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M.Sc. Thesis

Cost estimation for building construction projects in Gaza Strip using Artificial Neural Network (ANN)

تقدير تكلفة مشاريع المباني الانشائية في قطاع غزة

باستخدام الشبكات العصبية الاصطناعية

Researcher

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A thesis submitted in partial fulfillment of the requirement for the degree of master of science in civil engineering

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"وأنزل الله عليك الكتاب والحكمة وعلمك ما لم تكن تعلم

وكان فضل الله عليك عظيما"

النساء آية 113

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Dedication

I would like to dedicate this thesis

To My parents "Dr.Mohammed" and "Samira" for their endless support and unlimited encouragement,

To my loving wife "Hend" and my loving daughter "Samira" who were missing my direct care during my study.

To my dearest sister "Fatma" and brothers "Abedelrahman & Mahmoud", colleagues and friends for their sustainable support.

Omar M Shehatto

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Acknowledgement

First of all, all thanks and appreciations to Allah for his unlimited blessings and for giving me the ISLAM and the strength to complete this thesis.

I wish to express my profound gratitude to Dr. Nabil EL-Sawalhi for his continued guidance, supervision, and comments throughout the course of this research. He has been ever-present force in helping me to mature as a student and as a researcher. His dedication to helping me succeed is deeply appreciated.

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Finally, I would like to thank my parents, wife and lovely brothers, sister, and all of my family for their love, support and for tolerating the time I spent working with my research.

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Abstract

Early stage cost estimate plays a significant role in the success of any construction project. All parties involved in the construction of a project; owners, contractors, and donors are in need of reliable information about the cost in the early stages of the project, where very limited drawings and details are available during this stage.

This research aims at developing a model to estimate the cost of building construction projects with a high degree of accuracy and without the need for detailed information or drawings by using Artificial Neural Network (ANN). ANN is new approach that is used in cost estimation, which is able to learn from experience and examples and deal with non-linear problems. It can perform tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex problems.

In order to build this model, quantitative and qualitative techniques were utilized to identify the significant parameters for the building project costs including skeleton and finishing phases. A database of 169 building projects was collected from the construction industry in Gaza Strip. The ANN model considered eleven significant parameters as independent input variables affected on one dependent output variable "project cost". Neurosolution software was used to train the models. The results of the trained models indicated that neural network reasonably succeeded in estimating the cost of building projects without the need for more detailed drawings. The average error of test dataset for the adapted model was largely acceptable (less than 6%). The performed sensitivity analysis showed that the area of typical floor and number of floors are the most influential parameters in building cost.

One of the main recommendations of this research is to join the developed model with cost index to give an accurate estimate in any time. In addition, it encourages all parties involved in construction industry to pay more attention for developing ANN in cost estimation by archiving all projects data, and conducting more studies and workshops to obtain maximum advantage of this new approach and join more outputs in a model.

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ملخص البحث

يلعب تقدير التكلفة للمشاريع الانشائية في المراحل المبكرة, دورا هاما في نجاح أي مشروع انشائي، لا سيما وان جميع الأطراف المعنية في بناء المشروع؛ كأصحاب المشاريع والمقاولين والجهات المانحة في حاجة إلى معلومات موثوق بها عن التكلفة الكلية في المراحل المبكرة من المشروع في ظل عدم توافر تفاصيل ورسومات كافية. يهدف هذا البحث إلى تطوير نموذج لتقدير تكلفة المشاريع الانشائية بدرجة عالية من الدقة ودون الحاجة إلى معلومات أو رسومات تفصيلية وذلك من خلال استخدام الشبكات العصبية الاصطناعية , حيث تعتبر الشبكات العصبية الاصطناعية أحد اهم الأساليب الحديثة في تقدير التكاليف للمشاريع الانشائية والتي تتميز بالقدرة على التعلم من التجارب والأمثلة والتعامل مع المشاكل غير الخطية مما يؤهلها لأداء المهام مع البيانات غير المكتملة او غير الواضحه او بالغة التعقيد. من أجل بناء نموذج ذو دقة عالية من الشبكات العصبية الاصطناعية، تم استخدام الطرق الكمية والنوعية في تحديد ابرز العوامل المؤثرة على تكاليف المشاريع الانشائية بما يشمل مرحلة البناء الهيكلي ومراحل التشطيب .وقد تم جمع قاعدة بيانات مكونة من 169 مشروع من المؤسسات ذات العلاقة في قطاع غزة . وقد اعتمد نموذج الشبكات العصبية الاصطناعية أحد عشر عاملاً كمدخلات مستقلة تؤثر على متغير خارجي وهو "تكلفة المشروع".

تم استخدام برنامج (Neurosolution) لتدريب نماذج الشبكات، حيث أشارت النتائج المخرجة من عملية التدريب بأن الشبكة العصبية نجحت بشكل ملحوظ في تقدير تكلفة مشاريع البناء من دون الحاجة إلى رسومات تفصيلية، وكان متوسط الخطأ من مجموعة اختبار البيانات للنموذج المعتمد في هذه الدراسة مقبولا إلى حد كبير والذي بلغ 6٪ .وأظهر تحليل الحساسية للنتائج بأن مساحة الطابق االمتكرر وعدد الطوابق هما العاملان الأكثر تأثيرا على تكلفة البناء. وكاحد التوصيات الرئيسية من هذا البحث هو ان يتم ربط نموذج الشبكات الاصطناعية بمؤشر التكلفة لإعطاء تقدير دقيق في أي وقت .وبالإضافة إلى ذلك، تشجيع جميع الأطراف المشاركة في صناعة البناء والتشييد إلى إعطاء المزيد من الاهتمام لتطوير استخدام الشبكات الاصطناعية في تقدير التكاليف من خلال أرشفة كافة بيانات المشاريع، وإجراء المزيد من الدراسات وورش العمل للحصول على الاستفادة القصوى من هذا النهج الجديد وربط نماذج الشبكات العصبية باكثر من مخرج.

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List of Abbreviations

ANN	Artificial Neural Network
CER	Cost Estimate Relationship
AI	Artificial Intelligence
PE	Processing Elements
LR	Linear Regression
MLP	Multi-layer Preceptron
GFF	General FeedForward
RNN	Recurrent Neural Network
MSE	Mean Square Error
GA	Genetic Algorithm
r	Correlation factor
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
AP	Accuracy Performance
TAP	Total Accuracy Performance
UNRWA	United Nations Relief and Works Agency
C.V	Cross Validation
NN	Neural Network
HVAC	Heating, Ventilation and Air Conditioning
AACE	American Association of Cost Engineering

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CHAPTER 1

Introduction

1.1 Background

Cost is one of the three main challenges for the construction manager, where the success of a project is judged by meeting the criteria of cost with budget, schedule on time, and quality as specified by the owner (Rezaian, 2011). In which, poor strategy or incorrect budget or schedule forecasting can easily turn an expected profit into loss (Cheng, et al., 2010). Therefore, effective estimating is one of the main factors of a construction project success (Al-Shanti, 2003). Accordingly, cost estimate in early stage plays a significant role in any construction project (Ayed, 1997), where it allows owners and planners to evaluate project feasibility and control costs effectively (Feng, et al., 2010).In addition, the cost of a building is significantly affected by decisions made at the early phase. While this influence decreases through all phases of building project (Gunaydın & Dogan, 2004).

Due to this prominence of cost estimate in early stage and limited availability of information during the early phase of a project, construction managers typically leverage their knowledge, experience and standard estimators to estimate project costs. As such, intuition plays a significant role in decision-making. Inasmuch the essential needs of project owners and planners to a tool to help them in their early decisions; researchers have worked hard to develop cost estimate technique that maximize the practical value of limited information in order to improve the accuracy and reliability of cost estimation work (Cheng, et al., 2010). Thus, many methods either traditional or artificial intelligence methods were studied and examined for their validity in estimating the project cost at conceptual stage.

In the last years a new approach, based on the theory of computer systems that simulate the learning effect of the human brain as Artificial Neural Networks (ANNs) has grown in popularity (Cavalieri, et al., 2004).

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One major benefit of using ANN is its ability to understand and simulate more complex functions than older methods such as linear regression (Weckman, et al., 2010). In addition, it can approximate functions well without explaining them. This means that an output is generated based on different input signals and by training those networks, accurate estimates can be generated. (Verlinden, et al., 2007).

1.2 Problem Statement

In preliminary stage of a construction project in Gaza Strip, there is a limited available data and a lack of appropriate cost estimate methods, where most of common estimate techniques that are used in Gaza Strip are still inadequacy traditional methods (Al-Shanti, 2003).

All parties involved in construction project are in need of reliable information about the cost of a project in the early stages. Therefore, many researchers are still searching and developing a new technique that is capable of dealing with very limited data and giving more accurate cost estimate.

However, many researchers in recent years applied ANN approach in various fields of engineering prediction and optimization, but the authors reckon that the researches and studies on utilizing neural networks to estimate the cost of construction projects at various stages are very limited until now (Arafa & Alqedra, 2011; Gunaydın & Dogan, 2004; Harding, et al., 1999; Adeli & Wu, 1998; Sonmez, 2004).

1.3 Research Aim

The aim of this research is to develop a new model for early cost estimate of building projects in Gaza Strip by developing an Artificial Neural Network (ANN) model. This model is able to help parties involved in construction projects (owner, contractors, consultants, and others) in obtaining a cost estimate at the early stages of projects with limited available information and within possible time and high accuracy.

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1.4 Research Objectives

The principal objectives of this study are:

1. Identify the most prominent parameters affecting the accuracy of estimating the building project cost in Gaza Strip.
2. Develop a comprehensive tool for parametric cost estimation using the optimum Neural Network model.

1.5 Research Importance

The contributions of this thesis are expected to be relevant to both researchers and practitioners:

- To researchers, the findings should help to investigate the accuracy of applying Artificial Neural Network model on several building types (not only one type), in addition to identifying the most influential parameters on the total cost of these several types.
- As for practitioners, the findings should help to easily estimate the cost of new building projects after programing the developed model into marketing programs.

1.6 Research Scope and Limitation

This research focuses on buildings sector of construction projects in Gaza Strip; including the main two phases of construction building; skeleton and finishing phases. Thus, many building projects that were implemented between 2009 and 2012 were collected, and some types of these building projects were excluded according to lack of available frequency such as hospitals, laboratories and universities.

1.7 Methodology Outline

The objectives of this study will be achieved through performing the following steps:

- Conduct a literature review of previous studies that are related to construction cost estimate and paying special attention of using ANN.
- Conduct quantitative and qualitative survying techneques to ldentify the influntial factors on cost of building projects in Gaza Strip.

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- Conduct exploratory interviews with all engineering institutions to obtain the relevant data of building projects; to be used in building the model.
- Select the application Neurosolution software to be used in modeling the neural network.
- Examine the validity of the adopted model by using statistical performane measurements and applying sesitivity analysis.

1.8 Research Layout

The current study was included six chapters explained as follow:

Chapter (1) Introduction

An introductory chapter defines the problem statement, the objectives of this study, the methodology and an overview of this study.

Chapter (2) literature Review

Presents a literature review of traditional and present efforts that are related to the parametric cost estimating, and application of Artificial Neural Network (ANN) model in related field with its characteristics and structures.

Chapter (3) Research Methodology

The adopted methodology in this research was presented in this chapter including the data-acquisition process of influential factors that relate to cost estimating of building projects and historical data of building projects that necessary for the proposed model.

Chapter (4) Data Results

Presents statistical analysis for questionnaire surveying, Delphi technique and data frequency. It also presents the adopted influential factors in this study and the encoded data for model implementation.

Chapter (5) Model Development

Presents the selected application software and type of model chosen and displays the model implementation, training and validation. As well, the results of the best model with a view of influence evaluation of the trained ANN model are showed.

Chapter (6) Conclusion and Recommendations

Presents conclusions and recommendations outlines for future work.

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CHAPTER 2

Literature Review

2.1 Introduction

Cost estimating is an essential part of construction projects, where cost is considered as one of the major criteria in decision making at the early stages of building design process (Gunaydın & Dogan, 2004). The accuracy of estimation is a critical factor in the success of any construction project, where cost overruns are a major problem, especially with current emphasis on tight budgets. Indeed, cost overruns can lead to cancellation of a project. In some cases, a potential overrun may result in changing a project to a design-to-cost task (Feng, et al., 2010).

Subsequently, the cost of construction project needs to be estimated within a specific accuracy range, but the largest obstacles standing in front of a cost estimate, particularly in early stage, are lack of preliminary information and larger uncertainties as a result of engineering solutions. As such, to overcome this lack of detailed information, cost estimation techniques are used to approximate the cost within an acceptable accuracy range (Verlinden, et al., 2007).

Cost models provide an effective alternative for conceptual estimation of construction costs. However, development of cost models can be challenging as there are several factors affecting on project costs. There are usually various and noisy data available for modeling (Sonmez, 2011).

2.2 Definitions

2.2.1 Cost and Price Concepts

Cost as defined by (Stewart, 1991), as the total amount of all the resources required to perform the activity. However, the price is the total amount paid for that activity. Mathematically, price equals the cost plus the desired profit (Price = Cost + Profit).

2.2.2 Cost Engineering

Cost engineering is a field of engineering practice that engineering judgment and experience are utilized in the application of scientific principles and techniques

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to problems of estimation, cost control, business planning and management science, profitability analysis (AACE International Recommended Practice, 2010).

2.2.3 Cost Estimate

Association for the Advancement of Cost Engineering (AACE) International defines the cost estimation as it provides the basis for project management, business planning, budget preparation and cost and schedule control (cited in (Marjuki, 2006)).

Dysert in (2006) defined a cost estimate as, “the predictive process used to quantify cost, and price the resources required by the scope of an investment option, activity, or project”. Moreover, Akintoye & Fitzgerald (1999) defined cost estimate as, “is crucial to construction contact tendering, providing a basis for establishing the likely cost of resources elements of the tender price for construction work”. Another definition was given by Smith & Mason (1997) which is “Cost estimation is the evaluation of many factors the most prominent of which are labor, and material“.

The Society of Cost Estimating and Analysis (SCEA) defined the cost estimation as "the art of approximating the probable worth or cost of an activity based on information available at the time" (Stewart, 1991).

2.2.4 Construction Cost

The sum of all costs, direct and indirect, inherent in converting a design plan for material and equipment into a project ready for start-up, but not necessarily in production operation; the sum of field labor, supervision, administration, tools, field office expense, materials, equipment, taxes, and subcontracts (AACE International, 2007).

2.3 Purpose of Cost Estimate

In recent decades, researchers and participants in construction industry have recognized the potential impact of early planning to final project outcomes. Therefore, they started to put more emphasis on early planning process, where the project definition in the early planning process is an important factor leading to project success (Wang, et al., 2012). The cost estimate becomes one of the main elements of information for decision making

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at preliminary stage of construction. Thus, Improved cost estimation techniques will facilitate more effective control of time and costs in construction projects (Kim, et al., 2004).

Actually, estimates are prepared and used for different purposes including feasibility studies, tendering phase, avoidance misuse of funds during the project, etc. The primary function of cost estimation is to produce an accurate and a credible cost prediction of a construction project. However, the predicted cost depends on the requirements of a client and upon the information and data available (Elhag, et al., 2005). Antohie, (2009) stated that the purpose of an estimate is to postulate the costs required to complete a project in accordance with the contract plans and specification (Cited in (Abdal-Hadi, 2010)).

The other functions of cost estimate; that it allows the designer and engineer to be aware of the cost implications for the design decisions they make while still in the design phase. Reliable cost estimates also allow management to make an informed decision as to what items will be profitable and what items should be redesigned (Weckman, et al., 2010).

Moreover, cost estimate is of great importance in tendering phase, for example, Carty and Winslow (cited in (ElSawy, et al., 2011)), have considered that cost estimate as a key function for acquiring new contracts at right price and hence providing gateway for long survival in the business. Therefore an accurate estimate of the bid price for a construction project is important to securing the project contract and achieving a reasonable profit, where in practice, the available bid-estimation time is often insufficient (Akintoye & Fitzgerald, 1999).

Therefore, conducting comprehensive and detailed cost estimations are not always possible; taking into account, that detailed cost estimation process is both costly and time consuming. Thus, a method that does not take much time and can approximate a proper bid price is one of the strongest needs for contractors to help them in making bid-price decisions when the available bid estimation time is insufficient (Wang, et al., 2012).

Likewise and Weatney (cited in (Marjuki, 2006)) and (Jitendra, et al., 2011) outlined the purpose of cost estimate through the following points:

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- Provides an assessment of capital cost for a specified piece of project.
- Can help to classify and prioritize development projects with respect to an overall business plan.
- Forms the basis for planning and control by defining the scope of work and its associated estimated cost.
- Determine what resources to commit to the project with providing much of the basic information (hours, resources, tasks, and durations) which is needed for preparing a schedule.
- Projects can be easier to manage and control when resources are better matched to real needs.
- Provides the financial input required to prepare a cash flow curve.
- Customers expect actual development costs to be in line with estimated costs.
- Is a catalyst for discussion, idea generation, team participation, clarity and buy-in, it ties together much of the relevant project information within a simple document.
- Can be used to assess the impact of changes and support re-planning.

2.4 Accuracy of Cost Estimate

The word "accuracy" has two definitions as defined in Webster's College Dictionary (1999) as:

- The condition or quality of being true, correct, or exact; precision; exactness.
- The extent to which a given measurement agrees with the standard value for that measurement.

Regarding to structural perspective, Dysert (cited in (Abdal-Hadi, 2010)) defined the accuracy as the degree to which a measurement or calculation varies to its actual value; so estimate accuracy is an indication of the degree to which the final cost outcome of a project may vary from the single point value used as the estimated cost for the project.

In general, the accuracy of any estimates depends on the amount of information available at the time of the estimate. The range of accuracy increases as the quantity and quality of information increase through the life of a project. This infers that estimate accuracy is a function of available information. Good estimating practice and

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experienced personnel are also found to have considerable impact on estimate accuracy. In particular, on conceptual estimates, since the level of scope definition at this stage is low and often poorly defined (CII, Construction industry institute, 1998).

Liu and Zhu (2007) enhanced the earlier concept by stating that accurate estimation of construction costs is heavily dependent upon the availability of perfect historical cost data and the level of professional expertise among other factors. The limited information available at an early stage of a construction project may mean that the quantity surveyor must make assumptions about the design details of a project, which may not eventuate as the design, planning, and construction evolve.

The CII's (1998) study highlights the major factors influencing on estimate 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.

According to earlier concepts, the relationship between the accuracy of estimate and time phases of project can be expressed by the following Figure 2.1, which presents the percentage of estimated error during the project phases. As shown, the more advanced time in the project, the less estimated error of project cost. Moreover, the positive error curve is not similar to negative error curve because the opportunity of increasing the project budget more than expected, is greater than decreasing. This is because in common; the probability of increasing the prices as materials, labors, etc. of a project is more than decreasing.

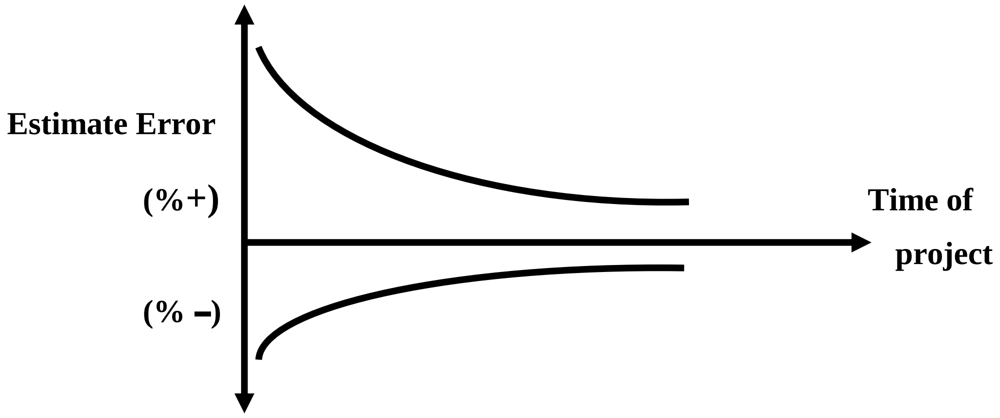

Figure 2.1 Relationship between time and estimate accuracy

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As long as, the required accuracy is directly related to the availability of information, time, available resources (people, equipment, and money), and estimating methodology or algorithm. These four trade-offs describe the classic estimating contradiction (Westney, 1997):

- The more accurate the estimate, the more information is required;
- The more information required, the more time is required to produce the estimate;
- The more resources are required to develop the estimate, the more money it will cost to produce the estimate;
- The more money spent the more pressure to reduce resources, time, information, and accuracy.

2.5 Types of Construction Cost Estimates

The type of estimate is a classification that is used to describe one of several estimate functions. However, there are different types of estimates which vary according to several factors including the purpose of estimates, available quantity and quality of information, range of accuracy desired in the estimate, calculation techniques used to prepare the estimate, time allotted to produce the estimate, phase of project, and perspective of estimate preparer (Humphreys, 2004; Westney, 1997).

Generally, the main common types of cost estimates as Marjuki, (2006) outlined are:

(1) **Conceptual estimate**: a rough approximation of cost within a reasonable range of values, prepared for information purposes only, and it precedes design drawings. The accuracy range of this stage is -50% to +100% .

(2) **Preliminary estimate**: an approximation based on well-defined cost data and established ground rules, prepared for allowing the owner a pause to review design before details. The accuracy range in this stage is -30% to +50%.

(3) **Engineers estimate**: Based on detailed design where all drawings are ready, prepared to ensure design is within financial resources and it assists in bids evaluating. The accuracy in this stage is -15% to +30%.

(4) **Bid estimate**: which done by contractor during tendering phase to price the contract. The accuracy in this stage is -5% to +15%.

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Halpin (cited in (Marjuki, 2006)) commented on previous four levels saying that as the project proceeds from concept through preliminary, to final and bidding phase, the level of detail increases, allowing the development of a more accurate estimate.

Some researchers classified estimate types into three main types as Samphaongoen (2010) which are conceptual, semi-detailed, and detailed cost estimates types where the error percentage ranges from 20% in conceptual stage to 5% in detailed estimate. However, according to (AACE Recommended Practice and standard, 1990) there are three specific types of estimate based on the degree of definition of a project are:

1- Order of magnitude range of accuracy is between (- 30% to +50%)
2- Budget estimate range of accuracy is between (- 15% to +30%)
3- Definitive estimate range of accuracy is between (- 5% to +15%)

Otherwise, Some researchers as (Clough, 1986), abbreviated previous types into two main levels by merging conceptual and preliminary estimate into Conceptual (Preliminary) Estimates, and integrating Engineers and Bid estimates into Detailed (Definitive) Estimates. In general, building projects have two types of estimates: conceptual estimates (sometime called preliminary, approximate or budget estimates) and detailed estimates (sometimes called final, definitive, or contractor's estimates),

Conceptual estimate is normally produced with an accuracy range of – 15% to +30%, while definitive estimates are detailed and normally produced within an accuracy range of –5% to + 15% (Enshassi, et al., 2007).

The following Table 2.1 summarizes the views of researchers about conceptual and detailed estimate (Leng, 2005; Choon & Ali, 2008; Al-Thunaian, 1996; Hinze, 1999; Humphreys, 2004; Abdal-Hadi, 2010):

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Table 2.1 Conceptual and Detailed Cost Estimates

	Conceptual Estimate	Detailed Estimate
When	At the beginning of the project in feasibility stage and no drawing and details are available.	The scope of work is clearly defined and the detailed design is identified and a takeoff of their quantities is possible.
Available of information	No details of design and limited information on project scope are available.	Detailed specifications, drawings, subcontractors are available.
Accuracy range	-30% to +50%	-5% to +15%
Purpose	Determine the approximate cost of a project before making a final decision to construct it.	Determine the reliable cost of a project and make a contract.
Requirements	Clear understanding of what an owner wants and a good "feel" for the probable costs.	Analysis of the method of construction to be used, quantities of work, production rate and factors that affect each sub-item.

2.6 Estimating Process

Process is a series of steps or actions that produces a result. However, estimating is one of many steps in the project management process, yet it is a process into itself, which has 11 steps as (Westney, 1997) stated as the following:

- **Step 1: Project Initiation**

The purpose of project Initiation is to set a definition for overall parameters of a project where the key of project success is beginning with a project definition.

- **Step 2: Scope Definition**

The purpose of definition the scope is to make an overview of the project by providing design basis, detailed scope of work, work breakdown structures, categorical breakdowns, code of accounts, and formatting required by end users.

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- **Step 3: Pre-Estimate Planning**

  It reduces the total effort that can be spent to develop the estimate, it also provides associated information to other project participants.

- **Step 4: Quantity Take-Offs and Item Descriptions**

  Estimate items must be listed and quantity take-offs start with estimate detail sheets for all work items in the project (Popescu, et al., 2003).

- **Step 5: Data Sources and Costs**

  There are numerous sources that data can be obtained as quotes, histories or commercially available data sources, or old estimates in the estimating files.

- **Step 6: Summary and cover sheets**

  The main purpose of the summary sheet is to state the total estimated cost for the project by providing a format for summarizing all the project's direct costs and indirect costs. Where;

  Direct cost: are mainly the materials, labor, plant, and subcontractor costs involved in executing the works (Al-Shanti, 2003).

  Indirect cost: are costs other than direct costs of construction activities, and they are not physically traceable (Marjuki, 2006).

- **Step 7: Documentation and checking**

  Documentation and checking is essential for verifying that calculations are valid.

- **Step 8: Management review**

  Management plays a key role in reviewing the estimate because they are usually responsible for oversight of estimate preparation and they typically have the insight and experience to know "what could go wrong".

- **Step 9: Estimate issue and filing**

  The estimate numbering systems need to be well thought out to be easyfor retrieval and comfortable for users.

- **Step 10: Cost feedback continual improvement**

  This is step is very important to develop the accuracy of the estimating data, estimator performance, and project histories.

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2.7 Classification of Construction Costs

According to researches (Ostwald, 2001; Marjuki, 2006; Hinze, 1999); construction costs can be classified into five types, which constitute the total cost of the project; they can be classified as follows: material cost, labor cost, equipment cost, overheads, and markup. These types are briefed in Figure 2.2 below.

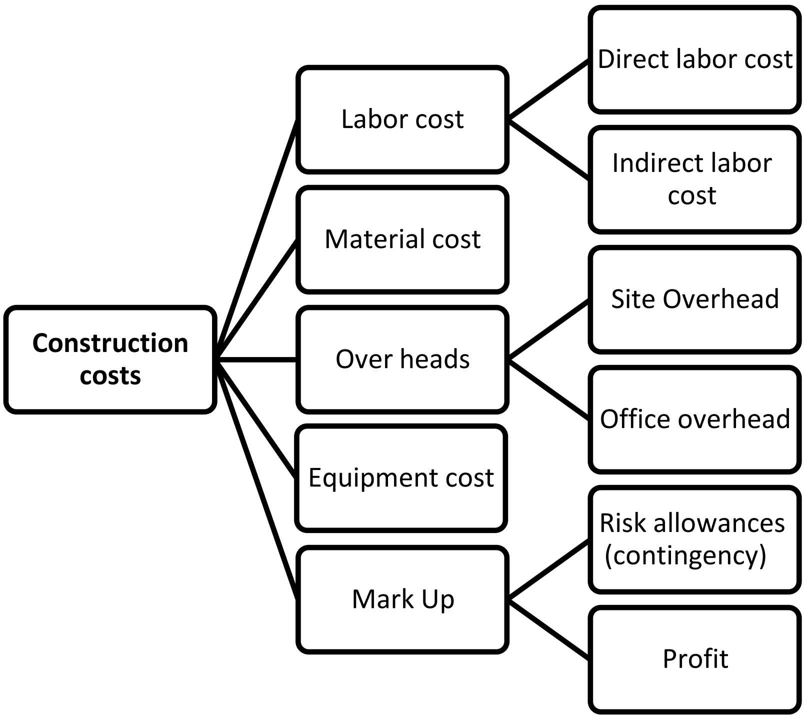

Figure 2.2 Classification of construction costs

2.7.1 Material Cost

The cost of materials includes not only the direct cost of the material items, but also any other costs that may be obtained except labor or equipment for installation. Additional items of cost to be considered are; transportation, sales taxes and freight costs, delivery, storage, sales and other taxes and losses.

2.7.2 Labor Cost

The labor cost component in a building project often ranges from 30% to 50%, and can be as high as 60% of the overall project cost. It consists of direct and indirect labor cost which vary depending on the extent of their relationship to the project.

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2.7.3 Equipment Costs

Equipments can be classified as specific use or general use as following:

I. Specific use equipment:

This equipment is only for specific construction operations and it is removed from the jobsite soon after the task is completed.

II. General use equipment:

General use equipment has shared utilization by all subcontractors on the construction site and it is not associated with any particular work item or items.

2.7.4 Overheads

Overheads cost are construction costs of any kind that cannot be attributed to any specific item of work. In general, Overheads are a significant item of expense and will generally run from (5% to 15 %) of the total project cost, depending somewhat on where certain project costs are included in the cost estimate.

2.7.5 Markup

In construction industry, markup is defined as the amount added to the estimated direct cost and estimated job into overhead cost to recover the firm's main office allocated overhead (general overhead) and desired profit. In general, markup can be classified into two main categories as:

I. Risk allowance (Contingency)

The contingency is a specific provision; it must be included to account for unforeseen elements of cost (Ahuja et al. cited in (Al-Shanti, 2003)).

Ostwald (2001) stated that contingency is the amount of money added to an estimate to cover unforeseen needs of the project, construction difficulties, or estimating accuracy. In addition, he quoted the main items that make many chief estimators or contractor to executives add a contingency to the estimate to cover one or possibly more of the following:

- Unpredictable price escalation for materials, labor, and installed equipment for projects with an estimated duration greater than 12 months;
- Project complexity;
- Incomplete working drawings at the time detail estimate is performed;

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- Incomplete design in the fast-track or design-build contracting approach;
- Soft spots in the detail estimate due to possible estimating errors, to balance an estimate that is biased low;
- Abnormal construction methods and startup requirements;
- Estimator personal concerns regarding project, unusual construction risk, and difficulties to build; and
- Unforeseen safety and environmental requirements.

Accordingly, contingency is not a potential profit and it should not be treated as an allowance. It includes risk and uncertainty but explicitly excludes changes in the project scope (change orders).

II. Profit

The amount of profit is generally computed as a percentage of the contract, or in some cases, as a percentage of each item in the contract. Generally, the magnitude of desired profit must be decided by the owner for each individual bid, depending on local market conditions, competition, and the contractor's need for new work.

2.8 Methods of Cost Estimation

Cost estimation methods can be categorized into several techniques as;

2.8.1 Quantitative and Qualitative Technique

Qualitative approaches rely on expert judgment or heuristic rules, and quantitative approaches classified into statistical models, analogous models and generative-analytical models (Duran, et al., 2009; Caputo & Pelagagge, 2008). Quantitative approach has been divided into three main techniques according to (Cavalieri, et al., 2004).

(a) Analogy-Based Techniques

This kind of techniques allows obtaining a rough but reliable estimation of the future costs. It based on the definition and analysis of the degree of similarity between the new project and another one. The underlying concept is to derive the estimation from actual information. However, many problems exist in the application of this approach, such as:

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- The difficulties in the measure of the concept of ‘‘degree of similarity’’.
- The difficulty of incorporating in this parameter the effect of technological progress and of context factors.

(b) Parametric Models

According to these techniques, the cost is expressed as an analytical function of a set of variables. These usually consist in some features of the project (performances, type of materials used), which are supposed to influence mainly the final cost of the project (known also as ‘‘cost drivers’’). Commonly, these analytical functions are named ‘‘Cost Estimation Relationships’’ (CER), and are built through the application of statistical methodologies.

(c) Engineering Approaches

In this case, the estimation is based on the detailed analysis and features of the project. The estimated cost of the project is calculated in a very analytical way, as the sum of its elementary components, comprised by the value of the resources used in each step of the project process (raw materials, labor, equipment, etc.).

Due to this more details, the engineering approach can be used only when all the characteristics of the project process are well defined.

2.8.2 Preliminary and Detailed Techniques

For both preliminary and detailed technique its own methods, especially since preliminary methods are less numeric than detailed methods. However, most of researchers seek for s perfect preliminary method that gives good results. Ostwald (2001) outlined commonly methods that are divided into two sets qualitative preliminary methods as opinion, conference, and comparison similarity or analogy and quantitative preliminary methods as unit method, unit quantity, linear regression...etc.

2.8.3 Traditional and Artificial Intelligence Based Techniques

In fact, most of earlier traditional methods fall into one of the following categories; Time referenced cost indices, cost capacity factors, component ratio, and parameter costs. However, many researches addressed these traditional parametric methods as (Mahamid & Bruland, 2010) and (Kim, et al., 2004),.. etc.

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Recently new approaches were introduced in the last years based on the concept of parametric models that based on computerized techniques such as artificial intelligence, which attempt to simulate human intelligence such as Artificial Neural Network (ANN), Fuzzy logic, etc., where it stills under research and development especially in construction sector.

2.9 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) as the name suggests are inspired by the biology of a brain's neuron. Human brain can perform a wide range of complex tasks in a relatively easier way as compared to computers. Therefore, researchers were looking for ways in which human intelligence can be incorporated into machines so that they can also perform certain complex tasks easily. ANNs resembles the human brain in two aspects; the knowledge acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights used to store the knowledge (Edara, 2003).

In early stage of a project, there is a limited availability of information, and limited application of traditional methods that require a precise knowledge of all parameters and their interrelations. Therefore, the researchers have worked to develop cost estimate system that maximize the practical value of limited information available in order to improve cost estimate accuracy and reliability by developing many cost estimation models. In recent years, new approaches of artificial intelligence have been grown in popularity that are applicable to cost estimation problems related to expert systems, case-based reasoning (CBR), artificial neural networks (ANNs), fuzzy logic (FL), genetic algorithms (GAs), ..etc. (Cheng, et al., 2010).

ANNs is one of these new approaches that is able to perform tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex and ill-defined problems. ANNs can learn from examples and able to deal with non-linear problems. One of the distinct characteristics of ANN is its ability to learn from experience and examples and then to adapt to changing situations. It has a natural propensity for storing experiential knowledge and making it available for use (Doğan, 2005).

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According to Kim, et al., (2004), ANN is an applicable alternative for predicting construction costs because it can find a good cost estimating relationship that mathematically describes the cost of a system as a function of the variables that have the most effect on the cost of that system. Weckman, et al., (2010) see that, the major benefit of ANN is its ability to understand and simulate complex functions including those dimensions, attributes, and other factors. In concerning of the structure of ANNs, they are inspired to the human brain functionality and structure which consist of a set of neurons, grouped in one or more hidden layers connected by means of synapse connections. The connections between neurons are called synapses and could have different levels of electrical conductivity, which is referred to as the weight of the connection. This network of neurons and synapses stores the knowledge in a ‘‘distributed’’ manner: the information is coded as an electrical impulse in the neurons and is stored by changing the weight (i.e. the conductivity) of the connections (Cavalieri, et al., 2004).

2.9.1 Historical Background of ANNs

The applications of ANN in construction management go back to the early 1980’s. These applications of ANN cover a very wide area of construction issues (ElSawy, et al., 2011). The early attempts to embed ANN techniques within the cost estimation area were conductedby Shtub and Zimerman (1993) who developed models for estimating the cost of assembly systems.Ehrlenspiel, Schaal (1992), Becker and Prischmann (1993) who developed cost models using curve-fitting multi-layer networks, where performance evaluation and a systematic comparison with conventional methods were not undertaken through theirwork (Wang, 2007).

Internationally, neural network models have been developed to assist the construction managers or contractors in many crucial construction decisions. Some of these models were designed for cost estimation, decision making, predicting the percentage of mark up, predicting production rate …etc (ElSawy, et al., 2011).

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2.9.2 Definition of ANN

There is no universally accepted definition of Neural Network (NN), but most of definitions are similar to some extent with each other, as such, Swingler (1996) defined neural networks as "statistical models of real world systems which are built by tuning a set of parameters. These parameters, known as weights, describe a model which forms a mapping from a set of given values known as inputs to an associated set of values the outputs".

Bouabaz and Hamami (2008) agreed with Haykin (1998) that artificial neural networks are inspired from the biological structure of the human brain, which acquires knowledge through a learning process, and an interneuron connection strengths known as synaptic weights are used to store the knowledge. However, the word "neural" is used because of historical reasons since most of the earlier researchers came from biological or psychological backgrounds, not engineering or computer science.

Kim, et al., (2004) defined Neural Network (NN) as a computer system that simulates the learning process of the human brain that can be applied in many industrial areas, including construction industries.

2.9.3 Neural Networks versus Conventional Computers

The main difference between the neural network and conventional computers lies in the way they tackle the problem of pattern recognition (Minin, cited in (Aneja, 2011)). Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer processing is sequential-one task, then the next, then the next, and so on. Unless the specific steps that the computer needs to follow are known, the computer cannot solve the problem. In comparison, ANNs are not sequential or necessarily deterministic. There are no complex central processors, rather there are many simple ones which generally do nothing more than take the weighted sum of their inputs from other processors. Another fundamental difference between conventional computers and artificial neural networks is the way in which they function. Conventional computers use a cognitive approach to problem solving;

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where they must learn only by doing different sequences or steps in an algorithm and the problem must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program like C++ or Java,.. etc., and then into machine code that the computer can understand. Nevertheless, in artificial neural networks the network is composed of large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem, and they can learn by example. They cannot be programmed to perform a specific task.

In summary, conventional algorithmic computers and neural networks are not in competition but complement each other. There are tasks, which are more suited to an algorithmic approach like arithmetic operations, and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches where normally a conventional computer is used to supervise the neural network in order to perform at maximum efficiency (Kshirsagar & Rathod, 2012).

2.9.4 Neural Network Structure

Neural network structure plays a significant role in model accuracy. (Dindar ,2004). However, there are no applicable rules for the optimal setting of control variables and topologies (Caputo & Pelagagge, 2008).

Otherwise, Generalization and over fitting is directly related to the architecture used in the neural network to model the data, since training iterations and the number of hidden units are key elements during the training of the network, and adjusting these elements could lead to great improvements in the networks modeling capability (Dindar, 2004).

Bouabaz & Hamami, (2008), demonstrated that there is a number of factors for selecting the neural network structure and rules, such as the nature of the problem, data characteristics, complexity of data and the number of sample data.

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The network architecture refers to the number of hidden layers and the number of nodes within each hidden layer. As a matter of fact, there are two questions in designing a neural network that have no specific answers because they are mainly depend on application; the first is the required data to train a network, and the best number of hidden layers and nodes to be used. Generally, the more data and the fewer hidden layers and hidden nodes that can be used, is the better. There is a subtle relationship between the number of facts and the number of hidden layers/nodes. Having too few facts or too many hidden layers/nodes can cause the network to "Memorize". When this happens, it performs well during training but tests poorly (ElSawy, et al., 2011).

As a rule of thumb, determining the number of hidden layer/neurons is one of the main drawbacks of NNs, because there is no specific rule and it requires many trial and error processes while considerable time must be spent (Kim, et al., 2004). Hegazy & Moselhi, (1995) stated that one hidden layer with a number of hidden neurons as 0.5 m, 0.75m, m, or 2m+1, where m is the number of input neurons, is suitable for most applications.

The main building elements of ANNs are neurons or nodes and the links connecting between them. Each link has a weight parameter associated with it. These nodes or neurons are assorted into three categories, which are input, output, and hidden neurons. Each neuron receives stimulus from the neighboring neurons connected to it, processes the information and produces an output. Neurons that receive stimuli from outside the network (i.e., not from neurons of the network) are called input neurons. Neurons whose outputs are used externally are called output neurons. Neurons that receive stimuli from other neurons and whose output is a stimulus for other neurons in the neural network are known as hidden neurons. There are different ways in which information can be processed by a neuron, and different ways of connecting the neurons to one another. In general, different neural network structures can be constructed by using different neurons or nodes and by the specific manner in which they are connected (Cengiz, et al., 2005).

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Figure 2.3 displays the above structure of ANN, which consists of three basic layers, input, hidden and output layer. Each one contains several neurons except output layer; it contains one neuron that represents the output of training process.

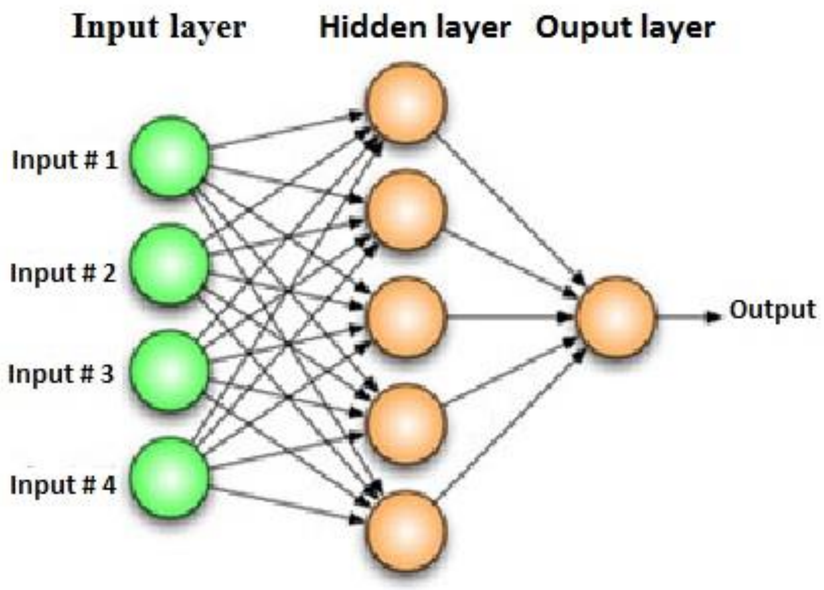

Figure 2.3 Artificial Neural Network structure

For hidden neurons, Figure 2.4 presents the schematic diagram that shows weight's summation part and transfer function part inside these neurons.

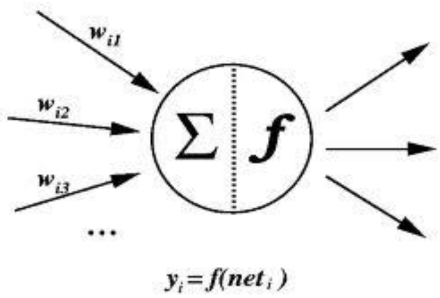

Figure 2.4 Schematic diagram of processing element (Mohaghegh, 2000)

2.9.5 Terminology Used In Artificial Neural Network

- **Weight**: In an artificial neural network, A weight is a parameter associated with a connection from one neuron, M, to another neuron N. It determines how much notice the neuron N pays to the activation it receives from neuron M (Al-Najjar, 2005).

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- **Learning algorithm:** Is a systematic procedure for adjusting the weights in the network to achieve a desired input/output relationship (Al-Najjar, 2005). The goal of the learning process is to minimize the error between the desired output and the actual output produced by the network. After learning process, the neural network has learned to produce an output that closely matches to the desired output (Jitendra, et al., 2011).The learning algorithms of neural networks are divided into three categories;

    - **Reinforcement learning method**: The network is not provided with the output but it is informed if the output is a good fit or not (Karna & Breen, 1989).
    - **Unsupervised learning method:** The target output is not presented to the network. Thus, the network follows a self-supervised method and makes no use of external influences for synaptic weight modification (Jitendra, et al., 2011).
    - **Supervised learning method**: The network is provided with number of layers, the number of neurons per layer of the network and the type of activation function used, and the synaptic weights, then the network adjusts the weights after comparing the results from the network with the output to minimize the error. Moreover, supervised learning method has several learning algorithms as Back-propagation Learning rule, Gradient Descent Learning, Delta Rule (Jitendra, et al., 2011). Where Back-propagation Learning rule, which is adopted in this research, is the most common learning method, and it has various algorithms like Levenberg-Marquardt and Momentum for backpropagation algorithm (Principe, et al., 2010).

- **Activation Functions:** Activated functions experimentally change based on the placed independent variables in model and expected outputs (Attal, 2010).The activation function performs a mathematical operation on the signal output. Depending upon the type of input data and the output required (Kriesel, 2005). Over the years, the researchers tried several functions to convert the input into output, various mathematical functions have been used as activation

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functions, These functions can take many forms: Linear, Logistic, and tangent, etc. Most commonly used are threshold function (Hard limit), sigmoid function, tanh function, and Bias function, etc. (Nygren, 2004; Principe, et al., 2010). Figure 2.5 presents the most three activation functions

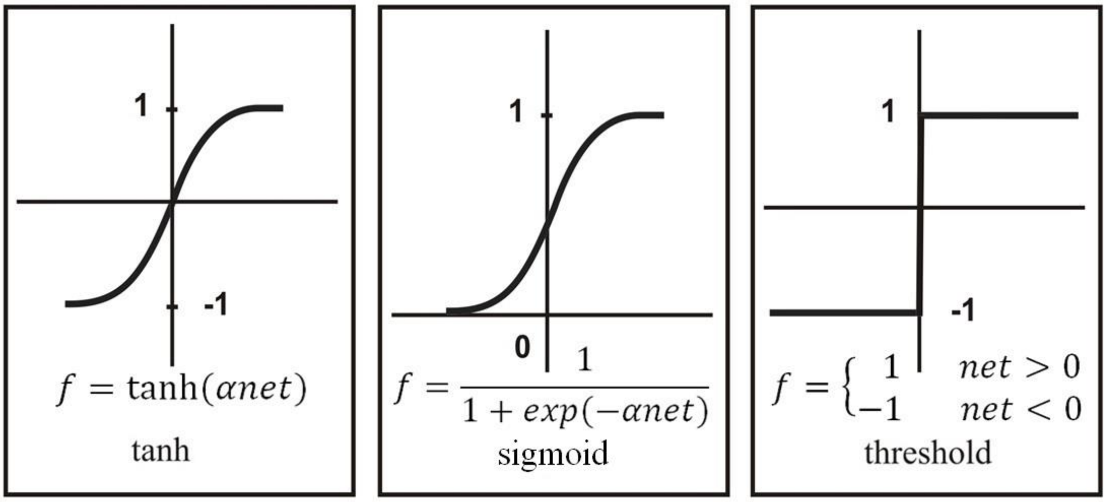

Figure 2.5 Three of the most commonly used transfer functions (Principe et al., 2010)

- **Normalization and Denormalization Data:** Before starting the training phase It is usually necessary to scale the data, or normalize it to the network's paradigm (Kshirsagar & Rathod, 2012), Gunaydın & Dogan, (2004) stated that data is generally normalized for the purpose of confidentiality and for effective training of the model being developed, where the input data must be normalized between an upper and lower bound ((Principe, et al., 2010) . The normalization of training data is recognized to improve the performance of trained networks.

2.9.6 Types of Artificial Neural Networks

There are several types of ANNs which can be classified according to their connection geometries or by the algorithms used in the training process, such as Feed forward network, Radial basis function networks (RFB), self-organizing map (SOM),.. etc. (Cengiz, et al., 2005). The following paragraph classifies the most common ANN types, which are:

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- **Single-Layer Feed Forward Networks**

It is the simplest form of a layered network, which consists of a single layer of weights, where the inputs are directly connected to the outputs by series of weights. Such a network is called a single-layer network, with the designation "single layer" referring to the output layer of computation nodes (neurons). The input layer of source nodes is not counted because no computation is performed there (Al-Najjar, 2005). Figure 2.6 shows the single layer feed forward network.

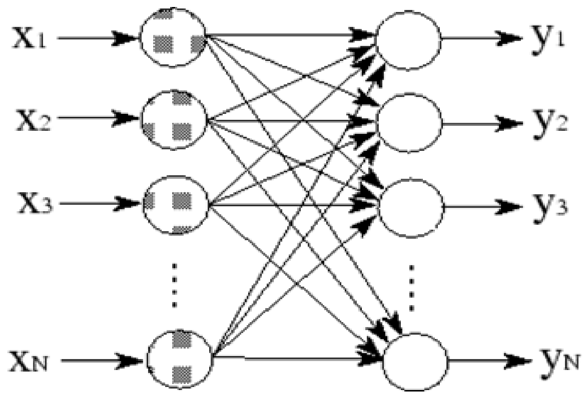

Figure 2.6 Single layer feed forward network (Al-Najjar, 2005)

- **Feed Forward Network**

In this network, the information moves just in one direction, forward, from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network (Kshirsagar & Rathod, 2012). Feedforward networks can be classified into several types as Multi-Layer Preceptron, General FeedForward (GFF), etc., the most common types are MLP and GFF networks (Pawar, 2007).

- **Multilayer Perceptron (MLP)**

The most popular type of neural network in use currently is multilayer perceptron (MLP) which is commonly used in regression and classification problems. They are capable of modeling many functions but require a large amount of time, epochs, and nodes (Weckman, et al., 2010).

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In (MLP), neurons are organized in several layers: the first is the input layer (fed by a pattern of data), while the last is the output layer (which provides the answer to the presented pattern). Between input and output layers there is one or more hidden layers which are comprised of the nodes chosen in the design phase. Each node of these takes the input values, associated weights, and runs them through the chosen function. The chosen function affects how and how well the network is able to learn. The node then uses a transfer function to produce a weight-associated output. The hidden node values and weights are run through the output node (layer) algorithm, and a final output value is calculated (Dowler, 2008). See Figure 2.7

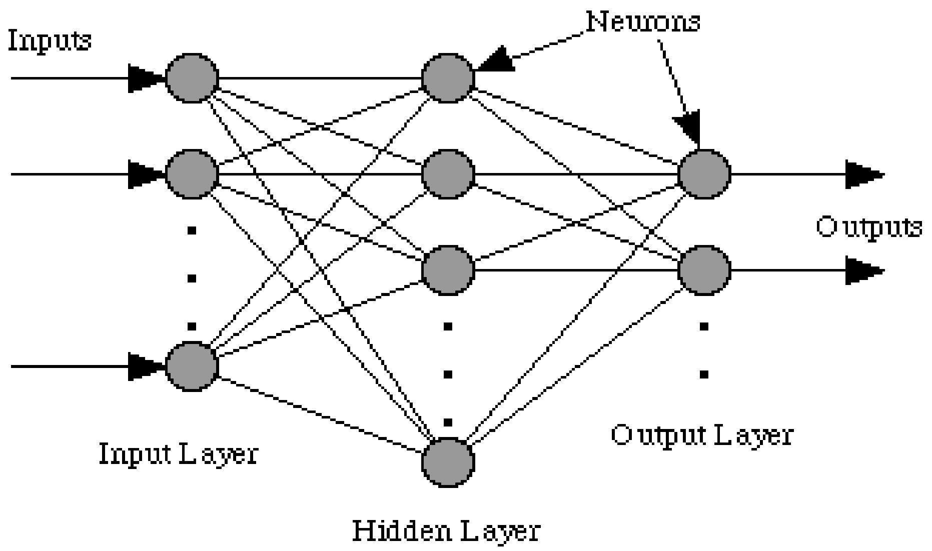

Figure 2.7 Multilayer Perceptron (Christian, et al., 2000)

- **General FeedForward (GFF)**

GFF networks are a special case of MLP such that connections can jump over one or more layers, The GFF networks often solve the problem much more efficiently. A classic example of this is the two-spiral problem. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more epochs of training than the generalized feedforward (for the same size network).(Principe, et al., 2010). See Figure 2.8

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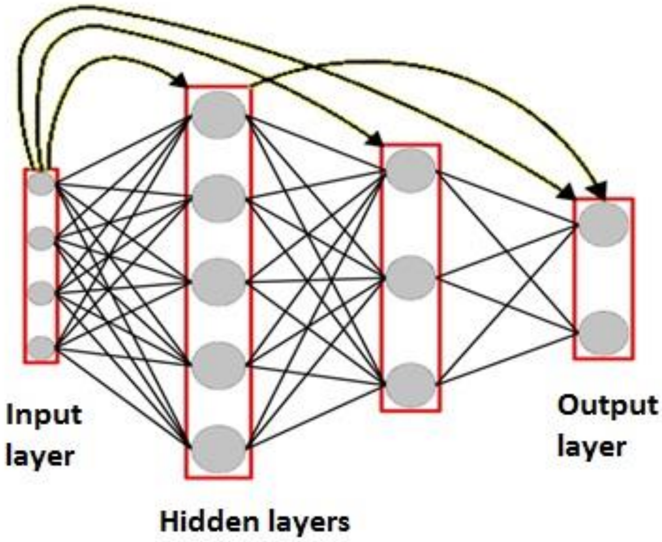

Figure 2.8 General FeedForward networks structure (Principe, et al., 2010)

- **Recurrent Networks**

A recurrent neural network differs than a feed forward neural network that it has at least one feedback loop. They are developed to deal with the time varying or time-lagged patterns and are usable for the problems where the dynamics of the considered process is complex and the measured data is noisy (Nygren, 2004).

2.9.7 Artificial Neural Network Design

The design of the network has a large impact on its performance, so the overall structure of ANN is defined in this stage, and two essential issues must be determined when designing it. Firstly is the number of nodes are required, where they are typically decided through a process of trial and error. Hegazy, et al., (1994) suggested as a recommendation, that the number of hidden nodes should be set as one-half of the total input and output nodes (Sodikov, 2005). However, the number of nodes directly affects the network's ability to learn and generalize the desired function. Such that, if there are too few nodes, the network will not be able to fully learn and will provide poor results for the training and testing data (Schenker and Agarwal, cited in (Weckman, et al., 2010)).The second issue is determining what learning algorithm should be used in training phase of NNs.

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2.9.8 Training of Neural Network

The objective of training a neural network is to adjust the neural network weights to bring its output closer to the desired output, where the weights after training contain meaningful information, whereas before training, they are random and have no meaning.

This process of changing or adapting the connection weights in some orderly fashion using a suitable learning method is referred to as the learning rule of the network (Doğan, 2005).

The first step in training process is to initialize the weight of parameters that randomly assigned to the links between nodes. The output of the neural network is compared with desired values, and an error is calculated by learning algorithm then the weights associated with each link are adjusted in an attempt to minimize the network's mean square error.The input values are run through the network with the adjusted weights and the process restarts from the beginning. The process is repeated for the predetermined number of epochs. An epoch represents one cycle of the training process (Dowler, 2008). When the training reaches a satisfactory level, the network holds the weights constant and uses the trained network to make decisions, or define associations in new input data sets not used to train it (Doğan, 2005).

As mentioned earlier, there are several training algorithms to be chosen for training process, one of the most common and powerful algorithm that is adopted in this study is Back propagation algorithm which belongs to the realm of supervised learning (Gunaydın & Dogan, 2004). On one hand, Back propagation was invented in 1969 to learn a multilayer network for a given set of input patterns with known classifications. It tries to improve the performance of the neural network by reducing the total error through changing the weights along its gradient (Jitendra, et al., 2011). The error can be expressed by the mean-square error (MSE), which is calculated by:

$$MSE = \frac{\sqrt{\sum_{i=1}^{n} (x_i - E(i))^2}}{n} \quad \text{Eq. 2.1}$$

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Where: - n is the number examples to be evaluated in the training set,

- xi is the network output (target) related to the example (i=1,2,…,n),

- and E(i) is the desired output.

As the error converges to zero, the output patterns computed by the ANN perfectly match the expected values, and the network is well trained (Dogan, 2005).The algorithm involves two phases, Forward phase to compute the output and the backward phase to perform modifications in the backward direction (Jitendra, et al., 2011).

These two phases compose on cycle, where each training cycle is called an epoch, and the weights are updated in each cycle. Each training cycle stops when one of the following three conditions is met (Weckman, et al., 2010):

1) The maximum number of epochs was reached,

2) The cross validation error started increasing, or

3) Very large number of epochs without improvement in error are reached.

Eventually, the network's weights are continuously adjusted until the error in the calculated outputs converges to an acceptable level or stopping the training process if one of previous condition is reached.

2.9.9 Cross-validation of Neural Network

A simple method to compare the performance of neural networks is to test the errors of the networks using a separate validation / test data set. Basically, the available data is always divided into three parts prior to the training including training data, cross-validation data, and testing data. The cross-validation data is used during the training but for monitoring not to train the network, instead to check the learning of the network during the training; and the testing data is used to validate the training network after finishing training process (Edara, 2003).

Cross validation uses its own data set to monitor the neural network’s ability to produce generalized cost estimates; this is done by training many networks on a training set and comparing the errors of the networks on the validation set. The networks that performed best on the validation data set are then selected (Dindar, 2004). The network continues to learn as the error for the cross validation and the training data set continue to

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decrease. Once the error for the cross validation data set starts to increase, the training stops and the weight values that provided the lowest error for the cross validation data set are considered the best. The training set error value may continue to decrease once the cross validation error starts to rise. At this point, the network is over-fitting and memorizing the training data. If cross validation is not used, then a testing data set is critical to prove that memorization and over-fitting is not occurring (Weckman, et al., 2010), (Dowler, 2008).

The next Figure 2.9 illustrates the earlier mechanism of cross validation process that it appears the point at which the training process stops due to start increasing error curve of cross validation set.

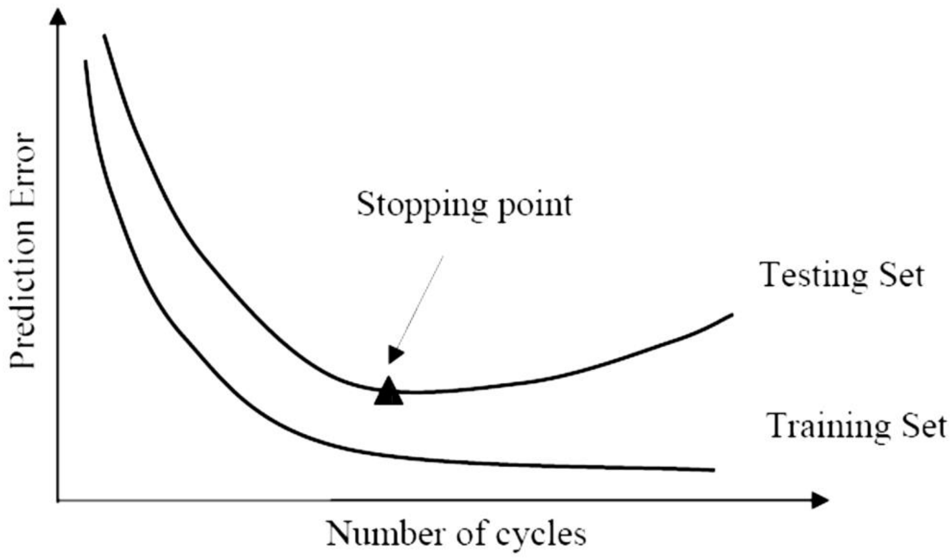

Figure 2.9 Typical error graph for NN using cross validation (Weckman et al., 2010)

2.9.10 Testing of Neural Network

Testing the network is essentially the same as training (ElSawy, et al., 2011). The testing set is critical to confirm that the network has not simply memorized a given set of data but has learned the general patterns involved within an application (Kshirsagar & Rathod, 2012).

The testing data is totally a different set of data that the network is unaware of; after finishing the training process testing data is used for validation and generalization of the trained network. If the network is able to generalize rather precisely the output for this

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testing data, then it means that the neural network is able to predict the output correctly for new data and hence the network is validated. Moreover, the amount of data that is to be used for training and testing purposes is depending on the availability of the data, but in general the training data is 2/3rd of the full data and the remaining is used for testing purposes. The cross-validation data can be 1/10th of the training data (Edara, 2003).

2.9.11 Performance Measures of ANN model

The most common approaches have been utilized to determine the estimation accuracy in testing phase are:

- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Total Mean Absolute Percentage Error (Total MAPE)
- Correlation Coefficient (r)

I. Mean Absolute Error (MAE):

It is one of many ways to quantify the difference between an estimated and the actual value of the projects being estimated. According to Willmott & Matsuura, (2005) the MAE is relatively simple; It involves summing the magnitudes (absolute values) of the errors to obtain the 'total error' and then dividing the total error by n, it can be defined by the following formula:

$$MAE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left|dy_{ij}-dd_{ij}\right|}{N\ P} \qquad \text{Eq. 2.2}$$

Where: P = number of output PEs.
N = number of exemplars in the data set.
dy_{ij}= denormalized network output for exemplar i at PE j.
dd_{ij}= denormalized desired output for exemplar i at PE j.

II. Mean Absolute Percentage Error (MAPE):

The mean absolute error is a quantity used to measure how close forecasts or predictions are to the eventual outcomes, according to Principe, et al., (2010) The MAPE is defined by the following formula:;

$$MAPE = \frac{100}{N\ P}\sum_{j=0}^{P}\sum_{i=0}^{N}\frac{\left|dy_{ij}-dd_{ij}\right|}{dd_{ij}} \qquad \text{Eq. 2.3}$$

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Where: P = number of output PEs.
N = number of exemplars in the data set.
$dy_{i\,j}$= denormalized network output for exemplar i at PE j.
$dd_{i\,j}$= denormalized desired output for exemplar i at PE j.

Note that this value can easily be misleading. For example, say that your output data is in the range of 0 to 100. For one exemplar your desired output is 0.1 and your actual output is 0.2. Even though the two values are quite close, the percent error for this exemplar is 100 (Principe, et al., 2010).

III. Correlation Coefficient (r):

According to Principe et al., (2010) the size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it doesn't necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, we can change the MSE without changing the directionality of the data. The correlation coefficient (*r*) solves this problem.

By definition, the correlation coefficient between a network output *x* and a desired output *d* is:

$$r = \frac{\frac{\sum_i (x_i - \bar{x})(d_i - \bar{d})}{N}}{\sqrt{\frac{\sum_i (d_i - \bar{d})^2}{N}}\sqrt{\frac{\sum_i (x_i - \bar{x})^2}{N}}} \qquad \text{Eq. 2.4}$$

The correlation coefficient is confined to the range [-1,1]. When *r* =1 there is a perfect positive linear correlation between *x* and *d*, that is mean *x* and *d* vary by the same amount. When *r*=-1, there is a perfectly linear negative correlation between *x* and *d*, that means they vary in opposite ways (when *x* increases, *d* decreases by the same amount). When *r* =0 there is no correlation between *x* and *d*, i.e. the variables are called uncorrelated. Intermediate values describe partial correlations. For example a correlation coefficient of 0.88 means that the fit of the model to the data is reasonably good (Principe, et al., 2010).

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IV. Total Mean Absolute Percentage Error (Total MAPE):

According to Hegazy & Ayed, (1998); the total MAPE methdology is defined by determinig the total MAPE. Training phase were represented fifty percent of the total MAPE likewise the test set is equal the remaining fifty percent.

$$Total\ MAPE = \frac{(\boldsymbol{MAPE}_{Tr}\times\boldsymbol{N}_{Tr}+\boldsymbol{MAPE}_{C.V}\times\boldsymbol{N}_{C.V})/(\boldsymbol{N}_{Tr}+\boldsymbol{N}_{C.V})+\boldsymbol{MAPE}_{Test}}{2} \qquad \text{Eq. 2.5}$$

Where: $MAPE_{Tr}$ = Mean absolute percentage error for training data set.
N_{Tr} = number of exemplars in the training data set.
$MAPE_{C.V}$ = Mean absolute percentage error for cross validation data set.
N_{Tr} = number of exemplars in the cross validation training data set.
$MAPE_{Test}$ = Mean absolute percentage error for test data set.

2.9.12 Sensitivity Analysis of ANN model

Once the optimum Neural Network model has been selected as described early, Sensitivity analysis was run on the best model to evaluate the influence of each input parameters to output variable. This provides a feedback as to which input parameters are the most significant, it allows the user to see how the input affects the output over a range of values if all other inputs remain constant. As well, it will reduce the size of the network by removing the less significance factors and in turn the complexity of the model and the training times (Gunaydın & Dogan, 2004) (Bouabaz & Hamami, 2008). However, the small effect parameters doesn't necessary means should be excluded from the model because these parameters could enhance the learning capability of the model to achieve the best output (Arafa & Alqedra, 2011).

Sensitivity analysis was carried out on the best model by using Neurosolution tool, which was run after fixed the best weights, first started by varying the first input between the mean $\pm$ one standard deviation, while all other inputs are fixed at their respective means. The concept of calculating the sensitivity analysis of input factors based on determining the standard deviation of each by using the following formula :

$$\sigma = \sqrt{\frac{(x-\bar{x})^2}{(n-1)}} \qquad \text{Eq. 2.6}$$

Where x: is the output value.
$\bar{x}$: is the mean of the output values.
n: is the number of the outputs in the sample.

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2.9.13 Neural Network Properties

NNs have some properties, as they are non-parametric and make weaker assumptions. However, it is able to model interdependencies between input data which will inevitably occur when considering construction cost significant variables. For example, the model variables, such as number of floors, gross floor area and number of lifts, will almost certainly be correlated.

An important property of NNs is their ability to detect hidden relationships among case data and to apply these relationships to new data. They can be used to classify data (clustering), to approximate functions (curve), and to extract orthogonal factors (principle components) from interdependent data. Moreover, NNs are robust; they are able, within limits, to deal with inexact or missing data. However, the suitability of the result depends on the type of application and the architecture of the network. Another property is the robustness of NNs against physical failure of a single component. The low level of complexity and the small number of training samples allow NNs to run on a single microcomputer (Bode, 1998).

According to these properties of the NNs; it achieves many pros in estimate cost area include accuracy, time, and the ability for a person with very little knowledge about the part or neural networks to produce a good cost estimate once the network has been trained (Dowler, 2008).

Neural networks can deal more readily with multivariate non-linear relationships problems. More significantly, these relationships are determined implicitly by the model, and do not therefore require them to be specified (Harding, et al., 1999).

Al-Najjar, (2005) summarized some advantages of ANN from several researches as the following:

1- ANN are well suited to model complex problems where the relationship between the model variables is unknown.
2- Neural networks have the capability of producing correct or nearly correct outputs when presented with partially incorrect or incomplete inputs.

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3- ANN do not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANN have compared with most empirical and statistical methods.
4- ANN can always be updated to obtain better results by presenting new training examples as new data become available.
5- Artificial Neural Networks have the advantage that it gives you the output without the need to perform any manual work such as using tables, charts, or equations.
6- It is often faster to use neural networks than a conventional approach.
7- Engineers often deal with incomplete and noisy data which is one area where ANN are most applicable.
8- ANN can learn and generalize form examples to produce meaningful solutions to problems.
9- Data presented for training ANN can be theoretical data, experimental data, empirical data based on good and reliable experience or a combination of these.

Eventually, ANN can solve problems that are too complex for conventional technologies, and create its own organization or representation of the information that it receives during the learning time by automated transformation of variables in the network.

2.9.14 Problems and Challenges

Despite the good performance of Neural Networks in the previous studies essentially in cost estimation, the process of developing and implementing Neural Networks to parametric cost estimation has a number of problems associated with it. One of the main problems is the black box nature of neural networks and their inability to duplicate results. That is because the initial weights being randomly assigned, By another word, it is hard to persuade individuals who do not have a broad understanding of the technology that the neural network is producing a reliable cost estimate because it is very difficult to recreate a network (Dowler, 2008).

These problems usually highlighted in previous researches as (Kim, et al., 2004) who stated that NN approach is a black box technique and its knowledge acquisition process is very time consuming. In addition, Islam, et al., (2009) declared that the most problem

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of NN is its hidden internal structure and it is very difficult to duplicate even using the same input variables.

Otherwise, designing the network architecture and setting its parameters is not a straight-forward approach; it actually requires some trial and error process, and there is no explicit set of rules to determine whether a given learning algorithm is suitable for a particular application or not. However, some problems related to back-propagation algorithm are the speed of convergence, the possibility of ending up in a local minimum of the error function and requiring optimization of the network training in order to achieve adequate generalization. In addition, the sample size of data has to be large, so a large amount of time must be spent in determining the best network architecture and the network parameters that best fit the application under consideration.

Finally, Neural Networks do not perform well with applications where precise numerical computations are required, like detailed estimating and cost control (Ayed, 1997).

2.9.15 Application of ANN In Cost Estimation

In general, applications of ANN (Artificial Neural Network) in construction management go back to the early 1980's. These applications cover a very wide area of construction issues. Neural network models have been developed internationally to assist the managers or contractors in many crucial construction decisions. Some of these models were designed for cost estimation, decision making, predicting the percentage of mark up, predicting production rate …etc. (ElSawy, et al., 2011). However, despite the large number of researchers who applied neural network approach in various fields of engineering, but the studies and researches on utilizing neural networks to estimate the cost of construction projects at various stages of the work are very limited (Arafa & Alqedra, 2011). The early attempts to embed ANN technique within the cost estimation area was in (1993) by Shtub and Zimer who developed models for estimating the cost of assembly systems (Wang, 2007).

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Locally, there is a lack of cost estimation researches based on ANN. According to Al-Shanti (2003) study; the most of contracting companies are still estimating the projects manually, and a little use friendly estimating software packages due to a lack of available qualified personnel in using computer-based estimating systems. Therefore, he (AL-Shanti) tried to develop a cost estimating system that is familiar with many cost estimators, and it has been designed to run under Microsoft Excel sheets.

Arafa and Alqedra (2011) developed an ANN model to estimate the cost of building construction projects at early stages. A database of 71 building projects as collected from the construction industry of the Gaza Strip was used in a developed ANN model that had one hidden layer with seven neurons. The results obtained from the trained models indicated that neural networks reasonably succeeded in predicting the early stage cost estimation of buildings using basic information of the projects and without the need for a more detailed design.

Regionally, Elsawy et al. (2011) developed a neural network model to assess the percentage of site overhead costs for building projects in Egypt, which can assist the decision makers during the tender analysis process. Fifty-two actual real-life cases of building projects constructed in Egypt during the seven year period 2002-2009 were used as training materials. The neural network architecture was presented for the estimation of the site overhead costs as a percentage from the total project price. The results of the testing model indicated an accuracy of (80%), as the model wrongly predicted the percentage of site overhead costs for only one project (20%) from the testing sample.

Internationally, Kim et al. (2005) applied hybrid models of ANN and Genetic Algorithm (GA) to estimate the preliminary cost of residential buildings. Data used for training and performance evaluation were for residential buildings constructed from 1997 to 2000 in Seoul, Korea. They first optimized the parameters of the back-propagation algorithm using genetic algorithms and then obtained a set of trained weights for the ANN model using GA. The results of the research revealed that optimizing each parameter of back-propagation networks using GA is most effective in

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estimating the preliminary costs of residential buildings. They concluded that GA may help estimators to overcome the problem of the lack of adequate rules for determining the parameters of ANN.

Gunaydin and Dogan (2004) developed an ANN model to estimate the cost of a square meter of the structural system of buildings in early phases of design processes. They collected cost and design data from 30 projects of 4 to 8 storey residential buildings in Turkey. The input layer of the trained ANN model comprised eight parameters available at the early design stage. The trained ANN model was capable of providing accurate estimates of at least 93% of buildings cost per square meter.

Sonmez (2004) developed conceptual cost models for continuing care retirement community projects with regression analysis and neural networks. The results obtained from the models were compared for closeness of fit and prediction performance. He indicated that while regression analysis requires a decision about the class of relations to be used in modeling neural network was able to identify the relations between variables and the project cost. It was also shown that by using regression analysis and neural network techniques simultaneously, a satisfactory conceptual cost model (which fits the data adequately and has a reasonable prediction performance) can be achieved.

Emsley et al. (2002) trained neural network cost models using a database of data nearly 300 building projects. They used linear regression techniques as a benchmark for evaluation of the neural network models..The results showed the ability of neural networks to model the nonlinearity in the data, where the model was capable of evaluating the total cost of the construction, and the trained ANN model obtained a mean absolute percentage error of 16.6 %.

The above researches and many other reviewed by the authors indicated that the application of artificial neural networks to estimate the early cost of construction projects is a promising area and more studies should be carried out in this field.

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2.10 Neurosolution 5.07 Application

Several applications support the establishment of neural networks like SPSS, MATLAB, etc. In this research, NeuroSolution application was selected. where NeuroSolutions is the premier neural network simulation environment. As mentioned in NeuroDimension, Inc., (2012) NeuroSolutions combines a modular, icon-based network design interface with advanced learning procedures and genetic optimization. Perform cluster analysis, sales forecasting, sports predictions, medical classification, and much more with NeuroSolutions, which is:

- powerful and flexible: neural network software is the perfect tool for solving data modeling problems, so it's flexible to build fully customizable neural networks or choose from numerous pre-built neural network architectures. Modify hidden layers, the number of processing elements and the learning algorithm (NeuroDimension, Inc., 2012).
- Easy to use: NeuroSolutions is an easy-to-use neural network development tool for Microsoft Windows and intuitive, it does not require any prior knowledge of neural networks and is seamlessly integrated with Microsoft Excel and MATLAB. NeuroSolution also includes neural wizards to ensure both beginners and advanced users can easily get started. (NeuroDimension, Inc., 2012).

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CHAPTER 3

Research Methodology

3.1 Introduction

This chapter discusses the methodology used in this research. The adopted methodology to accomplish this study used historical data analysis as the base of providing a relation between the main factors affecting the cost of the building projects to make estimates for new projects.

This chapter provides the information about the research strategy and design, factors affecting cost of the building projects, process of data collection and analysis.

3.2 Research Strategy

Research strategy in general means a plan of action which the research objectives can be questioned, and it can be classified into two types namely, quantitative approach and qualitative approach (Naoum, 2007).

Qualitative approach seeks to gain insights and to understand people's perceptions, or opinion towards a particular object. As well, it is used when a limited amount of knowledge about the topic are available (Naoum, 2007).

Quantitative approach seeks to collect factual data and to study relationship between facts and how such facts and relationships accord with theories and findings of any research executed previously (Al-Shanti, 2003).

In this study both qualitative and quantitative approaches were used to get the factual information of the main factors affecting the cost of building projects in Gaza Strip at conceptual phase. As well as collecting the data from several resources, by filling a form for each project, which contains the input factors and the actual cost of the project.

3.3 Research Design

The purpose of this research is to develop a model of ANN to use in estimating cost of building projects as an alternative technique of traditional approach.

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The procedures that were used to achieve the study objectives can be summarized as shown in Figure 3.1:

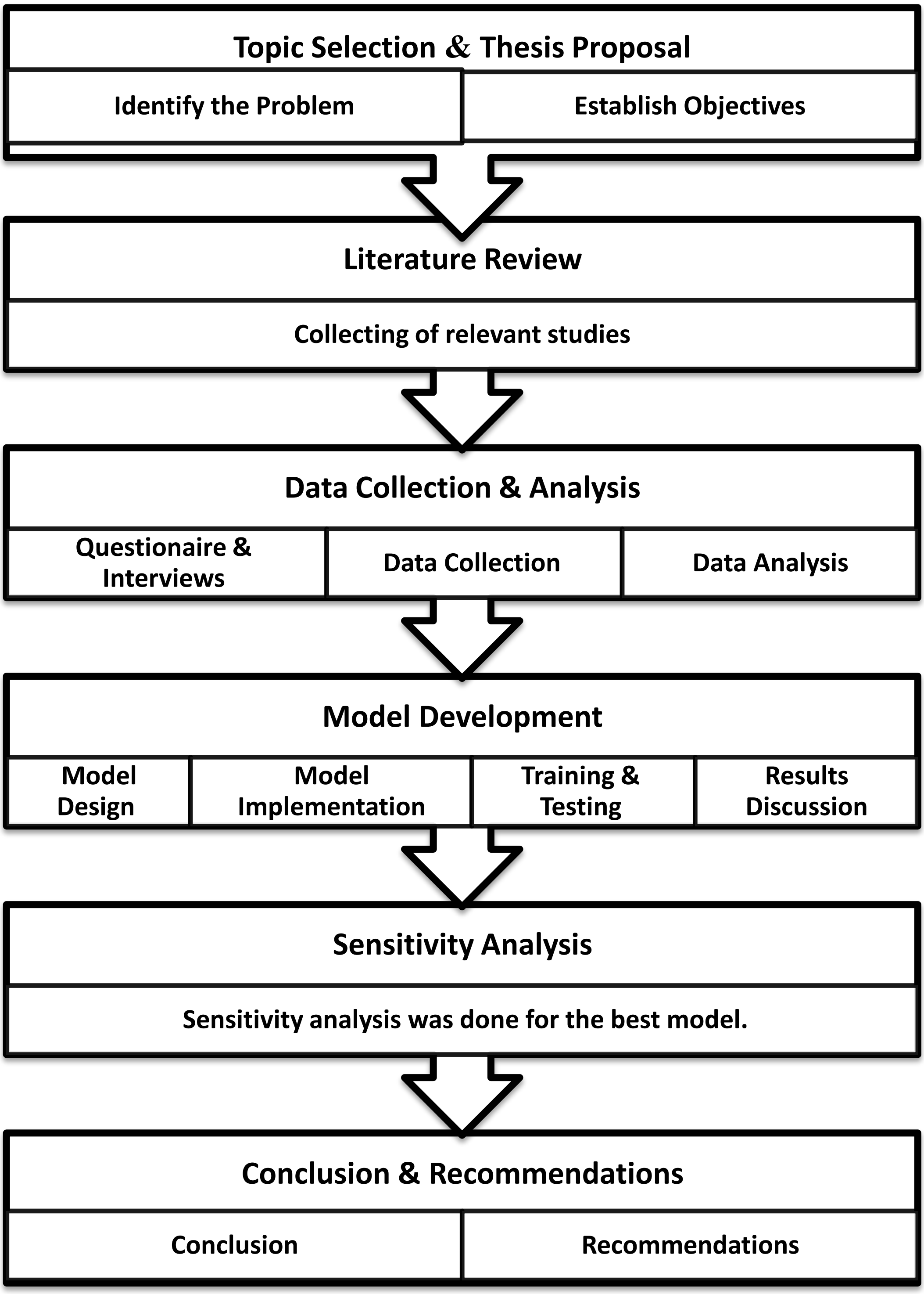

Figure 3.1 Research design

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As shown in Figure 3.1 the adopted methodology for the completion of this study follows the following stages:

Topic selection and thesis proposal phase

After selection the topic, problems are defined, objectives are established and, research plan is developed.

Literature review phase

Previous papers, reports thesis, models, and books, which relevant to cost estimation in construction industry were reviewed, essentially that studied new approach of cost estimation like Artificial Neural Networks models.

Data collection phase

A structured questionnaire in addition to expert interviews were used together in this research, to identify the main parameters affecting cost of building projects in Gaza Strip. For the need of many data in building the neural network models, many historical building projects that were done between 2009 and 2012 in Gaza Strip were collected from municipalities, Government ministries, Engineering institutions, contractors and consultants in this period especially due to resumption of implementing construction projects in those years after several Interruption years because of the Israeli blockade.

Model Development phase

After analyzing the data, many models were built and trained with various structures by using NeuroSolution 5.07. Accordingly, the best model was tested and the sensitivity analysis have been assessed by variation in the cost of projects.

Conclusion and recommendation phase

In this stage, the content of the thesis was written and the research chapters were covered. Moreover, the research was summarized in the conclusion section with many recommendations.

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CHAPTER 4

Data Collection and Results

4.1 Factors Affecting Cost of the Building Projects

In fact, one of the most significant keys in building the neural network model is identifying the factors that have real impact on the cost of building projects. Depending on this great importance of selecting these factors, several techniques were adopted carefully to identify these factors in Gaza Strip building projects; as reviewing literature studies and bill of quantities (BOQ), surveying a questionnaire, and Delphi technique by conducting expert interviews.

4.1.1 Questionnaire Analysis

Eighty questionnaires were distributed to various engineering institutions, where, fifty-seven questionnaires, as a response rate 71% of the total number of questionnaires, have been correctly answered and submitted. These questionnaires were cleaned, and some of them were omitted due to incomplete or inaccurate data. More details and analysis are discussed in this section for the questionnaire results.

I. Study population characteristics

The characteristics of study population comprise of type of company, job title, years of experience, and the experience in building projects.

a. Type of company

Table 4.1 shows that (51%) of respondents were contracting companies, while (35%) of them were consultant companies, and (14%) were owner of projects. This indicates that all type of experience are included and the highest percentage is for who design and estimated the initial cost of projects, and for the companies which implement and deemed the real cost of projects. However, contracting companies recorded the highest percentage of respondents due to great number of contracting companies in comparing with consultant companies in Gaza Strip.

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Table 4.1 Distribution of questionnaire according to company type

No.	Description	%	No.
1	Contracting company	51%	29
2	Consulting company	35%	20
3	Owner (Municipality, ministry,..)	14%	8

The total number of respondents=57 respondent

b. Job title

From Table 4.2, it has been found that the survey included most job levels of engineers, where (46%) of them are project managers, while (39%) site engineer, and (16%) are owners and others. As shown below, the most level of job title is project managers who have the whole vision about all of project cost details.

Table 4.2 Distribution of questionnaire according to job tittle

No.	Description	Percent	Frequency
1	Owner of company	7%	4
2	Project manager	46%	26
3	Site engineer	38%	22
4	Others	9%	5

c. Years of experience in construction projects

Table 4.3 presents the work experience of participants, where (25%) of them have high experience exceeds than 10 years, while (26%) have 7 to10 year experience, and (49%) have less 6-year experience. This indicates that the greatest percentage of respondents have suitable experience in construction field to make them able to determine the critical factors affect on the cost of projects.

Table 4.3 Distribution of questionnaire according to number of experience years

Description	Percent	Frequency
1 – 3 years	17%	10
4 – 6 years	32%	18
7 – 10 years	26%	15
More than 10	25%	14

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d. Experience in Building Projects

Table 4.4 ensures the specialized experience criteria for respondents in building projects at last few years, in order to assure that they have an update prices of project's cost. Three-quarters of respondents(86%) have worked in less than 10 building projects in last four years, and (14%) have worked in more than 10 buildings.

Table 4.4 Distribution of questionnaire according to experience in building projects

No.	No. of projectsn	Percent	Frequency
1	1-5	44%	25
2	6 - 10	42%	24
3	11 - 15	9%	5
4	More than 15	5%	3

The total number of respondents=57 respondents

Regarding to the experience of the respondents, it is found that high percent of them have good experience in construction field, and have advanced positions in job level, which gives more logic and reality of surveyed results to some extent.

II. Skeleton phase cost factors

As known, building project passess through two basic phasis; skeleton and finishing phase, each one has its influential factors that affects on total project,cost. Table 4.5 includes 13 skeleton factors, where most of respondents see that the area of typical floor and number of floors are the most influntial factors on building cost, while area of retaining wall, type of building, type of foundation, number of elevators and type of slab have a moderate influence. For remaining parameters as, length of span between columns, number of columns, number of rooms, location of project, number of stair cases, and type of contract have lower inflluence on the project cost.

Another observation from Table 4.5, all parameters have considerable effect where all of these have a rate more than 50%. This indicates that the selection of parameters was logical and realistic in its impact on building cost.

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Table 4.5 Influence of skeleton factors on building cost

No.	Description	Rate/5	Percent
1	Area of typical floor	4.5	90%
2	Number of floors in the building	4.5	90%
3	Area of retaining walls	3.8	75%
4	Type of building	3.7	73%
5	Type of used foundation in the building	3.6	72%
6	Number of elevators in the building	3.6	71%
7	Type of slab (Solid, ribbed…)	3.5	71%
8	Length of spans between columns	3.5	69%
9	Number of columns	3.3	65%
10	Number of rooms	3.0	59%
11	Location of project	2.9	57%
12	Number of staircases in the building	2.8	57%
13	Type of contract	2.5	51%

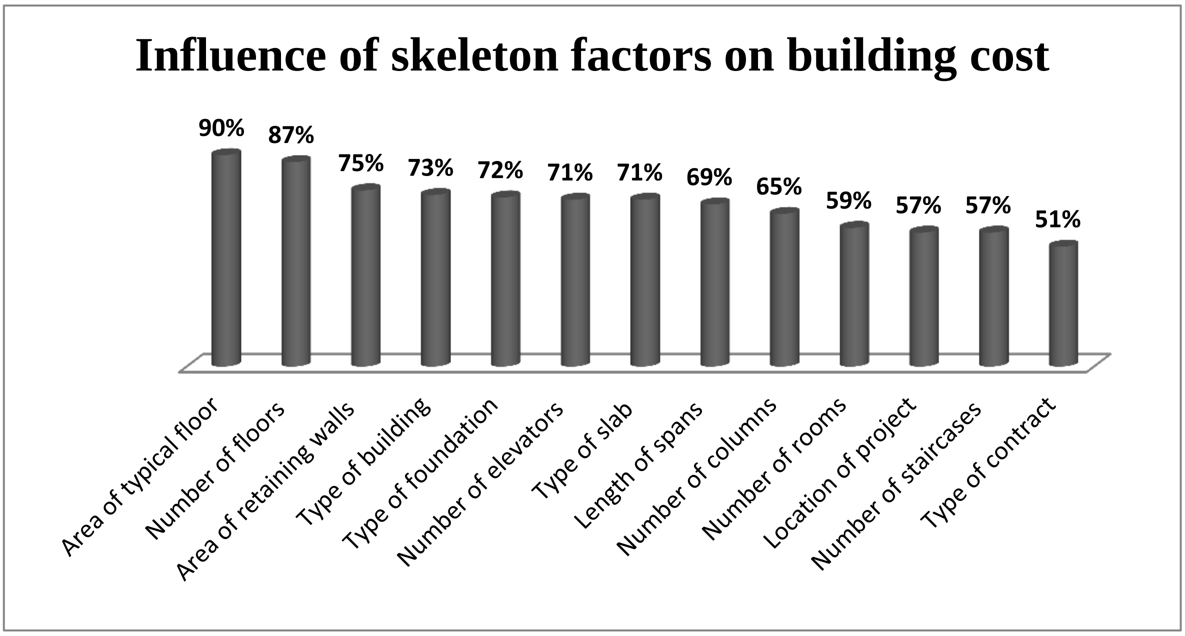

Figure 4.1 Influence of skeleton factors on building cost

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III. Finishing phase cost factors

Figure 4.2 shows the respondents views for the influence of 18 finishing parameters on total building cost. It is found that the external finishing type has the highest rate (78%), while volume of air-conditioning, area of curtain walls, type of tiling, type of sanitary, and type of electrical works have a rate between 27%-76%.

These results reveal how convergence exists between most of parameters, and there is no dominant parameter existing among them. However, as illustrated in Table 4.5 about the indication of this convergence, but all of these parameters was subjected to evaluate by relevant experts who presented their views and suggestion in next section.

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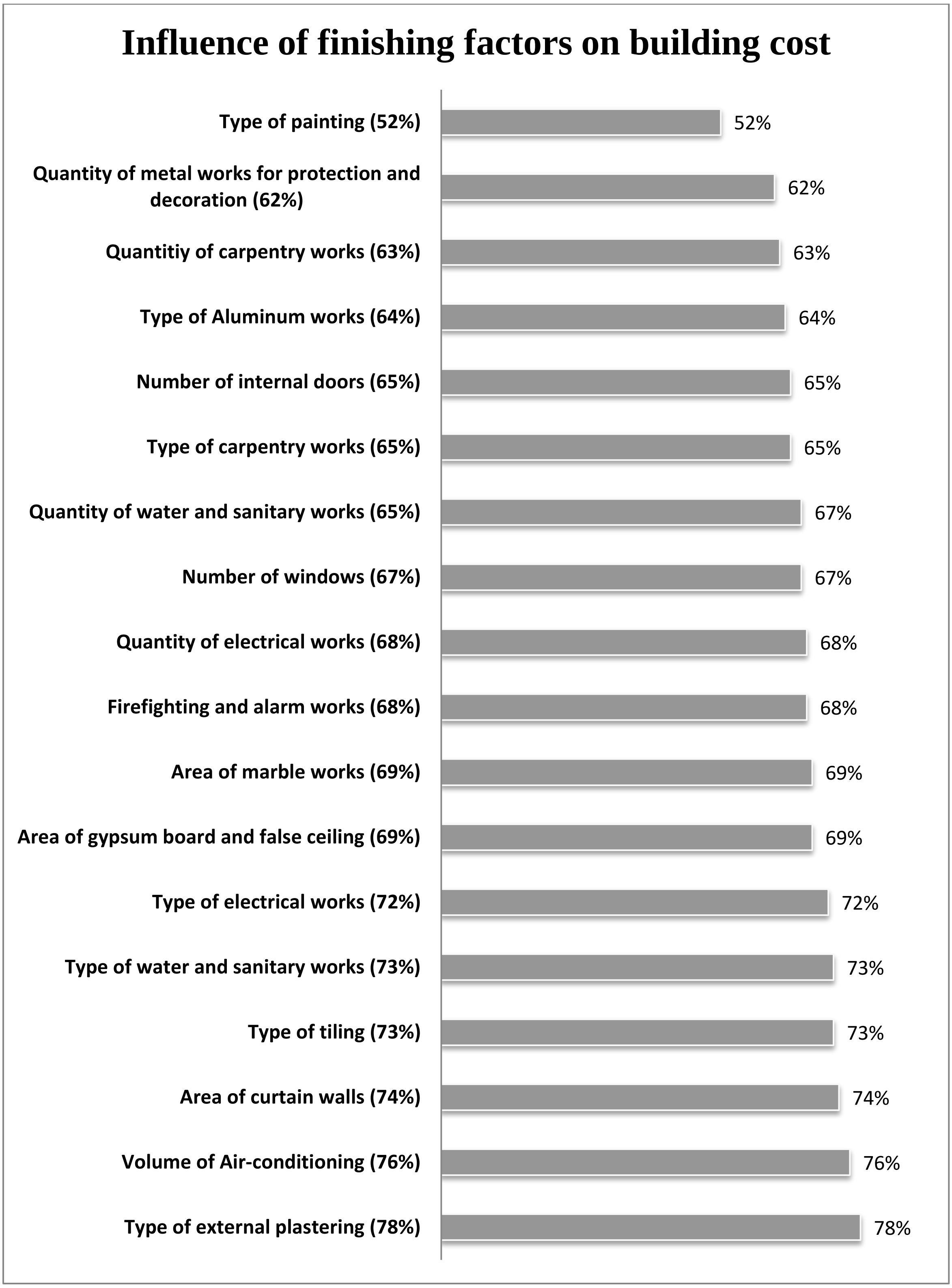

Figure 4.2 Influence of finishing factors on building cost

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4.1.2 Delphi Technique

Different technique has been used to determine the effective factors on building project cost. This technique relies on the concept of Delphi technique, which aimed to achieve a convergence of opinion on factors affecting the cost of the project. It provides feedback to experts in the form of distributions of their opinions and reasons. Then, they are asked to revise their opinions in light of the information contained in the feedback. This sequence of questionnaire and revision is repeated until no further significant opinion changes are expected (Creedy, et al., 2006).

For Delphi process, several rounds should be conducted where first round begins with an open-ended questionnaire. The open-ended questionnaire serves as the cornerstone of soliciting specific information about a content area from the Delphi subjects, then after receiving the responses, the researcher converts the collected information into a well-structured questionnaire to be used as the survey instrument for the second round of data collection. In the second round, each Delphi participant receives a second questionnaire and is asked to review the items summarized by the investigators based on the information provided in the first round, where in this round areas of disagreement and agreement are identified. However, in third round Delphi panelist are asked to revise his/her judgments or to specify the reasons for remaining outside the consensus. In the fourth and often final round, the list of remaining items, their ratings, minority opinions, and items achieving consensus are distributed to the panelists. This round provides a final opportunity for participants to revise their judgments. Accordingly, the number of Delphi iterations depends largely on the degree of consensus sought by the investigators and can vary from three to five (Hsu, 2007).

Five experts in construction field were selected to reach a consensus about specifying the key cost parameters The results with those five experts were significantly close to the questionnaire results, and only three rounds were conducted due to largely degree of consensus. where they proposed to exclude retaining wall and curtain wall from these factors because of their rarity in Gaza's projects, In addition, for the two factors; type of slab and length of span, they recommended to combine them with one factor that contains slab with drop beams. Moreover, they suggested merging area of gypsum board with HVAC (Heating Ventilation and Air-conditioning) to

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avoid existing dependent parameters in input factors because gypsum boards are installing in case of installing central air-conditioning.

4.1.3 Literature Studies

There are several key parameters that effect on buildings cost. Selecting the most influential parameters is one of the superior challenge of building the model. Therefore, many researchers studied these parameters and implemented their models according to various parameters. After studying most of these parameters, part of these were included in questionnaire survey while others were excluded due to several reasons based on experts in this field, such as:

- Little impact on Gaza's building projects as temporary facilities.. etc.
- Rare use of these factors in Gaza's projects as vinyl exterior finish, Landscaping, Usage of basement, parking area ..etc.
- Convergence of factors like area of gorund floor and area of typical floor, The ratio of the typical floor area to the total area of the building, …etc.
- Assumptions and limitations that have been used in this study as year of project, duration of implementing the project, ..etc.

Table 4.6 presents the influential factors that endorsed in former empirical models and compatible with the adopted factors in this research.

Table 4.6 Influential factors adopted in previous researches

No.	Chosen Factors	References
1	Floor Area	▪ **(Kim, et al., 2004)** ▪ **(Gunaydın & Dogan, 2004)** ▪ **(Arafa & Alqedra, 2011)** ▪ **(Cheng, et al., 2010)** ▪ **(Sonmez, 2011)** ▪ **(Wang, et al., 2012)**
2	Number of storeys	▪ **(Kim, et al., 2004)** ▪ **(Gunaydın & Dogan, 2004)** ▪ **(Wang, et al., 2012)** ▪ **(Arafa & Alqedra, 2011)** ▪ **(Sonmez, 2011)**

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No.	Chosen Factors	References
3	Slab type	▪ **(Kim, et al., 2004)** ▪ **(Doğan, 2005)**
4	Finishing grades	▪ **(Kim, et al., 2004)**
5	Foundation type	▪ **(Kim, et al., 2004)** ▪ **(Gunaydın & Dogan, 2004)** ▪ **(Wang, et al., 2012)** ▪ **(Arafa & Alqedra, 2011)**
6	Number of elevator	▪ **(Wang, et al., 2012)** ▪ **(Arafa & Alqedra, 2011)** ▪ **(Sonmez, 2011)**
7	Type of project	▪ **(ElSawy, et al., 2011)**
8	Type of contract	▪ **(ElSawy, et al., 2011)**
9	External finishing	▪ **(Wang, et al., 2012)** ▪ **(Sonmez, 2011)**

4.1.4 Influential Factors Adopted in the Research

Literature studies was the first process in determining the key parameters, then the questionnaire that was designed according to these literatures as long as specialists opinions, and finally Delphi technique that acquired a final identification of most influential factors on building projects cost.

According to previous techniques, it is obvious that there is a substantial convergence in identifying factors affecting on cost of building projects in Gaza Strip. Therefore, it can be simply adopted the most influential factors (skeleton and finishing factors). Table 4.7 shows the most influential factors that were adopted in this study and were used in building the models as input parameters. It contains five skeleton factors and six finishing factors.

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Table 4.7 Influential Factors of building project Cost adopted in this research

No.	Description	Range
1	Area of typical floors	Less than 1200 m2
2	Number of storeys	(1-8) storey
3	Use of building	Prayer place-Resedential-Extension of schools-Schools-Public buildings-Mosques
4	Type of foundation	None-Isolated-Strap-Piles-Mat
5	Type of slab	Solid- Ribbed - Drop beams
6	Number of elevators	(0-1-2)
7	Type of external finishing	None-Normal plaster- Marmarina- Natural stone
8	Presence of HVAC and false ceiling	None -Central conditioning-Split units
9	Type of tilling	Ceramic –Terrazzo -Porcelain
10	Type of electricity works	Basic - Luxury
11	Type of mechanical works	Basic -Luxury

4.2 Data Collection

In fact, the process of collecting information that is related to cost estimation problems is a difficult task especially in Gaza Strip, because such information is the property of each construction firm. Construction firms usually do not agree to share their cost data with other competing construction firms. Moreover, most firms believe that such information usually makes a difference in being more competitive in the market. However, great effort and time were exposed to collect adequate account of building projects to establish an accurate neural network model. The methodology for collecting these data was based on personal contacts with construction firms, institutions and government ministries across Gaza Strip.

4.3 Data Validation

Data validation is paramount before developing any predictive model, which allows identifying uncommon cases, invalid cases, erroneous variables and incorrect data values in the dataset. If the data is prepared properly, it will be able to develop a more realistic parametric cost model and give better results.

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In order to overcome any defect in collected data, some basic assumptions and criteria were defined and performed, which are:

- The project has to be completely finished or has approval for the funding (Arafa & Alqedra, 2011).
- Project implemtation period less than one year (Arafa & Alqedra, 2011).
- Implementation of the project was during the period 2009 – 2012.
- Unifying currency of projects prices.
- Incomplete data, missing one or more values.
- Duplicate data, two projects are the same in all related values.
- Misleading data.
- The maximum amount of projects in a single category should not be more than 95% (Islam, et al., 2009).
- the maximum amount of categories with count of one (1) should not be more than 90% (Islam, et al., 2009).

As a result of this filtering and checks, 24 projects of 193 projects were eliminated. Subsequently, 169 projects were used to build the model.

4.4 Data Results

In this section, a detailed analysis of data and results will be presented and elaborated by using frequency analysis. The data used in this study was collected from 193 bids submitted to their office in the past three years. A data sheet was prepared and used to extract all useful information from each project. Table 4.8 presents the main sources of data and the number of projects that have been obtained from these sources.

Table 4.8 Data resources

Data Resources	**No. of projects**	**Percentage (%)**
Engineering Consulting Companies	23	12%
Contractors	77	40%
Government Ministries	38	20%

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Data Resources	No. of projects	Percentage (%)
UNRWA	6	3%
Engineering Institutions	49	25%
Total	**193**	**100%**

As shown from Table 4.8, most institutions concerned with construction engineering in Gaza strip were visited. 23 projects were obtained from engineering consulting companies, 77 projects were gathered from contractors, and also 38 projects were collected from government ministries concerned with construction projects; as Ministry of Public Works and Housing, Ministry of local government and Ministry of education, while 6 projects were obtained from UNRWA office, and finally 49 projects were collected from various institutions.

❖ **Use of building**

Use of building factor includes six subtypes as shown in Table 4.9, some subtypes were excluded like hospitals, laboratories, and universities because there is no sufficient number of these types were implemented during (2009-2012).

As shown in Table 4.9, all subtypes have a good distribution of projects, where residential subtype (30.8%), and public building (20%) have the maximum rate, while schools have (17.8%), mosques (15.4%), Prayer place (6.5%), and school extension (9.5%),

Table 4.9 Use of building factor

Use of building	No. of projects	Percentage (%)
Prayer place	11	6.5 %
Residential	52	30.8 %
School extension	16	9.5 %
Schools	30	17.8 %
Public building	34	20 %
Mosques	26	15.4 %
Total	**169**	**100 %**

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❖ Area of typical floor

The second input factor is the area of typical floors, which bears a strong linear relation to the total cost of the building. Area of typical floors was divided into 12 categories; each one contained 100 m2 except the first category.

Table 4.10 presents the classification of these areas and the percentage of each to the total number of projects, where the categories start with are 60 m2 up to 1200 m2. Part of categories have a little percentage of frequency as (1000-1100) category (3%), but it not cause a problem because all of these subtypes reflect the variation in one type which is area of typical floor.

Table 4.10 Area of typical floor factor

Area of typical floor	No. of projects	Percentage (%)
60 – 100 m2	16	9.5 %
100 – 200 m2	24	14.2 %
200 – 300 m2	15	8.9 %
300 – 400 m2	20	11.8 %
400 – 500 m2	23	13.6 %
500 – 600 m2	10	5.9 %
600 – 700 m2	9	5.3 %
700 – 800 m2	6	3.6 %
800 – 900 m2	15	8.9 %
900 – 1000 m2	18	10.6 %
1000 – 1100 m2	5	3 %
1100 – 1200 m2	8	4.7%
Total	**169**	**100 %**

❖ Number of floors

Number of floors also becomes an important factor; it begins with one floor up to eight floors as shown Table 4.11. In which, basement or roof considered as one floor. Despite the number of projects in last categories is not as much as the first categories, but it gives a clearly indicator in training the model that increase the number of floors in the building leads to increase the cost of projects.

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Table 4.11 Number of floors factor

Number of floors	No. of projects	Percentage (%)
1	30	17.8 %
2	39	23.1 %
3	66	39 %
4	16	9.5 %
5	6	3.6 %
6	2	1.2 %
7	3	1.8 %
8	7	4 %
Total	**169**	**100 %**

❖ **Type of foundation**

The most common foundation subtypes are isolated, strap, piles, and mat respectively. Table 4.12 shows the number of projects in each subtype of foundation and the percentage of each to the total number of projects. For the first subtype "None", it means there is existing foundation in the building but it need an extension through building more floors. As presented, isolated foundation has the highest rate (50.3%), and strap foundation has (25.4%), while piles and mat foundation have (21.3%).

Table 4.12 Type of foundation factor

Type of foundation	No. of projects	Percentage (%)
None	5	3 %
Isolated	85	50.3 %
Strap	43	25.4 %
Piles	19	11.2 %
Mat	17	10.1 %
Total	**169**	**100 %**

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- **Type of slab**

The type of slab affect on the total cost of project by the volume of concrete and the amount of reinforcement. Table 4.13 presents three subtypes of slab solid slab (5.3 %), Ribbed slab (39.6 %), and slab with drop beams (55.1 %).

Table 4.13 Type of slab factor

Type of slab	No. of projects	Percentage (%)
Solid slab	9	5.3 %
Ribbed slab	67	39.6 %
Slab with Drop beams	93	55.1 %
Total	**169**	**100 %**

- **Number of elevators**

The following Table 4.14 shows that over 89% of the data has no elevators in buildings, 7.1% have one elevator and another 3% has two elevators in its structure building.

Table 4.14 Number of elevator factor

Number of elevators	No. of projects	Percentage (%)
0	152	89.9 %
1	12	7.1 %
2	5	3 %
Total	**169**	**100 %**

- **Type of external finishing**

Numerous subtypes of external finishing are using in Gaza Strip, Table 4.15 demonstrates these types and frequency for each, where Normal plaster has (44%), and Marmarina (38.5%), while Natural stone (14%). For subtype “None” (4%) it means the 4% of building haven’t any type of external finishing.

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Table 4.15 Type of external finishing factor

Type of external finishing	No. of projects	Percentage (%)
None	7	4.1 %
Normal plaster	74	43.8 %
Marmarina	65	38.5 %
Natural stone	23	13.6 %
Total	**169**	**100 %**

❖ **Size of air-conditioning**

As shown in Table 4.16 more than 92% of projects don't have Air-conditioning, while (2.4%) of them have Split units. Due to lack of use central-air conditioning and more projects don't have installing split units in tender quantities, high rate was for "None" parameter.

Table 4.16 Type of air-conditioning

Size of air condetioning	No. of projects	Percentage (%)
None	157	92.9 %
Central AC + false ceiling	8	4.7 %
Split unit	4	2.4 %
Total	**169**	**100 %**

❖ **Type of tilling**

A large proportion of projects in Gaza Strip especially in schools, mosques and residential projects are using Terrazzo and Ceramic tiles. Therefore, it is notable from Table 4.17 that most tilling subtypes are Terrazzo and Ceramic (89%), while Porcelain (11.2%).

Table 4.17 Type of tilling factor

Type of tilling	No. of projects	Percentage (%)
Ceramic	46	27.3 %
Terrazzo	104	61.5 %
Porcelain	19	11.2 %
Total	**169**	**100 %**

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- **Type of electricity**

The electricity type was divided into two main parts which are Basic and Luxury type, where normal refers to commercial types and works, and Luxury refers to high quality type and works. According to Table 4.18 most of electricity type is Basic (85.2 %), and (15 %) have an Luxury type.

Table 4.18 Type of electricity factor

Type of electricity	No. of projects	Percentage (%)
Basic	144	85.2 %
Luxury	25	14.8 %
Total	**169**	**100 %**

- **Type of sanitary**

As electricity was classified, also sanitary type has the same. Table 4.19 shows that most of sanitary works are Basic (87.6 %), and 12 % have Luxury subtype.

Table 4.19 Type of sanitary factor

Type of sanitary	No. of projects	Percentage (%)
Basic	148	87.6 %
Luxury	21	12.4 %
Total	**169**	**100 %**

4.5 Data Encoding

Artificial networks only deal with numeric input data. Therefore, the raw data must often be converted from the external environment to numeric form (Kshirsagar & Rathod, 2012). This may be challenging because there are many ways to do it and unfortunately, some are better than others are for neural network learning (Principe, et al., 2010). In this research data were converted to numeric form as shown in

Table 4.20

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Table 4.20 Inputs/Output encoding

No.	Input Factors	Encode	Code
1	Use of project	- Prayer place	=1
		- Residential	=2
		- School extension	=3
		- Schools	=4
		- Public building	=5
		- Mosques	=6
2	Area of typical floors	- 60 – 100 m2	=1
		- 100 – 200 m2	=2
		- 200 – 300 m2	=3
		- 300 – 400 m2	=4
		- 400 – 500 m2	=5
		- 500 – 600 m2	=6
		- 600 – 700 m2	=7
		- 700 – 800 m2	=8
		- 800 – 900 m2	=9
		- 900 – 1000 m2	=10
		- 1000 – 1100 m2	=11
		- 1100 – 1200 m2	=12
3	Number of storeys	- Number from	(1 – 8)
4	Type of foundation	- None	=0
		- Isolated	=2
		- Strap	=3
		- Piles	=4
		- Mat	=5
5	Type of slab	- Solid	=1
		- Ribbed	=2
		- Drop beams	=3
6	Number of elevators	- Number from	(0 – 2)
7	Type of external finishing	- None	=0
		- Normal plaster	=1
		- Marmarina	=2
		- Natural stone	=3

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No.	Input Factors	Encode	Code
8	Size of air-conditioning	- None - Central AC+False ceiling - Split unit	=0 =1 =2
9	Type of tilling	- Ceramic - Basalt- Terrazzo - Porcelain	=1 =2 =3
10	Type of electricity	- Basic - Luxury	=1 =2
11	Type of sanitary	- Basic - Luxury	=1 =2
No.	**Output Parameter**	**Encode**	**Code**
1	Total Project cost	- in dollars	($)

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CHAPTER 5

Model Development

5.1 Introduction

A Neural Network training program, NeuroSolution, was used as a standalone environment for Neural Networks development and training. Moreover, for verifying this work, a plentiful trial and error process was performed to obtain the best model architecture.

The following sections present the steps performed to design the artificial neural network model, the limitation of adopted model, and finally the discussion and analysis of results.

5.2 Model Limitations

In spite of great accuracy of using ANN in cost estimation, it has a considerable defect, as it depends mainly on historical data; this dependency has several disadvantages as the following;

- Diversity of variables for effective factors is limited to what available in collected data.
- Data should contain sufficient projects for each variable.
- New variables which was not included in adopted model will not be handled.

Therefore, in this study most of construction variables used in Gaza Strip were included except those that haven't enough frequency. After analyzing the collected data, there was found that some limitations on input parameters should be assigned to give the best output. Table 5.1 illustrates the available range of input data in ANN model as; Area of typical floor has a range between 60 - 1200 m2, Number of floors ranges from 1floor up to 8 floors, and Number of elevators also ranges from 0 to 2. For remaining input factors as use of project, type of foundation... etc, they are also limited to earlier mentioned choices. See section (4.1.4)

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Table 5.1 Input limitations in model

Models numeric variables	Minimum value	Maximum value
Floor Area	60 m^2	1200 m^2
Number of floors	1 storey	8 storey
Number of elevators	0	2

5.3 Model Building

There are several types of ANNs softwares are used to predict the future values based on the past data like SPSS, MATLAB, NeuroSolution …etc. Many researchers used NeuroSolution application in building their neural networks that it achieved good performance as (Edara, 2003; Gunaydın & Dogan, 2004; Bouabaz & Hamami, 2008; Dowler, 2008; Attal, 2010; Wang, et al., 2012).

The developed model in this research based on NeuroSolution 5.07 for Excel program. It was selected for its ease of use, speed of training, flexibility of building and executing the NN model. In addition, the modeler has the flexibility to specify his own neural network type, learning rate, momentum, activation functions, number of hidden layers/neurons, and graphical interpretation of the results. Finally, It has multiple criteria for training and testing the model.

1) Data Organization

Initially, the first step in implementing the neural network model in NeuroSolution application is to organize the Neurosolution excel spreadsheet. Then, specifying the input factors that have been already encoded, which consist of 11 factors; Type of project, area of typical floor, number of floors, type of foundation, type of slab, number of elevators, type of external finishing, type of air-conditioning, type of tilling, type of electricity, and type of sanitary. The desired parameter (output) which is (total cost of the project).

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2) Data Set

The available data were divided into three sets namely; training set, cross-validation set and test set. Training and cross validation sets are used in learning the model through utilizing training set in modifying the network weights to minimize the network error, and monitoring this error by cross validation set during the training process. However, test set does not enter in the training process and it hasn't any effect on the training process, where it is used for measuring the generalization ability of the network, and evaluated network performance (Arafa & Alqedra, 2011).

In the present study, the total available data is 169 exemplars that were divided logical randomly, according to previous literatures in section (2.9.4), into three sets with the following ratio:

- Training set (includes 116 exemplars ≈ 69%).
- Cross validation set (includes 27 exemplars ≈ 16%).
- Test set (includes 26 exemplars ≈ 15%).

3) Building Network

Once all data were prepared, then the subsequent step is represented in creating the initial network by selecting the network type, number of hidden layer/nodes, transfer function, learning rule, and number of epochs and runs.

An initial neural network was built by selecting the type of network, number of hidden layers/nodes, transfer function, and learning rule. However, before the model becomes ready, a supervised learning control was checked to specify the maximum number of epochs and the termination limits, Figure 5.1 presents the initial network of Multilayer Perceptron (MLP) network that consists of one input, hidden, and output layer.

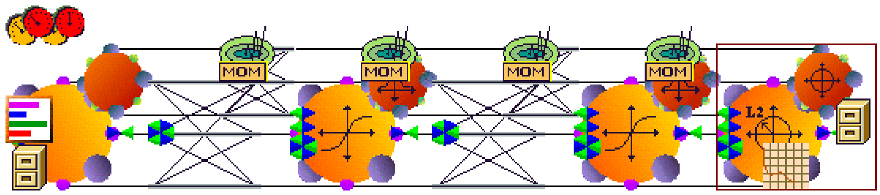

Figure 5.1 Multilayer Perceprtorn (MLP) network

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Before starting the training phase, the normalization of training data is recognized to improve the performance of trained networks by Neurosolution program which as shown in Figure 5.2 which ranging from (-1 to +1).

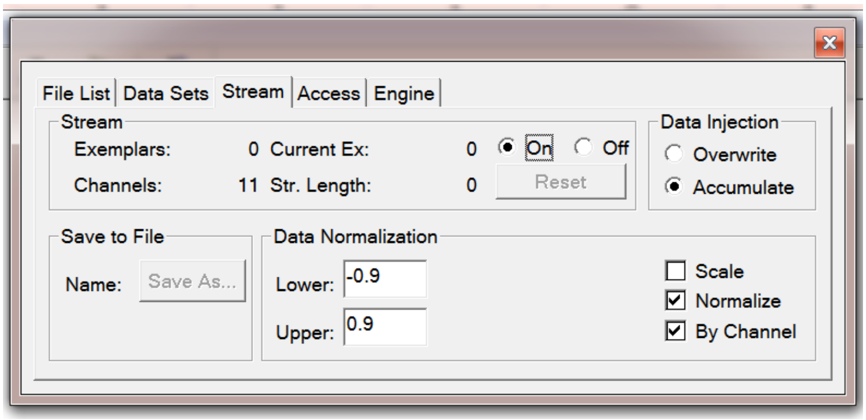

Figure 5.2 Selecting the normalization limits of data

5.4 Model Training

The objective of training neural network is to get a network that performs best on unseen data through training many networks on a training set and comparing the errors of the networks on the validation set (Dindar, 2004). Therefore, several network parameters such as number of hidden layers, number of hidden nodes, transfer functions and learning rules were trained multiple times to produce the best weights for the model.

As a preliminary step to filter the preferable neural network type, A test process was applied for most of available networks in the application. Two types Multilayer Perceptron (MLP) and General feed Forward (GFF) networks were chosen to be focused in following training process due to their good initial results.

It is worthy to mention that, previous models that have been applied in the field of cost estimation by neural networks used earlier two types of networks because of giving them the best outcome.

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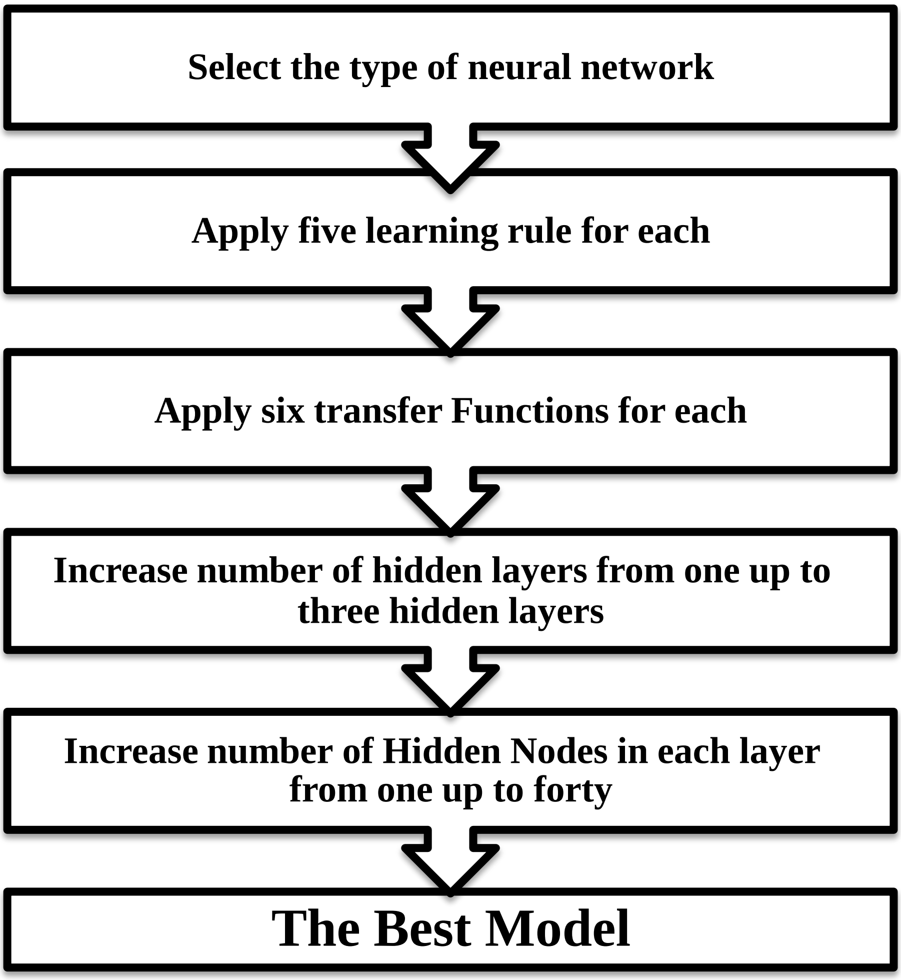
The following chart illustrates the procedures of training process to obtain the best model having the best weight and minimum error percentage.



The chart shows the procedures of the model training, which starts with selecting the neural network type either MLP or GFF network. For each one, five types of learning rules were used, and with every learning rule six types of transfer functions were applied, and then 3 separate hidden layers were utilized with increment of hidden nodes from 1 node up to 40 nodes in each layer.

By another word, more than one and a half thousand trials contains 40 variable hidden nodes for each were executed to obtain the best model of neural network. Figure 5.3 clarifies training variables for one trial. It compromises of number of epochs, runs, hidden nodes, and other training options.

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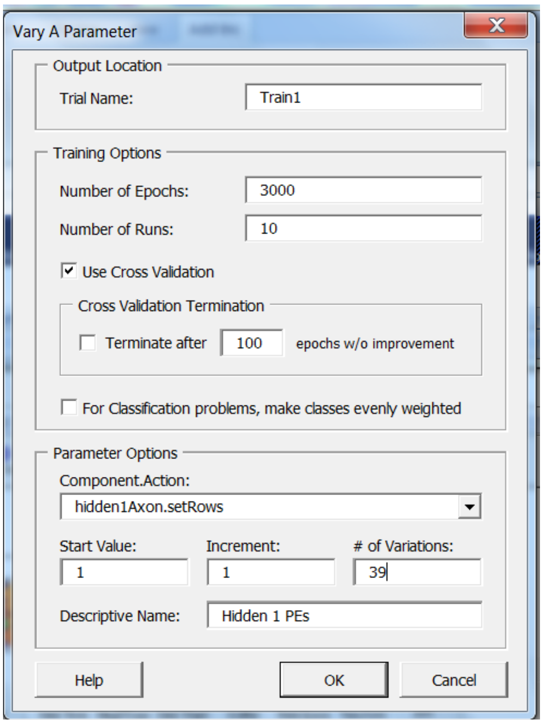

Figure 5.3 Training options in Neurosolution application

Ten runs in each one 3000 epochs were applied, where a run is a complete presentation of 3000 epochs, each epoch is a one complete presentation of all of the data (Principe, et al., 2010). However, in each run, new weights were applied in the first epoch and then the weights were adjusted to minimize the percentage of error in other epochs.

To avoid overtraining for the network during the training process, an option of using cross-validation was selected, which computes the error in a cross validation set at the same time that the network is being trained with the training set.

The model was started with one hidden layer and one hidden node in order to begin the model with simple architecture, and then the number of hidden PEs was growing up by one node up to 40 hidden nodes.

5.5 Model Results

As mentioned above, the purpose of testing phase of ANN model is to ensure that the developed model was successfully trained and generalization is adequately achieved. Through a system of trial and error guided by earlier recommendation in section (2.9.4), the best model that provided more accurate cost estimate without

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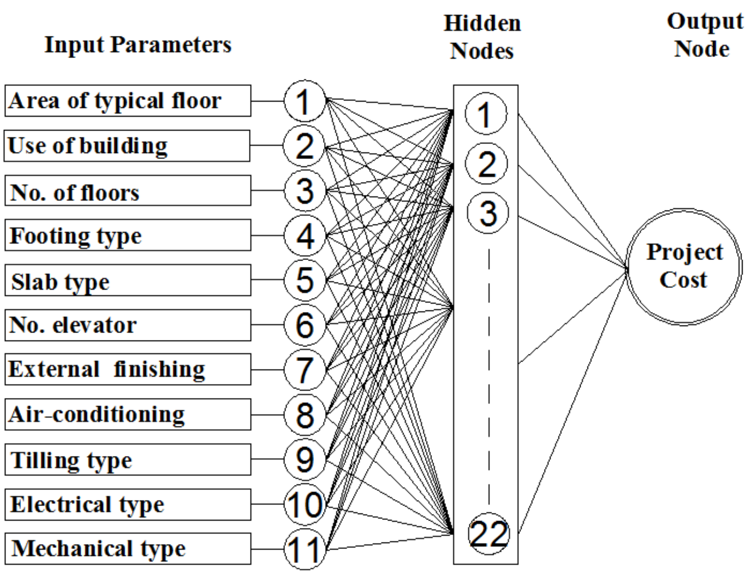
being overly complex was structured of Multilayer Preceptron (MLP) includes one input layer with 11 input neurons and one hidden layer with (22 hidden neurons) and finally one output layer with one output neuron (Total cost). However, the main downside to using the Multilayer Preceptron network structure is that it required the use of more nodes and more training epochs to achieve the desired results. Table 5.2 summarizes the architecture of the model as number of hidden layer/nodes, type of network and transfer function.

Table 5.2 Architecture of the model

<table>
<tr><th colspan="4">Architecture of the model</th></tr>
<tr><td colspan="4">
</td></tr>
<tr><td>Model Type</td><td>Transfer Function</td><td>Update Methods</td><td>Gradient Search</td></tr>
<tr><td>Multilayer Perceptron</td><td>Tanh</td><td>Batch</td><td>Momentum</td></tr>
<tr><td>No. of hidden layer</td><td>No. of PEs in the input layer</td><td>No. of PEs in the 1st Hidden layer</td><td>No. of PEs in the output layer</td></tr>
<tr><td>1</td><td>11</td><td>22</td><td>1</td></tr>
</table>

5.6 Results Analysis

The testing dataset was used for generalization that is to produce better output for unseen examples. Data from twenty-six projects were used for testing purposes.

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A Neurosolution test tool was used for testing the adopted model accordingly to the weights adopted. Table 5.3 presents the results of these twenty-six projects with comparing the real cost of tested project with estimated cost from neural network model, and an absolute error with both price and percentage are also presented.

Table 5.3 Results of neural network model at testing phase

No.	**Actual Cost ($)**	**Estimated Cost ($)**	**Absolute Error AE ($)**	**Absolute Percentage Error (%)**
Project 1	23,200	25,624	2,424	10%
Project 2	34,710	35,366	656	1.8%
Project 3	211,200	220,043	8,843	4%
Project 4	441,600	399,836	41,764	9%
Project 5	318,450	297,602	20,848	7%
Project 6	286,000	310,767	24,767	9%
Project 7	33,050	35,366	2,316	7%
Project 8	720,000	751,343	31,343	4%
Project 9	444,540	440,324	4,216	0.9%
Project 10	616,150	650,536	34,386	6%
Project 11	320,000	272,113	47,887	15%
Project 12	355,238	272,113	83,125	23%
Project 13	112,980	108,282	4,698	4%
Project 14	1,106,640	914,035	192,605	17%
Project 15	936,660	856,575	80,085	9%
Project 16	375,000	356,332	18,668	5%
Project 17	901,236	881,406	19,830	2%
Project 18	835,395	778,954	56,441	7%
Project 19	1,051,400	994,410	56,990	5%
Project 20	977,208	994,410	17,202	2%
Project 21	1,032,105	994,410	37,695	4%
Project 22	1,012,194	994,410	17,784	2%
Project 23	997,000	994,410	2,590	0.2%
Project 24	1,110,000	1,108,615	1,385	0.1%
Project 25	2,030,400	2,087,698	57,298	3%
Project 26	1,149,000	1,137,167	11,833	1%

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- **Mean Absolute Error**

The Mean Absolute error (MAE) for the presented results in Table 5.3 equals (33,757 $), it is largely acceptable for projects worth hundreds of thousands dollars. However, it is not a significant indicator for the model performance because it proceeds in one direction, where the mentioned error may be very simple if the total cost of the project is large, and in turn; it may be a large margin of error in case the total cost of the project is small.

- **Mean Absolute Percentage Error**

The mean absolute percentage error of the model is calculated from the test cases as shown in Table 5.3, which equals 6%, this result can be expressed in another form by accuracy performance (AP) according to Wilmot and Mei, (2005) which is defined as (100−MAPE) %.

$$AP = 100\% - 6\% = 94\%$$

That means the accuracy of adopted model for building projects estimate in conceptual phase is 94%. It is a good result especially when this estimate in conceptual phase where no details or drawings are available.

- **Total Mean Absolute Percentage Error**

As mentioned in section (2.5) the allowable percentage error in cost estimation at conceptual phase equals ±50%. Moreover, by reviewing many researches that used ANN in cost estimation, it is shown that no specific percent of allowable error for model estimate is available. However, the acceptable accuracy performance for ANN model is equal 10% according to (Bakhary, et al., 2004) and (Samphaongoen, 2010).

In this study and according to Equation 2.5, the Total MAPE = 10%, where this error includes all datasets as training, cross validation , and test datasets.

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➢ **Correlation Coefficient (R)**

Regression analysis was used to ascertain the relationship between the estimated cost and the actual cost. The results of linear regressing are illustrated graphically in Figure 5.4. The correlation coefficient (R) is 0.995, indicating that; there is a good linear correlation between the actual value and the estimated neural network cost at tested phase.

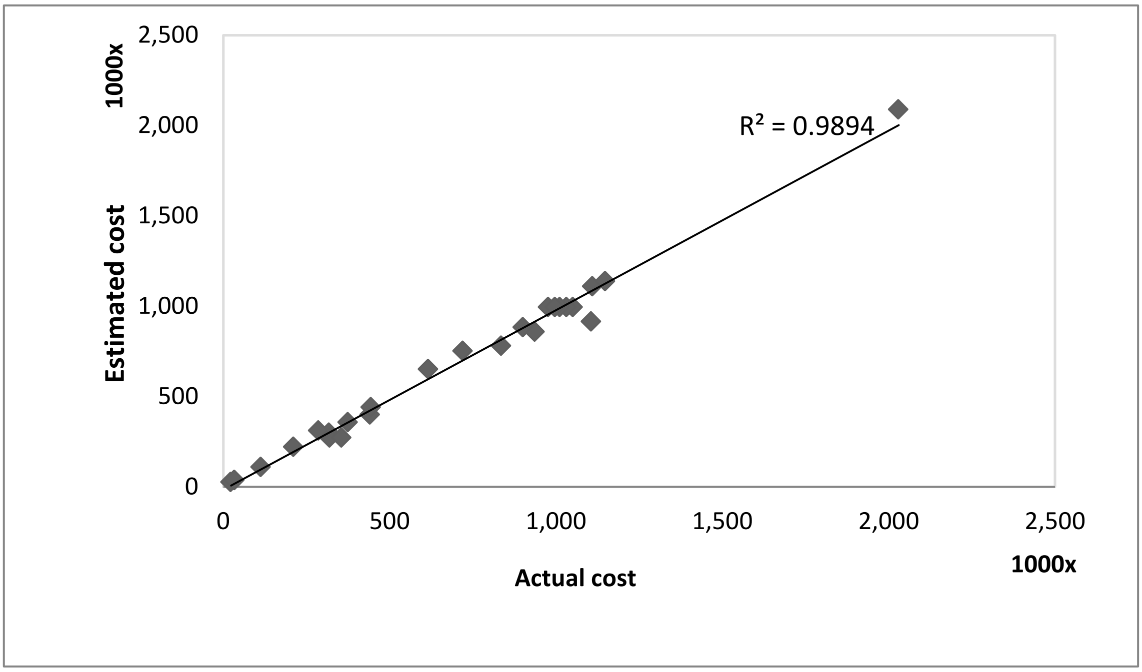

Figure 5.4 Linear regression of actual and estimated costs

The results of performance measures are presented in Table 5.4, where the accuracy performance of adopted model is 94%. In which the average error is 6%.

Table 5.4 Results of performance measurements

	MAE	MAPE	AP	R	Total MAPE
MLP Model	33,757	6%	94 %	0.995	10 %

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Figure 5.5 describes the actual cost comparing with estimated costs for cross validation (C.V) dataset. It is noted that there is a slight difference between two cost lines.

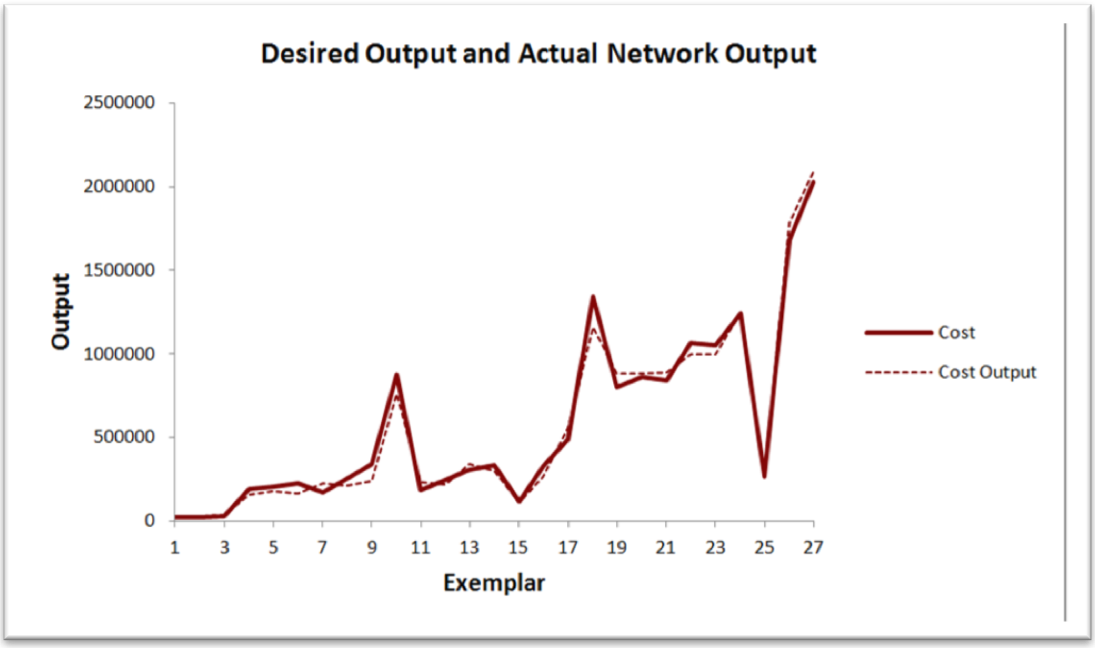

Figure 5.5 Comparison between desired output and actual network output for C.V set

For test dataset, A perfect agreement between the actual and estimated cost is shown in Figure 5.6 which means the estimated values equal the actual ones.

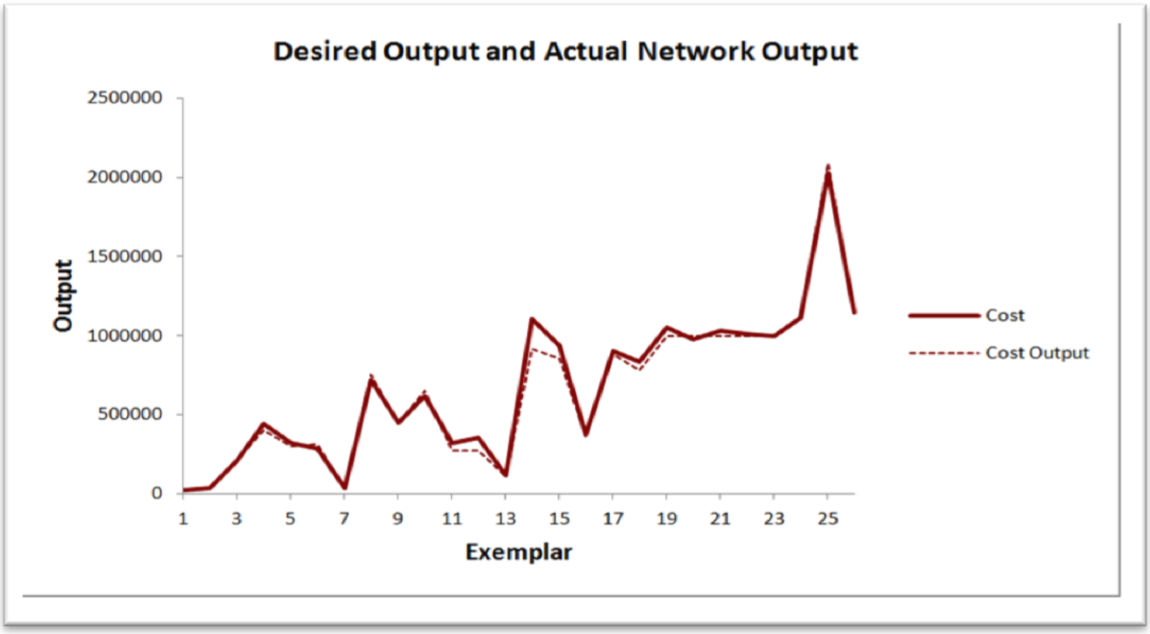

Figure 5.6 Comparison between desired output and actual network output for Test set

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As presented, the average estimate accuracy of the adopted model is (6%). By comparing this estimate accuracy, where no drawings or details are available, with literature studies as Enshassi, et al., (2007) who stated that the level of accuracy for a project with no design work it may range from +40% to –20%. After preliminary design work, it may range from +25% to –10%. On completion of detailed design work it may range from +10% to –5%., it clearly shows the high potential of the use of neural network models in cost estimate.

5.7 Sensitivity Analysis

Sensitivity analysis was carried out by Neurosolution tool to evaluate the influence of each input parameter to output variable for understanding the significance effect of input parameters on model output. Figure 5.7 presents the sensitivity analysis results for each input parameter.

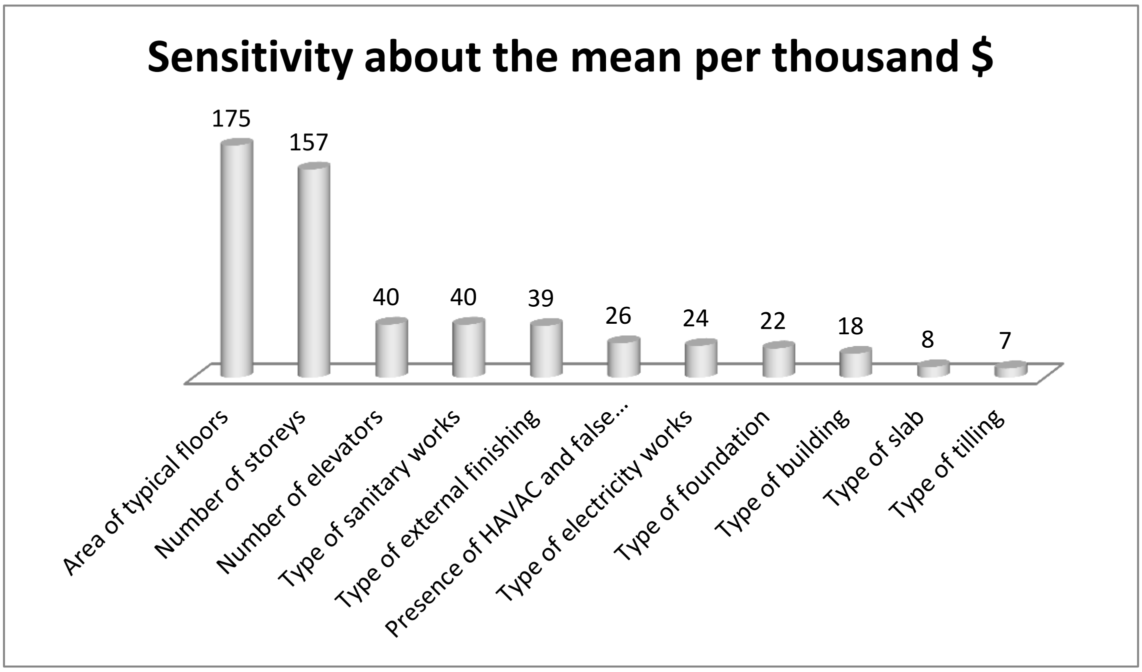

Figure 5.7 Sensitivity about the mean

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The increase of Standard Deviation refers to the strength influence of this parameter on the overall cost of the project, Figure 5.7 shows that the Area of typical floor has the highest rate of influence on the total cost of projects.

The value 175 for the area of typical floor input parameter is the value of the standard deviation for 116 output values. These output values are recorded after training the model with fixing the best weights on the mean value for each raw except the area of typical floor value which is varied between (the mean – standard deviation) to (the mean + standard deviation).

Number of storeys has also a very significant influence, while the other parameters have a considerable gab of influence on total cost than previous parameters. That means for example; when changing type of foundation for a specific project and then changing the area of typical floor for the same project, the comparison of influence of last parameter on the output variable will be relatively great compared with effect of foundation type.

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CHAPTER 6

Conclusion and Recommendations

6.1 Conclusion

This study aimed at developing a new technique for early cost estimate of building projects in Gaza Strip, through developing a model that is able to help parties involved in construction projects (owner, contractors, and others) in obtaining the total cost information at the early stages of project with limited available information.

Several steps and procedures were conducted in order to achieve this aim as following:

1- A questionnaire survey, expert interviews and exploratory search of previous studies were used to identify the cost effective factors on building projects. Eleven key parameters were adopted as most influential factors on building costs which are use of building, area of typical floor, number of floors, type of foundation, type of slab, number of elevators, type of air conditioning, external finishing, type of tile, type of electricity, and type of sanitary.

2- Historical data of building projects were collected. The projects were executed between 2009 and 2012 in Gaza Strip, from government ministries, UNRWA, engineering institutions, contractors and consultants. The data was analyzed and some of data were excluded due to some basic conditions. The final available data were 169 projects which were divided randomly into three sets as training set (116 projects), cross validation set (27 projects), and testing set (26 projects).

3- Developing ANN model passed through several steps started with selecting the application to be used in building the model. The Neurosolution5.07 program was selected for its efficiency in several previous researches in addition to its ease of use and extract results. The data sets were encoded and entered into MS excel spreadsheet to start training process for different models.

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4- Many models were built but the best model that provided more accurate results was Multilayer Perceptron network model (MLP) which structured from one input layer included 11 input neurons, one hidden layer contained 22 hidden neurons, one output neuron, tanh transfer function, and Moentum learning rate which belongs to Backpropagation algorithm.
5- The accuracy performance of the adopted model recorded 94% where the model performed well and no significant difference was discerned between the estimated output and the actual budget value. The acceptable error rate in early stage of building projects as mentioned in researches and studies is ranging between (20-50%) while the average percentage error of this model is 6%.
6- In order to ensure the validity of the model in estimating the cost of new projects, many statistical performance measures were conducted i.e; Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Total Mean Absolute Percentage Error (Total MAPE), and Correlation Coefficient (r). The results of these performance measures were acceptable and reliable, where the mean percentage error of the model was 6%, and the total mean absolute percentage error was 10%.
7- Sensitivity analysis was performed using Neurosolution tool to study the influence of adopted factors on building costs, the concept of calculating sensitivity analysis of input factors based on determining the standard deviation of each. However, the performed sensitivity analysis was in general logically where the area of typical floor and number of floors had the highest influence, then number of elevators, sanitary type, number of elevators, electricity type, type of external finishing, type of electricity, type of foundation, type of building, type of slab, and type of tilling respectively had less effect respectively.
8- The approach as presented is capable of providing accurate estimates of project cost by using eleven parameters at the early design phase.
9- Some assumption and limitation were assumed in the study according to available collected data. These limitations include the available choices of each factor as Area of typical floors for example, has limited area between 60 m2 to 1000 m2, as well as the other input factors.

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6.2 Recommendations

The current study showed very promising results in predicting the cost of building projects, and this approach will continue to make impressive gains especially in civil engineering field. However, some recommendations should be presented for decision-makers in the construction sector and future studies to support the findings of this study;

1. All construction parties are encourged to be more aware about cost estimation development and pay more attention for using this developed technique in estimation process.
2. Government and engineering assosiations are recommended to establich a database for executed projects for researchers to develop cost estimation process.
3. For future studies, it is recommended to obtain more training data from newly projects and add them to the training data. This will improve the training process and produce more input choices.
4. Finally, Cost estimates in neural network models are related to the input costs that the model was built upon, so changing time or cost will increase the estimate error or make the model unusable. Therefore, It is recommend to link the model with price changes through cost index technique.

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CHAPTER 7

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Annex 1: Questionnaire

The questionnaire (In Arabic & English)

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The Islamic University –Gaza
Higher Education Deanship
Faculty of Engineering
Construction Management

الجامعة الإسلامية – غزة
عمادة الدراسات العليا
كلية الهندسة – إدارة التشييد

استبانة حول

العوامل المؤثرة على عملية التسعير في مشاريع إنشاء المباني في قطاع غزة

Influential factors on prices of building projects in Gaza Strip

الأخ المهندس/ الأخت المهندسة ...   تحية طيبة وبعد,

نظرا لأهمية قطاع الإنشاءات في قطاع غزة , فإننا نتقدم لسيادتكم بجزيل الشكر واالعرفان لمساهمتكم في الاجابة على هذه الاستبانة التي تهدف الى دراسة العوامل المؤثرة على تسعير مشاريع انشاء المباني في قطاع غزة, وذلك من خلال التركيز على اهم العوامل الحرجة التي تؤثر على التسعير , كما نود ان نؤكد لسيادتكم على النقاط التالية:

1- يركز هذا البحث على تسعير العطاءات في مشاريع انشاء المباني في قطاع غزة من خلال دراسة العوامل الداخلية للمباني والتي تؤثر بشكل قوي على عملية التسعير وعلى السعر الاجمالي لتكلفة المشروع.
2- جميع المعلومات التي يتم الحصول عليها منكم سوف تستخدم لغرض البحث العلمي بهدف التطوير وسيتم الالتزام بالمحافظة على سرية المعلومات الخاصة بكم.

مكونات الاستبيان :

الجزء الاول: التعريف بالجهة المعنية.

االجزء الثاني: العوامل التي تؤثر على عملية التسعير في مشاريع انشاء المباني في قطاع غزة ويتكون من قمسين :

- العوامل المتعلقة بعملية الانشاء الاساسية للمباني (البناء الهيكلي).
- العوامل المتعلقة بعملية تشطيب المبنى.

علماً بأن هذه الدراسة هي جزء من البحث التكميلي لنيل درجة الماجستير في إدارة المشاريع الهندسية، للباحث

المهندس/ **عمر محمد شحتو**, تحت **إشراف الدكتور / نبيل الصوالحي**

وإنني أثمن جهدكم وإجاباتكم على الأسئلة المطروحة في الاستبيان

وتقبلوا فائق الاحترام والتقدير

الباحث / م. عمر محمد شحتو

سبتمبر/2012

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أولا: التعريف بالجهة المعنية

الجهة التي تقوم بتعبئة الاستبانة

__ شركة مقاولات　　__مكتب استشاري　　__ مالك (وزارة, بلدية, مؤسسة اهلية محلية او دولية)

الموقع الوظيفي لمن يقوم بتعبئة الاستبانة

__صاحب شركة　　__ مدير مشروع　　__ مهندس موقع　　__ أخرى ....

عدد سنوات الخبرة في مجال الانشاءات لمن يقوم بتعبئة الاستبانة

__ 1-3 سنوات　　__ 4-6 سنوات　　__7-10 سنوات　　__ أكثر من 10 سنوات

عدد المشاريع المتعلقة بانشاء المباني المنجزة خلال السنوات الخمس الأخيرة لمن يقوم بتعبئة الاستبانة

__1-5 مشاريع　　__6-10 مشاريع　　__11-15 مشروع　　__أكثر من 15 مشروع

الجزء الثانى: العوامل المؤثرة على عملية التسعير فى مشاريع انشاء المبانى فى قطاع

- الارقام من (0) إلى (5) تحدد مدى قوة تأثير العامل على عملية التسعير في مشاريع إنشاء المباني من وجهة نظرك, حيث ان الرقم (0) يشير الى عدم تاثير هذا العامل نهائيا على عملية التسعير بينما يشير الرقم (5) الى العامل الاكثر تأثيرا.
- الرجاء وضع اشارة (×) في المربع حسب قوة التأثير

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- ❖ **Organization characteristics**

__Contracting __Consultant __Owner (ministry, municipality,..)

- ❖ **Job title**

__Company owner __ Project manager __Site engineer __Other

- ❖ **Experience years in construction industry**

__1-3 years __4-6 years __ 710 years __more than 10 years

- ❖ **Number of building projects worked in during last five years**

__1-5 projects __ 6-10 projects __ 11-15 projects __ more than 15 projects

Second part: Factors affecting the pricing process in the construction

- Numbers between (0-5) determine the weight of parameter on the total cost of building cost.
- Number zero refers that this parameter does not has effect on the cost, while number five refers that this parameter haa a huge influence on cost.

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أولا: العوامل المتعلقة بعملية الانشاء الاساسية للمبنى (البناء الهيكلي)

الرقم	العامل المؤثر (Factor)	درجة تأثير العامل على عملية التسعير					
		0	1	2	3	4	5
1.1	Type of used foundation in the building نوع القواعد المستخدمة في المبنى						
1.2	Area of typical floor مساحة الطابق المتكرر للمبنى						
1.3	Number of floors in the building عدد الطوابق في المبنى.						
1.4	Number of columns عدد الاعمدة في المبنى						
1.5	Number of rooms عدد الغرف في المبنى						
1.6	Number of elevators in the building عدد المصاعد في المبنى.						
1.7	Type of slab (Solid, Ribbed …) نوع السقف للمبنى(مصمت, مفرغ, ..).						
1.8	Number of staircases in the building عدد الادراج في المبنى						
1.9	Type of contract (Ls, unit) نوع العقد (مقطوعية,وحدات محسوبة) .						
1.10	Length of spans between columns المسافات بين الاعمدة						
1.11	Area of retaining walls in project مساحة الجدران الاستنادية لتنفيذ المبنى						

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						Location of project موقع انشاء المبنى	1.12
						Use of building استخدام المبنى	1.13

ثانيا: العوامل المتعلقة في عملية تشطيب المبنى

درجة تأثير العامل على عملية التسعير						العامل المؤثر (Factor)	الرقم
5	**4**	**3**	**2**	**1**	**0**		
						Type of external plastering نوع الكسوة الخارجية	2.1
						Type of painting نوع الدهان	2.2
						Type of tiling نوع البلاط	2.3
						Area of marble works كمية اعمال الرخام	2.4
						Area of curtain walls مساحة الواجهات الزجاجية	2.5
						Number of internal doors عدد الابواب الداخلية	2.6
						Quantity of metal works for protection and decoration كمية الحديد المستخدم للحماية والديكور	2.7
						Type of water and sanitary works نوع الاعمال الصحية المستخدمة	2.8

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						Quantity of water and sanitary works كمية الاعمال الصحية المستخدمة	2.9
						Firefighting and alarm works. وجود اعمال انذار واطفاء للحريق	2.10
						Volume of HVAC works. حجم اعمال التكييف	2.11
						Quantity of electrical works كمية الاعمال الكهربائية	2.12
						Type of electrical works نوع الاعمال الكهربائية	2.13
						Area of gypsum board and false ceiling مساحة اعمال الجبس والاسقف المستعارة	2.14
						Type of carpentry works نوع اعمال النجارة	2.15
						Quantity of carpentry works كمية اعمال النجارة	2.16
						Number of windows عدد الشبابيك	2.17
						Type of Aluminum works نوع الالمنيوم المستخدم	2.18

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Annex 2 : Collected Projects

Collected projects

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No	Cost ($)	Area of typical floor	Use of building	No. Floors	Footing Type	Slab Type	No. Elevator	Ex. Finishing	Air-conditioning	Tilling type	Electrical type	Mechanical type
1	7,810	34	2	1	1	1	0	1	0	1	1	1
2	38,350	65	2	2	4	2	0	1	0	2	1	1
3	20,250	75	2	1	4	2	0	1	0	2	1	1
4	20,510	76	2	1	1	2	0	0	0	2	1	1
5	21,300	79	2	1	4	2	0	1	0	2	1	1
6	21,760	80	2	1	4	2	0	1	0	2	1	1
7	21,520	80	2	1	1	2	0	0	0	2	1	1
8	23,200	82	2	1	1	2	0	1	0	1	1	1
9	23,700	84	2	1	1	2	0	1	0	1	1	1
10	22,954	85	2	1	1	2	0	0	0	2	1	1
11	22,780	85	2	1	1	2	0	0	0	2	1	1
12	24,300	86	2	1	1	2	0	1	0	1	1	1
13	24,971	87	2	1	1	2	0	1	0	1	1	1
14	25,276	89	2	1	1	2	0	1	0	1	1	1
15	56,550	95	2	2	3	1	0	2	0	3	1	1
16	29,963	100	2	1	1	2	0	1	0	1	1	1
17	77,700	105	5	3	1	2	0	1	0	1	1	1
18	26,740	111	2	1	1	2	0	1	0	2	1	1
19	28,065	117	2	1	1	2	0	1	0	2	1	1

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20	29,499	118	2	1	1	2	0	1	0	2	1	1
21	32,075	125	2	1	1	2	0	1	0	2	1	1
22	104,608	130	5	2	1	2	0	2	0	2	1	1
23	33,050	130	2	1	1	2	0	1	0	2	1	1
24	34,710	135	2	1	1	2	0	1	0	2	1	1
25	35,710	140	2	1	1	2	0	1	0	2	1	1
26	94,464	148	3	2	2	3	0	1	0	2	1	1
27	157,100	150	5	3	1	2	0	3	2	1	1	1
28	190,205	150	2	4	3	2	1	3	0	1	1	1
29	170,650	150	3	3	3	3	0	2	0	2	1	1
30	173,900	160	6	3	1	3	0	1	0	2	1	1
31	211,200	165	2	4	3	2	1	3	0	1	1	1
32	185,130	170	6	3	1	3	0	1	0	2	1	1
33	189,150	175	5	3	1	2	0	3	2	1	1	1
34	231,450	180	2	4	3	2	1	3	0	1	1	1
35	203,400	180	3	3	2	3	0	1	0	2	1	1
36	155,420	185	1	2	3	3	0	3	0	2	1	1
37	275,520	190	5	4	3	2	1	2	2	3	2	1
38	221,756	195	3	3	2	3	0	1	0	2	1	1
39	163,800	195	2	3	1	1	0	1	0	2	1	1
40	222,350	195	3	3	3	3	0	2	0	2	1	1

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41	173,100	215	1	2	1	3	0	3	0	2	1	1
42	223,542	220	2	4	1	2	0	1	0	1	1	1
43	213,750	225	5	3	1	2	0	3	0	1	1	1
44	491,250	250	2	5	1	2	1	3	0	3	2	1
45	313,750	255	2	4	1	2	0	2	0	3	1	1
46	273,200	260	3	3	2	3	0	2	0	2	1	1
47	228,137	260	3	3	2	3	0	1	0	2	1	1
48	224,788	269	5	2	0	2	0	2	0	2	1	1
49	259,200	270	2	3	1	2	0	2	0	1	1	1
50	273,241	270	5	2	1	2	0	2	0	2	1	1
51	444,540	279	2	4	1	2	1	3	0	3	2	1
52	554,050	280	2	5	1	2	1	3	0	3	2	1
53	266,100	295	5	2	1	3	0	2	0	3	1	1
54	178,000	300	6	2	1	3	0	0	0	2	1	1
55	225,000	300	1	3	1	3	0	0	0	2	1	1
56	441,600	320	5	3	1	3	0	2	0	3	1	1
57	279,000	330	3	3	2	3	0	1	0	2	1	1
58	252,000	330	3	2	2	3	0	1	0	2	1	1
59	243,540	330	6	2	1	3	0	1	0	2	2	1
60	318,450	330	3	3	3	3	0	1	0	2	1	1
61	680,000	340	2	8	1	2	0	1	0	1	1	1

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62	700,000	350	2	8	4	2	0	2	0	1	1	1
63	257,000	350	6	2	1	3	0	1	0	2	2	1
64	286,000	350	6	2	1	3	0	1	0	2	1	2
65	485,985	360	5	3	1	3	0	1	0	1	1	1
66	720,000	360	2	8	1	2	0	2	0	1	1	1
67	621,600	370	2	6	3	2	0	2	0	1	1	1
68	181,861	370	5	2	0	2	0	1	0	2	1	1
69	336,700	370	5	2	1	3	0	1	0	1	1	1
70	97,370	380	3	1	0	3	0	1	0	2	1	1
71	190,000	380	6	2	1	3	0	1	0	2	1	1
72	873,600	390	2	8	3	2	0	2	0	1	1	1
73	250,000	400	1	3	1	3	0	1	0	2	1	1
74	340,000	400	1	3	1	3	0	1	0	2	1	2
75	305,000	400	6	2	1	3	0	1	0	1	2	2
76	820,000	410	2	8	1	2	0	2	0	1	1	1
77	438,970	410	3	3	2	3	0	2	0	2	1	1
78	308,000	410	6	2	1	3	0	1	0	1	2	2
79	228,000	420	6	2	1	3	0	1	0	2	1	1
80	356,304	420	5	2	2	2	0	2	0	3	1	1
81	349,624	420	5	2	2	2	0	2	0	3	1	1
82	329,994	420	5	2	2	2	0	2	0	3	1	1

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83	616,150	425	2	4	1	2	0	3	0	3	1	1
84	251,000	430	6	2	4	3	0	1	0	2	1	2
85	355,238	430	6	2	1	3	0	1	0	2	1	1
86	833,490	450	6	5	1	3	0	2	0	1	2	1
87	196,898	450	5	1	1	3	0	2	0	2	2	1
88	111,612	450	1	1	1	3	0	1	0	2	1	1
89	267,100	450	6	2	4	3	0	1	0	2	1	2
90	112,980	460	1	1	1	3	0	1	0	2	1	1
91	112,980	460	1	1	1	3	0	1	0	2	1	1
92	465,900	465	2	3	3	2	0	1	0	1	1	1
93	114,980	470	1	1	1	3	0	1	0	2	1	1
94	415,334	480	5	2	1	2	0	2	0	3	1	1
95	327,231	480	3	2	2	3	0	1	0	2	1	1
96	320,000	490	6	2	1	3	0	1	0	2	1	1
97	875,000	500	2	7	1	2	0	2	0	1	1	1
98	320,000	500	6	2	1	3	0	1	0	2	1	1
99	785,700	540	5	3	1	3	0	3	0	1	1	2
100	358,000	550	6	2	4	3	0	1	0	1	2	1
101	1,015,000	580	2	7	1	2	0	2	0	1	1	1
102	1,106,640	580	5	4	1	3	0	3	0	1	1	2
103	562,608	590	3	3	2	3	0	2	0	2	1	1

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104	579,630	590	5	3	1	2	0	1	0	2	2	1
105	1,152,000	600	2	8	1	2	0	2	0	1	1	1
106	452,000	600	6	2	3	3	0	1	0	2	1	2
107	320,190	600	5	1	1	3	0	1	0	0	1	2
108	335,881	600	5	1	3	3	0	1	0	0	1	1
109	520,806	617	3	3	2	3	0	2	0	2	1	1
110	1,388,800	620	2	8	4	2	0	2	0	1	1	1
111	208,000	630	6	2	0	1	0	3	0	1	1	1
112	119,511	630	5	1	0	3	0	1	0	2	1	1
113	433,000	630	5	4	1	2	0	1	0	3	1	1
114	936,660	670	5	3	1	2	0	2	0	1	2	1
115	1,038,000	670	2	5	1	2	1	3	0	3	1	1
116	644,000	700	2	4	1	2	0	2	0	1	1	1
117	1,343,000	700	5	4	1	2	0	2	0	1	2	1
118	1,363,000	710	5	4	1	2	0	2	0	1	2	1
119	1,147,000	750	6	5	1	3	0	1	0	2	2	2
120	375,000	750	1	2	1	3	0	1	0	2	1	1
121	379,000	755	1	2	1	3	0	1	0	2	1	1
122	363,780	780	3	2	3	3	0	1	0	2	1	1
123	565,685	780	6	3	1	3	0	3	0	1	1	1
124	782,460	810	4	3	2	3	0	1	0	2	1	1

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125	835,395	830	4	3	2	3	0	1	0	2	1	1
126	297,130	835	6	3	1	3	0	0	0	0	0	0
127	901,236	850	4	3	2	3	0	2	0	2	1	1
128	880,486	850	4	3	2	3	0	2	0	2	1	1
129	902,025	850	4	3	2	3	0	2	0	2	1	1
130	847,535	850	4	3	2	3	0	1	0	2	1	1
131	907,229	850	4	3	2	3	0	2	0	2	1	1
132	813,945	850	4	3	2	3	0	2	0	2	1	1
133	802,235	850	4	3	2	3	0	2	0	2	1	1
134	863,193	850	4	3	2	3	0	2	0	2	1	1
135	901,236	850	4	3	2	3	0	2	0	2	1	1
136	3,287,454	870	5	6	1	3	1	2	2	3	2	2
137	860,246	900	4	3	2	3	0	1	0	2	1	1
138	902,025	900	4	3	2	3	0	2	0	2	1	1
139	840,971	920	4	3	2	3	0	1	0	2	1	1
140	977,208	930	4	3	2	3	0	2	0	2	1	1
141	997,000	955	4	3	2	3	0	2	0	2	1	1
142	510,000	960	2	2	1	1	1	1	0	1	2	1
143	1,012,194	970	4	3	2	3	0	2	0	2	1	1
144	1,070,000	980	4	3	2	3	0	2	0	2	1	1
145	1,020,426	980	4	3	2	3	0	2	0	2	1	1

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146	1,071,278	980	4	3	2	3	0	2	0	2	1	1
147	1,157,901	980	4	3	3	3	0	2	0	2	1	1
148	1,167,559	980	4	3	3	3	0	2	0	2	1	1
149	1,020,696	980	4	3	2	3	0	2	0	2	1	1
150	993,000	980	4	3	2	3	0	2	0	2	1	1
151	1,066,946	980	4	3	2	3	0	2	0	2	1	1
152	1,053,495	980	4	3	2	3	0	2	0	2	1	1
153	1,032,105	980	4	3	2	3	0	2	0	2	1	1
154	1,051,400	995	4	3	2	3	0	2	0	2	1	1
155	850,000	1000	6	2	3	3	0	2	1	2	1	2
156	1,586,561	1000	5	7	4	2	3	1	0	2	2	2
157	897,143	1020	4	3	2	3	0	2	0	2	1	1
158	1,036,080	1050	4	3	2	2	0	1	0	2	1	1
159	1,050,000	1070	2	3	3	1	0	2	0	2	1	1
160	1,610,000	1100	6	3	4	3	0	3	1	2	2	2
161	2,305,000	1100	5	5	4	2	2	2	1	1	2	2
162	1,241,000	1150	2	4	1	1	0	2	0	1	1	1
163	1,681,290	1170	6	3	4	3	0	3	1	2	2	2
164	1,578,000	1180	5	3	1	3	2	3	1	3	2	2
165	1,110,000	1200	2	3	4	1	1	3	0	3	1	1
166	2,031,200	1200	5	4	4	2	2	2	1	1	2	2

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167	1,110,000	1200	2	3	4	1	1	3	0	3	1	1
168	2,030,400	1200	5	4	4	2	2	2	1	1	2	2
169	1,149,000	1200	6	2	2	3	0	3	1	2	1	2

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