMBOK (2004), Tools and Techniques for Cost Estimating:

1. Analogous Estimating:

   Analogous cost estimating means using the actual cost of a previous, similar project as the basis for estimating the cost of the current project.

   Analogous cost estimating is frequently used to estimate total project costs when there is limited amount of detailed information about the project (e.g., in the early phases). Analogous estimating is a form of expert judgment.

   Analogous estimating is generally less costly than other techniques, but it is also generally less accurate. It is most reliable when the previous projects are similar in fact and not just in appearance, and the persons or groups preparing the estimates have the needed expertise.

2. Determine Resource Cost Rates:

   The person determining the rates or the group preparing the estimates must know the unit cost rates, such as staff cost per hour and bulk material cost per cubic yard, for each resource to estimate schedule activity costs. Gathering quotes is one method of obtaining rates. For products, services, or results to be obtained under contract, standard rates with escalation factors can be included in the contract. Obtaining data from commercial databases and seller published price lists is another source of cost rates. If the actual rates are not known, then the rates themselves will have to be estimated.

3. Bottom-up Estimating:

   This technique involves estimating the cost of individual work packages or individual schedule activities with the lowest level of detail. This detailed cost is then summarized or “rolled up” to higher levels for reporting and tracking purposes. The cost and accuracy of bottom-up estimating is typically motivated by the size and complexity of the individual schedule activity or work package. Generally, activities with smaller associated effort increase the accuracy of the schedule activity cost estimates

4. Parametric Estimating:

   Parametric estimating is a technique that uses a statistical relationship between historical data and other variables (e.g., square footage in construction, lines of code in software development, required labour hours) to calculate a cost estimate for a schedule activity resource. This technique can produce higher levels of accuracy depending upon the sophistication, as well as the underlying resource quantity and cost data built into the model. A cost-related example involves multiplying the planned quantity of work to be performed by the historical cost per unit to obtain the estimated cost.

5. Project Management Software:

   Project management software, such as cost estimating software applications, computerized spreadsheets, and simulation and statically tools, are widely used to assist with cost estimating. Such tools an simplify the use of some cost estimating techniques and thereby facilitate rapid consideration of various cost estimating alternatives.

Several techniques have been suggested for conceptual cost estimation. Regression analysis, simulation, and neural networks are among these cost estimation techniques that are used during the early project stages. (Sonmez 2004).

In recent years, artificial intelligent (AI) have been applied to many engineering problems with some degree of success. NN is one of these methods which used from many researchers to develop a cost estimate models and for other models.

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS

This chapter presents artificial neural network definitions, history, concept, architecture and its structures. This chapter also highlights the application of neural network in construction management

3.1 Background Introduction

Neural network like a human brain. It demonstrates the ability to learn, recall, and generalize from training pattern or data. The processing element in artificial neural networks (ANNs) are called “Neuron”.

A human brain consists of 10 billions neurons. Each biological neuron is connected to several thousands of other neurons. The connectivity of neurons in ANN, is similar to that of human brain as shown in Fig 3.1.

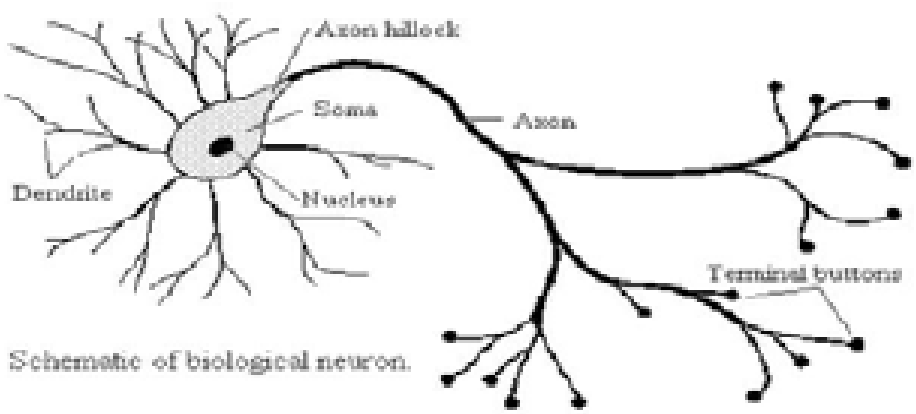


Fig 3.1: Schematic of Biological Neuron

According to Boussabaine (1996), Artificial neural networks (ANNs) offer an approach to computation that is different from conventional analytic methods. ANNs are an information processing technology that simulate the human brain and the nervous system. Like the human brain, neural networks learn from experience, generalize from previous examples to new ones and abstract essential characteristics from inputs containing irrelevant data. Network components with names such as neurons (sometime referred to as cells, units or nodes) and synaptic transmissions with weight factors are used to mimic the nervous system (analogous to synaptic connections in the nervous system) in a way which allows signals to travel through the network in parallel as well as serially. Although neural networks have some qualities in common with the human brain, this resemblance is only superficial. The ANN will most likely never be able to duplicate completely the functions of the human brain.

Various ANN models have been proposed over the past decades and impressive results have been obtained with some of the designs. The most popular model for many applications is the non-linear multilayered network. This method is an outgrowth of the single-neuron linear neural network approach that started in the 1960s. The original models consisted of two layers of computational neurons: input and output neurons. These models are easier to train and have found widespread commercial application (Fausett 1994). Unfortunately, only a limited number of applications could be solved with this technique. The introduction of non-linear multi-element ANNs and algorithms for calculating and correcting errors of the network's performance (e.g. the back-propagation method) made ANNs very productive in the 1980s.

ANNs are suited to such problems because of their adaptively owing to their structure; that is, non-linear activation functions (Flood and Kartam 1994a, b). Adaptively allows the neural network to perform well even when the environment or the system being modeled varies with time (Boussabaine 1996).

ANNs have many advantages over traditional methods of modeling in situations where the process to be modeled is complex to the extent it cannot be explicitly represented in mathematical or statistical terms or that explicit formation causes loss of sensitivity due to over-simplification. Traditional models lack the ability to learn by themselves, generalize solutions and respond adequately to highly correlated, incomplete or previously unknown data.. The most important advantage of ANNs over mathematical and statistical models is their adaptively. ANN systems can automatically adjust their weights to optimize their behavior as decision makers, predictors, etc. Self-optimization allows the neural to design itself (Salem 2006).

In the construction management field ANNs will probably be seen as components of larger systems which make use of expert-given rules or statistical inference techniques as required. Such systems, in turn, will be able to provide decision support for experts, help decision makers perform at a higher level, assist in the training of inexperienced personnel and help scenario planning (i.e. what if?) by managers. A useful ANN decision support system must be robust, easy to use and it should enhance the process of decision making. An ANN that simply models the decision-making behavior of the user is likely to be of limited use (Salem 2006).

3.2 Neural Network Concepts

There is a diverse range of ANN models in terms of topology and mode of operation. However, each model can be specified by the following seven major concepts (Lippman 1987; Hall 1992; Hush and Horne 1993).

1- A set of processing neurons.
2- A state of activation for each neuron.
3- A pattern of connectivity among the neurons or topology of the network.
4- A propagation method to propagate the activities of the neurons through the network.
5- An activation rule to update the activities of each node.
6- An external environment that provides information to the network and interacts with it.
7- A learning method to modify the pattern of connectivity by using information provided by the external environment.

Fig 3.2 illustrates a multilayered ANN with three layers. These consist of a number of nodes with each of the nodes in one layer linked to each node in the next layer. The communication with the outside world occurs through the nodes of the input and output layers. The middle layer, which is hidden from the outside, gives a critical computational ability to the system. The functioning of the nodes is illustrated in Fig 3.3. In a simple case the node receives only two inputs $X(1)$ and $X(2)$, respectively, with corresponding weight factors $W(1)$ and $W(2)$. The node calculates the sum, $X(1)W(1) + X(2)W(2)$ and delivers an output value obtained from a special sigmoid function, the activation functions, which can take on a variety of forms.

The output reached in this fashion is delivered to nodes in the next layer, where a computation similar to the one described above takes place. If the node is in the output layer the obtained value has reached its final destination. The pattern of connectivity or the network topology specifies how each node is connected to the other units in the network. The strength of each connection is represented by a real number (weight). The weights represent the knowledge that is encoded into the network. As the network learns, the numerical values of the weights may change according to the new information that is circulating in the network. A learning method (for example, back propagation) is used to change the weight of the network and other adaptable parameters.

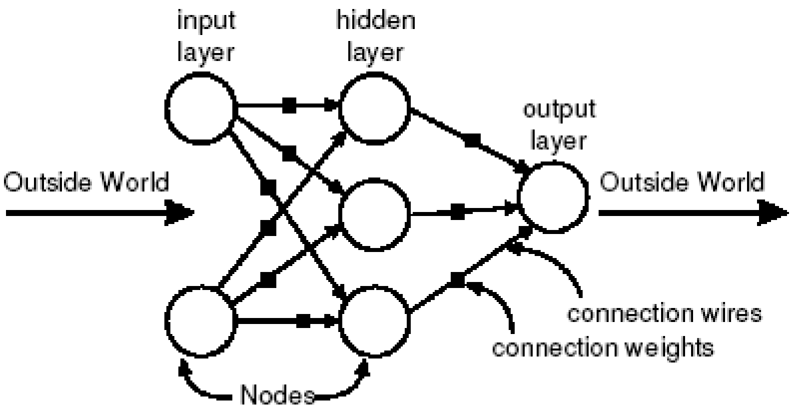


Fig 3.2: A multilayered ANN with three layers

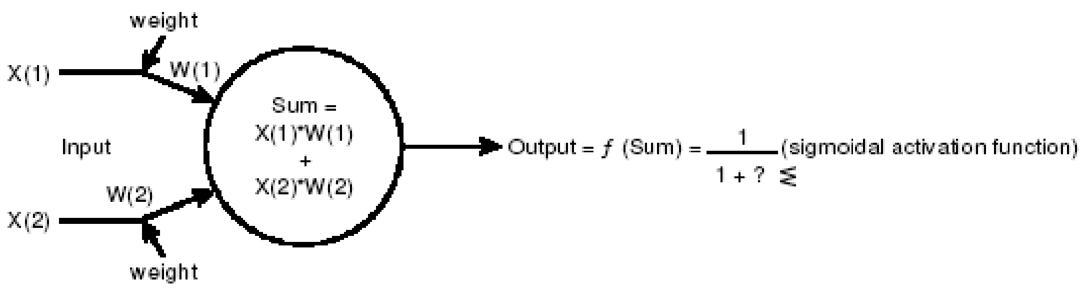


Fig 3.3: The functioning of the nodes

3.3 The Working Principals of The Neural Network

According to Boussabaine (1996), The working principles of the three-layered network with back-propagation are shown in Fig 3.4 Input information is presented to the ANN for each sample and the specified target number given, if supervised training is used. During training, the input layer broadcasts a pattern to all the hidden nodes. The system is then asked to calculate an output value in a feed forward way following the specification stated in Fig 3.3. The hidden nodes broadcast their results to all output nodes. Each output node then calculates a weighted sum as shown in Fig 3.3 and passes it to the output node to generate an actual result. The result is compared with the target value, which the trainer has established at the onset of a training session. The difference yields the system output error. At this stage the system has to decide whether further learning is required. This is accomplished by comparing the obtained total difference with a specified acceptable error given by the system developer. If the decision is to continue, the output nodes calculate the derivatives of the error with respect to the weights and the result is sent back through the system to all the hidden nodes. Each hidden node calculates the weighted sum of the error. Then, each hidden layer node and output-layer node change their weights to compensate for the corrections. Once the weights have been changed, the feed-forward computation starts all over again. New output values are obtained and the cycle continues until a desired result is obtained. At this stage we can say that the training of the system is complete and the testing phase can start this called (ANN learning terminology) as shown in Fig 3.5. The system can now be used to predict the outcome of an input not previously seen by the ANN.

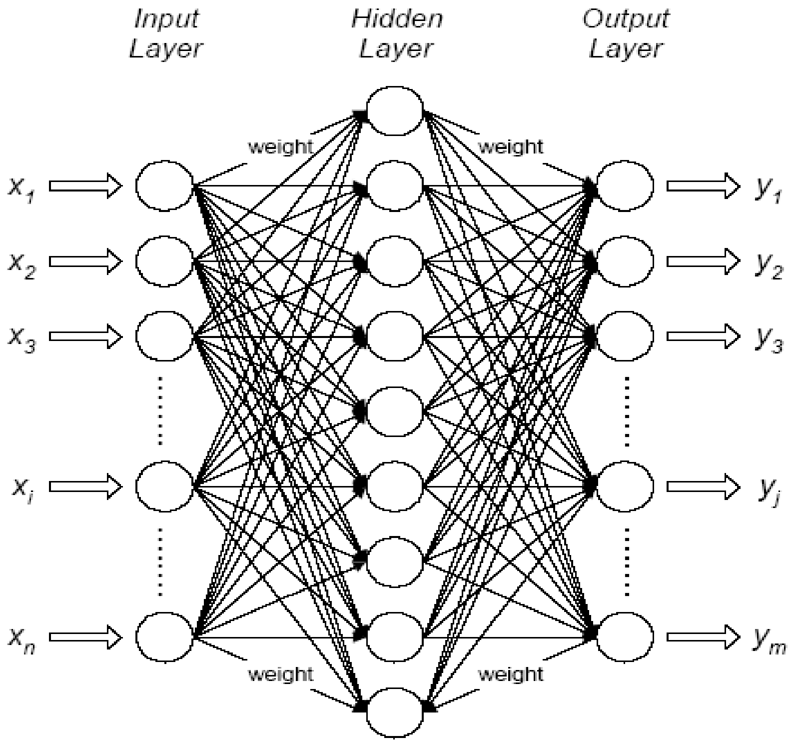


Fig. 3.4: Schematic diagram of artificial neural network (ANN) architecture

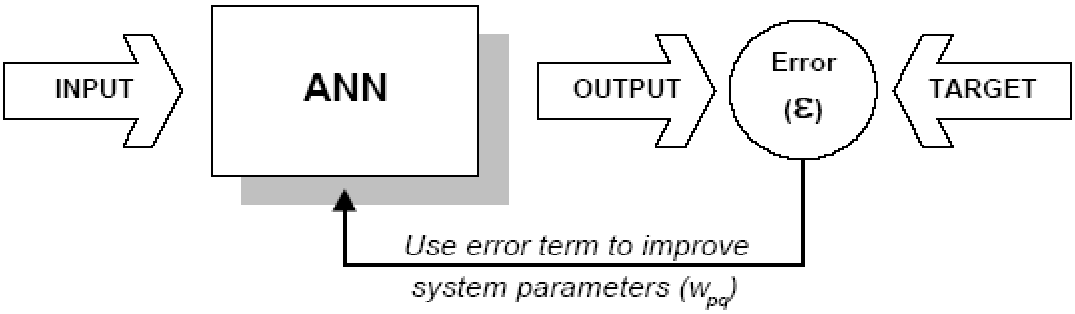


Fig 3.5: ANN learning terminology

3.4 Applications of Artificial Neural Networks

According to Mosilhi (1991), The neural networks described earlier can be used for the efficient modeling of some problems in construction that are frequently treated in current practice based on analogy with past-related experiences. Some potential areas of neural network applications include:

1- Selection between alternatives. For example, a pattern representing the soil conditions of a construction site could be associated with an approximate value for the bearing capacity, degrees of suitability of different types of foundation, appropriate dewatering methodology, and so on. Other examples include formwork and equipment selection.

2- Estimation and classification. For example, a pattern representing a protect environment could associate an estimated productivity factor or select one of tile existing productivity classes, representing different performance levels of a certain trade. As another example, a project deformation pattern could associate estimated values for the schedule and the cost indices. Probability and percentage of cost overruns could also be estimated.

3- Function synthesis, such as optimum markup, estimation under different bid situations.

4- Diagnostic problems such as those encountered in building, and facility defects and the needed establishment of causation in construction dispute man agreement and their respective claim analyses.

5- Dynamic modeling. For example, construction projects with varying performance levels measured in the different reporting periods could indicate a projection of relative time and / or cost overruns. Another example is modeling during periods of rapid fluctuations in inflation or escalation rates. These data could be used to give an indication about the market condition so that proper bidding decisions could be made.

6- Optimization tasks. For example, applications regarding the optimization of construction activity and resource usage could be experimented.

7- Real-time applications such as those associated with time-dependent changes (e.g. material costs, inflation, rate, etc.).

3.5 Neural Network Applications in Construction Management

Applications of ANNs in construction management go back to the early 1990s. These applications cover a wide of topics. The following section demonstrated some of these applications. For example,

Flood in (1989 in Boussabaine 1996) stated that Flood in (1989)) described the development of an ANN-based method for optimizing the sequencing of construction tasks with the objective of minimizing production time. The basic idea behind this work is that when a matrix of times spent by each job at each process is presented to the input layer, the network will respond by producing an optimal job sequence across the output layer. The sequence is dictated by the relative levels of activation of the output neurons. The testing results proved that the network had formed a valid model of the problem. However, this model lacks a rigorous analysis to assess the performance of the model in relation to variance between patterns and alternative network topologies.

Moselhi (1991) reported on the development of a trial neural network system for optimum mark-up estimation under different bid situations. The system uses as its input the number of typical competitors, the mean of the distribution of the ratio of the competitors' bid prices to the contractor's estimated cost in previous encounters and the standard deviation of the latter distribution. Three bidding strategy models were used to provide the desired network output (optimum mark-ups) in response to the different bid situations. The authors claimed that the model was able to generalize solutions and capture the probabilistic nature of ten bid situations used in training. This seems to contradict the fact that the data sample used for training is too small which may have contributed to an over fitting problem. If over fitting had occurred then the model cannot generalize (interpolate) from new data because every training item has been learned perfectly at the expense of learning the underlying regularities of the domain.

Mckim (1993a). in this study, a Neural Network model was developed to predict the cost of pumps. The input variables to the Neural Network model were the pump flow and head. A set of 23 pumps with their associated flow, head and actual prices was used as training cases. The Neural Network model was trained for 50,000 cycles. The results were compared to other industrial methods commonly used in practice for predicting pumps' cost. These methods were: 1) 0.6 exponent scaling method, 2) Best-fit exponent scaling method. and 3) Empirical best-fit equation method. The standard deviation error and the coefficient of determination were calculated for each method. Similar to the previous study by Creece, it was concluded that the Neural Networks method provides a more accurate estimate than the other regression methods. A similar conclusion has also been arrived at by the same author (Mckim. 1993b) in another study.

Williams (1994) developed a back-propagation ANN model to predict the changes in construction cost index for one month and six month ahead. The system uses as input the recent trends, the prime lending rate, housing starts and the month of the year. The model produces three outputs: (1) prediction of the percentage change of the construction cost index 1 month ahead, (2) prediction of the percentage change in the construction index 6 months ahead and one prediction. The output from the ANN system was compared with predictions made by an exponential smoothing and simple linear regression models. The author found that the prediction produced by the ANN model gave a greater error than statistical models. He concluded that the movement of the cost indexes is a complex problem that cannot be predicted accurately by a back-propagation ANN model. These findings contradict the advantages claimed for ANNs over statistical methods. The failure of this model could be attributed to the selection and design of input data or failure to find an optimum network topology and fine-tune the network structure (weights, nodes and layers) to obtain a suitable model.

Chao and Skibniewski (1994) developed two ANN modules for estimating excavation capacity based on job conditions and estimating excavator efficiency based on the attributes of operation elements. The training data were generated from a desktop excavator model and a simulation program. The output of the first module, excavator cycle time, is used as an input to the second module. The outputs of the second module include hourly productivity plus the mean and standard deviation. Test results show that the NN approach can produce a sufficiently accurate estimate with a limited data-collection effort, and thus has the potential to provide an efficient tool for construction productivity estimation. This work is limited because the number of hidden layers was fixed and there was no search for the optimum set-up of ANN parameters. However, it demonstrated the potential for applying neural networks to estimate the construction operation productivity.

Murtaza and Fisher (1994) described a model for decision making about construction modularization using ANNs. The decision is based on factors such as plant location, project risks etc. The neural network is trained using 40 cases collected from several engineering and construction firms and owner firms of industrial process plants, and the performance of the model is tested on ten separate cases. The validation tests showed that the ANN decisions were accurate.

Garza and Rouhana (1995) compared the results of Neural Networks with those of regression models for predicting the material cost of carbon steel pipes. Ten sets of cost data were used to train the Neural Networks and six sets were used in testing. The costs for these 6 sets were estimated using three methods (linear regression, non-linear regression and Neural Networks). The mean square error was calculated for each model. It was found that Neural Networks produced the lowest mean square error compared with the other two models. The accuracy level was between 66.8% and 77.96%. This study proves that the Neural Networks approach could be used to resolve some of the major drawbacks of the regression-based parametric estimation.

Creese and Li (1995). In this study. Three models were developed to estimate the cost of timber bridges. A set of actual cases of 12 timber bridges was collected from West Virginia department of highways. Three variables were used as the main factors affecting the total cost: cost of the web. cost of the deck. and weight of the steel used. The study experimented with three Neural Network models to identify the optimum one. The three models consider either one input variable, two input variables, or three input variables, respectively, to predict the total cost. It was observed that the overall training accuracy increased as more input variables were used and as such. the model with three input variables was the best. The initial training of the Neural Networks used al1 available bridges' data and 1,500 training cycles were used. The standard linear regression approach was used to predict the actual cost for the three models using the same variables and r-square values (coefficient of determination) were calculated to evaluate the three models. The study also compared the Neural Networks approach to linear regression analysis and concluded that the estimation accuracy of Neural Networks approach is better than linear regression analysis in timber bridges' types. Another important conclusion of the study is that the cost prediction ability of Neural Networks to improves when more independent variables are introduced in training.

Kartam (1996) use neural network to determine optimal equipment combination for earthmoving operations.

Adli and Karim (1997) present a general mathematical formulation for scheduling of construction projects and apply it to the problem of highway construction scheduling. Repetitive and non repetitive tasks, work continuity consideration, multiple-crew strategies, and the effect of the varying job conditions on the performance of a crew can be modeled. An optimization formulation is presented for the construction project-scheduling problem with the goal of minimizing the direct construction cost.

Chua (1997) used a neural network approach to identity the key management factors that affect budget performance in a project. Field data of project performance has been used to build the budget performance model. Altogether eight key determining factors were identified covering areas related to the project manager, project team, and planning and control efforts, namely: number of organizational levels between project manager and craftsmen, project manager experience on similar technical scope, detailed design complete at start of construction, constructability program, project team turnover rate, frequency of control meetings during construction, frequency of budget updates, and control system budget. The model is able to give good predictions even with previously unseen data and incomplete information on the key factors.

George (1997) development a neural network model to predict preliminary quantities estimate of main items in the navigable spans superstructure of overhead pre-stressed concrete bridges over the river Nile in Egypt. A set of 20 training examples has been collected from the final invoices and bills of quantities of bridge. Brain-Maker professional, a commercially available neural network simulator, was used to train the model. This simulator will be used in this study to predict production rate of pouring ready mix concrete. Multi-layer feed-forward neural network model architecture is used .The model has one input layer of four neurons, one hidden layer with 10 neurons, and output layer with one neurons. Conducting five cross-validation experiments tested the model. Test results showed that the error was less than 11%.

Portas and Abou-Rizk (1997) presented an approach based on artificial neural network to estimate construction productivity for concrete formwork tasks. The system utilizes historical information and input from experienced superintendents employed by a leading construction general contractor. A number of alternatives neural network structures were investigated, the adopted one was a three-layered network with a fuzzy output structure it was found that this structure provided the most suitable model since much of the input was subjective. The model was compared to an existing statistical model developed by the same contractor and was found to improve the quality of the estimates attained.

Elazouni et al. (1997) use the back propagation (BP) algorithm to estimate the construction resource requirement at the conceptual design stage and apply the model to the construction of concrete silo walls.

Adli and Wu (1998) presented a regularization neural network and architecture for estimating the cost of construction projects. The model is applied to estimate the cost of reinforced concrete pavement as an example. The author found that the result of estimation from the regularization neural network depends only on the training examples. It does not depend on the architecture of the neural network, the parameters, and the number of iterations required for training the system. Moreover, the problem of noise in the data is taken into account in a rational manner.

Albino and Garavelli (1998) used a model of neural network to subcontractor rating in construction firms. Neural networks, being able to learn directly by examples the managers' logic, are suitable to support the solution of this type of problem. By an application case related to an assembly operation in a construction site, the neural network implementation and the related managerial and technical innovations are investigated.

Boussabaine and Kaka (1998) developed a model of neural network to forecast cash flow of construction projects. The model takes *n* inputs and produces a forecast of the next *m* periods. The cost curves of 50 projects of medium size ranging in duration from 7 months to 12 months were used in the training. A further l5 cases were used in the testing and verification of the system. The comparison between the actual and forecast cost curves showed very little difference. The testing results are very encouraging, but further testing is required before concluding that a neural networks approach is more accurate than traditional methods.

Hegazy and Ayed (1998) used a neural network (NN) approach to effectively manage construction cost data and develop a parametric cost-estimating model highway projects. Eighteen actual cases of highway projects constructed in Newfoundland, Canada, have, been used as the source of cost data. As an alternative to NN training, two techniques were used to determine network weights: (1) simplex optimization; and (2) genetic algorithms (GAs). Accordingly, the weights that produced the best cost prediction for the historical cases were used to find the optimum NN. To facilitate the use of this NN on new projects , a user - friendly interface was developed using spreadsheet macros to simplify user input and automate cost prediction.

Moselhi and Siqueira (1998) presented an automated cost estimating system for structural steel framing. The system provides quick cost estimates, facilitating negotiations with owners and permitting the checking detailed cost estimates prepared at a later stage. Neural networks were used in the system design in view of their learning and generalization capabilities that suits the cost estimating process. Thirty-four projects collected from a large structural steel fabricator in Canada, with indexed costs, were analyzed and guidelines for data scrutiny were presented. The system run on PC based Windows95 environment, and the data is stored in MS-Exel 7.0 NeuroShell 2, a commercial software, is used for design and training the neural network model. The developed model was designed to estimate direct cost. Markup, overhead and profit were left to the discretion of the management team.

Karim and Adli (1999d) present an object-oriented information model for construction scheduling, cost optimization, and change order management based on the new neural network-based construction-scheduling model of Adli and Karim (1997). The model can be use by the owner/client who has to approve any change order-requests made by the contractor, as well as by the contractor.

Li and Love (1999) use neural network model for construction markup estimation in order to explain how a particular recommendation is made.

Shi (1999) developed a model of neural network for predicting earthmoving operations, this network was then trained using the data patterns obtained from simulation because there are insufficient data available from industrial sources. The trained networks were then incorporated as the computation engine of NN-earth. In practice, NN-earth enables a user to predict the performance of a given earthmoving crew, or to assist the user in the selection of the number of trucks to minimize the unit cost of a project. Simulation has been employed as an alternative approach for obtaining data for training neural networks. The approach seems appropriate because of the lack of high quality data in the construction industry.

Sinha and McKim, (2000) applied an artificial neural network based methodology for predicting the level of organizational effectiveness in a construction firm. The methodology uses the competing value approach to identify 14 variables. These are conceptualized from four general categories of organizational characteristics relevant for examining effectiveness: structural context; person-oriented processes; strategic means and ends; and organizational flexibility, rules, and regulations. In this study, effectiveness was operationalized as the level of performance in construction projects accomplished by the firm in the past 10 years. A multilayer back-propagation neural network based on the statistical analysis of training data has been developed and trained. Findings showed that by applying a combination of the statistical analysis and artificial neural network to a realistic data set, high prediction accuracy is possible.

AbouRizk (2001) developed neural network model that enables an estimator to produce accurate labor production rates (labor/unit) for industrial construction tasks such as welding and pipe installation. This study first reviews factors that were found to affect labor production rates on industrial construction tasks, current estimating practices and their limitations, and the process followed in collecting historical production rates. An artificial neural network model is then described. The model is composed of a two-stage artificial neural network, which is used to predict an efficiency multiplier (an index) based on input factors identified by the user. The multiplier is then used to adjust an average production rate given in man-hours/unit for use on a specific project. Estimates of production rates from the new approach are compared to the existing estimating practices.

Wanous et al. (2003) used a model of neural network as a tool on bid/no bid decision-making process. This model was based on the findings of a questionnaire through which key factors that affect the 'bid/no bid' decision were identified and ranked according to their importance to contractors operating in Syria. The model offers a simple and easy-to-use tool to help contractors consider the most influential bidding variables and to improve the consistency of the bid/no bid decision-making process.

Attalla and Hegazy (2003) investigated the challenging environment of reconstruction projects and described the development of a predictive model of cost deviation in such high-risk projects. Based on a survey of construction professionals, information was obtained on the reasons behind cost overruns and poor quality from 50 reconstruction projects. For each project, the specific techniques used for project control were reported along with the actual cost deviation from planned values. Two indicators of cost deviation were used in this study: cost overrun to the owner, and the cost of rework to the contractor. Based on the information obtained, 36 factors were identified as having direct impact on the cost performance of reconstruction projects. Two techniques were then used to develop models for predicting cost deviation: statistical analysis, and artificial neural networks (ANNs). While both models had similar accuracy, the ANN model is more sensitive to a larger number of variables. Overall, this study contributes to a better understanding of the reasons for cost deviation in reconstruction projects and provides a decision support tool to quantify that deviation.

Rajasekaran (2004) functional networks (FN) proposed by Castillo as an alternative to neural networks are discussed. Unlike neural networks, the functions are learned instead of weights. In general, topology is selected based on data, domain knowledge (properties of the function such as associativity, commutativity, and invariance), or a combination of the two. The object of this paper is to show the application of some functional network architectures to model and predict the behavior of structural systems which are otherwise modeled in terms of differential or difference equations or in terms of neural networks. In this paper, four examples in structural engineering and one example in mathematics are discussed. The results obtained by functional networks are compared with those obtained by neural networks for the first four examples, and it is shown that functional networks are more efficient and powerful and take much less computer time as compared to predictions by conventional neural networks such as the back-propagation network.

Shahin et al. (2004) the issue of data division and its impact on ANN model performance is investigated for a case study of predicting the settlement of shallow foundations on granular soils. Four data division methods are investigated: (1) random data division; (2) data division to ensure statistical consistency of the subsets needed for ANN model development; (3) data division using self-organizing maps (SOMs); and (4) a new data division method using fuzzy clustering. The results indicate that the statistical properties of the data in the training, testing, and validation sets need to be taken into account to ensure that optimal model performance is achieved. It is also apparent from the results that the SOM and fuzzy clustering methods are suitable approaches for data division.

Gunaydin and Dogan (2004) described a model of neural network to overcome cost estimation problem in early phases of building design processes. Cost and design data from thirty projects were used for training and testing the neural network for estimating the square meter cost of reinforced concrete structural systems of 4–8 storey residential buildings in Turkey, an average cost estimation accuracy of 93% was achieved.

Dikmen and Birgonul (2004) developed a neuronet model as a decision support tool that can classify international projects with respect to attractiveness and competitiveness based on the experiences of Turkish contractors in overseas markets. Because the bidding for international construction projects is a critical decision for companies that aim to position themselves in the global construction market and the determination of attractive projects and markets where the competitive advantage of a company is high requires extensive environmental scanning, forecasting, and learning from the experience of competitors in international markets. The model can be used to guide decision makers on which type of data should be collected during international business development and further help them to prepare priority lists during strategic planning. Information derived from the model demonstrates that the most important factors that increase attractiveness of an international project are availability of funds, market volume, economic prosperity, contract type, and country risk rating. Similarly, level of competition, attitude of host government, existence of strict quality requirements, and cultural / religious similarities are the most important factors that affect competitiveness of Turkish contractors in international markets.

Kim et al. (2004a) used ANNs with multiple regression analysis (MRA) and case-based reasoning (CBR) models for estimating construction costs of Korean residential buildings. These three approaches used a data set containing 530 historical costs between 1997 and 2000. Although the best NN estimating model gave more accurate estimating results than either the MRA or the CBR estimating models, the CBR estimating model performed better than the NN estimating model with respect to long-term use, available information from result, and time versus accuracy tradeoffs.

Leu and Lo (2004) used the artificial neural networks to predict the magnitude and the location of maximum ground surface settlement in deep excavation. The validation tests showed the neural network solutions clearly outperformed multiple regression functions in predictive accuracy of ground surface settlement under varying training and testing conditions. For a repetitive construction process like deep excavation, the neural networks learn and extract valuable information from monitoring data of finished excavation stages, and then this information can be feedback to estimate the ground surface settlement prior to the next excavation stage. This data extraction and feedback process will significantly improve the control of ground surface settlement.

Ling and Liu (2004) used neural network technique to construct a model to predict performance of design-build (DB) projects; this model is tested using data from five new projects. Sixty-five factors that may affect DB project success are identified. This study 5nds that six performance metrics can be predicted with a reasonable degree of accuracy: project intensity; construction and delivery speeds; turnover, system and equipment quality. To ensure project success, contractors should have adequate staffing level, a good track record for completion on budget, and ability in financial management and quality control. Consultants should have a high level of construction sophistication, and have handled DB projects in the past.

Clients also play an important part in ensuring DB project success. They would need to have construction experience and handled DB projects in the past.

Kim et al. (2004b) applied the back-propagation network (BPN) model incorporating genetic algorithms (GAs) to cost estimation. GAs were adopted in the BPN to determine the BPN's parameters and to improve the accuracy of construction cost estimation. The construction cost data for 530 residential buildings constructed in Korea between 1997 and 2000 were used for training and evaluating the performance of the model. This study showed that a BPN model incorporating a GA was more effective and accurate in estimating construction costs than the BPN model using trial and error.

Elazouni et al. (2005) employed artificial neural network to anticipate the acceptability of new formwork systems. The study collected data from a group of 40 users in Egypt. A set of six performance characteristics that mostly pertain to acceptability estimating were identified, and used the analytical hierarchy process to produce pairs of a performance characteristics' vector and the corresponding acceptability value, and utilized the developed pairs to train ANN. Finally, tests on trained ANN using unseen data indicated satisfactory performance.

Kim et al. (2005) applied hybrid models of neural networks (NN) and genetic algorithms (GA) to cost estimation of residential buildings to predict preliminary cost estimates. Data used in this study are for residential buildings constructed from 1997 to 2000 in Seoul, Korea. These were used in training each model and evaluating its performance. The models applied were Model I, which determines each parameter of a back-propagation network by a trial-and-error process; Model II, which determines each parameter of a back-propagation network by GAs; and Model III, which trains weights of NNs using genetic algorithms. The research revealed that optimizing each parameter of back-propagation networks using GAs is most effective in estimating the preliminary costs of residential buildings. Therefore, GAs may help estimators overcome the problem of the lack of adequate rules for determining the parameters of NNs.

Wilmot and Mei (2005) developed artificial neural networks to estimate the escalation of highway construction costs over time. The highway construction costs, described in terms of a highway construction cost index, to the cost of construction material, labor, and equipment, the characteristics of the contract and the contracting environment prevailing at the time the contract was let. Results demonstrate that the model is able to replicate past highway construction cost trends in Louisiana with reasonable accuracy.

Ezeldin and Sharara (2006) developed three neural networks to estimate the productivity, within a developing market, for formwork assembly, steel fixing, and concrete pouring activities. Eighteen experts working in six projects were carefully selected to gather the data for the neural networks. Ninety-two data surveys were obtained and processed for use by the neural networks. Commercial software was used to perform the neural network calculations. The processed data were used to develop, train, and test the neural networks. The results of the developed framework of neural networks indicate adequate convergence and relatively strong generalization capabilities. When used to perform a sensitivity analysis on the input factors influencing the productivity of concreting activities, the framework has demonstrated a good potential in identifying trends of such factors.

Achim et al. (2007) development of a new application of neural networks (NN) for prediction of pipeline failure. Results show higher correlations with recorded data when compared with the two existing statistical models. The shifted time power model gives results in total number of failures and the shifted time exponential model gives results in number of failures per year. The database was large but neither complete and nor fully accurate. Factors influencing pipeline deterioration were missing from the database. Using the NN technique on this database produced models of pipeline failure, in terms of failures/km/year, that more closely matched the number of failures of a particular asset recorded for the period.

Jain et al. (2008) developed Artificial neural network (ANN) and regression models for the estimation of concrete slump using concrete constituent data. The concrete mix constituent and slump data from laboratory tests have been employed to develop all models. The results obtained in this study demonstrate the superiority of the ANN models. It was found that combining one or more concrete mix constituents and treating them as an independent input variable is not advantageous when using regression but can be very useful when using ANNs for modeling concrete slump. Sensitivity analyses based on the ANN models were carried out to evaluate the impact of different concrete mix constituents on the slump values. It was found that the slump attains a minimum value at the critical levels of mortar and coarse aggregates, and tends to increase with paste content and decrease with sand content in the concrete mix.

This review was concentrate on the ANN techniques and concepts useful in construction management and help to identify opportunities where this new technology is applicable in assisting decision makers. This review provides guidance and tips for the development of successful applications in construction management.

However, until now there is no research in Egypt applied ANNs technique to predict the weight of LRSB. Therefore and because of the importance of the ANNs as an essential tool that used in construction industry, the ANN will be applied as a main objective of this thesis to achieve or target.

CHAPTER 4

PARAMETERS AFFECTING THE MATERIAL WEIGHT OF STEEL STRUCTURE OF LOW RISE STEEL BUILDING

4.1 Parameters Identification

The developing of the proposed ANN model necessitated the identification of the various design factors that influence the material weight of steel structure of LRSB. A thorough review of the literature resulted in identifying 19 potential factors that could affect the material weight of steel structure of LRSB. These factors are:

1. Type of the building (rigid frame or truss)
2. Width of the building
3. Length of the building
4. Eave Height of the building
5. Roof slope
6. No. of interior columns
7. First bay spacing
8. Intermediate bay spacing
9. Last bay spacing
10. Earthquake load
11. Wind load
12. Steel grade (37, 44 & 52)
13. End wall columns
14. Side wall bracing
15. Roof bracing
16. End wall opening area
17. Side wall opening area
18. Code of design
19. Roof opening

To determine the relative importance of these factors, data were collected from engineers working in specialty steel fabrication companies and specialty consultants working in Egypt.

The method used for the collection of the information is the interview based on a written questionnaire.

4.2 Interviewers Result

The interviews were conducted with a randomly selected sample of steel manufacturing companies and consultants. The sample of steel companies was selected from the 2008 classified companies list which is published by Mesteel (2008). According to Mesteel (2008), there are only 6 classified steel manufacturing companies, that work in Cairo – Egypt and that their work volume ranges between 20-50 thousand ton of fabricated steel per year (mesteel 2008). The interviews were conducted with random numbers of engineers working in a random selected four from six classified steel manufacturing companies. Also interviews were conducted with randomly selected consultants. A total of 20 interviews were conducted, 12 interviews with engineers working in steel manufacturing companies and 8 interviews with specialty consultants. During the interviews, each of the respondents was asked to assign a one-to-five rating for each of the 19 parameters, where **1** is a **very low** impact, **2** is a **low** impact, **3** is a **medium** impact, **4** is a **high** impact and **5** is a **very high** impact. The questionnaire which was the basis for formal interviews with the participants was divided into two main parts. The first part dealt with personal data about the participant (name, position, and years of experience). The second part presents the 19 most common parameters and asks the participants to mention the degree of importance for each parameter due to the above mentioned grade, a free space also left for any additional parameters.

The companies' names and the numbers of conducted interviews for the specialty steel manufacturing companies and the specialty consultants are listed in Table 4.1.

Table 4.1: Sample size

Name	No. of conducted interviews
Steel Manufacturing Companies	
Energya Steel Co.	4
Zamil Steel Co.	4
DSD- Ferrometalco for Metallic Construction	2
ARESCO - ASEC for casting & heat treatment	2
Consultant Engineers	
Arab Consulting Engineers (ACE)	2
ECG	2
EGEC	2
Dar Al-Handasa	2

The following equation was applied to calculate the mean score (MS) for each parameter (Chan and Kumaraswamy (1996)).

$$MSi = \Sigma (f \times S) / N$$

where S = score given to each parameter by the respondents; f = frequency of responses to each score for each parameter; N = total number of responses; and i = respective parameter.

The mean scores of the parameters were calculated and the relative rankings of their significance and effectiveness were obtained in descending order.

Tables 4.2 and 4.3 illustrate the score and the mean score of each parameter from point of view of both the specialty manufacturing companies and the specialty consultants respectively.

Table 4.2: Score and the mean score of parameters from manufacturing companies point of view

Manufacturing Companies Questionnaires Result			
Parameters	Score	Mean Score	Rank
- Length of building	58	4.83	1
- Width of building	56	4.67	2
- Steel grade (37, 44 & 52)	55	4.58	3
- Type of building (rigid frame or truss)	55	4.58	4
- Intermediate bay spacing	54	4.50	5
- Code of design	54	4.50	6
- No. of interior columns	51	4.25	7
- Eave Height of building	51	4.25	8
- Last bay spacing	41	3.42	9
- First bay spacing	41	3.42	10
- Roof slope	32	2.67	11
- Side wall bracing	29	2.42	12
- Wind load	28	2.33	13
- End wall columns	27	2.25	14
- Roof bracing	26	2.17	15
- Roof opening	21	1.75	16
- Side wall opening area	21	1.75	17
- End wall opening area	19	1.58	18
- Earthquake load	16	1.33	19

Tables 4.3 illustrated that the most effective parameters from the manufacturing companies point of view were the length of building, the width of building, steel grade, type of the building (rigid frame or truss), intermediate bay spacing, design code, No. of interior columns, eave height, last and first bay spacing in the building respectively.

Table 4.3: Score and the mean score of parameters from specialty consultants point of view

Consultants Questionnaires Result			
Parameters	Score	Mean Score	Rank
- Length of building	38	4.75	1
- Width of building	38	4.75	2
- Type of building (rigid frame or truss)	37	4.63	3
- Intermediate bay spacing	36	4.50	4
- Eave Height of building	35	4.38	5
- Code of design	34	4.25	6
- No. of interior columns	33	4.13	7
- Steel grade (37, 44 & 52)	33	4.13	8
- Last bay spacing	27	3.38	9
- First bay spacing	27	3.38	10
- Roof slope	22	2.75	11
- Side wall bracing	21	2.63	12
- Wind load	18	2.25	13
- End wall columns	17	2.13	14
- Roof bracing	16	2.00	15
- Side wall opening area	15	1.88	16
- Roof opening	13	1.63	17
- End wall opening area	13	1.63	18
- Earthquake load	10	1.25	19

Tables 4.2 illustrated that the most effective parameters from the specialty consultants point of view were the length of building, the width of building, type of the building (rigid frame or truss), intermediate bay spacing, eave height, design code, number of interior columns, steel grade, eave height, last and first bay spacing in the building respectively.

Table 4.2 and 4.3 illustrated that the most effective parameters between the manufacturing companies and the specialty consultants are very close. Therefore, the distributed questionnaire were sufficient. The result of all questionnaires are illustrated in Table 4.4.

Table 4.4: Overall ranking

All Questionnaires Result			
Parameters	Score	Mean Score	Rank
- Length of building	96	4.8	1
- Width of building	94	4.7	2
- Type of building (rigid frame or truss)	92	4.6	3
- Intermediate bay spacing	90	4.5	4
- Code of design	88	4.4	5
- Steel grade (37, 44 & 52)	88	4.4	6
- Eave Height of building	86	4.3	7
- No. of interior columns	84	4.2	8
- Last bay spacing	68	3.4	9
- First bay spacing	68	3.4	10
- Roof slope	54	2.7	11
- Side wall bracing	50	2.5	12
- Wind load	46	2.3	13
- End wall columns	44	2.2	14
- Roof bracing	42	2.1	15
- Side wall opening area	36	1.8	16
- Roof opening	34	1.7	17
- End wall opening area	32	1.6	18
- Earthquake load	26	1.3	19

4.3 Most Important Parameters

Parameters with mean score equal to or greater than three are considered as the most important parameters. The results indicated that ten parameters could be considered as the most important parameters. They are length of the building, width of the building, type of the building, intermediate bay spacing, steel grade, code of design, eave height of the building, number of interior columns, first bay spacing, and last bay spacing.

Following considerations are taken into account for some of these parameters: (1) the type of building is considered to be rigid frame. (2) the building should has no interior columns to provide a greater area for production and plant movement - clear span (see Fig 4.1) except the end wall columns to resist the wind load (see Fig 4.2). (3) the steel grade is St. 52 which is the most common used for LRSB in Egypt. (4) the code of design is the Egyptian code. The remaining six parameters were considered to be the main input parameters to be used in the modeling and training of the network. They are length of the building, width of the building, intermediate bay spacing, eave height of the building, first bay spacing, and last bay spacing.

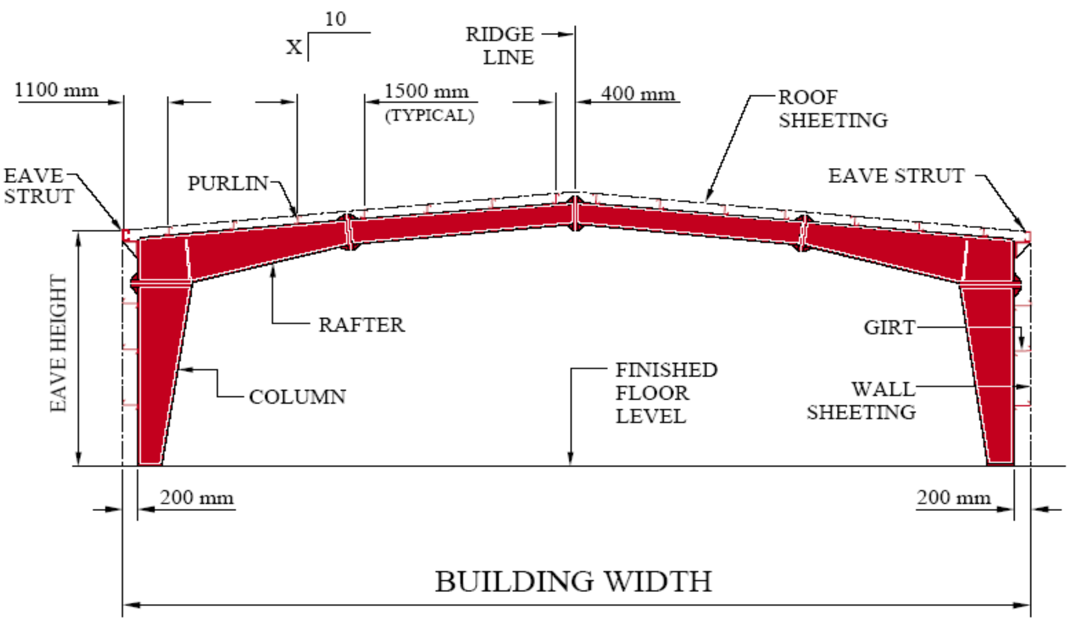


Fig 4.1: Shape of the clear span type

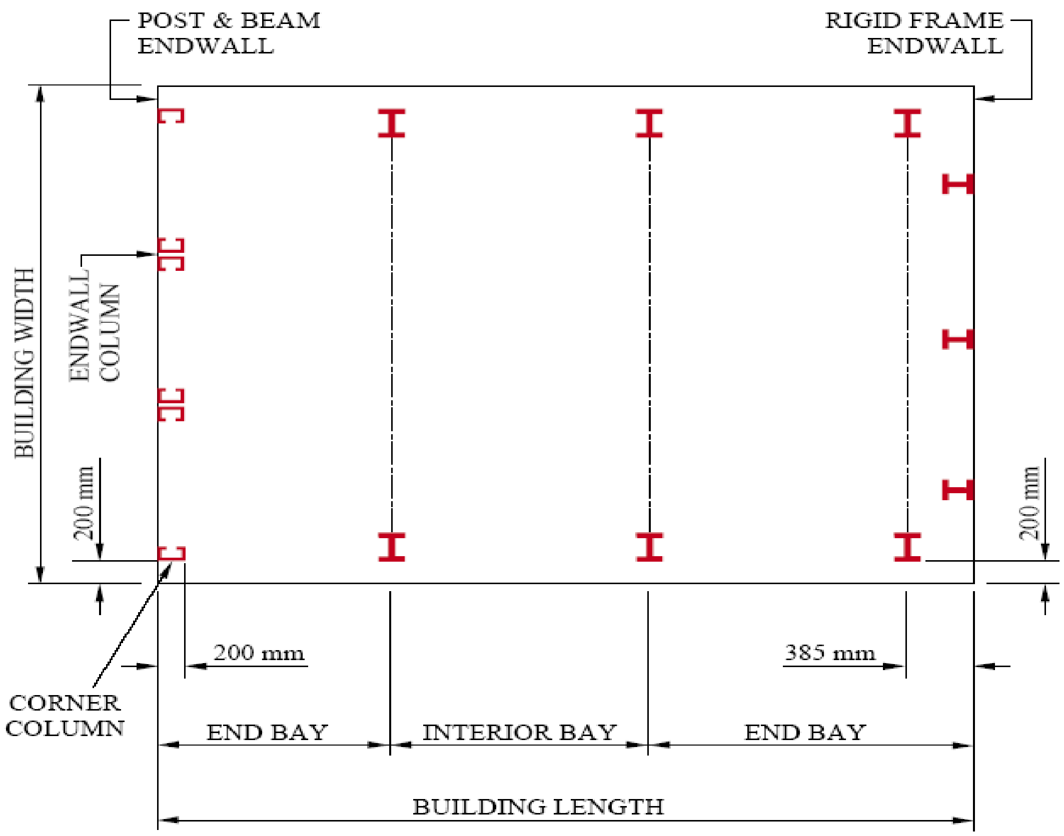


Fig 4.2: Plan View of LRSB

The importance of these parameters can be summarized as follow:

Length of building: the length of building has a larger affection on the no. of frames (see Fig 4.1) and the no. of bay spacing (see Fig 4.2), whereas, increasing/decreasing in length can generate more/less own weight load coming from the increasing/decreasing in the purlin length which means increasing/decreasing in the internal force (bending moment, shear and normal force) that affecting on the type and shape of cross section. Sometimes, increasing in length can not be covered by increasing in the purlin length which will force to put another frame and the same case can be understanding also if the length decreased. Therefore, the minor effect in the building length can generate a larger affection on the building weight.

Width of building: the width of building has a larger affection on the frame weight (see Fig 4.1), whereas, increasing/decreasing in width can generate more/less own weight load coming from the increasing/decreasing in the rafter length which means increasing/decreasing in the internal force (bending moment, shear and normal force) that affecting on the type and shape of cross section of the rafter. Sometimes, increasing/decreasing in width can increase/decrease the size and shape of columns which transfer the load from rafter to footing which means increasing/decreasing in the frame weight. Therefore, the minor effect in the building width can generate a larger affection on the building weight.

Eave height of building: the height of building has a larger affection on the columns weights (see Fig 4.1), whereas, increasing in building height can generate buckling affection which means increasing in the column cross section to be more stiff to resist this buckling affection. Therefore, the size and shape of columns mostly coming from the internal force (bending moment, shear and normal force) from rafter and from the buckling affection. The increasing/decreasing in the columns cross section have a strong affection on the footing size and also in the anchor bolts numbers and size. Therefore, the building height has a larger affection on the building weight.

Bay spacing (first, intermediate and last) of building: the bay spacing of building (see Fig 4.2) has a larger affection on the no. of frames (see Fig 4.1), whereas, increasing/decreasing in the bay spacing can generate more/less own weight load coming from the increasing/decreasing in the purlin length which means increasing/decreasing in the internal force (bending moment, shear and normal force) and special form deflection effect will affect on the type and shape of cross section which mostly prepared from cold formed section to be light and to achieve the stresses requirements. Sometimes, increasing in length can not be covered by increasing in the purlin length which will force to put another frame. Therefore, the minor effect in the bay spacing length can generate a larger affection on the building weight.

CHAPTER 5

THE DESIGN OF ARTIFICIAL NEURAL NETWORK MODEL

5.1 Developing Neural Network Model

Two programmes are used to train the NN model one of them is developed by Hegazy and Ayed (1998) and the other programme is **BrainMaker** Professional version 3.73 (2001) which development by California university.

The records of 80 **LRSB** that contain data on all of the selected six design parameters and the corresponding weight of the structural steel framing are used in developing the proposed ANN model. There are only 6 classified steel manufacturing companies, which work in Cairo – Egypt and that their work volume ranges between 20-50 thousand ton of fabricated steel per year (mesteel 2008). The design data and weight of these 80 projects were gathered from one of these companies during the time frame 2003 and 2005. The range of data for these design parameters are presented in Table 5.1 and the collected date are presented in Table 5.2.

Table 5.1: Data range

Design parameter	Definition	Range
x1	The width of the building	14.00 (m) – 30.70 (m)
x2	The length of the building	23.00 (m) – 192.77 (m)
x3	The eave height of the building	4.10 (m) – 10.00 (m)
x4	The first bay spacing	5.16 (m) – 8.16 (m)
x5	The intermediate bay spacing	6.00 (m) – 8.00 (m)
x6	The last bay spacing	4.19 (m) – 8.16 (m)
y	The weight of the steel structure	6.59 (ton) – 100.98 (ton)

Table 5.2: Collected data

Project No.	Area (m2)	Weight (Ton)		Project No.	Area (m2)	Weight (Ton)
1	1885.26	30.40		41	1056.45	22.14
2	1062.74	17.13		42	618.15	12.95
3	1000.00	23.07		43	896.86	30.10
4	1600.00	36.92		44	1430.38	48.00
5	783.47	19.24		45	806.20	19.15
6	527.37	12.95		46	1286.20	30.55
7	723.84	18.45		47	1008.00	20.50
8	518.64	13.22		48	648.00	13.18
9	695.20	14.02		49	1344.00	31.64
10	1081.28	21.80		50	896.00	21.09
11	864.00	17.16		51	576.00	13.91
12	1382.40	27.45		52	1008.00	24.34
13	902.75	20.81		53	834.42	22.32
14	602.75	13.89		54	1331.22	35.61
15	585.72	11.03		55	1369.04	32.17
16	911.00	17.16		56	983.54	23.11
17	421.08	10.84		57	2472.58	52.17
18	635.58	16.37		58	1428.78	30.14
19	480.00	12.66		59	608.00	17.48
20	960.00	25.32		60	400.00	11.50
21	720.00	21.56		61	582.13	11.73
22	480.00	14.38		62	877.82	17.68
23	322.00	6.59		63	1851.52	38.27
24	644.00	13.18		64	1160.77	23.99
25	540.00	17.84		65	1210.89	26.94
26	864.00	28.54		66	866.80	19.28
27	1197.17	20.30		67	1413.21	31.64
28	753.92	12.78		68	893.01	19.99
29	577.50	9.77		69	1450.00	41.23
30	924.00	15.63		70	1035.59	29.44
31	627.21	13.49		71	4761.42	100.98
32	1092.96	23.51		72	752.75	16.41
33	1068.75	18.79		73	618.80	15.66
34	753.75	13.25		74	691.20	17.81
35	1056.02	22.65		75	1200.00	33.63
36	744.02	15.96		76	1542.96	43.23
37	462.84	12.03		77	1450.00	44.80
38	689.04	17.91		78	1035.59	32.00
39	1544.21	32.98		79	1012.50	21.65
40	1083.71	23.15		80	1687.50	36.09

The weight and design parameters related data from 80 projects were divided into two sets: one set for training the neural network including 65 projects; and the second set for testing the neural network containing 15 projects that were selected at random. There are no acceptable generalized rules to determine the size of the training data for suitable training; however, the training sample should cover all spectrums of data available (Günaydin and Doğan 2004).

Data are generally normalized for confidentiality and for effective training of the model being developed. The normalization of training data is recognized to improve the performance of trained networks (Hegazy et al. 1994). Also in this study, the input and output values were normalized for training and testing purposes.

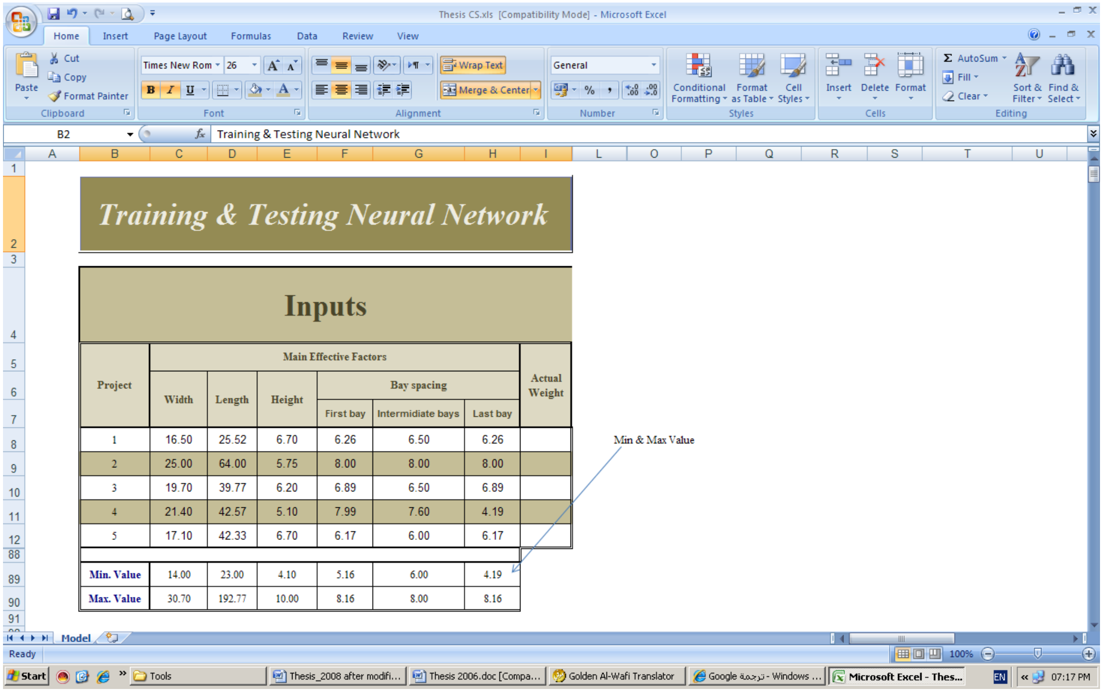
5.1.1 Spreadsheet Model:

Hegazy and Ayed (1998) developed a simple and more transparent approach to NN modeling. A spreadsheet simulation of a three-layer NN with one output node was implemented on Microsoft Excel. The spreadsheet represents a template for one hidden-layer NN that is suitable for most applications. The processing of the template incorporates seven steps, following the widely known back-propagation formulation.

The main steps are applied to develop the proposed neural network model to predict the weight of steel structure of LRSB with a new interface as follow:

Step 1. Data Organization: As a preliminary stage to NN modeling, the problem at hand needs to be thoroughly analyzed. Through this process, the independent factors affecting the problem are identified and considered as (N) input parameters represented by nodes at the input buffer of an NN. Similarly, the number of associated outputs or conclusions (O) are represented by nodes at the output layer. Once input and output parameters are identified their corresponding data are collected from the (P) case studies. To implement this step in an Excel spreadsheet, the data is first transformed into numerical values and stored in a data list that is a matrix of (N + 0) columns and (P) rows as shown in Fig. 5.1. Depending on the type of transformation used, the number of NN nodes (N) will be determined and, accordingly, the size of the spreadsheet matrix.

For each variable, the minimum and maximum values were also put in spreadsheet formulas to be used in Step 2 as shown in Fig 5.1.



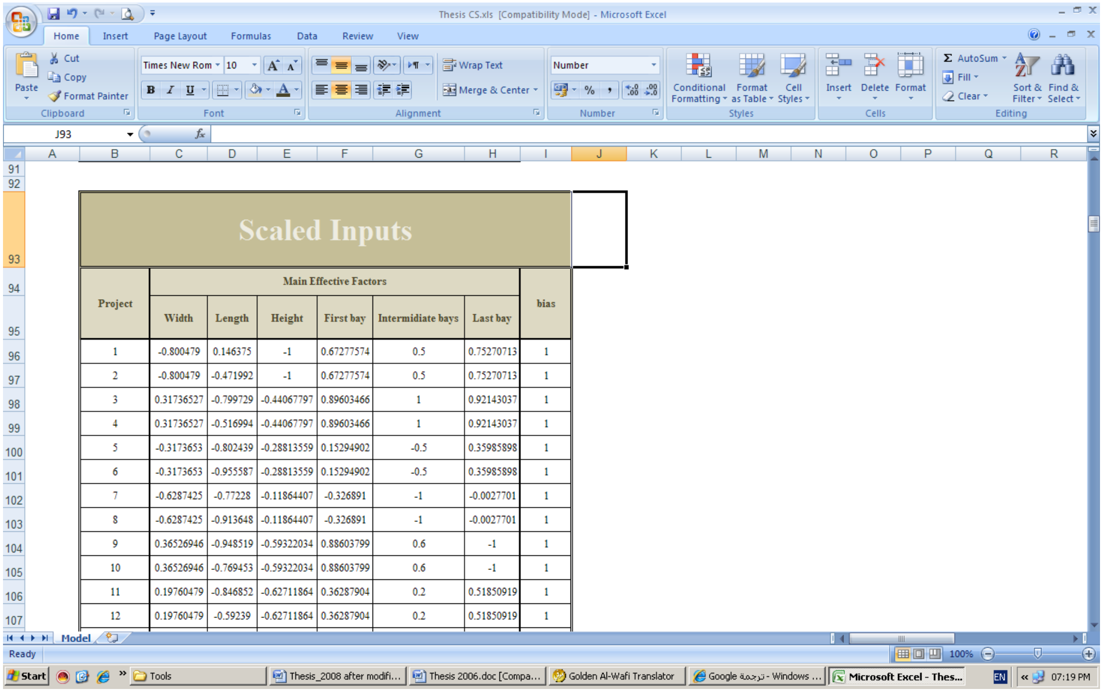
Project	Main Effective Factors						Actual Weight
	Width	Length	Height	Bay spacing			
				First bay	Intermidiate bays	Last bay	
1	16.50	25.52	6.70	6.26	6.50	6.26	
2	25.00	64.00	5.75	8.00	8.00	8.00	
3	19.70	39.77	6.20	6.89	6.50	6.89	
4	21.40	42.57	5.10	7.99	7.60	4.19	
5	17.10	42.33	6.70	6.17	6.00	6.17	
Min. Value	14.00	23.00	4.10	5.16	6.00	4.19	
Max. Value	30.70	192.77	10.00	8.16	8.00	8.16	

Fig 5.1: Organization of data

Step 2. Data Scaling: In this step, the input-data part of the first matrix (N columns by P rows) is scaled to a range from [-1 to 1] to suit NN processing. This is done by constructing a second matrix with a linear formula for scaling the values of the first matrix, as follows:

$$\text{Scaled Value} = \frac{2 \times (\text{Unscaled Value} - \text{Column Min})}{(\text{Column Max} - \text{Column Min})} - 1$$

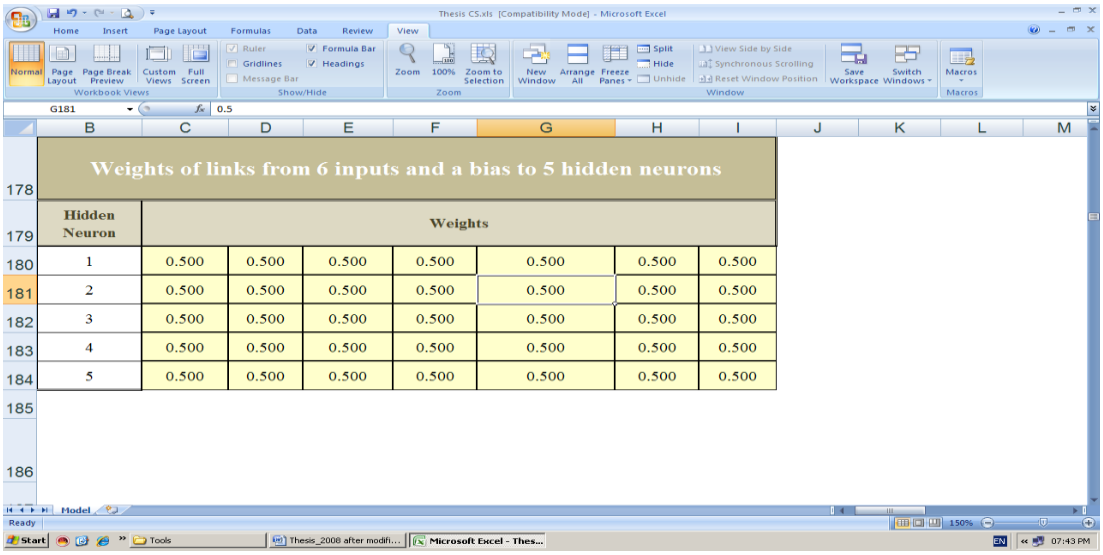
This scaling formula is written in only one cell, and then copied to all cells in the scaling matrix. To the right of this matrix, a column was added with unit values associated with the bias node, as shown in Fig. 5.2.



Scaled Inputs							
Project	Main Effective Factors						bias
	Width	Length	Height	First bay	Intermidiate bays	Last bay	
1	-0.800479	0.146375	-1	0.67277574	0.5	0.75270713	1
2	-0.800479	-0.471992	-1	0.67277574	0.5	0.75270713	1
3	0.31736527	-0.799729	-0.44067797	0.89603466	1	0.92143037	1
4	0.31736527	-0.516994	-0.44067797	0.89603466	1	0.92143037	1
5	-0.3173653	-0.802439	-0.28813559	0.15294902	-0.5	0.35985898	1
6	-0.3173653	-0.955587	-0.28813559	0.15294902	-0.5	0.35985898	1
7	-0.6287425	-0.77228	-0.11864407	-0.326891	-1	-0.0027701	1
8	-0.6287425	-0.913648	-0.11864407	-0.326891	-1	-0.0027701	1
9	0.36526946	-0.948519	-0.59322034	0.88603799	0.6	-1	1
10	0.36526946	-0.769453	-0.59322034	0.88603799	0.6	-1	1
11	0.19760479	-0.846852	-0.62711864	0.36287904	0.2	0.51850919	1
12	0.19760479	-0.59239	-0.62711864	0.36287904	0.2	0.51850919	1

Fig 5.2: Scaling of input values

Step 3. Weight Matrix (W): The third step is to construct and initialize the weight matrix between the inputs and the hidden layer. All inputs (1 to N) and a bias node were fully connected to the hidden nodes. The number of hidden nodes (L) was set as five hidden nodes. All of the values in the weight matrix are considered variables to be determined in NN modeling. Through preliminary experimentation, it was found that setting the initial weight values to a range (0.5 to 1) is appropriate for inputs scaled to a range (-1 to 1) As shown in Fig. 5.3.



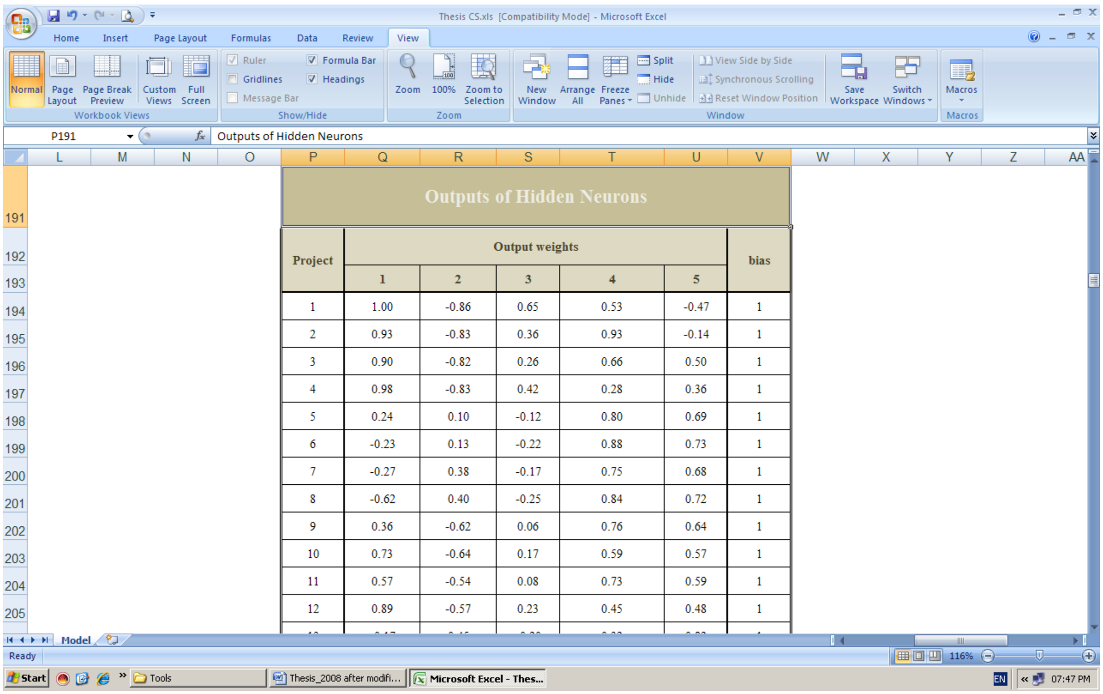
Weights of links from 6 inputs and a bias to 5 hidden neurons							
Hidden Neuron	Weights						
1	0.500	0.500	0.500	0.500	0.500	0.500	0.500
2	0.500	0.500	0.500	0.500	0.500	0.500	0.500
3	0.500	0.500	0.500	0.500	0.500	0.500	0.500
4	0.500	0.500	0.500	0.500	0.500	0.500	0.500
5	0.500	0.500	0.500	0.500	0.500	0.500	0.500

Fig 5.3: weight matrix

Step 4. Output of Hidden Nodes: This step is to allow the hidden nodes to process the input data and produce values to be forwarded to the next layer. According to NN processing as shown in Fig. 5.5, each hidden node j receives an activation X,, which is the sum product of scaled inputs by their associated connection weights. Accordingly, each hidden node produces an output Xj that is a function of its activation, as follows:

$$X_j = \sum_{i=1}^{N} (I_i \times W_{ij}) + B_{1j} \times 1.0$$

$$X_j' = \tanh(X_j)$$



Outputs of Hidden Neurons

Project	Output weights 1	2	3	4	5	bias
1	1.00	-0.86	0.65	0.53	-0.47	1
2	0.93	-0.83	0.36	0.93	-0.14	1
3	0.90	-0.82	0.26	0.66	0.50	1
4	0.98	-0.83	0.42	0.28	0.36	1
5	0.24	0.10	-0.12	0.80	0.69	1
6	-0.23	0.13	-0.22	0.88	0.73	1
7	-0.27	0.38	-0.17	0.75	0.68	1
8	-0.62	0.40	-0.25	0.84	0.72	1
9	0.36	-0.62	0.06	0.76	0.64	1
10	0.73	-0.64	0.17	0.59	0.57	1
11	0.57	-0.54	0.08	0.73	0.59	1
12	0.89	-0.57	0.23	0.45	0.48	1

Fig 5.4: Outputs of hidden nodes

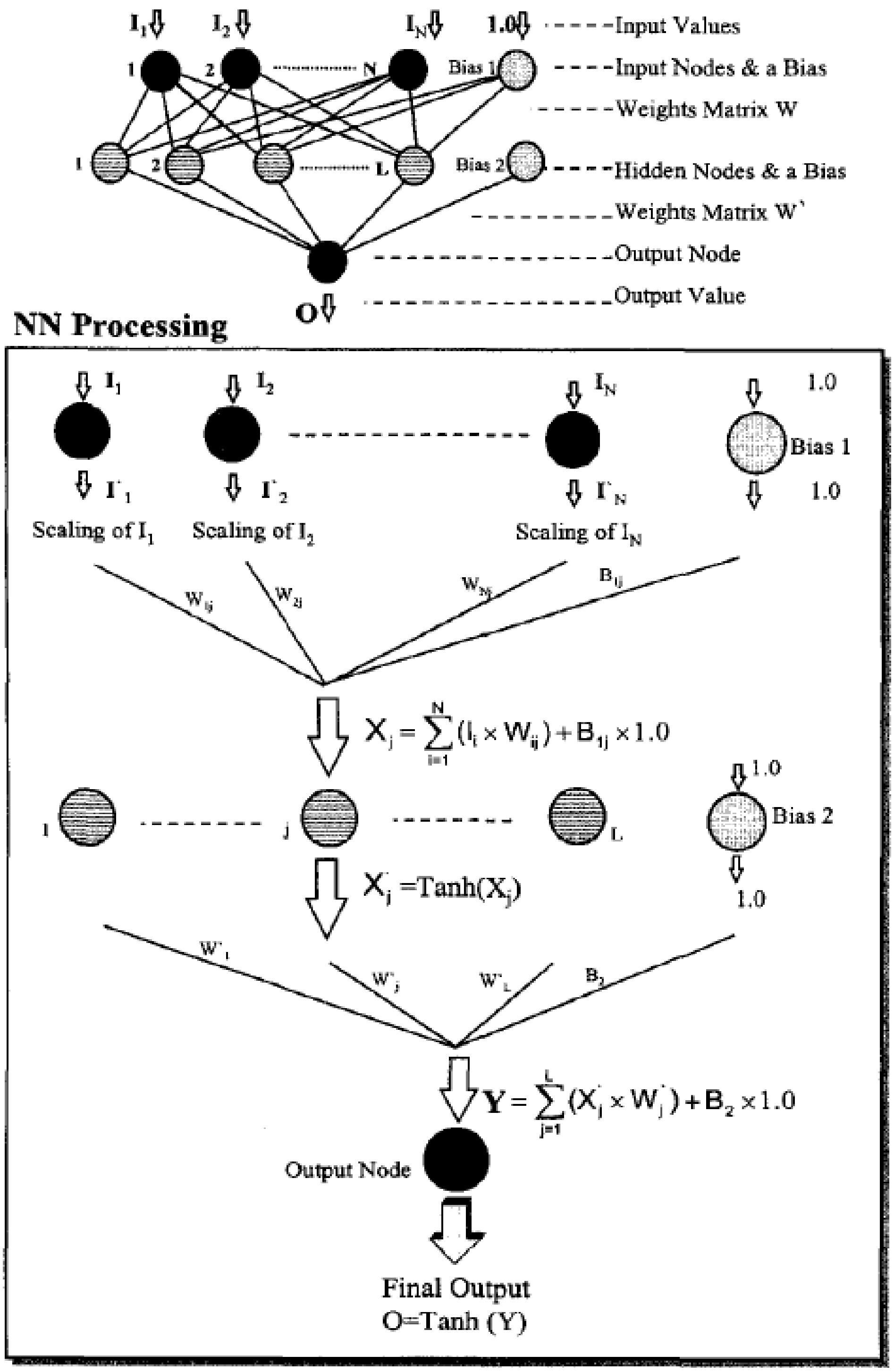
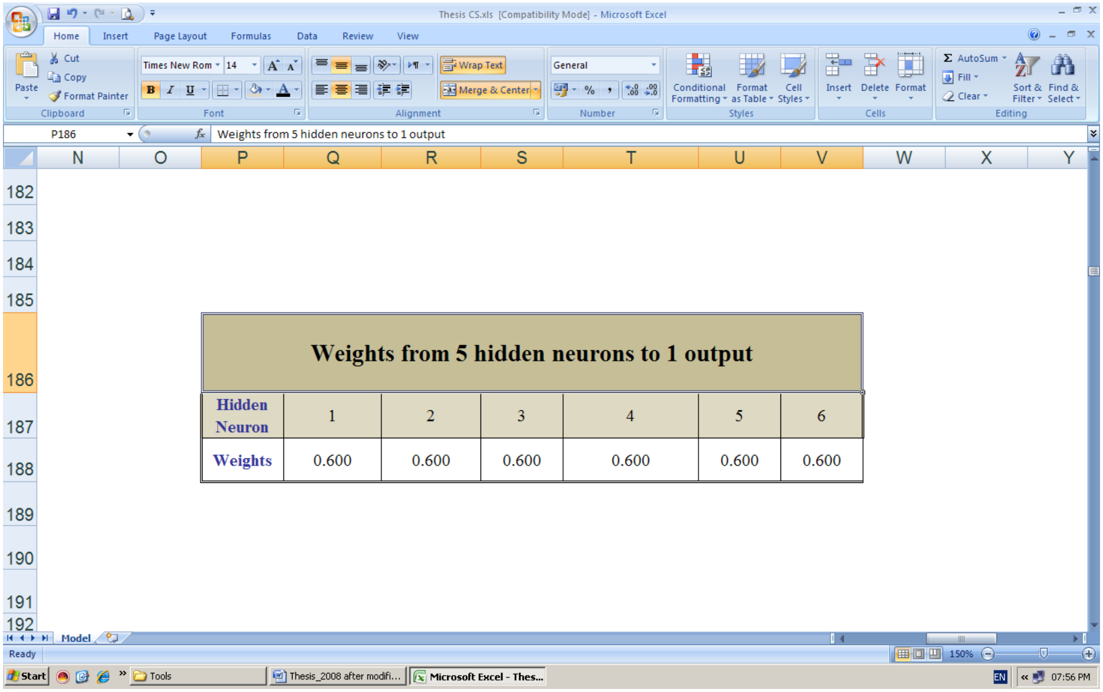


Fig 5.5: Schematic diagram of NN

Step 5. Weight Matrix (W'): Similar to the weight matrix constructed in Step 3, a second matrix was constructed to connect the (L) hidden and bias nodes to the single output node. These weights are additional variables in the model and were initialized as previously described as shown in Fig. 5.6.



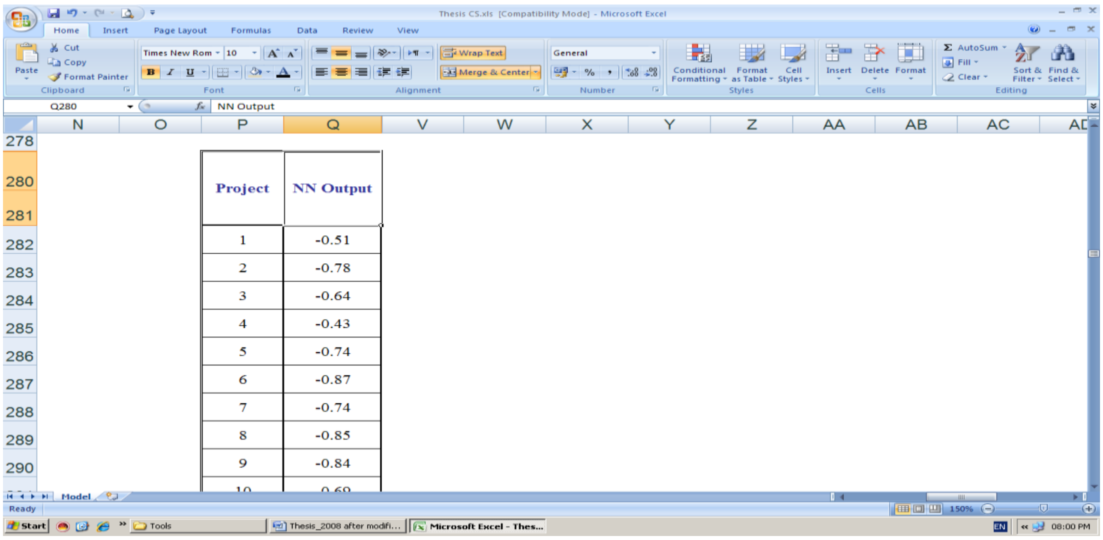
Weights from 5 hidden neurons to 1 output						
Hidden Neuron	1	2	3	4	5	6
Weights	0.600	0.600	0.600	0.600	0.600	0.600

Fig 5.6: Weights from hidden nodes to output node

Step 6. Final NN Output: Similar to Step 4, the output of the NN (0) is computed by calculating the sum product (Y) of each hidden node by its connection weight and then processing this value through the tanh function as shown in Step 6 of Fig. 5.7 as follows:

$$Y = \sum_{j=1}^{L} (X'_j \times W'_{j1}) + B_2 \times 1.0$$

$$O = \tanh(Y)$$



Project	NN Output
1	-0.51
2	-0.78
3	-0.64
4	-0.43
5	-0.74
6	-0.87
7	-0.74
8	-0.85
9	-0.84

Fig 5.7: Final NN outputs

Step 7. Scaling Back NN Output and Calculating the Error-In this step, the NN output (0) is scaled back to the original range of values using the reverse of scaled value equation in step 2 as follows:

$$\text{Output Scaled Back} = \frac{(\text{Output Value} + 1)(\text{Max Output} - \text{Min Output})}{2} + \text{Min Output}$$

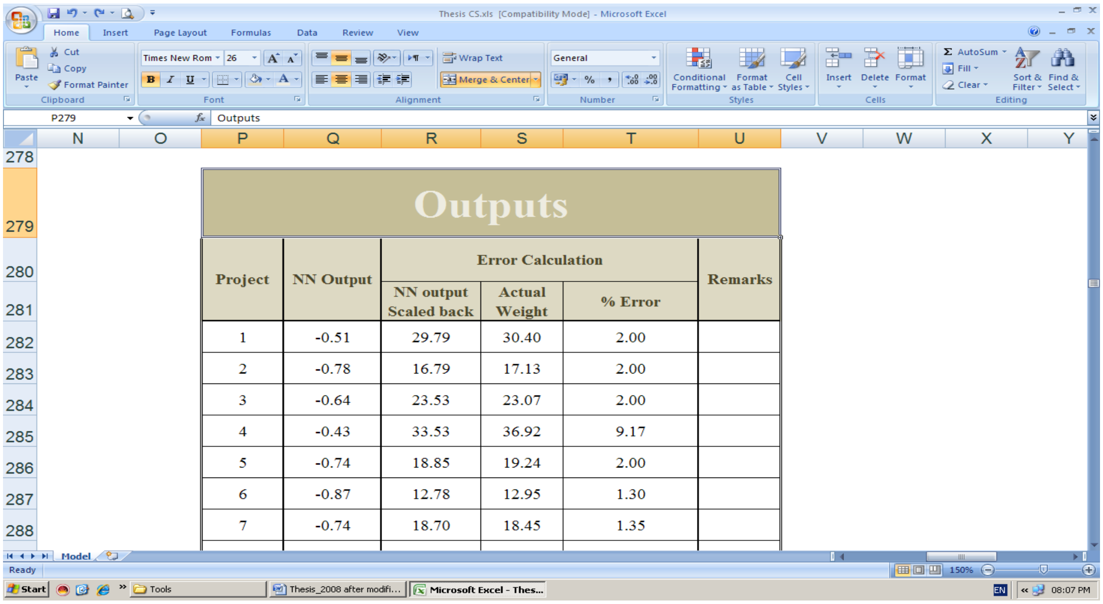
To calculate a measure of the NN performance, a column is constructed for determining the error between the actual output and NN output as follows:

$$\text{Estimating Error (\%)} = \frac{(\text{Neural Network Output} - \text{Actual Output})}{\text{Actual Output}} \times 100$$

It is also possible in the NN simulation to use some cases for training and others for testing. The average error of each group of cases can be calculated in a different cell and then combined in a cell that calculates the performance measure of the NN, for example:

Weighted Error (%) = 0.5 (Test set average error) + 0.5 (Training set average error)

where weights of 0.5 and 0.5 were assumed for illustration. This approach gives more emphasis to the test cases (which are usually a small number as compared to training cases), to ensure good generalization performance and avoid overtraining As shown in of Fig. 5.8.



Outputs

Project	NN Output	Error Calculation			Remarks
		NN output Scaled back	Actual Weight	% Error	
1	-0.51	29.79	30.40	2.00	
2	-0.78	16.79	17.13	2.00	
3	-0.64	23.53	23.07	2.00	
4	-0.43	33.53	36.92	9.17	
5	-0.74	18.85	19.24	2.00	
6	-0.87	12.78	12.95	1.30	
7	-0.74	18.70	18.45	1.35	

Fig 5.8: Scaling output back & calculating the error

5.1.1.1 Modeling Phase:

The modeling phase includes the design of the neural network architecture. It is a complex and dynamic process that requires the determination of the internal structure and rules (i.e., the number of hidden layers and neurons and the type of activation function). The model is designed according to the type of the data and the response required by the application. The current model has been designed to include an input layer of six processing elements (neurons) corresponding to the six input parameters and an output layer of one processing element (neuron) as the target. One hidden layer of five processing elements was selected after several trials during the testing phase shown in Fig. 5.9. The function of the hidden layer is to extract and remember the useful features and the sub-features from the input patterns to predict the outcome of the network (values of the output layer) (Rafiq et al. 2001). Therefore, an effective number of processing elements is usually determined by trials for the hidden layers, since there is no rule to determine it (Albino and Garaveli 1998; Rafiq et al. 2001). The neural network model is empirically, rather than theoretically derived.

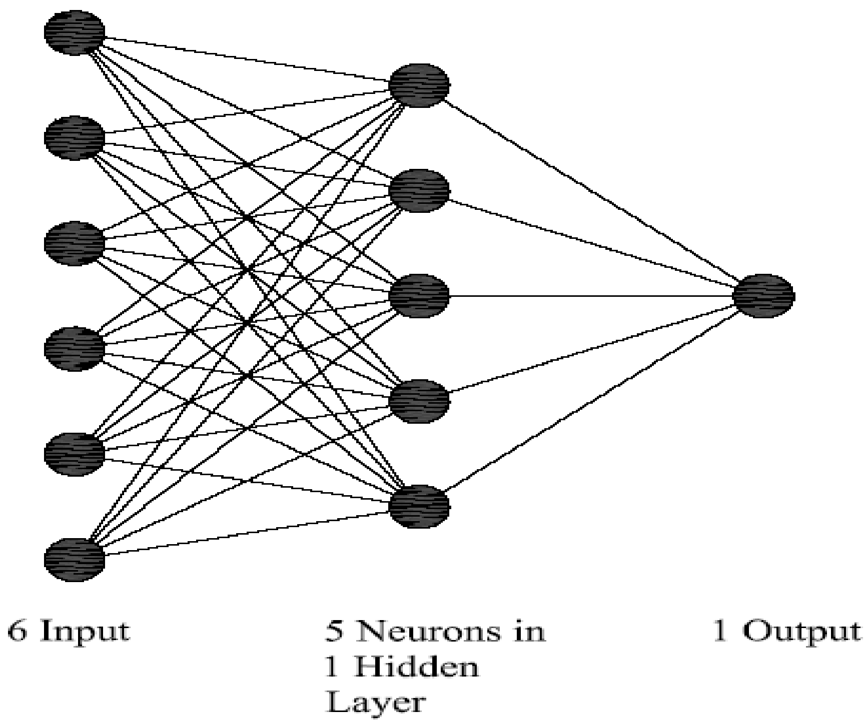


Fig 5.9: the structure of successful neural network spreadsheet model

5.1.1.2 Training Phase:

An important issue to be resolved when applying neural networks to a problem is to determine which training procedure to adopt (Albino and Garavelli 1998). There are many other alternative paradigms to choose from. The back propagation algorithm which belongs to the realm of supervised learning is the most widely used training technique for problems similar to the current study (Hegazy and Ayed 1998; Siqueira 1999).

All trial models experimented in this study was trained in a supervised mode by a back-propagation learning algorithm. Accordingly, the connection weights are modified continuously until the error between the desired output and the model output is minimized and the modeler has decided on the size of the training set and training type, network architecture, and the number of iterations for achieving best model outputs.

The Back-propagation algorithm involves the gradual reduction of the error between model output and the target output. Hence it develops the input to output mapping by minimizing the percentage error of the steel structure weight function.

The percentage error formula between the actual output and the NN output is expressed as Eq.:

$$\text{Estimating Error (\%)} = \frac{\text{(Neural Network Output - Actual Output)}}{\text{Actual Output}} \times 100$$

It was used for evaluating the performance of the model during the training process. Generally, there is no advantage to train a neural network beyond the point where its performance ceases to improve for the set of test observations. Training should be stopped when the absolute mean error remains unchanged. This is done in order to avoid overtraining, in which case the network memorizes the training values and is unable to make predictions when an unknown example is presented to it (Günaydin and Doğan 2004).

5.1.1.3 Testing Phase:

Data from 15 projects were used for testing purposes. Results show 93.55% average accuracy with a mean absolute percentage error calculated for the neural network model over the entire testing data set equals 6.45%. These figures are considered to be good weight estimation for this trained model. The minimum and maximum deviations of the weight estimate from the actual steel structure weight are 1.18% and 14.93%, respectively as shown in Fig 5.10 and presented in Table 5.3.

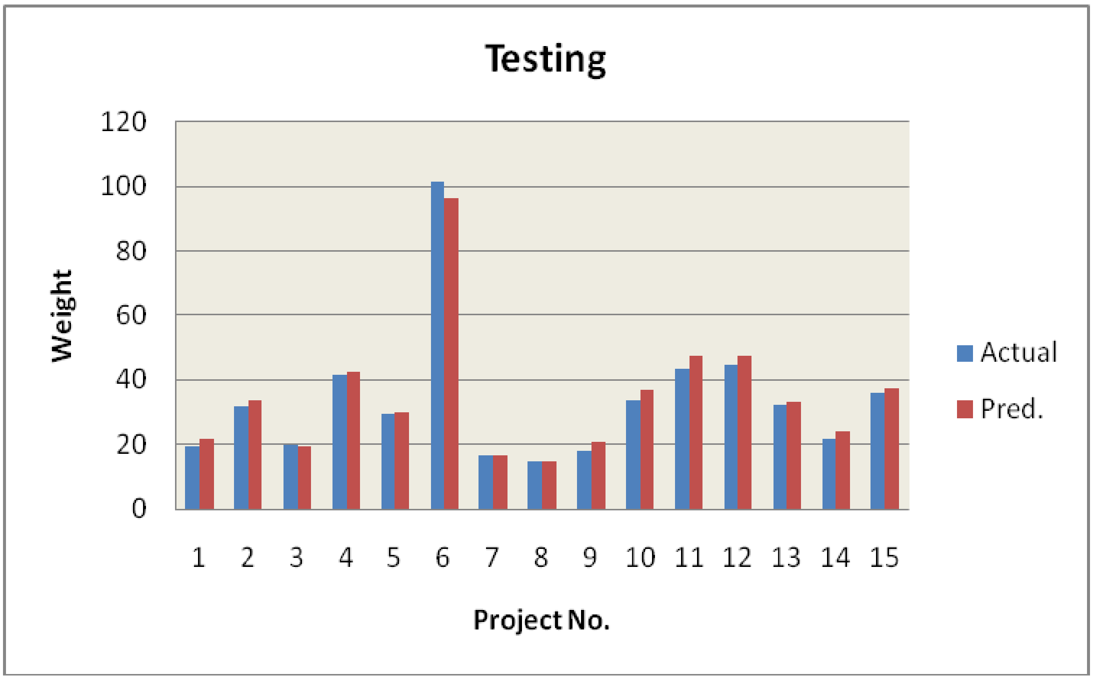


Fig 5.10: The variance between the actual & predication weight of testing process (Spreadsheet)

Table 5.3: Estimated weights vs. actual weights for the fifteen testing samples (Spreadsheet model)

Project No.	Main Effective Factors						Actual Weight (Ton)	Final NN Prediction (Ton)	% Error in Estimate
	Width (m)	Length (m)	EH (m)	Bay spacing					
				First bay (m)	Inter. bays (m)	Last bay (m)			
1	22.30	38.87	7.00	7.86	7.71	7.86	19.28	21.69	12.48
2	28.90	48.90	7.00	6.45	6.00	6.45	31.64	33.44	5.69
3	28.90	30.90	7.00	6.45	6.00	6.45	19.99	19.14	4.27
4	29.00	50.00	9.00	7.14	7.14	7.14	41.23	42.16	2.26
5	29.00	35.71	9.00	7.14	7.14	7.14	29.44	29.79	1.18
6	24.70	192.77	6.60	6.39	6.00	6.39	100.98	95.93	5.00
7	25.00	30.11	6.00	6.06	6.00	6.06	16.41	16.67	1.61
8	27.20	22.75	8.00	6.15	6.00	4.60	15.66	14.55	7.08
9	16.00	43.20	8.30	7.20	7.20	7.20	17.81	20.47	14.93
10	24.00	50.00	9.00	7.14	7.14	7.14	33.63	36.77	9.35
11	24.00	64.29	9.00	7.14	7.14	7.14	43.23	47.55	10.00
12	29.00	50.00	10.00	7.14	7.14	7.14	44.80	47.29	5.56
13	29.00	35.71	10.00	7.14	7.14	7.14	32.00	33.31	4.08
14	22.50	45.00	6.70	7.50	7.50	7.50	21.65	23.91	10.46
15	22.50	75.00	6.70	7.50	7.50	7.50	36.09	37.10	2.81
Absolute Mean Error %					**6.45 %**				

5.1.2 Brain Maker Model

This program has been made by California Scientific Software. The human brain is made up of billions of cells called neurons. Each of these cells is like a tiny computer with extremely limited capabilities; however, connected together, these cells from the most intelligent system known. Neural network are a new class of computing systems formed from hundreds or thousands of simulated neurons connected to each other in much the same way that the brain's neurons are connected (Brain Maker Manual 1998).

Neural networks, just like people, learn by example and repetition. At a fundamental level, all neural networks learn associations. When the network sees particular input data or something very much like it, it responds with particular output data. So far, anural network appears to be a black box; you put questions in one end and get answers out the other end (Brain Maker Manual 1998).

A neural network is a collection of neurons which are organized as layers. The neurons in one layer are connected to the neurons in the next layer. Neurons in one layer listen to the neurons in the previous layer and send results to neurons in the next layer. The connections, represented by lines between the layers, are what get corrected during training. Brain Maker strengthens some connections and weakens others so that the next time the fact is presented, the neural network will produce a more correct answer. Brain Maker creates a file which contains the neural network connections in the form of numbers (and some other information) which are written to your disk. Brain Maker creates, trains, tests, runs, and analyzes the neural network you design using the data you provide (Brain Maker Manual 1998).

Data which used in the Brain maker programme is the same data which used in the spreadsheet model.

The Creating Data File for NetMaker and result has been done as follow:

1. Start NetMaker and select the Read in data File for loading the Excel file as shown in Fig 5.11.
2. Select Manipulate Data and look at the columns as shown in Fig 5.12.
3. To mark the columns as inputs and outputs select each column and from the Label menu, choose Mark Column as Input or Pattern as shown in Fig 5.13.

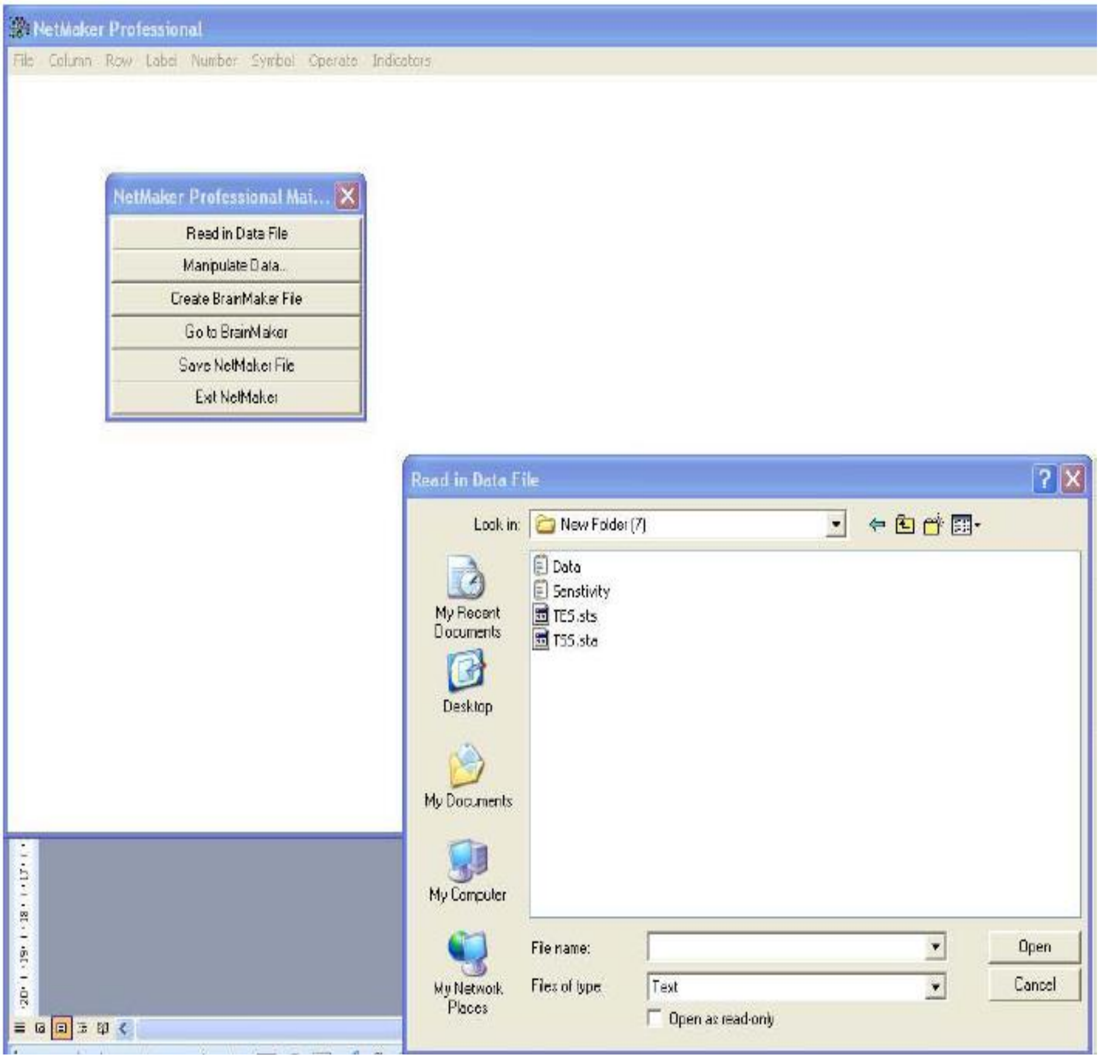


Fig 5.11: NetMaker start-up

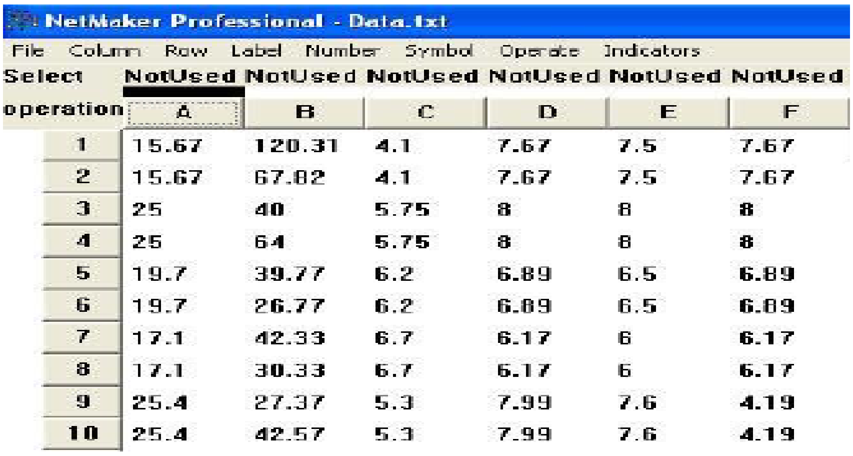


Fig 5.12: NetMaker data show

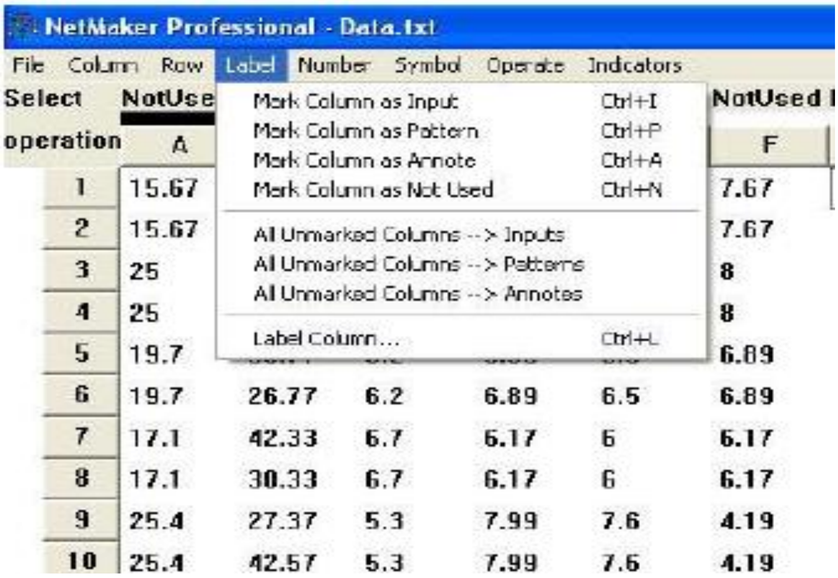


Fig 5.13: Assign the inserted columns

4. Make BrainMaker file. From the File menu, choose Create BrainMaker Files.
5. When it offers the filenames for definition, training facts and testing facts, accept the default names by pressing Enter. It is okay to overwrite as shown in Fig 5.14.

Fig 5.14: Create BrainMaker files

6. Select Return to Main Menu from File menu and then select Go to BrainMaker as shown in Fig 5.15.

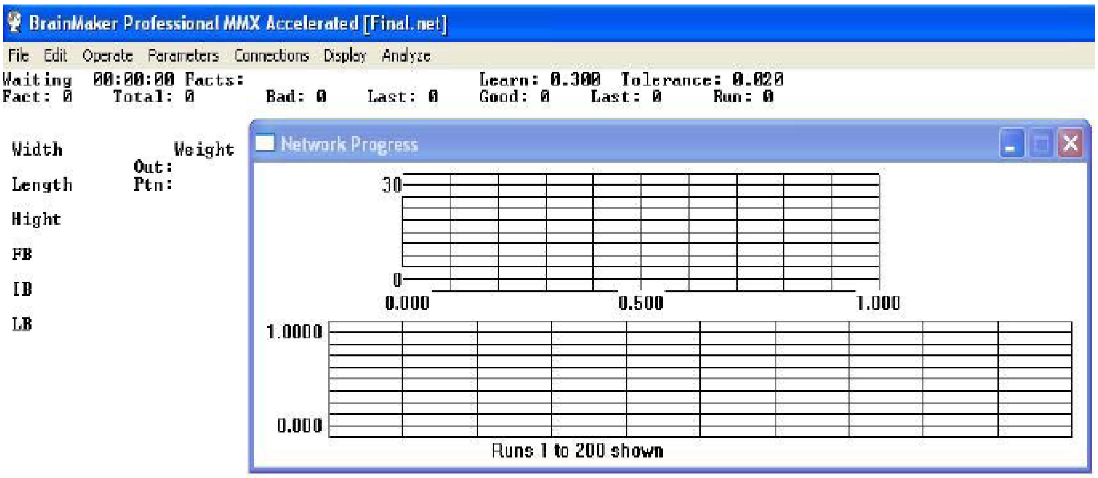


Fig 5.15: BrainMaker interface

7. Choose Change Network Size from the Connections menu. According to the guideline 2 of BrainMaker that suggested that, a good number of hidden neurons are 6.
8. Select Edit Network Display from Display menu, and mark input, output and error as number.
9. Select Learning Setup from Parameters menu to setup the learning rate to 0.3 as shown in Fig 5.16
10. Select Training Control Flow from Parameters menu to setup the training tolerance, testing tolerance and errors as shown in Fig 5.17.

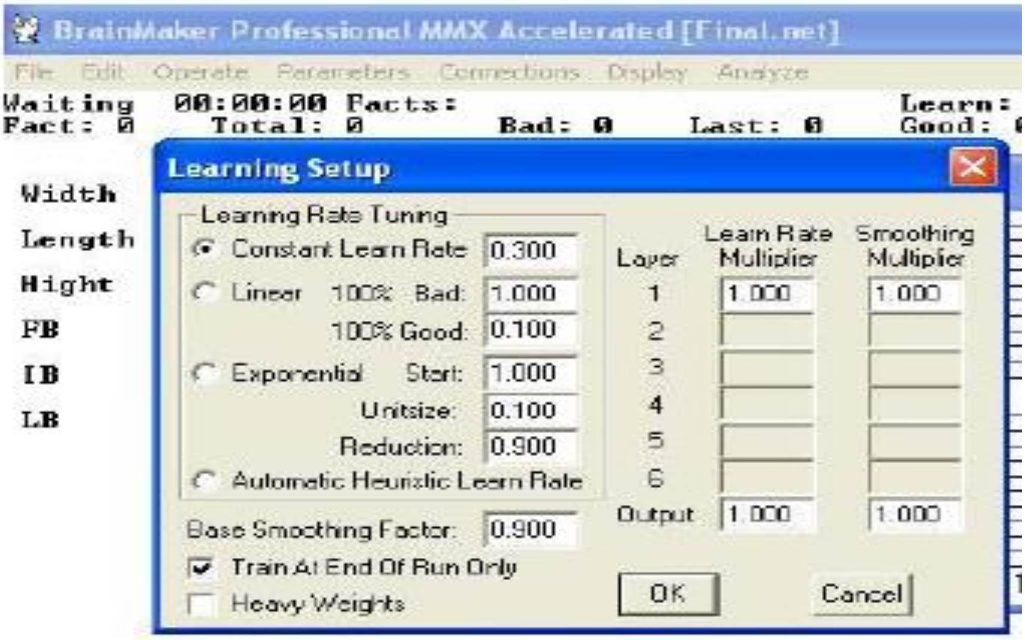


Fig 5.16: Assign the learning rate

Fig 5.17: Assign the tolerance of training and testing

11. Save Training Statistics and Testing Statistics by select them from File menu.
12. Start trains the network. Select Train Network from Operate menu as shown in Fig 5.18.

13. When the train process stop, select Save Network from File menu.

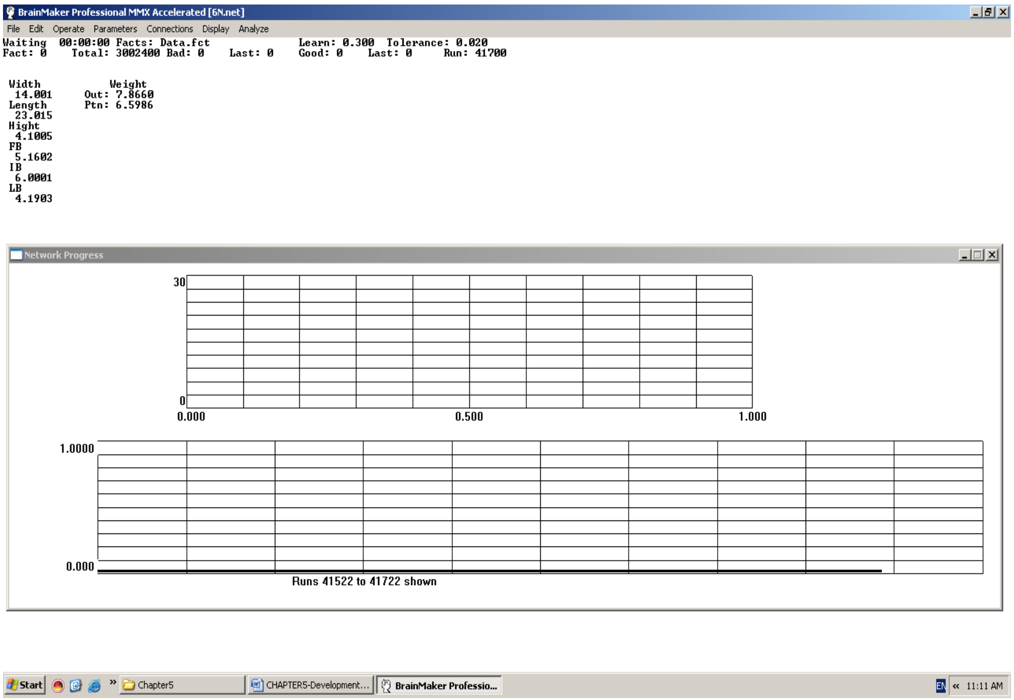


Fig 5.18: BrainMaker running

5.1.2.1 Modeling Phase:

The current model has been designed to include an input layer of six processing elements (neurons) corresponding to the six input parameters and an output layer of one processing element (neuron) as the target. One hidden layer of six processing elements was selected after several trials during the testing phase shown in Fig. 5.19.

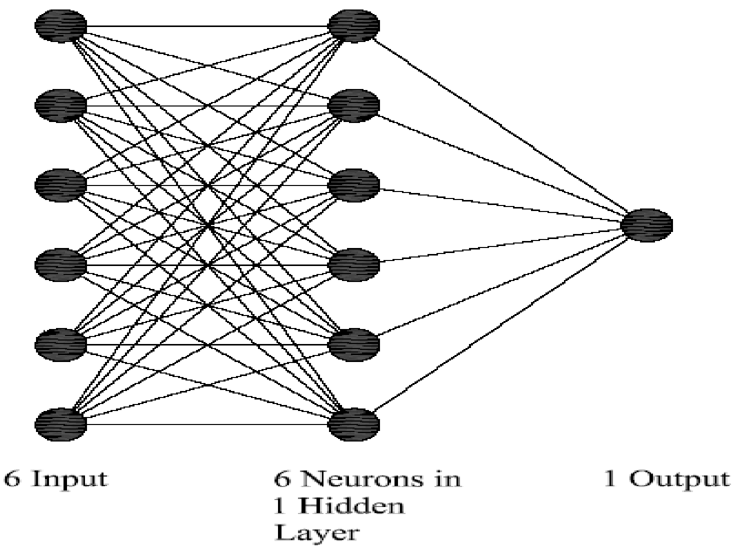


Fig 5.19: The structure of successful neural network

5.1.2.2 Training Phase:

All trial models experimented in this study was trained in a supervised mode by a back-propagation learning algorithm. Accordingly, the connection weights are modified continuously until the error between the desired output and the model output is minimized and the modeler has decided on the size of the training set and training type, learning rate and momentum coefficients, network architecture, and the number of iterations for achieving best model outputs.

Other important network training parameter is the learning rate. This constant term is specified at the start of the training cycle. The learning rate determines the amount of weight modification among the neurons during each training iteration (Al-Tabtabai and Alex 2000). This value ranges between 0.0 and 1.0, where a value closer to 1 indicates significant modification in weight, while a value close to 0 indicates little modification. In this study, a small learning rate of 0.3 was found to perform well.

5.1.2.3 Testing Phase:

Data from 15 projects were used for testing purposes. Results show 94.60% average accuracy with a mean absolute percentage error calculated for the neural network model over the entire testing data set equals 5.40%. These figures are considered to be good weight estimation for this trained model. The minimum and maximum deviations of the weight estimate from the actual steel structure weight are 0.29% and 15.19%, respectively as shown in Fig 5.20 and presented in Table 5.4.

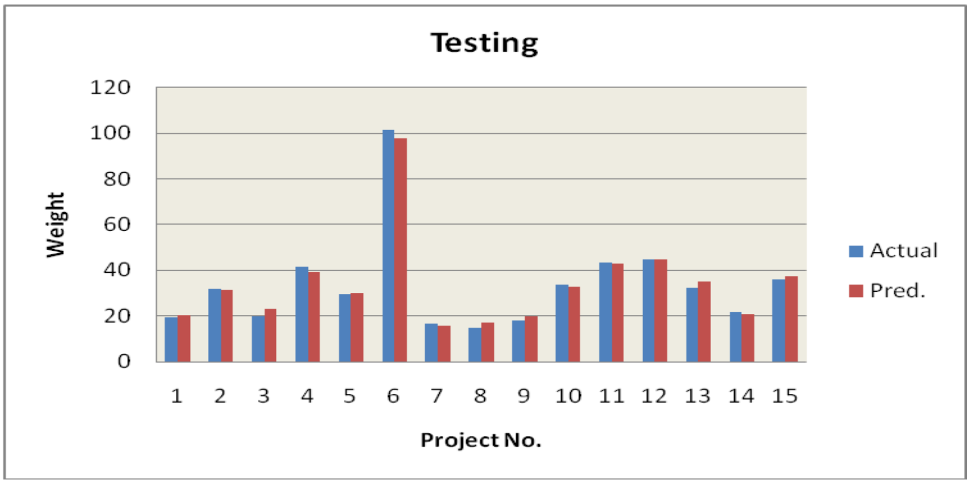


Fig 5.20: The variance between the actual & predication weight of testing process (BrainMaker)

Table 5.4: Estimated weights vs. actual weights for the fifteen testing samples (BrainMaker model)

Project No.	Main Effective Factors						Actual Weight (Ton)	Final NN Prediction (Ton)	% Error in Estimate
	Width (m)	Length (m)	EH (m)	Bay spacing					
				First bay (m)	Inter. bays (m)	Last bay (m)			
1	22.30	38.87	7.00	7.86	7.71	7.86	19.28	20.26	5.09
2	28.90	48.90	7.00	6.45	6.00	6.45	31.64	31.30	1.06
3	28.90	30.90	7.00	6.45	6.00	6.45	19.99	23.03	15.19
4	29.00	50.00	9.00	7.14	7.14	7.14	41.23	39.07	5.23
5	29.00	35.71	9.00	7.14	7.14	7.14	29.44	29.85	1.38
6	24.70	192.77	6.60	6.39	6.00	6.39	100.98	97.42	3.53
7	25.00	30.11	6.00	6.06	6.00	6.06	16.41	15.82	3.62
8	27.20	22.75	8.00	6.15	6.00	4.60	15.66	17.91	14.39
9	16.00	43.20	8.30	7.20	7.20	7.20	17.81	19.99	12.21
10	24.00	50.00	9.00	7.14	7.14	7.14	33.63	32.82	2.39
11	24.00	64.29	9.00	7.14	7.14	7.14	43.23	42.64	1.37
12	29.00	50.00	10.00	7.14	7.14	7.14	44.80	44.67	0.29
13	29.00	35.71	10.00	7.14	7.14	7.14	32.00	34.83	8.84
14	22.50	45.00	6.70	7.50	7.50	7.50	21.65	20.84	3.75
15	22.50	75.00	6.70	7.50	7.50	7.50	36.09	37.02	2.58
Absolute Mean Error %					**5.40 %**				

5.2 Models Application

In order to demonstrate the capabilities of the developed ANN models and its performance, data from three LRSB projects executed during 2008 were collected, see Table 5. The percentage of errors in estimating the weight of steel structure between the actual projects weight and the output results of the developed ANN models are presented in Table 5.6

Table 5.5: Projects information

No.	Project Name	Project Location	width (m)	Length (m)	Height (m)	Weight (Ton)
1	Modern Motors "Suzuki"	Abu Rawash	31	106	6	67.36
2	Mr. Ehab Kamal	Abu Rawash	22.68	23.8	5.9	13.923
3	Egyptian Co. for Paper	10th of Ramadan	19.3	64.24	8.76	41.88

Table 5.6: Results for the examples application

Project No.	Actual Weight (Ton)	Prediction Weight by Spreadsheet model (Ton)	% Error in Estimate	Prediction Weight by Brain Maker model (Ton)	% Error in Estimate
1	67.36	66.49	1.29	74.579	10.72
2	13.923	13.1	5.91	13.285	4.58
3	41.88	45.28	8.12	41.81	0.17
Absolute Mean Error %			5.11 %		5.16 %

Results show 94.89% average accuracy with a mean absolute percentage error calculated for the Spreadsheet model over the entire projects data set equals 5.11%. These figures are considered to be good weight estimation for this model. The minimum and maximum deviations of the weight estimate from the actual steel structure weight are 1.29% and 8.12%, respectively. Also the results show 94.84% average accuracy with a mean absolute percentage error calculated for the BrainMaker model over the entire projects data set equals 5.16%. These figures are considered to be good weight estimation for this model. The minimum and maximum deviations of the weight estimate from the actual steel structure weight are 0.17% and 10.72%, respectively.

5.3 The User Interface

Estimators are the personnel employed in the estimating department charged with the responsibility of producing the estimates and managing the estimating process (Abdel-Razek 2004).

A spreadsheet form has been developed to calculate an average final estimate price for new LRSB project based on the estimate weight of the steel structure of LRSB which provided from the neural network model. Fig 5.21 illustrated the LRSB elements breakdown which will be considered in the price estimate.

The interface of the spreadsheet is presented in Fig 5.22. PELRSB is abbreviation for **P**rice **E**stimate of **L**ow **R**ise **S**teel **B**uilding. This program contains 4 items as follow:

1- First item is prepared to insert the input data of the new project to provide a final estimate price.
2- Second item is prepared to check the previous projects data, and the error percentage between the estimate and the actual weight for these projects.
3- Third item is prepared to present the overall NNM accuracy based on the variance between the estimate and actual weight of the cumulated previous projects.
4- Forth item is prepared to delete any unnecessary project.

Fig 5.23 shows the required input data to calculate the estimated weight of the steel structure of LRSB.

Fig 5.24 presents the price break down to determine the total price for the estimated steel structure weight. Whereas, the User's can assign the cost and mark up to calculate the total steel structure price.

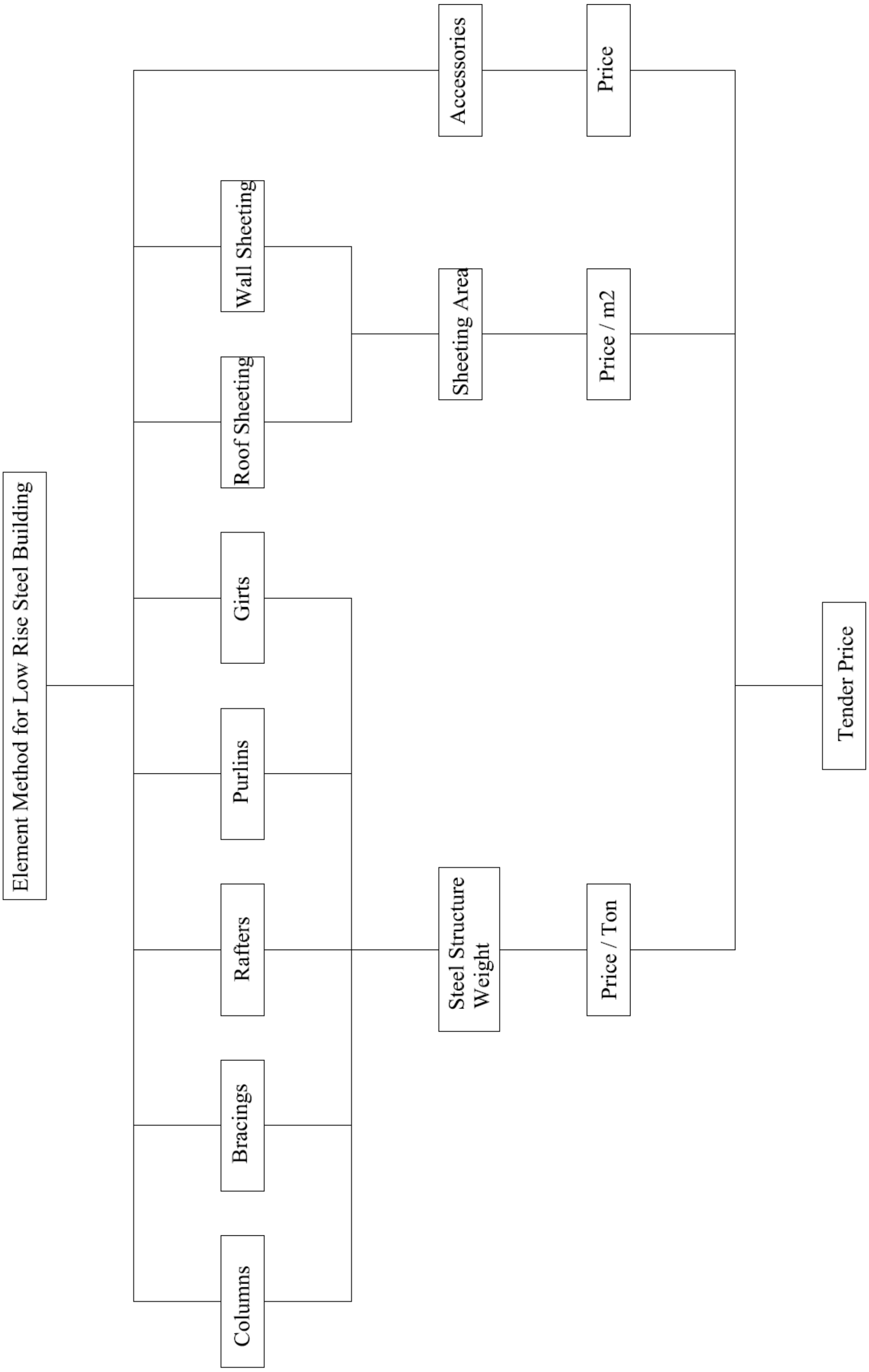


Fig 5.21: The breakdown elements of LRSB

PELRSB

New Project	Previous Project
Statistic	Delete Project

Fig 5.22: Spreadsheet interface

Client:			Type of Project				
			Project Location				
Qut. No.	Prepared By:		Document : Quotation				Sheet
	Month: --200		Building No.		Area No.		1
Rev.							
Data							

Building Information

Building Parameters:

Type	Width (m)	Length (m)	Eave Height (m)	First Bay Spacing (m)	Intermideate Bay Spacing (m)	Last Bay Spacing (m)	Expected Weight (Ton)	Remark
Clear span								

Fig 5.23: Interface of the entered building parameters

Price Break Down								
S.N	Item	Qty. (Ton)	Cost (L.E)		Mark Up (%)		Price (L.E)	
			Per Ton	Total	Per Ton	Total (L.E)	Per Ton	Total
1	Steel Strcture			0.00		0.00	0	0.00
Total Price (L.E)					0.00			

Fig 5.24: Interface of the price break down

5.4 The Limitations and Potential Application

The best use of this system when the input parameters within the range for which the neural network were trained. Database must be updated and neural network model retrained to calculate the new cases.

These models can be used for project planning, procurement and control, creating standers throughout the company. As will, these models can capture and build on the company's experience and, as such, grow with the company adapting to its dynamically changing the business strategy. In general, the type of neural networks described in this thesis can be used to develop a number of decision support systems to assist in various management functions

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the major conclusions from the results obtained, and recommendations.

6.1 Conclusions

The main objective of this thesis was to develop a neural network model for material weight estimating of the steel structural system of LRSB to improve the accuracy during the early stages of estimating process.

The main conclusions of this study are outlined in the following :

1- The most effective parameters affecting on the weight of steel structure of LRSB weight were identified in six parameters; (1) length of the building, (2) width of the building, (3) intermediate bay spacing, (4) eave height of the building, (5) last bay spacing and (6) first bay spacing.

2- The developed ANN model based on the spreadsheet developed by Hegazy and Ayed (1998) consists of one input layer with six neurons, one hidden layer with five neurons, and one output layer with one neuron. This model has succeed to gain a mean absolute percentage error equals 6.45% during the testing phase and 5.11% during the validation phase.

3- The developed ANN model that used BrainMaker Professional software, version 3.73 (2001), consists of one input layer with six neurons, one hidden layer with six neurons, one output layer with one neuron. This model has succeed to gain a mean absolute percentage error over the entire testing data set by 5.40% and 5.16% over the entire examples application.

4- A user-friendly interface was developed using spreadsheet to simplify user inputs and automat cost/price.

5- Feed-forward ANN model is found to be able to estimate weight of steel structure of LRSB with an acceptable degree of accuracy. This finding suggests that feed forward ANN model may be capable of modeling other similar material estimation processes, which have not been studied.

6.2 Models Limitation

1- The developed models can best be used to predict the weight of steel structure of low rise steel buildings for projects which have input parameters within the following ranges: (1) the width of building between 14.00 m and 30.70 m, (2) the length of building between 23.00 m and 192.77 m, (3) the eave height of building between 4.10 m and 10.00 m, (4) the first bay spacing between 5.16 m and 8.16 m, (5) the intermediate bay spacing between 6.00 m and 8.00 m and (6) the last bay spacing 4.19 m and 8.16 m.

2- Live loads for maintenance and rehabilitation works were not taken into account in designing the ANN model.

6.3 Recommendations for Future Work

This study has successfully demonstrated the feasibility of applying neural network techniques to predict the weight of LRSBs. However, the neural network methodology described in this thesis could readily be applied in other domains in construction management where traditional algorithmic tools may prove inadequate.

1- Database must be updated and neural network models retrained with more wide range than the applied range to account for new cases.

2- Neural network models should be developed to take into account for multi-span, different steel grade, truss type and another design codes.

3- Neural network models should be designed to predicted the fabrication duration and the erection time to help the planning department.

4- Expanding the areas of neural network implementation for including another types such as: masonry construction, formwork, fixing reinforced,…etc.

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Appendix A

Name: ……………………………

Position: ……………………………

No. of Years of Experience: ……………………………

Company / Office Name: …………………………

The aim of this questionnaire is to determine the most important factors that can affect the weight of the low rise steel building (Fig. 1). The weight of the steel structure of the low rise steel building plays an important role in estimating its price.

Please, determine the importance of each factor by choosing the suitable degree, where:

1: The factor has a **very low** impact

2: The factor has a **low** impact

3: The factor has a **medium** impact

4: The factor has a **high** impact

5: The factor has a **very high** impact

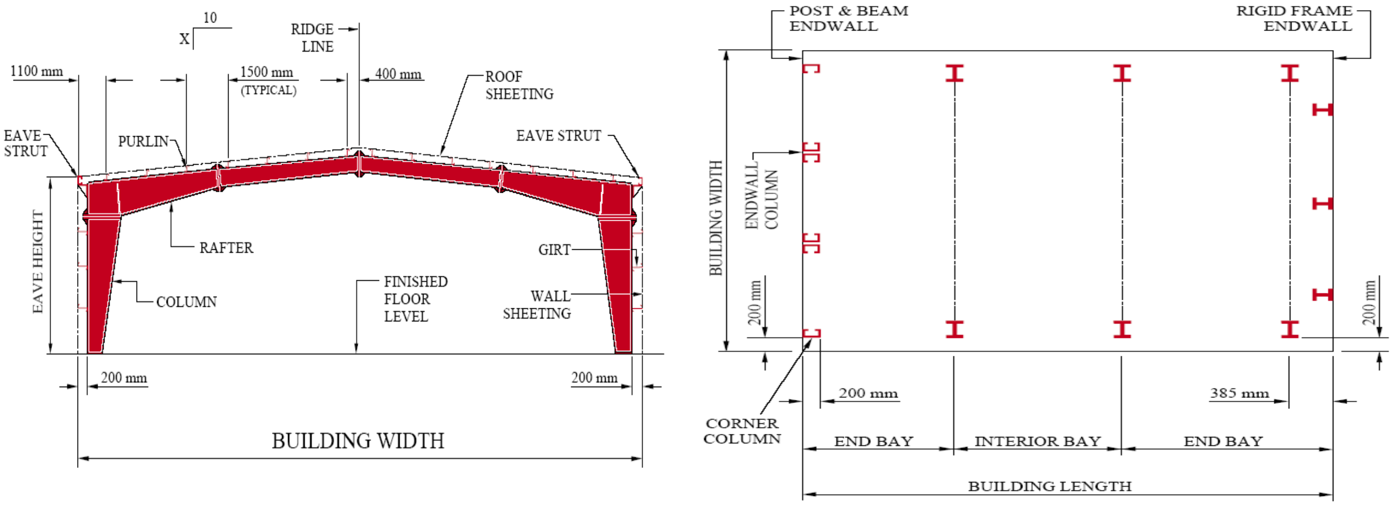

Fig 1

Factors Affecting the Weight of Low Rise Steel Building		
* Type of the building (rigid frame or truss)	_______	1 2 3 4 5 *
* Width of the building	_______	1 2 3 4 5 *
* Length of the building	_______	1 2 3 4 5 *
* Eave Height of the building	_______	1 2 3 4 5 *
* Roof slope	_______	1 2 3 4 5 *
* First bay spacing	_______	1 2 3 4 5 *
* Intermediate bay spacing	_______	1 2 3 4 5 *
* Last bay spacing	_______	1 2 3 4 5 *
* Earthquake load	_______	1 2 3 4 5 *
* Wind load	_______	1 2 3 4 5 *
* Steel grade (37, 44 & 52)	_______	1 2 3 4 5 *
* End wall columns	_______	1 2 3 4 5 *
* Side wall bracing	_______	1 2 3 4 5 *
* Roof bracing	_______	1 2 3 4 5 *
* End wall opening area	_______	1 2 3 4 5 *
* Side wall opening area	_______	1 2 3 4 5 *
* Code of design	_______	1 2 3 4 5 *
* Roof opening	_______	1 2 3 4 5 *

*** 1:** Very Low**; 2:** Low**; 3:** Medium**; 4:** High**; 5:** Very High

Please, when, from your opinion, there is any other important factor, please write it down:

……………………………………………………………………………………
……………………………………………………………………………………
……………………………………………………………………………………

بسم الله الرحمن الرحيم

الملخص العربى

" تقدير سعر المباني الحديدية ذات الارتفاع المنخفض اعتمادا على نظام الشبكة العصبية "

تعتبر أهمية دقة تقدير التكاليف خلال المراحل المبكرة لمشروعات التشييد محض اهتمام لعدة سنوات. حيث أن تقدير تكلفة المشروع في مراحله الأولى تعد الأساس في تمويل المشروع واختيار نظام انجاز المشروع الملائم وتقييم العطاءات و اتخاذ القرار للتقدم بالعطاءات وغيرها. أظهرت الدراسات الحديثة أن المواد المكونة للمنشأ لها تأثير كبير على تكلفته حيث تمثل تكلفة المواد أكثر من 50% من تكاليف مشروع التشييد. إن عدم الدقة في تقدير تكلفة المواد سوف يؤثر على تكلفة المشروع. الغرض من هذا البحث هو ابتكار نموذج شبكات عصبية اصطناعية والذي يمكن أن يتنبأ بوزن الهيكل الحديدي للمباني الحديدية ذات الارتفاع المنخفض في المراحل الأولى للمشروع بدقة معقولة مما يؤدي إلي زيادة الدقة في تقدير التكاليف المبدئية للمشروع.

تم تصميم نموذجان يعملان بنظام الشبكة العصبية احداهما يعرف باسم (BrainMaker Professional) و يتكون من طبقة المدخل (input layer) وبها ستة خلايا عصبية ، وطبقة متوسطة (hidden layer) بها ستة خلايا عصبية (hidden neuron) وذلك بالاضافة إلى طبقة المخرج (output layer) وبها خلية واحدة, والاخر يعرف باسم (Spreadsheet Model) و يتكون من طبقة المدخل (input layer) وبها ستة خلايا عصبية ، وطبقة متوسطة (hidden layer) بها خمسة خلايا عصبية (hidden neuron) وذلك بالاضافة إلى طبقة المخرج (output layer) وبها خلية واحدة. تم تحديد العوامل المؤثرة علي وزن الهيكل الحديدي للمباني ذات الارتفاع المنخفض عن طريق عمل لقاءات مع شركات متخصصة في هذا المجال و استشاريون.

تم استخدام بيانات ثمانون مشروع مبني حديدي ذوات الارتفاع المنخفض في مصر لتدريب و اختبار النموذج. حيث تم استخدام بيانات خمسة وستون مبني لتدريب النموذج وبيانات خمسة عشر مبني لاختبار النموذج.

متوسط نسبة الخطأ في النموذج (BrainMaker Professional) أثناء مرحلة الاختبار كانت 5,4%, أما متوسط نسبة الخطأ في نموذج (Spreadsheet Model) أثناء مرحلة الاختبار كانت 6,1% وهذه الدقة معقولة لهذا النموذج المقترح.

تم استخدام بيانات ثلاثة مشروعات تم تنفيذها في مصر للتأكد من كفأة النموذجين الذين تم تطويرهما حيث جاء متوسط نسبة الخطأ في النموذج (BrainMaker Professional) أثناء مرحلة الاختبار كانت 5,16%, أما متوسط نسبة الخطأ في نموذج (Spreadsheet Model) أثناء مرحلة الاختبار كانت 5,11% وهذه الدقة مقبولة لهذان النموذجان المقترحان.

تم عمل واجهة للتسهيل الاستخدام حيث يمكن للمستخدم وضع أبعاد المبنى ومن ثم يتم احتساب الوزن المتوقع للهيكل الحديدي للمبنى عن طريق احدى النماذج التي تم تطويرها من قبل ,ثم يتم تقدير سعر الهيكل الحديدي للمبنى عن طريق وضع التكلفة و هامش الربح المطلوب.

الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحرى

كلية الهندسة والتكنولوجيا

قسم هندسة التشييد والبناء

"تقدير سعر المباني الحديدية ذات الارتفاع المنخفض اعتمادا علي نظام الشبكة العصبية"

رسالة ماجستير
في
هندسة وإدارة التشييد

مقدمة من :

م / محمد عادل عبد المنعم مغربي

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