Estimating Productivity Losses Due to Change Orders

Ihab Assem

A Thesis
in
The Department of
Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Applied Science at
Concordia University
Montreal, Quebec, Canada

December 2000

0-612-59294-4

Abstract

Estimating Productivity Losses Due to Change Orders

Ihab Assem, M. A. Sc.
Concordia University, 2000

Change orders occur frequently during the delivery of construction projects, creating disruptions and modifying the orderly sequence of performance, leading to adverse impact on construction productivity. The quantification of this impact is a major source of disputes as it is generally underrated, and even sometimes goes completely unrecognized by owners.

This thesis presents a computer model for quantifying the adverse impact of change orders on construction productivity. In order to provide an in-depth analysis of change orders and develop a reliable model, a comprehensive field study was carried out. The field study was conducted at a Montreal based firm, specialized in project management and construction claims. A total of 117 actual projects, constructed in Canada and the USA between 1990 and 1998, were initially analyzed for possible use in the developments made in this thesis. Only 33 work-packages from these projects were utilized in the development of the present model. These work packages have an original total value of more than $110M, planned direct hours of 1,023,583 for the original scope of work and a total of change orders direct hours of 166,002. Additional cases, obtained from the literature, were used to supplement the collected data in order to improve the reliability of the developed model.

The analyzed cases are used to model the timing effect of change orders as well as the work type on productivity losses. The cases are statistically analyzed in order to evaluate the correlation of the productivity loss and a set of identified independent variables, used to represent the intensity of change orders. The data collected was used in the development of ten neural network models for predicting percent productivity loss. Two models representing the influence of the timing of change orders were developed using the distribution of direct man-hours over its construction period. The eight remaining models account for the type of work (i.e. architectural, civil, electrical, mechanical) and consider the ratio of change orders hours to both: 1) the planned hours of the original scope of work, and 2) the actual hours spent to complete the original scope of work (excluding change orders direct hours).

The developed neural network models, in addition to four widely used regression models developed by others, are incorporated in a prototype software application coded in Visual Basic. A number of actual cases have been analyzed to demonstrate the use and capabilities of the developed model. This software application provides an automated, user-friendly tool that quantifies productivity loss, during design and/or construction phase, due to change orders alone or change orders plus one or two additional causes of impact. Such a tool is useful to owners, consultants, and contractors, and could assist them in negotiations and timely settlement of disputes arising from change orders.

Acknowledgements

Praise is to GOD, the all mighty, the most merciful, and the most compassionate.

I wish to express my deepest gratitude and appreciation to Dr. O. Moselhi for his solid support, valuable advice, constructive guidance, inspiration and patience. His influence far exceeds the scope of the work presented in this Thesis.

I am truly grateful to Dr. K. El-Rayes for his supervision, invaluable guidance, critical insights, and encouragement.

I am also thankful to Revay Associates Limited for allowing in-house investigation that provided the cases used in the developments done in this research.

I also wish to express my sincere gratitude to the faculty, staff and colleagues at the Department of Building, Civil and Environmental Engineering. Thanks are also due to Wael Hamed, for his contribution in the choice of the main interface of the prototype software system.

The financial support for this work, provided by the Construction Research Institute of Canada (CRIC) is gratefully acknowledged.

To BOTH My Families

&

To ALL My Children

TABLE OF CONTENTS

Nomenclature

A	total Area under the direct resource-loading curve.
A/C/E/M	Architectural/Civil/Electrical/Mechanical, work types.
ADOCH	Actual Direct Original Contract Hours, which includes the total direct hours less the change orders hours. Also referred to as "actual hours".
a_i	area under the direct resources loading curve for a certain project period "i", where i varies from 1 to 5.
ASCOs	Average Size of Change Orders, which is the ratio of the total change orders' direct hours to their total number.
BDOCH	Base Direct Original Contract Hours, which includes the total direct planned hours for the original project's scope of work. Also referred to as "base hours" or "planned hours".
$(BDOCH)_i$	Base Direct Original Contract Hours for a certain project period "i", where i varies from 1 to 5.
CORA	Change Orders direct hours Ratio to the Actual hours (i.e. HCOs/ADOCH).
CORB	Change Orders direct hours Ratio to the Base (planned) hours (i.e. HCOs/BDOCH).
$CORB_i$	Change Orders direct hours Ratio to the Base (planned) hours for a certain project period "i", where i varies from 1 to 5.

COs	Change Orders.
FCOs	Frequency of Change Orders, which is the ratio of the number of change orders to the actual hours.
HCOs	total direct Hours of Change Orders.
$(HCOs)_i$	direct Hours of Change Orders for a period "i".
k	number of independent variables in a data set.
MLRA	Multiple Linear Regression Analysis.
n	number of cases in a data set.
NCOs	total Number of Change Orders in a work package.
$(NCOs)_i$	the Number of Change Orders for a certain project period "i".
NNs	Neural Networks.
P_i	the work package duration is divided into five equal periods where the Period is designated by the letter "P" while its number is designated by the subscript "i" which value varies from 1 to 5.
PL	Productivity Loss which may be expressed in hours, or in percentage (non-productive hours to the actual direct hours worked).
TDH	Total Direct Hours, which includes the base (planned) hours of the original project's scope of work, the change orders hours, and the total non-productive hours (including the inefficient hours).

TI Type of Impact, which is the number of major causes of productivity loss. A TI of 1 occurs when the only reason for productivity loss is change orders, while TI of 2 or 3 occur in the case of one or two additional major causes of productivity loss.

WT Work Type (i.e. Architectural, Civil, Electrical, Mechanical work types).

$\in$ the random error resulting in a regression equation.

LIST OF FIGURES

List of Tables

Chapter 1

Introduction

1.1 Productivity in Construction

Construction industry forms a major sector of the national economies. It involves multitudes of resources, often known as the 3M (Manpower, Material, & Machinery). The productivity of labor and equipment are the basis for any project cost estimate and as such they collectively influence the profit margin for any contractor. As construction is a labor-intensive industry, many research studies focused on measuring, evaluating, reporting, and improving construction labor productivity. In course of this research, the word "productivity" is used to describe the construction labor productivity.

Thomas and Mathews (1986), Thomas and Kramer (1988), Dozzi and AbouRizk (1993), and Schwartzkoph (1995) provided various definitions for the productivity. In general, it can be defined as production rate (i.e. m^3/hr), man-hour rate (i.e. labor/m^3), cost rate (i.e. \$/m^3), performance factor, and/or the ratio of input/output (i.e. hr/m^3) that is usually utilized. Available research, that took place in the last 15 years, confirms the negative impact of change orders on productivity losses as they, in addition to their own impact, give rise to many other causes of productivity loss (e.g. disruption, over manning, congestion, stack of trades, ...etc). Quantifying this impact still is a major challenge that needs to be overcome in order to avoid, or at least minimize, the resulting costly disputes and claims.

1.2 Change Orders

Virtually all construction projects change as they progress; these changes are commonly referred to as change orders, variation orders, bulletins, field changes, fieldwork orders, field memorandums, and field directives. “Change Order(s)” is the commonly used expression, especially in North America, to designate any change or variation from the original scope of the construction contract. A change order: 1) increases, decreases, or omits, 2) changes the character or quality of material, and/or 3) changes the level, position, or dimension of any part in the original contract scope of work (Civitello 1987). In most cases, change orders are responsible for a series of impacts as they disrupt the work and affect its orderly sequence, adversely impacting productivity and accordingly causing schedule delays and cost overruns (Halyalimana 1989, Moselhi et al. 1991a, Ehrenreich-Hansen 1994, Coffman 1997). Section D of the "Gazette" of Montreal, in its issue dated September 21st, 2000 showed an article titled: "Forum project delayed: too few workers, too many design changes blamed". The recent opening of the $100M forum, in Montreal (Canada), is delayed until March 2001 and will not meet its scheduled opening date of November 2000. The spokesman stated that the work began last year, but was put on hold for three month while the contractor "wrestled" with design changes demanded by one of the large tenants. She added that "last minute changes” had to be done to incorporate the latest games and technological effects. The spokesman explained that one of the major resulting problems is that they "are having troubles finding enough construction labor to get the work done". This recent article emphasizes the effect that change orders have on construction projects.

Barrie and Paulson (1996) concluded that change orders occur in almost all projects causing delays, disruptions, and resulting-in disputes. If the resulting disputes cannot be resolved by mutual agreement, it will become a claim. Claims are often subject to a formal process, as spelled out in the contract. Unresolved claims are adjudicated by arbitration, litigation or other dispute resolution methods, as set forth in the contract. Simpson (1998) recognized disputes to be a "way of life in the construction industry". He stated that dispute resolution is a cost of doing business and reported the estimate of its monetary value to be 3.5% to 5.0 % of the project cost. The huge administrative and technical efforts put behind this operation and the high dollar value spent provide enough motivation to devise methods and procedures to reduce these disputes.

Many cases indicate that the main cause for claims is the disagreement between the parties about equitable compensation. A striking example is found in ENR editorials (1998), this article reports the legal struggle between a contractor (Ebasco Services Inc.) and an owner (Exxon Corp.) over the nature and degree of change orders at an Exxon oil and gas treatment facility in California. The jury awarded the contractor a financial compensation of $33.3M as additional compensation for 9800 change orders on the $105M project. The contractor made it clear that the compensation suggested covers only for time and material actually spent on the authorized changes not for the stalled crews. Field personnel provided strong testimony on impact of change orders on productivity losses. Quantifying these losses and their associated impact costs is essential in order to provide a fair pricing for change orders and equitable compensation for contractors (Moselhi 1998).

A number of professional organizations (i.e. AIA, CII, AACE) recommend settling the pricing of change orders up-front. This would charge the whole risk to contractors', unless a mean is found to identify and quantify impact costs. This cost is generally divided into 1) time-related, and 2) productivity-related (Moselhi 1998). The time extension cost could be determined in a straightforward manner once an equitable time extension has been established. On the other hand, unlike time-related costs, productivity-related costs can rarely be estimated accurately simply because it is difficult to demonstrate what costs would have been incurred without the adverse effect of changes on productivity (Moselhi 1998).

1.3 Objectives

The main objective of this research is to develop a practical model for quantifying the impact of change orders on construction productivity in order to provide an up-front equitable pricing for change orders. In order to achieve this main objective, the sub-objectives of this research are:

1) To review the available methods that quantify the adverse effect of change orders on productivity,

2) To study and identify the major factors influencing the adverse impact of change orders,

3) To analyze real case studies and generate a set of actual cases in order to provide a better understanding of the impact of change orders,

4) To conceive, develop and validate a computer-based model for quantifying the impact of change orders on construction productivity, accounting for the timing of these changes and their type of work, and

5) To implement and validate the developed model in user-friendly software system for estimating the impact of change orders on productivity.

1.4 Methodology

In order to achieve the above-studied objectives, the methodology of the research encompassed three main stages, as shown in Figure 1-1: 1) data collection and analysis stage, 2) models development stage, and 3) models validation stage.

In the data collection and organization stage, a field investigation is performed to provide cases to be used in modeling the timing and work type effects of change orders. Data is organized and supplementary data is adopted to increase the reliability of the model. Data is then prepared using the change orders intensity factors, as sets of independent variables. The intensity factors found to be in correlation with the productivity loss are used in the formulation of Data Sets for modeling purpose. In the models development stage, the formulated Data Sets are used to develop the regression models to ascertain the relevance of the independent variables in estimating productivity loss. Neural networks, known for their pattern recognition capabilities, are then used to develop models that are included, in addition to four regression models developed by others, in a user-friendly prototype software application. In the validation stage, actual cases are used to validate the developed prototype and to evaluate its performance.

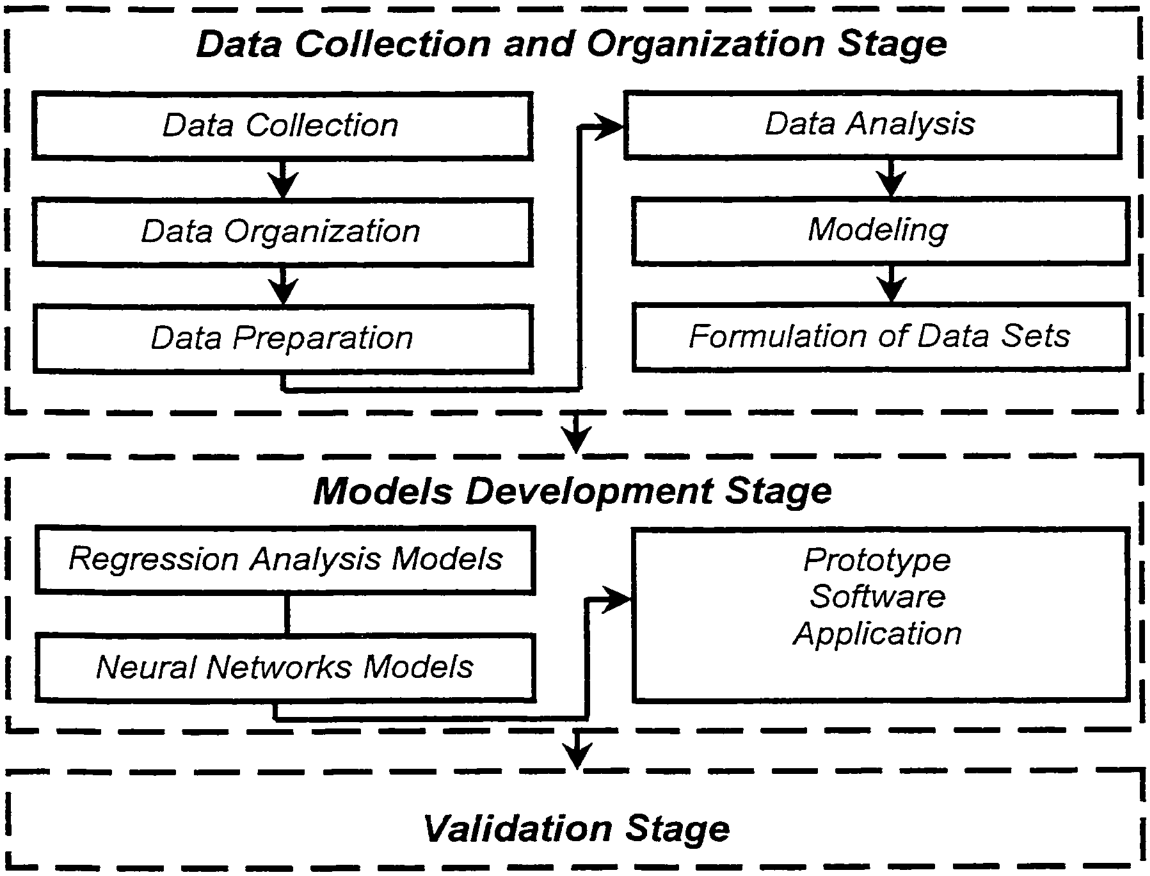


Figure 1-1 Research Methodology

1.5 Thesis Organization

Chapter 2 presents the literature review comprising 1) productivity, 2) change orders, and 3) neural networks. The different methods of productivity measurement are discussed, and the major causes of its impact are presented all with the developed quantification models. Change orders different definitions and types are introduced along with their causes, processing, impacts, change management, pricing, and quantification models. Neural networks history, the structure and performance of the back propagation paradigm are presented along with its applications, advantages, and disadvantages.

In Chapter 3, data collection and organization is outlined. The factors affecting their impact are used in data preparation. Statistical analysis is used to determine the factors correlating with the resulting productivity loss. These factors are used to quantify the change orders timing effect and work type effect. Modeling concepts are discussed and data sets are formulated for use in models development.

Chapter 4 describes the developed regression models, neural networks models, and prototype software system. The data sets developed in Chapter 3 are analyzed using regression analysis. The evaluation procedure of the regression models is presented and the results are discussed. The relevant data sets are, hence, used to train the neural networks and to develop the quantification models. The evaluation parameters are presented and discussed along with the models numerical limits. The algorithm used to develop the prototype software system is presented as well as the different screens, and the error messages incorporated.

Chapter 5 presents the validation of the developed neural network models. First, the models are validated against the regression analysis models. Afterward, the neural network models are validated against regression models developed by others. The performance of the developed model is analyzed and the results are presented and discussed.

In Chapter 6, summary and concluding remarks, in addition to contributions are presented along with recommendations for future work.

Chapter 2

Literature Review

2.1 Introduction

Construction is a labor-intensive industry, and accordingly the variations in labor productivity have a significant impact on the overall project cost and schedule. In this chapter, the presented comprehensive litterateur review is divided into three parts: 1) productivity, 2) change orders, and 3) neural networks. In the first part, the methods used to measure the productivity along with the causes that negatively impact it, and the developed quantification models are presented. In the second part, change orders definition, types, causes, process, management, pricing, and quantification models are discussed. The last part covers the neural networks history, structure and performance, applications, advantages, and disadvantages.

2.2 Productivity Analysis

The two important measures of productivity are the effectiveness and the efficiency (Leonard et al. 1988, Dozzi and AbouRizk 1993). The effectiveness is the efficacy with which labor is used (e.g. the money value required to produce a square foot of housing). The efficiency is having the labor doing the required at a given time and place (e.g. number of square foot of formwork per man-hour). As mentioned earlier in Section 1.1, productivity is best expressed by the ratio of input/output (e.g. man-hours per cubic yard of concrete) as it facilitates the calculation of the project cost by multiplying the productivity (i.e. man-hr. / m^3) by the estimated quantity times the wage rate. The input could be expressed in terms of any resource used. Usually it is expressed in terms of labor, where it is best defined as function of labor cost or hours. On the other hand, the output is expressed "as some physical achievement" (Leonard et al. 1988), e.g. meters of pipefitting or cubic meters of concrete. Halpin (1985), Thomas and Mathews (1986), Thomas and Kramer (1988), Oberlender (1993), and Dozzi and AbouRizk (1993) reported several methods to measure the output on a project that could be summarized as follow:

1) The estimated percent complete method, which depends on the estimation of the overall percentage completed. It is simple and inexpensive, however it is subjective (i.e. depending on an individual's guess), and not sensitive to scope changes.

2) The physical measurement method, which requires the actual measuring of the number of units completed. It is objective, detailed, and capable of recording scope changes, however it is time consuming and expensive.

3) The earned value (EV) method, which is a more objective than the estimated percent complete method but not as detailed or expensive as the physical measurement method. The earned value equals the actual quantities done multiplied by the estimated (or budgeted) productivity per unit of quantity. For example, consider a concrete activity where the earned value of man-hours

can be estimated by multiplying the cubic meters installed by the estimated man-hours per cubic meter.

4) Performance Factor (PF) method, which is equal to the estimated, or earned, man-hours over the actual man-hours. This method exhibits short-comes such as the wrong estimate of earned man-hours, the incorrectly charged worked hours, and/or the inaccurate measurement of the physical progress.

The factors that affect productivity, causing its losses, have been analyzed in several studies that focused on: 1) qualitative analysis (i.e. modeling the influencing factors and analyzing their effects), and 2) quantitative analysis (i.e. quantifying the effect of the influencing factors).

2.2.1 Qualitative Analysis

The qualitative analysis was the focus of several studies, which provided a long list of factors that are identified as affecting productivity. In general, any factor that may affect a human working in an opened environment can be considered as a factor that has an effect on construction productivity. Warren (1984), and Diekman and Nelson (1985) identified 6 main factors for causing productivity loss: 1) change orders, 2) type of contract, 3) type of contractor, 4) differing site conditions, 5) weather, and 6) strikes. Horner et al. (1987) divided the factors affecting labor productivity into two categories: management controlled, and project related and environmental as summarized in Table 2-1.

Table 2-1 Factors Affecting the Productivity (Horner et al. 1987)

Management Controlled	Project Related and Environmental
Skill of labor force	Skill of labor force
Size of labor force	Size of project
Balance of labor force	Absenteeism
Morale of labor force	Unemployment rate
Motivation of labor force	Lack of motivation
Union attitudes	Union attitudes
Working hours	Weather
Welfare provisions	National/Local politics
Continuity	Continuity of work for trades
Working methods	Complexity
Mechanization	Constructability
Availability of resources	Availability of resources
Quality of finished work	Quality specified
Performance of subcontractors	Holidays
Relationships with client	Type of contract
Degree of management control	Variations (change orders)

Thomas and Yiakoumis (1987) presented a productivity curve that accounts for effect of the numerous factors that affect crew performance as shown in Figure 2-1. Those factors are divided into: 1) design factors, 2) management factors, 3) site factors, and 4) environmental factors. Design factors include constructability, specification requirements, quality of documents, and quality control requirements. Management factors include management control, manning level, crew size and structure, methods, work schedule. Site factors include congestion, accessibility, and layout. Environmental factors include weather and absenteeism.

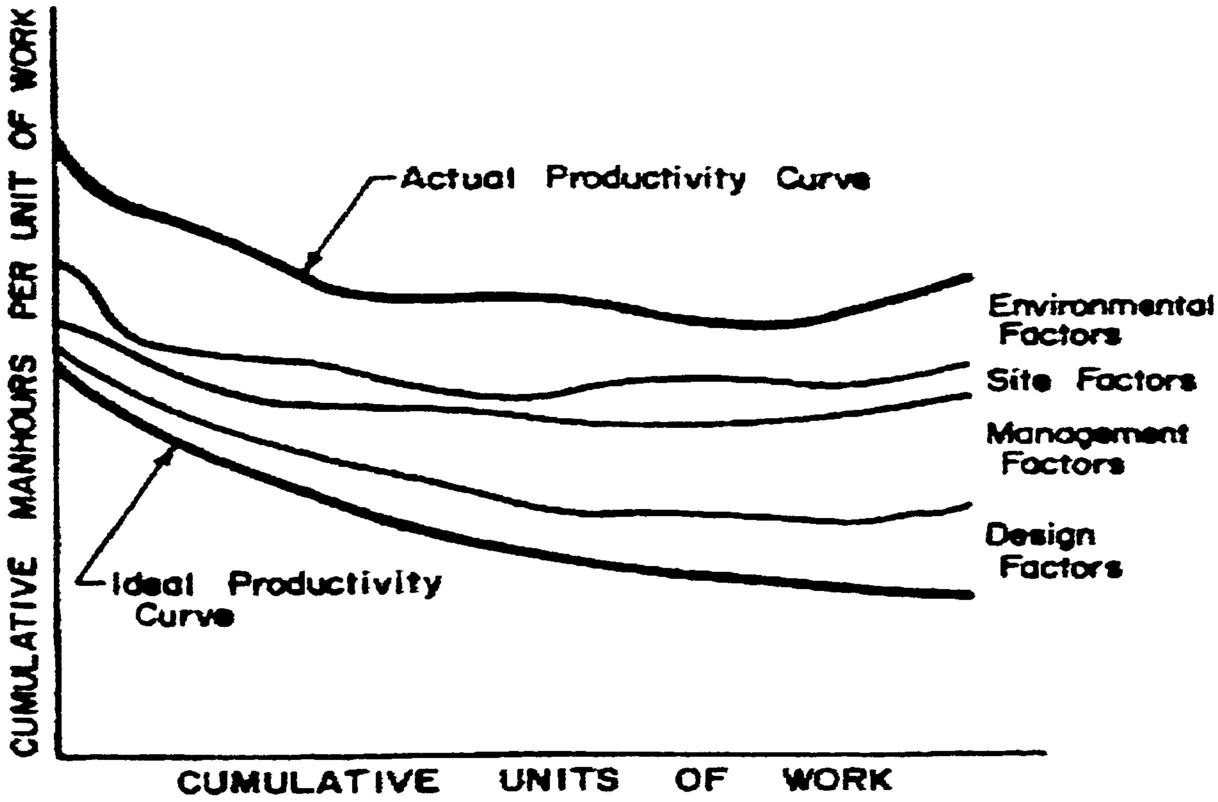


Figure 2-1 Factors Affecting Productivity (Thomas and Yiakoumis 1987)

Leonard (1988), and Thomas and Kramer (1988) grouped the factors affecting the productivity into: 1) extraneous, 2) labor, and 3) management. The extraneous factors are those over which management has little or no control. These include project location, project size, project type, regulations and unions. The labor factors are those directly related to labor productivity such as skill, availability and attitude. The management factors are those related to project management. This group is the richest as management, which has control over many job related factors, significantly influences the level of productivity and motivation of the work force. The factors involved in this group may include inefficiency, poor planning, acceleration, low communication, job morale, design quality, site supervision, crew formation, motivation, and security (i.e. psychological, social, safety).

Dozzi and AbouRizk (1993) divided the factors affecting productivity into two categories: 1) human factors, and 2) management issues. The human factors include motivation, job site planning, safety issues and miscellaneous human factors. On the other hand, the management issues include the quality of supervision, the material management, the constructability, and the change management, which will be discussed in detail later in this chapter.

Diekman and Girard (1995) divided the main factors that affect productivity and give rise to disputes into: 1) People, 2) Project, and 3) Process. "People" factors include the key players (i.e. owner and contractor) in addition to business relationship. "Project" factors comprehend the external and internal factors, while "Process" factors are divided into pre-construction, planning, and construction contract. Thomas et al. (1999) proved, through a case study that included three projects, that productivity is function of the complexity of design and material management procedures.

2.2.2 Quantitative Analysis

Numerous field studies, data analyses, and models have been implemented either: 1) to create integrated productivity models that consider a combination of factors, or 2) to quantify the effect of an individual factor. Examples of integrated models may include those developed by: 1) Thomas and Yiakoumis (1987), 2) Moselhi et al. (1991a), and 3) AbouRizk and Portas (1997). The first model was illustrated in Figure 2-1. The second model (Moselhi et al. 1991a) studied the combined impact of change orders and other major causes of productivity loss, and will be discussed later in this chapter. The third model (AbouRizk and Portas 1997) provided a computerized tool based on neural networks to evaluate the productivity of formwork tasks depending on the performance factors of both the activity and the project.

On the other hand, many studies have focused on quantifying the effect of an individual factor on productivity. As examples of those factors, we can mention: weather conditions, overtime, learning curve, congestion of trades, over manning, in addition to change orders, that will be individually discussed later in this chapter. Unfavorable weather conditions directly influence productivity. Several studies tried to quantify the effect of adverse weather. Kohen and Brown (1985) reported that it is difficult to achieve efficient construction operations below –10° F and above 110° F (i.e. –23.3° C to 43.3° C). They developed a table to predict the construction productivity percentage as a function of the temperature and the percentage of relative humidity. They advised that other factors such as task complexity, activity duration, labor skills involved, and mental concentration should be considered when using this table. The National Electrical Contractors Association (NECA) developed a table that shows the expected percentage of productivity for a corresponding temperature (°C) and relative humidity percentage, as shown in Table 2-2. Dozzi and AbouRizk (1993) stated that this table could be used for most construction tasks and reported that heat stress occurs for temperatures over 120°F (49°C) and relative humidity

10%, or for temperatures around 88°F (31°C) at relative humidity 100%. They also studied the effect of cold weather for gross and fine motor skills assuming 100% efficiency at 70°F (21°C) as shown in Table 2-3.

Table 2-2 Effect of Temperature and Humidity (NECA 1983)

R.H.	Temperature (°C)												
	-23	**-18**	**-12**	**-7**	**-1**	**4**	**10**	**16**	**21**	**27**	**32**	**38**	**43**
90	56	71	82	89	93	96	98	98	96	93	84	57	0
80	57	73	84	91	95	98	100	100	98	95	87	68	15
70	59	75	86	93	97	99	100	100	99	97	90	76	50
60	60	76	87	94	98	100	100	100	100	98	93	80	57
50	61	77	88	94	98	100	100	100	100	99	94	82	60
40	62	78	88	94	98	100	100	100	100	99	94	84	63
30	62	78	88	94	98	100	100	100	100	99	93	83	62
20	62	78	88	94	98	100	100	100	100	99	93	82	61

Table 2-3 Effect of Cold Weather (Dozzi and AbouRizk 1993)

Temperature (°C)		4	-2	-7	-13	-18	-23	-28	-34
Loss of Efficiency (%)	Gross Skills	0	0	0	5	10	20	25	35
	Fine Skills	15	20	35	50	60	80	90-95	—

The effect of overtime made the focus of a number of studies that reported loss of productivity when work is scheduled beyond 8 hours per day or when it sums up to more than 40 hours per week. Overtime is directly responsible for problems such as fatigue, demotivation, absenteeism, reduction of workspace, accidents, turnover of labor, and supervision problems (Thomas 1992). Leonard (1988) reported that the most commonly used indexes to estimate the loss of productivity due to overtime, are those prepared by the Construction User's Anti-Inflation Roundtable in 1973, shown in Figure 2-2.

Thomas (1992) proved that the numerical results showed about 10% decrease in efficiency for each additional 10 hours, beyond 40 hours per week, added to the schedule, based on a summary of efficiencies collected from different studies for 50, 60, and 70 hours of work per week. Dozzi and AbouRizk (1993) suggested that the loss of productivity due to overtime could be quantified using a Detroit-area study performed in 1964 as shown in Table 2-4. They stated that this table is found to fit quite well with studies by the Mechanical Contractors Association, the Electrical Contractor's Association, a Proctor and Gamble evaluation, and a major Engineering Procurement and Construction contractor's estimating guide. They also advised that the alternative of overtime is shift-work that reduces on-site population, decreases overall time for completion, reduces equipment demands, and avoids fatigue. Thomas and Raynar (1997) described the effects of scheduled overtime on labor productivity through a study to assess the influence of three types of disruptions: resource deficiencies, rework, and management deficiencies. Statistically analysis of the data, collected over a period of 121 weeks from 4 industrial projects, indicated losses of efficiency of 10-15% for 50 and 60 hours workweeks. The analysis showed that the disruption frequency is increasing as more days per week are worked, concluding that the loss of efficiency is mainly caused by the inability to provide labors with materials, tools, equipment, and information at an accelerated rate.

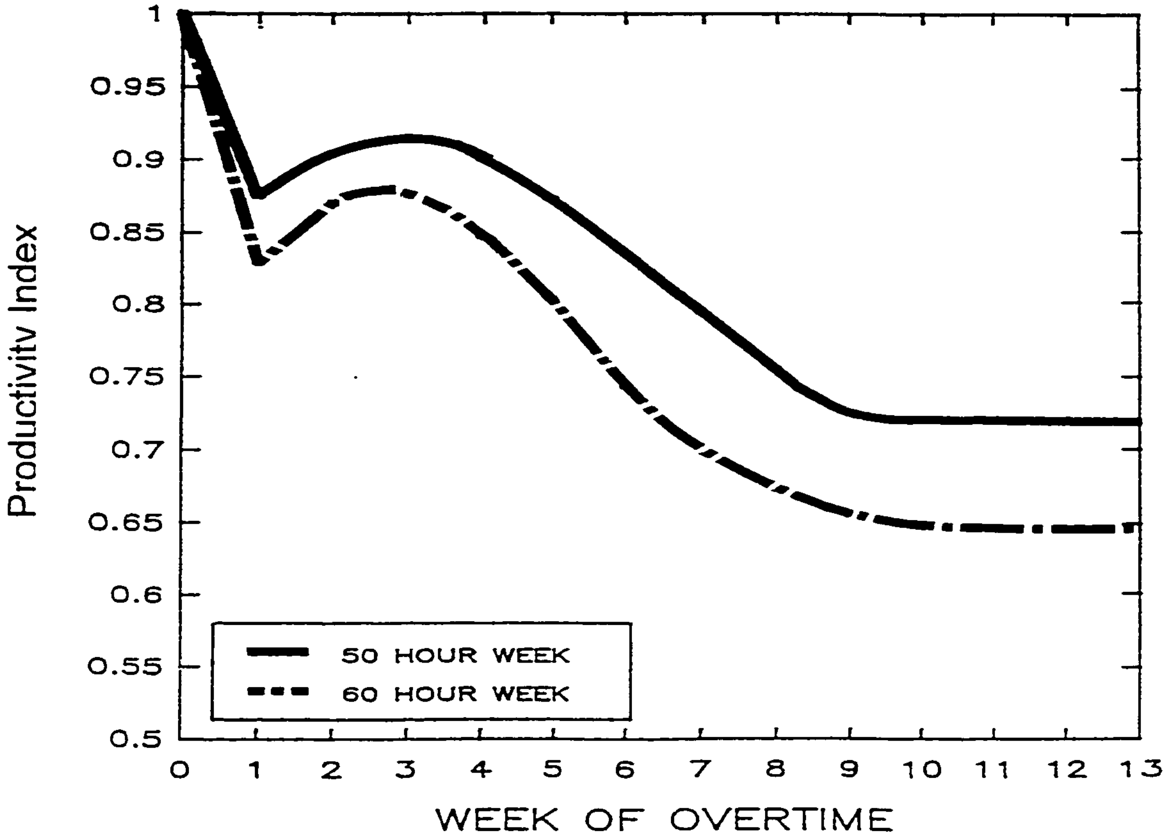


Figure 2-2 Effect of Overtime (Leonard 1988)

Table 2-4 Effect of Overtime (Dozzi and AbouRizk 1993)

Days/ Week	Daily Hours	Weekly Hours	Inefficiency Factor 7 Days	14 Days	21 Days	28 Days
5	9	45	1.03	1.05	1.07	1.1
5	10	50	1.06	1.08	1.12	1.14
5	11	55	1.1	1.14	1.16	1.2
6	9	54	1.05	1.07	1.1	1.12
6	10	60	1.08	1.12	1.16	1.21
6	12	72	1.13	1.2	1.26	1.32
7	8	56	1.1	1.15	1.2	1.25
7	9	63	1.12	1.19	1.24	1.31
7	10	70	1.15	1.23	1.3	1.38
7	12	84	1.21	1.32	1.42	1.53

The learning curve theory states that whenever the production quantity of a new or changed product doubles, the unit or cumulative average cost (hours, man-hours, dollars, etc.) declines by a certain percentage or by a cumulative average rate of the previous unit (Belkaoui et al. 1986). A number of researches were carried out to develop mathematical models and/or learning curve shapes in order to quantify its impact. Thomas et al. (1986) compared five learning curve models, shown in Figure 2-3, for the construction industry in an attempt to obtain a generalized one. The study concluded that the best predicting model for construction is the cubic model. Diekman et al. (1982) developed a curve to illustrate the effect of disruption, as shown in Figure 2-4, and proved that disruptions that may occur due to several reasons, specially change orders, are a direct cause for the loss of learning curve, and hence the loss of productivity. Leonard (1988) reported an inefficiency curve developed by Foster Wheeler, illustrating the effect of re-mobilization, shown here in Figure 2-5, he also reported that the drawback of this curve is that it does not consider the loss of productive rhythm or the demotivation. Dozzi and AbouRizk (1993) reported an "unlearning" curve illustrated in Figure 2-6.

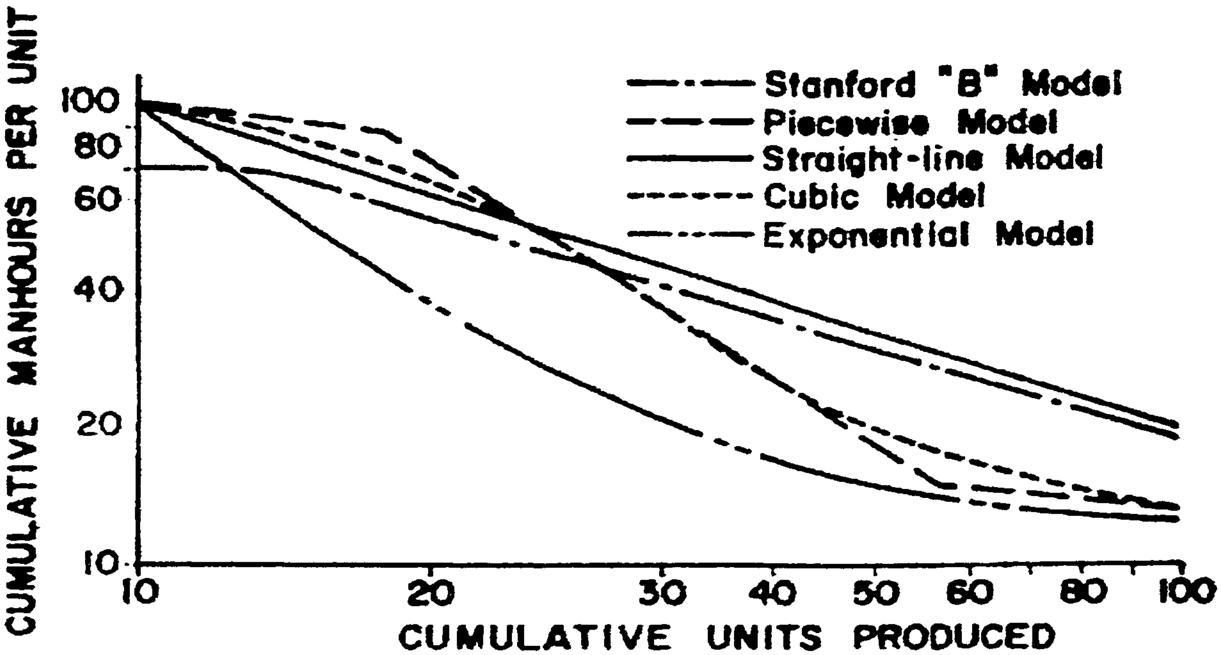


Figure 2-3 Shapes of Various Learning Curves (Thomas et al. 1986)

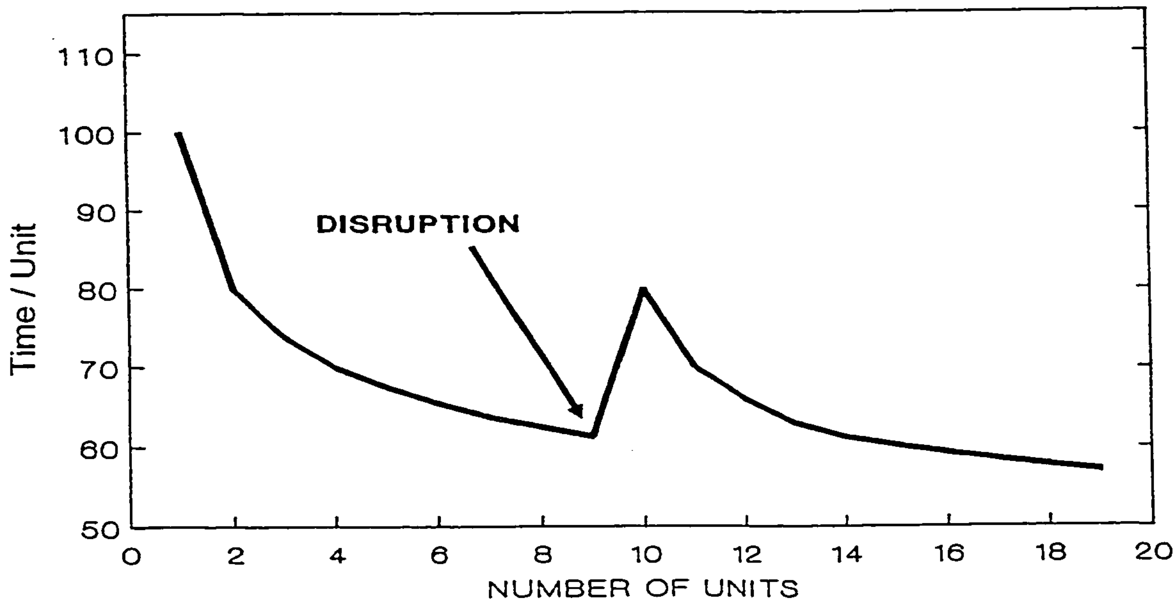


Figure 2-4 Effect of Disruption on Learning Curve (Diekman et al. 1982)

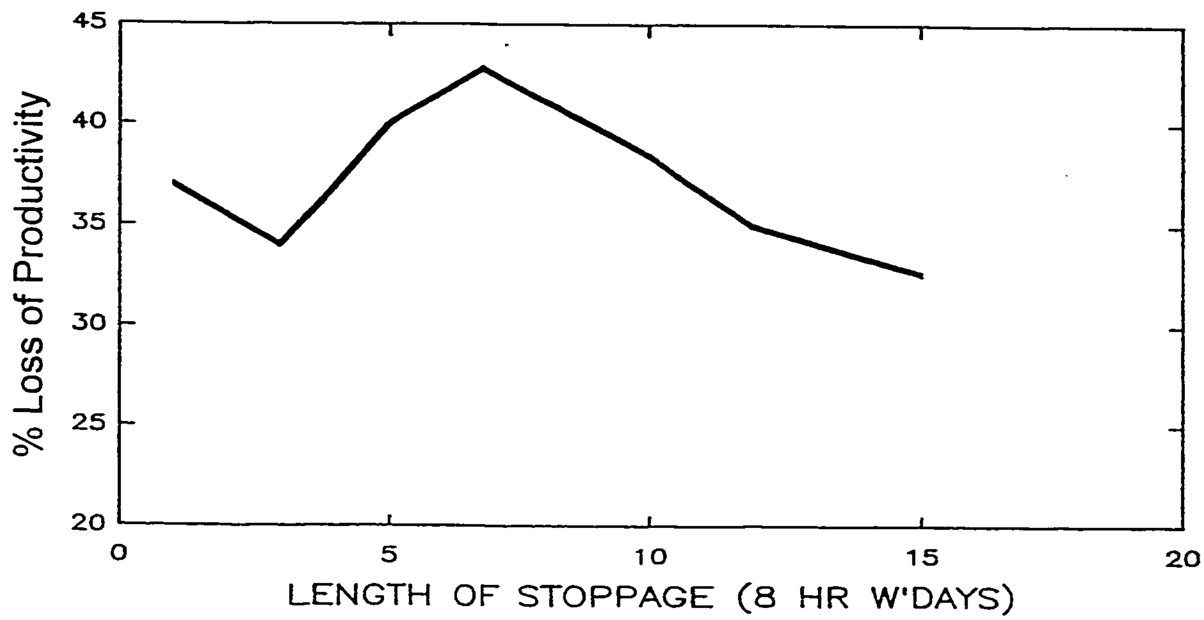


Figure 2-5 Effect of Remobilization (Leonard 1988)

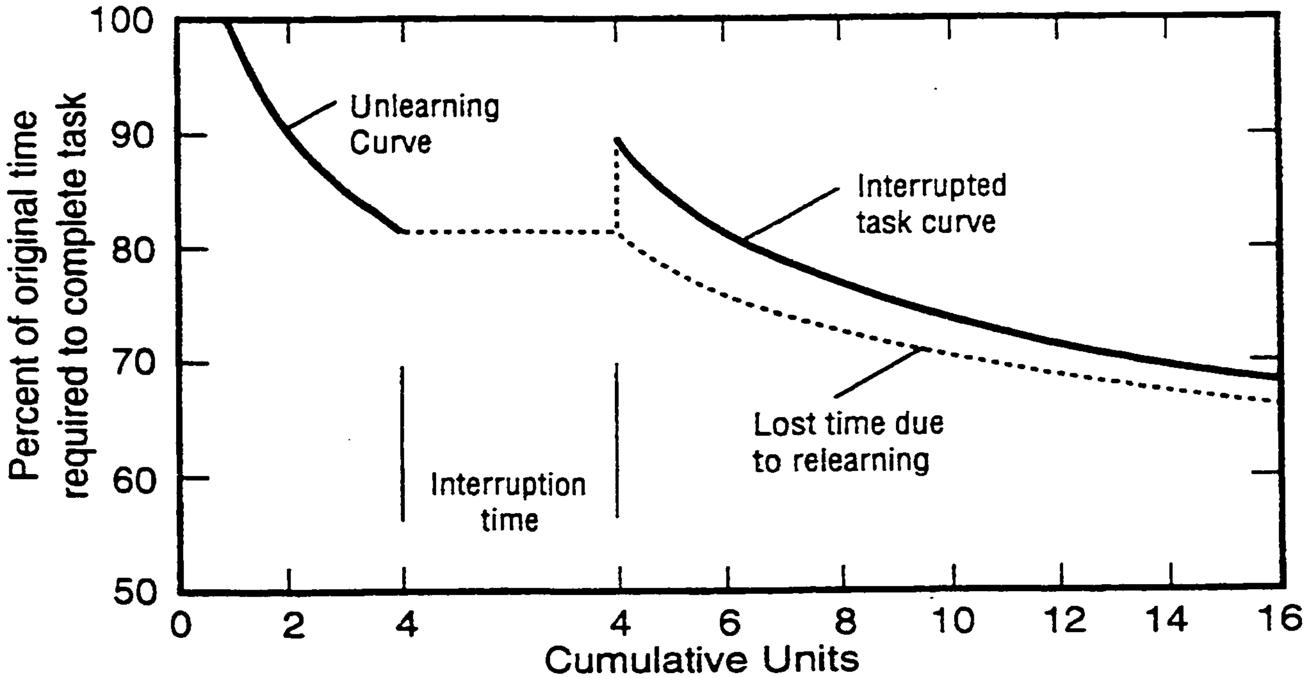


Figure 2-6 Unlearning Curve (Dozzi and AbouRizk 1993)

Congestion of trades impacts construction productivity when different trades, that were supposed to be working sequentially, are obliged to work simultaneously in a limited workspace. The sequence of activities is no longer coordinated and newly completed work often has to be torn out creating, at least, demotivation in additions to unsafe practices. The Modification Impact Evaluation Guide developed by the US Army - Corps of Engineers (1979) developed a typical curve to illustrate the productivity loss due to congestion of trades as shown in Figure 2-7.

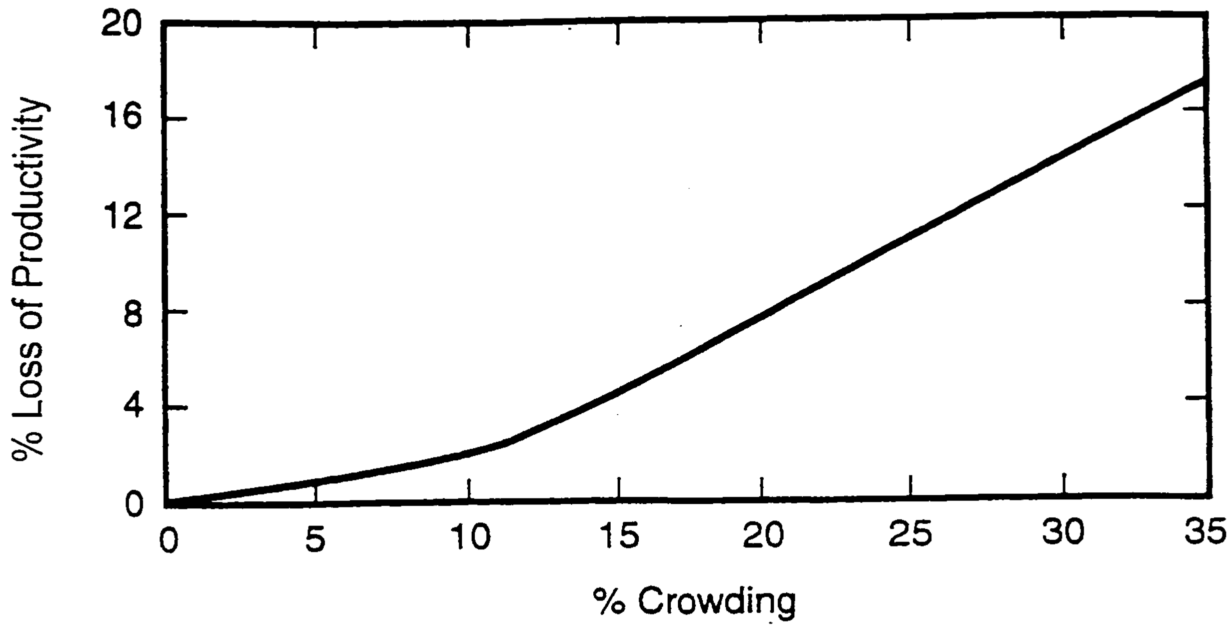


Figure 2-7 Effect of Congestion of Trades (US Army - Corps of Engineers 1979)

Over manning occurs when the number of workers assigned to a task exceeds a certain optimum limit. It may happen in the form of overstaffing or the deployment of multiple crews and often leads to loss of productivity (Dozzi and AbouRizk 1993). The Modification Impact Evaluation Guide developed by the US Army -

Corps of Engineers (1979) and Leonard (1988) reported curves illustrating the effect of crew overstaffing, as shown in Figures 2-8 and 2-9.

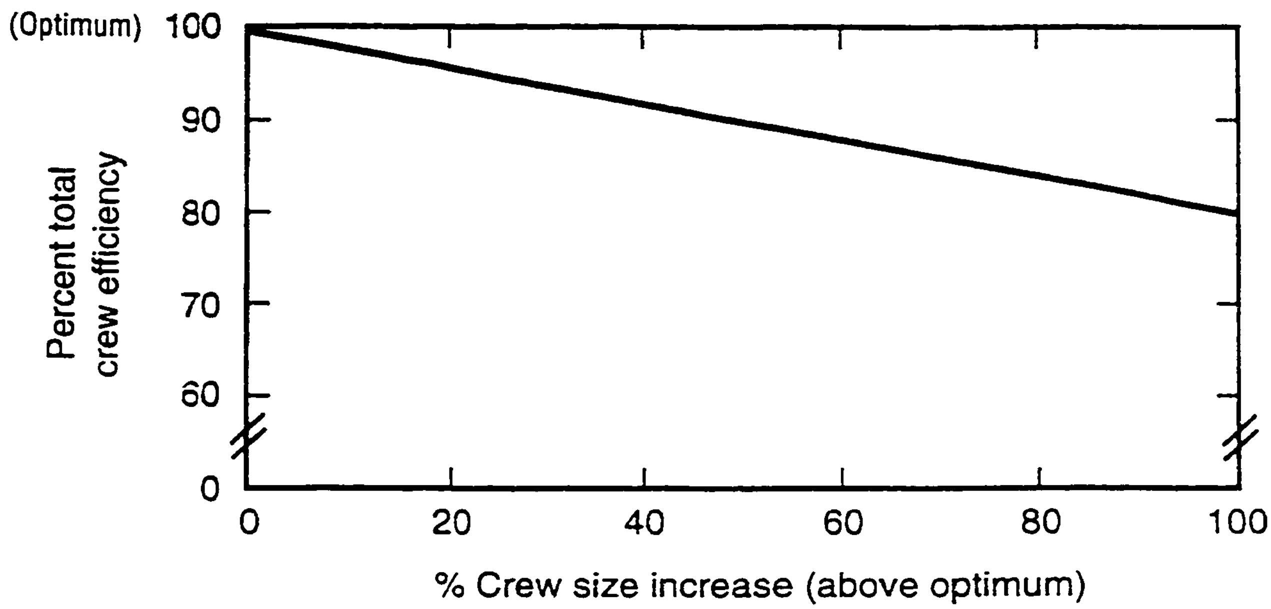


Figure 2-8 Effect of Over manning (US Army Corps of Engineers 1979)

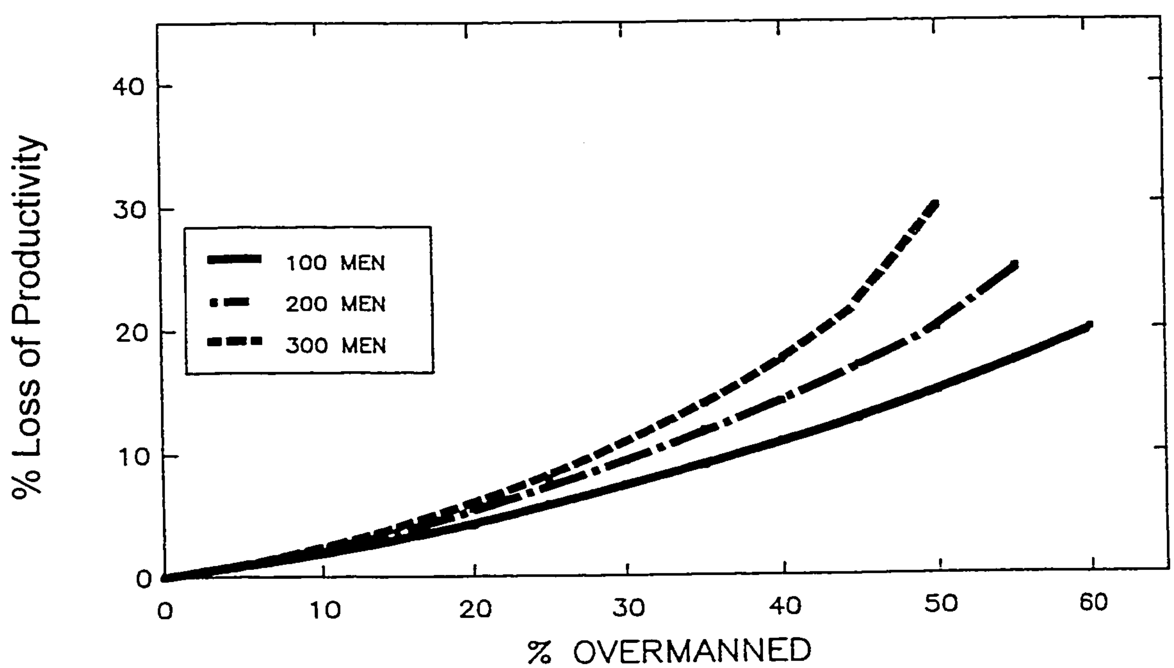


Figure 2-9 Effect of Over manning (Leonard 1988)

2.3 Change Orders

The US Army – Corps of Engineers (1990), set principles for the implementation and processing of change orders. It also gives a strict clear definition for change orders as "a written order, signed by the contracting officer, directing the contractor to make a change, that the changes clause authorizes the contracting officer to order, without the contractor's consent". R. S. (1991) defines the change order as "written authorization provided to a contractor approving a change from the original plans, specifications, or other contract documents, as well as change in the cost". Smith (1996) defines change orders as "any change in the scope of the original contract, resulting changes in cost and/or time, that have to be mutually agreed".

The American Institute for Architects (AIA) provided general conditions of the construction contract (1997) that defined the change order as a "written adjustment signed by all contracting parties". It should bear their agreement upon a change: 1) in the work, 2) the amount of adjustment (i.e. addition or deduction to the contract sum), and 3) the extent of the adjustment in contract time (if any). The PMI's guide to project management body of knowledge (1996), stated that change order requests may occur in many forms: oral or written, direct or indirect, externally or internally initiated, and legally mandated or optional. O'Brien (1998) and Bailey (1999) confirmed that change orders are legal documents that combine with the original contract to describe one of three conditions discovered during the course of a project: 1) clarifications, 2) deletions, 3) additional requests.

Kuprenas (1988) reported four fundamental elements of the "change" clause in a contract: 1) allow owner or representative to initiate the change without the consent of the contractor, 2) stipulate that the work must be within the general scope of the contract, 3) indicate that the order must be in writing, 4) indicate that the contractor must be compensated if additional costs or additional time is required to complete the work. He also summarized the legal considerations involved with change orders into compensation considerations, notice considerations, and limits to recovery considerations. On the other hand, he summarized the project management considerations involved with change orders into cost and schedule adjustments considerations, change impacts considerations, and documentation considerations.

Civitello (1987), Brams and Lerner (1996), and O'Brien (1998) classified the different types of change orders into the following five categories:

1) Bilateral: agreed upon by both parties and hence reducing the risk of disputes or claims.
2) Unilateral: ordered by the owner and carried out by the contractor in accordance to the relative contractual clauses. Disagreement not only will increase the risk of claims but also of job non-completion.
3) Formal: given to the contractor in written format that guarantees the contractor right to perform change work within the general scope and to appeal for equitable adjustment.

4) Informal: also called constructive, given to the contractor in an oral format mainly as a result of defective specification.
5) Cardinal: a change order or a series of change orders beyond the scope of the contract. The failure to perform them would not constitute a breach of contract.

Kupernas (1988) reported many types of informal change orders, and stated that courts consider both formal and informal types to have the same effect.

2.3.1 Change Orders Causes

Leonard et al. (1988) analyzed 90 cases obtained through a field investigation. Based on this analysis, he reported the major causes of change orders to be: 1) design errors and omissions (65%), 2) design changes (30%), and 3) unforeseen conditions (5%).

Halyalimana (1989) reported many causes of change orders: defective contract documents, differing site conditions, contract interpretation, third party caused delay, acceleration of work (i.e. acceleration could be a cause and an effect), regulatory requirements, owner-furnished property, collateral work, work method restrictions, and value engineering. Zeitoun and Oberlender (1993) performed a macro study of the pre-construction factors that are considered as early warning signs for project changes based on 106 responses to a questionnaire dispatched to governmental and private sector contractors. The study presented 7 factors that were found to correlate with the occurrence of change orders:

1) Money Left On Table (MLOT), i.e. the difference between the lowest bid and the next higher bid. Remarkably low bid (MLOT > 4%) correlates with more change orders occurrence.
2) Number of bidders, where a lower number of bidders (i.e. <5) correlates with more change orders occurrence.
3) Project execution format (i.e. construction management, design/build, design/bid/build), where the design/build and the construction management execution formats correlates less with change orders occurrence.
4) Bid solicitation (i.e. approved bidders list, open bid), where an open bid correlates with more change orders occurrence,
5) Owner type (i.e. private, government), where a private sector owner correlates with more change orders occurrence.
6) Primary driving factor (quality, cost, schedule), where schedule, as driving factor, correlates with less change orders occurrence.
7) Work distribution (direct hire, subcontract), where the direct hire correlates with more change orders occurrence.

Hasegawa (1995) reported the following 7 reasons for change orders occurrence:

1) Customer/client requested change order based on new or revised functional requirements or desires.
2) Overall criteria change; change to a building or design code after award or the identification of criteria after construction has begun.
3) Design deficiency where the designer was not held liable.

4) Design error or omission where the designer was held liable.

5) An additive bid item.

6) Unforeseen condition encountered.

7) Initiated value-engineering change.

Thomack (1996) studied 38 electrical cases, obtained through an investigation, and derived that lack of information was recognized as a cause, and also an effect, in all cases that suffered cumulative impacts of change orders. He reported that this is mainly due to: late issuance of construction drawings, late approval of shop drawings, untimely response to requests for clarifications, insufficient details on drawings, and/or incomplete design. Bailey (1999) reported four main reasons that cause change orders: 1) addition requests, 2) deletions, 3) clarifications, 4) unknown conditions, and/or 5) design errors/omissions. It could be concluded that design problems are considered to be a major cause of change orders. Fisk (1992) advised that 1 hour spent in the engineering office checking design documents prior to their issuance to the contractor saves at least 10 hours on site.

2.3.2 Change Orders Process

Bruggink (1997) divided the life cycle of a change order into 6 stages: 1) prospecting the need for a change, which includes the preparation of the RFI (Request For Information) for the change needed, 2) preparing the change order, which includes the investigation of all changed conditions to ascertain the time and costs expected, 3) pricing the change order, which includes pricing all items included within the scope of the change order, 4) agreeing the change order which involves the agreement of all parties involved on the scope, time and cost of the change order and sometimes the impact, 5) performing the change order, and 6) payment of the change order. The data collection for this research showed that it is rare for this ideal sequence to take place. Normally, the contractor carries-out the change as soon as he/she receives a Notice For Change (NFC), especially when the change influences the work in progress, as confirmed by Civitello (1987) and O'Brien (1998). Semple (1996) analyzed the data obtained from 76 questionnaire responses and interviews with a panel of construction experts. She implemented a standard change order process which can be divided into two main parts: a) processing of change order, and b) determination of the associated impact costs. In addition, she developed an estimate for the duration of each step involved in the process and its average relative time as shown in Figure 2-10.

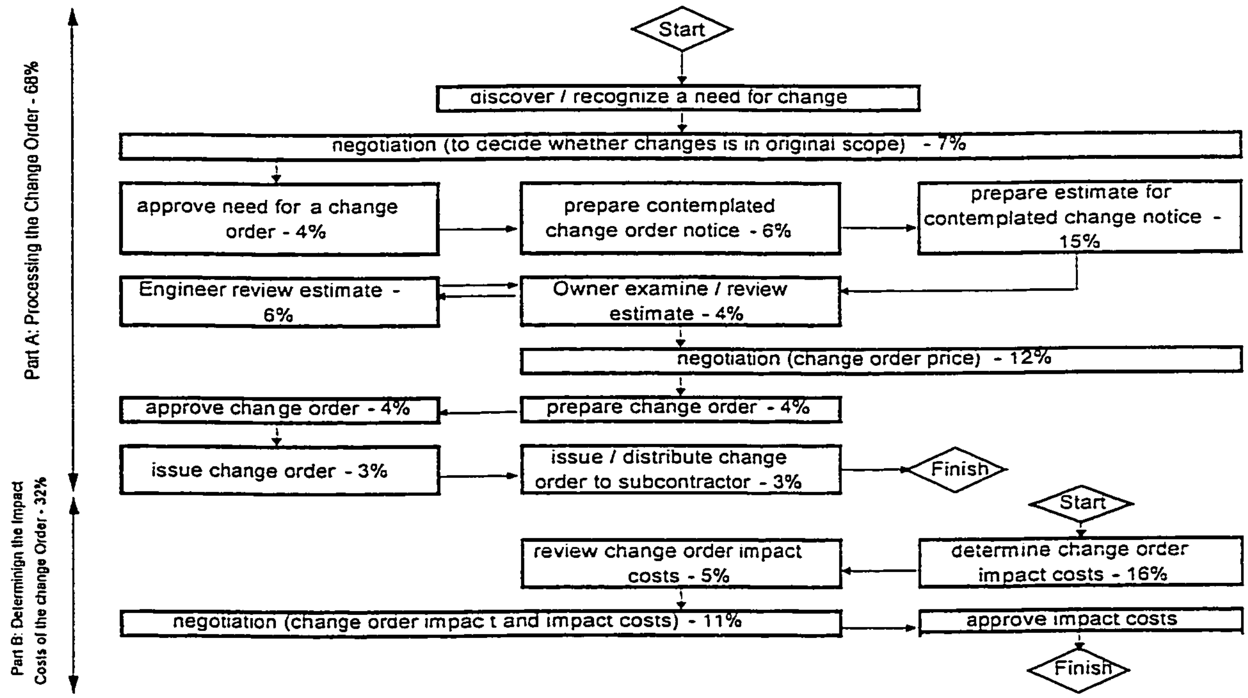


Figure 2-10 Standard Change Order Process (Semple 1996)

2.3.3 Change Orders Impacts

The word Impact originated with the Latin word "impengere", meaning to push or hit. During the data collection for this research, interviews with the experts working in the field of construction claims revealed that change orders are responsible for a number of impacts, including: 1) change of project scope, rendering the original plan incomplete, 2) loss of labor productivity due to: disruption (hence, loss of learning curve and demotivation), congestion of trades (hence, interference, crowd, lack of availability of tools and material), 3) difficulty of determining the equitable adjustment for the contractor, 4) increase of administrative costs, and 5) increase of management costs resulting from negotiations and re-planning.

Warren (1984), and Diekman and Nelson (1985) reported that change orders run up costs and advised to eliminate them during the early stages. US Army Corps of Engineers (1979), National Electrical Contractor's Association - NECA (1980), Leonard (1988), Leonard et al. (1988), Hester et al. (1991), and Semple (1996) explained that the most frequently encountered effect of change orders was found to be disruption and delay. This could be translated into stop-and-go operations, out-of-sequence or revised operations, learning curve related losses, delay-related losses of productivity. In addition to disruption and delay, the ripple effect of change orders is considered to have a significant cumulative influence on the performance of the work. Leonard (1988) presented the following contractor's statement that expressed the ripple effect of change orders on project schedule: "Comparing as-planned to as-built schedules proved that orderly sequenced operations were broken down into several isolated activities as a result of running into bottlenecks and could not proceed further in any intelligent patterns caused largely by changes". This indicated that scheduling could be significantly affected by change orders instead of its conventional parameters.

Work force motivation was also found to be significantly affected in cases where progress was continually disrupted by change orders. In addition, losses in job rhythm have a ripple effect on the productivity of the activities indirectly affected by change orders. Delays and disruptions often result in unbalanced crews, increased cost, and reduced productivity. This also affects the supervisory influence of foremen over crew numbers. In cases of working foremen, productivity decreases as he becomes involved in re-planning and coordination of the affected work. Change orders also cause unplanned fluctuation in manpower levels resulting in layoffs, rehiring and retraining of workers, which adversely affects productivity. The contractor is accordingly forced to accelerate the work as, in most cases, the owner refuses to accord him time extension. This acceleration is caused by the owner refusal to accord time extension to the contractor. In general, the measures taken to accelerate work often give rise to productivity loss (Thomas and Napolitan 1995).

Civitello (1987), Hester et al. (1991), Semple (1996), and O'Brien (1998) confirmed that the occurring disagreement on pricing and production rate involved with change orders results in delays in its processing. This increases the adverse impacts of change orders and negatively affects the relation between contractors, owners, and A/E's, which affects communication and flow of information.

In addition, requesting, negotiating, and carrying out change orders often requires site management to perform considerable efforts (Semple 1996). The increased workload, which can reach 10%, is to be carried by the contractor's site management. This interferes with its original tasks (i.e. planning, coordination, and technical support), and accordingly leads to losses in productivity.

Ibbs and Allen (1995), as part of the activities of the change management task force of the Construction Industry Institute (CII), studied 89 cases that presented a variety of project types. Regression analysis was used to examine three main hypotheses about the impacts of change orders: 1) changes that occur late in a project are implemented less efficiently, 2) the more change there is on a project the greater the labor productivity is negatively impacted, and 3) the hidden or unforeseeable costs of change (i.e. the change orders ripple effect) increase with more project change. The authors acknowledged their inability to support the first hypothesis as the industry does not collect data on the actual labor hours expended on changes. The second hypothesis was supported proving that labor productivity is negatively affected by the changed work performed on a project. Data indicated that most estimators expected inefficiencies associated with implementing the change, yet few considered the difficult-to-predict effects on overall productivity of the project. The third hypothesis was supported by examining the relationship between the amount of project change and the hidden cost. Hidden cost is another interpretation for the impact cost. These findings demonstrate that the ripple effect of change orders is directly proportional to the amount of change orders.

Vandenberg (1996) reported a checklist of possible impacts of change orders that is divided into the following five main factors:

1) Management Factors: ripple effect on other trades, management non-availability, lack of supervision, increased project administration, increased need for communication, more meetings, re-engineering time, increased errors and omissions, obsolete plans and specifications.
2) Material factors: materials expediting delays, material non-availability.
3) Equipment factors: equipment and tools availability, unusual scaffolding requirement.
4) Crew factors: overtime, shift work, crew fatigue, crew morale, labor non-availability, crew make-up, reassignment of manpower, unbalanced crews, excessive fluctuation in manpower, learning curve loss, stop and go operations, working out of normal sequence, loss of job rhythm and momentum, acceleration.
5) Work space factors: crew congestion, trade stacking, weather change, site access, beneficial occupancy, joint occupancy, protection of finished work, poorly accessible work areas, more hazardous surroundings.

Bruggink (1996) developed a graphical summary for the influencing factors and the possible effects of change orders, shown in Figure 2-11. Coffman (1997) illustrated the impact of change orders on productivity using the man-hour loading curve as shown in Figure 2-12. Moselhi et al. (1991) derived that contractors can carry out changes for almost 10% of the Actual Hours with minor impact on productivity.

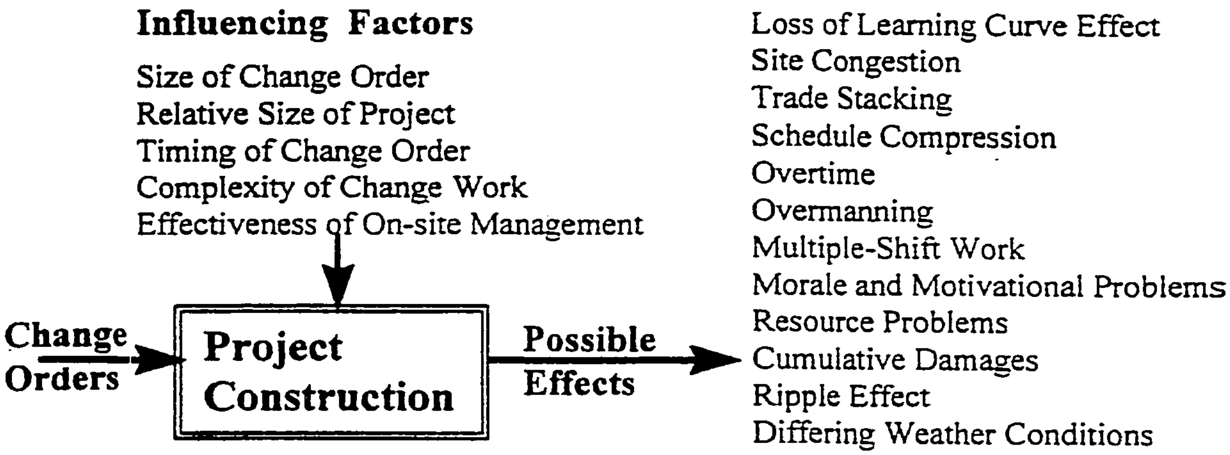


Figure 2-11 Change Orders Factors and Impacts (Bruggink 1996)

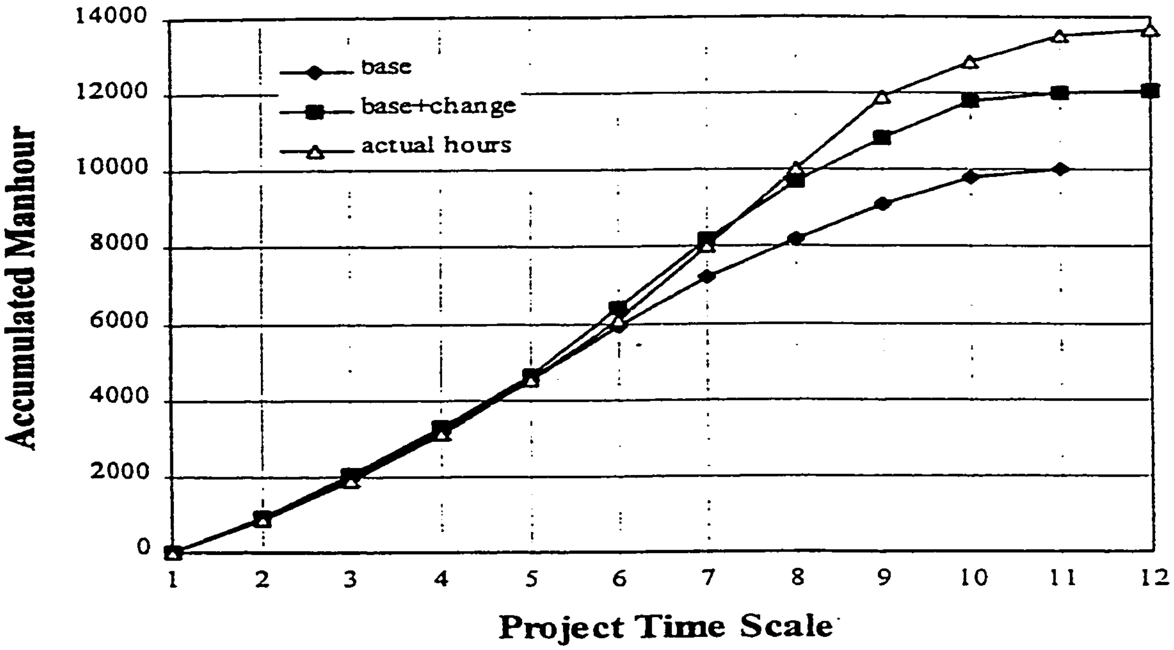


Figure 2-12 Change Orders Impact on Performance (Coffman 1997)

2.3.4 Change Management

Unlike project management, which attempts to minimize the occurrence of change orders, change management is a new rising branch that aims to absorb change orders and reduces their impacts (CII Project Change Management Research Team 1994). CII change management task force set the principles of effective change management to be: 1) promote a balanced change culture, 2) recognize the change, 3) evaluate change, 4) implement change, 5) Continuously improve from lessons learned. This is associated to a multitude of practices that was reported to be beneficiary from both schedule and cost point of views for both owners and contractors (CII Project Change Management Research Team 1994).

The project management body of knowledge (PMI Standards Committee 1996) provided basic principals for scope change control. This control is concerned with: 1) influencing the factors which create scope changes to ensure that changes are beneficial, 2) determining that a scope change has occurred, and 3) managing the actual changes when and if they occur. The scope change control, which is divided into: 1) inputs, 2) tools and techniques, and 3) outputs, must be thoroughly integrated with the other control processes (i.e. time control, cost control, quality control, and others). The inputs to the scope change control include: 1) the work breakdown structure (WBS) which defines the project's scope baseline, 2) performance reports providing information on scope performance and alerting the project team to issues which may cause problems in the future, 3) change requests that may occur in many forms: oral or written, direct or indirect, externally or internally initiated, and legally mandated or optional, and 4) scope management plan describing how project scope will be managed and how scope changes will be integrated. The tool and techniques for scope change management include: 1) scope change control system which defines the procedures by which the project scope may be changed, including the paperwork, tracking systems, and approval levels necessary for authorizing changes, 2) performance measurement that helps to assess the magnitude of any variations which may occur, and determine the cause of the variance, and decide if it requires corrective action, and 3) additional planning which may require modifications to the WBS or analysis of alternative approaches. The outputs of the scope change control include: 1) scope changes which is any modification to the agreed-upon project scope as defined by the approved WBS, and they often require adjustments to cost, time, quality, or other project objectives, 2) corrective action is anything done to bring expected future project performance into line with the project plan, and 3) lessons learned which comprise any lessons learned from scope change control that should be documented to form part of the historical database for both this project and other projects of the performing organization.

The Modification Impact Evaluation Guide (US Army Corps of Engineers 1979) as well as many contractors associations (MCAA, SMACNA, ASA) developed procedures to manage change orders and reduce their impact depending on tracking, filing, evaluating and reporting change orders. Leonard (1988) ranked the factors that would negatively influence the impact of change orders as follows: 1) timing of change orders, 2) complexity of work, 3) processing time, 4) interdependencies, 5) intensity of work, 6) frequency of design omissions, 7) contractor management, and 8) lack of architect/engineer supervision. Ehrenreich and Hansen (1994) suggested a change management methodology that recommends preparing a detailed project plan accounting for controls of change orders procedure and pricing in addition to the conventional schedule and risk items. They concluded that this is an effective method of handling change orders that fosters the completion of projects more effectively within budget, schedule, and scope requirements. To help manage the change orders and evaluate their impacts, Vandenberg (1996) suggested a Monthly Change Order Summary (MCOS) and a Project Change Order Summary (PCOS), while Thomack (1996) proposed a Daily Change Order Log (DCOL). Semple (1996) and Constance (2000) suggested certain success factors for change orders implementation. These factors are hereinafter ranked according to their order of importance:

1) Well-defined change order scope.
2) Fair Owner/Consultant/Contractor.
3) Non-confrontational environment.
4) Expedient decision-making.
5) Early detection of the change.
6) Discussion of change orders procedure / calculations.
7) Complete engineering in original contract.
8) Effective change management / control process.

9) Clear change order impact assessment process.

10) Existence of dispute resolution process.

11) Overhead profit and markups based on sliding or relative scale.

12) Incorporation of computer in the change order process to facilitate data storage.

Stocks and Singh (1999) reported a method titled "Functional Analysis Concept Design" according to which owners and designers can partner during the design phase of projects. This method realized reductions in the amount of change orders resulting from:

1) Customer/client requested change order based on new or revised functional requirements or desires.
2) Overall criteria change; change to a building or design code after award or the identification of criteria after construction has begun.
3) Design deficiency where the designer was not held liable.
4) Contractor initiated value-engineering change.

2.3.5 Change Orders Pricing

Most owners believe that contractors use change orders to collect additional compensation for either an inappropriate bid or a poor field performance. On the other hand, contractors prefer to claim for other reason else than change orders since their efficiency is better and their administrative burden is less (Sarvi 1992). Semple (1996), based on interviews with a panel of construction experts, identified the problems associated with change orders pricing as follow:

1) Change order costs classification varies greatly.

2) Current change orders markups are underestimated.

3) Change orders negotiation is extensive and often leads to disagreement, and the contractor has to prove his costs, especially impact costs.

4) Change orders processing involves many channels and can be repetitive, lengthy, and time consuming.

5) The risk accounted for in the overhead and/or profit is not accounted for in change orders pricing.

The items to be included in a change order pricing were the focus of a lot of studies and practices. Pricing change orders can be contract dependent when the contract mentions the items that are to be considered for the pricing. The American Subcontractors Association divides pricing of change orders into four major categories: 1) direct costs, 2) indirect costs, 3) impact costs, and 4) miscellaneous costs. Semple (1996), based on a study done on 76 investigation responses, related the change orders costs to the main contract costs and divided then into: 1) direct cost, 2) indirect cost, and 3) overhead costs. She reported the commonly used markup ranges for change orders and suggested new overhead ranges as shown in Table 2-5. In addition, she also developed a logarithmic relationship between the overhead markup and the $ value for different values of change orders as shown in Figure 2-13.

Table 2-5 Change Orders Markup Ranges (Semple 1996)

Item	Current	New
Markup on Direct Change Orders Cots to Cover Indirect Change Order Costs	8% - 24%	7% - 26%
Markup on Direct and Indirect Change Orders Costs to Cover Change Order Overhead	9% - 20%	7% - 17%
Markup on Direct and Indirect Change Orders Costs to Cover Change Order Profit	5% - 8%	7% - 9%

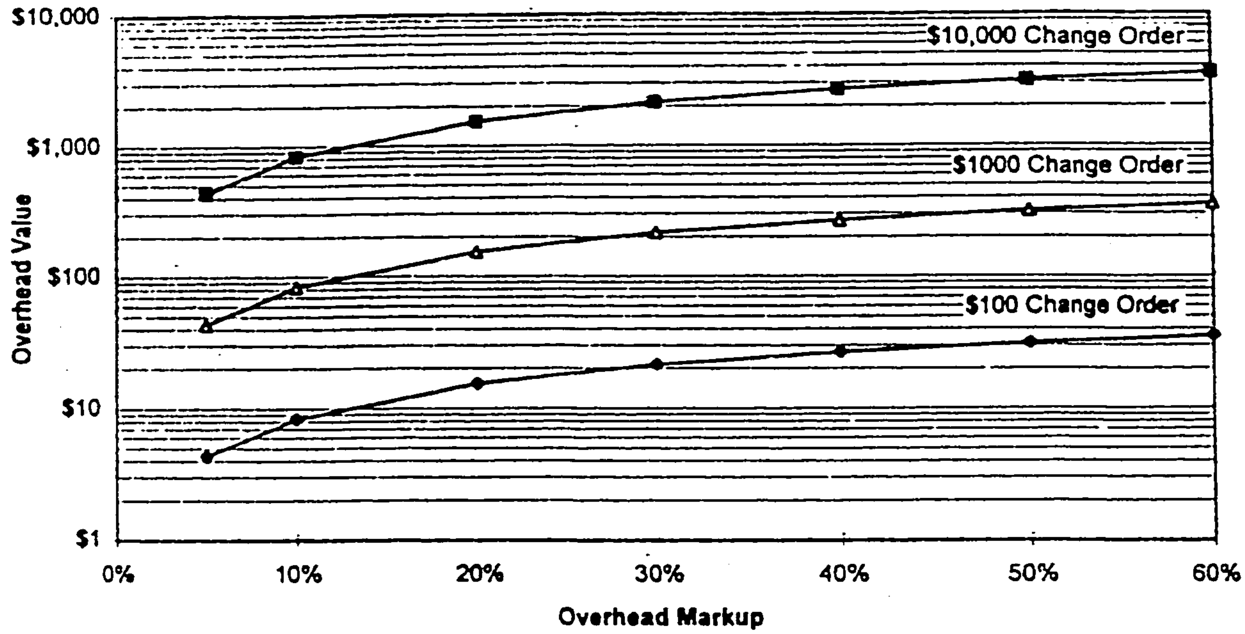


Figure 2-13 Change Orders Overhead Value (Semple 1996)

Barnes (1997) divided the pricing of change orders into three phases: 1) the direct and indirect cost for the actual work to be performed, 2) the impacts on job time extension, and 3) the impact on productivity. Moselhi (1998) studied and illustrated the items that should be included in the change order cost estimate as shown in Figure 2-14. As mentioned earlier in Section 1.2, most of the change orders cost items can be determined in a straightforward manner with the exception of the productivity-related impact cost, simply because it is difficult to demonstrate what costs would have been incurred without the adverse effect of changes on productivity (Moselhi 1998).

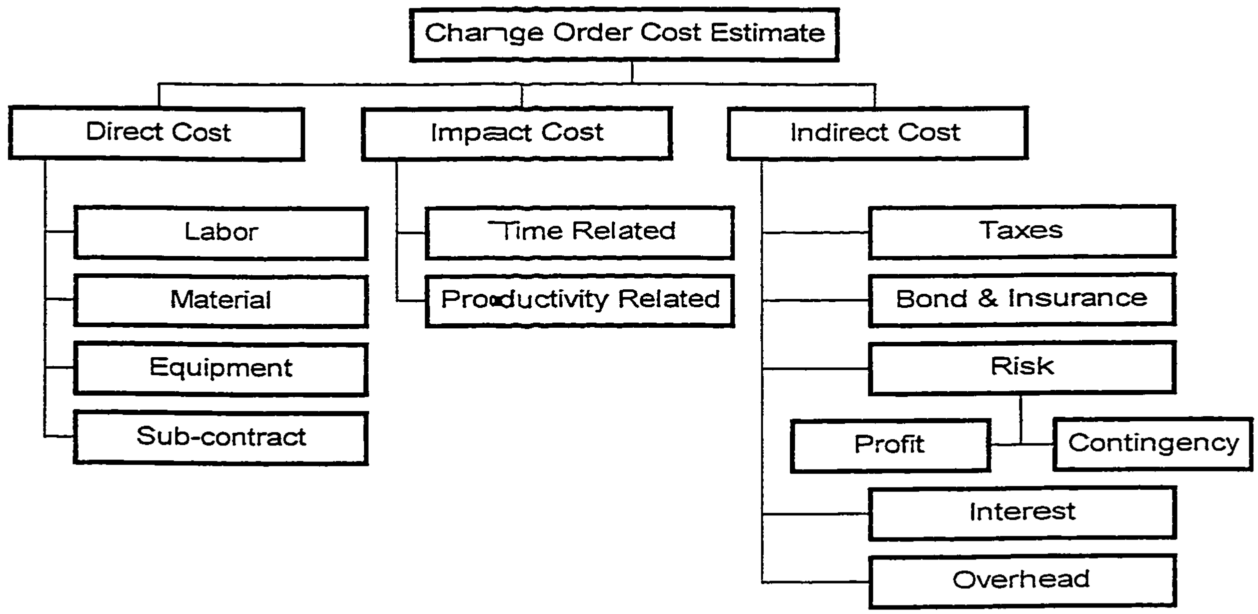


Figure 2-14 Change Orders Cost Estimate (Moselhi 1998)

The productivity-related costs are caused by the loss of productivity taking place as a result of change orders. In general, the developed methods to estimate the impact of change orders on productivity loss could be grouped into 2 major categories: 1) after-the-fact methods, 2) up-front methods. After-the-fact methods are methods requiring information that can be obtained only after completion of work. Those methods are generally used in the quantification of impact-related claims and not particularly for change orders. Up-front methods are models developed, particularly for change orders, to predict the resulting productivity loss. They can be applied any time during the execution of the project, and also after work completion.

2.3.5.1 After-the-Fact Methods

Heather (1989) reported a curve developed by A. A. Mathews, Inc., in 1967, called "Mathews Curve". This curve was created in the course if the evaluation of a contractor's claim in litigation arising out of a freeway construction project in Seattle. The basis of the analysis is that if changes have disrupted a project, this would affect the unchanged work by a corresponding amount of the curve. According to Heather (1989), the validity of this curve has been verified by its application in the construction industry for a period that exceeded 20 years. The mechanics of the curve are as follows:

1) Determine the number of days of owner-caused delays occurring during the actual job duration (excluding any contractor-caused delays or any other impact-type delay),

2) Determine the total contract time (in days),

3) Get the percentage of delays or acceleration by dividing the previously obtained numbers, and

4) Use the curve, shown in Figure 2-15, to get a percentage loss of productivity.

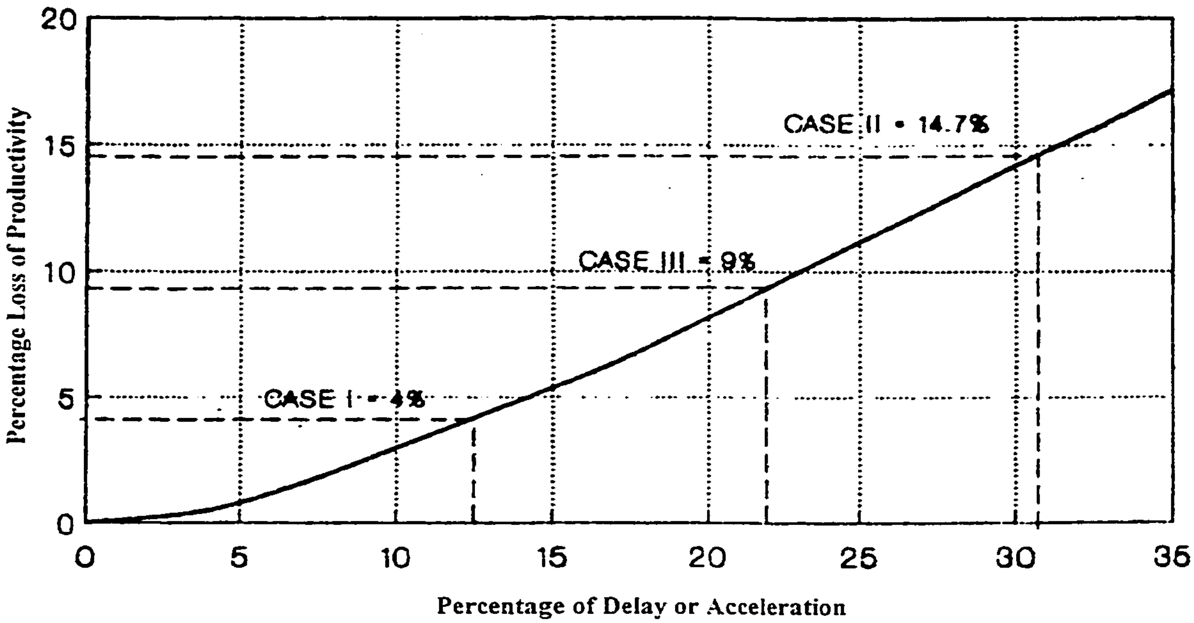


Figure 2-15 Mathews Curve (Heather 1989)

The Total Cost Method (TCM), reported by Ginsburg (1985), is one of the earliest impact quantification methods. It allows the contractor to receive full compensation by considering that the cost overrun is a result of the impact that took place. As this method assumes that the contractor has been 100% efficient, it is only used if: 1) no other methods are available, and 2) the contractor's estimate is judged reasonable. Because of the nonspecific, speculative nature of this method, it is considered inappropriate by courts, boards of contract appeals, and owners (Revay 1985).

The Modified Cost Method (MCM) is a modified version that was developed to overcome the draw back of the TCM. In the MCM, the contractor's estimate is compared to a theoretical estimate. This estimate would be either published tables or the next qualified bidder's estimate. If the contractor's estimate is greater than the next qualified bidder estimate with more than 3%-5%, then the latter's estimate is considered (Ginsburg 1985, Revay 1985).

The Measured Mile Method (MMM), also called Quantum Merit or Differential Cost Method (DCM), is a more reliable methodology for impact quantification (Zink 1986). The application of this method is based on the comparison between the normal productivity (i.e. without impacts) and the actual productivity (i.e. impacted), considering the learning-curve development period in case of repetitive work. Accordingly, the percentage loss of productivity (%PL) can be estimated using Equation 2-1:

$$\%PL = 1 - \frac{\text{Normal Productivity - Impacted Productivity}}{\text{Normal Productivity}} \qquad \textbf{Eq. 2-1}$$

This method requires contractors to cite known sources for the loss of productivity and claim those resulting from impact reasons. In addition, it is time consuming and most contractors do not keep the necessary records.

Zink (1987) presented a methodology to assign productivity loss to the responsible party based on an assumption that lost efficiency rarely rests on one side or the other of a claim. The impact severity is weighted from 1 to 3 and the responsibility for each impact is assigned to the responsible party. Supposing that the total project accumulated 100 impact, if the owner is found responsible for 80 of those impacts then he would be responsible for 80% of the loss of productivity experienced.

Zink (1990) also reported the Partial Total Cost Method (PTCM), which is an advanced application of the MMM that can be used when only certain aspects of the work are impacted. The un-impacted part of the job is not considered and "normal" hours are determined for the impacted portion only. This requires a cost control system that permits extraction of the estimated and actual costs for only those particular portions of work. The major draw back of these methods is that the quantification of the productivity loss can only take place after the work is impacted and not up-front.

2.3.5.2 Up-Front Methods

The Modification Impact Guide (US Army 1979) provided productivity loss figures due to changed work as a result of: loss of learning curve, crowding, crew over manning, disruptions, morale and work schedule acceleration. Means Electrical Change Orders Cost Data (1993) provided cost guidelines to price the change orders based on labor productivity through different graphs. Both of previously mentioned references do not provide any data about the origin of the data used to formulate the values.

Rosenbaum (1995) and Bruggink (1997), reported the Forward Pricing Method (FPM). This method, said to be encouraged by the American Subcontractors Association (ASA), calls for owners and contractors to decide up front how to assess impact costs. This is done by identifying all the elements that will be affected, in case of change orders occurrence, and estimating the degree of impact of each element. Kasen and Oblas (1996) reported a successful application of the forward pricing method, according to which an impact formula is established, at the beginning of the work, to deal with impacts. For example, the formula that was used in the construction of a water treatment plant in Seattle is:

$$\text{Impact} = D \times (T+C+F) \times M_v \times M_n \qquad \textbf{Eq. 2-2}$$

Where:

Impact: is the resulting impact cost in dollars

D: is the sum (in dollars) of all direct costs that have impacts,

T: is the timeliness factor representing the lead-time between notice to proceed and the actual schedule of the changed activity start date. This factor ranges between 0 (i.e. lead time of 16 weeks or more), and 0.2 (i.e. lead time of 5 weeks or less).

C: is the complexity factor of the disciplines involved (i.e. site/civil, structural, electrical, mechanical, and/or architectural). A value of 0.05 is assigned to each discipline; hence, its value varies from 0 to 0.25.

F: is the future factor relating the timing of the change and the current schedule float. This factor ranges between 0 for activities with high float (i.e. 12 weeks and more), and 0.1 for activities with small float (i.e. 5 weeks and less).

M_v: is the cumulative value multiplier. This value ranges between 0 for a small percentage of changed work value (less than 2% compared to the original contract value), and 1.2 for a high percentage of changed work value (more than 11% compared to the original contract value).

M_n: is the cumulative number multiplier that starts with a value of 1 and increases with a value of 0.1 for each agreed-upon change order to a maximum value of 2.

All of these factors are negotiated at the beginning of the contract, and can be subject to future negotiation if one of the parties desires. Kasen and Oblas (1996) advised that this forward pricing system worked well for this project, but it must be tailored to other construction projects. Although the used variables seem appropriate, the authors did not explain how the formula was developed. Although Forward Pricing is reported effective by McMillan (1996) and Matthews (1996), this method shifts the whole risk to the contractor's side.

Moselhi et al. (1991) developed a regression model that quantifies the productivity loss due to change orders accounting for architectural/civil (A/C) work type and electrical/mechanical (E/M) work type. This model is based on data obtained through a field investigation that resulted 90 cases. The model indicated a direct correlation between the percentage productivity loss (i.e. Hours of Productivity Loss to the Actual Hours) and each of the percentage change order (i.e. Change Orders Hours to the Actual Hours) and the type of impact. The type of impact (TI) equals 1 in case change orders are the only cause of impact, 2 or 3 in case of change orders and 1 or 2 additional major causes of loss of productivity loss as illustrated in Figure 2-16. This model is widely used in construction disputes settlement, yet it exhibits some limitations such as the combination of work types (Hanna et al. 1999a).

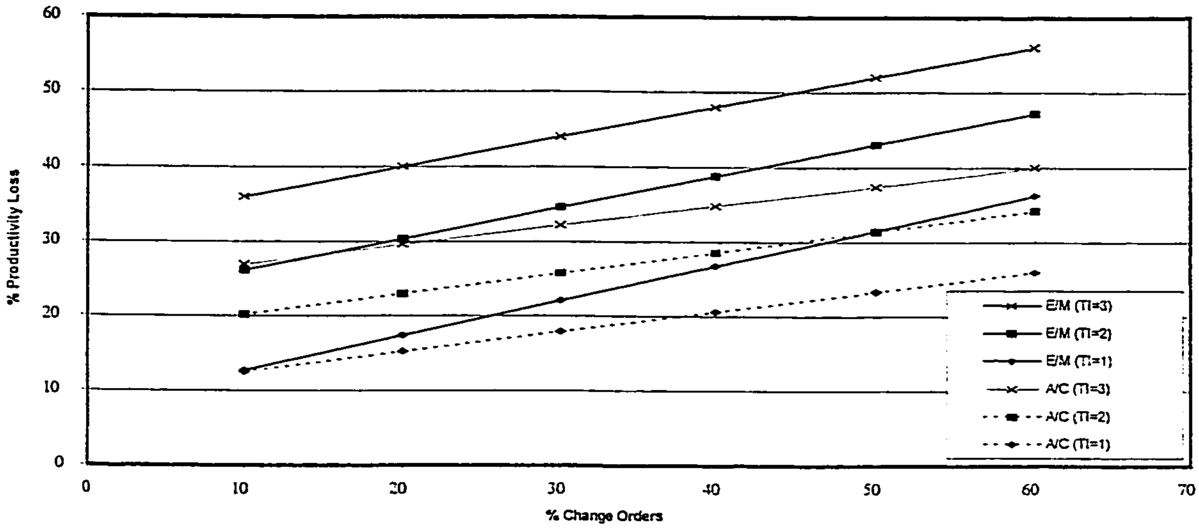


Figure 2-16 Estimating Loss of Productivity (Moselhi et al. 1991)

Thomas and Napolitan (1995) quantified the effects of change orders on productivity through a study that used daily productivity values for 522 days from three electro-mechanical projects constructed over a period of four years. The data obtained from these projects was statistically analyzed using regression analysis to develop a general model that estimates the performance ratio as per Equation 2-3:

$$PR = 2.57 + (1.07 \times CI) \qquad \textbf{Eq. 2-3}$$

Where:

PR: is the performance ratio.

CI: is the Change Indicator. Its value is either 0 (i.e. un-impacted) or 1 (i.e. impacted).

The efficiency is then calculated using Equation 2-4:

$$\text{Efficiency} = \frac{\text{Average Performance Ratio with Factor Present}}{\text{Average Performance Ratio under Normal Conditions}} \qquad \textbf{Eq. 2-4}$$

According to Equations 2-3 and 2-4, the resulting loss of efficiency is about 30% in case of change orders. Other developed equations showed that the loss of efficiency in case of change orders ranged between 25% and 31%.

Thomack (1996) studied 38 electrical cases and used regression analysis to develop a model for electrical work, as shown in the Equation 2-5:

$$\text{Delta\%Total} = 1.01 - 0.944*\text{EstCO\%Tot} - 0.0867*\text{Ln(EstHr)} \qquad \textbf{Eq. 2-5}$$

Where:

$$\text{Delta\%Total} = \frac{\text{Total Hours - Change Orders Hours – Base (Planned) Hours}}{\text{Total hours}} \times 100,$$

$$\text{EstCO\%Tot} = \frac{\text{Change Orders Hours}}{\text{Total Hours}} \times 100$$

EstHr = Base (Planned) Hours.

Bruggink (1997) summarized a number of problems associated with this model, such as: 1) the size of data used, 2) the inaccurate values of some data, and 3) the inclusion of a variable (EstCO%Tot) that represents a true relationship violating the rules of regression analysis.

Hanna et al. (1999b) studied 61 electrical cases and used regression analysis to develop a model for electrical work as shown in Equation 2-6:

$$\text{Delta\%Total} = -22.00 - 0.14 * \text{MgrYears} + 6.47 \ln(\text{EstCO\%Est}) - 9.66 \ln(\text{EstCO}) - 0.90 [\ln(\text{EstCO})]^2 \quad \textbf{Eq. 2-6}$$

Where:

$$\text{Delta\%Total} = \frac{\text{Total Hours - Change Orders Hours - Base (Planned) Hours}}{\text{Total hours}} \times 100,$$

MgrYears = the years of experience of the project manager in the industry,

$$\text{EstCO\%Est} = \frac{\text{Change Order Hours}}{\text{Base (Planned) Hours}} \times 100,$$

EstCO = Change Order Hours,

Vandenberg (1996) analyzed 43 mechanical cases and used regression analysis to develop a quantification model for mechanical work, that incorporates the effect of change orders timing, as shown by Equation 2-7:

$$\text{Delta\%Tot} = -21.3 - 0.3\,(\text{ESTCHNG\%TOT}) + 8.8\,(\text{WTIMING}) \quad \textbf{Eq. 2-7}$$

Where:

$$\text{Delta\%Total} = \frac{\text{Total Hours - Change Orders Hours - Base (Planned) Hours}}{\text{Total hours}} \times 100,$$

$$\text{ESTCHNG\%TOT} = \frac{\text{Change Orders Hours}}{\text{Total Hours}}$$

WTIMING = the weighted timing impact discussed later.

On the other hand, Hanna et al. (1999a) studied 61 mechanical cases and used the regression analysis to develop a model for mechanical work, avoiding the drawbacks of the model presented in Equation 2-7, that accounts for the change orders' timing effect as shown in Equation 2-8:

$$\text{Delta\%Total} = -\,0.1619 - 0.001534 * \text{CHGEST} - 0.00073 * \text{NUMCHG} + 0.07934 * \text{WTIMING} + 0.000032 * \text{NUMCHG} * \text{CHGEST} \qquad \textbf{Eq. 2-8}$$

Where:

$$\text{Delta\%Total} = \frac{\text{Total Hours - Change Orders Hours - Base (Planned) Hours}}{\text{Total hours}} \times 100,$$

$$\text{CHGEST} = \frac{\text{Change Orders Hours}}{\text{Base (Planned) Hours}},$$

NUMCHG = number of change orders on the project,

WTIMING = the weighted timing impact discussed later.

The calculation of WTIMING is based on the hypothesis that change orders happening towards the end of the project have a more severe impact on productivity, hence a higher impact value. Accordingly, the project is divided into: 1) design phase, and 2) construction phase. The design phase represents the first period (i.e. i=1), while the construction phase is divided into 5 equal periods (i.e. i=2 to 6). The impact factor value has a linear relation with the time progress, and is equal to the corresponding period numbering (i.e. 1 for the design period, 2 for the first construction period, ...etc). WTIMING can be interpreted by Equation 2-9:

$$\text{WTIMING} = \sum_{i=1}^{i=6} \frac{(\text{Change Orders Hours})_i}{\text{Total Change Orders Hours}} \times (\text{Impact Factor})_i \qquad \textbf{Eq. 2-9}$$

This hypothesis violates the typical resource loading concepts, known in the construction industry, which indicate that only few direct resources are left to be impacted towards the end of the project.

Ibbs (1997) studied the size of change orders and its impact on the productivity during detailed design and construction. Data is obtained through an investigation that resulted in 104 projects. Regression analysis was used to develop a quantification model that confirmed that the amount of change, illustrated by the percentage of Change Orders Hours to the Actual Hours, correlates negatively with productivity. This model dealt with the design phase, but it did not distinguish between different work types. Figure 2-17 illustrates the results of this study.

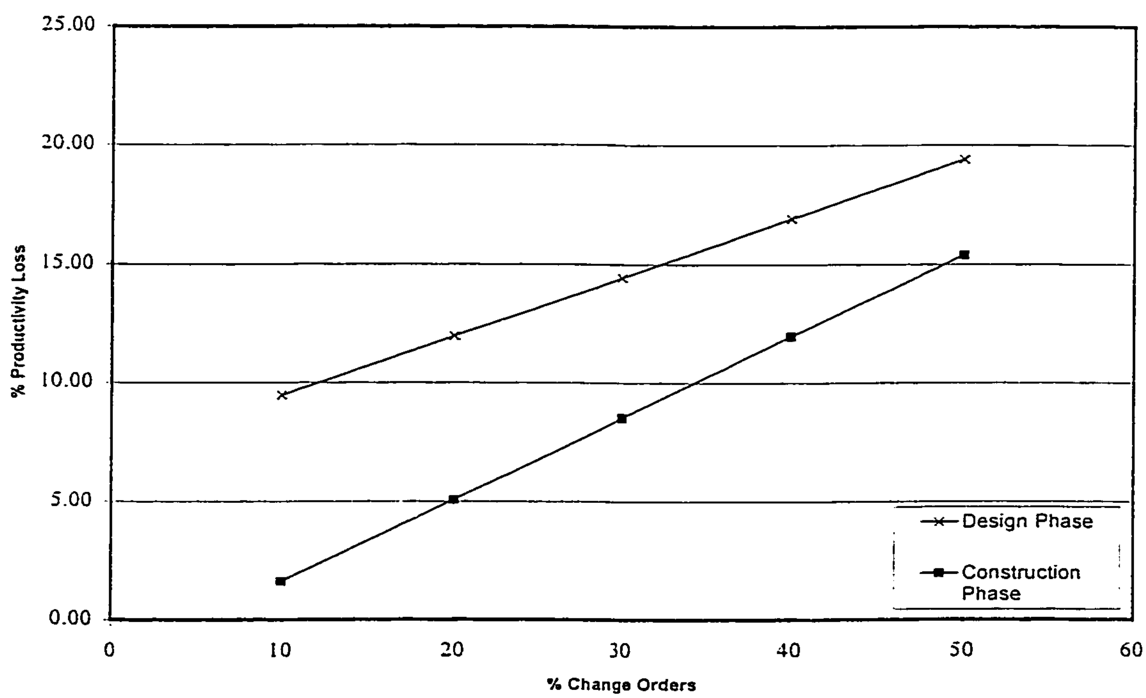


Figure 2-17 Estimating Loss of Productivity (Ibbs 1997)

Moselhi (1998), and Abdo (1999) used a selected part of the cases collected by Leonard (1988) to develop neural networks models predicting the loss of productivity due to change orders. Table 2-6 presents the different parameters of the developed models, as well as the input parameters while the output parameter is always the estimated percentage loss of productivity. As shown, the neural network models in reference did not distinguish between work types.

Table 2-6 Neural Network Models (Moselhi 1998 and Abdo 1999)

Model By	#	Number of Cases				Input Parameters					
		Total	Training	Testing	Production	Work Type	Type of Impact	Number of Change Orders	Ratio of Change Orders Hours to the Actual Hours	Frequency of Change Orders	Average Size of Change Orders
Moselhi (1998)	1	34	22	6	6	General	General	✓	✓	✓	✓
	2	34	22	6	6	General	General		✓		
Abdo (1999)	1	32	28	0	4	General	2	✓	✓	✓	
	2	32	28	0	4	General	2		✓		✓
	3	32	28	0	4	General	2		✓		
	4	12	10	0	2	General	3	✓	✓	✓	✓
	5	12	10	0	2	General	3		✓	✓	✓
	6	12	10	0	2	General	3		✓		
	7	40	34	0	6	General	2&3	✓	✓	✓	✓
	8	40	34	0	6	General	2&3		✓	✓	✓
	9	40	34	0	6	General	2&3		✓		
	10	20	16	0	4	E/M	2&3	✓	✓	✓	✓
	11	20	16	0	4	E/M	2&3		✓	✓	✓
	12	20	16	0	4	E/M	2&3		✓		
	13	13	11	0	2	C/A	2&3	✓	✓	✓	✓
	14	13	11	0	2	C/A	2&3		✓	✓	✓
	15	13	11	0	2	C/A	2&3		✓		

2.4 Neural Networks

The human brain contains almost 100 billion neurons linked by 10^{15} inter-connections that, when functioning actively, would be firing at the rate of almost 1000 pulses/second (Siqueira 1999). Neural Network is an artificial information processing system that mimics, in structure and behavior, the neural biology of the human brain by learning from the given cases.

They consist of a number of interconnected artificial processing elements, also called neurons, representing respectively neural cells, neurons, axons or semi connectors. The architecture (or structure) of the network depends on the type of the network, also called paradigm (Moselhi 1998a, Moselhi et al. 1991b, Hegazy et al. 1994). Figure 2-18 illustrates the research history of Neural Networks and Expert Systems. It indicates that the first artificial neural network model was developed in 1943 as a main branch of the field of artificial intelligence. A sharp decline in their use and development occurred in the early 1970's and then they started going in the 1980's as a result of the increasing computational power and declining cost of computers (Fausset 1994, Kartapoulos 1996, Hegazy et al. 1994, Moselhi 1996, Moselhi 1998a, Moselhi 1998b). Moselhi (1996) studied human problems solving techniques and the corresponding engineering solving techniques. He concluded that neural networks are the most efficient tool in modeling problems where the solutions are generated based on analogy with a similar problem in a holistic manner.

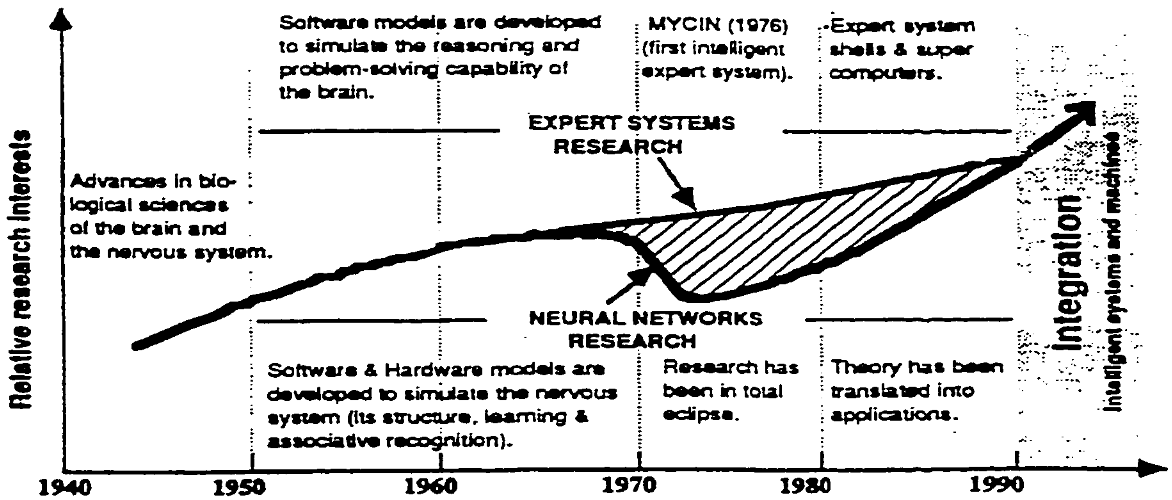


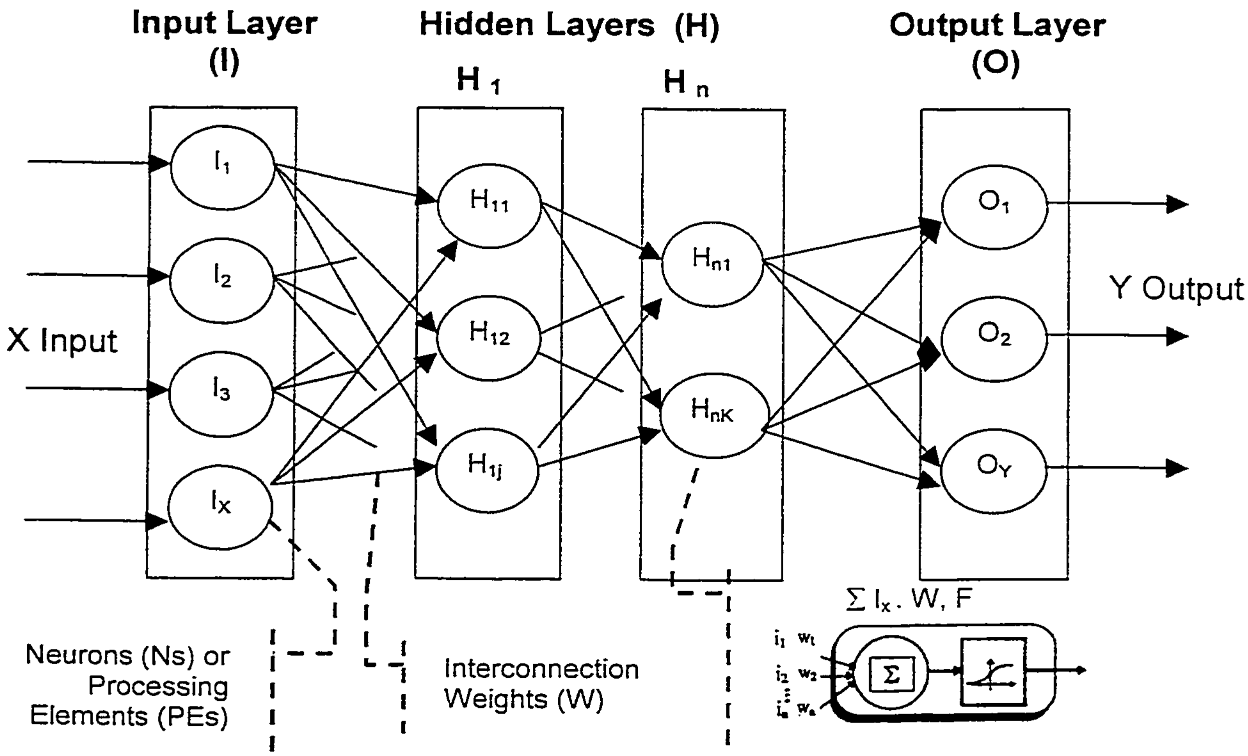
Figure 2-18 Research History of Neural Networks (Moselhi 1996)

2.4.1 Structure and Mechanism

There are a number of possible structures for neural networks. Back-propagation is the most utilized paradigm for its relatively simple mathematical proofs and good generalizations capabilities (Hegazy et al. 1994, Moselhi 1998a, Siqueira 1999). This paradigm gains its knowledge and problem-solving capabilities by learning from the cases encountered in a manner similar to human in experience gaining. By associating the input to the desired output, the network generalizes the knowledge implicitly included in the training example. Accordingly, the network becomes capable of providing solutions to new problems, even with noisy and incomplete data (Fausset 1994, Kartapoulos 1996, Hegazy et al. 1994, Moselhi 1998a, Flood and Kartam 1994). The performance mechanism and the structure of a multi-layer back propagation neural network are illustrated in Figure 2-19.

In back-propagation neural networks, each normalized variable is presented to the input layer (one input variable for each processing elements) where it is multiplied by the connection weight and processed to the hidden layer using an activation function. Hidden layer sums the received variables, applies the connection weights and processes the variables to the next layer using a transfer function. Variables are received in the output layer (an output variable for each processing element), where they are compared to the actual ones. The error is hence calculated and the weight is re-adjusted for a backward run in the hidden layer(s). At the end of the training set, the average error is calculated and checked (Fausset 1994, Kartapoulos 1996, Hegazy et al. 1994, Moselhi et al.

1992, Siqueira 1999). A more detailed discussion of the different phases of the design of neural network design will be presented in Chapter 4 including user-



defined parameters, heuristics, hypothesizes and practices.

Figure 2-19 Structure and Performance of Multi-layer Back-Propagation Paradigm (Hegazy et al. 1994, Al-Tabtabai et al. 1999)

2.4.2 Engineering Applications

Neural networks are excellent tools for data pattern recognition, however their applications in civil engineering only go back to late 1980's (Flood and Kartam 1994). During the last decade, the body of knowledge reported developments done using neural networks that covered a wide range of diverse civil engineering applications. Back-propagation paradigm has been used in the development of a number of engineering applications such as modeling:

reinforced concrete (Mukherjee and Deshpande 1995), concrete strength (Williams et al. 1992), pile capacity (The et al. 1997), damages of pre-stressed concrete piles (Yeh et al. 1993), detection of defects in sewer pipes (Moselhi and Shehab-Eldeen 2000), construction productivity estimation (Sonmez and Rowings 1998, AbouRizk and Portas 1997, Chao and Skibniewski 1994, Karshenas and Feng 1992, Siqueira 1999, Al-Tabtabai, 1999), structures damages identification (Barai and Pandey 1995, Elkordy et al. 1993), resource requirements estimation (Elazouni et al. 1997), quantification of loss of productivity due to change orders (Moselhi 1998b, Abdo 1999), bid preparation (Hegazy 1993), and resolution of disputes (Cheung et al. 2000).

2.4.3 Advantages and Disadvantages

Neural networks exhibit a number of advantages that makes them suitable for pattern recognition and, hence, prediction of a certain parameter, (Flood and Kartam 1994, Kartam et al. 1993, Moselhi et al. 1991b). These advantages include: 1) the ability to account for complex cases requiring large number of parameters to be considered in parallel, 2) learning by example, associating inputs to output(s), 3) speed of computation, 4) generalization capabilities, 5) non-linearity, and 6) ability of extracting essential information from noisy data.

Neural networks, however, exhibit also some limitations and shortcomings (Flood and Kartam 1994, Kartam et al. 1993, Moselhi et al. 1991b). These limitations include: 1) they are not transparent enough to provide explanation facility or reasoning behind the generated solution, 2) they are sensitive to the organization and preparation of the data used in training, as well as, to a larger degree, to the configuration of the network itself, and 3) they require the availability of a sizable number of training examples that may be difficult to assemble.

2.5 Summary

A comprehensive literature review has been conducted. The review has been divided into three parts: 1) productivity, 2) change orders, and 3) neural networks. In the first part, productivity measurement has been presented along with the major causes for its loss and the models developed to quantify this loss. In the second part, change orders causes; process, impacts, change management concepts, and pricing were presented. The models developed to quantify the productivity related costs of change orders on construction productivity have been divided into after-the-fact and up-front methods and have been discussed. Finally, neural networks history, structure and mechanism, engineering applications as well as their advantages and disadvantages were reviewed.

Chapter 3

Data Collection and Analysis

3.1 Introduction

This chapter presents the procedure of data collection and analysis through six stages: 1) data collection, 2) data organization, 3) data preparation, 4) data analysis, 5) modeling, 6) formulation of data sets. The data collection stage outlines the collection of the data used in this research. The data organization stage describes how data is arranged for analysis and evaluation. The data preparation introduces the use of the change orders intensity factors to form preliminary sets of data. The objective of the data analysis stage is to evaluate the preliminary sets of data, produced through the previous stage, using scatter plots and association measuring. In the modeling stage, the intensity factors found to correlate with the resulting productivity loss are processed to model the influence of the timing and the type of work on the adverse effect of change orders. The formulation of the data sets stage is performed in order to generate 10 useful data sets that can be utilized in the development of regression and neural networks models in Chapter 4.

3.2 Data Collection Stage

In impact-related studies, there are two commonly used approaches to collect data: questionnaire and/or case study. The questionnaire approach, in general, "does not permit to examine the particular circumstances of each case and to analyze the project data in detail" (Leonard 1988). In addition, the inaccurate data and the low response rate are also two main limitations of this approach. On the other hand, the case-study approach provides in-depth knowledge and useful information, however it does not generally produce a large number of cases.

In this research, the case-study approach is used to collect the data necessary to model the effect of the timing and the work type on the adverse effect of change orders. A field investigation is conducted over a period of 6 month at Revay and Associates Limited (RAL) in Montreal (Canada). RAL is a firm specialized in project management and claims management founded in 1970. During its thirty years of history, it has been involved in the resolution of more than 2,500 construction disputes, with about 10% of those proceeding to arbitration or litigation. The firm carried out assignments throughout Canada, the United States, Australia, and many European, African, Asian and South American countries. The firm's clients include government departments, developers, owners, construction companies, subcontractors and law firms. According to a mutual agreement with the Building, Civil and Environmental Engineering Department at the University of Concordia and RAL, access was granted to a set of actual cases. The investigation of the cases included the analysis of the final report of each case and its supporting documents (if available), and interviews with the experts that were involved in the treatment of the cases.

3.3 Data Organization Stage

A total of 117 actual projects were initially examined for possible use in the developments made in this thesis. The cases involved projects constructed in Canada and USA during 1990 to 1998. The case-study investigation was divided into two main stages: 1) preliminary investigation stage, 2) detailed investigation stage.

During the preliminary investigation stage, the above mentioned cases were categorized into five categories of cases with: 1) complete change orders data and complete productivity loss data, 2) complete change orders data and limited productivity loss data, 3) limited change orders data and limited productivity loss data, 4) no reference to change orders, 5) insufficient information. The number of cases grouped in each category is summarized in Table 3-1. For each case of the first 4 categories, the general information including the report type, the plaintiff and defendant, as well as the project location, type, sector, and work type, grouped by category, could be found in Appendix 1.

Table 3-1 Preliminary Investigation Results

Number of Projects in Category					Total
1	**2**	**3**	**4**	**5**	**117**
12	4	35	13	53	

During the detailed investigation stage, the cases grouped in categories 1 and 2 were reviewed, to the level of work packages, to collect the data needed for this research. Those cases represent projects that suffered from the adverse impact of change orders. Table 3-2 summarizes the number and work type of the work packages found relevant.

Table 3-2 Detailed Investigation Results

	Number of Work Packages		
Work Type	**Category 1 Cases**	**Category 2 Cases**	**Total**
Architectural	3	0	**3**
Civil	0	0	**0**
Electrical	8	1	**9**
Mechanical	15	6	**21**
Total	**27**	**7**	**33**

The data collected for each work package (hereinafter referred to as "case") is divided into:

1) Contractual data that include: the work type, project delivery system, contract type, original duration, actual duration, case monetary value, the base hours (BDOCH), and the actual hours (ADOCH).

2) Change orders data that include: the total monetary value of change orders, the total number of change orders, and the total direct hours of change orders both distributed over five equal periods of the original duration of the case.

3) Productivity loss data that include: the percentage of productivity loss (PL), the type of impact (TI), which could be interpreted as the number of major causes of productivity loss. TI=1 when the only reason for productivity loss is change orders, while TI=2 or 3 for one or two additional major causes of productivity loss.

The results of this detailed investigation stage are included in Appendix 2. As shown in Table 3-2, 33 cases are collected in this stage with very few architectural cases and no civil cases resulted. This data needed to be expanded in order to improve the reliability of the model. As such, the current data is supplemented by historical change order impacted cases that were originally collected by Leonard (1988). Those cases were also collected at RAL's office in Montreal assuring consistency with the recently collected ones. The supplementary cases are arranged similarly to the recently collected ones as shown in Appendix 3. A summary of the cases derived from the detailed investigation stage and the supplementary cases from Leonard (1988) is shown in Table 3-3.

Table 3-3 Available Cases

Work Type	Recently Collected Cases	Supplementary Cases from Leonard (1988)	Total
Architectural	3	6	**9**
Civil	0	12	**12**
Electrical	9	26	**35**
Mechanical	21	25	**46**
Total	**33**	**69**	**102**

3.4 Data Preparation Stage

According to the comprehensive literature review presented in Chapter 2 and to the data collection performed, the factors influencing the impact of change orders could be categorized as follows:

1) Timing of change orders: Coffman (1997) confirmed that "when evaluating change orders, regardless of their cause, the most significant factor is when the change occurs". This factor was introduced in a model by Vandenberg (1997) that used a linear relation, as explained in Section 2.3.5.2, to derive the timing weight (WTIMING) for Equation 2-7. This distribution expects the higher labor impact to happen in the lowest labor-intensive period. Such a procedure was not supported by the findings of Bruggink (1996) who, based on the analysis of 61 electrical cases, concluded that the highest impact of change orders occur in the third quarter (50% - 75%) of the project duration. On the other hand, Ibbs and Allen (1995) failed to prove that "changes which occur late in a project are implemented less efficiently than changes that occur early". Coffman (1997) realized that the highest impact occurs when change orders appear in the 3rd quarter of the project duration, while the least impact occurs when they appear in the first two quarters.
2) Work Type: Construction work is sequential, and in most cases inter-dependent (Coffman 1997). The degree of interdependency may vary from one work type to another and between work types, in addition to differences in the level of skill required to perform the work and its level of complexity

(Leonard 1988). Accordingly, all up-front methods considered the work type as a function in the level of skill required.

3) Relative size of change orders: this category includes change order hours, their ratios to the planned and/or actual hours, and their ratio to the change orders number (i.e. average size of change orders).
4) Frequency of change orders: this category includes change orders number, and their ratio to the actual hours (i.e. change orders frequency).
5) Type of Impact: this illustrates whether the work is impacted with change orders or with 1 or 2 more additional causes of productivity impacts, as explained for the model of Moselhi et al (1991a), in Section 2.3.5.2.
6) Project phase: this illustrates whether the work done is during the design phase or the construction phase as presented the model of Ibbs (1997), in Section 2.3.5.2.
7) On-site management: this category was only presented by a variable that accounts for the Project Manager's years of experience, as shown in the model of Hanna et al. (199b), Section 2.3.5.2.

In this stage, preliminary sets of data are prepared using the above-mentioned change orders impact factors that are available in the data collected. The factors considered include: 1) number of change orders (NCOs), 2) frequency of change orders (the ratio of change orders number to the actual hours referred to as FCOs), 3) average size of change orders (the ratio of change orders hours to the number of change orders referred to as ASCOs), 4) change orders hours

(HCOs), 5) change orders hours ratio to the planned hours (CORB), 6) change orders hours ratio to the actual hours (CORA), and 7) Type of Impact (TI).

Accordingly, formulated preliminary data sets can be classified as follow:

1) A data set that includes the cases appointed to model the timing influence. Those cases are based on the data recently collected as they contain the repartition of change order hours and numbers over the project duration for potential use to model the timing effect of change orders.

2) Four data sets each include the cases appointed to model a certain work type (i.e. architectural, civil, electrical, or mechanical). Those cases are based on the recently collected data as well as the supplemented data. A column titled "By" is added to distinguish the data recently collected, designated by the letter "I", and the data adopted from Leonard (1988), designated by the letter "L".

In each preliminary data set, data is grouped by the type of impact (TI) and sorted by the productivity loss (PL) as shown in Appendix 4.

3.5 Data Analysis Stage

The main objective of this analysis is to explore the existence of correlation between the productivity loss and any of the independent variables included in the five preliminary data sets formulated in the previous section. This is achieved using: 1) scatter plots, and 2) association measuring.

3.5.1 Scatter Plots

Scatter plots are two-dimensional graphs for two variables. The X-axis is dedicated to the independent variables (i.e. the change orders intensity factor), while the Y-axis is dedicated to the dependent variable (i.e. the productivity loss). They often reveal a pattern or a trend that is supposed to indicate whether a common variation would exist between the variables and what would be the shape of this relation (Meyer 1975, Mezei 1990). Figure 3-1 illustrates the potential relationships expected.

Scatter plots are developed for each independent variable in all preliminary data sets against the dependent variable (i.e. the productivity loss referred to as PL) with respect to each type of impact. Examining the scatter plots revealed that the most clear potential relationship observed in all preliminary sets, for all types of impact, was found to be between the productivity loss and the ratio of change orders hours to the planned or the actual hours (i.e. CORB and CORA). The scatter plots of the mechanical work type data (see Table 5 in Appendix 4) is taken as an example for the developed scatter plots as shown in Figures 3-2 to 3-7.

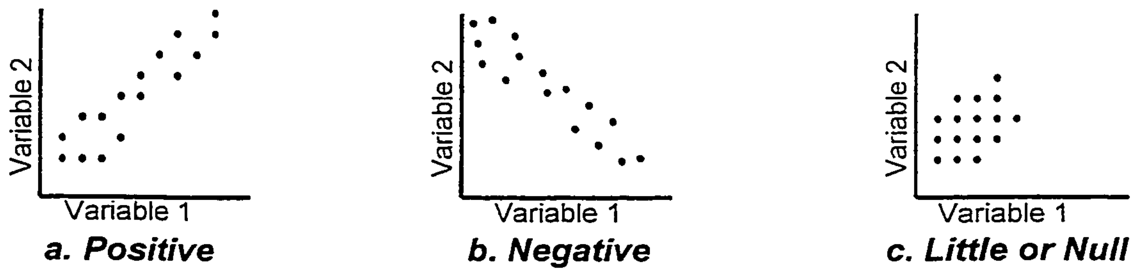


Figure 3-1 Scatter Plots: Potential Relationships (McCuen, 1975)

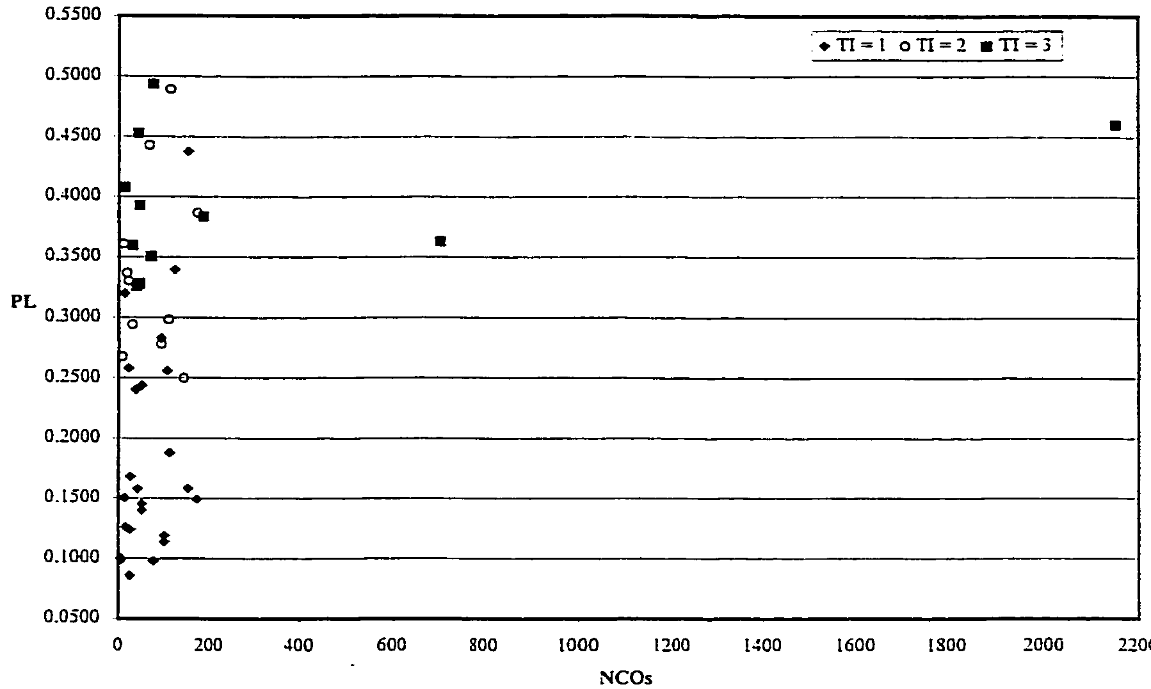


Figure 3-2 Scatter Plots of NCOs vs. PL

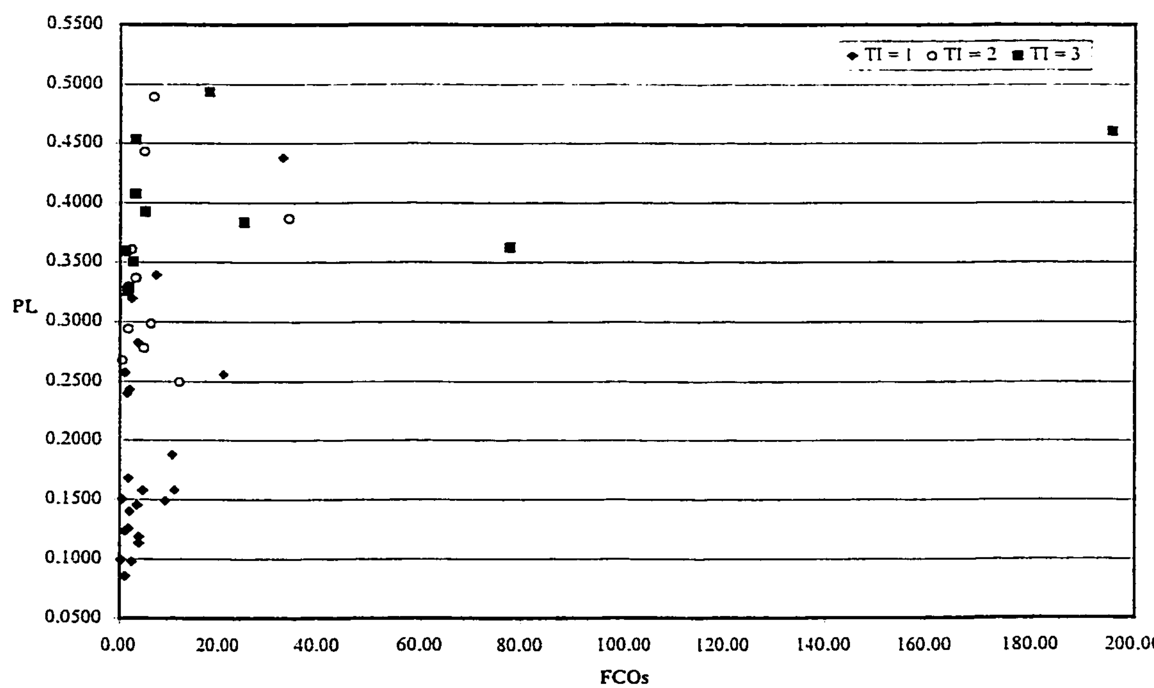


Figure 3-3 Scatter Plots of FCOs vs. PL

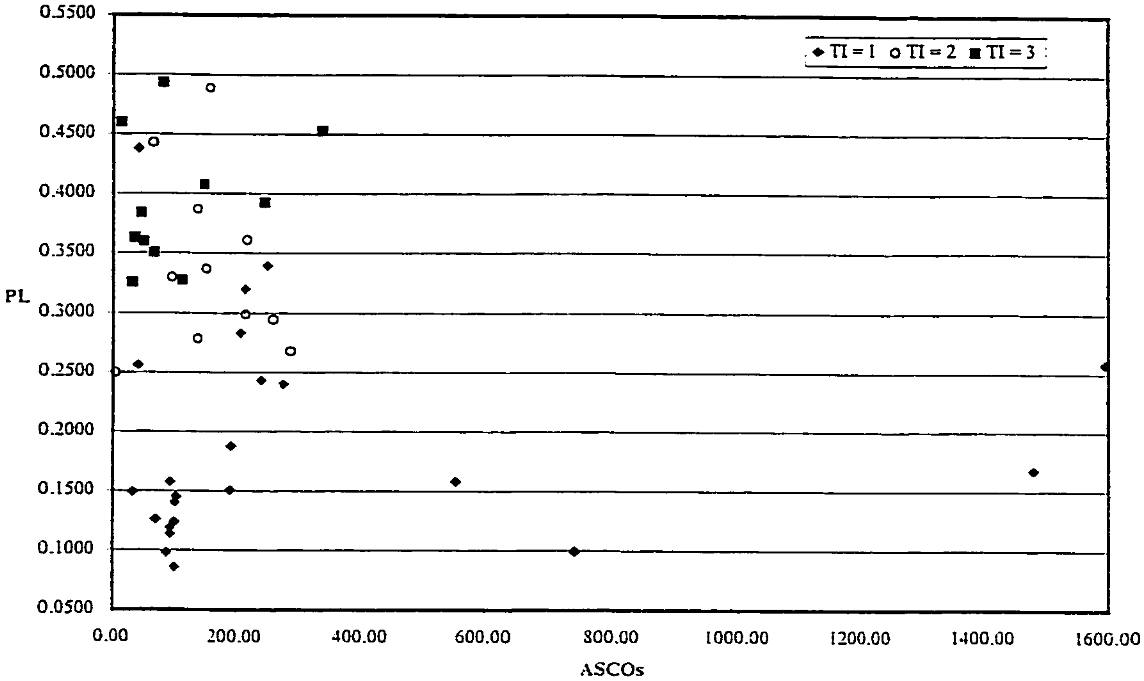


Figure 3-4 Scatter Plots of ASCOs vs. PL

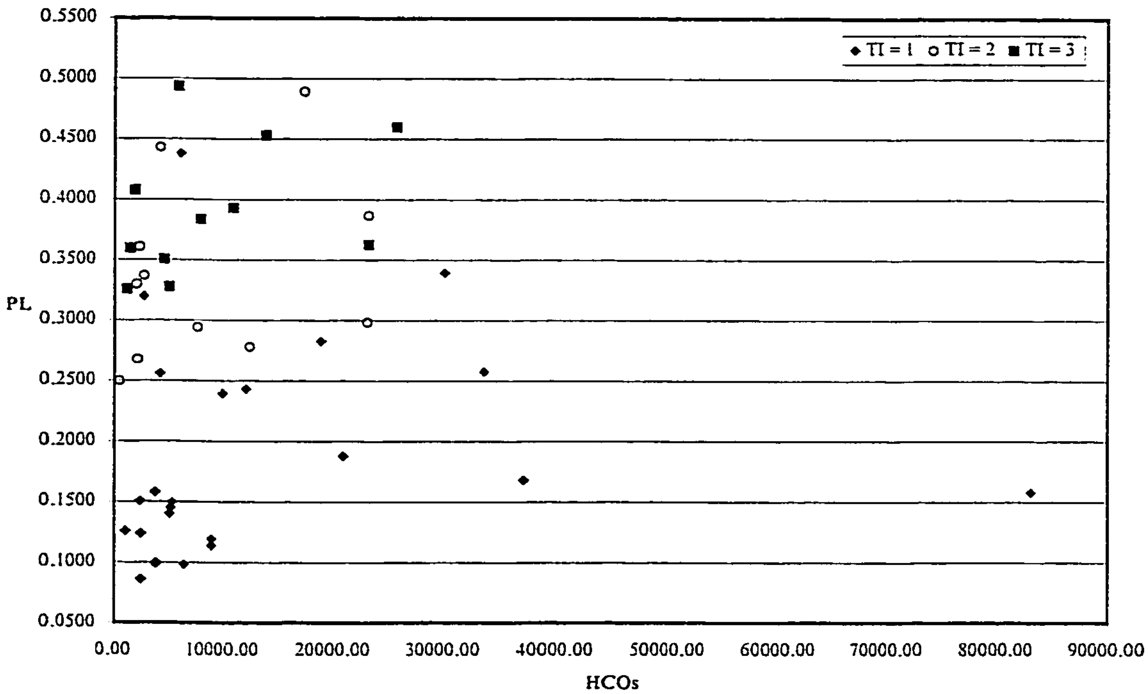


Figure 3-5 Scatter Plots of HCOs vs. PL

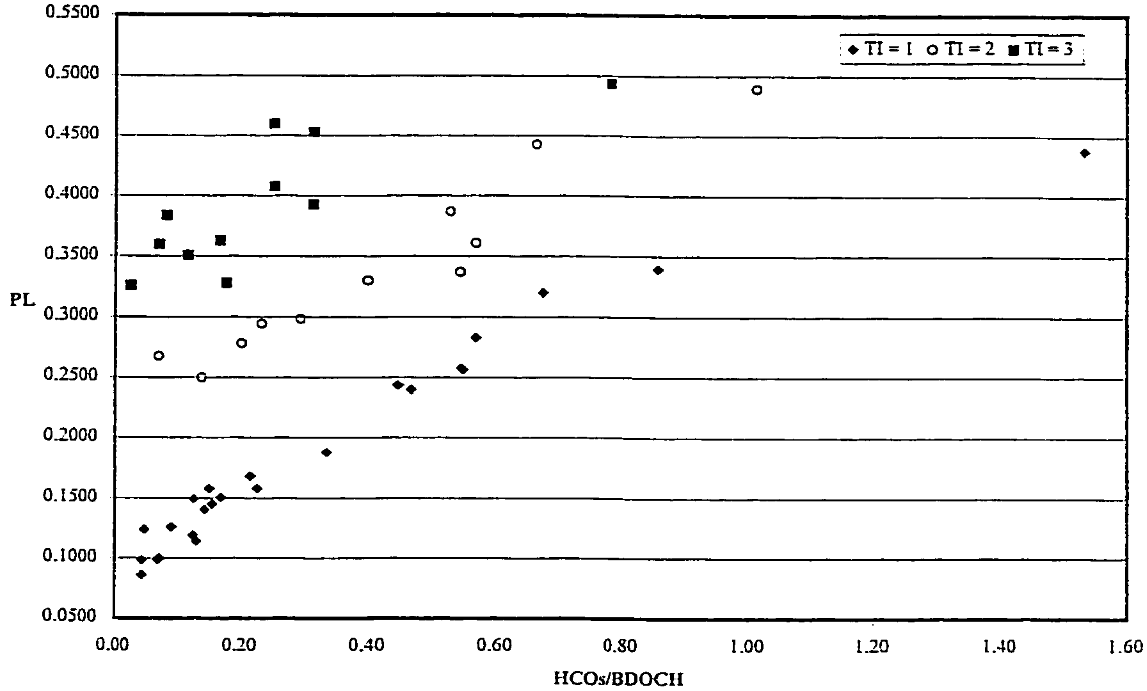


Figure 3-6 Scatter Plots of CORB vs. PL

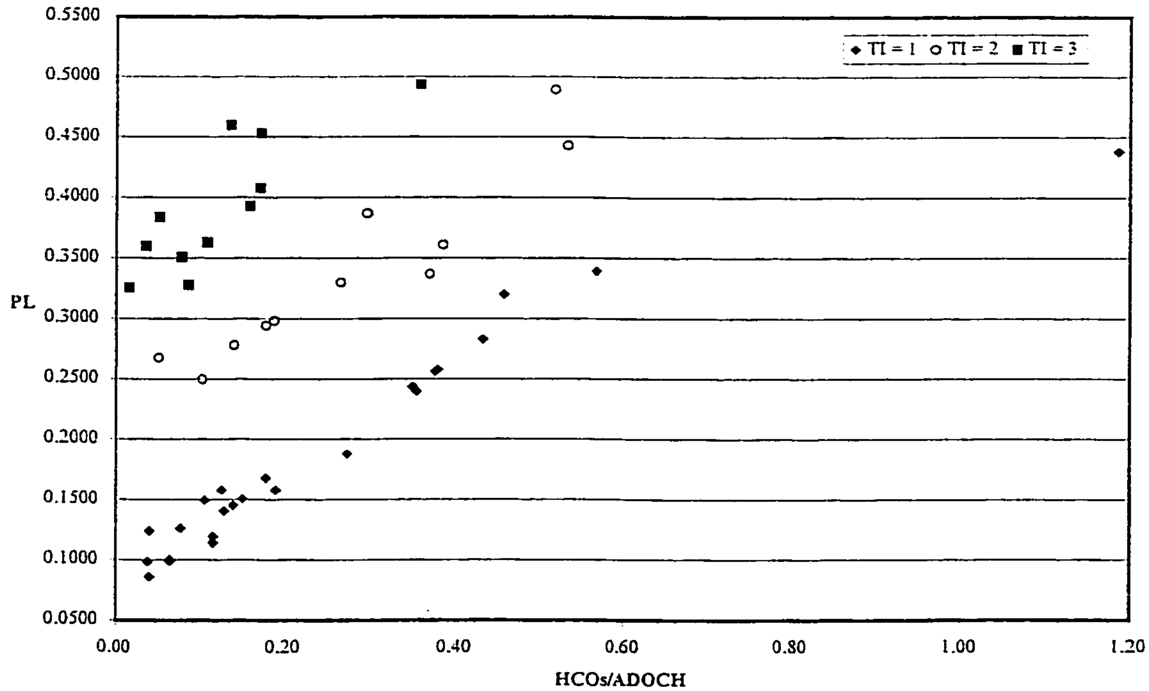


Figure 3-7 Scatter Plots of CORA vs. PL

3.5.2 Association Measuring

The association measuring, also called the correlation analysis, is used to quantify the degree of association between the dependent variable and the independent ones (McCuen, 1985). Consequently, the coefficient of correlation (r) is applied on all the preliminary sets, for each type of impact. This coefficient provides a quantitative measure of the strength of the linear association between two variables (Horvath, 1985). Its value varies from +1 (i.e. strong positive linear association between the variables) to –1 (i.e. strong negative linear association between the variables). A value of 0 indicates little or no association, while an absolute moderate value less than 0.5 indicates that the mean value of the cases in the data set is more effective to represent it (Sincich et al., 1999). For a sample of n cases, r would be calculated as follow:

$$r = \frac{SSxy}{\sqrt{SSxx\ SSyy}} \qquad \textbf{Eq. 3-1}$$

Where:

$$SSxy = \sum xy - \frac{\sum x \sum y}{n}$$

$$SSxx = \sum x^2 - \frac{(\sum x)^2}{n}$$

$$SSyy = \sum y^2 - \frac{(\sum y)^2}{n}$$

The results obtained for each preliminary set, for each type of impact, are shown in Table 3-4.

Table 3-4 Correlation Coefficient for Preliminary Sets

Prelim. Set	Cases No. (n)	Type of Impact (TI)	Coefficient of Correlation (r) of Productivity Loss with Change Orders': Number	Frequency	Average Size	Hours	Hours/ Planned	Hours/ Actual
Timing (see Table 1 – Appendix 4)	14	1	0.3708	0.6600	-0.2598	0.0686	0.9705	0.9562
	10	2	-0.1492	0.3757	0.2470	-0.0956	0.9271	0.9093
	3	3	0.3257	0.4366	0.6116	0.5569	0.6203	0.6799
	Weighted Average		0.2009	0.5129	0.1314	0.1520	0.8618	0.8666
Architectural (see Table 2 – Appendix 4)	2	1	NA	NA	NA	NA	NA	NA
	6	2	0.2427	-0.6890	0.4024	0.4883	0.9020	0.8876
	1	3	NA	NA	NA	NA	NA	NA
	Weighted Average		0.3840	-0.2371	0.0461	0.5478	0.8236	0.8140
Civil (see Table 3 – Appendix 4)	3	1	0.3856	0.4896	0.7413	0.5387	0.9582	0.9381
	9	2	0.7798	0.7566	-0.0114	0.4755	0.9078	0.8870
	0	3	NA	NA	NA	NA	NA	NA
	Weighted Average		0.6812	0.6899	0.1768	0.4913	0.9204	0.8998
Electrical (see Table 4 – Appendix 4)	12	1	-0.0670	-0.3200	0.4949	0.4229	0.9827	0.9816
	17	2	0.5699	0.6649	0.3113	0.5858	0.8829	0.8645
	6	3	0.5387	0.2560	0.7202	0.6098	0.9564	0.9485
	Weighted Average		0.3462	0.2571	0.4444	0.5341	0.9297	0.9191
Mechanical (see Table 5 – Appendix 4)	24	1	0.3366	0.6077	0.0034	0.1343	0.9687	0.9506
	11	2	0.1590	0.1972	-0.1588	0.2882	0.9616	0.9360
	11	3	0.3451	0.3728	0.2938	0.3797	0.8057	0.8303
	Weighted Average		0.2962	0.4533	0.0341	0.2298	0.9280	0.9183

NA: not available due to insufficient number of cases.

$$\text{Weighted Average} = \frac{\sum_{TI=1}^{TI=3} r_{TI} \times n_{TI}}{\sum_{TI=1}^{TI=3} n_{TI}}$$

The tabulated results reveal the following observations:

1) The results reinforce the observations of the scatter plots and confirm the strong correlation between the ratio of the change order hours to the planned or the actual hours (i.e. CORB or CORA).
2) Low and negative correlation coefficient values suggest that there is little or no correlation between the considered factor and the productivity loss.
3) The preliminary set representing the civil work type effect was the only one to reveal correlation with NCOs and FCOs, but with a moderate coefficient of correlation.

3.6 Modeling Stage

The results obtained from the scatter plots and the correlation analysis indicated a strong correlation between the ratio of change order hours to the base (planned) hours and to the actual hours (i.e. CORB and CORA) and the productivity loss (i.e. PL) for all types of impact (TI). Consequently, those two factors are used to model the work type influence and the timing influence on the adverse impact of change orders. For the work type influence, both of the above mentioned intensity factors are already calculated for each particular work type (see Tables 2 to 5 in Appendix 4). Accordingly, they could be used straightforward in modeling the influence of the different work types on the impact of change orders.

To model the timing effect, the relevant factors (i.e. CORB and CORA) need to be conceptualized to enable the consideration of the timing influence of change orders. This is hypothesized by identifying the value of this ratio for each period of the project. The data collected provides the value of the change orders hours distributed over five equal periods of the work duration (i.e. $(HCOs)_i$), the base (planned) hours (BDOCH), and the actual hours (ADOCH). Hence, we need to obtain distribution coefficients for ADOCH and BDOCH over the work duration. ADOCH depends on how severe the impact is and how it is dealt with, i.e. it lacks consistency and could not, accordingly, be used in generalizing a model. On the other side, BDOCH is expected to be more consistent as it would follow the conventional trapezoidal shape for direct resource loading. This is supported by the graphs of the planned and actual direct manpower loading versus the work duration shown in Figures 3-8 to 3-10.

In order to identify a reliable and practical methodology for dividing BDOCH over the five equal periods of the work duration, the distribution of the direct manpower loading over the project duration needs to be identified. This is achieved by performing: 1) a complementary study of the direct manpower loading for the analyzed cases, and 2) a review of the literature to identify studies in this area.

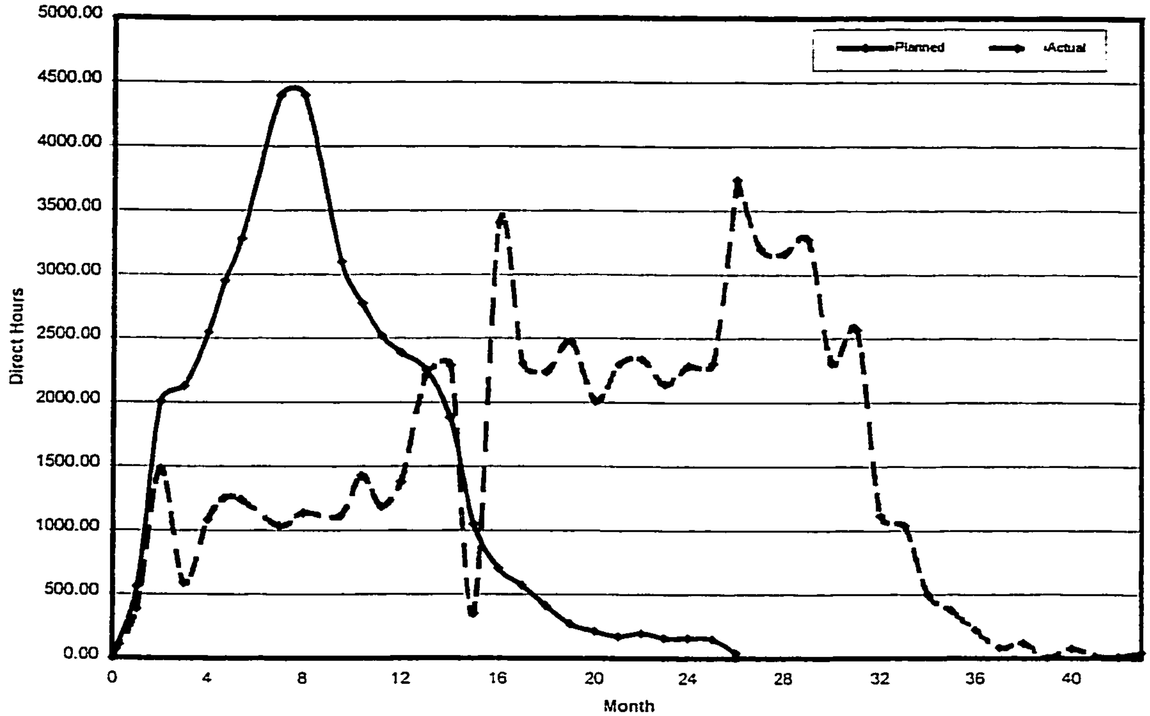


Figure 3-8 Direct Manpower Loading for Case #15 (see Table 1, Appendix 4)

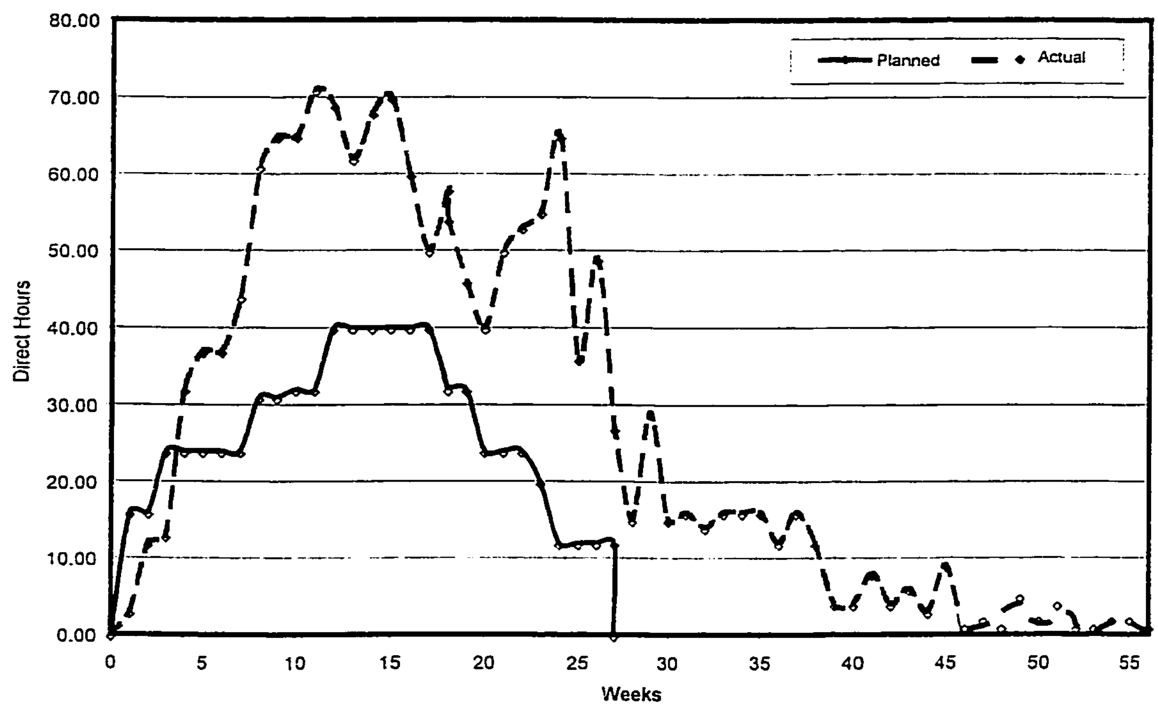


Figure 3-9 Direct Manpower Loading for Case #19 (see Table 1, Appendix 4)

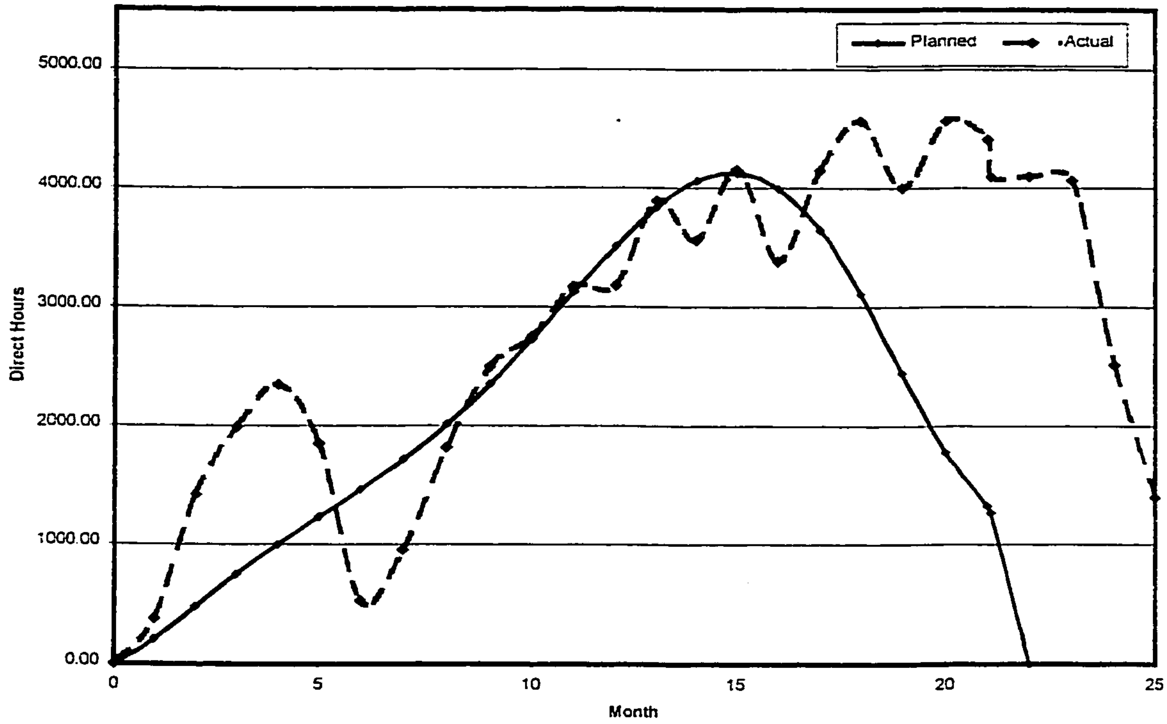


Figure 3-10 Direct Manpower Loading for Case #33 (see Table 1, Appendix 4)

3.6.1 Complementary Study

The direct manpower loading is investigated for the 33 recently collected cases analyzed in this study. Relevant data are successfully obtained for the 3 architectural cases, 5 of the 12 electrical cases, and 11 of the 21 mechanical. This data consisted of the base (planned) hours repartitioned over the original work duration (in month or in weeks). The collected data is normalized distortedly by normalizing the base direct original contract hours to 1 and the original duration to 5 (i.e. in correspondence with the number of periods). The area under the normalized curve is calculated for each period in order to estimate the total base direct hours activated during the period (a_i). The value of a_i is divided by the total area (A), representing the total direct planned hours, to identify the ratio of base hours for a period "i" to the total base (planned) hours, as shown in Table 3-5.

Table 3-5 Direct Manpower Loading Ratios for Studied Cases

Work Type	Period %Duration	P_1 0% - 20 %	P_2 20% - 40%	P_3 40% - 60%	P_4 60% - 80%	P_5 80% - 100%
Architectural	1	0.05	0.15	0.28	0.35	0.18
	2	0.05	0.15	0.27	0.33	0.20
	3	0.05	0.15	0.27	0.34	0.19
	Min	0.05	0.15	0.27	0.33	0.18
	Average	0.05	0.15	0.27	0.34	0.19
	Max	0.05	0.15	0.28	0.35	0.20
Electrical	1	0.05	0.15	0.23	0.28	0.28
	2	0.08	0.20	0.21	0.29	0.22
	3	0.05	0.15	0.26	0.32	0.23
	4	0.05	0.15	0.25	0.31	0.23
	5	0.19	0.48	0.25	0.07	0.02
	Min	0.05	0.15	0.21	0.07	0.02
	Average	0.08	0.23	0.24	0.25	0.20
	Max	0.19	0.48	0.26	0.32	0.28
Mechanical	1	0.21	0.27	0.22	0.22	0.08
	2	0.08	0.28	0.28	0.28	0.09
	3	0.14	0.30	0.35	0.13	0.08
	4	0.03	0.16	0.41	0.29	0.11
	5	0.03	0.13	0.31	0.35	0.19
	6	0.14	0.22	0.29	0.23	0.12
	7	0.10	0.11	0.16	0.33	0.29
	8	0.09	0.22	0.40	0.18	0.10
	9	0.04	0.16	0.34	0.34	0.13
	10	0.02	0.22	0.44	0.26	0.06
	11	0.22	0.34	0.26	0.14	0.03
	Min	0.02	0.11	0.16	0.13	0.03
	Average	0.10	0.22	0.31	0.25	0.12
	Max	0.22	0.34	0.44	0.35	0.29

3.6.2 Available Studies

In addition to the analysis of the cases used in this study, a comprehensive literature review is conducted to identify available studies that can be applied to estimate the direct manpower loading. The following studies are found to be relevant and reliable:

1) Bent and Thumann (1988) suggested a typical trapezoidal shape to model the direct manpower loading for the construction phase as illustrated in Figure 3-11. The same trapezoidal shape was reported by AACE Education Board (1989).

2) The National Electrical Contractors Organization (NECA) in a report about the rate of manpower consumption in electrical construction (1983) suggested an industry average rate of manpower consumption as illustrated in Figure 3-12.

The results of the direct manpower loading, as obtained from each study, are compared to those obtained from analyzing the present cases as shown in Table 3-6.

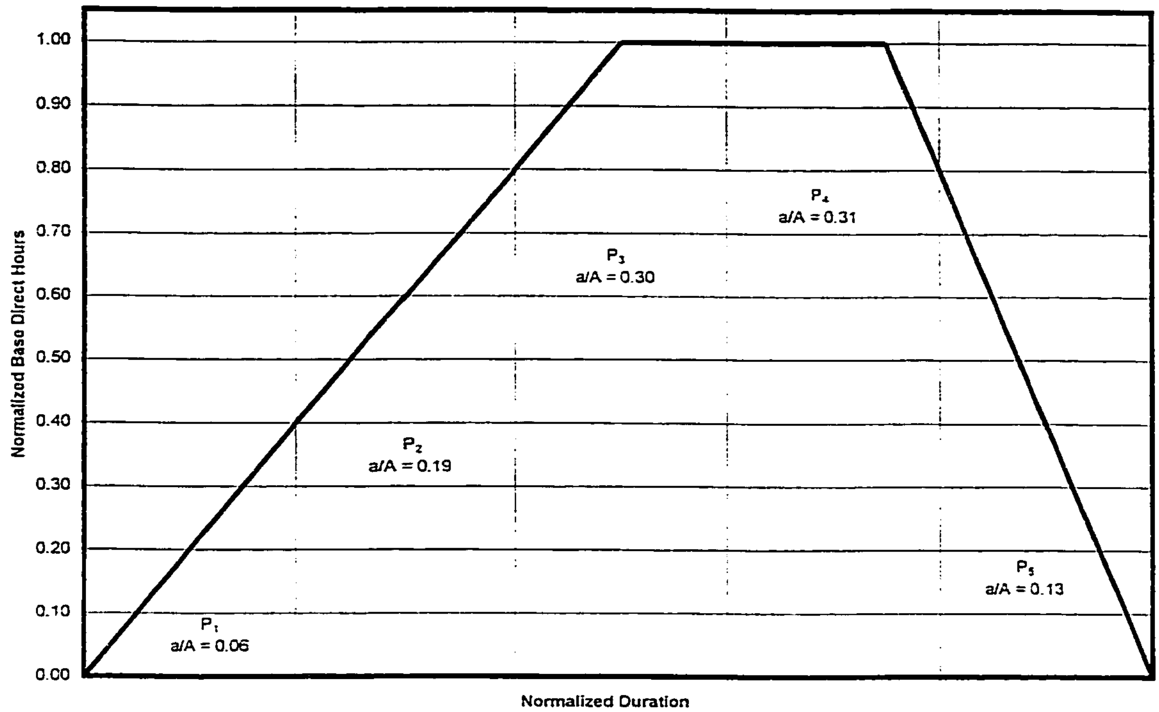


Figure 3-11 Base Direct Manpower Loading (Bent and Thumann 1988)

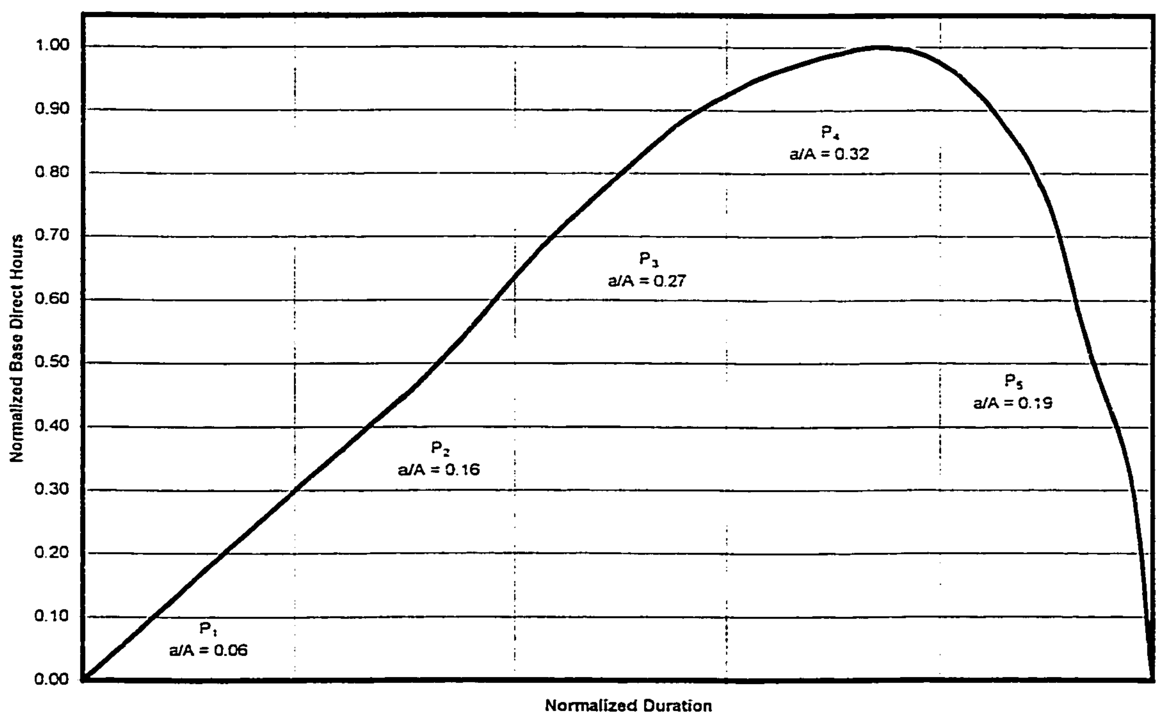


Figure 3-12 Base Direct Manpower Loading (NECA 1983)

Table 3-6 Direct Manpower Loading Ratios

Period	% Duration	Weighted Average of Studied Cases	Industry Average	NECA Average
P1	0% - 20 %	0.09	0.06	0.06
P2	20% - 40%	0.21	0.19	0.16
P3	40% - 60%	0.29	0.30	0.27
P4	60% - 70%	0.26	0.31	0.32
P5	70% - 80%	0.15	0.13	0.19
Total		1.00	1.00	1.00

$$\text{Weighted Average} = \frac{\sum_{WT=1}^{WT=3} \text{Average}_{WT} \times n_{WT}}{\sum n}$$

WT=1, 2, or 3 for Architectural, Electrical, Mechanical

Table 3-6 indicates that the ranges of the results are close. As it is driven from a bigger pool of data, the industry average is expected to be more accurate, and therefore is adopted for the architectural and mechanical cases. The NECA average, on the other hand, is adopted for the electrical cases. Multiplying the base (planned) hours (BDOCH) of the case by the corresponding fraction (i.e. a_i / A) for a particular period "i" can be used to estimate the base hours for this particular period (i.e. $(BDOCH)_i$).

3.6.3 Change Orders Timing Influence Modeling

The change orders timing influence on their impact on construction productivity is conceptualized using two main concepts:

1) As mentioned earlier in Section 2.3.3, a change order has a significant impact on the direct resources utilized during the period in which it appears. The degree of this impact can be represented using the ratio of the change orders hours occurring in a period "i" (i.e. $(HCOs)_i$) to the base (planned) hours for the same period (i.e. $(BDOCH)_i$). This ratio is denoted by the symbol "DP_i" which stands for the Direct impact on the resources of a certain Period (P_i) as follows:

$$DP_i = (HCOs/BDOCH)_i \qquad \textbf{Eq. 3-2}$$

2) Change orders are often associated with a ripple effect on the direct resources in the succeeding periods (See Chapter2, Section 2.3.3). This impact, for a certain period (i), can be represented by multiplying the above-calculated ratio of DP_i, in Eq. 3-5, by a second ratio that represents the direct resources to be impacted during the coming periods. In other words, this second ratio represents the direct resources affected by the change orders ripple effect in the periods to follow period "i", where the change order appears, as expressed by the following equation follows:

$$RP_i = (HCOs/BDOCH)_i \; [(A - \sum_{n=1}^{n=i} a_n)/A] \qquad \textbf{Eq. 3-3}$$

For the fifth period, the above equation is modified assuming that what is left to be impacted is half the direct resources of the fifth period:

$$RP5 = (HCOs/BDOCH)_i \; [(a_5 / 2)/A] \qquad \textbf{Eq. 3-4}$$

3.7 Formulation of Data Sets

The results of the previous stages are used to formulate 10 data sets. These data sets will be used later in Chapter 4 to model the timing influence and the work type influence on the adverse impact of change orders. For the timing influence, the 2 concepts, presented in Section 3.6.3, in addition to the type of impact, are used to develop the first two data sets. For the work type influence, the 2 change orders factors found in correlation with the resulting productivity loss (i.e. CORB and CORA) in addition to the type of impact are used to develop the rest 8 data sets.

Each data set is coded using DS (i.e. Data Set), along with: 1) a serial subscript number for the data set (i.e. 1,2...10), 2) a letter to designate the model that the data set represents (i.e. T for timing models, A for architectural models, C for civil models, E for electrical models, and M for mechanical models), and 3) a serial subscript number for the model (i.e. T_1 and T_2 for both concepts of Timing modeling, A_1 and A_2 for both concepts of architectural work type modeling, ...etc.). The code and the independent variables of each data set are presented in Table 3-7.

Table 3-7 Data Sets Coding and Independent Variables

Data Set Code	Data Set Independent Variables
DS_1T_1	TI, DP_1, DP_2, DP_3, DP_4, DP_5 (timing cases)
DS_2T_2	TI, RP_1, RP_2, RP_3, RP_4, RP_5 (timing cases)
DS_3A_1	TI, CORB (architectural cases)
DS_4A_2	TI, CORA (architectural cases)
DS_5C_1	TI, CORB (civil cases)
DS_6C_2	TI, CORA (civil cases)
DS_7E_1	TI, CORB (electrical cases)
DS_8E_2	TI, CORA (electrical cases)
DS_9M_1	TI, CORB (mechanical cases)
$DS_{10}M_2$	TI, CORA (mechanical cases)

Where:

TI is the Type of Impact, as explained in Section 3.3.

DP_i is the Direct impact of change orders for a period i, as explained in Section 3.6.3 and Equation 3-5.

RPi is the Ripple effect of change orders occurring in a period i, as explained in Section 3.6.3 and Equation 3-6 and Equation 3-7.

CORB is the ratio of change orders hours (HCOs) to the base (planned) hours (BDOCH).

CORA is the ratio of change orders hours (HCOs) to the actual hours (ADOCH).

The data sets are accordingly formulated grouped by the Type of Impact (TI) and sorted by the Productivity Loss (see Appendix 5).

3.8 Summary

In this chapter, the data collection and analysis has been presented in six stages. The data collection stage outlined the collection of the data used in this research. The data organization stage described how data is arranged for analysis and evaluation. The factors that are used to quantify the impact of change orders on construction productivity were categorized into 7 categories. The data preparation used the available change orders intensity factors to form preliminary sets of data that are analyzed using scatter plots and association measures. In the modeling stage, the intensity factors found to be in correlating with the resulting productivity loss are used to model the influence of timing of change orders and their type of work. The results, revealing a high association with the ratio of change orders hours to both the base (planned) and the actual (i.e. CORB and CORA) and the productivity loss for each type of impact, formed the basis for the conceptualization to model the timing effect and the work type effect on the adverse impact of change orders. The work type influence is modeled in a straightforward approach, using the intensity factors in correlation with the productivity loss for each specific work type. The timing effect is modeled using two concepts: 1) the direct impact, and 2) the ripple impact. The formulation of the data sets stage generated 10 useful data sets that are going to be utilized in the development of regression and neural networks models in Chapter 4.

Chapter 4

Models Development

4.1 Introduction

The objective of this chapter is to model the influence of the timing and the work type on the impact of change orders on construction productivity by developing a number of regression and neural networks models. The regression models are developed using multiple linear regression analysis. The objective of those regression models is: 1) to verify whether the identified combination of variables, included in the data sets formulated in Chapter 3, are relevant to present the resulting productivity loss or not, 2) to be compared, in a later stage, to the developed neural network models. Accordingly, a total of 10 neural network models are developed using back propagation algorithm. The chapter also introduces the development of a prototype software application that provides an automated environment, for the calculation of construction productivity loss, and provides a user-friendly interface for the developed neural network models, in addition to four other regression models obtained from the literature.

4.2 Regression Models

The main objective for developing the regression models is to determine whether or not the independent variables, and their combination, included in the 10 data sets (Section 3.7) have the ability to represent and predict the resulting productivity loss. The present regression models are developed using Microsoft Excel97 data analysis feature in three main steps: 1) model type identification, 2) model coefficients calculation, and 3) model verification.

4.2.1 Model Type Identification

The first step in regression analysis is to identify the relation type: linear, logarithmic, or polynomial. Based on the assumption of linear relation between the productivity loss due to change orders impact and its independent variables (Moselhi et al. 1991a, Ibbs 1997), which is reinforced by the observations of the scatter plots and the correlation analysis presented earlier in Section 3.5.1 and Section 3.5.2, the linear type is adopted and Multiple Linear Regression Analysis (MLRA) is utilized in developing the present models.

4.2.2 Model Coefficients Calculation

The second step is to calculate the unknown coefficients using the least square method. Table 4-1 illustrates the developed regression models and the associated coefficients for each data set.

Table 4-1 Developed Regression Models

Data Set Code	Regression Model
DS_1T_1	$PL = -0.0181 + 0.1120\ TI - 0.0139\ DP_1 + 0.0667\ DP_2 + 0.0703\ DP_3 + 0.0782\ DP_4 + 0.0389\ DP_5 + \epsilon$
DS_2T_2	$PL = -0.0211 + 0.1124\ TI + 0.0106\ RP_1 + 0.0985\ RP_2 + 0.1280\ RP_3 + 0.4037\ RP_4 + 0.6554\ RP_5 + \epsilon$

Table 4-1 Developed Regression Models (Continued)

Data Set Code	Regression Model
DS_3A_1	PL = 0.0332 + 0.0848 TI + 0.1598 CORB + ϵ
DS_4A_2	PL = 0.0180 + 0.0912 TI + 0.2268 CORA + ϵ
DS_5C_1	PL = 0.0270 + 0.0118 TI + 0.0385 CORB + ϵ
DS_6C_2	PL = -0.0157 + 0.0896 TI + 0.3800 CORA + ϵ
DS_7E_1	PL = 0.0062 + 0.1001 TI + 0.2939 CORB + ϵ
DS_8E_2	PL = -0.0145 + 0.1087 TI + 0.4346 CORA + ϵ
DS_9M_1	PL = -0.0085 + 0.1157 TI + 0.2555 CORB + ϵ
$DS_{10}M_2$	PL = -0.0284 + 0.1271 TI + 0.3700 CORA + ϵ

Where:

PL is the Productivity Loss ratio (unproductive hours / actual hours)

TI is the Type of Impact, as explained in Section 3.3

DP_i (where i= 1 to 5) is the Direct impact of change orders for a period i, as explained in Section 3.6.3 and Equation 3-5

RP_i (where i= 1 to 5) is the ripple effect of change orders happening in a period i, as explained in Section 3.6.3 and Equation 3-6 and Equation 3-7

CORB is the ratio of change orders hours (HCOs) to the base (planned) hours (BDOCH).

CORA is the ratio of change orders hours (HCOs) to the actual hours (ADOCH).

For example, the developed model for the first data set (DS_1T_1), is represented in the following regression equation:

$$PL = -0.0181 + 0.1120\ TI - 0.0139\ DP_1 + 0.0667\ DP_2 + 0.0703\ DP_3$$

$$+ 0.0782\ DP_4 + 0.0389\ DP_5 + \epsilon \qquad \textbf{Eq. 4-1}$$

The coefficients (i.e. 0.1120, -0.0139, 0.0667, 0.0703, 0.0782, and 0.0389) can be interpreted to represent the increase that can be caused to the productivity loss as a result of an increase of one unit in any one of the corresponding independent variable, having all other independent variables constant. For example, an increase of one unit in the type of impact (TI) would result in an increase of 11.20 % in the productivity loss (PL).

4.2.3 Model Verification

The most important step in regression analysis is to verify the derived model, this is achieved in four main steps: 1) overall model test, 2) independent variables test, 3) statistical parameters test, and 4) random error assumptions test (McCuen 1985, Mezei 1990, McClave et al. 1997, Dretzeke and Heilman 1998, Sincich et al. 1999).

The purpose of the overall model test is to determine whether the multiple linear regression model is useful to predict its dependent variable, i.e. the productivity loss (PL). This hypothesis is tested using the analysis of variance (ANOVA) (Sincich et al., 1999). The hypothesis test involves all the coefficients of the model, also called β parameters, and is modeled as follows:

Null Hypothesis, H_0: $\beta_1 = \beta_2 = \dots \beta_k = 0$

Alternative Hypothesis, H_a: At least one of the βs $\neq 0$

To refuse the null hypothesis we have to fulfill two conditions: 1) ANOVA F-test value must be greater than the critical value of F (i.e. $F > F\alpha$), and 2) the level of significance "α" must be greater than the corresponding p-value (i.e. $\alpha >$ p-value). Accordingly, there would be sufficient evidence to reject H_0 and to conclude that at least one of the β factors is nonzero. The significance level is defined as the probability of making a type I error for a hypothesis test. In hypothesis testing, type I error is the error that would occur when we reject a null hypothesis when it is true, while type II error would occur when we accept a null hypothesis when it is false. The value of "α" is usually set to 0.05 (Evans and Olson, 2000).

The F value, given by Excel, can be calculated using equation 4-2:

$$F = \frac{\text{Mean square for Model}}{\text{Mean square for Error}} = \frac{SS(\text{Model})/k}{SSE/[n-(k+1)]} \qquad \textbf{Eq. 4-2}$$

Where: SS= Sum of Squared ($\Sigma (y)^2$)

SSE= Sum of the Squared Errors ($= \Sigma (y-\hat{y})^2$)

n = number of observations (i.e. number of cases)

k = number of parameters in the model (i.e. independent variables), excluding β_0

F_α is driven from the corresponding statistical tables of critical F values (see Table 1 in Appendix 6) as function of: 1) the numerator degrees of freedom (k), and 2) the denominator degrees of freedom (n-(k+1)). The p-value is also given by Excel. Table 4-2 illustrates the overall model test resulting for each of the developed regression models. The results in this table reveal that we have sufficient evidence to reject H_0 and to conclude that at least one of the independent variables coefficients (i.e. βs) is nonzero. Those results imply that the first order model is useful for predicting the dependent variable, hence the productivity loss (McClave et al. 1997, Sincich et al. 1999, Evans and Olson 2000).

Table 4-2 Overall Regression Models Test

Data Set Utilized	n	k	α	F	F_α	p-value	Evaluation
DS_1T_1	33	6	0.05	112.37	2.47	3E-17	Pass
DS_2T_2	33	6	0.05	120.90	2.47	1E-17	Pass
DS_3A_1	9	2	0.05	31.70	5.14	6E-04	Pass
DS_4A_2	9	2	0.05	29.42	5.14	8E-04	Pass
DS_5C_1	12	2	0.05	31.15	4.26	9E-05	Pass
DS_6C_2	12	2	0.05	23.79	4.26	3E-04	Pass
DS_7E_1	35	2	0.05	281.76	3.32	5E-21	Pass
DS_8E_2	35	2	0.05	249.75	3.32	3E-20	Pass
DS_9M_1	46	2	0.05	469.80	3.23	6E-30	Pass
$DS_{10}M_2$	46	2	0.05	325.99	3.23	1E-26	Pass

The independent variables test checks whether or not the β coefficients are capable to represent the dependent variable. This hypothesis is tested through one or more t-tests on the β coefficients. The number of tests has to be limited to avoid the previously mentioned type I error. The hypothesis test is modeled as follow:

Null Hypothesis, H_0: $\beta_k = 0$

Alternative Hypothesis, H_a: $\beta_k \neq 0$

If the data support the alternative hypothesis H_a, it can be concluded that the independent variable under investigation contributes to the prediction of the dependent one using the straight-line model. To reject the null hypothesis, two conditions have to be fulfilled: 1) the absolute value of the two tailed t-test must be greater than the critical value of t (i.e. $|t| > t_{\alpha/2}$), and 2) the level of significance "α" must be greater than the value of the corresponding p-value (i.e. $\alpha >$ p-value).

The t value is given by Excel, and can be calculated using equation 4-3:

$$t = \frac{\beta_k \left(\sum y^2 - \frac{\left(\sum y\right)^2}{n} \right)}{s} \qquad \textbf{Eq. 4-3}$$

Where: β_k = the value of the coefficient (β parameter)

s = the standard deviation error of the β_k factor data set

y = the variable's data

n = the number of observations

The critical value of t for the two tailed test (i.e. $t_{\alpha/2}$) is driven from the corresponding tables (see Table 2 in Appendix 6) as function in: 1) $t_{0.025}$ (i.e. $t_{\alpha/2}$), and 2) the denominator degrees of freedom (n-(k+1)). The corresponding p-value is also given by Excel. Table 4-3 illustrates the independent variable test results for the developed regression models. As shown in the table, the independent variables passed the test with the exception of DP_1 and DP_5 in data set DS_1T_1, and RP_1 in data set DS_2T_2. Dretzek and Heilman (1998), Sincich et al. (1999), and Evans and Olson (2000) advised that this is not a sufficient reason to assume their relative β value is equal to 0. It rather acknowledges that additional data or a relationship that is more complex might exist between the independent and dependent variables. Consequently, the test of the independent variables implies that they contribute to the prediction of the independent variable (i.e. the resulting productivity loss).

Table 4-3 Independent Variables Test

Data Set Utilized	n	k	α	Independent Variable	|t|	$t_{0.025}$	P-value	Evaluation
DS_1T_1	33	6	0.05	TI	21.12	2.056	7E-18	**Pass**
				DP_1	0.82		4E-01	**Fail**
				DP_2	7.71		4E-08	**Pass**
				DP_3	5.48		9E-06	**Pass**
				DP_4	2.56		2E-02	**Pass**
				DP_5	1.50		2E-02	**Fail**
DS_2T_2	33	6	0.05	TI	21.89		3E-18	**Pass**
				RP_1	0.65		5E-1	**Fail**
				RP_2	8.71		3E-09	**Pass**
				RP_3	5.41		1E-05	**Pass**
				RP_4	2.52		2E-02	**Pass**
				RP_5	2.13		4E-02	**Pass**
DS_3A_1	9	2	0.05	TI	6.93	2.447	4E-04	**Pass**
				HCOs/BDOCH	5.47		2E-03	**Pass**
DS_4A_2	9	2	0.05	TI	7.01		4E-04	**Pass**
				HCOs/ADOCH	5.25		2E-03	**Pass**
DS_5C_1	12	2	0.05	TI	6.77	2.262	8E-05	**Pass**
				HCOs/BDOCH	7.15		5E-05	**Pass**
DS_6C_2	12	2	0.05	TI	6.27		1E-04	**Pass**
				HCOs/ADOCH	6.23		2E-04	**Pass**
DS_7E_1	35	2	0.05	TI	21.69	2.042	1E-20	**Pass**
				HCOs/BDOCH	16.26		5E-17	**Pass**
DS_8E_2	35	2	0.05	TI	21.30		2E-20	**Pass**
				HCOs/ADOCH	15.25		3E-16	**Pass**
DS_9M_1	46	2	0.05	TI	24.91	2.021	4E-27	**Pass**
				HCOs/BDOCH	19.98		2E-23	**Pass**
$DS_{10}M_2$	46	2	0.05	TI	22.59		2E-25	**Pass**
				HCOs/ADOCH	16.42		4E-20	**Pass**

At this stage, the model is proved robust and its independent variables are proved to be contributing to the prediction of the dependent one. Accordingly, a statistical parameters test should be performed, to evaluate the strength of the model, by evaluating 4 statistical parameters:

1) The standard error (S), which is the standard deviation of the errors around the regression line (Evans and Olson, 2000), can be calculated as follows:

$$S = \sqrt{\frac{\sum (y - \hat{y})^2}{n - 2}}$$ **Eq. 4-4**

Where:

y = the dependent variable data

$\hat{y}$ = the dependent variable predicted value

n = the number of observations

The predicted values of the dependent variables (i.e. loss of productivity) must fall within a range of ±2s of its actual value (Sincich et al., 1999). Hence, an increased value of s results is an extended error range which threatens the accuracy of the predicted values (Meyer 1975, Mezei 1990, McClave et al. 1997).

2) The coefficient of correlation (r), which measures the linear association of the dependent variable with the independent ones, presented in Equation 3-1. Its value varies from +1 (ideal positive association) to –1 (ideal negative association). A negative association is not expected to occur for the relation between the change orders intensity factors and the resulting loss of productivity.

3) The coefficient of multiple determination (R^2), also known as coefficient of determination, can be calculated using the following equation:

$$R^2 = \frac{SST - SSE}{SST} = \frac{SSR}{SST}$$ **Eq. 4-5**

Where:

$$SSR = [SST] - [SSE]$$

$$SSR = \left[\sum (y-\bar{y})^2\right] - \left[\sum (y-\hat{y})^2\right]$$

$\bar{y}$ = the dependent variable average

The value of the coefficient of determination varies from 0 to +1. A regression model with a high R^2 (i.e. > 0.5) provides a better tool for predicting the dependant variable (McClave et al. 1997, Evans and Olson, 2000).

4) The adjusted coefficient of determination (R_a^2), is more accurate than R^2 as it accounts for the number of cases (n) used to develop the model and the number of independent variables (k) as shown in Equation 4-6:

$$R_a^2 = 1 - \left\{\left[\frac{n-1}{n-(k+1)}\right]\left(1-R^2\right)\right\} \qquad \textbf{Eq. 4-6}$$

Models with high R^2_a provide better tools for predicting the dependant variable (Dretzek and Heilman 1998, Sincich et al. 1999).

Table 4-4 Statistical Parameters Test

Data Set Utilized	S	Prediction Range (±2S)	r	R^2	R^2_a	Outliers Limits (±3S)
DS_1T_1	0.024	0.048	0.981	0.963	0.954	0.072
DS_2T_2	0.023	0.046	0.983	0.965	0.957	0.069
DS_3A_1	0.020	0.040	0.956	0.914	0.885	0.060
DS_4A_2	0.021	0.042	0.953	0.908	0.877	0.063
DS_5C_1	0.015	0.030	0.935	0.874	0.846	0.045
DS_6C_2	0.016	0.032	0.917	0.841	0.806	0.048
DS_7E_1	0.018	0.036	0.973	0.946	0.943	0.054
DS_8E_2	0.019	0.038	0.969	0.940	0.936	0.057
DS_9M_1	0.026	0.052	0.978	0.956	0.954	0.078
$DS_{10}M_2$	0.031	0.062	0.969	0.938	0.935	0.093

As shown in Table 4-4, the results for the statistical parameters test were satisfactory. The expected error in prediction ranges between 3.0% and 6.2%. The coefficient of correlation (r) revealed a fair linear relation between the predicted and actual values ranging from 0.92 to 0.98. The coefficient of determination (R^2) ranged between 0.84 and 0.97, while the adjusted coefficient of determination ranged between 0.81 and 0.96 revealing a high capability of predicting the dependant variable (i.e. productivity loss).

The random error (ϵ) represents the difference between the actual and the predicted values. To build a regression model, there are four pre-made assumptions should be fulfilled once the model is created. The assumptions to be tested are: 1) mean of ϵ is 0, 2) variance of ϵ is constant, 3) outliers check, and 4) probability distribution of ϵ is normal (McClave et al. 1997, Sincich et al. 1999, Evans and Olson, 2000).

1) Mean of ϵ equals 0: this assumption is violated if the model is misspecified, (i.e. if it is hypothesized to be a straight-line relationship while the true relationship is more complex). To detect the model misspecification, the values of the independent variable (x) are plotted against the corresponding residuals ($y-\hat{y}$). This plot is expected to vary randomly as x increases and not to give any specific shape or strong pattern (Sincich et al. 1999), as shown in Figure 4-1.

a. Random *b. Pattern*

Figure 4-1 Residuals Plots Patterns (Sincich et al. 1999)

The residual is simply the actual less the predicted values for the dependent variable for each case. The residual plots of the regression model developed using data set DS_1T_1 is displayed in Figures 4-2 to 4-7. As shown, the pattern shows random progress that indicates that the assumption that the mean of ϵ equals 0 is fulfilled, which implies that the linear model was not a misspecification (McClave et. al. 1997). The same conclusion is drawn from the corresponding plots for the other regression models developed.

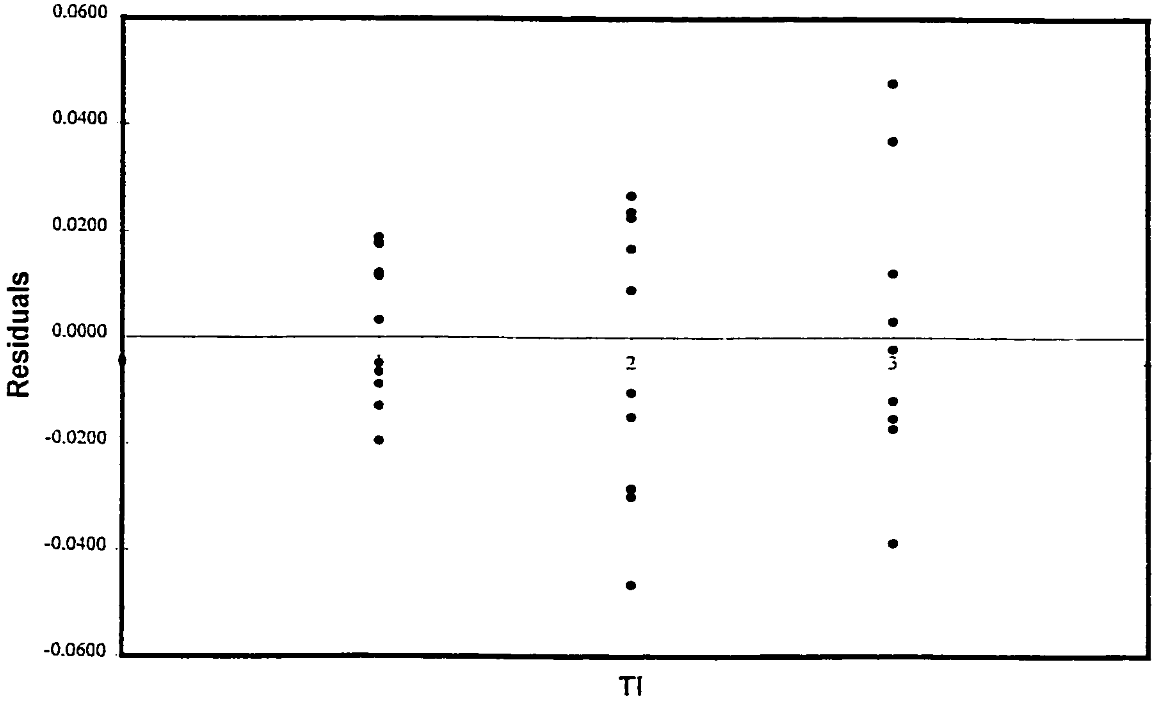


Figure 4-2 Residual Plot for Independent Variable "TI"

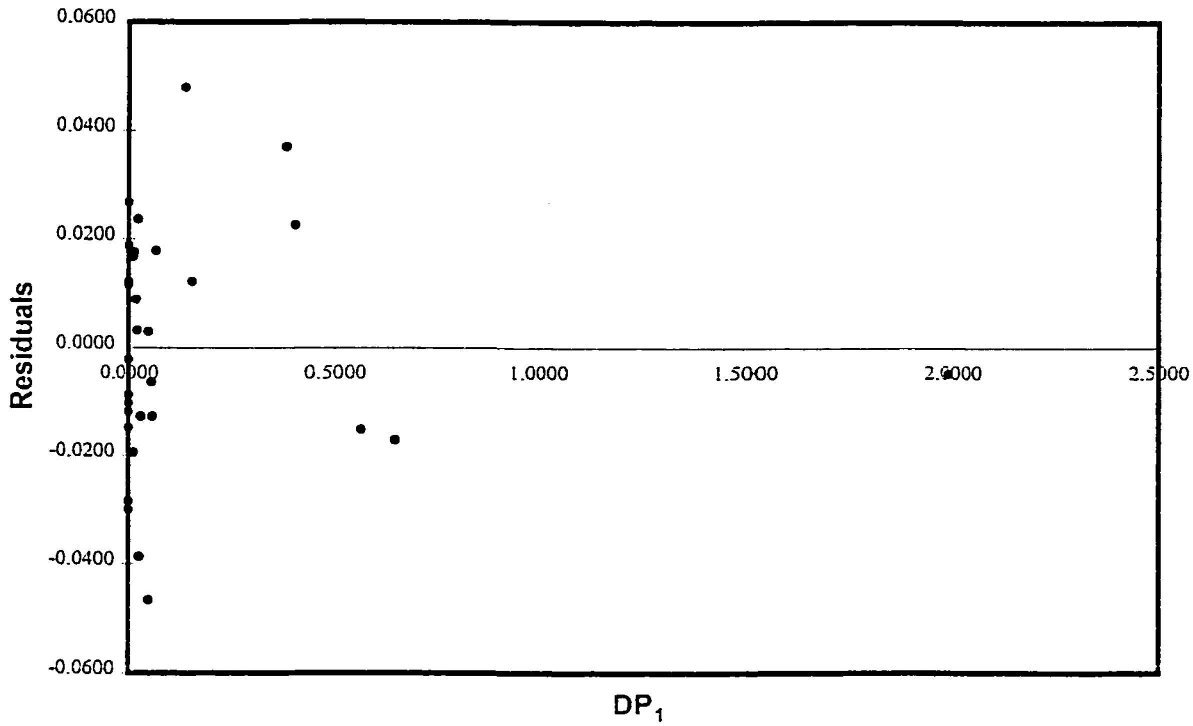


Figure 4-3 Residual Plot for Independent Variable "DP_1"

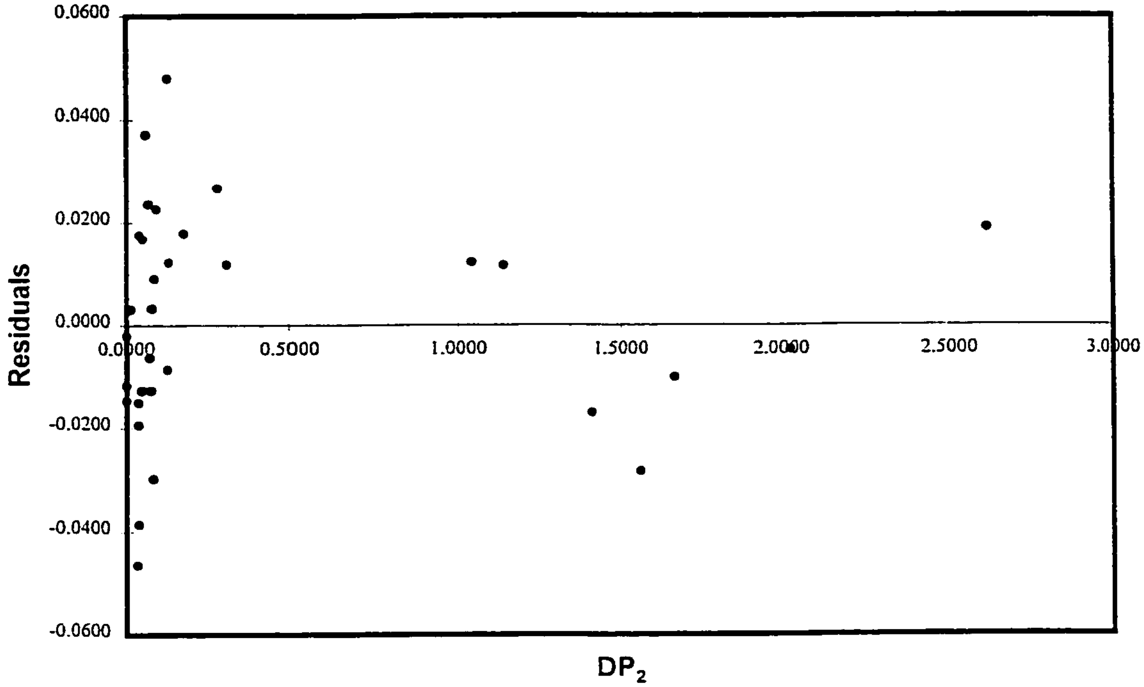


Figure 4-4 Residual Plot for Independent Variable "DP2"

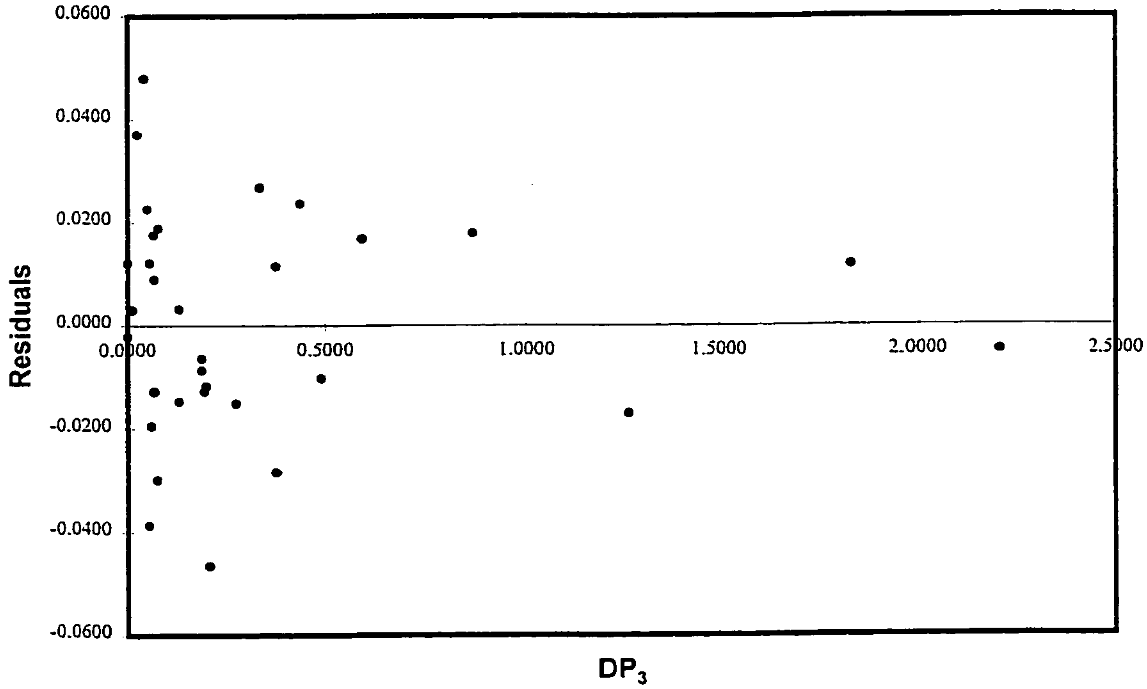


Figure 4-5 Residual Plot for Independent Variable "DP_3"

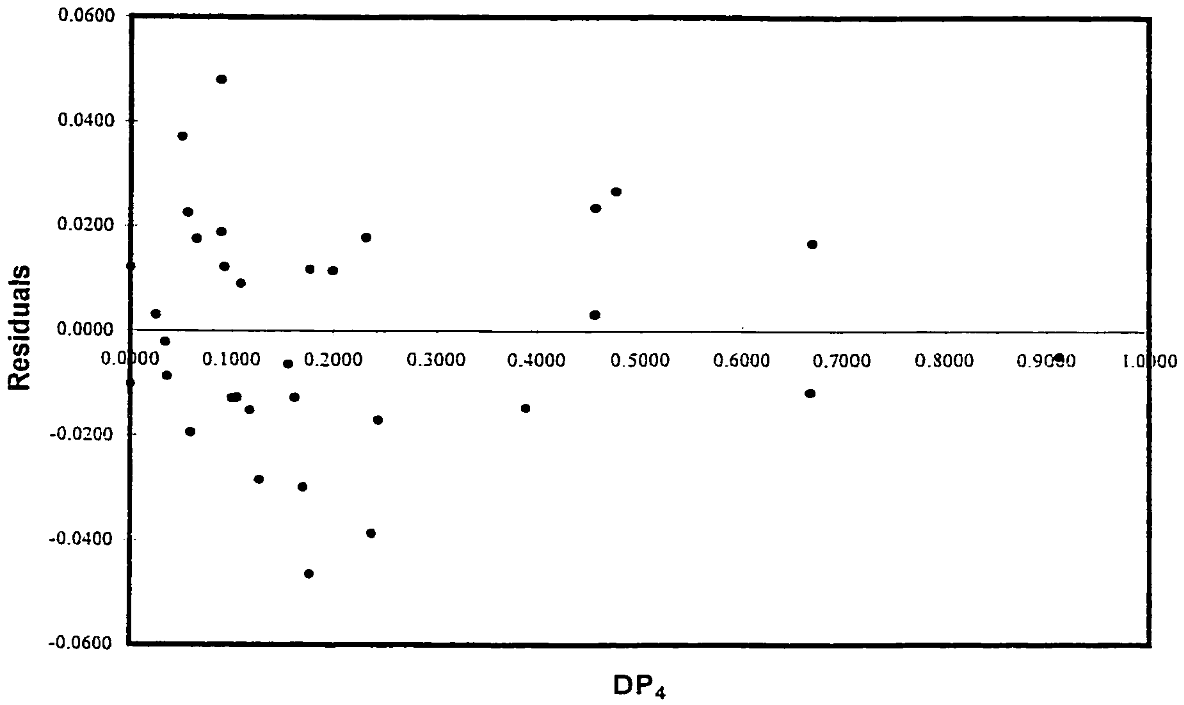


Figure 4-6 Residual Plot for Independent Variable "DP_4"

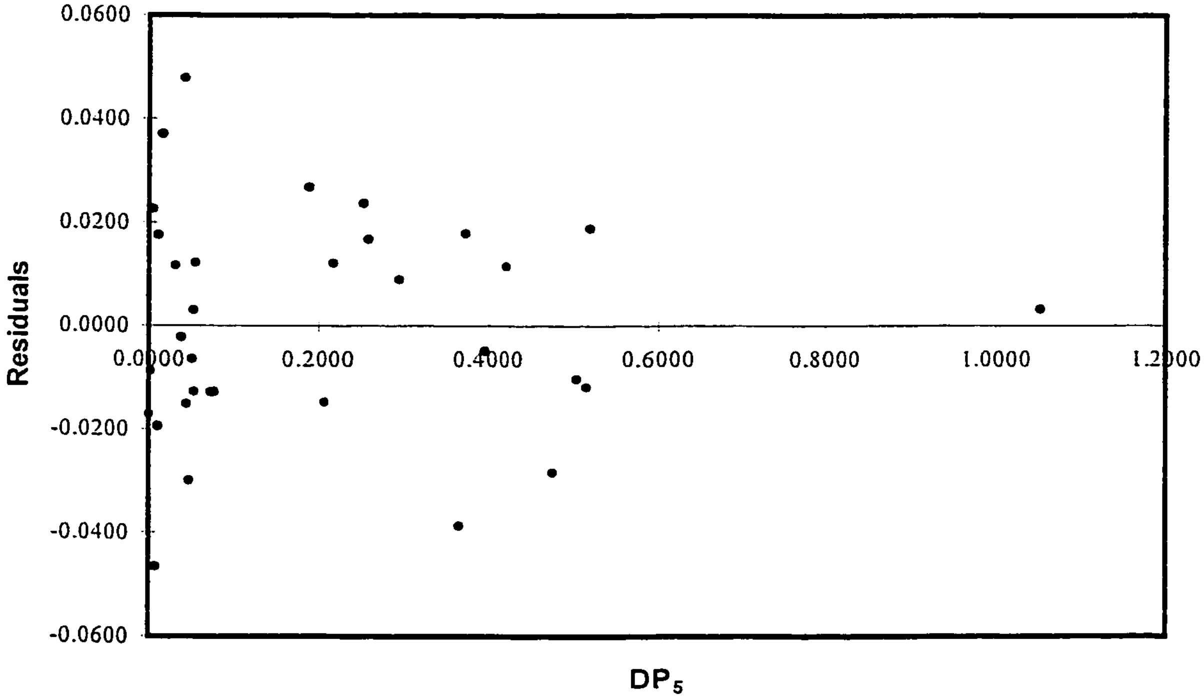


Figure 4-7 Residual Plot for Independent Variable "DP_5"

2) The variance of ϵ is constant: this is also verified by using the residual plots that are supposed to reveal a constant variance error pattern shown in Figure 4-8. If the plots reveal a violation, a variance-stabilizing transformation may be performed on the dependent variable (e. g. using natural logarithm).

Constant Error Variance *Non-constant Error Variance*

Figure 4-8 Error Variance (Sincich et al. 1999)

By re-examining the residual plots of DS_1T_1 displayed in Figures 4-2 to 4-7, the assumption that the variance of ϵ variance is constant is considered fulfilled. The same conclusion is drawn from the corresponding plots for the other regression models developed.

3) Outliers check is done by checking the values of y that appear to be in disagreement with the model using the plot of "$\hat{y}$" against "y- $\hat{y}$". It is expected that all values of $\hat{y}$ are to lie within ±3S (standard error previously presented earlier in this chapter). Figure 4-9 shows that the values of $\hat{y}$, for DS_1T_1, are within ±0.06. This is less than the verification value of ±3S that is equal to

±0.072, as per Table 4-4. The same conclusion is drawn from the corresponding plots for the other regression models developed.

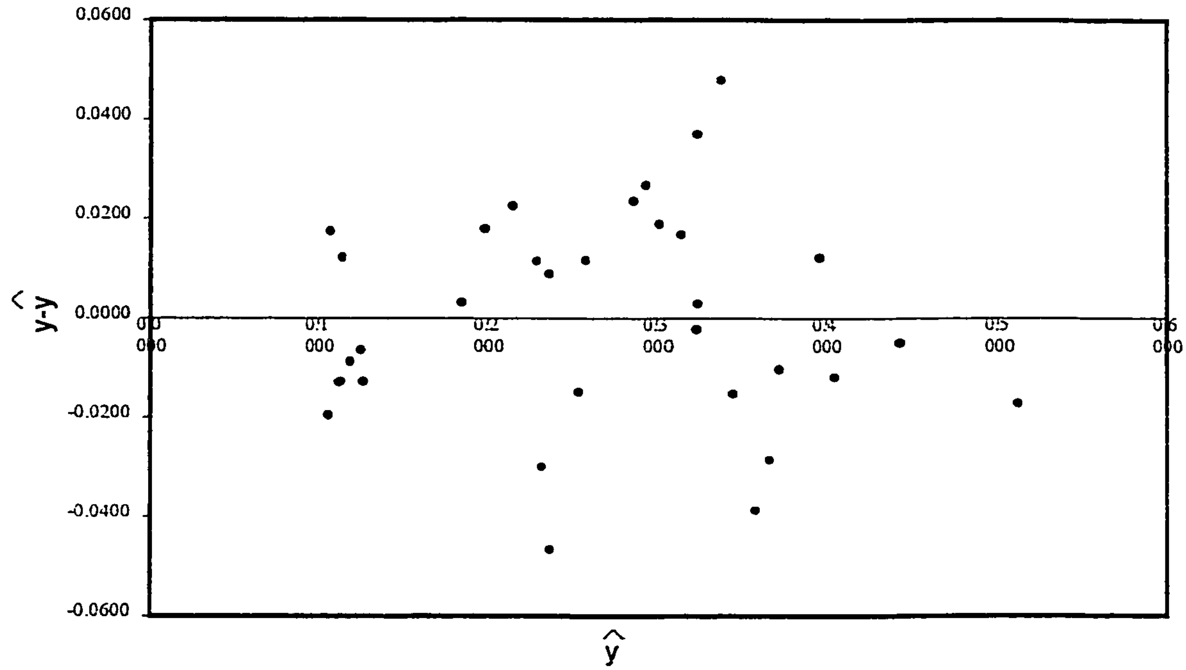


Figure 4-9 Outliers Plot

4) The probability distribution of Є is normal: the assumption that Є is normally distributed is the least restrictive; as it is data dependent, when applying regression analysis in practice, the assumption that Є is normally distributed is the least restrictive (Sincich et al., 1999). However, In order to determine whether the developed model violates this assumption or not, the actual values of y (i.e. productivity loss) are plotted against the frequency of their occurrence. The shape has to follow the bell shape of the normal distribution. Figure 4-10 shows the plot for DS1T1. Although the plot does not follow a bell shape, this does not influence the relevancy of the model (McClave et al.

1997, Sincich et al. 1999), it acknowledges the need for extra data and /or transformation of data. The same conclusion is

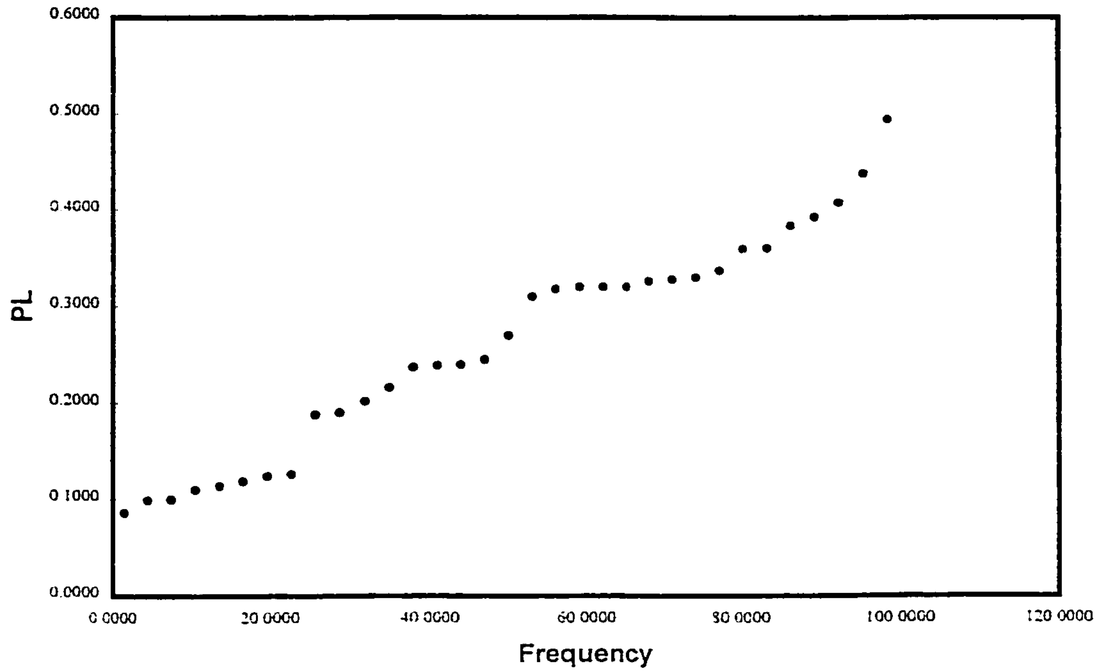


Figure 4-10 Normal Probability Plot

4.3 Neural Network Models

Through regression analysis, it has been proved that the combination of independent variables for all the data sets (i.e. DS_1 to DS_{10}) is relevant to the prediction of the dependent variable (i.e. productivity loss). Consequently, the data sets are utilized to develop ten neural network models using a commercially available software (NeuroShell2 1996). This shell operates in "Microsoft Windows" environment and contains a wide set of ready-to-use neural network paradigms, as shown in Figure 4-11, that are capable of mimicking the human brain's ability to classify patterns or to make predictions or decisions based upon previous experience (NeuroShell2 1996).

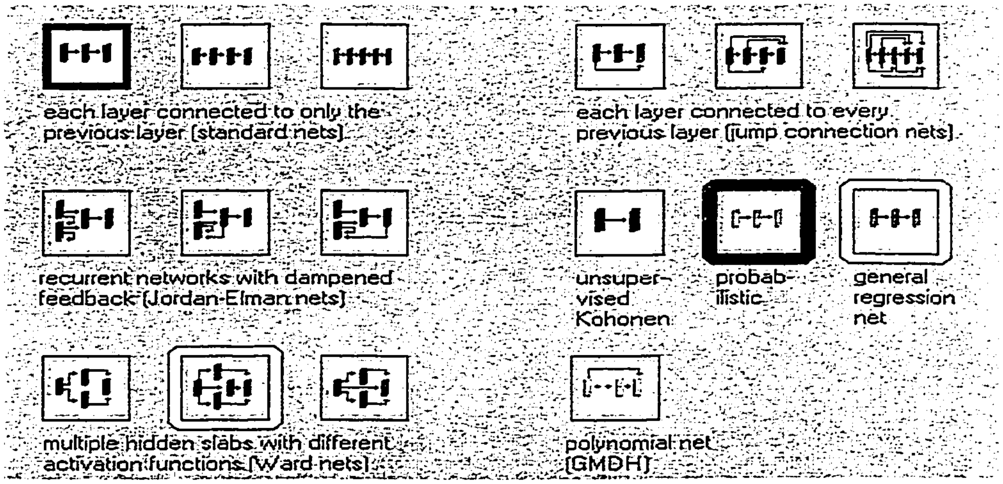


Figure 4-11 Neural Network Paradigms (NeuroShell2 1996)

The development of the present neural network models is divided into five main phases, as shown in Figure 4-11: 1) paradigm selection phase, 2) problem analysis and structuring phase, 3) design phase, 4) learning phase, and 5) evaluation phase (Hegazy 1993, NeuroShell2 1996).

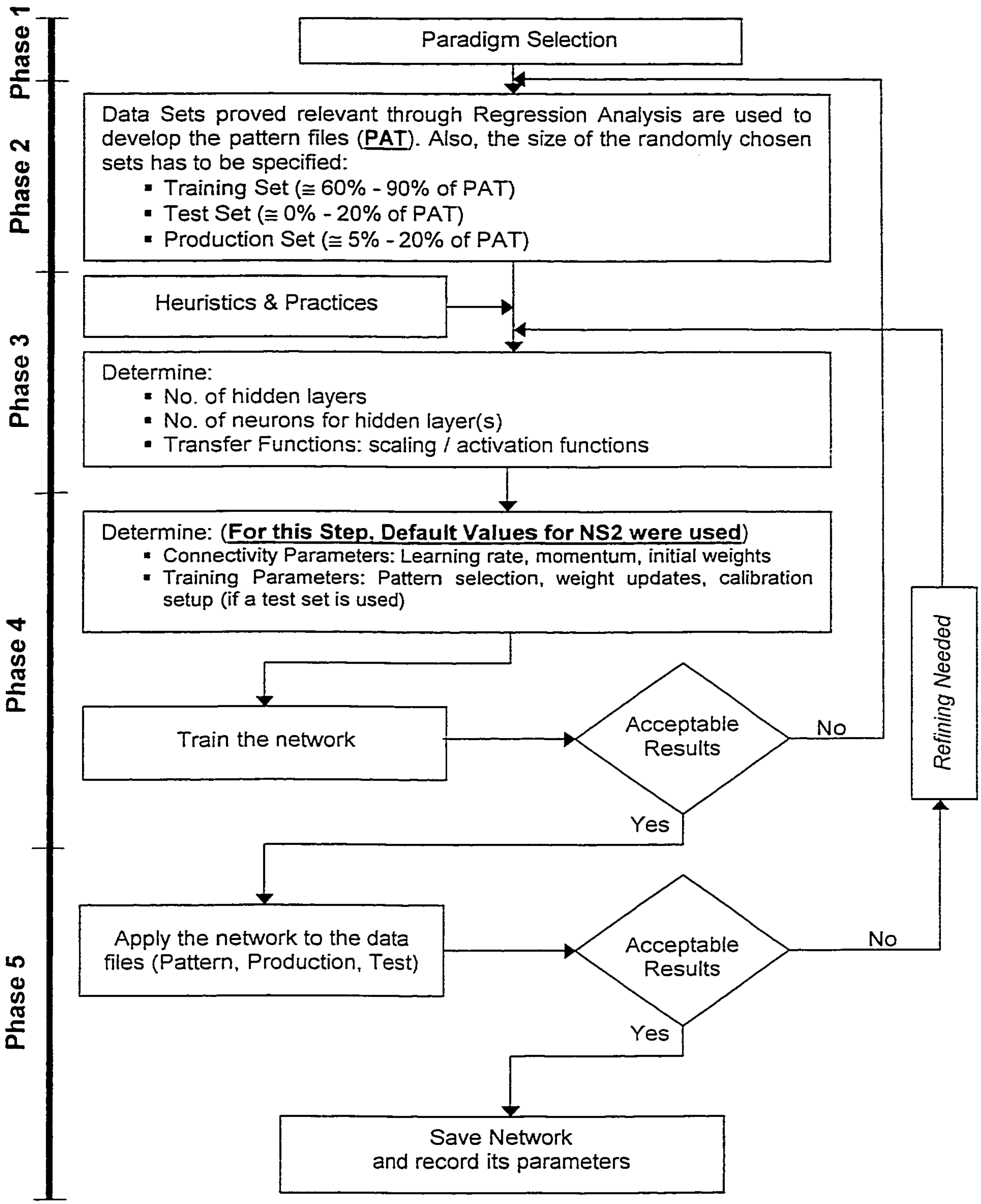


Figure 4-12 Neural Network Model Development Phases

4.3.1 Paradigm Selection Phase

The first phase of developing a neural network involves the selection of an appropriate paradigm. Back propagation paradigm is known for its capabilities to generalize well on a wide variety of problems (Hegazy et al. 1994, Moselhi 1998a, Siqueira 1999, NeuroShell2 1996). Two types of back propagation paradigms are available in NeuroShell2: standard and recurrent. The standard type is suitable for modeling all kinds of problems while the recurrent type is mainly used to model problems with time series data as it can learn sequence (NeuroShell2 1996). Accordingly, the back propagation standard type is more suitable for the present application and is used for the development of the present models.

4.3.2 Problem Analysis and Structuring Phase

This phase requires the preparation of the inputs and outputs, arranged in an ascending order, as recommended by NeuroShell2, in order to form a pattern file (PAT) to be fed into the neural network. This type of organization assists the network to detect the patterns in the data. The data sets used in developing the present models are accordingly prepared. This phase also includes the choice of a training set that would form at least 60% of the cases available in the data set, a test set and a production set that each would form 20% or less. The training set has to be maximized and has to cover the whole data range. The test set, in general, is used to prevent over-training of the neural network (NeuroShell2 1996). The alternative approach to the utilization of the test set is to set a maximum rate to the training epochs (an epoch is a complete pass through the training set). This approach is preferred when the data set has a limited number of cases, as it allows for a bigger training set. The production set is used to test the network results with data that it has never seen before. In the development of the present neural network models, good results are obtained with randomly chosen training set of 80% and production set of 20% of the available cases respectively (i.e. without a test set).

4.3.3 Design Phase

This phase requires the determination of: 1) number of hidden layers, 2) number of neurons, and 3) transfer functions. These user-defined parameters are specified using heuristics (Hegazy et al., 1994), in addition to the default values recommended by the utilized neural networks shell (NeuroShell2 1996).

The hidden layers act as layers of abstraction, pulling features from the input layer and firing them to the output layer. To determine the number of hidden layers, Dutta and Shekhar (1988), Bailey and Thompson (1990a, 1990b), and Caudill (1990) suggested, as a rule of thumb, to start with one hidden layer and add more as long as the performance of the network is improving. Adding hidden layers leads to more degrees of freedom that would increase the ability of the network to store much complex patterns (NeuroShell2 1996). Increasing the number of hidden layers, on the other hand, increases both the time and number of training examples necessary to train the network properly. NeuroShell2 provides the ability to choose between 1, 2 or 3 hidden layers, each with the ability to have different activation function and different number of neurons. The development of the present models followed the above-mentioned rule of thumb, and the number of hidden layers that provided good results has been found to be 2 or 3 layers.

The neuron is a basic building block of the simulated neural network, which processes one or more input values to produce one or more output values by applying a non-linear function to the inputs (NeuroShell2 1996). Thus the neurons are also called processing elements (PEs) (Moselhi et al. 1991b). For the input and output layers, NeuroShell2 sets the number of neurons to be equal to the number of input and output parameters respectively, assuming that each neuron processes a single parameter. The violation to this default is not accepted by the shell (NeuroShell2 1996). For the hidden layer(s) neurons, Moselhi et al. (1991b) advised that the proper number is determined by experimentation. The optimum configuration is the one achieving minimum error during the training session, and giving the best results when applied to the data pattern file. Too few neurons in the hidden layer, as compared to the number of training examples, limit the network from correctly mapping inputs to outputs. On the other hand, too many neurons cause the network to memorize the cases without enabling any extraction of the important features. The smallest network that can learn the cases well is expected to have optimum performance (Hegazy, 1993). However, a network should be larger than the minimum necessary to perform the task (Bishop et al., 1991).

To size the neurons of the first hidden layer, a number of heuristics can be used including: a) Bailey and Thompson (1990a,1990b) suggested the number of neurons to be around 75% of the number of cases in the training set, b) Caudill (1988) suggested a number of neurons of 2m+1 where m is the number of neurons in the input layer (hence number of inputs), and c) NeuroShell2 user's manual suggested that the number of neurons in the first hidden layer to be as per the following equation:

$$\frac{\text{Number of Inputs} + \text{Number of Outputs}}{2} + \sqrt{t} \qquad \textbf{Eq. 4-7}$$

Where "t" is the number of cases in the training set. All the above-mentioned references recommend reducing the number of neurons gradually for each subsequent hidden layer (if any). For the purpose of the development of the present models, the recommendations of NeuroShell2 user's manual are considered as a threshold that is modified in an iterative manner in order to reach the best possible network that gave the minimum error during training and the best results when applied to the production set.

The transfer function is the function applied by the neuron on the input to reach the output. There are two types of transfer functions depending on the type of the layer: 1) the scaling function, and 2) the activation function.

1) The scaling function is applied to the input layer in order to scale the variables loaded into the neural network from their numeric range into another numeric range that the network deals with efficiently. There are two

main types of scaling functions: linear and non-linear (Hegazy 1993, NeuroShell2 1996). The linear scaling functions have two main numeric ranges: 0 to 1 denoted [0, 1] or «0,1», and -1 to 1 denoted [-1, 1] or «-1,1». To clarify the difference between the two denotations, consider a data set from 0 to 100 that is scaled to [0, 1], then a later data value of 120 will get scaled to 1, but if the same data were scaled to «0, 1», then 120 would be scaled to 1.2. This implies that the angle-bracket denotation is more flexible and more inclusive of data values outside the specified range.

The non-linear function, on the other hand, includes two main non-linear scaling functions: a) the logistic function, b) and the "Tanh" function. The logistic function scales data to (0,1). The use of brackets instead of the straight brackets indicates that the data never actually gets to 0 or to 1. The logistic function is interpreted by the Equation 4-8:

$$1/(1+e^{-[(\text{mean-value})/s]}) \qquad \textbf{Eq. 4-8}$$

While the "Tanh" function is interpreted by Equation 4-9:

$$\text{Tanh } [(\text{mean-value})/s] \qquad \textbf{Eq. 4-9}$$

Where:

Mean: is the average of all the values of that variable in the pattern file,

Value: is each value of that variable in the pattern file, and

s : is the standard deviation of all the values of that variable in the pattern file.

Both of these functions will tend to squeeze together data at the low and high ends of the original data range. They may thus be helpful in reducing the effects of "outliers". They have an additional advantage in that no new data is ever clipped or scaled out of range. However, NeuroShell2 also offers the ability to move the data to the input layer "as is", but this option should only be used when some other method is used to scale input data into the range of [0, 1] or [-1, 1], or a similar range. For the present models, the "Tanh" function is used in all models as it has been found to provide good results.

2) The activation function, also called the squashing function, is the function applied by the neurons on the sum of the weighted values of the inputs to reach an output that is then "fired" to the next layer. This function is needed for the neurons of each layer to which data propagates, i.e. hidden and output layers. In the development of the present models, the iterative procedure revealed that a combination of the gaussian and logistic functions is found to give good results. Table 4-5 illustrates the parameters of the activation functions: their available types, their shape and range, in addition to there applications as suggested by Hegazy et al. (1994), and NeuroShell2 (1996).

It should be noted that all the above-described heuristics serve as a threshold in the development of the present neural network models, which is an iterative process that should continue as long as the obtained results are improving.

Table 4-5 Neural Networks Activation Functions

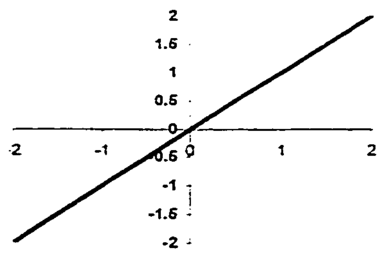
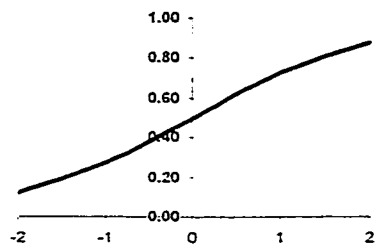
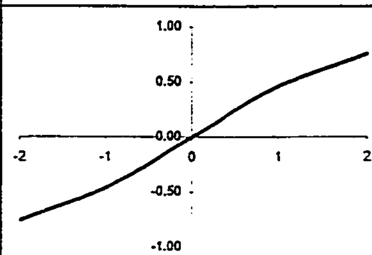
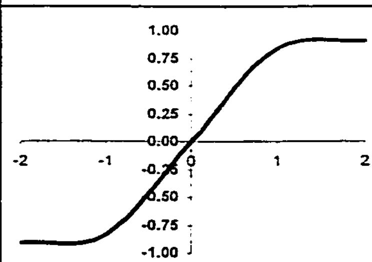
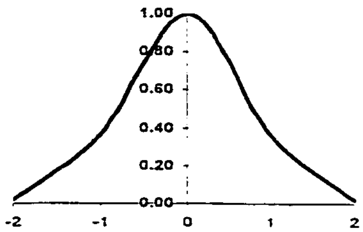
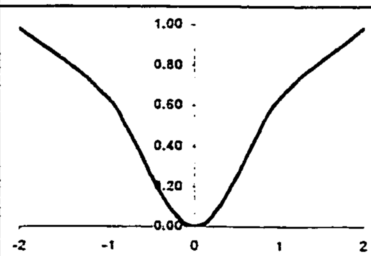
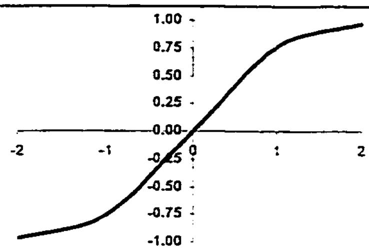
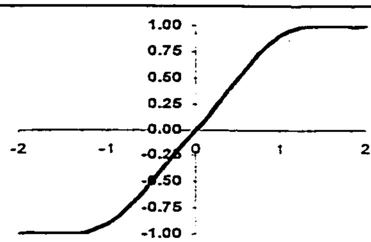
Function Type	Shape and Range	Application
Linear: F(x) = x		Recommended for output layer Useful if the input variables are continuous, and not a category Not recommended as It detracts form the power of the network.
Logistic (sigmoid): f(x) = 1/(1+(exp (-x)))		Recommended for both hidden layer(s) and output layer Recommended for most neural network models applications.
Symmetric-Logistic: f(x) = (2/(1+exp(-x)))-1		Recommended for both hidden layer(s) and output layer Rcommended when one of the output is a category
Sine : f(x) = sin(x)		Recommended for the output layer only. Can be used with most of problem types

Table 4-5 Neural Networks Activation Functions (Continued)

Function Type	Shape and Range	Application
Gaussian: $f(x) = e(-(x^2))$		Recommended for the hidden layer(s) Found very useful in a small set of problems as it brings out meaningful characteristics
Gaussian-Complement: $f(x) = 1 - e(-(x^2))$		Recommended for the hidden layer(s) It detects meaningfull characteristics in the extremes of data, thus recommended for data with outliers
Tanh: $f(x) = \tanh(x)$		Recommended for both hidden layer(s) and output layer Recommended for all kinds of problems
Tanh15: $f(x) = \tanh(1.5 X)$		Recommended for both hidden layer(s) and output layer Recommend exclusively for all kinds of problems and was reported to be more powerfull than the tanh

4.3.4 Learning Phase

The user-defined parameters of the neural network learning phase (i.e. phase 4) are also guided by heuristics and rules of NeuroShell2. The main purpose or this phase is to determine: 1) the connectivity parameters, and 2) the training parameters.

The setup of connectivity parameters involves determining: 1) the learning rate, 2) the momentum, and 3) the initial weights:

1) The learning rate, ranging between 0 and 1, is multiplied by the resulting error of the used pattern to modify the weights leading to the output during learning in order to produce a smaller error the next time the same pattern is presented. For example, if the learning rate is 0.5, the weight change will be 0.5 the resulting error. The larger the learning rate, the larger the weight changes, and the faster the learning will proceed. A large learning rate, however, may cause oscillation or non-convergence which leads to an incomplete learning process, or causes the model to converge to a solution that is not optimum (NeuroShell2 1996).

2) The momentum, ranging from 0 to1, prevents the effect of a miss-determined learning rate, by determining the proportion of the last weight change that is added into the new weight. Accordingly, the weight change is a function of the previous weight that provides a smoothing factor and allows faster learning, without oscillation (NeuroShell2 1996).

3) Initial weights are the initial values presenting connection strength between neurons; they range from -0.3 to +0.3. As each pattern passes though the network, the weight is raised to reinforce a connection, or lowered to inhibit a connection (NeuroShell2 1996).

Heuristics presented by Moselhi et al. (1991b), Hegazy et al. (1994), and NeuroShell2 (1996) recommend using a large learning rate and momentum such as 0.9 and 0.6 respectively for simple problems. For problems that are more complicated or predictive networks, where outputs can be continuous values rather than categories, it is recommended to use a smaller learning rate and momentum such as 0.1 and 0.1 respectively. If the data is very noisy, it is recommended to use a learning rate of 0.05 and a momentum of 0.5. However, for application of neural networks using NeuroShell2, it is generally recommended to keep the default values, i.e. 0.6 for the learning rate, 0.9 for the momentum factor, and 0.3 for the initial weight (NeuroShell2 1996). The development of the present models has been done using the defaults of NeuroShell2.

The training parameters are set by the user in order to determine how the training of the network is supposed to proceed. It includes: 1) training pattern selection, 2) weight updates, and 3) network calibration.

1) The training pattern selection can be rotational, or random. In a rotational selection, the training patterns are selected in the order they appear in the pattern file while in a random selection, the training patterns are randomly chosen which does not guarantee that every pattern will be equally chosen. The rotational selection is preferred when order is important or with binary problems while the random selection is generally recommended (NeuroShell2 1996).

2) The weight updates is controlling the procedure with which the network updates the weights. They can follow one of the three available algorithms:

Vanilla, Momentum, or TurboProp. The Vanilla algorithm applies the previously described learning rate to update the weights. The Momentum algorithm causes the weight updates not only to include the change dictated by the learning rate, but also to include a portion of the last weight change. The TurboProp algorithm implies that training proceeds through an entire epoch before the weights are updated, and is not recommended with back propagation neural networks (NeuroShell2 1996).

3) The network calibration tells how frequent the network should be evaluated against the test set. This is done by applying the network to the independent test set during training, and computing the mean squared error (i.e. the mean of $(y-\hat{y})^2$) for all training and test patterns. The calibration alerts when the network ceases to make any progress and starts memorizing the data. The calibration rate is usually set between 50-500 event (number of training patterns), and the training should stop when the number of events, since the last minimum error recorded for the test set, reaches 20000 to 40000 epochs (i.e. full round on the whole training patterns), otherwise the network will start memorizing the training pattern. If the data size does not allow the use of a test set, an alternative approach can be applied: a) to check the network results frequently in order to decide when the training should be stopped, and b) to set the training epochs to a maximum to prevent memorization. This alternative approach is applied in the development of the present models. Table 4-6 illustrates the values obtained for the different design parameters of the developed neural network models.

Table 4-6 Design Parameters for the Developed Neural Network Models

Data Set Utilized	No Inputs	No Outputs	Hidden Layers		Scaling Function	Activation Function (Hidden – Output)	Pattern Selection	Weight Update
			No.	No. of Neurons				
DS_1T_1	6	1	2	23/21	Tanh	Gaussian / Gaussian - Logistic	Random	Momentum
DS_2T_2	6	1	2	29/23	Tanh	Gaussian / Gaussian - Logistic	Random	Momentum
DS_3A_1	2	1	2	35/25	Tanh	Gaussian / Gaussian - Logistic	Rotation	Momentum
DS_4A_2	2	1	2	19/15/11	Tanh	Gaussian / Gaussian / Gaussian - Logistic	Rotation	Momentum
DS_5C_1	2	1	3	35/34/33	Tanh	Gaussian / Gaussian / Logistic - Logistic	Rotation	Momentum
DS_6C_2	2	1	2	35/27	Tanh	Gaussian / Gaussian - Logistic	Rotation	Momentum
DS_7E_1	2	1	3	15/14/13	Tanh	Gaussian / Gaussian / Gaussian - Logistic	Random	Momentum
DS_8E_2	2	1	3	17/16/15	Tanh	Gaussian / Gaussian / Gaussian - Logistic	Random	Momentum
DS_9M_1	2	1	3	31/27/23	Tanh	Gaussian / Gaussian / Gaussian - Logistic	Random	Momentum
$DS_{10}M_2$	2	1	3	23/22/21	Tanh	Gaussian / Gaussian / Gaussian - Logistic	Random	Momentum

NB: Other parameters used in the design; such as the learning rate, the momentum, and the initial weights, has been set according to the default values used in NeruoShell2.

4.3.5 Evaluation Phase

"The bottom line of this whole operation is NOT how well the network would learn the training set or sample cases, but how well the network predicts the production or verification set that it has never seen before" (NeuroShell2 1996). Accordingly, NeuroShell2 is used to process a data file through the trained neural network to produce the network's predictions for each pattern in the file. The file may be the whole data set file, the training set file, or the production set file. This process produces some evaluation parameters that are the basis for evaluating the neural network. The different evaluation parameters displayed during this process are:

1) The coefficient of multiple determination (R^2), which is function in the predicted value and the actual one (see Equation 4-5). Accordingly, it is a good indicator of the accuracy of the model.

2) The coefficient of correlation (r), which measures the strength of the linear association between the actual and predicted values (see Equation 3-1). According to the user's manual of NeuroShell2 (1996), this is not a strong measurement of the network strength.

3) The errors calculated by NeuroShell2, which include:

- Mean Squared Error (i.e. mean of $(y-\hat{y})^2$) .
- Mean Absolute Error (i.e. mean of $|y-\hat{y}|$).
- Minimum Absolute Error (i.e. min $|y-\hat{y}|$).
- Maximum Absolute Error (i.e. max $|y-\hat{y}|$).

4) Prediction Percentage: This important parameter evaluates the performance of the developed network. NeuroShell2 displays the percentage of predicted values within a specified percentage error (i.e. ((|Actual – Predicted|)/Actual)*100), that can be less than 5%, 10%, 20%, 30%, and over 30%, of the actual answers in the data set file. If the actual answer is 0, the percent cannot be computed and that pattern is not included in a percentage group. That is the reason why the total of computed percentage may not add up to 100%.

Table 4-7 presents the different evaluation parameters obtained for the developed neural network models.

Table 4-7 Evaluation Parameters for the Developed Neural Network Models

Data Set Utilized	Set	No of Cases	R^2	r	Error (Actual – Predicted)				Percent Predicted within				
					Mean Square	Absolute			< 5%	5% - 10%	10% - 20%	20% - 30%	> 30%
						Mean	Min	Max					
DS_1T_1	Data	33	0.9972	0.9972	0.000	0.002	0.000	0.021	90.91	3.03	6.06	0.00	0.00
	Train	29	0.9978	0.9989	0.000	0.002	0.000	0.021	93.10	0.00	6.90	0.00	0.00
	Prod	4	0.9926	0.9979	0.000	0.007	0.002	0.019	75.00	25.00	0.00	0.00	0.00
DS_2T_2	Data	33	0.9845	0.9923	0.000	0.005	0.000	0.063	87.88	3.03	6.06	3.03	0.00
	Train	30	0.9979	0.9990	0.000	0.002	0.000	0.021	93.33	0.00	6.67	0.00	0.00
	Prod	3	0.8565	0.9285	0.002	0.034	0.000	0.063	33.33	33.33	0.00	33.33	0.00
DS_3A_1	Data	9	0.9407	0.9733	0.000	0.009	0.000	0.031	66.67	22.22	11.11	0.00	0.00
	Train	7	0.9755	0.9877	0.000	0.006	0.000	0.019	71.43	28.57	0.00	0.00	0.00
	Prod	2	-	-	0.002	0.019	0.007	0.031	50.00	0.00	50.00	0.00	0.00
DS_4A_2	Data	9	0.9132	0.9640	0.000	0.010	0.000	0.039	77.78	0.00	22.22	0.00	0.00
	Train	7	0.9949	0.9978	0.000	0.003	0.000	0.009	100.00	0.00	0.00	0.00	0.00
	Prod	2	-	-	0.001	0.034	0.029	0.039	0.00	0.00	100.00	0.00	0.00
DS_5C_1	Data	12	0.9817	0.9912	0.000	0.003	0.000	0.011	100.00	0.00	0.00	0.00	0.00
	Train	11	0.9833	0.9919	0.000	0.003	0.000	0.011	100.00	0.00	0.00	0.00	0.00
	Prod	1	-	-	0.000	0.005	0.005	0.005	100.00	0.00	0.00	0.00	0.00
DS_6C_2	Data	12	0.9841	0.9921	0.000	0.003	0.000	0.012	91.67	8.33	0.00	0.00	0.00
	Train	11	0.9892	0.9951	0.000	0.002	0.000	0.012	90.91	9.09	0.00	0.00	0.00
	Prod	1	-	-	0.000	0.009	0.009	0.009	100.00	0.00	0.00	0.00	0.00

Table 4-7 Evaluation Parameters for the Developed Neural Network (Continued)

Data Set Utilized	Set	No of Cases	R^2	r	Error (Actual – Predicted)				Percent Predicted within				
					Mean Square	Absolute			< 5%	5% - 10%	10% - 20%	20% - 30%	> 30%
						Mean	Min	Max					
DS_7E_1	Data	35	0.9618	0.9812	0.000	0.009	0.000	0.047	80.00	8.57	8.57	2.86	0.00
	Train	32	0.9611	0.9814	0.000	0.009	0.000	0.047	78.13	9.38	9.38	3.13	0.00
	Prod	3	0.9658	0.9996	0.000	0.009	0.003	0.013	100.00	0.00	0.00	0.00	0.00
DS_8E_2	Data	35	0.9701	0.9852	0.000	0.007	0.000	0.050	80.00	11.43	5.71	2.86	0.00
	Train	32	0.9722	0.9860	0.000	0.007	0.000	0.050	81.25	9.375	6.25	3.13	0.00
	Prod	3	0.9237	0.9916	0.000	0.014	0.003	0.020	66.67	33.33	0.00	0.00	0.00
DS_9M_1	Data	46	0.9793	0.9899	0.000	0.010	0.000	0.064	71.74	8.70	19.57	0.00	0.00
	Train	40	0.9919	0.9961	0.000	0.007	0.000	0.030	77.50	7.50	15.00	0.00	0.00
	Prod	6	0.8916	0.9515	0.002	0.028	0.002	0.064	33.33	16.67	50.00	0.00	0.00
$DS_{10}M_2$	Data	46	0.9829	0.9916	0.000	0.009	0.000	0.075	71.74	10.87	17.39	0.00	0.00
	Train	40	0.9930	0.9966	0.000	0.007	0.000	0.024	75.00	10.00	15.00	0.00	0.00
	Prod	6	0.9132	0.9564	0.001	0.022	0.001	0.075	50.00	16.67	33.33	0.00	0.00

4.3.6 Model Limits

The limits of the models developed in this study stem from the data used in the development. This includes the number of cases utilized. In general, the use of more cases in training is expected to improve the accuracy of the developed model. Another thing is the range of data used in developing the model, referred to as numerical limits. The numerical limits were set as constraints for the application of the models in the developed prototype software system presented later in this chapter. Tables 4-8 and 4-9 display the numerical limits of the independent factors for all developed neural network models grouped by the type of impact.

Table 4-8 Numerical Limits for the Timing Effect Models

Data Set DS1T1							
Type of Impact	No. of cases	Limits	Direct Impact for Periods (DP_i)				
			P_1	P_2	P_3	P_4	P_5
1	14	Min	0.0000	0.0352	0.0556	0.0357	0.0021
		Max	1.9892	2.6158	2.2024	0.9116	1.0529
2	10	Min	0.0000	0.0000	0.0492	0.0000	0.0049
		Max	0.4060	1.6676	0.5920	0.6702	0.5052
3	9	Min	0.0000	0.0000	0.0000	0.0000	0.0000
		Max	0.6457	1.4095	1.2658	0.6686	0.5170
Data Set DS2T2							
Type of Impact	No. of cases	Limits	Ripple Effect for Periods (RP_i)				
			P1	P2	P3	P4	P5
1	14	Min	0.0000	0.0247	0.0230	0.0082	0.0002
		Max	1.8151	1.8384	0.9983	0.1367	0.0789
2	10	Min	0.0000	0.0000	0.0204	0.0000	0.0004
		Max	0.3705	1.1720	0.2452	0.1091	0.0379
3	9	Min	0.0000	0.0000	0.0000	0.0000	0.0000
		Max	0.5892	0.9906	0.5242	0.1003	0.0388

Table 4-9 Numerical Limits for the Work Type Effect Models

Data Set DS_3A_1				Data Set DS_4A_2			
Type of Impact	No of cases	Limits	Change Orders Ratio (CORB)	Type of Impact	No of cases	Limits	Change Orders Ratio (CORA)
1	2	Min	0.1639	1	2	Min	0.1408
		Max	0.5402			Max	0.4372
2	6	Min	0.0841	2	6	Min	0.0649
		Max	0.8226			Max	0.5730
3	1	Min	0.1429	3	1	Min	0.0875
		Max	0.1429			Max	0.0875
Data Set DS_5C_1				Data Set DS_6C_2			
Type of Impact	No of cases	Limits	Change Orders Ratio (CORB)	Type of Impact	No of cases	Limits	Change Orders Ratio (CORA)
1	3	Min	0.1774	1	3	Min	0.1562
		Max	0.4886			Max	0.3772
2	9	Min	0.0577	2	9	Min	0.0475
		Max	0.3840			Max	0.2697
3	0	Min	0.0000	3	0	Min	0.0000
		Max	0.0000			Max	0.0000
Data Set DS_7E_1				Data Set DS_8E_2			
Type of Impact	No of cases	Limits	Change Orders Ratio (CORB)	Type of Impact	No of cases	Limits	Change Orders Ratio (CORA)
1	12	Min	0.0773	1	12	Min	0.0641
		Max	0.6360			Max	0.4441
2	17	Min	0.0088	2	17	Min	0.0065
		Max	0.5362			Max	0.3478
3	6	Min	0.0195	3	6	Min	0.0133
		Max	0.3421			Max	0.2148
Data Set DS_9M_1				Data Set $DS_{10}M_2$			
Type of Impact	No of cases	Limits	Change Orders Ratio (CORB)	Type of Impact	No of cases	Limits	Change Orders Ratio (CORA)
1	24	Min	0.0430	1	24	Min	0.0385
		Max	1.5348			Max	1.1868
2	11	Min	0.0697	2	11	Min	0.0510
		Max	1.0118			Max	0.5312
3	11	Min	0.0246	3	11	Min	0.0156
		Max	0.7817			Max	0.3562

4.4 Prototype Software System

A prototype software system is developed in order to provide a tool for quantifying the negative impact of change orders on the labor productivity. The prototype software is named "***ChangeOrders.E***", which stands for **Change Orders** Estimator. The system provides a user friendly interface to estimate the impact of change orders using the developed neural networks models in addition to previously developed regression models for: 1) general construction (Moselhi et al. 1991a, Ibbs 1997), 2) mechanical construction (Hanna et al. 1999a), and 3) electrical construction (Hanna et al. 1999b). The system is implemented, using Microsoft Visual Basic (VB6), as a Windows Application that runs under Microsoft Windows 1995, 1998, 2000, and NT. Figure 4-13 illustrates the algorithm adopted to implement the prototype software system.

4.4.1 Incorporating Neural Network Models

In order to incorporate the developed neural network models in the prototype software application, a DEFinition File (*.DEF) is first created using the Dynamic Link Library (DLL) module in NeuroShell2. Afterward, having the file "NS2-32.DLL" in the "SYSTEM" directory under the Operating System directory, a three-step procedure is followed:

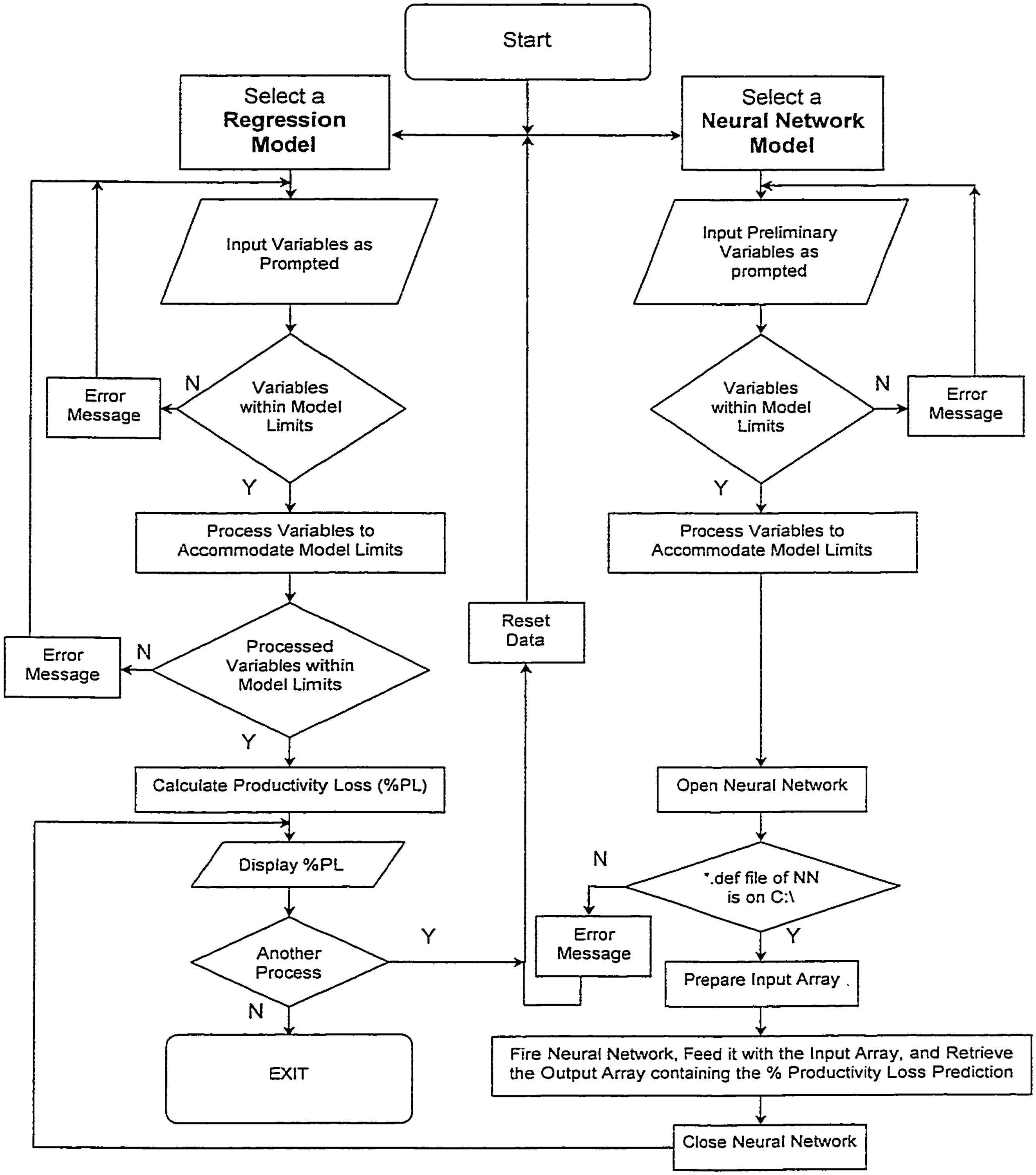


Figure 4-13 Prototype Software System Algorithm

1) Execute the first DLL function "OpenNet" that reads the *.def file and returns a network number which refers to the network, gives the number of inputs the network expects and the number of outputs with which it will respond (those numbers are known to the user), and keeps the network opened.

2) Execute the second DLL function "FireNet" which passes inputs to the network and receives back outputs, both in double precision floating point arrays designated by the programming software.

3) Execute the last DLL function "CloseNet" when the network is no longer needed, releasing any memory retained by the network. The next time the user needs to execute the network, an "OpenNet" DLL function is executed as explained in step1.

In Visual Basic (VB), those functions are called like any other VB function by loading a file called nshell2.bas, that contains the VB function prototypes in it, into the project. It should be noted that the path of the definition files of each network must be defined in the code and the file should be accordingly located.

4.4.2 System Interface

Multiple Document Interface (MDI) is used to serve as a simple and user-friendly interface for the developed system. As shown in Figure 4-14, the system interface includes:

- A title bar displaying the title of the program;
- A status bar displaying the time, the date, the Num-lock status, and a display for the active method;
- A right wide strip where the screens of the different methods are displayed;
- A left narrow strip that includes: 1) the command buttons used to activate the different interface screens for the different models, as indicated by the caption text on each button and the tool tip text that appears when the pointing device (i.e. mouth) is passed over it, 2) the "quit" command button, and 3) displays the prototype information and copy right data.

4.4.3 Methods Interface Screens

The interface screens for the different models are used to facilitate data input and output. As shown in Figures 4-15 to 4-20, the user is prompted for input through: 1) text boxes with labels indicating clearly the required input data, 2) option buttons to choose between different options. The output in all models is the percentage loss of productivity, which can be obtained by pressing the "Process" button. Two extra buttons are found in all screens: 1) the "Reset Data" button that clears any entered data in all text boxes, and 2) the "exit button" that closes the model's screen.

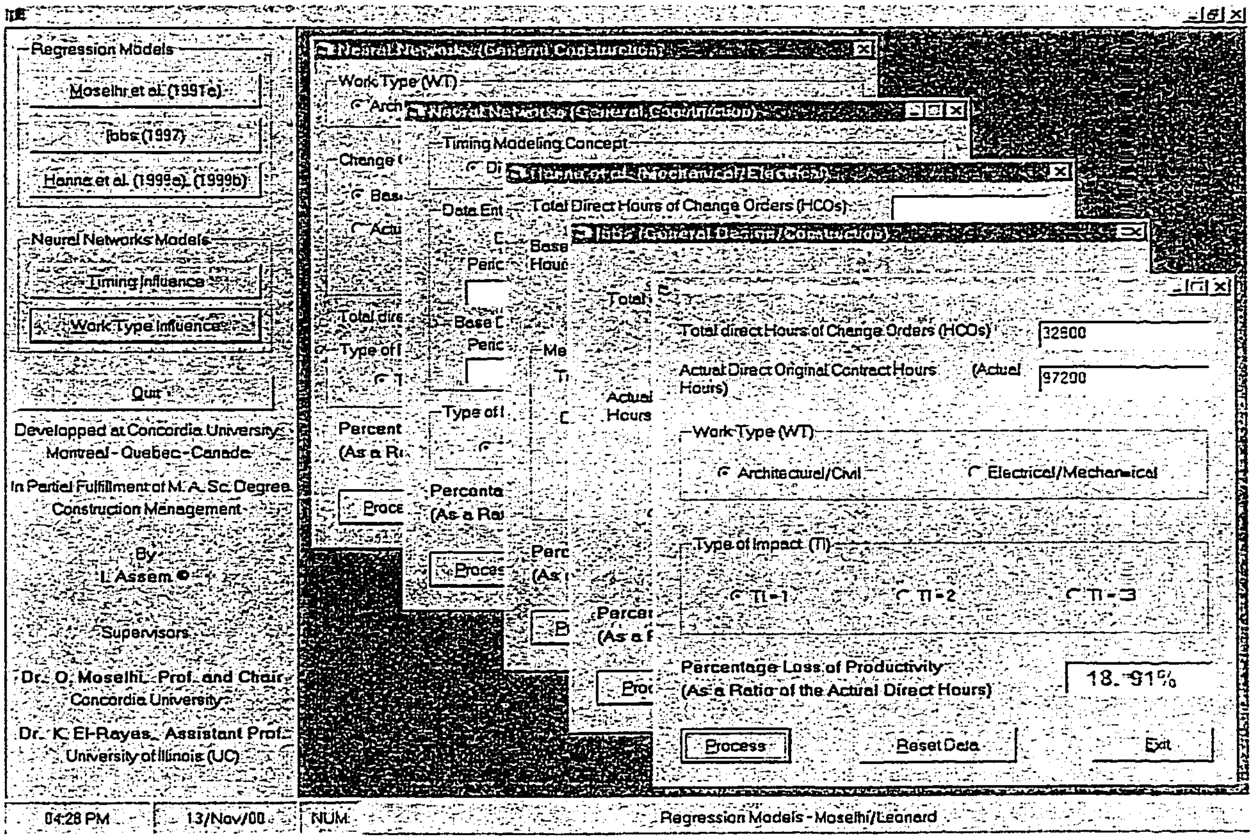


Figure 4-14 Main Screen of the Prototype Software System

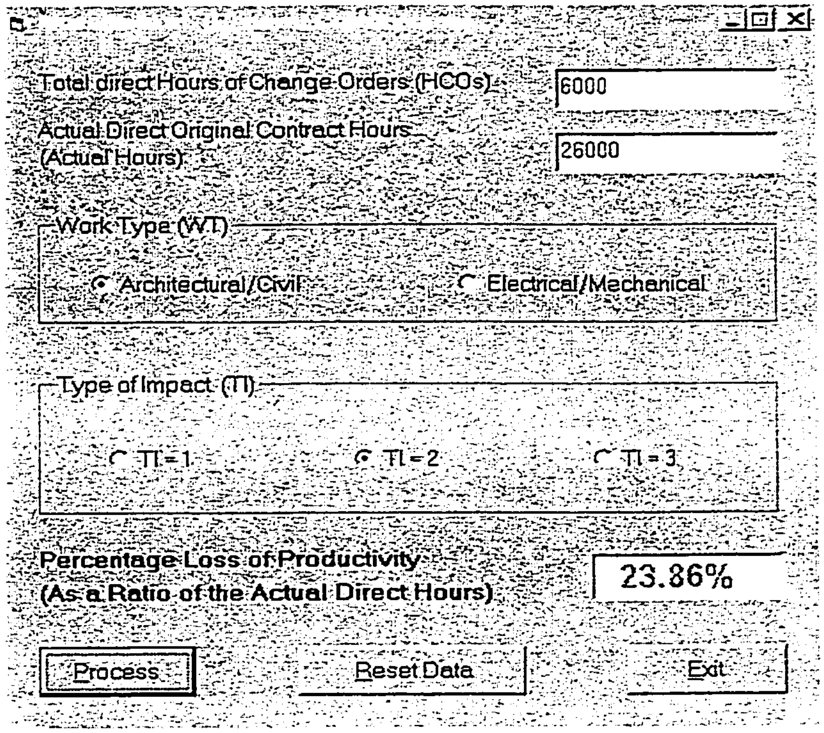


Figure 4-15 Interface Screen for Moselhi et al. (1991a)

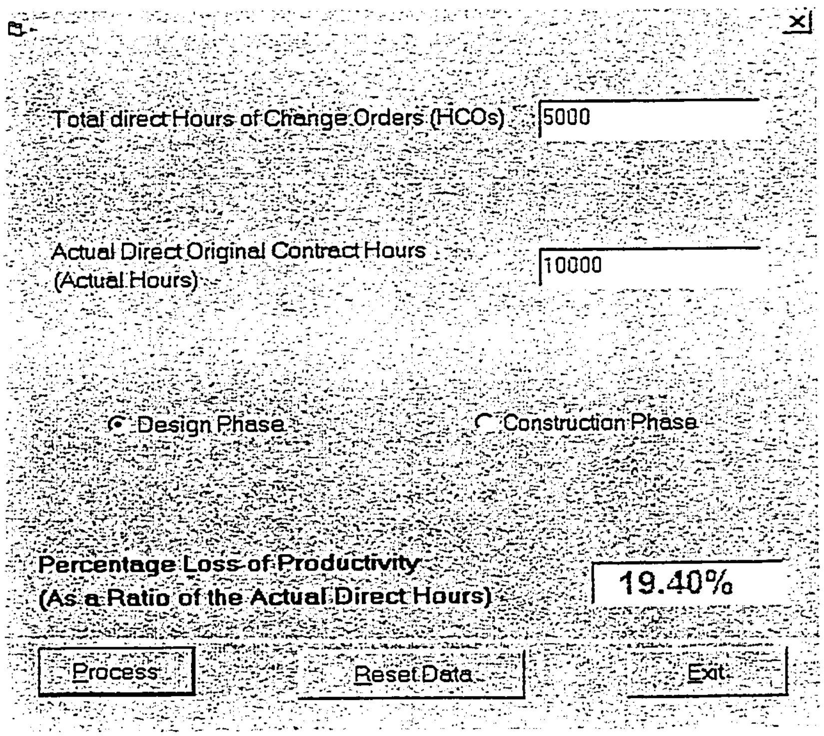


Figure 4-16 Interface Screen for Ibbs (1997)

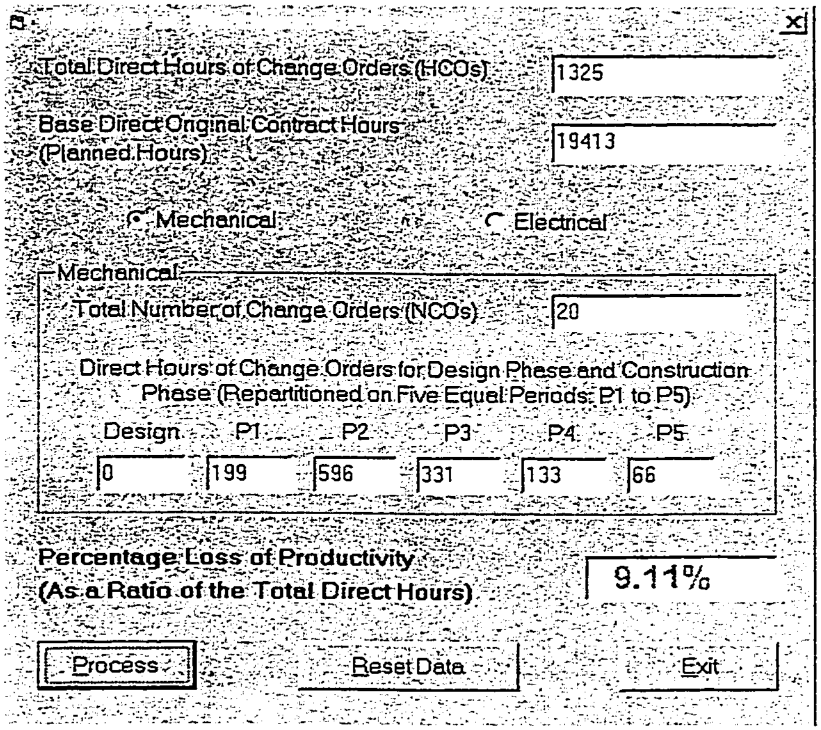


Figure 4-17 Interface Screen Hanna et al. (1999a)

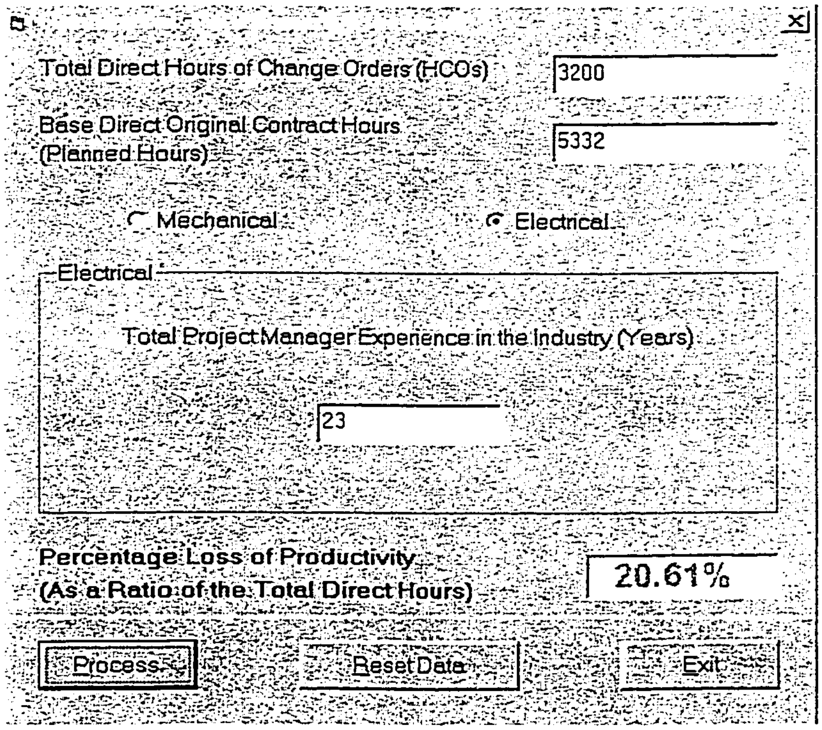


Figure 4-18 Interface Screen Hanna et al. (1999b)

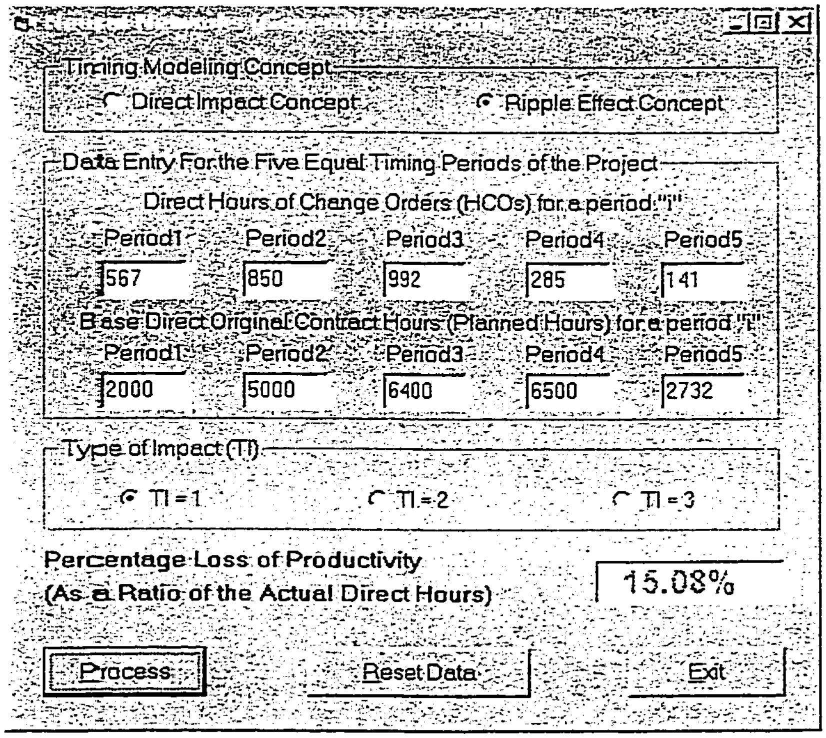


Figure 4-19 Interface Screen for Timing Effect Neural Network Models

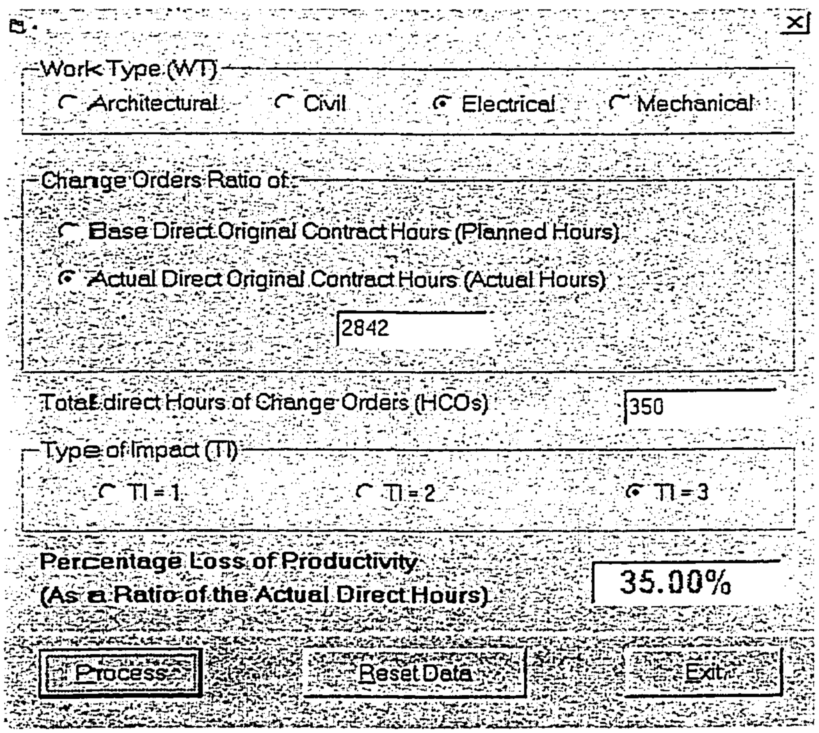


Figure 4-20 Interface Screen for Work Type Effect Neural Network Models

4.4.4 Prototype Software System Errors

The prototype software system is coded to detect errors such as: 1) input is off the corresponding model range, 2) Non-numerical inputs, as all inputs are expected to be numerical, and/or 3) division by zero errors. In case one of those errors is detected, the user will be prompted with an error screen, after pressing the "Process" button, as shown in Figures 4-21 and 4-22.

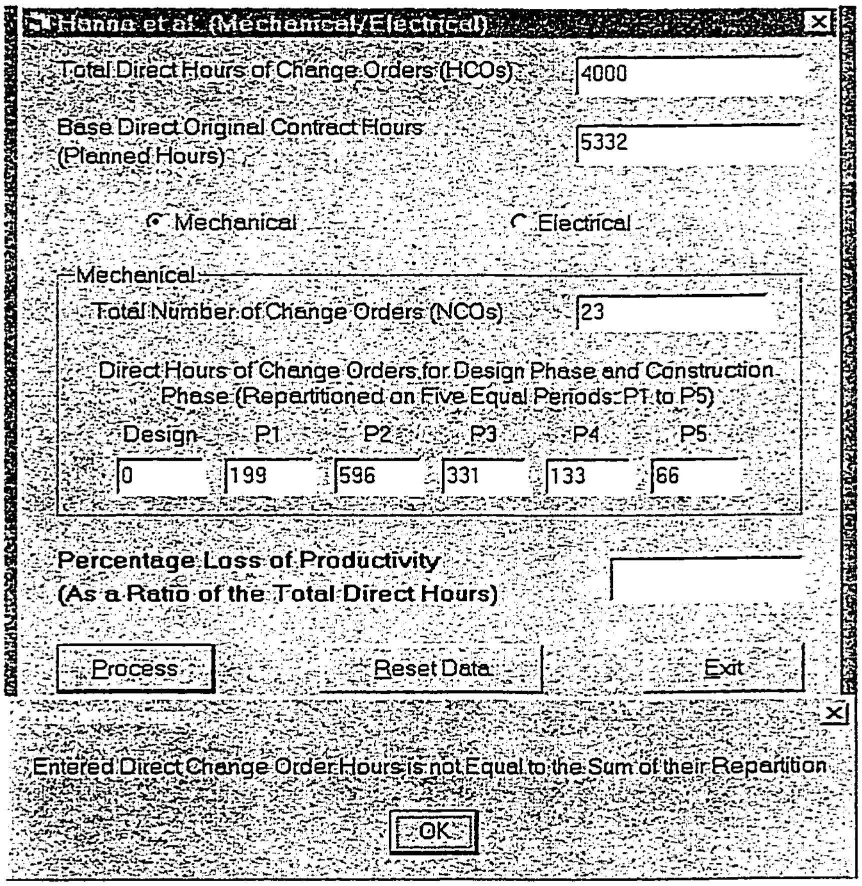


Figure 4-21 Example of Error Messages

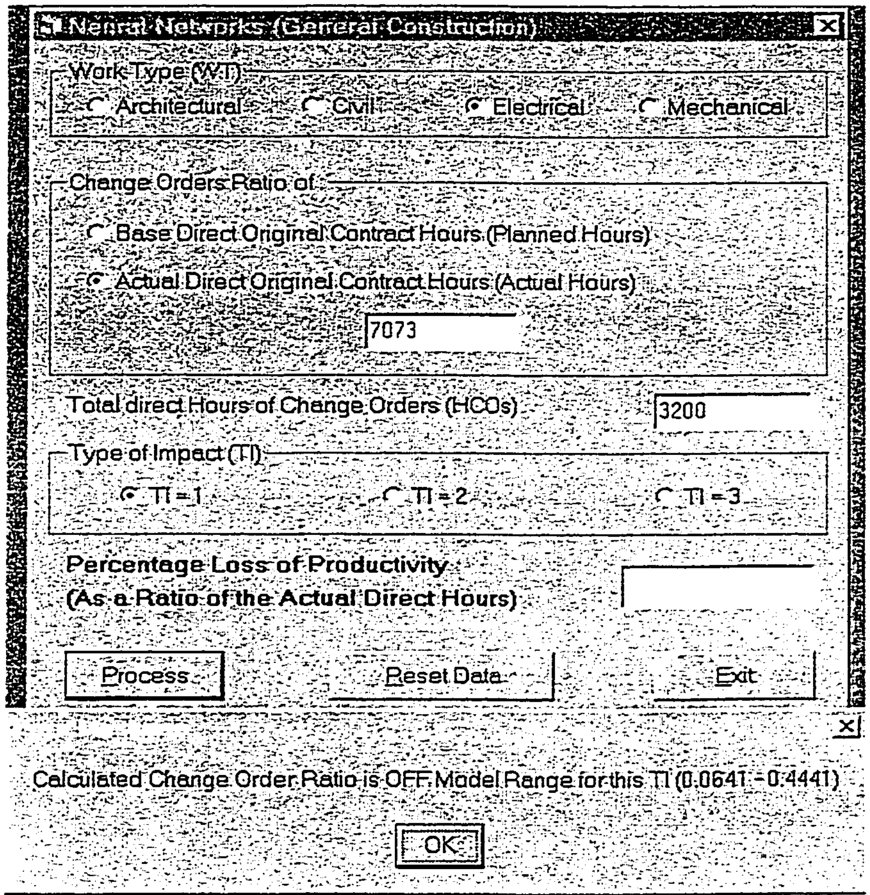


Figure 4-22 Example of Error Messages

4.5 Summary

In this chapter, the ten data sets formulated in Chapter 3 were processed using multiple linear regression analysis. The use of regression analysis confirmed that the combination of data used is relevant to the prediction of the productivity loss resulting from the impact of change orders. Accordingly, the data sets were used to develop ten neural network models. Heuristics, common practices, and default values of the used shell, NeuroShell2 (1996), are applied to develop the network models that gave satisfactory results. This chapter also presented the development of a prototype software system, using Visual Basic. This prototype system incorporates four regression models that were previously developed in the course of other research work, and acts as interface for the developed neural network models.

Chapter 5

Developed Models Validation

5.1 Introduction

This chapter presents the validation of the developed neural network models. This validation is performed by comparing the results of the developed neural network models to: 1) the ten regression models, developed earlier in Section 4.1, 2) the models developed by others, which include Moselhi et al. (1991a), Hanna et al. (1999a), and Hanna et al. (1999b). Furthermore, the performance of the timing module of the developed neural network models model is tested using a multi-scenario case.

5.2 Validation Against Developed Regression Models

The first validation analysis is performed by comparing the evaluation parameters of the developed neural network models to those of the developed regression models. Three categories of evaluation parameters are used: 1) statistical measurements, 2) prediction error, and 3) the percentage of predicted values within a specified percentage error (i.e. ((|Actual – Predicted|)/Actual)*100). The results obtained for each category are shown in Table 5-1.

Table 5-1 Neural Network (NN) Models vs. Multiple Linear Regression (MLR) Models

Data Set	Model	Statistical Measurements			Error (|Actual – Predicted|)				Number of cases within %[(|Predicted – Actual|)/Actual)]					
		r	R^2	R^2_a	Mean Square	Absolute Mean	Absolute Min	Absolute Max	= 0%	< 5%	5% - 10%	10% - 20%	20% - 30%	> 30%
DS_1T_1	MLR	0.9813	0.9629	0.9543	0.45E-3	0.0177	2.19E-3	0.0480	0	12	11	8	2	0
	NN	0.9986	0.9972	0.9965	0.03E-3	0.0023	1.22E-8	0.0205	0	30	1	2	0	0
DS_2T_2	MLR	0.9825	0.9654	0.9574	0.42E-3	0.0156	3.02E-4	0.0485	0	15	9	8	1	0
	NN	0.9923	0.9845	0.9810	0.19E-3	0.0046	1.95E-5	0.0628	0	29	1	2	1	0
DS_3A_1	MLR	0.9558	0.9136	0.8847	0.27E-3	0.0143	1.82E-4	0.0243	0	3	5	1	0	0
	NN	0.9733	0.9407	0.9210	0.19E-3	0.0087	2.98E-8	0.0305	0	6	2	1	0	0
DS_4A_2	MLR	0.9526	0.9075	0.8766	0.29E-3	0.0145	1.17E-3	0.0253	0	4	3	2	0	0
	NN	0.9640	0.9132	0.8842	0.27E-3	0.0101	1.07E-4	0.0385	0	7	0	2	0	0
DS_5C_1	MLR	0.9348	0.8738	0.8457	0.16E-3	0.0105	6.01E-4	0.0272	0	8	4	0	0	0
	NN	0.9912	0.9817	0.9776	0.02E-3	0.0034	1.71E-8	0.0105	0	12	0	0	0	0
DS_6C_2	MLR	0.9170	0.8409	0.8056	0.20E-3	0.0107	1.00E-3	0.0319	0	8	2	2	0	0
	NN	0.9921	0.9841	0.9805	0.02E-3	0.0026	1.54E-7	0.0118	0	11	1	0	0	0

Table 5-1 Neural Network (NN) Models vs. Multiple Linear Regression (MLR) Models (Continued)

Data Set	Model	Statistical Measurements			Error (|Actual – Predicted|)				Number of cases within %[(|Predicted – Actual|) /Actual)]					
		r	R^2	R^2_a	Mean Square	Absolute Mean	Absolute Min	Absolute Max	= 0%	< 5%	5% - 10%	10% - 20%	20% - 30%	> 30%
DS_7E_1	MLR	0.9728	0.9463	0.9429	0.29E-3	0.0140	4.56E-6	0.0515	0	16	14	4	1	0
	NN	0.9812	0.9618	0.9595	0.21E-3	0.0094	8.20E-5	0.0466	0	28	3	3	1	0
DS_8E_2	MLR	0.9694	0.9398	0.9360	0.33E-3	0.0141	5.26E-4	0.0552	0	15	9	8	1	0
	NN	0.9852	0.9701	0.9683	0.16E-3	0.0074	1.00E-4	0.0499	0	29	1	2	1	0
DS_9M_1	MLR	0.9779	0.9562	0.9542	0.63E-3	0.0194	8.14E-4	0.0612	0	22	11	8	4	1
	NN	0.9899	0.9793	0.9783	0.30E-3	0.0100	1.22E-8	0.0637	0	33	4	9	0	0
$DS_{10}M_2$	MLR	0.9686	0.9381	0.9352	0.89E-3	0.0221	1.04E-3	0.0999	0	17	16	8	4	1
	NN	0.9916	0.9829	0.9821	0.24E-3	0.0087	2.77E-5	0.0751	0	33	5	8	0	0

As shown in Table 5-1, the results indicate that the neural network models outperformed the regression models in the three evaluation parameters categories. As an example, in the statistical measurements parameters, the adjusted determination factor (R^2_a) for the neural network models ranged between 0.89 and almost 1 as compared to a range of 0.81 to 0.96 for the regression models. The most significant example could be found in the results of data set DS_6C_2, where R^2_a for the regression models is 0.81 while that for the neural network models is 0.98. In the prediction error parameters, the mean absolute error for the neural network ranged between 0.0023 and 0.0101 while the same parameter, for the regression models, ranged between 0.0105 and 0.0221. As an example for the number of cases within a certain percentage of error range, there were no cases within 0% error for both models, however there are more cases in favor of neural network models in the "<5%" range of error. These results provide indicate the pattern recognition capabilities of the neural networks as compared to regression. The original data supporting the results shown in Table 5-1, for all data sets, is included in Appendix 7.

Another useful form of validation is to plot prediction error (i.e. Actual-Predicted), for each case, for regression and neural networks. This graphical comparison gives clear indication about the retrieving accuracy of each modeling tool. The prediction errors plot for data set DS_1T_1, shown in Figure 5-1, indicates that the neural network model outperformed the regression model in 32 of the 33 cases available in the Data Set. The remaining plots, for the rest of the data sets, are included in Appendix 8.

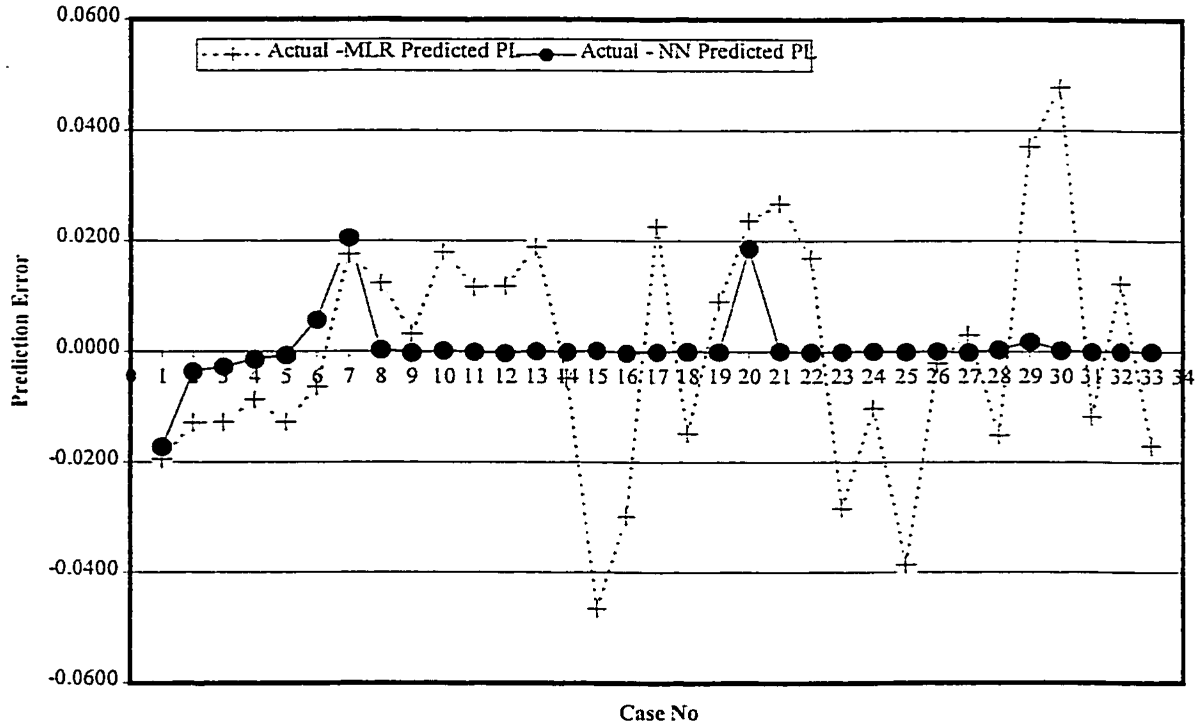


Figure 5-1 Prediction Errors for Data Set DS_1T_1

5.3 Validation Against Models Developed by Others

The results obtained using the developed neural network models are compared to those obtained using the regression models developed by: 1) Moselhi et al. (1991a), 2) Hanna et al. (1999a), and 3) Hanna et al (1999b).

The neural networks models developed using data sets: DS_3A_1, DS_4A_2, DS_5C_1, DS_6C_2, DS_8E_1, DS_8E_2, DS_9M_1, and $DS_{10}M_2$ (i.e. modeling the work type effect on the impact of change orders) are validated against the regression model for general work developed by Moselhi et al. (1991a). For validation purpose, a total number of 8 actual cases obtained from the data used to develop both models, are chosen. An effort was made in the selection of these cases so that they represent different work types (WT), different types of impact (TI), and a wide range of change orders hours ratio to the base hours (CORB) and to the actual hours (CORA). The data of the cases used is shown in Table 5-2. The values of the average absolute error percentage, shown in Table 5-3, indicate that the developed NN models outperformed the regression model of Moselhi et al. (1991a). In the case number 8, the absolute error of prediction is 8.63% for the regression model and 0.03% for the neural network model (CORA). On the other hand, the average absolute prediction error is 1.85% for the regression model and 0.51% for the neural network models (CORA) and 0.64% for the neural networks (CORB).

Table 5-2 Used Cases Data (Leonard 1988)

NO.	WORK TYPE	TYPE OF IMPACT	Change Orders Hours	BASE HOURS	ACTUAL HOURS	% Productivity Loss
1	M	2	450	3300	4400	25.00%
2	M	3	25500	102000	18900	46.03%
3	E	3	7185	21000	35288	40.49%
4	E	2	6500	19845	28700	30.85%
5	A	2	6000	20000	26000	23.00%
6	C	1	32800	79300	97200	18.42%
7	E	1	9933	17211	24440	29.58%
8	M	1	30000	35000	53000	33.96%

Table 5-3 Estimated Productivity Loss

No.	% Productivity Loss						
	Actual (1)	Regression (2)	Absolute Error |1-2|	Neural Network (CORA) (3)	Absolute Error |1-3|	Neural Network (CORB) (4)	Absolute Error |1-4|
1	25.00%	25.72%	0.72%	26.30%	1.30%	25.37%	0.37%
2	46.03%	37.40%	8.63%	46.06%	0.03%	43.77%	2.29%
3	40.49%	40.14%	0.35%	40.52%	0.03%	40.56%	0.03%
4	30.85%	31.51%	0.66%	30.42%	0.09%	31.27%	0.42%
5	23.00%	23.86%	0.86%	23.13%	0.73%	22.27%	0.73%
6	18.42%	18.91%	0.49%	18.91%	0.00%	18.34%	0.08%
7	29.58%	27.10%	2.48%	27.80%	1.78%	28.67%	0.91%
8	33.96%	34.60%	0.64%	33.81%	0.15%	34.24%	0.28%
Average Absolute Error %			1.85%		0.51%		0.64%

The neural network models developed using DS_1T_1, DS_2T_2, and DS_9M_1, and $DS_{10}M_2$ are validated against the regression model developed for mechanical work (Hanna et al. 1999a). It should be noted that the regression model predicts the percentage productivity loss as a ratio of the total hours (i.e. TDH), while the neural network models predict it as a ratio of the actual hours (i.e. ADOCH). For validation purpose, an unbiased source, Bruggink 1997, that contains such detailed information about change orders was used, and the 5 cases that fall within the limits of the developed models were chosen. The data of the cases used are shown in Table 5-4, the change orders detailed data and the planned hours distribution, as per NECA 1983 (see Figure 3-12), are shown in Tables 5-5 and 5-6, respectively. It should be noted that, for certain cases, the actual productivity loss, compared to the percentage change orders, indicated that the project was impacted with more than one major cause of productivity loss. Accordingly, the analysis has been repeated considering type of impact 2 for case number 5, and type of impact 3 for case number 4. The original and adjusted productivity loss estimates are summarized in Table 5-7 and Table 5-8.

Table 5-4 Used Cases Data (Bruggink 1997)

Case No.	Number of Change Orders	Work Hours		
		Planned	Actual	Total
1	80	2461	3262	4262
2	25	5332	7073	10273
3	20	10213	12873	14393
4	50	8394	13533	14543
5	170	18170	28745	36170

Table 5-5 Change Orders Data (Bruggink 1997)

Case No.	Change Orders Total Hours	Change Orders Hours For Period				
		P_1	P_2	P_3	P_4	P_5
1	1000	200	200	200	200	200
2	3200	256	544	960	1056	384
3	1520	85	67	49	286	1033
4	1010	0	303	303	202	202
5	7425	297	965	2079	2599	1485

Table 5-6 Planned Hours (based on Distribution of Neca 1983)

Case No.	Total	Base (Planned) Hours For Period				
		P_1	P_2	P_3	P_4	P_5
1	2461	148	394	664	788	468
2	5332	320	853	1440	1706	1013
3	10213	613	1634	2758	3268	1940
4	8394	504	1343	2266	2686	1595
5	18170	1090	2907	4906	5814	3452

Table 5-7 Original Productivity Loss Estimate

Case No.	Hours of Productivity Loss										
	Actual	Hanna et al. 1999a)	% Error	Neural Networks developed using data set							
				DS_9M_1	%Error	$DS_{10}M_2$	%Error	DS_1T_1	%Error	DS_2T_2	%Error
1	801	592	26%	781	3%	670	17%	940	17%	818	2%
2	1741	1153	34%	2236	28%	2197	26%	2674	54%	2877	65%
3	2660	3426	29%	1824	31%	1734	35%	2699	1%	1801	32%
4	5139	2088	59%	1702	67%	1537	70%	1601	69%	1425	72%
5	10575	8457	20%	6905	18%	5191	39%	7077	33%	8523	19%
Abs. Average % Error			34%		29%		37%		49%		38%

Table 5-8 Adjusted Productivity Loss Estimate

Case No.	Hours of Productivity Loss										
	Actual	Hanna et al. 1999a)	% Error	Neural Networks developed using data set							
				DS_9M_1	%Error	$DS_{10}M_2$	%Error	DS_1T_1	%Error	DS_2T_2	%Error
1	801	592	26%	781	3%	670	17%	940	17%	818	2%
2	1741	1153	34%	2236	28%	2197	26%	2674	54%	2877	65%
3	2660	3426	29%	1824	31%	1734	35%	2699	1%	1801	32%
4	5139	2088	59%	4923	4%	4853	6%	5078	1%	4419	14%
5	10575	8457	20%	9368	11%	9515	10%	9816	7%	NA	NA
Abs. Average % Error			34%		15%		19%		16%		28%

NA: Not Applicable (i.e. off model range)
% Error = 100 (|Actual – Estimated|/Actual)

As shown in Table 5-8, the developed neural network models yielded smaller errors than the regression analysis model. The performance of the regression and neural network models, which account for the timing effect, will be further discussed later in this chapter.

The neural network models developed using data sets DS_7E_1 and DS_8E_2 are validated against the regression model for electrical work developed by Hanna et al. (1999b). It should be noted that the regression model predicts the percentage productivity loss as a ratio of the total hours (TDH), while the neural network models predicts it as a ratio of the actual hours (ADOCH). For validation purpose, Table 5-9 shows the data of the 9 cases utilized: 8 from Bruggink (1997), and 1 from Hanna et al. (1999b). For certain cases, the actual productivity loss, compared to the percentage change orders, indicated that the project was impacted with more than one cause of productivity impact. Accordingly, the analysis has been repeated considering a type of impact 2 for cases number 3 and 8, and a type of impact 3 for cases number 2 and 6. The original and adjusted productivity loss estimates are summarized in Table 5-9 and Table 5-10.

Table 5-9 Used Cases Data (Bruggink 1997, Hanna et al. 1999b)

Case No.	Project Manager Experience (Years)	Work Hours			Change Orders Hours
		Planned	Actual	Total	
1	18	2461	3262	4262	1000
2	15	1769	2842	3192	350
3	15	4419	6012	7012	1000
4	23	5332	7073	10273	3200
5	6	10213	12873	14393	1520
6	25	8394	13533	14543	1010
7	25	735	59982	74173	14191
8	26	1937	28745	36170	7425
9	20	10000	12500	14000	1500

Table 5-10 Original Productivity Loss Estimate

Case No.	Productivity Loss						
	Actual (1)	Regression (2)	% Error	Neural Network[1] (3)	% Error	Neural Network[2] (4)	% Error
1	801	650	19%	726	9%	726	9%
2	1073	713	34%	561	48%	486	55%
3	1593	1467	8%	1210	24%	1261	21%
4	1741	2041	17%	2048	18%	NA	NA
5	2660	2966	12%	2213	17%	2103	21%
6	5139	2485	52%	1960	62%	1531	70%
7	13713	10644	22%	12182	11%	12266	11%
8	10575	2438	77%	6433	39%	5706	46%
9	2500	1816	27%	2161	14%	2079	17%
Abs. Average % Error			30%		27%		31%

[1] and [2]: Neural Network models developed using data sets DS_7E_1 and DS_8E_2 respectively.

NA: Not Applicable (i.e. off model range)

% Error = 100 (|Actual – Estimated|/Actual)

Table 5-11 Adjusted Productivity Loss Estimate

Case No.	Productivity Loss						
	Actual (1)	Regression (2)	% Error	Neural Network[1] (3)	% Error	Neural Network[2] (4)	% Error
1	801	650	19%	726	9%	726	9%
2	1073	713	34%	1009	6%	995	7%
3	1593	1467	8%	1727	8%	1478	7%
4	1741	2041	17%	2048	18%	NA	NA
5	2660	2966	12%	2213	17%	2103	21%
6	5139	2485	52%	4401	14%	4268	17%
7	13713	10644	22%	12182	11%	12266	11%
8	10575	2438	77%	9242	13%	10498	1%
9	2500	1816	27%	2161	14%	2079	17%
Abs. Average % Error			30%		12%		11%

[1] and [2]: Neural Network models developed using data sets DS_7E_1 and DS_8E_2 respectively.

NA: Not Applicable (i.e. off model range)

% Error = 100 (|Actual – Estimated|/Actual)

The results shown in Table 5-11 clearly demonstrate that the developed neural network models outperformed the regression model of Hanna et al. (1999b). The percentage error in all but one case favors the neural network models. The calculated average percentage error for the 9 cases is almost 1/3 that of the regression model.

5.4 Performance of the Developed Neural Network Models

The developed models that consider the work type influence were validated using many cases, as shown in the previous sections of this chapter, and have been found consistent and reliable. The developed models that consider the timing influence of change orders (i.e. models developed using data sets DS_1T_1 and DS_2T_2) were validated against the regression model of Hanna et al. (1999a), as shown earlier in Section 5.3. Although, the results shown in Table 5-8 favorite the Neural Network models, an evaluation of the performance of both models is done. For this purpose, a multi-scenario case that involves the variables of both models is used and the results obtained from both models are evaluated. The project data is as follow:

Base (Planned) Direct Original Contract Hours (BDOCH) = 10,000 Hours.

Direct Change Orders Hours (HCOs) = 2,500 Hours.

Actual Direct Original Contract Hours (ADOCH) = 15000 Hours.

Total Direct Hours (TDH) = 17500 Hours.

Maximum productivity loss = 17500 –2500 -10000= 5000 Hours

Accordingly, the productivity loss hours would range between 0 hours and 5000 hours. Table 5-12 shows the distribution of the planned hours of the original project's scope of work as well as two figures of change order numbers (NCOs): a low figure of 40 change orders, and a high of 250 change orders, each applied to four scenarios. The scenarios of change orders occurrence are: front loaded, evenly distributed, normally distributed, and back loaded. The predicted values of productivity loss hours are shown in Table 5-13.

Table 5-12 Different Scenarios Data

Parameters	Project Periods					Total
	P1	P2	P3	P4	P5	
Planned Hours	600	1900	3000	3200	1300	10000
Scenario 1: NCOs=40, Front Loaded HCOs	1000	1000	200	200	100	2500
Scenario 2: NCOs=40, Evenly Distributed HCOs	500	500	500	500	500	2500
Scenario 3: NCOs=40, Normally Distributed HCOs -	250	500	1000	500	250	2500
Scenario 4: NCOs=40, Back Loaded HCOs	100	200	200	1000	1000	2500
Scenario 5: NCOs=250, Front Loaded HCOs	1000	1000	200	200	100	2500
Scenario 6: NCOs=250, Evenly Distributed HCOs	500	500	500	500	500	2500
Scenario 7: NCOs=250, Normally Distributed HCOs	250	500	1000	500	250	2500
Scenario 8: NCOs=250, Back Loaded HCOs	100	200	200	1000	1000	2500

Table 5-13 Productivity Loss Prediction Results

Scenario	Productivity Loss (Hours)		
	Regression (Hanna et al. 1999a)	Neural Network (Direct Effect)	Neural Network (Ripple Effect)
Scenario 1	655	3926	4008
Scenario 2	2098	3554	2688
Scenario 3	2098	2934	2675
Scenario 4	3542	2925	2751
Scenario 5	912	3926	4008
Scenario 6	2356	3554	2688
Scenario 7	2356	2934	2675
Scenario 8	4181	2925	2751

As shown in the Table 5-13, both models predicted the loss of productivity within the expected range. Regarding the performance of both models, the following should be observed:

1) The prediction figures of the regression model show that it is not influenced by the difference in the timing of change orders occurrence in scenarios 2, 3, 6, and 7. This is due to the linear method used in the calculation of the timing impact, presented earlier in Section 2.3.5.2. On the other hand, the neural network models are responsive to the timing of change orders occurrence.

2) Comparing the estimated productivity loss hours for all scenarios, we can notice a tendency for a lower estimate by the regression model, except for the back loaded scenarios. This is mainly due to the negative value associated with the number of change orders (see Equation 2.6), implying an inverse relationship with the productivity loss. For example, in scenarios 1

and 5, where there are a sizable percentage of change orders (25%), the predicted percentage productivity loss is clearly under estimated.

5.5 Summary

This chapter presented validation analysis for the developed ten neural network models. The results obtained using the developed models are compared to those produced by: 1) the regression models developed in Chapter 4, 2) the regression models developed by Moselhi at al. (1991a) for general construction, Hanna et al. (1999a) for mechanical works, Hanna et al. (1999b) for electrical works. In addition, eight scenarios were used to evaluate the performance of the timing models. The results have shown that the developed neural network models are reliable, and, in most cases, have outperformed the regression models.

Chapter 6

Summary and Concluding Remarks

6.1 Summary

A model has been developed for quantifying the impact of change orders on construction productivity taking into account: 1) the type of impact (equivalent to: 1 in case of change orders only; 2 and 3 for one or two additional causes respectively), 2) the change orders intensity (expressed with the ratio of change orders direct hours to the base (planned) hours or to the actual hours, 3) the type of work (architectural, civil, electrical, mechanical), and 4) the timing of the change order occurrence. The model has been implemented in a prototype software application, named ***CHANGEORDERS.E***. The software application is developed using the MDI (Multiple Document Interface) feature available in Visual Basic (VB6) in order to provide a user-friendly interface. The developed software incorporates four widely used regression models, developed by others, in addition to ten neural network models developed in the course of this research. The incorporated models include regression models for: 1) general work (Moselhi et al. 1991), 2) general design/construction (Ibbs 1995), 3) mechanical work (Hanna et al. 1999a), and 4) electrical work (Hanna et al. 1999b).

The developed ten neural network models can be grouped into five groups. The first group is developed to model the influence of timing on construction productivity using two different concepts, based on the direct resource loading, in addition to the type of impact. The other four groups are developed to model four different work types (i.e. architectural, civil, electrical, and mechanical). Each of the four groups is developed using two concepts, in addition to the type of impact, based on the ratio of the direct change orders hours to: 1) the planned hours of the original project's scope of work, and 2) the actual original project's scope of work.

The data used in modeling the influence of timing and work type on the adverse impact of change orders is based on actual cases. It was collected, through a field investigation, conducted at a Montreal based firm specialized in project management and construction claims. A total of 117 actual projects constructed in Canada and the USA between 1990 and 1998, were initially analyzed for possible use in the developments made in this thesis. Only 33 work-packages from these projects were found relevant to be utilized in the development of the present model. These work packages have an original total value of more than $110M, planned direct hours of 1,023,583 for the original scope of work and a total of change orders direct hours of 166,002. These cases were supplemented by others, collected at the same firm, in an earlier study by Leonard (1988).

The independent variables used in the neural network models were identified using correlation and regression analysis. The correlation analysis confirmed the correlation of each individual variable with the resulting loss of productivity. Consequently, regression analysis was used to develop ten models. Upon completion of the regression analysis, the data sets were used to train and test the developed back propagation neural network models.

The results of the developed neural networks outperformed the regression models. In addition, they were also validated against regression models developed by others. In all cases, the developed neural network models yielded satisfactory results showing reliable performance.

6.2 Contributions

The primary contribution of this research is the study conducted for understanding the impact of change orders on construction productivity and, subsequently, the development of a model that accounts for the: 1) type of impact, 2) intensity of change orders, 3) timing of change orders, and 3) type of work executed in those changes. The developed models, in addition to 4 models developed by others, were coded in a software application named "***ChangeOrders.E***" to facilitate their use. The developed software application runs in Microsoft Windows environment (i.e. Windows95, 98, 2000, NT). It provides an automated user-friendly environment that permits objective, and timely evaluation of the adverse impact of change orders on productivity. The development of the present software is expected to facilitate negotiations, reduce disagreements and disputes by providing up-front pricing of change orders. The developments achieved are based on the following contributions:

1) The preparation of a state-of-the-art review on change orders definitions, causes, processes, impacts, management concepts, and existing quantification methods.

2) The data collection and organization of real case studies that enables researchers and practitioners to analyze, in detail, and appreciate the impact of change orders and/or their influencing factors.

3) The consideration of the timing impact of change orders using a concept based on project's direct resource loading.

4) Modeling the work type effect using two concepts, the ratio of change orders hours to the planned hours or the actual hours of the original project scope of work, in order to provide the users with more flexibility in estimating the resulting percentage loss of productivity

5) The development of ten regression models, utilized to check the correlation of each independent variable considered in studying the impact of change orders on construction productivity.

6) The development of ten neural networks for modeling the influence of timing and that of work type (i.e. architectural, civil, electrical, and mechanical).

7) The development of a prototype software application that provides a user-friendly interface for estimating the percentage productivity loss due to change orders, using the developed neural network models, and widely used regression models developed by others.

6.3 Recommendations

A practical model for the quantification of the adverse effects of change orders on productivity loss was developed. The model is flexible and provides reliable quantification based on actual cases obtained from a field investigation. In order to expand and build on the research developments made in this study, it is recommended to:

1) Refine and expand the concept used to model the timing effect of change orders based on the direct resource availability.

2) Investigate the combination of change orders and one or more causes of productivity loss.

3) Study the uncertainty allocated with change orders, and to assess its influence on the estimated productivity loss.

4) Investigate, study, and model other factors that affect the impact of change orders (e.g. project delivery system).

References

AACE Education Board (1989) "Practical Project Control," **33rd Annual Meeting**, AACE, Skills and Knowledge of Cost Engineers, Section 4.6, San Diego, California.

Abdo, D. (1999) "**A neural Network Model for Quantifying the Impact of Change Orders on Construction Productivity**," M. Eng. Major Technical Report, University of Concordia, Montreal, Quebec.

AbouRizk, S., and Portas, J. (1997) "Neural Network Model for Estimating Construction Productivity," **Journal of Construction Engineering and Management**, ASCE, 123 (4), pp. 399-410.

AIA (1997) "General Conditions of the Contract for Construction," Document A201, American Institute of Architects, **www.aiane.org/Info/documents/DocSynopsis/synopsis-10.htm**.

Al-Tabtabai, H., Alex, A., Tantash, M. (1999) "Preliminary Cost Estimation of Highway Construction Using Neural Networks," **Cost Engineering**, AACE, 41 (3), pp. 19-24.

Bailey, D. (1999) "An Effective Change Order Procedure Ensures Fair Payment for Additional Work," Journal of Light Construction on-line, JLC, **www.jlconline.com/jlc/archive/business.computers/changeorders**.

Bailey, D., and Thompson, D. (1990a) "How to Develop Neural-Network Applications," **AI Expert**, Miller Freeman Inc., 5 (6), pp. 38-47.

Bailey, D., and Thompson, D. (1990b) "Developing Neural-Network Applications," **AI Expert**, Miller Freeman Inc., 5 (9), pp. 34-41.

Barai, S., and Pandey, P. (1995) "Vibration Signature Analysis Using Artificial Neural Networks," **Journal of Computing in Civil Engineering**, ASCE, 9(4), pp. 259-265.

Barnes, F. (1997) "Change Orders and Effects of Impact," Constructor, 28 (11), AGC California, **www.agc-a.org/constractor/change_orders_and_effects_of_impact.html**.

Barrie, D., and Paulson, B. (1996) "**Professional Construction Management**," 3rd Edition, McGraw Hill, New Jersey.

Belkaoui, A., Bushnell, M., Usher, A., and Westland, S. (1986) "**The Learning Curve**", Quorum Books, Westport, Connecticut.

Bent, J., and Thuman, A. (1989) "**Project Management for Engineering and Construction**," Prentice Hall, New Jersey.

Bishop, J., Bushnell, M., Usher, A., and Westland, S. (1991) "Neural Networks in the Colour Industry," in **Applications of AI in Engineering VI**, Rzevski and Adey (eds.), Computational Mechanics Publications, Elsevier Applied Science, pp. 423-434.

Brams, R., and Lerner, C. (1996) "**Construction Claims Deskbook**," Wiley Law Publications, John Willey & Sons, New York.

Bruggink, M. (1997) "**An Investigation into the Impacts of Change Orders on Labor Efficiency in the Electrical Construction Industry**," M. Sc. Thesis, University of Wisconsin-Madison, Wisconsin.

Caudill, M. (1990) "Using Neural Pets, Part IV: Making an Expert Network," **AI Expert**, Miller Freeman Inc., 5 (7), pp. 41-45.

Chao, L., and Skibniewski, M. (1994) "Estimating Construction Productivity: Neural Network-Based Approach," **Journal of Computing in Civil Engineering**, ASCE, 8(2), pp. 234-251.

Cheung, S., Tam, C., and Harris, F. (2000) "Project Dispute Resolution Classification through Neural Networks," **Journal of Management in Engineering**, ASCE, 16 (1), peer-reviewed.

CII Project Change Management Research Team (1994) "**Project Change Management**," Special Publication 43-1, Construction Industry Institute, Austin, Texas.

Civitello, A. (1987) "**Contractors Guide to Change Orders**," Prentice Hall, Toronto.

Coffman, G., 1997 "Effect of Change Orders on Labor Productivity", **Proceedings of Construction Congress V**, ASCE, Minneapolis, Minnesota, pp. 141-148.

Constance, J. (2000) "**The Ten Commandments of Construction Change Orders**," FMI Management Consultants, http://www.fminet.com/news/General_Contractors/10command.html.

Deikman, J., and Girard, M. (1995) "Are Contract Disputes Predictable," **Journal of Construction Engineering and Management,** ASCE, 121 (4), pp. 335-363.

Deikman, J., Horr, D., and O'Connor, M. (1982) "Utilization of Learning Curves in Damages for Delay Claims", **Project Management Quarterly**, PMI, 13 (4), pp. 67-71.

Diekman, J., and Nelson, M. (1985) "Construction Claims: Frequency and Severity", **Journal of Construction Engineering and Management**, ASCE, 111 (1), pp. 74-81.

Dozzi, S., and AbouRizk, S. (1993) "**Productivity in Construction**," Institute for Research in Construction, National Research Council Canada, Ontario.

Dretzke, B., and Heilman, K. (1998) "**Statistics with Microsoft Excel**," Prentice Hall, New Jersey.

Dutta, S., and Shekhar, S. (1988) "Bond-Rating: A non Conservative Application of Neural Networks," **Proceedings of the International Conference on Neural Networks**, IEEE, San Diego, California, 2, pp. 443-450.

Ehrenreich-Hansen, F. (1994) "Change Order Management For Construction Projects," **Cost Engineering**, AACE, 36 (3).

Elazouni, A., Nosair, I., Mohieldin, Y. and Mohamed, A. (1997) "Estimating Resource Requirements at Conceptual Stage Using Neural Networks," **Journal of Computing in Civil Engineering**, ASCE, 11(4), pp. 217-223.

Elkordy, M., Chang, K., and Lee, G., (1993) "Neural Networks Trained by Analytically Simulated Damage States," **Journal of Computing in Civil Engineering**, ASCE, 7(2), pp. 130-145.

ENR Editorials (1998) "Change Orders Can Make or Break a Project," **Engineering News Record**, ENR, 240 (20), pp. 160.

Evans, J., and Olson, D. (2000) "**Statistics, Data Analysis, and Decision modeling**," Prentice Hall, New Jersey.

Fausset, L. (1994) "**Fundamentals of Neural Networks**," Prentice Hall, New Jersey.

Fisk, E. (1992) "**Construction Project Administration**," 4th Edition, Prentice Hall, New Jersey.

Flood, I., and Kartam, N. (1994a) "Neural Networks in Civil Engineering, I: Principles and Understanding, and II: Systems and application" **Journal of Computing in Civil Engineering**, ASCE, 8 (2), pp. 131-162.

Ginsburg, G. (1985) "Loss of Efficiency: Basic Principles and Guidelines," **Construction Briefings**, Federal Publications, 85 (12), pp. 1-16.

Halpin, D. (1985) "**Financial and Cost Control Concepts for Construction Management**," John Willey and Sons, New York.

Halyalimana, B. (1989) "**Change Orders and Construction Projects Characteristics: a Relational Quantitative Study**," Ph. D. Thesis, University of Missouri-Colombia, Colombia.

Hanna, A., Russel, J., Gotzion, T., and Nordheim, E. (1999a) "Impact of Change Orders on Labor Efficiency for Mechanical Construction," **Journal of Construction Engineering and Management**, ASCE, 125 (3), pp. 176-184.

Hanna, A., Russel, J., Nordheim E., and Bruggink M. (1999b) "Impact of Change Orders on Labor Efficiency for Electrical Construction," **Journal of Construction Engineering and Management**, ASCE, 125 (4), pp. 224-232.

Hasegawa, K. (1995) "**Pending Change/Modification Codes**," Documents of the Pacific Division of the Naval Facilities Engineering Command, Pearl Harbor Construction Office, Arizona.

Heather, P. (1989) "Mathews Curve: A Model for Evaluating Impact," **AACE 33rd Annual Meeting**, San Diego, California, pp. I.4.1- I.4.6.

Hegazy, T. (1993) "**Integrated bid preparation with emphases on risk assessment using Neural Networks**", Ph. D. Thesis, University of Concordia, Montreal, Quebec.

Hegazy, T., Fazio, P., and Moselhi O. (1994) "Developing Practical Neural Network Application Using Back Propagation," **Microcomputers in Civil Engineering**, 9 (3), pp. 145-159.

Hester, W, Kupernas, J., and Chang, T. (1991) "**Construction Changes and Change Orders: their Magnitude and Impact**," Source Document 66, Construction Industry Institute, Austin, Texas.

Hohns, M. (1980) "Effect of Management on Productivity in Construction," **Project Management Quarterly**, PMI, December.

Horner, R., Talhouni, B., and Whitehead R. (1987) "Measurement of Factors Affecting Labor Productivity on Construction Sites," in **Managing Construction Worldwide**, Volume II: Productivity and Human Factors in Construction, Lansely, P. and Harlow, P. (eds.), E. & F. N. Spon, New York.

Horvath, T. (1985) "**Basic Statistics for Behavioral Sciences**," Little Brown & Company, Boston.

Ibbs, C. (1997) "Quantitative Impacts of Project Change: Size Isuues," **Journal of Construction Engineering and Management**, ASCE, 23(3), pp. 308-311.

Ibbs, C., and Allen, W. (1995) "**Quantitative Effects of Project Change**," Source Document 108, Construction Industry Institute, Austin, Texas.

Karshenas, S., and Feng, X. (1992) "Application of Neural Networks in Earthmoving Equipment Production Estimating," **Proceedings of the 8th Computing in Civil Engineering and Geographic Information Systems Symposium**, ASCE, New York, N.Y., pp. 841-847.

Kartam, N., Flood, I., and Tongthong, T. (1993) "Artificial Neural Networks and Knowledge-Based Systems: Complementary AI Techniques for Civil Engineering," **Proceedings of The Fifth International Conference on Computing in Civil and Building Engineering**, ASCE, Anaheim, California, pp. 1398-1403.

Kartapoulos, S. (1996) "**Understanding Neural Networks & Fuzzy Logic**," IEEE Press, New Jersey.

Kasen, B., and Oblas, V. (1996) "**Forward Pricing Impact on Construction Projects**," 40th Annual Meeting, AACE, Section C, pp. C.5.1-C.5.6.

Kohen, E., and Brown, G. (1985) "Climatic Effects On Construction," **Journal of Construction Engineering and Management**, ASCE, 122 (2), pp. 299-302.

Kupernas, J., 1988, "**Use of Influence diagrams to Assess the Cost and Schedule Impact of Construction Changes**," Doctor of Engineering Thesis, University of California, Berkeley, California.

Leonard, C. (1988) "**The Effect of Change Orders on productivity**," M. Eng. Thesis, Center for Building Studies, Concordia University, Montreal, Quebec.

Leonard, C., Fazio, P., and Moselhi, O. (1988) "Construction Productivity: Major Causes of Impact," **32nd Annual Meeting transactions**, Morgantown, West Virginia, AACE, pp. D10:1-D10.7.

Matthews, N. 1996, "Forward Pricing is Effective", **Engineering News Record**, ENR, 237 (9), pp. 137.

McClave, J., Dietrich, F., and Sincich, T. (1997) "**Statistics**," Prentice Hall, New Jersey.

McCuen, R. (1985) "**Statistical Methods for Engineers**," Prentice Hall, New Jersey.

McMillan, H., 1996, "Seeking a Balanced Mechanism to Speed Contractor Payment", **Engineering News Record**, 236 (23), pp. 11.

Meyer, S. (1975) "**Data Analysis for Scientists and Engineers**," John Willey and Sons, New Jersey.

Mezei, L., 1990, "**Practical Spreadsheets Statistics and Curve Fitting for Scientists and Engineers**", Prentice Hall, New Jersey.

Moselhi, O. (1998a) "Neural Networks and their application in civil engineering," **Proceedings of the 1st International Conference on New Information Technologies for Decision Making in Civil Engineering**, Montreal, Quebec, pp. 17-27.

Moselhi, O. (1998b) "Estimating the Cost of Change Orders," **42nd Annual Meeting**, AACE, pp. EST06.1-EST.06-5.

Moselhi, O. (1996) "Neural Network Applications in Civil Engineering," **Proceeding of the 2nd International Conference in Civil Engineering on Computer Applications, Research, and Practice**, Bahrain, pp. 7-14.

Moselhi, O., Charles, L., and Fazio, P. (1991a) "Impact of Change Orders on Construction Productivity," **Canadian Journal of Civil Engineering**, 18 (4), pp. 484-492.

Moselhi, O., Hegazy, T., and Fazio, P. (1992) "Potential Applications of Neural Networks in Construction," **Canadian Journal of Civil Engineering**, 19 (3), pp. 521-529.

Moselhi, O., Hegazy, T., and Fazio, P. (1991b) "Neural Networks as Tools in Construction," **Journal of construction Engineering and Management**, ASCE, 117 (4), pp. 606-625.

Moselhi, O., Shehab-Eldeen, T. (2000) "Automated detection of Effects in sewer pipes using Neural Networks," **Journal of Infrastructure Systems**, ASCE, 6 (3), pp. 97-105.

Mukherjee, A., and Deshpande J. M. (1995) "Modeling Initial Design Process using Artificial Neural Networks," **Journal of Computing in Civil Engineering**, ASCE, 9(3), pp. 194-200.

NECA (1980) "**The Effects of Job Schedule Delays on Construction Costs**," Report, National Electrical Contractors Association, Washington DC.

NECA (1983) "**Rate of Manpower Consumption in Electrical Construction**," Report, National Electrical Contractors Association, Washington DC.

NeuroShell2 (1996) "**NeuroShell2 User's Manual**," Ward Systems Group, Maryland.

Oberlender, C. (1993) "**Project Management for Engineering and Construction**," McGraw Hill, New Jersey.

O'Brien, J. (1998) "**Construction Change Orders**," McGraw Hill, New Jersey.

PMI Standards Committee (1996) "**Project Management Body of Knowledge**," PMI, Pennsylvania.

R. S. Means (1991) "**Means Illustrated Construction Dictionary**," R. S. Means Company, Construction Consultants & Publishers, Kingston, Maryland.

R. S. Means (1993) "**Means Electrical Change Orders Cost Data**," R. S. Means Company, Construction Consultants & Publishers, Kingston, Maryland.

Revay, S. (1985) "Impact Costs," **Construction Law Reports**, Carswell Co. Ltd., 11, pp. 15-26.

Rosenbaum, D. (1995) "Change Orders Organized," **Engineering News Record**, ENR, 235 (11), pp. 20.

Sarvi, H. (1992) "Overhead and Profit on Change Orders," **Civil Engineering**, ASCE, 62 (7), pp. 59-61.

Schwartzkoph, W. (1995) "**Calculating Lost Labor Productivity in Construction Claims**," Aspen Law and Business, Maryland.

Semple, C. (1996) "**Construction Change Order Impacts**," M. A. Sc. Thesis, Department Of Civil Engineering, University of Calgary, Calgary, Alberta.

Simpson, G. (1998) "Agreeing to Agree," **Magazine of Canada's Development Industry**, Canadian Developers, 48 (4), www.narer.com/building/48-4/48-4-41.htm.

Sincich, T., Levine, D., and Stephan, D. (1999) "**Practical Statistics by Example using Microsoft Excel**," Prentice Hall, New Jersey.

Siqueira, I. (1999) "**Neural Network-Base Cost Estimating**," M. A. Sc. Thesis, University of Concordia, Montreal, Quebec.

Smith, M. (1996) "Quantifying Lost Efficiency Claims," **Journal of Construction Accounting and Taxation**, 6 (4), pp. 10-16.

Sonmez, R. and Rowings, J. (1998) "Construction Labor Productiivty Modeling with Neural Netwroks," **Journal of Construction Engineering and Management**, E & FN SPON, 124 (6), pp. 498-504.

Stocks, S., and Singh, A. (1999) "Studies on the Impact of Functional Analysis Concept Design on Reduction in Change Orders", **Journal of Construction Management and Economics**, ASCE, 17, pp. 251-267.

The, C., Wong, K., Goh, A. and Jaritngam, S. (1997). "Prediction of Pile Capacity Using Neural Networks," **Journal of Computing in Civil Engineering**, ASCE, 11(2), pp. 129-138.

Thomack, D. (1996) "**The Impact of Change Orders on Electrical Construction Labor Efficiency**," M. Sc. Thesis, University of Wisconsin-Madison, Wisconsin.

Thomas, R. (1992) "Effects of Scheduled Overtime on Labor Productivity," **Journal of Construction Engineering and Management**, ASCE, 118 (1), pp. 60-76.

Thomas, R., and Kramer, D. (1988) "**The Manual of Construction Productivity Measurement and Performance Evaluation**," Pennsylvania State University, Pennsylvania.

Thomas, R., and Mathews, C. (1986) "**An Analysis of the Methods for Measuring Construction Productivity**," Pennsylvania State University, Pennsylvania.

Thomas, R., and Mathews, C., Ward, G. (1986) "Learning Curve Models of Construction Productivity," **Journal of Construction Engineering and Management**, ASCE, 112 (2), pp. 245-258.

Thomas, R., and Napolitan, C. (1995) "Quantitative Effects of Construction Changes on Labor Productivity," **Journal of Construction Engineering and Management**, ASCE, 121 (3), pp. 290-296.

Thomas, R., and Raynar, A. (1997) "Scheduled Overtime and Labor Productivity: Quantitative Analysis," **Journal of Construction Engineering and Management**, ASCE, 121 (3), pp. 290-296.

Thomas, R., and Yiakoumis, I. (1987) "Factor Model of Construction Productivity," **Journal of Construction Engineering and Management**, ASCE, 113 (4), pp. 623-639.

Thomas, R., Riley, D., and Sanvido, V. (1999) "Loss of Labor Productivity due to Delivery Methods and Weather," **Journal of Construction Engineering and Management**, ASCE, 125 (1), pp. 39-46.

US Army – Corps of Engineers (1979), "**Modification Impact Evaluation Guide**," EP 415-1-3, Washington D.C.

US Army - Corps of Engineers (1990) "**Construction Resident-Engineer Management Guide**," EP 415-1-260, Washington D.C.

Vandenberg, P. (1996) "**The Impact of Change Orders On Mechanical Construction Labor Efficiency**," M. Sc. Thesis, Department of Civil and Environmental Engineering, University of Wisconsin-Madison, Wisconsin, Madison.

VB6 (1998) "**Visual Basic 6.0 User's Manual**," Microsoft Incorporation.

Warren, T. (1984) "Work Smarter not Harder," **Journal of Highway and Heavy Construction**, 127, 60-61.

Williams, T., Khajuria, A., and Balaguru, P. (1992) "Neural Network for Predicting Concrete Strength," **Proceedings of the 8th Computing in Civil Engineering and Geographic Information Systems Symposium**, ASCE, New York, pp. 1082-1088.

Yeh, Y., Kuo, Y., and Hsu, D. (1993). "Building KBES for diagnosing PC Pile with Artificial Neural Network," **Journal of Computing in Civil Engineering**, ASCE, 7(1), pp. 71-93.

Zeitoun, A., and Oberlender, G. (1993) "**Early Warning signs of Project Changes**," Source Document 91, Construction Industry Institute, Austin, Texas.

Zink, D. (1986) "The measured Mile: Proving Construction Inefficiency Costs," **Cost Engineering**, AACE, 28 (4), pp. 19-21.

Zink, D. (1987) "Minimizing Costs of Delay Construction Claims," **31st Annual Meeting**, AACE, Section H, pp. H.4.1 – H.4.4, Morgantown, West Virginia.

Zink, D. (1990) "Impacts and Construction Inefficiency," **Cost Engineering**, AACE, 32 (11), pp. 21-23.

Appendix 1 General Information of the Cases Examined during the Preliminary Investigation Stage

Table 1 Category 1 Cases

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
1	Claim	Additional Compensation	Sub-contractor	General Contractor	New-Brunswick	Military	Public	Mechanical
2	Claim	Additional Compensation	General Contractor	Owner	Quebec	Building	Private	Mechanical
3	Claim	Equitable adjustment to contract price	General Contractor	Owner	Ontario	Heavy	Public	Mechanical
4	Expert Report	Report on delays and quantum of damages	General Contractor	Owner	New-Brunswick	Industrial	Private	Mechanical
5	Expert Report	Time extension and additional compensation	Sub-contractor	General Contractor	Quebec	Building	Private	Mechanical
6	Claim	Time extension and additional compensation	Sub-contractor	General Contractor	Quebec	Building	Private	Mechanical
7	Claim	Time extension and additional compensation	Sub-contractor	General Contractor	Quebec	Recreational	Private	Electrical
8	Claim	Time extension and additional compensation	Sub-contractor	General Contractor	New-Brunswick	Building	Public	Electrical
9	Expert Report	Analysis of claim	Sub-contractor	General Contractor	New-Brunswick	Industrial	Private	Mechanical
10	Claim	Time extension and additional compensation	Sub-contractor	General Contractor	New-Brunswick	Building	Public	Architectural
11	Expert Report	Delays and quantum of damages	Sub-contractor	General Contractor	Ontario	Building	Public	Electrical
12	Claim	Time extension and additional compensation	Sub-contractor	General Contractor	Nova-Scotia	Building	Public	Architectural

Table 2 Category 2 Cases

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
1	Expert Report	Time extension and additional compensation	Sub-contractor	General Contractor	Quebec	Building	Private	Mechanical
2	Claim	Supplementary indemnity	Sub-contractor	Owner	Ontario	Building	Private	Mechanical
3	Claim	Additional Compensation	Contractor	Owner	New-Brunswick	Industrial	Private	Mechanical
4	Claim	Time extension and additional compensation	General Contractor	Owner	Nova-Scotia	Industrial	Private	Electrical

Table 3 Category 3 Cases

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
1	Expert Report	Delay analysis	General Contractor	Owner / Construction Manager	Ontario	Residential	Private	General
2	Claim	Time extension and additional compensation	General Contractor	Owner / Construction Manager	Quebec	Commercial	Private	General
3	Expert Report	Loss Analysis report (Arbitration)	Sub Contractor	General Contractor	Ontario	Industrial	Private	Mechanical
4	Claim	Additional compensation	General Contractor	Owner	Quebec	Industrial	Private	General
5	Expert Report	Project delays and damages incurred	Sub Contractor	Owner / General Contractor	New Brunswick	Industrial	Private	Electrical
6	Expert Report	Study of contractor claim	General Contractor	Owner	Quebec	Industrial	Private	General
7	Claim	Additional compensation	General Contractor	Owner	Ontario	Institutional	Public	General
8	Claim	Additional compensation	General Contractor	Owner	Ontario	Institutional	Private	General
9	Expert Report	Final report	General Contractor	Owner	Ontario	Recreational	Public	General
10	Expert Report	Evaluation of claim arising from installation of critical and cycle piping	General Contractor	Sub-Contractor	British Colombia	Industrial	Public	Mechanical
11	Claim	Request for additional compensation	Sub-Contractor	General Contractor	British Colombia	Industrial	Public	Civil

Table 3 Category 3 Cases (Continued)

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
12	Claim	Additional compensation	Sub-contractor	General Contractor	Quebec	Institutional	Private	Mechanical
13	Claim	Request for additional compensation	Sub-Contractor	Owner	Manitoba	Institutional	Public	Civil
14	Claim	Request for additional compensation	General Contractor	Owner	Northwest Territories	Institutional	Public	General
15	Expert Report	Analysis of extended duration and additional costs incurred	General Contractor	Ower	Nova Scotia	Institutional	Public	Civil / Architectural
16	Expert Report	Claim for additional compensation	Sub-Contractor	Owner	Ontario	Rehabilitation	Public	Architectural
17	Claim	Time extension and additional compensation	Sub-Contractor	General Contractor	South Carolina	Industrial	Private	Mechanical
18	Expert Report	Delays and the quantum of damages	Owner	Sub-Contractor	Ontario	Institutional	Private	Civil
19	Claim	Extension of time	EPC contractor	Owner	Perusahaan - Indonesia	Industrial	Public	EPC
20	Claim	Additional compensation	EPC contractor	Owner	New Brunswick	Industrial	Public	EPC
21	Claim	Additional compensation	Sub-Contractor	General Contractor	Ontario	Institutional	Public	Mechanical
22	Expert Report	Report on Delays	General Contractor	Owner	Ontario	Institutional	Public	General
23	Claim	Extension of Time and Additional Compensation	General Contractor	Owner	New Brunswick	Institutional	Public	General

Table 3 Category 3 Cases (Continued)

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
24	Expert Report	Evaluation of claim for additional compensation (litigation)	Main contractor	Owner	Manitoba	Industrial	Public	Civil / Electrical
25	Expert Report	Arbitration report	Owner	Main Contractor	Manitoba	Industrial	Public	Civil / Mechanical / Electrical
26	Expert Report	Claim Analysis	owner	Architect	Ontario	Industrial	Public	Design
27	Claim	Extension of time and additional compensation	General Contractor	Owner	Nova Scotia	Institutional	Public	General
28	Claim	Extension of time and additional compensation	Main Contractor	Owner	Nova Scotia	Institutional	Public	General
29	Claim	Extension of time and additional compensation	EPC Contractor	Construction Manager	Ontario	Commercial	Private	EPC
30	Claim	Extension of time and additional compensation	General Contractor	Owner	Rio Lajas - Costa Rica	Industrial	Public	General
31	Expert Report	Loss of productivity	Sub-Contractor	Owner	Ontario	Industrial	Private	Civil
32	Expert Report	Entitlement of Contractor to additional compensation	General Contractor	Engineer	Florida	Recreational	Private	Civil
33	Claim	Request for equitable adjustment of contract price	General Contractor	Owner	Texas	Commercial	Private	Civil
34	Expert Report	Claim for compensation	Owner	General Contractor	Texas	Institutional	Public	General
35	Claim	Additional compensation	Owner	Construction Manager	Ontario	Institutional	Public	Civil / Electrical

Table 4 Category 4 Cases

No.	Report Type	Subject	Plaintiff	Defendant	Location	Project type	Sector	Work Type
1	Expert Report	Analysis of delays	General Contractor	Owner	Ontario	Industrial	Public	General
2	Expert Report	Claim Analysis	Sub-Contractor	General Contractor	Ontario	Industrial	Private	Electrical
3	Expert Report	Analysis of contractual holdbacks	General Contractor	Owner	Quebec	Industrial	Private	General
4	Claim	Additional Compensation	Sub-Contractor	Construction Manager	London - England	Industrial	Private	Mechanical
5	Expert Report	Review of formwork Design	Contractor	Owner	Quebec	Industrial	Public	Civil
6	Expert Report	Quantum of damages	General Contractor	Owner	British Colombia	Industrial	Private	General
7	Expert Report	Extended duration and corresponding damages	General Contractor	Owner	British Colombia	Commercial	Private	Mechanical
8	Claim	Claim for additional Compensation	Sub-contractor	General Contractor	British Colombia	Industrial	Private	Mechanical
9	Expert Report	Quantum of damages	General Contractor	Owner	New Brunswick	Industrial	Public	General
10	Claim	Request for extension of time and additional compensation	EPC Contractor	Owner	Lavrion - Greece	Industrial	Public	EPC
11	Claim	Request for extension of time and additional compensation	EPC Contractor	Owner	Lavrion - Greece	Industrial	Public	EPC
12	Expert Report	Evaluation of a Claim	Owner	Architect	Ontario	Institutional	Public	Design
13	Claim	Additional Compensation	General Contractor	Owner	Quebec	Commercial	Public	Mechanical

Appendix 2 Results of the Detailed Investigation Stage

Appendix 2.1 Contractual Data

Table 1 Contractual Data Resulting from the Detailed Investigation of the Cases in Category 1 and 2

No.	Work Type	Project Delivery System	Contract Type	Original Duration (Month)	Actual Duration (Month)	Original $ Value	Planned Hours	Actual Hours
1	Architectural	Phased	Fixed Price	10	11	$441,928.00	6,539.00	8,746.00
2	Architectural	Phased	Fixed Price	22	25	$3,085,000.00	48,508.50	66,070.50
3	Architectural	Phased	Fixed Price	6	10	$383,072.00	6,261.00	9,571.00
4	Electrical	Traditional	Unit Price	2	4	$1,219,025.00	12,249.75	13,886.00
5	Electrical	Traditional	Fixed Price	14	21	$284,000.00	2,015.99	3,275.00
6	Electrical	Phased	Lump Sum	26	44	$4,459,994.00	46,314.77	58,514.00
7	Electrical	Traditional	Lump Sum	24	24	$10,410,715.00	130,047.41	166,241.46
8	Electrical	Traditional	Lump Sum	4	4	$774,200.00	5,350.15	7,513.50
9	Electrical	Traditional	Lump Sum	15	15	$785,000.00	6,782.56	9,402.00
10	Electrical	Phased	Lump Sum	16	23	$1,958,931.83	15,053.61	24,251.90
11	Electrical	Phased	Fixed Price	20	26	$5,798,000.00	53,096.03	86,950.59
12	Electrical	Phased	Fixed Price	15	19	$168,752.44	5,544.52	8,205.00
13	Mechanical	Traditional	Lump Sum	18	25	$5,007,857.00	52,351.34	57,496.50
14	Mechanical	Traditional	Lump Sum	20	26	$3,924,664.00	50,530.28	56,488.00
15	Mechanical	Traditional	Lump Sum	17	26	$8,338,827.00	66,197.06	76,331.25
16	Mechanical	Traditional	Fixed Price	7	9	$1,948,000.00	11,178.57	12,934.00
17	Mechanical	Phased	Fixed Price	18	25	$3,658,000.00	18,908.64	27,996.00
18	Mechanical	Traditional	Fixed Price	21	26	$1,752,276.40	46,222.30	69,100.00
19	Mechanical	Traditional	Fixed Price	17	26	$1,088,213.70	36,312.94	56,379.00
20	Mechanical	Traditional	Fixed Price	19	28	$779,537.50	23,865.68	38,054.00
21	Mechanical	Traditional	Lump Sum	4	5	$496,857.09	3,580.29	10,940.00
22	Mechanical	Traditional	Lump Sum	3	4	$1,299,011.91	5,228.93	15,844.00
23	Mechanical	Traditional	Lump Sum	20	26	$3,924,664.00	50,470.10	56,488.00

Table 1 Contractual Data Resulting from the Detailed Investigation of Cases in Category1 and 2 (Continued)

No.	Work Type	Project Delivery System	Contract Type	Original Duration (Month)	Actual Duration (Month)	Original $ Value	Planned Hours	Actual Hours
24	Mechanical	Traditional	Lump Sum	20	26	$8,338,827.00	66,622.87	76,331.25
25	Mechanical	Traditional	Lump Sum	18	25	$5,007,857.00	50,077.89	57,496.50
26	Mechanical	Traditional	Lump Sum	11	13	$491,268.17	4,231.67	7,268.00
27	Mechanical	Phased	Cost +	6	9	$23,172,000.00	37,091.70	68,088.00
28	Mechanical	Phased	Lump Sum	9	11	$4,540,000.00	57,587.43	75,715.75
29	Mechanical	Traditional	Fixed Price	3	5	$903,668.48	3,001.42	5,621.50
30	Mechanical	Traditional	Fixed Price	2	6	$826,689.31	3,735.16	6,930.00
31	Mechanical	Traditional	Fixed Price	3	5	$903,668.48	3,450.84	6,621.50
32	Mechanical	Phased	Lump Sum	6	7	$3,447,884.00	89,792.69	150,616.75
33	Mechanical	Traditional	Fixed Price	3	4	$1,060,973.73	5,381.42	10,297.00

Appendix 2.2 Change Orders Data

Table 1 Change Orders Data Resulting from the Detailed Investigation of Cases in Category 1 and 2

No.	$ Attributed to Change Orders	Change Orders Number						Change Orders Direct Hours					
		P_1	P_2	P_3	P_4	P_5	Total	P_1	P_2	P_3	P_4	P_5	Total
1	$17,710.01	1	10	4	1	1	17	240.00	127.00	96.00	100.00	5.00	568.00
2	$380,636.90	2	4	3	18	7	34	88.00	883.00	979.00	1,444.00	2,217.00	5,611.00
3	$25,926.95	2	2	3	5	0	12	14.00	45.00	92.00	366.00	320.00	837.00
4	$509,290.00	0	9	20	10	0	39	0.00	232.00	611.00	140.00	6.00	989.00
5	$106,927.00	0	2	5	2	1	10	0.00	110.00	1,128.00	133.00	17.00	1,388.00
6	$476,731.56	2	9	24	21	24	80	115.00	235.00	2,605.00	2,650.50	87.00	5,692.50
7	$1,055,655.35	0	8	7	17	27	59	0.00	1,618.20	2,634.58	7,231.01	1,453.23	12,937.02
8	$262,760.64	1	1	3	6	14	25	20.00	161.00	1,356.00	445.00	520.00	2,502.00
9	$154,941.87	0	0	14	17	9	40	0.00	0.00	259.70	936.40	361.90	1,558.00
10	$500,804.67	15	8	56	7	0	86	19.00	164.00	1,870.00	2,403.00	964.00	5,420.00
11	$2,422,902.84	1	34	56	26	15	132	0.00	2,438.39	5,110.47	8,774.82	2,521.23	18,844.91
12	$71,288.45	0	3	3	5	3	14	0.00	0.00	0.00	60.00	49.00	109.00
13	$37,325.00	3	5	14	2	0	24	61.00	400.00	937.00	847.00	86.00	2,331.00
14	$41,147.00	9	7	16	5	0	37	144.00	517.00	1,008.00	1,427.00	595.00	3,691.00
15	$56,108.00	17	14	59	8	0	98	351.00	1,062.00	3,943.00	2,928.00	546.00	8,830.00
16	$7,074.00	7	6	1	0	1	15	151.00	304.00	179.00	272.00	92.00	998.00
17	$3,275.00	0	9	6	8	13	36	0.00	5,074.00	2,330.00	1,120.00	1,344.00	9,868.00
18	$42,428.00	6	2	9	4	16	37	185.00	109.00	151.00	287.00	345.00	1,077.00
19	$26,349.00	13	7	11	7	6	44	1,348.00	204.00	2,211.00	855.00	180.00	4,798.00
20	$18,875.00	9	6	7	4	3	29	664.00	242.00	144.00	261.00	47.00	1,358.00
21	$3,820.00	26	30	70	18	6	150	665.00	1,623.50	2,428.50	920.00	226.00	5,863.00
22	$7,220.00	13	17	35	7	1	73	408.00	2,134.00	2,638.00	464.00	0.00	5,644.00

Table 1 Change Orders Data Resulting from the Detailed Investigation of Cases in Category 1 and 2 (Continued)

No.	$ Attributed to Change Orders	Change Orders Number						Change Orders Direct Hours					
		P_1	P_2	P_3	P_4	P_5	Total	P_1	P_2	P_3	P_4	P_5	Total
23	$41,147.00	9	7	16	5	0	37	144.00	517.00	1,008.00	1,427.00	595.00	3,691.00
24	$56,108.00	17	14	59	8	0	98	351.00	1,062.00	3,943.00	2,928.00	546.00	8,830.00
25	$37,325.00	3	5	14	2	0	24	61.00	400.00	937.00	847.00	86.00	2,331.00
26	$3,200.00	5	3	11	2	0	21	5.00	50.00	830.00	860.00	188.00	1,933.00
27	$34,497.00	0	0	8	18	18	44	0.00	0.00	2,023.00	6,088.00	2,672.00	10,783.00
28	$51,571.00	9	9	22	42	27	109	115.00	995.00	2,367.00	7,463.00	9,771.50	20,711.50
29	$3,900.00	0	5	1	1	5	12	0.00	2,092.50	85.75	90.00	298.00	2,566.25
30	$4,622.00	0	5	2	3	7	17	0.00	1,539.50	516.75	158.00	336.00	2,550.25
31	$3,558.00	0	5	2	0	3	10	0.00	1,334.00	538.50	0.00	289.00	2,161.50
32	$87,904.00	27	56	28	49	22	182	1,176.50	2,547.00	1,185.00	2,263.75	607.00	7,779.25
33	$7,458.00	0	5	0	0	7	12	0.00	1,523.00	0.00	0.00	228.00	1,751.00

Appendix 2.3 Productivity Loss Data

Table 1 Productivity Loss Data Resulting from the Detailed Investigation of Cases in Category 1 and 2

No.	Type of Impact	Additional Major Reasons of Productivity Loss (PL) Else than Change Orders	Actual %PL
1	2	Acceleration	23.70
2	2	Congestion	24.50
3	3	Congestion and Acceleration	31.80
4	1		11.00
5	1		27.00
6	2	Weather impact	19.00
7	2	Over-time	20.20
8	2	Over-time	21.60
9	2	Over-time	23.90
10	2	Over-time	31.00
11	2	Congestion	32.00
12	2	Congestion	32.00
13	1		8.60
14	1		9.90
15	1		11.90
16	1		12.60
17	1		24.00
18	1		32.60

Table 1 Productivity Loss Data Resulting from the Detailed Investigation of Cases in Category 1 and 2 (Continued)

No.	Type of Impact	Additional Major Reasons of Productivity Loss (PL) Else than Change Orders	Actual %PL
19	1		32.80
20	1		36.00
21	1		43.80
22	1		49.40
23	2	Overtime	10.00
24	2	Overtime	11.40
25	2	Overtime	12.40
26	2	Acceleration	33.00
27	2	Weather impact due to wind speed	39.30
28	3	Weather impact and Untimely delivery of equipment	18.80
29	3	Acceleration and Congestion	32.00
30	3	Acceleration and Congestion	33.70
31	3	Acceleration and Congestion	36.10
32	3	Acceleration and Over-manning	38.40
33	3	Acceleration and Congestion	40.80

Appendix 3 Cases Adopted From Leonard (1988)

Appendix 3.1 Contractual Data

Table 1 Contractual Data for the Cases adopted from Leonard (1988)

No.	Work Type	Contract Type	Original Duration (Month)	Actual Duration (Month)	Original $ Value	Planned Hours	Actual Hours
1	Architectural	Lump Sum	9	20	$2,200,000.00	30,500.00	35,500.00
2	Architectural	Lump Sum	8	8	$1,980,000.00	17,400.00	21,500.00
3	Architectural	Lump Sum	2	11	$320,000.00	13,000.00	15,450.00
4	Architectural	Lump Sum	6	11	$430,000.00	12,300.00	15,250.00
5	Architectural	Lump Sum	6	10	$3,780,000.00	20,000.00	26,000.00
6	Architectural	Lump Sum	13	19	$300,000.00	6,200.00	8,900.00
7	Civil	Lump Sum	9	9	$3,200,000.00	46,800.00	53,150.00
8	Civil	Lump Sum	16	21	$1,970,000.00	79,300.00	97,200.00
9	Civil	Unit Price	9	9	$1,000,000.00	44,000.00	57,000.00
10	Civil	Lump Sum	12	15	$2,000,000.00	23,000.00	26,800.00
11	Civil	Lump Sum	12	15	$3,760,000.00	52,000.00	63,220.00
12	Civil	Lump Sum	6	14	$260,000.00	14,250.00	17,600.00
13	Civil	Lump Sum	12	12	$6,400,000.00	105,000.00	133,000.00
14	Civil	Unit Price	2	4	$760,000.00	19,500.00	25,500.00
15	Civil	Lump Sum	10	10	$940,000.00	52,000.00	69,000.00
16	Civil	Lump Sum	6	14	$1,310,000.00	27,750.00	37,700.00
17	Civil	Lump Sum	5	7	$2,700,000.00	14,000.00	22,500.00
18	Civil	Lump Sum	15	20	$3,675,000.00	13,160.00	179,000.00
19	Electrical	Unit Price	17	27	$650,000.00	56,776.00	68,500.00
20	Electrical	Lump Sum	11	23	$1,658,000.00	10,500.00	12,200.00
21	Electrical	Lump Sum	15	26	$7,100,000.00	107,600.00	127,850.00
22	Electrical	Lump Sum	17	27	$3,924,664.00	47,350.00	53,800.00
23	Electrical	Lump Sum	17	27	$1,299,011.91	66,300.00	80,600.00
24	Electrical	Lump Sum	24	24	$4,394,000.00	16,567.00	24,834.00

Table 1 Contractual Data for the Cases adopted from Leonard (1988) (Continued)

No.	Work Type	Contract Type	Original Duration (Month)	Actual Duration (Month)	Original $ Value	Planned Hours	Actual Hours
25	Electrical	Lump Sum	10	14	$1,476,000.00	25,000.00	31,150.00
26	Electrical	Lump Sum	12	28	$537,000.00	17,211.00	24,440.00
27	Electrical	Lump Sum	17	27	$6,615,000.00	37,500.00	53,700.00
28	Electrical	Lump Sum	17	17	$2,326,000.00	11,400.00	15,350.00
29	Electrical	Lump Sum	16	18	$3,318,000.00	36,000.00	63,000.00
30	Electrical	Lump Sum	14	17	$1,465,000.00	44,500.00	56,900.00
31	Electrical	Lump Sum	7	16	$1,055,000.00	18,600.00	26,067.00
32	Electrical	Lump Sum	5	20	$1,034,000.00	48,000.00	59,451.00
33	Electrical	Lump Sum	15	23	$1,694,000.00	45,950.00	68,486.00
34	Electrical	Unit Price	22	37	$4,506,000.00	53,671.00	79,873.00
35	Electrical	Lump Sum	6	10	$460,000.00	21,100.00	29,743.00
36	Electrical	Unit Price	6	10	$297,000.00	43,000.00	54,700.00
37	Electrical	Lump Sum	6	10	$460,000.00	19,845.00	28,700.00
38	Electrical	Unit Price	8	10	$439,000.00	95,068.00	141,304.00
39	Electrical	Lump Sum	8	9	$1,800,000.00	46,621.00	71,887.00
40	Electrical	Lump Sum	15	22	$4,801,000.00	45,000.00	67,677.00
41	Electrical	Lump Sum	28	31	$1,800,000.00	45,600.00	78,260.00
42	Electrical	Lump Sum	10	14	$1,399,000.00	136,540.00	216,500.00
43	Electrical	Lump Sum	15	26	$2,251,000.00	21,000.00	35,288.00
44	Electrical	Lump Sum	16	28	$1,650,000.00	154,000.00	225,130.00
45	Mechanical	Lump Sum	24	32	$5,000,000.00	145,000.00	162,500.00
46	Mechanical	Lump Sum	23	26	$1,829,000.00	34,400.00	38,000.00
47	Mechanical	Lump Sum	9	15	$1,751,000.00	32,500.00	36,000.00
48	Mechanical	Lump Sum	11	19	$317,000.00	41,000.00	48,200.00

Table 1 Contractual Data for the Cases adopted from Leonard (1988) (continued)

No.	Work Package type	Contract Type	Original Duration (Month)	Actual Duration (Month)	Original $ Value	Planned Hours	Actual Hours
49	Mechanical	Lump Sum	16	30	$2,359,000.00	13,600.00	15,120.00
50	Mechanical	Lump Sum	6	9	$1,070,000.00	16,000.00	19,000.00
51	Mechanical	Lump Sum	15	14	$8,029,000.00	557,000.00	661,600.00
52	Mechanical	Lump Sum	14	15	$3,220,000.00	173,000.00	207,932.00
53	Mechanical	Lump Sum	14	27	$458,000.00	27,000.00	34,500.00
54	Mechanical	Lump Sum	2	5	$476,000.00	7,313.00	10,675.00
55	Mechanical	Lump Sum	12	22	$1,450,000.00	61,500.00	88,500.00
56	Mechanical	Lump Sum	15	26	$4,889,000.00	33,000.00	43,300.00
57	Mechanical	Lump Sum	9	17	$2,725,000.00	35,000.00	53,000.00
58	Mechanical	Lump Sum	8	12	$5,960,000.00	3,300.00	4,400.00
59	Mechanical	Lump Sum	17	18	$5,700,000.00	28,700.00	39,200.00
60	Mechanical	Lump Sum	10	20	$600,000.00	61,600.00	88,300.00
61	Mechanical	Lump Sum	10	18	$473,000.00	32,400.00	42,200.00
62	Mechanical	Lump Sum	11	18	$246,000.00	78,000.00	121,990.00
63	Mechanical	Lump Sum	5	5	$1,362,000.00	33,800.00	57,800.00
64	Mechanical	Lump Sum	14	14	$2,046,000.00	6,050.00	7,530.00
65	Mechanical	Lump Sum	13	17	$2,293,000.00	17,000.00	33,300.00
66	Mechanical	Lump Sum	14	28	$815,000.00	37,700.00	55,750.00
67	Mechanical	Lump Sum	8	9	$1,650,000.00	140,000.00	213,500.00
68	Mechanical	Lump Sum	5	14	$463,000.00	44,000.00	80,500.00
69	Mechanical	Lump Sum	7	11	$1,948,000.00	102,000.00	189,000.00

Appendix 3.2 Change Orders Data

Table 1 Change Orders Data for the Cases adopted from Leonard (1988)

No.	Change Orders			Planned Hours	Actual Hours
	$ attributed	Number	Direct Hours		
1	$290,000.00	46	5,000.00	30,500.00	35,500.00
2	$400,000.00	100	9,400.00	17,400.00	21,500.00
3	$40,000.00	20	1,300.00	13,000.00	15,450.00
4	$50,000.00	25	2,000.00	12,300.00	15,250.00
5	$240,000.00	20	6,000.00	20,000.00	26,000.00
6	$200,000.00	25	5,100.00	6,200.00	8,900.00
7	$2,500,000.00	150	8,300.00	46,800.00	53,150.00
8	$890,000.00	253	32,800.00	79,300.00	97,200.00
9	$830,000.00	190	21,500.00	44,000.00	57,000.00
10	$200,000.00	12	2,300.00	23,000.00	26,800.00
11	$450,000.00	11	3,000.00	52,000.00	63,220.00
12	$60,000.00	10	1,900.00	14,250.00	17,600.00
13	$350,000.00	75	14,200.00	105,000.00	133,000.00
14	$236,000.00	10	6,500.00	19,500.00	25,500.00
15	$120,000.00	65	8,000.00	52,000.00	69,000.00
16	$200,000.00	13	5,808.00	27,750.00	37,700.00
17	$60,000.00	100	2,700.00	14,000.00	22,500.00
18	$1,000,000.00	235	35,000.00	13,160.00	179,000.00
19	$140,000.00	200	4,388.00	56,776.00	68,500.00
20	$7,458.00	10	1,200.00	10,500.00	12,200.00
21	$1,500,000.00	195	14,625.00	107,600.00	127,850.00
22	$41,147.00	114	13,450.00	47,350.00	53,800.00
23	$7,220.00	77	21,150.00	66,300.00	80,600.00
24	$1,667,000.00	62	9,452.00	16,567.00	24,834.00
25	$1,540,000.00	200	12,000.00	25,000.00	31,150.00
26	$200,000.00	76	9,933.00	17,211.00	24,440.00
27	$4,550,000.00	137	23,850.00	37,500.00	53,700.00
28	$250,000.00	15	100.00	11,400.00	15,350.00
29	$700,000.00	73	800.00	36,000.00	63,000.00
30	$262,000.00	54	2,600.00	44,500.00	56,900.00
31	$435,000.00	50	2,287.00	18,600.00	26,067.00
32	$710,000.00	100	5,882.00	48,000.00	59,451.00
33	$300,000.00	150	8,000.00	45,950.00	68,486.00
34	$8,857,000.00	250	10,000.00	53,671.00	79,873.00
35	$50,000.00	100	5,264.00	21,100.00	29,743.00
36	$330,000.00	124	10,000.00	43,000.00	54,700.00
37	$50,000.00	100	6,500.00	19,845.00	28,700.00
38	$625,000.00	75	47,400.00	95,068.00	141,304.00
39	$350,000.00	322	25,000.00	46,621.00	71,887.00
40	$3,565,000.00	92	7,523.00	45,000.00	67,677.00
41	$350,000.00	125	9,727.00	45,600.00	78,260.00

Table 1 Change Orders Data for the Cases adopted from Leonard (1988) (Continued)

No.	Change Orders			Planned Hours	Actual Hours
	$ attributed	Number	Direct Hours		
42	$100,000.00	250	29,200.00	136,540.00	216,500.00
43	$6,321,000.00	86	7,185.00	21,000.00	35,288.00
44	$83,000.00	203	48,360.00	154,000.00	225,130.00
45	$210,000.00	75	6,250.00	145,000.00	162,500.00
46	$258,000.00	50	4,880.00	34,400.00	38,000.00
47	$1,258,000.00	50	5,000.00	32,500.00	36,000.00
48	$17,000.00	169	5,100.00	41,000.00	48,200.00
49	$100,000.00	12	2,270.00	13,600.00	15,120.00
50	$275,000.00	40	3,600.00	16,000.00	19,000.00
51	$1,650,000.00	150	83,000.00	557,000.00	661,600.00
52	$1,094,000.00	25	37,000.00	173,000.00	207,932.00
53	$150,000.00	50	12,000.00	27,000.00	34,500.00
54	$150,000.00	104	4,000.00	7,313.00	10,675.00
55	$331,000.00	21	33,500.00	61,500.00	88,500.00
56	$390,000.00	91	18,700.00	33,000.00	43,300.00
57	$71,000.00	120	30,000.00	35,000.00	53,000.00
58	$250,000.00	140	450.00	3,300.00	4,400.00
59	$1,600,000.00	7	2,000.00	28,700.00	39,200.00
60	$120,000.00	91	12,300.00	61,600.00	88,300.00
61	$5,000.00	29	7,500.00	32,400.00	42,200.00
62		107	22,890.00	78,000.00	121,990.00
63	$1,000,000.00	170	23,000.00	33,800.00	57,800.00
64	$200,000.00	65	4,000.00	6,050.00	7,530.00
65	$200,000.00	110	17,200.00	17,000.00	33,300.00
66	$294,000.00	68	4,300.00	37,700.00	55,750.00
67	$331,000.00	700	23,000.00	140,000.00	213,500.00
68	$100,000.00	41	13,800.00	44,000.00	80,500.00
69	$400,000.00	2150	25,500.00	102,000.00	189,000.00

Appendix 3.3 Productivity Loss Data

Table 1 Productivity Loss Data for the Cases adopted from Leonard (1988)

No.	Type of Impact	Additional Major Reasons of Productivity Loss (PL) Else than Change Orders	%PL
1	1		14.00
2	1		21.60
3	2	Delays to structural discrepancies	19.76
4	2	Delays to structural discrepancies	21.07
5	2	Acceleration	23.00
6	2	Increased difficulty	33.44
7	1		11.95
8	1		18.42
9	1		22.81
10	2	Delays to structural discrepancies	14.18
11	2	Delays to structural discrepancies	17.75
12	2	Delays to structural discrepancies	19.03
13	2	Acceleration	21.05
14	2	Acceleration	23.53
15	2	Acceleration	24.64
16	2	Dimensional Discrepancies	26.39
17	2	Inadequate coordination	37.78
18	2	Acceleration	92.65
19	1		6.41
20	1		9.84
21	1		11.44
22	1		25.00
23	1		26.24
24	1		38.06

Table 1 Productivity Loss Data for the Cases adopted from Leonard (1988) (Continued)

No.	Type of Impact	Additional Major Reasons of Productivity Loss (PL) Else than Change Orders	%PL
25	1		38.52
26	1		40.64
27	1		44.41
28	2	Inadequate coordination	0.65
29	2	Inadequate coordination	1.27
30	2	Inadequate coordination	4.57
31	2	Inadequate coordination	8.77
32	2	Acceleration	9.89
33	2	Late release of drawings	11.68
34	2	Late release of drawings	12.52
35	2	Equipment interfacing problems	17.70
36	2	Acceleration	18.28
37	2	Acceleration	22.65
38	2	Inadequate coordination	33.54
39	2	Acceleration	34.78
40	3	Inadequate coordination and Acceleration	11.12
41	3	Impeded access, Change of priorities and Acceleration	12.43
42	3	Inadequate coordination and Acceleration	13.49
43	3	Inadequate coordination and Acceleration	20.36
44	3	Inadequate coordination and Acceleration	21.48
45	1		9.81
46	1		14.04
47	1		14.53
48	1		14.94

Table 1 Productivity Loss Data for the Cases adopted from Leonard (1988) (Continued)

No.	Type of Impact	Additional Major Reasons of Productivity Loss (PL) Else than Change Orders	%PL
49	1		15.06
50	1		15.79
51	1		15.81
52	1		16.80
53	1		24.35
54	1		25.61
55	1		25.79
56	1		28.30
57	1		33.96
58	2	Interference & obstructions	25.00
59	2	Inadequate Coordination	26.79
60	2	Inadequate Coordination	27.85
61	2	Inadequate Coordination	29.46
62	2	Inadequate Coordination	29.88
63	2	Acceleration	38.71
64	2	Acceleration	44.31
65	2	Acceleration	48.95
66	3	Inadequate Coordination and Acceleration	35.09
67	3	Inadequate Coordination and Increased complexity	36.31
68	3	Inadequate Coordination and Acceleration	45.34
69	3	Inadequate Coordination and Increased complexity	46.03

Appendix 4 Preliminary Sets of Data

Table 1 Preliminary Timing Influence Set

No.	Work Type	Type of Impact	Change Orders						Productivity Loss
			Number	Frequency	Average Size	Hours	Hours / Planned	Hours / Actual	
1	M	1	24	0.94	97.13	2331.00	0.0430	0.0405	0.0860
2	M	1	5	0.19	738.20	3691.00	0.0683	0.0653	0.0990
3	M	1	5	0.19	738.20	3691.00	0.0719	0.0653	0.1000
4	E	1	39	9.58	25.36	989.00	0.0798	0.0712	0.1100
5	M	1	98	3.71	90.10	8830.00	0.1285	0.1157	0.1140
6	M	1	98	3.71	90.10	8830.00	0.1233	0.1157	0.1190
7	M	1	24	0.94	97.13	2331.00	0.0470	0.0405	0.1240
8	M	1	15	1.65	66.53	998.00	0.0895	0.0772	0.1260
9	M	1	109	10.31	190.01	20711.50	0.3346	0.2735	0.1880
10	E	1	25	5.64	100.08	2502.00	0.4104	0.3330	0.2160
11	M	1	36	1.44	274.11	9868.00	0.4638	0.3525	0.2400
12	E	1	10	0.48	138.80	1388.00	0.5806	0.4238	0.2700
13	M	1	12	2.26	213.85	2566.25	0.6727	0.4565	0.3200
14	M	1	150	32.82	39.09	5863.00	1.5348	1.1868	0.4380
15	E	2	80	1.83	71.16	5692.50	0.1195	0.0973	0.1900
16	E	2	59	2.45	219.27	12937.02	0.0959	0.0778	0.2020
17	A	2	17	1.56	33.41	568.00	0.0841	0.0649	0.2370
18	E	2	40	2.67	38.95	1558.00	0.2042	0.1657	0.2390
19	A	2	34	1.37	165.03	5611.00	0.1116	0.0849	0.2450
20	E	2	86	3.80	63.02	5420.00	0.3257	0.2235	0.3100
21	E	2	132	5.04	142.76	18844.91	0.3229	0.2167	0.3200
22	M	2	21	1.58	92.05	1933.00	0.3980	0.2660	0.3300
23	M	2	17	2.98	150.01	2550.25	0.5423	0.3680	0.3370
24	M	2	10	2.22	216.15	2161.50	0.5666	0.3845	0.3610
25	A	3	12	1.19	69.75	837.00	0.1429	0.0875	0.3180
26	E	3	14	0.74	7.79	109.00	0.0195	0.0133	0.3200
27	M	3	37	1.42	29.11	1077.00	0.0246	0.0156	0.3260
28	M	3	44	1.68	109.05	4798.00	0.1747	0.0851	0.3280
29	M	3	29	1.05	46.83	1358.00	0.0691	0.0357	0.3600
30	M	3	182	24.93	42.74	7779.25	0.0805	0.0516	0.3840
31	M	3	44	4.78	245.07	10783.00	0.3129	0.1584	0.3930
32	M	3	12	2.79	145.92	1751.00	0.2506	0.1700	0.4080
33	M	3	73	17.68	77.32	5644.00	0.7817	0.3562	0.4940

Table 2 Preliminary Architectural Work Type Influence Set

No.	By	Type of Impact	Change Orders						Productivity Loss
			Number	Frequency	Average Size	Hours	Hours / Planned	Hours / Actual	
1	L	1	46	2.30	108.70	5000.00	0.1639	0.1408	0.1400
2	L	1	100	12.50	94.00	9400.00	0.5402	0.4372	0.2160
3	L	2	20	1.82	65.00	1300.00	0.1000	0.0841	0.1976
4	L	2	25	2.27	80.00	2000.00	0.1626	0.1311	0.2107
5	L	2	20	2.00	300.00	6000.00	0.3000	0.2308	0.2300
6	I	2	17	1.56	33.41	568.00	0.0841	0.0649	0.2370
7	I	2	34	1.37	165.03	5611.00	0.1116	0.0849	0.2450
8	L	2	25	1.32	204.00	5100.00	0.8226	0.5730	0.3344
9	I	3	12	1.19	69.75	837.00	0.1429	0.0875	0.3180

Table 3 Preliminary Civil Work Type Influence Set

No.	By	Type of Impact	Change Orders						Productivity Loss
			Number	Frequency	Average Size	Hours	Hours / Planned	Hours / Actual	
1	L	1	150	16.67	55.33	8,300.00	0.1774	0.1562	0.1402
2	L	1	253	12.05	129.64	32,800.00	0.4136	0.3374	0.1842
3	L	1	190	21.11	113.16	21,500.00	0.4886	0.3772	0.2281
4	L	2	11	0.73	272.73	3,000.00	0.0577	0.0475	0.1873
5	L	2	10	0.71	190.00	1,900.00	0.1333	0.1080	0.1903
6	L	2	12	0.80	191.67	2,300.00	0.1000	0.0858	0.1980
7	L	2	65	6.50	123.08	8,000.00	0.1538	0.1159	0.2065
8	L	2	100	14.29	27.00	2,700.00	0.1929	0.1200	0.2076
9	L	2	10	2.50	650.00	14,200.00	0.1352	0.1068	0.2105
10	L	2	13	0.93	446.77	5,808.00	0.2093	0.1541	0.2171
11	L	2	10	2.50	650.00	6,500.00	0.3333	0.2549	0.2353
12	L	2	190	21.11	113.16	9,600.00	0.3840	0.2697	0.2978

Table 4 Preliminary Electrical Work Type Influence Set

No.	By	Type of Impact	Change Orders						Productivity Loss
			Number	Frequency	Average Size	Hours	Hours / Planned	Hours / Actual	
1	I	1	39	9.58	25.36	989.00	0.0798	0.0712	0.1100
2	L	1	200	12.50	21.94	4388.00	0.0773	0.0641	0.1101
3	L	1	10	0.43	120.00	1200.00	0.1143	0.0984	0.1393
4	L	1	195	7.50	75.00	14625.00	0.1359	0.1144	0.1584
5	L	1	114	4.22	117.98	13450.00	0.2841	0.2500	0.1975
6	L	1	77	2.85	274.68	21150.00	0.3190	0.2624	0.2033
7	I	1	25	5.64	100.08	2502.00	0.4104	0.3330	0.2160
8	L	1	62	2.58	152.45	9452.00	0.5705	0.3806	0.2589
9	L	1	200	14.29	60.00	12000.00	0.4800	0.3852	0.2611
10	I	1	10	0.48	138.80	1388.00	0.5806	0.4238	0.2700
11	L	1	76	2.71	130.70	9933.00	0.5771	0.4064	0.2958
12	L	1	137	5.07	174.09	23850.00	0.6360	0.4441	0.3017
13	I	2	80	1.83	71.16	5692.50	0.1195	0.0973	0.1900
14	I	2	59	2.45	219.27	12937.02	0.0959	0.0778	0.2020
15	L	2	15	0.88	6.67	100.00	0.0088	0.0065	0.2227
16	L	2	73	4.06	10.96	800.00	0.0222	0.0127	0.2253
17	I	2	40	2.67	38.95	1558.00	0.2042	0.1657	0.2390
18	L	2	54	3.18	48.15	2600.00	0.0584	0.0457	0.2392
19	L	2	50	3.13	45.74	2287.00	0.1230	0.0877	0.2568
20	L	2	100	5.00	58.82	5882.00	0.1225	0.0989	0.2616
21	L	2	150	6.52	53.33	8000.00	0.1741	0.1168	0.2691
22	L	2	250	6.76	40.00	10000.00	0.1863	0.1252	0.2726
23	L	2	100	12.50	52.64	5264.00	0.2495	0.1770	0.2906
24	L	2	124	12.40	80.65	10000.00	0.2326	0.1828	0.2968
25	L	2	100	10.00	65.00	6500.00	0.3275	0.2265	0.3085
26	I	2	86	3.80	63.02	5420.00	0.3257	0.2235	0.3100
27	I	2	132	5.04	142.76	18844.91	0.3229	0.2167	0.3200
28	L	2	75	7.50	632.00	47400.00	0.4986	0.3354	0.3272
29	L	2	322	35.78	77.64	25000.00	0.5362	0.3478	0.3515
30	I	3	14	0.74	7.79	109.00	0.0195	0.0133	0.3200
31	L	3	92	4.18	81.77	7523.00	0.1672	0.1112	0.3351
32	L	3	250	17.86	116.80	29200.00	0.2139	0.1349	0.3693
33	L	3	125	4.03	77.82	9727.00	0.2133	0.1243	0.3697
34	L	3	86	3.31	83.55	7185.00	0.3421	0.2036	0.4049
35	L	3	203	7.25	238.23	48360.00	0.3140	0.2148	0.4059

Table 5 Preliminary Mechanical Work Type Influence Set

No.	By	Type of Impact	Change Orders Number	Frequency	Average Size	Hours	Hours / Planned	Hours / Actual	Productivity Loss
1	I	1	24	0.94	97.13	2331.00	0.0430	0.0405	0.0860
2	L	1	75	2.34	83.33	6250.00	0.0431	0.0385	0.0981
3	I	1	5	0.19	738.20	3691.00	0.0683	0.0653	0.0990
4	I	1	5	0.19	738.20	3691.00	0.0719	0.0653	0.1000
5	I	1	98	3.71	90.10	8830.00	0.1285	0.1157	0.1140
6	I	1	98	3.71	90.10	8830.00	0.1233	0.1157	0.1190
7	I	1	24	0.94	97.13	2331.00	0.0470	0.0405	0.1240
8	I	1	15	1.65	66.53	998.00	0.0895	0.0772	0.1260
9	L	1	50	1.92	97.60	4880.00	0.1419	0.1284	0.1404
10	L	1	50	3.33	100.00	5000.00	0.1538	0.1389	0.1453
11	L	1	169	8.89	30.18	5100.00	0.1244	0.1058	0.1494
12	L	1	12	0.40	189.17	2270.00	0.1669	0.1501	0.1506
13	L	1	40	4.44	90.00	3600.00	0.2250	0.1895	0.1579
14	L	1	150	10.71	553.33	83000.00	0.1490	0.1255	0.1581
15	L	1	25	1.67	1480.00	37000.00	0.2139	0.1779	0.1680
16	I	1	109	10.31	190.01	20711.50	0.3346	0.2735	0.1880
17	I	1	36	1.44	274.11	9868.00	0.4638	0.3525	0.2400
18	L	1	50	1.85	240.00	12000.00	0.4444	0.3478	0.2435
19	L	1	104	20.80	38.46	4000.00	0.5470	0.3747	0.2561
20	L	1	21	0.95	1595.24	33500.00	0.5447	0.3785	0.2579
21	L	1	91	3.50	205.49	18700.00	0.5667	0.4319	0.2830
22	I	1	12	2.26	213.85	2566.25	0.6727	0.4565	0.3200
23	L	1	120	7.06	250.00	30000.00	0.8571	0.5660	0.3396
24	I	1	150	32.82	39.09	5863.00	1.5348	1.1868	0.4380
25	L	2	140	11.67	3.21	450.00	0.1364	0.1023	0.2500
26	L	2	7	0.39	285.71	2000.00	0.0697	0.0510	0.2679
27	L	2	91	4.55	135.16	12300.00	0.1997	0.1393	0.2785
28	L	2	29	1.61	258.62	7500.00	0.2315	0.1777	0.2946
29	L	2	107	5.94	213.93	22890.00	0.2935	0.1876	0.2988
30	I	2	21	1.58	92.05	1933.00	0.3980	0.2660	0.3300
31	I	2	17	2.98	150.01	2550.25	0.5423	0.3680	0.3370
32	I	2	10	2.22	216.15	2161.50	0.5666	0.3845	0.3610
33	L	2	170	34.00	135.29	23000.00	0.5263	0.2959	0.3871
34	L	2	65	4.64	61.54	4000.00	0.6612	0.5312	0.4431
35	L	2	110	6.47	156.36	17200.00	1.0118	0.5165	0.4895
36	I	3	37	1.42	29.11	1077.00	0.0246	0.0156	0.3260
37	I	3	44	1.68	109.05	4798.00	0.1747	0.0851	0.3280
38	L	3	68	2.43	63.24	4300.00	0.1141	0.0771	0.3509
39	I	3	29	1.05	46.83	1358.00	0.0691	0.0357	0.3600
40	L	3	700	77.78	32.86	23000.00	0.1643	0.1077	0.3631
41	I	3	182	24.93	42.74	7779.25	0.0805	0.0516	0.3840
42	I	3	44	4.78	245.07	10783.00	0.3129	0.1584	0.3930
43	I	3	12	2.79	145.92	1751.00	0.2506	0.1700	0.4080
44	L	3	41	2.93	336.59	13800.00	0.3136	0.1714	0.4534
45	L	3	2150	195.45	11.86	25500.00	0.2500	0.1349	0.4603
46	I	3	73	17.68	77.32	5644.00	0.7817	0.3562	0.4940

Appendix 5 Data Sets

Table 1 Variables of Data Set "DS_1T_1"

No.	Independent Variables						Dependent Variable
	Type of Impact	Direct Impact (as per Equation 3-5) for Periods					Productivity Loss
		P_1	P_2	P_3	P_4	P_5	
1	1	0.0129	0.0352	0.0599	0.0592	0.0106	0.0860
2	1	0.0305	0.0456	0.0646	0.1000	0.0735	0.0990
3	1	0.0320	0.0480	0.0680	0.1052	0.0772	0.1000
4	1	0.0000	0.1261	0.1912	0.0357	0.0021	0.1100
5	1	0.0584	0.0737	0.1989	0.1614	0.0530	0.1140
6	1	0.0560	0.0707	0.1907	0.1548	0.0508	0.1190
7	1	0.0141	0.0385	0.0655	0.0647	0.0116	0.1240
8	1	0.1548	0.1300	0.0556	0.0924	0.0550	0.1260
9	1	0.0212	0.0767	0.1325	0.4564	1.0529	0.1880
10	1	0.0675	0.1780	0.8631	0.2310	0.3719	0.2160
11	1	0.0000	1.1372	0.3794	0.1993	0.4213	0.2400
12	1	0.0000	0.3101	1.8307	0.1761	0.0310	0.2700
13	1	0.0000	2.6158	0.0779	0.0893	0.5210	0.3200
14	1	1.9892	2.0268	2.2024	0.9116	0.3945	0.4380
15	2	0.0497	0.0332	0.2121	0.1761	0.0080	0.1900
16	2	0.0000	0.0809	0.0758	0.1697	0.0470	0.2020
17	2	0.4060	0.0897	0.0492	0.0560	0.0049	0.2370
18	2	0.0000	0.0000	0.1321	0.3885	0.2068	0.2390
19	2	0.0200	0.0838	0.0675	0.1088	0.2942	0.2450
20	2	0.0235	0.0664	0.4361	0.4571	0.2526	0.3100
21	2	0.0000	0.2816	0.3397	0.4758	0.1883	0.3200
22	2	0.0118	0.0491	0.5920	0.6702	0.2581	0.3300
23	2	0.0000	1.5612	0.3807	0.1272	0.4765	0.3370
24	2	0.0000	1.6676	0.4890	0.0000	0.5052	0.3610
25	3	0.0273	0.0367	0.0544	0.2366	0.3645	0.3180
26	3	0.0000	0.0000	0.0000	0.0339	0.0381	0.3200
27	3	0.0483	0.0119	0.0120	0.0248	0.0526	0.3260
28	3	0.5610	0.0354	0.2790	0.1179	0.0437	0.3280
29	3	0.3860	0.0587	0.0254	0.0503	0.0159	0.3600
30	3	0.1390	0.1256	0.0425	0.0886	0.0419	0.3840
31	3	0.0000	0.0000	0.2033	0.6686	0.5170	0.3930
32	3	0.0000	1.0394	0.0000	0.0000	0.2176	0.4080
33	3	0.6457	1.4095	1.2658	0.2433	0.0000	0.4940

Table 2 Variables of Data Set "DS_2T_2"

No.	Independent Variables						Dependent Variable
	Type of Impact	Ripple Effect as per (Equations 3-6 and 3-7) for Periods:					Productivity Loss
		P_1	P_2	P_3	P_4	P_5	
1	1	0.0117	0.0247	0.0248	0.0089	0.0008	0.0860
2	1	0.0278	0.0321	0.0268	0.0150	0.0055	0.0990
3	1	0.0292	0.0337	0.0282	0.0158	0.0058	0.1000
4	1	0.0000	0.1013	0.1043	0.0082	0.0002	0.1100
5	1	0.0533	0.0518	0.0824	0.0242	0.0040	0.1140
6	1	0.0511	0.0497	0.0790	0.0232	0.0038	0.1190
7	1	0.0128	0.0271	0.0271	0.0097	0.0009	0.1240
8	1	0.1412	0.0914	0.0230	0.0138	0.0041	0.1260
9	1	0.0194	0.0539	0.0549	0.0684	0.0789	0.1880
10	1	0.0642	0.1430	0.4707	0.0530	0.0427	0.2160
11	1	0.0000	0.7992	0.1571	0.0299	0.0316	0.2400
12	1	0.0000	0.2491	0.9983	0.0404	0.0036	0.2700
13	1	0.0000	1.8384	0.0322	0.0134	0.0391	0.3200
14	1	1.8151	1.4244	0.9121	0.1367	0.0296	0.4380
15	2	0.0472	0.0267	0.1157	0.0404	0.0009	0.1900
16	2	0.0000	0.0649	0.0413	0.0389	0.0054	0.2020
17	2	0.3705	0.0630	0.0204	0.0084	0.0004	0.2370
18	2	0.0000	0.0000	0.0720	0.0891	0.0237	0.2390
19	2	0.0183	0.0589	0.0279	0.0163	0.0221	0.2450
20	2	0.0223	0.0534	0.2378	0.1048	0.0290	0.3100
21	2	0.0000	0.2261	0.1853	0.1091	0.0216	0.3200
22	2	0.0107	0.0345	0.2452	0.1005	0.0194	0.3300
23	2	0.0000	1.0972	0.1576	0.0191	0.0357	0.3370
24	2	0.0000	1.1720	0.2025	0.0000	0.0379	0.3610
25	3	0.0249	0.0258	0.0225	0.0355	0.0273	0.3180
26	3	0.0000	0.0000	0.0000	0.0078	0.0044	0.3200
27	3	0.0441	0.0084	0.0050	0.0037	0.0039	0.3260
28	3	0.5119	0.0249	0.1155	0.0177	0.0033	0.3280
29	3	0.3522	0.0413	0.0105	0.0075	0.0012	0.3600
30	3	0.1269	0.0883	0.0176	0.0133	0.0031	0.3840
31	3	0.0000	0.0000	0.0842	0.1003	0.0388	0.3930
32	3	0.0000	0.7305	0.0000	0.0000	0.0163	0.4080
33	3	0.5892	0.9906	0.5242	0.0365	0.0000	0.4940

Table 3 Variables of Data Set "DS_3A_1"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Planned Hours (HCOs/BDOCH)	Productivity Loss
1	1	0.1639	0.1400
2	1	0.5402	0.2160
3	2	0.1000	0.1976
4	2	0.1626	0.2107
5	2	0.3000	0.2300
6	2	0.0841	0.2370
7	2	0.1116	0.2450
8	2	0.8226	0.3344
9	3	0.1429	0.3180

Table 4 Variables of Data Set "DS_4A_2"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Actual Hours (HCOs/ADOCH)	Productivity Loss
1	1	0.1408	0.1400
2	1	0.4372	0.2160
3	2	0.0841	0.1976
4	2	0.1311	0.2107
5	2	0.2308	0.2300
6	2	0.0649	0.2370
7	2	0.0849	0.2450
8	2	0.5730	0.3344
9	3	0.0875	0.3180

Table 5 Variables of Data Set "DS_5C_1"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Planned Hours (HCOs/BDOCH)	Productivity Loss
1	1	0.1774	0.1402
2	1	0.4136	0.1842
3	1	0.4886	0.2281
4	2	0.0577	0.1873
5	2	0.1333	0.1903
6	2	0.1000	0.1980
7	2	0.1538	0.2065
8	2	0.1929	0.2076
9	2	0.1352	0.2105
10	2	0.2093	0.2171
11	2	0.3333	0.2353
12	2	0.3840	0.2978

Table 6 Variables for Data Set "DS_6C_2"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Actual Hours (HCOs/ADOCH)	Productivity Loss
1	1	0.1562	0.1402
2	1	0.3374	0.1842
3	1	0.3772	0.2281
4	2	0.0475	0.1873
5	2	0.1080	0.1903
6	2	0.0858	0.1980
7	2	0.1159	0.2065
8	2	0.1200	0.2076
9	2	0.1068	0.2105
10	2	0.1541	0.2171
11	2	0.2549	0.2353
12	2	0.2697	0.2978

Table 7 Variables for Data Set "DS_7E_1"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Planned Hours (HCOs/BDOCH)	Productivity Loss
1	1	0.0798	0.1100
2	1	0.0773	0.1101
3	1	0.1143	0.1393
4	1	0.1359	0.1584
5	1	0.2841	0.1975
6	1	0.3190	0.2033
7	1	0.4104	0.2160
8	1	0.5705	0.2589
9	1	0.4800	0.2611
10	1	0.5806	0.2700
11	1	0.5771	0.2958
12	1	0.6360	0.3017
13	2	0.1195	0.1900
14	2	0.0959	0.2020
15	2	0.0088	0.2227
16	2	0.0222	0.2253
17	2	0.2042	0.2390
18	2	0.0584	0.2392
19	2	0.1230	0.2568
20	2	0.1225	0.2616
21	2	0.1741	0.2691
22	2	0.1863	0.2726
23	2	0.2495	0.2906
24	2	0.2326	0.2968
25	2	0.3275	0.3085
26	2	0.3257	0.3100
27	2	0.3229	0.3200
28	2	0.4986	0.3272
29	2	0.5362	0.3515
30	3	0.0195	0.3200
31	3	0.1672	0.3351
32	3	0.2139	0.3693
33	3	0.2133	0.3697
34	3	0.3421	0.4049
35	3	0.3140	0.4059

Table 8 Variables for Data Set "DS_8E_2"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Planned Hours (HCOs/BDOCH)	Productivity Loss
1	1	0.0712	0.1100
2	1	0.0641	0.1101
3	1	0.0984	0.1393
4	1	0.1144	0.1584
5	1	0.2500	0.1975
6	1	0.2624	0.2033
7	1	0.3330	0.2160
8	1	0.3806	0.2589
9	1	0.3852	0.2611
10	1	0.4238	0.2700
11	1	0.4064	0.2958
12	1	0.4441	0.3017
13	2	0.0973	0.1900
14	2	0.0778	0.2020
15	2	0.0065	0.2227
16	2	0.0127	0.2253
17	2	0.1657	0.2390
18	2	0.0457	0.2392
19	2	0.0877	0.2568
20	2	0.0989	0.2616
21	2	0.1168	0.2691
22	2	0.1252	0.2726
23	2	0.1770	0.2906
24	2	0.1828	0.2968
25	2	0.2265	0.3085
26	2	0.2235	0.3100
27	2	0.2167	0.3200
28	2	0.3354	0.3272
29	2	0.3478	0.3515
30	3	0.0133	0.3200
31	3	0.1112	0.3351
32	3	0.1349	0.3693
33	3	0.1243	0.3697
34	3	0.2036	0.4049
35	3	0.2148	0.4059

Table 9 Variables for Data Set "DS_9M_1"

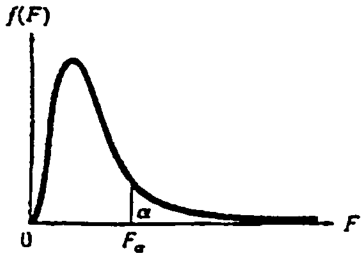
No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Planned Hours (HCOs/BDOCH)	Productivity Loss
1	1	0.0430	0.0860
2	1	0.0431	0.0981
3	1	0.0683	0.0990
4	1	0.0719	0.1000
5	1	0.1285	0.1140
6	1	0.1233	0.1190
7	1	0.0470	0.1240
8	1	0.0895	0.1260
9	1	0.1419	0.1404
10	1	0.1538	0.1453
11	1	0.1244	0.1494
12	1	0.1669	0.1506
13	1	0.2250	0.1579
14	1	0.1490	0.1581
15	1	0.2139	0.1680
16	1	0.3346	0.1880
17	1	0.4638	0.2400
18	1	0.4444	0.2435
19	1	0.5470	0.2561
20	1	0.5447	0.2579
21	1	0.5667	0.2830
22	1	0.6727	0.3200
23	1	0.8571	0.3396
24	1	1.5348	0.4380
25	2	0.1364	0.2500
26	2	0.0697	0.2679
27	2	0.1997	0.2785
28	2	0.2315	0.2946
29	2	0.2935	0.2988
30	2	0.3980	0.3300
31	2	0.5423	0.3370
32	2	0.5666	0.3610
33	2	0.5263	0.3871
34	2	0.6612	0.4431
35	2	1.0118	0.4895
36	3	0.0246	0.3260
37	3	0.1747	0.3280
38	3	0.1141	0.3509
39	3	0.0691	0.3600
40	3	0.1643	0.3631
41	3	0.0805	0.3840
42	3	0.3129	0.3930
43	3	0.2506	0.4080
44	3	0.3136	0.4534
45	3	0.2500	0.4603
46	3	0.7817	0.4940

Table 10 Variables for Data Set "$DS_{10}M_2$"

No.	Independent Variables		Dependent Variable
	Type of Impact	Change Orders Hours / Actual Hours (HCOs/ADOCH)	Productivity Loss
1	1	0.0405	0.0860
2	1	0.0385	0.0981
3	1	0.0653	0.0990
4	1	0.0653	0.1000
5	1	0.1157	0.1140
6	1	0.1157	0.1190
7	1	0.0405	0.1240
8	1	0.0772	0.1260
9	1	0.1284	0.1404
10	1	0.1389	0.1453
11	1	0.1058	0.1494
12	1	0.1501	0.1506
13	1	0.1895	0.1579
14	1	0.1255	0.1581
15	1	0.1779	0.1680
16	1	0.2735	0.1880
17	1	0.3525	0.2400
18	1	0.3478	0.2435
19	1	0.3747	0.2561
20	1	0.3785	0.2579
21	1	0.4319	0.2830
22	1	0.4565	0.3200
23	1	0.5660	0.3396
24	1	1.1868	0.4380
25	2	0.1023	0.2500
26	2	0.0510	0.2679
27	2	0.1393	0.2785
28	2	0.1777	0.2946
29	2	0.1876	0.2988
30	2	0.2660	0.3300
31	2	0.3680	0.3370
32	2	0.3845	0.3610
33	2	0.2959	0.3871
34	2	0.5312	0.4431
35	2	0.5165	0.4895
36	3	0.0156	0.3260
37	3	0.0851	0.3280
38	3	0.0771	0.3509
39	3	0.0357	0.3600
40	3	0.1077	0.3631
41	3	0.0516	0.3840
42	3	0.1584	0.3930
43	3	0.1700	0.4080
44	3	0.1714	0.4534
45	3	0.1349	0.4603
46	3	0.3562	0.4940

Appendix 6 Table of Critical Values of the F-Statistic and T-Test

Table1 Critical Values of F-Statistic (adopted from Sincich et al., 1999)

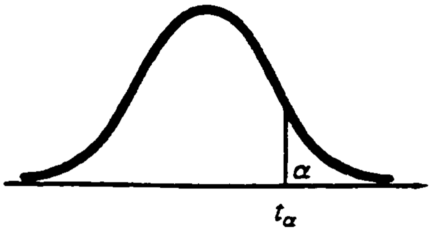


ν_2 \ ν_1	NUMERATOR DEGREES OF FREEDOM 1	2	3	4	5	6	7	8	9
1	161.4	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38
3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39
21	4.32	3.47	3.07	2.84	2.68	2.57	2.49	2.42	2.37
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.77
27	4.21	3.35	2.96	2.73	2.57	2.46	2.37	2.31	2.25
28	4.20	3.34	2.95	2.71	2.56	2.45	2.36	2.29	2.24
29	4.18	3.33	2.93	2.70	2.55	2.43	2.35	2.28	2.22
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21
40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04
120	3.92	3.07	2.68	2.45	2.29	2.17	2.09	2.02	1.96
∞	3.84	3.00	2.60	2.37	2.21	2.10	2.01	1.94	1.88

DENOMINATOR DEGREES OF FREEDOM

Source: From M. Merrington and C. M. Thompson. "Tables of Percentage Points of the Inverted Beta (*F*)-Distribution." *Biometrika*, 1943, 33, 73–88. Reproduced by permission of the *Biometrika* Trustees and Oxford University Press.

Table 2 Values of t_α (adopted from Sincich et al., 1999)



Degrees of Freedom	$t_{.100}$	$t_{.050}$	$t_{.025}$	$t_{.010}$	$t_{.005}$	$t_{.001}$	$t_{.0005}$
1	3.078	6.314	12.706	31.821	63.657	318.31	636.62
2	1.886	2.920	4.303	6.965	9.925	22.326	31.598
3	1.638	2.353	3.182	4.541	5.841	10.213	12.924
4	1.533	2.132	2.776	3.747	4.604	7.173	8.610
5	1.476	2.015	2.571	3.365	4.032	5.893	6.869
6	1.440	1.943	2.447	3.143	3.707	5.208	5.959
7	1.415	1.895	2.365	2.998	3.499	4.785	5.408
8	1.397	1.860	2.306	2.896	3.355	4.501	5.041
9	1.383	1.833	2.262	2.821	3.250	4.297	4.781
10	1.372	1.812	2.228	2.764	3.169	4.144	4.587
11	1.363	1.796	2.201	2.718	3.106	4.025	4.437
12	1.356	1.782	2.179	2.681	3.055	3.930	4.318
13	1.350	1.771	2.160	2.650	3.012	3.852	4.221
14	1.345	1.761	2.145	2.624	2.977	3.787	4.140
15	1.341	1.753	2.131	2.602	2.947	3.733	4.073
16	1.337	1.746	2.120	2.583	2.921	3.686	4.015
17	1.333	1.740	2.110	2.567	2.898	3.646	3.965
18	1.330	1.734	2.101	2.552	2.878	3.610	3.922
19	1.328	1.729	2.093	2.539	2.861	3.579	3.883
20	1.325	1.725	2.086	2.528	2.845	3.552	3.850
21	1.323	1.721	2.080	2.518	2.831	3.527	3.819
22	1.321	1.717	2.074	2.508	2.819	3.505	3.792
23	1.319	1.714	2.069	2.500	2.807	3.485	3.767
24	1.318	1.711	2.064	2.492	2.797	3.467	3.745
25	1.316	1.708	2.060	2.485	2.787	3.450	3.725
26	1.315	1.706	2.056	2.479	2.779	3.435	3.707
27	1.314	1.703	2.052	2.473	2.771	3.421	3.690
28	1.313	1.701	2.048	2.467	2.763	3.408	3.674
29	1.311	1.699	2.045	2.462	2.756	3.396	3.659
30	1.310	1.697	2.042	2.457	2.750	3.385	3.646
40	1.303	1.684	2.021	2.423	2.704	3.307	3.551
60	1.296	1.671	2.000	2.390	2.660	3.232	3.460
120	1.289	1.658	1.980	2.358	2.617	3.160	3.373
∞	1.282	1.645	1.960	2.326	2.576	3.090	3.291

Source: This table is reproduced with the kind permission of the Trustees of Biometrika and Oxford University Press from E. S. Pearson and H. O. Hartley (eds.), *The Biometrika Tables for Statisticians*, Vol. 1, 3rd ed., *Biometrika*, 1966.

Appendix 7 Prediction Results of Productivity Loss

Table 1 Prediction Results of Productivity Loss for DS_1T_1

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.0860	0.1054	-0.0194	0.0004	0.0194	22.54%	0.1031	-0.0171	0.0003	0.0171	19.92%
2	0.0990	0.1118	-0.0128	0.0002	0.0128	12.94%	0.1026	-0.0036	0.0000	0.0036	3.59%
3	0.1000	0.1127	-0.0127	0.0002	0.0127	12.73%	0.1027	-0.0027	0.0000	0.0027	2.73%
4	0.1100	0.1187	-0.0087	0.0001	0.0087	7.90%	0.1114	-0.0014	0.0000	0.0014	1.26%
5	0.1140	0.1267	-0.0127	0.0002	0.0127	11.17%	0.1147	-0.0007	0.0000	0.0007	0.57%
6	0.1190	0.1254	-0.0064	0.0000	0.0064	5.38%	0.1133	0.0057	0.0000	0.0057	4.79%
7	0.1240	0.1065	0.0175	0.0003	0.0175	14.15%	0.1035	0.0205	0.0004	0.0205	16.55%
8	0.1260	0.1138	0.0122	0.0001	0.0122	9.71%	0.1257	0.0003	0.0000	0.0003	0.27%
9	0.1880	0.1848	0.0032	0.0000	0.0032	1.71%	0.1882	-0.0002	0.0000	0.0002	0.11%
10	0.2160	0.1981	0.0179	0.0003	0.0179	8.29%	0.2159	0.0001	0.0000	0.0001	0.06%
11	0.2400	0.2284	0.0116	0.0001	0.0116	4.82%	0.2400	0.0000	0.0000	0.0000	0.02%
12	0.2700	0.2583	0.0117	0.0001	0.0117	4.34%	0.2703	-0.0003	0.0000	0.0003	0.10%
13	0.3200	0.3011	0.0189	0.0004	0.0189	5.90%	0.3199	0.0001	0.0000	0.0001	0.02%
14	0.4380	0.4429	-0.0049	0.0000	0.0049	1.11%	0.4381	-0.0001	0.0000	0.0001	0.02%
15	0.1900	0.2365	-0.0465	0.0022	0.0465	24.49%	0.1898	0.0002	0.0000	0.0002	0.08%
16	0.2020	0.2318	-0.0298	0.0009	0.0298	14.77%	0.2023	-0.0003	0.0000	0.0003	0.13%
17	0.2370	0.2144	0.0226	0.0005	0.0226	9.55%	0.2371	-0.0001	0.0000	0.0001	0.05%
18	0.2390	0.2537	-0.0147	0.0002	0.0147	6.17%	0.2390	0.0000	0.0000	0.0000	0.00%
19	0.2450	0.2360	0.0090	0.0001	0.0090	3.66%	0.2451	-0.0001	0.0000	0.0001	0.03%
20	0.3100	0.2864	0.0236	0.0006	0.0236	7.63%	0.2914	0.0186	0.0003	0.0186	6.00%
21	0.3200	0.2932	0.0268	0.0007	0.0268	8.37%	0.3200	0.0000	0.0000	0.0000	0.01%
22	0.3300	0.3132	0.0168	0.0003	0.0168	5.09%	0.3301	-0.0001	0.0000	0.0001	0.04%
23	0.3370	0.3654	-0.0284	0.0008	0.0284	8.41%	0.3371	-0.0001	0.0000	0.0001	0.02%
24	0.3610	0.3712	-0.0102	0.0001	0.0102	2.84%	0.3609	0.0001	0.0000	0.0001	0.03%
25	0.3180	0.3566	-0.0386	0.0015	0.0386	12.15%	0.3181	-0.0001	0.0000	0.0001	0.02%
26	0.3200	0.3222	-0.0022	0.0000	0.0022	0.68%	0.3200	0.0000	0.0000	0.0000	0.01%
27	0.3260	0.3230	0.0030	0.0000	0.0030	0.92%	0.3261	-0.0001	0.0000	0.0001	0.05%
28	0.3280	0.3431	-0.0151	0.0002	0.0151	4.61%	0.3276	0.0004	0.0000	0.0004	0.11%
29	0.3600	0.3229	0.0371	0.0014	0.0371	10.30%	0.3582	0.0018	0.0000	0.0018	0.49%
30	0.3840	0.3360	0.0480	0.0023	0.0480	12.49%	0.3838	0.0002	0.0000	0.0002	0.05%
31	0.3930	0.4048	-0.0118	0.0001	0.0118	3.00%	0.3931	-0.0001	0.0000	0.0001	0.02%
32	0.4080	0.3958	0.0122	0.0001	0.0122	2.98%	0.4080	0.0000	0.0000	0.0000	0.00%
33	0.4940	0.5110	-0.0170	0.0003	0.0170	3.45%	0.4940	0.0000	0.0000	0.0000	0.00%

Table 2 Prediction Results of Productivity Loss for DS_2T_2

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.0860	0.1011	-0.0151	0.0002	0.0151	17.58%	0.1024	-0.0164	0.0003	0.0164	19.05%
2	0.0990	0.1078	-0.0088	0.0001	0.0088	8.91%	0.1002	-0.0012	0.0000	0.0012	1.24%
3	0.1000	0.1087	-0.0087	0.0001	0.0087	8.68%	0.1004	-0.0004	0.0000	0.0004	0.40%
4	0.1100	0.1181	-0.0081	0.0001	0.0081	7.33%	0.1101	-0.0001	0.0000	0.0001	0.06%
5	0.1140	0.1199	-0.0059	0.0000	0.0059	5.14%	0.1167	-0.0027	0.0000	0.0027	2.37%
6	0.1190	0.1187	0.0003	0.0000	0.0003	0.26%	0.1150	0.0040	0.0000	0.0040	3.33%
7	0.1240	0.1020	0.0220	0.0005	0.0220	17.71%	0.1028	0.0212	0.0005	0.0212	17.11%
8	0.1260	0.1130	0.0130	0.0002	0.0130	10.30%	0.1249	0.0011	0.0000	0.0011	0.87%
9	0.1880	0.1832	0.0048	0.0000	0.0048	2.57%	0.1876	0.0004	0.0000	0.0004	0.20%
10	0.2160	0.2156	0.0004	0.0000	0.0004	0.17%	0.2161	-0.0001	0.0000	0.0001	0.05%
11	0.2400	0.2229	0.0171	0.0003	0.0171	7.14%	0.2399	0.0001	0.0000	0.0001	0.06%
12	0.2700	0.2622	0.0078	0.0001	0.0078	2.87%	0.2702	-0.0002	0.0000	0.0002	0.07%
13	0.3200	0.3075	0.0125	0.0002	0.0125	3.91%	0.3200	0.0000	0.0000	0.0000	0.01%
14	0.4380	0.4422	-0.0042	0.0000	0.0042	0.96%	0.4382	-0.0002	0.0000	0.0002	0.04%
15	0.1900	0.2385	-0.0485	0.0024	0.0485	25.53%	0.1902	-0.0002	0.0000	0.0002	0.12%
16	0.2020	0.2346	-0.0326	0.0011	0.0326	16.13%	0.2016	0.0004	0.0000	0.0004	0.19%
17	0.2370	0.2200	0.0170	0.0003	0.0170	7.15%	0.2371	-0.0001	0.0000	0.0001	0.03%
18	0.2390	0.2644	-0.0254	0.0006	0.0254	10.63%	0.3018	-0.0628	0.0039	0.0628	26.26%
19	0.2450	0.2343	0.0107	0.0001	0.0107	4.38%	0.2451	-0.0001	0.0000	0.0001	0.05%
20	0.3100	0.3009	0.0091	0.0001	0.0091	2.94%	0.3105	-0.0005	0.0000	0.0005	0.17%
21	0.3200	0.3079	0.0121	0.0001	0.0121	3.79%	0.3205	-0.0005	0.0000	0.0005	0.15%
22	0.3300	0.2918	0.0382	0.0015	0.0382	11.57%	0.3301	-0.0001	0.0000	0.0001	0.02%
23	0.3370	0.3630	-0.0260	0.0007	0.0260	7.72%	0.3369	0.0001	0.0000	0.0001	0.04%
24	0.3610	0.3698	-0.0088	0.0001	0.0088	2.45%	0.3611	-0.0001	0.0000	0.0001	0.03%
25	0.3180	0.3540	-0.0360	0.0013	0.0360	11.31%	0.3185	-0.0005	0.0000	0.0005	0.15%
26	0.3200	0.3220	-0.0020	0.0000	0.0020	0.64%	0.3205	-0.0005	0.0000	0.0005	0.16%
27	0.3260	0.3221	0.0039	0.0000	0.0039	1.21%	0.3260	0.0000	0.0000	0.0000	0.01%
28	0.3280	0.3480	-0.0200	0.0004	0.0200	6.10%	0.3282	-0.0002	0.0000	0.0002	0.05%
29	0.3600	0.3290	0.0310	0.0010	0.0310	8.61%	0.3601	-0.0001	0.0000	0.0001	0.03%
30	0.3840	0.3358	0.0482	0.0023	0.0482	12.56%	0.3459	0.0381	0.0015	0.0381	9.93%
31	0.3930	0.3927	0.0003	0.0000	0.0003	0.08%	0.3929	0.0001	0.0000	0.0001	0.02%
32	0.4080	0.3987	0.0093	0.0001	0.0093	2.29%	0.4078	0.0002	0.0000	0.0002	0.04%
33	0.4940	0.5017	-0.0077	0.0001	0.0077	1.56%	0.4939	0.0001	0.0000	0.0001	0.02%

Table 3 Prediction Results of Productivity Loss for DS_3A_1

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1400	0.1442	-0.0042	1.8E-05	0.0042	3.02%	0.1407	-0.0007	4.4E-07	0.0007	0.47%
2	0.2160	0.2043	0.0117	1.4E-04	0.0117	5.42%	0.2161	0.0000	2.3E-09	0.0000	0.02%
3	0.1976	0.2188	-0.0213	4.5E-04	0.0213	10.77%	0.2163	-0.0187	3.5E-04	0.0187	9.48%
4	0.2107	0.2288	-0.0181	3.3E-04	0.0181	8.60%	0.2078	0.0029	8.7E-06	0.0029	1.40%
5	0.2300	0.2508	-0.0208	4.3E-04	0.0208	9.04%	0.2227	0.0073	5.4E-05	0.0073	3.19%
6	0.2370	0.2163	0.0207	4.3E-04	0.0207	8.74%	0.2188	0.0182	3.3E-04	0.0182	7.67%
7	0.2450	0.2207	0.0243	5.9E-04	0.0243	9.92%	0.2145	0.0305	9.3E-04	0.0305	12.45%
8	0.3344	0.3343	0.0002	3.3E-08	0.0002	0.05%	0.3344	0.0000	8.9E-16	0.0000	0.00%
9	0.3180	0.3105	0.0075	5.6E-05	0.0075	2.35%	0.3179	0.0001	1.2E-08	0.0001	0.03%

Table 4 Prediction Results of Productivity Loss for DS_4A_2

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1400	0.1412	-0.0012	1.4E-06	0.0012	0.83%	0.1436	-0.0036	1.3E-05	0.0036	2.54%
2	0.2160	0.2084	0.0077	5.9E-05	0.0077	3.55%	0.2165	-0.0005	2.1E-07	0.0005	0.21%
3	0.1976	0.2195	-0.0220	4.8E-04	0.0220	11.12%	0.2065	-0.0090	8.0E-05	0.0090	4.54%
4	0.2107	0.2302	-0.0195	3.8E-04	0.0195	9.24%	0.2044	0.0063	4.0E-05	0.0063	2.98%
5	0.2300	0.2528	-0.0228	5.2E-04	0.0228	9.90%	0.2313	-0.0013	1.8E-06	0.0013	0.58%
6	0.2370	0.2152	0.0218	4.8E-04	0.0218	9.21%	0.2083	0.0287	8.3E-04	0.0287	12.13%
7	0.2450	0.2197	0.0253	6.4E-04	0.0253	10.32%	0.2065	0.0385	1.5E-03	0.0385	15.73%
8	0.3344	0.3304	0.0041	1.7E-05	0.0041	1.22%	0.3316	0.0028	8.0E-06	0.0028	0.85%
9	0.3180	0.3115	0.0065	4.2E-05	0.0065	2.05%	0.3181	-0.0001	1.1E-08	0.0001	0.03%

Table 5 Prediction Results of Productivity Loss for DS_5C_1

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1402	0.1338	0.0064	4.0E-05	0.0064	4.54%	0.1402	0.0000	2.9E-16	0.0000	0.00%
2	0.1842	0.1990	-0.0148	2.2E-04	0.0148	8.03%	0.1834	0.0008	6.0E-07	0.0008	0.42%
3	0.2281	0.2196	0.0084	7.1E-05	0.0084	3.70%	0.2281	0.0000	3.0E-11	0.0000	0.00%
4	0.1873	0.1806	0.0067	4.5E-05	0.0067	3.60%	0.1873	0.0000	1.2E-09	0.0000	0.02%
5	0.1903	0.2014	-0.0111	1.2E-04	0.0111	5.81%	0.1996	-0.0092	8.5E-05	0.0092	4.85%
6	0.1980	0.1922	0.0058	3.4E-05	0.0058	2.93%	0.1928	0.0053	2.8E-05	0.0053	2.65%
7	0.2065	0.2071	-0.0006	3.6E-07	0.0006	0.29%	0.2046	0.0019	3.6E-06	0.0019	0.92%
8	0.2076	0.2178	-0.0102	1.0E-04	0.0102	4.92%	0.2120	-0.0044	1.9E-05	0.0044	2.11%
9	0.2105	0.2019	0.0086	7.4E-05	0.0086	4.08%	0.2000	0.0105	1.1E-04	0.0105	4.99%
10	0.2171	0.2224	-0.0052	2.7E-05	0.0052	2.40%	0.2119	0.0052	2.7E-05	0.0052	2.41%
11	0.2353	0.2566	-0.0213	4.5E-04	0.0213	9.04%	0.2357	-0.0004	1.3E-07	0.0004	0.15%
12	0.2978	0.2705	0.0272	7.4E-04	0.0272	9.14%	0.2952	0.0026	6.6E-06	0.0026	0.86%

Table 6 Prediction Results of Productivity Loss for DS_6C_2

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1402	0.1332	0.0070	4.9E-05	0.0070	4.99%	0.1406	-0.0005	2.1E-07	0.0005	0.33%
2	0.1842	0.2021	-0.0179	3.2E-04	0.0179	9.72%	0.1842	0.0000	2.4E-14	0.0000	0.00%
3	0.2281	0.2172	0.0109	1.2E-04	0.0109	4.78%	0.2282	-0.0001	1.8E-08	0.0001	0.06%
4	0.1873	0.1814	0.0058	3.4E-05	0.0058	3.12%	0.1901	-0.0029	8.1E-06	0.0029	1.52%
5	0.1903	0.2044	-0.0141	2.0E-04	0.0141	7.40%	0.2022	-0.0118	1.4E-04	0.0118	6.22%
6	0.1980	0.1960	0.0020	4.0E-06	0.0020	1.01%	0.1946	0.0035	1.2E-05	0.0035	1.75%
7	0.2065	0.2075	-0.0010	1.0E-06	0.0010	0.49%	0.2058	0.0007	4.7E-07	0.0007	0.33%
8	0.2076	0.2090	-0.0014	2.0E-06	0.0014	0.68%	0.2077	-0.0001	3.4E-09	0.0001	0.03%
9	0.2105	0.2040	0.0065	4.3E-05	0.0065	3.11%	0.2017	0.0089	7.8E-05	0.0089	4.21%
10	0.2171	0.2219	-0.0048	2.3E-05	0.0048	2.22%	0.2191	-0.0020	3.8E-06	0.0020	0.90%
11	0.2353	0.2603	-0.0250	6.2E-04	0.0250	10.61%	0.2360	-0.0008	5.7E-07	0.0008	0.32%
12	0.2978	0.2659	0.0319	1.0E-03	0.0319	10.71%	0.2974	0.0004	1.2E-07	0.0004	0.12%

Table 7 Prediction Results of Productivity Loss for DS_7E_1

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1100	0.1297	-0.0197	3.90E-04	0.0197	17.94%	0.1118	-0.0018	3.18E-06	0.0018	1.62%
2	0.1101	0.1290	-0.0189	3.58E-04	0.0189	17.17%	0.1104	-0.0003	7.19E-08	0.0003	0.24%
3	0.1393	0.1399	-0.0006	3.42E-07	0.0006	0.42%	0.1389	0.0004	1.29E-07	0.0004	0.26%
4	0.1584	0.1462	0.0122	1.48E-04	0.0122	7.67%	0.1602	-0.0018	3.20E-06	0.0018	1.13%
5	0.1975	0.1898	0.0077	5.95E-05	0.0077	3.91%	0.2021	-0.0046	2.15E-05	0.0046	2.35%
6	0.2033	0.2001	0.0032	1.05E-05	0.0032	1.59%	0.2038	-0.0005	2.57E-07	0.0005	0.25%
7	0.2160	0.2269	-0.0109	1.20E-04	0.0109	5.06%	0.2247	-0.0087	7.59E-05	0.0087	4.03%
8	0.2589	0.2740	-0.0151	2.28E-04	0.0151	5.83%	0.2857	-0.0268	7.20E-04	0.0268	10.37%
9	0.2611	0.2474	0.0137	1.88E-04	0.0137	5.25%	0.2612	-0.0001	6.72E-09	0.0001	0.03%
10	0.2700	0.2769	-0.0069	4.82E-05	0.0069	2.57%	0.2872	-0.0172	2.94E-04	0.0172	6.35%
11	0.2958	0.2759	0.0199	3.95E-04	0.0199	6.72%	0.2867	0.0091	8.30E-05	0.0091	3.08%
12	0.3017	0.2932	0.0085	7.16E-05	0.0085	2.80%	0.2926	0.0091	8.31E-05	0.0091	3.02%
13	0.1900	0.2415	-0.0515	2.65E-03	0.0515	27.10%	0.2366	-0.0466	2.17E-03	0.0466	24.51%
14	0.2020	0.2346	-0.0326	1.06E-03	0.0326	16.12%	0.2322	-0.0302	9.10E-04	0.0302	14.94%
15	0.2227	0.2089	0.0138	1.89E-04	0.0138	6.18%	0.2243	-0.0016	2.49E-06	0.0016	0.71%
16	0.2253	0.2129	0.0124	1.54E-04	0.0124	5.50%	0.2250	0.0003	8.29E-08	0.0003	0.13%
17	0.2390	0.2664	-0.0274	7.51E-04	0.0274	11.47%	0.2735	-0.0345	1.19E-03	0.0345	14.43%
18	0.2392	0.2235	0.0157	2.45E-04	0.0157	6.55%	0.2277	0.0115	1.33E-04	0.0115	4.82%
19	0.2568	0.2425	0.0143	2.04E-04	0.0143	5.56%	0.2374	0.0194	3.78E-04	0.0194	7.57%
20	0.2616	0.2424	0.0192	3.69E-04	0.0192	7.34%	0.2373	0.0243	5.92E-04	0.0243	9.30%
21	0.2691	0.2575	0.0116	1.34E-04	0.0116	4.29%	0.2558	0.0133	1.77E-04	0.0133	4.95%
22	0.2726	0.2611	0.0115	1.31E-04	0.0115	4.21%	0.2625	0.0101	1.03E-04	0.0101	3.72%
23	0.2906	0.2797	0.0109	1.19E-04	0.0109	3.75%	0.2984	-0.0078	6.02E-05	0.0078	2.67%
24	0.2968	0.2747	0.0221	4.87E-04	0.0221	7.44%	0.2907	0.0061	3.76E-05	0.0061	2.07%
25	0.3085	0.3026	0.0059	3.43E-05	0.0059	1.90%	0.3127	-0.0042	1.74E-05	0.0042	1.35%
26	0.3100	0.3021	0.0079	6.22E-05	0.0079	2.54%	0.3125	-0.0025	6.23E-06	0.0025	0.81%
27	0.3200	0.3013	0.0187	3.51E-04	0.0187	5.85%	0.3122	0.0078	6.05E-05	0.0078	2.43%
28	0.3272	0.3529	-0.0257	6.62E-04	0.0257	7.86%	0.3370	-0.0098	9.57E-05	0.0098	2.99%
29	0.3515	0.3640	-0.0125	1.56E-04	0.0125	3.55%	0.3424	0.0091	8.20E-05	0.0091	2.58%
30	0.3200	0.3122	0.0078	6.14E-05	0.0078	2.45%	0.3191	0.0009	8.60E-07	0.0009	0.29%
31	0.3351	0.3556	-0.0205	4.20E-04	0.0205	6.11%	0.3375	-0.0024	5.91E-06	0.0024	0.73%
32	0.3693	0.3693	0.0000	2.08E-11	0.0000	0.00%	0.3669	0.0024	5.68E-06	0.0024	0.65%
33	0.3697	0.3691	0.0006	3.09E-07	0.0006	0.15%	0.3665	0.0032	1.03E-05	0.0032	0.87%
34	0.4049	0.4070	-0.0021	4.47E-06	0.0021	0.52%	0.4056	-0.0007	5.55E-07	0.0007	0.18%
35	0.4059	0.3987	0.0072	5.11E-05	0.0072	1.76%	0.4053	0.0006	4.21E-07	0.0006	0.16%

Table 8 Prediction Results of Productivity Loss for DS_8E_2

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.1100	0.1252	-0.0152	2.30E-04	0.0152	13.77%	0.1114	-0.0014	1.85E-06	0.0014	1.23%
2	0.1101	0.1220	-0.0119	1.43E-04	0.0119	10.84%	0.1100	0.0001	1.00E-08	0.0001	0.09%
3	0.1393	0.1369	0.0024	5.54E-06	0.0024	1.69%	0.1341	0.0052	2.68E-05	0.0052	3.71%
4	0.1584	0.1439	0.0145	2.10E-04	0.0145	9.15%	0.1577	0.0007	5.05E-07	0.0007	0.45%
5	0.1975	0.2029	-0.0054	2.86E-05	0.0054	2.71%	0.1986	-0.0011	1.29E-06	0.0011	0.58%
6	0.2033	0.2082	-0.0049	2.44E-05	0.0049	2.43%	0.2003	0.0030	9.08E-06	0.0030	1.48%
7	0.2160	0.2389	-0.0229	5.26E-04	0.0229	10.61%	0.2153	0.0007	4.27E-07	0.0007	0.30%
8	0.2589	0.2596	-0.0007	5.12E-07	0.0007	0.28%	0.2594	-0.0005	2.92E-07	0.0005	0.21%
9	0.2611	0.2616	-0.0005	2.77E-07	0.0005	0.20%	0.2635	-0.0024	5.63E-06	0.0024	0.91%
10	0.2700	0.2784	-0.0084	7.05E-05	0.0084	3.11%	0.2861	-0.0161	2.60E-04	0.0161	5.97%
11	0.2958	0.2708	0.0250	6.23E-04	0.0250	8.44%	0.2780	0.0178	3.15E-04	0.0178	6.00%
12	0.3017	0.2872	0.0145	2.10E-04	0.0145	4.80%	0.2926	0.0091	8.30E-05	0.0091	3.02%
13	0.1900	0.2452	-0.0552	3.05E-03	0.0552	29.06%	0.2399	-0.0499	2.49E-03	0.0499	26.26%
14	0.2020	0.2368	-0.0348	1.21E-03	0.0348	17.20%	0.2245	-0.0225	5.05E-04	0.0225	11.13%
15	0.2227	0.2058	0.0169	2.87E-04	0.0169	7.61%	0.2251	-0.0024	5.73E-06	0.0024	1.08%
16	0.2253	0.2085	0.0168	2.84E-04	0.0168	7.48%	0.2241	0.0012	1.50E-06	0.0012	0.54%
17	0.2390	0.2750	-0.0360	1.29E-03	0.0360	15.04%	0.2442	-0.0052	2.74E-05	0.0052	2.19%
18	0.2392	0.2228	0.0164	2.69E-04	0.0164	6.86%	0.2196	0.0196	3.83E-04	0.0196	8.18%
19	0.2568	0.2411	0.0157	2.48E-04	0.0157	6.13%	0.2307	0.0261	6.83E-04	0.0261	10.18%
20	0.2616	0.2459	0.0157	2.45E-04	0.0157	5.99%	0.2418	0.0198	3.91E-04	0.0198	7.56%
21	0.2691	0.2537	0.0154	2.37E-04	0.0154	5.72%	0.2657	0.0034	1.19E-05	0.0034	1.28%
22	0.2726	0.2573	0.0153	2.33E-04	0.0153	5.60%	0.2722	0.0004	1.47E-07	0.0004	0.14%
23	0.2906	0.2799	0.0107	1.16E-04	0.0107	3.70%	0.2807	0.0099	9.71E-05	0.0099	3.39%
24	0.2968	0.2824	0.0144	2.08E-04	0.0144	4.86%	0.2996	-0.0028	8.05E-06	0.0028	0.96%
25	0.3085	0.3014	0.0071	5.09E-05	0.0071	2.31%	0.3042	0.0043	1.88E-05	0.0043	1.40%
26	0.3100	0.3001	0.0099	9.87E-05	0.0099	3.21%	0.3098	0.0002	6.14E-08	0.0002	0.08%
27	0.3200	0.2971	0.0229	5.23E-04	0.0229	7.15%	0.3203	-0.0003	1.02E-07	0.0003	0.10%
28	0.3272	0.3487	-0.0215	4.63E-04	0.0215	6.58%	0.3278	-0.0006	3.53E-07	0.0006	0.18%
29	0.3515	0.3541	-0.0026	6.64E-06	0.0026	0.73%	0.3429	0.0086	7.31E-05	0.0086	2.43%
30	0.3200	0.3174	0.0026	6.55E-06	0.0026	0.80%	0.3189	0.0011	1.26E-06	0.0011	0.35%
31	0.3351	0.3600	-0.0249	6.19E-04	0.0249	7.42%	0.3325	0.0026	6.74E-06	0.0026	0.77%
32	0.3693	0.3703	-0.0010	9.69E-07	0.0010	0.27%	0.3687	0.0006	4.15E-07	0.0006	0.17%
33	0.3697	0.3657	0.0040	1.61E-05	0.0040	1.09%	0.3519	0.0178	3.18E-04	0.0178	4.83%
34	0.4049	0.4002	0.0047	2.25E-05	0.0047	1.17%	0.4052	-0.0003	7.41E-08	0.0003	0.07%
35	0.4059	0.4050	0.0009	7.64E-07	0.0009	0.22%	0.4037	0.0022	4.91E-06	0.0022	0.55%

Table 9 Prediction Results of Productivity Loss for DS_9M_1

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.0860	0.1181	-0.0321	1.03E-03	0.0321	37.37%	0.0990	-0.0130	1.69E-04	0.0130	15.14%
2	0.0981	0.1182	-0.0201	4.02E-04	0.0201	20.45%	0.0990	-0.0009	8.67E-07	0.0009	0.95%
3	0.0990	0.1246	-0.0256	6.55E-04	0.0256	25.86%	0.1045	-0.0055	2.97E-05	0.0055	5.51%
4	0.1000	0.1255	-0.0255	6.50E-04	0.0255	25.50%	0.1054	-0.0054	2.96E-05	0.0054	5.44%
5	0.1140	0.1400	-0.0260	6.75E-04	0.0260	22.79%	0.1304	-0.0164	2.68E-04	0.0164	14.35%
6	0.1190	0.1386	-0.0196	3.86E-04	0.0196	16.51%	0.1275	-0.0085	7.15E-05	0.0085	7.11%
7	0.1240	0.1192	0.0048	2.34E-05	0.0048	3.90%	0.0997	0.0243	5.90E-04	0.0243	19.59%
8	0.1260	0.1300	-0.0040	1.61E-05	0.0040	3.19%	0.1114	0.0146	2.13E-04	0.0146	11.59%
9	0.1404	0.1434	-0.0030	8.92E-06	0.0030	2.13%	0.1378	0.0026	6.59E-06	0.0026	1.83%
10	0.1453	0.1464	-0.0011	1.32E-06	0.0011	0.79%	0.1443	0.0010	1.02E-06	0.0010	0.70%
11	0.1494	0.1389	0.0105	1.10E-04	0.0105	7.01%	0.1281	0.0213	4.56E-04	0.0213	14.29%
12	0.1506	0.1498	0.0008	6.62E-07	0.0008	0.54%	0.1505	0.0001	1.60E-08	0.0001	0.08%
13	0.1579	0.1646	-0.0067	4.52E-05	0.0067	4.26%	0.1609	-0.0030	9.16E-06	0.0030	1.92%
14	0.1581	0.1452	0.0129	1.66E-04	0.0129	8.15%	0.1417	0.0164	2.67E-04	0.0164	10.34%
15	0.1680	0.1618	0.0062	3.86E-05	0.0062	3.70%	0.1608	0.0072	5.21E-05	0.0072	4.30%
16	0.1880	0.1926	-0.0046	2.15E-05	0.0046	2.47%	0.1881	-0.0001	1.89E-08	0.0001	0.07%
17	0.2400	0.2256	0.0144	2.07E-04	0.0144	5.99%	0.2377	0.0023	5.15E-06	0.0023	0.95%
18	0.2435	0.2207	0.0228	5.20E-04	0.0228	9.37%	0.2435	0.0000	7.56E-10	0.0000	0.01%
19	0.2561	0.2469	0.0092	8.50E-05	0.0092	3.60%	0.2562	-0.0001	6.86E-09	0.0001	0.03%
20	0.2579	0.2463	0.0116	1.34E-04	0.0116	4.50%	0.2536	0.0043	1.81E-05	0.0043	1.65%
21	0.2830	0.2519	0.0311	9.66E-04	0.0311	10.99%	0.2806	0.0024	5.62E-06	0.0024	0.84%
22	0.3200	0.2790	0.0410	1.68E-03	0.0410	12.81%	0.3175	0.0025	6.18E-06	0.0025	0.78%
23	0.3396	0.3261	0.0135	1.82E-04	0.0135	3.97%	0.3424	-0.0028	7.63E-06	0.0028	0.81%

Table 9 Prediction Results of Productivity Loss for DS_9M_1 (Continued)

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
24	0.4380	0.4992	-0.0612	3.75E-03	0.0612	13.98%	0.4403	-0.0023	5.24E-06	0.0023	0.52%
25	0.2500	0.2577	-0.0077	5.88E-05	0.0077	3.07%	0.2537	-0.0037	1.34E-05	0.0037	1.46%
26	0.2679	0.2406	0.0273	7.43E-04	0.0273	10.18%	0.2638	0.0041	1.71E-05	0.0041	1.54%
27	0.2785	0.2738	0.0047	2.17E-05	0.0047	1.67%	0.2727	0.0058	3.40E-05	0.0058	2.09%
28	0.2946	0.2820	0.0126	1.60E-04	0.0126	4.29%	0.2979	-0.0033	1.07E-05	0.0033	1.11%
29	0.2988	0.2978	0.0010	9.95E-07	0.0010	0.33%	0.3289	-0.0301	9.07E-04	0.0301	10.08%
30	0.3300	0.3245	0.0055	3.02E-05	0.0055	1.67%	0.3282	0.0018	3.20E-06	0.0018	0.54%
31	0.3370	0.3614	-0.0244	5.94E-04	0.0244	7.23%	0.3360	0.0010	1.09E-06	0.0010	0.31%
32	0.3610	0.3676	-0.0066	4.34E-05	0.0066	1.82%	0.3593	0.0017	2.98E-06	0.0017	0.48%
33	0.3871	0.3573	0.0298	8.89E-04	0.0298	7.70%	0.3237	0.0634	4.02E-03	0.0634	16.38%
34	0.4431	0.3917	0.0514	2.64E-03	0.0514	11.59%	0.4424	0.0007	4.53E-07	0.0007	0.15%
35	0.4895	0.4813	0.0082	6.71E-05	0.0082	1.67%	0.4904	-0.0009	7.55E-07	0.0009	0.18%
36	0.3260	0.3448	-0.0188	3.54E-04	0.0188	5.77%	0.3291	-0.0031	9.49E-06	0.0031	0.94%
37	0.3280	0.3832	-0.0552	3.04E-03	0.0552	16.82%	0.3370	-0.0090	8.08E-05	0.0090	2.74%
38	0.3509	0.3677	-0.0168	2.81E-04	0.0168	4.78%	0.3651	-0.0142	2.02E-04	0.0142	4.05%
39	0.3600	0.3562	0.0038	1.47E-05	0.0038	1.06%	0.3622	-0.0022	4.71E-06	0.0022	0.60%
40	0.3631	0.3805	-0.0174	3.02E-04	0.0174	4.79%	0.3453	0.0178	3.16E-04	0.0178	4.90%
41	0.3840	0.3591	0.0249	6.21E-04	0.0249	6.49%	0.3657	0.0183	3.35E-04	0.0183	4.77%
42	0.3930	0.4184	-0.0254	6.48E-04	0.0254	6.48%	0.4567	-0.0637	4.05E-03	0.0637	16.20%
43	0.4080	0.4025	0.0055	2.98E-05	0.0055	1.34%	0.4381	-0.0301	9.09E-04	0.0301	7.39%
44	0.4534	0.4186	0.0348	1.21E-03	0.0348	7.67%	0.4568	-0.0034	1.19E-05	0.0034	0.76%
45	0.4603	0.4024	0.0579	3.35E-03	0.0579	12.58%	0.4377	0.0226	5.11E-04	0.0226	4.91%
46	0.4940	0.5382	-0.0442	1.96E-03	0.0442	8.95%	0.4940	0.0000	1.48E-16	0.0000	0.00%

Table 10 Prediction Results of Productivity Loss for $DS_{10}M_2$

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
1	0.0860	0.1138	-0.0278	7.72E-04	0.0278	32.30%	0.1011	-0.0151	2.29E-04	0.0151	17.60%
2	0.0981	0.1130	-0.0149	2.22E-04	0.0149	15.20%	0.1006	-0.0025	6.05E-06	0.0025	2.51%
3	0.0990	0.1230	-0.0240	5.74E-04	0.0240	24.20%	0.1097	-0.0107	1.14E-04	0.0107	10.78%
4	0.1000	0.1230	-0.0230	5.27E-04	0.0230	22.95%	0.1097	-0.0097	9.36E-05	0.0097	9.68%
5	0.1140	0.1416	-0.0276	7.60E-04	0.0276	24.19%	0.1335	-0.0195	3.80E-04	0.0195	17.09%
6	0.1190	0.1416	-0.0226	5.10E-04	0.0226	18.97%	0.1335	-0.0145	2.10E-04	0.0145	12.17%
7	0.1240	0.1138	0.0102	1.04E-04	0.0102	8.24%	0.1011	0.0229	5.23E-04	0.0229	18.44%
8	0.1260	0.1273	-0.0013	1.76E-06	0.0013	1.05%	0.1147	0.0113	1.28E-04	0.0113	8.97%
9	0.1404	0.1463	-0.0059	3.47E-05	0.0059	4.20%	0.1398	0.0006	4.10E-07	0.0006	0.46%
10	0.1453	0.1502	-0.0049	2.36E-05	0.0049	3.35%	0.1446	0.0007	4.23E-07	0.0007	0.45%
11	0.1494	0.1379	0.0115	1.32E-04	0.0115	7.68%	0.1285	0.0209	4.36E-04	0.0209	13.98%
12	0.1506	0.1543	-0.0037	1.39E-05	0.0037	2.47%	0.1495	0.0011	1.26E-06	0.0011	0.75%
13	0.1579	0.1689	-0.0110	1.20E-04	0.0110	6.95%	0.1619	-0.0040	1.57E-05	0.0040	2.51%
14	0.1581	0.1452	0.0129	1.67E-04	0.0129	8.16%	0.1383	0.0198	3.91E-04	0.0198	12.51%
15	0.1680	0.1646	0.0034	1.15E-05	0.0034	2.02%	0.1589	0.0091	8.24E-05	0.0091	5.40%
16	0.1880	0.2000	-0.0120	1.43E-04	0.0120	6.37%	0.1864	0.0016	2.63E-06	0.0016	0.86%
17	0.2400	0.2292	0.0108	1.17E-04	0.0108	4.51%	0.2427	-0.0027	7.12E-06	0.0027	1.11%
18	0.2435	0.2275	0.0160	2.57E-04	0.0160	6.59%	0.2394	0.0041	1.68E-05	0.0041	1.68%
19	0.2561	0.2374	0.0187	3.49E-04	0.0187	7.30%	0.2551	0.0010	1.09E-06	0.0010	0.41%
20	0.2579	0.2388	0.0191	3.64E-04	0.0191	7.40%	0.2567	0.0012	1.51E-06	0.0012	0.48%
21	0.2830	0.2586	0.0244	5.98E-04	0.0244	8.64%	0.2817	0.0013	1.63E-06	0.0013	0.45%
22	0.3200	0.2677	0.0523	2.74E-03	0.0523	16.35%	0.3183	0.0017	2.93E-06	0.0017	0.53%
23	0.3396	0.3082	0.0314	9.87E-04	0.0314	9.25%	0.3381	0.0015	2.13E-06	0.0015	0.43%

Table 10 Prediction Results of Productivity Loss for (Continued)

#	Actual (A)	Regression					Neural Networks				
		Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]	Predicted (B)	(Actual – Predicted)	(Actual - Predicted)^2	|Actual - Predicted|	%Error %[| A-B| /A]
24	0.4380	0.5379	-0.0999	9.97E-03	0.0999	22.80%	0.4326	0.0054	2.96E-05	0.0054	1.24%
25	0.2500	0.2638	-0.0138	1.89E-04	0.0138	5.50%	0.2572	-0.0072	5.17E-05	0.0072	2.88%
26	0.2679	0.2448	0.0231	5.34E-04	0.0231	8.62%	0.2642	0.0037	1.34E-05	0.0037	1.37%
27	0.2785	0.2775	0.0010	1.09E-06	0.0010	0.38%	0.2692	0.0093	8.68E-05	0.0093	3.34%
28	0.2946	0.2917	0.0029	8.58E-06	0.0029	0.99%	0.2946	0.0000	7.67E-10	0.0000	0.01%
29	0.2988	0.2953	0.0035	1.20E-05	0.0035	1.16%	0.3027	-0.0039	1.51E-05	0.0039	1.30%
30	0.3300	0.3243	0.0057	3.23E-05	0.0057	1.72%	0.3268	0.0032	1.05E-05	0.0032	0.98%
31	0.3370	0.3621	-0.0251	6.28E-04	0.0251	7.44%	0.3357	0.0013	1.75E-06	0.0013	0.39%
32	0.3610	0.3682	-0.0072	5.14E-05	0.0072	1.99%	0.3603	0.0007	4.80E-07	0.0007	0.19%
33	0.3871	0.3354	0.0517	2.68E-03	0.0517	13.36%	0.3120	0.0751	5.64E-03	0.0751	19.41%
34	0.4431	0.4224	0.0207	4.27E-04	0.0207	4.66%	0.4368	0.0063	4.02E-05	0.0063	1.43%
35	0.4895	0.4170	0.0725	5.25E-03	0.0725	14.81%	0.4748	0.0147	2.17E-04	0.0147	3.01%
36	0.3260	0.3588	-0.0328	1.08E-03	0.0328	10.07%	0.3222	0.0038	1.45E-05	0.0038	1.17%
37	0.3280	0.3845	-0.0565	3.20E-03	0.0565	17.24%	0.3284	-0.0004	1.23E-07	0.0004	0.11%
38	0.3509	0.3816	-0.0307	9.42E-04	0.0307	8.75%	0.3515	-0.0006	3.47E-07	0.0006	0.17%
39	0.3600	0.3663	-0.0063	3.92E-05	0.0063	1.74%	0.3584	0.0016	2.65E-06	0.0016	0.45%
40	0.3631	0.3929	-0.0298	8.89E-04	0.0298	8.21%	0.3619	0.0012	1.42E-06	0.0012	0.33%
41	0.3840	0.3722	0.0118	1.40E-04	0.0118	3.08%	0.3817	0.0023	5.10E-06	0.0023	0.59%
42	0.3930	0.4117	-0.0187	3.48E-04	0.0187	4.75%	0.4311	-0.0381	1.45E-03	0.0381	9.69%
43	0.4080	0.4160	-0.0080	6.36E-05	0.0080	1.95%	0.4319	-0.0239	5.73E-04	0.0239	5.87%
44	0.4534	0.4165	0.0369	1.36E-03	0.0369	8.14%	0.4324	0.0210	4.40E-04	0.0210	4.62%
45	0.4603	0.4030	0.0573	3.29E-03	0.0573	12.45%	0.4606	-0.0003	7.91E-08	0.0003	0.06%
46	0.4940	0.4848	0.0092	8.38E-05	0.0092	1.85%	0.4935	0.0005	2.53E-07	0.0005	0.10%

Appendix 8 Prediction Errors Comparison

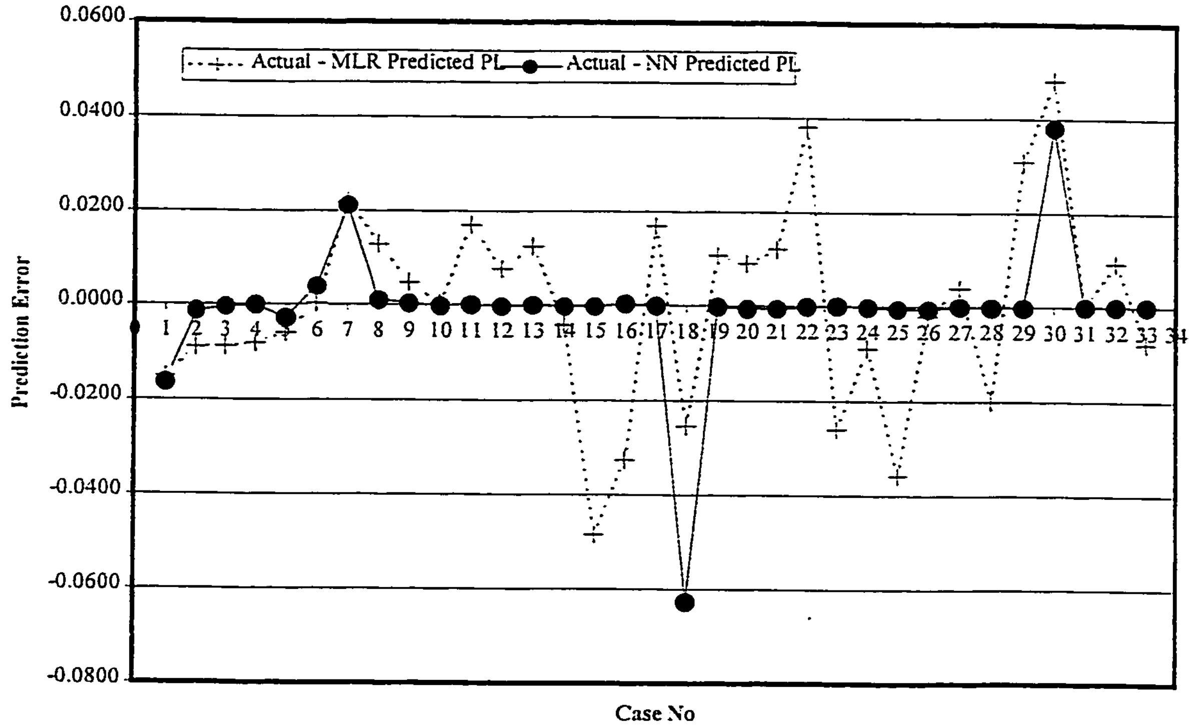


Figure 1 Prediction Errors for Data Set DS_2T_2

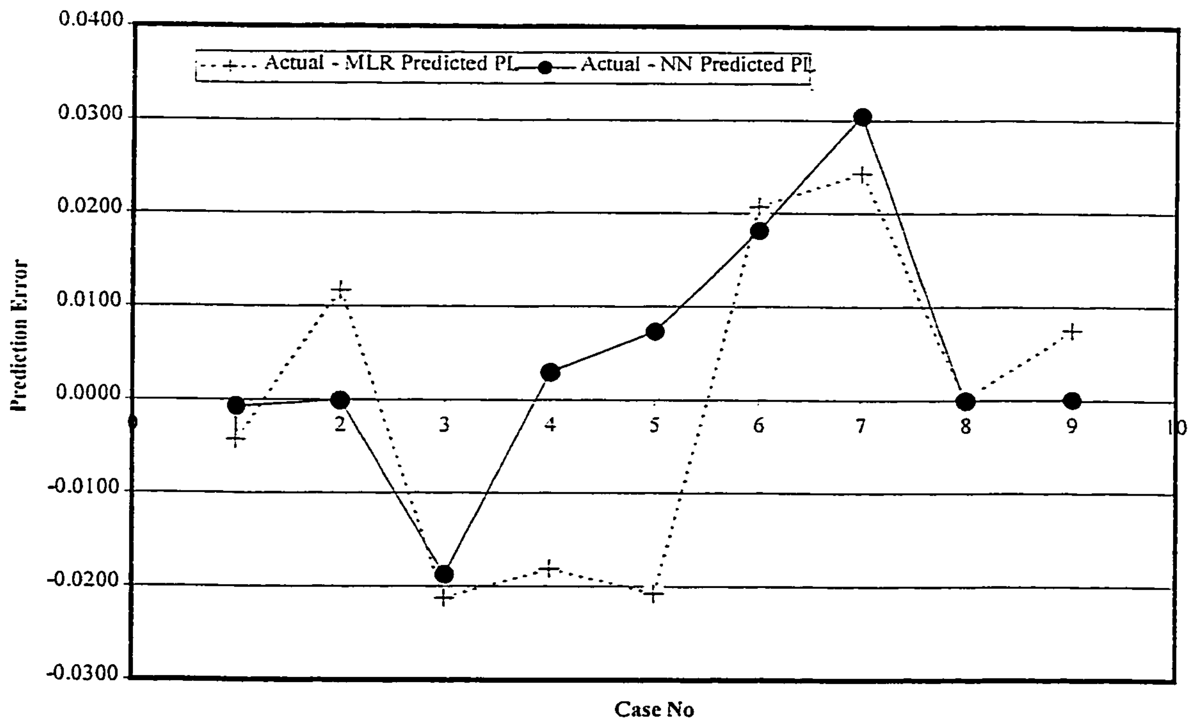


Figure 2 Prediction Errors for Data Set DS_1A_1

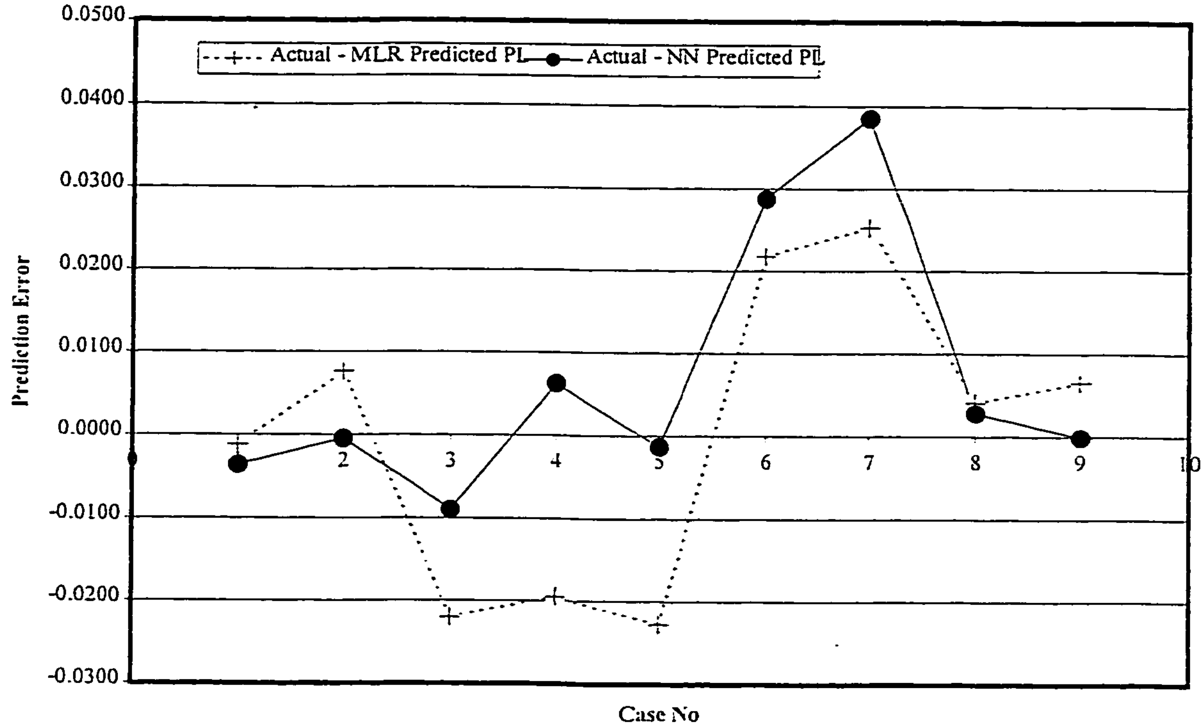


Figure 3 Prediction Errors for Data Set DS_4A_2

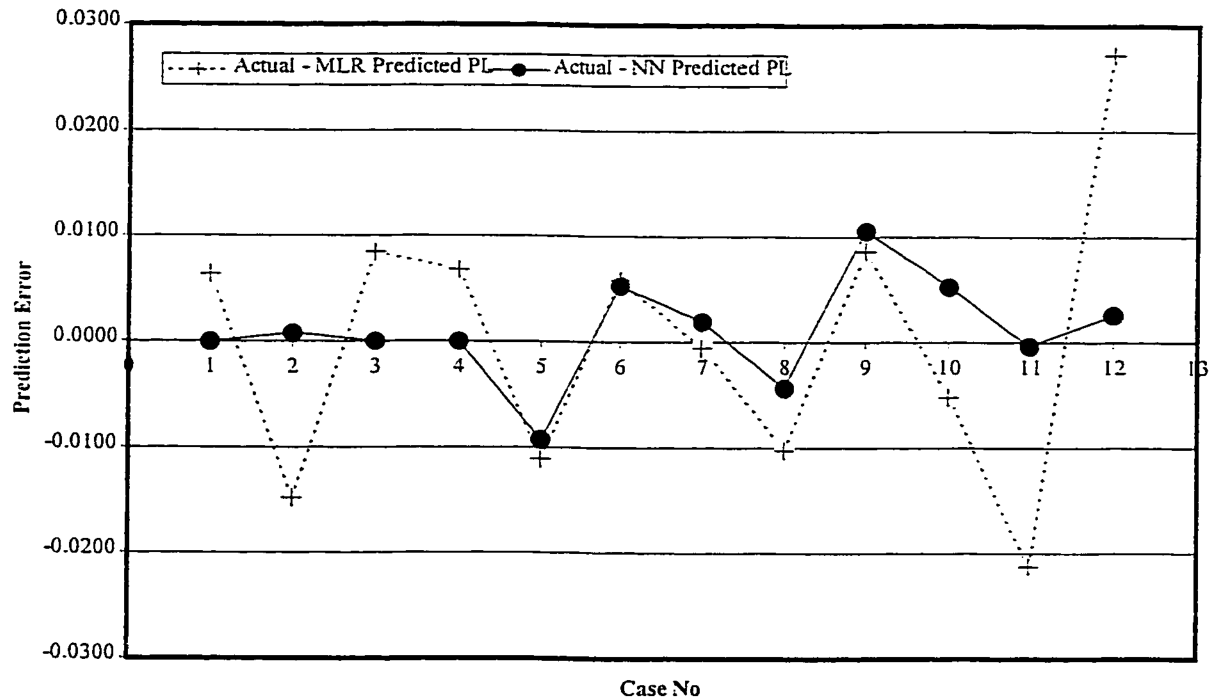


Figure 4 Prediction Errors for Data Set DS_5C_1

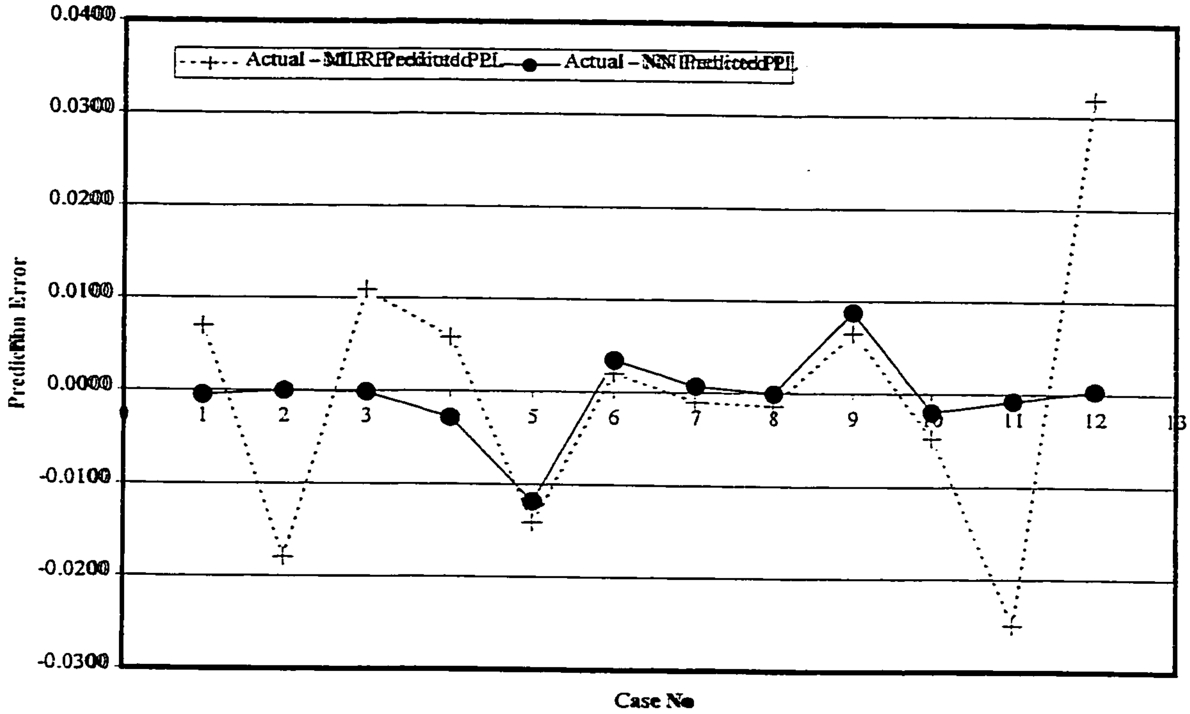


Figure 5 Prediction Errors for Data Set DS_6C_2

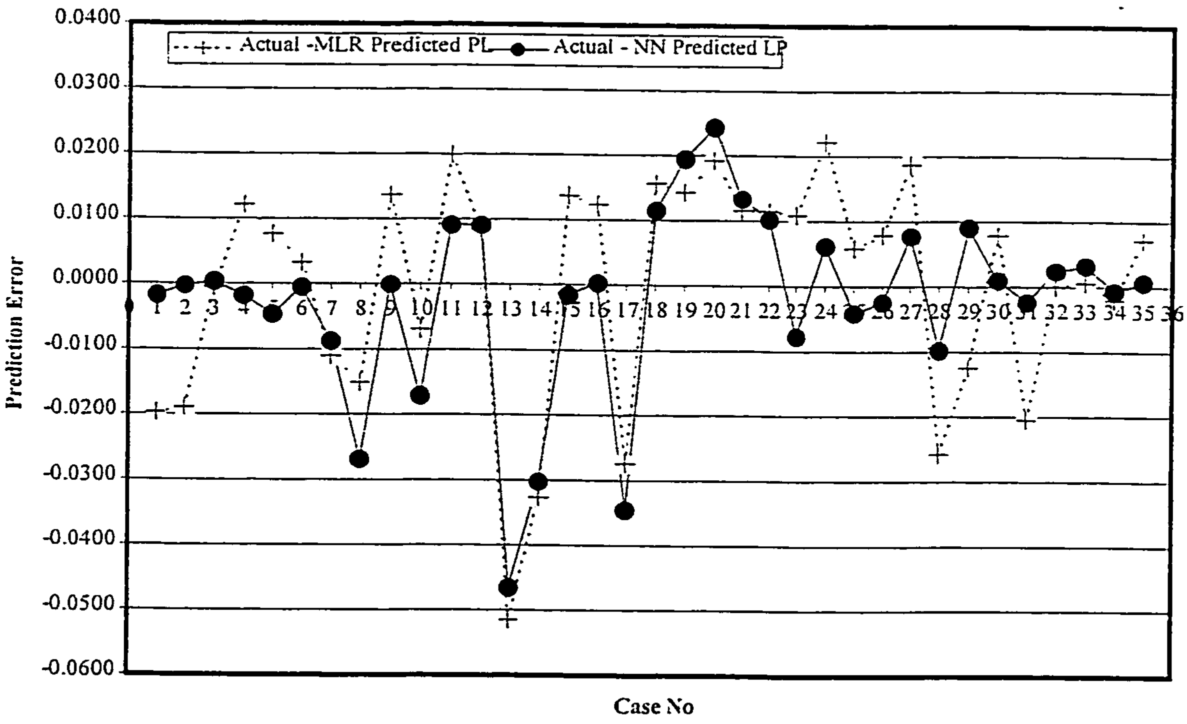


Figure 6 Prediction Errors for Data Set DS_7E_1

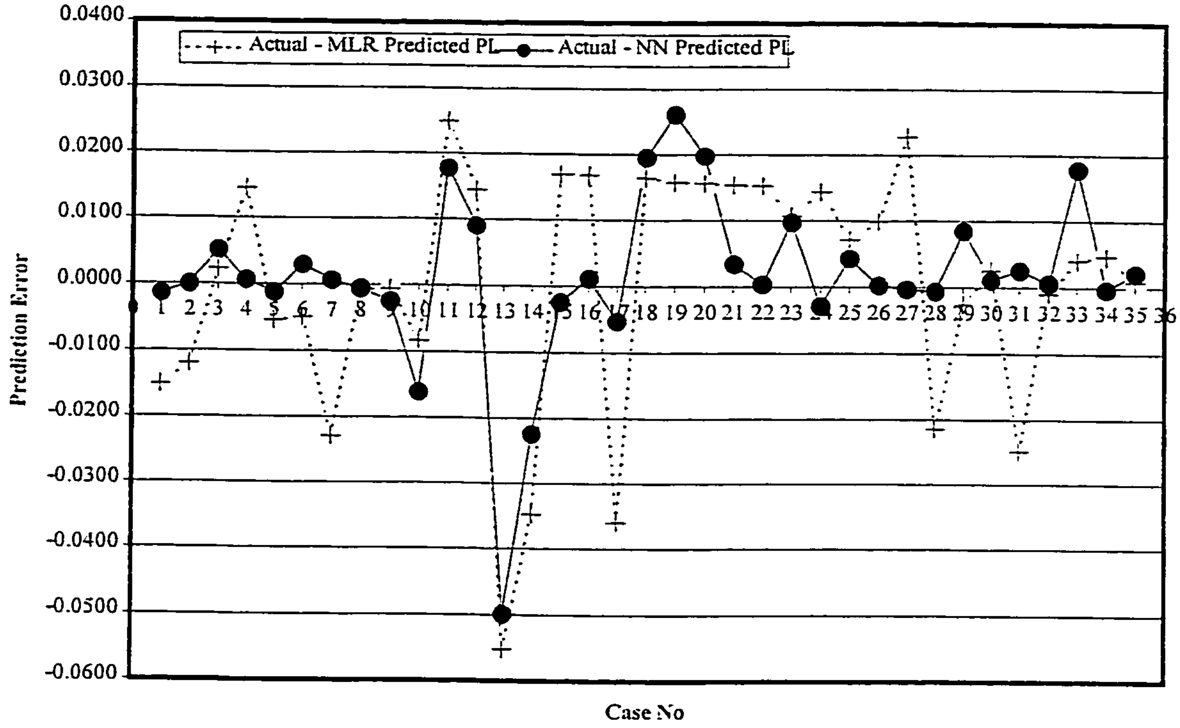


Figure 7 Prediction Errors for Data Set DS_8E_2

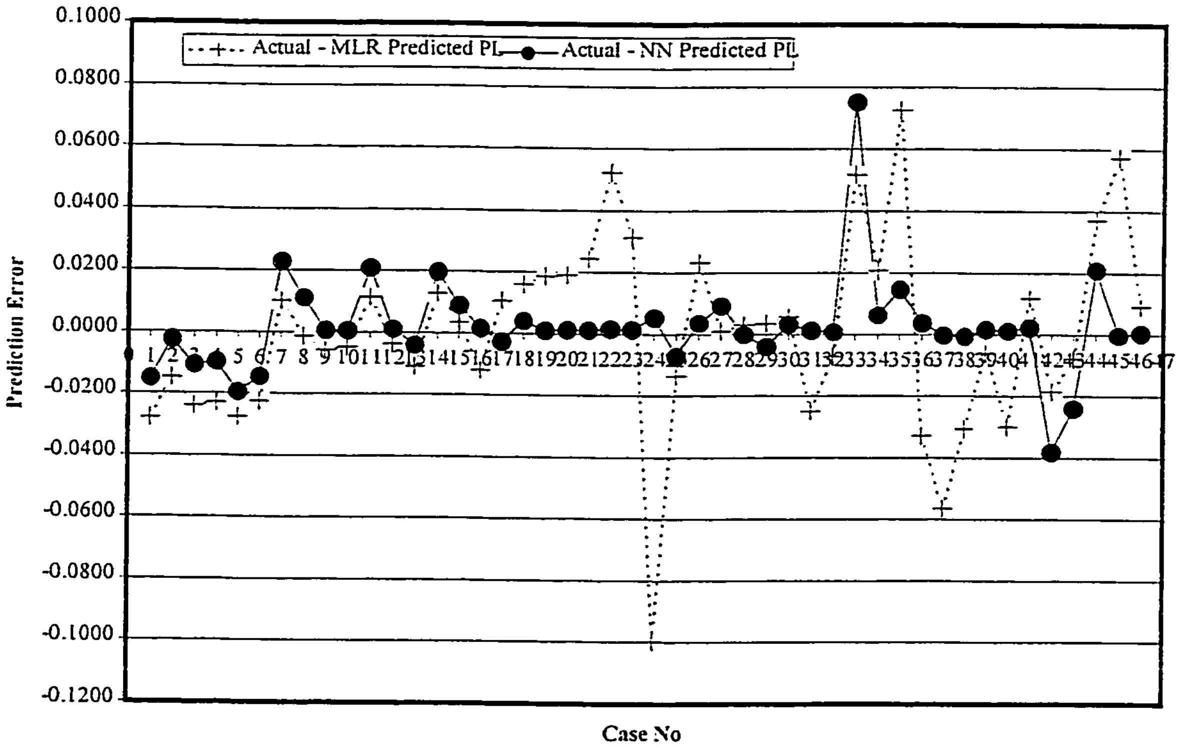


Figure 8 Prediction Errors for Data Set DS_9M_1

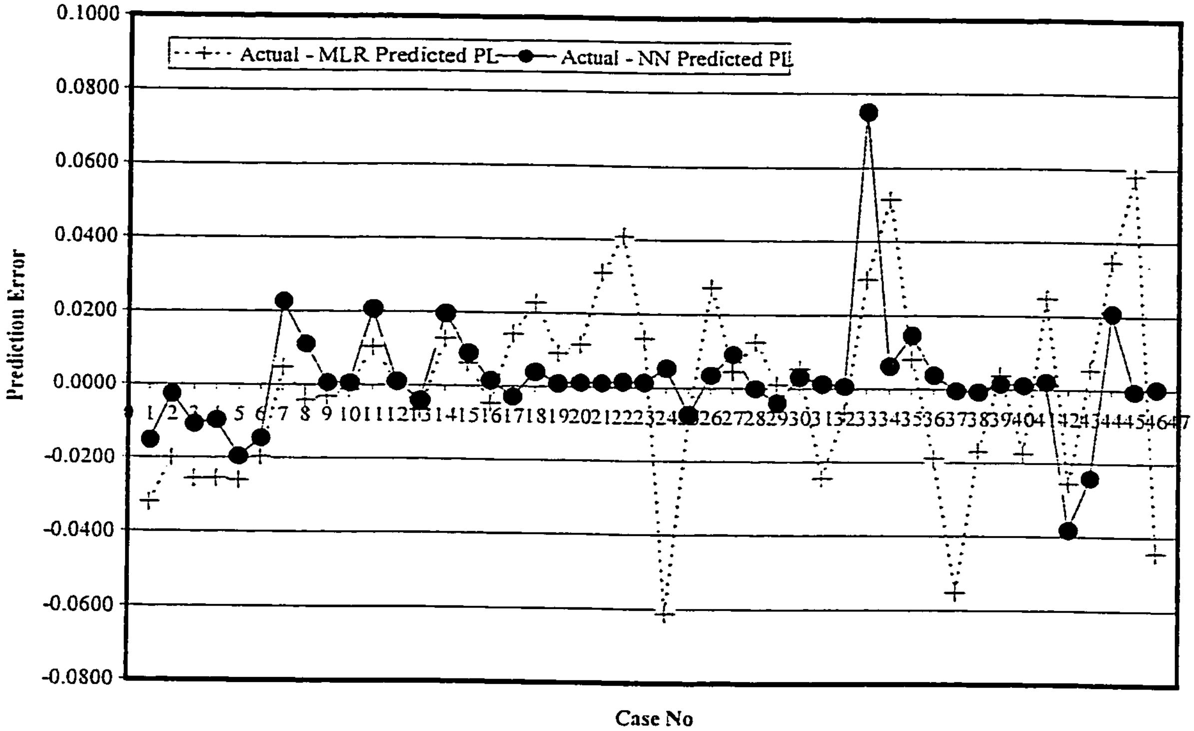


Figure 9 Prediction Errors for Data Set $DS_{10}M_2$