

University of Bahrain

College of Engineering



**Department of
Mechanical Engineering**

Modeling of Construction Labor Productivity in Kingdom of Bahrain

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Master Degree in Engineering Management

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The Discussion Committee met on ____ (day and date) 14-162 in Hall no. ____ (hall/room no.) _____. Upon discussing the student whose details are stated above in public, the discussion committee recommends the following:

The student awarded grade A In the thesis subject I EN 598

- ☐ Without making any changes to the thesis
☒ After making the modifications attached with this decision

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Abstract

Construction is a key contributing sector to the economy for almost all the countries around the world and in Kingdom of Bahrain particularly. This sector is booming as a result of Gulf Cooperation Council development funded projects and the government directions towards economic diversification, which provides abundant opportunities for non-oil sectors such as the construction sector. Construction however, is labor intensive and affected by various factors resulting into labor productivity variations; therefore the aim of this research is to identify and assess the productivity influencing factors for key construction activities (namely: steel fixing, concrete pouring, formwork, and block work). To achieve this objective, a concise literature review was conducted about construction labor productivity and significant factors influencing it. The conclusions drawn in addition to industry's experts' opinion were utilized to develop a questionnaire to identify the most influencing factors in Bahrain. The targeted population were grades A and AA contractors. Conversely historical data for construction projects were collected to be used in Construction Labor Productivity (CLP) modeling along with the outputs of the questionnaire. The productivity models for the selected activities were developed using artificial neural network (ANN) technique (in NeuroXL) and three types of regression analysis which are linear, stepwise, and nonlinear regression (in Minitab). These models quantified the effect of various factors on the productivity and enabled predicting it with new data. The goodness of fit and prediction performance of the models were assessed based on the error measures: Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE) in addition to Coefficient of Determination (R^2). The performance of neural network models was better in predicting CLP for steel fixing, formwork, and blockwork, however, for concrete pouring the linear regression was more suitable. The study emphasized on the importance of CLP data records keeping for future analysis, and the effectiveness of ANN in modeling CLP, and suggested potential improvement to CLP through dealing effectively with the identified significant influencing factors.

Dedication

I dedicate this thesis to...

- *My beloved country hoping it adds to the construction industry in Kingdom of Bahrain*
- *To his Excellency the Minister of Works, Municipalities Affairs and Urban Planning, Engineer Essam Bin Khalaf*
- *To my beautiful family for their unconditional love and support hoping that I continue to make them proud*

Lamya Ali

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List of Abbreviations

Abbreviation	Description
GDP	Gross Domestic Product
GCC	Gulf Cooperation Council
MOF	Ministry of Finance
MOW	Ministry of Works, Municipalities Affairs and Urban Planning
CLP	Construction Labor Productivity
RII	Relative Importance Index
RMSE	Root Mean Square Error
MAD	Mean Absolute Error
MSE	Mean Square Error
MAPE	Mean Absolute Percentage Error
R²	Coefficient of Determination
ANN	Artificial Neural Network

List of Notations

Symbol	Description
A	Confidence Level
n_1	Number of Respondents Who Answered "Not at all influential"
n_2	Number of Respondents Who Answered "Insignificant influence"
n_3	Number of Respondents Who Answered "Somewhat influential"
n_4	Number of Respondents Who Answered "Very influencing"
n_5	Number of Respondents Who Answered "Extremely influential"
P	P- value

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CHAPTER 1

Introduction

1.1 Overview

1.2 Problem Statement

1.3 Research Questions

1.4 Objectives of the Research

1.5 Significance of the Research

1.6 Study Limitation

1.7 Thesis Outline

Chapter 1

Introduction

1.1 Overview

Construction is a key contributing sector to the economy for almost all the countries around the world. In Kingdom of Bahrain, the GDP (Gross domestic product) from construction increased from BD 169.10 million in the third quarter of 2012 to BD 230.68 million in the third quarter of 2018, this growth is credited to the government investment plan backed by financial assistance from the GCC's \$10bn Gulf Development Programme which included the prioritization of infrastructure and housing projects. In addition, to transport construction and expansion projects set to aid development under the auspices of the kingdoms' Economic Vision 2030 plan.

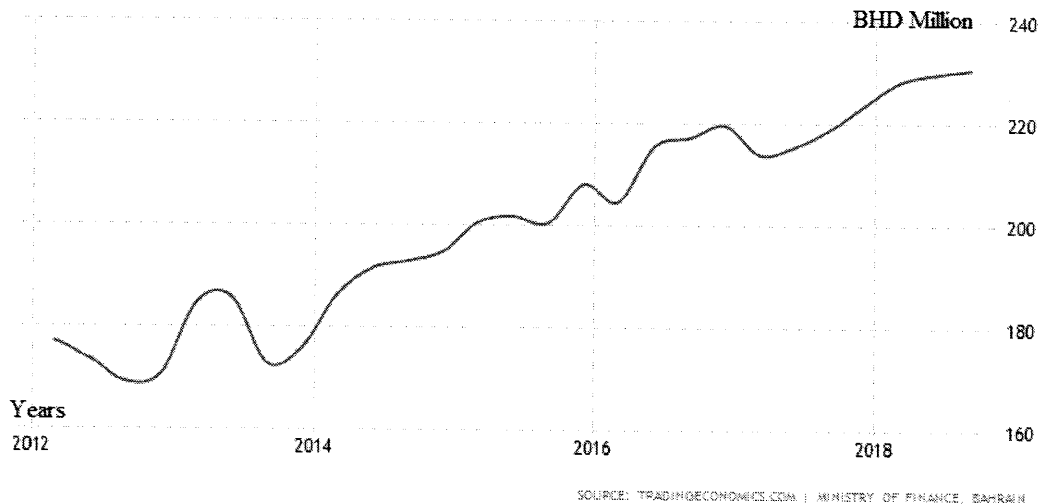


Fig. 1.1: Kingdom of Bahrain GDP from Construction (Years 2012- 2018)
(TradingEconomics.com/MOF, Bahrain)

The fact that construction industry is labor intensive makes labor productivity very critical to the success and competitiveness of every construction company. Above and beyond the advantage that construction companies may gain over their competitors by improving on labor productivity to win contracts and turn a profit; Construction Labor Productivity (CLP) models provide companies management with valuable piece of information for estimation purposes, forecasting performance, scheduling and strategic planning.

CLP must be measured effectively and the factors that affect productivity must be viewed and considered if any meaningful intervention strategies are to be put in place to improve construction productivity (Chigara and Moyo, 2014). Productivity models can weigh the impact of various factors on CLP. The term "Productivity modeling" can be defined as the method of examining and evaluating the effect of influencing factors on CLP using historical records (Sonmez and Rowings, 1998).

Even though Bahrain's construction sector continues to grow at a fast – pace, there is a lack of sufficient research on CLP in Bahrain and an absence of methodical approaches to measure then estimate CLP. For planning and estimating purposes, estimators usually use Individual experience; expert opinion and historical information from previous construction projects. The accurateness of these approaches nevertheless is affected by personal prejudgment, employee turnover and the quality of historical data (Song and AbouRizk, 2008).

This thesis aims for putting forward a generic approach for measuring and modeling productivity that can be applied for any construction company.

1.2 Problem Statement

CLP is of great importance to almost all construction companies, and being able to make use of the past and current projects data to predict productivity on future projects is a great benefit that can be gained from building a reliable productivity model. However, due to some facts including the current practices followed by some local companies with this regard, CLP becomes very challenging to researchers. Among these facts and current practices, the following:

- There is no generally accepted method for measuring productivity, the available data about productivity are usually difficult to interpret and comprise some inconsistencies that prevent its use for modeling purposes.
- There are a lot of CLP influencing factors and some of them are difficult to quantify
- There is a lack of accurate and comprehensive historical information about previously constructed projects in many local organizations that do not pay attention to the importance of keeping records for future analysis purposes. Some data are simply does not exist in the records and some are recorded at a summary level with no further details
- Some companies still rely on paper based systems to record productivity data and this makes it difficult and time consuming to be retrieved.

Therefore, there is a need for a local study that propose a generic – and user friendly - approach to measure and model productivity to enhance future planning, estimation and performance management.

1.3 Research Questions

- What are the key factors that might influence CLP in Bahrain?
- What is the impact of each influencing factors on CLP?
- What is the type of relationship between the CLP and the influencing factors? / Which model best fits CLP data?
- How could this thesis contribute in CLP improvement?

1.4 Objectives of the Research

The main objectives of the thesis are to identify and evaluate the factors influencing CLP, to develop models that can predict CLP, and put forward recommendations for CLP improvement

1.5 Significance of the Research

This research shall contribute to the construction sector in Bahrain as its outputs will be of great benefit to:

- **Contractors:** CLP models shall be very helpful to contractors for estimation purposes, forecasting performance, scheduling and strategic planning.

- **Stakeholders:** the identification of the significant CLP influencing factors will allow stakeholders to put intervention strategies to improve CLP.

1.6 Study Limitation

The data used for modeling were collected from three companies (two grade AA and one grade A) due to the availability which does not reflect the same population considered in questionnaire. Also, there were significant factors identified by the questionnaire and were not included in the models because they were not measurable, or due to lack of relevant historical data. Moreover, in building the neural network models there were a lot of options to build the networks however, a theme was introduced to shortlist trials and to facilitate the comparison.

Finally, the hold out method (explained in page 57) was used for validation because of its practicality, and other methods were excluded, such as k-fold, which would test all the observations, because it involves lengthy computational procedure.

1.7 Thesis Outline

The thesis is divided into six chapters, where the first chapter provides an introduction about the CLP and its importance for contractors and construction stakeholders, states the difficulties in measuring CLP and modeling it, and highlight the objective of the thesis. Chapter Two presents a concise literature review about some relevant topics to this research such as CLP measurements and its importance to companies' management, the

factors influencing CLP and CLP modeling based on previous researches and studies. This is followed by Chapter Three which describes the CLP influencing factors identification, then the historical data collection. Chapter Four which presents CLP models 'development with neural networks, and with linear and nonlinear regression. A comparison of models and evaluation of factors influencing CLP is presented in Chapter Five. Finally, Chapter Six includes conclusion, recommendations, and limitations of the research with suggestion for future studies.

CHAPTER 2

Literature Review

- 2.1 Introduction**
 - 2.2 Productivity Definitions and Method of Measurement**
 - 2.3 Productivity Influencing Factors**
 - 2.4 Modelling of Construction Labor Productivity**
 - 2.5 Chapter Summary**
-

Chapter 2

Literature Review

2.1 Introduction

Construction industry remains labor intensive despite of the present technological developments in the industry. The profitability and competitiveness of any construction organization is directly related to the high labor productivity. This makes productivity on top of construction industry frequently discussed topics.

Numerous research efforts have been dedicated to construction labor productivity and its relevant topics. Major research areas were identified as: CLP Influencing factors, CLP modeling and estimation, approaches and techniques for CLP improvement, trends and comparisons of CLP, effects of variation orders on CLP, and baseline/benchmarking CLP. (Yi and Chan 2014)

This literature review will examine the following topics:

- Definitions of CLP and various methods of measuring it.
- CLP influencing factors
- The most commonly used techniques for modeling of CLP

2.2 Productivity and Method of Measurement

The term "productivity" can be defined as a measure of outputs that are obtained by certain inputs or a relationship between an output and some associated inputs used in the production process. However, the most suitable definition of productivity would be according to the most suitable approach of measuring it for a given task. In construction, productivity is usually regarded as labor productivity; that is units of work placed or produced per man-hour. (El-Gohary and Aziz, 2014). There are various methods of measuring productivity which depend extremely on the purpose for which the results will be used. In addition to various techniques to measure productivity at construction sites such as field surveys and charting techniques (such as crew balance charts) as well as techniques to measure it from cost reporting systems.

The two measures of construction productivity used by the majority of researchers, Robles et al., (2014) and others, are: the partial factor productivity (PFP) and total factor productivity (TFP). Partial factor productivity (PFP): Single factor productivity is a synonym for the same used by the Organization for Economic Cooperation and Development (OECD), where output is evaluated with regards to a single factor of production. A similar definition for the measure given by Song and AbouRizk (2008) would be "productivity at activity level", which is measuring the output in terms of work produced or unit of work by labor or man hours with other resource inputs, such as equipment.

$$\text{Labor productivity} = \frac{\text{Output Quantity}}{\text{Labor hours}} \quad (2.1)$$

This method is most commonly used because of its manifold advantages such as its practicality and that manpower is the dominant productive resource which justify the use of this measure. Moreover, by observing the quantities produced by a labor for a specific activity enables the identification of productivity influencing factor and the measurement process becomes more controllable. It is also preferred by researches who wish to develop labor productivity models as it provides a relatively accurate data regardless of the construction complex nature

On the other hand, Total Factor Productivity (TFP), or Multi-factor productivity as used by OECD, it is the ratio of total output to total input where the total input is the sum of labor, material, energy, capital, plant and any input used to produce the total output. TFP is a comprehensive measure that considers all outputs and inputs whether tangible or intangible if they have a common measurement unit, and it is measured as:

$$TFP = \frac{\text{Total output}}{\Sigma \text{ of all input resources}} \quad (2.2)$$

$$TFP = \frac{\text{Total output}}{\text{Labor} + \text{Materials} + \text{Equipment} + \text{Energy} + \text{Capital}} \quad (2.3)$$

The impracticality of measuring and determining all of the input resources used to achieve the output accurately is considered to be the main disadvantage of total factor productivity measure. Additionally, TFP makes it difficult to interpret the effect of specific selected factors on the output.

2.3 Productivity Influencing Factors

CLP is affected by several factors called by some researches, Thomas and Sudhakumar (2014) and others, "productivity influencing factors". Therefore it is crucial for every construction organization to study and identify these factors to be able to take needful actions and measures for improving the labor productivity. Many researchers have investigated factors that influence or affect the construction labor productivity around the world. Some of them considered a single factor effect on CLP such as Bryson and Forth (2007), who suggested that labor productivity may fluctuate among week days for several reasons such as physical, physiological. While others explored many factors categorized, based on their characteristics, in main groups and ranked them in accordance with their importance or severity such as Thomas and Sudhakumar (2014) who examined the effect of 44 factors on Kerala's construction productivity using the severity index, and found that the CLP is mostly influenced by "timely availability of materials at the worksite". Moreover, Hicksona and Ellis (2014) investigated the influence of 42 factors gathered from previous studies on Trinidad and Tobago CLP through a survey and the results were analyzed using RII %.

In Spain, Robles et al. (2014) selected a set of 35 factors, they believed it affect the construction labor productivity, overall RIIs of factors were computed upon the receipt of distributed questionnaire results, and factors were arranged in descending order according to their ranks. The maximum impact was resulted from "shortage or late supply of materials" which the factor scoring the highest RII%.

Furthermore, Makulsawatudom and Emsley (2004) conducted a research to identify the most influencing factors of CLP in Thailand and found the

top three factors to be lack of material, incomplete drawings and Inspection delay. While in Gaza, the top CLP influencing factors were: materials shortages, lack of labor experience and lack of labor surveillance (Enshassi et al (2007)). The studied factors were categorized by majority of researchers into groups to facilitate the analysis of the results. Slight differences were noticed in the groups' categorization, for example Enshassi et al (2007), categorized the factors affecting the CLP in Gaza strip into 10 groups which are manpower group, leadership group, motivational group, time group, materials/tools group; supervision group, project group, safety group, quality group and external group. While Ailabouni (2010) identified four generic groups for the productivity influencing factors which are environmental, organizational, group dynamics and individual. Contrariwise, Jarkas (2011) on the other hand, classified the factors under four primary groups which are: management, technological, human/labor and external. Although groups' names and categorization may vary amongst researches, conclusions about the most influencing factors are compatible mostly.

The findings of various published studies about productivity influencing factors have been corroborated by more recent ones and the most influencing factors in construction industry according to the literature review are labor skill and experience, lack of supervision/incompetent supervisors, unavailability of material and equipment, payment delay and external weather in hot and very cold countries such as Uganda (Alinaiwe et al., 2007) and USA (Gundecha, 2012).A summary of literature review on factors influencing construction labor productivity is presented in Table (2.1)

Table (2.1): Literature Summary of the Factors Influencing CLP

Country	Reference	Number of studied factors	Top ten influencing factors
Bahrain	Jarkas (2015)	37	(1) Labor skills (2) Coordination among design disciplines (3) Lack of labor supervision (4) Errors and omissions in design drawings (5) Delay in responding to requests for information (6) Rework (7) Stringent inspection by the engineer (8) Working overtime (9) Lack of incentive scheme (10) Inclement weather.
India	Thomas and Sudhakumar (2014)	44	(1) Timely availability of materials at the worksite (2) Delayed material delivery by the supplier (3) Strikes called by political parties (4) Frequent revisions of drawings/design, resulting in additional work/rework (5) Timely availability of drawings at the worksite (6) Craftsmen absenteeism (7) Improper project coordination (8) Harsh weather conditions (9) Craftsmen turnover (10) Poor project planning and scheduling
Egypt	El-Gohary and Aziz (2014)	30	(1) Labor experience and skills (2) Incentive programs (3) Availability of the material and ease of handling (4) Leadership and competency of construction management (5) Competency of labor supervision (6) Construction technology (construction method and material) (7) Labor operating system (daily wage, lump sum) (8) Planning, work flow, and site congestion (9) Constructability (integrated design and construction) (10) Clarity of instructions and information exchange.
KSA	Mahamid, et al. (2013)	32	(1) Lack of labor experience (2) Poor communication and coordination between construction parties (3) Bad relations between labors and management team (4) Payments delay by owner (5) Misuse of time schedule (6) Rework (7) Labor's low wage (8) Financial conditions of contractor (9) Poor site management (10) Frequent change order

Table (2.1): Literature Summary of the Factors Influencing CLP Cont.

Country	Reference	Number of studied factors	Top ten influencing factors
Spain	Robles, et al. (2014)	35	(1) Shortage or late supply of materials (2) Clarity of the Drawings and project documents (3) Clear and daily task assignment (4) Tools or equipment shortages (5) Level of skill and experience of laborers (6) Delays in payments to workers (7) Coordination between crews (8) Improper coordination of subcontractors (9) Insufficient supervision of subcontractors (10) Communication problems
Trinidad and Tobago	Hicksona and Ellis (2014)	42	(1) The lack of labor supervision (2) Unrealistic scheduling and expectation of labor performance (3) Shortage of experienced labor (4) Construction manager's lack of leadership skills (5) Skillset of laborers (6) Delay in responding to requests for information (RFI) (7) Payment delay (8) Communication problems between site management and labor (9) Rain (10) Late arrival, early quitting, and frequent unscheduled breaks.
Zimbabwe	Chigara and Moyo (2014)	43	(1) Unavailability of materials (2) Late payment of salaries and wages (3) Suitability/adequacy of plant and equipment (4) Supervisory incompetence (5) Lack of manpower skills (6) Lack of labor experience (7) Plant Breakdown (8) Late Deliveries of Material (9) Shortage of Tools and Equipment (10) Low remuneration
Palestine	Mahamid (2013)	40	(1) Political situation (2) Equipment shortages (3) Old and inefficient equipment (4) Lack of labor experience (5) Poor site management (6) Poor communication and coordination between construction parties (7) Delay payments by the owner (8) Low wages (9) Rework (10) Misuse of time schedule

Table (2.1): Literature Summary of the Factors Influencing CLP Cont.

Country	Reference	Number of studied factors	Top ten influencing factors
USA	Gundecha (2012)	40	(1) Lack of required construction material (2) Shortage of power and/or water supply (3) Accidents during construction (4) Lack of required construction tools/equipment (5) Poor site condition (6) Insufficient lighting (7) Weather condition (8) Differing site conditions from plan (9) Material storage location (10) Working overtime
Kuwait	Jarkas and Bitar (2012)	45	(1) Clarity of technical specifications (2) The extent of variation/change orders during execution (3) Coordination level among design disciplines (4) Lack of labor supervision (5) Proportion of work subcontracted (6) Design complexity level (7) Lack of incentive scheme (8) Lack of construction manager's leadership (9) Stringent inspection by the engineer (10) Delay in responding to requests for information
UAE	Ailabouni (2010)	42	(1) Proper work timings giving a balance between work and recreation and time with family (2) Leadership skills of supervisors (3) Salaries on time (4) Technical qualified / educated for the trade (5) Reasonably well-paying job (6) Safe secured job (7) Transparency and accountability of each level of management (8) Overtime paid for work done beyond normal working hours (9) Materials available on time (10) Defined policies and procedures by management
Uganda	Alinaitwe, et al. (2007)	36	(1) Incompetent supervisors (2) Lack of skills from the workers (3) Rework (4) Lack of tools/equipment (5) poor construction methods (6) Poor communication (7) Stoppages because of work being rejected by consultants (8) Political insecurity (9) Tools/equipment breakdown (10) Harsh weather conditions

Table (2.1): Literature Summary of the Factors Influencing CLP Cont.

Country	Reference	Number of studied factors	Top ten influencing factors
Gaza	Enshassi, et al. (2007)	45	(1) Materials shortages (2) Lack of labor experience (3) Lack of labor surveillance (4) Misunderstanding between labor and superintendents (5) Drawings and specification alteration during execution (6) Payment delay (7) Labor disloyalty (8) Inspection delay (9) Working seven days per week without holiday (10) Tool / equipment shortages.
Thailand	Makulsawatudom and Emsley (2004)	34	(1) Lack of material (2) Incomplete drawings (3) Inspection delay (4) Incompetent supervisors (5) Instruction time (6) Lack of tools and equipment (7) Poor communication (8) Poor site conditions (9) Change orders (10) Poor site layout

2.4 Modeling of Construction Labor Productivity

Construction productivity models explicate the effect of nominated influencing factors on associated productivity; this allows users, such as construction contractors, to make decisions about the optimum utilization of construction recourses. CLP models are crucial for construction planning, estimation, and scheduling. In planning for example, productivity models would reveal the effect of manageable factors (such as crew size and working hours) for site management allowing them to adjust their plans and goals whether to achieve higher productivity rate or minimizing the cost of working overtime.

Whereas in estimation and scheduling, productivity predictive models can generate useful predictions about labor costs and activity durations, (Sonmez and Rowings, 1998).

Over the years, many studies have been conducted to study the effect of a single factor on the productivity, while few addressed the effect of multiple factors on the same. Researches have explored several modeling techniques including statistical and regression models, expert systems, artificial intelligence, and simulation to study the relationship between the productivity and the factors influencing it, (Yi and Chan, 2014). For example, Ailabouni (2010) has examined the influence of a number of factors affecting the construction productivity by means of linear regression models. Ailabouni focused on UAE construction industry and investigated the influence of 42 factors through questionnaire surveys on key construction activities (which are excavation, formwork, reinforcement, concreting, block work, plastering and tiling). By analyzing the significance of the studied factors, he identified six most influencing factors which are work timings, level of supervision, group dynamics, and availability of materials, control by procedures, and the climate to include into his models. The developed models were capable of providing accurate predictions considering the effect of the said factors, these models can be used as an indicator by construction companies to improve site conditions with an aim of improving productivity rates.

Sonmez (1996) on the contrary argued that artificial neural network models are more suitable for modeling construction labor productivity. He developed productivity models for concrete pouring, concrete finishing, formwork and granular fill with regression and neural network to justify his argument. His objective was to evaluate the impact of multiple factors on construction labor productivity simultaneously. The methodology applied can be summarized as: field data were collected and ten influencing factors were included in the models. Regression models and neural networks were developed and

subsequently were compared in terms of closeness of fit and prediction performance. Sonmez concluded that neural networks are capable of quantifying the impact of multiple factors on the productivity especially when interactions or nonlinear relationship exists.

Another technique used in productivity modeling is simulation. Song and AbouRizk (2008) defined a practical CLP measurement method then developed a data acquisition system to collect the productivity data. Subsequently neural networks and discrete-event simulation were successfully applied to model steel drafting and fabrication productivities.

Regression models were used by researchers such as Ailabouni (2010) who developed models to evaluate the variability in CLP and to predict the percentage change in the same for selected activities, namely: excavation; formwork; reinforcement, concreting, block work, plastering and tiling works.

Considering the effect of subjective variables on construction productivity, some researchers developed models that can detect and analyze the hidden patterns in data sets to predict construction productivity using fuzzy approach, such as Mirahadi and Zayed (2013) whom developed a modified *Neural Network Driven Fuzzy Reasoning* system to model construction labor productivity for concrete pouring operation considering nine influencing factors, which are: temperature, humidity, precipitation, wind speed, gang size, labor percentage, work type, floor level and work method. Followed by, Seresht and Fayek (2015) who claimed that the resultant of integrating system dynamics with fuzzy logic is a powerful construction productivity simulation tool. Integrated fuzzy system dynamics models can explain the dynamic characteristics of a construction project and capture the subjective and uncertain or even lack of information using fuzzy logic. The methodology followed was to identify system variables first, then the relationships between these variables so that it can be modeled using fuzzy logic techniques. A

dynamic simulation of the developed model was performed and sensitivity analysis to examine the performance of system. Similarly, Elwakil et al. (2015) selected nine productivity influencing factors, which are: temperature measured in °C, humidity (%), precipitation, wind speed (km/h), floor height, work type, gang size (workers), labor percent (%) and time (in min), to build fuzzy sets and generated fuzzy rules/models prior to building fuzzy knowledge base. The developed model was validated thereafter to predict construction process productivity.

2.5 Chapter Summary

Because of its significance to the industry, (CLP) is one of the most frequently discussed topics in construction. Researchers used different measures to define CLP, and around the world they have identified factors affecting CLP in which some of these factors were recurring in many researches, and other factors were geographically specific. They have also investigated methods and technology for CLP improvement, trends and comparisons of CLP, effects of change/variation on CLP, and baseline/benchmarking CLP. However only few considered modeling and evaluation of CLP, the reasons might be the challenges in measuring CLP and lack of productivity records keeping. Artificial neural networks, regression analysis and fuzzy logic were the most commonly used modeling techniques and they were proven to be effective. Nevertheless, there was no single study published for CLP modeling in kingdom of Bahrain not even in GCC countries – except UAE - therefore it was necessary to introduce CLP modeling concepts and techniques to the local construction industry.

CHAPTER 3

Data Identification and Collection

- 3.1 Introduction**
 - 3.2 Identifying Factors Influencing CLP**
 - 3.3 Historical Data Collection**
 - 3.4 Chapter Summary**
-

Chapter 3

Data Identification and Collection

3.1 Introduction

Many previous studies identified CLP influencing factors at several countries around the world, but yet most of the researchers stopped at the factors identification stage and did not go further to use these factors in productivity modeling. With the aim of developing a model that analyzes the effect of certain factors on CLP and predict it thereafter, it was necessary to identify the required data and the methodology with which it will be collected. This chapter identifies the two types of data that were used in CLP modeling and its collection methodology (which are the data gathered from questionnaires and the historical data for ongoing and completed projects).

3.2 Identifying Factors Influencing Construction Labor Productivity in Kingdom of Bahrain

This section describes in detail the design and distribution of the questionnaire used to identify the productivity influencing factors in Kingdom of Bahrain, furthermore it highlights the questionnaire's outcomes and results.

3.2.1 Questionnaire Design and Distribution

In order to identify the factors influencing CLP in Bahrain, a structured close -ended questionnaire with a rank order scaled questions was

formulated. The questionnaire included 43 factors selectively gathered from various relevant studies taking into consideration the opinion of some experts in Bahrain's construction field (such as Mr. Nigel Hector from NASS Contracting and Mr. Yusuf Taha from Ministry of Works).

Each factor was selected based on its recurrence in the relevant studies and its suitability for Bahrain's construction environment. Whenever different phrasing for a specific factor was encountered, the dominant phrase was selected to represent all the factors having the same meaning. For example, the factor "Lack of supervision" was phrased as "Incompetent supervisors" by Makulsawatudom et al. (2004) and as "Lack of labor supervision" by Hicksona and Ellis (2014).

The factor "Material shortage at project site" was verbalized as "Timely availability of materials at the worksite" by Thomas and Sudhakumar (2014), as "Availability of the material and ease of handling" by El-Gohary and Aziz (2014) and as "Shortage or late supply of materials" by Robles et al. (2014). An additional example would be the factor "Communication problems" which was phrased as "Poor communication" by Makulsawatudom and Emsley (2004), and as "Misunderstanding between labor and superintendents" by Enshassi, et al. (2007). Then used as it is by Robles et al. (2014), and phrased more specifically as "Communication problems between site management and labor" by Hicksona and Ellis (2014).

To facilitate the process of analysis, factors were categorized into four main groups in accordance with their nature. The four groups were: Management Factors, Technological Factors, Workforce / Manpower Factors and External Factors. In the management factors group, ten factors were selected such as: lack of supervision by the construction project's supervisors, communication problems, lack of training, and management

leadership. Whereas in the technological factors group, twelve factors were included such as: availability of tools and equipment, rework, crew size and composition, design complexity, and project type. Moreover, the workforce/manpower factors group covered thirteen factors such as labor skill, overtime, labor motivation, labor age, and repetition of work. The last group, which is the external factors, included eight factors such as: temperature, noise, government laws, and work at height.

It was more convenient to follow this categorization which was also used by other researchers, for example by Jarkas and Bitar (2012) and Sherif, et al. (2014). Table (3.1) shows the recurrence of selected questionnaire factors in previous studies.

The design of the questionnaire considered number of pages used which is an important aspect; hence the length of the questionnaire improved after combining similar factors and groups.

The questionnaire was designed into sections; the first section gathers general information about the respondents such as their names (for future reference if required however it was kept optional for the respondents), position, and years of experience. The second section has a table that contains listed factors and a space for adding new factors with columns for ranking these factors in a Likert scale of five steps (where 1 stands for not at all influential factors, 2 for Insignificant factors, 3 for factors that influence productivity to some extent, 4 for very influencing factors, and 5 for extremely influential factors). The Likert scale is followed by a column for remarks and suggestions for improvement. Additionally, a "Not Applicable" titled column so as to exclude those factors which respondents believe that should not be considered. The questionnaire was submitted for the approval of the Post Graduate Collage of University of Bahrain afterwards, and minor comments regarding the layout was received and

addressed immediately prior to the official distribution process. A covering letter declaring the objective of the research was attached to the hard copies of the distributed questionnaire, and on the other hand a brief introduction preceded the soft copy of the same questionnaire. The soft copy of the questionnaire was created to expedite the distribution process and to increase the response rate. Many users found the soft version of the same to be more flexible and handy because it was easily accessed by personal computers and mobile phones. (Sample of the questionnaire is presented in Appendix 1)

To assess the views of contractors whom generally more interactive with the labor, the targeted population was considered to be grade A and grade AA prequalified contractors which are listed in the latest updated list of Ministry of Works. Ministry of works plays a key role in kingdoms of Bahrain public works and infrastructure engineering and emphasizes on the highest standards in performing construction projects. All contractors who wish to tender on Ministry of works projects are required to be prequalified and classified according to their financial stability, overall performance, manpower and resources and other criteria. Thus, it was appropriate to select the participants from Ministry of works prequalified contractors list. Additionally, the selection of grade A and AA contracting companies thereafter was because these companies usually undertake large projects and thus hiring more manpower. Other reasons were that these organizations are expected to be more interested in investigating labor productivity as they wish to stay competitive in the market; and that records keeping is assumed to be more advanced and well-kept, and therefore easier to collect and study for the next stage.

Table (3.1): Recurrence of Selected Questionnaire Factors in Previous Studies

Author's reference	El-Gohary and Aziz (2014)	Hicksona and Ellis (2014)	Chigara and Moyo (2014)	Robles et al. (2014)	Gundecha (2012)	Jarkas and Bitar (2012)	Song and AbouRizk (2008)	Enshassi , et al.(2007)	Alinaitwe, et al. (2007)	Makulsawatudom and Emsley (2004)	Sonmez and Rowings (1998)	Frequency
Factors Influencing Productivity												
<i>1. Management factors</i>												
Lack of supervision	X	X	X	X		X		X	X	X		8
Communication problems		X	X	X					X	X		5
Lack of training provided		X	X		X							3
Incentive programs		X	X	X		X						4
Management leadership	X	X				X						3
Work planning and scheduling	X	X		X								3
Management of subcontractors	X			X								2
Lack of labor recognition programs			X					X				2
Safety requirements and regulations	X	X	X		X			X	X			6
Payment delay	X	X	X	X	X			X				6
<i>2. Technological factors</i>												
Crew size and composition	X	X	X				X		X			5
Inspection delays	X	X	X		X	X		X	X	X		8
Rework	X	X	X	X	X			X	X	X		8

Table (3.1): Recurrence of Selected Questionnaire Factors in Previous Studies Cont.

Author's reference	El-Gohary and Aziz (2014)	Hicksona and Ellis (2014)	Chigara and Moyo (2014)	Robles et al. (2014)	Gundecha (2012)	Jarkas and Bitar (2012)	Song and AbouRizk (2008)	Enshassi , et al.(2007)	Alinaitwe, et al. (2007)	Makulsawatudom and Emsley (2004)	Sonmez and Rowings (1998)	Frequency
Clarity of drawings and specifications	X	X	X	X	X	X			X	X		8
Design complexity	X	X		X		X	X		X			6
Variation/change orders	X	X	X			X			X	X		6
Availability of tools and equipment		X	X	X	X			X	X	X		7
Site layout and condition	X	X	X		X				X	X		6
Storage location	X	X		X	X							4
Project type							X					1
Project duration	X											1
Material shortage at project site	X	X	X	X	X			X	X	X		8
<i>3. Workforce factors</i>												
Labor skill	X	X	X	X					X			5
Labor experience	X	X	X	X	X			X				6
Labor age					X			X				2
Labor motivation	X	X		X								3
Labor education	X											1
Overtime	X	X		X	X		X	X	X	X		8
Repetition of work											X	1

Table (3.1): Recurrence of Selected Questionnaire Factors in Previous Studies Cont.

Author's reference	El-Gohary and Aziz (2014)	Hicksona and Ellis (2014)	Chigara and Moyo (2014)	Robles et al. (2014)	Gundecha (2012)	Jarkas and Bitar (2012)	Song and AbouRizk (2008)	Enshassi , et al.(2007)	Alinaitwe, et al. (2007)	Makulsawatudom and Emsley (2004)	Sonmez and Rowings (1998)	Frequency
Shift work										X		1
Working for long periods without holidays			X					X				2
Workers turnover or changing crewmembers									X	X		2
Absenteeism			X		X				X	X		4
Labor personal problems					X							2
Rest time(s) per day		X										1
<i>4. External factors</i>												
Noise												1
Political unrest									X			1
Temperature	X	X	X		X				X	X		7
Humidity	X										X	2
Precipitation / rain	X	X										2
Wind or dust	X											1
Government laws			X		X				X			4

In order to ensure that the published list in the website of the Ministry is the latest updated, Cost Engineering Directorate at Ministry of Works was contacted to confirm the same prior to the distribution of the questionnaire. The list showed 46 grade AA contractors and 26 grade A contractors at the time of carrying out the survey (refer to Appendix 2 for MOW list), hence the targeted population was the total 72 contractors.

In view of the relatively small population size and the possibility of contacting all of the said contractors it was decided to survey the entire population. Targeted contractors were contacted by phone and emails and some were directly interviewed.

3.2.2 Questionnaire's Outcomes and Findings

A total of 67 questionnaires (refer to Appendix 3 for a sample of response) out of 72 distributed were received two months later representing approximately 93% of the target population. The received questionnaires were filled mostly by project managers, quantity surveyors, planning engineers, site engineers and supervisors with an average age of 41.25 years and average years of experience of more than 15 years. Results of all responses are presented in detailed in Appendix 4.

Relative Importance Index (RII) technique was used to analyze the questionnaire results in line with the following formula (Lim and Alum, 1995; Enshassi et al., 2007; and Jarkas and Bitar, 2012):

$$\text{Relative Imporatnce Index} = \frac{5(n5)+4(n4)+3(n3)+2(n2)+n1}{5(n1+n2+n3+n4+n5)} \quad (3.1)$$

Where: n1, n2, n3, n4 and n5 are the number of respondents who selected:

(1) Not at all influential (2) Insignificant influence (3) Somewhat

influential (4) Very influencing, (5) Extremely influential. The relative importance index was multiplied by 100 afterwards to turn it into a percent.

Table (3.2) shows the relative importance index, and rank of each productivity factor surveyed and its associated group. The top ten influencing factors are labor skill, temperature, lack of supervision, labor experience, humidity, work planning and scheduling, availability of tools and equipment, material shortage at project site, management leadership and payment delay, respectively.

Table (3.2): importance Indices and Rankings of Factors Surveyed, and their Relative Groups

Factor	%RII	Group	Rank
Labor skill	85.161	Workforce / Manpower factors	1
Temperature	83.939	External factors	2
Lack of supervision	83.692	Management factors	3
Labor experience	83.548	Workforce / Manpower factors	4
Humidity	82.121	External factors	5
Work planning and scheduling	81.818	Management factors	6
Availability of tools and equipment	81.212	Technological factors	7
Material shortage at project site	80.625	Technological factors	8
Management leadership	79.692	Management factors	9
Payment delay	77.500	Management factors	10
Lack of training provided	77.273	Management factors	11
Communication problems	76.250	Management factors	12
Management of subcontractors	75.152	Management factors	13
Clarity of drawings and specifications	75.152	Technological factors	14
Labor motivation	73.651	Workforce / Manpower factors	15
Working for long periods without holidays	73.636	Workforce / Manpower factors	16
Safety requirements and regulations	73.030	Management factors	17

Table (3.2): importance Indices and Rankings of Factors Surveyed, and their Relative Groups Cont.

Factor	%RII	Group	Rank
Absenteeism	72.727	Workforce / Manpower factors	18
Design complexity	72.121	Technological factors	19
Wind or dust	72.121	External factors	20
Incentive programs	70.303	Management factors	21
Variation/change orders	70.303	Technological factors	22
Crew size and composition	69.836	Technological factors	23
Lack of labor recognition programs	69.688	Management factors	24
Rework	69.688	Technological factors	25
Work at heights	69.394	External factors	26
Overtime	69.091	Workforce / Manpower factors	27
Workers turnover or changing crewmembers	68.788	Workforce / Manpower factors	28
Precipitation / rain	68.485	External factors	29
Site Layout and condition	68.182	Technological Factors	30
Government laws	67.273	External factors	31
Labor age	67.097	Workforce / Manpower Factors	32
Inspection delays	66.984	Technological Factors	33
Project duration	66.769	Technological Factors	34
Repetition of work	66.769	Workforce / Manpower Factors	35
Storage location	66.462	Technological Factors	36
Political unrest	66.364	External factors	37
Project type	66.061	Technological Factors	38
Rest time(s) per day	65.625	Workforce / Manpower Factors	39
Labor education	64.063	Workforce / Manpower Factors	40
Labor personal problems	63.030	Workforce / Manpower Factors	41
Shift work	61.212	Workforce / Manpower Factors	42
Noise	60.909	External factors	43

With almost 50% of the factors scoring RII of more than 70%, it appears that the selection of the factors was appropriate. The results obtained show that the top ten i.e. the most critical factors influencing labor productivity in Bahrain's construction industry are the following: (1) Labor skills (2) Temperature (3) Lack of Supervision (4) Labor experience (5) Humidity (6) Work planning and scheduling (7) Availability of tools and equipment (8) Material shortage at project site (9) Management leadership and (10) Payment delay. The results were to a certain extent expected and can be justified as follows:

- Labor skills: is the most influencing factor of CLP according to a lot of researches investigating this topic. The main reason is that unskilled workers are not able to perform the construction activities correctly, and if they do, it could be in a very slow progress or bad quality resulting in a lot of problems such as rework which would certainly cause a drop-in productivity. On the other hand, skilled labors achieve higher productivity, and better quality of production.
- Temperature: because of the geographical location of Bahrain and the desert terrain nature, Bahrain experiences a very hot and long summer where the temperature reaches up an average of 40° C and in the worst condition (during the months of June, July, August and September) it soars to 50°C making working outdoor especially very difficult and intolerable. As a result, government of Bahrain represented by Ministry of Labor imposes a summer work ban on open construction sites during the months July and August between 12 noon to 4 after noon, which guards the labor health, however, affects the production rates at construction sites.
- Lack of supervision: the presence of incompetent supervisors at construction sites may result in slack work by the workers or poor-

quality production. It may also lead to accidents at work place or slow progress of works. Hence, lack of supervision is critical for the CLP.

- Labor experience: construction companies are "projectized" organizations which mostly employ workers temporarily, labors are unable to survive without experience and skill. Labor experience shortens labor learning time of an activity and boosts his skills enabling more production in less man-hours.
- Humidity: Bahrain is surrounded by the sea, and humidity is at its highest, reaching above 80 to 90% especially in the summer. High humidity levels at work directly affect employee health and business productivity.
- Work planning and scheduling: lack of work planning and scheduling lead to delays in work progress. A good project manager pays a great attention of long lead items, and plans when to order it and a good site supervisor can foresee work needs effectively so as to minimize the idling time and maximizing the productive time.
- Availability of tools and equipment: labors will be idle without the right tools and equipment. Shortage of tools or faulty equipment would surely affect labor productivity at construction sites.
- Material shortage at project site: without materials masons will not be able to do plastering and painters will not be able to paint and this is the case with most of construction activities that involve the use of materials.
- Management Leadership: with effective management leadership, construction firms will be able to motivate workers, grasp their trust and respect and resolve problems as they arise which will improve the productivity and the competitiveness.

- Payment delay: the payment delay affects the contractor considerably and may result in "Late payment of salaries" to the labors affecting their productivity at work. (Nasser, 2013)

The questionnaire findings substantiate to some extent the results obtained by Jarkas (2015) who published the only study about the factors influencing labor productivity in Kingdom of Bahrain. He concluded that labor skill is the most influencing factor on the CLP, and that lack of supervision and inclement weather ranked within the top ten influencing factors. These are similar findings to those discussed in the aforementioned paragraph.

However, some differences were noticed, for example Jarkas (2015) found that "Rework" is a critical factor that is ranked as the sixth in the top ten according to his survey, although the same factor was not considered critical among the population surveyed in this study (grade A and AA contractors), which are known for their quality of work. The differences found might be due to the fact that he included grade B contractors in his population and selected a representative sample instead of targeting all grade A and AA contractors. The other reason may be because he considered slightly different factors to the ones considered in this thesis, such as "Coordination among design disciplines", which was concluded by Jarkas (2015) as a critical factor influencing CLP. However, it was not considered to be a big problem to the respondents from grade A and AA firms who participated in the questionnaire. As well as the factor "Inclement weather" in Jarkas (2015) study which was subdivided to "Temperature", "Humidity", "Perception/Rain", and "Wind or dust" as they have different impact on CLP, suggested by Sonmez and Rowings (1998), Hicksona and Ellis (2014) and others.

3.3 Historical Data Collection

The second type of data is the historical data for current and completed projects done by the construction companies who participated in the questionnaire. The historical data about the productivity or production rates (measured as production of an activity over man-hours spent during performing it) will be required to be used as the dependent variable (Y) or "response" of the developed predictive models. Conversely, the historical data about the productivity influencing factors will be needed to construct the models as it will represent the independent variable of the model (X1, X2...etc.) or in another word the "predictors".

Surprisingly, not all the companies were keeping productivity records and in fact only two companies of grade AA and one company of grade A were able to provide such data. The reason is mainly because many construction companies relies on norms that are used in estimation and planning purposes, these norms are usually generated from senior employees who has an experience in the construction field and it is recorded at a summary level which cannot be used for productivity analysis purposes. Hence, keeping productivity records would be a major improvement area that construction companies' needs to consider.

The databases of the contractors, who keep records, included several tasks but only some of them had sufficient number of data points that can be used for modeling purposes, which were: concrete pouring, formwork, block work and steel fixing. The data was collected from building construction projects in Kingdom of Bahrain at various levels of progress during 2015 to 2017-time frame, and consisting of total of 113 data points for block, 55 for concrete, 144 for formwork and 109 for steel fixing. Sample of daily

report used by one of the contractors to record resources and activities is shown in Appendix 5 while the complied data is shown Appendix 6

Although 43 construction productivity influencing factors were identified in the previous stage, not all of them were measurable and even if they were there was lack of relevant records. For example, if the top ten ranked factors are considered, which are: (1) Labor skills (2) Temperature (3) Lack of Supervision (4) Labor experience (5) Humidity (6) Work planning and scheduling (7) Availability of tools and equipment (8) Material shortage at project site (9) Management leadership and (10) Payment delay, then labor skills, management leadership and work planning are not measurable.

On the other hand, there is no information in the contractor records about labor experience and whether material shortage or payment delay is faced at project or not. Hence, the included factors for developing the models were decided based on: how critical is the factor based on the RII analysis, if it is a measurable factor, and if sufficient data/ records are available for this factor. The selected factors for steel fixing, concrete pouring, form work and block work CLP models are elaborated as follows:

- **For steel fixing productivity models:**

1. Daily production of steel fixing: or the daily quantity of fixed steel by steel fixers measured in kg
2. Number of steel fixers carrying out the steel fixing activity at a particular day
3. Floor level at which the activity is being carried
4. Number of daily working hours
5. Number of overtime hours if any
6. Element type: indicating which structural element is being reinforced; whether it is a beam, column, slab...etc.

7. Weekday whether it is Sunday, Monday...etc.
8. Season: the working time changes during August, July and Ramadan
9. Daily average temperature during working hours measured in °C
10. Daily maximum and minimum temperature during working hours measured in °C
11. Number of total plant equipment used in a working day to facilitate carrying out the construction activities which may be cranes, forklifts and others
12. Daily total direct manpower at site which includes steel fixers, other trades, non-skilled labors and supervisors
13. Daily average humidity during working hours expressed as a percent %
14. Daily average wind speed during working hours measured in km/hour

• **For concrete pouring productivity models:**

1. Daily production of concrete pouring: or the daily quantity of placed concrete by the masons measured in cubic meter
2. Number of masons carrying out the concrete pouring activity at a particular day
3. Element type: indicating which structural element is being concreted whether it is a beam, column, slab...etc.
4. Floor level at which the activity is being carried
5. Daily total direct manpower at site which includes masons, other trades, non-skilled labors and supervisors
6. Daily average humidity during working hours expressed as a percent %
7. Daily average wind speed during working hours measured in km/hour
8. Daily average temperature during working hours measured in °C
9. Weekday whether it is Sunday, Monday...etc.
10. Number of daily working hours

11. Number Labors/ non-skilled workers in a working day
12. Work method: whether a concrete pump is hired to carry out the concrete pouring
13. Concrete placing time in minutes (i.e. the time required to discharge the concrete from the ready-mix truck)
14. Concrete mix which affect the workability and hence the concrete pouring activity.

- **For formwork productivity models:**

1. Daily production of formwork or total area of molds built/dismantled by carpenters measured by square meter.
2. Number of carpenters carrying out the formwork activity at a specific working day.
3. Weekday whether it is Sunday, Monday...etc.
4. Number of daily working hours
5. Number of overtime hours if any
6. Daily total direct manpower at site which includes carpenters, other trades, non-skilled labors and supervisors
7. Number of total plant equipment used in a working day to facilitate carrying out the construction activities which may be cranes, forklifts and others
8. Season: the working time changes during August, July and Ramadan
9. Daily average humidity in during working hours expressed as a percent %
10. Daily average wind speed during working hours measured in km/hour
11. Daily average temperature during working hours measured in °C
12. Daily maximum and minimum temperature during working hours measured in °C

- **For block work productivity models:**

1. Daily production of block work measured in number of blocks.

2. Daily number of masons carrying out the block work activity
3. Weekday whether it is Sunday, Monday...etc.
4. Number of daily working hours
5. Daily total direct manpower at site which includes masons, other trades, non-skilled labors and supervisors
6. Number of total plant equipment used in a working day to facilitate carrying out the construction activities which may be cranes, forklifts and others
7. Season: the working time changes during August, July and Ramadan
8. Number of labors / non-skilled workers in a working day
9. Daily average humidity during working hours expressed as a percent
10. Daily average wind speed during working hours measured in km/hour
11. Daily average temperature during working hours measured in °C
12. Number of direct supervisors supervising the block work activity
13. Number of subcontractors engaged in block work activity if any

The non- numerical values were replaced with numerical values for modeling purposes, for example the weekdays such as Sunday and Monday were changed to 1 for Sunday, 2 for Monday and so on. In addition to the season, the element type, the floor level, the mix type and the use of concrete pump all were represented in terms of numerical values. The same is illustrated in detail in Table 3.3.

The slight dissimilarity noticed in the factors among the four construction activities is due to the different technical requirement of each activity and to the availability of the data for the same.

Table 3.4 shows the relationship between the selected factors for modeling and the relevant factors concluded from the questionnaire such as temperature which was substituted in the models with the average daily temperature during a working day.

In some models such as steel fixing daily maximum and minimum temperatures during working hours were also considered. The lack of supervision was substituted with the number of direct supervisors supervising the activities. The humidity was reported as the daily average humidity in a working day.

Weather data were obtained from Bahrain Meteorological Directorate web portal, and averages of temperature, humidity and wind speed were calculated during working hours.

Combined tables were established afterwards for each of the four construction activities in Microsoft Excel (refer to Appendix 6).

Table (3.3): Replacing Non- Numerical Variables with Numerical Values

Variables	Description
Floor level	Reported as: ground floor = 0, first floor =1, second floor =2, boundary wall =3, roof = 4
Element type	For concrete pouring, reported as: 0 = blinding 1= footing, 2= retaining wall, 3= ground beam ,4= beam, 5=ground slab, 6= lift, 7=post- tensioned slab and for steel fixing: 1= footing, 2 = retaining wall footing, 3 = column and lintel, 4= slab and beam 5= retaining wall and ground beam, 6= boundary wall, footing, lintel, 7= lift and staircase, 8= retaining wall, ground beam, footing, 9= retaining wall and footing, 10= retaining wall footing and column, 11= footing column and lintel, 12= footing and ground beam
Weekday	Represented in terms of seven numerical values: Sunday =1, Monday =2, Tuesday =3, Wednesday =4, Thursday =5, Friday =6, and Saturday =7

Table (3.3): Replacing Non- Numerical Variables with Numerical Values Cont.

Variables	Description
Season	Reported as: 0= Normal work time, 1= Ramadan timing, 2= Summer timing
Mix type	Reported as: 1= grade C45 mix, 2= grade C55 mix, 3= grade C50 mix
Pump	Reported as :0= concrete pouring without pump, 1= concrete pouring using pump

Table (3.4): The Questionnaire Factors versus the Modeling Factors

Factors used in modeling	Factors from questionnaire	RII rank
Average temperature during working hours	Temperature	2
Maximum and minimum temperature during working hours		
Number of direct supervisors	Lack of supervision	3
Average humidity during working hours	Humidity	5
Number of total plant equipment	Availability of tools and equipment	7
Pump – <i>in concrete pouring model</i>		
Number of subcontractors if any	Management of subcontractors	13
Average wind speed during working hours	Wind or dust	20
Number of skilled workers (<i>e.g. steel fixers in steel fixing models</i>)	Crew size and composition	23
Number of non-skilled workers		
Total direct manpower at site		
Floor level	Work at heights	26
Overtime	Overtime	27
Season	Season – suggested by respondents	-
Weekday	Weekday– suggested by respondents	-

3.4 Chapter Summary

In this chapter, the CLP influencing factors in Kingdom of Bahrain were identified through a survey targeted grade A and AA contractors. The questionnaire design, distribution and results were discussed in detail, RII analysis was used to rank the identified factors followed by a justification of the findings and a comparison with other researchers' findings. Also, the procedure of historical data collection was explained, the encoding of the information (i.e. replacing the non-numerical data with numbers to be fed into the models) and the factors that will be included in steel fixing, concrete pouring, formwork and block work models were selected.

CHAPTER 4

Construction Labor Productivity Modeling with Neural Network

- 4.1 Introduction**
 - 4.2 Modeling Methodology**
 - 4.3 Models Training and Testing**
 - 4.4 Models Comparison**
 - 4.5 Chapter Summary**
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Chapter 4

Construction Labor Productivity Modeling with Neural Networks

4.1 Introduction

Artificial neural networks and regression analysis were selected -among other modeling techniques- to build the productivity models because of their proven effectiveness and widespread use in many areas of construction research. Hence, the aim of this chapter and the succeeding chapter is to develop predictive models which are capable of utilizing the statistics and knowledge gained from the collected data to forecast the selected activities' productivity with neural network first, followed by regression analysis in Chapter 5.

Neural networks have the ability to learn from different scenarios (represented by number of inputs and their associated outputs), generalize the knowledge gained (during a process called "training") and predict outcomes of modeled systems for given input patterns. Many researches have proved that neural networks can solve complex prediction problems even those that are relevant to construction industry, such as Kulkarni et al. (2017) who suggested that the ANN is highly beneficial in interpreting inadequate information to arrive at meaningful conclusions related to prediction of costs, risk and safety. In that direction, Nasser (2013) developed a model based on neural networks to measure the risk of payment delay in Gaza strip construction industry.

NeuroXL Predictor, which is a program utility that can enhance the primary program which is Microsoft Excel, was used to predict CLP in productivity combined tables -stored in spreadsheets form- by its advanced neural network-based methods.

NeuroXL Predictor provides accurate results in a short time and without the need of prior knowledge of neural networks. It is easy to use, intuitive and capable of attending the most demanding professionals. Prime applications of NeuroXL Predictor include: forecasting stocks and other investments (such as oil and gas trading), sales forecasting and sports predictions. NeuroXL Predictor hides the complexity of its advanced neural network-based methods and takes advantage of user's knowledge of Microsoft Excel spreadsheets where most of the records and data are being stored/kept. Users shall select the input and output values from Excel spreadsheets, set neural network parameters and NeuroXL Predictor will do the rest to generate required predictions and display it on the same spreadsheets.

4.2 Modeling Methodology

Predictive models for steel fixing, concrete pouring, formwork and block work were developed using NeuroXL Predictor. The methodology of productivity modeling with NeuroXL Predictor can be summarized as follows: The combined data tables for each of the four activities were divided into training set and testing set. The training set was used to develop the model using different neural network parameters available in NeuroXL Predictor while the testing set was used to validate the model by predicting the productivity of new points that were not used in developing the model. NeuroXL Predictor dialog box shown in Figure (4.1) allows the

NeuroXL Predictor

Neural Network Parameters Settings

Training parameters

Training Inputs: Concrete (1)!IC2:P45

Training Outputs: Concrete (1)!B2:B45

☒ Show learning process

New Start Save Load

Prediction parameters

Prediction Inputs: Concrete (1)!IC46:P56

Prediction Outputs: Concrete (1)!Q46:Q56

Predict

Epoch: 3000 Weight Delta: 0.0000930

Actual Predicted

Epoch	Actual	Predicted
0	-10	-10
10	10	10
15	130	120
20	10	10
30	10	10
40	20	20
50	0	0

The training parameters are the training inputs, training output, number of epochs and minimum weight delta. Explained as follows:

- i. *Training inputs*: which are the productivity influencing factors (The independent variables of the model) in the training set. These factors are: production, floor level, workers number, working hours, the overtime - if any, element type, week day, season, minimum and maximum temperature, total plant, total manpower, humidity and the wind.
- ii. *Training outputs*: represented by the dependent variable of the model which is the productivity rates (PR) obtained by dividing the production over the man-hours spent during performing an activity in the training set.
- iii. *Number of epochs*: where an epoch is a full cycle training of a neural network on the entire training set and the term "Number of epochs" represents the maximum learning cycles of epochs to reach the specified minimum weight delta.
- iv. *Minimum weight delta*: This describes the desired lowest weight correction value when the network is considered to be trained adequately.

While the prediction parameters are the prediction inputs and outputs:

- i. *Prediction inputs*: which are the productivity influencing factors from the combined data tables given to the developed model to produce productivity predictions.
- ii. *Prediction outputs*: which are the predicted productivities of an activity by a model given the prediction inputs and subjected to neural network parameters.

The neural network parameters however are as shown in Figure (4.2):

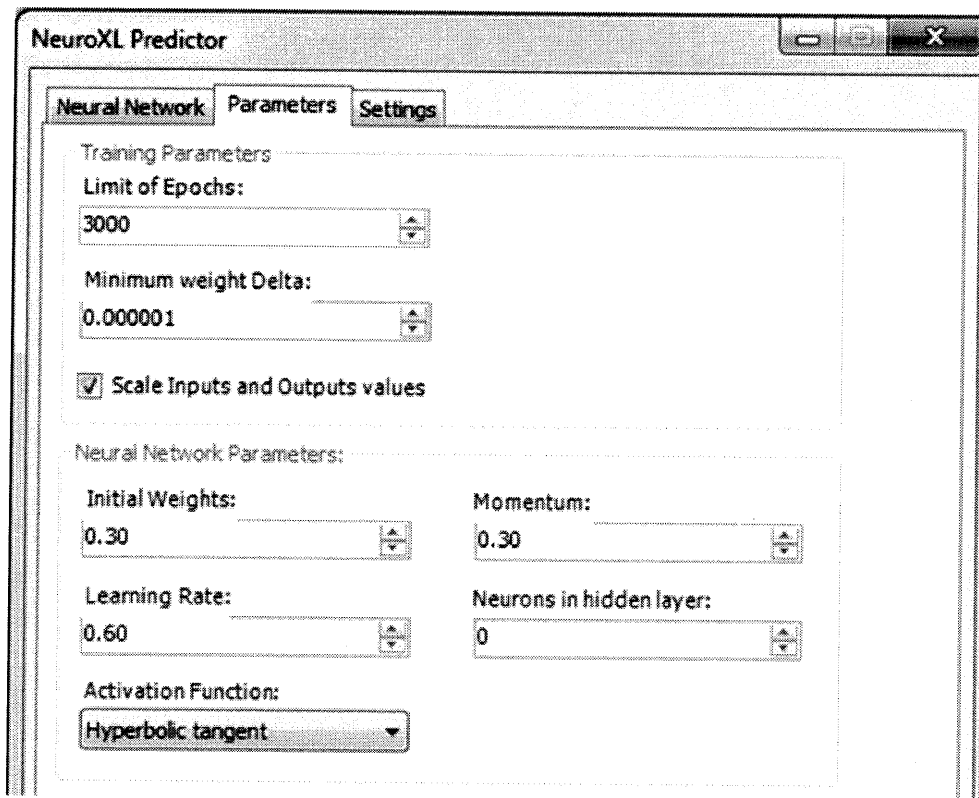


Fig. 4.2: NeuroXL Predictor Dialog Box: Neural Network Parameters

- i. *Initial weights*: initial weights of synapses (where neural network neurons communicate with each other), the amount of signal transmitted depends on the synapse weight (strength of connection). Synapses of every neuron will be initialized with random values from 0 to the initial weights.
- ii. *Learning rate*: a value between 0 and 1 affecting the rate at which the network learns. Faster convergence of the network is expected with larger learning rate; however, too high learning rate would result in fluctuation and non-convergence.
- iii. *Momentum*: a value between 0 and 1 that determines the amount added to the next weight change by the previous weight change.
- iv. *Activation function*: transfer function in the neural network used to convert an input signal of a node to an output signal. There are four linear and nonlinear functions available in NeuroXL Predictor which are: Threshold, Hyperbolic tangent, Zero-based log-sigmoid, Log-sigmoid.

- a) Threshold: depending on whether the total input is greater than or less than a specific threshold value, the output is set at one of two levels.

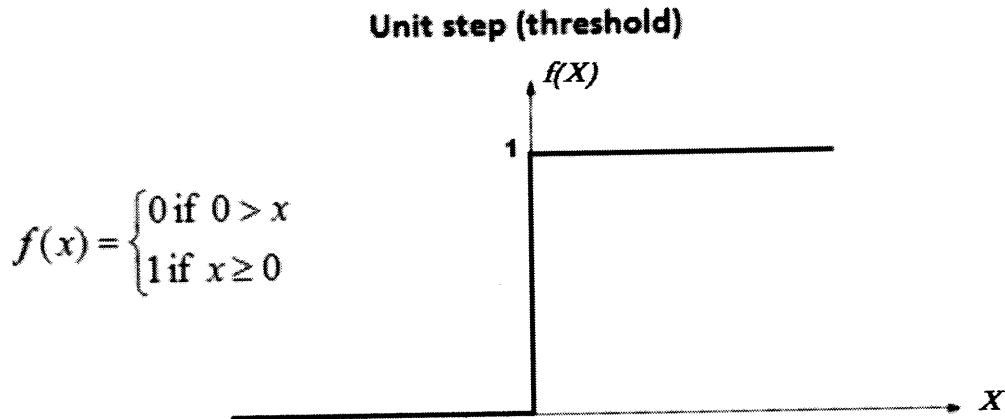


Fig. 4.3: Threshold Activation Function Illustration

- b) Hyperbolic tangent: the ratio between the hyperbolic sine and the cosine functions.as shown in Figure (4.5)

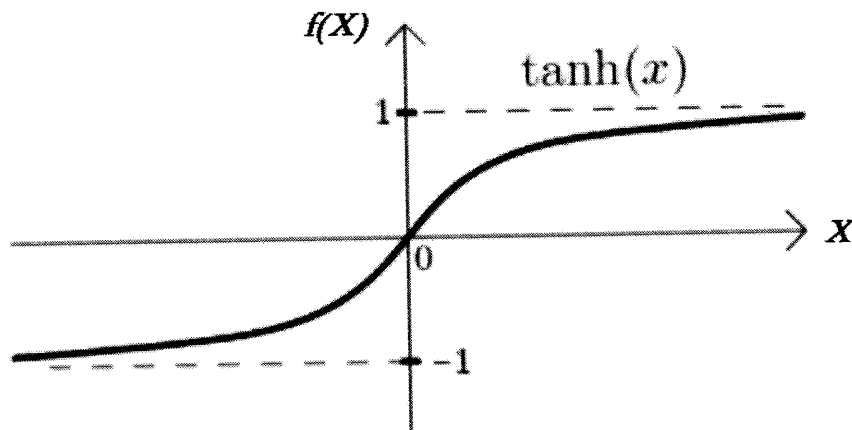


Fig. 4.4: Hyperbolic Tangent Activation Function Illustration

- c) Zero-based log-sigmoid and Log-sigmoid: the two types of sigmoid function are logistic and tangential. The values of logistic function (zero based) range from 0 and 1, and -1 to +1 for tangential.

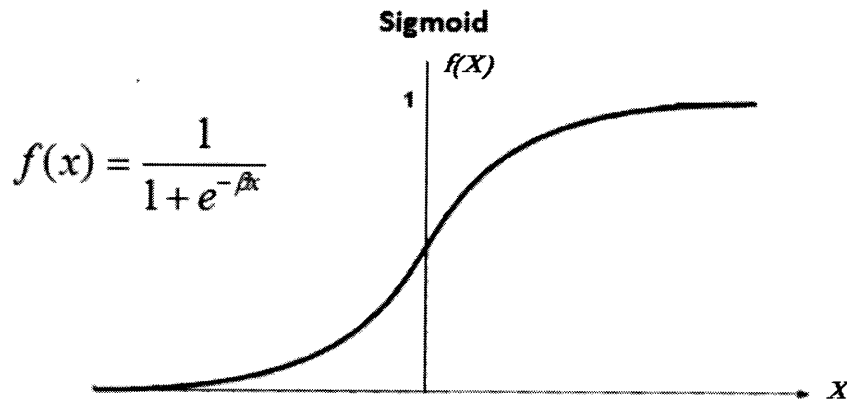


Fig. 4.5: Sigmoid Activation Function Illustration

- v. *Neurons in hidden layer:* many researchers (such as Panchal and Panchal (2014) and Sonmez and Rowing (1998)) have suggested rules and guidelines for setting number of neurons in hidden units, such as the rule of thumb, simple and two phases method. The studies showed that if too many hidden units are used in the neural network it may result in poor prediction performance. Conversely, if insufficient number of hidden units is used, the model may not have enough parameters to identify the mapping function.

Having defined neural network and prediction parameters, the settings and range of values are saved using the dialogue box shown in Figure (4.6).

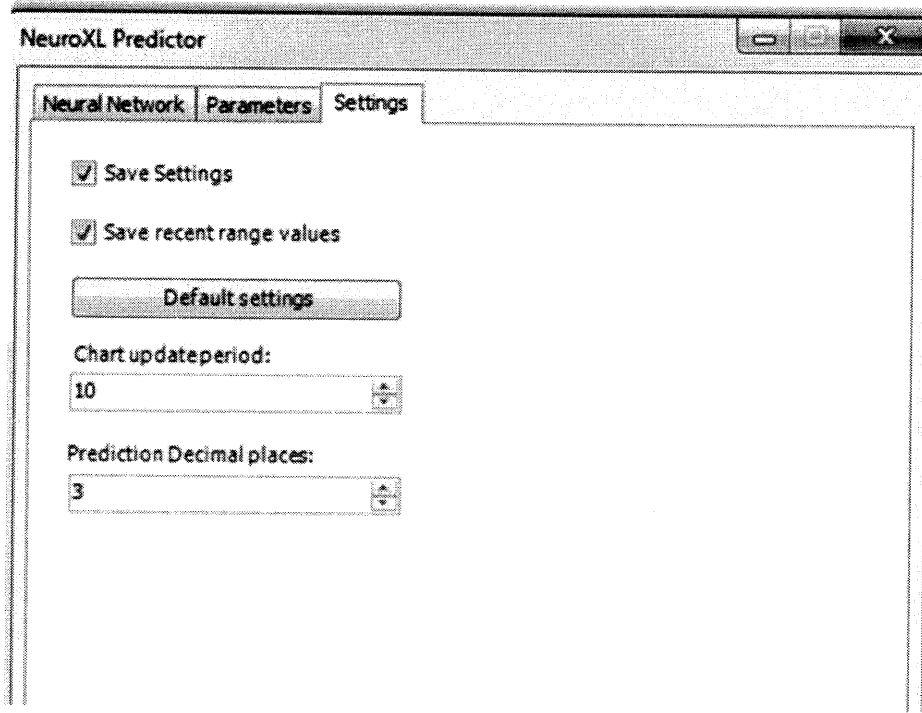


Fig. 4.6: NeuroXL Predictor Dialog Box: Settings

The criteria used to shortlist the modeling trials and to select the best model among different models developed with different neural network parameters was to compare these models with each other in terms of closeness of fit and prediction performance. Several error measures were used to compare goodness of fit (i.e. how well a model fits a set of data points or observations) and prediction performance (prediction accuracy of a predictive model) of the models which are: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percent Error (MAPE) calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Actual_i - Predicted_i)^2}{n}} \quad (4.1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (Actual_i - Predicted_i)^2 \quad (4.2)$$

$$MAD = \frac{\sum_{i=1}^n |Actual - Forecast|}{n} \quad (4.3)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|Actual_i - Predicted_i|}{Actual_i} \times 100 \quad (4.4)$$

Where n is the total number of data points for the model.

Because of the high variation found in the production rate values, all the aforementioned measures used together to provide better insight of the closeness of fit and prediction performance of the models. Additionally, the coefficient of determination (R^2) was calculated for all the models, to show the extent to which the dependent variable (CLP) is predictable, given as:

$$R^2 = 1 - \frac{\sum (Y_i - \hat{Y}_i)^2}{\sum (Y_i - \bar{Y})^2} \quad (4.5)$$

Where,

Y_i = i^{th} average productivity change reading

$\bar{Y}$ = Mean Response

$\hat{Y}_i$ = i^{th} fitted response

A scheme was established to shortlist the developed models' trials using different neural network parameters, and to support the analysis of the results. The scheme can be summarized as follows:

- The recommended default values for the neural network parameters -excluding the activation function - were used in the initial models

for each of the four activities being studied. The default values given by NeuroXL are:

- Initial weights are 0.3
 - Learning rate is 0.3
 - Momentum is 0.6
 - Neurons in hidden layers are 0
- In each trial conducted, one of the available activation functions which are threshold, hyperbolic tangent, zero-based log-sigmoid and log-sigmoid was used. The prediction performance of each developed model was calculated and the activation function indicating best performance was selected for the next stage.
- More trials were conducted using the same activation function (with the best performance) but with setting learning rate and momentum values to 0.3 and 0.6 initially and to 0.5 and 0.9 later (suggested by Sonmez (1996)). The number of neurons in hidden layer was changed from zero to:
- $2n+1$, where n being the number of input units (in this case number of productivity influencing factors)
 - $n/2 + 1$
 - more than $2n+1$ taken equal to 100

Both $2n+1$ and $n/2+1$ were suggested by Sonmez and Rowing (1998).

The model trials conducted for steel fixing, concrete pouring, formwork and block work are presented in Figures 4.7, 4.8, 4.9, and 4.10 respectively. In order to evaluate the predictive performance of developed models, the collected data was divided into a training set and a test set. The training set is used to construct and train the model while the test set is used to evaluate it; this procedure is called "cross validation".

There are common methods for cross validation such as k-fold, leave one out, and holdout method. The last method was selected to avoid over-training and for its practicality.

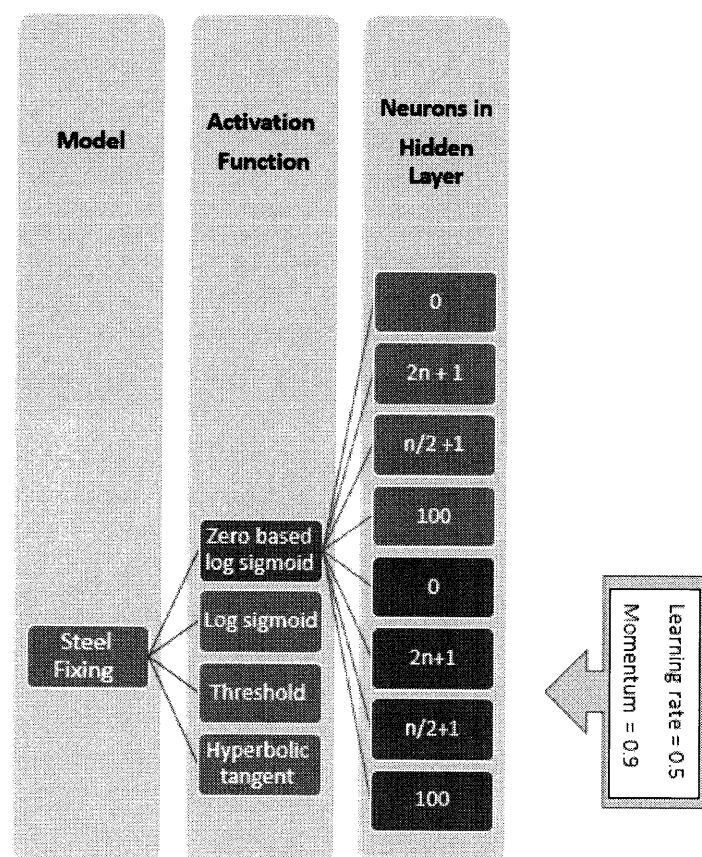


Fig. 4.7: Steel Fixing Modeling Trials with NeuroXL

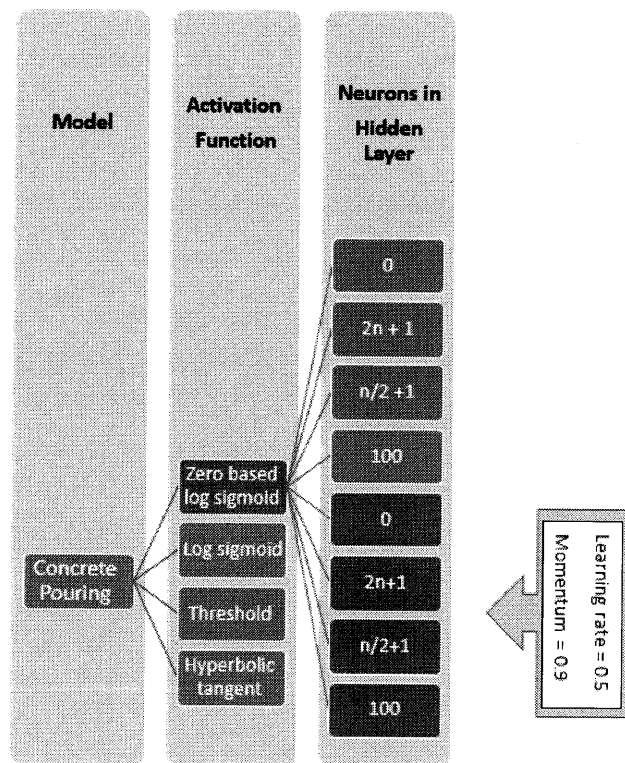


Fig. 4.8: Concrete pouring Modeling Trials with NeuroXL

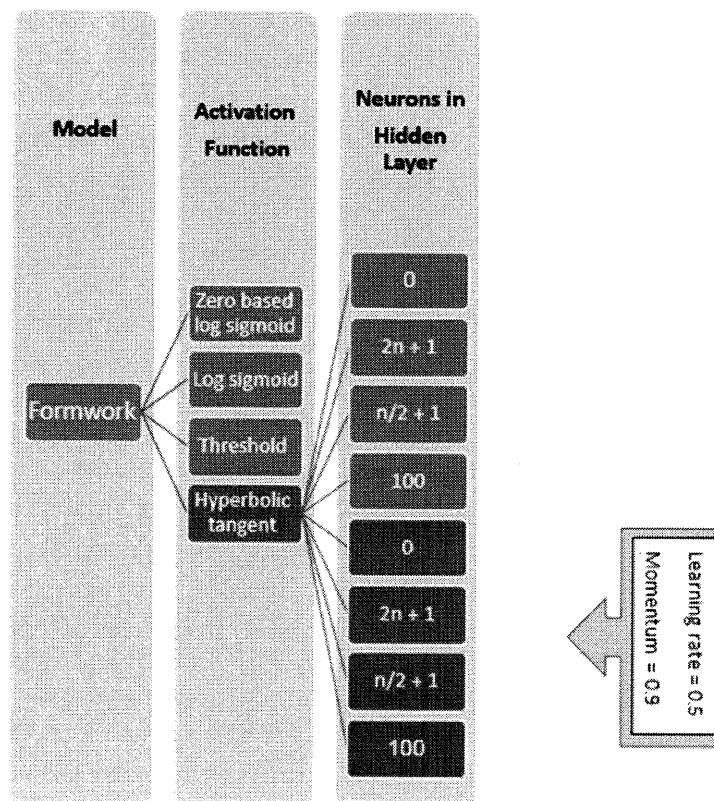


Fig. 4.9: Formwork Modeling Trials with NeuroXL

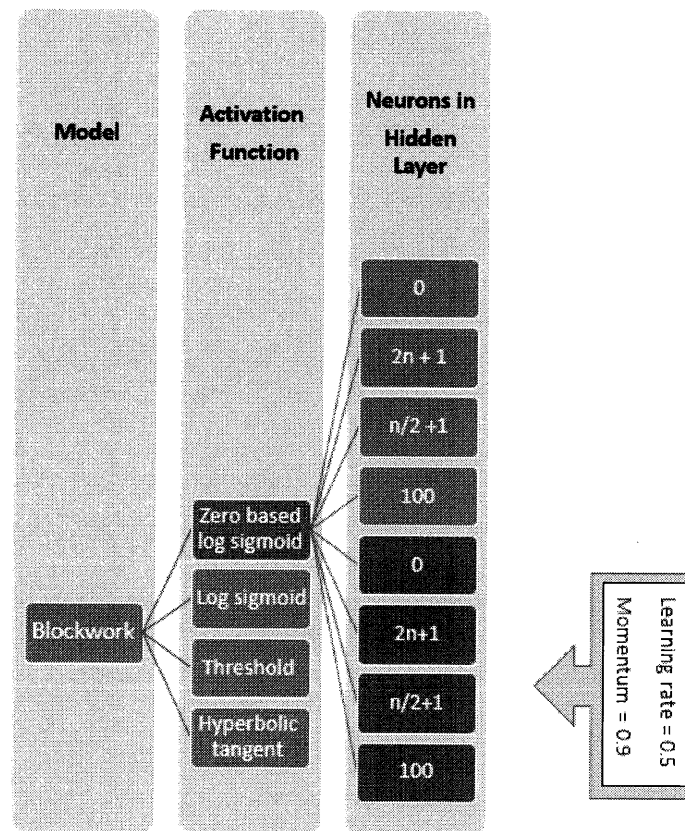


Fig. 4.10: Block work Modeling Trials with NeuroXL

In the holdout method, data points are randomly assigned to two sets of different size. The selection of splitting criterion is arbitrary although typically the test set is smaller than the training set. A frequently used splitting criterion is 70 -30, where 70 % of the data is used to calibrate the predictive model whereas the other 30 % for validation.

The procedure with which the cross validation was done can be summarized in the following steps:

1. 70 % of data collected for modeling were used for model development and training and the remaining 30% were retained for validating the model, i.e. testing the performance of the model in terms of predictions accuracy.
2. The same training set and the same testing set were used for all the models to avoid unbiased comparison as evaluation may be

significantly different depending on which data points end up in the training set and which end up in the test set.

3. The errors in the developed model's prediction were accumulated to evaluate the performance of the model. MSE, MAPE, RMSE, MAD, and R^2 were calculated for the training and the test set for the final comparison and the optimum model selection.
4. The same validation procedure was applied to all neural network and later regression models.

4.3 Models Training and Testing

The artificial neural network learns the patterns of training data and apply this knowledge to get predictions close to desired values in a process called "Model training". The combined data tables of steel fixing, concrete work, formwork and block work were preserved in Excel spreadsheet format -as it is compatible with the NeuroXL predictor- then the training set was separated from the testing set in the same spreadsheet. The training set was used to develop neural network models that will predict CLP values for the same set to be compared later with the actual values.

In NeuroXL Predictor dialog box the training parameters were set as: first the training inputs which were CLP influencing factors data in the training set, then the training output which is the actual CLP values for the training set. The numbers of epochs taken as 3000 (which is the default value) and the minimum weight delta fixed as 0.000001(the preset value). This means that the neural network will be trained for 3000 full cycles on the entire training set and the weights will be adjusted to achieve minimum weight delta of 0.000001. Also, the neural network parameters which are Initial weights, learning rate, momentum, activation function and number of

neurons in hidden layer were changed in accordance to the scheme described in Section 4.2.

Upon the completion of model training, the dialog box shows a graphical representation for the relationship between the actual values and the predicted values. Thus, the model is ready to predict the output of the training set which will give the "training error" and test set error. The error measures were calculated in the same spreadsheet for each of the developed models to facilitate the assessment of their accuracy and performance as described in Section 4.2. In the last spread sheet for each activity however all the models were gathered in a single table for further comparison. The remaining 30% of the data thereafter was used to assess the prediction performance of the developed models and to validate it. Predicting CLP for the testing set accurately will give an indication that the model is capable of predicting CLP for new data. In the NeuroXL predictor dialog box, the CLP influencing factors data for the test set were selected as prediction inputs and the empty cells in the spreadsheets were selected as prediction outputs in which trained model predicts the CLP.

In the same spreadsheets of the combined data tables the calculations of the test error were made, and in the last sheet of the same excel file comparison tables were developed and the models were ranked to facilitate the selection of the optimum model based on its performance in predicting the CLP for the test set.

4.3.1 Neural Network for Steel Fixing

The neural network developed to model the steel fixing activity included 15 inputs which are: the daily production of steel fixing in kg; the floor level where the activity is being carried; the number of steel fixers carrying out activity; the day of the week (whether it is Sunday, Monday etc.); the

season (whether it is Ramadan or else); the maximum and minimum temperature recorded during the working hours; the average temperature during the working hours; the total plant/equipment at site (such as forklift or cranes); the total manpower at site; the average humidity during the working hours; the overtime hours; the average wind speed during the working hours; and the total working hours for a working day. Initially the trials were conducted using different activation functions while keeping the default neural network parameters in NeuroXL (which are setting zero neurons in hidden layer, a value of 0.6 for the momentum, and learning rate value of 0.3).

4.3.2 Neural Network for Concrete Pouring

In the concrete pouring models 14 inputs were considered which are: the daily production of poured concrete in m^3 ; the floor level where the activity is being carried; which element is being casted (e.g. columns, beams etc.) the number of masons carrying out activity; the day of the week (whether it is Sunday , Monday etc.); the poured concrete mix type (i.e. C35 or C50 etc. which represent the concrete mix physical and chemical characteristics); the concrete placing time (the time between starting the concrete pouring until the transit mixer discharges all its content) in min; the average temperature during the working hours; whether a pump was used in concrete pouring or not; the total manpower at site; the average humidity during the working hours; the average wind speed during the working hours; and the total daily working hours. Using different activation functions while keeping the default neural network parameters in NeuroXL at first and then changing the parameters for the model with the best fit activation function (in this case the log sigmoid).

4.3.3 Neural Network for Formwork

Conversely, 13 factors were considered in the formwork models which are: the daily production in m^2 ; the number of carpenters participated in formwork; the total working hours for a day; the overtime hours if any; the week day; the season; the minimum and maximum temperature recorded during the working hours, the average temperature during the working hours; the total plant/equipment used; the total manpower; the average humidity; and wind speed during the working hours.

4.3.4 Neural Network for Block work

In the block work neural network models included the following 14 factors: the total daily production of block work measured in number of blocks; the average temperature; humidity and wind speed during the working hours; number of masons carried out the block work activity; number of subcontractor involved if any; number of supervisor supervising the block work activity; the total number of labors; the total number of plants; the working hours; the total workforce ; the week day; and the season. The model's performance with hyperbolic tangent activation function excelled the other models using different activation functions, thus the next step was to develop models using hyperbolic tangent function but with changing the number of neurons in the hidden layer or the momentum and learning rate values.

4.4 Models Comparison

Tables 4.1, 4.2, 4.3, and 4.4 shows the training error of the developed models for steel fixing, concrete pouring, formwork and block work, respectively.

The first four rows in the tables demonstrate the effect of changing the activation function (Log sigmoid, zero based sigmoid, hyperbolic tangent and threshold) on models' performance without changing the number of neurons (from zero). The following three rows show the effect of changing number of neurons from zero to $n/2+1$, $2n+1$, and 100 on the models' performance for the best activation function. Followed by the last four rows which illustrate the effect of changing the preset parameters, specifically the learning rate and the momentum to 0.5 and 0.9 (the preset values are 0.3 and 0.6 respectively) on the various error measures.

Table (4.1): Steel Fixing Models Training Error

Training set						
Model	RMSE	MAPE	MSE	MAD	R ²	Configuration
1	21.320	6.757	454.523	15.361	0.975	Log Sigmoid, 0 neurons
2	275.273	105.661	75775.213	258.471	0.297	Threshold, 0 neurons
3	1.946	0.732	3.787	1.443	1.000	Hyperbolic tangent, 0 neurons
4	8.024	3.079	64.392	6.129	0.997	Zero based, 0 neurons
5	6.468	2.107	41.832	4.633	0.998	Zero based, 9 neurons
6	7.752	2.897	60.091	5.804	0.997	Zero based, 31 neurons
7	11.877	2.897	141.052	8.808	0.993	Zero based, 100 neurons
8	7.398	2.444	54.732	5.353	0.993	Zero based, <i>diff</i> , 0 neurons
9	6.496	2.053	42.198	4.715	0.998	Zero based, <i>diff</i> , 9 neurons
10	7.302	2.553	53.316	5.327	0.997	Zero based, <i>diff</i> , 31 neurons
11	11.748	4.259	138.026	8.481	0.993	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

For steel fixing models, the best training results were obtained with hyperbolic tangent function and zero neurons in the hidden layer resulting in: RMSE= 1.946, MAPE = 0.732, MSE= 3.787, MAD= 1.443 and R² approximately= 1.000. While the worst training was with the threshold

activation function, resulting in: RMSE= 275.273, MAPE=105.661, MSE= 75775.213, MAD= 258.471 and $R^2= 0.297$.

Table (4. 2): Concrete Pouring Models Training Error

Training set						
Model	RMSE	MAPE	MSE	MAD	R2	Configuration
1	7.307	72.613	53.393	5.065	0.865	Log Sigmoid, 0 neurons
2	0.234	7.040	0.055	0.141	0.999	Hyperbolic tangent, 0 neurons
3	34.610	541.451	1197.861	27.315	0	Threshold, 0 neurons
4	3.906	54.625	15.262	2.729	0.983	Zero based, 0 neurons
5	5.898	106.988	34.790	4.409	0.962	Zero based, 8 neurons
6	3.539	53.775	12.526	2.576	0.986	Zero based, 29 neurons
7	4.434	85.383	19.663	3.399	0.978	Zero based, 100 neurons
8	3.907	54.626	15.262	2.729	0.983	Zero based, <i>diff</i> , 0 neurons
9	3.944	67.738	15.557	2.910	0.983	Zero based, <i>diff</i> , 8 neurons
10	3.769	64.049	14.208	2.802	0.984	Zero based, <i>diff</i> , 29 neurons
11	4.113	74.188	16.917	3.089	0.981	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

While for concrete pouring, the best training results were attained with hyperbolic tangent function and zero neurons in the hidden layer resulting in: RMSE= 0.234, MAPE = 7.040, MSE= 0.055, MAD= 0.141 and $R^2= 0.999$. While the worst training was with the threshold activation function, resulting in: RMSE= 34.610, MAPE= 541.451, MSE= 1197.861, MAD= 27.315 and $R^2= 0$. One data point was excluded from the concrete pouring models training because the actual productivity was equal to zero on a very windy day which would affect the calculations of the MAPE.

Table (4. 3): Formwork Models Training Error

Training set						
Model	RMSE	MAPE	MSE	MAD	R2	Configuration
1	2.364	27.402	5.588	1.503	0.975	Log Sigmoid, 0 neurons
2	0.829	11.015	0.688	0.584	0.997	Zero based, 0 neurons
3	17.501	223.428	306.270	13.873	0.000	Threshold, 0 neurons
4	0.204	3.197	0.041	0.149	0.999	Tangent, 0 neurons
5	0.257	3.697	0.066	0.176	0.999	Tangent, 8 neurons
6	0.263	3.637	0.069	0.174	0.999	Tangent, 27 neurons
7	0.234	3.377	0.055	0.163	0.999	Tangent, 100 neurons
8	0.269	3.642	0.073	0.174	0.999	Tangent, <i>diff</i> , 0 neurons
9	0.266	3.554	0.071	0.175	0.999	Tangent, <i>diff</i> , 8 neurons
10	0.233	3.330	0.054	0.158	0.999	Tangent, <i>diff</i> , 27 neurons
11	0.313	3.969	0.098	0.199	0.999	Tangent, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

For formwork on the other hand, the best training results were achieved with hyperbolic tangent function and zero neurons in the hidden layer resulting in: RMSE= 0.204, MAPE = 3.197, MSE= 0.041, MAD= 0.149 and $R^2= 0.999$. Whereas the worst training was with the threshold activation function, resulting in: RMSE= 17.501, MAPE= 223.428, MSE= 306.270, MAD= 13.873 and $R^2= 0$ approximately.

Finally, for the block work, the best training results were obtained with hyperbolic tangent function and zero neurons in the hidden layer resulting in: RMSE= 0.452, MAPE = 0.352, MSE= 0.204, MAD= 0.354 and $R^2= 1$ approximately. While the worst training was with the threshold activation function, resulting in: RMSE= 116.135, MAPE= 117.519, MSE= 13487.289, MAD= 113.999 and $R^2= 0.26$

Table (4. 4): Block work Models Training Error

Training set						
Model	RMSE	MAPE	MSE	MAD	R2	Configuration
1	4.040	2.657	16.325	2.637	0.980	Log Sigmoid, 0 neurons
2	1.371	0.954	1.880	0.982	0.998	Zero based, 0 neurons
3	116.135	117.519	13487.289	113.999	0.260	Threshold, 0 neurons
4	0.452	0.352	0.204	0.354	1.000	Hyperbolic tangent, 0 neurons
5	0.856	0.675	0.733	0.666	0.999	Zero based, 8 neurons
6	1.311	0.943	1.718	1.038	0.998	Zero based, 29 neurons
7	1.920	1.248	3.685	1.364	0.996	Zero based, 100 neurons
8	1.293	1.008	1.671	1.009	0.998	Zero based, <i>diff</i> , 0 neurons
9	1.038	0.813	1.077	0.791	0.999	Zero based, <i>diff</i> , 8 neurons
10	1.276	0.943	1.628	0.952	0.998	Zero based, <i>diff</i> , 29 neurons
11	1.721	1.248	2.962	1.267	0.996	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

The noticeable difference in the error values among the different activities is due to the fact that these measures are scale's dependent i.e. their scale depend on the scale of the productivity and its influencing factors, for example block work is measured by number of blocks per mason conversely steel fixing productivity is measured in kg per steel fixer.

The test error results for each of the four activities are given in Tables 4.5, 4.6, 4.7, and 4.8. The best model for each activity was selected based on its performance on the test set (based on the lowest error of RMSE, MSE, MAPE, and MAD), this should give a hint on the model performance in predicting new data other than what was used for development.

Table (4. 5): Steel Fixing Models Testing Error

Test set						
Model	RMSE	MAPE	MSE	MAD	R2	Configuration
1	22.733	38.589	516.790	19.842	0.755	Log Sigmoid, 0 neurons
2	270.444	345.000	73139.941	190.013	0.098	Threshold, 0 neurons
3	49.503	75.081	2450.573	41.041	0.614	Hyperbolic tangent, 0 neurons
4	7.090	10.740	50.268	5.567	0.939	Zero based, 0 neurons
5	10.080	16.028	101.607	8.227	0.886	Zero based, 9 neurons
6	6.838	9.253	46.756	5.362	0.938	Zero based, 31 neurons
7	12.798	21.601	163.791	11.221	0.915	Zero based, 100 neurons
8	7.207	10.378	51.936	5.815	0.914	Zero based, <i>diff</i> , 0 neurons
9	10.174	12.438	103.513	7.914	0.915	Zero based, <i>diff</i> , 9 neurons
10	6.436	8.904	41.423	5.180	0.947	Zero based, <i>diff</i> , 31 neurons
11	14.304	24.782	204.611	12.702	0.912	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

Table (4. 6): Concrete Pouring Models Testing Error

Test set						
Model	RMSE	MAPE	MSE	MAD	R2	Configuration
1	33.334	361.916	1111.150	22.023	0.503	Log Sigmoid, 0 neurons
2	70.528	816.419	4974.155	54.152	0.581	Hyperbolic tangent, 0 neurons
3	35.948	397.870	1292.256	33.699	0.000	Threshold, 0 neurons
4	53.731	277.614	2886.972	35.381	0.659	Zero based, 0 neurons
5	52.520	347.348	2758.346	35.852	0.662	Zero based, 8 neurons
6	53.897	252.928	2904.901	34.289	0.680	Zero based, 29 neurons
7	52.825	350.100	2790.462	36.047	0.619	Zero based, 100 neurons
8	55.365	266.193	3065.282	35.629	0.666	Zero based, <i>diff</i> , 0 neurons
9	55.958	392.757	3131.337	37.472	0.633	Zero based, <i>diff</i> , 8 neurons
10	53.376	289.853	2849.006	35.037	0.653	Zero based, <i>diff</i> , 29 neurons
11	53.095	309.397	2819.040	35.334	0.641	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

Table (4.7): Formwork Models Testing Error

Test set						
Model	RMSE	MAPE	MSE	MAD	R²	Parameter
1	3.119	69.731	9.726	2.101	0.497	Log Sigmoid, 0 neurons
2	1.762	34.372	3.105	1.273	0.546	Zero based, 0 neurons
3	9.814	267.765	96.323	9.710	0.000	Threshold, 0 neurons
4	0.562	13.727	0.316	0.449	0.953	Tangent, 0 neurons
5	0.546	11.892	0.298	0.415	0.942	Tangent, 8 neurons
6	0.484	9.756	0.234	0.363	0.964	Tangent, 27 neurons
7	0.450	10.346	0.202	0.347	0.963	Tangent, 100 neurons
8	0.521	10.393	0.272	0.377	0.953	Tangent, <i>diff</i> , 0 neurons
9	0.466	9.047	0.217	0.334	0.956	Tangent, <i>diff</i> , 8 neurons
10	0.478	10.363	0.229	0.362	0.967	Tangent, <i>diff</i> , 27 neurons
11	0.448	8.311	0.201	0.327	0.957	Tangent, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

Table (4. 8): Block work Models Testing Error

Test set						
Model	RMSE	MAPE	MSE	MAD	R²	Parameter
1	27.448	34.120	753.408	18.710	-0.115	Log Sigmoid, 0 neurons
2	84.790	128.316	7189.318	83.964	0.000	Threshold, 0 neurons
3	33.109	36.970	1096.187	19.615	-0.200	Hyperbolic tangent, 0 neurons
4	16.474	19.093	271.404	10.411	0.249	Zero based, 0 neurons
5	16.347	19.551	267.219	11.260	0.331	Zero based, 8 neurons
6	20.145	23.579	405.816	12.707	0.088	Zero based, 29 neurons
7	21.389	27.281	457.491	15.142	0.037	Zero based, 100 neurons
8	20.948	25.290	438.815	13.814	0.045	Zero based, <i>diff</i> , 0 neurons
9	17.771	19.610	315.820	10.816	0.234	Zero based, <i>diff</i> , 8 neurons
10	17.092	19.967	292.153	10.948	0.241	Zero based, <i>diff</i> , 29 neurons
11	21.389	27.281	457.491	15.142	0.037	Zero based, <i>diff</i> , 100 neurons

*Where *diff* means that learning rate and the momentum were changed to 0.5 and 0.9

For steel fixing models, the best prediction performance was obtained with zero-based log sigmoid function, 31 neurons in the hidden layer, learning rate of 0.5 and momentum of 0.9 resulting in: RMSE= 6.436, MAPE = 8.904, MSE= 41.423, MAD = 5.180 and $R^2 = 0.947$. While the worst was with the threshold activation function, resulting in: RMSE= 270.444, MAPE= 345.000, MSE= 73139.941, MAD= 190.013 and $R^2= 0.098$.

For concrete pouring, the best model based on the test set was the zero-based log sigmoid with 29 neurons in the hidden layer resulting in: RMSE= 53.897, MAPE = 252.928, MSE= 2904.901, MAD= 34.289 and $R^2= 0.680$. While the worst was the hyperbolic tangent if the coefficient of determination is ignored, with: RMSE= 70.528, MAPE= 816.419, MSE= 4974.155, MAD= 54.152 and $R^2= 0.581$. The threshold model had the poorest fit in terms of R^2 with value equal to zero approximately.

For formwork the best CLP prediction was achieved with hyperbolic tangent function models and insignificant differences were noticed when the number of neurons was changed. The best model would be the hyperbolic tangent with: RMSE= 0.448, MAPE= 8.311, MSE= 0.201, MAD= 0.327 and $R^2= 0.957$. However, the poorest fit would be achieved by threshold function with: RMSE= 9.814, MAPE= 267.765, MSE= 96.323, MAD= 9.710 and $R^2= 0$ approximately.

Lastly for the block work, the best testing results were obtained with zero-based log sigmoid function and 8 neurons in the hidden layer resulting in: RMSE= 16.347, MAPE = 19.551, MSE= 267.219, MAD= 11.260 and $R^2= 0.331$. While the worst prediction was by the threshold activation function, resulting in: RMSE= 84.790, MAPE= 128.316, MSE= 7189.318, MAD= 83.964 and $R^2= 0$ approximately.

4.5 Chapter Summary

One of the major objectives of this research was to develop CLP models that are capable of predicting CLP given information about its influencing factors and this was achieved in this chapter using artificial neural networks technique. First an introduction was given about the neural networks and NeuroXL Predictor which is the software used to develop and test the CLP models for steel fixing, concrete pouring, and formwork and block work. Followed by a presentation of models training and testing methodology, wherein training and prediction parameters were explained with an emphasis on neural network parameters and how different configurations were derived.

The last part of this chapter presents a comparison between the models developed with different parameters in terms of RMSE, MSE, MAPE, MAD and R^2 and explains the selection of the best models.

CHAPTER 5

Construction Labor Productivity Regression Models

5.1 Introduction

5.2 Modeling Methodology

5.3 Models Development and Testing

5.4 Elevation of Factors Affecting Productivity

5.5 Models Comparison

5.6 Chapter Summary

Chapter 5

Construction Labor Productivity Models

5.1 Introduction

Subsequent to modeling with neural network in Chapter 4, this chapter presents CLP modeling with various types of regression analysis. Additionally, it analyzes the unique effect of each productivity influencing factor included in the models; this is measured in percentage contribution to the change in productivity and demonstrates the relationship between the CLP influencing factors identified by the models and those identified by the questionnaire in Chapter 3. Regression analysis is a very popular form of predictive modeling techniques that investigates the relationship between a dependent variable (the productivity of an activity in this case) and independent variables (the productivity influencing factors collected in the data collection stage). There are multiple advantages of using regression analysis, such as that it indicates the significant relationships between dependent variable and independent variable. In addition to the strength of impact of multiple independent variables on a dependent variable. There are various types of regression analysis techniques that can be used to produce predictive models and the technique selection is governed by: the independent variables number, the type of dependent variables and the type of relationship between the dependent and independent variable(s).

5.2 Modeling Methodology

Minitab software which is the statistical analysis software with great features and functionality was used to perform the regression analysis. In

this study three types of regression techniques were used, which are: linear regression the basic and commonly used in both research and business, stepwise regression for model simplification as it has the ability to manage too many potential predictor variables, and finally nonlinear regression.

For a fair comparison, the same data splitting (the same hold out method used to validate NN models) was used to develop the regression models and to test their prediction performance, i.e. using 70 % of the data for model development and holding 30% for testing the models. Based on the models' performance in predicting CLP values for the test set, best models were selected.

5.2.1 Linear Regression Models

Linear Regression is a linear approach to establish a relationship between the dependent variable and one or more explanatory variables.

- The linear regression was performed in the Minitab for steel fixing, concrete pouring, formwork, and block work using the general regression option. The productivity data were copied from the combined tables preserved in excel and pasted in the Minitab. In the general regression dialog box (Figure 5.1) the productivity was selected as the "response" and all productivity influencing factors from the combined data tables in the "Model" box.
- Minitab performed the analysis on the training data and generated the regression equation in addition to error measures, graphs and other information.
- The developed model was assessed in accordance to the coefficient of determination value which is defined as the ratio of the variation

explained by the model to the total variation in the response (Equation 4.5), usually a higher value of R^2 indicates better results.

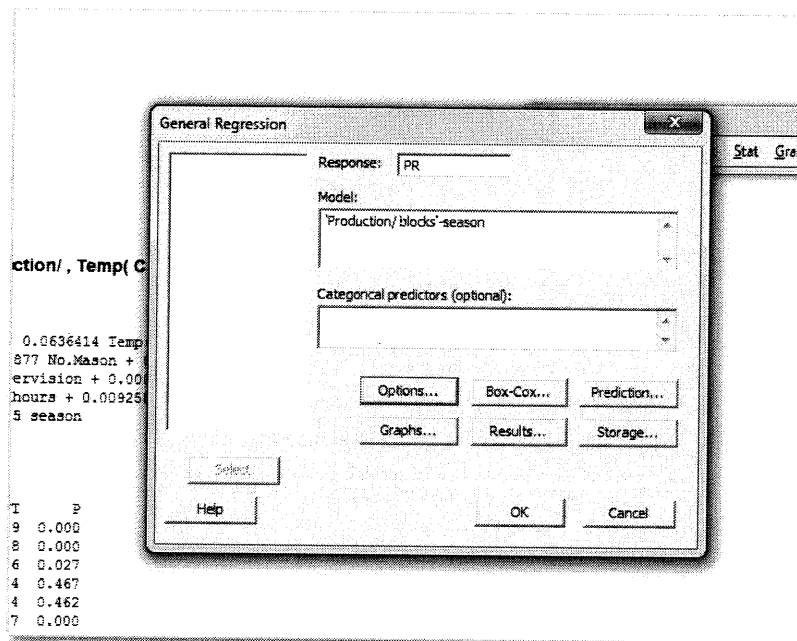


Fig. 5.1: General Regression Dialog Box

- The developed model was assessed in accordance to the coefficient of determination value which is defined as the ratio of the variation explained by the model to the total variation in the response (Equation 4.5), usually a higher value of R^2 indicates better results.
- Whenever unusual observations (outliners) are encountered, it will be removed from the model to enhance the performance until R^2 coefficient of determination percent is 70% or above. (As suggested by Ailabouni 2010).
- The regression equation of the model was copied to the combined tables in excel and was used to predict the CLP values for the training set and training error was calculated.

- The generated model including all influencing factors was validated using the test set in accordance to the holdout validation procedure described in the aforementioned sections.

5.2.2 Stepwise Regression Models

The aim of this modeling technique is to minimize the number of independent variables while improving prediction accuracy. In Minitab, the stepwise regression necessary calculations are performed through an automatic process. Minitab offers three options for stepwise regression, the standard option, forward selection and backward selection elimination:

- a. In forward selection, Minitab starts modeling with no predictors and adds the significant predictors (have p-values less than or equal to the specified alpha to enter i.e. results are statistically significant) successively for each step. The process continues until all insignificant predictors are excluded from the model.
- b. While in the backward elimination, Minitab starts with all predictors and continues to remove the least significant predictor (have p-values less than or equal to the specified alpha to remove i.e. results are statistically significant) one after one in each step. When only significant predictors remain, Minitab stops the process.
- c. The standard option in Minitab adds and removes predictors one at a time and stops when all significant variables are included in the model and all insignificant ones are excluded on the other hand.

Upon performing the stepwise regression, users can display the stepwise procedure, the coefficients of the factors and p-values and a model summary showing the statistics for each step. The standard option was selected to develop the models in this study because it resulted in relatively

accurate results in comparison with the other options. (To support this statement, trials with different options were conducted to model block work, and presented in detail in the Appendix 7).

The training data was copied to the Minitab worksheets to be used in model development. In the stepwise regression dialog box, the presets (α to enter = 0.15, α to remove = 0.15) were retained, and the CLP column was selected as the "response" while the other columns of CLP influencing factors were entered as "predictors". The stepwise regression was performed and a model summary was generated showing the relevant regression equation and statistics. The equation subsequently was copied to the combined tables in excel and it was used to predict the CLP for both training and testing set, and MSE, MAPE, RMSE, MAD, and R^2 were calculated. In the stepwise regression, the predictors "which are the CLP influencing factors" entered and removed automatically by a procedure based on a specified significance level (which is $\alpha=0.15$ in this research).

5.2.3 Nonlinear Regression Models

Minitab also allows users to choose the most appropriate data analysis tool and to interpret the results of a particular analysis smoothly through the *Assistant* interactive menu (shown in Figure 5.2). Based on the number of independent variables X's, a user can perform a simple regression (in case of one independent variable) or multiple regression (for two to five predictors) to either fit models only or optimize the dependent variable Y (whether to maximize or minimize the Y or to achieve a target value).

Choose a Regression Analysis

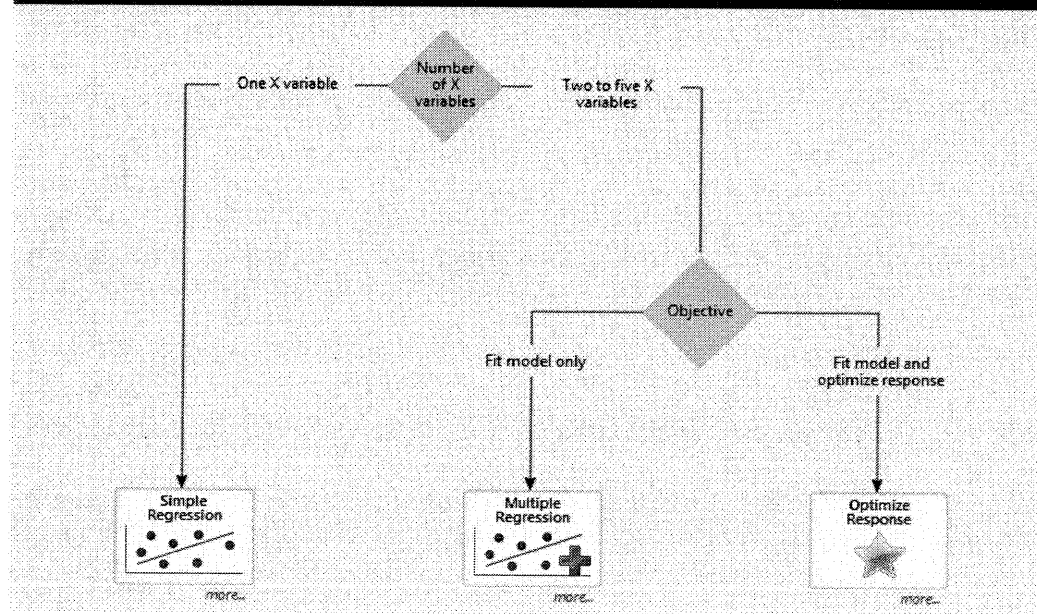


Fig. 5.2: Assistant Menu in Minitab 18

The Assistant also performs three important checks on data, and reports the findings in the Report Card which are: amount of data whether it is enough to provide power for the test; accurate estimate of the relationship strength between x and y; unusual data that may affect the results of the analysis; and normality. The fit model-multiple regression analysis was selected to develop the nonlinear models. In the Assistance menu, regression was selected and the objective was to fit a model with multiple regression. CLP was nominated as the response variable and the other variables were the influencing factors. Only 5 predictors can be selected at a time to carry out the analysis therefore several trials were conducted to find the best set of predictors which would result in the maximum R^2 .

5.3 Models Development and Testing

For each of the four activities, three regression models were developed. The same training and test set were used to develop all regression models

for fair comparison. Models with $R^2 = 70\%$ or more were selected to predict the CLP for the test set that is holdout for validation (30% of the data). The regression equations of the developed models and a summary about their performance in predicting the output of the test set is presented below for steel fixing productivity, concrete pouring productivity, formwork productivity, and block work productivity.

5.3.1 Regression Models for Steel Fixing

Linear regression model:

Model Equation

$$\begin{aligned} \text{Steel fixing productivity} = & 311 + 0.04836 * \text{Production} + 11.63 * \text{Floor level} - \\ & 12.65 * \text{Steel Fixers} + 3.5 * \text{Working hours} + 4.68 * \text{Overtime} - 0.48 * \text{Element} + 2.7 \\ & * \text{Week day} - 10.6 * \text{Season} + 1.56 * \text{Minimum Temperature} - 0.709 * \text{Maximum} \\ & \text{Temperature} + 1.62 * \text{Total Plant} - 0.864 * \text{Total Manpower} - 0.490 * \text{Humidity} + \\ & 0.210 * \text{Wind} \end{aligned} \quad (5.1)$$

Model Summary:

$$R^2 = 93.44\% \quad R^2(\text{adj}) = 91.96\%$$

Model Prediction:

$$\text{RMSE} = 13.679, \text{MSE} = 187.106, \text{MAPE} = 21.375, \text{MAD} = 11.898, R^2 = 0.813$$

Stepwise regression models:

Model Equation

$$\begin{aligned} \text{Steel fixing productivity} = & 345.9 + 0.05094 * \text{Production} + 13.05 * \text{Floor level} \\ & - 13.206 * \text{Steel Fixers} + 2.47 * \text{Week day} - 0.805 * \text{Total Manpower} \end{aligned} \quad (5.2)$$

Model Summary:

$$R^2 = 92.90\% \quad R^2(\text{adj}) = 92.40\%$$

Model Prediction:

RMSE=29.237, MSE=854.800, MAPE= 46.796, MAD=25.898, $R^2= 0.764$

Nonlinear regression model:

Model Equation

$$\begin{aligned} \text{Steel fixing productivity} = & 186.7 + 0.13722 * \text{Production} - 26.38 * \text{Steel fixers} \\ & + 13.4 * \text{Overtime} + 0.000002 * \text{Production}^2 + 0.7228 * \text{Steel fixers}^2 + 5.99 * \text{Overtime}^2 - \\ & 0.00373 * \text{Production} * \text{Steel fixers} - 0.01111 * \text{Production} * \text{Overtime} \end{aligned} \quad (5.3)$$

Model Summary:

$$R^2 = 98.89\%$$

Model Prediction:

RMSE=32.799, MSE=1075.772, MAPE= 58.867, MAD=30.548, $R^2=0.884$

5.3.2 Regression Models for Concrete Pouring

Linear regression model:

Model Equation

$$\begin{aligned} \text{Concrete pouring productivity} = & 4.6 + 0.1091 * \text{Production} + 1.05 * \text{Mix} \\ & - 0.811 * \text{Element} - 0.571 * \text{Number of Mason} + 0.197 * \text{Labor} - 0.0053 * \text{Total Workforce} \\ & - 0.008 * \text{Temperature} - 0.0126 * \text{Humidity} + 0.042 * \text{Wind} + 0.498 * \text{Day} \end{aligned} \quad (5.4)$$

Model Summary:

$$R^2 = 77.48\% \quad R^2(\text{adj}) = 66.70\%$$

Model Prediction:

RMSE=6.169, MSE=38.053, MAPE= 92.576, MAD=5.064, $R^2=0.872$

Stepwise regression models:

Model Equation

$$\text{Concrete pouring productivity} = 9.76 + 0.1210 \cdot \text{Production} - 1.587 \cdot \text{Mix} - 0.315 \cdot \text{Element} - 0.4649 \cdot \text{Number of Mason} \quad (5.5)$$

Model Summary:

$$R^2 = 92.97\% \quad R^2(\text{adj}) = 91.93\%$$

Model Prediction:

$$\text{RMSE} = 18.291, \text{MSE} = 334.583, \text{MAPE} = 43.041, \text{MAD} = 4.994, R^2 = 0.6535$$

Nonlinear regression model:

Model Equation

$$\begin{aligned} \text{Concrete pouring productivity} = & 5.96 + 0.2292 \cdot \text{Production} + 3.75 \cdot \text{Mix} - \\ & 0.00296 \cdot \text{Placing time} - 2.685 \cdot \text{Element} + 0.039 \cdot \text{Number of masons} - 0.000152 \cdot \text{Placing} \\ & \text{time}^2 + 0.1993 \cdot \text{Element}^2 + 0.02235 \cdot \text{Number of masons}^2 - 0.01196 \cdot \text{Production} \\ & \cdot \text{Element} - 0.006372 \cdot \text{Production} \cdot \text{Number of masons} - 0.961 \cdot \text{Mix} \cdot \text{Number of masons} + \\ & 0.01412 \cdot \text{Element} \cdot \text{Placing time} + 0.0409 \cdot \text{Element} \cdot \text{Number of masons} \quad (5.6) \end{aligned}$$

Model Summary:

$$R^2 = 99.39\%$$

Model Prediction:

$$\text{RMSE} = 13.519, \text{MSE} = 182.770, \text{MAPE} = 113.124, \text{MAD} = 9.469, R^2 = 0.823$$

5.3.3 Regression Models for Formwork

Linear regression model:

Model Equation

$$\begin{aligned} \text{Formwork productivity} = & 19.91 + 0.09445 * \text{Production} - 0.6270 * \text{Carpenters} \\ & - 0.327 * \text{Overtime} - 0.1048 * \text{Week day} + 1.44 * \text{Season} + 0.013 * \text{Min Temperature} \\ & - 0.1665 * \text{Max Temperature} - 0.611 * \text{Total Plant} - 0.0327 * \text{Total Manpower} \\ & - 0.0146 * \text{Humidity} + 0.0026 * \text{Wind} \end{aligned} \quad (5.7)$$

Model Summary:

$$R^2 = 96.02\% \quad R^2(\text{adj}) = 95.51\%$$

Model Prediction:

$$\text{RMSE} = 2.783, \text{MSE} = 7.744, \text{MAPE} = 71.350, \text{MAD} = 1.357, R^2 = 0.675$$

Stepwise regression models:

Model Equation

$$\begin{aligned} \text{Formwork productivity} = & 14.59 + 0.09379 \text{ Production} - 0.6086 \text{ Carpenter} \\ & + 1.199 \text{ Season} - 0.2283 \text{ avg. Temperature} - 0.379 \text{ Total Plant} \end{aligned} \quad (5.8)$$

Model Summary:

$$R^2 = 95.73\% \quad R^2(\text{adj}) = 95.50\%$$

Model Prediction:

$$\text{RMSE} = 2.685, \text{MSE} = 7.207, \text{MAPE} = 68.319, \text{MAD} = 1.265, R^2 = 0.677$$

Nonlinear regression model:

Model Equation

$$\begin{aligned} \text{Formwork productivity} = & 15.2 + 0.3949 * \text{Production} - 3.329 * \text{Carpenters} - \\ & 3.847 * \text{Overtime} - 0.242 * \text{Weekday} + 0.1067 * \text{Carpenters}^2 + 0.687 * \text{Overtime}^2 - \\ & 0.010854 * \text{Production} * \text{Carpenters} - 0.08137 * \text{Production} * \text{Overtime}^2 - \\ & 0.00358 * \text{Production} * \text{Weekday} + 0.5095 * \text{Carpenters} * \text{Overtime} + 0.0475 * \\ & \text{Carpenters} * \text{Weekday} \end{aligned} \quad (5.9)$$

Model Summary:

$$R^2 = 97.03\%$$

Model Prediction:

$$RMSE=10.002, MSE=100.038, MAPE= 210.936, MAD=3.894, R^2=0.048$$

5.3.4 Regression Models for Block work

Linear regression model:

Model Equation

$$\begin{aligned} \text{Block work productivity} = & 95.0 + 0.011599 * \text{Production} + 0.377 * \text{Temperature} \\ & - 0.0256 * \text{Humidity} + 0.0228 * \text{Wind} - 1.036 * \text{No. of Masons} + 3.164 * \text{No. of Subcontractor} \\ & + 1.17 * \text{No. of Supervisors} - 0.090 * \text{Labor} - 0.97 * \text{Total Plant} - 1.09 * \text{Working hours} \\ & - 0.095 * \text{Total Workforce} + 0.361 * \text{Week day} + 18.59 * \text{Season} \end{aligned}$$

(5.10)

Model Summary:

$$R^2 = 95.72\% \quad R^2(\text{adj}) = 94.87\%$$

Model Prediction:

$$RMSE=22.279, MSE=496.335, MAPE= 27.787, MAD=15.243, R^2=0.058$$

Stepwise regression models:

Model Equation

$$\begin{aligned} \text{Blockwork productivity} = & 85.23 + 0.011559 * \text{Production} + 0.472 * \text{Temperature} \\ & - 1.1655 * \text{No. of Masons} + 2.622 * \text{No. of Subcontractor} - 0.1733 * \text{Labor} \\ & + 18.9 * \text{Season} \end{aligned}$$

(5.11)

Model Summary:

$$R^2 = 95.45\% \quad R^2(\text{adj}) = 95.07\%$$

Model Prediction:

$$RMSE=22.735, MSE=516.869, MAPE= 29.380, MAD=16.426, R^2=0.110$$

Nonlinear regression model:

Model Equation

$$\begin{aligned} \text{Block work productivity} = & 125.61 + 0.025643 * \text{Production} + 0.1785 * \text{Humidity} \\ & + 0.18 * \text{Wind} - 3.2681 * \text{No. of masons} - 0 * \text{Production}^2 + 0.01299 * \text{No. of masons}^2 - \\ & 0.000098 * \text{Production} * \text{Wind} - 0.000074 * \text{Production} * \text{No. of masons} - \\ & 0.00869 * \text{Humidity} * \text{Wind} + 0.0122 * \text{Wind} * \text{No. of masons} \end{aligned} \quad (5.12)$$

Model Summary:

$$R^2 = 98.89\%$$

Model Prediction:

$$\text{RMSE} = 20.797, \text{MSE} = 432.513, \text{MAPE} = 26.100, \text{MAD} = 17.796, R^2 = 0.876$$

Detailed Minitab calculations are presented in Appendix 8.

5.4 Models Comparison

The aim of using different techniques to model the construction labor productivity is to assess the performance of each technique and present various options of modeling methods to targeted users.

A comparison between the best linear and nonlinear models are presented in Table 5.1.

The comparison shows that the linear regression generally resulted in better predictions for most of the activities when applied to new set of data except for block work activity which was better explained by the nonlinear regression model. Moreover, stepwise regression does provide good results that are close to the linear regression performance but with less predictors in the models or in another word less complicated models.

Table (5.1): A Comparison between Best Linear and Nonlinear Models

Activity	Regression	RMSE	MSE	MAPE	MAD	R ²
Steel Fixing	Linear	13.679	187.106	21.375	11.898	0.813
	Stepwise	29.237	854.800	46.796	25.898	0.7641
	Nonlinear	32.799	1075.772	58.867	30.548	0.884
Concrete Pouring	Linear	6.169	38.053	92.576	5.064	0.872
	Stepwise	18.291	334.583	43.041	4.994	0.6535
	Nonlinear	13.519	182.770	113.124	9.469	0.823
Formwork	Linear	2.783	7.744	71.350	1.357	0.675
	Stepwise	2.685	7.207	68.319	1.265	0.677
	Nonlinear	10.002	100.038	210.936	3.894	0.048
Block Work	Linear	22.279	496.335	27.787	15.243	0.058
	Stepwise	22.735	516.869	29.380	16.426	0.110
	Nonlinear	20.797	432.513	26.100	17.796	0.876

Also, it was necessary to compare the performance of the best regression models to the best neural network models obtained from Chapter 4.

Table 5.2 demonstrate a comparison between the said models in terms of error measures.

The aforesaid comparison emphasis was on the effectiveness of both regression and neural networks in CLP modeling. For instance, in steel fixing, formwork and block work activities neural networks showed an improvement in the results in terms of error measures. However, in concrete pouring the regression model excelled in predicting CLP for the given data.

Table (5.2): A Comparison between Best Regression and NN Models

Activity	Model	RMSE	MSE	MAPE	MAD	R ²
Steel Fixing	Linear Regression	13.679	187.106	21.375	11.898	0.813
	Zero-based Sigmoid	6.436	41.423	8.904	5.180	0.947
Concrete Pouring	Linear Regression	6.169	38.053	92.576	5.064	0.872
	Zero-based Sigmoid	53.897	252.928	2904.9	34.289	0.680
Formwork	Stepwise Regression	2.685	7.207	68.319	1.265	0.677
	Hyperbolic tangent	0.448	0.201	8.311	0.327	0.957
Block Work	Nonlinear Regression	20.797	432.513	26.100	17.796	0.876
	Zero-based Sigmoid	16.347	267.219	19.551	11.260	0.331

5.5 Evaluation of Factors Affecting Productivity

The value of regression equation coefficients represents the mean change in the response, which is the CLP, given a one-unit increase in the productivity influencing factors. However, the unit of measurement varies among these different factors such as temperature, production, and number of workers, making it difficult to compare. Minitab18 solves this problem by offering options for standardizing the regression coefficients through the **"Coding"** button in the main regression dialog box. Regression coefficients standardizing options include: specifying low and high levels to code as -1 and +1; subtracting the mean then dividing by the standard deviation; subtracting the mean; dividing by the standard deviation; and subtracting a specified value then divide by another. Coding puts different predictors at a same scale and allows direct comparison of regression equations coefficients. After fitting the regression model using standardized predictors, the *coded coefficients* will represent the

standardized coefficients and the most influencing factors will be those with the largest absolute values of standardized coefficients.

In this study the selected option for standardizing regression coefficients in all regression models was subtracting the mean then dividing by the standard deviation. The difference occurred in choosing which factors to be included in each model was due to the availability of data and the nature of the construction activity.

A summary of factors affecting productivity and their contribution in each activity based on the regression models is presented below:

For Steel Fixing: Table 5.3 shows the included factors in the linear regression model, their coded coefficient and p-value to distinguish the significant ones. The identified influencing factors based on the same are: the production quantity, number of steel fixers and the total manpower available at site including steel fixers and other trades. This supports the findings of the survey conducted in Chapter 3 as planning the total daily manpower requirement and the work to be done (i.e. how many kg or what element to be fixed) was ranked the sixth most influencing factor, also the number of steel fixers representing the crew size factor which was ranked as 23rd according to the RII analysis. The regression analysis demonstrates the relationship between the CLP and the significant variables (influencing factors) in the model. The CLP increases with more production and decreases with deploying more steel fixers and extra total manpower, also the high temperature and humidity have an adverse effect on the labor productivity.

Table (5.3): Steel Fixing Regression Model Factors Significance

	Term	Coef	P-Value
No	Constant	251.12	0.000
1	Production in kg	91.60	0.000
2	Floor level	7.52	0.214
3	Steel Fixers	-83.45	0.000
4	Working hours	0.81	0.822
5	Overtime	4.77	0.310
6	Element	-1.30	0.775
7	Week day	5.46	0.114
8	Season	-4.0	0.776
9	Min Temp	5.23	0.299
10	Max Temp	-6.28	0.432
11	Total Plant	3.39	0.440
12	Total Manpower	-15.97	0.071
13	Humidity	-7.29	0.162
14	Wind	1.71	0.663

For Concrete Pouring: Table 5.4 shows that production quantity of concrete pouring and the number of masons are the most significant factors in the concrete pouring activity which substantiate the questionnaire's findings that revealed crew size influence on the CLP. The regression analysis also relates the CLP increment to the increment in production quantity. On the other hand more masons and hot humid climate affect CLP adversely.

For Formwork: Table 5.5 shows that production quantity of formwork and the number of carpenters are the most significant factors in the formwork activity. This confirms the questionnaire's findings regarding the crew size impact on CLP. Deploying more carpenters decreases CLP

according to the regression analysis and this is expected as CLP measured by dividing the production over the manpower utilized.

Table (5.4): Concrete Pouring Regression Model Factors Significance

	Term	Coef	P-Value
No	Constant	7.964	0.000
1	Production/m3	3.47	0.015
2	Mix	0.46	0.675
3	placing time in min	0.00	0.999
4	Element	-1.41	0.227
5	Number of Mason	-6.71	0.006
6	Labor	0.99	0.360
7	Total Workforce	-0.14	0.928
8	Temp	-0.06	0.976
9	Humidity	-0.167	0.850
10	Wind	0.288	0.741
11	Day	0.947	0.258

Table (5.5): Formwork Regression Model Factors Significance

	Term	Coef	P-Value
No	Constant	6.706	0.000
1	Production	7.263	0.000
2	Carpenter	-2.818	0.000
3	Overtime	-0.284	0.583
4	Week day	-0.204	0.196
5	Season	0.92	0.398
6	Min Temp	0.044	0.922
7	Max Temp	-1.405	0.034
8	Total Plant	-0.625	0.077
9	Total Manpower	-0.587	0.442
10	Humidity	-0.246	0.255
11	Wind	0.027	0.882

For Block Work: Table 5.6 shows the significant factors in the linear regression model for block work. Production quantity, number of masons working in block work, number of subcontractors hired and the season effect on the productivity are the most CLP influencing factors based on the regression analysis. The findings of this analysis supports the findings of the questionnaire were management of subcontractors and crew size was ranked 13 and 23 respectively. Additionally, the season effect which was included based on the respondents' suggestion is considered to be important as shown by the regression analysis. The analysis also relates humidity, number of masons, and number of labors (non-skilled workers), working hours and total workforce increment to CLP decreasing.

Table (5.6): Block work Regression Model Factors Significance

	Term	Coef	P-Value
No	Constant	97.786	0.000
1	Production (blocks)	31.61	0.000
2	Temperature(C)	1.71	0.107
3	Humidity (%)	-0.323	0.647
4	Wind (km/h)	0.222	0.729
5	No. of Masons	-23.64	0.000
6	No. of Subcontractor	3.842	0.000
7	No. of Supervisors	0.51	0.663
8	Labor	-1.52	0.587
9	Total Plant	-0.598	0.352
10	Working hours	-0.976	0.307
11	Total Workforce	-4.66	0.539
12	Week day	0.715	0.190
13	Season	3.554	0.000

5.6 Chapter Summary

In this chapter CLP models were developed with linear and nonlinear regression. The methodology of models' development and validation was described in detail for steel fixing, concrete pouring, formwork, and block work models. Followed by a comparison of developed models- in terms of MSE, MAPE, RMSE, MAD, and R^2 - for each of the four selected activities, and finally an evaluation of CLP influencing factors based on their contribution to the best regression models. The analysis of factors significance indicated that larger crew size resulted in a CLP reduction among all investigated activities which is an expected effect if the "optimal crew/ team size" is exceeded, however this size shall be determined by conducting sensitivity analysis for CLP against crew size.

CHAPTER 6

Conclusions and Recommendations

- 6.1 Introduction**
 - 6.2 Summary of Work Accomplished**
 - 6.3 Major Findings**
 - 6.4 Recommendations**
 - 6.5 Limitations of the Research**
 - 6.6 Future Recommended Studies**
-

Chapter 6

Conclusions and Recommendations

6.1 Introduction

Construction has a significant impact on the economy and it is connected to wide range of other industries. Over the past years, Bahrain's public and private sectors invested in infrastructure and residential construction projects causing a growth in the industry which is expected to continue as government aims to diversify the country's economy away from oil, and support economic growth. This major contributing sector is, however, depending heavily on labor productivity which is the focus of this research. This chapter presents a summary of the research undertaken indicating to what extent intended outcomes were accomplished. It also includes discussion of major findings, limitations, recommendations and directions for future research.

6.2 Summary of Work Accomplished

As indicated in Section 1.4, the objectives of the thesis were to evaluate the factors influencing CLP, to develop models that are capable of predicting CLP for major construction activities, and put forward recommendations for CLP improvement. A literature review was conducted to explore various CLP influencing factors and modeling methods identified by other researchers. The mostly recurring factors in addition to factors suggested by industry experts were then used to develop

a questionnaire that targeted grade A and grade AA contractors aiming to identify factors influencing CLP in Bahrain. The identified factors were ranked subsequently in accordance to RII (Table 3.2 in Chapter 3), then historical field data were collected to be used in modeling. CLP models were developed with neural networks in NeuroXL predictor and with linear and nonlinear regression analysis in Minitab. The models' accuracy and prediction performance were assessed in accordance to the error measures: MSE, RMSE, MAD, and MAPE, in addition to coefficient of determination R^2 . Finally, the significance of the factors included in the models was evaluated based on its contribution to models' performance, and was compared to the influencing factors identified by the questionnaire.

6.3 Major Findings

The objectives of the thesis were met as the factors affecting CLP in Kingdom of Bahrain were identified, and labor productivity models were established. Accordingly, the major findings of this research would be:

The survey conducted at Chapter 3 to identify factors affecting CLP revealed 43 factors from which 50% were scoring RII of more than 70%, and the minimum RII score was not less than 60%. The top ten identified factors influencing labor productivity in Bahrain's construction industry are the following: (1) Labor skills (2) Temperature (3) Lack of Supervision (4) Labor experience (5) Humidity (6) Work planning and scheduling (7) Availability of tools and equipment (8) Material shortage at project site (9) Management leadership and (10) Payment delay. Furthermore, respondents suggested that the effect of Ramadan season and the effect of

the weekday may have an influence on CLP. This finding substantiates to some extent the results obtained by other researchers highlighted in the literature review such as Jarkas (2015).

CLP models were developed with artificial neural networks and regression analysis which have proven very effective in many applications. The models were able to predict CLP for four major construction activities namely; steel fixing, concrete pouring, formwork, and block work, given data about some productivity influencing factors. Different configurations were tested to select the best models (based on the test set) from neural network models. With regression analysis different models were established with linear, stepwise and nonlinear methods. The performance of neural network models was better in predicting CLP for steel fixing, formwork, and block work where:

- The best steel fixing model was obtained with zero based log sigmoid activation function, 31 neurons, learning rate = 0.5, and momentum= 0.9 resulting in: MSE= 41.422, RMSE=6.436, MAD= 5.179, MAPE= 8.904 and $R^2= 0.946$.
- Whereas, the best formwork model was attained with 100 neurons, hyperbolic tangent activation function, learning rate= 0.5 and momentum = 0.9 resulting in: MSE= 0.201, RMSE= 0.448, MAD= 0.327, MAPE= 8.311 and $R^2= 0.957$.
- The best block work model was obtained with the zero-based log sigmoid model with zero neurons in the hidden layer and using the default values for the learning rate and momentum of 0.3 and 0.6, respectively, resulting in: MSE= 271.404, RMSE= 16.474, MAD= 10.411 and MAPE= 19.093.

However, for concrete pouring best fit was achieved with the linear regression resulting in: MSE= 38.053, RMSE=6.169, MAD=5.064 and

MAPE= 92.576. Due to lack of record keeping and insufficient field information, not all influencing factors identified by the questionnaire were included in the models, thus, it was necessary to distinguish the significant factors included in the developed models. This was done by examining the coefficients of the best performing regression equations. Based on this analysis it was found that the most influencing factors are:

- In steel fixing models: production quantity; number of steel fixers; overtime hours; and total manpower at site (i.e. steel fixers and other trades).
- In concrete pouring models: production quantity; number of masons; mix type; placing time and element type.
- In formwork models: production quantity; number of carpenters; temperature, overtime hours; total number of plant; weekday.
- In block work models: production quantity; number of masons; humidity; temperature and number of subcontractors (hired by the main contractor to perform the masonry work).

6.4 Recommendations

During data collection stage a major lack of record keeping was noticed in the local construction companies, many of them still depend on norms that are used in estimation and planning, and are recorded at a summary level which cannot be used for productivity analysis purposes. Unfortunately, there were a number of important factors excluded from CLP models due to lack of information (such as labor experience and improper planning of works). There is a need of establishing proper systems for CLP measurement and recording, which would be a major improvement area

that construction companies need to look into for effective and fruitful analysis.

Also, it is suggested to deal with CLP identified significant influencing factors effectively for productivity improvement, considering the top ten for example: labor skills and experience can be improved by training that would allow mastering new skills and enhance hands-on experience; hot temperature and humidity effect may be minimized by providing facilities such as cool and shaded working areas in addition to frequent breaks; lack of supervision may be enhanced with providing competent supervisors and splitting the total workforce to crews with team leader; proper work planning and scheduling would improve CLP considerably; availability of tools, equipment and material when needed shall expedite site works; better management leadership increase employee motivation and productivity in the workplace; and payment delay which would result in loss of productivity and efficiency; in addition to re-scheduling and re-sequencing of works sometimes.

6.5 Limitations of the Research

The intention was to collect historical data from all the contactors participated in the survey, however, there was a lack of historical data keeping in the local companies and data were collected from three companies only (two grade AA and one grade A), although the number of data points was sufficient to build the models ((Based on the report cards generated by Minitab in Appendix 8) it did not reflect the same population considered in questionnaire. (Minitab performs checks to verify whether the amount of data used in the analysis is enough to provide power for the test refer to 5.2.3) Moreover, some activities such as block work was

subjected to many constraints that would change the productivity rate, yet this was not reflected in the row data, For example laying the block of a solid wall would go faster than a wall with window or door openings. Also, there were significant factors identified by the questionnaire and were ignored in the models because they were not measurable such as labor skill, and labor motivation, or due to lack of relevant historical data which made the evaluation of their effect on CLP not possible.

6.6 Future Recommended Studies

This research covered identifying the CLP for major construction activities which are steel fixing, concrete pouring, formwork, and block work, thus future studies may consider other activities such as earth work, plastering, painting etc. Further recommended studies may focus on modeling techniques such as fuzzy logic which was highlighted in the literature review. It is also recommended to examine the CLP difference among other contractor's grades such as B and C. Moreover, future studies may tackle the challenges in CLP measuring and other relevant research areas. Although the proposed modeling methodology was used to address workers' productivity in construction industry it may be applied to other industries such as manufacturing in further studies.

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Appendices

Appendix (1)

Questionnaire Format

Appendix (2)

Ministry of Works Prequalified Contractors List (Grades A& AA)

Appendix (3)

Sample of Filled Questionnaire

Appendix (4)

Questionnaire Results and Calculations

Appendix (5)

Sample of Contractor's Record

Appendix (6)

Data Collected (Combined Tables)

Appendix (7)

Stepwise Trials for Block work

Appendix (8)

Minitab 18 Calculations

Appendix (1)

Questionnaire Format

This appendix presents the questionnaire format used to identify the factors influencing CLP in Kingdom of Bahrain. The questionnaire includes 43 factors that respondents can rank -in accordance to their importance- from 1 to 5 (where 5 representing the most influencing) and allows them to add more CLP influencing factors if any.



University of Bahrain
College of Engineering
Department of Mechanical Engineering
Engineering Management Master's Program

Questionnaire on Factors Influencing Construction Labor Productivity in Bahrain

Name (Optional): -----

Age (Optional): -----

Organization: -----

Type of Construction Organization: -----

Job title: -----

Years of experience: -----

Please indicate to what extent following factors affect construction labor productivity:

- 1- Not at all influential ,2- Slightly influential, 3- Somewhat influential, 4- very influential, 5- extremely influential

Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
1. Management Factors							
1.1 Lack of Supervision							
1.2 Communication problems							
1.3 Lack of training provided							
1.4 Incentive programs							
1.5 Management Leadership							
1.6 Work planning and scheduling							
1.7 Management of subcontractors							

1.8 Lack of labor recognition programs							
1.9 Safety requirements and regulations							
Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
1.10 Payment delay							
2. Technological Factors							
2.1 Crew size and composition							
2.2 Inspection delays							
2.3 Rework							
2.4 Clarity of drawings and specifications							
2.5 Design complexity							
2.6 variation/change orders							
2.7 Availability of tools and equipment							
2.8 Site Layout and condition							
2.9 Storage location							
2.10 Project Type							
2.11 Project Duration							
2.12 Material shortage at project site							
3. Workforce / Manpower Factors							
3.1 Labor skill							
3.2 Labor experience							
3.3 Labor Age							
3.4 Labor motivation							
3.5 Labor Education							
3.6 Overtime							
3.7 Repetition of work							
3.8 Shift work							
3.9 Working for long periods without holidays							
3.10 Workers turnover or Changing Crewmembers							

3.11 Absenteeism							
3.12 Labor Personal problems							
3.13 Rest time(s) per day							
Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
4. External factors							
4.1 Noise							
4.2 Political unrest							
4.3 Temperature							
4.4 Humidity							
4.5 Precipitation / Rain							
4.6 Wind or Dust							
4.7 Government laws							
4.8 Work at heights							
Other factors :							

Appendix (2)

Ministry of Works Prequalified Contractors List

This appendix presents two lists of building contractors registered with Ministry of Works in Kingdom of Bahrain (at the time of conducting the survey), the first list shows the grade AA contractors whom are capable of handling construction projects of over than BD 6 million value whereas the second list shows grade A contractors who can handle construction projects of a value between BD 2 to 6 million.



LIST OF BUILDINGS CONTRACTORS
REGISTERED WITH MINISTRY OF WORKS

(UP TO BD.: 6,000,000/-)

CONSTRUCTION PROJECTS- GRADE A

Sno	Contractor Name	CR No.	PO Box	Tel. No.	FAX No.	Comments	Email
1	ALDHHRANI CONTRACTING COMPANY W.L.L.	13171-1	5763	17611332	17611553		dahrani5@bateko.com.bh
2	CHARILAOS APOSTOLIDES & CO. (BAHRAIN) W.L.L.	12640	1987	17830190	17830183		
3	M. & I. CONSTRUCTION LTD. CO.	5697	5697	17728340	17727321		spacekr@bateko.com.bh
4	AL KHALIDIA CONTRACTING CO. W.L.L.	12059-1	5406	17346802	17340136		alkhalidya@olympicsgroup.com
5	YOUSUF AL-ZAYANI TRADING & CONTRACTING CO. W.L.L.	1245	5542	17227146	17224181		zayanko@bateko.com.bh
6	KHALID ALI AL-KHARAFI & BROS. CO./KHARAFI STEEL W.L.L.	50045-1	574	17531316	17531314		
7	AL NASIR CONTRACTING W.L.L.	8187-1	15858	17714609	17713247		nasirconst.com
8	ALARGAN NATIONAL GENERAL TRADING & CONTRACTING CO.	66493-1	21186	17563600	17564128		
9	AAA HOMES CONTRACTING W.L.L.	47915-3	31191	17811353	17826768		
10	SHADE CORPORATION LTD	62789-1	75883	17588249	17464023		
11	GANNON DUNKERLEY MIDDLE EAST W.L.L.	68193-1	76162	17310012	17310018		
12	ABDUL AAL CONSTRUCTION SERVICES	7520	20418	17533999	17533236		amsconet@bateko.com.bh
13	MOSOBLOPROMSTROY	53076-1	BLOCK3, BUID3 +74991889738 +74991889738, MOSCOW			International	
14	SAUDI BUILD INTERNATIONAL CONTRACTING W.L.L.	65838	75754	13333651	13324010		
15	SKYLINE TRADING CORPORATION	37958	3207	17598008	17590338		stc3207@bateko.com.bh
16	DADABHAI CONSTRUCTION	47989	20531	17255209	17251995		
17	ABDULLA HASSAN ALDURAZI & SONS CO.	19015-1	697	17564664	17564644		admin@ahahderazi.com
18	AHMED OMER TRADING & CONTRACTING EST. W.L.L.	1659-1	5098	17258545	17233882		aogroup@bateko.com.bh
19	ABDULRAHMAN ABDULLA ALMANSOORI CONTRACTING CO. W.L.L.	29389-1	37263	17786698	17785598		info@asmcontracting.net



الوزارة
Ministry of Works

MINISTRY OF WORKS

LIST OF BUILDINGS CONTRACTORS
REGISTERED WITH MINISTRY OF WORKS

(UP TO BD.: 6,000,000/-)

CONSTRUCTION PROJECTS- GRADE A

Sno	Contractor Name	CR No.	PO Box	Tel. No.	FAX No.	Comments	Email
20	ALHEDAYA CONTRACTING COMPANY	769-1	5705	17728800	17725121		ALHEDAYA@ALHEDAYACO.COM
21	ALSHAHEEN CONTRACTING ESTABLISHMENT	8917-3	32323	17683576	17781682		ALSHAHEEN@LSC.COM.BH
22	AL QAWAREER CONTRACTING CO.W.L.L	55362-1	24260	17786149	17786349		aqcc.bh@gmail.com
23	DOWN TOWN CONSTRUCTION COMPANY W.L.L.	8899-1	26312	17404866	17404714		downtown@batelco.com.bh
24	ASEERI CONSTRUCTIONS	50697-1	26083	17744122	17744133		aseerco@batrlco.com.bh
25	NASS CONTRACTING COMPANY W.L.L.	17537-1	669	17708333	17701714		INFO@NASSCONTRACTING.COM
26	FUNDAMENT SPC	69393-1	659	17369322	17369344		info@fundamentspc.com
Count : 26							

LIST OF BUILDINGS CONTRACTORS
REGISTERED WITH MINISTRY OF WORKS

(OVER BD.: 6,000,000/-)

CONSTRUCTION PROJECTS- GRADE AA

Sno	Contractor Name	CR No.	PO Box	Tel. No.	FAX No.	Comments	Email
1	CHINA JIANGSU CONSTRUCTION CORPORATION (THE AGENT : SINOGIC INVESTMENT HOLDING COMPANY W.L.L.)	1	5780	17790090	17790154	International	
2	JACOVU BROTHERS (CONSTRUCTIONS) LIMITED (LOCAL AGENT : MOHAMMED JALAL CONTRACTING CO. W.L.L.)	1		357-2482444	357- 24650051	International	
3	ALMOAYYED CONTRACTING W.L.L	76979-1	32571	17404949	17402639		contracting@almoayyedcg.com
4	ARADOUS CONTRACTING & MAINTENANCE CO. W.L.L.	69183-1	2807	17740523	17740515		
5	CYPRUS BUILDING & ROAD CONSTRUCTION COMPANY LIMITED W.L.L	63728-1	15954	17275787	17262744		cybarco01@bateko.com.bh
6	AL HAFEERA CONTRACTING COMPANY W.L.L.	13336-1	28411	17730343	17732187		info@hafaera.com
7	OLYMPIC CONTRACTING CO. W.L.L.	44242	20628	17343981	17343984		info@olympic.bh
8	POULLAIDES CONSTRUCTION COMPANY W.L.L.	48613	33411	17826660	17827008		
9	TECHNICAL CONSTRUCTION COPMANY W.L.L.	1840-1	5174	17730036	17730064		tccbn@bateko.com.bh
10	A. AHMED NASS CONTRACTING CO. W.L.L	17537-3	669	17708333	17701714	Not valid needed to be Renewed[Pending Renewal]	estimation@nasscontracting.com
11	AHMED MANSOOR AL A'ALI CONTG. & TRADG. CO. BSC C	571-2	778	17250521	17262323		headoffice@al-aali.com
12	BAHRAIN MOTORS COMPANY	18673-1	33078	77006262	77006161		karimg@bateko.com.bh
13	BOKHOWA GROUP	4702	5422	17259980	17256836		info@bokhowagroup.com
14	CEBARCO BAHRAIN S.P.C	27738	28812	17722237	17722001		Cebarco@kar-group.com
15	G.P.ZACHARIADES OVERSEAS LIMITED	4595	5632	17598800	17598801		info@gpzgroup.com
16	HABIB ALI AWACHI & SONS CONTRACTING CO. W.L.L.	31094-1	2041	17400056	17400399	Not Valid - To be Renewed[Pending Renewal]	
17	HAFEERA-IJM CONTRACTING W.L.L.	67455-1	28141	17730343	17732187/17 737881		
18	JOINT STOCK COMPANY RUSSIAN RAILWAY (THE AGENT, GR GROUP W.L.L.)	1		17587001	17587006	International	

LIST OF BUILDINGS CONTRACTORS
REGISTERED WITH MINISTRY OF WORKS

وزارة الأشغال
Ministry of Works

(OVER BD.: 6,000,000/-)

CONSTRUCTION PROJECTS- GRADE AA

Sno	Contractor Name	CR No.	PO Box	Tel. No.	FAX No.	Comments	Email
19	KAZEROONI CONTG. W.L.L.	1567-2	5385	17742595	17712184		
20	KOOHEJI CONTRACTORS W.L.L.	3247	1041	17786500	17786565		
21	MOHAMED JALAL CONTRACTING CO. W.L.L	50795-1	113	17255360	17259839 /17259723		mjcont@bateko.com.bh
22	M-10 BUILDERS W.L.L.	69850-1	75704	17552935	17369883		
23	PROJECTS CONSTRUCTION COMPANY W.L.L.	5141	801	17731298	17732673		construction@projectsbahrain.com
24	SALEH ABDULLA KAMESHKI	1474-1	2219	17250627	17270478		info@kameshki.com
25	BURHAN INTERNATIONAL CONSTRUCTION CO. BAHRAIN S.P.C.	67534-1	11762	00965 24645184	17530618	International	Mustafas@burhaninternational.com
26	NAMKWANG ENGINEERING AND CONSTRUCTION CO. LTD	1		822-30110482	822- 30110468	International	
27	TAMCON CONTRACTING CO. BSC (CLOSED)	67130-1	10119	17468888	17468877		zahmed@tamcon.bh
28	ALGHANAH CONTRACTING	15648-1	2510	17722333	17722233		INFO@ALGHANAH.COM
29	CONCTRUTORA OAS LTDA (BRASIL)	14.310.577/C		39718305/551 - 121241122		International	
30	ALHABTOOR LEIGHTON BAHRAIN SPC	75986	20750	17502770	17503030	GCC	
31	ROBODH CONTRACTING CO.LLC	48504	60889	+97142820844 +971428208 42			
32	GRANDI LAVORI FINCOSIT S.P.A	1	-	+3906881711	+390688130 51	International	
33	KUWAIT MANAGER CONTRACTING S.P.C	55344	2307	77722722	77722711	International	
34	SHAPOORJI PALLONJI MIDEAST L.L.C	-	21928	+97172690334 +971426903 35		International	
35	KYERYONG CONSTRUCTION INDUSTRAIL CO .	80828-1	KOREA	+82424807434 +824248072 88		International	
36	UNAL AKPINAR CONSTRUCTION INDUSTRY TOURISM MINING AND TRADE INC. (LOCAL AGENT : ALWARDI CONSTRUCTION)	306207	23678	+90-312- 4687960	+90-312- 4689341	International	akpinar@akpinargroup.com.tr
37	CONSOLIDATED CONTRACTORS (BAHRAIN) COMPANY	703	583	17221511	17221154	International	

LIST OF BUILDINGS CONTRACTORS
REGISTERED WITH MINISTRY OF WORKS

(OVER BD.: 6,000,000/-)

CONSTRUCTION PROJECTS- GRADE AA

Sno	Contractor Name	CR No.	PO Box	Tel. No.	FAX No.	Comments	Email
38	RIZZANI DE ECHEER BAHRAIN S.P.C.	76012-1		+3904326071	+390432607373	International	ugare@rde.it
39	SAMCRETE ENGINEERING AND CONTRACTING	16866		002023389110002023389110	22	International	
40	ALAMIAH BUILDING COMPANY K.S.C.C	20980	280	00965 00965 25661095	00965 25661086	GCC	info@alamiah.net
41	PWT WASSER-UND ABWASSTERTECHNIK GMBH	HRB 25471		004962519804 01	004962519804 498	International	boeckle.nuediger@pwt.de
42	CHINA GEZHOUBA GROUP COMPANY LIMITED	1200000000C		008610595258 28	008610595258 859	International	dirkyoung@hotmail.com
43	DAR AL KHALEJ TRADING & CONTRACTING W.L.L.	20888-1	54727	17292851	17295742		daak@batelco.com.bh
44	AL WARDI CONSTRUCTION	12131	26378	17730626	17731565	not valid needed to be renewed[Pending Renewal]	info@alwardi.com
45	TERNA CONTRACTING W.L.L.	68262-1	54368	17721048	17741096		MAIN@TERNA.BH
46	SIX CONSTRUCT CO.LIMITED	47390-1	50491	77001931	77001947	International	TEC@SIXCO.AE

Count : 46

Appendix (3)

Sample of Filled Questionnaire

This appendix presents a filled questionnaire by one of the contractors whom participated in this research.



University of Bahrain
College of Engineering
Department of Mechanical Engineering
Engineering Management Master's Program

Questionnaire on Factors Influencing Construction Labor Productivity in Bahrain

Name (Optional): -----

Age (Optional): -----

Organization: NASS CONTRACTING Type of Construction Organization: -----

Job title: WORKS MANAGER

Years of experience: 20

Please indicate to what extent following factors affect construction labor productivity:

- 1- Not at all influential ,2- Slightly influential, 3- Somewhat influential, 4- very influential,
 5- extremely influential

Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
1. Management Factors							
1.1 Lack of Supervision					✓		
1.2 Communication problems				✓			
1.3 Lack of training provided					✓		
1.4 Incentive programs						✓	
1.5 Management Leadership				✓			
1.6 Work planning and scheduling						✓	
1.7 Management of subcontractors				✓			
1.8 Lack of labor recognition programs				✓			
1.9 Safety requirements and regulations					✓		

Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
1.10 Payment delay						✓	
2. Technological Factors							
2.1 Crew size and composition					✓		
2.2 Inspection delays					✓		
2.3 Rework						✓	
2.4 Clarity of drawings and specifications						✓	
2.5 Design complexity					✓		
2.6 variation/change orders					✓		
2.7 Availability of tools and equipment					✓		
2.8 Site Layout and condition					✓		
2.9 Storage location					✓		
2.10 Project Type				✓			
2.11 Project Duration			✓				
2.12 Material shortage at project site						✓	
3. Workforce / Manpower Factors							
3.1 Labor skill					✓		
3.2 Labor experience						✓	
3.3 Labor Age						✓	
3.4 Labor motivation						✓	
3.5 Labor Education					✓		
3.6 Overtime						✓	
3.7 Repetition of work				✓			
3.8 Shift work				✓			
3.9 Working for long periods without holidays						✓	
3.10 Workers turnover or Changing Crewmembers				✓			
3.11 Absenteeism						✓	
3.12 Labor Personal problems				✓			
3.13 Rest time(s) per day				✓			

✓

Factor	Not Applicable	Relevant					Potential for improvement / Remarks
		1	2	3	4	5	
4. External factors							
4.1 Noise			✓				
4.2 Political unrest			✓				
4.3 Temperature					✓		
4.4 Humidity				✓			
4.5 Precipitation / Rain					✓		
4.6 Wind or Dust					✓		
4.7 Government laws		✓					
4.8 Work at heights				✓			
Other factors:							

Appendix (4)

Questionnaire Results

This appendix shows the results of all gathered questionnaire's responses and the relative importance index (RII) calculations for each of the factors as ranked in Table 3.2.

Appendix (5)

Sample of Contractor's Record

This appendix displays a sample of activities record or daily report for one of the contractors. It shows the production of block work (measured in number of blocks) for building project at a specific day, number of resources utilized to carry out the work and other details such as weather information, number of subcontractors if any, location of work and general information about the project.

DAILY REPORT / DIARY

Project Information

DOC NO.110236-G.1.24

Project No. 110236

Date 04/04/2015

Day of Week Saturday

Project Name

CONSTRUCTION & MAINTENANCE OF 483 VILLAS

Area / Town

EAST HIDD

Contractor

Nass Contracting

Weather

Clear	Fair	Cloudy	Rain	Shower	Snow
☒	☐	☐	☐	☐	☐
TEMP	10-20	20-30	30-40	40-50	Over 50
	☐	☒	☐	☐	☐
WIND		Still	Light	Strong	Gale
		☒	☐	☐	☐
HUMIDITY		Dry	Low	Medium	High
		☐	☒	☐	☐

Number of Resources (Personel & Major Equipment)

[illegible]**Location / Area**

**B3 Area First Floor and Roof Parapet
and Stair Room**

Activity / Description of Work

Block Laying, Steel fixing ,Concrete filling, Fixing of DB box ,
Fixing of A/C box and exhaust fan frame,Block work curing
Block laying by Nass Mason 5700 block(per mason per Day=118 Block)

Hindrance / Effect to Normal Progress (weather, accidents, breakdowns, delays, etc)

Material Deliveries

Supplier	Description	Qty
Al Kamis block	Supplying Block	1100 block
National block	Supplying Block	4950 block
Kingdom block	Supplying Block	19630 block

Hassan Isa - Sr. Engineer

MR. JIMMY STEWART - PROJECT MANAGER

Appendix (6)

Data Collected

This appendix presents collected data for each of the studied activities which are: steel fixing, concrete pouring, formwork, and block work. For the best predictive models, the actual productivity and all CLP influencing factors data are shown in tables as well as the predicted productivity and the error measures calculations. While for the other models, the actual CLP vs. predicted and the error measures of the same are presented.

Appendix (7)

Stepwise trials for Block work

This appendix presents the different stepwise trials conducted with different options for block work regression model to justify choosing the standard option (Section 5.2.2). First, the forward selection method was used resulting in: $R^2 = 95.5 \%$. Secondly, the backward elimination method was selected and resulted in: $R^2 = 95.4 \%$ and finally the standard option $R^2 = 95.45 \%$. With no big difference noticed in the accuracy of the three methods, the standard option was selected to conduct the stepwise regression for all the models for the consistency.

Block work Stepwise Regression Trials:

a. Forward selection method

Regression Analysis: PR(Block/mason) versus Production ... ay, Season

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production (blocks)	7784.82	2725.02
Temperature(C)	30.64	4.53
Humidity (%)	42.09	12.61
Wind (km/h)	21.23	9.73
No. of Masons	79.54	22.83
No. of Subcontractor	6.76	1.21
No. of Supervisors	2.21	0.44
Labor	101.74	16.86
Total Plant	2.85	0.62
Working hours	9.80	0.89
Total Workforce	206.15	49.35
Week day	3.76	1.98
Season	0.04	0.19

Forward Selection of Terms

α to enter = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	7	30726.0	4389.43	218.28	0.000
Production (blocks)	1	9326.0	9326.01	463.77	0.000
Temperature(C)	1	142.4	142.38	7.08	0.010
No. of Masons	1	4487.4	4487.43	223.16	0.000
No. of Subcontractor	1	496.2	496.24	24.68	0.000
Labor	1	108.8	108.78	5.41	0.023
Total Plant	1	16.9	16.92	0.84	0.362
Season	1	490.1	490.10	24.37	0.000
Error	72	1447.8	20.11		
Total	79	32173.8			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.48430	95.50%	95.06%	90.40%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.786	0.501	195.04	0.000	
Production (blocks)	31.15	1.45	21.54	0.000	8.22
Temperature(C)	1.997	0.750	2.66	0.010	2.21
No. of Masons	-26.08	1.75	-14.94	0.000	11.97
No. of Subcontractor	3.271	0.658	4.97	0.000	1.70
Labor	-3.05	1.31	-2.33	0.023	6.77
Total Plant	-0.555	0.606	-0.92	0.362	1.44
Season	3.763	0.762	4.94	0.000	2.28

Regression Equation in Uncoded Units

$$\begin{aligned} \text{PR(Block/mason)} = & 88.18 + 0.011430 \text{ Production (blocks)} + 0.440 \text{ Temperature(C)} \\ & - 1.1422 \text{ No. of Masons} + 2.694 \text{ No. of Subcontractor} - 0.1811 \text{ Labor} \\ & - 0.898 \text{ Total Plant} + 19.68 \text{ Season} \end{aligned}$$

Fits and Diagnostics for Unusual Observations

Obs	PR(Block/mason)	Fitted	Resid	Std Resid		
9	50.95	49.15	1.80	0.50		X
16	55.63	65.26	-9.63	-2.73	R	X
19	0.00	-6.71	6.71	2.14	R	X
35	144.11	120.43	23.68	6.72	R	X
59	78.29	69.03	9.26	2.59	R	X
77	92.51	80.33	12.18	3.37	R	X
78	79.71	79.82	-0.11	-0.03		X
79	78.01	77.85	0.16	0.04		X
80	77.42	77.47	-0.05	-0.01		X

R Large residual

X Unusual X

b. Backward elimination method

Regression Analysis: PR(Block/mason) versus Production ... ay, Season

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
-----------	------	-------

Production (blocks)	7784.82	2725.02
Temperature(C)	30.64	4.53
Humidity (%)	42.09	12.61
Wind (km/h)	21.23	9.73
No. of Masons	79.54	22.83
No. of Subcontractor	6.76	1.21
No. of Supervisors	2.21	0.44
Labor	101.74	16.86
Total Plant	2.85	0.62
Working hours	9.80	0.89
Total Workforce	206.15	49.35
Week day	3.76	1.98
Season	0.04	0.19

Backward Elimination of Terms

α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	6	30695.3	5115.9	252.58	0.000
Production (blocks)	1	10394.1	10394.1	513.18	0.000
Temperature(C)	1	215.0	215.0	10.62	0.002
No. of Masons	1	715.3	715.3	35.32	0.000
No. of Subcontractor	1	444.4	444.4	21.94	0.000
Total Workforce	1	87.0	87.0	4.30	0.042
Season	1	439.4	439.4	21.69	0.000
Error	73	1478.6	20.3		
Total	79	32173.8			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.50047	95.40%	95.03%	91.58%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.786	0.503	194.34	0.000	
Production (blocks)	31.77	1.40	22.65	0.000	7.67
Temperature(C)	2.341	0.719	3.26	0.002	2.01
No. of Masons	-21.87	3.68	-5.94	0.000	52.81
No. of Subcontractor	3.030	0.647	4.68	0.000	1.63

Total Workforce	-7.82	3.77	-2.07	0.042	55.46
Season	3.828	0.822	4.66	0.000	2.63

Regression Equation in Uncoded Units

PR(Block/mason) = 82.42 + 0.011657 Production (blocks) + 0.516 Temperature(C)
- 0.958 No. of Masons + 2.496 No. of Subcontractor
- 0.1584 Total Workforce
+ 20.02 Season

Fits and Diagnostics for Unusual Observations

Obs	PR(Block/mason)	Fit	Resid	Std Resid		
9	50.95	48.98	1.97	0.54		X
16	55.63	65.58	-9.96	-2.79	R	X
19	0.00	-6.85	6.85	2.15	R	X
35	144.11	119.02	25.09	6.45	R	
59	78.29	68.39	9.89	2.65	R	X
77	92.51	80.44	12.07	3.48	R	X
78	79.71	79.57	0.14	0.04		X
79	78.01	77.93	0.07	0.02		X
80	77.42	77.63	-0.21	-0.06		X

R Large residual

X Unusual X

c. Standard option

Regression Analysis: PR(Block/mason) versus Production ... ay, Season

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production (blocks)	7784.82	2725.02
Temperature(C)	30.64	4.53
Humidity (%)	42.09	12.61
Wind (km/h)	21.23	9.73
No. of Masons	79.54	22.83
No. of Subcontractor	6.76	1.21
No. of Supervisors	2.21	0.44
Labor	101.74	16.86
Total Plant	2.85	0.62
Working hours	9.80	0.89
Total Workforce	206.15	49.35
Week day	3.76	1.98
Season	0.04	0.19

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	6	30709.1	5118.2	255.08	0.000
Production (blocks)	1	10255.4	10255.4	511.11	0.000
Temperature(C)	1	171.4	171.4	8.54	0.005
No. of Masons	1	5258.1	5258.1	262.05	0.000
No. of Subcontractor	1	480.1	480.1	23.93	0.000
Labor	1	100.8	100.8	5.03	0.028
Season	1	473.3	473.3	23.59	0.000
Error	73	1464.8	20.1		

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.47942	95.45%	95.07%	90.97%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.786	0.501	195.25	0.000	
Production (blocks)	31.50	1.39	22.61	0.000	7.64
Temperature(C)	2.142	0.733	2.92	0.005	2.11
No. of Masons	-26.61	1.64	-16.19	0.000	10.64
No. of Subcontractor	3.184	0.651	4.89	0.000	1.67
Labor	-2.92	1.30	-2.24	0.028	6.69
Season	3.623	0.746	4.86	0.000	2.19

Regression Equation in Uncoded Units

$$\begin{aligned} \text{PR(Block/mason)} = & 85.23 + 0.011559 \text{ Production (blocks)} + 0.472 \text{ Temperature(C)} \\ & - 1.1655 \text{ No. of Masons} + 2.622 \text{ No. of Subcontractor} - 0.1733 \text{ Labor} \\ & + 18.95 \text{ Season} \end{aligned}$$

Fits and Diagnostics for Unusual Observations

Obs	PR(Block/mason)	Fit	Resid	Std Resid	
9	50.95	49.21	1.74	0.48	X
16	55.63	65.68	-10.06	-2.83	R X
19	0.00	-7.13	7.13	2.25	R X
35	144.11	120.88	23.23	6.54	R X
59	78.29	67.68	10.60	2.75	R
77	92.51	81.28	11.23	2.99	R X
78	79.71	79.84	-0.13	-0.04	X
79	78.01	77.84	0.17	0.05	X
80	77.42	77.45	-0.03	-0.01	X

Appendix (8)

Minitab Calculations

This appendix shows the Minitab 18 detailed calculations for each of the steel fining, concrete pouring, formwork and block work best regression models (linear , stepwise and nonlinear).

Concrete Pouring Models

a. General Regression

Regression Analysis: PR versus Production/m3, Mix, ... idity, Wind, Day

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production/m3	58.271	31.8407
Mix	1.257	0.4434
placing time in min	125.429	82.2404
Element	2.371	1.7335
Number of Mason	14.371	11.7425
Labor	25.543	5.0372
Total Workforce	135.829	26.5922
Temp	28.500	6.8653
Humidity	55.514	13.2651
Wind	16.671	6.8320
Day	3.514	1.9000

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	11	1329.88	120.899	7.19	0.000
Production/m3	1	115.85	115.851	6.89	0.015
Mix	1	3.04	3.041	0.18	0.675
placing time in min	1	0.00	0.000	0.00	0.999
Element	1	25.88	25.879	1.54	0.227
Number of Mason	1	154.95	154.947	9.22	0.006
Labor	1	14.65	14.654	0.87	0.360
Total Workforce	1	0.14	0.139	0.01	0.928
Temp	1	0.02	0.016	0.00	0.976
Humidity	1	0.61	0.614	0.04	0.850
Wind	1	1.88	1.876	0.11	0.741
Day	1	22.65	22.645	1.35	0.258
Error	23	386.61	16.809		
Total	34	1716.49			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.09988	77.48%	66.70%	52.36%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	7.964	0.693	11.49	0.000	
Production/m3	3.47	1.32	2.63	0.015	3.54
Mix	0.46	1.09	0.43	0.675	2.42
placing time in min	0.00	1.45	0.00	0.999	4.26
Element	-1.41	1.13	-1.24	0.227	2.60
Number of Mason	-6.71	2.21	-3.04	0.006	9.87
Labor	0.99	1.07	0.93	0.360	2.29
Total Workforce	-0.14	1.55	-0.09	0.928	4.85
Temp	-0.06	1.86	-0.03	0.976	6.96
Humidity	-0.167	0.871	-0.19	0.850	1.53
Wind	0.288	0.861	0.33	0.741	1.50
Day	0.947	0.816	1.16	0.258	1.35

Regression Equation in Uncoded Units

PR = 4.6 + 0.1091 Production/m3 + 1.05 Mix + 0.0000 placing time in min - 0.811 element
- 0.571 Number of Mason + 0.197 Labor - 0.0053 Total Workforce - 0.008 temp
- 0.0126 Humidity + 0.042 Wind + 0.498 Day

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid
18	6.33	13.24	-6.90	-2.05 R
24	28.50	16.70	11.80	3.25 R

R Large residual

b. Stepwise Regression

Regression Analysis: PR versus Production/m3, Mix, ... idity, Wind, Day

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production/m3	57.094	31.6418
Mix	1.219	0.4200
placing time in min	125.000	85.2825

element	2.438	1.7949
Number of Mason	15.031	11.8525
Labor	25.688	5.1709
Total Workforce	137.625	26.0703
temp	28.438	7.0273
Humidity	55.797	13.4439
Wind	17.016	7.0224
Day	3.406	1.9487

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	1020.08	255.019	89.23	0.000
Production/m3	1	417.11	417.110	145.94	0.000
Mix	1	10.10	10.103	3.53	0.071
element	1	6.98	6.983	2.44	0.130
Number of Mason	1	535.91	535.909	187.51	0.000
Error	27	77.17	2.858		
Total	31	1097.24			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.69057	92.97%	91.93%	90.56%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	6.974	0.299	23.33	0.000	
Production/m3	3.829	0.317	12.08	0.000	1.09
Mix	-0.667	0.355	-1.88	0.071	1.36
element	-0.565	0.362	-1.56	0.130	1.42
Number of Mason	-5.511	0.402	-13.69	0.000	1.76

Regression Equation in Uncoded Units

PR = 9.76 + 0.1210 Production/m3 - 1.587 Mix - 0.315 element - 0.4649 Number of Mason

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid	
6	3.522	6.962	-3.440	-2.11	R
29	10.500	7.247	3.253	2.10	R

R Large residual

c. Nonlinear Regression

Multiple Regression for PR Report Card

Check	Status	Description
Amount of Data		The sample size ($n = 32$) is not large enough to provide a very precise estimate of the strength of the relationship. Measures of the strength of the relationship, such as R-Squared and R-Squared (adjusted), can vary a great deal. To obtain a precise estimate, larger samples (typically 60 or more) should be used for a model of this size.
Unusual Data		4 data points have large residuals and are not well fit by the equation. These points are marked in red on the Diagnostic Report. You can hover over a point or use Minitab's brushing feature to identify the worksheet rows. Because unusual data can have a strong influence on the results, try to identify the cause for their unusual nature. Correct any data entry or measurement errors. Consider removing data that are associated with special causes and redoing the analysis.
Normality		Because you have at least 15 data points, normality is not an issue. If the number of data points is small and the residuals are not normally distributed, the p-values used to determine whether there is a significant relationship between the Xs and Y may not be accurate.

Multiple Regression for PR Model Building Report

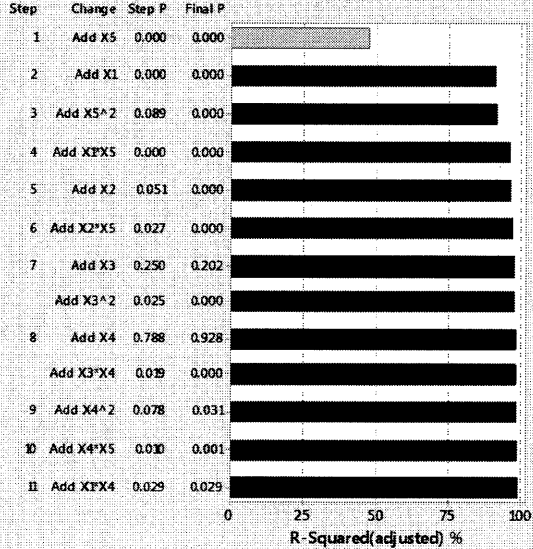
X1: Production/m X2: Mix X3: placing time X4: element X5: Number of Ma

Final Model Equation

$$PR = 5.96 + 0.2292 X1 + 3.75 X2 - 0.00296 X3 - 2.685 X4 + 0.039 X5 - 0.000152 X3^2 + 0.1993 X4^2 + 0.02235 X5^2 - 0.01196 X1 \cdot X4 - 0.006372 X1 \cdot X5 - 0.961 X2 \cdot X5 + 0.01412 X3 \cdot X4 + 0.0409 X4 \cdot X5$$

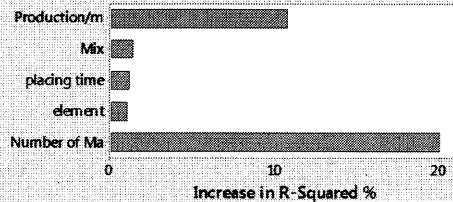
Model Building Sequence

Displays the order in which terms were added or removed.



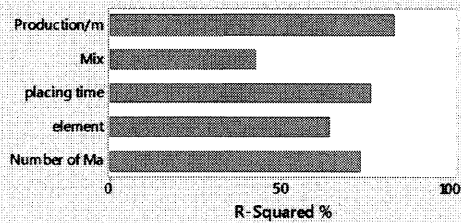
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

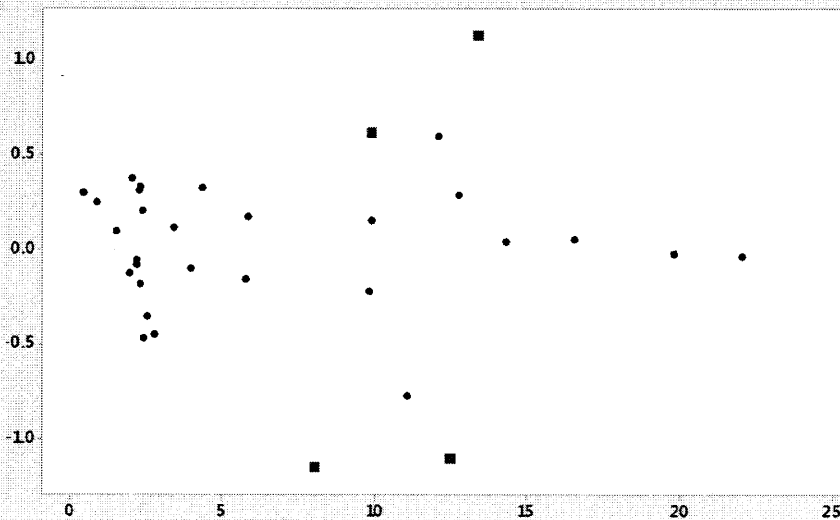
Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

Multiple Regression for PR Diagnostic Report

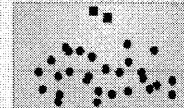
Residuals vs Fitted Values



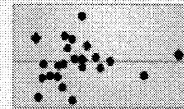
Look for patterns, such as strong curvature or clusters, that may indicate problems with the regression model. Ideally, the points should fall randomly on both sides of zero. Identify any large residuals that could have a strong influence on the model.

Look for these patterns:

Large Residuals



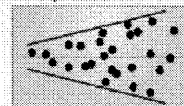
Unusual X Values



Clusters



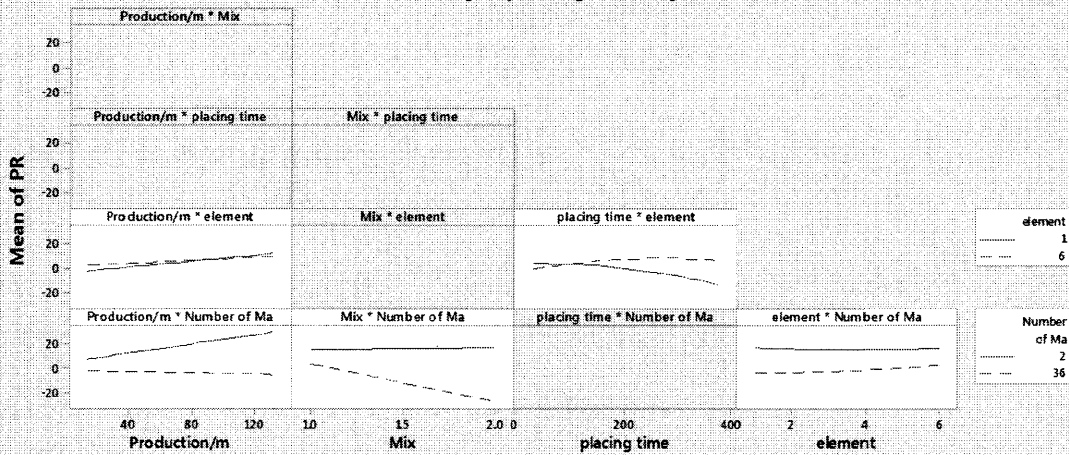
Unequal Variation



Multiple Regression for PR Effects Report

Interaction Plots for PR

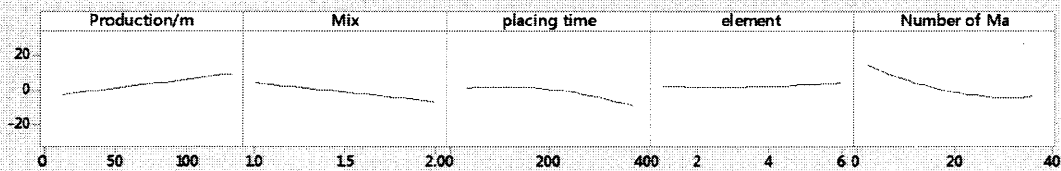
Describes how PR changes if you change the settings of two X variables.



Main Effects Plots for PR

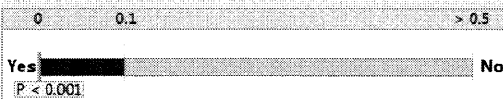
Describes how PR changes if you change the settings of one X variable.

If there is an interaction between X variables, use the interaction plots to determine the best variable settings.



Multiple Regression for PR Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant ($p < 0.10$).

% of variation explained by the model



99.39% of the variation in Y can be explained by the regression model.

Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:

X1: Production/m3

X2: Mix

X3: placing time in min

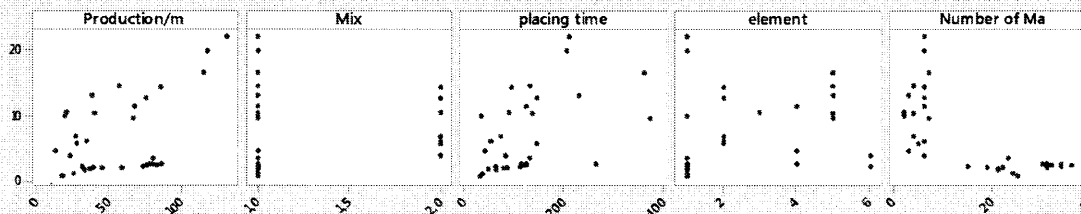
X4: element

X5: Number of Mason

$X3^2$, $X4^2$, $X5^2$, $X1 \times X4$, $X1 \times X5$, $X2 \times X5$, $X3 \times X4$, $X4 \times X5$

If the model fits the data well, this equation can be used to predict PR for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for PR.

PR vs X Variables



A gray background represents an X variable not in the model.

Block work Regression Models

a. General Regression

Regression Analysis: PR(Block/mason) versus Production ...

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production (blocks)	7784.82	2725.02
Temperature(C)	30.64	4.53
Humidity (%)	42.09	12.61
Wind (km/h)	21.23	9.73
No. of Masons	79.54	22.83
No. of Subcontractor	6.76	1.21
No. of Supervisors	2.21	0.44
Labor	101.74	16.86
Total Plant	2.85	0.62
Working hours	9.80	0.89
Total Workforce	206.15	49.35
Week day	3.76	1.98
Season	0.04	0.19

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	13	30796.0	2368.92	113.47	0.000
Production (blocks)	1	7440.6	7440.58	356.41	0.000
Temperature(C)	1	55.7	55.71	2.67	0.107
Humidity (%)	1	4.4	4.41	0.21	0.647
Wind (km/h)	1	2.5	2.53	0.12	0.729
No. of Masons	1	440.8	440.78	21.11	0.000
No. of Subcontractor	1	427.1	427.08	20.46	0.000
No. of Supervisors	1	4.0	4.01	0.19	0.663
Labor	1	6.2	6.23	0.30	0.587
Total Plant	1	18.4	18.37	0.88	0.352
Working hours	1	22.1	22.14	1.06	0.307
Total Workforce	1	8.0	7.96	0.38	0.539
Week day	1	36.6	36.55	1.75	0.190

Season	1	330.0	329.99	15.81	0.000
Error	66	1377.9	20.88		
Total	79	32173.8			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.56911	95.72%	94.87%	62.32%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.786	0.511	191.42	0.000	
Production (blocks)	31.61	1.67	18.88	0.000	10.61
Temperature(C)	1.71	1.04	1.63	0.107	4.13
Humidity (%)	-0.323	0.703	-0.46	0.647	1.87
Wind (km/h)	0.222	0.638	0.35	0.729	1.54
No. of Masons	-23.64	5.15	-4.59	0.000	100.18
No. of Subcontractor	3.842	0.850	4.52	0.000	2.73
No. of Supervisors	0.51	1.17	0.44	0.663	5.22
Labor	-1.52	2.78	-0.55	0.587	29.18
Total Plant	-0.598	0.637	-0.94	0.352	1.54
Working hours	-0.976	0.948	-1.03	0.307	3.40
Total Workforce	-4.66	7.55	-0.62	0.539	215.85
Week day	0.715	0.540	1.32	0.190	1.10
Season	3.554	0.894	3.98	0.000	3.02

Regression Equation in Uncoded Units

PR(Block/mason) = 95.0 + 0.011599 Production (blocks) + 0.377 Temperature(C)
 - 0.0256 Humidity (%) + 0.0228 Wind (km/h) - 1.036 No. of Masons
 + 3.164 No. of Subcontractor + 1.17 No. of Supervisors - 0.090 Labor
 - 0.97 Total Plant - 1.09 Working hours - 0.095 Total Workforce
 + 0.361 Week day + 18.59 Season

Fits and Diagnostics for Unusual Observations

Obs	PR(Block/mason)	Fit	Resid	Std Resid		
9	50.95	46.54	4.41	2.01	R	X
16	55.63	63.80	-8.18	-2.68	R	X
19	0.00	-3.23	3.23	3.66	R	X
29	81.53	89.44	-7.90	-2.03	R	
35	144.11	121.15	22.96	6.89	R	
59	78.29	69.28	9.00	3.21	R	X
72	99.19	105.46	-6.27	-2.08	R	X

77 92.51 79.23 13.28 4.08 R
R Large residual
X Unusual X

b. Stepwise Regression

Regression Analysis: PR(Block/mason) versus Production ... ay,
Season

Method

Continuous predictor standardization
Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production (blocks)	7784.82	2725.02
Temperature(C)	30.64	4.53
Humidity (%)	42.09	12.61
Wind (km/h)	21.23	9.73
No. of Masons	79.54	22.83
No. of Subcontractor	6.76	1.21
No. of Supervisors	2.21	0.44
Labor	101.74	16.86
Total Plant	2.85	0.62
Working hours	9.80	0.89
Total Workforce	206.15	49.35
Week day	3.76	1.98
Season	0.04	0.19

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	6	30709.1	5118.2	255.08	0.000
Production (blocks)	1	10255.4	10255.4	511.11	0.000
Temperature(C)	1	171.4	171.4	8.54	0.005
No. of Masons	1	5258.1	5258.1	262.05	0.000
No. of Subcontractor	1	480.1	480.1	23.93	0.000
Labor	1	100.8	100.8	5.03	0.028
Season	1	473.3	473.3	23.59	0.000
Error	73	1464.8	20.1		

Total 79 32173.8

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
4.47942	95.45%	95.07%	90.97%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	97.786	0.501	195.25	0.000	
Production (blocks)	31.50	1.39	22.61	0.000	7.64
Temperature(C)	2.142	0.733	2.92	0.005	2.11
No. of Masons	-26.61	1.64	-16.19	0.000	10.64
No. of Subcontractor	3.184	0.651	4.89	0.000	1.67
Labor	-2.92	1.30	-2.24	0.028	6.69
Season	3.623	0.746	4.86	0.000	2.19

Regression Equation in Uncoded Units

PR(Block/mason) = 85.23 + 0.011559 Production (blocks) + 0.472 Temperature(C)
- 1.1655 No. of Masons + 2.622 No. of Subcontractor - 0.1733 Labor
+ 18.95 Season

Fits and Diagnostics for Unusual Observations

Obs	PR(Block/mason)	Fit	Resid	Std Resid		
9	50.95	49.21	1.74	0.48	X	
16	55.63	65.68	-10.06	-2.83	R	X
19	0.00	-7.13	7.13	2.25	R	X
35	144.11	120.88	23.23	6.54	R	X
59	78.29	67.68	10.60	2.75	R	
77	92.51	81.28	11.23	2.99	R	X
78	79.71	79.84	-0.13	-0.04		X
79	78.01	77.84	0.17	0.05		X
80	77.42	77.45	-0.03	-0.01		X

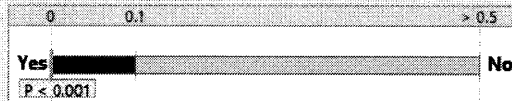
R Large residual

X Unusual X

c. Nonlinear Regression

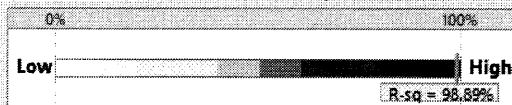
Multiple Regression for PR Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant ($p < 0.10$).

% of variation explained by the model



98.89% of the variation in Y can be explained by the regression model.

Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:

X1: Production in kg

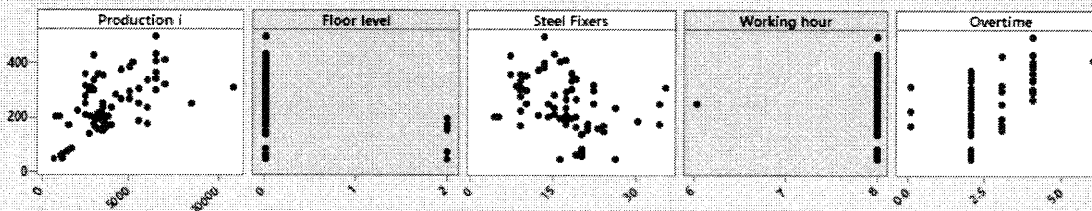
X3: Steel Fixers

X5: Overtime

$X1^2$, $X3^2$, $X5^2$, $X1 \cdot X3$, $X1 \cdot X5$

If the model fits the data well, this equation can be used to predict PR for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for PR.

PR vs X Variables



A gray background represents an X variable not in the model.

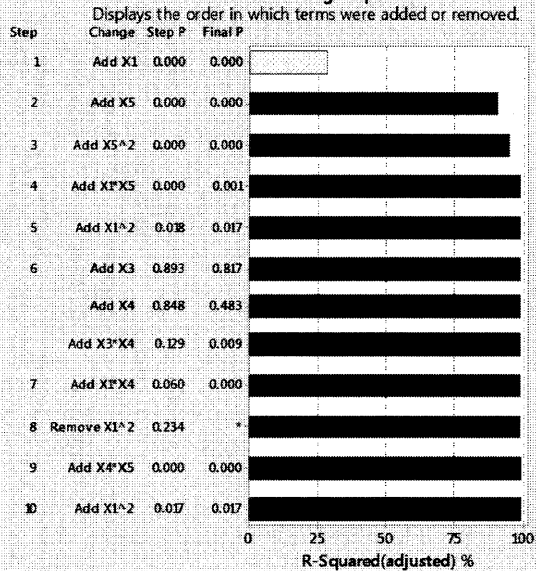
Multiple Regression for PR(Block/mas Model Building Report

X1: Production (X2: Temperature(X3: Humidity (%) X4: Wind (km/h) X5: No. of Mason

Final Model Equation

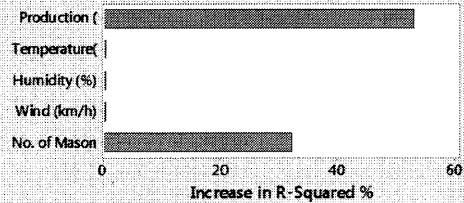
$$\text{PR(Block/mas)} = 125.61 + 0.025643 X1 + 0.1785 X3 + 0.180 X4 - 3.2681 X5 - 0.000000 X1^2 + 0.01299 X5^2 - 0.000098 X1^*X4 - 0.000074 X1^*X5 - 0.00869 X3^*X4 + 0.01220 X4^*X5$$

Model Building Sequence



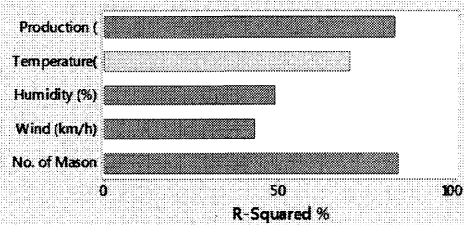
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

Multiple Regression for PR(Block/mas Report Card

Check Status Description

Amount of Data  Your sample is large enough (n = 80) to obtain a precise estimate of the strength of the relationship.

Unusual Data 

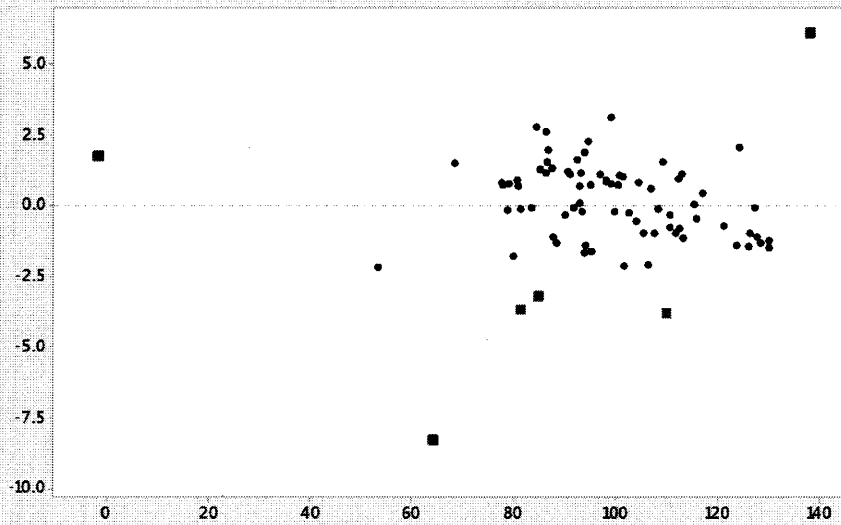
- Large residuals: 6 data points have large residuals and are not well fit by the equation. These points are marked in red on the Diagnostic Report.
- Unusual X values: 3 data points have unusual X values, which can strongly influence the model equation. These points are marked in red on the Diagnostic Report.

You can hover over a point or use Minitab's brushing feature to identify the worksheet rows. Because unusual data can have a strong influence on the results, try to identify the cause for their unusual nature. Correct any data entry or measurement errors. Consider removing data that are associated with special causes and redoing the analysis.

Normality  Because you have at least 15 data points, normality is not an issue. If the number of data points is small and the residuals are not normally distributed, the p-values used to determine whether there is a significant relationship between the Xs and Y may not be accurate.

Multiple Regression for PR(Block/mas Diagnostic Report

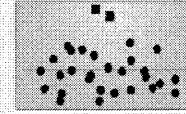
Residuals vs Fitted Values



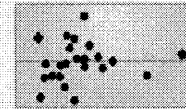
Look for patterns, such as strong curvature or clusters, that may indicate problems with the regression model. Ideally, the points should fall randomly on both sides of zero. Identify any large residuals that could have a strong influence on the model.

Look for these patterns:

Large Residuals



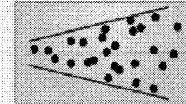
Unusual X Values



Clusters



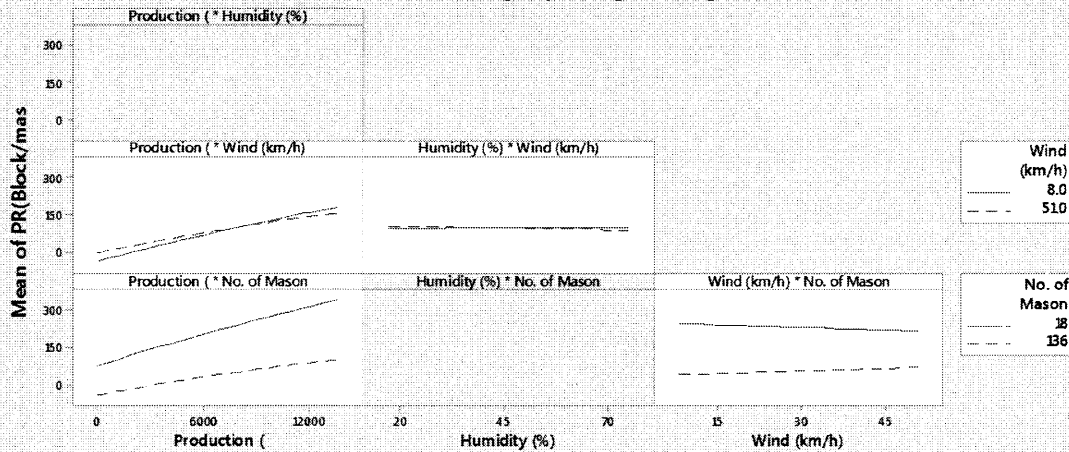
Unequal Variation



Multiple Regression for PR(Block/mas Effects Report

Interaction Plots for PR(Block/mas

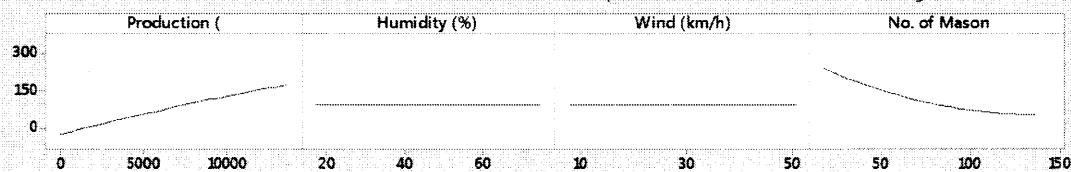
Describes how PR(Block/mas changes if you change the settings of two X variables.



Main Effects Plots for PR(Block/mas

Describes how PR(Block/mas changes if you change the settings of one X variable.

If there is an interaction between X variables, use the interaction plots to determine the best variable settings.



Steel fixing Models

a. Regression Models

Regression Analysis: PR versus Production in kg, Floor ... midity, Wind

The following terms cannot be estimated and were removed:

avg.Temp

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production in kg	3806.49	1894.20
Floor level	0.23	0.65
Steel Fixers	16.05	6.60
Working hours	7.97	0.23
Overtime	2.42	1.02
Element	3.60	2.69
Week day	3.61	2.00
Season	0.17	0.38
Min Temp	25.66	3.35
Max Temp	27.18	8.87
avg.Temp	26.42	5.61
Total Plant	6.70	2.10
Total Manpower	110.14	18.48
Humidity	60.92	14.87
Wind	16.56	8.11

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	14	665428	47531	63.05	0.000
Production in kg	1	116190	116190	154.14	0.000
Floor level	1	1191	1191	1.58	0.214
Steel Fixers	1	108917	108917	144.49	0.000
Working hours	1	39	39	0.05	0.822
Overtime	1	789	789	1.05	0.310
Element	1	62	62	0.08	0.775

Week day	1	1941	1941	2.58	0.114
Season	1	61	61	0.08	0.776
Min Temp	1	828	828	1.10	0.299
Max Temp	1	473	473	0.63	0.432
Total Plant	1	456	456	0.60	0.440
Total Manpower	1	2552	2552	3.38	0.071
Humidity	1	1511	1511	2.00	0.162
Wind	1	144	144	0.19	0.663
Error	62	46736	754		
Total	76	712164			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
27.4555	93.44%	91.96%	*

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	251.12	3.13	80.26	0.000	
Production in kg	91.60	7.38	12.42	0.000	5.49
Floor level	7.52	5.99	1.26	0.214	3.61
Steel Fixers	-83.45	6.94	-12.02	0.000	4.86
Working hours	0.81	3.56	0.23	0.822	1.28
Overtime	4.77	4.66	1.02	0.310	2.19
Element	-1.30	4.53	-0.29	0.775	2.07
Week day	5.46	3.40	1.60	0.114	1.17
Season	-4.0	14.0	-0.29	0.776	19.72
Min Temp	5.23	4.99	1.05	0.299	2.51
Max Temp	-6.28	7.94	-0.79	0.432	6.35
Total Plant	3.39	4.36	0.78	0.440	1.91
Total Manpower	-15.97	8.68	-1.84	0.071	7.59
Humidity	-7.29	5.15	-1.42	0.162	2.67
Wind	1.71	3.90	0.44	0.663	1.53

Regression Equation in Uncoded Units

PR = 311 + 0.04836 Production in kg + 11.63 Floor level - 12.65 Steel Fixers
 + 3.5 Working hours + 4.68 Overtime - 0.48 Element + 2.73 Week day - 10.6 Season
 + 1.56 Min Temp - 0.709 Max Temp + 1.62 Total Plant - 0.864 Total Manpower
 - 0.490 humidity + 0.210 Wind

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid	
22	200.0	271.4	-71.4	-2.84	R
30	428.6	347.9	80.7	3.10	R
37	166.7	224.7	-58.1	-2.33	R
44	200.0	258.9	-58.9	-2.30	R
49	250.0	250.0	0.0	*	X
64	308.6	327.9	-19.4	-1.14	X
74	46.2	-19.8	66.0	2.78	R

R Large residual

X Unusual X

b. Stepwise Regression

Regression Analysis: PR versus Production in kg, Floor ... midity, Wind

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation.

Predictor	Mean	StDev
Production in kg	3806.49	1894.20
Floor level	0.23	0.65
Steel Fixers	16.05	6.60
Working hours	7.97	0.23
Overtime	2.42	1.02
Element	3.60	2.69
Week day	3.61	2.00
Season	0.17	0.38
Min Temp	25.66	3.35
Max Temp	27.18	8.87
avg.Temp	26.42	5.61
Total Plant	6.70	2.10
Total Manpower	110.14	18.48
Humidity	60.92	14.87
Wind	16.56	8.11

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
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Regression	5	661607	132321	185.83	0.000
Production in kg	1	279243	279243	392.16	0.000
Floor level	1	3586	3586	5.04	0.028
Steel Fixers	1	238862	238862	335.45	0.000
Week day	1	1829	1829	2.57	0.113
Total Manpower	1	7634	7634	10.72	0.002
Error	71	50557	712		
Total	76	712164			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
26.6845	92.90%	92.40%	91.30%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	251.12	3.04	82.58	0.000	
Production in kg	96.49	4.87	19.80	0.000	2.53
Floor level	8.44	3.76	2.24	0.028	1.51
Steel Fixers	-87.09	4.76	-18.32	0.000	2.41
Week day	4.94	3.08	1.60	0.113	1.01
Total Manpower	-14.88	4.54	-3.27	0.002	2.20

Regression Equation in Uncoded Units

PR = 345.9 + 0.05094 Production in kg + 13.05 Floor level - 13.206 Steel Fixers
+ 2.47 Week day - 0.805 Total Manpower

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid	
7	176.5	151.4	25.1	1.12	X
22	200.0	260.7	-60.7	-2.37	R
30	428.6	338.9	89.6	3.44	R
37	166.7	237.0	-70.3	-2.76	R
44	200.0	260.1	-60.1	-2.34	R
64	308.6	338.4	-29.8	-1.43	X
74	46.2	-22.0	68.2	2.83	R

R Large residual

X Unusual X

c. Nonlinear Regression

Multiple Regression for PR Report Card

Check	Status	Description
Amount of Data		Your sample is large enough ($n = 77$) to obtain a precise estimate of the strength of the relationship.
Unusual Data		- Large residuals: 6 data points have large residuals and are not well fit by the equation. These points are marked in red on the Diagnostic Report. - Unusual X values: 4 data points have unusual X values, which can strongly influence the model equation. These points are marked on the Diagnostic Report. You can hover over a point or use Minitab's brushing feature to identify the worksheet rows. Because unusual data can have a strong influence on the results, try to identify the cause for their unusual nature. Correct any data entry or measurement errors. Consider removing data that are associated with special causes and redoing the analysis.
Normality		Because you have at least 15 data points, normality is not an issue. If the number of data points is small and the residuals are not normally distributed, the p-values used to determine whether there is a significant relationship between the Xs and Y may not be accurate.
Evaluate Solutions		The Prediction and Optimization Report displays the optimal solution, which is calculated using a numerical algorithm. It also displays a list of alternative solutions. When evaluating these solutions, consider the following: - The feasibility of the optimal solution from a practical perspective. - The sensitivity of Y to departures from the optimal X values. - The true optimal solution may not be located in the current sample space. - The alternative solutions may be more practical than the optimal solution. Once you have selected a solution, perform 20-30 confirmation runs to validate the optimal X values.

Multiple Regression for PR Prediction and Optimization Report

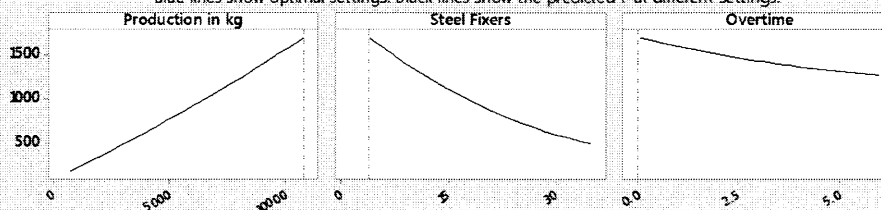
Goal: Maximize PR

Solution: Optimal Settings

Predicted Y	1687.58	X1: Production i	10800
95% PI	(1538.9, 1836.2)	X3: Steel Fixers	4
		X5: Overtime	0

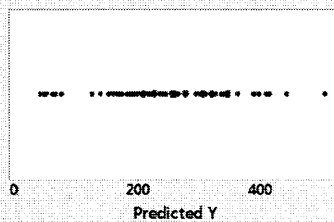
Settings and Sensitivity for Optimal Solution

Blue lines show optimal settings. Black lines show the predicted Y at different settings.



Predicted Y for All Sample Points

Use brushing to see the X values for any predicted Y.



Top Five Alternative Solutions

Sample points with predicted Y values closest to the optimal solution. Evaluate these and the optimal solution to determine if any are adequate.

X1	X3	X5	Predicted Y
6500	13	4	502.415
6500	15	4	441.646
6500	16	4	413.430
5200	13	4	409.125
7000	17	6	408.175

Multiple Regression for PR Model Building Report

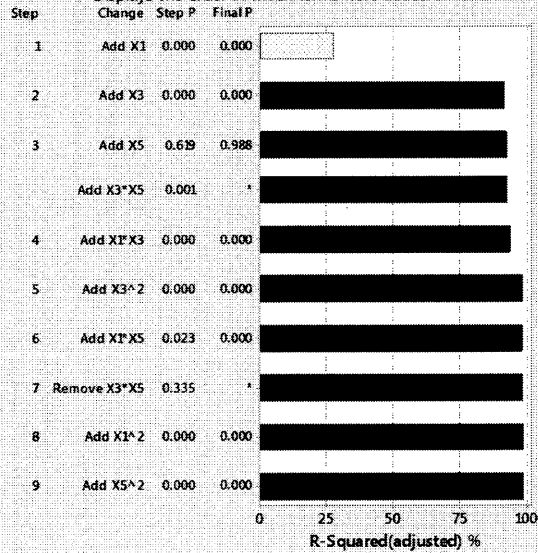
X1: Production i X2: Floor level X3: Steel Fixers X4: Working hour X5: Overtime

Final Model Equation

$$PR = 186.7 + 0.13722 X1 - 26.38 X3 + 13.40 X5 + 0.000002 X1^2 + 0.7228 X3^2 + 5.99 X5^2 - 0.003730 X1 \cdot X3 - 0.01111 X1 \cdot X5$$

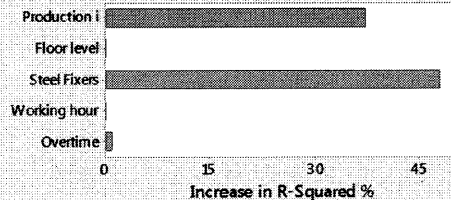
Model Building Sequence

Displays the order in which terms were added or removed.



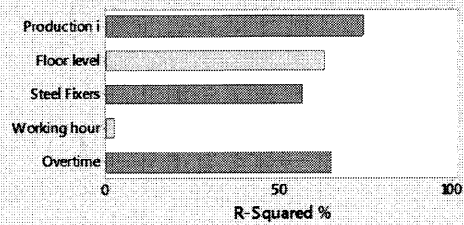
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

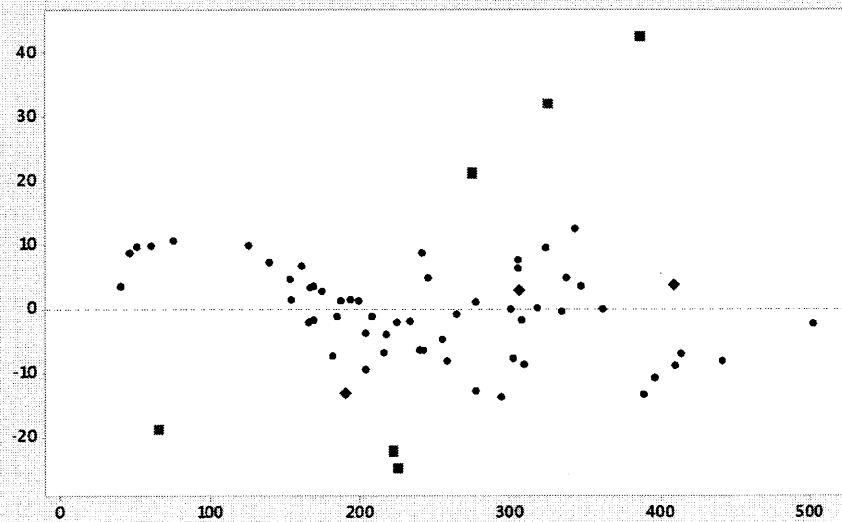
Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

Multiple Regression for PR Diagnostic Report

Residuals vs Fitted Values



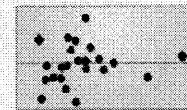
Look for patterns, such as strong curvature or clusters, that may indicate problems with the regression model. Ideally, the points should fall randomly on both sides of zero. Identify any large residuals that could have a strong influence on the model.

Look for these patterns:

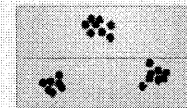
Large Residuals



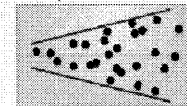
Unusual X Values



Clusters



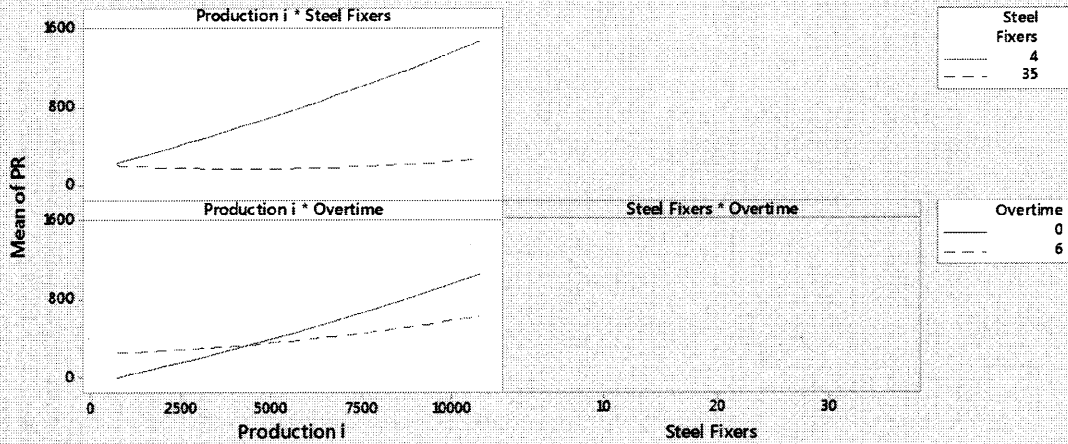
Unequal Variation



Multiple Regression for PR Effects Report

Interaction Plots for PR

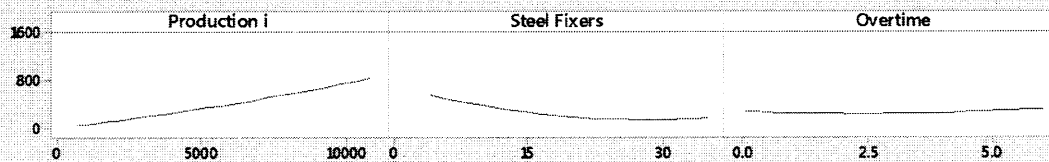
Describes how PR changes if you change the settings of two X variables.



Main Effects Plots for PR

Describes how PR changes if you change the settings of one X variable.

If there is an interaction between X variables, use the interaction plots to determine the best variable settings.



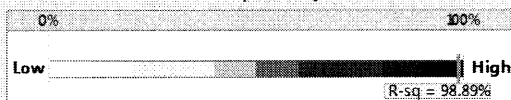
Multiple Regression for PR Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant ($p < 0.10$).

% of variation explained by the model



98.89% of the variation in Y can be explained by the regression model.

Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:

X1: Production in kg

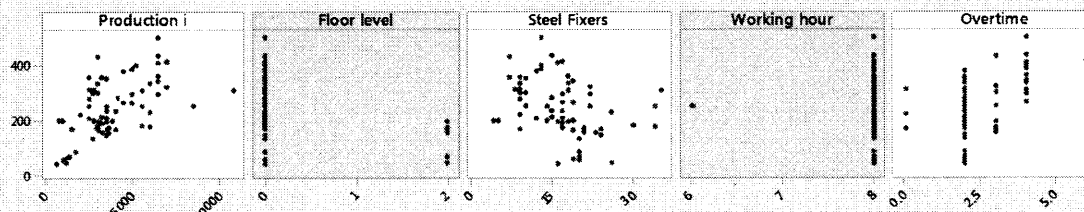
X3: Steel Fixers

X5: Overtime

$X1^2$, $X3^2$, $X5^2$, $X1 \cdot X3$, $X1 \cdot X5$

If the model fits the data well, this equation can be used to predict PR for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for PR.

PR vs X Variables



A gray background represents an X variable not in the model.

Formwork Models

a. General Regression

Regression Analysis: PR versus Production, Carpenter, r, humi, Wind

The following terms cannot be estimated and were removed:

avg.Temp

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production	71.754	76.8995
Carpenter	10.320	4.4943
Overtime	1.639	0.8683
Week day	3.845	1.9490
Season	1.010	0.6373
Min Temp	29.247	3.4188
Max Temp	36.804	8.4405
avg.Temp	33.026	5.8092
Total Plant	5.299	1.0223
Total Manpower	134.835	17.9709
Humi	47.134	16.8644
Wind	21.742	10.1348

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	11	3994.55	363.14	186.46	0.000
Production	1	3022.15	3022.15	1551.76	0.000
Carpenter	1	516.83	516.83	265.37	0.000
Overtime	1	0.59	0.59	0.30	0.583
Week day	1	3.31	3.31	1.70	0.196
Season	1	1.40	1.40	0.72	0.398
Min Temp	1	0.02	0.02	0.01	0.922
Max Temp	1	9.02	9.02	4.63	0.034
Total Plant	1	6.26	6.26	3.21	0.077
Total Manpower	1	1.16	1.16	0.60	0.442

humi	1	2.56	2.56	1.31	0.255
Wind	1	0.04	0.04	0.02	0.882
Error	85	165.54	1.95		
Total	96	4160.09			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.39555	96.02%	95.51%	94.72%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	6.706	0.142	47.32	0.000	
Production	7.263	0.184	39.39	0.000	1.68
Carpenter	-2.818	0.173	-16.29	0.000	1.47
Overtime	-0.284	0.515	-0.55	0.583	13.09
Week day	-0.204	0.157	-1.30	0.196	1.21
Season	0.92	1.08	0.85	0.398	57.42
Min Temp	0.044	0.448	0.10	0.922	9.89
Max Temp	-1.405	0.653	-2.15	0.034	21.03
Total Plant	-0.625	0.348	-1.79	0.077	5.99
Total Manpower	-0.587	0.759	-0.77	0.442	28.38
Humi	-0.246	0.215	-1.15	0.255	2.28
Wind	0.027	0.180	0.15	0.882	1.59

Regression Equation in Uncoded Units

PR = 19.91 + 0.09445 Production - 0.6270 Carpenter - 0.327 Overtime - 0.1048 Week day
+ 1.44 Season + 0.013 Min Temp - 0.1665 Max Temp - 0.611 Total Plant
- 0.0327 Total Manpower - 0.0146 humi + 0.0026 Wind

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid	
24	40.000	38.958	1.042	0.95	X
33	46.000	44.060	1.940	1.84	X
35	16.000	11.306	4.694	3.46	R
43	12.000	15.932	-3.932	-3.02	R
49	11.000	13.662	-2.662	-2.02	R
65	1.895	-2.978	4.873	3.73	R

R Large residual

X Unusual X

b. Stepwise Regression

Regression Analysis: PR versus Production, Carpenter, ... r, humi, Wind

Method

Continuous predictor standardization

Subtract the mean, then divide by the standard deviation

Predictor	Mean	StDev
Production	71.754	76.8995
Carpenter	10.320	4.4943
Overtime	1.639	0.8683
Week day	3.845	1.9490
Season	1.010	0.6373
Min Temp	29.247	3.4188
Max Temp	36.804	8.4405
avg.Temp	33.026	5.8092
Total Plant	5.299	1.0223
Total Manpower	134.835	17.9709
Humi	47.134	16.8644
Wind	21.742	10.1348

Stepwise Selection of Terms

α to enter = 0.15, α to remove = 0.15

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	3982.60	796.52	408.38	0.000
Production	1	3415.47	3415.47	1751.15	0.000
Carpenter	1	535.98	535.98	274.80	0.000
Season	1	19.77	19.77	10.14	0.002
avg.Temp	1	40.26	40.26	20.64	0.000
Total Plant	1	5.11	5.11	2.62	0.109
Error	91	177.49	1.95		
Total	96	4160.09			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.39657	95.73%	95.50%	94.87%

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	6.706	0.142	47.29	0.000	

Production	7.212	0.172	41.85	0.000	1.46
Carpenter	-2.735	0.165	-16.58	0.000	1.34
Season	0.764	0.240	3.18	0.002	2.83
avg.Temp	-1.326	0.292	-4.54	0.000	4.19
Total Plant	-0.388	0.239	-1.62	0.109	2.82

Regression Equation in Uncoded Units

PR = 14.59 + 0.09379 Production - 0.6086 Carpenter + 1.199 Season - 0.2283 avg.Temp
- 0.379 Total Plant

Fits and Diagnostics for Unusual Observations

Obs	PR	Fit	Resid	Std Resid	
23	4.500	5.485	-0.985	-0.78	X
24	40.000	38.779	1.221	1.06	X
33	46.000	43.876	2.124	1.94	X
35	16.000	11.280	4.720	3.45	R
43	12.000	15.901	-3.901	-2.93	R
49	11.000	13.683	-2.683	-2.02	R
65	1.895	-2.851	4.746	3.58	R
78	2.800	0.071	2.729	2.07	R

c. Nonlinear Regression

Multiple Regression for PR Report Card

Check	Status	Description
Amount of Data		Your sample is large enough ($n = 100$) to obtain a precise estimate of the strength of the relationship.
Unusual Data		• Large residuals: 5 data points have large residuals and are not well fit by the equation. These points are marked in red on the Diagnostic Report. • Unusual X values: 5 data points have unusual X values, which can strongly influence the model equation. These points are marked on the Diagnostic Report. You can hover over a point or use Minitab's brushing feature to identify the worksheet rows. Because unusual data can have a strong influence on the results, try to identify the cause for their unusual nature. Correct any data entry or measurement errors. Consider removing data that are associated with special causes and redoing the analysis.
Normality		Because you have at least 15 data points, normality is not an issue. If the number of data points is small and the residuals are not normally distributed, the p-values used to determine whether there is a significant relationship between the Xs and Y may not be accurate.

Multiple Regression for PR Model Building Report

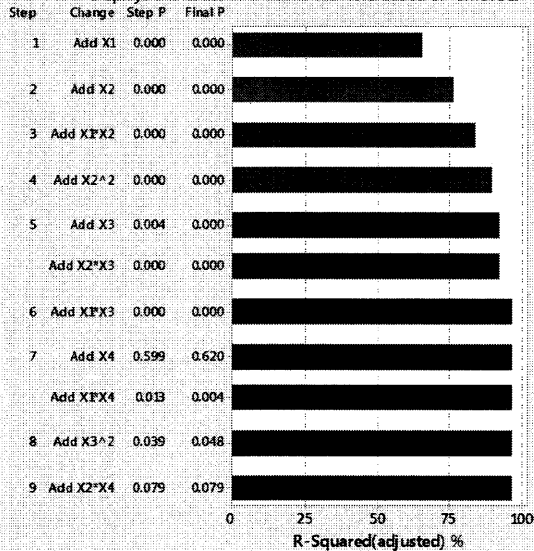
X1: Production X2: Carpenter X3: Overtime X4: Week day X5: Season

Final Model Equation

$$PR = 15.20 + 0.3949 X1 - 3.329 X2 - 3.847 X3 - 0.242 X4 + 0.1067 X2^2 + 0.687 X3^2 - 0.010854 X1 \cdot X2 - 0.08137 X1 \cdot X3 - 0.00358 X1 \cdot X4 + 0.5095 X2 \cdot X3 + 0.0475 X2 \cdot X4$$

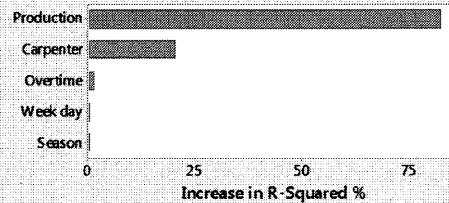
Model Building Sequence

Displays the order in which terms were added or removed.



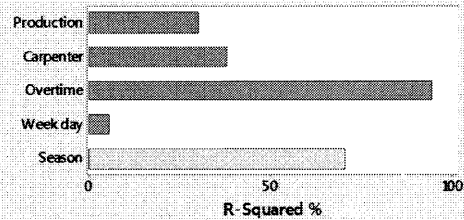
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

Multiple Regression for PR Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant ($p < 0.10$).

% of variation explained by the model



97.03% of the variation in Y can be explained by the regression model.

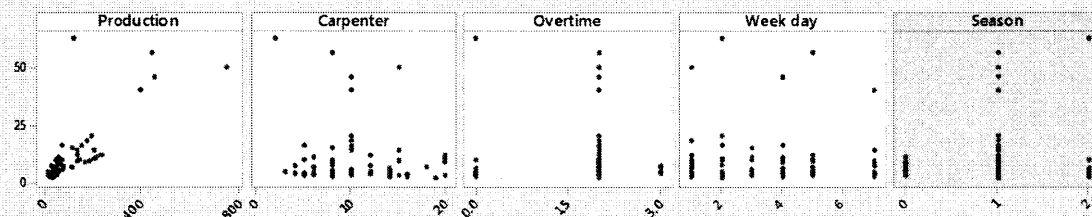
Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:

X1: Production
X2: Carpenter
X3: Overtime
X4: Week day
X2², X3², X1*X2, X1*X3, X1*X4, X2*X3, X2*X4

If the model fits the data well, this equation can be used to predict PR for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for PR.

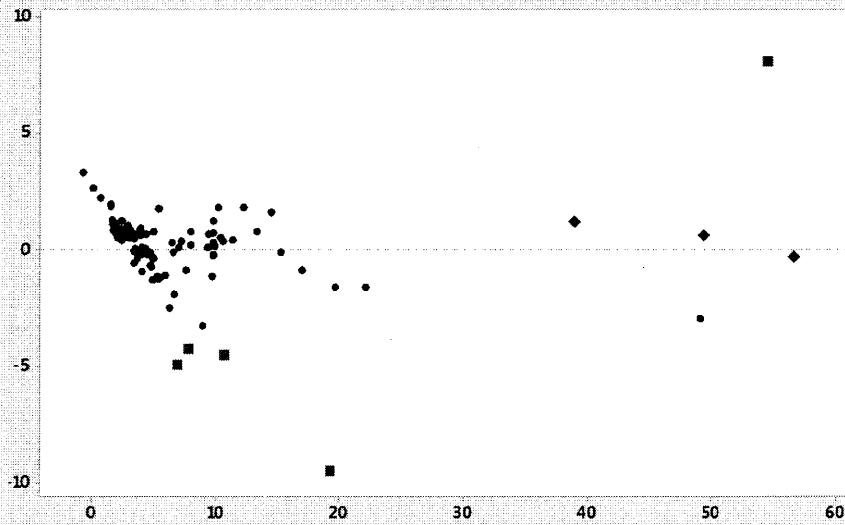
PR vs X Variables



A gray background represents an X variable not in the model.

Multiple Regression for PR Diagnostic Report

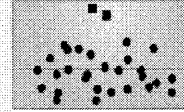
Residuals vs Fitted Values



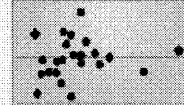
Look for patterns, such as strong curvature or clusters, that may indicate problems with the regression model. Ideally, the points should fall randomly on both sides of zero. Identify any large residuals that could have a strong influence on the model.

Look for these patterns:

Large Residuals



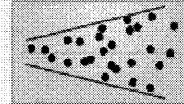
Unusual X Values



Clusters



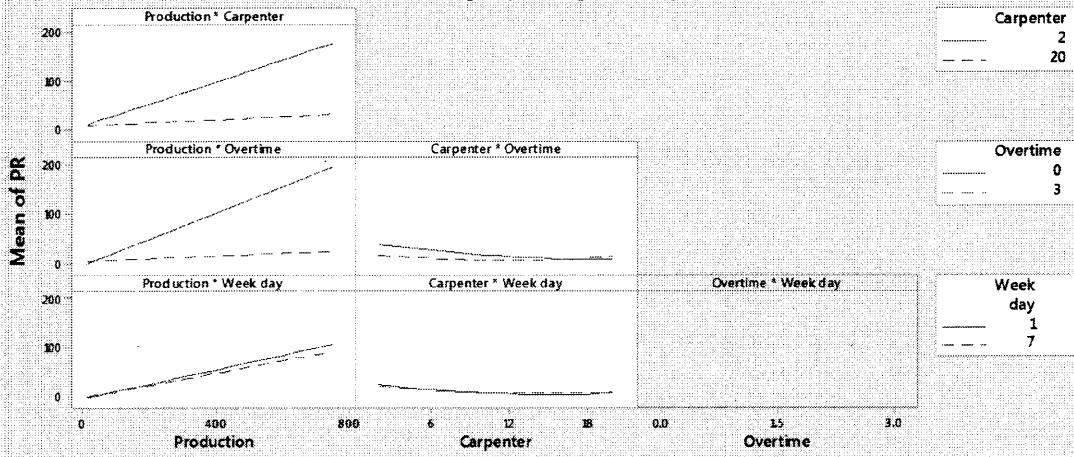
Unequal Variation



Multiple Regression for PR Effects Report

Interaction Plots for PR

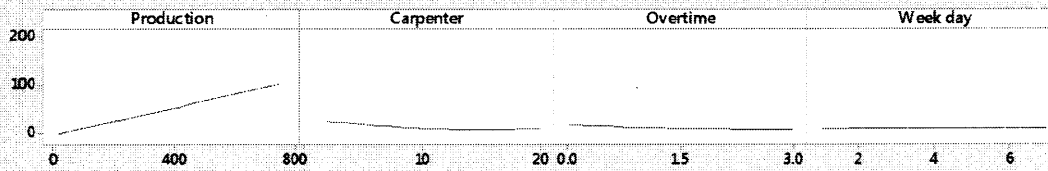
Describes how PR changes if you change the settings of two X variables.



Main Effects Plots for PR

Describes how PR changes if you change the settings of one X variable.

If there is an interaction between X variables, use the interaction plots to determine the best variable settings.



Respondents (Pxx) →	P67	P65	P64	P63	P62	P61	P60	P59	P58	P57	P56	P55	P54	P53	P52	P51	P50	P49	P48	P47	P46	P45	P44 S	P43 A
Management Factors																								
Lack of Supervision	5	3	4	3	4	4	4	5	3	4	4	5	4	3	4	5	4	4	5	4	5	3	5	4
Communication problems	3	2	4	4	3	4	1	2	5	2	4	5	4	2	5	3	5	3	4	3	5	3	5	4
Lack of training provided	1	4	4	3	4	4	2	4	4	1	5	4	2	4	5	3	3	5	4	4	3	5	5	4
Incentive programs	5	3	3	3	2	4	4	2	5	4	2	4	4	4	3	4	3	2	4	4	3	5	4	3
Management Leadership	4	4	4	4	4	4	3	4	5	5	3	4	4	4	4	5	5	4	5	4	4	5	4	4
Work planning and scheduling	4	2	5	5	4	3	5	5	5	4	3	5	4	4	5	3	5	5	4	5	5	5	5	5
Management of subcontractors	4	4	4	5	3	4	4	3	5	4	3	5	4	4	5	3	5	5	4	5	4	5	4	3
Lack of labor recognition programs	3	4	4	4	3	3	2	4	4	4	2	3	5	3	3	5	3	3	4	4	5	4	4	3
Safety requirements and regulations	3	5	4	4	5	4	3	5	3	2	2	5	2	2	5	4	5	4	5	2	5	5	5	4
Payment delay	3	2	5	5	4	2	3	3	1	2	4	3	3	3	3	5	5	3	2	5	5	1	5	5
Technological Factors																								
Crew size and composition	5	3	3	3	4	2	3	4	4	4	5	5	4	4	4	4	4	4	4	4	3	5	4	4
Inspection delays	3	4	4	5	3	3	2	5	3	2	4	3	3	2	3	3	4	4	4	4	5	3	5	3
Rework	3	4	4	4	3	3	2	5	4	4	2	4	4	2	4	4	4	3	3	5	5	3	5	5
Clarity of drawings and specifications	2	4	5	3	3	2	4	4	4	4	2	5	4	4	5	5	5	3	2	4	5	4	4	5
Design complexity	4	3	4	3	3	1	2	1	4	3	4	5	5	3	5	5	5	3	5	4	4	4	4	5
Variation/change orders	1	3	4	4	5	3	2	1	4	2	4	4	4	2	4	4	5	4	2	5	5	5	4	3
Availability of tools and equipment	3	5	4	3	5	4	3	5	2	5	5	5	4	4	3	5	5	5	5	5	5	4	4	5
Site layout and condition	2	4	4	4	2	4	2	1	3	2	4	4	4	4	3	5	5	5	4	4	4	5	4	4
Storage location	2	4	3	4	4	3	3	5	3	3	4	3	4	3	4	3	4	4	2	3	3	5	2	4
Project Type	1	3	3	3	3	4	2	3	3	3	4	4	4	4	3	5	5	4	2	3	3	5	2	3
Project Duration	4	4	4	4	4	1	3	4	1	4	4	4	4	4	4	3	5	4	2	3	3	5	2	3
Material shortage at project site	3	5	5	3	5	5	4	5	4	4	5	5	4	4	5	5	5	4	4	3	5	4	5	5
Workforce / Manpower Factors																								
Labor skill	4	1	3	3	4	4	4	5	4	4	5	5	4	4	5	4	4	5	4	5	5	3	4	4
Labor experience	3	5	4	4	3	4	4	5	2	4	3	4	5	4	5	3	5	5	5	4	5	3	4	4
Labor Age	1	5	3	3	3	5	2	2	4	3	3	4	4	3	4	3	3	4	4	4	4	2	4	5
Labor motivation	1	2	1	3	2	3	4	4	3	4	5	3	4	4	2	3	4	3	4	5	3	3	3	3
Labor Education	4	4	4	3	2	3	2	3	2	3	1	2	2	2	5	3	4	5	4	4	2	3	2	4
Overtime	3	3	1	4	4	2	4	5	3	3	4	5	4	4	3	3	3	3	4	5	2	3	2	4
Repetition of work	3	4	3	4	1	3	4	3	3	3	2	4	4	3	4	4	4	4	4	5	3	3	4	
Shift work	1	3	3	3	3	3	2	3	3	3	3	4	4	3	4	3	3	3	3	4	2	3	2	3
Working for long periods without holidays	3	5	1	3	2	4	2	4	3	1	3	3	4	3	3	3	4	4	5	3	3	3	4	5
Crewmembers	2	5	3	3	3	3	4	4	3	3	4	4	3	3	3	4	3	3	4	4	4	3	2	3
Absenteeism	2	5	2	4	4	4	5	5	2	1	2	4	5	3	4	4	5	5	5	4	4	3	4	5
Labor Personal problems	2	3	2	4	3	3	5	5	2	2	4	3	4	4	3	2	3	4	4	5	3	1	2	5
Rest time(s) per day	1	3	2	4	3	3	4	4	4	1	4	3	3	3	3	3	5	4	5	4	4	2	2	5
External factors																								
Noise	3	4	4	4	4	4	1	3	3	1	3	5	3	1	3	5	3	4	4	2	4	4	2	3
Political unrest	3	5	4	3	4	3	1	1	5	1	2	5	4	1	4	4	4	4	4	1	3	5	3	2
Temperature	2	5	4	4	5	5	3	5	5	4	4	5	5	4	5	5	4	5	5	4	5	5	3	5
Humidity	3	4	4	4	4	4	3	4	4	4	4	5	4	4	4	5	4	4	5	3	4	4	4	5
Precipitation / Rain	3	3	3	4	2	3	1	3	4	4	2	3	4	2	3	5	4	4	3	3	4	4	5	3
Wind or Dust	3	3	3	3	5	2	1	4	4	4	4	4	4	2	4	3	5	4	3	3	4	4	3	4
Government laws	3	3	2	3	3	1	1	1	4	4	1	4	4	4	5	5	4	4	4	4	5	5	3	2
Work at heights	5	3																						3

Table (3.2 A) : RII Calculations for each Factor

المخلص

يعد قطاع الانشاءات أحد أبرز القطاعات المؤثرة في الناتج المحلي الاجمالي لاقتصاد معظم الدول وبمملكة البحرين على الاخص فان هذا القطاع قد شهد نموا كبيرا وزيادة في حجم عدد المشاريع خلال السنوات الاخيرة نتيجة لدعم مجلس التعاون الخليجي لمشاريع التنمية بالمملكة وتوجهات الحكومة لتتويع مصادر الدخل والتي ساهمت في تنامي القطاعات الغير نفطية. وحيث ان قطاع الانشاءات يعتمد بشكل مكثف على انتاجية العمال فان ازدهار ونجاح هذا القطاع منوط برفع الكفاءة الإنتاجية للعاملين به لذلك هدفت الدراسة الى التعرف على العوامل المؤثرة على انتاجية العمال العاملين في مجال الانشاءات في مملكة البحرين ومن ثم تقييم اثر هذه العوامل حتى يتسنى لصناع القرار في الجهات المعنية اتخاذ تدابير من شأنها الحد من المعوقات وتحسين الأداء. ولتحقيق اهداف الدراسة تم تحليل المعلومات التي تم جمعها من دراسات سابقة تناولت تقييم اثر العوامل المؤثرة في انتاجية العمال في قطاع الانشاءات في مختلف الدول وقد تم تبويب ابرز العوامل التي خلص الباحثون إلى انها تعد الاكثر تأثيرا في انتاجية العمال وفق تحليلهم. بعد ذلك تم تطبيق استبانة على شريحة من المقاولين المحليين المصنفين تحت درجة AA ودرجة A لبحث هذه العوامل في مملكة البحرين تحديدا وقد تم استخدامها لبناء نموذج لتقييم العوامل المؤثرة على انتاجية العمال في قطاع الإنشاءات في مملكة البحرين باستخدام اسلوب الشبكات العصبية واسلوب الانحدار الخطي لأربع من اكثر النشاطات شيوعا في صناعة البناء والتشييد وهم التسليح وصب الخرسانة والأعمال الخشبية لصب الخرسانة واخيرا أعمال الطابوق. تم قياس دقة الاساليب المستخدمة في اعداد تلك النماذج بحساب مقدار الخطأ في النتائج المتنبأ بها وبناء على نتائج تلك المعايير توصلت الدراسة الى ان اسلوب الشبكات العصبية افضل من اسلوب الانحدار الخطي للتطبيق على بعض النشاطات كاعمال التسليح والأعمال الخشبية لصب الخرسانة والطابوق بينما اسلوب الانحدار الخطي اظهر ملائمة اكبر لنشاطات اخرى كاعمال صب الخرسانة. وقد خلصت الدراسة الى عدة توصيات من أبرزها أهمية جمع وحفظ البيانات المتعلقة بانتاجية عمال البناء لاستخدامها لأغراض التحليل والدراسة بالاضافة إلى ضرورة التعامل مع العوامل المؤثرة على انتاجية العمال في قطاع الانشاءات بفعالية بما يسهم في رفع الكفاءة الإنتاجية للعاملين.

جامعة البحرين

قسم الهندسة الميكانيكية



كلية الهندسة

نمذجة انتاجية العمال في قطاع الإنشاءات في مملكة البحرين

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير في الإدارة الهندسية

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