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أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

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أقر بأن ما اشتملت عليه هذه الرسالة إنما هو نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وإن هذه الرسالة ككل أو أي جزء منها لم يقدم من قبل لنيل درجة أو لقب علمي أو بحثي لدى أي مؤسسة تعليمية أو بحثية أخرى.

DECLARATION

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification

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Prediction Model of Construction Labor Production Rates in Gaza Strip using Artificial Neural Networks

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باستخدام الشبكات العصبية الاصطناعية

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بناءً على موافقة شئون البحث العلمي والدراسات العليا بالجامعة الإسلامية بغزة على تشكيل لجنة الحكم على أطروحة الباحث/ **محمد إسماعيل عبدالرحمن ماضى** لنيل درجة الماجستير في **كلية *الهندسة*** قسم الهندسة المدنية– إدارة المشروعات الهندسية وموضوعها:

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وبعد المناقشة التي تمت اليوم الأحد 18 ربيع الأول 1435هـ، الموافق 2014/01/19م الساعة العاشرة صباحاً، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق ،،،

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قالوا سبحانك لا علم لنا الا ما علمتنا

إنك أنت العليم الحكيم.

صدق الله العظيم.

DEDICATION

I dedicate this research

To the spirit of my father,

To my mother for her endless support,

To my dearest brother "Dr. Hosny", and sister "Amal",

colleagues and friends, for their sustainable support,

To my wife for her unlimited encouragement,

To my children Ghazal and Ismaiel who, were, missing

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ABSTRACT

Estimating the construction labor productivity considering the effect of multiple factors is important for construction planning, scheduling and estimating. In planning and scheduling, it is important to maximize labor productivity and forecast activity durations to achieve lower labor cost and shorter project duration. In estimating, it is important to predict labor costs. A company may lose money in the execution of the project if the labor cost were wrongly estimated. On the other hand, if the estimate is high, the company may lose the contract due to overpricing. The aim of this research is to develop an artificial neural networks model for giving an expert opinion to predict the production rate for slabs works. ANN is new approach that is used in prediction labor productivity, which is able to learn from experience and examples and deal with non-linear problems. In this research, the effective factors that affect on labor productivity were collected from literature review. A questionnaire survey was done to determine the most effective factors by calculating the Relative Important Index (RII). The target group was determined as the contracting companies which have first, second, and third categories. 110 questioners were distributed, and 77 useful questionnaires were collected. Factors which have RII more than 0.75 are used as independent input variables affected on one dependent output variable "labor productivity" in neural network model. The most important factors that affect labor productivity are, number of labors, material shortages, floor height, tool and equipment shortages, labor experiences, weather, complexity due to steel bars, drawings and specifications alteration during execution, easy to arrive to the project location, lack of labor surveillance and payment delay. Areal data for the most important factors which used in model development was collected by the second questionnaire from 107 building projects in Gaza Strip. Neurosolution software version 5.07 was used to build up the models. The best model was obtained through the traditional trial and error process. However, over 1000 network structures were experimented and the satisfactory model was obtained. This model consists of input layer with 11 neurons, 2 hidden layer with 6, 4 neurons for first and second layer respectively, and 1 output neuron in the output layer. The results of the trained models indicated that neural network reasonably succeeded in estimating the labor productivity. The average error of test dataset for the adapted model was largely acceptable (6.7%). The performed sensitivity analysis showed that the number of labor and weather have the most influential parameters in productivity while payment delay and alteration in drawing and specification during execution have lowest impact on productivity.

ملخص الدراسة

تعتبر عملية تقدير انتاجية عمال المشاريع الانشائية ذات اهمية كبيرة في عملية التخطيط والجدولة والتقييم في صناعة النشاءات مع الاخذ بعين الاعتبار العوامل المؤثرة علي الانتاجية, في عملية التخطيط والجدولة من المهم العمل علي زيادة انتاجية العامل والتنبؤ بمدة النشاط لتحقيق اقل سعر للعمالة واقل فترة زمنية للمشروع, وفي عملية التقييم من المهم تقدير تكلفة العمال, فاذا كان هذا التقدير خاطئ فسيؤدي ذلك الي خسارة الشركة في حالة تنفيذها للمشروع. من ناحية اخري اذا كان التقدير مرتفع فان الشركة ستفقد فرصتها بتنفيذ المشروع بسبب مغالاتها.

الهدف من هذا البحث هو تطوير نموذج للشبكات العصبية الاصطناعية للتنبوء بمعدل الانتاجية لاعمال الاسقف الخرسانية, حيث تعتبر الشبكات العصبية الصناعية منهج جديد يتم استخدامه للتنبوء بمعدل انتاجية العمال, وهي قادرة علي التعلم من الامثلة والتجارب وتتعامل مع المسائل الغير خطية, في هذا البحث تم جمع العوامل المؤثرة علي الانتاجية من الدراسات السابقة وتم اجراء استبيان لتحديد العوامل الاكثر تاثيرا علي الانتاجية من خلال حساب RII, تم تحديد الفئة المستهدفة والمكونة من شركات المقاولات التي تملك تصنيف درجة اولي وثانية وثالثة مباني, حيث تم توزيع 110 استبانة لمشاريع انشائية في قطاع غزة وتم قبول 77 استبانة من اصل 92 تم جمعها, تم اعتبار اكثر العوامل تاثيرا علي الانتاجية والتي لها RII اكثر من 0.750 كمدخلات مستقلة للمودل وتؤثر علي مخرج واحد وهو انتاجية العمال,وكانت اكثر العوامل تاثيرا علي الانتاجية كالتالي: عدد العمال, نقص المواد, ارتفاع الطابق, نقص المعدات والالات, خبرة العمال, الطقس, صعوبة حديد التسليح, تغيير المخططات والمواصفات اثناء التنفيذ, سهولة الوصول الي موقع العمل, عدم مراقبة العمال, تاخير الدفعات. وقد تم جمع البيانات الحقيقية لهذه العوامل والتي سيتم استخدامها في بناء المودل من خلال الاستبيان الثاني الذي تم توزيعه علي 107 مشروع انشائي في قطاع غزة.

تم استخدام برنامج نيوروسليوشن نسخة 5.07 لبناء وتدريب المودل, حيث تم تجربة اكثر من 1000 شبكة عصبية حتي تم الحصول الي افضل نموذج من خلال التجربة والخطأ والذي اعطي نتائج مرضية, ويتكون هذا النوذج من طبقة مدخلات تحتوي علي 11 خلية عصبية, وطبقتين مخفيتين تحتوي الاولي علي 6 خلايا والثانية علي 4 خلايا, وطبقة مخرجات واحدة تحتوي علي خلية عصبية واحدة, واشارت نتائج تدريب الخلايا العصبية الي نجاحها في تقدير انتاجية العمال بشكل مرضي, حيث كان متوسط الخطأ لعينة الاختبار 6.7% وهو مقبول بشكل كبير, وأظهر تحليل الحساسية ان عاملي عدد العمال وحالة الطقس لهما اكبر تاثير علي الانتاجية بينما التأخير في دفع رواتب العمال والتغيير في المواصفات والخرائط اثناء التنفيذ لهما اقل تاثير علي الانتاجية.

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LIST OF ABBREVIATIONS

AI	**Artificial Intelligence**
ANN	**Artificial Neural Network**
AP	**Accuracy Performance**
C.V	**Cross Validation**
CQS	**Craftsman Questionnaire Sampling**
GDP	**Gross Domestic Product**
GFF	**General Feed Forward**
GNP	**Gross National Product**
LM	**Levenberg-Marquardt**
LR	**Linear Regression**
M^2/H	**Square meter per hour**
MAE	**Mean Absolute Error**
MAPE	**Mean Absolute Percentage Error**
MLFF	**Multi-Layer Feed Forward**
MLP	**Multi-Layer Perceptron**
MSE	**Mean Square Error**
NMSE	**Normalized Mean Square Error**
NN	**Neural Network**
PCU	**Palestinian Contractors Union**
PE	**Processing Elements**
r	**Correlation factor**
RII	**Relative Importance Index**
RNN	**Recurrent Neural Network**
TAP	**Total Accuracy Performance**
TFP	**Total Factor Productivity**
US	**United States**

Chapter 1: Introduction

1.1 Construction industry

Construction sector is considered one of the most important economical sectors that affect the Palestinian national economy. It plays a major role in development and achievement the goals of society. Construction industry is one of the largest industries and contributes to about 10% of the Gross National Product (GNP) in industrialized countries. Construction industry has complexity in its nature because it contains large number of parties as clients, contractors, consultants, stakeholders, shareholders and regulators. The performance of the construction industry is affected by national economies (Navon, 2005).

1.2 Construction industry in Gaza Strip

The construction sector is an important sector of the economy and contributes significantly to Gross Domestic Product (GDP). The United Nations Environment Program has noted that about one-tenth of the global economy is dedicated to constructing and operating homes and offices. It is now widely recognized that construction activity plays a vital role in the process of economic growth and development, both through its products (infrastructure, buildings) and through the employment created in the process of construction itself. The development of an efficient industry is an objective of policy in most countries (Mitullah and Wachira, 2003). Notwithstanding the constraints of occupation, construction and housing have evolved into a major sector of the Palestinian economy, playing an important role in the generation of the employment and income. The sector has also carried significant forward and backward linkages, ranging from simple furniture manufacturing plants to major construction materials production and processing industries (Abdul Hadi, 1994). Through a complementary process, several parties contribute to the construction sector. Such stakeholders are the public and private sectors, universities and institutes, donor countries, international financing institutions and banking sector. Construction sector contributes largely to different sectors of investment, such as manufacturing of construction materials. In addition, it provides materials needed for construction, such as stone, marble, brick, floor tiles, etc. (PCU, 2003).

Construction industry in the Gaza Strip suffers from many problems such as closures, amendment of drawings, and amendment of designs. Poor management and leadership; poor relations and coordination; absence of motivation, absence of control, absence of monitor and decision making systems; inadequate infrastructure, political problems; cultural problems and economic conditions. Obstacles by client, non-availability of materials, road closure, amendment of the design and drawing, and variations. (UNRWA, 2006 & 2007).

1.3Construction productivity

Construction productivity is a very important aspect and mostly analyzed by researchers because it is one of the main indicator of the performance of the construction industry. Construction labor productivity is influenced by several factors that vary from project to project and from task to task within the same project. Standard values of production rates are the most essential information used to analyze the performance of construction labor productivity. The accuracy of estimating and scheduling of a project is mainly dependent on the validity and reliability of the production rates data available. The accurate estimation of construction labor productivity could be challenging when effects of multiple factors are considered simultaneously.

The estimation for the construction labor productivity with considering the effect of multiple factors is important for construction planning, scheduling and estimating. In planning and scheduling, it is important for maximizing labor productivity and forecast activity durations to achieve lower labor cost and shorter project duration. In estimating, it is important to predict labor costs, if the estimate is too low, a company may lose money in the execution of the project. On the other hand, if the estimate is high, the company may lose the contract due to overpricing.

Recently, prediction of labor productivity using artificial intelligence has become an emerging research field. Artificial Intelligence (AI) such as Artificial Neural Networks (ANN) is a promising tool towards achieving better estimates using historical data. Several researchers discussed potential applications of neural networks in construction industry in recent years (Salem, 2006).

1.4 Problem Statement

One of the most essential elements for a continuous improving of construction productivity is the observation and measurement. The slab work is one of the fundamental and main operations in construction industry which affects the overall cost and time of the project. It is very essential activity in construction and engineering projects. Therefore, the production rate of this activity must be measured and recorded to help the planners and estimators in the future to improve the accuracy of the production rate estimate. There are many factors affect on the production rate of casting concrete slabs. In addition the accuracy of estimating this production rate is very difficult when effect of multiple factors is considered simultaneously. The implementation of artificial neural networks (ANNs) can be useful to assist the planners and estimators to reduce the effort required for planning construction operations and to improve the accuracy of production rate estimates to complete a project within budget and schedule (Muqeem et al., 2011).

1.5 Research Aim

The aim of this research is to improve the contractor prediction of labor productivity for slab work in construction project.

1.6 Research Objectives

The objectives of this research can be summarized in the following points:

1) Identifying the most effective factors affect the production rate of casting concrete slab.
2) Developing a model of ANNs to predict labor productivity for slab works.
3) Compare ANN results with actual results derived from a realistic data.

1.7 Limitation

1- This research studied the building projects in Gaza Strip, which were done between 2009 and 2013.

2- Only the contractors registered in the Palestinian Contractors Union (PCU) and the consultants who are registered in the Engineering Association are involved in this study.

1.8 Research Scope

This research was concerned with estimating the production rate of casting concrete slab by using ANNs model. The actual data used for developing neural network model collected from many construction projects in Gaza Strip from the largest companies for construction that were qualified and registered in the Palestinian contractor union. The reason for selection of these companies is their ability for construction management.

1.9 Research Methodology

The methodology of this study can be summarized in the following points:

1) Conducting a literature review about productivity and labor productivity estimation techniques.
2) Conducting a literature review about ANNs and getting up-to-date with the latest improvements
3) Conducting interview with project managers; experts and site engineers to identify the most effective factors affect the production rate of casting concrete slab.
4) Conducting questionnaire survey to weight the factors that affect productivity and Gathering historical data about labor productivity
5) Second questionnaire survey to collect real data from 110 building projects.
6) Training the ANN using actual case studies.
7) Conducting test estimations on labor productivity simulating the conditions in which the historical data was obtained.
8) Performing labor productivity predictions on study cases and comparing the predicted values with actual values.
9) Draw up conclusion and recommendations.

1.10 Research Contents

This research included six chapters explained as follow

Chapter (1) Introduction

A general idea for this research was given in this chapter along with research statement of problem, aim, objectives, limitation, methodology outlined and thesis structure.

Chapter (2) literature Review

This chapter presents a literature review of past research studies in productivity, ANN applications in construction management and related fields

Chapter (3) Research Methodology and Data Collection

The methodology adopted in this research was presented in this chapter including building model criteria and testing methods. In addition, presents the factors that affect the productivity in construction project.

Chapter (4) Result and Analysis

This chapter presents a result for questionnaire analysis and discussion for the factors that affect on labor productivity.

Chapter (5) Models Development and Sensitivity Analysis

This chapter contains the application, which was selected, types of models chosen and displays of the structure design. Moreover, it is including the model development, training and validation also optimizing the error and testing the models. Finally this chapter shows the result of the best model with evaluation the influence of the input parameters on the performance of the trained ANN model by using sensitivity analysis.

Chapter (6) Conclusion and Recommendations

Finally, this chapter outlines the conclusions and recommendations of this study and recommendations for further studies.

Chapter 2: Literature Review

2.1 Construction Productivity

2.1.1 Definitions of construction productivity

The term of "Productivity" has different meanings for different people. Depending on who is explaining productivity, whether he is a politician, accountant, economist, industrial engineer, or construction manager, you will get a wide range of different meaning of the term 'Productivity'. Some will define it as production rate, efficiency, effectiveness, performance or merely production.(Abdel-Razek, 2004).

The Concise Oxford Dictionary (9^{th}edn) defines productivity as the 'capacity to produce, the state of being productive; effectiveness of productive effort; especially in industry; production per unit of effort'. While providing a good starting point, this definition uses the word 'productive' in defining productivity but, importantly, three distinct productivity concepts are brought out: (i) the capacity to produce, that is the force behind production itself, (ii) effectiveness of productive effort as a measure of how well the resources are utilized and (iii) the production per unit of effort (or rate) to measure output of the factors of production over a defined period time (Paul, Ananda and Frank, 1998).

In the construction industry, the meaning of the term productivity varies with its application to different areas. The term productivity usually refers to the output produced per unit input. Thomas(1992), defined labor productivity as the "ratio of the input in terms of labor hours to the output in terms of units of work".

$$P_i = \frac{WH_i}{Q_i} \qquad (1.1)$$

Where:

Pi = productivity for time period i.

WHi = total work hours charged by the crew for time period i.

Qi = quantity of work placed during time period i.

This measure of productivity has several advantages: the meaning of the term labor productivity is relatively well understood; labor productivity is often the greatest source of variation in overall construction productivity; and the productivity of other inputs can often be measured with respect to labor productivity. The inverse of labor productivity, unit man per hours, is also commonly used (Halligan et. al., 1994).

The term Productivity also defined as follows: "Productivity is a relationship (usually a ratio or an index) between output (goods and /or services) produced by a given organizational system and quantities of input (resources) utilized by the system to produce that output." (Sink in Hannula, 2002).

This definition can be directly connected to the financial effects of productivity changes. For example, the cost effect of input changes can be directly calculated when the amount and the unit cost of the input are both known (Hannula, 2002).

Consequently considerable effort has been directed to understanding the productivity concept, with the different approaches taken by researchers resulting in a wide variety of definitions of productivity.

2.1.2 Types of productivity

There are three types of productivity, namely single factor productivity, total factor productivity and total productivity which explain as the following:

2.1.2.1 Partial productivity :

is the ratio of output to one class of input. For example, output per man-hour (a labor productivity measure) is a partial productivity concept. So are output per ton of material (a material productivity ratio) and interest revenue generated per dollar of capital (a capital productivity ratio) and so on (Sumanth 1998;Einspruch in Hannula, 2002).

2.1.2.2 Total factor productivity (TFP):

is the ratio of net output to the sum of associated labor and capital (factor) inputs. The net output here is sometimes called value-added output (Sumanth 1998; Kendrick and Einspruch in Hannula, 2002).

In this ratio, we explicitly consider only the labor and capital input factors in the denominator. Since materials account for as much as 65% of product costs in consumer goods such as TVs, VCRs, and computers, this measure is not the best one in most cases (Sumanth, 1998).

Thomas in 1990 mentioned TFP that used by the several government agencies including the U.S. Department of commerce that defined it as follow:

$$TFP = \frac{TotalOutput}{Labor+Material+Equipment+Energy+Capital} \quad (1.2)$$

TFP is an economic model, in which input and output are measured in terms of dollars.

$$TFP = \frac{DollarsofOutput}{DollarsofInput} \quad (1.3)$$

TFP is not very useful for contractors, as it can be highly in accurate if applied to a specific project because of difficulties in predicting the various inputs.

2.1.2.3 Total productivity:

is the ratio of total output to the sum of all input factors. This is a holistic measure that takes into consideration the joint and simultaneous impact of all the input resources on the output, such as labors, materials, machines, capital, energy, etc. This measure has received much attention over the past ten years, as evidenced by many papers and case studies. Another term used in recent years is multifactor productivity, which considers more than one input factor in thedenominator of the productivity ratio, but is not necessarily a total factor or total productivity measure (Sumanth, 1998).

Various agencies may modify Eq. 2 by adding maintenance costs or deleting energy or capital costs. Outputs are expressed in terms of functional units (Thomas et. al. 1990). For example, the Federal Highway Administration may be interested in:

$$Productivity = \frac{Output}{Design + Inspection + Construction + Right - of - way} \quad (1.4)$$

$$Productivity = \frac{Lanemile}{DollarsofInput} \quad (1.5)$$

This definition is also useful in policy- making and for broad program planning (Thomas et al., 1990).

At the project site, contractors are usually interested in labor productivity, and it can be defined in one of the following ways (Thomas et al., 1990):

$$LaborProductivity = \frac{Output}{LaborCost} \quad (1.6)$$

Or

$$LaborProductivity = \frac{Output}{Work - hour} \quad (1.7)$$

Eq. 7 is usually referred to as the production rate. Sometimes inverse of equation 7 is used by the contractors:

$$LaborProductivity = \frac{LaborCostorWork - hour}{Output} \quad (1.8)$$

Eq.8 is usually referred to as unit rate. In this study, the production rate (total volume of the pour divided by the total pour time) will be use as a measure of productivity, because it fits into the classical definition of productivity: the ratio of output of a production process to the corresponding input (Martin, 1991). Table2.2 presents the advantages and limitations of using the basic types of productivity measures in companies.

2.1.3 Productivity measurement techniques

2.1.3.1 The direct observation technique

Direct observation is one of the continuous observation methods. A researcher observes workers activities throughout the work day. Tool time and Noon-tool time activities are easily and accurately identified because the times are recorded to the nearest minute.

The direct observation method is generally considered tedious and time wasting. One technique to increase this methods efficiency is to highlight only the non-tool time activities provided that the workers spend more time on tool time activities than non-tool time activities (Noor, 1998).

Another criticism of this method is that the observers presence may disturb workers. It is recommended that the observer could locate himself in a suitable vantage point where there is a full view of all workers but at the same time does not interfere with the operations progress (Noor, 1998).

The direct observation method has the following advantages:

a. The data collected is accurate and precise.
b. The length and pattern of time of each work task can be collected.

The disadvantages of the direct observation method are the following:

a. A crew of five workers is the maximum crew size one observer can manage.
b. If poorly managed the observation can interfere with the workers carrying out their tasks.

2.1.3.2 Time study technique

Time study was the fundamental approach to productivity improvement introduced by Frederick W. Taylor and Frank Gilbreth in the late 19th and early 20th centuries, and it is the principal technique of work measurement even today. In the current usage, it is not simply the timing of an operation but a process designed to develop standard time or standard output for any construction operation irrespective of the rate of work being observed (Salem, 2006). Time study therefore involves:

(a) Timing, to discover how long various operations are taking;

(b) Rating, to assess the worker being observed against a norm;

(c) Building up of time standards, by allowing for appropriate relaxation and Contingency allowances.

2.1.3.3 Activity sampling technique

It is a technique that measures the percent of time craftsmen spend in various categories of tasks, such as direct work, transporting materials, or waiting (Thomas, 1991). In addition, it is physically impossible to observe and record all the minute details of every repetition of any construction operation. Activity sampling refers to any measurement technique for which observations are non-continuous. Thus, the observations represent a sampling of the total activity (Oglasby and Parker, 1989; Adrian, 1987).

2.1.3.4 Forman delay survey

The objective of this technique is to identify the reasons for delays and the extent of it. In a delay survey, foremen are asked to report any delays greater than a specified time that were experienced during the day (Maloney, 1990). By correlating the reported lost time with the causes of delays, project management can take action to resolve the problems and to eliminate the delays (Alfeld, 1988).

2.1.3.5 Craftsman questionnaire sampling

Craftsman questionnaire sampling (CQS) was recently developed for performance measurements and productivity improvement at construction sites. The main idea of CQS is to use questionnaires as a means of data collection. CQS provides information regarding the sources of delay, the amount of rework performed, as well as creating a participating atmosphere on site. In performing the CQS, the administrator of CQS walks around the field as the work-sampling sampler does. The administrator randomly selects craftsmen to answer the questionnaires. Because of the manner of random selection and the determination of the activities, the craftsmen are involved in the immediate post. After the questionnaires are filled out by craftsmen and foreman, the administrator repeats the cycle until he gets an adequate sample size (Chang & Borcherding, 1986).

2.1.3.6 Recording methods

A detailed record of the current method must show exactly how the work is being done. This recording can be done in several ways. The most common uses the stopwatch or interval timer. The study consists of recording the times for different tasks or fractions of a task that a man or machine performs.

When observing activities of short duration with a stopwatch, on appreciable error is accumulated if the watch is stopped, read, and started each time. This error can be eliminated if the timer runs continuously. A second method of recording the activities of a crew is time-lapse photography. This method consists of taking single pictures at interval of one, two, three or four second for long periods. Exposures are made at precise intervals so that elapsed times can be computed accurately as a product of the number of pictures and the photographic time interval. The time-lapse camera has proved an excellent means of collecting information and data for work- improvement studies (Parker & Oglesby, 1972).

The camcorder technique offers a means to identify productivity problems and provides a systematic procedure to resolve them. A video camera, being a more accurate and superior data collection method, can take the place of several observers because it captures all concurrent activities. The camcorder technique involves several steps: Collection of video equipment, preplanning for the taping process, conducting brainstorming sessions, analysis of recorded data, and development of recommendations (Eldin & Egger, 1990).

2.1.4 Identification of possible factors affecting productivity in building construction

Based upon the literature review, this study extracts various factors affecting labor productivity in construction from the previous research studies. Some similar factors were merged together, and some new factors were added. Factors do not take into consideration any values. They are arranged on general criteria. Table 2.1 shows various factors affecting labor productivity in construction extracted from previous studies (Abo Mostafa, 2003).

Table 2.1: Factors affecting labor productivity in construction industry

Groups	Factors Affecting Labor Productivity
1	**Manpower issues**
	Increase of laborer age
	Lack of labor experiences
	Labor absenteeism
	Labor personal problems
	Labor dissatisfaction
	Labor disloyalty
	Misunderstanding among labor
	Lack of competition
2	**Leadership issues**
	Misunderstanding between labor and superintendents
	Lack of labor surveillance
	Lack of periodic meeting with labor
3	**Motivation issues**
	Lack of financial motivation system
	Lack of labor recognition programs
	Non-providing of transportation means
	Lack of place for eating and relaxation

Table 2.1 Cont…	
	Payment delay
	Lack of training sessions
4	**Time issues**
	Work overtime
	Working for 7 days of week without holiday
	Increasing No. of labor in order to accelerate work
	Misuse of time schedule
	Method of employment (using direct work system)
5	**Materials /Tools issues**
	Material shortages
	Equipment Efficiency
	Unsuitability of materials storage location
	Tool and equipment shortages
6	**Supervision issues**
	Rework
	Supervisors absenteeism
	Inspection delay
	Drawings and specifications alteration during execution
7	**Project issues**
	Type of activities in the project
	Construction method
	Interference
	Working in confined space
	Complexity Due to Steel Bars
	Floor area (m2)
	Level of Building (Floor No.)
	Number of Labor in project
8	**Safety issues**
	Violation of safety precautions
	Accidents
	Unemployment of safety officer in construction site
	Working at high place
	Bad ventilation
	Insufficient lighting
	Noise
9	**Quality issues**
	Low quality of raw materials
	High quality of required work

Table 2.1 Cont…	
	Inefficiency of equipments
10	**External issues**
	Weather changes
	Augmentation of Government regulations related to the construction sector

2.2 Artificial Neural Networks

2.2.1 Introduction

Artificial neural networks (ANNs) offer an approach to computation that is different from conventional analytic methods. ANNs are an information processing technology that simulates the human brain, and the nervous system. Like the human brain, neural networks learn from experience, generalize from previous examples to new ones and abstract essential characteristics from inputs containing irrelevant data.

Networks components with names such as neurons (sometime referred to as cells, unites, or nodes) and synaptic transmissions with weight factors are used to mimic the nervous system in a way which allows signals to travel through the network in parallel as well as serially.

The ANNs will most likely never be able to duplicate completely the functions of the human brain. Various ANN models have been proposed over the past decades and impressive results have been obtained with some of the designs.

2.2.2 Artificial neural networks definitions and features

Artificial Neural Networks are computational devices. They can be either implemented in the form of a computer chip or they can be simulated on conventional serial computers. Most researchers and application developers simulate their neural networks using software simulation.

Artificial neural networks are defined by many researchers such as:

- Tsoukalas and Uhrig (1997) defined the artificial networks as the following:

"A data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain."

- Haykin (1999) defined Neural Network as the following:

“A Neural Network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use.

- Picton (2000) defined the neural networks as the following:

"It is called a neural network because it is a neural of interconnected elements. These elements were inspired from studies of biological nervous system. In other words, neural network are an attempt to create machines that work in a similar way to the human brain by building these machines using components that behave like biological neurons."

- 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
- An artificial network consists of a pool of simple processing elements, which communicate by sending signals to each other over a large number of weighted connections (SPSS, 2007).
- According to Rumelhart et al. (1986), there are eight components of a parallel-distributed processing model such as the neural network. These eight components are the processing elements (PE) or neurons, the activation function f, the output function, the connectivity pattern wi,R, the propagation rule, the activation rule, the learning rule and the environment in which the system operates cited by (Krose&Smagt, 1996).
- Processing element (Neuron): which mimic the biological nerve cell, or neuron (Principe et al., 2010). NeuroSolutions divides the functionality of a neuron into two disjoint operations: a nonlinear instantaneous map, which mimics the neuron’s threshold characteristics; and a linear map applied across an arbitrary discrete time delay, which mimics the neuron’s synaptic interconnections.
- Weight: is a parameter associated with a connection from one neuron i, to another neuron j (Principe et al., 2010).
- Input unit: is a neuron with no input connections of its own. Its activation thus comes from outside the neural net (Principe et al., 2010).
- Output unit: is a neuron with no output connections of its own. Its activation thus serves as one of the output values of the neural net (Principe et al., 2010).
- Epoch: An epoch is a complete presentation of the training data to the network (Principe et al., 2010).

- Bias: In feed-forward and some other neural networks, each hidden unit and each output unit is connected via a trainable weight to a unit (the bias unit). As shown in figure (2.1) the neuron has a scalar bias, b. The bias as simply being added to the product wp as shown by the summing junction or as shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1 (Beale et al., 2011).

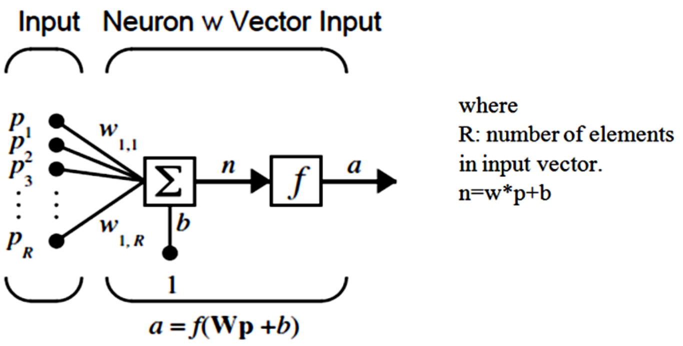

Figure 2.1: Typical structure of ANN (Beale et al., 2011)

Mechanism of ANNs

According to Ayed, (1997) neural networks are a series of interconnected processing elements (artificial neurons) in a number of layers. NNs are trained using available data to understand the underlying pattern see Figure 2.2.

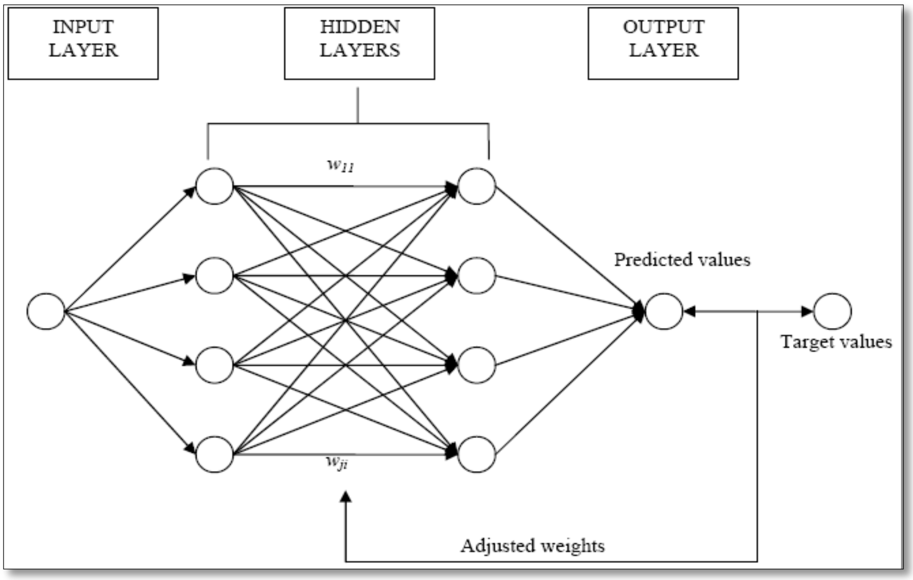

Figure 2.2: General structure of neural network (Pawar, 2007).

The output of any layer provides the input to the subsequent layer and the strength of the output is determined by the connection weights between the neurons of two adjacent layers. Neural Networks able to learn from a set of examples to detect by themselves the relationships that link inputs to outputs. During training, both the inputs (representing problem parameters) and outputs (representing the solutions) are presented to the network normally for thousands of cycles. At the end of each cycle, or iteration, the network evaluates the error between the desired output and actual output. Then use this error to modify the connection weights according to the training algorithms used. See Figure 2.3. (Demuth et al., 2007).

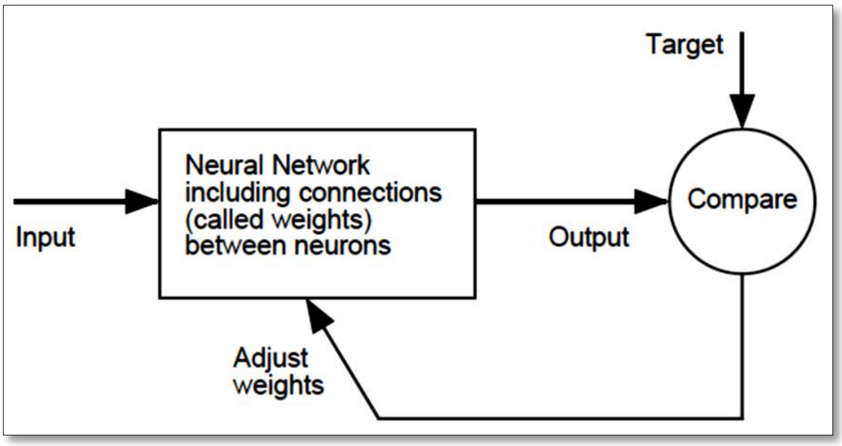

Figure 2.3: Correction of error using target data (Demuth et al., 2007).

After training, the network can be used to predict the solution for a new case not used in training. For background information regarding neural network formulations, mathematics and potential applications in constructions, the reader is referred to several publications (Beale et al., 2011) (Kriesel, 2005) (Krose&Smagt, 1996) and (Demuth et al., 2007).

2.2.3 How Do Neural Networks Work?

The working principles of the three-layered network with back-propagation are shown in figure (2-4). Input information is presented to the ANN for each sample and the specified target number given, if supervised training is used. During training, the input layer broadcasts a pattern to all the hidden neurons. The system is then asked to calculate an output value in a feed-forward way. The middle layer, which is hidden from the outside, gives a critical computational ability to the system. The functioning of the nodes is illustrated in figure (2-4). In a simple case the node receives only two inputs X (1) and X (2), respectively, with corresponding weight factors W (1) and W (2). The node calculates the sum, X(1)W(1) + X(2)W(2) and delivers an output value obtained from a special sigmoid function, the activation functions, which can take on a variety of forms. The output reached in this fashion is delivered to node is to the one described above takes place. If the node is in the output layer the obtained value has reach its final destination. The pattern of connectivity or the network topology specifies how each node is connected to the other units in the network. The strength of each connection is represented by a real number (weight) (Boussabaine, 1996).The difference yields the system output error. At this stage, the system has to decide whether further learning is required. This is accomplished by comparing the obtained total difference with a specified acceptable error given by the system developer. If the decision is to continue, the output neurons calculate the derivatives of the error with respect to the weights and the result is sent back through the system to all the hidden neurons. Each hidden neuron calculates the weighted sum of the error. Then, each hidden-layer neuron and output –layer neuron change their weights to compensate for the corrections. Once the weights have been changed, the feed-forward computation starts all over again. New output values are obtained and the cycle continues until a desired result is obtained. At this stage, we can say that the training of the system is complete and the testing phase can start. The system can now be used to predict the outcome of an input not previously seen by the ANN.

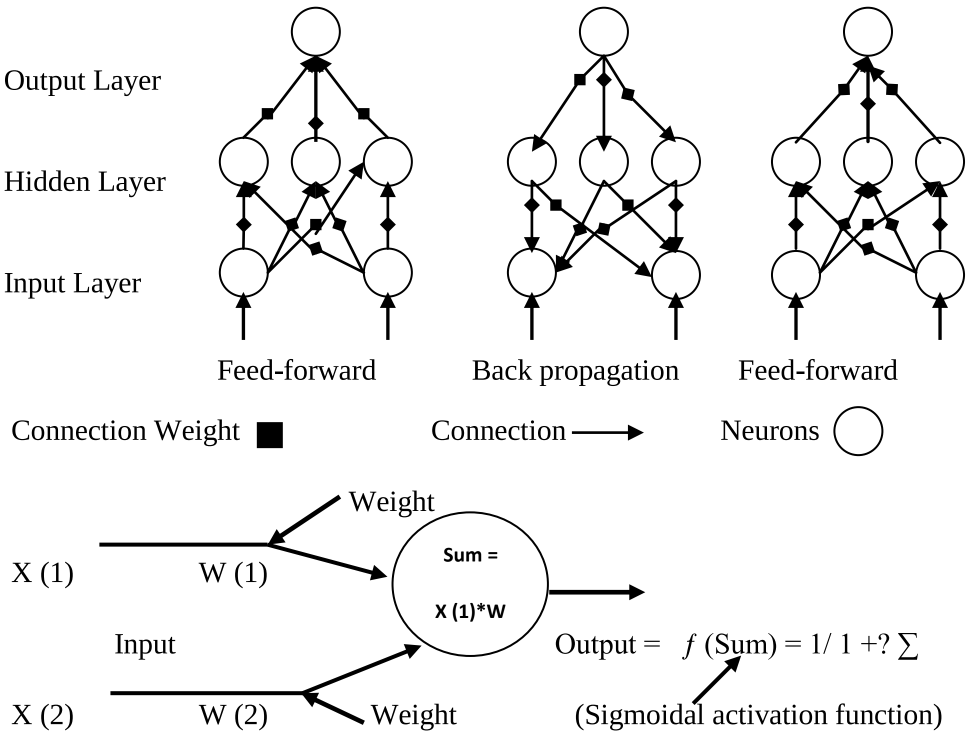

Figure 2.4: Activities at the Neural Network Node (Boussabaine, 1996)

2.2.4 Structures of neural networks

2.2.4.1 Introduction

There are many types of neural networks, but all have three things in common. A neural network can be described in terms of its individual neurons, the connections between them (topology), and its learning rule (Lawrence, 1994).

2.2.4.2 Artificial Neurons

Both biological and artificial neural networks contain neurons, real or simulated. These neurons have many connections to each other that transfer information. The knowledge of a network is distributed across the interconnections between the neurons.

Artificial neurons are also called processing elements, nodes, units, or cells. Each neuron receives the output signals from many other neurons. A neuron calculates its own output by finding the weighted sum of its inputs, generating an activation level and passing that through an output or transfer function. The point where two neurons communicate is called a connection (analogous to a synapse). The strength of the connection between two neurons is called a weight (Lawrence, 1994).

2.2.4.3 Layers

A neural network consists of layers of neurons that are connected to each other. The details of how the neurons interconnect represent some of the more important choices to be made when building a neural network. Some of the neurons will be used to communicate with us, the outside world. Some of the neurons communicate only with other neurons. They are the hidden neurons. Neurons are located in one of three types of places: the input layer, the output layer, or the hidden layers (Lawrence, 1994).

Figure 2.5 illustrates a multilayered ANNs with three layers. These consist of a number of nodes or neurons with each of the nodes in one layer linked to each node in the next layer. The communication with the outside world occurs through the nodes of the input and output layers.

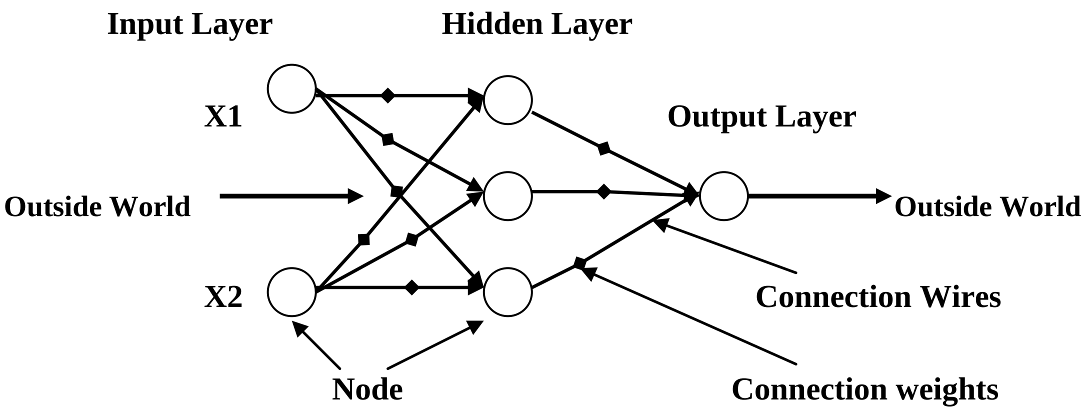

Figure 2.5: An Artificial Neural Network with three layers (Boussabaine, 1996).

2.2.5 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 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 2.6 presents the most three activation functions

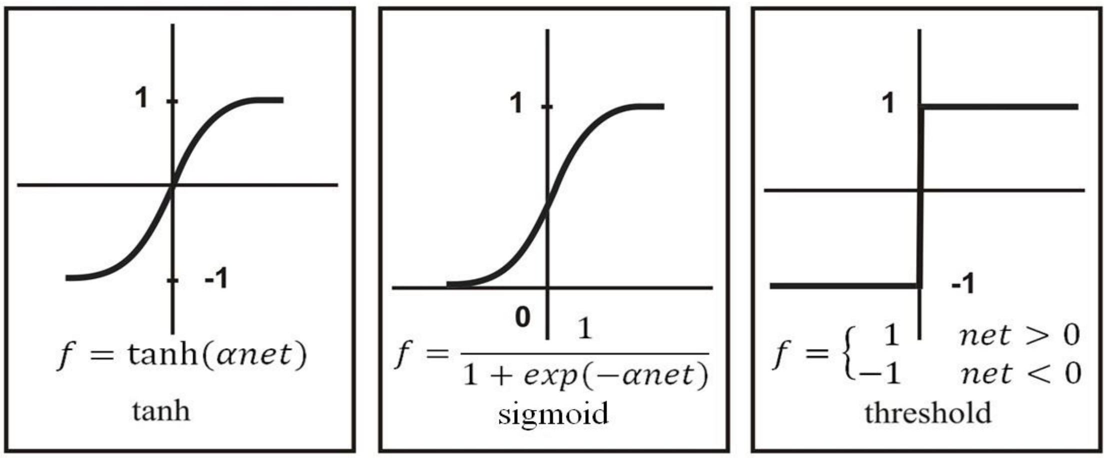

Figure 2.6: Three of the most commonly used transfer functions (Principe et al., 2010).

2.2.6 Normalization and denormalizationdata

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

2.2.7 Architecture of Neural Networks

Neural networks can be categorized according to their structure into feedforward networks and recurrent networks cited by (Pawar, 2007). Figure 2.7 explains the structural classification of neural networks.

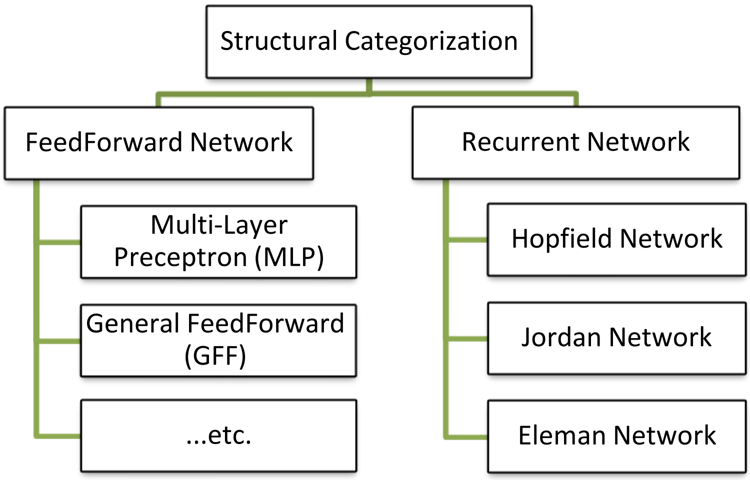

Figure 2.7: Structural classification of neural networks (Pawar, 2007).

- **Feedforward Networks**

A feedforward neural network has a layered structure. Each layer consists of PE's which receive their input from PE's in the previous layer directly and send their output signals to the next layer. The flow of information is unidirectional. There are no connections within a layer. The PE's in one layer are connected to the PE's in the next layer as shown in Figure 2.8.

MLPs are feedforward neural networks trained with the standard backpropagation algorithm. They are supervised networks so they require a desired response to be trained (Kim et al., 2005). They learn how to transform input data into a desired response, so they are widely used for pattern classification. Most neural network applications involve MLPs. There are two important characteristics of the MLP:

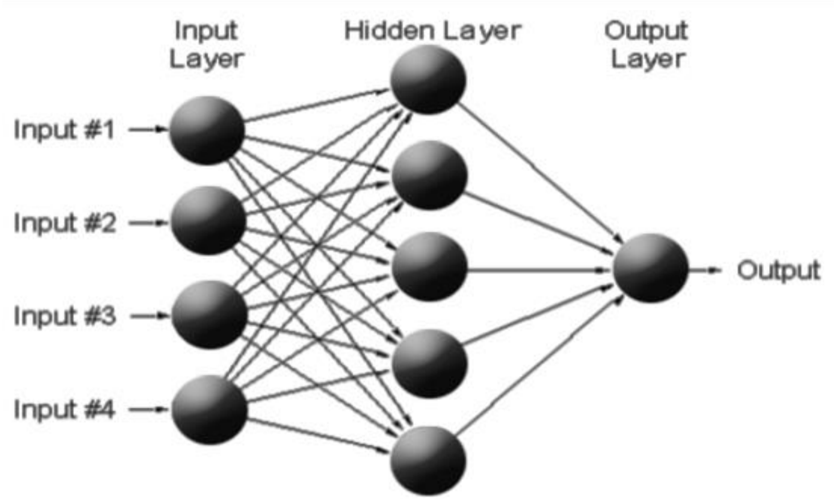

Figure 2.8: A feedforward with l layers of units (Dikmen & Akbiyikli, 2009).

First, its PEs is nonlinear. The nonlinearity function must be smooth (the logistic function and the hyperbolic tangent are the most widely utilized).

Second, they are massively (fully) interconnected such that any element of a given layer feeds all the elements of the next layer.The perceptron and the multilayer perceptron are trained with error correction learning, which means that the desired response for the system must be known. This is normally the case with pattern recognition (Principe et al., 2010).GFF nets are a special case of MLP such that connections can jump over one or more layers see Figure 2.9.

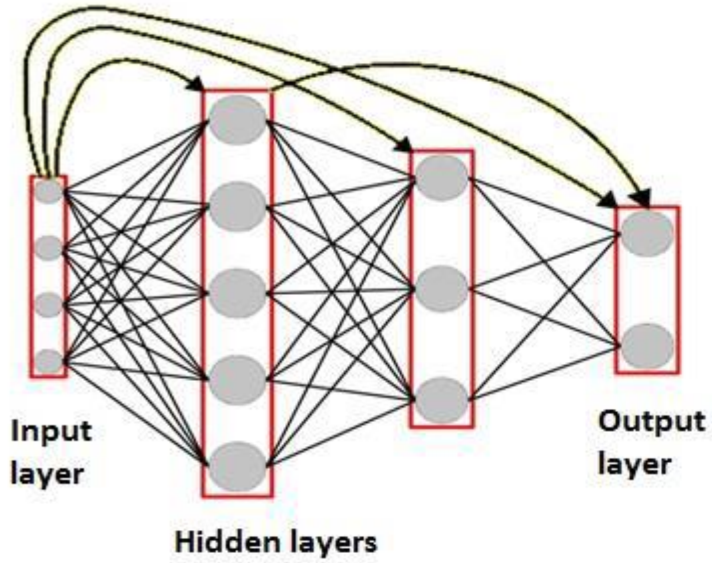

Figure 2.9: General FeedForward networks structure (Principe et al., 2010).

Therefore, the generalized feedforward 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). The advantage of the GFF network is in the ability to project activities forward by passing layers. The result is that the training of the layers closer to the input becomes much more efficient (Principe et al., 2010).

- **Recurrent Networks**

A recurrent neural network (RNN) distinguishes itself from a feedback loops. It has at least one feedback loop. RNN have a closed loop in the network topology. 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 (Kriesel, 2005) and (Krose&Smagt, 1996). Example of the architectural graph for RNN see Figure 2.10.

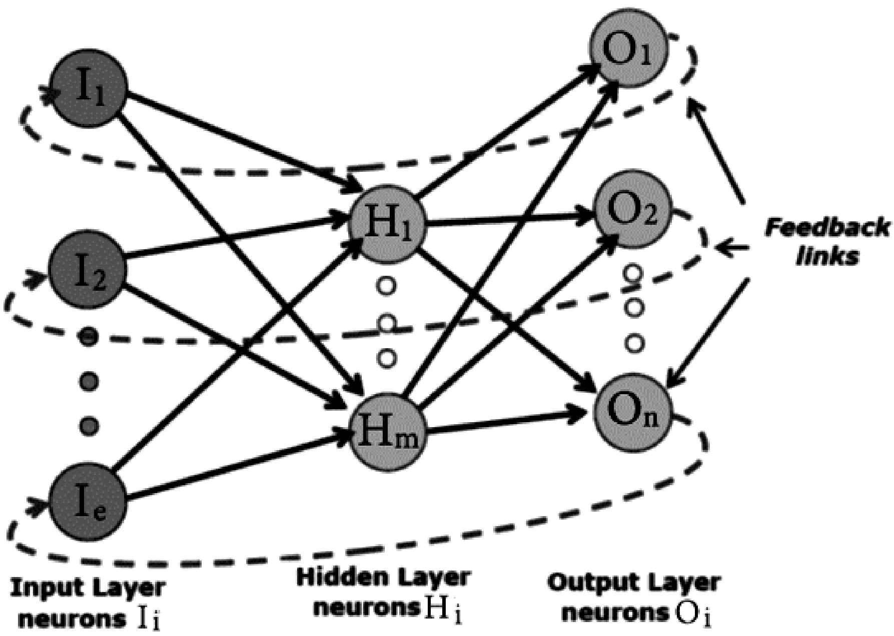

Figure 2.10: Recurrent neural network (Principe et al., 2000).

2.2.8 Algorithms used for training ANN

Pham and Liu (1995) have classified neural networks according to the learning algorithm used to train the network into supervised learning networks, reinforcement learning networks and unsupervised learning networks cited by (Pawar, 2007). The figure below represents the hierarchical classification of learning algorithms. In the supervised learning method, the network is provided with input and output, the network adjusts the weights after comparing the results from the network with the output to minimize the error. In reinforcement learning, the network is not provided with the output but it is informed if the output is a good fit or not (Karna, 1989). Pham and Liu (1995) said that in the unsupervised learning method, input is provided to the network, which adjusts the weights and segregates the input patterns into clusters with similar characteristics cited by (Pawar, 2007).

The error is propagated through the network and the network parameters modified it in an automated fashion. The gradient descent learning is the most common in supervised learning scheme (Principe et al., 2010). The back-propagation algorithm, which is essentially a gradient steepest descent method, is applied for training the ANN models (Lee &Ou-Yang, 2009).

There are many methods for searching the performance surface based on first order gradient information (e.g., Levenberg-Marquardt and Momentum for backpropagation algorithm) (Principe et al., 2010).

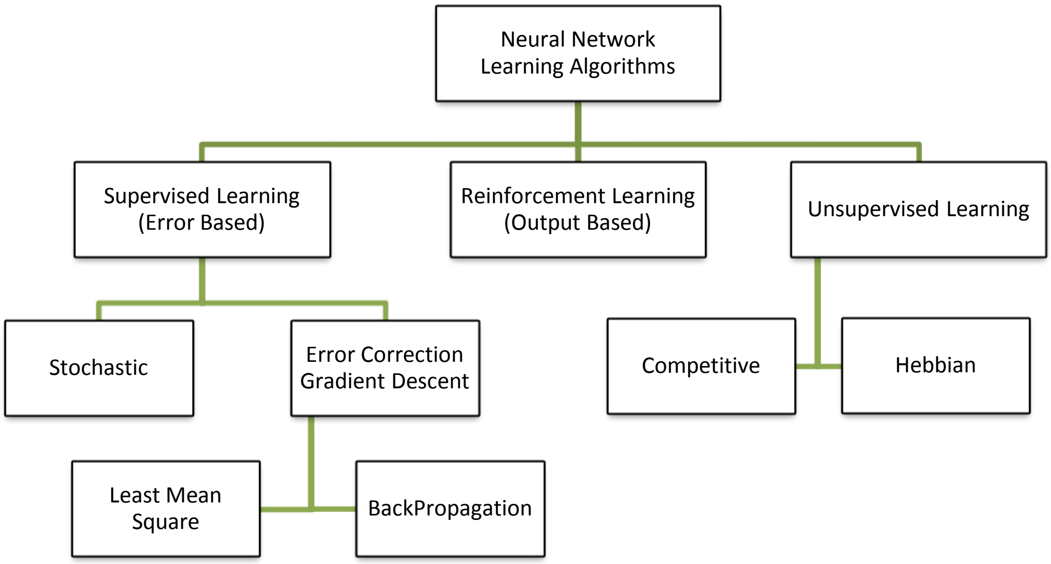

Figure 2.11: Classification of learning algorithms (Pawar, 2007)

The Levenberg-Marquardt (LM) algorithm is one of the most appropriate higher-order adaptive algorithms known for minimizing the MSE of a neural network (Principe et al., 2010). Momentum learning is an improvement to the straight gradient-descent search in the sense that a memory term (the past increment to the weight) is used to speed up and stabilize convergence (Principe et al., 2000).

- **Backpropagation algorithm**

Backpropagation is a common method of teaching artificial neural networks, which uses supervised learning. In principle, backpropagation algorithm is used to imply a backward pass of error to each internal node within the network, which is then used to calculate weight gradients for that node (Principe et al., 2010). The combination of weights, which minimizes the error function, is considered a solution of the learning problem (Rojas, 1996).

Rumelhart and McClelland, (1986) mentioned that backpropagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The backpropagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

2.2.9 Performance measures

The Performance Measures is important to evaluate models, there are five values that can be used to measure the performance of the network for a particular data set.

- **Mean Square Error (MSE):**

According to Principe et al., (2010) mean square error measures the average of the squares of the "errors". The error is the amount of value difference between the network output and the desired output. The formula for the mean squared error is:

$$MSE = \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} \left(d_{ij} - y_{ij}\right)^2}{NP} \tag{2.1}$$

Where:

P= number of output PEs.

N= number of exemplars in the data set.

yij= network output for exemplar i at PE j.

dij= desired output for exemplar i at PE j.

- **Normalized Mean Square Error (NMSE):**

According to Principe et al., (2010) the normalized mean squared error is defined by the following formula:

$$NMSE = \frac{P \times N \times MSE}{\sum_{j=0}^{P}\left(\frac{\left(N\sum_{i=0}^{N}\left(d_{ij}^{2}\right)-\left(\sum_{i=0}^{N} d_{ij}\right)^{2}\right)}{N}\right)} \tag{2.2}$$

Where:

P= number of output PEs.

N= number of exemplars in the data set.

MSE= mean square error.

dij= desired output for exemplar i at PE j.

- **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:

$$r = \frac{\frac{\sum_i (x_i-\bar{x})(d_i-\bar{d})}{N}}{\sqrt{\frac{\sum_i \left(d_i-\bar{d}\right)^2}{N}}\sqrt{\frac{\sum_i (x_i-\bar{x})^2}{N}}} \tag{2.3}$$

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. (Principe et al., 2010).

- **Mean Absolute Error (MAE):**

According to Willmott and Matsuura, (2005) the MAE is defined by the following formula:

$$MAE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left|dy_{ij} - dd_{ij}\right|}{NP} \tag{2.4}$$

Where:

P= number of output PEs.

N= number of exemplars in the data set.

dyij= denormalized network output for exemplar i at PE j.

ddij= denormalized desired output for exemplar i at PE j.

- **Mean Absolute Percentage Error (MAPE):**

According to Principe et al., (2010) The MAPE is defined by the following formula:

$$MAPE = \frac{100}{N\ P}\sum_{j=0}^{P}\sum_{i=0}^{N}\frac{\left|dy_{ij} - dd_{ij}\right|}{dd_{ij}} \tag{2.5}$$

Where:

P= number of output PEs.

N= number of exemplars in the data set.

dyij= denormalized network output for exemplar i at PE j.

ddij= 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).

After several studies were reviewed, then this research considered Hegazy and Ayed, (1998) methodology in determining the total MAPE. Training phase were represented fifty percent of the total MAPE likewise the test set is equal the remaining fifty percent. Total Accuracy Performance (TAP) can be calculated by the following formula:

$$TotalMAPE = \frac{(MAPE_{Tr} \times N_{Tr} + MAPE_{C.V} \times N_{C.V})/(N_{Tr} + N_{C.V}) + MAPE_{Test}}{2} \tag{2.6}$$

Where:

MAPETr = Mean absolute percentage error for training data set.

NTr = number of exemplars in the training data set.

MAPEC.V = Mean absolute percentage error for cross validation data set.

NTr = number of exemplars in the cross validation training data set.

MAPETest = Mean absolute percentage error for test data set.

- **Accuracy Performance (AP):**

According to Wilmot and Mei, (2005) Accuracy performance is defined as (100−MAPE) %. Total Accuracy Performance (TAP) can be calculated by the following formula:

$$TAP = 100 - Total\ MAPE \qquad (2.7)$$

- **Sensitivity analysis measures**

Once the ANN model was built and tested, the next step is to evaluate the influence of each input variable to the output. This serves as feedback, indicating which input channel has a significant effect. One might decide to remove input variables with less significance to reduce complexity of the ANN model and to save time on training (Sodikov, 2005) and (Gunaydın & Dogan, 2004).

During sensitivity analysis, the corresponding change in the output for any input is recorded as a column then the standard deviation for this column is calculated according to the following formula:

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{(n-1)}} \qquad (2.8)$$

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.

This is very easy to compute in the trained network and effectively measures how much a change in a given input affects the output across the training data set. Inputs that have large sensitivities have more importance in the mapping therefore, there should be kept but the inputs with small sensitivities can be discarded (Principe et al., 2000).

2.2.10 Advantages and disadvantages of ANN

Artificial neural networks have many advantages that made it increasingly used in several applications by many researchers. Some of these advantages can be summarized below:

- ANN is well suited to model complex problems where the relationship between the model variables is unknown (Shahin et al., 2002).
- Neural networks have the capability of producing correct or nearly correct outputs when presented with partially incorrect or incomplete inputs.
- ANN does not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANN has compared with most empirical and statistical methods (Shahin et al., 2002).
- ANN can always be updated to obtain better results by presenting new training examples as new data become available (Shahin et al., 2002).
- 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. It is often faster to use NNs than a conventional approach (Attal, 2010).
- Engineers often deal with incomplete and noisy data, which is one area where ANN is most applicable.
- ANN can learn and generalize form examples to produce meaningful solutions to problems.
- Data presented for training ANN can be theoretical data, experimental data, empirical data based on good and reliable experience or a combination of these.

Although the artificial neural networks have advantages, on the other hand there are disadvantages. Some of these are listed below:

- The principal disadvantage being that they give results without being able to explain how they were arrived to their solutions. Their accuracy depends on the quality of the trained data and the ability of the developer to choose truly representative sample inputs.

- Trial and error method is the best solution to obtain the formula to decide what architecture of ANN should be used to solve the given problem and which training algorithm to use. One looking at a problem and decide to start with simple networks or going on to complex ones to get the optimum solution is within the acceptable limits of error.
- There is no guideline for designing; the performance depends on large training data (Khatibi & Jawawi, 2010).

2.2.11 Applications of artificial neural networks

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

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

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

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

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

5. Dynamic modeling. For example, construction projects with varying performance levels measured in the different reporting periods could

indicate a projection of relative time and/or cost overruns. Another example is modeling during periods of rapid fluctuations in inflation or escalation rates. These data could be used to give an indication about the market condition so that proper bidding decisions could be made.

6. Optimization tasks. For example, applications regarding the optimization of construction activity and resource usage could be experimented.
7. Real-time applications such as those associated with time-dependent changes (e.g. material costs, inflation, rate, etc.).

2.2.12 Neural network applications in construction management

Applications of ANNs in construction management go back to the early 1990s. These applications cover a wide of topics. There are many applications of ANN in the field of construction management for predicting labor productivity.

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

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

Rifat (1996) has done construction labor productivity modeling using neural networks and regression analysis. Factors influencing construction operations have been identified and construction productivity of concrete pouring, formwork, concrete finishing and granular fill have been calculated to developed feed forward back propagation neural networks. These models have been proved to provide more accurate results with less error as after comparing with regression models.

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

Sonmez and Rowings (1998) presented a methodology based on the regression and neural network modeling techniques for quantitative evaluation of the impact of multiple factors on productivity. The methodology was applied to develop productivity models for formwork, and concrete finishing tasks, using data compiled from eight building projects. Brain-Maker professional, commercially available neural network simulator, was used to train the model. The predictive behavior of the models was compared with previous productivity studies model results, advantages of the methodology, and study limitations are discussed.

Lu et al. (2000) discussed the derivation of a probabilistic neural network classification model and its application in the construction industry. The probability inference neural network (PINN) model was based on the same concepts and those of the learning vector quantization method combined with a probabilistic approach. The classification and prediction network were combined in an integrated network, which required the development of a different training and recall algorithm. The PINN was tested on real historical productivity data at a local construction company and compared to the classical feed forward back-propagation neural network model. The test showed marked improvement in performance and accuracy.

Ming (2000) has estimated labor productivity using probability inference neural network which is the extension of neural network model developed by Jason in 1996 for estimating productivity of formwork activity. In this research classification and prediction models have been developed using kohenon learning vector quantization network and feed forward back propagation neural network. After classifying typical and non typical activities through kohenon classification network probabilistic inference neural network used to predict productivity of formwork activity with point estimates as an output along with the zones of production rates describing range of productivities.

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

Tam et al. (2002) developed a quantitative model for predicting the productivity of excavators using artificial neural network (ANN), which is then compared with the multiple regression model developed by Edwards & Holt (2000). Neural network using the architecture of multilayer feed forward (MLFF) is used to model the productivity of excavators. The results showed that the ANN model is suitable for mapping the non-linear relationship between excavation activities and the performance of excavators. It concludes that the ANN model is an ideal alternative for estimating the productivity of excavators.

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

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

Moselhi et al. (2005) has developed a model using neural network for estimating change order impact on labor productivity. By doing field investigation change order factors that affect labor productivity has been identified. Artificial neural network has been developed to predict the productivity loss occurred due to the impact of the change orders on construction operations. Neural network provides better results as compare to the other models that have been developed using different softwareSamer (2006) has estimated construction labor productivity for concreting activities using neural networks. Factors affecting concreting activities have been identified using questionnaire survey. Three networks using feed forward back propagation neural networks using hyperbolic tan transfer function have been developed for formwork activity, steel fixing and concrete pouring activities. These networks show adequate convergence with reasonable generalization capabilities.

Sana et al. (2011) used feed forward back propagation neural network to estimate the rates with least range of errors for Production rates of concreting the columns and influencing factors have been measured through Direct Observation from Malaysian construction Industry.

Al-Zwainy (2012) used Back propagation Feed-forward neural networks for productivity estimation of the finishing works with stone tiles for building project.

Chapter summary

As mentioned above, many researchers have used ANN for modeling production rates of different construction activities which includes concrete pouring, installing formwork, welding and installation of pipes etc. These researchers have taken more than one activities at a time, thus an influence on the production rate of individual activity has not being clearly identified and usually neglected. If influence of various factors on production rates of a single activity can be identified then prediction modeling can be done more accurately.

However, until now there is no research in Gaza Strip applied ANNs technique to predict the production rate for pouring concrete slab. Therefore, ANNs as an essential tool that used in construction industry was be used to build up the prediction model for labor productivity in casting concrete slabs.

Chapter 3: Research Methodology and Data Collection

3.1 Introduction

This chapter shows the data collection procedure and methodology used in this research. It provides information about the research strategy, questionnaire design, target population, survey samples, sample size and pilot study of the research questionnaire, factors affecting labor productivity, and process of data collection and analysis.

3.2 Research Strategy

The research strategy can be defined as "the way in which the research objectives can be questioned. The research strategy can be classified into two types namely, quantitative approach and qualitative approach" (Naoum, 2007). In this study, both quantitative and qualitative approaches were used. The qualitative approach was used to determine the main factors affecting the labor productivity for casting concrete slab in construction project in Gaza Strip. In addition, quantitative approach was used to gather the data from resources by filling a form for each project, which contains the input factors and the duration for each slab as output.

3.3 Research Design

1. The purpose of this research is to develop ANN model to be used in estimating the labor production rate for formwork, reinforcement and casting concrete slab in building projects.

The methodology of this study can be summarized in the following points:

3.3.1 Topic selection and thesis proposal phase

After defining the problem of the research, the exact topic was defined. The objectives of research were based on the problem of research and the topic. Finally, the research plan was designed.

3.3.2 Literature review phase

A comprehensive review of literature on productivity and neural networks was performed. It was also necessary to conduct interviews with project managers and site engineers to identify the most effective factors affecting the labor production rate.

3.3.3 Questionnaire design phase

In this section, the questionnaire investigating the most effective factors affecting the labor production rate for casting concrete slab was designed in order to collect the data from many projects in Gaza Strip.

3.3.4 Pilot questionnaire phase

The next phase of the research was pilot study. Contractors and engineers were contacted. The purpose of the pilot study is to prove that the questions are clear to be answered in a way that helps to achieve the target of the questionnaire. In addition, it was important to ensure that all the information received from the respondents would be useful in achieving the research objectives; the questionnaire was modified based on the results of the pilot study.

3.3.5 Data collection phase

A second questionnaire was made to collect the real data from many projects in Gaza Strip for the most effective factors resulting from the first questionnaire. Neural networks models require a lot of data. Therefore, a lot of historical productivity record for one hundred and seven questionnaires were collected from one hundred and ten to present real data for duration from the beginning of formwork to the casting day. All of this construction projects were done between 2009 and 2013 in Gaza Strip. The projects data were collected from direct observation and daily reports of contractors and consultants. Then, the data was analyzed, encoding and input to excel sheets to developing ANN model.

3.3.6 Model development phase

Conducting a number of experiments to develop a model of ANNs using NeuroSolution 5.07 application, to achieve the best model that gives minimum percentage of error. Many models were implemented with various structures and were trained many times with checking the validity. The final models were tested and the results were presented through comparison between models performance to choose the best. The sensitivity of the best model predictions has been assessed by variation in the project parameters.

3.3.7 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 recommendations.

The approach used to achieve the study objectives can be summarized as shown in Figure 3.1.

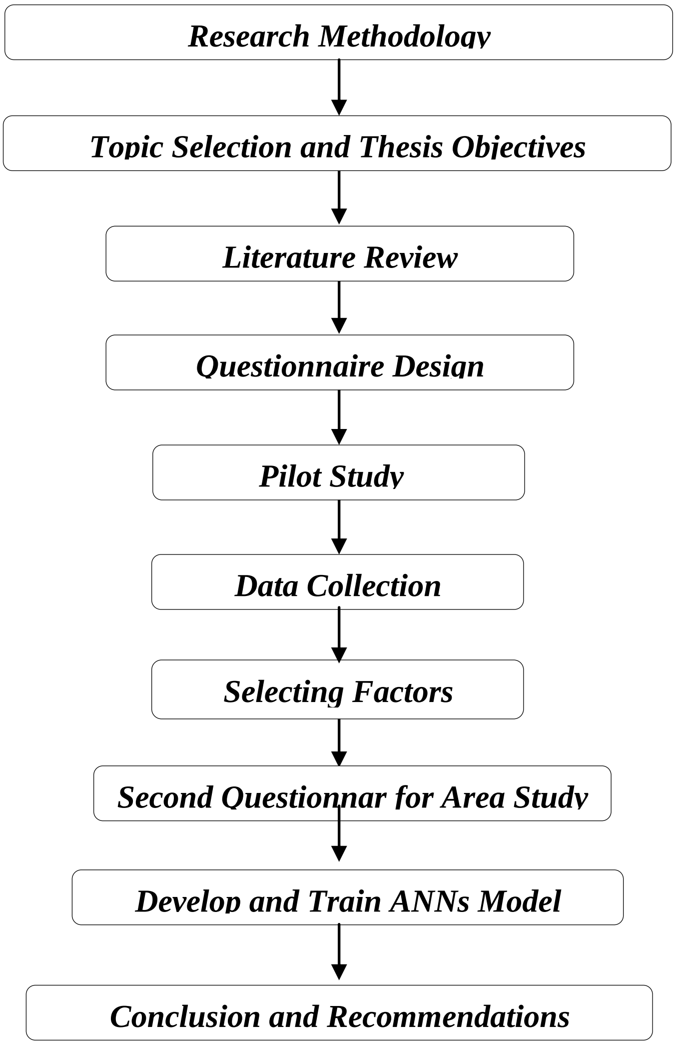

Figure 3.1: Illustration of study methodology

3.4 Questionnaire Design

According to literature review related to the concern subject and after discussions with the supervisor and interviewing sample of contractors, a well designed questionnaire was developed with mainly closed ended questions. The questionnaire was built from two sections that cover the main questions of the study. The first section is related to the company profile and some information about the project. This section includes 16 questions about companies' name, project name, project duration, project location, floor area, number of floor, floor height, slab thickness, number of crew, number of labor in each crew, working hours per day at site, classification of the company, the position of officer who fills the questionnaire, number of company's employees, number of executed projects during the last five years, and average value of executed projects per year during the last five years.

The second section is related to factors negatively affecting labor productivity. It includes 10 groups of factors such as manpower issues, leadership issues, motivation issues, time issues, materials / tools issues, supervision issues, project issues, safety issues, quality issues, and external issues. The original questionnaire was developed in English language. English language questionnaire is attached in (Annex 1). In order to avoid any misunderstanding. The questionnaire would be much effective and easier to be understood and to get more realistic results, the questionnaire was translated to the Arabic language and the Arabic language questionnaire is attached in (Annex 2). An explanatory letter was attached to explain the way of responding, the aim of the study and the security of the information. A draft questionnaire was designed with the help of supervisor. This draft was discussed with a group of specialists. They advised some changes such as modifying the wording of some questions. Some of them recommended adding questions. Some of them also recommended changing the answer options in questions. Other changes were also made after the pilot study to clarify confusion and ambiguity reported by the pilot study subjects.

3.5 Research Population

The studied population includes contractors who have a valid registration by the Palestinian Contractors Union (PCU) in buildings specialization in Gaza Strip at year 2012. The total number of contractors who have valid registration under first, second and third category are 154 companies. The first class has56 companies, the second class has 65 companies, and the third class has 33 companies.

3.6 Sample Size

A systematic random sample to ensure a representative sample of all contractors was selected. To choose the sample size from the population (contracting companies), which equal 154 company, the formula shown below was used for unlimited population (Creative Research System, 2001):

$$SS = \frac{Z^2 \times P \times (1 - P)}{C^2}$$

Where:

SS = Sample size

Z = Value (e.g. 1.96 for 95% confidence level)

P = Degree of variance between the elements of population (0.5)

C = Confidence interval (.05).

$$SS = \frac{1.96^2 \times 0.5 \times (1 - 0.5)}{0.05^2} = 384.16 \cong 385$$

Correction for Finite Population, use the formula below:

$$NewSS = \frac{SS}{1 + \frac{SS-1}{POP}}$$

Where:

POP= population

$$NewSS = \frac{385}{1 + \frac{385-1}{154}} = 110$$

This means that the questionnaire should be distributed to 110 contractors in order to achieve 95% confidence level

3.7 Sampling Method

The samples were selected randomly from each level of three contractor's categories. The contractor's union list is ordered by the company number, three lists of contractors were prepared to represent the first, second, and third categories. The randomly selection among three lists was done by the researcher using non-replacement random selection.

3.8 Instrument Validity

The questionnaire was reviewed by a group of experts in the field of the study. They were requested to identify the internal validity and to what extent it was suitable to be used as an instrument to realize the goals and aims of this research. The group of experts has agreed that the questionnaire is suitable to achieve the studying goals with some amendments. The researcher has made these amendments in the structure and language of the questionnaire to be consistent with the local environment.

3.9 Pilot questionnaire

In order to enforce the research, the used survey instrument should be piloted to measure its validity and reliability and test the collected data. The pilot study was done by distributing the prepared questionnaire to panels of experts – having experience in the same field of the research- to collect their remarks on the questionnaire. The pilot study was done before collecting the final data of the whole sample. A pilot study provides a trial run for the questionnaire, which involves testing the wording of question, identifying ambiguous questions, testing the techniques that used to collect data and measuring the effectiveness of standard invitation to respondents (Naoum,2007). The piloting process was conducted through many interviews with the concerned specialist from different organizations and they were provided with an explanation about the inclusion of the data and the objectives of this study and had been asked to fill the questionnaire, the respondents were given the opportunity to add their suggestions about the questionnaire form and contents. All the suggested modifications and comments were discussed with the supervisor before taking into consideration. The piloting stage served to increase the effectiveness of the questionnaire. Items that had weak reliability were either deleted or combined. At the end of this process, the agreed changes, modifications and addition were introduced as well as the final form of the questionnaire was constructed.

3.10 Data Measurement

In order to be able to select the appropriate method of analysis, the level of measurement must be understood. For each type of measurement, there are an appropriate methods that can be applied and not others. In this research, ordinal scales were used. Ordinal scale as shown in Table 3.1 is a ranking or a rating data that normally uses integers in ascending or descending order. The numbers assigned to the important (1, 2, 3, 4, 5) do not indicate that the interval between scales are equal, nor do they indicate absolute quantities. They are merely numerical labels. Based on likert scale illustrates the ranking order. Table 3.1 (Cheung et al., 2004; Iyer and Jha, 2005; Ugwu and Haupt, 2007)

Table 3.1: Ordinal scale used for data measurement

Item	Very High effect	High effect	Medium effect	Low effect	Very Low effect
Scale	5	4	3	2	1

The Relative Importance Index method (RII) is used here to determine the most important factors that affect on labor productivity in casting concrete slab in construction projects in Gaza Strip. The relative importance index computed as (Cheung et al., 2004; Iyer and Jha, 2005; Ugwu and Haupt, 2007):

$$Relative\ Importance\ Index\ (RII) = \frac{5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{5N}$$

Where:

N = the total number of respondents

n1 = number of respondents who answered "Very Low effect"

n2 = number of respondents who answered "Low effect"

n3= number of respondents who answered "Medium effect"

n4 = number of respondents who answered "High effect"

n5 = number of respondents who answered "Very high effect"

The importance index (I) for all factors had been calculated. The indexes had been ranked. The relative importance index range is from zero to one.

3.11 Data Collection

Data was collected quantitatively by the study survey instrument which was the prepared and piloted questionnaire. The personal interview was used for filling the questionnaire and collecting data.

1. The first questionnaire was made to identify the most important factors which influencing the labor production rates for casting concrete slab. The targeted sample, which were selected are 110, however 92 (84%) respondents returned the questionnaires, and just 77 (70%) of the received questionnaires were fully

completed so they were accepted for the analysis, while 15 incomplete questionnaires were neglected. As shown in table 3.2

Table 3.2: Number of the questionnaire respondents and response rate.

Type	Sample size	No. of Respondents	Response rate	Accepted questionnaire
Contracting	110	92	84%	77

2. Respondents are required to mark each factor on the likert scale of 1 to 5 where 1 means Very Low effect and 5 means Very high effect, according to their importance in influencing labor productivity in formwork, reinforcement and casting concrete for slabs.

3. For identification of the most effective factors based on the questionnaires returned, the relative importance index (RII) for all factors was calculated and analyzed. The researcher determined the most effective factors which have RII more than 0.75Analysis and calculating RII is attached in (Appendix A).

4. After determining the most effective factors, the designing of second questionnaire was performed for collecting real data from project sites. The English and Arabic version of this questionnaire are presented in (Annex 3,4). The factors in this questionnaire were divided into two categories: quantitative and qualitative factors. Quantitative data comprised actual numerical values; qualitative data was mainly rating and descriptions. Qualitative ratings were typically on a scale from very low to very high..

5. The personal interview was used for filling the second questionnaire to get accurate and real data, from daily report in construction projects.

6. One hundred and seven questionnaires were collected to present real data for duration from the beginning of formwork to the casting day. All of the collected data are presented in (Appendix B).

7. Neurosolution Software version 5.07 was used to develop and train the neural networks model. A number of alternative neural network structures were investigated to obtain the minimum percentage of error.

Chapter 4: Results and Analysis

Factors affecting labor productivity in 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 labor productivity for casting concrete slabs in building projects. Depending on this great importance of selecting these factors, a questionnaire survey, were conducted to identify these factors for building projects in Gaza Strip. This chapter describes the results that have been obtained from field study and analysis of the questionnaire using Microsoft excel.

Questionnaire Analysis

One hundred and ten questionnaires were distributed to three category of contracting companies, where, seventy-seven questionnaires, at a response rate 70% of the total number of questionnaires, have been correctly answered. After omitting incomplete or inaccurate data, the seventy-seven questionnaires were identified. More details and analysis are discussed in this section for the questionnaire results

4.1 Part One: General Information

This part of questionnaire is related to the company profile and provides information about characteristics of target companies and projects.

4.1.1 Project duration

As shown in Table 4.1, most of projects have duration between 7and 12 month, which indicate that most of project has duration less than one year.

Table 4.1: Frequency and percent of duration for projects

Duration	Frequency	Percent %
From 1 to 6 month	17	22.1%
From 7 to 12 month	51	66.2%
From 13 to 19 month	5	6.5%
More than or equal 20 month	4	5.2%
Total	77	100%

4.1.2 Project location

As shown in Table 4.2, most of projects were located in Gaza city and few of them in south area, which reflect the importance of Gaza city and it's contain for most of project, because it's the backbone for economic and construction industry.

Table 4.2: Frequency and percent of project location

Projects locations	Frequency	Percent %
North area	17	22.1%
Gaza area	37	48.1%
Middle area	16	20.8%
South Area	7	9%
Total	77	100%

4.1.3 Floor area (m^2)

As shown in Table 4.3, approximately 70% of the projects have a floor area less than 1000 m2, this result indicate that majority of executed projects have a medium size.

Table 4.3: Frequency and percent of floor area for projects

Floor area (m2)	Frequency	Percent %
From 100 to 500 m2	28	36.3%
From 501 to 1000 m2	26	33.8%
From 1001 to 1500 m2	11	14.3%
More than 1500 m2	12	15.6%
Total	77	100%

4.1.4 Number of floors

As shown in Table 4.4, 62.3% of the projects not exceed 3 floors, which mean there are no vertical expansions, because most of projects were governmental projects.

Table 4.4: Frequency and percent of number of floors for projects

Number of floors	Frequency	Percent %
From 1to 3 floors	48	62.3%
From 4 to 6 floors	16	20.8%
From 7 to 9 floors	10	13%
More than 9 floors	3	3.9%
Total	77	100%

4.1.5 Floor height

As shown in Table 4.5, most of the projects have floors height between 2.8 and 3.2 m, these results are logical and consistent with the height for most building and projects in Gaza Strip.

Table 4.5: Frequency and percent of floor height for projects

Floor height(m)	Frequency	Percent %
From 2.8 to 3.2 m	54	70.1%
From 3.21 to 3. 6 m	17	22.1%
More than 3.61 m	6	7.8%
Total	77	100%

4.1.6 Slabs thickness

As shown in Table 4.6, approximately 85% of the projects have slab thickness from 20 to 30 cm, so it's supported the known slabs thickness in Gaza strip which are between 20 , 30 cm.

Table 4.6: Frequency and percent of slab thickness for projects

Slab thickness (cm)	Frequency	Percent %
From 20 to 25 cm	44	57.1%
From 26 to 30 cm	22	28.6%
From 31 to 35 cm	7	9.1%
More than 35 cm	4	5.2%
Total	77	100%

4.1.7 Number of crew

As shown in Table 4.7, most of the projects have a crew number from 1 to 3 crews, which indicate that the results reveal the simple organization of contracting companies in the Gaza Strip.

Table 4.7: Frequency and percent of number of crew for projects

Number of crew	Frequency	Percent %
From 1 to 3	57	74%
From 4 to 6	11	14.3%
More than 6	9	11.7%
Total	77	100%

4.1.8 Number of labor

As shown in Table 4.8, 57.1% of the projects have number of labor from 1 to 10, that mean most of projects is simple and need medium number of labor.

Table 4.8: Frequency and percent of number of labor for projects

Number of labor	Frequency	Percent %
From 1 to 10	44	57.1%
From 11to20	22	28.6%
More than 21	11	14.3%
Total	77	100%

4.1.9 Working hours per day

As shown in Table 4.9, working hours per day for projects converging from 8 to 10 hours, and this is accepted result for working hours per day.

Table 4.9: Frequency and percent of working hours per day for projects

Working hours per day	Frequency	Percent %
8 hours	30	39%
9 hours	14	18.2%
10 hours	33	42.8%
Total	77	100%

4.1.10 Classification of contracting companies according to PCU

As shown in Table 4.10, three classes of contracting companies are surveyed, noted that 63.6 % of the investigated contracting companies are classified as first class, which increased the accuracy of this research.

Table 4.10: Frequency and percent of classification of contracting companies

Classification	Frequency	Percent %
First Class	49	63.6%
Second Class	19	24.7%
Third Class	9	11.7%
Total	77	100%

4.1.11. The position of officer who fills the questionnaire

As shown in Table 4.11, most of the respondents (63.6%) have the title of site engineer This indicates the high cooperation of those engineers in this study.

Table 4.11: Frequency and percent of position of respondent for projects

Position of respondent	Frequency	Percent %
Company Manger	4	5.2%
Projects Manger	18	23.4%
Site Engineer	49	63.6%
Foreman	6	7.8%
Total	77	100%

4.1.12 Number of company's employees

As shown in Table 4.12, most of the companies (87%) have less than 30 employees, which indicate that our contracting companies have a simple organization and small number of employees.

Table 4.12: Frequency and percent of number of company's employees for projects

No. of employees	Frequency	Percent %
Less than 10	28	36.4%
From 11 to 30	39	50.6%
From 31 to 50	3	3.9%
More than 50	7	9.1%
Total	77	100%

4.1.13 Number of projects executed in the last five years

As shown in Table 4.13, 57.1 % of the companies' volume of work is less than 10 projects in the last five years. This result reflect the pad situation of construction industry in Gaza strip in last five years,

Table 4.13: Frequency and percent of number of projects executed in the last five years

No. of executed projects	Frequency	Percent %
Less than 10	44	57.1%
From 11 to 20	24	31.2%
From 21 to 30	3	3.9%
More than 30	6	7.8%
Total	77	100%

4.1.14 The value of projects executed in the last five years in million dollars

As shown in Table 4.14, it is noticed that (51.9%) of the companies have executed a volume of work with a value from 0.51 to 2 million. It was also found that value of building projects executed by majority of contracting companies is small because the poor economic situation and siege in Gaza strip.

Table 4.14: Frequency and percent of the value of projects in the last five years

Value of executed projects	Frequency	Percent %
Less than 0.5 million	14	18.2%
From 0.51 to 2 million	40	51.9%
From 2.1 to 5 million	20	26%
More than 5 million	3	3.9%
Total	77	100%

4.2 Factors negatively affecting labor productivity

The questionnaire included 53 factors, which derived from previous studies as mention in chapter two. The factors are related to local contracting companies in the Gaza Strip. The factors were distributed into ten groups.

4.2.1 Manpower Group

Results indicate that lack of labor experiences is the most important factor in the manpower group as shown in Table 4.15. Also labor disloyalty is rated second while misunderstanding among labor rated third in this group. On the other hand, labor personal problems and labor absenteeism are lowest factors negatively affecting labor productivity in this group. This indicates that lack of labor experiences have very high effect on labor productivity. This result is supported by Abo Mostafa (2003) who mentioned that experiences of labor affect labor productivity. This result is justified as experience improves intellectual and physical abilities of labor which consequently increase labor productivity.

Table 4.15: Ranking manpower factors

No	Group	Factors	RII	Rank
1	Manpower Group	Increase of laborer age	0.590	6
		Lack of labor experiences	0.787	1
		Labor absenteeism	0.574	7
		Labor personal problems	0.551	8
		Labor dissatisfaction	0.647	4
		Labor disloyalty	0.709	2
		Misunderstanding among labor	0.662	3
		Lack of competition	0.603	5

4.2.2 Leadership Group

As shown in Table 4.16, lack of labor surveillance and misunderstanding between labor and superintendents are very important factors negatively affecting labor productivity. On the other hand, respondents believe that lack of periodic meeting with labor have some effect on labor productivity. This result is justified as lack of labor surveillance increases labor mistakes at work and also delays correction action for these mistakes.

Table 4.16: Ranking leadership factors

No	Group	Factors	RII	Rank
2	Leadership Group	Misunderstanding between labor and superintendents	0.732	2
		Lack of labor surveillance	0.774	1
		Lack of periodic meeting with labor	0.553	3

4.2.3 Motivation Group

Table 4.17 indicates that payment delay has an important effect on labor productivity but Lack of place for eating and relaxation and Lack of training sessions has low effect on labor productivity. Also table 4.17 shows that lack of financial motivation system rated second and Lack of labor recognition programs rated third in this group. This indicate that payment and motivations is essential for labor as it gives workers satisfaction at work site such as achievement, sense of responsibility and pleasure from the work itself.

Table 4.17: Ranking motivation factors

No	Group	Factors	RII	Rank
3	Motivation Group	Lack of financial motivation system	0.662	2
		Lack of labor recognition programs	0.639	3
		Non-providing of transportation means	0.582	4
		Lack of place for eating and relaxation	0.569	5
		Payment delay	0.758	1
		Lack of training sessions	0.532	6

4.2.4 Time Group

Table 4.18 indicates that working for 7 days of week without taking a holiday is rated first (RII= 0.673) in the time factors group while misuse of time schedule rated second (RII = 0.621) in this group. Also increasing number of labor in order to accelerate work rated third (RII = 0.613). Work overtime rated fourth (RII = 0.592) and method of employment rated fifth in time group (RII = 0.590). Abo Mostafa (2003) supported these results and stated that working for 7 days of week without holiday have negative impact on labor productivity.

Table 4.18: Ranking time factors

No	Group	Factors	RII	Rank
4	Time Group	Work overtime	0.592	4
		Working for 7 days of week without holiday	0.673	1
		Increasing number. of labor in order to accelerate work	0.613	3
		Misuse of time schedule	0.621	2
		Method of employment (using direct work system)	0.590	5

4.2.5 Materials / Tools Group

All materials / tools factors have high influence on labor productivity (see Table 4.19). Indeed material shortages are the most important factor in this group. Also shortage of tools and equipment has high impact on labor productivity (RII = 0.847). While Equipment Efficiency rated third (RII = 0.844). On the other hand, unsuitability of materials storage location has less impact than above factors on labor productivity. It should be noted that all materials and tools factors have some important effect on labor productivity. This is understandable in that work cannot be done without the necessary materials. This result is justified in the Gaza Strip as most of materials used in construction projects are imported from Israel and Egypt therefore any closure of crossing points between the Gaza strip and Israel or Egypt stops the work in large numbers of construction projects.

Table 4.19: Ranking materials / tools factors

No	Group	Factors	RII	Rank
5	Materials\Tools Group	Material shortages	0.862	1
		Equipment Efficiency	0.844	3
		Tool and equipment shortages	0.847	2
		Unsuitability of materials storage location	0.696	4

4.2.6 Supervision Group

Table 4.20 shows that drawings and specifications alteration during execution is the most important factor among other supervision issues. This result is supported by Thomas et al (1995) who stated that there is a 30% loss of efficiency when work changes are being performed. This result can be interpreted as changes of specifications and drawings require additional time for the adjustments of resources and manpower so that the change can be met. Also labor morale is affected by extensive numbers of changes. Rework ranked second while Supervisors absenteeism ranked third in supervision factors group. The least important factor in this group is Inspection delay.

Table 4.20: Ranking supervision factor

No	Group	Factors	RII	Rank
6	Supervision Group	Rework	0.732	2
		Supervisors absenteeism	0.704	3
		Inspection delay	0.634	4
		Drawings and specifications alteration during execution	0.790	1

4.2.7 Project Group

The degree of importance of project related factors is described in Table 4.21. The important factors in project group are complexity due to steel bars space and number of labor in project. While slab thickness and type of activities in the project have low importance in effecting labor productivity. This result might be justified because the building projects in the Gaza Strip are not complex and with small size therefore activities in different projects approximately have same features and any complexity in steel bars have high effect on productivity.

Table 4.21: Ranking project factors

No	Group	Factors	RII	Rank
7	Project Group	Type of activities in the project	0.657	10
		Construction method	0.694	5
		Interference	0.673	7
		Working in confined space	0.688	6
		Complexity due to steel bars	0.800	1
		Floor area (m2)	0.699	8
		Slab thickness	0.662	9
		Level of Building (Floor No.)	0.774	3
		Floor height	0.701	4
		Number of labor in project.	0.784	2

4.2.8 Safety Group

As illustrated in Table 4.22, workings at high place and insufficient lighting have large effect on labor productivity. On the other hand noise and unemployment of safety officer in construction site have lowest effect on labor productivity. Results also indicate that height of working place has large impact on productivity and unemployment of safety officer in construction site has low impact on labor productivity. This result is justified in the Gaza Strip as contractors seldom employ safety officers in building projects, therefore they, are not aware of the importance of employing safety officer in construction sites.

Table 4.22: Ranking safety factors

No	Group	Factors	RII	Rank
8	Safety Group	Violation of safety precautions	0.629	5
		Accidents	0.652	4
		Unemployment of safety officer in construction site	0.569	7
		Working at high place	0.769	1
		Bad ventilation	0.662	3
		Insufficient Lighting	0.735	2
		Noise	0.590	6

4.2.9 Quality Group

As detailed in table 4.23, inefficiency of equipment, high quality of required work and low quality of raw materials approximately have same effect on labor productivity. In fact, all quality factors have moderate effect on labor productivity.

Table 4.23**:** Ranking quality factors

No	Group	Factors	RII	Rank
9	Quality Group	Low quality of raw materials	0.634	3
		High quality of required work	0.649	2
		Inefficiency of equipments	0.686	1

4.2.10 External Group

Looking in Table 4.24, weather changes ranked first in external group whilst easy to arrive to the project location ranked second. Both factors have strong effect on labor productivity.

Table 4.24: Ranking external factors

No	Group	Factors	RII	Rank
10	External Group	Weather changes	0.810	1
		Augmentation of Government regulations in construction	0.605	3
		Easy to arrive to the project location	0.758	2

4.3 Overall ranking of factors negatively affecting labor productivity

As indicated in Table 4.25, 4.26, the most important factors negatively affecting labor Productivity, and factors which have RII more than 0.75% were identified and presented in second questionnaire to collect real data for casting concrete slabs for construction projects in Gaza Strip. The most effective factors are material shortages, tool and equipment shortages, equipment efficiency, weather changes, complexity due to steel bars, drawings and specifications alteration during execution, lack of labor experiences, number of labor in project, lack of labor surveillance, level of building (Floor No.), working at high place, payment delay, easy to arrive to the project location. Also results indicate that lowest factors which effects labor productivity are lack of place for eating and relaxation, unemployment of safety officer in construction site, Lack of periodic meeting with labor, Labor personal problems, Lack of training sessions

Table 4.25: Overall ranking of factors negatively affecting labor productivity

NO.	Groups	factors affecting labor productivity	RII	Rank
1	Manpower Group	Increase of laborer age	0.590	44
		Lack of labor experiences	0.787	7
		Labor absenteeism	0.574	48
		Labor personal problems	0.551	52
		Labor dissatisfaction	0.647	34
		Labor disloyalty	0.709	17
		Misunderstanding among labor	0.662	27
		Lack of competition	0.603	42
2	Leadership Group	Misunderstanding between labor and superintendents	0.732	15
		Lack of labor surveillance	0.774	9
		Lack of periodic meeting with labor	0.553	51
3	Motivation Group	Lack of financial motivation system	0.662	27
		Lack of labor recognition programs	0.639	35
		Non-providing of transportation means	0.582	47
		Lack of place for eating and relaxation	0.569	49
		Payment delay	0.758	12
		Lack of training sessions	0.532	53
4	Time Group	Work overtime	0.592	43
		Working for 7 days of week without holiday	0.673	25
		Increasing number. of labor in order to accelerate work	0.613	40
		Misuse of time schedule	0.621	39
		Method of employment (using direct work system)	0.590	44

5	Materials\Tools Group	Material shortages	0.862	1
		Equipment Efficiency	0.844	3
		Tool and equipment shortages	0.847	2
		Unsuitability of materials storage location	0.696	21
6	Supervision Group	Rework	0.732	15
		Supervisors absenteeism	0.704	18
		Inspection delay	0.634	36
		Drawings and specifications alteration during execution	0.790	6
7	Project Group	Type of activities in the project	0.657	31
		Construction method	0.694	22
		Interference	0.673	25
		Working in confined space	0.688	23
		Complexity due to steel bars	0.800	5
		Floor area (m^2)	0.699	20
		Slab thickness	0.662	27
		Level of Building (Floor No.)	0.774	9
		Floor height	0.701	19
		Number of Labor in project.	0.784	8
8	Safety Group	Violation of safety precautions	0.629	38
		Accidents	0.652	32
		Unemployment of safety officer in construction site	0.569	49
		Working at high place	0.769	11
		Bad ventilation	0.662	27

		Insufficient Lighting	0.735	14
		Noise	0.590	44
9	Quality Group	Low quality of raw materials	0.634	36
		High quality of required work	0.649	33
		Inefficiency of equipments	0.686	24
10	External Group	Weather changes	0.810	4
		Augmentation of Government regulations in construction	0.605	41
		Easy to arrive to the project location	0.758	12

Table 4.26: Ranking of important factors negatively affecting labor productivity

No.	Groups	factors	RII	Rank
1	Materials\Tools factors	Material shortages	0.862	1
2	Materials\Tools factors	Tool and equipment shortages	0.847	2
3	Materials\Tools factors	Equipment Efficiency	0.844	3
4	External factors	Weather changes	0.810	4
5	Project factors	Complexity due to steel bars	0.800	5
6	Supervision factors	Drawings and specifications alteration during execution	0.790	6
7	manpower factors	Lack of labor experiences	0.787	7
8	Project factors	Number of Labor in project.	0.784	8
9	Leadership factors	Lack of labor surveillance	0.774	9
10	Project factors	Level of Building (Floor No.)	0.774	9
11	Safety factors	Working at high place	0.769	11
12	Motivation factors	Payment delay	0.758	12
13	External factors	Easy to arrive to the project location	0.758	12

4.4 Ranking of groups affecting labor productivity

Survey results indicate that materials / tools group ranked most important among all groups of productivity (Table.4.27). On the other hand, time group ranked least important among all groups. External group ranked second important, supervision group ranked third important and project ranked fourth important.

Table 4.27: Ranking groups negatively affecting productivity among groups

Groups	RII	Rank
Materials\Tools Group	0.812	1
External Group	0.725	2
Supervision Group	0.715	3
Project Group	0.713	4
Leadership Group	0.687	5
Safety Group	0.658	6
Quality Group	0.656	7
Manpower Group	0.640	8
Motivation Group	0.624	9
Time Group	0.618	10

4.5 Labor Productivity Measurement

A second questionnaire was made to collect the real data from many projects in Gaza Strip for the most effective factors resulting from the first questionnaire. Neural networks models require a lot of data. Therefore, a lot of historical productivity records for casting concrete slabs were collected. One hundred and seven questionnaires were collected from one hundred and twenty to present real data for duration from the beginning of formwork to the casting day. All of the collected data are presented in Table 4.28. The projects data were collected from direct observation and daily reports of contractors and consultants. Then, the data was encoding and input to excel sheets to developing ANN model.

Table 4.28: Collected real data for duration and factors

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
20	15	2	2	2	2	3	3	3	2	3	4.69
5	15	1	1	2	2	3	3	3	3	2	4.13
6	3	2	2	3	3	2	3	3	2	3	1.94
12	3	2	3	3	3	3	3	2	3	3	2.00
12	3	2	3	2	3	3	3	2	2	3	2.50
55	32	2	2	3	3	2	2	2	2	3	6.90
7	3	3	3	3	2	3	3	3	3	2	4.00
8	8	2	2	3	2	3	3	3	2	3	2.96
9	3	2	2	2	3	2	3	2	2	2	2.18
50	24	2	2	3	3	2	2	2	2	3	7.69
8	3	2	2	3	2	3	3	2	2	3	1.88
7	16	2	1	2	3	1	2	2	2	2	4.38
8	3	3	1	1	3	3	2	3	3	1	1.69
8	3	2	2	2	3	2	3	1	2	3	2.67
9	5	2	3	1	1	2	3	3	2	3	3.64
7	3	3	2	3	2	3	2	2	3	3	1.89
8	3	2	2	3	3	2	2	2	2	1	2.50
9	3.5	2	3	2	3	2	3	2	3	3	5.47
10	3	2	3	3	3	2	3	2	2	2	1.67
8	3	2	2	2	3	3	3	3	3	3	3.00
10	45	2	2	3	2	2	2	2	2	3	2.08
10	15	1	2	3	2	3	3	3	2	3	6.55
11	3	2	1	2	3	2	3	3	2	3	6.67
7	3.5	1	2	2	3	2	3	3	3	2	4.50
8	3	2	2	2	3	2	2	3	2	3	2.00
15	8	3	3	2	3	2	2	3	3	3	3.47
35	20	2	2	2	3	3	2	3	2	3	7.07
12	4	3	2	2	3	3	3	2	2	3	2.83
7	3	3	2	2	2	2	3	3	3	2	4.73
8	3	2	3	3	3	2	3	3	3	3	1.50
12	12	2	2	2	3	3	3	3	3	3	9.26
13	6	3	3	2	3	1	3	3	3	3	2.71
35	4	3	3	3	3	1	2	2	2	3	9.09
13	3.3	3	2	2	2	2	3	3	3	2	5.94
15	3.2	2	2	3	3	3	3	3	3	3	3.89
8	3.5	2	3	3	2	3	3	2	3	3	1.70
8	3	2	2	3	2	3	2	2	3	2	1.82
10	3	3	2	3	3	2	3	2	3	3	1.82
10	3	2	3	3	3	3	3	2	3	3	2.00
12	9	3	2	2	3	3	3	3	3	3	4.40
15	3	3	3	3	2	3	3	3	3	3	4.55

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
13	12	2	2	3	3	3	2	3	2	3	8.75
15	3.2	3	3	3	3	3	3	3	3	3	5.95
10	6	3	3	2	3	1	2	3	2	1	3.06
35	4	1	2	3	3	2	2	3	2	2	5.67
16	6.6	3	2	2	3	2	3	3	3	3	6.60
12	12	2	1	2	3	1	2	2	2	2	6.00
18	9	2	2	3	3	1	3	2	2	3	2.67
20	21	3	3	2	2	2	2	2	3	2	3.14
8	4	2	2	3	2	3	3	3	2	3	3.56
8	3	3	3	2	2	2	3	3	3	3	4.60
10	9	3	3	1	1	2	3	3	2	3	3.28
20	12	2	2	3	1	2	3	1	3	3	4.35
13	3.5	1	1	2	3	1	1	2	1	1	5.00
23	8	3	2	3	2	1	2	2	2	3	8.08
26	28	3	3	3	2	2	3	3	3	3	11.11
30	16	3	3	3	3	3	3	3	2	2	6.07
42	12	2	3	3	3	2	2	2	2	3	7.69
7	8	2	2	1	2	3	3	3	3	1	3.13
7	12	2	1	2	3	1	2	2	2	2	3.75
15	11.5	2	3	2	3	3	2	3	2	2	4.46
30	12	2	2	3	1	3	3	3	2	2	7.86
33	8	2	2	3	3	2	2	3	2	2	5.00
35	36	2	3	2	2	2	2	3	3	3	5.67
10	16	1	1	2	3	1	2	2	2	2	3.00
15	4	2	2	3	2	1	2	3	3	3	9.67
12	3.3	2	2	2	1	3	3	3	2	3	8.04
36	12	3	3	3	3	2	2	3	2	2	5.31
37	4	3	3	2	1	1	2	2	3	3	6.92
40	27	3	3	2	3	2	1	3	3	2	5.00
15	3.2	2	2	1	1	2	2	2	1	3	4.58
6	3	2	2	2	2	2	3	3	3	3	1.75
16	12	2	1	2	3	1	2	2	2	2	8.75
40	8	3	3	3	3	1	2	2	2	3	8.33
10	6	3	2	3	2	3	3	3	3	3	3.65
42	16	2	3	3	3	2	2	2	2	3	7.14
15	16	2	1	2	3	1	2	2	2	2	7.00
45	4	3	2	2	2	2	3	2	3	3	9.52
14	4	1	1	1	2	3	3	2	3	2	4.31
15	6	2	2	3	3	3	3	3	3	3	2.08
11	16	2	1	2	3	1	2	2	2	2	5.00
6	3	2	2	3	3	2	3	2	2	2	1.50
9	5	2	3	1	1	2	3	3	2	3	3.62

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
8	3.5	2	3	3	2	3	3	2	3	3	1.70
8	3	3	3	2	2	2	3	3	3	3	4.59
10	3	2	3	3	3	3	3	2	3	3	2.00
45	20	2	3	2	3	2	2	3	3	3	9.58
10	3	2	3	3	3	2	2	2	1	2	2.50
10	3	2	2	2	3	3	3	3	3	3	3.00
55	28	2	2	3	3	2	2	2	2	3	7.69
50	20	2	2	3	3	2	2	2	2	3	8.30
25	19	2	2	2	3	3	2	3	3	3	11.12
12	9	3	2	2	3	3	3	3	3	3	4.39
12	12	2	1	2	3	1	2	2	2	2	5.95
13	9	3	2	2	3	3	3	3	3	3	4.40
10	3	2	3	3	3	3	3	2	3	3	2.00
52	20	2	2	3	3	2	2	2	2	3	8.20
12	12	2	1	2	3	1	2	2	2	2	5.90
10	3	2	2	2	3	3	3	3	3	3	2.90
10	5	2	3	1	1	2	3	3	2	3	3.63
7	3	2	2	3	3	2	3	2	2	2	1.49
9	3	3	3	2	2	2	3	3	3	3	4.59
44	20	2	3	2	3	2	2	3	3	3	9.58
15	3	3	3	3	2	3	3	3	3	3	4.55
53	28	2	2	3	3	2	2	2	2	3	7.70
9	4	2	3	3	2	3	3	2	3	3	1.68
10	3	2	3	3	3	2	2	2	1	2	2.45

Chapter 5: Models Development and Sensitivity Analysis

One of the objectives of this study is to design the neural network model to predict the production rate for casting concrete slabs in construction projects in Gaza strip. This chapter presents the steps of design this model.

5.1 Introduction

Many neural network models have been developed to assist the project managers or contractors in their jobs. This chapter describes the design of an ANNs model for estimating production rate. The most effective factors affect production rate for casting concrete slabs were identified as outlined in previous chapters. These factors were considered as inputs variables for the neural network model, whereas the production rate in (m2/ hour) considered as the output variable to this model. The data used in model development was collected from the second questioner survey as a tool to collect actual data from contractors (Appendix B) for many projects in Gaza Strip. These questionnaires provided 107 examples of casting slabs. 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. A structured methodology for developing the model has been used to solve the problem at hand. This methodology incorporates five main phases: 1) Select application 2) Design structure 3) Model implementation 4) Training and testing 5) Discussion (analysis) of results.

5.2 Selection of the Neural Network Simulation Software

Many design software are used for creating neural network models. 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).
- ❖ Many researchers used NeuroSolution application in building their neural networks that it achieved good performance and it has multiple criteria for training and testing the model.

5.3 Structure Design

The choice of ANN architecture depends on a number of factors such as the nature of the problem, data characteristics and complexity, the numbers of sample data … etc. (Sodikov, 2005). With the eleven inputs readily identified, the outputs describing the productivity for casting concrete slabs (m2/hour) project can be modeled in different ways. The choice of artificial neural network in this study is based on prediction using feedforward neural network architectures and backpropagation learning technique.

The design of the neural network architecture is a complex and dynamic process that requires the determination of the internal structure and rules (i.e., the number of hidden layers and neurons, update weights method, and the type of activation function) (Gunaydın & Dogan, 2004).

A common recommendation is to start with a single hidden layer. In fact, unless the researcher is sure that the data is not linearly separable, he may want to start without any hidden layers. The reason is that networks train progressively slower when layers are added (Principe et al., 2010).

Based on the literature review, the neural network type deemed suitable for productivity estimation has been identified as feed-forward pattern recognition type (Back propagation) to suit the desired interpolative and predictive performance of the model. Two kinds of feed-forward patterns were chosen to build the models multilayer perceptron and general feed forward. ANN architecture was chosen after several trials, which can be seen the final architecture in section 5.6.

5.4 Model Implementation

Once there is a clear idea about feasible structures and the information needed to be elicited, the implementation phase starts with knowledge acquisition and data preparation (Hegazy et al., 1994). The flow chart for model structure is show in Figure 5.1.

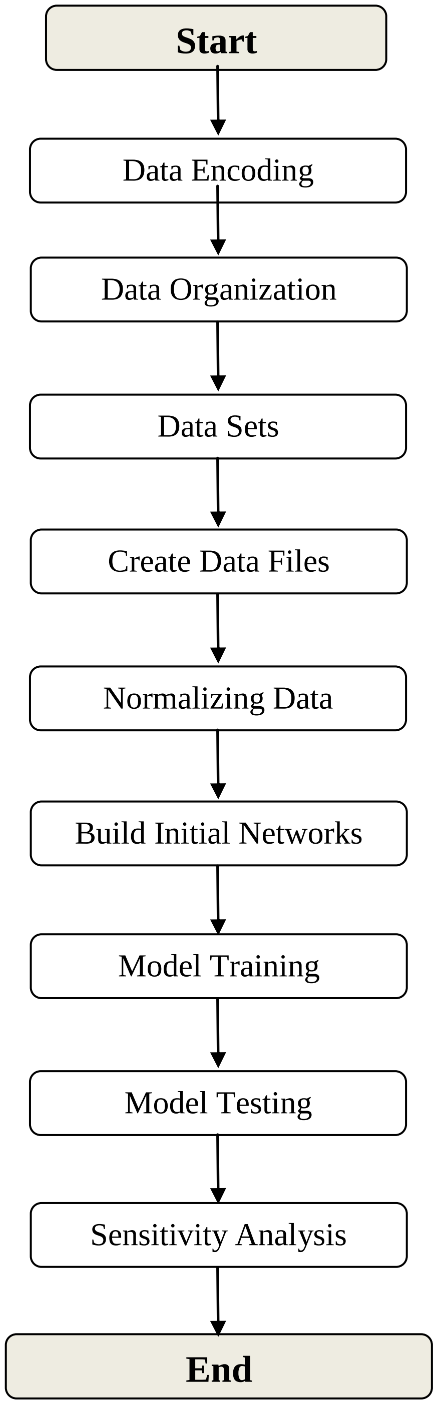

Figure 5.1: Model implementation steps flowchart

5.4.1 Data Encoding

Because the data is not in numeric format, so the data should be coded into a numeric format. This may be challenging because there are many ways to do it and unfortunately some are better than others for neural network learning (Principe et al., 2010). In this research, the data is textual and numeric, so it is encoded to be only numeric or integer according to Table 5.1.

Table 5.1: Inputs/Output encoding

No.	Input Factors	Code
1.	Number of Labor	Number
2.	Floor height	M length
3.	Material shortages	Low quantity= 1 Medium quantity= 2 High quantity= 3
4.	Tool and equipment shortages and Efficiency	Low Efficiency= 1 Medium Efficiency= 2 High Efficiency= 3
5.	labor experiences	Low experiences = 1 Medium experience = 2 High experiences= 3
6.	Weather	Rain = 1 Hot = 2 Moderate= 3
7.	Complexity due to steel bars	Complex= 1 Medium = 2 Easy= 3
8.	Drawings and specifications alteration during execution	High alteration = 1 Medium alteration = 2 Low alteration= 3
9.	Easy to arrive to the project location	Difficult= 1 Medium = 2 Easy= 3
10.	Lack of labor surveillance	Low surveillance=1 Medium surveillance=2 High surveillance=3
11.	Payment delay	High delay=1 Medium delay =2 Low delay=3
No.	**Output Parameter**	**Code**
1	Labor productivity	M^2/hour

The data has been re-written according to the encoding described in Table (5.1). Figure 5.2 shows a snapshot of the Excel program that represents part of the data matrix.

	A	B	C	D	E	F	G	H	I	J	K	L
1	No. Labor	Floor h.	Material short.	Tools short.	labor exp.	Weather	Steel bar.	Drawing variation	Location	Labor surv.	Pay. delay	Productivity m2/h
2	20	15	2	2	2	2	3	3	3	2	3	4.69
3	5	15	1	1	2	2	3	3	3	3	2	4.13
4	6	3	2	2	3	3	2	3	3	2	3	1.94
5	12	3	2	3	3	3	3	3	2	3	3	2.00
6	12	3	2	3	2	3	3	3	2	2	3	2.50
7	55	32	2	2	3	3	2	2	2	2	3	6.90
8	7	3	3	3	3	2	3	3	3	3	2	4.00
9	8	8	2	2	3	2	3	3	3	2	3	2.96
10	9	3	2	2	2	3	2	3	2	2	2	2.18
11	50	24	2	2	3	3	2	2	2	2	3	7.69
12	8	3	2	2	3	2	3	3	2	2	3	1.88

Figure 5.2: Snapshot showing the data matrix

5.4.2 Data organization

As a preliminary stage to neural network modeling, the problem at hand needs to identify and tag the data as input or as output. Neurosolution provides Microsoft Excel by add-in tools, which is used through this step. Figure (5.3) shows how the independent factors affecting the problem are identified and considered as (N) input parameters, which are represented by nodes at the input buffer of a neural network.

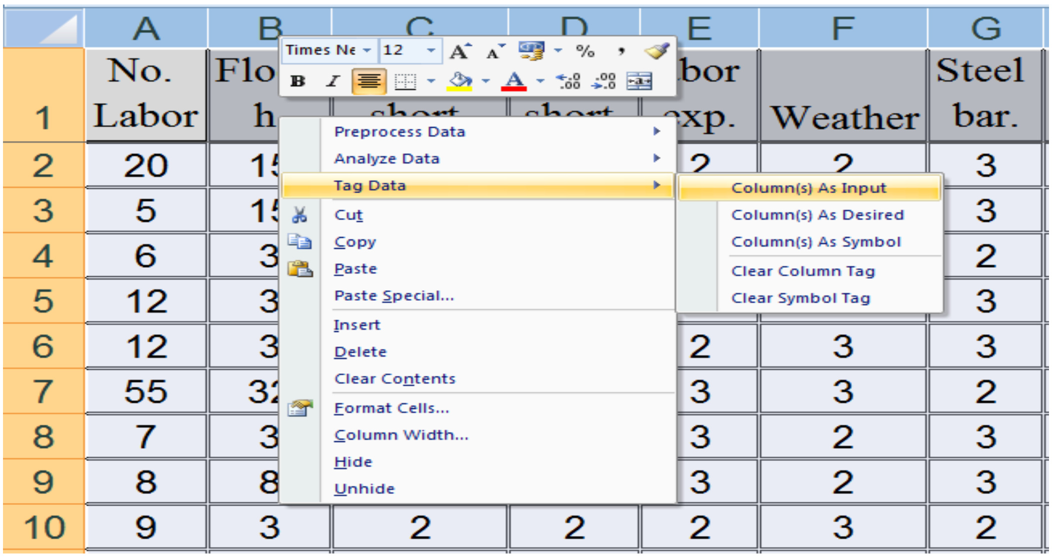

Figure 5.3: Tag columns of data as input parameter

Similarly, Figure 5.4 shows how the desired column was tagged that was represented by nodes at the output layer.

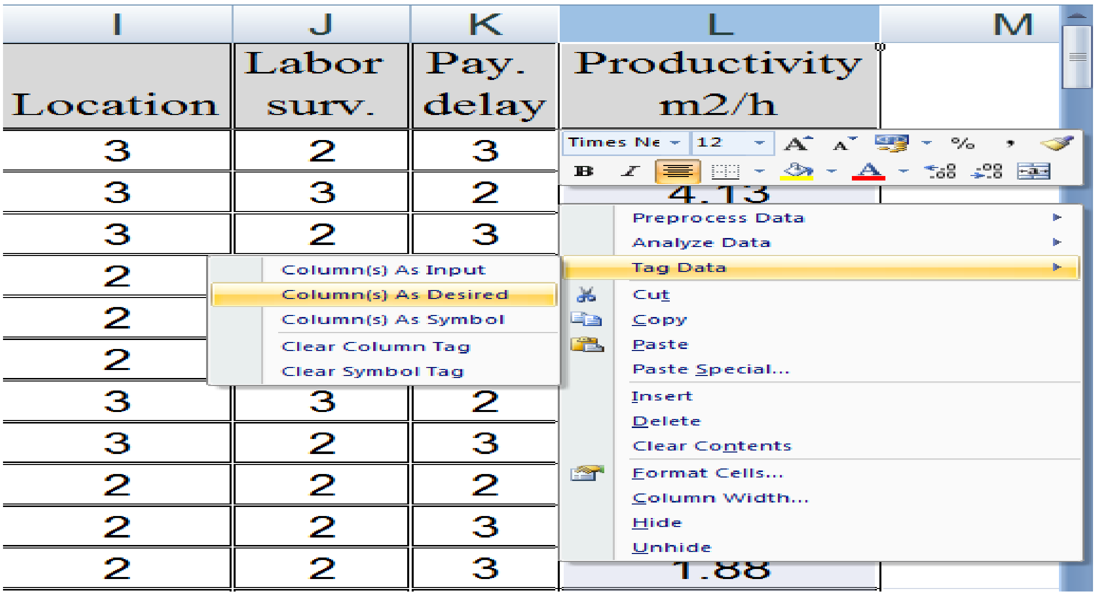

Figure 5.4: Tag column of data as a desired parameter

5.4.3 Data sets

Any model selection strategy requires validation by the process data. Traditionally, available data is divided into three sets (Ghiassi et al., 2005). `Where the three sets are training set (in-sample data), cross-validation set and a test set (out-of-sample). Learning is performed on the training set, which is used for estimating the arc weights while the cross validation set was used for generalization that is to produce better output for unseen examples (Sodikov, 2005). However, the test set is used for measuring the generalization ability of the network, and evaluated network performance (Zhang et al., 1998). To achieve statistically significant results, it is generally necessary to perform several independent splits and then average the results to obtain an overall estimate of performance. While cross-validation is a widely accepted method, it can be extremely time-consuming in neural networks because of the lengthy learning times required for each of the splits (Boussabaine, 1996).The total available data is 107 exemplars that are divided randomly into three sets with the following ratio:

I. Training set (includes 80 exemplars ≈ 75%).

II. Cross validation set (includes 14 exemplars ≈ 13%).

III. Test set (includes 13 exemplars ≈ 12%).

See Figure 5.5, 5.6 and 5.7 which explain how the data was distributed into sets and defined each exemplar for the corresponding.

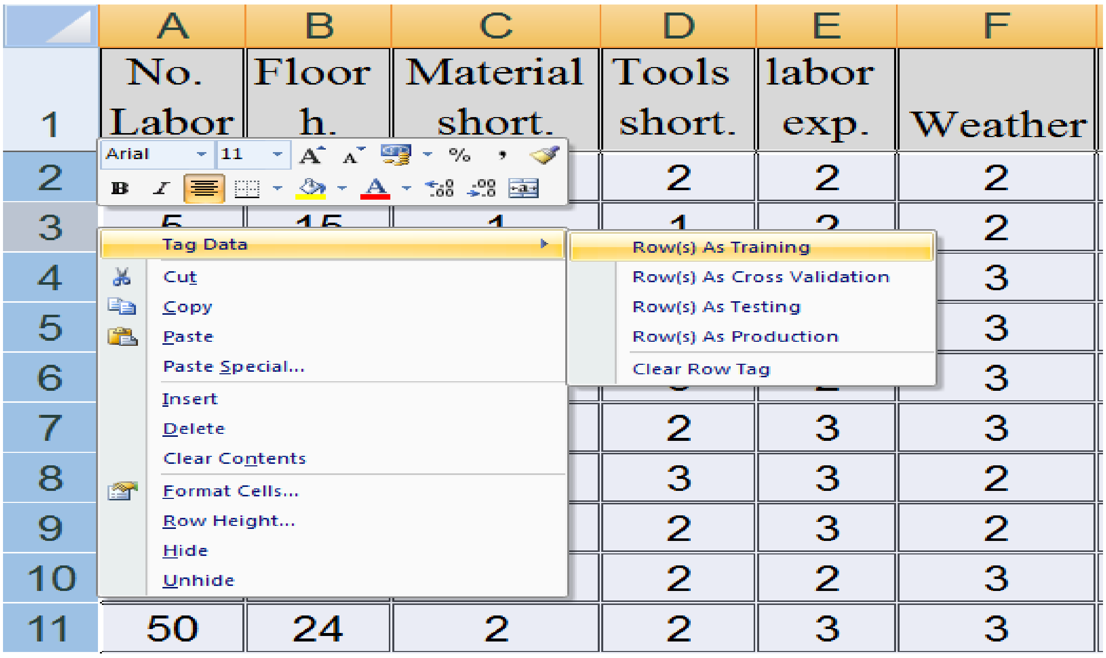

Figure 5.5: Tag rows of data as a training set

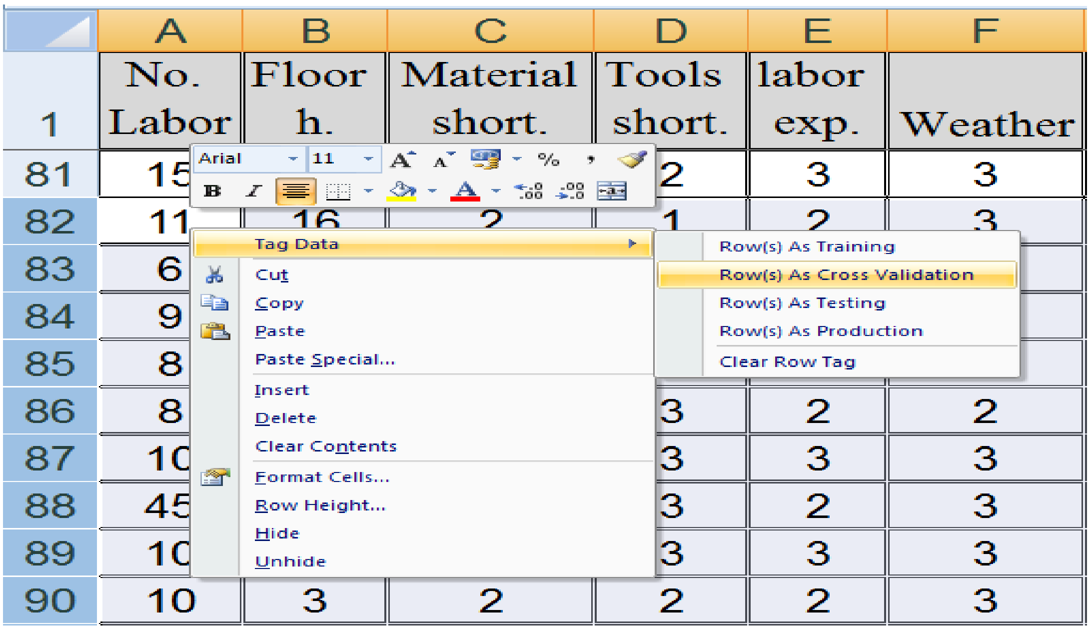

Figure 5.6: Tag rows of data as a cross-validation set

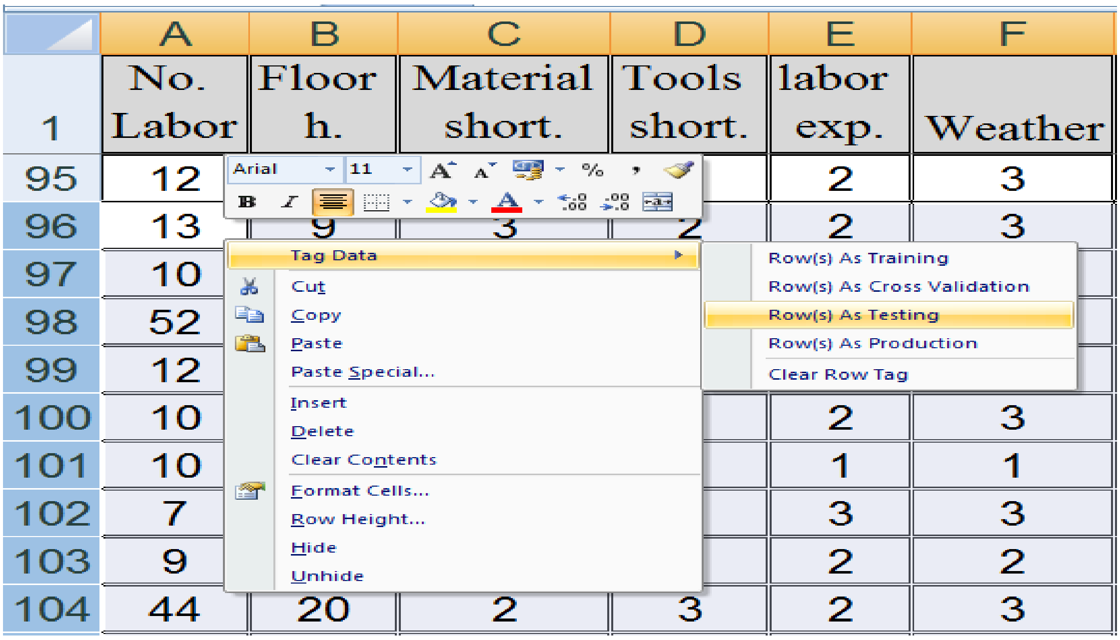

Figure 5.7: Tag rows of data as a test set

5.4.4 Data files creation

Neurosolution needs special file extension to read. After building the data matrix in Excel, the data files were created as ".csv" format by excel Add-in tool, see Figure 5.8.

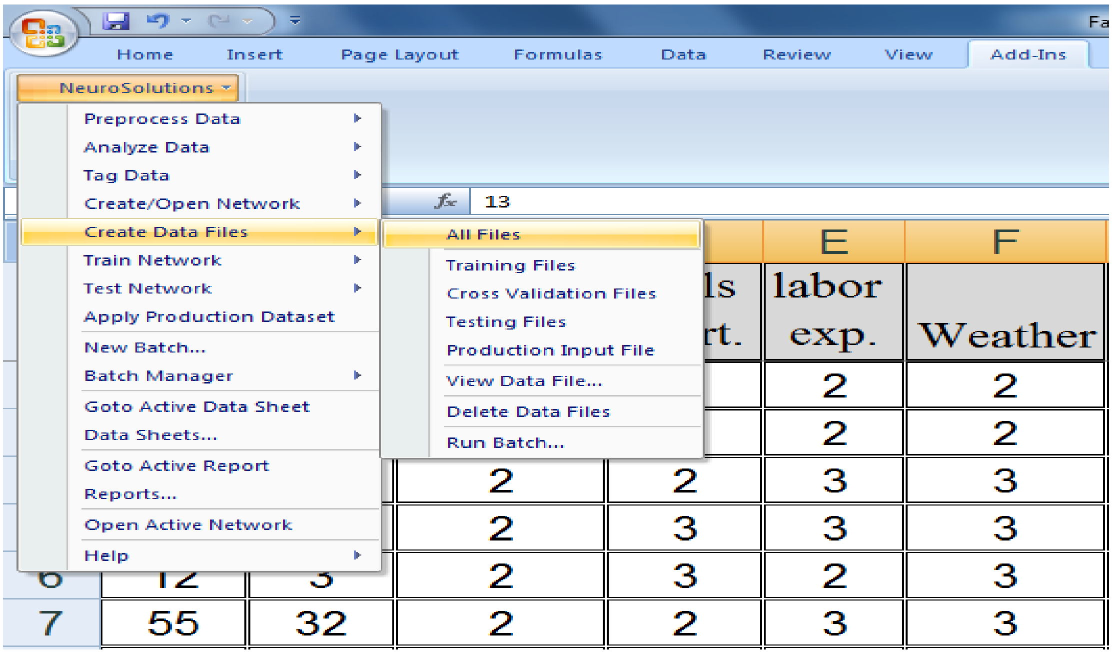

Figure 5.8: Data files creation

5.4.5 Normalizing data

Data is generally normalized for confidentiality and for effective training of the model being developed. The normalization of training data is recognized to improve the performance of trained networks (Gunaydin & Dogan, 2004).

The input/output data is scaled, zero is the lower bound and the upper bound is one to suit neural networks processing. This is done by NeuroSolution program that is used special equations to normalize the data. Figure 5.9 shows how the upper and lower bound is defined in NeuroSolution.

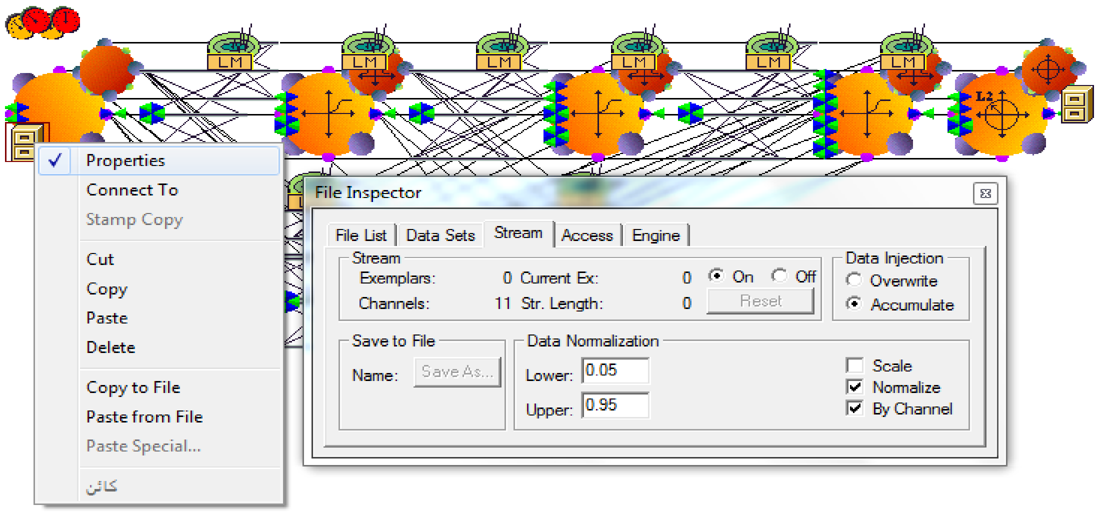

Figure 5.9: Normalization limits (snapshot of Neurosolution breadboard)

5.4.6 Build initial networks

This research depends on the school which thought recommends starting with small networks and increasing their size until the performance in the test set is appropriate. This method of growing neural topologies proposes that ensures a minimal number of weights, but the training can be fairly long (Principe et al., 2010).

As mentioned in chapter two MLP and GFF are the main types of networks that were used to build many topologies and architectures of networks. Neural builder tool in Neurosolution is used to build initial networks. For example: steps of building the best model GFF network which have the strongest result will be explained below with illustrations.

I. From add-ins tool in Excel, there is an icon for Create new network. See Figure 5.10.

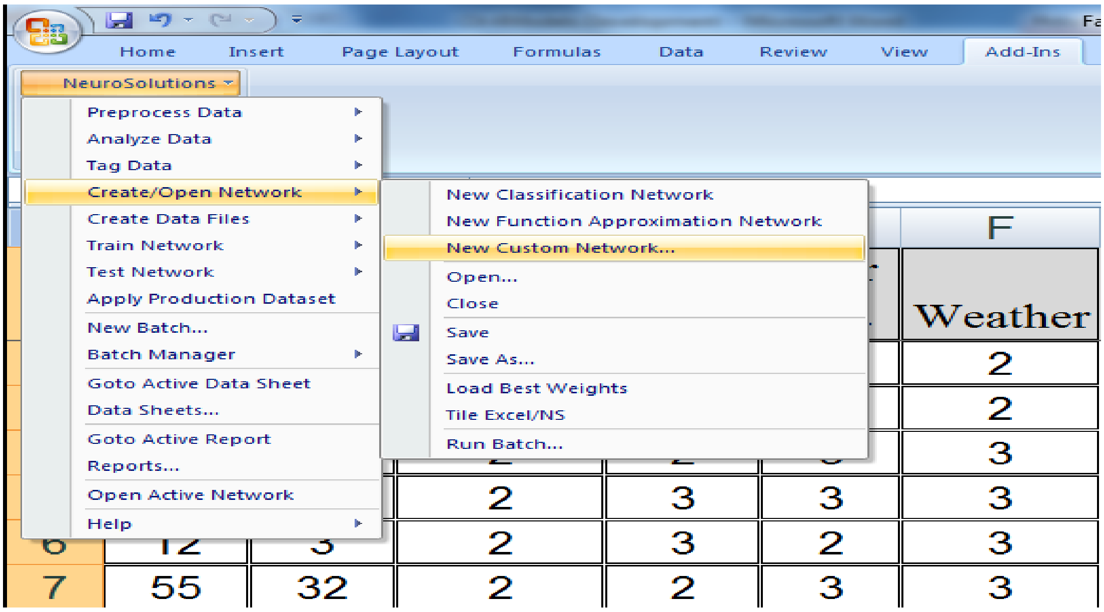

Figure 5.10: Creation of new network

II. Then a neural builder tool will be opened as shown in Figure 5.11, subsequently the type of the network is chosen.

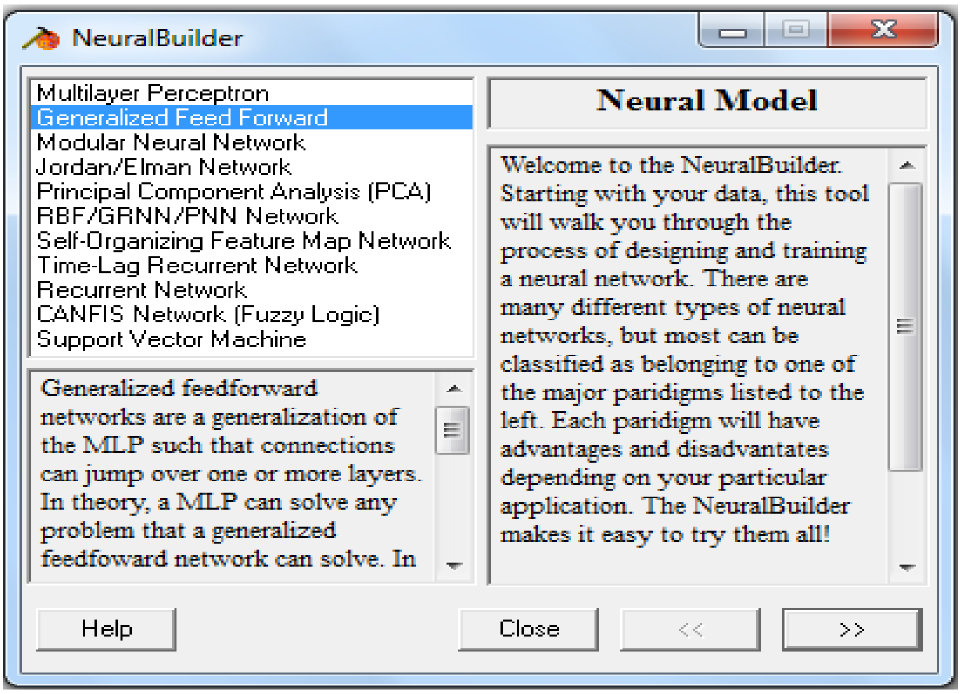

Figure 5.11: Choice of the network type

III. . After choosing the GFF as the type of network, a new screen will appear as shown in Figure 5.12 to determine the number of hidden layers

IV. Determination number of hidden layers.

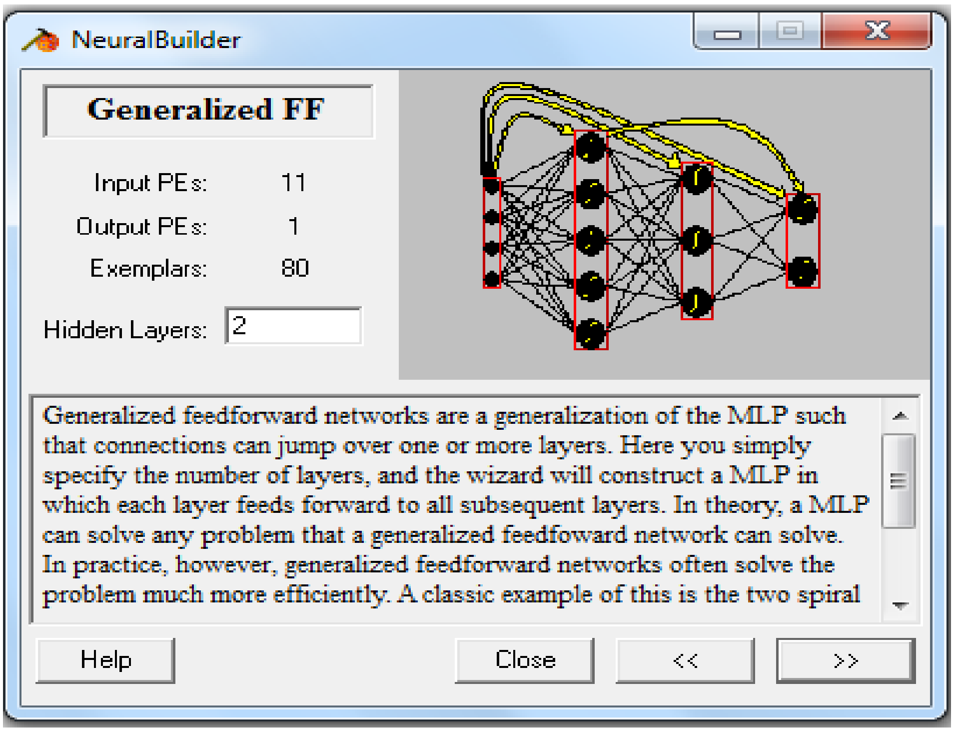

Figure 5.12: Determination number of hidden layers

The next screen enables the modeler to specify the PEs in the first and second hidden layer (number, transfer function, and learning rule). In this model six and four PEs, sigmoidaxon transfer function, and Levenberg-Marquardt learning rule are selected, see Figure 5.13 and 5.14.

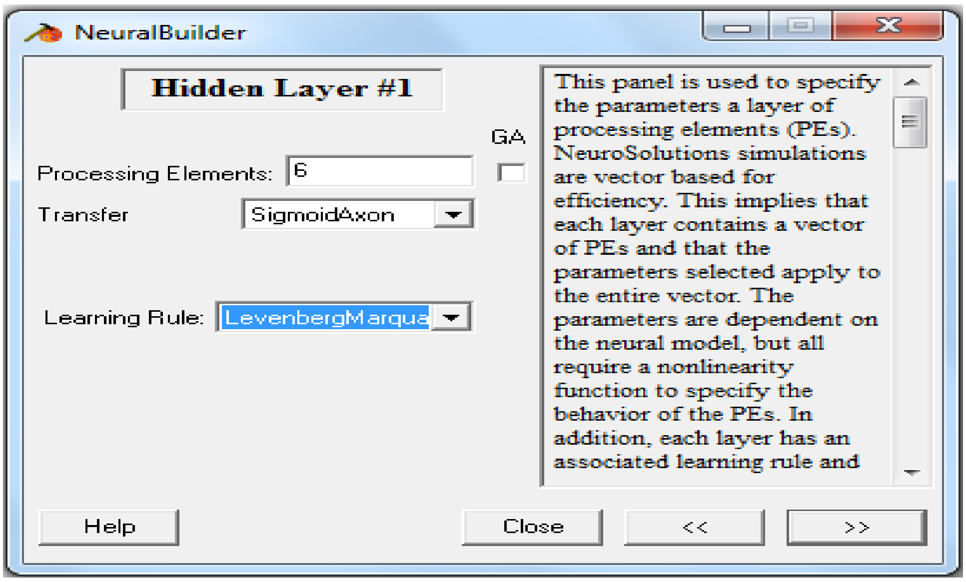

Figure 5.13: Specify components and characteristics of hidden layer number 1

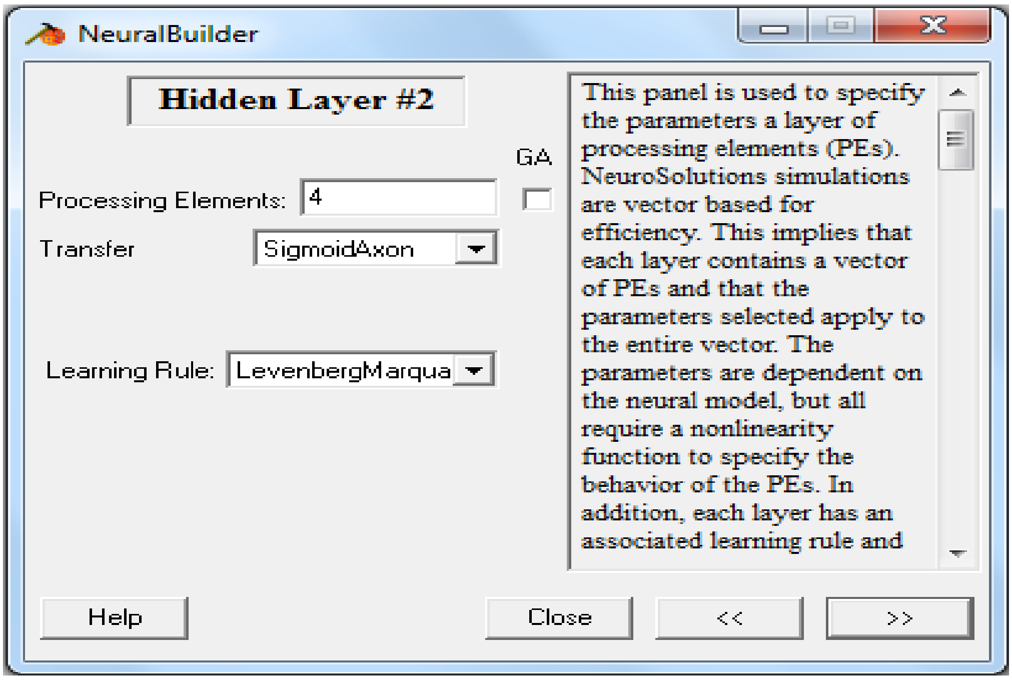

Figure 5.14: Specify components and characteristics of hidden layer number 2

V. The step for output layer is similar to the previous step except the number of PE's cannot be changed because it is determined in Excel in data organization step, see Figure 5.15.

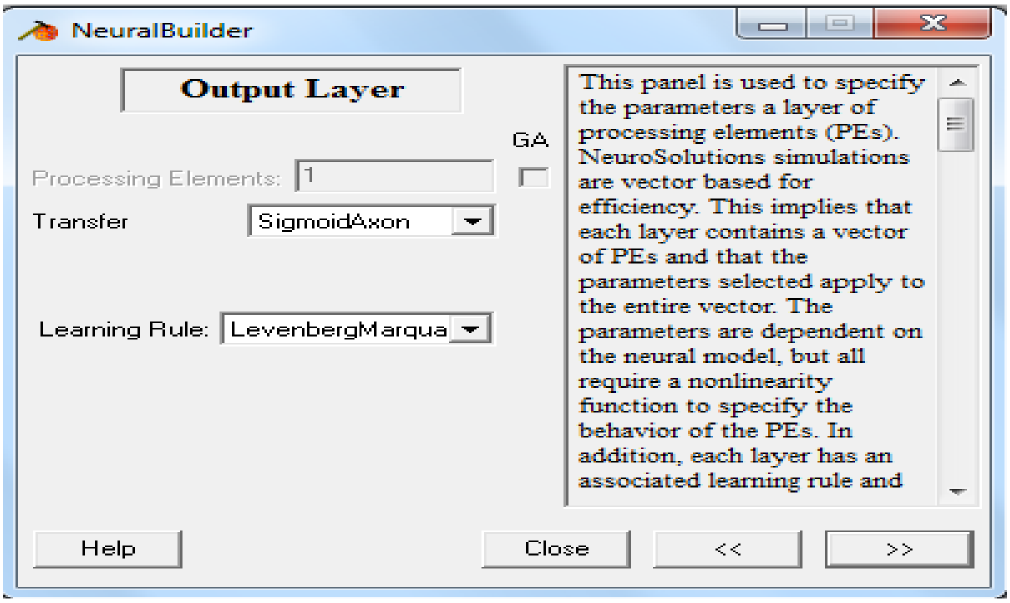

Figure 5.15: Specify output layer components and characteristics

After that, a supervised learning control screen appears to set maximum epoch, termination condition, and weights updating methods. See Figure 5.16.

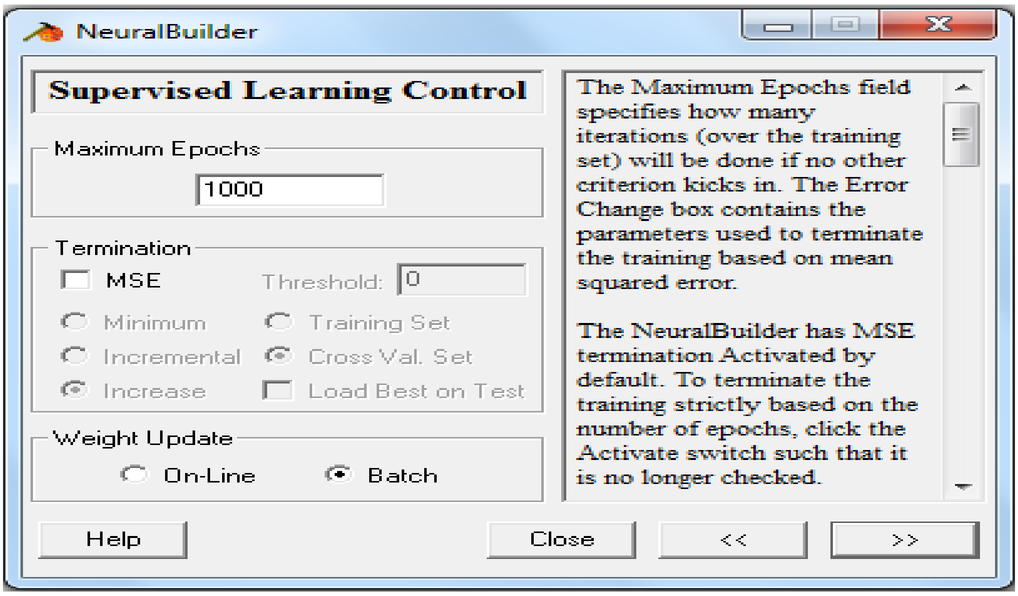

Figure 5.16: Supervised learning control

Two choices for update weights; on-line learning that updates the weights after the presentation of each exemplar (pattern) and batch learning that updates the weights after the presentation of all exemplars (i.e., after each epoch).

VI. Probe configuration screen then appears that contains items displaying program's ability to view what is related to the inputs, outputs, desired errors and performance measures. See Figure 5.17.

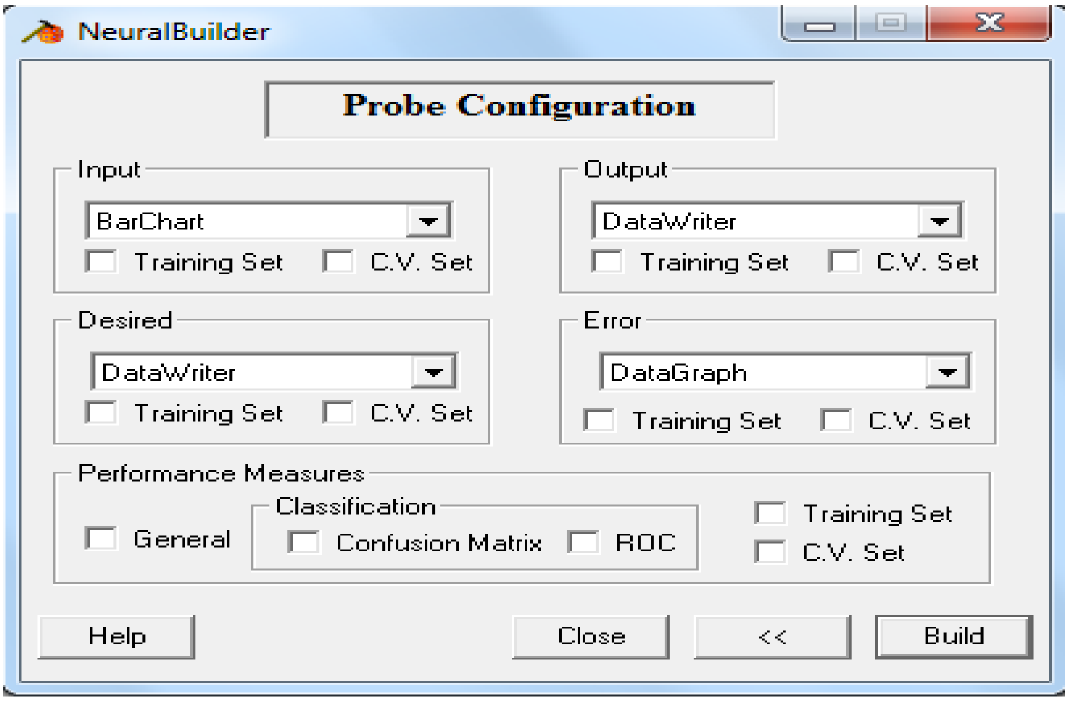

Figure 5.17: Probe configuration

Finally, the network is built and viewed on the Neurosolution breadboard as shown in Figure 5.18.

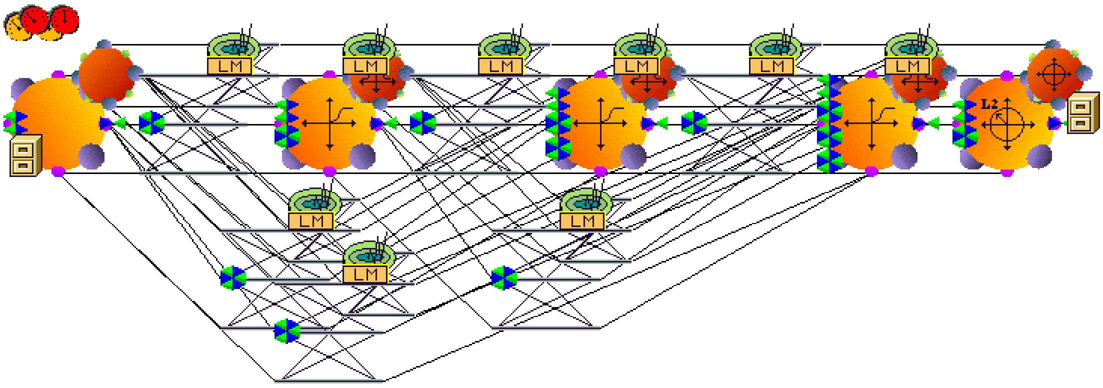

Figure 5.18: GFF network (snapshot from Neurosolution breadboard)

5.5 Training Models and Testing

Training network is a process that uses one of several learning methods to modify weight, or connection strengths.. A Training data set is presented to the network as inputs, and the outputs are calculated. The differences between the calculated outputs and the actual outputs are then evaluated and used to adjust the network's weights in order to reduce the differences. As the training proceeds, the network's weights are continually adjusted until the error in the calculated outputs converges to an acceptable level.

Neural networks are able to generalize solutions to problems by learning from pairs of input patterns and their associated output pattern. Training a NN is an iterative process of feeding the network with the training examples and changing the values of its weights in a manner that is mathematically guaranteed to reduce consecutively the error between the network's own results and the desired output (Moselhi & Hegazy, 1993).

It is important to determine suitable network architecture in ANN modeling. The architecture consists of the number of layers, the number of processing elements (nodes) in each layer, and the interconnection scheme between the layers in ANN. The optimum architecture is often achieved by trial and error according to the complexity of the respective problem, also by testing few proposed designs to select the one that gives the best performance (Bakhary et al., 2004).

After building topology as viewed in the above section, training with cross-validation and testing phase will begin. The following chart illustrates the procedures of training process to obtain the best model having the best weight and minimum error percentage. See Figure 5.19.

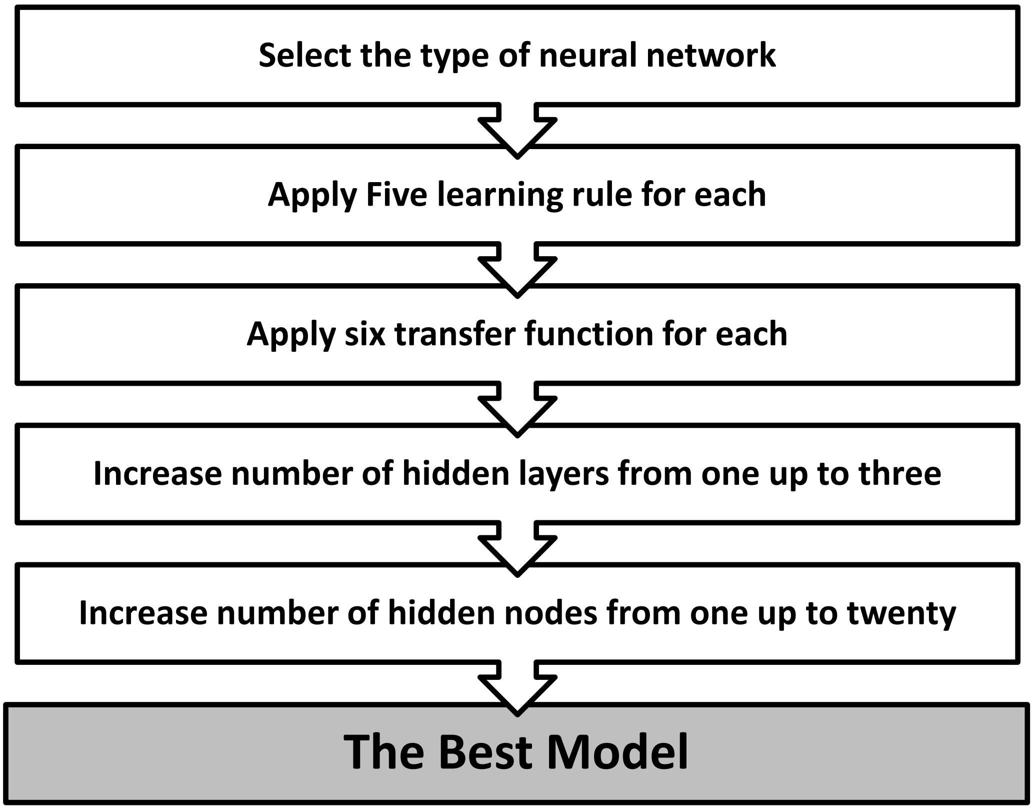

Figure 5.19: The steps for selection the best model

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 2 separate hidden layers were utilized with increment of hidden nodes from 1 node up to20 nodes in each layer and training variables for one trial. It compromises of number of epochs, runs, hidden nodes, and other training options to obtain the best model of neural network.

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 20 hidden nodes.

Testing the network is essentially the same as training, except that the network is shown facts it has never seen before, and no corrections are made when the network is wrong. It is an important to evaluate the performance of the network after the training process. If the results are good, the network ready to use. If not, this need more or better data or redesign the network.

5.6 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. From previous procedures of training and testing, many topologies of networks were trained through a system of trial and error. The best model that provided more accurate productivity estimate was structured of General Feed Forward (GFF) includes one input layer with 11 input neurons and two hidden layer with (6 hidden neurons for first layer, 4 hidden neurons for second layer) and finally one output layer with one output neuron (productivity). However, the main downside to using the General Feed Forward 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: GFF model architecture

Architecture of the model			
Model Type	Transfer Function	Gradient Search	No. of PEs in the input layer
Generalized Feed Forward	Sigmoid	LevenbergMarqardt	11
No. of hidden layer	No. of PEs in the 1st hidden layer	No. of PEs in the second hidden layer	No. of PEs in the output layer
2	6	4	1

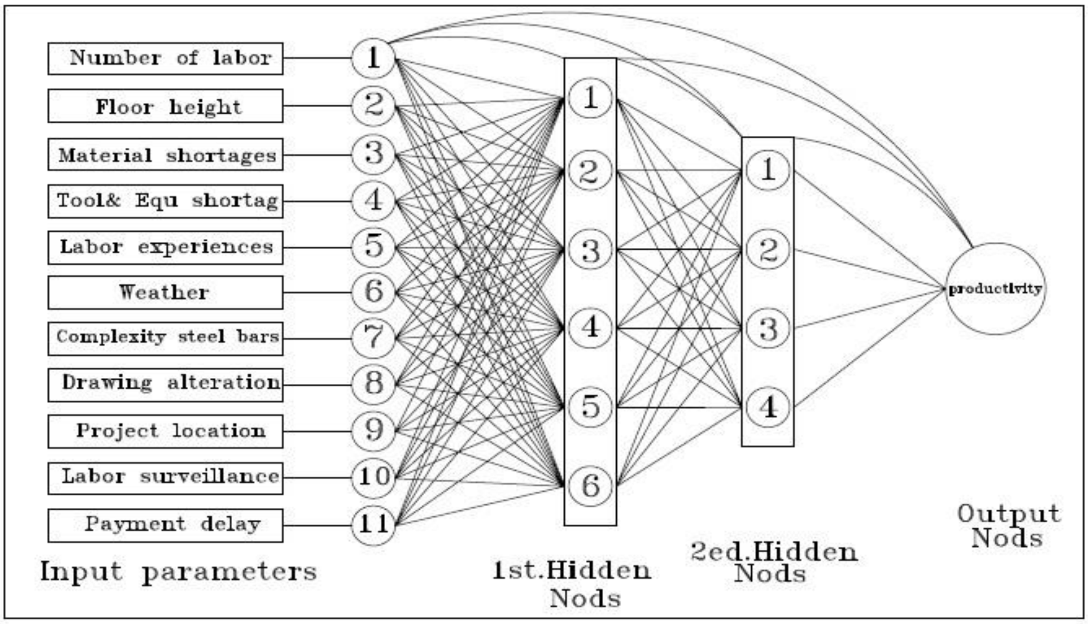

Figure 5.20: GFF model architecture.

5.7 Results Analysis

The models were trained on eighty exemplars while fourteen exemplars of cross validation set were used for generalization to produce better output for unseen examples. The models tested on thirteen exemplars. Table (5.3) presents the results of these thirteen projects with comparing the real productivity of tested project with estimated productivity from neural network model, and an absolute error with both productivity and percentage are also presented.

Table 5.3**:** Results of neural network model at testing phase

No.	**Actual Productivity (m^2/hr.)**	**Estimated Productivity (m^2/hr.)**	**Absolute Error AE (m^2/hr.)**	**Absolute Percentage Error (%)**
1	4.4	4.872	0.472	9.695
2	2	1.942	0.058	2.999
3	8.2	8.504	0.304	3.572
4	5.9	6.557	0.657	10.018
5	2.9	3.467	0.567	16.342
6	3.63	3.727	0.097	2.608
7	1.49	1.280	0.210	16.418
8	4.59	4.873	0.283	5.806
9	9.58	9.255	0.325	3.516
10	4.55	4.841	0.291	6.015
11	7.7	7.393	0.307	4.156
12	1.68	1.653	0.027	1.639
13	2.45	2.350	0.100	4.269

Table 5.4: summarized the results of Performance measurement for model

	Data sets	MSE	NMSE	r	MAE	MAPE	AP
GFF Model	**Training set**	0.020	0.004	0.998	0.0560	1.81%	98.19%
	C.V set	0.182	0.021	0.991	0.253	8.25%	91.75%
	Test set	0.115	0.018	0.992	0.285	6.69%	93.31%

The previous results show that the models have excellent performance. The accuracy of the best model developed by General Feed Forward sounds very favorably with data based from test set. It has been shown from the results that the model performs well and no significant difference could be discerned between the estimated output and the desired value. An average accuracy of 93.3% indicates that; there is a good linear correlation between the actual value and the estimated value.

Results of training, cross validation and test set are shown in Figures 5.21, 5.22 and 5.23 respectively.

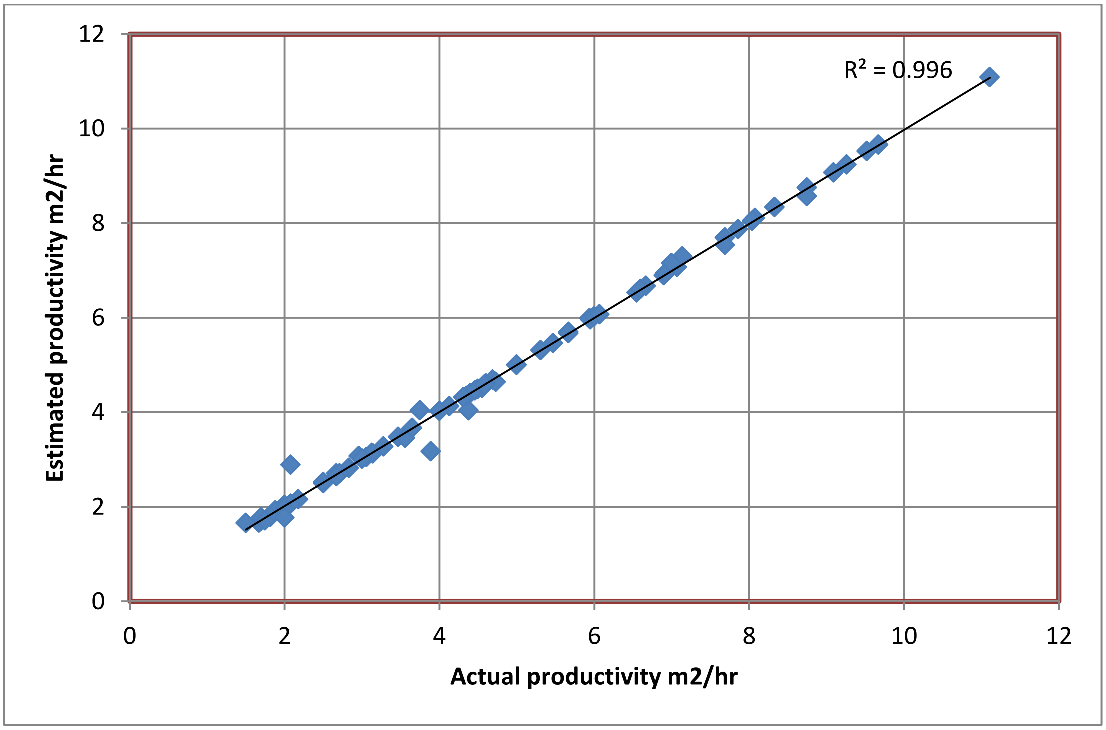

Figure 5.21: Desired output and actual network output for training set exemplar

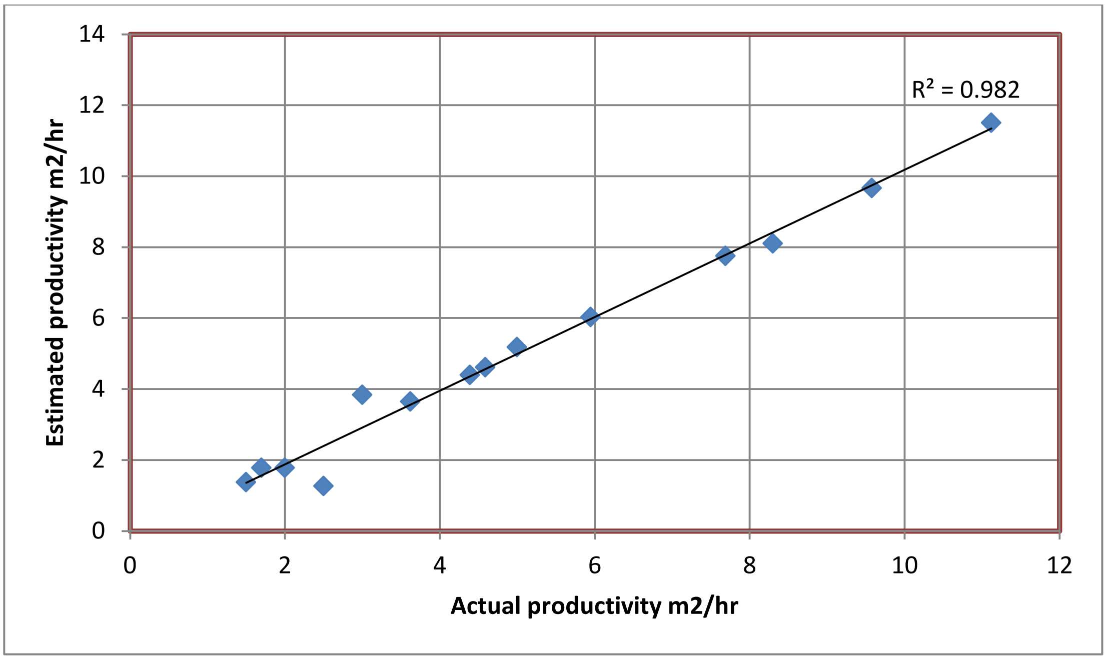

Figure 5.22: Desired output and actual network output for C.V set exemplar

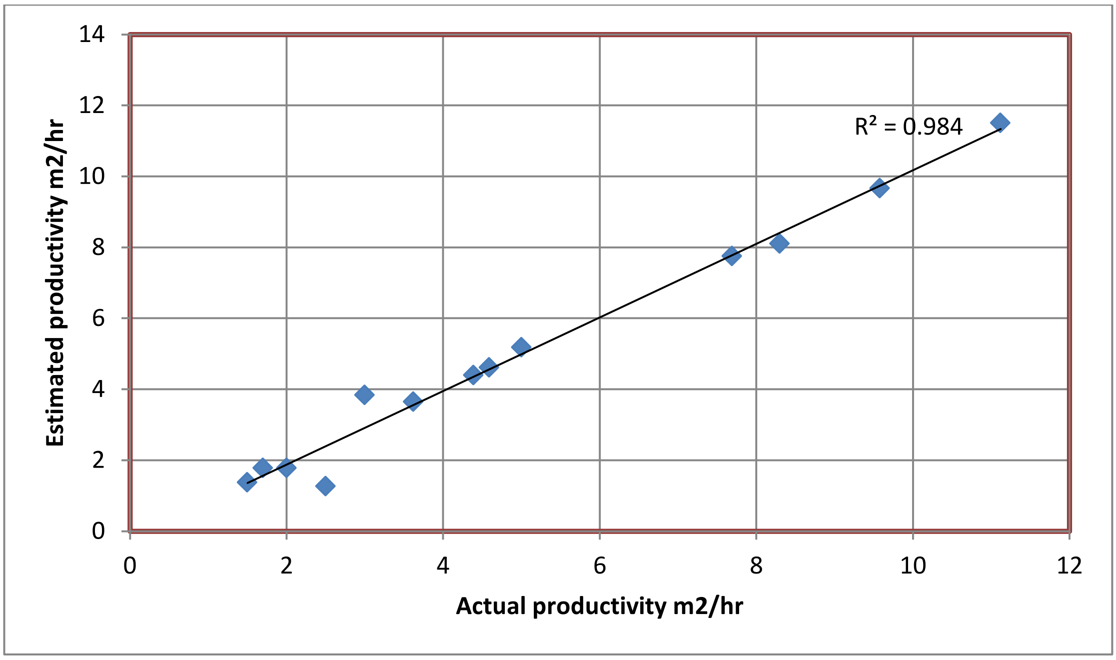

Figure 5.23: Desired output and actual network output for test set exemplar

Network as shown in Figures gives excellent agreement between the actual and predicted values draws a 45-degree line, which means that the actual productivity values are similar the predicted ones figures 5.21, 5.22 and 5.23 indicates a reasonable concentration of the predicted values around the 45-degree line. The coefficient of determination between the actual and the predicted productivity values were 0.996, 0.982 and 0.984 for training, cross validation and test set respectively.

For training dataset, an excellent agreement between the actual and estimated productivity is shown in Figure 5.24 which means that the estimated values are similar the actual ones.

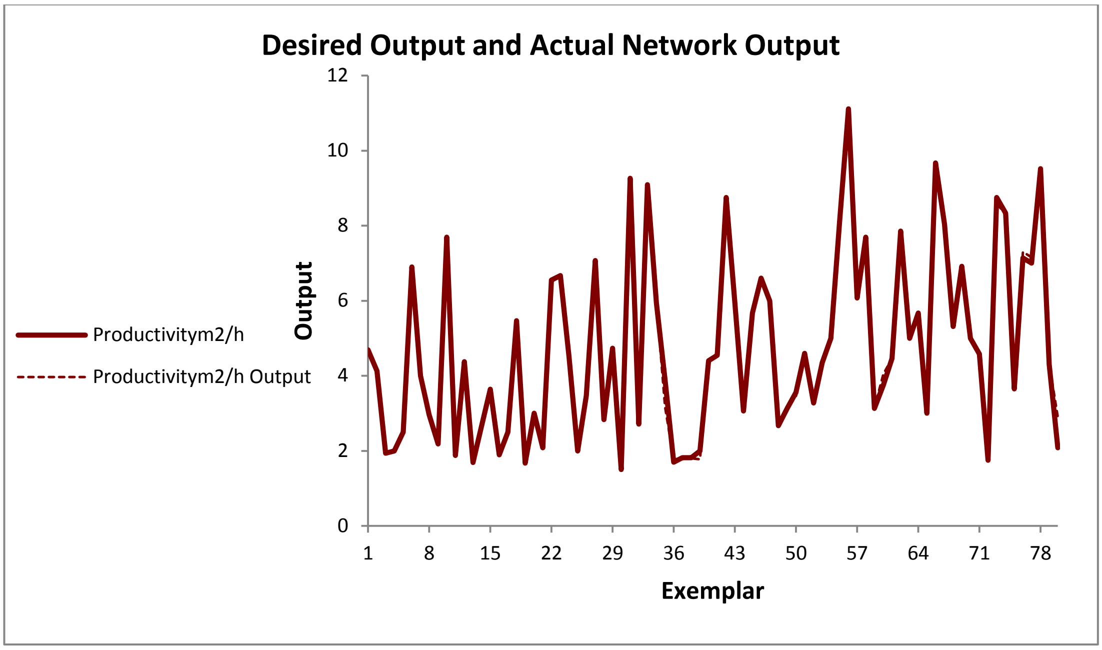

Figure 5.24: Comparison between desired output and actual network output for training set

The actual productivity comparing with estimated productivity for cross validation (C.V) and testing dataset shown in Figure 5.25, 5.26. It is noted that there is a slight difference between two productivity lines.

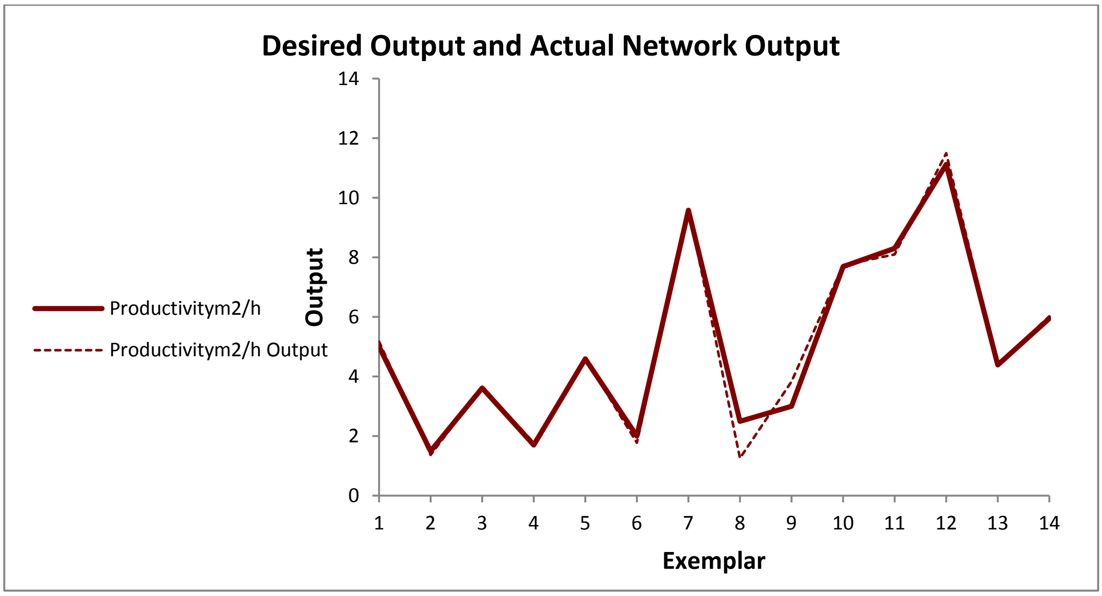

Figure 5.25: Comparison between desired output and actual network output for C.V set

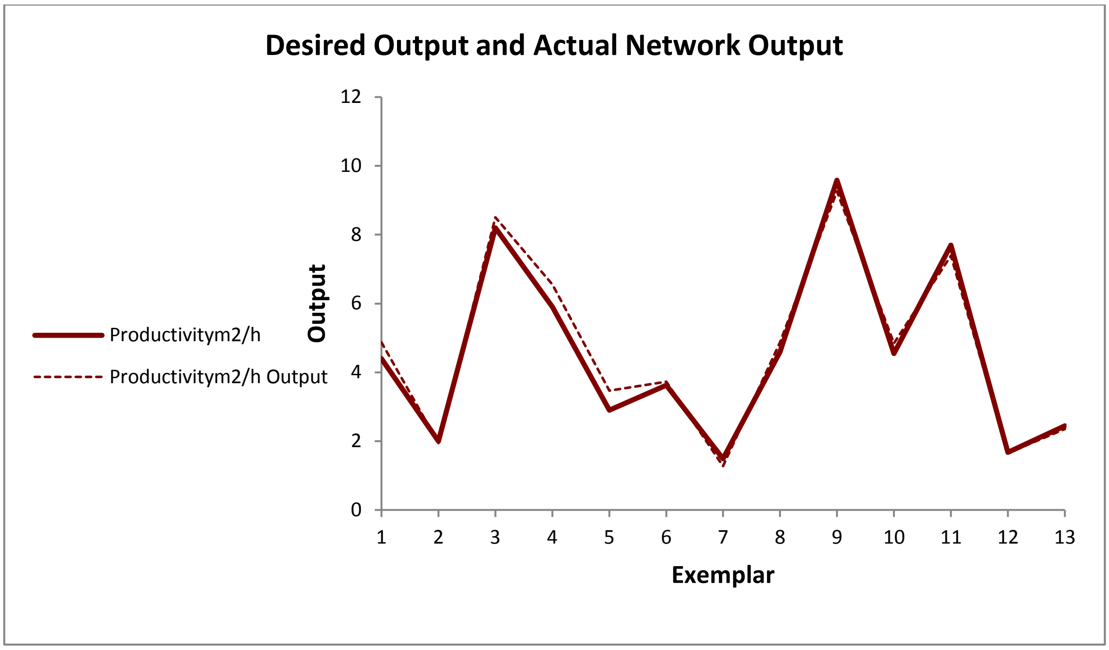

Figure 5.26: Comparison between desired output and actual network output for test set

5.8 Sensitivity Analysis

Sensitivity analysis is the method that discovers the cause and effect relationship between input and output variables of the network. The network learning is disabled during this operation so that the network weights are not affected. The basic idea is that the inputs to the network are shifted slightly and the corresponding change in the output is reported either as a percentage or as a raw difference (Principe et al., 2010). The NeuroSolution program provides a useful tool to identify sensitive input variables called ‘‘Sensitivity about the Mean’’. The sensitivity analysis was run by batch testing on the GFF model after fixing the best weights then started by varying the first input between the mean ± one standard deviation, while all other inputs are fixed at their respective means. The network output was computed for 50 steps above and below the mean. This process was then repeated for each input. Finally, a report summarizing the variation of output with respect to the variation of each input was generated.

Figure (5.27) shows the sensitivity analysis of the GFF model which includes eleven graphs each of them represents the relation between one input and the output (productivity m2/hr).

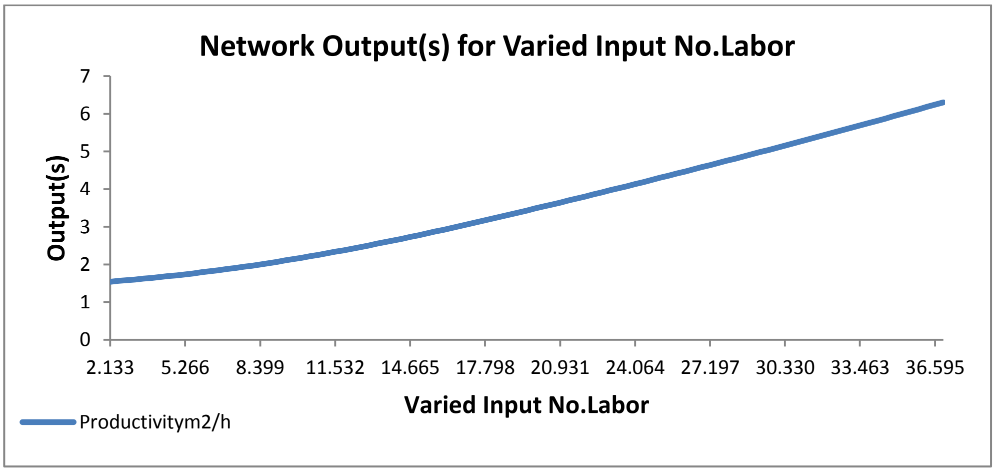

Figure 5.27: Sensitivity analysis for number of labor

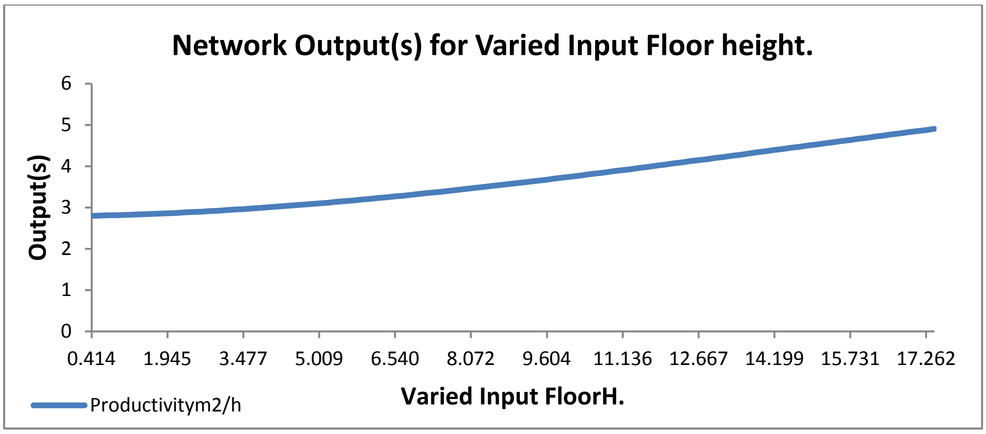

Figure 5.28: Sensitivity analysis for floor height

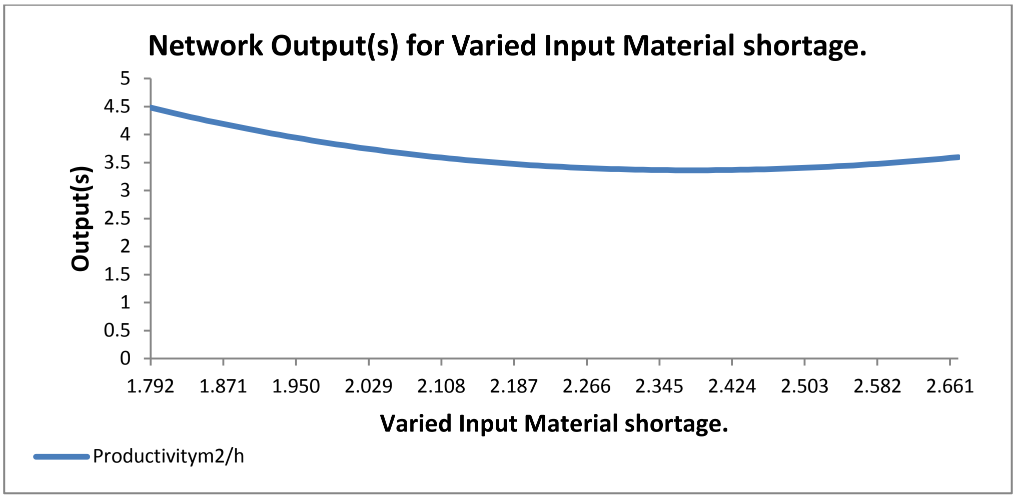

Figure 5.29: Sensitivity analysis for materials shortage

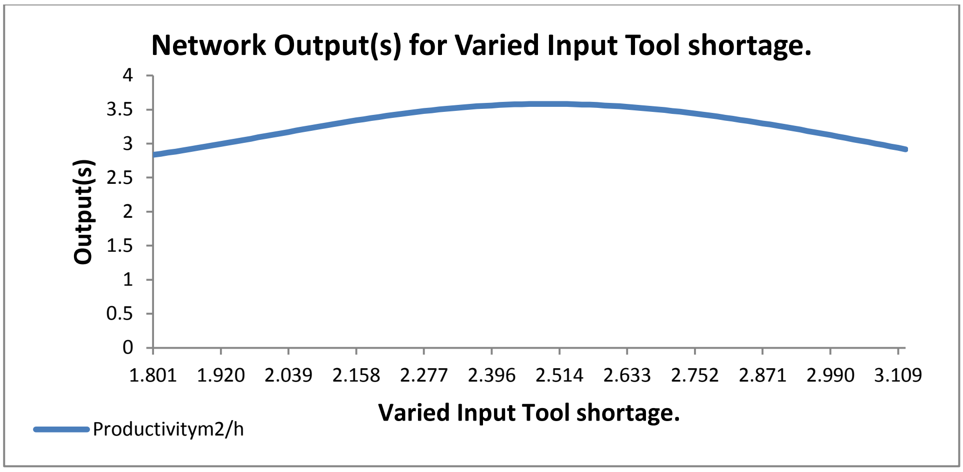

Figure 5.30: Sensitivity analysis for tools shortage

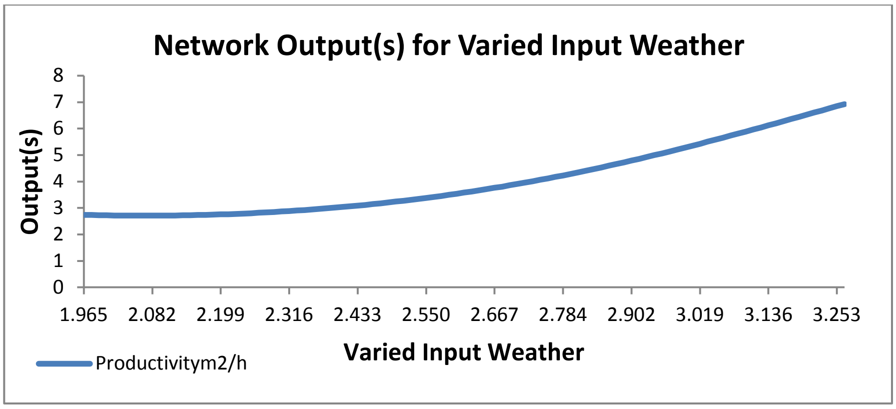

Figure 5.31: Sensitivity analysis for weather

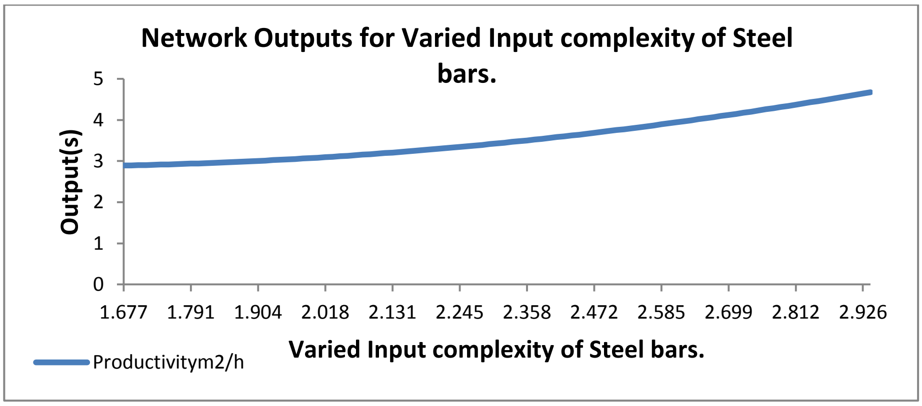

Figure 5.32: Sensitivity analysis for complexity of steel bars

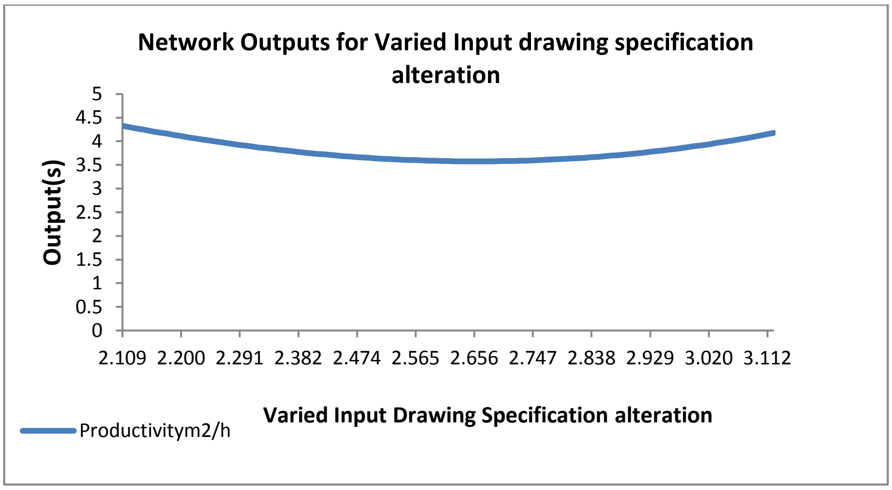

Figure 5.33: Sensitivity analysis for drawing and specification alteration

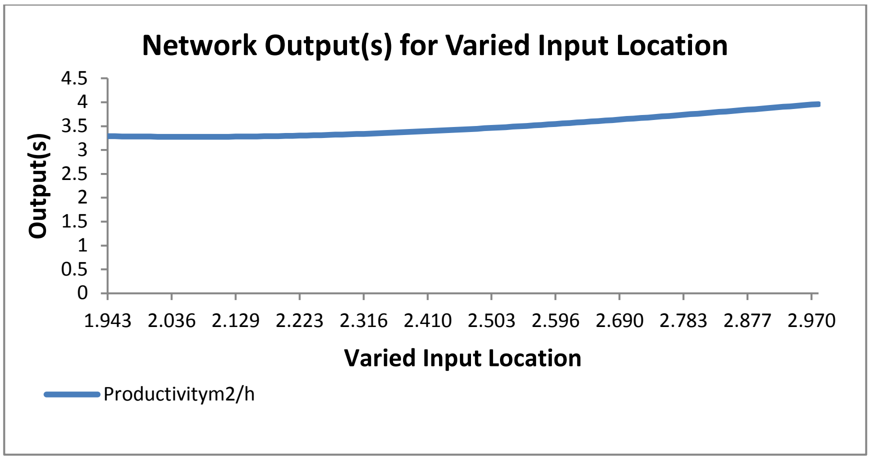

Figure 5.34: Sensitivity analysis for location

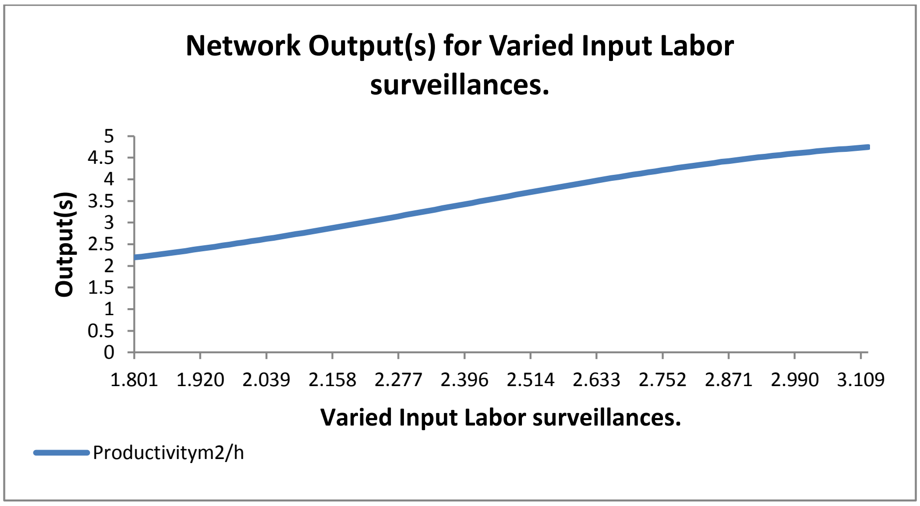

Figure 5.35: Sensitivity analysis for labor surveillances

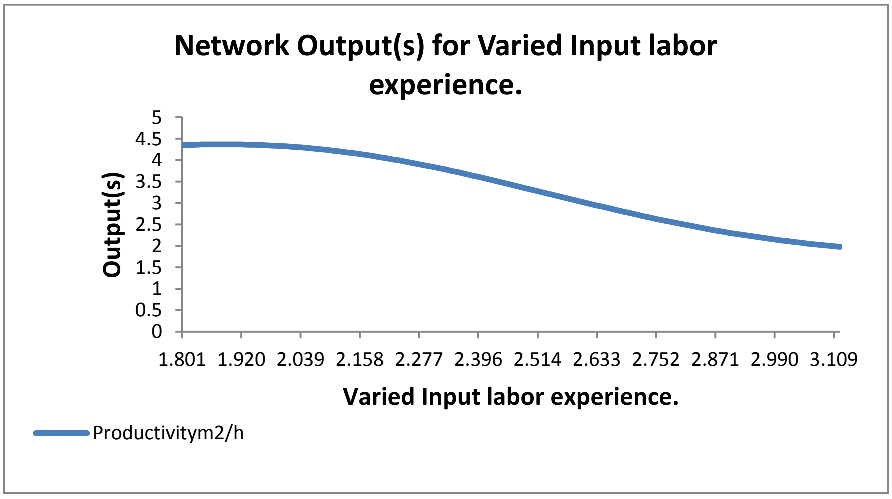

Figure 5.36: Sensitivity analysis for labor experience

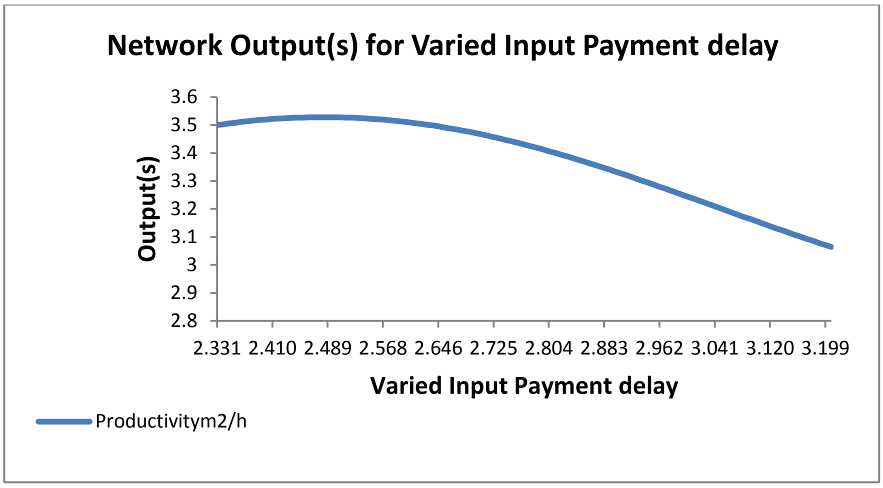

Figure 5.37: Sensitivity analysis for payment delay

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. The sensitivity analysis for the best GFF model was performed and the result is summarized and presented in figure (5.38)

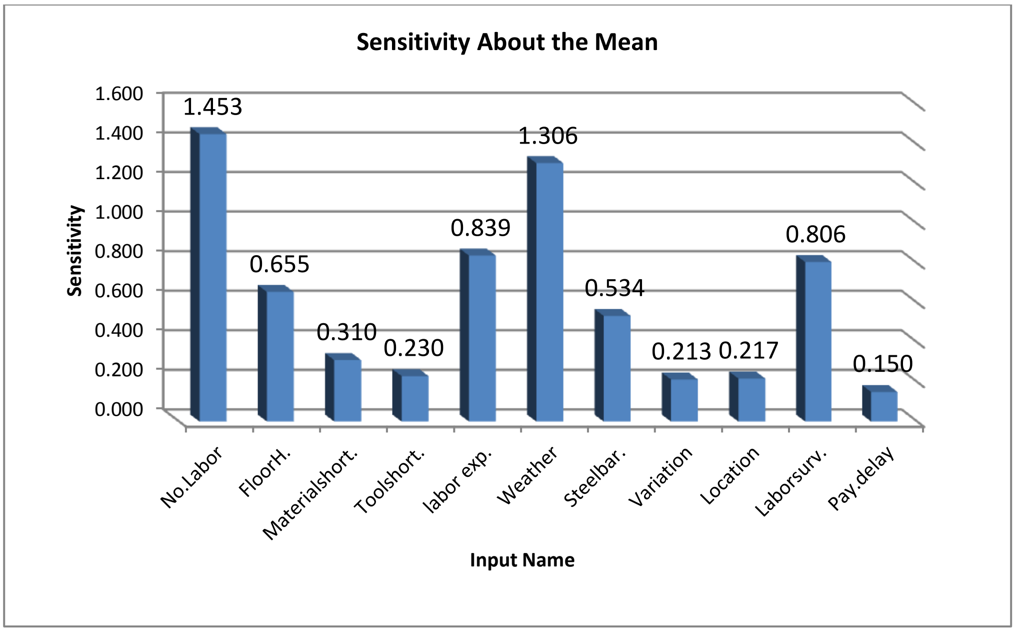

Figure 5.38:Sensitivity about the mean

Figure 5.38 shows number of labor parameter has the greatest effect on the productivity output where its influence exceeds the impact of other factors combined. The value 1.45 for the number of labor input parameter is the value of the standard deviation for 80 output values. These output values are recorded after training the model with fixing the best weights on a matrix data. All inputs are fixed on the mean value for each raw except the number of labor value which varied between (the mean – standard deviation) to (the mean + standard deviation). The second parameter affecting the total productivity is weather which has great effect on productivity. While for parameter (labor experience, labor surveillance, floor height, complexity due to steel bars and drawing) has moderate effect on productivity. It is clearly from Figure 5.38 that the remaining parameters have low impact on the output.

Chapter 6: Conclusion and Recommendations

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

6.1 Conclusion

The main aim of this research is to develop artificial neural networks model to predict labor productivity for casting concrete slabs, at early stage of construction projects in Gaza Strip. Neural network model developed was able to achieve the objectives of this research. The following is the most important conclusion drown from the research:

1- The most effective factors that affect production rate for formwork, reinforcement and casting concrete slab were identified from analysis of 77 questionnaires. Eleven key parameters were adopted as most effective factors on productivity which are, Number of Labor, Material shortages, Floor height, Tool and equipment shortages and Efficiency, labor experiences, Weather, Complexity due to steel bars, Drawings and specifications alteration during execution, Easy to arrive to the project location, Lack of labor surveillance and Payment delay.

2- Historical data of building projects were collected from second questionnaire. The projects were executed between 2009 and 2013 in Gaza Strip. 107 case studies were divided randomly into three sets as training set (80 projects 75%), cross validation set (14 projects 13%), and testing set (13 projects 12%).

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.

4- Many models were built but GFF model was found the best model, which structured from one input layer included 11 input neurons, and included two hidden layer with six and four neurons for first and second hidden layer respectively. Both of hidden layer and the output neurons had a sigmoid transfer function, and LevenbergMarqardt learning rate which belongs to Backpropagation algorithm.

5- The accuracy performance of the adopted model recorded 93.3% where the model performed well and no significant difference was discerned between the estimated output and the actual productivity value.

6- In order to ensure the validity of the model in estimating the productivity 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. The GFF model had Mean Absolute Percentage Error (MAPE) 1.81%, 8.25% and 6.69% for training, cross validation and test sets respectively.

7- Sensitivity analysis was performed using Neurosolution tool to study the influence of adopted factors on labor productivity. The performed sensitivity analysis was in general logically where the number of labor and weather had the highest influence, while labor experience, labor surveillance, floor height, complexity due to steel bars and drawing, respectively has moderate effect on productivity. Material shortages, Tool and equipment shortages and Efficiency, Easy to arrive to the project location, Drawings and specifications alteration during execution and Payment delay respectively had less effect respectively.

6.2 Recommendations

1- Other neural network models for masonry construction, plastering, tiling, painting and other construction works should be performed.

2- The more data feed during training phase the less percentage error got during testing phase. Therefore, it is recommended to obtain more training data from newly projects and add them to the training data. This will improve the training process.

3- A local construction productivity study may help to establish labor productivity code for construction project in Gaza Strip.

4- Feed-forward NN model is found to be able to produce production rate estimates of casting concrete slabs to an acceptable degree of accuracy. This finding suggests that feed forward NN model may be capable of modeling other similar construction processes, which yet have not been studied.

5- All construction parties are encouraged to be more aware about productivity estimation development and pay more attention for using this developed technique in estimation process.

6- Government and engineering associations are recommended to establish a database for executed projects for researchers to develop productivity estimation process.

7- Construction companies are recommended to have their own data base system for the actual production rate of the different construction operations.

8- Contracting companies have to conduct productivity study such as studying factors affecting labor productivity and labor productivity measurement to describe the detailed tasks performed for an activity and proposes ways to improve labor productivity.

9- Contracting companies are encouraged to keep historical data of productivity study in finished projects to improve the effectiveness and accuracy of estimation for future projects.

10- It is necessary to use modern technique and software for predicting productivity which will improve contractor in estimation productivity.

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Annex 1: Questionnaire 1

The questionnaire (In English)

THE ISLAMIC UNIVERSITY

FACULTY OF ENGINEERING

Questionnaire

For Master Thesis in Construction Management

Prediction Model of Construction Labor Production Rates in Gaza Strip using Artificial Neural Networks

Researcher : Eng. Mohammed Mady

Supervised by : Dr. Nabil EL Sawalhi

Partial fulfillment of the requirement for the degree of Master of Science in Civil Engineering

Gaza, Palestine

2013

Dear contractor,

To start, I would like to present my appreciation and thanks to you for taking part of your time and effort to complete this questionnaire. Pouring concrete slabs is an essential activity in engineering projects and construction sector. For this reason, this questionnaire aims to study the factors affect productivity in construction industry and the production rate for pouring concrete slabs in Gaza Strip.

This is part of partial fulfillment of the requirements for degree of Master of Science in construction management from Islamic University.

Information in the questionnaire:-

All information in the questionnaire will be used for research with complete commitment for absolute secrecy to your information.

Please, your answer will be as the following:

a. Select a suitable degree (1-5) for the qualitative factors.
   Where:
   1: Very Low 2: Low 3: Medium
   4: High 5: Very High
b. Identifying the value for the quantitative factors.
c. Marking (X) for a suitable answer

<u>First Part:</u>

1. Name of the Company:……………………………………………………………

2. Project name: ……………………………………………………………………..….

3. Project duration: ………………………………………………………………..…

4. Project location: ……………………………………………………………………….

5. Floor area (m2): ………………………………………………………………………

6. Number of floors: ……………...……………………………...……………...…….

7. Floor height: ……………………………….………………………..…………

8. Slab thickness: …………………………………..……………………………..………

9. Number of crew: ………………………………..………..……………………………..

10. Number of labor in each crew: ………………..……………….………………………

11. Working hours per day at site: …………………………….……………………..….

12. Classification of the company / according to Contractors Union:

☐ First Class ☐ Second Class ☐ Third Class

13. The position of officer who fills the questionnaire:

☐ Company Manger ☐ Projects Manger ☐ Site Engineer ☐ Foreman

14. Number of company's employees:

☐ Less than 10 ☐ 11 – 30 ☐ 31 – 50 ☐ More than 50

15. Number of executed projects during the last five years:

☐ Less than 10 ☐ 11 – 20 ☐ 21 – 30 ☐ More than 30

16. Average value per year of executed projects during the last five years (in million dollars):

☐ Less than 0.5 ☐ 0.51 - 1 ☐ 1.1 – 2 ☐ More than 2

Second Part

Factors affecting labor productivity

In the table below there are numbers of factors negatively affecting labor productivity in building projects. Please define the degree of importance of these factors in affecting labor productivity.

No	Groups	Factors negatively affecting labor productivity	Degree of effectiveness				
1	Manpower factors	Increase of laborer age	1	2	3	4	5
		Lack of labor experiences	1	2	3	4	5
		Labor absenteeism	1	2	3	4	5
		Labor personal problems	1	2	3	4	5
		Labor dissatisfaction	1	2	3	4	5
		Labor disloyalty	1	2	3	4	5
		Misunderstanding among labor	1	2	3	4	5
		Lack of competition	1	2	3	4	5
2	Leadership factors	Misunderstanding between labor and superintendents	1	2	3	4	5
		Lack of labor surveillance	1	2	3	4	5
		Lack of periodic meeting with labor	1	2	3	4	5
3	Motivation factors	Lack of financial motivation system	1	2	3	4	5
		Lack of labor recognition programs	1	2	3	4	5
		Non-providing of transportation means	1	2	3	4	5
		Lack of place for eating and relaxation	1	2	3	4	5
		Payment delay	1	2	3	4	5
		Lack of training sessions	1	2	3	4	5
4	Time factors	Work overtime	1	2	3	4	5
		Working for 7 days of week without holiday	1	2	3	4	5
		Increasing number of labor in order to accelerate work	1	2	3	4	5
		Misuse of time schedule	1	2	3	4	5
		Method of employment (using direct work system)	1	2	3	4	5
5	Materials / Tools factors	Material shortages	1	2	3	4	5
		Equipment efficiency					
		Unsuitability of materials storage location	1	2	3	4	5
		Tool and equipment shortages	1	2	3	4	5

No	Groups	Factors negatively affecting labor productivity	Degree of effectiveness				
6	Supervision factors	Rework	1	2	3	4	5
		Supervisors absenteeism	1	2	3	4	5
		Inspection delay	1	2	3	4	5
		Drawings and specifications alteration during execution	1	2	3	4	5
7	Project factors	Type of activities in the project	1	2	3	4	5
		Construction method	1	2	3	4	5
		Interference	1	2	3	4	5
		Working in confined space	1	2	3	4	5
		Complexity due to steel bars	1	2	3	4	5
		Floor area (m2)	1	2	3	4	5
		Level of Building (Floor No.)	1	2	3	4	5
		Number of Labor in project.	1	2	3	4	5
8	Safety factors	Violation of safety precautions	1	2	3	4	5
		Accidents	1	2	3	4	5
		Unemployment of safety officer in construction site	1	2	3	4	5
		Working at high place	1	2	3	4	5
		Bad ventilation	1	2	3	4	5
		Insufficient Lighting	1	2	3	4	5
		Noise	1	2	3	4	5
9	Quality factors	Low quality of raw materials	1	2	3	4	5
		High quality of required work	1	2	3	4	5
		Inefficiency of equipments	1	2	3	4	5
10	External factors	Weather changes	1	2	3	4	5
		Augmentation of Government regulations related to the construction sector	1	2	3	4	5

Please, write any effective factors do not mentioned in the above table:

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

Annex 2: Questionnaire 1

The questionnaire (In Arabic)

بسم الله الرحمن الرحيم

الجامعة الإسلامية

عمادة الدراسات العليا

كلية الهندسة - قسم الهندسة المدنية

استبيان

"دراسة العوامل المؤثرة علي الإنتاجية ومعدل الإنتاج للمشاريع الإنشائية في قطاع غزة"

وذلك كجزء من البحث التكميلي لنيل درجة الماجستير في إدارة التشييد

الباحث

م.محمد ماضي

إشراف

الدكتور/ نبيل الصوالحي

غزة - فلسطين

2013

استبيان يهدف إلي دراسة العوامل المؤثرة علي الإنتاجية ومعدل الإنتاج للمشاريع الإنشائية في قطاع غزة

السيد المقاول/المهندس: السلام عليكم ورحمة الله وبركاته

بداية أتقدم لكم بجزيل الشكر والتقدير لمساهمتكم بجزء من وقتكم وجهدكم في تعبئة هذا الاستبيان.

يعتبر صب البلاطات الخرسانية من الأنشطة الأساسية والمهمة في المشاريع الإنشائية وقطاع التشييد والبناء لذلك فان هذه الاستبانة تهدف إلي دراسة العوامل المؤثرة علي الإنتاجية ومعدل الإنتاج , لصب البلاطات الخرسانية في المشاريع الإنشائية في قطاع غزة, وهي جزء من البحث التكميلي لنيل درجة الماجستير في إدارة التشييد في الجامعة الإسلامية بغزة.

المعلومات الواردة في الاستبيان:-

إن كافة المعلومات الواردة في هذا الاستبيان سوف يتم استخدامها لأغراض البحث العلمي مع الالتزام التام بالمحافظة علي سرية المعلومات الخاصة بكم.

أرجو أن تكون طريقة الإجابة على الاستبيان كالأتي:

أ- تقييم العوامل الكيفية وذلك بإعطاء كل عامل الدرجة المناسبة من(1 – 5).

1- منخفض جدا 2 - منخفض 3 - متوسط 4- مرتفع 5- مرتفع جدا

ب- تحديد الكمية المناسبة للعوامل الكمية.

ج- وضع العلامة (X) لبعض العوامل الأخرى.

<u>الجزء الأول:</u>

1-اسم الشركة..

2- اسم المشروع...

3-مدة المشروع...

4-موقع المشروع...

5- مساحة الطابق(م2)...

6-عدد الطوابق...

7- ارتفاع الطابق...

8- سماكة السقف...

9- عدد طواقم العمل (فرق العمل)..

10- عدد العمال في كل طاقم ....

11- عدد ساعات العمل اليومية في الموقع..

12- تصنيف الشركة حسب تصنيف اتحاد المقاولين:

درجة أولي ☐ درجة ثانية ☐ درجة ثالثة ☐

13- الوظيفة الإدارية لمن يقوم بتعبئة الاستبانة:

مدير الشركة ☐ مدير المشاريع ☐ مهندس الموقع ☐ المراقب ☐

- عدد الموظفين في الشركة:14

اقل من 10 ☐ 30-11 ☐ 50-31 ☐ أكثر من 50 ☐

15-عدد المشاريع المنفذة خلال السنوات الخمس الماضية في مجال المباني:

اقل من 10 ☐ 20-11 ☐ 30-21 ☐ أكثر من 30 ☐

16-متوسط حجم أعمال الشركة سنويا خلال السنوات الخمس الماضية في مجال المباني (مليون دولار).

اقل من 0.5 ☐ 2-0.5 ☐ 5-2.1 ☐ أكثر من 5 ☐

الجزء الثاني:

العوامل المؤثرة علي الإنتاجية:

في الجدول التالي عدد من العوامل التي تؤثر سلبا علي إنتاجية العمل في صناعة التشييد في مشاريع البناء يرجي تحديد درجة تأثير هذه العوامل علي إنتاجية العمال .

1-يؤثر بدرجة قليلة. 2-يؤثر بعض الشيء. 3-يؤثر بدرجة متوسطة. 4-يؤثر بدرجة كبيرة. 5-يؤثر بدرجة كبيرة جدا

الرقم	**المجموعة**	**العوامل المؤثرة علي الإنتاجية**	**درجة التأثير**				
1	عوامل متعلقة بالقوي البشرية (العمال)	زيادة عمر العامل	1	2	3	4	5
		قلة خبرة العامل	1	2	3	4	5
		غياب احد أو بعض العمال في مجموعة العمل	1	2	3	4	5
		المشاكل العائلية والخاصة التي يتعرض لها العامل	1	2	3	4	5
		عدم رضا العامل عن نفسه(عدم وجود رضا وظيفي)	1	2	3	4	5
		عدم شعور العامل بالانتماء والولاء للشركة	1	2	3	4	5
		عدم التفاهم بين العمال في مجموعة العمل	1	2	3	4	5
		عدم وجود روح التنافس بين العمال في مجموعة العمل	1	2	3	4	5
2	عوامل متعلقة بالقيادة	غياب التفاهم بين العمال والمراقب أو المهندس المسئول	1	2	3	4	5
		عدم مراقبة ومتابعة العمال أثناء العمل من المراقب أو المسئول	1	2	3	4	5
		عدم عقد اجتماعات دورية مع العمال لدراسة المشاكل التي تواجه العمل	1	2	3	4	5
3	عوامل متعلقة بالحوافز	عدم استخدام نظام الحوافز المادية	1	2	3	4	5
		عدم استخدام نظام الحوافز المعنوية	1	2	3	4	5
		عدم توفير المواصلات للعامل	1	2	3	4	5
		عدم توفير مكان للراحة والأكل للعامل	1	2	3	4	5
		التأخير في دفع رواتب العمال	1	2	3	4	5
		عدم حصول العامل علي دورات تدريبية	1	2	3	4	5
4	عوامل متعلقة بالوقت	العمل لساعات إضافية	1	2	3	4	5
		العمل كل أيام الأسبوع بدون اخذ يوم إجازة	1	2	3	4	5
		زيادة عدد العمال في موقع العمل بغرض تسريع العمل	1	2	3	4	5
		عدم استعمال الجداول الزمنية في إدارة المشاريع	1	2	3	4	5
		العمل بنظام اليومية بدلا من نظام المقاولة	1	2	3	4	5
5	عوامل متعلقة بالمواد و المعدات	نقص المواد	1	2	3	4	5
		كفاءة المعدات والآلات	1	2	3	4	5
		النقص في عدد المعدات والآلات	1	2	3	4	5
		بعد مكان تشوين المواد في المشروع عن مكان العمل	1	2	3	4	5
6	عوامل متعلقة بالإشراف	إعادة العمل بسبب رفض العمل من قبل الإشراف	1	2	3	4	5
		غياب جهاز الإشراف	1	2	3	4	5
		تأخر فحص الأعمال الجاهزة من قبل الإشراف	1	2	3	4	5

		التغيير في المواصفات والخرائط أثناء التنفيذ	1	2	3	4	5
7	عوامل متعلقة بطبيعة المشروع	نوع الأعمال والفعاليات المطلوب تنفيذها في المشروع	1	2	3	4	5
		الطريقة الفنية المتبعة في تنفيذ الأعمال في المشروع	1	2	3	4	5
		التداخل بين الأعمال ومجموعات العمل	1	2	3	4	5
		ضيق مساحة منطقة العمل	1	2	3	4	5
		صعوبة وعدم وضوح المخططات وشكل المبني	1	2	3	4	5
		مساحة السقف	1	2	3	4	5
		سماكة السقف	1	2	3	4	5
		عدد الطوابق	1	2	3	4	5
		ارتفاع الطابق	1	2	3	4	5
		عدد العمال في المشروع	1	2	3	4	5
8	عوامل متعلقة بالسلامة والأمان في المشروع	عدم إتباع إجراءات السلامة والأمان أثناء العمل	1	2	3	4	5
		وقوع الحوادث في موقع العمل	1	2	3	4	5
		عدم تعيين موظف مسئول عن إجراءات السلامة والأمان في الموقع	1	2	3	4	5
		ارتفاع مكان العمل	1	2	3	4	5
		سوء التهوية في مكان العمل	1	2	3	4	5
		ضعف الإضاءة في مكان العمل	1	2	3	4	5
		وجود ضوضاء في موقع العمل	1	2	3	4	5
9	عوامل متعلقة بالجودة	سوء جودة صناعة المواد الأولية المستخدمة	1	2	3	4	5
		ارتفاع جودة العمل المطلوب تنفيذه	1	2	3	4	5
		قلة كفاءة المعدات المستخدمة في العمل	1	2	3	4	5
10	عوامل خارجية	التغير في الأحوال الجوية	1	2	3	4	5
		ازدياد القوانين الحكومية والبلدية المتعلقة بقطاع التشييد	1	2	3	4	5
		سهولة الوصول إلي موقع العمل	1	2	3	4	5

يرجي كتابة أي عوامل مؤثرة علي الإنتاجية ولم يتم ذكرها في هذا الاستبيان:

....

....

Annex 3: Questionnaire 2

The questionnaire (In English)

THE ISLAMIC UNIVERSITY

FACULTY OF ENGINEERING

Questionnaire

For Master Thesis in Construction Management

Predicting Productivity Rates for casting concrete slabs in construction project in Gaza strip.

Researcher : Eng. Mohammed Mady

Supervised by : Dr. Nabil EL Sawalhi

Partial fulfillment of the requirement for the degree of Master of Science in Civil Engineering

Gaza, Palestine

2013.

All information in the questionnaire will be used for research with complete commitment for absolute secrecy to your information. Please identify the value of factors that affect on productivity for casting concrete slabs in your project.

1. Project name……………………………………………….……..……………….…….

2. Floor area (m2)……………………………………………………………………

3. Slab thickness……………………………….…………………………….………

4. Duration of formwork and casting slab ………………………………………..…

5. Working hours per day at site………………………...……………………...….

6. Number of Labor ………………..………………..……………………………………

7. Floor height……………………….………..………………….……...………………..……

8. Material shortages:

☐ Low quantity ☐ Medium quantity ☐ High quantity

9. Tool and equipment shortages and Efficiency:

☐ Low Efficiency ☐ Medium Efficiency ☐ High Efficiency

10. Labor experiences:

☐ Low experiences ☐ Medium experience ☐ High experiences

11. Weather:

☐ Rain ☐ Hot ☐ Moderate

12. Complexity due to steel bars:

☐ Complex ☐ Medium ☐ Easy

13. Drawings and specifications alteration during execution:

☐ High alteration ☐ Medium alteration ☐ Low alteration

14. Easy to arrive to the project location:

☐ Difficult ☐ Medium ☐ Easy

15. Lack of labor surveillance:

☐ Low surveillance ☐ Medium surveillance ☐ High surveillance

16.Payment delay:

☐ High delay ☐ Medium delay ☐ Low delay

Annex 4: Questionnaire 2

The questionnaire (In Arabic)

بسم الله الرحمن الرحيم

الجامعة الإسلامية

عمادة الدراسات العليا

كلية الهندسة - قسم الهندسة المدنية

اســتـبـيــان

"دراسة معدل الإنتاجية لصب الاسقف في المشاريع الإنشائية في قطاع غزة"

وذلك كجزء من البحث التكميلي لنيل درجة الماجستير في إدارة التشييد

الباحث

م.محمد ماضي

إشراف

الدكتور/ نبيل الصوالحي

غزة - فلسطين

2013

ان كافة المعلومات الواردة في هذا الاستبيان سوف يتم استخدامها لأغراض البحث العلمي مع الالتزام التام بالمحافظة علي سرية المعلومات الخاصة بكم.

يرجي تحديد درجة تأثير هذه العوامل علي إنتاجية العمال في صب الاسقف الخاصة بمشروعكم.

1- اسم المشروع ....

2- مساحة السقف (م2)..

3- سماكة السقف..

4- المدة الزمنية لطوبار وصب السقف..

5-عدد ساعات العمل اليومية في الموقع..

6-عدد العمال..

7- ارتفاع مكان العمل..

8- وفرة المواد

متوفرة بكمية قليلة ☐ متوفرة بكمية متوسطة ☐ متوفرة بكميات كبيرة ☐

9-وفرة وكفاءة المعدات والآلات

بدرجة قليلة ☐ بدرجة متوسطة ☐ بدرجة كبيرة ☐

10-خبرة العمال

خبرة قليلة ☐ خبرة متوسطة ☐ خبرة كبيرة ☐

11- حالة الطقس

شتوي ☐ صيفي ☐ معتدل ☐

12-صعوبة وعدم وضوح المخططات وشكل المبني

صعب ☐ متوسط ☐ سهل ☐

13-التغيير في المواصفات والخرائط أثناء التنفيذ

تغيير كبير ☐ تغيير متوسط ☐ تغيير قليل ☐

14-سهولة وصول المواد والعمال لموقع العمل

صعب ☐ متوسط ☐ سهل ☐

15-مراقبة ومتابعة العمال أثناء العمل من المراقب أو المسئول

لاتوجد رقابة ☐ رقابة جزئية ☐ رقابة دائمة ☐

16-التأخير في دفع رواتب العمال

تأخير كبير ☐ تأخير متوسط ☐ تأخير قليل ☐

Appendix A: Analysis and calculating RII for most effective factor

Factors Affecting Labor Productivity	*Very Low (1)*	*Low (2)*	*Medium (3)*	*High (4)*	*Very High (5)*	*Total*	*RII*	*Rank*
Material shortages	3	5	6	14	49	77	0.862	1
Tool and equipment shortages	2	1	10	28	36	77	0.847	2
Equipment Efficiency	1	3	13	21	39	77	0.844	3
Weather changes	2	4	16	21	34	77	0.810	4
Complexity due to steel bars	1	7	11	30	28	77	0.800	5
Drawings and specifications alteration during execution	0	6	17	29	25	77	0.790	6
Lack of labor experiences	0	7	20	21	29	77	0.787	7
Number of Labor in project	1	4	20	27	25	77	0.784	8
Lack of labor surveillance	2	7	14	30	24	77	0.774	9
Level of Building (Floor No.)	0	7	21	24	25	77	0.774	9
Working at high place	1	9	18	22	27	77	0.769	11
Payment delay	4	6	18	23	26	77	0.758	12
Easy to arrive to the project location	1	8	23	19	26	77	0.758	12
Insufficient Lighting	1	8	17	40	11	77	0.735	14
Rework	2	7	20	34	14	77	0.732	15
Misunderstanding between labor and Superintendents	1	12	15	33	16	77	0.732	15
Labor disloyalty	1	9	28	25	14	77	0.709	17
Supervisors absenteeism	3	12	13	40	9	77	0.704	18
Floor height	8	11	16	18	24	77	0.701	19
Floor area (m2)	3	16	22	12	24	77	0.699	20
Unsuitability of materials storage location	2	17	21	16	21	77	0.696	21
Construction method	1	11	26	29	10	77	0.694	22
Working in confined space	1	11	25	33	7	77	0.688	23
Inefficiency of equipments	4	9	27	24	13	77	0.686	24
Interference	0	17	24	27	9	77	0.673	25
Working for 7 days of week without holiday	10	10	19	18	20	77	0.673	25
Bad ventilation	5	11	23	31	7	77	0.662	27

Appendix A: Analysis and calculating RII for most effective factor

Factors Affecting Labor Productivity	*Very Low (1)*	*Low (2)*	*Medium (3)*	*High (4)*	*Very High (5)*	*Total*	*RII*	*Rank*
Slab thickness	10	16	14	14	23	77	0.662	27
Lack of financial motivation system	2	15	27	23	10	77	0.662	27
Misunderstanding among labor	3	19	18	25	12	77	0.662	27
Type of activities in the project	2	16	25	26	8	77	0.657	31
Accidents	4	17	22	23	11	77	0.652	32
High quality of required work	6	8	30	27	6	77	0.649	33
Labor dissatisfaction	6	15	25	17	14	77	0.647	34
Lack of labor recognition programs	7	11	27	24	8	77	0.639	35
Inspection delay	6	15	18	36	2	77	0.634	36
Low quality of raw materials	2	15	35	18	7	77	0.634	36
Violation of safety precautions	3	17	29	22	6	77	0.629	38
Misuse of time schedule	10	13	21	25	8	77	0.621	39
Increasing number of labor in order to accelerate work	10	12	27	19	9	77	0.613	40
Augmentation of Government regulations in construction	4	16	35	18	4	77	0.605	41
Lack of competition	6	21	24	18	8	77	0.603	42
Work overtime	12	11	26	24	4	77	0.592	43
Noise	7	21	20	27	2	77	0.59	44
Increase of laborer age	7	16	32	18	4	77	0.59	44
Method of employment (using direct work system)	12	12	27	20	6	77	0.59	44
Non-providing of transportation means	11	15	28	16	7	77	0.582	47
Labor absenteeism	7	20	27	22	1	77	0.574	48
Lack of place for eating and relaxation	10	20	28	10	9	77	0.569	49
Unemployment of safety officer in construction site	11	20	23	16	7	77	0.569	49
Lack of periodic meeting with labor	11	20	24	20	2	77	0.553	51
Labor personal problems	11	17	31	16	2	77	0.551	52
Lack of training sessions	16	15	28	15	3	77	0.532	53

Appendix B: Collected real data for duration and factors

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
20	15	2	2	2	2	3	3	3	2	3	4.69
5	15	1	1	2	2	3	3	3	3	2	4.13
6	3	2	2	3	3	2	3	3	2	3	1.94
12	3	2	3	3	3	3	3	2	3	3	2.00
12	3	2	3	2	3	3	3	2	2	3	2.50
55	32	2	2	3	3	2	2	2	2	3	6.90
7	3	3	3	3	2	3	3	3	3	2	4.00
8	8	2	2	3	2	3	3	3	2	3	2.96
9	3	2	2	2	3	2	3	2	2	2	2.18
50	24	2	2	3	3	2	2	2	2	3	7.69
8	3	2	2	3	2	3	3	2	2	3	1.88
7	16	2	1	2	3	1	2	2	2	2	4.38
8	3	3	1	1	3	3	2	3	3	1	1.69
8	3	2	2	2	3	2	3	1	2	3	2.67
9	5	2	3	1	1	2	3	3	2	3	3.64
7	3	3	2	3	2	3	2	2	3	3	1.89
8	3	2	2	3	3	2	2	2	2	1	2.50
9	3.5	2	3	2	3	2	3	2	3	3	5.47
10	3	2	3	3	3	2	3	2	2	2	1.67
8	3	2	2	2	3	3	3	3	3	3	3.00
10	45	2	2	3	2	2	2	2	2	3	2.08
10	15	1	2	3	2	3	3	3	2	3	6.55
11	3	2	1	2	3	2	3	3	2	3	6.67
7	3.5	1	2	2	3	2	3	3	3	2	4.50
8	3	2	2	2	3	2	2	3	2	3	2.00
15	8	3	3	2	3	2	2	3	3	3	3.47
35	20	2	2	2	3	3	2	3	2	3	7.07
12	4	3	2	2	3	3	3	2	2	3	2.83
7	3	3	2	2	2	2	3	3	3	2	4.73
8	3	2	3	3	3	2	3	3	3	3	1.50
12	12	2	2	2	3	3	3	3	3	3	9.26
13	6	3	3	2	3	1	3	3	3	3	2.71
35	4	3	3	3	3	1	2	2	2	3	9.09
13	3.3	3	2	2	2	2	3	3	3	2	5.94
15	3.2	2	2	3	3	3	3	3	3	3	3.89
8	3.5	2	3	3	2	3	3	2	3	3	1.70
8	3	2	2	3	2	3	2	2	3	2	1.82
10	3	3	2	3	3	2	3	2	3	3	1.82
10	3	2	3	3	3	3	3	2	3	3	2.00
12	9	3	2	2	3	3	3	3	3	3	4.40
15	3	3	3	3	2	3	3	3	3	3	4.55
13	12	2	2	3	3	3	2	3	2	3	8.75
15	3.2	3	3	3	3	3	3	3	3	3	5.95
10	6	3	3	2	3	1	2	3	2	1	3.06
35	4	1	2	3	3	2	2	3	2	2	5.67
16	6.6	3	2	2	3	2	3	3	3	3	6.60
12	12	2	1	2	3	1	2	2	2	2	6.00
18	9	2	2	3	3	1	3	2	2	3	2.67

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
20	21	3	3	2	2	2	2	2	3	2	3.14
8	4	2	2	3	2	3	3	3	2	3	3.56
8	3	3	3	2	2	2	3	3	3	3	4.60
10	9	3	3	1	1	2	3	3	2	3	3.28
20	12	2	2	3	1	2	3	1	3	3	4.35
13	3.5	1	1	2	3	1	1	2	1	1	5.00
23	8	3	2	3	2	1	2	2	2	3	8.08
26	28	3	3	3	2	2	3	3	3	3	11.11
30	16	3	3	3	3	3	3	3	2	2	6.07
42	12	2	3	3	3	2	2	2	2	3	7.69
7	8	2	2	1	2	3	3	3	3	1	3.13
7	12	2	1	2	3	1	2	2	2	2	3.75
15	11.5	2	3	2	3	3	2	3	2	2	4.46
30	12	2	2	3	1	3	3	3	2	2	7.86
33	8	2	2	3	3	2	2	3	2	2	5.00
35	36	2	3	2	2	2	2	3	3	3	5.67
10	16	1	1	2	3	1	2	2	2	2	3.00
15	4	2	2	3	2	1	2	3	3	3	9.67
12	3.3	2	2	2	1	3	3	3	2	3	8.04
36	12	3	3	3	3	2	2	3	2	2	5.31
37	4	3	3	2	1	1	2	2	3	3	6.92
40	27	3	3	2	3	2	1	3	3	2	5.00
15	3.2	2	2	1	1	2	2	2	1	3	4.58
6	3	2	2	2	2	2	3	3	3	3	1.75
16	12	2	1	2	3	1	2	2	2	2	8.75
40	8	3	3	3	3	1	2	2	2	3	8.33
10	6	3	2	3	2	3	3	3	3	3	3.65
42	16	2	3	3	3	2	2	2	2	3	7.14
15	16	2	1	2	3	1	2	2	2	2	7.00
45	4	3	2	2	2	2	3	2	3	3	9.52
14	4	1	1	1	2	3	3	2	3	2	4.31
15	6	2	2	3	3	3	3	3	3	3	2.08
11	16	2	1	2	3	1	2	2	2	2	5.00
6	3	2	2	3	3	2	3	2	2	2	1.50
9	5	2	3	1	1	2	3	3	2	3	3.62
8	3.5	2	3	3	2	3	3	2	3	3	1.70
8	3	3	3	2	2	2	3	3	3	3	4.59
10	3	2	3	3	3	3	3	2	3	3	2.00
45	20	2	3	2	3	2	2	3	3	3	9.58
10	3	2	3	3	3	2	2	2	1	2	2.50
10	3	2	2	2	3	3	3	3	3	3	3.00
55	28	2	2	3	3	2	2	2	2	3	7.69
50	20	2	2	3	3	2	2	2	2	3	8.30
25	19	2	2	2	3	3	2	3	3	3	11.12
12	9	3	2	2	3	3	3	3	3	3	4.39
12	12	2	1	2	3	1	2	2	2	2	5.95
13	9	3	2	2	3	3	3	3	3	3	4.40
10	3	2	3	3	3	3	3	2	3	3	2.00
52	20	2	2	3	3	2	2	2	2	3	8.20
12	12	2	1	2	3	1	2	2	2	2	5.90
10	3	2	2	2	3	3	3	3	3	3	2.90
10	5	2	3	1	1	2	3	3	2	3	3.63

No. of Labor	Floor Height	Material Shortage	Tools Shortage	Labor Experience	Weather	Complexity of steel bars	Drawings alteration	Location	Labor Surveillance	Payment Delay	Productivity m2/h
7	3	2	2	3	3	2	3	2	2	2	1.49
9	3	3	3	2	2	2	3	3	3	3	4.59
44	20	2	3	2	3	2	2	3	3	3	9.58
15	3	3	3	3	2	3	3	3	3	3	4.55
53	28	2	2	3	3	2	2	2	2	3	7.70
9	4	2	3	3	2	3	3	2	3	3	1.68
10	3	2	3	3	3	2	2	2	1	2	2.45