University of Alberta

Predicting Construction Labour Productivity Using Neural Networks

by

R. Paul Knowles ©

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Name of Author: R. Paul Knowles

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743 Wells Wynd
Edmonton, Alberta
T6M-2J9

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled **Estimating Construction Labour Productivity Using Neural Networks** submitted by **R. Paul Knowles** in partial fulfillment of the requirements for the degree of **Master of Science in Construction Engineering & Managment**.

Dr. S.M. AbouRizk

Dr. S.T. Ariaratnam

Dr. S. Kresta

Dr. S. Frimpong

Date: 8/25/97

Abstract

This research focuses on the prediction of labour productivity rates within the construction industry using neural network artificial intelligence. Two distinct types of construction, commercial and industrial, are investigated within the research. Within commercial construction, wall and slab formwork neural network models were studied and within industrial construction, pipe handling and welding models were developed.

Neural network stability and accuracy characteristics were the focus of the research. The use of descriptive, and where possible quantitative, data collection techniques proved to increase neural network stability. Furthermore, the development of a dual neural network system using both classification and prediction produced very accurate results. Supervised Kohonen classification networks were used as means of defining an activity to a specific prediction network. Each prediction neural network uses a feed forward back, propagation training algorithm and is trained using a different set of records, based on the record's achieved productivity rate.

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1. Introduction

1.1 Overview

Construction is an extremely labour intensive industry. Depending on the specific activity, labour can contribute to a high portion of the cost. Thus the ability to accurately estimate labour costs in a construction environment is of critical importance.

Estimation of labour productivity has historically focused on past performances as a means of predicting for the future. This focus, however, has at most been limited to simple statistical analysis. In recent years, the focus of deriving productivity rates has begun to shift. Increased competition in combination with accelerated developments in the area of computer modeling have resulted in the introduction of complicated statistical and artificial intelligence techniques designed to aid in the estimation of productivity.

This research studies the development and implementation of neural network artificial intelligence as a means of improving the abilities of an estimator to predict construction labour productivity rates. In doing so, two distinct types of construction are studied.

Commercial construction involves the construction of large building structures such as schools, business buildings, and highrises. This type of structure is primarily composed of two materials: steel and concrete. This research specifically focuses on concrete commercial construction and, more specifically, on the activities involved with the construction of formwork. Formwork activities are labour intensive and are often a major cost item for a contractor. Because of the simplicity of the material involved and the ability to reuse formwork material, labour is essentially the key cost for the activity. The different characteristics of each individual project, activity, and site conditions, however, make each formwork activity unique in nature. Therefore, labour productivity estimation is difficult. This is why the use of an artificial intelligence technique capable of learning from past performances and predicting unknown future activities from incomplete data, has potential to help estimators. The type of artificial intelligence referred to here is neural networks. Previous research (Portas 1996) has proven the applicability of neural network artificial intelligence to the estimation of formwork labour productivity, but this research further studies the issues of stability and accuracy enhancement in the development of the neural network models needed for successful implementation.

Industrial construction involves the construction of piping systems, typically for oil and gas, petrochemical, mining, or other industrial-related fields. Industrial construction activities include duties such as pipe handling, equipment installation, and welding activities. This research specifically focuses on two of these activities: pipe handling and pipe welding. These activities, however, are vastly different in nature and process than a commercial formwork activity. The flexibility of neural networks, therefore, is tested by this research to see if the findings and developments of the formwork research can be applied to other areas of construction. Flexibility is a critical characteristic of neural networks that must be proven before successful implementation of the artificial intelligence can be achieved within a construction industry which involves many different activities and processes. As a result, this research focuses on defining the factors that affect the productivity of an industrial activity and implementing these factors within a neural network application.

1.2 Objectives

This research intends to prove the relevancey of neural network artificial intelligence to the construction industry by proving the ability of such applications to be dynamic and flexible in nature so that the influence of different users and different types of construction activities can be effectively accounted for. As a means of effectively meeting this goal, the following sections define the objectives for each of the two types of construction included in this research.

1.2.1 Commercial Formwork Project Objectives

1. Perform a stability enhancement for the neural network models. Stability, in this case, refers to the ability of the technology to behave in a consistent and sound manner. By doing so, the predictions made by the neural networks will be of a suitable and legitimate nature. The following defines the key areas in which enhancement is to be studied:

    - Incorporation of new input factors and an expansion of the historic database were both stated as recommendations of previous research. Ideas for additional input factors arose during previous research (Portas 1996) and the influence of such factors is to be determined in this research. Previous research (Portas 1996) also stated that data limitation was a primary drawback to effective neural network training. This research expands the data collection as a means of determining the influence of limited data on training capabilities.
    - Identification and implementation of a method to deal with the effects of subjective data within the training and testing phases of a neural network application.

2. Perform accuracy enhancement for the neural network models. Accuracy simply defines the neural networks ability to predict correctly. Therefore, this research aims to develop a neural network training method that makes more accurate predictions than obtained in previous research, with respect to the extremely high and low productivity rates.

1.2.2 Industrial Construction Project Objective

Development and implementation of neural network artificial intelligence for the purposes of estimating labour productivity rates within the field of industrial construction. This will involve the identification of factors affecting productivity and development of a neural network training scheme capable of increasing the abilities of estimators to accurately define a productivity rate.

1.3 Methodology of the Solution

A procedure was set out for each of the projects included in this research such that all the objectives, listed above, could be met. The following defines each of the procedures:

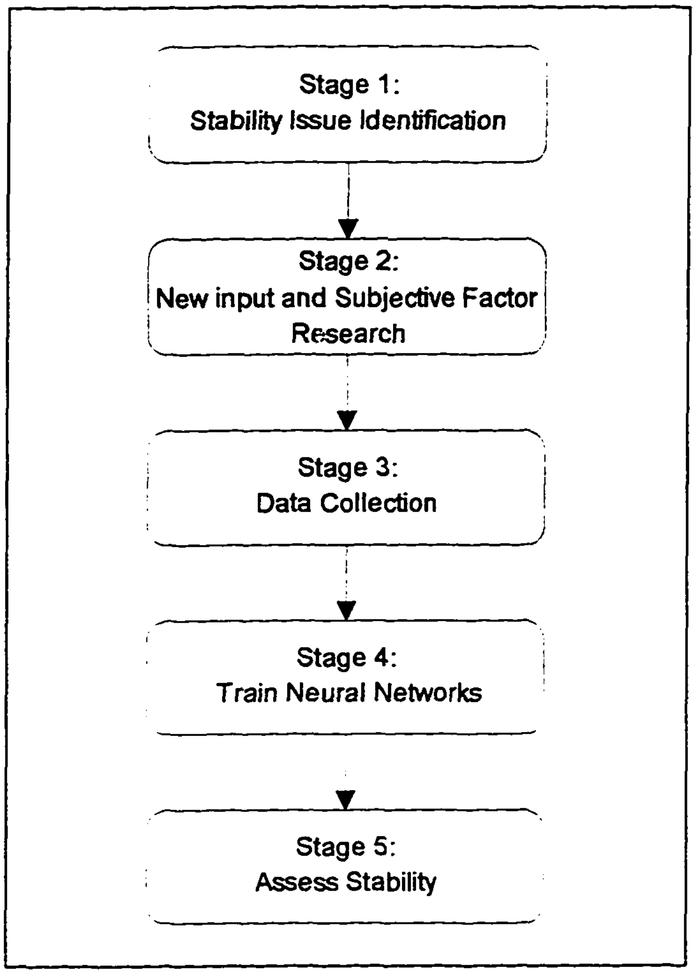
1.3.1 Commercial Formwork Project

Previous research includes (Portas 1996) preliminary research into construction productivity, specifically formwork construction, completion of an initial data collection, and the development of a neural network training methodology and media. This research, as defined in the objectives, focuses on enhancing both the stability and accuracy of the neural network models. The following describes the methodologies utilized to meet each of these objectives.

1.3.1.1 Stability Enhancement

The flowchart in Figure 1.1 outlines the stages taken to enhance the stability of the commercial neural network models.

Figure 1.1 Commercial Formwork Flowchart - Stability Enhancement



The first stage consists of an analysis of the current status of the formwork neural network models to identify the sources of instability.

The second stage involves a detailed study into the new factors to be tested within the neural networks and research into how to capture subjective factors more effectively. Subjective factors are inputs which are by nature qualitative, and must be converted to a quantitative value in order to be used effectively within a neural network.

The third stage involves detailed data collection. Included in the collection is a resampling of all previously sampled projects, so that new and changed factors may be collected, and a number of new projects added.

In the fourth stage the newly collected data and developed techniques are tested by training a number of neural network models. Among the neural networks trained are different combinations of new input factors. These networks are compared for accuracy to ensure that the abilities of the original models have not decreased in the developed models.

The final stage assesses the stability of the new network structure. Comparisons are made with the original models as a means of verifying the changes made throughout the research.

1.3.1.2 Accuracy Enhancement

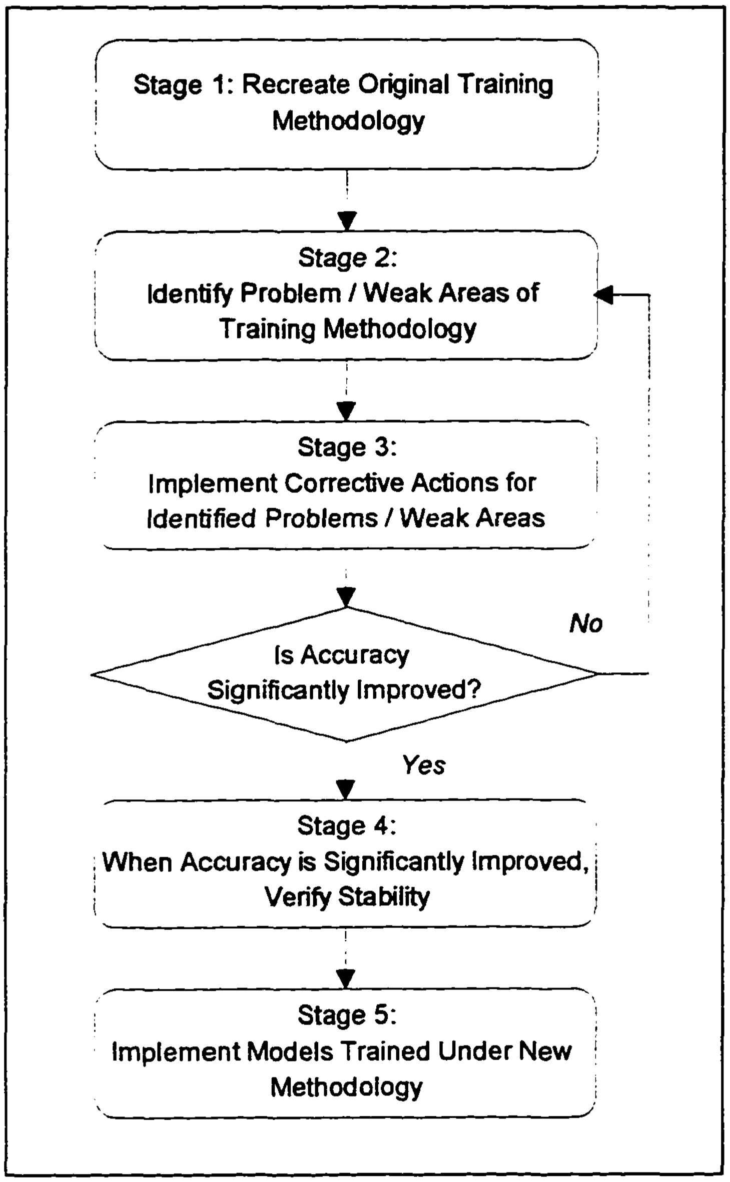
The method used for accuracy enhancement is not as clear cut as for the other topics of this research. The method for increasing the accuracy, however, focuses strictly on the neural network training. The flowchart in Figure 1.2 captures the essentials of the process.

The first stage of accuracy enhancement involves recreating the neural network structure used by previous research as a means of defining a baseline. This baseline will be different from previous research, because the stability enhancement findings will have been implemented.

The second stage involves investigation of the training accuracy and properties to identify what aspects of accuracy need to be addressed.

The third stage involves developing a new training method so that any concerns exposed by stage two can be rectified. This stage also involves training of the new network structures and determining whether the accuracy reaches the desired levels. This decision will result in a return to stage two if the accuracy enhancement is unsuccessful or a move to stage four if the accuracy objectives are met.

Figure 1.2 Commercial Formwork Flowchart - Accuracy Enhancement



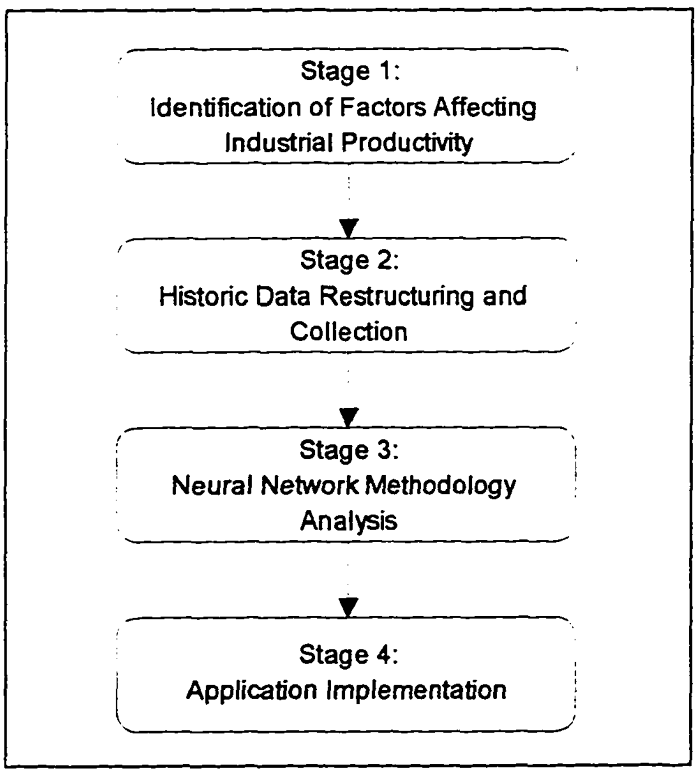
The fourth stage involves verifying that the stability of the network is maintained despite a new neural network training methodology.

The fifth stage consists of conducting an input sensitivity analysis as a final verification of the new models and the construction and implementation of a new recall program for the estimators to use.

1.3.2 Industrial Construction Project

The following flowchart, Figure 1.3, identifies the method followed for the development of neural network models capable of aiding an estimator in the estimation of an industrial activity productivity rate.

Figure 1.3 Industrial Formwork Flowchart - Neural Network Development



The first stage of the industrial construction project involves identification of the factors that have the potential to influence labour productivity rates. This is accomplished through interviews of experienced personnel as well as by using productivity factor knowledge gained from the formwork research.

The second stage of the project involves the restruction and collection of the historic data to be used as inputs for the neural networks. This involves the development of a common cost coding system for the collaborating contractor, consolidation of the contractors' historical records, and a sampling of site personnel for additional, non cost coded information.

The third stage of the project involves development of the neural network training technique which best suits the collected data using knowledge obtained from the development of the formwork training method.

The final stage of this project is the implementation of an industrial construction neural network application.

1.4 Thesis Organization

Chapter 2 presents the literature review for this research. The literature review focuses on neural network artificial intelligence's applicability to construction, specifically the area of labour productivity. The review identifies and provides analysis of previous studies into the use of artificial intelligence for the purposes of labour productivity prediction, both in terms of neural networks and other forms of artificial intelligence. Chapter 3 presents the research completed on enhancing the stability of the commercial formwork neural network models developed by previous research. Chapter 4 implements the findings of Chapter 3 and develops a new method for training neural networks so that the accuracy of the models is enhanced. Chapter 5 presents the research undertaken for the industrial construction project, including discussion of the procedures used throughout development of the industrial neural network models. Finally, Chapter 6 provides a conclusion to this research and identifies recommendations for future work.

1.5 Confidentiality

For the purposes of this thesis, all productivity figures collected from the general contractor have been normalized in order to maintain confidentiality for the general contractor. All productivity figures, therefore, have been normalized equally so that the full effect of their relationships can still be expressed in this thesis. Furthermore, a number of appendices providing background data and research have been declared confidential and not included as part of this thesis.

2. Literature Review

2.1 Introduction

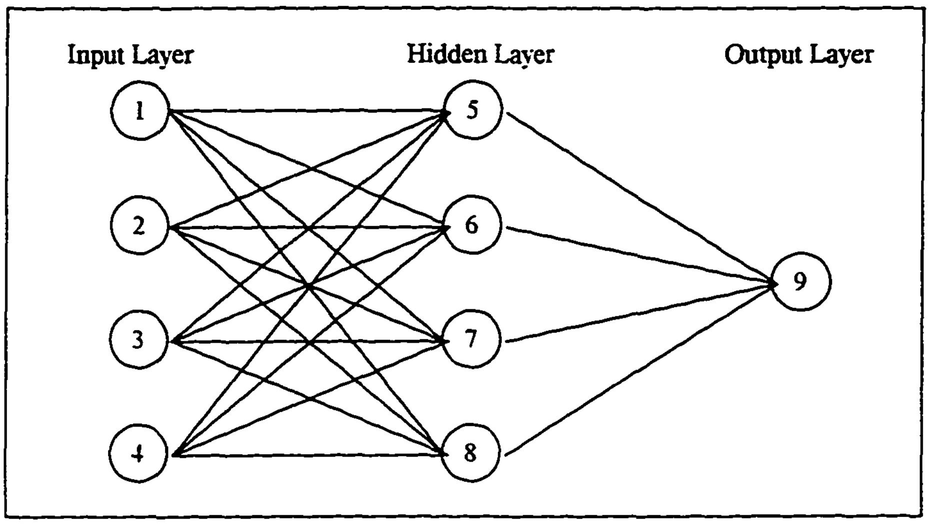
The purpose of this literature review is to identify the applicability of neural network artificial intelligence within the construction industry as a tool for predicting labour productivity. As a result, three topics are discussed in this review. First, background information on neural network technology is discussed in detail. Second, previously developed neural network applications used for the purposes of predicting labour productivity are identified. Finally, other methods of computer modeling of labour productivity for prediction purposes are discussed.

2.2 Neural Network Artificial Intelligence

Neural networks are an emerging field of artificial intelligence being used by the construction industry. Neural networks mimic the human brain in the way it learns and recalls information. In the human brain, neurons transmit and receive signals from one another. The total signal on a neuron is either increased or reduced through the interaction. In a neural network, nodes, also referred to as processing elements, act similarly to the neurons of the brain. Within a neural network, signals are transmitted and combined so that a receiving node will fire an output in the form of another signal if the input it receives is stronger than a designated threshold value.

Neural networks are made up of an input layer, one or more hidden layers, and an output layer. Each layer is composed of a number of nodes and the nodes from differing layers are connected by weighted factors. Therefore, information is sent by a node in one layer, multiplied by a connection weight, and received by the node of another layer. Once the information is received by a node, a transfer function converts the input to an output so that the received data is consistent in range to that of the rest of the layer. Figure 2.1 provides an sample layout of the structure of a simple neural network

Figure 2.1 Sample Neural Network Structure



The operation of a neural network includes training and recall. Training involves the process of adapting or modifying the connection weights according to a data training set. Recall involves testing a trained neural network with input sets upon which the network was not trained. Recall acts to define how well the network has been trained.

There are two uses of neural networks: prediction and classification. These uses are common in format and operation, as described above, but serve two different purposes. Prediction neural networks are used to make numerical predictions. The most common type of prediction neural network uses a back propagation architecture. Training involves feeding inputs into a neural network, allowing the network to calculate an output, feeding the actual output to the network, and the network back propagating the error in its calculated value back to the connection weights. This is done for each of the input records and then the process is repeated for many iterations until the network has learned the correct connection weights for the input data. This technique is defined as supervised learning because actual output values are used as the basis for determining the connection weights. Classification networks act to classify a record according to chosen input factors to one of a number of classes. The most common type of classification network is the Kohonen network. Unsupervised learning (actual outputs are not used to define the weightings of the connections) is commonly used for training Kohonen networks, although supervised learning can also be used. For unsupervised learning, connection weights are updated during the forward pass of each individual record. The input record set is repeatedly passed through the network until sufficient training has been established. In the case of supervised learning, discrepancies between the actual and predicted classification of each record are used to update connection weights. Once again, the input record set is repeatedly passed through the network in a similar process until sufficient training has been established.

The applicability of neural network artificial intelligence to the construction industry has begun to develop rapidly in the past few years. The following literature review provides a summary of developments in the 1990's defining the use of neural networks in construction. In the process, many of the researchers use comparisons with other modeling techniques in order to expose the key advantages of neural networks.

Moselhi, Hegazy, and Fazio (1991) argue that neural networks offer a much better alternative to using expert systems for modeling construction systems. They identify the key difference between the two types of artificial intelligence to be in the way in which the technology processes data. Expert systems are simply decision making models built on expert knowledge criteria while neural networks are decision making models trained upon actual decision making. Moselhi et al. state that although expert systems provide three key requirements for resolving construction problems incorporate (expert knowledge, judgment, and experience), they are limited in domain, present knowledge acquisition problems, and can be complex, slow, and costly. On the other hand, in addition to the three requirements for resolving construction problems, neural networks exhibit the following advantageous characteristics:

1. a large number of attributes can be considered in parallel
2. neural networks learn by example, therefore, knowledge acquisition is not difficult
3. quick responses can be provided by a neural network model
4. classification based on given inputs can be attained and, input classification characteristics can be extracted
5. an incomplete data set can be analyzed due to the neural network's ability to generalize
6. a fault tolerant property allows for small errors in training data to have only a slight effect on the processing elements
7. only a small amount of memory is required as only network weights need to be stored for recall programs

Based on this analysis, Moselhi et al. recommend that neural network technology either replace or be used to compliment expert systems for construction modeling problems. Furthermore, a number of neural network applications were suggested as potential uses in the construction industry:

1. selection between alternatives - such as choosing a dewatering methodology, a formwork type, or an equipment type.
2. estimation and classification - such as estimating or classifying productivity, cost control, and performance levels.
3. function synthesis - estimation of optimum markup based on bid criteria and motivations.
4. diagnostic problems - such as exposing cause recognition of construction defects.
5. dynamic modeling - cost escalation and inflation could be predicted.
6. optimization tasks - such as optimizing resource usage.
7. real-time applications - such as predicting time dependent cost on a project.

Garrett (1992) states that modeling of complex phenomena and complex system behavior is a need in modern civil engineering and neural network modeling represents a useful tool that can meet this need. Garrett cites the neural network's ability to acquire, represent, and apply mapping from a training data set to a testing data set as its key advantage of the artificial intelligence. In a comparison to another branch of artificial intelligence, expert systems, Garrett presented the following advantages to the use of neural networks:

1. Neural networks have the ability to present a model for a situation where only examples are present. No other acceptable theory has the ability to describe an input/output response, a common type of data to describe many civil engineering processes, as neural networks can.
2. Expert systems require "certainty factors" or "levels of belief" as means of accounting for uncertainty, whereas neural networks are trained to deal with uncertainty since training data is obtained from situations very close to the situations in which the network will operate.
3. Expert systems are very brittle in that all data must be complete and correct in order for a system to be analyzed. On the other hand, neural networks have the ability to allow for minor errors or omissions in input data and also for slight deviations form existing training cases.

Garrett goes on to state that engineers are the interpreters of incomplete, noisy data. Furthermore, engineers are modelers and controllers of complex systems in which exact behavior is unknown. Based on these two characteristics of an engineers duties, Garrett believes neural networks are a solution to systems analysis which an engineer should investigate. Garrett points out the following civil engineering applications as potential applications of neural networks:

- classification of distributed, noisy patterns of field data
- interpretation of nondestructive evaluation sensory feedback
- modeling of complex system behaviour
- control of complex engineering facilities

Kartam, Flood, and Tongthong (1993) researched the use of knowledge based systems, artificial neural networks, and an integrated system using both technologies for the purposes of solving engineering problems. They identify the following advantages and disadvantages of neural network artificial intelligence:

Advantages

- provides a solution for problems in which domain expertise cannot be easily described in rules
- allows for speedy computation due to fairly simple processing
- eliminates need for extensive knowledge acquisition
- neural networks present inherent learning and generalization capability
- neural networks are excellent at pattern recognition and classification

Disadvantages

- there is no explanation of rationale behind the solutions neural networks generate
- neural networks lack deduction ability (cannot predict precisely)
- a comprehensive data set is required for adequate training

NeuralWare (1993) compares the abilities of neural networks to other means of artificial intelligence. Table 2.1 presents a comparison of neural networks to other means of modeling problems:

Table 2.1 NeuralWare Modeling Comparison

Technique	Limitation	Advantage of Neural Networks
Traditional Programming	The number of variations is limited as each variation is required to be programmed into the model.	Neural networks are trained and, therefore, can handle unlimited numbers of variations without additional work.
Expert Systems	System requires that an expert knowledgeable in the topic set rule basis for processing.	Knowledge and explicit setting of rules is not necessary for neural networks since historical data is used for training (knowledgeable checks and input, however, are still advisable).
Regression Analysis	Level of analysis is limited to a certain number of parameters.	There are less limitations, such as the need for a sufficient training data, to the number of inputs that can be analyzed by a neural network.

Chao and Skibniewski (1994) note that productivity rates have historically been estimated using average rates from historical information that have been adjusted to specific project characteristics based on estimator experience. The experience factor is required due to the unique work requirements and differing environment of each project. Chao and Skibniewski defined an alternative to using the experience factor by using neural networks to "perform complex mapping of environment and management factors." A neural networks approach will not only be able to draw from experiences of the past, but would also provide three additional benefits:

- qualitative inputs could be quantified
- the influence of factors could be better defined
- combined effects of factors could be accounted for

The adaptability of a neural network's architecture was cited as the source of these three benefits.

Steidley (1994) notes that despite the introduction of neural networks to the construction industry in the 1980's, many researchers are still reluctant to use the technology. Lack of use is blamed on ignorance of both the abilities and operation of neural networks. Steidley argues that neural networks do represent a valid technology if they are adequately understood and pointed out three applications to which neural networks are best suited:

1. Pattern Recognition - neural networks offer a valid replacement for common filtering operations.
2. Nonlinear Processes - processes in which the inputs are not directly proportional to the outputs can be best analyzed by the structure of neural networks.
3. Number Crunching - Number intensive problems can be swiftly analyzed by neural networks.

All of these three applications represent possible solutions to many of the problems which artificial intelligence is being asked to deal with within the construction industry.

Flood and Kartam (1994) outline the reasoning behind the rapid development of neural networks in civil engineering. They cite the following characteristics of neural networks for this new trend in artificial intelligence:

- the ability to learn from examples and generalize solutions
- adaptability to adjust to changing circumstances in the nature of the problem
- the ability to produce meaningful solutions despite errors or incomplete input data
- the ability to process information quickly
- the flexibility to be transported between computer systems

Flood and Kartam also disclose a number of shortcomings in neural networks. Among these are lack of precision, limited theory dealing with design or rationale of solutions provided, and lack of a guarantee of finding an acceptable solution. These shortcomings, however, are typically a result of blind use of an artificial intelligence when in fact the models can be very sensitive to settings and configurations during training. A number of training components must be properly analyzed if a neural network is to produce the desired outputs:

1. Number of hidden layers - one to two layers have been proven in differing circumstances to be most effective.
2. Number of hidden nodes - no precise method has been developed for determining the number of nodes in the hidden layer, but experimentation should show training patterns are not accurately learned with too few hidden nodes and cumbersome with too many hidden nodes.
3. Architecture of training - the node connection (learning rule) and transfer function can alter the training capability of a data set.
4. Number, Distribution, and Format of Training Patterns - a training record set of too few records will not allow the neural network to effectively learn possible patterns, while too many records can result in the network training to a local minimum.

Validation of the network is cited as a critical step in neural network training as a means of verifying that all components have been developed to appropriate values. Validation should take place with records with which the network was not trained with in order to determine the true applicability of neural networks to the problem.

Flood and Kartam stress that the success of proper implementation of a neural network into a civil engineering environment is only partially dependent on the input data, as component settings in training can be equally important. If neural network artificial intelligence is properly understood, it may serve many uses in a decision-oriented industry such as civil engineering.

2.3 Labour Productivity Models

Research in the 1990's into modeling construction problems has taken a strong focus on artificial intelligence techniques. This is especially true in research efforts to improve the development of models for the purpose of predicting labour productivity rates. Development of neural networks, expert systems, regression models and other artificial techniques as aids for productivity estimation has become a need in today's increasingly competitive construction industry. The following presents a literature review of the recent developments that have been made in this aspect of construction. In doing so, two sections are presented, one identifying current developments in neural networks and the second examining developments with other technologies.

2.3.1 Neural Network Labour Productivity Models

Moselhi, Hegazy, and Fazio (1991) cite the prediction of a realistic productivity level for a certain trade as an aspect of construction that can be modeled with neural networks. Factors such as job size, building type, overtime work, and management conditions are typically considered by an estimator and can easily be manipulated to be used as neural network inputs. They identify two techniques as means of transforming the input factors into a format that can be used by neural networks:

1. Binary-Value Transformation - ones are assigned to applicable attributes and zeros are assigned to attributes which are not applicable
2. Continuous-Value Transformation - a vector of real numbers is assigned to each attribute so that the assigned value represents the relative score of the factor compared to other factors

Moselhi et al. do not, however, provide any analytical proof defining the applicability of such an application or of the transformation techniques.

Karshenas and Feng (1992) analyzed earthmoving equipment productivity with a neural network application. A modular neural network structure was used to make it possible to add specifications of new equipment with only a brief training session. Each module represents a distinct type of equipment which was trained with two inputs, four hidden nodes, and one output within a back propagation training algorithm. The two input factors used for each module were gross equipment weight and total haul road resistance. The output was the equipment speed, which may be used to determine the productivity of the equipment based on cycle times. The neural network application proved to train to minimal error, and could therefore provide accurate and consistent outputs.

Wales and AbouRizk (1993) used neural networks as means of applying the effects of environmental site conditions to the labour productivity rate on an activity. Daily average temperature, precipitation, and cumulative precipitation over the previous seven days were identified as three key environmental site conditions and used as inputs into a feed forward back propagation neural network training algorithm. The output was a productivity factor such that a value above one indicates that environmental site conditions produce a greater than average productivity. On the other hand, a productivity factor of less than one indicates that the environmental site conditions result in below average productivity.

Wales and AbouRizk propose that this neural network technology could be used during scheduling as a means of accounting for weather effects in advance for weather sensitive activities. This would simply involve generation of weather conditions based on historic data, determination of a neural network-derived productivity factor based on the conditions, and alteration of the activity duration within the schedule accordingly.

Chao and Skibniewski (1994) performed a case study in which a neural network was used to predict the productivity of an excavator. They identify two main factors that affect an excavator's productivity: job conditions and operation elements. Job conditions include the characteristics of the environment, such as soil conditions, and specific characteristics of the excavator and excavation, such as the vertical position of the cutting edge.

Operational elements, on the other hand, include characteristics not directly related to the excavating operation, for example, the effect of wait time for trucks and extra tasks other than excavating. Two neural networks were used for the purpose of this case study. The first was used to estimate the excavator cycle time. Four key factors were identified as having an influence: cycle time (including swing angle), horizontal reach, vertical position, and soil type (job conditions). The output of the first network was then incorporated into the second network, which examined the effect of the operational elements on the productivity. Two cases were examined with the second neural network. The first identified the effects of empty truck queues, and the second examined the effect of empty truck queues combined with extra tasks for the excavator to perform. A robotic excavator was used to simulate an excavating activity, and site and operational characteristics were randomized so that training and testing data could be developed. Large testing sets were used, and training was optimized through experimentation with various hidden layers, hidden nodes, and learning rates until the testing data accuracy dropped to within range of the training data. The result was that the networks were successfully trained and a minimal level of error was determined through testing. The case study successfully tested two neural networks and accounted for varying characteristics that affect an excavators productivity.

Flood and Kartam (1994) explain that the versatility of neural networks gives the artificial intelligence the capability to analyze transitory problems. They cite production rates as a transitory problem as they will alter over time. This variability can be handled by neural networks by adding transitory inputs to the network structure. Flood and Kartam depict this point by using an example of an excavation operation. As excavation work continues on an activity, the productivity rate will begin to increase. An input such as number of cycles would draw from the effect of the number of cycles on activities in which the network was trained and would account for the effects of the crew acquiring experience with the specific activity. Flood and Kartam did not, however, provide any analytical proof of the abilities of such an application.

Creese and Li (1995) identify neural networks as particularly effective for problems in which the relationship between the input and output cannot be expressed by a simple mathematical relationship. Furthermore, Creese and Li characterize the process of estimating as a long and expensive task. Defined relationships specifying costs, schedules, and productivity rates that are used by estimators can be fairly simple to use, but difficult and expensive to maintain in a constantly changing construction industry due to their dependence on a large number of unpredictable inputs. As a result, they recommend neural networks as an effective means for keeping such relationships up to date.

As validation of these comments, Creese and Li developed a neural network model capable of estimating the cost of timber bridges (although this application does not directly apply to labour productivity rates, it is a tool intended for use during estimation, and therefore, very close in nature to the models used for predicting labour productivity rates). Web volume, deck volume, and steel weight were used as inputs, four hidden nodes were experimentally derived, and the estimated cost of the timber bridge was the output. Simplicity of the network structure allowed for detailed research into the effect of both the architecture and the number of inputs on the neural network. As a result, the validity of neural networks when applied to an estimating problem was proven through the accuracy that the neural network models were able to achieve. Furthermore, the ability of a neural network to accurately predict in situations in which mathematical relationships are no longer possible was proven as the neural networks were able to predict more accurately and with more inputs.

Creese and Li continued with this research to compare the validity of neural networks to another type of model. A common linear regression model was chosen as an alternate prediction technique. The same variables were analyzed but the prediction ability of linear regression proved to be less accurate than the neural network.

McCabe, Saadi, AbouRizk (1996) used neural networks in order to predict the productivity of two pipeline activities: trenching and welding. The objective of the study was to improve the accuracy of estimating each of these activities

Factors incorporated for estimating a trenching activity included weather characteristics, equipment type, hours worked per day, and the cumulative percent of the activity complete. A feed forward back propagation neural network was trained with historic data from two projects, with daily productivity used as the output. Results provided better accuracy than estimators have historically been able to achieve, but the training data was deemed very noisy (due to inaccurate daily production reporting and inadequate equipment breakdown documentation). In an attempt to obtain better accuracy, a noise reduction procedure was performed on the training data. Five-day averages of the productivity rates (two days prior, two days following, and the actual day were averaged) were calculated for each day and training was repeated. This procedure successfully removed the variability in the data but accuracy was not significantly increased. Furthermore, the procedure masked the effect of the inputs and each inputs true effect was no longer being realized.

Welding neural networks were trained using crew size, hours work per day, air temperature, pipe grade, and the cumulative percent complete of the activity as factors of productivity. Feed forward back propagation neural networks were first used to estimate crew size as this was deemed to be valuable information for an estimator to have. These networks trained very accurately. Networks were then trained to predict the number of joints welded per day. This network also trained accurately with the exception of a few individual records that were very poorly predicted. As with trenching, the source of the error was traced to inaccurate production reporting. As a result, the research focused on the development of a project average productivity rate. This technique would allow for data to be used despite the erratic nature of daily records. However, they encountered difficulty in collecting enough projects using current pipeline technologies and method in order for sufficient training to take place.

Sonmez (1996) studied the ability of neural network models to predict the labour productivity rates of concrete construction activities. The objective of the models was to develop a more effective and accurate predicting tool than techniques currently used by estimators, with the added ability to explain variations due to influencing productivity factors.

Data collection for training consisted of eight projects from a building contractor. Characteristics of the data collection, such as limited data and reporting periods, required the implementation of a number of limitations in the model development. First, focus was shifted to only four concrete construction tasks, including concrete pouring, formwork, concrete finishing, and granular filling. Second, data was only compiled on a weekly basis, therefore, daily variations could not be accounted for. Third, only a limited number of productivity factors were available to be incorporated into the models. The factors chosen included:

- Job Complexity
- Crew Size and Composition
- Repetition
- Weather
- Equipment
- Motivation and Fatigue

Regression analysis was used to determine the most influential productivity factors that affected each of the studied tasks. As a result, the number of inputs was reduced to four to six inputs per task prior to development of the neural network models. Feed forward back propagation neural network models were trained for each task and their results were more accurate than those obtained by other productivity prediction models developed previous to the research (results were compared to statistical techniques and a form of linear regression analysis). Furthermore, Sonmez studied the applicability of regression analysis as means of predicting productivity rates. The regression models proved to be slightly more accurate for three out of four of the tasks studied. However, comparisons of the abilities of the regression and neural network models demonstrated that the neural networks have a distinct ability to identify the effects of input factors when the interactions and nonlinear relationships are present.

Portas (1996) researched the use of neural networks as a means of predicting formwork labour productivity rates. The intention of the application was to build an aid for estimators for an area of construction which has historically proven to be very difficult to predict accurately. Contractor estimates of actual costs based on traditional estimating techniques are only accurate, on average, to within 15%, 40% of the time for formwork activities. Two formwork activities, loose walls and loose slabs (where loose refers to typical non repetitive formwork, were the formwork structure is constructed to fit a specific shape and torn apart following its use), were chosen as tests for the applicability of neural network artificial intelligence to aid in prediction abilities. An extensive data search focused on the collection of a large number of input factors determined to have an influence on formwork productivity. Collection focused on both project and activity factors, including:

Project Factors

- staff characteristics
- size
- location
- site characteristics

Activity Factors

- crew characteristics
- formwork design aspects
- quantity
- repetition
- working conditions

Feed forward back propagation neural networks were used and individual records provided over 40 inputs. The complicated network structure also included 35 hidden nodes and 14 output nodes. Among the 14 output nodes, 13 nodes composed the fuzzy output format and the 14th a point prediction. The fuzzy output format presented a graphical distribution of productivity and was implemented so that an estimator would be presented with a reasonable range of productivity rates as opposed to just a single numerical prediction. As a result, the developed application was intended to act only as an aid, and estimator judgment remained necessary in the estimating process.

The resulting application using neural network artificial intelligence in the manner discussed above was accurate to within 15% of the actual, 80% of the time, a significant improvement over historical accuracy given the context and limitations of the solution.

2.3.2 Other Labour Productivity Models

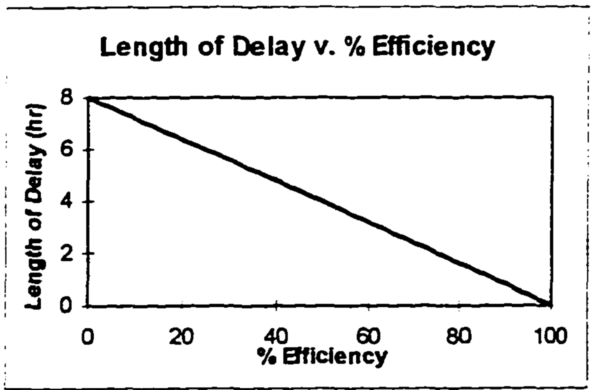
Hendrickson, Martinelli, and Rehak (1987) note that project planning usually involves an intuitive and unstructured method and relies highly on engineering judgment. In particular, they identify activity duration as an aspect of project planning that is indispensable as input for planning and management, but it is too reliant on this intuitive and unstructured method. In response, Hendrickson et al. researched a knowledge-based expert system capable of modifying average productivity rates for special conditions of a job or site. The objective here was to eliminate the intuitive and unstructured method involved in deriving construction productivity rates.

Hendrickson et al. used a hierarchical rule-based estimation approach in the development of a prototype masonry duration estimation model, MASON. An estimation hierarchy decomposes the estimation process into a number of specifications and estimations of various detailed factors used to derive an activity duration. Levels of hierarchy are set up in such a system where factors are used to derive the factors in each subsequent level. The derivation of a new level, however, is dependent on a number of expert-based rules. The rules define an operation if a factor is present and use an "if-then" format. MASON was developed in order to demonstrate the hierarchical rule based estimation model proposed by Hendrickson et al. A dozen factors were chosen to be incorporated into the model and the knowledge of two experts was used to develop rules for MASON. The experts provided input as to the magnitude to which the presence, absence, or magnitude of a factor would adjust the magnitude of the duration. The model prompts the user to input data on a number of productivity factors and returns the activity duration information. The accuracy of the model was not discussed as MASON was only developed as a prototype to demonstrate the hierarchical rule-based activity duration estimation.

Thomas, Maloney, Horner, Smith, Handa, and Sanders (1990) identify three simplistic prediction models used by the construction industry for labour productivity derivation.

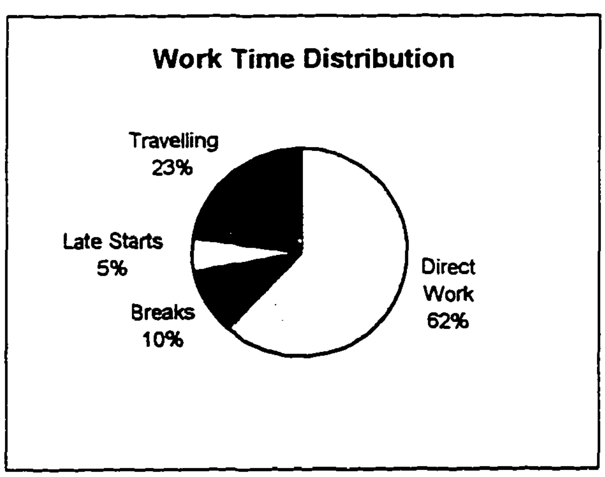
1. Delay Model - Only the relationship between delays and worker productivity can be expressed by this model. Time studies would be used to verify this relationship within an individual industry or company. Figure 2.2 provides an example of the delay model.

Figure 2.2 Delay Model



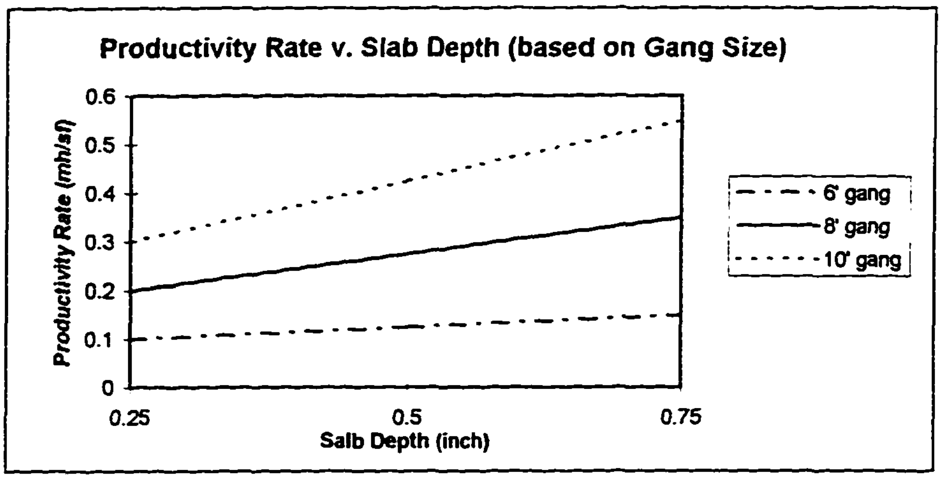
2. Activity Model - This model is based on time studies and provides an indicator of the time that a worker applies to direct work. The direct work percentage can then be used in productivity calculation. Figure 2.3 presents a typical activity model.

Figure 2.3 Activity Model



3. Task Model - This model has the ability to relate a number of factors of productivity in a graphical format. Time studies, again, would be the source of the task model. Figure 2.4 provides an example of a task model.

Figure 2.4 Task Model



Thomas et al. state that use of such statistical models is limited due to each model's inability to incorporate a significant number of factors simultaneously. In place of such models, they propose an expectancy model. The expectancy model accounts for the factor of worker motivation by defining performance as a function of job conditions, management actions, relevance of work, and rewards. As a result, the expectancy model derives the effect of motivation as a function of the following seven components:

1. duration
2. intensity
3. knowledge
4. skill
5. direction
6. absence of organizational barriers
7. nature of work

The expectancy model empirically analyzes the effect of each factor on performance based on a expert-developed knowledge base. An application defining the abilities of the expectancy model, however, was not documented.

Sanders and Thomas (1993) developed an additive linear regression model for the purposes of determining the combined effects of factors on the labour productivity rate of masonry construction. The technique offers three benefits over typical labour productivity forecasting models:

1. factors not previously accounted for in forecasting labour productivity rates are incorporated into the models.
2. methodology of program is easily implemented within a database or spreadsheet program.
3. model can be used on a daily basis for forecasting daily labour productivity rates.

The following defines the format of the model:

$$E(P) = B_o + \sum_{i=1}^{n-3} B_i X_i + B_{n-2} CS + B_{n-1} CS^2 + B_n CS^3 \text{, where}$$

$E(P)$ = expected productivity

B_o = base productivity rate

B_i, B_{n-2}, B_{n-1}, B_n = model coefficients for factors

$n-3$ = number of factors

i = factor number

CS = crew size

Sanders and Thomas (1991) define the factors and the coefficients used within the regression models through an extensive study into masonry labour productivity. They identify work type, building elements, construction method, design requirement, weather zone, and crew size as the most influential factors and, therefore, these factors are the focus of the models. A data search on masonry projects between the years of 1984 and 1986 constituted the source of the masonry labour productivity factors. The historical data was used to develop the coefficients that determine the impact of each factor on the productivity rate. Coefficient derivation first involved the identification of a standard condition for each factor. The range of historically achieved productivity rates for the other conditions was then compared to the historic productivity range of the standard condition. This comparison was represented as a ratio and became identified as the coefficient for the condition of an input factor in the model.

Thomas and Sakarcan (1994) continued the focus of the research by Sanders and Thomas (1993) by developing a factor model for the purposes of forecasting labour productivity. The factor model works with the recognition that labour productivity varies over time in unique but predictable ways.

Thomas and Sakarcan summarize the factors that affect labour productivity into two classifications:

1. Organizational Continuity - work content and physical components of the work are included in this classification. These factors affect the productivity by up to 15%.
2. Executional Continuity - the work environment, including both organization and management factors, are included in this classification. These factors affect the productivity by up to 25%.

The factor model focuses on only organizational continuity as these factors are definable whereas executional continuity is not normally predictable. The algorithm used for predicting a productivity rate with the factor model is much like the additive regression model and is as follows:

$$E_t = I_s + \sum_{i=1}^{m} a_i x_i + \sum_{j=1}^{n} f(y)_j \text{, where}$$

E_t = predicted productivity rate

I_s = standard conditions productivity rate

$\sum_{i=1}^{m} a_i x_i$ = effect of all organizational continuity conditions, where

a_i = coefficient of condition variable

x_i = presence of condition (1 if present, 0 if not present)

m = number of variables in the problem

$\sum_{j=1}^{n} f(y)_j$ = submodels effect (such as the effect of crew size)

The key component to the factor model, therefore, is the coefficient of condition variable as this variable will define the effect of a present condition on the activity productivity rate. The coefficients used for verifying the factor model were, as with the additive regression model, developed by Sanders and Thomas (1991) and based on the results of a two year historical study.

The predicted productivity rates calculated by the factor model, however, must be factored based on the productivity rates achieved during the first few days of construction. In other words, the factor model must be initialized by an order of magnitude in order for it to predict accurately.

Thomas and Sakarcan present an example of the factor model within an application developed for the purposes of predicting masonry productivity. Twenty-five site factors were incorporated into the model and equivalent quantity calculations are used to account for the various material sizes and equipment types. The model predicted approximately 20% high following five days of operation and so the model was factored by 20% so that the remaining productivity rates could be forecast. As a result, the forecast productivity sufficiently matched the actual productivity for the remainder of the project.

Kuntz and Sanvido (1995) developed a framework which identifies productivity factors to management. The framework only focuses on factors which are in the control of management and acts to quantify and evaluate the effect that the factors have on labour productivity. Eight factors were incorporated into the framework with a number of subfactors and attributes within each:

1. Design - finish requirements, dimensions, details, and materials
2. Team - craft type, experience, motivation, knowledge, group dynamics, composition, size, task assignment, and cohesiveness
3. Tool / Equipment - job, discipline, crew and individual equipment characteristics
4. Method - processes and procedures
5. Material Supply - flow rate and level of effort required to supply materials
6. Area of Operation - existing work, physical characteristics, energy supply, environmental conditions, and activity in the area
7. Goal / Feedback - downward communication and upward feedback
8. Planning Information - addressing of previous factors, implementation, and sequence of work

The framework developed by Kuntz and Sanvido, however, is only a road map to guide planning and estimating. Therefore, no empirical relationships are set to the evaluated factors, but the system is intended to expose possible factors of a project that may have a distinct effect on the labour productivity rate.

Christian and Hachey (1995) identify the applicability of expert systems for predicting construction labour productivity rates through the development of a system for predicting the productivity of concrete placement. In developing rules for the systems, they used heuristic and published knowledge in combination with data obtained from field studies. Field data focused on time studies which established the duration of aspects of an activity. Tasks such as direct work, waiting time, material handling, and breaks were all logged so that direct work hours could be separated from the actual manhours. This technique is referred to as "work sampling" and assumes that direct work is related to productivity. The expert system developed by Christian and Hachey, however, had many limitations in its abilities due to variations and inconsistencies in the data sources used for rule derivations, as well as having only limited time studies. Furthermore, no validation of the model was undertaken.

Boussabaine and Duff (1996) argue that forecasting construction productivity can only be effectively accomplished though an experience based model. Mathematical and statistical models are simply unable to capture complex situations due to the arbitrary assumptions necessary to simplify the mathematics. Furthermore, the estimator's technique of intuitively adjusting base rate productivity to account for project characteristics lacks the influence of relating the present project to past patterns. As a result, Boussabaine and Duff have developed an expert-simulation system model that simulates the expected occurrence of productivity factors, and analyzes and quantifies their combined effects on a productivity rate. The prototype system consists of two modules:

Module 1: schedules the project based on elemental project characteristics and base rate productivity.

Module 2: modifies the assigned productivity rates using Monte Carlo simulation to determine the most likely factor conditions with the effects of the factors assigned based on a extensive knowledge base made up of 300 productivity rules.

The prototype system, however, is only applicable to reinforced concrete buildings up to five floors in height. Certainty factors for each productivity factor are assigned so that the degree to which the factor is to influence the productivity rate can be adjusted by the user to assign a higher certainty to a factor in which the value was entered in high confidence.

2.3.3 Discussion of Labour Productivity Models

The other labour productivity models present a number of limitations that would not be encountered if the problem were addressed by neural network artificial intelligence. Table 2.2 identifies some key limitations in the research reviewed in this literature search.

Table 2.2 Other Labour Productivity Model Limitations

Model	Type	Limitations
MASON (Hendrickson, Martinelli, Rehak (1987))	Hierarchical Expert System	• hierarchy and rules are specific for a masonry activity and a change of scope would require an entire rebuilding of the system
Delay, Activity, and Task Model (Thomas, Maloney, Horner, Smith, Handa, Sanders (1990))	Statistical	• number of inputs limited • insufficient level of analysis
Expectancy Model (Thomas, Maloney, Horner, Smith, Handa, Sanders (1990))	Framework	• a method of quantifying motivational factors is necessary
Masonry Productivity Forecasting Model (Sanders and Thomas (1993))	Additive Linear Regression	• coefficients defining the influence of a defined condition factor are derived independently of other inputs; combined effects not accounted for • structure of model is rigid so that it can not be easily adapted to other construction activities

Table 2.2 cont.

Model	Type	Limitations
Factor Model (Thomas and Sakarcan (1994))	Linear Regression	• coefficients defined in same manner as Masonry Productivity Forecasting Model • executional continuity factors, identified to effect the productivity rate by up to 25%, is not accounted for by the model • structure of model is rigid meaning that it cannot be easily adapted to other construction activities • is only a forecasting model and can only be used following initiation of an activity
Construction Crew Evaluation Model (Kuntz and Sanvido (1995))	Framework	• empirical relationships of all the factors identified are required for the model to predict a productivity rate
Activity Duration Model (Christian and Hachey (1995))	Expert System	• inconsistencies and limitations in data collection resulted in limited rule derivations
Construction Productivity Forecasting Model (Boussabaine And Duff (1996))	Expert - Simulation Model	• rules are set by experts, therefore prejudices and other attitudes affect the rules • prototype system is very specific and only applies to under five story reinforced concrete buildings (300 rules would be need to be altered should expansion or change of the scope be necessary)

In reviewing the limitations identified in Table 2.2, it is apparent that one key characteristic of all the other labour productivity models is that they are very rigid. Both the structure and rules of these models are unique to the construction activity and to the factors for which models were built. Therefore, the structure and rules would need to be completely rebuilt if the technology were to be extended to another activity or to incorporate new factors. The structure of neural networks, on the other hand, is much looser as it is learned rather than built. Furthermore, once a learning technique is established, learning becomes a fast process so that new activities could be trained or new factors be added to existing models without great difficulty. Other limitations identified in Table 2.2, such as quantification of input factors, limited number of inputs, and the effects of incomplete or inconsistent data, are sufficiently dealt with by neural networks through the learning process.

2.4 State of the Art Discussion

Research into the topic of computer-aided labour productivity prediction has taken a number of steps in recent years. Neural network artificial intelligence, in particular, is rapidly being applied to labour productivity rate prediction scenarios as a means of increasing estimation accuracy. The unique ability of neural networks to learn the influence of a large number of factors provides a distinct advantage for use as a construction prediction tool. Portas (1996) states that the current state of factors affecting productivity is inconclusive. The large number and unique combination of factors on historically recorded activities has made the derivation of the actual effect of individual factors unrealistic. However, applications described in this literature review, summarized in Table 2.3, have demonstrated the ability of neural networks to capture the effect of all of the factors in an construction activity.

Table 2.3 Neural Network Applications Successful in Modeling Construction Productivity Rates

Neural Network Model	**Source**
Earthmoving Equipment Productivity	Karshenas and Feng (1992)
Effect of Environmental Conditions on Productivity	Wales and AbouRizk (1993)
Excavation Productivity	Chao and Skibniewski (1994)
Timber Bridge Estimation	Creese and Li (1995)
Pipeline Trenching and Welding Productivity	McCabe, Saadi, AbouRizk (1996)
Wall and Slab Formwork Productivity	Portas (1996)
Concrete Construction Productivity	Sonmez (1996)

Methods of artificial intelligence other than neural networks have historically been the technology applied to predicting labour productivity rates. Statistical techniques, regression systems, and expert systems, however, have suffered from many limitations. The most important of these limitations is the inability of these systems to account for changing and unique situations or characteristics. One distinctive characteristic of the construction industry is the variability of each project and, therefore, successful implementation of an inflexible system is unlikely.

The current state of the art in the use of neural network artificial intelligence for the purposes of predicting construction labour productivity rates is a continued verification of acceptability but limited implementation. Portas' (1996) development of formwork activity neural networks model is the only system developed which resulted in implementation. All other neural network applications discussed in this literature review have only been prototypes used to test the applicability of neural networks to a problem.

The construction industry has yet to accept neural network technology despite the advancement of research in recent years. Lack of trust in a technology that provides no explanation for its predicted output, an inability to predict precisely, and no guarantee of a correct solution appear to be inhibiting implementation of the technology. Very little work has taken place in addressing these disadvantages and until research can overcome the mistrust, implementation will remain limited.

3. Stability Enhancement of Formwork Neural Network Labour Productivity Models

3.1 Introduction

Stability within artificial intelligence refers to the ability of a technology to behave in a consistent and sound manner. In the case of a prediction neural network, stability refers to the ability of a neural network model to predict a consistent and legitimate output. Neural network stability can be more effectively achieved when the following characteristics are present:

- all factors that influence the output are included in the model,
- the neural network is trained with sufficient data so that the effects of all input factors are captured and,
- the factors affecting the output are entered in so that training properly captures the effect of the factor.

The estimation of labour productivity for a construction activity is a function of a large number of input factors. As a result, the complexity of this problem can make stability very difficult to attain. This chapter identifies issues of stability of the formwork neural network models and describes a detailed analysis for rectifying these issues.

3.2 Stability Issues of Formwork Neural Network Models

Previous research (Portas 1996) involved the development of neural network models which focus on predicting formwork labour productivity. Wall, slab, and column (both loose and repetitive) formwork activities have all been studied. For each of these activities, historical information was researched from over 40 completed general contractor projects. The historical information included all data that had an effect on the formwork productivity. The factors studied are summarized in Table 3.1 and Table 3.2.

Table 3.1 Activity Input Factors

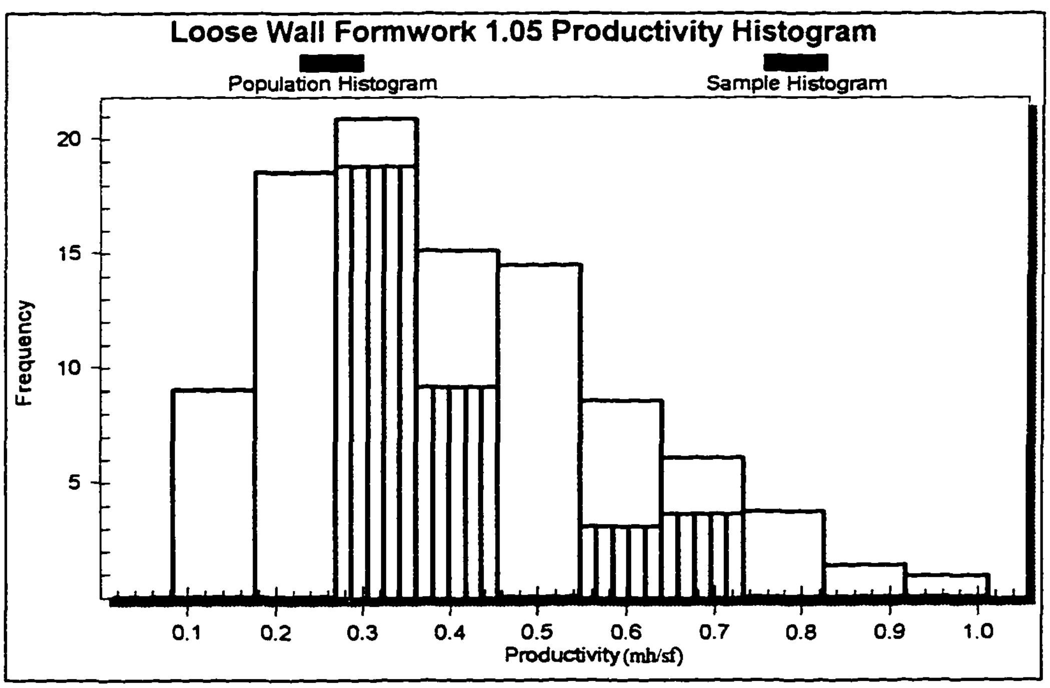
Activity Factors		
Performance	• Complexity	
Staff	• Superintendent Skill	• Activity District Performance
Crew	• Crew Skill • Crew Size	• Union
Design	• Cost Code • Formwork Duty • Tie Type Group	• Tie Spacing Group • Accuracy of Design
Dimensions	• Quantity	• Thickness / Height
Repetition	• Degree of Repetition • Number of Reuses	• Panel Area
Working Conditions	• Crane Time • Continuity of Cycle	• Shift Duration

Table 3.2 Project Input Factors

Project Performance		
Complexity	• Staffing • Superintendent Skill	• District Performance
Structure	• Gross Building Area	
Size	• Original Company	• Original Total Contract
Location	• District	• Climate - Temperature
Site	• Congestion • Access	• Conditions

These factors were determined through research and neural network experimentation. Both qualitative and quantitative factors were included in the study. Each one of the factors was implemented as input. Note that each type of formwork forms an individual neural network. Actual productivity from the historical projects were used as outputs since a feed-forward, back-propagation neural network training algorithm was used. A fuzzy format was used for the output nodes. This format does not predict one output, but rather narrows the range of practical solutions. For these models, 13 output zones are used to depict the distribution of predicted output. The histogram in Figure 3.1 illustrates the fuzzy format used in the models. The striped bars represent the fuzzy prediction by a model and can be compared to the hollow bars which represent the distribution of the historical productivity for a loose wall formwork activity.

Figure 3.1 Fuzzy Format



The final accuracy of the networks was +/- 15%, approximately 80% of the time. This was an increase from the estimator's historic accuracy of +/- 15% only 40% of the time.

The result of the study was the implementation of the models into the general contractor's estimating system.

Following completion of the research, a number of issues concerning the stability of the neural network were identified, including:

1. a number of additional input factors can potentially affect the labour productivity.
2. limitations in the quantity of historical training data may result in incomplete capture of the effect of all inputs.
3. current structure of the models places too high a weighting on the difficulty input.
4. development of a method to accurately and consistently use subjective factors provided by project superintendents.
5. development of a method to account for estimator use of a model trained upon superintendent input.

3.3 Method of Enhancing Stability

In order to address stability issues of the model, three characteristics of stability are studied. First, an evaluation of the input factors is undertaken in order to identify additional input factors. It is very important to the stability of a neural network model that all influencing factors are present. If, for instance, a factor that would influence the predicted output was not included as an input, its influence would be incorrectly attributed to another factor. As a result, stability of the neural network would not be attained. Second, this research extends the collection of training records so that lack of input stability due to insufficient data can be avoided. Increasing the level of training data is necessary in order to meet adequate stability. The formwork neural network models studied by this research were developed based on a training set of 45 records. However, 53 inputs were used. With 53 inputs, a large number of combinations of inputs were possible, and it is questionable as to whether 45 records were sufficient for training such a network. For example, one of the 53 inputs may have been a binary input (a one is entered when this factor is applicable and a zero when the factor is not applicable) in which a one was entered for only two records and a zero for the remaining 43 records. The input in question, when applicable to an activity and assigned a value of one, is a factor of productivity that makes an activity easier to do, then should result in a better productivity. If the two records, for instance, had very poor productivity (due to other factors), the lack of sufficient training records defining this factor may result in the neural network assigning weights to the input resulting in a decreasing productivity when a one is assigned to the input than when a zero is assigned. Third, one input factor is analyzed in detail in order to obtain stability in its influence. The factor defining the difficulty of an activity proved to be a overly dominant input factor in the formwork neural network models and, therefore, analysis into stabilizing the effect of difficulty on a predicted labour productivity is discussed.

In addition to addressing these three characteristics of stability, the effect of subjective factors used as inputs on the stability of the formwork neural network models is addressed. The use of many subjective inputs stresses the need for analysis of the stability of this type of factor in the models. The subjective factors addressed in the formwork neural network models include:

- degree of repetition
- level of cycle continuity maintained
- accuracy and detail of design
- characteristics of the crew
- effect of material and equipment scheduling and availability
- level of owner inspection, safety, and quality requirements
- degree of difficulty of the activity

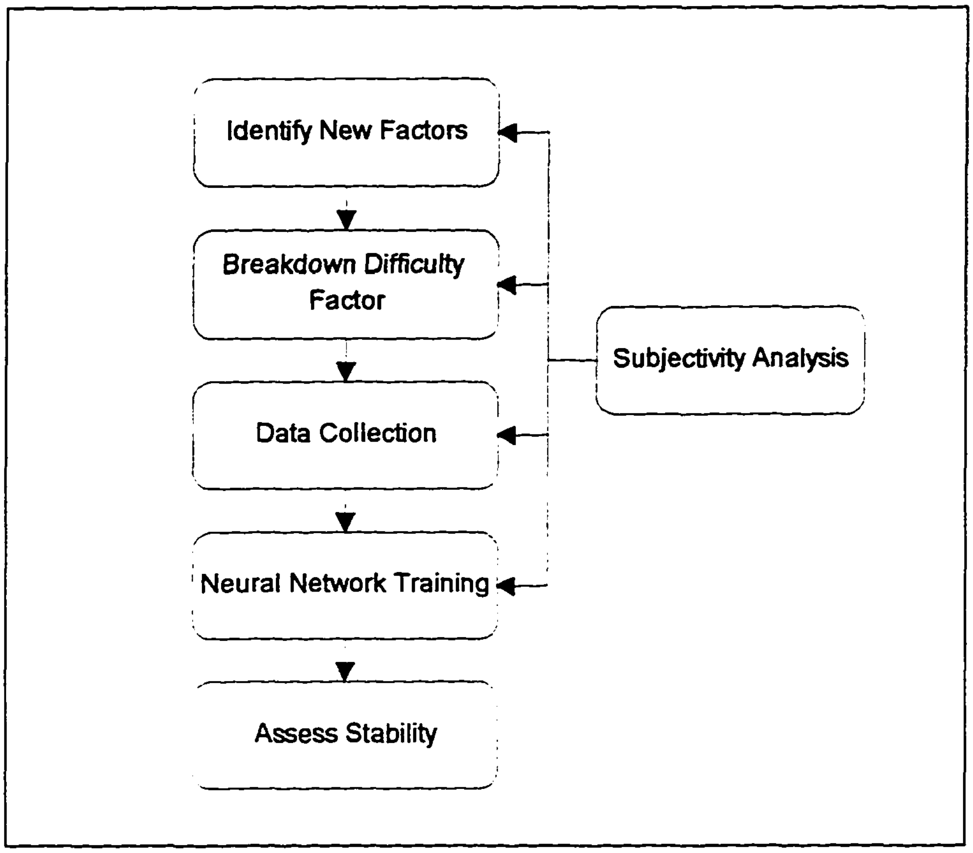
The following three issues are relevant when using subjective inputs, such as the factors listed above, for training the formwork neural network models:

1. Prejudice, attitude, experience, and aggression can all affect how an individual will respond to a subjective question. But these emotions and characteristics will vary among individuals, therefore, similar circumstances may be analyzed and input differently. Consideration needs to be given to determining a method of normalizing inputs among different individuals so that all training record inputs of are consistent.
2. *Superintendents* provided all the subjective information for activities used as training records of the formwork neural network models. This information was provided by the superintendents *following completion* of the projects. The application developed based on the formwork neural network models, however, requires *estimators* to input the subjective factors *prior to initiation* of the project. Therefore, two major variables, person inputting the data and timing of analysis, are different for the subjective inputs. Consideration needs to be given to this inconsistency of subjective input value determination.
3. Subjective factors are typically addressed with qualitative rather than quantitative responses. The responses are then converted to a numerical format in order to be used as an input in the formwork neural network models. The conversion, however, must be made so that the neural network will properly capture the effect that the input has on the productivity of an activity. Consideration into a conversion technique is, therefore, necessary for the proper interpretation of subjective data with the formwork neural network models.

Proper incorporation of subjective data is an aspect of the third characteristic of neural network stability being shifted. In order for a subjective input to provide a stable influence on the formwork neural network models, each of the three identified issues of subjective data need to be considered.

The following sections of this chapter address the three characteristics of stability. In addition, issues of subjective data are addressed at applicable points in the analysis. The flowchart in Figure 3.2 depicts this method.

Figure 3.2 Stability Enhancement Methodology Flowchart



3.4 New Factor Identification

Previous data collection of historical projects for use as formwork neural network model inputs involved surveying superintendents from each project. To do this, sampling sheets that question the superintendent on various factors were used. The factors included on the sampling sheets were developed based on an extensive search of literature and discussions with experienced personnel (estimators, superintendents, and project managers) who would be able to identify the key characteristics. But following the sampling of 40 historic projects, new factors became apparent based on additional comments from the sampled superintendents. Furthermore, analysis of the received data and results from the neural network models demonstrated a need for the new factors. As a result, the following lists the new factors to be added to the neural network models.

1. Location of Work (above, below, or at grade & floor numbers) - the ability to move and work freely, work hazards, and material and equipment availability will all vary based on the location of the work. All these characteristics can be a function of the productivity and were not accounted for by the neural network models.
2. Formwork Design Drawings Prepared - the use of drawings and plans can be time saving and, hence, improve productivity. This factor was not accounted for by the neural network models.
3. Average Crew Experience - the performance of the crew has been previously captured with only a single subjective question on crew performance. Crew experience can compliment the original factor and more effectively capture the work performance of a crew.
4. Level of Owner Inspection, Safety, and Quality Requirements - stringent requirements can hamper productivity. This factor was not accounted for by the formwork neural network models.

3.5 Difficulty Factor Breakdown

Difficulty experienced on an activity can have a strong influence on the ability of a crew to perform. As a result, difficulty is deemed to be one of the most important impacts on labour productivity. In the formwork neural network models difficulty is addressed in two ways. First, a number of inputs addressing the design, materials used, and other technical aspects is used to define the difficulty of the duty. Second, difficulty associated with completing the duty is addressed based on a superintendent's judgment of difficulty associated with completing the duty.

Training of the neural network models developed the influence of each of the inputs for a formwork activity on the labour productivity. The influence is reflected by the weights which the neural network assigns to the links between input nodes and hidden nodes in a model. Table 3.3 provides a sample of the typical ranking of the top 25 out of 53 factors used for one of the formwork activities. The *Sum* column in Table 3.3 indicates the absolute sum of all of the weights connecting a single input node to each of the nodes in the hidden layer. This summation is a very good indication of the influence that the neural network has defined for each input as all inputs in a neural network are scaled to enable equal comparison. Therefore, the higher the absolute sum of the weights for an input, the greater the influence it has on the output.

Table 3.3 Ranking of Inputs from Network Analysis

Rank	Input Factor	Sum
1	ACTIVITY PERFORMANCE	17.48
2	CREWSIZE INPUT 1	13.02
3	Activity - Superintendent Score	12.01
4	NUMBER OF REUSE INPUT 4	9.91
5	TIE TYPE_WALL_SNAP TIE	9.90
6	# FLOORS_ABOVE_HIGH	9.42
7	TIE SPACING_VERTICAL	9.33
8	NUMBER OF REUSE INPUT 3	9.25
9	NUMBER OF REUSE INPUT 1	9.04
10	DISTRICT_6_INPUT	8.93
11	PANEL AREA INPUT 2	8.67
12	# FLOORS_BELOW_HIGH	8.51
13	Crew Skill Rating	8.17
14	PANEL AREA INPUT 1	8.04
15	# FLOORS_BELOW_LOW	7.76
16	PANEL AREA INPUT 3	7.50
17	CREWSIZE INPUT 2	7.46
18	CREWSIZE INPUT 4	7.04
19	Season Mean Temperature	6.94

Table 3.3 cont.

Rank	Input Factor	Sum
20	TIE TYPE_WALL_TAPER TYPE&BURKE	6.71
21	LOG_TOTAL_CONTRACT	6.71
22	HEIGHT_WALL_1	6.64
23	CREWSIZE INPUT 3	6.51
24	TIE TYPE_WALL_ANCHOR&CAMLOCK	6.42
25	Design Rating	6.39

The formwork neural network models are stable in terms of their ability to address the difficulty of a duty through technical inputs. This is demonstrated in Table 3.3 by the ranking of such factors as tie type and wall height being in the top 25 factors. But in terms of addressing difficulty associated with completing the duty, stability was not attained.

The Activity Performance factor is used in the formwork neural network models as the characteristic defining difficulty associated with completing a duty. As seen in Table 3.3, this factor is not only the top ranked factor, but weighted considerably greater than all other factors. Three issues of stability can be identified relating to this factor:

1. This factor has an overwhelming influence on the output of the models (this is a major concern of network stability). By simply changing this input factor, a neural network prediction can be drastically altered.

   The following provides the results of the sensitivity of the Activity Performance factor on the application's prediction (note: application addresses this factor by asking "What is the Activity Complexity?").

Project: Sample (Health Sciences Centre, Winnipeg)

Activity: Cost Code 1-01 (Foundation/Retaining Wall)

Actual Productivity: 0.1587 mh/sf

Complexity Input Value	Weighted Average Predicted Productivity	% Difference from Actual Productivity
Low	0.152	-1.7%
Medium	0.339	+48.0%
High	0.600	+117.3%

As can be seen by this sample activity, changing the value of the complexity results in the predicted productivity changing drastically. The range of predictions given in the table for this example activity span almost from the 10th percentile to the 90th percentile for the type of formwork activity. Therefore, for this example activity the influence of all the other factors included in analysis are essentially overwritten by the Activity Performance factor.

The Activity Performance factor is a function of both the subjective response of a superintendent on the degree of difficulty of the activity and the productivity performance of the activity compared to the general contractor's historic average productivity for that activity (i.e. the factor is biased). This method of derivation is the source of the other two issues of the stability for the factor defining difficulty in the formwork neural network models.

2. Subjective factors can be very difficult to analyze because the respondent will answer based on his/her experience and knowledge, however, levels of experience and knowledge differ from person to person. Therefore, the problem arises as to how to convert a subjective answer to a quantitative answer so that the neural network can analyze the factor.

3. It is difficult to justify defining a portion of this factor as a function of an activity's actual productivity. This is because, when studying a new project, an estimator is going to have to provide a response to the Activity Performance factor for an activity that has not taken place and does not yet have an actual productivity. Therefore, the most influential factor on the network can not be derived in the same way as it was for training the network. This inconsistency will result in a loss of accuracy in the output from the network.

To rectify these issues, the following lists the new difficulty factors to be added to the neural networks:

1. Complexity of Geometry - accounts for difficulty associated with complex geometry such as curved surfaces
2. Formwork Irregularities - accounts for difficulty associated with blockouts, openings, and inserts
3. Required Finishes - accounts for difficulty associated with the type of concrete finish that is required
4. Working Conditions - many problems with congestion, site access, weather, and other conditions are accounted for with this factor
5. Overall Difficulty - this factor is intended to capture overall difficulty and the effects of any other difficulties not addressed by the previous four factors. This factor is equivalent to the subjective portion of the Activity Performance factor

The use of these five difficulty factors as a replacement for the Activity Performance factor will rectify the three identified issues of stability based on the following benefits:

- the difficulty originally defined with one input will now be defined with five inputs. The overwhelming influence of the original factor is to be distributed among the five and the ability of difficulty to control the prediction of the neural network models will be dampened

- by defining difficulty as having five components, superintendent subjective responses will be more controlled as differing opinions as to which component contributes more to difficulty is eliminated.
- the biased aspect of the Activity Performance factor is eliminated and research into implementing the five new difficulty factors following only subjective analysis is necessary.

3.6 Data Collection

3.6.1 Collection Technique

One of the keys to successful training of neural network models is the data upon which the networks are trained. For the purposes of this research, data collection focused on the collection of information from historic commercial building projects. Formwork activities in which a significant level of formwork quantities were used were chosen to be collected and used as training records. Also, the period of time in which the construction took place was a consideration. Data collection was deemed difficult for projects over five years old and changing construction methods over time deterred the collection of information from older projects. Data collected included all project and activity factors used to train the formwork neural network models plus the new input and difficulty factors identified by this research.

Two types of data were collected. First, quantitative data, the numerical information defining specific project and activity factors. Second, qualitative data, the information in a descriptive form that describes project and activity factors. Included in the qualitative data are details on the duty of the formwork activity (i.e. tie types, panel use, support systems, etc.) and the subjective inputs.

Two sources were used for data collection. First, historical records were searched as means of collecting the majority of the quantitative inputs. The general contractor's *Project List* database is used to store data on all of its historic projects and was the source of a number of the project related inputs. A general contractor database containing historic productivity for cost coded activities was used as a source for many of the quantitative activity related inputs. Government produced means index and climatic databases were also used to determine inputs. Second, data collection questionnaires were sent to project superintendents as a means of collecting undocumented quantitative data and all qualitative data. Figure 3.3 presents a sample data collection questionnaire. One questionnaire represents one activity, therefore, a superintendent would typically be sent a number of these questionnaires, dependent on the number of formwork activities deemed applicable.

Figure 3.3 Sample Data Collection Sheets

Commercial Formwork Report

Prepared By: ____________________ Report Date: ____________________

* Note : subjective questions should be answered comparative to conditions of a typical project, where choosing a 5 indicates an increase in productivity and a response of 1 indicates a decrease in productivity.

1. General Information

Project # : ____________ Project Name : ____________________

Cost Code: ____________ Cost Code Decription: ____________________

Report CC : ____________________ + ____________________

Activity Start Date: ____________ Season: Spring Summer Fall Winter All

Activity Finish Date: ____________ Duration : ________ days weeks months

Superintendent ____________ Foreman: ____________

2. Project Classification (check applicable responses)

( ) Wall ( ) Column ( ) Beam ( ) Slab ( ) Core

Formwork Duty	Formwork Tie Type	Formwork Support System
( ) N/A	( ) Snap Tie & Wedge	( ) Ellis Shores
( ) Light Duty - Handset	( ) Camlock	( ) Loose Scaffold (Alum Beam)
( ) Medium Duty - Semi Panelized	( ) Taper Tie	( ) Loose Scaffold (Timber Beam)
( ) Heavy Duty - Panelized (Gang)	( ) Single Waler Bracket	( ) Panelized Scaffold (Alum Beam)
( ) Fly Formwork (Slabs - Hi-Flyer)	( ) Burke Bracket	( ) Panelized Scaffold (Timber Beam)
( ) *Patented System	( ) Light Duty Column Clamp	( ) PCL Leg
( ) *Other	( ) Heavy Duty Column Clamp	( ) Vertical Shores
	( ) Column Ties and Wedge	( ) Trusses (Alum. or Steel)
	( ) *Other	( ) *Other
	( ) Not Applicable	( ) Not Applicable

*Specify: ____________________

3. Design

Total Formed Area	____ sf	____ m2	Tie (H, V) Spacing	__ x __ in	__ x __ mm
Prefabricated Form Area	____ sf	____ m2	Tie Capacity	____ lb	____ kg
Number of Reuses	____		Component Height (wall, slab, etc.)	____ ft	____ m
Cycle Duration	____ day				
Panel (L, W)	__ x __ ft	__ x __ m	Wall Thickness	____ in	____ mm
Number of Panels	____		Column (D, W)	__ x __ in	__ x __ mm
Typ. Panel Weight	____ lb	____ kg	Beam (D,W)	__ x __ in	__ x __ mm
Location of Work	above / at / below grade		Span of Beam	____ ft	____ m
Floor Numbers:	____		Slab Thickness	____ in	____ mm

Additional Notes

Rate the degree of repetition.......... 1 2 3 4 5
(1 - none formed with panels, 3 - 50% formed with panels, 5- 100% formed with panels)

Was Cycle Continuity maintained for the activity ?.......... 1 2 3 4 5
(1 - numerous disruptions, 5- construction progressed in a linear and uninterupted manner)

Rate the accuracy and detail of the design.......... 1 2 3 4 5
(1 - numerous errors and changes, 5- negligible errors and changes)

Was there a detailed formwork design of lift drwg prepared (by PCL or others)?.......... Yes No N/A

Figure 3.3 Cont. Sample Data Collection Sheets

4. Productivity

A. Labour - Typical Crew Composition:

Foreman ________ # Labor ________
Carpenters ________ # Other Skilled Labor ________
Apprentice ________ Total Crew Size ________

Estimate the average experience of the crew........ 1 2 3 4 5
(1 - < 5 years, 3 - approximately 10 years, 5 - > 15 years)

Rate the crew performance for the activity........ 1 2 3 4 5
(1 - poor crew, 5 - excellent crew)

Did individual crews work extended hours?........ 1 2 3 4 5
(1 - >70 total hrs/week, 3 - 50 total hrs/week, 5 - no overtime)

Was the crew unionized?........ Yes No N/A

B. Equipment

Tower Crane ____ # ____ hrs Hoist ____ # ____ hrs
Mobile Crane ____ # ____ hrs Other ________ ____ # ____ hrs
Forklift ____ # ____ hrs

Was material handling or crane time a problem for this activity?........ 1 2 3 4 5
(1 - large time loss incurred, 5 - no time loss)

C. Rates

	Manhrs	Quantity		Productivity Rate		Corporate P%10		Corporate Mode		Corporate P%90	
	mh	sf	m2	mh/sf	mh/m2	mh/sf	mh/m2	mh/sf	mh/m2	mh/sf	mh/m2
Actual											
Estimated											

5. Costs

Fab Material Cost ________ Fab Hardware Cost ________
Total Fab Cost/ Total Area ____ $/sf ____ $/m2 Crew Rate ________ $/mh

Were the following items charged to this cost code ?

Fabrication	Yes No N/A	Openings	Yes No N/A	Cleanup	Yes No N/A
Modifications	Yes No N/A	Bulkheads	Yes No N/A	Scaffolding	Yes No N/A
Repair Forms	Yes No N/A	Concrete Repair	Yes No N/A	Reshoring	Yes No N/A
Dismantle	Yes No N/A	Operator	Yes No N/A	Overtime	Yes No N/A

6. Activity Difficulty

Rate the complexity of geometry........ 1 2 3 4 5
(1 - majority of formwork on curved surfaces, 5- straight walls, 90 deg corners)

Rate degree of formwork irregularities........ 1 2 3 4 5
(1 - numerous blockouts, opening and/or inserts, 5- negligible irregularities)

Rate the level of required finishes........ 1 2 3 4 5
(1 - architectural finish, 5- no exposed finish)

Rate the site working conditions........ 1 2 3 4 5
(1 - many problems with congestion, site access and/or weather, 5- no problems)

Rate the owner inspection, safety and quality requirements........ 1 2 3 4 5
(1 - extremely detailed inspection, 5- highly tolerant requirements)

Rate the overall degree of difficulty for the activity........ 1 2 3 4 5
(1 - high, 3 - average, 5- low)

Additional Notes:

____
____

The strategy used for the questionnaire data collection involved:

1. identification of applicable formwork activities and preparation of the data collection questionnaires. Preparation involved printing of the questionnaires as reports from a database. This technique extracts all information already collected for an activity along with details of the activity, such as estimated and achieved productivity, to prevent duplication of data collection is avoided and given information will act to refresh the superintendent's memory of the activity.
2. superintendents were contacted and informed as to the purpose and requirements of the data collection.
3. data collection questionnaires were sent to superintendents along with a memo which reiterate the purpose and requirements of the data collection.
4. a phone interview of the superintendent which took place during or following completion of the questionnaires to verify that the assumptions and interpretations of superintendents were consistent

3.6.2 Collection of Subjective Inputs

Normalizing the input of subjective factors from superintendents to eliminate the effect of prejudice, attitudes, experience, and aggression on the response to a subjective question that has been identified as an issue of subjectivity. Furthermore, the ability of both the superintendent and the estimator to respond, while at differing projects stages, to a subjective question in a consistent manner has also been identified as an issue of subjectivity. Data collection is the first stage in neural network development, and therefore, it is the best point in which to begin to deal with subjective data. A couple of techniques, therefore, were explored prior to initiation of data collection:

1. Fuzzy Set Theory - Fuzzy logic provides a method of representing human language in mathematical form. This artificial intelligence has the capability of generating

solutions to problems despite the use of subjective data. The method used by fuzzy logic for analyzing subjective data assigns a membership value to a data point. The membership value can range from zero to one, where a zero represents no membership, a value in the range from zero and one indicates an certain level of membership, and a one means full membership. By assigning membership values, therefore, a crisp number or answer is converted to a most likely value. Techniques are then used by fuzzy set theory as a means of determining the relationship between data sets and objectives or events.

For analyzing subjective factors of formwork labour productivity the use of membership functions could act to decrease the effects of subjectivity on a superintendents response. The fuzzy set theory would be used to analyze the relationship between the characteristics of a superintendent and the subjective responses given. For example, for the analysis of the overall difficulty factor it may be determined that weather conditions, past experiences, and crew performance are the three influences on how a superintendent responds. By establishing membership values between each of the three influences and how the superintendent responds, a fuzzy set technique could be used to determine the value of overall difficulty based on the three influences.

A limitation to this method of analyzing subjective data would be the establishment of the necessary membership values. This could be accomplished through a detailed superintendent sampling procedure, but again all input would be highly subjective. Furthermore, the intent of this research is for the neural networks to determine the influence of characteristics such as weather conditions and crew performance.

2. Quantifying Subjective Questions - This technique is intended to normalize subjectivity and obtain consistency in subjective inputs by simply eliminating subjectivity. Finding a way to quantitatively capture a subjective factor eliminates all uncertainties associated with subjectivity. The subjective factors of the formwork neural network

models are subjective in the manner in which a response must be made. The subjective factors on the data collection questionnaires all ask for an opinion as to whether the factor was at a high, medium, or low level. For example, the following subjective question addressed repetition on an activity:

What was the Degree of Repetition for the project? .... ( )Low ( )Medium ( )High

This is the format which was used for data collection of subjective factors of the formwork neural network models. The technique proposed here, however, simply rewords the question and replaces the choices of responses with quantified responses. The following depicts this technique for the same subjective factor as above:

Rate the Degree of Repetition 1 2 3 4 5
(1 - none formed with panels, 3 - 50% formed with panels, 5 - 100% formed with panels)

The following advantages of this new technique over using the previous format in terms of both normalizing and providing a consistent basis for subjective factors include:

- the prejudice, attitudes, experience, and aggressive emotions and characteristics of the individual responding to the question are eliminated as the responses have essentially been quantified. For example, if an activity was 50% formed with panels all superintendents will now respond with a 3, whereas with the old format, a more experienced superintendent may feel 50% formed with panels is a high level of repetition compared to previous projects while a less experienced superintendent on the same activity would rate it as a medium degree of repetition.
- the nature of the formwork neural network models is such that they are trained on actual data and will be used to predict based on estimated data. This has been identified as a concern for subjective data as many of the factors that are subjective in nature are quite easily determined following completion of a project but much

less identifiable prior to start of the project. This is due to many of the potential risks on a project that may complicate a number of aspects of a formwork activity and, as a result, decrease productivity. On the other hand, quantities on a project are more definable prior to start of a project. Furthermore, changes in quantities are more easily addressed through change orders and extra work so that financial losses are not incurred. Therefore, estimated quantities are consistent for use in the formwork neural network models for predicting a productivity of an activity on an upcoming project. As a result, this technique of quantifying subjective responses provides a much more consistent approach for the estimator's use of the formwork neural networks.

- five possible responses are available as compared to the previous use of three responses. This allows for input factors to be more pronounced as inputs of one and five now become extreme responses as compared to inputs of two, three, or four.

This technique is chosen for this research because two key issues of subjectivity are effectively addressed. Furthermore, implementation of the technique into the formwork neural network models is deemed more consistent than implementing a fuzzy set technique. As a result, the following lists the new format of the subjective questions to be used for data collection.

Rate the Degree of Repetition 1 2 3 4 5

(1 - none formed with panels, 3 - 50% formed with panels, 5 - 100% formed with panels)

Was Cycle Continuity maintained for the activity? 1 2 3 4 5

(1 - numerous disruptions, 5 - construction progressed in a linear and uninterrupted manner)

Rate the Accuracy and Detail of Design 1 2 3 4 5

(1 - numerous errors and changes, 5 - negligible errors and changes)

Estimate the Average Experience of the crew 1 2 3 4 5

(1 - <5 years, 3 - approximately 10 years, 5 - >15 years)

*Rate the Crew Performance for the activity 1 2 3 4 5

(1 - poor crew, 5 - excellent crew)

Was Material Handling or Crane Time a problem for the activity 1 2 3 4 5

(1 - large time loss incurred, 5 - no time loss)

Rate the Complexity of Geometry 1 2 3 4 5

(1 - majority of formwork on curved surfaces, 5 - straight walls, 90° corners)

Rate degree of Formwork Irregularities 1 2 3 4 5

(1 - numerous blockouts, openings and/or inserts, 5 - negligible irregularities)

Rate the Level of Required Finishes 1 2 3 4 5

(1 - architectural finish, 5 - no exposed finish)

Rate the Site Working Conditions 1 2 3 4 5

(1 - many problems with congestion, site access, and/or weather, 5 - no problems)

Rate the Owner Inspection, Safety, and Quality Requirements 1 2 3 4 5

(1 - extremely detailed inspection, 5 - highly tolerant requirements)

*Rate the Overall Degree of Difficulty 1 2 3 4 5

(1 - high, 3 - average, 5 - low)

(* - exceptions)

Many of the factors included in this list are not quantified in the same manner as the repetition factor. However, each factor is detailed in such a manner that the responses are labeled to represent a magnitude of quantity. This research does establish this technique as capable of reducing the effect of subjective data on the stability of the data but further research into developing a detailed quantity for each response is another potential step. The development of help pages for the users of the formwork neural network models which discuss in detail what constitutes a one, two, three, four, or five for each factor would act to completely eliminate all subjectivity in the models. The exceptions (*) are the crew performance and the overall degree of difficulty factor. Crew performance was deemed to be a characteristic of too many possible components and the intent of the overall difficulty factor is to capture the overall difficulty and the effects of any other difficulties not addressed by the other four difficulty factors. As a result, there is no way to quantify either of these factors. As a result, techniques of handling subjective data so that these two factors are further addressed must be developed at later stages (following data collection) in the development of the formwork neural networks.

3.6.3 Collection Discussion

Two data collections took place. First, data collection questionnaires were sent to the 40 projects previously used for training the formwork neural network models examined by this research. The objective of this data collection was to update the previous data to include the new inputs and to sample the subjective factors under the new format technique. Second, 20 new projects were sampled in order to obtain a more complete database of training data. The objective of this data collection was to eliminate stability problems, as previously identified, due to data limitations.

For the purposes of chapter 3, enhancing neural network stability, only one type of formwork activity was analyzed. Loose wall formwork activities were examined, including the formwork activities related to foundation/retaining walls, walls/pilasters, low walls/upstand beams, and curved walls. All four of these activities are close enough in nature and historical statistics to be grouped into one network. The type of activity, however, is used as an input such the neural network can differentiate and account for differences between the activities. The data search was cut off at about 60% complete, resulting in the collection of 53 historical loose wall activity records. This is only slightly higher than the 45 records with which the formwork neural network models were previously trained on. Although an improvement in stability due to increased data will not be obtained at this point, a training record count close to 45 was determined to be better for identifying stability changes due to the new input factors and the breakdown of the difficulty factor.

Within chapter 4, enhancing neural network accuracy, the remainder of the data collection is added as training records. Therefore, the full effects of the stability due to increased training data will occur in the analysis in chapter 4. Furthermore, loose slabs activities are analyzed in addition to loose wall activities within chapter 4.

3.7 Neural Network Training

3.7.1 Subjective Data Conversion

Key issues associated with using subjective data within the formwork neural network models have primarily been addressed by the technique of presenting descriptive and quantitative responses to the subjective factor questions during data collection. However, two subjective factors, crew performance and activity difficulty, were not effectively quantified by the developed technique and, hence, require further analysis. The stage of analysis is now following data collection and, therefore, examination of the actual responses to the subjective factors is now possible.

3.7.1.1 Crew Performance Analysis

A correlation test is used to determine the status of the subjective data collected. This test compares two variables in order to determine if a relationship exists. For this research, a simple correlation indicating an improved productivity when a higher crew performance response is given, is expected. In this case a correlation of -0.147 is present (a correlation value of 0 indicates their is no correlation, while a 1 or -1 would indicate a strong correlation). Therefore, a small correlation indicating the expected relationship was obtained. Although the correlation is closer 0 than 1, the relationship is deemed valid as this correlation is a simple comparison of only one variable to the productivity, while actually over 50 variables are influencing the productivity.

Further analysis into the performance of the crew as compared to the achieved productivity involves including the crew experience and extended work hours factors in the correlation. Each of these factors were also collected on a one to five scale and a similar relationship with the productivity as with the crew performance factor is expected. Therefore, summing the responses of all three factors and checking the correlation with the achieved productivity a stronger correlation (-0.213) was determined. Again, this correlation, although not a strong correlation, indicates that crew performance subjective inputs are consistent. As a result, any normalization tactics on the crew performance factor are not deemed necessary.

3.7.1.2 Overall Difficulty Analysis

A correlation testing the relationship between overall difficulty and the achieved productivity indicates there are essentially no correlation (0.02). However, by combining all the difficulty factors, as done with crew performance, a small correlation is developed

(-0.17). Table 3.4 summarizes the correlation of the difficulty factors with the achieved productivity of an activity.

Table 3.4 Difficulty Factors - Correlation Values

Factor	Correlation
Complexity of Geometry	-0.27
Formwork Irregularities	-0.10
Required Finishes	-0.09
Working Conditions	-0.06
Overall Difficulty	+0.02
Total Difficulty (sum of all factors)	-0.17

From this table, it is apparent that other than the complexity of geometry factor, the remainder of the difficulty factors show little if any correlation with the achieved productivity. Furthermore, the only reason for the combined correlation of -0.17 is that the complexity of geometry factor. The lack of correlation in these factors is attributed to their subjective nature.

Based on the correlation of all the difficulty factors with the achieved productivity, this section researches a method to eliminate the subjectivity present in the overall difficulty factor along with the remaining subjectivity in the other four difficulty factors. The following defines six techniques researched and the results of testing each technique.

Test 1

A superintendent activity rating factor was established. This rating is defined as an individual superintendent's average productivity for a specific activity divided by the company's average productivity for the activity. This rating was used to identify a superintendent's ability. A rating of less than one indicates a superintendent is better than average and a rating of greater than one indicates the superintendent is below average.

The subjective difficulty factors are adjusted in this test according to the rating of the superintendent. For this test, the assumption is made that a superintendent would subjectively rate difficulty according to how the difficulty affects the activity's productivity. An activity, therefore, would be made easier by a good superintendent and more difficult by a poor superintendent. This assumption was incorporated into the difficulty factors by dividing each factor by the rating of the applicable superintendent. This would, for example, increase the 5 given to a difficulty factor by a good superintendent to above 5 and decrease the difficulty factor given by a poor superintendent to below 5. The correlation study results of this test are given in Table 3.5.

Table 3.5 Difficulty Factor Correlation - Test 1

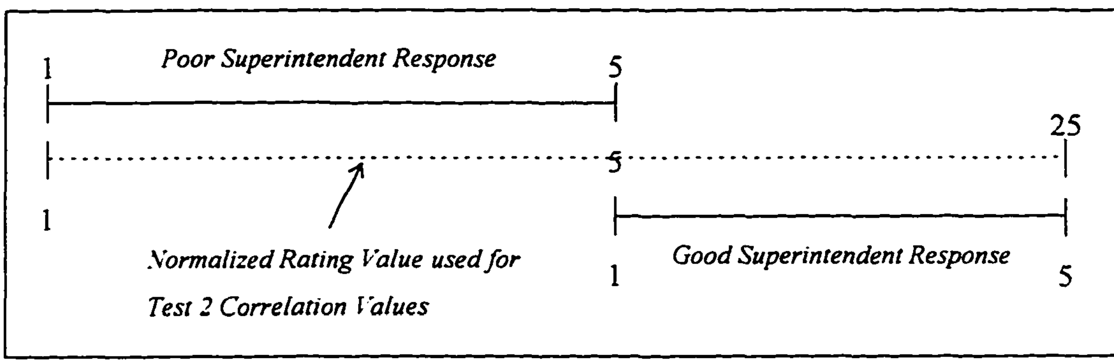
Factor	**Correlation**
Complexity of Geometry	-0.42
Formwork Irregularities	-0.30
Required Finishes	-0.28
Working Conditions	-0.32
Overall Difficulty	-0.25
Total Difficulty(sum of all factors)	-0.41

As can be seen from Table 3.5, the assumption on the superintendents abilities affecting their subjective ranking of difficulty is valid as the correlation of the factors are much better. The following tests, therefore, study further into the superintendent ability adjustment to determine if better correlation can be obtained.

Test 2

For test 2 the superintendent activity rankings are scaled so that the superintendent who has the best average productivity for the activity is given a five, and the superintendent with the worst average productivity is given a one. The assumption behind this test is that because of good superintendent abilities he/she may be able to make the difficulty on a hard project affect the productivity to the same degree as a poor superintendent would on a easy project. The scaling, therefore is intended to normalize the subjective answers. Note, scaling to other intervals (1 to 2, 1 to 3, etc.) was tested but the results were not as good as those obtained for the interval (1 to 5) described in this test). Figure 3.4 shows how this method would theoretically normalize the effect of difficulty a project regardless of the superintendent.

Figure 3.4: Test 2 - Normalization of Subjective Factors



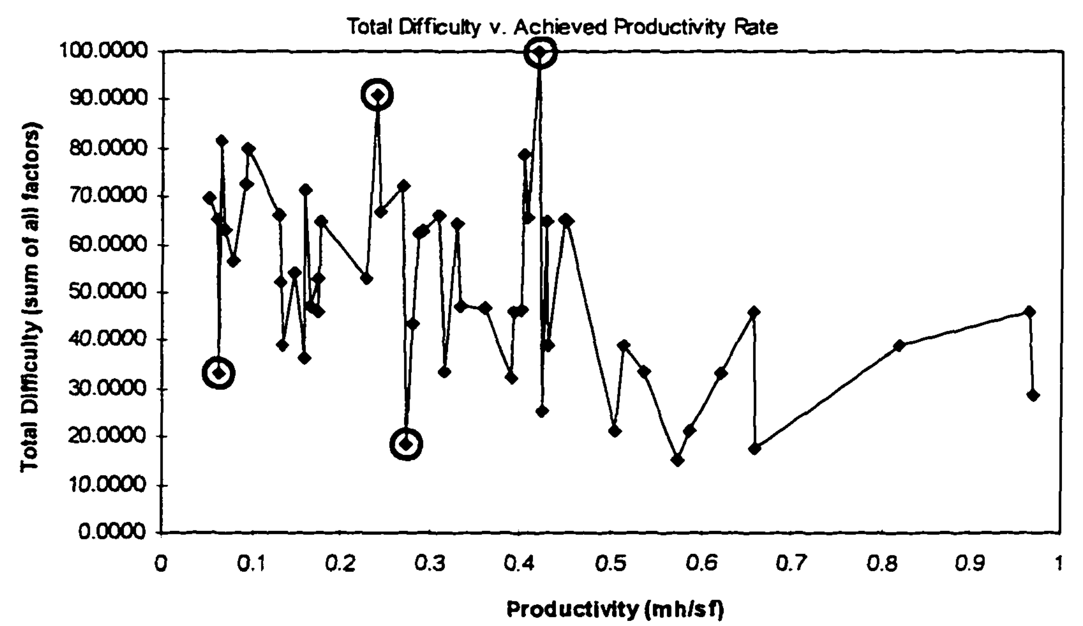
The a normalized rating for a difficulty factor would be entered as an input into the neural network, rather than the rating given by the superintendent. This test produces the results in Table 3.6.

Table 3.6: Difficulty Factor Correlation - Test 2

Factor	**Correlation**
Complexity of Geometry	-0.43
Formwork Irregularities	-0.33
Required Finishes	-0.31
Working Conditions	-0.36
Overall Difficulty	-0.31
Total Difficulty(sum of all factors)	-0.45

These correlations are slightly better than the previous test. A problem with this technique was determined, however. The technique is unable to effectively account for records in which a good productivity was obtained, but the superintendent had a poor record. The same occurred on the other extreme, as records of poor productivity, but good superintendents, were not adequately captured. The overall result was a better correlation, but as can be seen in Figure 3.5, a number of records have been shifted even further out of correlation based on the achieved productivity (note: this characteristic of the correlation is based on graphical analysis only).

Figure 3.5 Total Difficulty Scatter Plot - Poor Record Correlations



O - highlights a record placed well outside of correlation due to test 2 technique.

Test 3

Due to the problems identified with test 2, test 3 backtracks to simply dividing the given complexity rating by the superintendent score. In this test, however, the superintendent score was taken to the power of 1.5 so that the factor would be more affected by the superintendents ability. The results are summarized in Table 3.7.

Table 3.7: Difficulty Factor Correlation - Test 3

Factor	Correlation
Complexity of Geometry	-0.44
Formwork Irregularities	-0.34
Required Finishes	-0.32
Working Conditions	-0.36
Overall Difficulty	-0.32
Total Difficulty(sum of all factors)	-0.43

The result of this test was much like the results of test 2. The correlation is slightly better than test 1, but a number of records are overly affected by the superintendent activity rating adjustment (individual records are pushed further from the desired trend rather than closer).

Test 4

This test attempted to stop the superintendent score from having to great an effect on an individual record. As discussed in test 2, extreme records in terms of their productivity were not being properly captured. This was assumed to be due to extreme superintendent activity ratings. Therefore, to minimize this effect six categories of superintendent activity ratings were developed. Categories were developed based on a distribution of the superintendent ratings. The distribution was in the form of a histogram and the number of cells was defined based on Sturges' Rule (AbouRizk, Halpin 1990), an defined as follows:

$Numberofcells = 1 + 3.3\log(n)$, where n = number of observations

$Widthofcell = \frac{X_{max} - X_{min}}{Numberofcells}$, where $X_{max} - X_{min}$ = highest and lowest observations

$Lowestcell = X_{min}$

The histogram in Figure 3.6 was developed and used to determine a number of superintendent rating categories. The categories were determined experimentally by testing the correlation associated with each set of categories along with examining the extreme records. The determined categories are defined in Table 3.8.

Figure 3.6: Category Determination Histogram

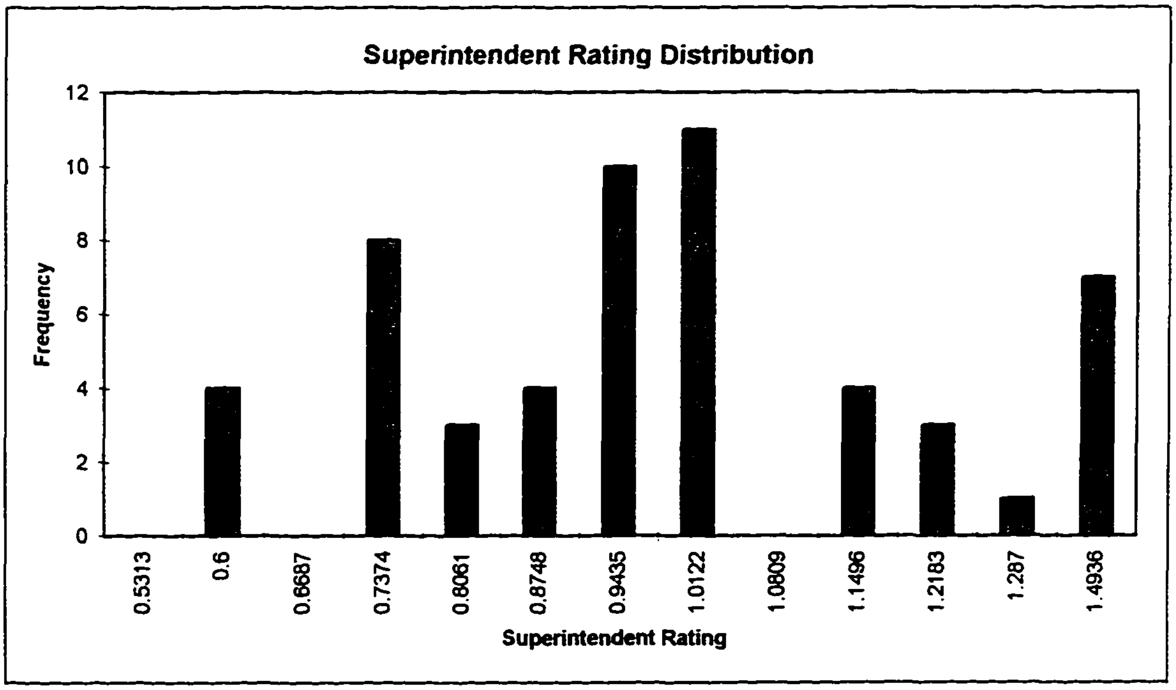


Table 3.8: Superintendent Activity Rating Categories

Range	Assigned Rating
< 0.6687	0.60
0.6687-0.8061	0.737
0.8062-0.9435	0.875
0.9436-1.0809	1.0
1.0810-1.287	1.18
>1.288	1.4

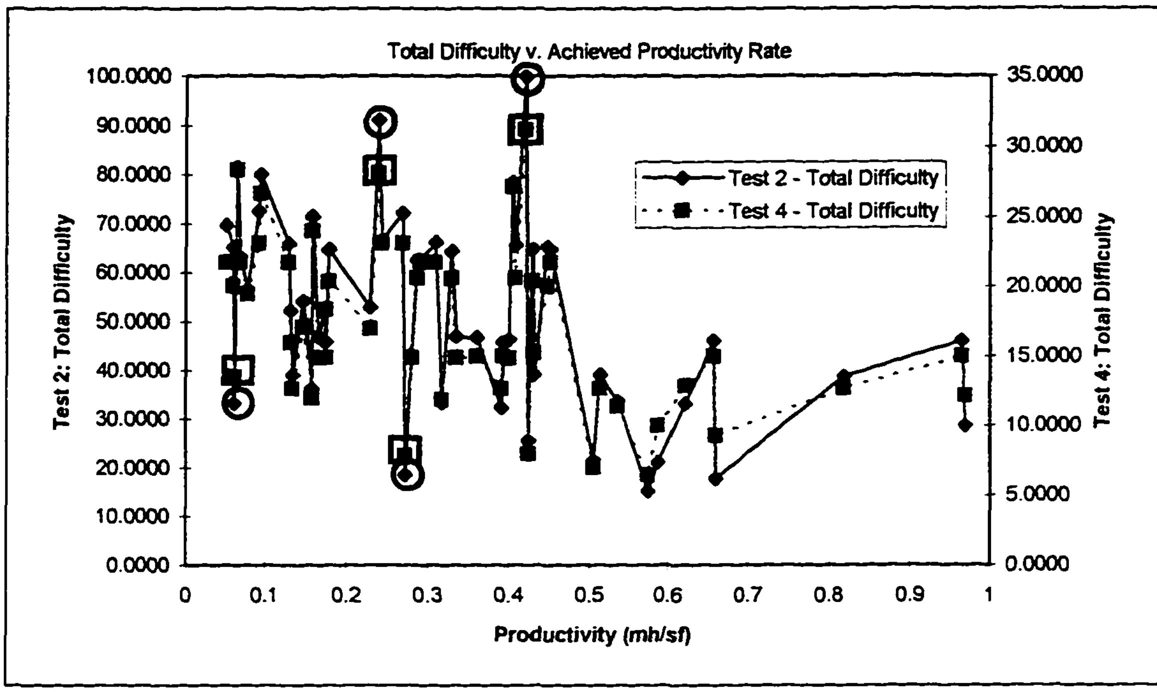
The assigned ratings in Table 3.8 are calculated as the average of the boundaries for each category with the exception of the first and last categories where an adjustment of 10% away from the boundary value was assigned as the rating. With these categories, the most that any record can be affected is by a factor of 0.6 or 1.4. In the previous tests, records were being affected by factors of over 0.5 and 1.5. The results of this test are listed in Table 3.9.

Table 3.9: Difficulty Factor Correlation - Test 4

Factor	Correlation
Complexity of Geometry	-0.43
Formwork Irregularities	-0.31
Required Finishes	-0.29
Working Conditions	-0.32
Overall Degree of Difficulty	-0. 26
Total Difficulty(sum of all factors)	-0.43

This test produced similar correlations to that in the previous tests, but the distribution of individual records is now limited. Figure 3.7 compares correlation of the data from test 2 to that in this test. This figure shows that the strategy employed in test 4 was successful in reducing the negative effect that the superintendent rating adjustment was causing to some individual records.

Figure 3.7 Total Difficulty Scatter Plot - Record Correlation Test Comparison



○ - individual records of concern (from test 2)

□ - new value of record (from test 4)

Test 5

The categories established in the previous test are reused in this test. Once each record was assigned a category, however, the categorized values were scaled, much like test 2, again to between 1 and 5. This produced the correlations in Table 3.10.

Table 3.10: Difficulty Factor Correlation - Test 5

Factor	**Correlation**
Complexity of Geometry	-0.46
Formwork Irregularities	-0.38
Required Finishes	-0.37
Working Conditions	-0.41
Overall Degree of Difficulty	-0.38
Total Difficulty(sum of all factors)	-0.48

This test produced a better correlation than all previous tests, but the problem of individual records being over effected by the factoring arose again.

Test 6

The formwork neural network models developed by previous research (Portas 1996) use the activity performance factor to define activity difficulty. This factor, however, is biased because it uses a percentage of the achieved productivity as means of obtaining a better correlation. The following equation defines the derivation of the activity performance factor:

$ActivityPerformance = (ActivityComplexity * 0.75) + (DegreeofDifficulty * 0.25)$ where,

$ActivityComplexity$ = a value of 1, 3, or 5 depending on the achieved productivity for the historic activity (1 defines an activity in the highest third of the historic range of productivity for the activity, 3 in the mid third, and 5 in the lower third).

$DegreeofDifficulty$ = a value between 1 and 5, where a higher the number reflects a lower level of difficulty.

This final test, as a comparison to the previous 5 tests, incorporates the actual productivity into each difficulty factor, as was done for the activity performance factor. The results in Table 3.11 were obtained.

Table 3.11: Difficulty Factor Correlation - Test 7

Factor	Correlation
Complexity of Geometry	-0.66
Formwork Irregularities	-0.61
Required Finishes	-0.59
Working Conditions	-0.63
Overall Degree of Difficulty	-0.64
Total Difficulty(sum of all factors)	-0.71

A correlation very close to that established in the current formwork neural network models is obtained through this analysis. However, the correlations prove to be only slightly better than those obtained in the previous tests. This method, therefore, will not be used as strong correlations are available through means other than using biased factors.

As a result of these tests, the categorized superintendent activity rating (test 4) was determined to be the best method. The correlation obtained via this method produced competitive correlations with all the other tests, but this method prevented the adverse effect on individual records caused by the other methods.

Another method investigated, but not included as one of the tests, involved taking a superintendent's historical ranges of productivity into account. On all six tests, only the superintendents average productivity was used. Using the superintendents range would examine the idea that a superintendent will rate difficulty based on what previously experiences. For example, a superintendent who has only worked on simple jobs may rate the complexity of a certain activity as very difficult. But a superintendent who has experience on many difficult activities would rate this same activity as only average difficulty. However, due to lack of historical data on the superintendents this method was not pursued further.

3.7.2 Training Structure

3.7.2.1 Conversion of Subjective Factors into Numerical Inputs

The use of subjective data within a neural network requires the conversion of a descriptive response into a numeric value. Although the new data collection format has all responses made on a numeric level (i.e. a one, two, three, four, or five is chosen by the superintendent), scaling is necessary so that the neural network properly analyzes the subjective factors. If the value from the data collection was used as the input, the neural network would simply read a value of five as an indication that the input is a strong attribute of the activity while a one would be read as an indication that the factor was a weak attribute of the activity. The subjective factors, however, have been set up so that a five indicates that the characteristics of the factor have had a positive influence on the productivity, and a value of one indicates the factor had negative influence on the productivity for the activity. Within this methodology, a three indicates that the factor is a normal condition of the activity and did not influence the productivity to any degree.

In order to present the data from subjective factors so that the correct influence could be established the scaling technique in Table 3.12 was implemented. This scaling technique is based on one of the options available within the neural network trainer.

Table 3.12 Subjective Data Scaling Technique

Subjective Factor Response	Neural Network Input
5	-0.8
4	-0.4
3	0
2	+0.4
1	+0.8

Note: Factoring to -1, 0, or 1 was not used as it is best to avoid extremities such as these during training of neural networks.

This scaling technique, however, is tested during neural network training to determine if this measure effects training of the subjective factors as expected. Therefore, scaling to between 0.2 and 0.8 is also tested. In determining whether the expected scaling technique is better, accuracy comparisons will be performed between the methods.

3.7.2.2 Neural Network Architecture

A Neural Windows Application is used for all neural network training of the commercial formwork labour productivity models discussed in this chapter. Microsoft Access is used for all data storage and manipulation.

Three neural network models are trained and tested within this analysis. The difference between each of the models are the input factors used. The first model includes all of the new factors, the second includes all new factors but the five difficulty factors are combined into one input (as this was found to have a better correlation than each factor on its own), and the final network includes the activity performance factor and none of the new factors.

Settings for the training program were configured based on what was experimentally determined in the development of the formwork neural network models for this types of activity. This architecture includes:

- 1 hidden layer with 35 nodes
- 14 nodes in the output layer (13 fuzzy zones and 1 point prediction zone)
- symmetric logistic transfer function, 0.1 learning rate, 0.4 momentum rate
- 0.01 error threshold

The only configuration that was tested was the function of the training program that factors the input values. Two options were tested for each network; factoring to between 0.2 to 0.8 and to between -0.8 and 0.8. Also, due to the increased number of factors being examined by the new models, each model, with the exception of the model using only the activity performance factor, was tested once for each configuration with all input factors included, weight analysis was completed on the input factors, and the network was re-tested excluding insignificant inputs. In total, 10 networks were trained, Table 3.13 defines each of the networks.

Table 3.13 Developed Neural Network Models

Network	Input Factors	Input Factored Range	Number of Inputs
1a	All New Factors	-0.8 to 0.8	All
1b	All New Factors	0.2 to 0.8	All
2a	All New Factors	-0.8 to 0.8	Reduced
2b	All New Factors	0.2 to 0.8	Reduced
3a	All New Factors (Difficulty Factors Combined)	-0.8 to 0.8	All
3b	All New Factors (Difficulty Factors Combined)	0.2 to 0.8	All
4a	All New Factors (Difficulty Factors Combined)	-0.8 to 0.8	Reduced
4b	All New Factors (Difficulty Factors Combined)	0.2 to 0.8	Reduced
5a	Activity Performance Factor	-0.8 to 0.8	As Previous research (Portas 1996)
5b	Activity Performance Factor	0.2 to 0.8	As Previous research (Portas 1996)

3.7.2.3 Training Strategy

45 training records and 8 testing records were used (note: the same records were used as testing and training records for each network). Testing records were chosen so that at least one of each type of wall formwork activity was tested. A diverse representation of the sample was chosen for the testing, but none of the testing records chosen had extremely high or low productivity. This strategy was employed as stability is the only issue being tested at this point. Chapter 4 will extend the testing strategy to involve a

much more diverse set of testing records so that the accuracy can be tested. Table 3.14 summarizes the testing records used for the analysis of formwork neural network stability.

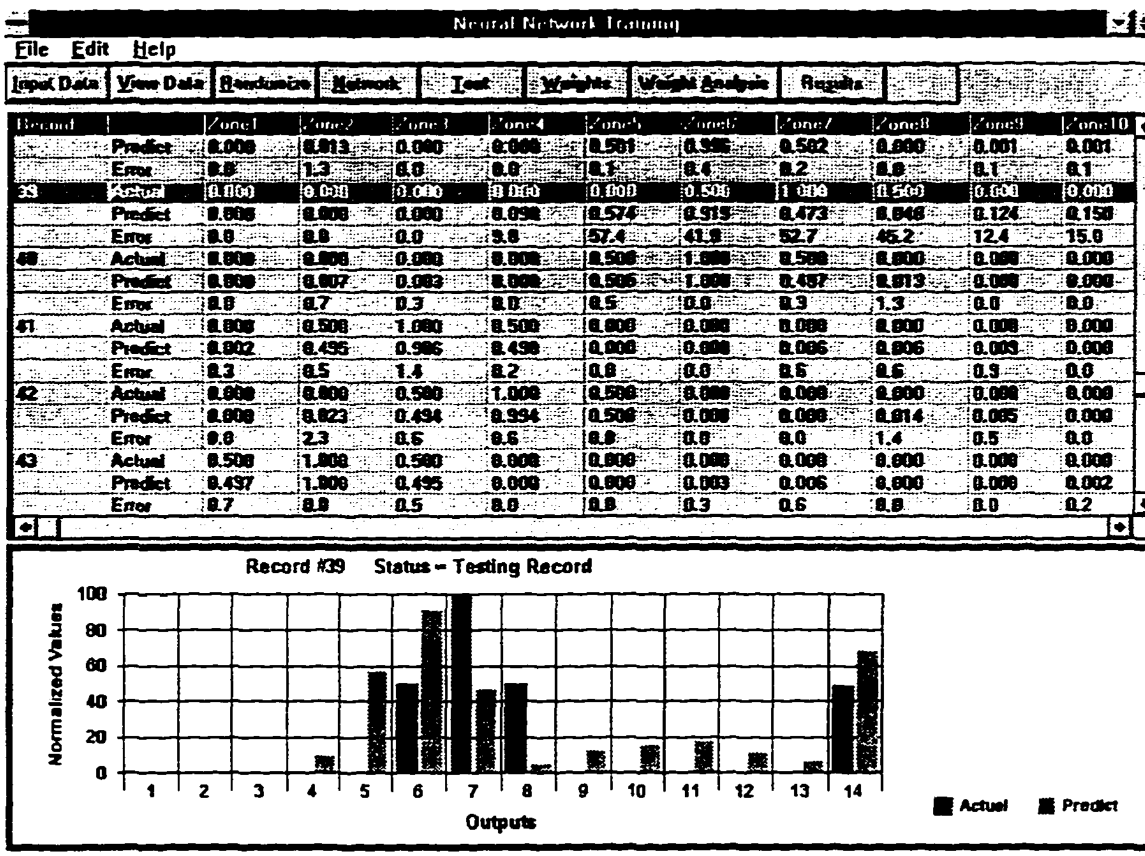
Table 3.14: Testing Records Listing

Record #	Type	Project #	Prod Rate
3	Fdn/Retaining Walls	0400056	0.430
4	Walls/Pilasters	0400056	0.309
6	Fdn/Retaining Walls	0400061	0.391
16	Walls/Pilasters	5002151	0.270
24	Walls/Pilasters	1100504	0.587
28	Low Walls/Upstand Beam	1100512	0.283
39	Curved Walls	5002151	0.504
45	Fdn/Retaining Walls	5130417	0.178

3.7.3 Training Results

For training purposes, a actual productivity (AP) for each record is compared to both the network predicted productivity (PP) and the weighted average predicted productivity (WAPP). The PP is a single number that the network defined to its 14th output node. The WAPP is equal to the value that the network defined to each of its first 13 output nodes multiplied by the weighting of the respective zone. The AP is compared to each of these, but the comparison to the WAPP value is of greater value because the intent of the networks was to provide a range of reasonable productivity and not a single number (note: a more detailed accuracy analysis is completed and discussed in chapter 4 of this research. This discussion only intends to provide a brief explanation of the technique used in determining the accuracy resulting from a new level of stability in the formwork neural network models). Figure 3.8 provides a sample printscreen of the output for a testing record. Within the histogram in the figure, the 14 output zones can be seen. The first 13 represent the distribution, where the lighter bars represent the predicted distribution and the darker bars represent the actual data. In this case the highest prediction bar missed the highest actual bar by only one zone. The 14th zone compares the single number prediction to the actual productivity. In this case again, the accuracy of the distribution is more important the single number prediction.

Figure 3.8: Sample Neural Network Trainer Test Result



3.8 Stability Enhancement Discussion

Three characteristics of stability were identified in the introduction to this chapter as the keys to a stable neural network. The first involved the examination of the impact of a number of new factors on the formwork neural network models. The second involved ensuring that sufficient data was being used to train the formwork neural network models so that stability of all inputs was properly established. Finally, an alternate way to capture the effect of difficulty on a formwork activity was deemed necessary. The following summarizes the findings of this research:

Characteristics 1: Evaluation of New Factors

Table 3.15 defines the influence the new factors had on each of the neural networks. The rank of each factors defines its standing of influence compared to all other factors. The percentile column simply defines the percentile standing of the rank for each factor.

Table 3.15 Importance of New Factors

	NN 1a		NN 1b		NN 2a		NN 2b		NN 3a	
Factor	Rank /69	Perc.	Rank /69	Perc.	Rank /57	Perc.	Rank /57	Perc.	Rank /65	Perc.
Location of Work	14	63	26	45	16	57	21	61	18	55
Floor Numbers	34	47	7	60	14	60	14	66	22	50
Formwork Design	36	47	9	60	47	24	11	68	46	29
Crew Experience	31	46	36	38	34	38	27	58	23	47
Complexity	20	57	13	53	15	58	12	68	-	-
Irregularities	18	60	46	30	32	31	43	43	-	-
Required Finishes	23	55	37	37	31	39	36	50	-	-
Site Conditions	52	26	47	30	54	12	52	28	-	-
Owner Inspection	15	61	3	68	20	53	5	77	17	57
Total Difficulty	-	-	-	-	-	-	-	-	58	16

Table 3.15 cont. Importance of New Factors

	NN 3b		NN 4a		NN 4b		Average	
Factor	Rank /65	Perc.	Rank /53	Perc.	Rank /53	Perc.	Rank	Perc.
Location of Work	15	54	30	40	24	61	21	55
Floor Numbers	21	49	16	51	10	81	17	58
Formwork Design	16	54	31	40	23	61	27	48
Crew Experience	22	49	25	41	45	42	30	45
Complexity	-	-	-	-	-	-	15	59
Irregularities	-	-	-	-	-	-	35	41
Required Finishes	-	-	-	-	-	-	32	45
Site Conditions	-	-	-	-	-	-	51	24
Owner Inspection	11	59	12	62	4	90	11	66
Total Difficulty	23	48	43	28	35	50	40	36

As illustrated by Table 3.15, all of the new factors had a greater influence on the network than a number of the older factors did (based on rankings and percentiles). Owner inspection, location of work, floor numbers, and complexity of geometry appear to have the greatest influence, while the effect of site conditions appears to be the only new factor with only a small significance on the network.

Characteristic 2: Training Data Stability

As previously discussed, in order to properly analyze the effect of both new input factors and the new method of analyzing difficulty, the quantity of training data used was kept equivalent to that for the formwork neural network models. Chapter 4, however, does expand the data collection so that any remaining stability problems following the analysis of chapter 3 will be rectified through the use of a greater training data quantity.

Characteristic 3: Difficulty of Activity Analysis

Of the ten networks trained, three variations as to capturing the difficulty of a formwork activity were tested. Tests 1 and 2 attempted to define difficulty through five different factors, tests 3 and 4 attempted to define difficulty through the summation of the five factors, and test 5 used the activity performance factor developed in the current model. Table 3.16 summarizes the accuracy obtained by each of these networks.

Table 3.16: Network Result Analysis

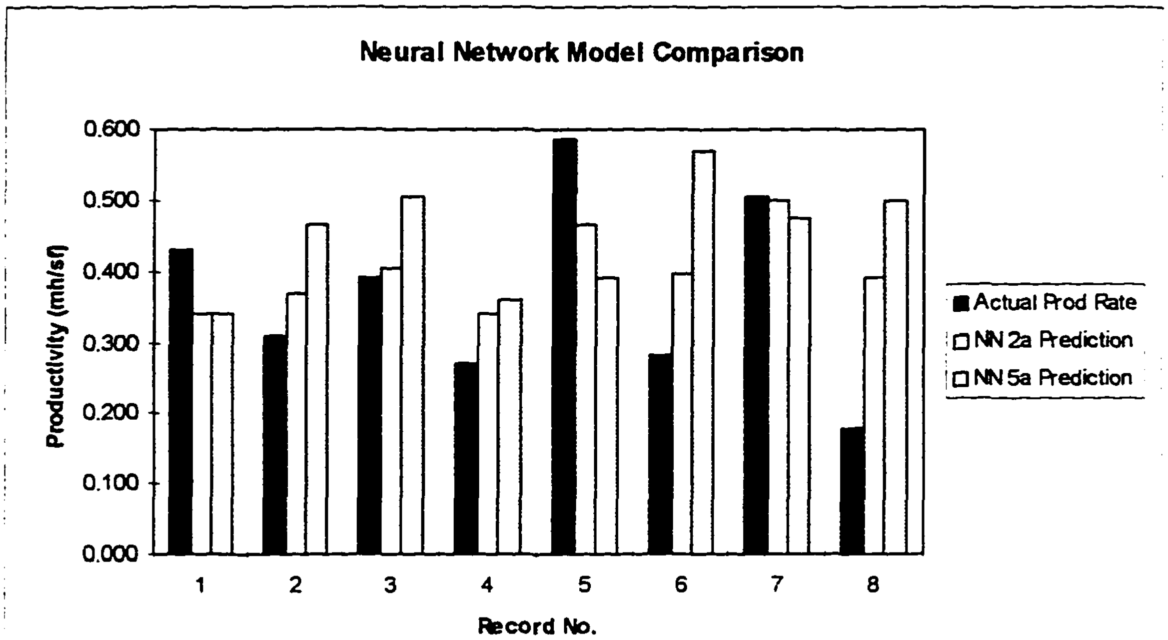
Net-work	# of Hits PP/AP	# of Hits WAPP/AP	Average % Difference between WAPP and AP	Greatest % Difference between WAPP and AP	# Testing Records Missed by >1 Zones	# Testing Records Missed by >2 Zones	Absolute Sum of # Zones Missed by for 8 Tests
1a	4	3	12.6	29	3	1	11
1b	**5**	**5**	11.6	29	5	3	15
2a	4	**5**	**10.0**	25	**2**	**0**	**8**
2b	4	3	12.8	28	3	1	12
3a	4	**5**	12.2	24	3	1	11
3b	2	4	11.1	22	2	1	9
4a	2	3	14.6	25	4	3	13
4b	3	4	12.6	30	4	1	14
5a	2	4	10.3	23	2	0	9
5b	1	4	11.5	**21**	3	1	10

note: **bold** indicates best value in category

Based on the data in Table 15, network 2a produces the most accurate output. This network provided the best results in five out of seven of the categories. Networks 3b and 5a produced results second best to the results of 2a.

Figure 3.9 graphically compares the abilities of this research and previous research (Portas 1996) to predict to chosen productivity:

Figure 3.9 Neural Network Prediction Ccmparison



Based on the ability of the new neural network model to predict as well as the original formwork neural network models, it can be concluded that the replacement of the Activity Performance factor with the five difficulty factors has been successful. Furthermore, the assumption that the five difficulty factors would effectively divide the influence of the Activity Performance factor between them was found to be true. This can be seen by the weightings and rankings applied to the difficulty factors by the neural network model in Table 3.15. No longer are the difficulty factors, as the Activity Performance factor was, the dominant factor in terms of weight analysis. As a result, the neural network models are no longer controlled by difficulty as they were by Activity Performance. Figure 3.10 and Figure 3.11 depict the influence of difficulty in both the original and new neural network models.

Figure 3.10 Influence of Activity Performance Factor

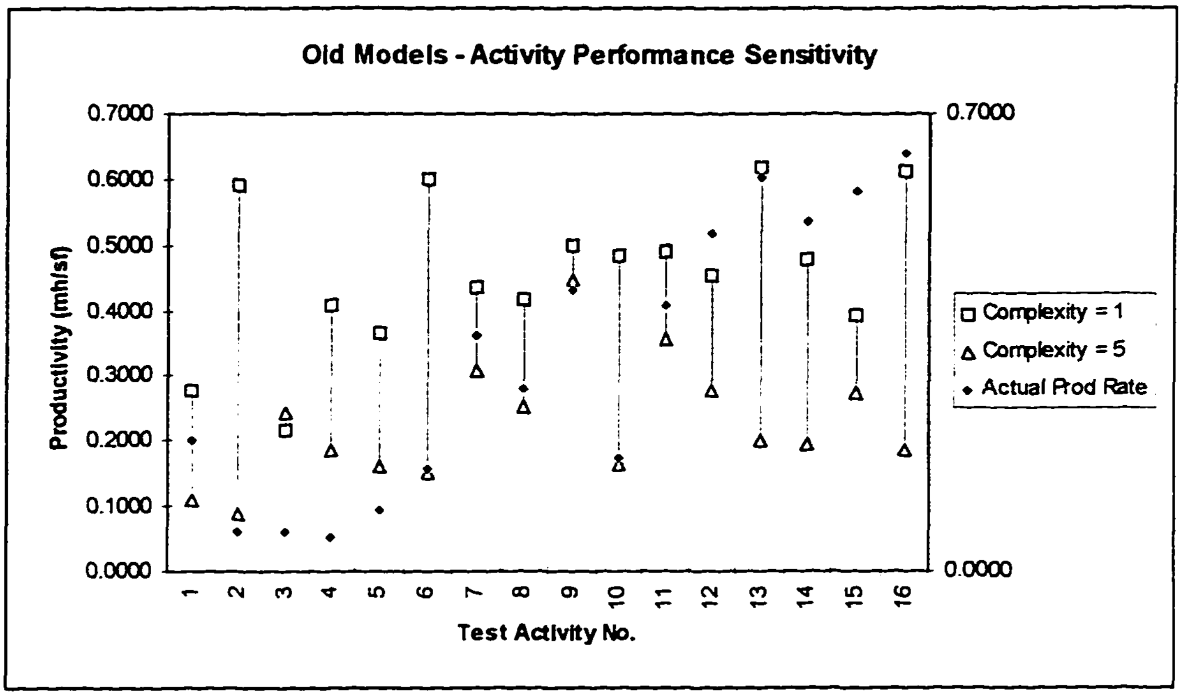
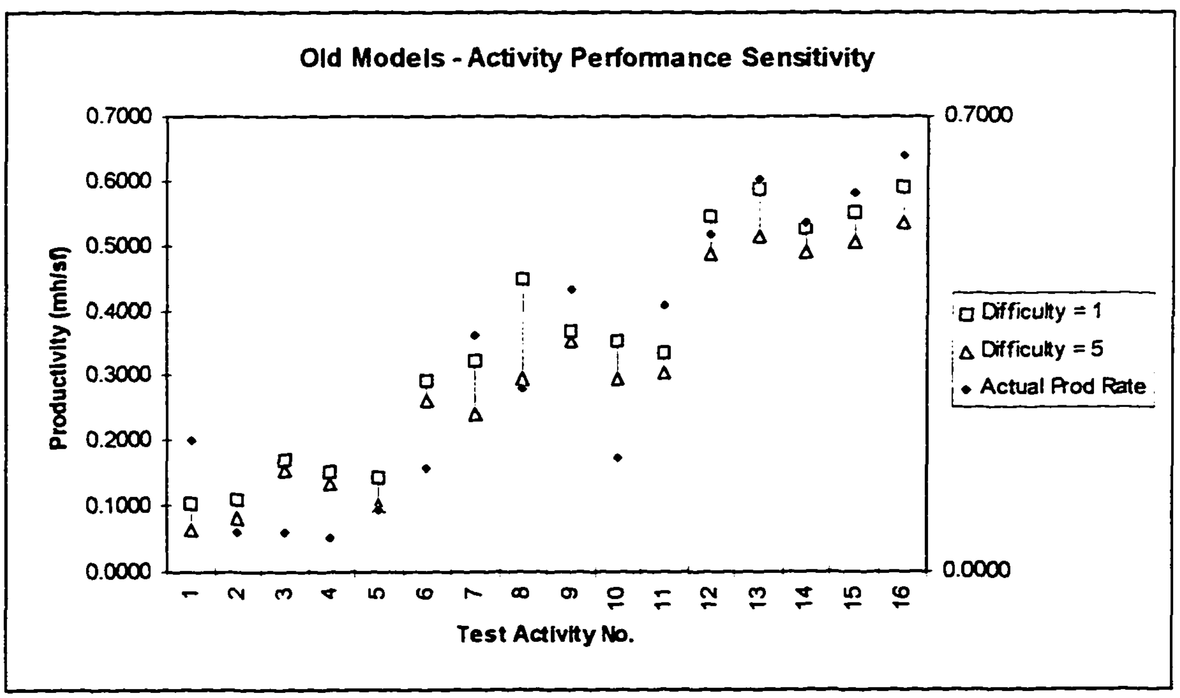


Figure 3.11 Influence of Five Difficulty Factors



As shown by the above figures, the issue of activity performance governing the prediction of the formwork neural network models is eliminated through the use of the five difficulty factors (Note: the training methodology developed in chapter 4 was used for examination of the influence of the five difficulty factors. A comparison of the completely enhanced neural network models to the original neural network models was deemed necessary to demonstrate the true change of the difficulty issue).

Subjectivity has been identified as an additional impact on stability to the three characteristics discussed above. Three subjectivity issues were relevant and dealt within this research for the formwork neural network models.

The use of descriptive and quantitative response choices for the collection of subjective data proved to deal with two of the issues. Superintendent prejudices, attitudes, experience, and aggressive emotions and characteristics can not effect a descriptive and quantitative response. Furthermore, estimators can now effectively address a subjective factor based on examination of the drawings and estimating documents through the use of descriptive and quantitative responses. Consistency, therefore, can be maintained between how the neural network is trained and used.

Subjective data conversion into numerical, neural network format was the third identified issue associated with subjective factors. Two steps were taken for addressing this issue. First, a detailed analysis into the two of the most subjective characteristics, crew performance and activity difficulty, acts to further reduce subjectivity beyond the achievements of the descriptive and quantitative response technique. Based on an analysis of collected data, crew performance, alone as an individual factor and in combination with two of crew related factors, did provide a significant correlation with the achieved productivity. The overall difficulty factor did not provide a similar correlation, and upon further investigation it was found the correlations of all the difficulty factors were not very strong. As a result, a technique was developed that used superintendent ability to adjust the superintendent chosen subjective response. The result was a stronger correlation for all the difficulty factors and the incorporation of the methodology into the neural network training methodology. Second, a method of scaling the subjective responses from a range of one to five to -0.8 to 0.8 proved to best represent the descriptive and quantitative responses implemented during data collection. Two of the three most stable neural network models tested used the technique of scaling to -0.8 to 0.8, thus, proving the use of the scale technique.

3.9 Conclusion

Stability is a very important characteristic of a neural network application. In the case of the formwork neural network models, stability was definitely an issue. Furthermore, this issue could inhibit the successful implementation of the artificial intelligence into a contractor's estimating procedure for a couple of reasons. First, instability may result in the neural network models producing invalid predictions. An estimating tool that is not reliable will not be useful in a highly competitive construction estimating market. Second, illogical prediction behavior by the neural network models may also result from instability. Once this illogical behavior becomes apparent to an estimator the result will be a loss of confidence in the artificial intelligence and lack of use. The research discussed in this chapter implemented a number of new techniques into the formwork neural network models so that each of these characteristics of instability may be avoided: the most important of these include;

- the incorporation of a number of new productivity influencing factors so that all factors in the models will properly capture their own influence,
- the addition of more training data so that inputs of limited quantity will not inadequately train, and
- the breakdown of difficulty into five descriptive difficulty factors as opposed to one. Following a normalization of these subjective inputs, the need for a biased activity complexity factor is overcome.

4. Accuracy Enhancement of Formwork Neural Network Labour Productivity Models

4.1 Introduction

Accuracy is a characteristic of neural networks which defines how well they are able to predict. Many factors contribute to the accuracy of a neural network:

- applicability of the problem to neural network artificial intelligence
- architecture of neural network
- stability of neural network model
- training method used

The formwork neural network models evaluated in chapter 3 are re-addressed in this chapter. The objective of this chapter, however, is to increase the accuracy of the models. Of the four identified factors of neural network accuracy, this chapter focuses on the methods used for training the models. The other three factors have been addressed and satisfied by previous research.

By studying the accuracy achievements of the neural network models from previous research (Portas 1996) a key characteristic of neural networks is exposed. This artificial intelligence can more accurately predict an activity if the activity is similar to the activities on which the neural network is trained. This is apparent in the formwork neural network models' ability to most accurately predict near mode activities, but have difficulty with extreme, beyond the 10^{th} and 90^{th} percentile, activities. This chapter introduces a new training method which can improve the overall prediction abilities of a neural network by:

1. classifying an activity to a group of similar activities
2. predicting the activity from a neural network only trained on records from the similar group.

Within this chapter, the hypothesis of using classification as a means of more accurately predicting the entire range of a formwork activity is tested. The method used in previous research (Portas 1996) is used by this research as a comparison to the new hypothesis.

4.2 Accuracy Concerns of the Formwork Neural Network Models

An overview of the previous research (Portas 1996) undertaken involving the development of neural network models for the purposes of predicting formwork labour productivity has been given in section 3.2 of this research. In terms of accuracy, previous research (Portas 1996) was successful in predicting formwork labour productivity to within 15%, on average 80% of the time. This was deemed a significant improvement as estimators were historically only successful in predicting to within 15%, only 40% of the time. Two concerns, however, about the accuracy of the formwork neural network models have been identified:

1. Although the neural networks are significantly more accurate than the historic estimates, estimator confidence is required before the formwork models can be successfully implemented. This confidence will be primarily placed in the ability of the models to provide accurate predictions. Therefore, the best possible level of accuracy is required.
2. The nature of neural networks is such that they can predict based only on what they are trained upon. Neural networks, therefore, are best at making a prediction where the prediction record is similar to many of the training records. On the other hand, neural networks are not as capable of making a prediction where the characteristics of the prediction record are unlike the characteristics of the training records. In other words, neural networks will best predict values which lie near the mode of the training

record output values and will have the most difficulty predicting values that are further from the mode of the training record output values.

This characteristic of neural networks is a concern for the formwork neural network models. Typical formwork activities of near modal productivity, are easy for the models to predict, but these activities are also fairly easy for an estimator to predict. Furthermore, a miss by an estimator on a typical activity will seldom result in large dollar loss as the amount of the miss will not be very large. But in the case were a formwork activity productivity nears or passes the 10^{th} or 90^{th} percentile of the historical statistics for the activity's historical productivity is when the ability to predict becomes more difficult. These extreme productivity activities are the activities in which an estimator has historically missed by a significant amount with the result being very costly. Therefore, the need for a neural network model to aid in the estimation of a productivity for an activity becomes most important on the extreme activities. Due to the nature of the neural networks, the formwork models are least reliable for the extreme activities.

4.3 Method of Enhancing Accuracy

In order to address the two concerns on the accuracy of the formwork neural network models the method used to train the networks is examined and tested. In doing so, the data collection initiated in chapter 3 is completed so that 69 records for loose walls and 58 records for loose slabs are used for training. This volume of data deemed sufficient for the concerns of stability identified in the previous chapter. Training methods are then examined so that the two concerns of accuracy can be effectively addressed.

4.4 Experimental Characteristics

4.4.1 Model Inputs

Research for this step contributed additional historical data and uses the new factors and techniques developed in the stability analysis with the intent of developing a new neural network training philosophy. Table 4.1 and Table 4.2 define the factors analyzed and inputs used for the wall and slab neural networks in this research:

Table 4.1 Loose Walls Formwork Input Factors

Factor	Neural Network Inputs
1 Historic Superintendent Activity Ability	Activity Superintendent Score
2 Historic Superintendent Project Ability	Project Superintendent Score
3 Historic District Performance	District Activity Score
4 Crew Size	CREW_SIZE_1 (<6) CREW_SIZE_2 (6-10) CREW_SIZE_3 (11-15) CREW_SIZE_4 (16-20) CREW_SIZE_5 (>20)
5 Activity Type	COSTCODE1 (Fdn/Ret Wall) COSTCODE2 (Wall) COSTCODE3 (Low Wall) COSTCODE4 (Curved Wall)
6 Formwork Duty	DUTY_LOOSE DUTY_SEMI-PANELIZED
7 Tie Type	TT_W_SNAP TIE & WEDGE TT_W_CAMLOCK TT_W_TAPER TIE TT_W_WALER BRACKET
8 Accuracy of Design	Design Accuracy Rating Code

Table 4.1 cont.

Factor	Neural Network Inputs
9 Activity Formwork Quantity	LOG_QUANT
10 Height of Wall	HEIGHT_W (>16')
11 Thickness of Wall	WALL_THICK (>12")
12 Activity Repetition	Degree of Repetition Rating Code
13 No. of Panel Reuses	REUSE_1 REUSE_2 REUSE_3 REUSE_4
14 Area of Panels	PANEL_AREA_0 PANEL_AREA_1 PANEL_AREA_2 PANEL_AREA_3
15 Difficulty of Activity	Factored Complexity Factored Irregularities Factored Finishes Factored Conditions Factored Difficulty
16 Overtime Work Hours	Extended Work Hours
17 Use of Lift Drawings	Lift Drawings Prepared
18 Crew Ability	Crew Experience
19 Worker Classification	Unionized Crew
20 Degree of Inspection	Owner Inspection
21 Location of Activity I	Location_1 (above grade) Location_2 (below grade) Location_3 (at grade) Location_4 (both above and below grade)
22 Location of Work II	FLOOR_NO_1 FLOOR_NO_2 FLOOR_NO_3-5 FLOOR_NO_>=6

Table 4.1 cont.

Factor	Neural Network Inputs
23 Location of Project	DIST_4 DIST_5 DIST_6 DIST_8 DIST_9 DIST_11 DIST_50 DIST_51 DIST_52
24 Temperature	Mean Temp

Table 4.2 Loose Slabs Formwork Input Factors

Factor	Neural Network Inputs
1 Historic Superintendent Activity Ability	Activity Superintendent Score
2 Historic Superintendent Project Ability	Project Superintendent Score
3 Historic District Activity Performance	District Activity Score
4 Historic District Project Performance	District Project Score
5 Crew Size	CREW_SIZE_1 (<6) CREW_SIZE_2 (6-10) CREW_SIZE_3 (11-15) CREW_SIZE_4 (16-20) CREW_SIZE_5 (>20)
6 Activity Type	COSTCODE1 (Flat Slabs) COSTCODE2 (Slabs/Dropheads/Beams)
7 Formwork Duty	DUTY_LOOSE DUTY_SEMI-PANELIZED

Table 4.2 cont.

Factor	Neural Network Inputs
8 Formwork Support System	SS_S_General_Contractor LEGS SS_S_PANELIZED SCAFFOLD SS_S_LOOSE SCAFFOLD SS_S_ELLIS SHORES
9 Accuracy of Design	Design Accuracy Rating Code
10 Activity Formwork Quantity	LOG_QUANT
11 Height of Slab	HEIGHT_S_1 HEIGHT_S_2 HEIGHT_S_3
12 Thickness of Slab	SLAB_THICK_1 SLAB_THICK_2 SLAB_THICK_3
13 Activity Repetition	Degree of Repetition Rating Code
14 No. of Panel Reuses	REUSE_1 REUSE_2 REUSE_3 REUSE_4
15 Area of Panels	PANEL_AREA_1 PANEL_AREA_2 PANEL_AREA_3
16 Difficulty of Activity	Factored Complexity Factored Irregularities Factored Finishes Factored Conditions Factored Difficulty
17 Overtime Work Hours	Extended Work Hours
18 Equipment/Material Constraints	Material Handling Problems
19 Use of Lift Drawings	Lift Drawings Prepared
20 Crew Ability	Crew Experience
21 Worker Classification	Unionized Crew

Table 4.2 cont.

Factor	Neural Network Inputs
22 Location of Activity I	Location_1 (above grade) Location_2 (below grade) Location_3 (at grade) Location_4 (both above and below grade)
23 Location of Work II	FLOOR_NO_1 FLOOR_NO_2 FLOOR_NO_3-5 FLOOR_NO_>=6
24 Location of Project	DIST_4 DIST_5 DIST_6 DIST_8 DIST_9 DIST_11 DIST_50 DIST_51 DIST_52
25 Temperature	Mean Temp

As seen from the inputs shown in the above tables, four types of general contractor formwork have been chosen for inclusion in the loose walls analysis and two types in the loose slabs analysis. These groupings are justified due to the similarities of work and the correlation of the statistical productivity. Table 4.3 summarizes the statistics of the formwork types grouped within each activity:

Table 4.3 Formwork Cost Code Statistics

Cost Code Description	10th Percentile	Mode	90th Percentile	No. of Records
Loose Walls				
Foundation/Retaining Walls	0.117	0.261	0.557	23
Walls	0.091	0.278	0.630	32
Low Walls	0.122	0.261	0.939	8
Curved Walls	0.230	0.348	1.383	6
Loose Slabs				
Flat Slabs	0.0970	0.2848	0.5758	13
Slabs/Dropheads/Beams	0.1152	0.2424	0.7333	45

4.4.2 Accuracy Determination

Accuracy is addressed in this research through comparing a neural network predicted productivity with the actual productivity for a testing record. For testing purposes, approximately 15% of all the records were withheld from the training of a neural network. The data withheld from training was used as testing records and as a basis for accuracy. 15% of the records, however, typically turned out to be less than 10 records, and was deemed insufficient as an accuracy determinant. Therefore, for each model developed, the networks were trained and tested using a different combinations of 85% training and 15% testing records until a significant database of tested records was developed. The developed database typically included 40 different tested records and was determined to provide a sufficient representation of the accuracy of a model. The accuracy of a prediction was determined in two ways:

1. A weighted average predicted productivity (WAPP) is calculated for each testing record. WAPP is equal to the summation of the predicted weight given to a zone times the average value of the respective zone divided by the total range of

productivity for all the zones. The following calculation determines whether the prediction is a hit or a miss:

$$\% = \frac{(WAPP) - (Actual\Pr odRate)}{Total\Pr odRange} \times 100$$

if $|\%| \leq 15\%$, hit

if $|\%| > 15\%$, miss

2. Graphical output analysis was undertaken for each testing record. If a significant predicted weight is given to the actual productivity zone, the record is labeled a hit based on graphical analysis. If a significant predicted weight is not given to the actual productivity zone, the record is labeled a miss based on graphical analysis. Graphical analysis was deemed necessary due to the possibly deceiving nature of the WAPP value or in a case were the model predicts a binomial distribution.

Sample accuracy determinations:

The following graph, shown in Figure 4.1, depicts a neural network prediction which would be classified as a hit according to both the WAPP value and graphical analysis. In this case, the WAPP only missed the actual productivity by 7% and a significant weight is graphically predicted to the actual productivity zone.

Figure 4.1 Accuracy Determination Graph 1

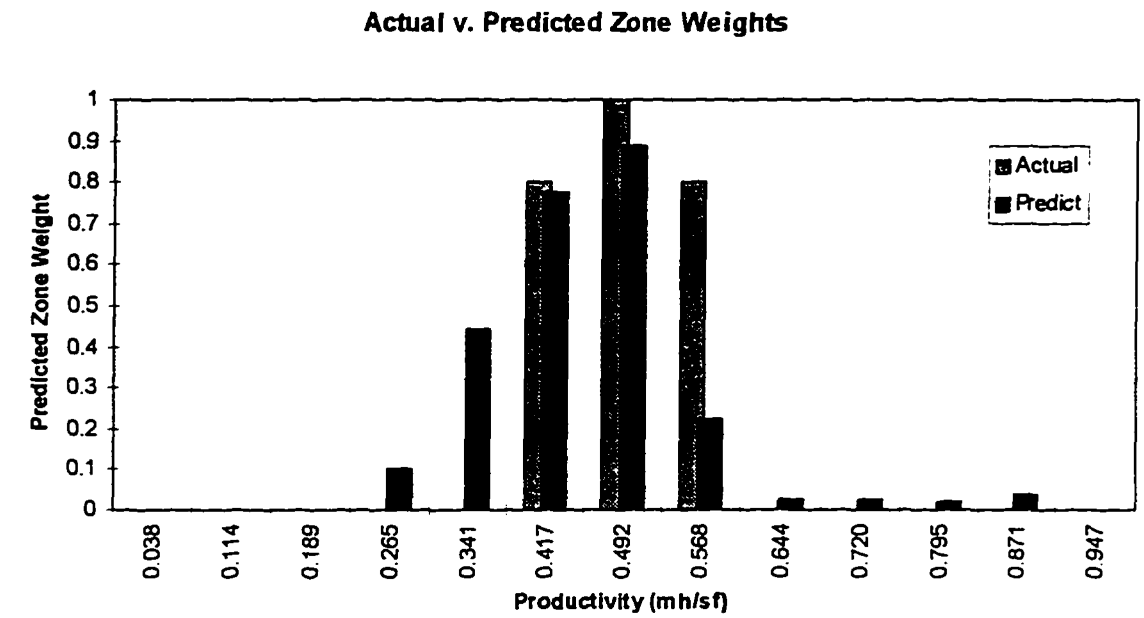
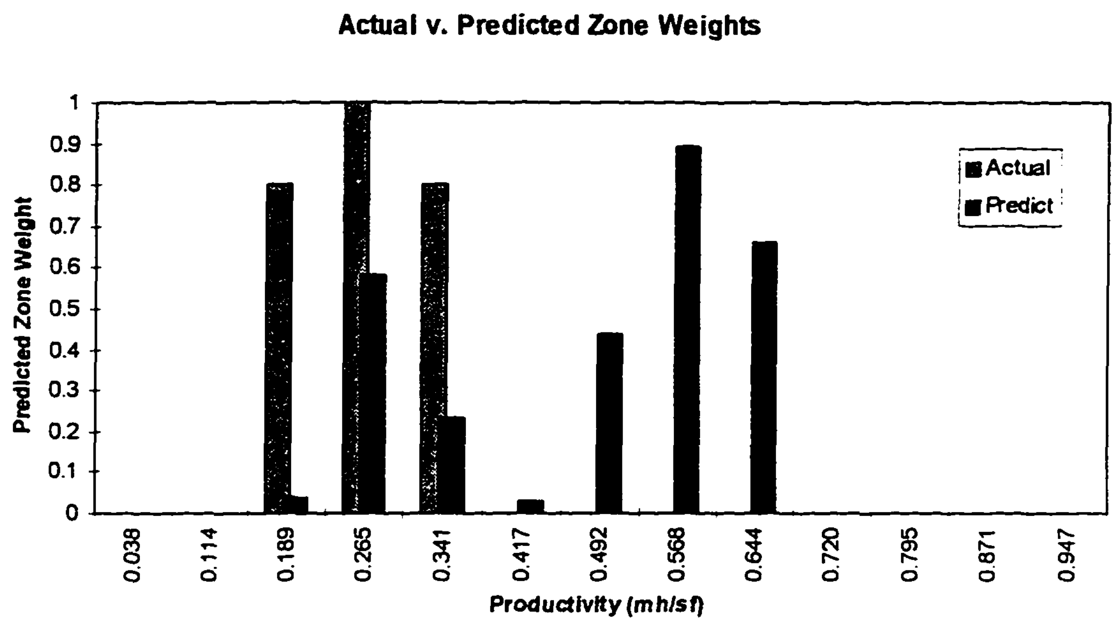


Figure 4.2 represents a testing record which is a miss in terms of the WAPP but a hit in terms of graphical analysis; the WAPP is out 21% from the actual productivity but a significant prediction weighting is given to the actual productivity zone. If an estimator were to receive a binomial output prediction such as given in this graph, an estimator's judgment would be necessary to decide which peak would be the best to use.

Figure 4.2 Accuracy Determination Graph 2



4.5 Training Method Development

4.5.1 Feed-Forward Back-Propagation Neural Networks

This training method uses all the data for each respective network and trains based on the entire range. This was the method used for the testing of stability in chapter 3. The neural architecture is as follows:

- 1 hidden layer with 35 nodes
- 14 nodes in the output layer (13 fuzzy zones and 1 point prediction zone)
- symmetric logistic transfer function, 0.1 learning rate, 0.4 momentum rate
- 0.01 error threshold

This architecture, proven to best suit this application by previous research (Portas 1996), is used for all training of feed forward back-propagation networks in this research, and therefore, will not be restated.

The training method tested here so that its results can be compared to the new methods which will be developed. The following results were determined for the loose wall and slab networks under this method:

4.5.1.1 Loose Wall Model

67 of the 69 collected records were used for analysis. Two records with extremely poor productivity were not analyzed as it was deemed that due to the magnitude of their productivity, they would be difficult use in training. Table 4.4 defines the accuracy obtained by the loose wall neural network.

Table 4.4 Loose Walls Accuracy - Feed Forward Back Propagation Network

Accuracy Method	No. Records	Hits	% Hit
WAPP	42	28	66.7%
Graph Analysis	42	31	73.8%
WAPP or Graph Analysis	42	34	78.6%

The 79% accuracy obtained from these networks proves that the new data, factors, and techniques described in chapter 3 prove to produce accuracy equivalent to that of the original application. Further breakdown of the accuracy is given in Table 4.5.

Table 4.5 Loose Walls Accuracy Breakdown - Feed Forward Back Propagation Network

Range of Testing Records	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
<25th percentile data	54.5	81.8	72.7
>25th percentile, <75th percentile data	77.8	77.8	85.2
>75th percentile data	50.0	25.0	50.0

From this table, it is apparent that the extreme productivity (i.e. <25th percentile and >75th percentile) do not predicting accurately. This is a characteristic that was also present in previous research (Portas 1996).

4.5.1.2 Loose Slab Model

56 of the 57 collected records were used for analysis. The productivity of one record was determined to be too low and not suitable for training. Table 4.6 provides a summary of the results obtained from the loose slab feed forward back-propagation neural networks.

Table 4.6 Loose Slabs Accuracy - Feed Forward Back Propagation Network

Accuracy Method	No. Records	Hits	% Hit
WAPP	29	20	69.0%
Graph Analysis	29	19	65.5%
WAPP or Graph Analysis	29	22	75.9%

The 76% overall accuracy obtained by the loose slabs networks is very close to the benchmark of 80% (obtained in previous research (Portas 1996)), and as a result, the new data, factors, and techniques described in chapter 3 are deemed viable. This has not been previously proven, as chapter 3 only examined the of effect the stability enhancement on the loose walls data. Therefore, this analysis further proves the applicability of the changes made to the previous research (Portas 1996). Further breakdown of the accuracy of the loose slab neural network produces the results in Table 4.7.

Table 4.7 Loose Slabs Accuracy Breakdown - Feed Forward Back Propagation Network

Range of Testing Records	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
<25th Percentile data	50.0	50.0	50.0%
>25th percentile, <75th percentile data	93.8	81.3	93.8%
>75th percentile data	33.3	44.4	55.6%

From the above table, it is apparent that the loose slab neural network has a similar difficulty to the loose walls neural network in predicting extreme values. Based on these similar results, it has been determined that the current use of feed forward back-propagation neural networks is the source of the poor accuracy and the error in the extreme records.

4.5.2 Kohonen Classification Neural Networks

This method aims at obtaining more accurate predictions for extreme productivity through utilization of a Kohonen classification neural network. The intent of a classification network is to classify an activity as either a high, medium, or low productivity activity. Once the activity is classified, a productivity prediction is made by one of three feed-forward back-propagation neural networks, based on the record's assigned classification. Each of the three neural networks, high, medium, and low, are trained in the same way as the feed-forward back-propagation neural networks previously developed. The intent of this method is to reduce the range of productivity in training records for each of the feed-forward back propagation neural networks so that the accuracy of a prediction increases. This technique is useful for predicting the extreme values as opposing extreme productivity records will not unjustly generalize a prediction.

4.5.2.1 Literature Background

A classification neural network predicts to range or zone as opposed to the prediction neural network which predicts a value. Very few classification neural network applications have been developed for modeling purposes in civil engineering. In the past, only two fields of civil engineering have really begun to use the abilities of classification neural networks.

Transportation uses the technology as means as classifying roadways, intersections, and traffic patterns in order to determine maintenance and expansion needs. For instance, Lingras (1995) developed a model that uses Kohonen neural networks to classify highway patterns. The purpose of the model is group highways to set classifications that specify the construction, upgrading, and maintenance requirements for highway agencies. The model replaces the hierarchical grouping and other statistical methods currently used for classification because the Kohonen neural networks has less stringent data nature and format requirements. The ability of neural networks to handle incomplete data offers highway agencies the ability to classify highways despite limited traffic pattern collection, whereas previous approaches have limited the ability to classify all roadways. Lingras used unsupervised Kohonen neural networks to prove the ability of the neural network artificial intelligence above statistical methods.

The structural field has also uses classification neural networks for analysis problems. Classification of possible locations of cracking, fatigue, and failure behavior in a structure is the primary focus of the technology. Almeida and Hill (1994), for example, used classification neural networks to monitor fatigue in metal joints. Acoustic emissions, elastic waves used to measure how materials react to stress, can be used to detect the growth of flaws in aluminum lap joints, but current technology was unable to decipher the emissions as either crack growth or fretting, in a correct and timely manner. Classification neural networks, however, have proven to analyze the emission and provide a very accurate status. Almeida and Hill used supervised classification training and developed back propagation Kohonen neural networks. The neural network was trained with normalized spectra mapped to a 25 input self organized map and two output classifications, crack growth and rivet rubbing. The result was a model that was able to classify, in a timely manner, to an accuracy of 94%.

Few applications of classification neural networks have been developed for use in the construction industry. As discussed in chapter 2, neural network artificial intelligence has been rapidly growing in the construction industry, but the focus has primarily been on prediction neural networks. One application, however, has been developed for the purposes of modeling construction using classification neural networks. Murtaza and Fisher (1994) used a classification neural network model to determine whether a project's characteristics make modular construction more feasible than on-site construction. Neural network artificial intelligence was chosen as the best model for this situation for two reasons. First, many factors within the major factor groups of plant location, labor consideration, environmental and organizational factors, plant characteristics, and project risks can most effectively managed and analyzed by a typical neural network system. Second, the nature of this problem provides no concrete outputs, and therefore an unsupervised classification neural network application was used. The model is parallel and multilayered. Each major factor group represents a distinct two-layered network and each of these groups are set in parallel. The second layer of each network acts as an input to the third layer which ties in the total system. Five neurons are present in the third (output) layer and were classified in five degrees of modularization. The network was then tested with ten sets of data. The test data consisted of historical projects, hypothetical projects, and projects with incomplete inputs. The network was found to predict to the correct classification eight out of ten times.

The use of classification neural networks is fairly rare in civil engineering fields. The construction industry, although currently expanding into the artificial intelligence area of neural networks, has seldom explored the use of classification neural networks. The technology, however, does provide an industry of high variability a technology that enables analysis on classified and better defined basis.

For this research, Linear Vector Quantization (LVQ) neural networks are used. This is a special type of Kohonen classification that uses supervised learning. (Appendix 1 provides a detailed description of LVQ neural networks)

4.5.2.2 Kohonen Classification Neural Networks - Solid Record Divisions

A supervised classification neural network is used for this method. This type of neural network requires input data to specify an output so that during training proper classification weights can be derived. Therefore, data for a supervised classification network is prepared by assigning a classification. The network is to classify a new activity based on training from these set classifications. Input data includes all factors in which previous training of feed forward back propagation neural networks have been used. The bottom 25th percentile records were assigned a low classification, records between the 25th and 75th percentile were assigned a medium classification, and records with productivity above the 75th percentile were assigned a high classification. The following defines the development of Kohonen neural networks for loose walls and loose slabs strictly using these boundaries (solid divisions).

4.5.2.2.1 Loose Walls

Classifications were assigned to each of the 67 records. The divisions between the low and medium and the medium and high were set near the 25th and 75th percentiles, at points in the records where a significant jump in the productivity takes place. 19 records were assigned a low classification, 31 assigned a medium classification, and 17 assigned a high classification.

Neural Works software was used for training and Learning Vector Quantization (LVQ), supervised classification neural networks, were trained and tested. The following characteristics for these networks were developed experimentally:

- 1 hidden layer with 42 nodes
- 3 output nodes (binary)
- 0.06 learning rate, LVQ2 (used to reduce favoritism) = 0
- 1770 iterations

The classification neural network achieved the accuracy defined in Table 4.8.

Table 4.8 Loose Walls Accuracy - Classification Neural Networks (Solid Divisions)

Classification	No. Records	Correct Classification	% Correct Classification
Low Classification	10	6	60.0%
Medium Classification	19	15	78.9%
High Classification	10	5	50.0%
Overall	39	26	66.7%

Each of the low, medium, and high neural networks were trained and tested as feed forward back-propagation neural networks and produced the accuracy in Table 4.9.

Table 4.9 Loose Walls Accuracy - Low, Medium, and High Neural Networks (Solid Divisions)

Neural Network	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
Low Network	100.0	100.0	100.0%
Medium Network	93.4	100.0	100.0%
High Network	58.3	83.3	83.3%
Overall	85.0	95.0	95.0%

From this table, it is apparent that by using three feed forward back-propagation neural networks, very good accuracy can be obtained (95%). The problem, however, is that the classification network is only correct 67% of the time. By combining the accuracy of the classification and feed forward back-propagation neural networks, the accuracy in Table 4.10 is obtained.

Table 4.10 Loose Walls Accuracy - Combined Networks (Solid Divisions)

Records	WAPP or Graph Hit %
Low Classification	60.0%
Medium Classification	78.9%
High Classification	41.7%
Overall	63.4%

This table assumes that if a record is classified to the wrong network, it will not be a hit. Therefore, from this accuracy it is apparent the extreme values have not been corrected and the entire accuracy of the system has decreased.

Positive developments, however, have emerged from this test; if a classification network can be trained to accurately classify a record, a more defined feed-forward back-propagation neural networks has the ability to predict the actual productivity with a very high level of accuracy.

4.5.2.2.2 Loose Slabs

Loose slabs data was not tested using this method due to the poor results of the loose wall networks.

4.5.2.3 Kohonen Classification Neural Networks - Overlapping Record Divisions

As means of improving the ability of the classification network to properly classify a record, the divisions of classification are overlapped by 10 percent. Supervised training of the classification network stays the same under this method, but training of each of the feed-forward back-propagation neural networks increases to include records 10 percent past the original division points. Therefore, the low classification neural network includes all records below the 35th percentile, the medium classification neural network includes all records between the 15th and 85th percentile, and the high classification neural network includes all records above the 65th percentile. Under this method, a record can be incorrectly classified to it's neighbour classification, but still be predictable within the range of the corresponding feed forward back-propagation neural network. Another advantage of this method is more records will be used to train each of the three feed forward back-propagation neural networks than with the solid divisions method. The following defines the development of Kohonen neural networks for loose walls and loose slabs using overlapping divisions.

4.5.2.3.1 Loose Walls

The high, medium, and low loose wall neural networks now learn from 29, 49, and 30 records, respectively. Table 4.11 shows the classification neural network's ability to hit the overlapping classifications.

Table 4.11 Loose Walls Accuracy - Classification Neural Networks (Overlapping Divisions)

Classification	No. Records	Classification Hits	Neighbour Classification Hits	% Hits
Low Classification	10	6	3	90.0%
Medium Classification	19	15	2	89.5%
High Classification	10	5	1	60.0%
Overall	39	26	6	82.1%

The classification network's ability to classify to the overlapping divisions gave an accuracy of 82% This is approximately 15% better than that with the solid division. However, the accuracy of the feed-forward back-propagation neural networks slightly decreases, as each of their ranges broadened. This is shown in the Table 4.12.

Table 4.12 Loose Walls Accuracy - Low, Medium, and High Neural Networks (Overlapping Divisions)

Neural Network	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
Low Network	87.5	87.5	87.5%
Medium Network	81.0	90.0	90.0%
High Network	60.0	80.0	80.0%
Overall	79.4	88.2	88.2%

The ability of the neural networks to predict decreased for each network, approximately 7% in total. By combining the accuracy of the classification and feed forward back-propagation neural networks, the accuracy in Table 4.13 is obtained.

Table 4.13 Loose Walls Accuracy - Combined Networks (Overlapping Divisions)

Classification	WAPP or Graph Hit %
Low Classification	78.8%
Medium Classification	80.6%
High Classification	48.0%
Overall	72.3%

This table assumes that if a record is classified to the wrong network, it will not be a hit. The overlapping technique improved the accuracy. The results, however, are not an improvement to those obtained using only a single feed-forward back-propagation neural network with all the data. Furthermore, the ability of the new method to better capture extreme records is not apparent in the accuracy totals. Based on the analysis, however, the use of three feed forward back-propagation neural networks can effectively predict extreme productivity, but the propagation of error from the classification network is reduces accuracy.

The initial division of the data into three classifications is reexamined as a possible contributor of error. From inspection of the records, it appears as though the initial two divisions were justly placed in gaps between the productivity, as well as near the 25th and 75th percentiles. The existence of a third division, however, may be viable. This division would be placed near the 95th percentile where a third significant gap in productivity exists. This would place two records in a new classification, entitled very high.

The very high classification contains only two records, and therefore, could not be considered in further analysis. Data in this classification will need to be thoroughly examined so that the factors of each activity properly reflect a very high productivity. Data simulation may be necessary to provide enough data for future development of this classification.

The overlapping method was reanalyzed following the establishment of the fourth classification. Because this new classification will not be included in the analysis, analysis is essentially the same, minus two records. Table 4.14 gives the accuracy obtained from the classification network:

Table 4.14 Loose Walls Accuracy - Classification Neural Networks (Overlapping Divisions - 4 classes)

Classification	No. Records	Classification Hits	Neighbour Classification Hits	% Hits
Low Classification	10	4	4	80.0%
Medium Classification	20	18	1	95.0%
High Classification	10	5	1	60.0%
Overall	40	27	6	82.5%

The accuracy of the classification is only slightly better than the accuracy obtained with three classifications, as expected. Each of the 40 test records were then analyzed within the neural network in which the classification neural network predicted. The accuracy of this analysis is summarized in Table 4.15.

Table 4.15 Loose Walls Accuracy - Low, Medium, and High Neural Networks (Overlapping Divisions - 4 classes)

Records	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
Low Classification	60.0	80.0	80.0%
Medium Classification	65.0	85.0	90.0%
High Classification	50.0	60.0	60.0%
Overall	60.0	77.5	80.0%

These results provide a significant improvement over the accuracy of the original method which uses only one feed-forward back-propagation neural network. Each classification has a slightly better accuracy, and records of extreme classification are better predicted by about 10%.

4.5.2.3.2 Loose Slabs

Following the analysis of the loose walls data, the viability of the overlapping method of classification with three feed forward back-propagation neural networks was tested on the loose slab records. First, the records used were reduced from 56 to 54, where one extreme point off of either end of the productivity scale appeared to require a classification of its own. Though a very high and very low classification were developed, lack of data in these classifications prevented them from being included in the analysis. As a result, the low classification included 26 records, the medium classification contained 46 records, and the high classification contained 17 records (note: as with loose walls, loose slab divisions were overlapped by 10%).

Experimentation was used to determine the proper classification network characteristics for the loose slabs data. The determined characteristics include:

- 1 hidden layer with 15 nodes
- 3 output nodes (binary)
- 0.06 learning rate, LVQ2 (used to reduce favoritism) = 0
- 1380 iterations

Table 4.16 summarizes the accuracy of the classification network.

Table 4.16 Loose Slabs Accuracy - Classification Neural Networks (Overlapping Divisions - 5 classes)

Classification	No. Records	Classification Hits	Alternate Classification Hits	% Hits
Low Classification	10	5	4	90.0%
Medium Classification	20	15	2	85.0%
High Classification	10	6	2	80.0%
Overall	40	26	8	85.0%

Each of the 40 test records were then analyzed within the neural network where the classification network predicted. The accuracy of the overlapping method for loose slabs is given in Table 4.17.

Table 4.17 Loose Slabs Accuracy - Low, Medium, and High Neural Networks (Overlapping Divisions - 5 classes)

Records	WAPP Hit %	Graph Hit %	WAPP or Graph Hit %
Low Classification	80.0	90.0	90.0%
Medium Classification	75.0	85.0	95.0%
High Classification	60.0	60.0	70.0%
Overall	70.0	80.0	88.0%

This method produced a very significant increase in accuracy over that obtained by the original method of one feed-forward back-propagation neural network. Records classified as a medium classification gave slightly better accuracy, while the extreme classification records, on both the high and low ends, are drastically more accurate.

4.5.3 Summary of Results

Using Kohonen neural networks with overlapping divisions proved to provide the best accuracy. Furthermore, the ability of the application to predict extreme productivity has been drastically improved. Table 4.18 and Table 4.19 summarize the results by comparing the abilities of a classification / feed forward back propagation system versus the original feed forward back propagation only method.

Table 4.18 Loose Walls Accuracy - Comparison of Original and New Method

Records	Original Method	New Method	% Increase in Accuracy
Low Classification	72.7	80.0	10.0
Medium Classification	85.2	90.0	5.6
High Classification	50.0	60.0	20.0
Overall	78.6	80.0	1.8

Table 4.19 Loose Walls Accuracy - Comparison of Original and New Method

Classification	Original Method	New Method	% Increase in Accuracy
Low Classification	50.0	90.0	80.0
Medium Classification	93.8	95.0	1.3
High Classification	55.6	70.0	20.6
Overall	75.9	88.0	15.9

4.5.4 Comparison to Previous Research (Portas 1996)

This section compares the abilities of the new method using Kohonen neural networks to the original method using only a single feed forward back propagation neural network. Activities from two general contractor historic projects were chosen for this analysis (note: neither of the activities tested were used for training with the original or new method). Table 4.20 shows the results of the study.

Table 4.20 Individual Activity Study - Comparison of Original and New Method

			Original Application		Proposed Application	
Activity	Actual Prod Rate	Estimated Prod Rate	Predicted Prod Rate	% Difference (from actual)	Predicted Prod Rate	% Difference (from actual)
1. Fnd/Retain Wall - Test Project 1	0.391	0.430	0.378	-2.1%	0.387	-0.7%
2. Walls - Test Project 1	0.391	0.335	0.448	+9.3%	0.457	+10.7%
3. Flat Slab - Test Project 1	0.865	0.483	0.604	-24.1%	1.091	+20.9%
4. Walls - Test Project 2	0.535	0.287	0.378	-20.8%	0.478	-7.5%
5. Low Walls - Test Project 2	0.283	0.230	0.430	+29.6%	0.391	+21.7%

In comparing the two methods the following developments are apparent:

- in terms of absolute error, accuracy of the proposed application is slightly better than the original application. The prediction of the proposed application is closer to the actual productivity in 4 of the 5 activities.
- both applications predict the actual productivity more accurately than the value used in the estimate for 4 out of 5 records.
- the proposed application tends to predict more on the conservative side than does the original application. This is notable for two of the activities in which the original application was low by over 20% (this could result in a significant loss if the activity is

very large). On the two activities in question, the proposed model predicts on the conservatively for one, and only slightly low (7.5%) for the second.

4.6 Conclusion

The training method developed by this research is successful in addressing the two concerns of accuracy identified for the formwork neural network models. For loose wall formwork activities, only a small increase in overall prediction accuracy is achieved. However, a significant increase in the prediction ability of extreme records is obtained. For loose slab formwork activities, a significant improvement is obtained for both overall prediction and extreme record prediction abilities. The slight difference in the value of increased accuracy between the two types of formwork activities can be attributed to the more flexible nature of the loose walls neural network models to predict four duties as opposed to the loose slab neural network models ability to predict only two types of duties. In addition to the increased accuracy rates, other observations on the developed models include:

- sensitivity is still a problem (this was apparent during training within the districts factor in which the activity took place. The database has been expanded from four districts used by the original neural network models to 8 districts in the new models. Some of the new districts, however, are limited to two or three projects. As a result, poor results on one or two of these projects will cause the networks to become very biased against the district.) Stability due to data limitations, therefore, is still a concern due to the variability of the data added by the data collection in this research. The effects of this instability, however, will not be felt by a user as input values of high sensitivity (such as one of the new districts) will not be offered as an option.
- very extreme classes need to be developed for both the loose wall and slab networks so that the proposed model can obtain the flexibility necessary to predict the isolated, very extreme productivity. Data simulation may be necessary to develop enough data to train the very extreme classifications, as not enough historical records are available.

very extreme productivity. Data simulation may be necessary to develop enough data to train the very extreme classifications, as not enough historical records are available.

- the developed method offers very good potential for very accurate prediction abilities. This is proven because if a record can be classified to the correct productivity, the feed forward back propagation neural network will almost certainly predict accurately. Table 4.21 and Table 4.22 depict this ability.

Table 4.21 Loose Walls Accuracy - Summary

Classification	Overall Accuracy - All Records	Accuracy of Correctly Classified Record
Low Classification	80%	100%
Medium Classification	90%	94%
High Classification	60%	100%
Overall	80%	97%

Table 4.22 Loose Slabs Accuracy - Summary

Classification	Overall Accuracy - All Records	Accuracy of Correctly Classified Record
Low Classification	90%	100%
Medium Classification	95%	100%
High Classification	70%	83%
Overall	88%	96%

Based on the above tables and the increased accuracy abilities of the formwork neural network models, the use of Kohonen classification neural networks in combination with prediction neural networks has the potential to be almost 100% accurate with accurate record classification.

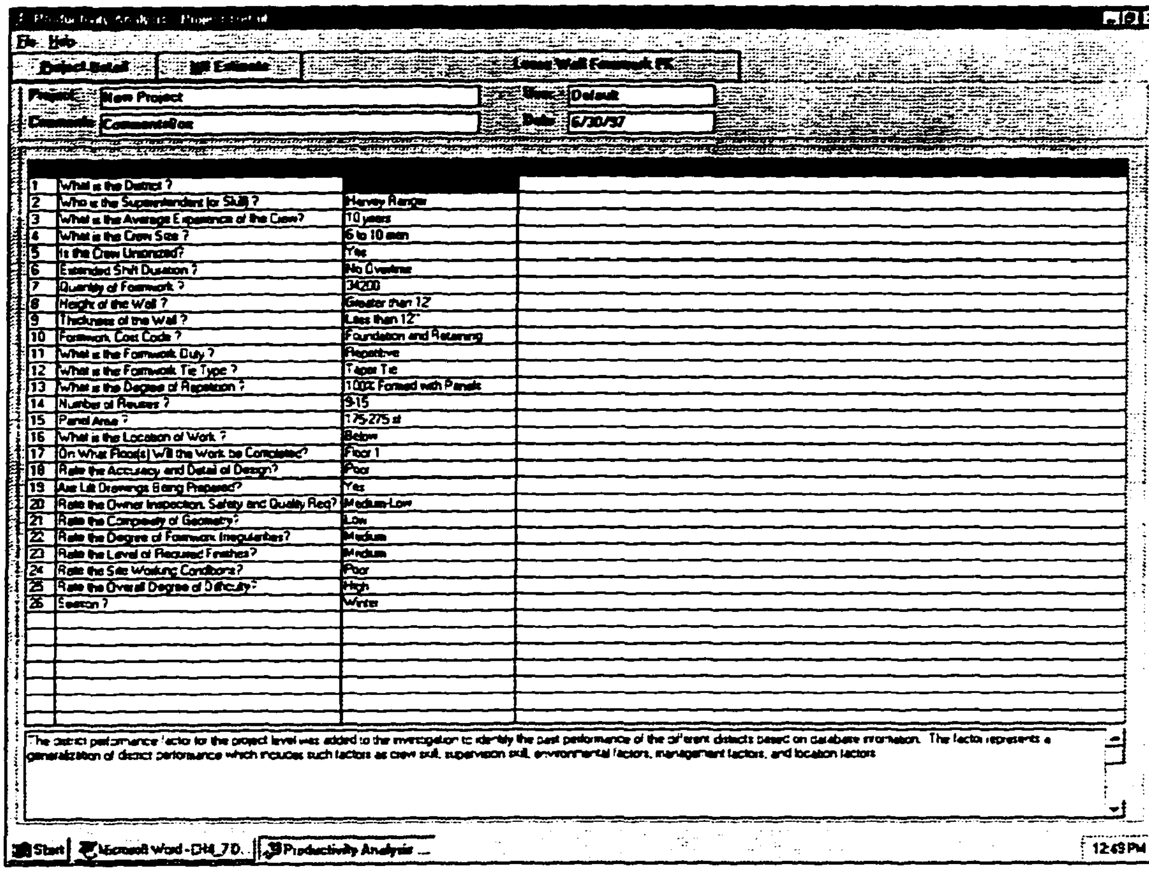
4.7 Neural Network Recall Program

4.7.1 Program Description

A neural network recall program uses the characteristics and developed weights of the training process to allow a user to predict an outcome. Previous research (Portas 1996) developed a recall program for formwork productivity for the general contractor. This program, however, only uses trained feed forward back propagation network information as means of predicting a labour productivity. The developments on sensitivity and accuracy discussed in this research have established a new training method. This section discusses the changes made to the previous recall program.

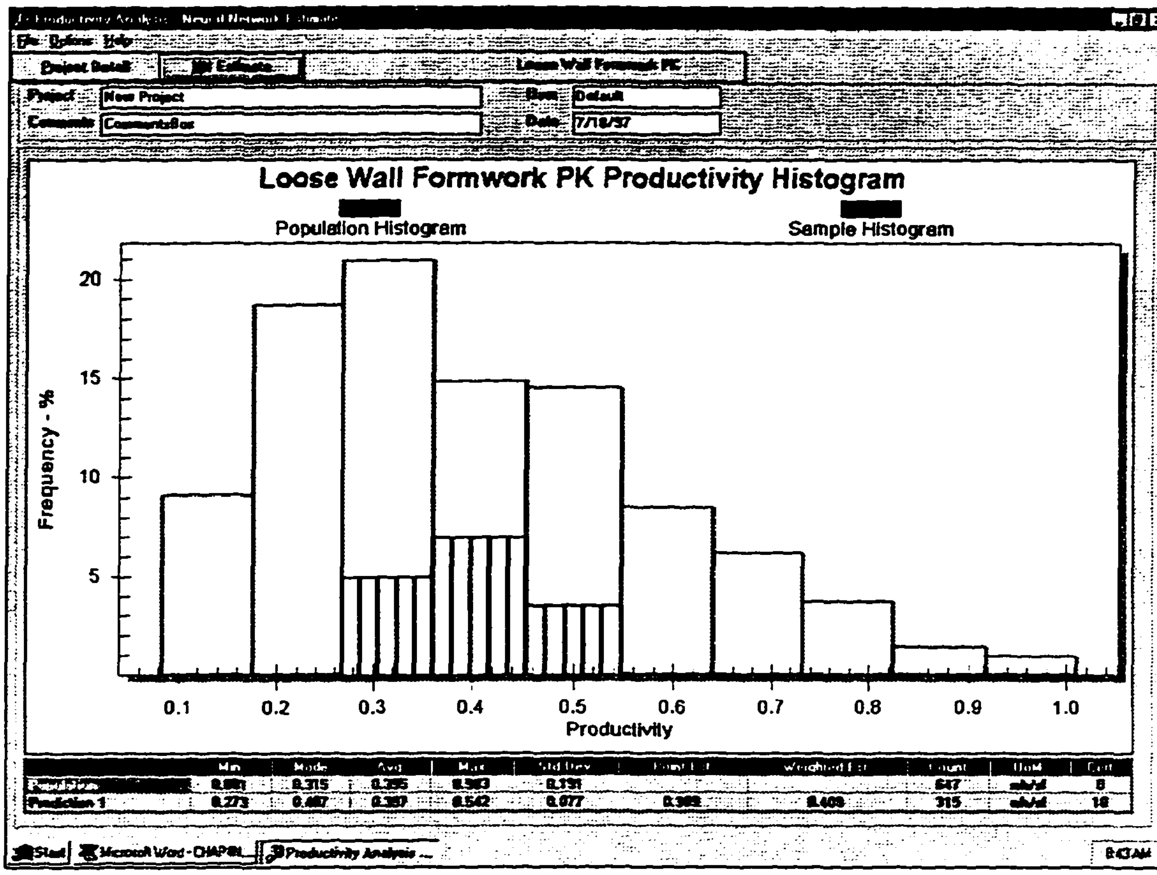
Microsoft Visual Basic was used to develop a program capable of recalling a formwork productivity based on a user's inputs. Within the program there is an option box and two screens. The option box simply prompts the user to choose the network to be used (in this case, loose wall or loose slab formwork). The first screen consists of a table which lists a number of questions for the user the answer (Figure 4.3). The response to each question is then converted to inputs and run through the trained neural network to produce a set of results on the second screen.

Figure 4.3 Recall Screen 1 - User Inputs



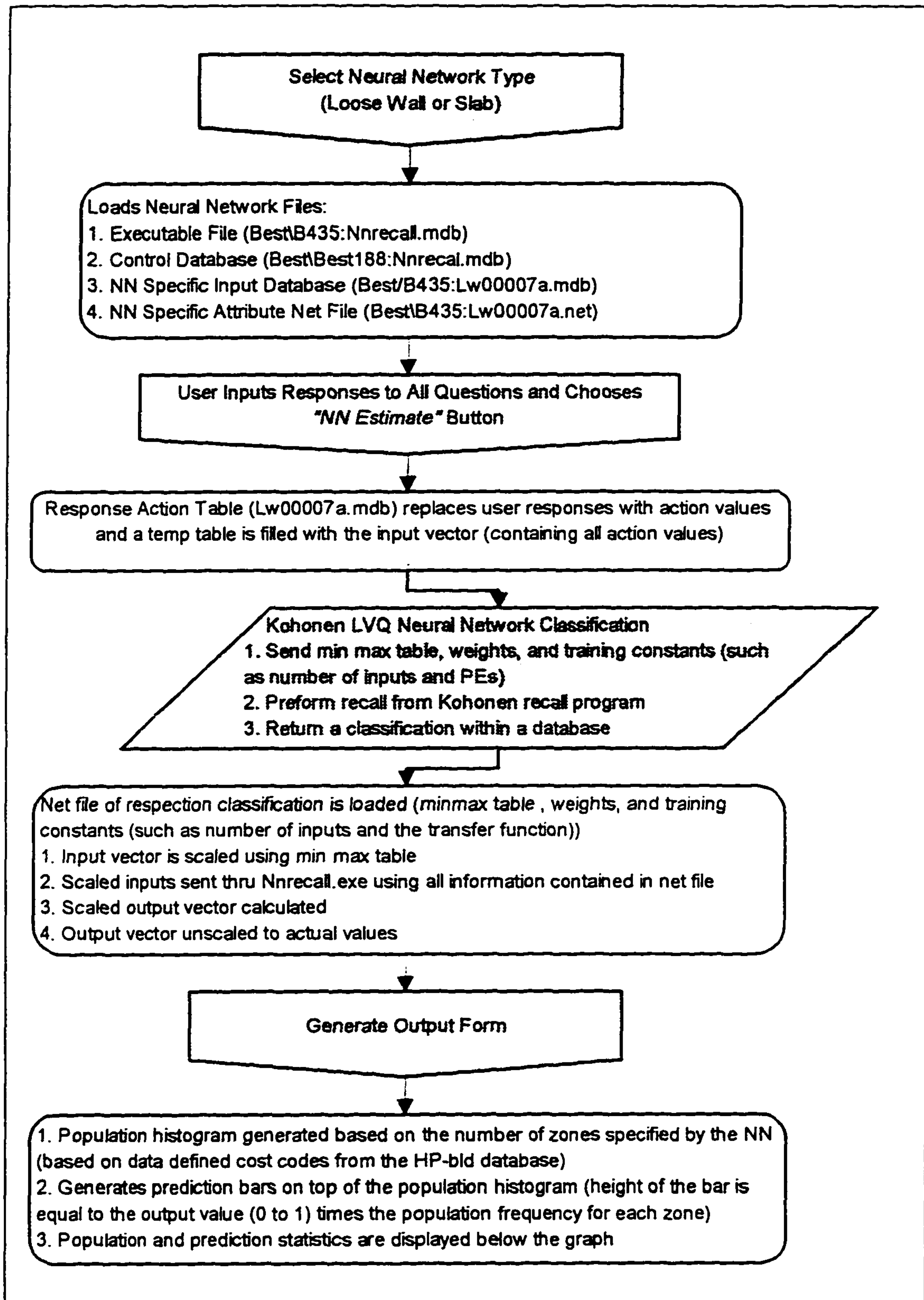
The second screen is composed of a graph and a small table (Figure 4.4). The graph presents a histogram depicting the frequency of historic productivity for the chosen activity for each of the fuzzy output zones (13 zones were used, each representing 1/13 of the productivity range for the activity). Within this histogram there are a number of shaded bars which represent the proportion of the historic frequency that the neural network predicts (the neural networks have been designed to output a value between zero and one to each zone and, therefore, a prediction of 0.5 to an output zone corresponds to the shaded bar reaching half the height of the historic frequency). The small table at the base of the screen provides statistical data on both the historic population and the predicted activity. Other graphs are available as options for the user to view. These graphs simply depict the same data in another format. Also in the table, there is a point and weighted prediction value of the productivity.

Figure 4.4 Recall Screen 2 - Prediction



The flowchart in Figure 4.5 describes the procedure programmed so that the recall program can make a prediction.

Figure 4.5 Neural Network Recall Flowchart



Within the flowchart it can be seen that the new procedure only involves the addition of a Kohonen recall function which returns whether to use the high, medium, or low productivity feed forward back propagation network. The Kohonen recall function was developed using the LVQ algorithm defined in Appendix 1.

4.7.2 Sensitivity Analysis

A sensitivity analysis was performed to prove the validity of the recall program and the neural network method used within it, and to check errors. This involved setting a baseline testing activity with a near average productivity, altering one factor at a time, and then checking the corresponding prediction. This was completed for each possible response of all input factors. The expected, logical result for each setting was compared to the actual result. Sensitivity of a neural network is very difficult to capture. Results of a baseline activity must consider the following factors:

- the nature of a neural network allows a model to train so that the combined effects of a factors is determined. This combined effect, however, may cause individual factors to be reflected in unexpected magnitudes when examined individually.
- baseline projects may project the influence of individual factors with a slight variation due to the combined effects of input factors with the baseline settings.

As a result of the above characteristics of a sensitivity study, average/typical baseline projects were chosen to test the wall and slabs neural network recall programs so that the effects would be minimized. Table 4.23 summarizes the findings of the sensitivity study. Within Table 4.23, the *"Percent Change"* column represents the largest productivity range between different responses to the same input. Therefore, the higher the percent change, the greater sensitivity the neural network has to the input. The percent change expressed in this table is a comparison of the weighted average predicted productivity (WAPP) values for an input. Although this research has focused on the WAPP value for accuracy determination, PP is also studied for sensitivity as it is found to fluctuate with input responses much more than the WAPP value does. The averaging technique used in the WAPP calculation eliminates a degree of the variability. Therefore, it can be seen in Figure 4.6 that where little sensitivity appears to be present according to the WAPP values, the PP values indicate a variation caused by different responses.

Table 4.23 Recall Input Sensitivity

Logical (Expected) Impact	**Neural Network Impact**	**Percent Change**
1. District		
Impact will vary randomly depending on historic	Loose Walls: - as expected	5.7%
productivity achievements of each district.	Loose Slabs: - as expected	7.8%
2. Superintendent Skill		
An excellent superintendent will achieve better productivity	Loose Walls: - as expected	1.8%
rates than would a poor superintendent.	Loose Slabs: - as expected	2.2%
3. Crew Experience		
A more experience crew would perform at a better	Loose Walls: - as expected	2.2%
productivity than a less experienced crew.	Loose Slabs: - as expected	0.7%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
4. Crew Size		
Crews that are to small or large may meet productivity limitations due to lack of resources or crowding, respectively. Therefore, a binomial relationship is expected to result.	Loose Walls: - as expected, except for the 1 to 3 and >20 men categories. Data limitations in each of these categories has trained the neural networks so that productivity appears to be better than it should be for these responses.	18.2%
	Loose Slabs: - as expected	6.4%
5. Union/Nonunion		
An expected result is difficult to identify, as a unionized crew may have more skill, but a non union crew may work under less stringent requirements.	Loose Walls: - as expected only a small relationship was been derived	0.7%
	Loose Slabs: - no relationship was derived by the neural network	0.0%
6. Extended Work Hours		
As the hours of work per week increase, the productivity is expected to decrease.	Loose Walls: - as expected	0.7%
	Loose Slabs: - as expected	3.9%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
7. Quantity of Formwork		
As the quantity of formwork increases the productivity is expected to increase (once the learning stage of an activity is overcome and the duty becomes repetitive, work can be completed faster).	Loose Walls: - the neural network derived this factor contrary to expectations. This is caused by the complex nature of some of the larger activities as opposed to the simple nature of a smaller activity.	1.1%
	Loose Slabs: - same as loose walls	0.7%
8. Height of Wall/Slab		
Higher walls and slab formwork activities are expected to be more difficult for workers to construct.	Loose Walls: - the relationship is as expected, but it is only a small relationship. Although height makes a wall duty more difficult, a higher wall represents more area being formed per linear foot.	1.4%
	Loose Slabs: - as expected, but to a much greater degree than the walls network. This may be due to the area not increasing as height increases, therefore only difficulty increases.	17.5%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
9. Thickness of Wall/Slab		
A thinner wall/slab is expected to be a little quicker as thickness is not considered in the productivity calculation.	Loose Walls: - as expected	0.4%
	Loose Slabs: - not as expected, but also very small and insignificant. This error was caused by combined input effects.	0.7%
10. Cost Code		
The simpler and more often completed cost code activities are expected to produce better productivity.	Loose Walls: - as expected, except for curved wall which were expected to be the most difficult cost code. Data limitation for the curved wall cost code is the reason for this unexpected result.	5.7%
	Loose Slabs: - as expected	10.7%
11. Duty		
Repetitive work is expected to be more productive as the forms do not need to be continually rebuilt.	Loose Walls: - as expected	3.2%
	Loose Slabs: - not as expected, but insignificant. This error was caused by combined input effects.	0.4%
12. Tie Type (Walls) / Support System (Slabs)		
Impact will vary randomly depending on historic productivity achievements of each tie type / support system.	Loose Walls: - as expected	2.1%
	Loose Slabs: - as expected	0.4%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
13. Degree of Repetition		
A higher degree of repetition will correspond to a better productivity as learning time is eliminated.	Loose Walls: - as expected	2.9%
	Loose Slabs: - as expected	5.0%
14. Number of Reuses		
As the number of reuses increases, the percentage of time used in building the forms decreases and productivity increases.	Loose Walls: - as expected the reuse of panels does increase the productivity, but having 0-9 reuses represents the best productivity. The maintenance associated with using a panel more than 9 times is deemed the reasoning for the neural network predicting higher productivity for >9 reuses.	7.2%
	Loose Slabs: - same as walls	3.2%
15. Panel Size		
An increase in panel size means more area can be formed with one setting, and productivity may increase.	Loose Walls: - as expected, for all but the highest category, >275sf. The reason for this is the difficulty associated with moving and maintaining a form of such size.	13.6%
	Loose Slabs: - same as walls, but to a much smaller degree	1.1%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
16. Location		
Activities performed closer to grade are expected to produce better productivity due to convenience of material and equipment to these locations.	Loose Walls: - as expected	8.6%
	Loose Slabs: - as expected	10.0%
17. Floor Number		
Work on higher floors is expected to be more difficult due to more stringent safety requirements and less convenient materials and equipment.	Loose Walls: - not as expected, productivity increased on higher floors. The reasoning, however, is the more repetitive nature of high floor work as compared to the unique nature of lower floor activities.	4.3%
	Loose Slabs: - same as walls	12.9%
18. Design Accuracy and Detail		
As the accuracy and detail of the design increases less changes, clarifications, or conflicts will result and productivity will not be disrupted.	Loose Walls: - as expected	0.7%
	Loose Slabs: - as expected	2.2%
19. Lift Drawing Prepared		
The presence of lift drawing is expected to increase productivity as less instruction is required.	Loose Walls: - as expected	4.3%
	Loose Slabs: - as expected	6.8%

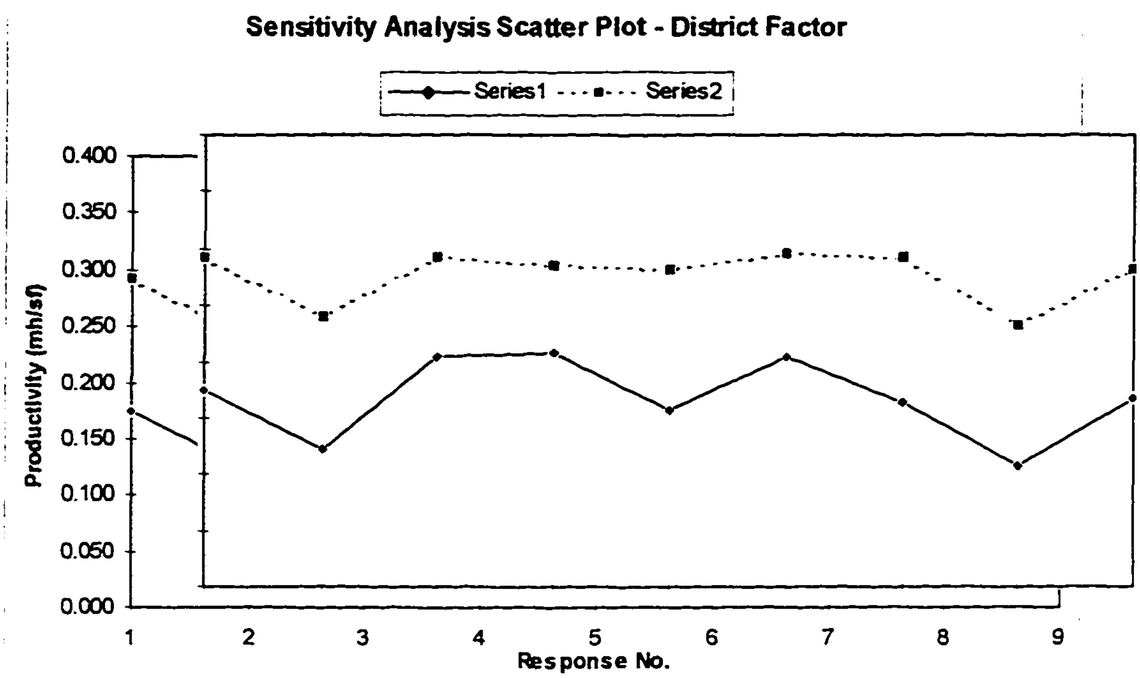
Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
20a. Owner Inspection, Safety, and Quality Requirements		
Increased owner requirements are expected to slow productivity due to increased duties and rules to be followed on the site.	Loose Walls: - not as expected, rather productivity is better on projects with high owner requirements and interaction. The reason for this is shorter delays as results of changes or problems, less rework, and a more focused effort due to the owners presence.	2.1%
	Loose Slabs: - factor not in slab neural network	-
20b. Material Handling / Crane Time Problems		
Material and equipment shortages are expected to reflect a decreased productivity achievement.	Loose Walls: - factor not in wall neural network	-
	Loose Slabs: - as expected	0.4%
21. Complexity of Geometry		
As an activity becomes more complex, difficulty increases and productivity is expected to decrease.	Loose Walls: - as expected	0.7%
	Loose Slabs: - as expected	0.7%
22. Formwork Irregularities		
As formwork irregularities increase, difficulty increases and productivity is expected to decrease.	Loose Walls: - not as expected, but insignificant. This error was caused by combined input effects.	0.4%
	Loose Slabs: - as expected	1.8%

Table 4.25 cont.

Logical (Expected) Impact	Neural Network Impact	Percent Change
23. Required Finishes		
As the required finish becomes more architectural, difficulty increases and productivity is expected to decrease.	Loose Walls: - as expected	0.8%
	Loose Slabs: - as expected	0.8%
24. Site Working Conditions		
As the site working conditions worsen, difficulty increases and productivity is expected to decrease.	Loose Walls: - as expected	1.1%
	Loose Slabs: - not as expected. This error was caused by combined input effects.	1.1%
25. Overall Difficulty		
As the difficulty increases on an activity, the productivity is expected to decrease.	Loose Walls: - as expected	1.5%
	Loose Slabs: - as expected	0.4%
26. Season		
The summer seasons is expected to produce the most ideal work conditions, and winter the worst/least ideal conditions.	Loose Walls: - not as expected, winter proved to provide the best productivity. The reason is the rush required on completion of projects undertaken in the winter (otherwise the project may be started in the spring) caused greater productivity.	2.9%
	Loose Slabs: - same as walls	1.4%

Figure 4.6 WAPP versus PP Sensitivity



Series 1 = Point Prediction (PP)
Series 2 = Weighted Average Predicted Productivity (WAPP)

As can be seen by Table 4.23, most of the input factors act to affect the prediction of the neural network in the expected direction. Some factors, however, were found to act contrary to expectations, but these relationships were explainable based on logic, lack of response data, or the combined effect caused by a very complicated neural network. The sensitivity defined by this study, as previously stated, is dependent on the settings of the baseline project. This dependence, however, is in the magnitude of the sensitivity and not in the direction in which the productivity will change upon response alteration. Table 4.24, Table 4.25, Figure 4.7, and Figure 4.8 demonstrate this characteristic of the neural network by examining one factor from each network using ten different baseline projects.

Table 4.24 Project Sensitivity - Loose Walls Degree of Repetition Factor

Name	Repetition = 1	Repetition = 2	Repetition = 3	Repetition = 4	Repetition = 5
Baseline Project 1	0.383	0.383	0.365	0.357	0.348
Baseline Project 2	0.413	0.365	0.330	0.252	0.235
Baseline Project 3	0.270	0.265	0.257	0.257	0.257
Baseline Project 4	0.530	0.526	0.526	0.526	0.522
Baseline Project 5	0.078	0.083	0.087	0.091	0.096
Baseline Project 6	0.843	0.835	0.835	0.835	0.830
Baseline Project 7	0.348	0.348	0.343	0.339	0.335
Baseline Project 8	0.513	0.513	0.448	0.383	0.343
Baseline Project 9	0.365	0.357	0.352	0.343	0.339
Baseline Project 10	0.517	0.483	0.461	0.383	0.326
90% Conf. Upper Boundary	0.684	0.669	0.652	0.630	0.616
90% Conf. Lower Boundary	0.169	0.162	0.149	0.123	0.110
Mean	0.426	0.416	0.400	0.377	0.363
Standard Deviation	0.200	0.196	0.195	0.196	0.196

Figure 4.7 Project Sensitivity Graph - Loose Walls Degree of Repetition Factor

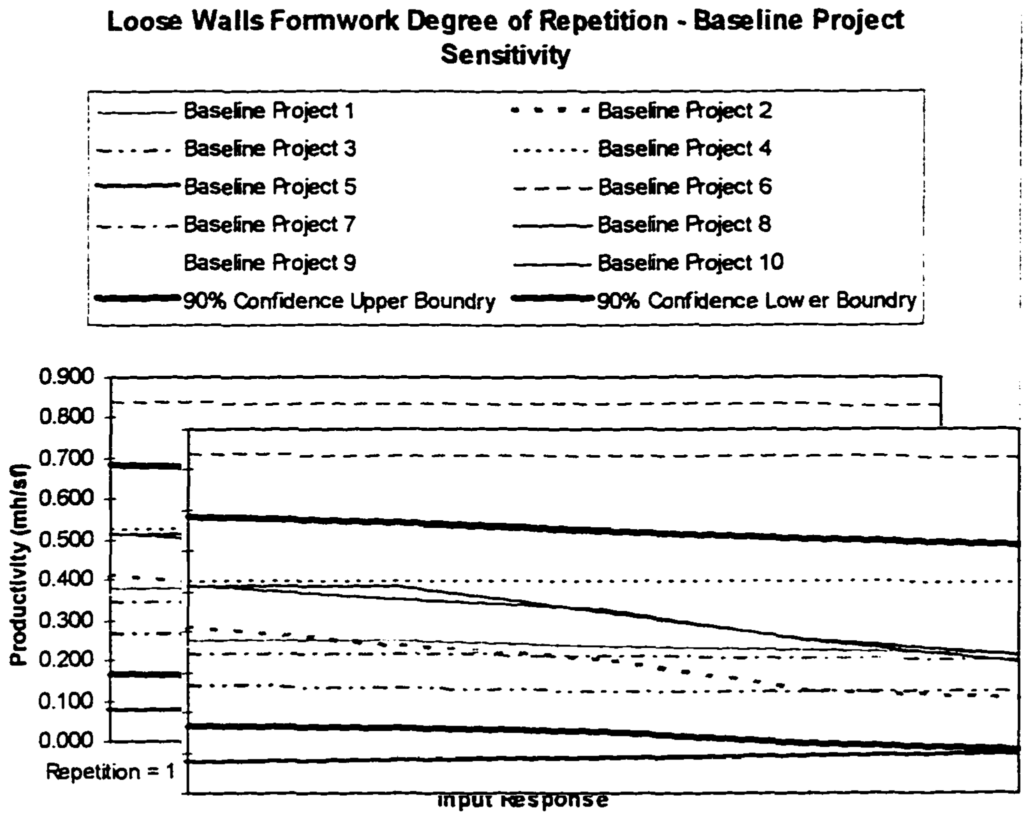


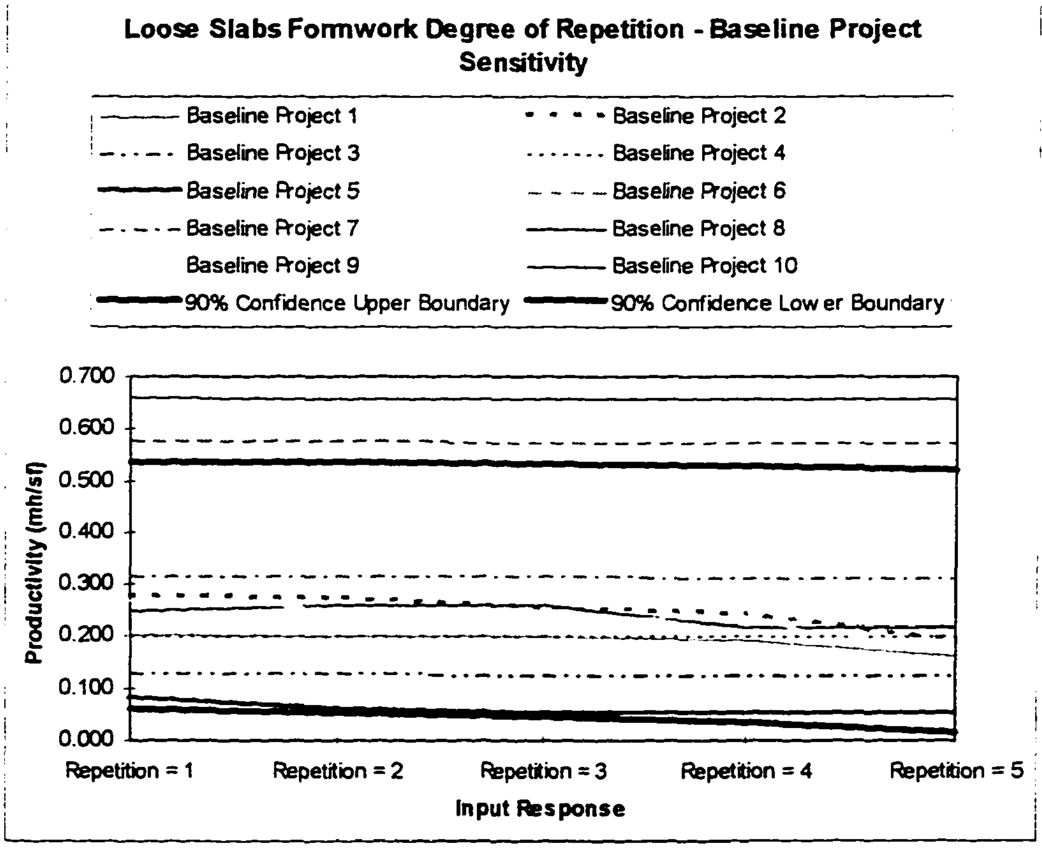
Table 4.25 Project Sensitivity - Loose Slabs Degree of Repetition Factor

Name	Repetition = 1	Repetition = 2	Repetition = 3	Repetition = 4	Repetition = 5
Baseline Project 1	0.206	0.203	0.200	0.194	0.164
Baseline Project 2	0.279	0.273	0.255	0.242	0.194
Baseline Project 3	0.130	0.130	0.127	0.127	0.127
Baseline Project 4	0.203	0.203	0.203	0.203	0.203
Baseline Project 5	0.082	0.061	0.055	0.055	0.052
Baseline Project 6	0.579	0.579	0.576	0.576	0.576
Baseline Project 7	0.315	0.315	0.315	0.312	0.312
Baseline Project 8	0.248	0.258	0.258	0.218	0.218
Baseline Project 9	0.270	0.255	0.242	0.230	0.176

Table 4.34 cont.

Name	Repetition = 1	Repetition = 2	Repetition = 3	Repetition = 4	Repetition = 5
Baseline Project 10	0.661	0.658	0.658	0.658	0.658
90% Conf. Upper Boundary	0.535	0.535	0.532	0.527	0.521
90% Conf. Lower Boundary	0.059	0.052	0.046	0.036	0.015
Mean	0.297	0.293	0.289	0.282	0.268
Standard Deviation	0.185	0.187	0.188	0.190	0.196

Figure 4.8 Project Sensitivity Graph - Loose Slabs Degree of Repetition Factor



From a study of the repetition factor for both neural networks, it is apparent that the magnitude of sensitivity does depend on the baseline project. However, the direction of sensitivity is consistent among the test baseline projects (with the exception of one baseline test project per neural network where the combination of other factors has caused a slight deviation in sensitivity of the repetition). Furthermore, the calculation of a 90%

confidence interval defines the high and low possible values to 90% certainty and depicts the consistent direction of sensitivity for the given factor.

4.7.3 Summary

The neural network recall program developed by this research and described in this section presents the necessary characteristics so that implementation with an estimating system can be successful. The sensitivity studies on the recall program by this research did not discover any key irregularities that would not be expected from a neural network program. Furthermore, only few, and relatively insignificant, discrepancies were discovered in the sensitivity of the recall abilities compared to logical input response influences. The program's common sense response capabilities may help to decrease estimator avoidance of a "black box" type program.

5. Industrial Construction Neural Network Models

5.1 Introduction

Previous research (Portas 1996) has established the use of neural networks as a viable means of modeling within the field of construction. Research discussed in chapters 3 and 4 has further solidified this conclusion and acted to improve the technique so that implementation may be successful. The key academic development, however, has been the flexibility defined within neural networks to fit to the most complicated of problems. The detail associated with the formwork neural network models is so that other methods of artificial intelligence are not practical. This chapter builds upon the research and developments of the formwork neural network models to apply the technology to another aspect of construction. Industrial construction is a field as labour intensive as commercial construction, but much different in nature. Once again, labour productivity is the focus of the research. Here the flexibility of neural networks with respect to a similar problem is tested within a vastly different environment.

5.2 Objective

The application of neural network artificial intelligence within industrial construction focuses on two activities; pipe handling and welding. These activities are typically two of the major cost items on an industrial project. Pipe handling involves installing a piping system or module within a plant site. Placement of piping sections, fitup of joints, installing valves, performing boltups and screw joints, and positioning pipe support systems and apparatus are all key components of a pipe handling activity. The productivity of an installation activity includes the performance of many duties. Pipe welding, on the other hand, strictly involves the performance of a welding duty on a piping section.

Within the two chosen activities, labour productivity is the focus of study. The need for such a study arose based on a comparison of the current general contractor labour productivity estimating procedure to the actual performance on a project. The current estimating procedure simply involves obtaining a base manhour value, calculated from a derived quantity total, and applying a multiplier to the value to adjust for desired conditions. The following equation defines this procedure:

$BaseManhours = BaseRateProductivity * Quantity$, where:

$BaseRateProductivity =$	industry developed productivity defining the productivity of an industrial activity under ideal conditions
$Quantity =$	quantity of work in appropriate units to the $BaseRateProductivity$

$EstimatedManhours = BaseManhours * Multiplier$

In the case of pipe handling, the multiplier is based on the location in which the work is to take place and ranges from 0.05 to 0.26. For pipe welding, the multiplier accounts for the material type of the pipe section being welded ranges from 0.38 to 0.62. Figures 5.1 and 5.2 show the multipliers that have actually been obtained on a number of historic general contractor projects. From these figures, it is apparent that the general contractor has not been using the correct range of multipliers.

Figure 5.1 Historic Pipe Handling Multipliers

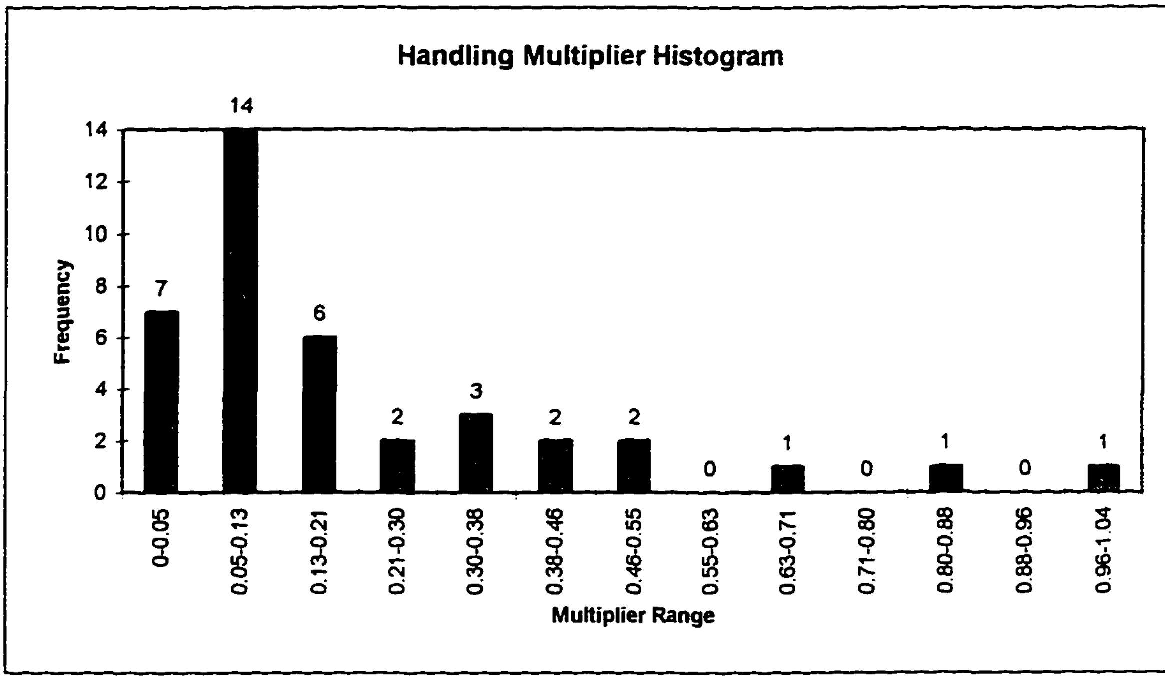
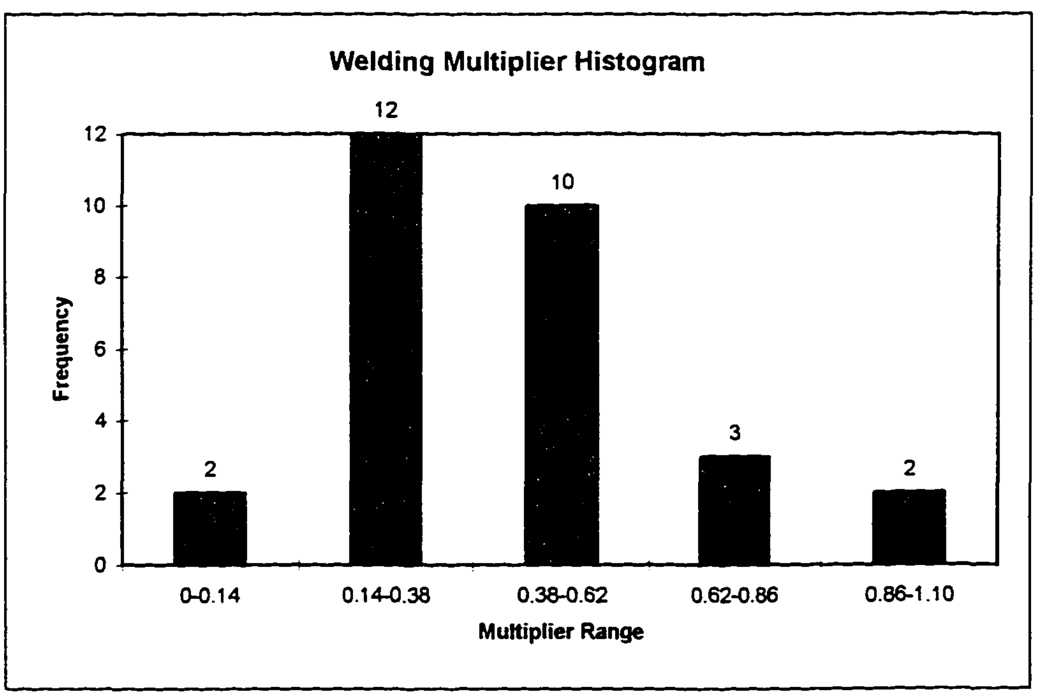


Figure 5.2 Historic Pipe Welding Multipliers



From the handling histogram, the actual multipliers on 19 historic projects (49%) were out of the multiplier range that the estimator has historically used. Multipliers on 11 historic projects (28%) were much higher than could have been used by the estimator and this cost a project up to 12 times the labour cost for an individual pipe handling activity. On the other end, 8 projects (21%) were overestimated. Overestimating the labour cost on a pipe handling activity may have increased a bid item by two to three times, and resulted in lost bids. From the welding histogram, a similar trend is apparent for pipe welding activities. In this case, multipliers on 19 historic projects (63%) proved to land outside the multiplier range used by estimators. Five historic welding activities (17%) have been underestimated resulting in activity costing up to nearly two times the estimated value and another 14 welding activities (47%) have been overestimated by up to four times the required labour contribution. Despite a lower range by which the welding activities have historically been incorrectly estimated, welding is one of the prime costs on an industrial project and the errors identified here are significant.

The objective of this chapter is to develop neural network applications capable of aiding industrial estimators during the estimation of labour productivity. The focus is to broaden the range of productivity upon which the estimators have historically relied on so that under and overestimating can be avoided. The knowledge learned from the development of the formwork productivity neural network models was used to guide the neural network research into this new area of construction.

5.3 Industrial Construction versus Commercial Formwork Neural Network Analysis

The implementation of a neural network development process similar to that of the formwork models for industrial productivity research encountered a number of limitations. These limitations can be attributed to two areas; the differences in the industrial and commercial construction industries and the different operating procedures used by the industrial and commercial arms of a general contractor. The following sections define these differences and their implications to the industrial research.

5.3.1 Industry Differences

The nature of work, although similarly labour intensive, of industrial activities greatly differs from that of commercial construction. Two key differences can be identified. First, a difference exists in the magnitude of the activities. Formwork is a very large activity which will take many hours to construct and prepare. On the other hand, industrial activities, such as welding and pipe installation, consist of many smaller tasks. Each of these tasks are completed in shorter, varying duration and compose only a small part of the total activity. The second difference is the size or portions of the crew working on the activity. On a formwork activity, the construction of the temporary structure includes direct input of all members of the crew in a team effort. Industrial activities, however, consist of individuals or small groups of the crew each completing a number of independent tasks. As a result of these major differences, formwork activities are typically much better defined and more easily tracked than the activities on an industrial site.

5.3.2 Company Differences

The general contractor's commercial and industrial arms both maintain a similar costing system (an in-house system). The way in which each of the companies uses this system varies. The following defines each of the company's cost tracking systems.

5.3.2.1 Commercial Arm of General Contractor

A cost code structure has been setup so that all types of formwork activities have their own specific cost code. These cost codes track both the quantity and manhour contributions to the activities. During both estimation and construction the same cost codes are used. A specific cost code is often used more than once on a project. This occurs when activities of the same classification involve different conditions, specifications, or other factors. In this case, split numbers (additional figures added to the end of a cost code number) are attached to similar cost codes, so that each of the activities can be differentiated.

The consistent use of this cost code structure provided very good historical data to be used for neural network training. Actual productivity, necessary as the outputs for training feed forward back propagation networks, were available specific to individual activities.

5.3.2.2 Industrial Arm of General Contractor

The cost code structure is setup differently for the industrial work. Due to the nature of the industry, cost codes that capture groups of tasks have been developed. Tasks include, for example, the performance of a specific weld or the installation of a specific length of pipe. It is not practical to cost code each individual task as hundreds, sometimes thousands, of these tasks occur on a project. Therefore, similar tasks are grouped and coded as one item. For example, a welding cost code may contain the quantities and manhour contributions for all welds of one type of metal.

Estimators and project cost tracking personnel use the cost coding system to different levels. Estimators are required to calculate both quantity and manhour contributions to a higher level of detail than the cost coding system, as data will be determined to the highest level of detail (e.g. detailed to the specific weld) and then summarized to the cost code level in order to be added to the estimate. On the other hand, on-site construction will only track their quantity and manhour contributions to a level that is most practical. This level of detail is at most, equal to the level of the cost coding structure. Often, especially on projects in which a shut down of the industrial plant under construction is required, quantities and manhours will only be documented following completion of the work and plant start-up. Therefore, all tasks of an activity are grouped as one and entered into the costing system (e.g. quantity and manhour contributions for all welds on the project).

The requirement for the neural network application is to develop a tool to aid estimators during the calculation of manhour costs to a project. The application, therefore, needs to predict to the level of detail required by the estimators, this being the highest level. This is the point at which the process used for the development of the formwork neural networks breaks down. No longer are actual productivity available for use as output nodes for the training of feed forward back propagation networks, as in the case of formwork activities.

5.3.3 The New Method

The level of detail of the historical project information is a major obstacle for the industrial research. This obstacle is present in the two major activities being addressed by the project, pipe handling and welding.

Current general contractor estimating procedures simply involve applying a multiplier to a base rate calculated manhour total for both pipe handling and welding activities. The multiplier for pipe handling activities accounts for the location of the work within the site (called a classification code) and welding activities for the type of metal being welded. The neural network models are to be developed based on historical industrial project information. Data available includes the following:

- actual welding quantities are obtained from the quality control (QC) records for projects where QC data was available. This data has been recorded to the highest level of detail. On projects in which the QC records are not available, detailed quantities from the estimates are obtained (note: only on projects in which extras are minimal or the extras can be accounted for, are the estimate quantities considered, otherwise the activity is discarded from analysis).

- actual pipe handling quantities to the highest level of detail are obtained from the estimates, in few cases only were actual records available for use (note: only on projects in which extras are minimal or the extras can be accounted for, are the estimate quantities considered, otherwise the activity is discarded from analysis).
- the most detailed breakdown of manhour quantities for both welding and handling activities are only available to the cost coded level. The level of detail recorded varies per project.
- factors affecting the productivity of an activity, to be analyzed by the neural network models, are obtained from other quantitative historic records, the cost coding system, and a qualitative sampling of site superintendents and project managers. Factors are collected to the cost coded level of detail, as it is not deemed practical to obtained this information to a task level.

The base productivity currently used by the general contractor estimators have been experimentally determined by industry and define the rate in which a pipe can be installed or a weld can be completed under ideal conditions in a controlled environment. This research uses these rates in combination with the detailed quantities so that an equivalent level of detail with the manhour quantities can be obtained. A comparison of the base manhours (equal to summation of each detailed quantity multiplied by it's respective base rate) with the actual manhours for an activity will expose the actual effect of both project and activity factors on the productivity of the work crews. The following example demonstrates this comparison:

Example multiplier calculation:

Welding Activity for Project A

Cost Coded for Total Carbon Steel Welding Activity: 500 Actual Manhours

Carbon Steel Quality Control Records

Diameter	Quantity (volume/thickness)	Base Rate Productivity (manhours per volume/thickness)	Base Rate Manhours (Column 2 x Column 3)
2"	100	2.50	250
4"	200	2.25	450
8"	150	1.10	165
12"	50	1.00	50
			Total = 915

$$\frac{ActualManhours}{BaseRateManhours} = \frac{500}{915} = 0.546$$

Multiplier for given activity and project factors = 0.546

This procedure will provide for the calculation of a multiplier for all the historical projects, despite the level of detail that the manhours were cost coded to. Then, neural networks will be used to predict the multiplier as opposed to the productivity as with formwork models. Neural networks can once again be used so that the input nodes will constitute all of the factors that affect the productivity of an activity and the output will simply be the multiplier.

Neural networks can be trained utilizing multipliers calculated using the actual detailed quantities, summarized manhours, and base productivity. A trained neural network in combination with the base rates has the capability to predict the manhours for one weld or many welds, based on the productivity factors chosen.

A concern with this method is the accuracy of the base productivity. Lack of accuracy in these values, however, will be rectified within the neural network models by adding input nodes for each detailed task to the models. The detailed quantities, used in the calculation of the base manhours will also be entered as input nodes. This will allow the neural network to account for errors in the base rates within the multiplier. Therefore, the sole purpose of using base rates is to provide the entire system with a relationship between the productivity of differing tasks within an activity. The large number of tasks that are to be analyzed by the neural networks makes this step necessary. Theoretically, the neural network should be able to solve the entire problem without the use of the base rates, but this would require an impractical level of data for which the neural networks would need to be trained. Therefore, the base rates provide a starting point to help the neural networks to train.

A benefit of the method is that the estimators procedure for producing an estimate will not be altered. Using a recall program to get the multiplier will simply replace the lookup of the value from a table. Limiting the change in the estimator's procedure may prove to be very beneficial to the successful implementation and use of the application developed by this research.

5.4 Input Factors

The identification of the factors which influence the productivity on an industrial activity is an important stage of this research. Improper use or missed inputs may be result in the inability to properly model the chosen industrial activities. This section identifies the factors to be considered and discusses data collection.

5.4.1 Factor Identification

The industrial productivity neural network input factors outlined in this section have been identified through questioning of experienced general contractor employees; superintendents, estimators, and project managers. Furthermore, characteristics of neural network input factors developed throughout the formwork research were considered. Table 5.1, Table 5.2 and, Table 5.3 define the identified factors and discussion on how each factor is expected to affect productivity and how it will be analyzed within the neural network is given. Table 5.1 identifies the global input factors. Global inputs are the factors of productivity that are common to both activities. Each of the factors in this table are to be collected on a global scale for one of two reasons. First, the effect of this factor on labour productivity can be determined for each activity using a common quality or quantity. For example, location of work, whether above or below ground, is a common characteristic of both activities. Second, the historical information for the factors may only be attainable to a global level. For example, crew size is a characteristic of an activity and, therefore, may differ from activity to activity. But in this case, it was determined to not be reasonable for a project superintendent to accurately remember crew sizes to the activity level, and so the global level was chosen for the factor.

Table 5.1 Global Factors

No.	Factor	Description
General Project Characteristics		
1	Location	Whether the project is located at an urban, rural, or camp job site may affect worker morale and the ability to obtain necessary or sufficient resources to properly undertake an activity. The skill level of the workers may also vary with the location. This factor will consist of three input nodes with in the neural network. The chosen location input will be assigned a value of one, and the other two inputs will be assigned zeros (binary inputs).

Table 5.1 Global Factors cont.

No.	Factor	Description
2	Province	This factor will distinguish the affect on productivity of differing working conditions, attitudes, practices, and regulations between provinces. This factor will also use binary inputs within the neural network.
3	Administrative Requirements	This factor compares the general expense manhours used to the total direct manhours spent on a project. This will indicate the level of planning and scheduling provided to the activities of the project. This ratio will be directly entered as an input into the neural network from a cost code of the historical records.
4	Year of Construction	This factor addresses differing work ethics, standards, and averages during different years of construction. This factor accounts for the differing time periods in which the historic projects took place. Binary inputs will be used within the neural network.
5	Client	Client policies on quality, safety practices, working hours and other conditions may influence the productivity of the workers. This factor will be analyzed by the neural network by comparing the historical achieved productivity for activities completed on previous projects for this client with the average total historic productivity for the respective activities. A value of below one would indicate the characteristics of the client provide an environment where better productivity can be achieved than with a client with value above one.
6	Engineering Firm	The engineering firms' abilities and practices may have a significant influence on productivity. For instance, an engineering firm that provides complete and well organized drawings can make the construction more simple and quick. Different firms will also have different response policies to queries during construction. This factor is to be analyzed by the neural network in the same way as the *Client* factor.

Table 5.1 Global Factors cont.

No.	Factor	Description
7	Superintendent	The ability of a superintendent to manage the workers on a work site may have a significant influence on productivity. This factor was analyzed by examining the superintendents historical performances on past projects compared to the average historical performance of all general contractor projects.
8	Project Manager	The ability of a project manager to manage a project may have a an influence on productivity that is similar to the influence of the superintendent. As a result, this factor will be addressed by the neural network in a similar way as the *Superintendent* factor.
Site Characteristics		
9	Project Definition	Industrial Projects can be defined as one of eleven types of projects, including; • Chemical Plants • Cogeneration Projects • Heavy Oil Plants • Mining • Oil & Gas Plants • Petrochemical • Pipeline & Compressor Stations • Power Production • Pump Stations • Synthetic Crude Projects • Water Treatment Project definition can effect the productivity as different projects may have differing safety requirements, work hours, work conditions, or other conditions. This factor can also represent different difficulties present in each type. This factor will be input into the neural network as a binary input.

Table 5.1 Global Factors cont.

No.	Factor	Description
10	Location of Work Scope	This factor accounts for conditions of the specific work location within an industrial site. By inputting either "work confined to specific area" or "work scattered throughout plant site(s)" the neural network will be able to capture the effect on productivity of moving and setting up a number of times for the same project.
11	Project Type	Whether the project is a plant upgrade where a shut down is required, a plant upgrade where no shut down is required, or new construction may have an influence on productivity. For example, in a shut down situation working rates may be increased so that the product loss for the plant is minimized. Also, operating plants require additional permits and procedures, thus, projects require additional planning. This factor will be input into the neural network in as a binary input.
12	Prefab, Modularization, Field Work Characteristics	This factor accounts for the effect on productivity of the location in which the piping system is constructed. Options include: • module prefabrication and site installation • shop prefabrication and site installation • site prefabrication and site installation Percentages of each option will be used for this factor when used by the neural network.
Labour Characteristics		
13	Average Crew Size	The influence of differing average crew sizes on the productivity of an activity is analyzed in this factor. Binary inputs will be used in the neural network for this input.
14	Peak Crew Size	Peak crew sizes occur during the high levels of construction on a project and may reflect a different of influence on the productivity than the *Average Crew Size* factor. This factor is analyzed based on five ranges, which will in turn become binary inputs in the neural network.

Table 5.1 Global Factors cont.

No.	Factor	Description
15	Unionized	Union rules and regulations and union worker's abilities and skills differ from those in a non-union situation. This factor addresses these differences with respect to labour productivity. Binary inputs are used for the union factor.
Equipment Characteristics		
16	Equipment & Material Cost per Direct Manhours	This factor is intended to identify what effect the ratio of equipment and material cost to the direct manhours in a project has on productivity. For example, a lower than average ratio may indicate some equipment and material restrictions and, in turn, a decreased productivity. The cost coded value from the historical project records will be used as the neural network input for this factor.
Difficulty Characteristics		
17	Extra Work	Extra work involves duties performed on a project that were beyond the original scope of the project. Extra work may indicate worse productivity achievements due to time spent on other activities and lower worker morale. This factor will be captured through a cost code comparing the original cost of the project of the final cost of the project.
18	Change Orders	Change orders require additional time for the adjustment of resources and man power so that the change can be met. Morale may also be effected by extensive numbers of change orders. (This factor will be captured from historical data by a cost code comparing the number of change orders to the total direct hours).
19	Drawing and Specifications Quality	This factor accounts for any difficulties encountered due to the provided drawings and specifications. Subjective judgment for this factor, in addition to the *Engineering Firm* factor was deemed necessary to account for variability in the firm's output quality.

Table 5.2 Pipe Handling Factors

No.	Factor	Description
General Activity Characteristics		
1	Learning	Extended duration may lead to better productivity due to the effects of the learning curve on an activity. A LOG value of the total install quantity (ft) for the activity will be entered into the neural network in order to eliminate extreme values.
2	Location Classification	This factor may determine the effect of the location of work within the site on productivity. Options include: • pipe installation in trench to 10 ft deep with battery Limits of a Process Area installed before or during foundation work (code 410) • pipe installed on piperacks maximum 12 ft above grade (code 430) • pipe installed in fabrication shop (code 431) • pipe installed in a single story building with maximum floor ceiling height of 20 ft (code 440) • pipe installed within the limits of a process area - i.e. vessels to 100 ft, pipe works to 20 ft max. (code 460) This factor will be handled by the neural network as a binary input.
Activity Quantities		
3	Installation Quantities	The actual handling quantities (ft) will be given to the neural network at a practical level of detail so that errors in the base productivity can be accounted for. LOG values of the quantities will be input so that the effect of extreme values is eliminated.
4	Material Type	Whether a material is a steel, plastic, wrapped pipe may have a considerable influence on the handling productivity as weight and flexibility drastically differs between the identified materials. Binary inputs will be used to capture this factor.

Table 5.2 Pipe Handling Factors cont.

No.	Factor	Description
Activity Design		
5	Method of Installation	This factor will analyze the effect of differing percentages of machine and hand rigging on productivity. Two input nodes will be used for this factor and percentages will be entered in each.
6	Pipe Supports	The quantity of pipe supports required for an activity may indicate the level of detail of the system being installed. Pipe supports, however, have only been tracked to a project level rather than activity level. Therefore, the project quantity of supports per foot of total pipe will be used by the neural network for all pipe handling activities for a project.
7	Boltups	Boltups, much like supports, may also indicate detail in an activity. This data is available to activity level, and therefore, this factor may be a better indicator of the effect of detail on the productivity of an activity in the neural network. The number of boltups per foot of pipe will be analyzed by the neural network.
8	Valves	Valve quantities are the third item which may indicate detail in an activity. This data is also available to an activity level, and therefore, this factor will be input into the neural network in the same manner as *Boltups*. The number of valves per foot of pipe will be analyzed by the neural network.
9	Screwed Joints	The quantity of screwed joints quantities are the final item which may indicate detail in an activity. This data is also available to an activity level, and therefore , this factor will be input into the neural network in the same manner as *Boltups*. The number of screwed joints per foot of pipe will be analyzed by the neural network.

Table 5.2 Pipe Handling Factors cont.

No.	Factor	Description
Activity Difficulty		
10	Season	Constraints or slow down in efficiency may result in pipe handling activities due to winter weather. The percentages of an activity completed in the summer and winter periods will be used by the neural network to analyze the effect.
11	Crew Ability	The ability or skill level of a crew may have a significant effect on productivity. This factor is only obtainable, however, in a subjective manner; the opinion of the project superintendent. The superintendent is asked to rate to ability of the crew, with a one being low and a five being high. Descriptive responses assigned to each number, however, may aid in eliminating a level of the subjective nature.
12	Working Conditions	Such problems as congestion, site access difficulties, or weather problems may have an influence on productivity. This factor is subjective, where a one reflects many problems and a rank of five reflects no problems.
13	Inspection, Safety, & Quality Requirements	The level of owner inspection, safety, and quality requirements on an activity may affect productivity. The superintendent ranks this factor, thus, it is subjective. One refers to extremely detailed requirements and a five reflects highly tolerant requirements.
14	Overall Degree of Difficulty	This factor is also subjective in nature. Its intent is to capture any difficulties that are not captured through the previous factors. The subjective nature of this input, however, may require normalization.

Table 5.3 Pipe Welding Factors

No.	Factor	Description
General Activity Characteristics		
1	Learning	Extended duration may lead to better productivity due to the effects of the learning curve for an activity. LOG value of the total weld quantity (DI) for the activity will be entered into the neural network in order to eliminate extreme values.
2	Location Classification	see pipe handling description
3	Rig Welders	The percentage of rig welders (contracted welders) may determine the different productivity of in-house welders. The percentage of rig welders used on an activity will be used as the input.
Activity Quantities		
4	Material Type	Whether the pipe being welded is carbon steel, stainless steel or alloy steel may make a significant difference in the productivity. Binary inputs will be used as inputs for this factor.
5	Weld Quantities	The actual weld quantities (Volume/Thickness) will be given to the neural network at a practical level of detail so that errors in the base productivity can be accounted for. A LOG values of the quantities will be input so that the effect of extreme values is eliminated.
Activity Difficulty		
6	Season	Welding requires that the pipe to be welded is above a certain temperature, otherwise it will require preheating, which in turn may require hoarding. These special conditions in cold weather may negatively affect productivity. The percentages of the activity completed at above and below 0°C temperatures will be used for the neural network to analyze this effect.
7	Crew Ability	see pipe handling description

Table 5.3 Pipe Welding Factors cont.

No.	Factor	Description
8	Working Conditions	see pipe handling description
9	Proximity of Equipment	The proximity of a welder's welding machine to the actual weld area may affect productivity. For example, a welder who is forced to consistently walk 100 ft back and forth from the welding machine is most likely to have a worse productivity than a welder whose machinery is only 10 ft away. The average distance is analyzed for this factor and the superintendent is asked to choose an average distance range for the activity.
10	Inspection, Safety, & Quality Requirements	see pipe handling description
11	Overall Degree of Difficulty	see pipe handling description

In total, 33 factors will be considered for a pipe handling activity and 30 factors for a pipe welding activity. Important notes on the factors chosen include:

- many cost figures are to be used as inputs. Inputs such as administration requirements, material and equipment expenditures, and extra work are expressed as ratios so that they can be compared among projects of different magnitudes.
- very few subjective inputs are to be used. As identified by the formwork research, by converting the responses into a descriptive form, the effect of prejudices, experience, and attitudes can be avoided. As a result, more consistent data will be entered into the neural network. Difficulty is now to be analyzed as a function of many quantitative inputs and only one subjective input. Among the quantitative inputs administrative requirements, client, engineering firm, location of work, equipment and material cost, extra work, and change orders all capture different aspects of difficulty.

- a collecticn of inputs via collection sheets uses the descriptive response method developed by the formwork research. Superintendents are asked to choose a value between one and five, but the numbers are quantitatively defined.

5.4.2 Data Collection

Data collection involved two stages. First, a consistent cost coding structure was developed and historical project information was transformed so that it could conform to the new structure. This process was very detailed as it involved breaking historical project records out of various levels and putting it into a consistent format. All information was set within a historical database within Microsoft Access. Second, project information not available from project records was collected using data collection sheets. The collection reports were developed in a similar way to the formwork neural network data collection reports in the manner in which information is requested. The quantified method of data collection on the sheets proved to be more successful in consistent data collection. As a second means of maintaining consistent data, the collection sheets were not sent to the superintendents to be filled out independently, but rather interviews were performed by an experienced general contractor employee. This ensured that all input questions would be interpreted in a consistent manner and answered under similar assumptions and understanding. Figure 5.3, Figure 5.4, and Figure 5.5 show the global pipe handling, and pipe welding data collection reports used by this research.

Figure 5.3 Global Input Report

Global Project Report

Prepared By: ______________________ Report Date: ______________________

1. General Information

Project #: *Sample* Project Name: ______________________

Location: ( ) Urban ( ) Rural - small town ( ) Camp job Province: ______________________

Year of Construction: ______________________ Duration: ______________________

Client: ______________________ Superintendent: ______________________

Engineering Firm: ______________________ Project Manager: ______________________

2. Project Classification

Project Definition: ______________________

Type of Project (Check one): ( ) Plant upgrade - Shut Down ( ) New Construction
( ) Plant Upgrade - No Shut Down

Location of Work Scope(Check one): ( ) Work confined to specific area
( ) Work scattered throughout plant site(s)

Prefab, Modularization, Field Work Characteristics (Provide % of project for each applicable method):

A. Module - Prefabrication and Site Installation ______ %

B. Shop Prefabrication and Site Installation ______ %

C. Site Prefabrication and Site Installation ______ %

3. Labour

Average Crew Size: ( ) 0-25 ( ) 25-50 ( ) 50-100 ( ) 100-150 ( ) >150

Peak Crew Size: ( ) 0-25 ( ) 25-50 ( ) 50-100 ( ) 100-150 ( ) >150

Did individual crews work extended hours? 1 2 3 4 5
(1 - > 70 total hours/week, 3 - 50 total hours/week, 5 - no overtime)

Was the labor unionized? .... Yes No N/A

Rates the quality of contract specs and drawings? 1 2 3 4 5
(1 - poor, 3 - average, 5 - excellent)

4. Other

Accuracy of Cost Coding (Check one): ( ) Very Good
( ) Average
( ) Poor

Additional Notes - use back side of page

Figure 5.4 Pipe Handling Report

Pipe Installation Report

Prepared By: ____________________ Report Date: ____________________

1. General Information

Project #: *Sample* Project Name: ____________________

Cost Code: *1* Classification: *1*

Cost Code Description: ____________________

2. Costs

Was fitup time included in the pipe handling cost code? Yes No N/A

Was hydrotesting coded separately? Yes No N/A

Were supports coded separately? Yes No N/A

Were valves coded separately? Yes No N/A

Was the assigned classification code adequate for this activity? Yes No N/A

3. Design

	Quantity	Quantity / Total Ft of Pipe
Total Pipe Supports		
Boltups		
Valves		
Screwed Joints		

3. Activity Difficulty

Method of Installation (Provide % of each): Machine Rigging ____ % Hand Rigging ____ %

What season was the activity completed in (assign % of activity time to each season)

Summer (above freezing): ____ % Winter (below freezing): ____ %

Rate the ability of the crew for this pipe handling activity 1 2 3 4 5
(1 - low, 5 - high)

Rate the site working conditions for the pipe handling activity 1 2 3 4 5
(1 - many problems with congestion, site access and/or weather, 5 - no problems)

Rate the owner inspection, safety and quality requirements 1 2 3 4 5
(1 - extremely detailed inspection, 5 - highly tolerant requirements)

Rate the overall degree of difficulty for the activity 1 2 3 4 5
(1 - high, 3 - average, 5 - low)

4. Productivity Rates

Cost Code	Cost Code Description	*Actual Project Stats* Quantity	MH	Prod.	*Corporate Stats* P% 10	Mode	P% 90
1							
1							
1							

Additional Notes

Figure 5.5 Pipe Welding Report

Welding Report

Prepared By: ______________________________ Report Date: ______________________________

1. General Information

Project # : *Sample* Project Name: ______________________________

Cost Code: *1* Classification: *1*

Cost Code Description: ______________________________

2. Costs

Was fitup time included in the welding cost code? Yes No N/A

What % of rig welders were used for this activity? *0* %

Was the assigned classification code adequate for this activity? Yes No N/A

3. Activity Difficulty

What was the Rejection Rate (%) ____ %

What season was the activity completed in (assign % of activity time to each season)?

Summer (above freezing): ____ % Winter (below freezing): ____ %

Rate the ability of the welders for the activity.. 1 2 3 4 5
(1 - low, 5 - high)

Rate the site working conditions for the welding activity.. 1 2 3 4 5
(1 - many problems with congestion, site access and/or weather, 5 - no problems)

Proximity of welding machine to weld 1 2 3 4 5
(1 - <25ft, 2 - 25-50 ft, 3 - 50-75 ft, 4 - 75-100 ft, 5 - >100ft)

Rate the owner inspection, safety and quality requirements 1 2 3 4 5
(1 - extremely detailed inspection, 5 - highly tolerant requirements)

4. Productivity Rates

3 4 5

Actual Project Stats *Corporate Stats*
Cost Code Cost Code Description Quantity MH Prod. P% 10 Mode P% 90
4. Productivity Rates

		Actual Project Stats			*Corporate Stats*		
Cost Code	Cost Code Description	Quantity	MH	Prod.	P% 10	Mode	P% 90
1							
1							
1							

Additional Notes

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As a result of the two stages of data collection, 39 pipe handling and 30 pipe welding activities were collected from a total of 27 historic general contractor projects.

5.5 Pipe Handling Analysis

39 pipe handling records were collected for the purposes of analyzing the estimating multiplier used for a pipe handling activity. This section describes the development of a neural network training method for this purpose. Also within this section, multiple linear regression is addressed as an alternative method of predicting the activity multiplier.

5.5.1 Data Analysis

Data analysis involved the examination of all collected data as means of determining preliminary factor influences on the multiplier value. Furthermore, the analysis was used as means of exposing data inconsistencies and errors. Microsoft Access was used to perform statistical tests on the collected data. Minimum, maximum, mean, mode, standard deviation and correlation values were developed for all factors. The correlation of an input provides an indication of whether an input will properly, or satisfactorily, train with a neural network. For instance, an input with a good correlation (value close to either 1 or -1) will typically be more influential in a neural network than an input with a poor correlation (value close to 0). The correlation, however, can be deceiving as it only accounts for the effect of a single factor. The intent of this research is to develop the combined effect of different factors. To this end, correlations were examined only as means of preliminary input influence determination and not used to eliminate factors deemed unimportant. A histogram and a scatter plot were also developed for each input factor. The purpose of the histogram is to provide a representation of the range and consistency of the collected data. The histograms exposed a number of gaps in the collected data and resulted in the redevelopment of a number of input categories so that all categories had sufficient data for training data. The scatter plots were primarily used to expose data inconsistencies. Furthermore, the scatter plots provided preliminary input influences, as did the correlation value. The changes in the inputs resulting from the data analysis are as follows:

- camp job site location eliminated due to no records collected. As a result, rural and urban are the only site locations to be studied.
- heavy oil plants project definition is combined with oil and gas plants project definition due to limited heavy oil plants data. As a result, only three project definition inputs are to be used.
- average crew size categories 50-100,100-150, and >150 combined to form >50 category due to data limitations.
- peak crew size categories 100-150 and >150 combined to form >100 category due to data limitations.
- classification 431 combined with 430 due to data limitations (430 and 431 codes have historically been estimated as equivalent in the degree they effect productivity).
- classification 440 combined with 410 due to data limitations (440 and 410 codes represent differing job conditions, but have historically been estimated as nearly equivalent in the degree they effect productivity).
- material type input is eliminated due to lack of non metal inputs.

Resulting from the data analysis, 54 neural network input nodes remain and compose 32 pipe handling factors.

5.5.2 Neural Network Training

The following describes in detail the procedure and conclusions developed for predicting a pipe handling multiplier value using neural networks for a given activity.

5.5.2.1 Accuracy Definition

Accuracy determination is handled differently for industrial activities than the method used for the formwork neural networks. For an industrial activity two accuracy techniques are being used. The first technique contributes the academic level of accuracy. Accuracy in academic terms focuses on the ability of the neural network learn and recall and examines how and why a neural network has predicted as it did. Therefore, a weighted average predicted multiplier (WAPM) is calculated. This value is calculated in the same manner as the WAPP value (defined in section 4.4.2) and provides an average value of a fuzzy neural network output. This is the only way, aside from graphical analysis, to examine the effects of the fuzzy output. The WAPM value is compared to the actual multiplier and divided by the overall range of historical multipliers to produce percentage by which the prediction has missed. As with the formwork neural network models, +/- 15% has been chosen as a benchmark to define a hit or miss. The academic importance of a percentage figure is that it compares all predictions, regardless of magnitude, at a consistent level and can define consistency, or lack there of in a neural network.

The second technique defines the industry level of accuracy. The industry accuracy does not consider the behavior or characteristics of the neural network, but only the value of the output. For this research, the WAPM value and the point prediction (PP) value are each compared to the actual multipliers so that the difference is the error for each prediction. The average and maximum errors for a set of predictions are used to define the industry accuracy. Determination of which value, WAPM or PP, is more applicable will be determined based on the results of the neural network training.

5.5.2.2 Feed Forward Back Propagation Neural Networks

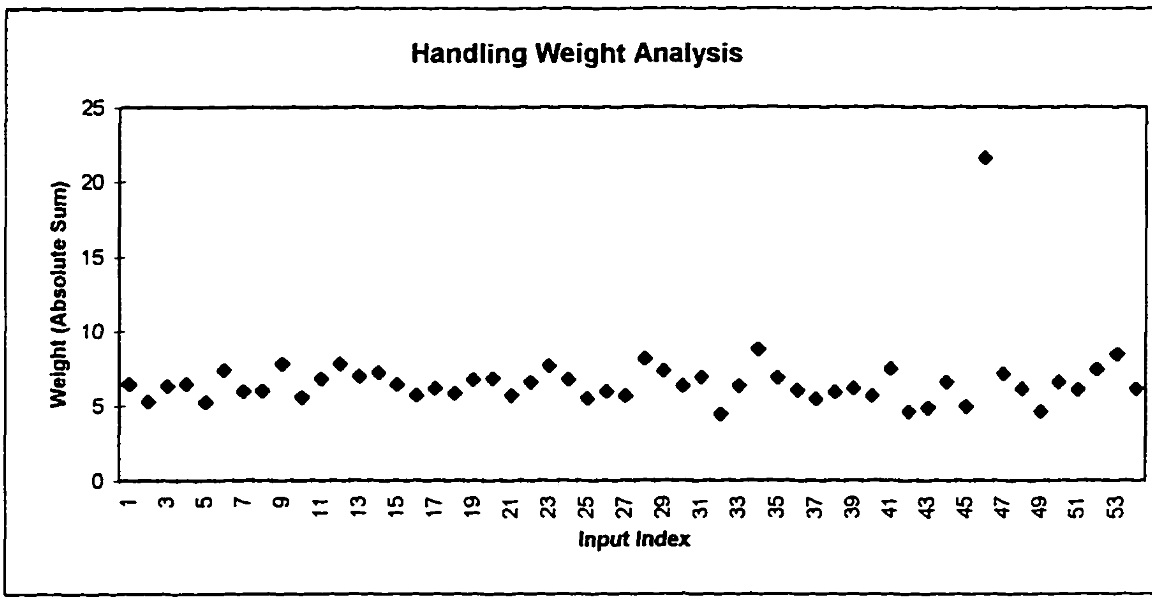
Feed forward back propagation neural networks are a simple type of supervised neural network training. For the pipe handling data, networks similar to those established for the formwork networks were developed for two purposes.

5.5.2.2.1 Continued Data Analysis

Training of the 39 pipe handling records within the simple network structure acted to identify problem records within the data set. Problem records were sets of data that did not conform to the rest of the data and acted to prevent proper training of a neural network. This data analysis involved stopping the training at points were it began to slow (i.e. the error value stops decreasing or the rate at which the error decreases becomes slower) and examining the current accuracy of all the training records. The records which were predicting furthest from the actual multiplier at that time were identified as the problem records. A second test involved holding back one record from the data set and training with the remainder. When a problem record is extracted, the network trains with much greater ease.

Both of the data analysis technique described above involved the examination of the rate and ability of a neural network to train. These methods were deemed sufficient in extracting obvious problem records, however, they proved insufficient in defining how well a network trains. How well a neural network trains, rather, was determined by examining the connection weights developed through training. First, if a neural network finds a strong correlation in one input and less obvious correlations, or (more likely) the existence of data conflicts, in other inputs it may place too great an influence on the one input and simply ignore the conflict or low correlation inputs. This would result in a poorly trained network. This can be spotted by an examination of absolute sum of weights connecting one input to all hidden layer nodes. Figure 5.6 provides an example of this occurring within the pipe handling data. Data conflicts were determined to be the cause of a very high absolute weight sum for one input. As a result, one record was held back during training in order to find the data conflict causing such a network reaction. In the case of the network defined in Figure 5.6, the problem was found to be two training records having the exact same inputs with the exception of the *"difficulty"* factor. These two records, however, have vastly different multiplier values and so the neural network was forced to place, inappropriately, an extremely high weighting on the connections to the *"difficulty"* input (factor number 46 in Figure 5.6).

Figure 5.6 Input Weight Analysis - Dominant Input Example



A second method of testing neural network validity involves testing the stability of the record set being used for training. By examining the absolute sums of the input weights trained upon for a differing 85% portion of the data set provides the level of stability. If the network consistently trains to the same input weights, the data is fairly stable, but if the absolute weight sums vary drastically it proves the data set either still has problems, or is too sensitive to individual records to be trained properly. The sensitivity, however, simply indicates further problems in the data and the methods described above must be used to eliminated the problem. Figure 5.7 and Figure 5.8 show plots of the absolute weight sums for the pipe handling data. Three neural networks, NNA, NNB and, NNC, trained with differing sets of pipe handling data are compared within each figure. Figure 5.7 gives the absolute weight sums for the inputs defined for pipe handling prior to cleaning up the problems from the data (Input 50, 52, and 53 show obvious instability). Figure 5.8 gives the absolute weight sums of the data following elimination of a number of problems and inconsistencies within the data.

Figure 5.7 Input Weight Analysis - Obvious Stability Problems

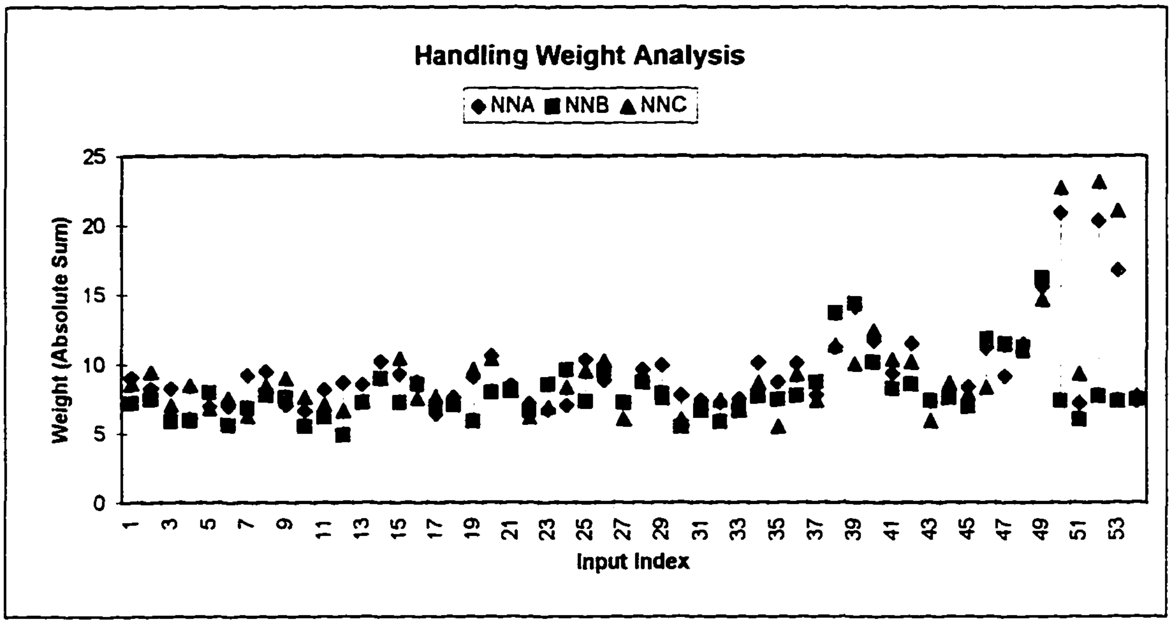
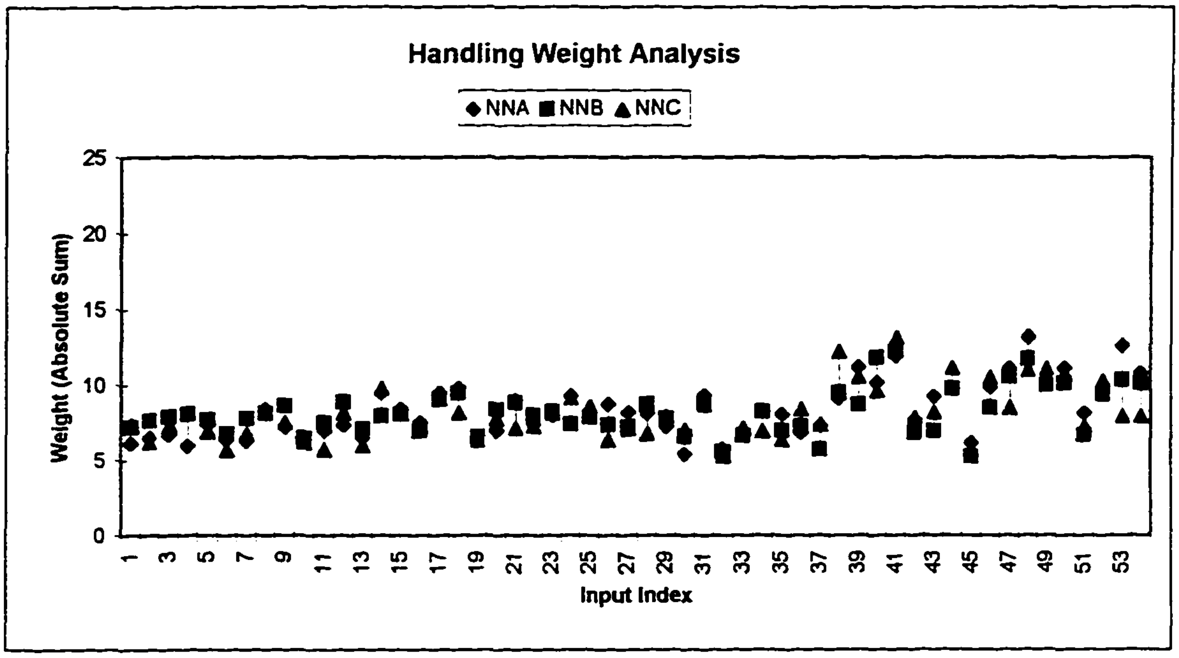


Figure 5.8 Input Weight Analysis - Stable Training Record Set



As a result of the detailed neural network data analysis, described above, a number of problems in the collected data were revealed and rectified. The following defines the changes made following data analysis:

- multiple records from individual projects were proven to cause sensitivity problems in a few cases. The high number of global factors defining a record, and common to records from the same project, caused records to be to similar in inputs, despite vast differences in multiplier values. This problem was rectified through further examination of the activity specific inputs so that the inputs of project records justified the achieved multiplier value.
- three records were withdrawn from the training set. Each of the removed records were inhibiting the neural network from both achieving stability and training to reasonable input weights.

5.5.2.2.2 Prediction Abilities

Once the data was proven to be stable and consistent, as shown in Figure 5.8, the abilities of the feed forward back propagation neural networks to train and test from the data set can be examined. The training techniques developed through training of the formwork neural network are used for this research. The network characteristics established by the previous research are assumed to be applicable for this research based on the similar structure and desired outputs of both productivity studies. The following, therefore, defines the neural network training characteristics that were used:

- 1 hidden layer with 35 nodes
- 14 nodes in the output zone (13 fuzzy nodes and 1 point prediction nodes)
- symmetric logistic transfer function, 0.1 learning rate, 0.4 momentum rate
- 0.04 maximum square error threshold
- 54 input nodes

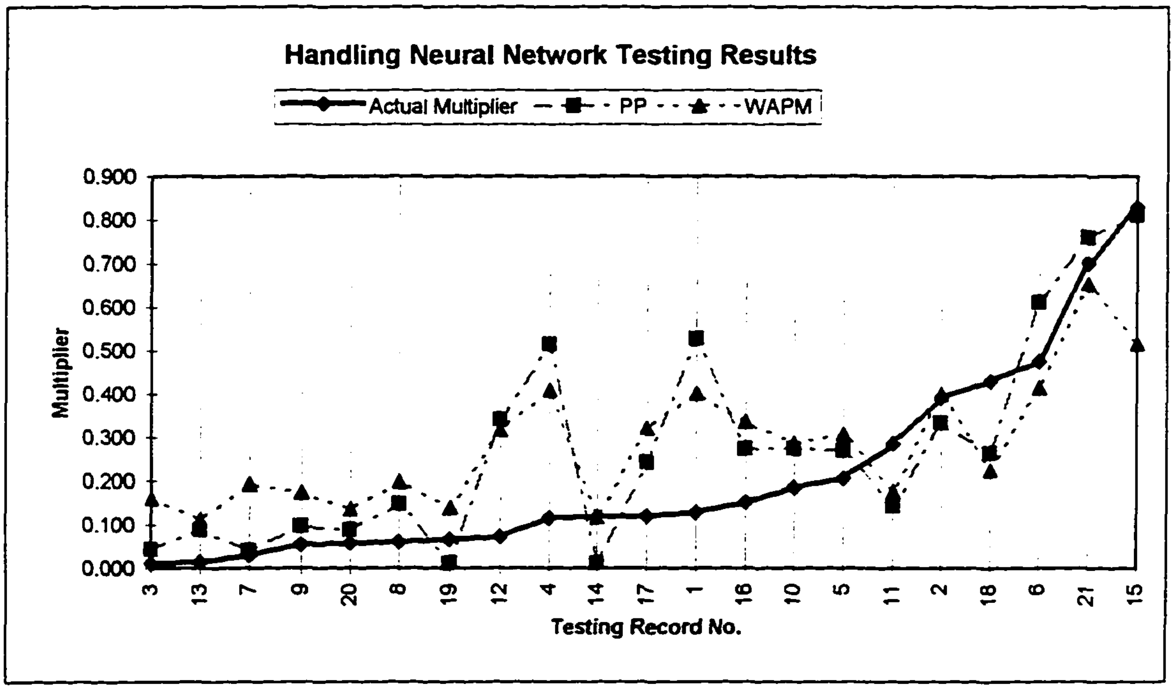
Training and testing was also undertaken in a similar fashion as with the formwork research. Approximately 85% of the data was used for training and the other 15% for testing. This was repeated using differing data in training and testing sets until a sufficient set of training results was compiled. This process and the settings for the feed forward back propagation neural networks is consistent for the remainder of the research on the industrial multiplier rates, and is not restated.

21 records compose the testing set for the pipe handling data. These points were chosen at random, but in a manner which ensures that the full range of the data is captured. Table 5.4 summarizes the accuracy achievements of the feed forward back propagation neural network. Figure 5.9 graphically shows the ability of the network to predict.

Table 5.4 Handling Testing Accuracy - Single Network

Accuracy Method	Result
Number of Hits (WAPM within +/- 15% of AM)	62%
PP - Average Absolute Error	0.118
PP - Maximum Absolute Error	0.399
WAPM - Average Absolute Error	0.141
WAPM - Maximum Absolute Error	0.312

Figure 5.9 Handling Testing Results Graph - Single Network



A number of conclusions were discovered based on the above results:

- the neural network's predictions, in general, follow the trend of the actual multiplier
- the prediction results of the network are consistently high on the lower actual multipliers. This indicates that the normalizing nature of a neural network is inhibiting this network from precisely predicting the low multipliers. This is a condition similar to the formwork models where the extreme productivity were the most often misses.

- the PP fluctuates more than the WAPM, but is more accurate in terms of the average error value. On only three or four records does the PP vary drastically from the actual multiplier.
- an average error in the range of 0.12 and the maximum error of magnitude 0.4 is poor accuracy for a historical value only estimated within a range of 1.0.

5.5.2.3 Kohonen Classification Neural Networks

Based on the conclusions of the previous section and a careful examination of the histogram presented in Figure 5.1, it is apparent the use of classification networks, in a similar manner to that used for the formwork models, may help to increase the prediction capabilities of pipe handling activities. The tendency of a neural network to normalize predictions (i.e. predict in a conservative manner towards the bulk, or average, of the training outputs) appears to be increasing the error within one network. This normalizing behavior caused the formwork models to predict very well near the average productivity, but high for very good productivity achievements and low for very poor achievements. This was identified as a major concern, as the use of the application was to identify the extreme productivity activities for estimators. The typical activities, which the models were accurately predicting, were also typical and easy for an estimators to determine, and hence, the application was of minimal use. By classifying an activity as either a good, average, or poor productivity activity, however, the models only use networks trained on similar activities and the normalizing effect is minimized. A similar condition appears to be affecting the pipe handling activities. From the histogram in Figure 5.1, it can be determined that a normal histogram distribution is present between the multiplier values of zero and four. From four to thirteen, however, the data appears to tail from the normal histogram. The normal histogram represents typical pipe handling activities as it is within the range of multipliers that the estimators have historically used. The tail of the histogram, however, represents nontypical activities which present a difficulty that the estimators have been historically unable to account for.

The pipe handling data, therefore, is divided into two classifications defining either a typical or nontypical activity. Overlapping divisions are implemented so that the ability of the Kohonen neural networks can be increased. As proven in the formwork classification research, the use of overlapping classification divisions proved to increase the accuracy of the predicted classification. Furthermore, the prediction abilities of the classification networks proved to be the controlling factor of the formwork models. Therefore, overlapping divisions spanning two multipliers are used for the pipe handling data. The zero to four multiplier classification is chosen based on the normalized histogram formed by the data in this range and the fact that this range matches that historically used by the industrial estimators. 25 records composed the typical multiplier classification. A multiplier value of two to thirteen was chosen for the nontypical classification. Although a range of three to thirteen would better define nontypical activities according to the historic multiplier range, data limitations required the extension of the classification into the two range multipliers. 17 records composed the nontypical multiplier classification.

5.5.2.3.1 Classification Accuracy

Linear Vector Quantitization (LVQ) neural networks, used for the formwork models, are tested for accuracy for the pipe handling activities. LVQ neural networks are supervised classification networks and are defined in detail in Appendix 1.

Training and testing of the LVQ neural networks was undertaken in a similar manner to the testing of the feed forward back propagation neural networks so that approximately 85% of the records are used for training and 15% for testing. This is repeated until the same test records which were used for testing the single feed forward back propagation neural networks were tested. The following are the characteristics of the LVQ neural network proven to predict the most accurately for the pipe handling data:

- 5 processing elements (PEs) per classification output node, 10 PEs total
- 2 classification output nodes
- 0.06 learning rate, 0.06 repulsion rate
- 1.0 conscience factor
- 54 input nodes

Table 5.5 defines the LVQ classification accuracy obtained for the pipe handling data.

Table 5.5 Handling Testing Accuracy - Classification Network

Classification	No. Records	Classification Hits	Overlap Classification Hits	% Hits
Typical Classification	15	11	1	80.0%
Nontypical Classification	6	5	1	100.0%
Overall	21	17	2	85.7%

The classification accuracy obtained for the pipe handling data is as good as that obtained for the formwork networks. Furthermore, two of the three pipe handling activities that are incorrectly classified as nontypical activities were within 10% of their value from actually being in the nontypical range. Therefore, classification is deemed a success and the addition of more training records is expected to increase the ability of the network to properly capture the close, borderline typical/nontypical activities.

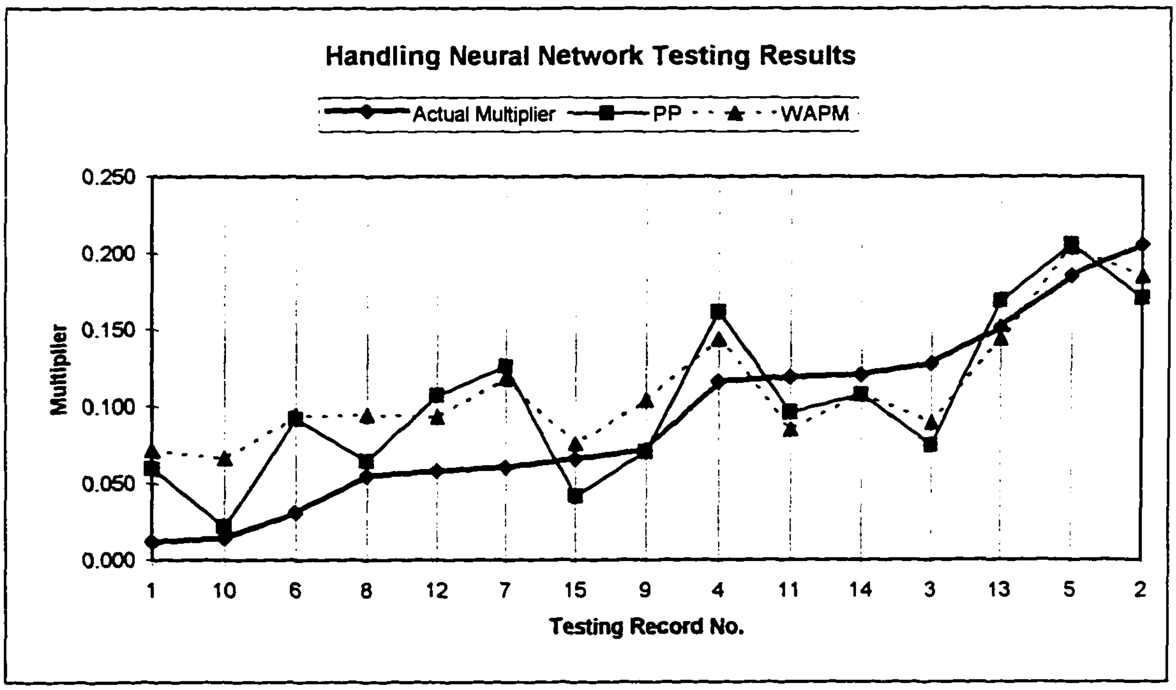
5.5.2.3.2 Typical Activity Feed Forward Back Propagation Neural Network

Typical pipe handling activities are defined as the historic activities which achieved multipliers within the range that the estimators used historically. As seen in Figure 5.1, these activities essentially range from multipliers of 0 to 0.3 and compose the majority of the historic data. The intent of the typical activity feed forward back propagation neural network is to predict more accurately via a reduced multiplier range of training records. The results of 15 typical testing records are given in Table 5.6 and shown in Figure 5.10.

Table 5.6 Handling Testing Accuracy - Typical Activity Network

Accuracy Method	**Result**
Number of Hits (WAPM within +/- 15% of AM, using typical activity range)	80%
Number of Hits (WAPM within +/- 15% of AM, using total activity range)	100%
PP - Average Absolute Error	0.031
PP - Maximum Absolute Error	0.065
WAPM - Average Absolute Error	0.034
WAPM - Maximum Absolute Error	0.063

Figure 5.10 Handling Testing Results Graph - Typical Activity Network



A number of conclusions can be derived based on the prediction abilities of the typical neural network:

- the neural networks predictions, in general, follow the trend of the actual multiplier
- the typical neural network increased the prediction ability to 100% over the total range of multipliers and 80% over only the typical activities. this is a vast increase compared to the 62% accuracy over the total range obtained by the single neural network.
- the prediction results of the network are still consistently high on the lower actual multipliers. This indicates that the normalizing nature of a neural network is still inhibiting the network from accurately predicting the low multipliers. This is occurring to a much smaller degree than with the single network. The average and maximum error values for the typical network are less than a quarter of the errors obtained by the single network. Therefore, the issue of normalizing neural network behavior has not been eliminated, rather, it has been minimized to a reasonable degree.
- the PP fluctuates more than the WAPM, but it is more accurate in terms of the average error value.
- an average error in the range of 0.03 and the maximum error of approximately 0.06 is very good accuracy for a value historical estimated within a range of 0.18.

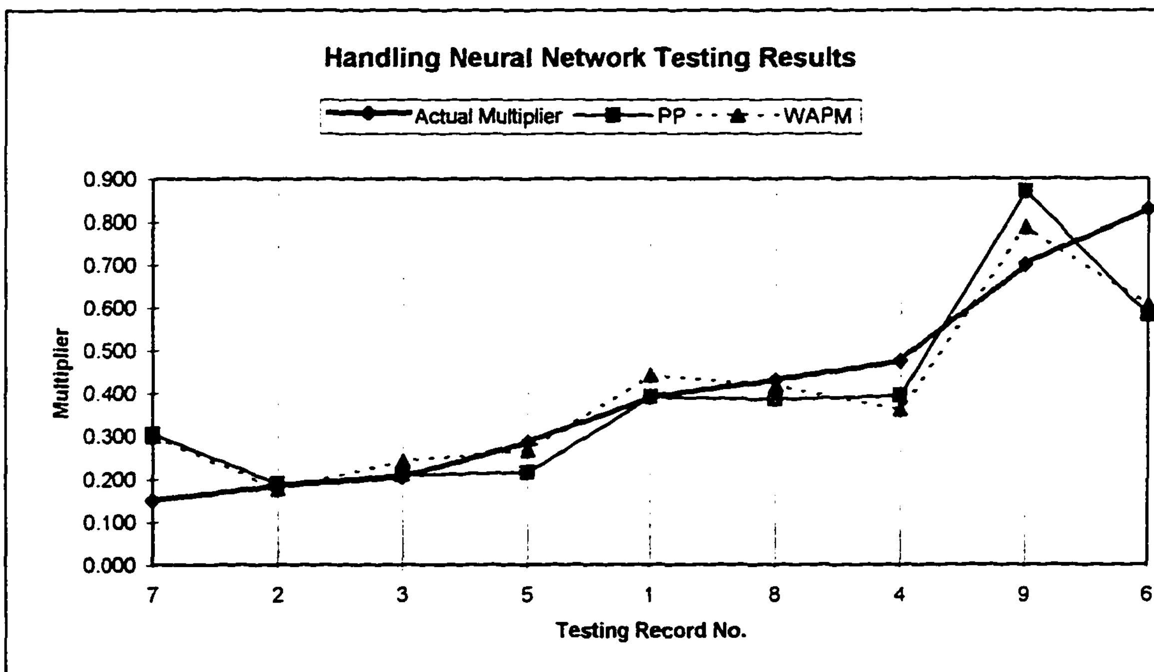
5.5.2.3.3 Nontypical Activity Feed Forward Back Propagation Neural Network

Nontypical pipe handling activities are the activities which produce multipliers which are not within the typical multiplier range that the estimators have historically used. Furthermore, these are the key activities that need to be identified because, historically they have negatively effected projects in labour costs to a significant magnitude. The results of training 17 nontypical records within a feed forward back propagation neural network are given in Table 5.7 and Figure 5.11.

Table 5.7 Handling Testing Accuracy - Nontypical Activity Network

Accuracy Method	Result
Number of Hits (WAPM within +/- 15% of AM, using typical activity range)	88%
Number of Hits (WAPM within +/- 15% of AM, using total activity range)	100%
PP - Average Absolute Error	0.086
PP - Maximum Absolute Error	0.246
WAPM - Average Absolute Error	0.077
WAPM - Maximum Absolute Error	0.222

Figure 5.11 Handling Testing Results Graph - Nontypical Activity Network



A number of conclusions can be derived based on the prediction abilities of the nontypical neural network:

- the neural networks predictions, in general, follow the trend of the actual multiplier
- the typical neural network increased the prediction ability to 100% over the total range of multipliers and 88% overall only the typical activities. This is a significant increase

compared to the 62% accuracy over the total range obtained by the single neural network.

- the PP fluctuates more than the WAPM, and is less accurate in terms of the average and maximum error value.
- the average and maximum error values are much higher for nontypical activities than for typical activities, but this is expected due to the much greater range defining a nontypical activities.
- an average error in the range of 0.08 and the maximum error of 0.22 is satisfactory accuracy, and significantly better than that obtained with the single neural network, for a value historically estimated within a range of 0.96. The average error is within 10% of the range, which is better than the benchmark percentage (15%) used for this productivity research.

5.5.2.3.4 *Combined Results*

The use of classification neural networks reduces the error in pipe handling activity predictions to a significant degree. The ability to classify, defined by the formwork neural network research to be the governing network for prediction capabilities, is accurate to 86%. Furthermore, by studying the activities that are not classified correctly it is determined that limited data is the source of almost all the classification errors and that increased training data will solidify the abilities of the LVQ network. The typical and non typical neural networks prove to produce hits (within 15%) a combined 84% of the time. This accuracy can also be expected to improve with increased data as both networks are trained with a minimal level of information. As a result, by accounting for incorrect classifications a combined classification / feed forward back propagation system will hit 75% of the time. The inability of the value to meet the 80% plateau obtained by the formwork neural networks is contributed to by data limitations.

The defined classification, typical feed forward back propagation, and nontypical feed forward back propagation neural networks all prove to be stable in nature and produce reasonable input influences. Extensive studies into these issues for the formwork models identified and rectified areas of instability and lack of accuracy. The development of pipe handling models, however, used these developments and as a result produced stable and accurate networks. Table 5.8, Table 5.9, and Table 5.10 list the influential weights for all the networks and Figure 5.12 and Figure 5.13 plot input sensitivity for both of the feed forward back propagation networks. Note from this data that in all of the networks, no single factor is significantly more influential (absolute weight sum is a direct indication of level of influence) than all other factors. Also, the extraction of records for testing only effects the training of the networks to small and insignificant degree.

Table 5.8 Top 5 Influencing Inputs - Classification Network

Input Factor	**Absolute Weight Sum**
Project Definition	8.438
Peak Crew Size	8.365
Year of Construction	8.272
Prefabrication Classification	8.212
Classification	7.796

Table 5.9 Top 5 Influencing Inputs - Typical Network

Input Factor	**Absolute Weight Sum**
Classification	11.393
Log >16 Quantity	11.231
Difficulty	8.865
Log 2-16 Quantity	8.575
Peak Crew Size	8.496

Table 5.10 Top 5 Influencing Inputs - Nontypical Network

Input Factor	Absolute Weight Sum
Hand Rigging	8.608
Year of Construction	8.106
Valves	7.801
Site Working Conditions	7.521
Bolt-ups	7.512

Figure 5.12 Input Sensitivity - Typical Activities

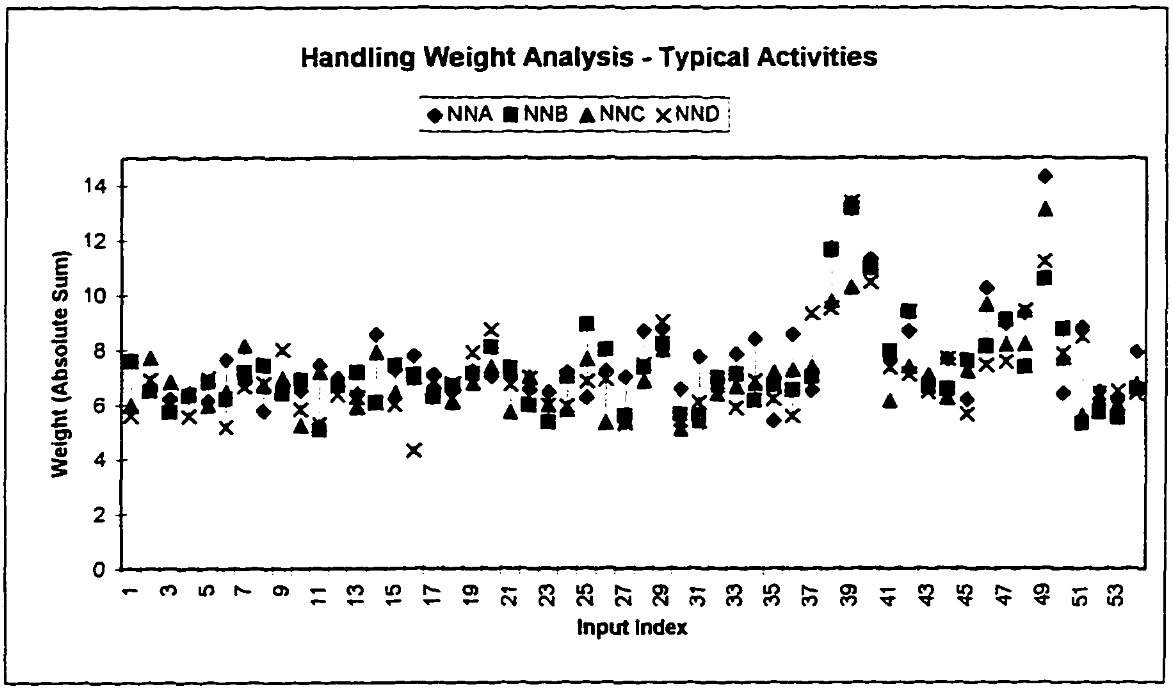
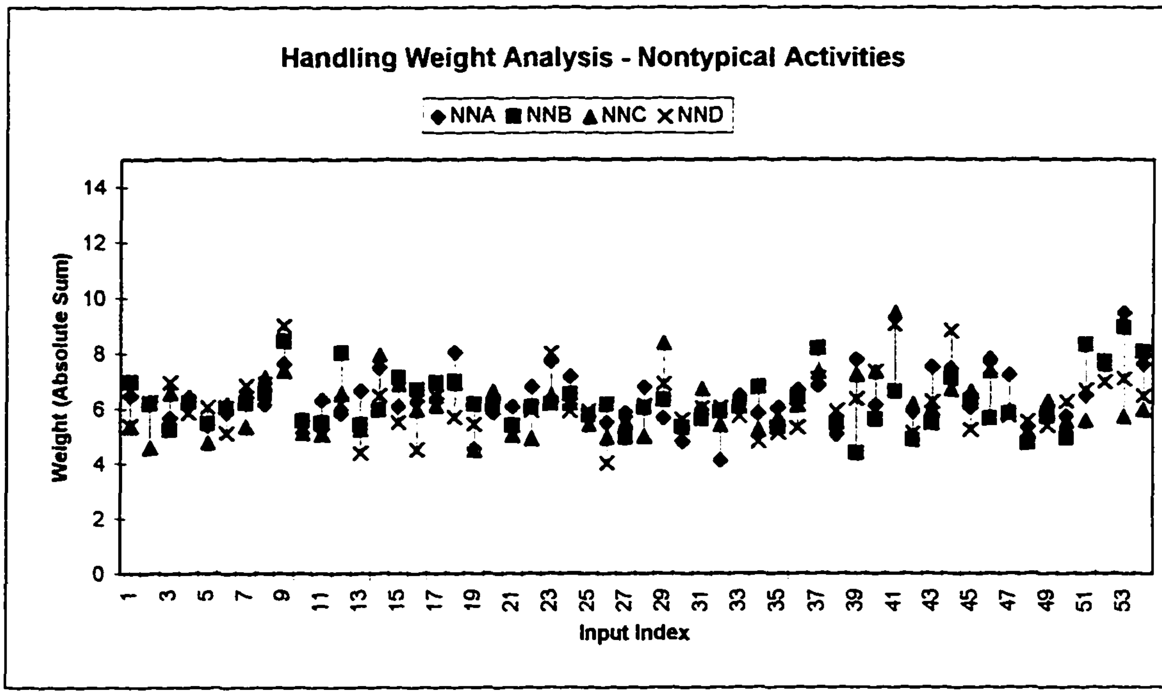


Figure 5.13 Input Sensitivity - Nontypical Activities

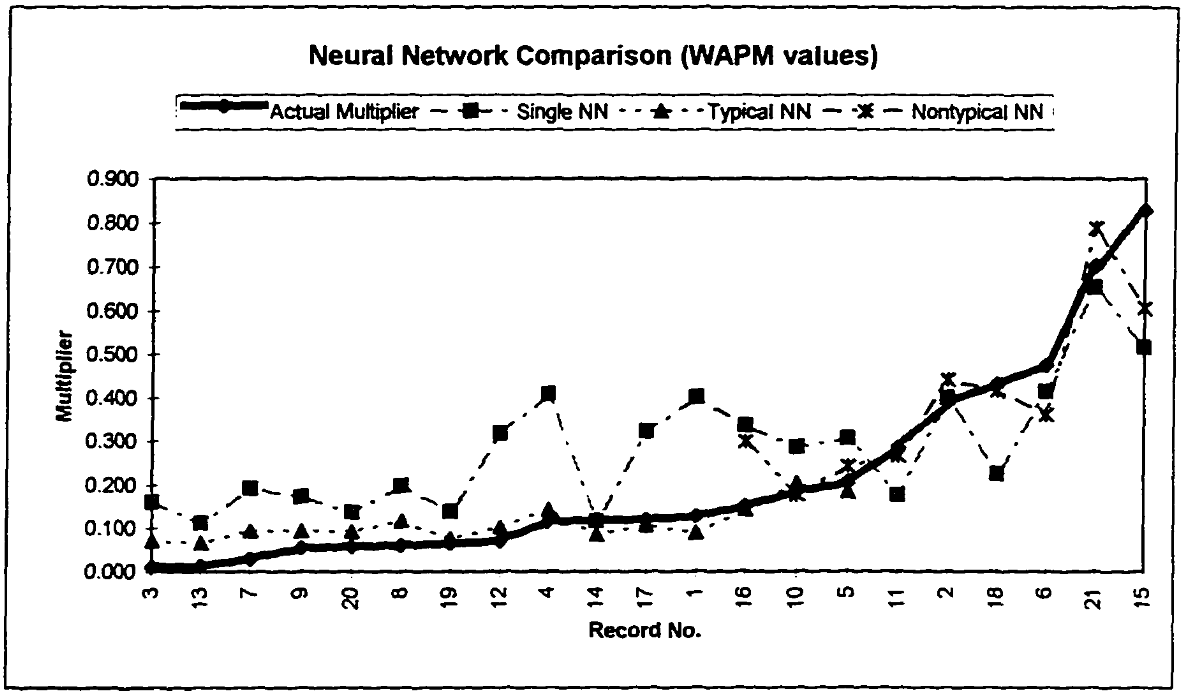


From the above tables and figures it is apparent that stability has been met in all of the networks and that sensitivity of the inputs within each of the feed forward back propagation networks is minimal.

5.5.2.4 Summary

In comparing the abilities of a single feed forward back propagation with the classification system, Figure 5.14, it is concluded that the classification method is not only a valid method but provides a much better method for predicting pipe handling activities.

Figure 5.14 Single Network versus Classification Method



Based on the analysis of the pipe handling data in this section, neural networks can effectively capture the various identified factors of pipe handling productivity and accurately predict the multiplier of an activity.

5.5.3 Multiple Linear Regression

Regression analysis is a statistical technique used to link a number of independent variables to one dependent variable. A mathematical formula expressing the relationship of the variables can exist in a number of different forms. The most common, and simple, of these expressions is linear. This assumes that each independent variable has a linear relationship with the dependent variable. Combining the linear relationships of each independent variable into one equation is called multiple linear regression. The following defines a multiple linear regression equation:

$Y = b_o + b_1X_1 + b_2X_2 + \ldots + b_nX_n$ where,

Y = dependent variable

X = independent variable

b = numerical constant defining the linear relationship between Y and the respective X

n = number of independent variables

Multiple linear regression analysis is tested on the pipe handling data as an alternate method to using neural networks. Although the previous section has shown that the pipe handling data responded well to neural networks and is predictable to a high level of success, multiple linear regression is a method that has been historically used for time dependent construction modeling. As discussed in Chapter 2, regression has historically been one of the most common methods of construction modeling. Therefore, this section studies the applicability of multiple linear regression for predicting the pipe handling data in order to verify the neural network abilities and / or to develop a more accurate and precise method of predicting a pipe handling activity multiplier.

5.5.3.1 Analysis Procedure

The relationship of 32 factors with the dependent variable, the multiplier, will produce a very complicated multi-linear regression model. Therefore, as a means of simplifying so that the process can be understood and justified, variables are added one at a time to the model. The effects of the added variable is analyzed, and a decision as to the relevance of the input dictates whether the variable is kept as part of the model. In doing so, a statistical software package, SPSS ®, is used. Variables are added based on three considerations. First, the correlation of the input with the variable is inspected. Second, the scatter plot displaying all the records and their values for an input is viewed. Finally, the importance of the inputs to the neural networks trained in the previous section is considered.

Testing and training involved the same process used by this research for testing neural networks (85% of the data is used for training, 15% of the data for testing, and the process repeated to develop a significant testing set)

5.5.3.2 Results

As a result of the procedure previously described, Table 5.11 defines the results of linear regression analysis for pipe handling.

Table 5.11 Handling Testing Accuracy - Regression Models

Model No.	Variables Considered	Average Error	Maximum Error	Hit %
1	Classification	0.091	0.377	90%
2	Classification, Difficulty, Learning	0.134	0.360	70%
3	Classification, Difficulty, Learning, Log 2-16&>16	0.133	0.342	80%
4	Classification, Difficulty, Learning, Log 2-16&>16, Supports, Valves, Screwed Joints	0.235	0.446	20%
5	Classification, Difficulty, Learning, Log 2-16&>16, Supports, Valves, Screwed Joints, Superintendent	0.229	0.418	20%
6	Classification, Difficulty, Learning, Log 2-16&>16, Supports, Valves, Screwed Joints, Superintendent, PM, Owner Inspection	0.210	0.412	40%
7	Classification, Difficulty, Learning, Log 2-16&>16, Supports, Valves, Screwed Joints, Superintendent, PM, Owner Inspection, Changes, Extras, Location	0.179	0.361	40%
8	All Factors	0.550	1.624	20%

From this table, the most accurate model is either model one or three. Model one has the lowest average error, the most hits, but the third lowest maximum error. Model three has the second lowest average error, the second most hits, and the lowest maximum error.

The following equations define the relationships established for each of these linear regression models:

Model 1:

$Multiplier = -0.070 + 0.132 * Classification$

(where: classifications are numerically ranked in order from easiest to most difficult)

Model 3:

$Multiplier = 0.361 + 0.104 * Classification - 0.067 * Difficulty - 0.068 * LearningRate +$
$0.022 * Log2 - 16" - 0.020 * Log > 16$

5.5.3.3 Summary

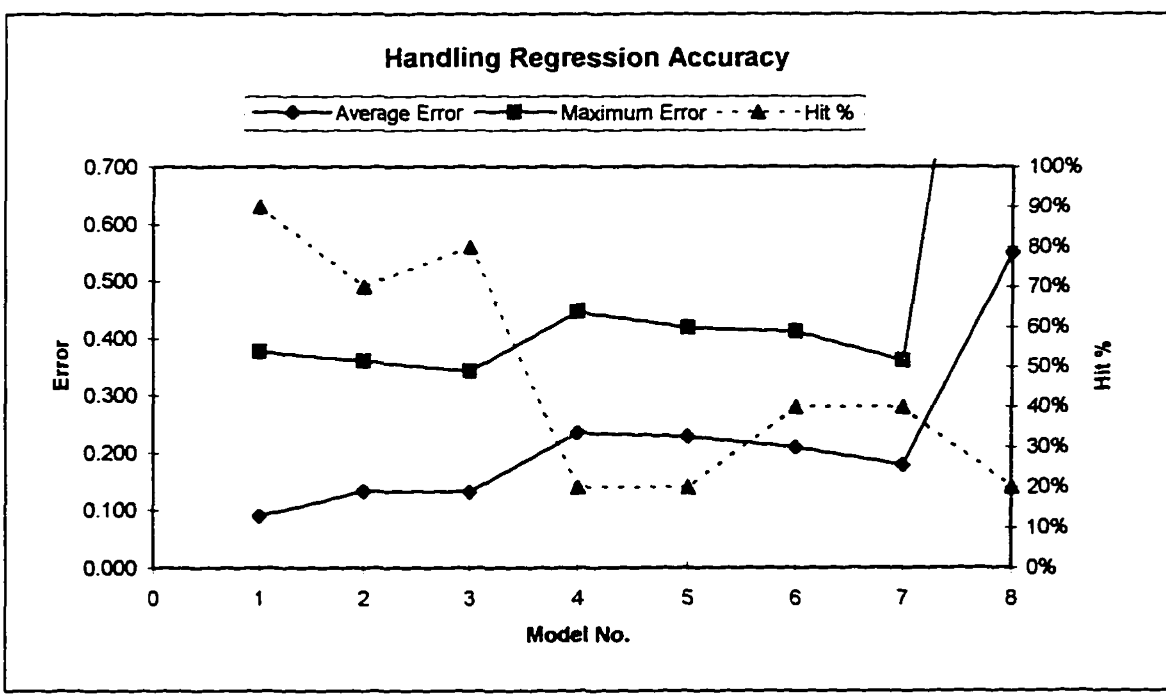
The neural network method using classification developed accuracy much better than that of models one and three. The typical activity accuracy of 0.03 average and 0.06 maximum is considerably better than the regression models could predict. Furthermore, the nontypical activity accuracy of 0.08 average and 0.22 maximum is also significantly better minimum errors of 0.09 average and 0.38 maximum obtained by the best regression models. The classification portion of the neural network method is the source of the better accuracy for the neural networks. Testing of linear multiple regression within the typical and nontypical ranges, however, is not considered. This is because regression does not offer a classifying technique. Furthermore, the scope of this research does not intend to experiment with combination of modeling techniques.

Based on the detailed analysis undertaken with multi-linear regression the following factors outline why statistical techniques fail to predict accurately:

- a linear relationship does not necessarily exist between each of the 33 factors and the multiplier value. Therefore, many variables may have been inaccurately accounted for.

- the factors examined for pipe handling contain a number of combined effects. For example, a helpful owner may make poor drawing and specifications have less or no impact on productivity, whereas a poor owner may give poor quality drawings and specifications resulting in a significant impact on productivity. Therefore, the quality of drawings and specifications will only have an impact when combined with a poor owner. Regression method is unable to capture such a relationship.
- the data set upon which the models are formed is limited in size for the number of inputs being trained upon. Unlike neural networks which learn and can infer solutions, in order for regression to properly predict, it must have been trained with an identical or near identical activity. This can be seen in Figure 5.15, where the accuracy increases and the hits decrease, in general, as the number of inputs increase. This is because more inputs represents more possible combinations of factors, and an increased probability of a predicted activity being unfamiliar to the model.

Figure 5.15 Handling Regression Models Accuracy



5.6 Pipe Welding Analysis

30 pipe welding records were collected for the purposes of analyzing the estimating multiplier used for an activity. This section describes the development of a neural network training method for this purpose. Also within this section, multi-linear regression is addressed as an alternative method of predicting the activity multiplier.

5.6.1 Data Analysis

Data analysis undertook the same process as pipe handling, summarized in section 5.5.1. As a result of examination of the statistics on these graphs the following changes to the inputs were made:

- camp job site location eliminated due to no records collected. As a result, rural and urban are the only site locations to be studied.
- only two projects outside of Alberta contained welding data, therefore province was eliminated as an input.
- year of construction 90-92 range was combined with 92-94 due to data limitations in the 90-92 category.
- heavy oil plants project definition was combined with oil and gas plants project definition due to limited heavy oil plants data. Three project definition inputs are to be used.
- average crew size categories 50-100,100-150, and >150 combined to form >50 category due to data limitations..
- peak crew size categories 100-150 and >150 combined to form >100 category due to data limitations.
- classification 431 combined with 430 due to data limitations (430 and 431 codes have historically been estimated as equivalent in the degree they effect productivity).

- classification 440 combined with 410 due to data limitations (440 and 410 codes represent differing job conditions, but have historically been estimated as nearly equivalent in the degree they effect productivity).
- all metal types other than carbon steel were combined into one group due to data limitations.

As a result of the data analysis, 52 inputs for 29 factors are considered for a pipe welding activity.

5.6.2 Neural Network Training

The following describes in detail the procedure and conclusions developed for predicting a pipe welding multiplier value for a given activity using neural networks.

5.6.2.1 Continued Data Analysis

Neural network training techniques described in section 5.5.2.2.1 were used once again for the historic pipe handling data as means of eliminating inconsistencies and problems in the data. As a result, no records were extracted from the data set, except for a couple of cases where records from the same project had inputs too similar to account for vast multiplier differences were identified. In these cases the inputs were simply reevaluated so that the conditions of each of the activities were distinctly captured.

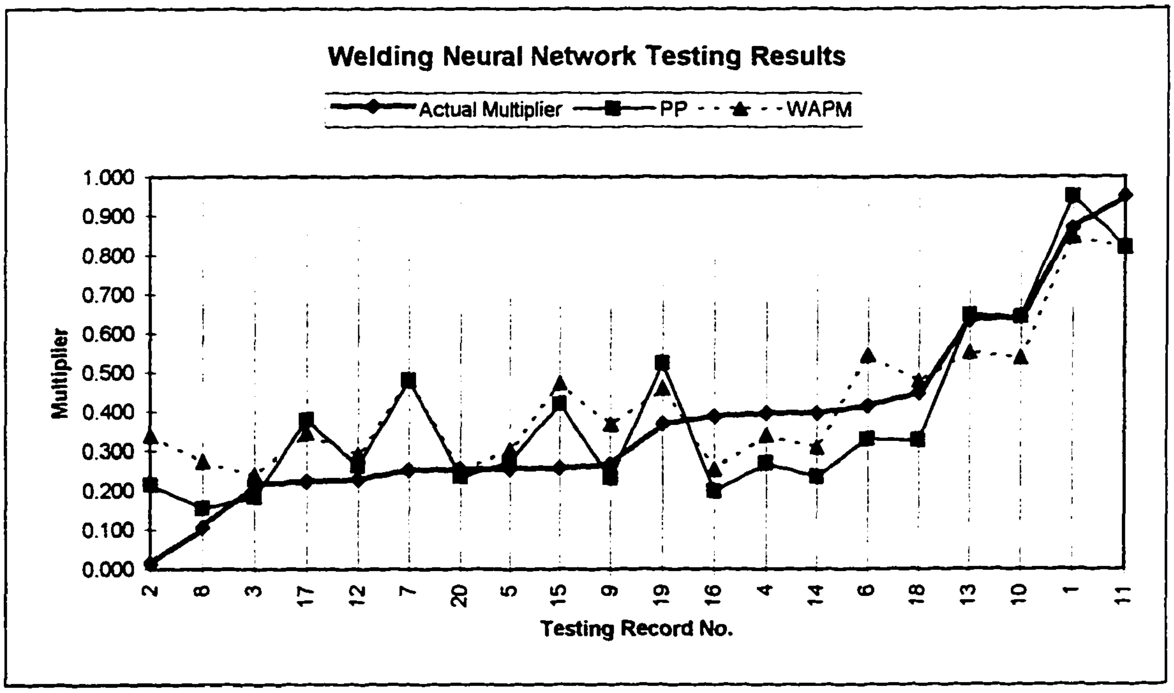
5.6.2.2 Feed Forward Back Propagation Neural Networks

The records collected for pipe welding activities produce a much better histogram distribution throughout the data than the pipe handling data (see Figure 5.2). Furthermore, the range of the data did not extend beyond the magnitude of multipliers historically used by estimators as did the pipe handling data. As a result a much more normal, and predictable data set is in place for pipe data. Training within a single feed forward back propagation, using identical training characteristics as for pipe handling, produced the results in Table 5.12 and Figure 5.16.

Table 5.12 Welding Testing Accuracy - Single Network

Accuracy Method	Result
Number of Hits (WAPM within +/- 15% of AM)	85%
PP - Average Absolute Error	0.099
PP - Maximum Absolute Error	0.228
WAPM - Average Absolute Error	0.108
WAPM - Maximum Absolute Error	0.325

Figure 5.16 Welding Testing Results Graph - Single Network



A number of conclusions were discovered based on the given results:

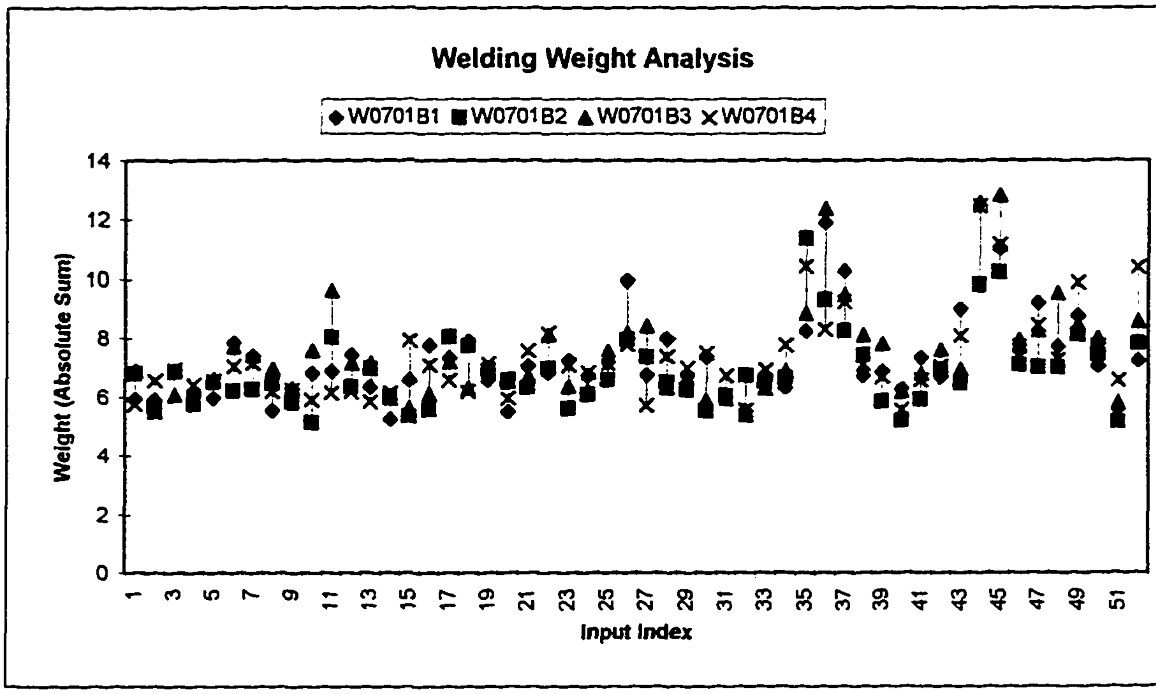
- the neural network predictions, in general, followed the trend of the actual multiplier
- the prediction results of the network are high on the low range multipliers. This is attributed to the normalizing affect of a neural networks predictions.
- The PP value is lower in average and maximum error WAPM, but neither value seems more fluctuate than the other.
- the average error of near 0.1 and the maximum error of under 0.23 indicates the data has trained very well within the structure and setup of the neural network. Furthermore, the average error of 0.1 is below the 15% error threshold used by the research for productivity predictions.

Both the pipe welding input data and the single feed forward back propagation neural network are also very stable. Table 5.13 defines the major influencing inputs and, because no one factor is governing the network, stabilization appears to met. Furthermore, Figure 5.17 shows that despite which records are withdrawn for testing, a stable state of input influence remains.

Table 5.13 Top 5 Influencing Inputs - Welding Network

Input Factor	Absolute Weight Sum
Material	11.576
Log Quantity 2-16	10.475
Log Quantity <2	9.724
Log Quantity >16	9.304
Site Working Conditions	8.806

Figure 5.17 Input Sensitivity - Welding Network



Based on the normal distribution of the pipe welding data, the range of the data only slightly exceeding the historical multiplier range used by estimators, the limited quantity of training records, the strong stability of the network, and the high prediction accuracy rate achieved, the use of classification is not examined for pipe welding. No need is identified for classification as in the case of pipe welding, since single feed forward back propagation neural network meets all the requirements necessary for predicting the multiplier value.

5.6.3 Multiple Linear Regression

Linear multiple regression was tested in a similar manner to pipe handling for the pipe welding data. Table 5.14 summarizes the models developed.

Table 5.14 Welding Testing Accuracy: Regression Models

Model No.	Variables Considered	Average Error	Maximum Error	Hit %
1	Material Type	0.169	0.311	60%
2	Material Type, Log Quantity <2. 2-16, >16	0.2404	0.429	40%
3	Material Type, Log Quantity 2-16, Peak Crew Size	0.155	0.368	40%
4	Material Type, Peak Crew Size, Difficulty	0.092	0.281	80%
5	Material Type, Peak Crew Size, Difficulty, Extras	0.087	0.283	80%
6	Material Type, Peak Crew Size, Difficulty, Extras, Designer Index	0.092	0.284	90%
7	Material Type, Peak Crew Size, Difficulty, Extras, Designer Index, Learning	0.130	0.320	80%
8	Material Type, Peak Crew Size, Difficulty, Extras, Designer Index, Learning, Proximity of Welders	0.130	0.402	70%
9	All Factors	0.270	0.705	40%

Regression models four, five and six predict the most accurate results from the developed regression models. The following equations define each of these models:

Model 4:

$$Multiplier = 0.443 + 0.263 * MaterialType + 0.079 * PeakCrew - 0.085 * Difficulty$$

(where CS MaterialType = 0 and Other Material Type = 1)

Model 5:

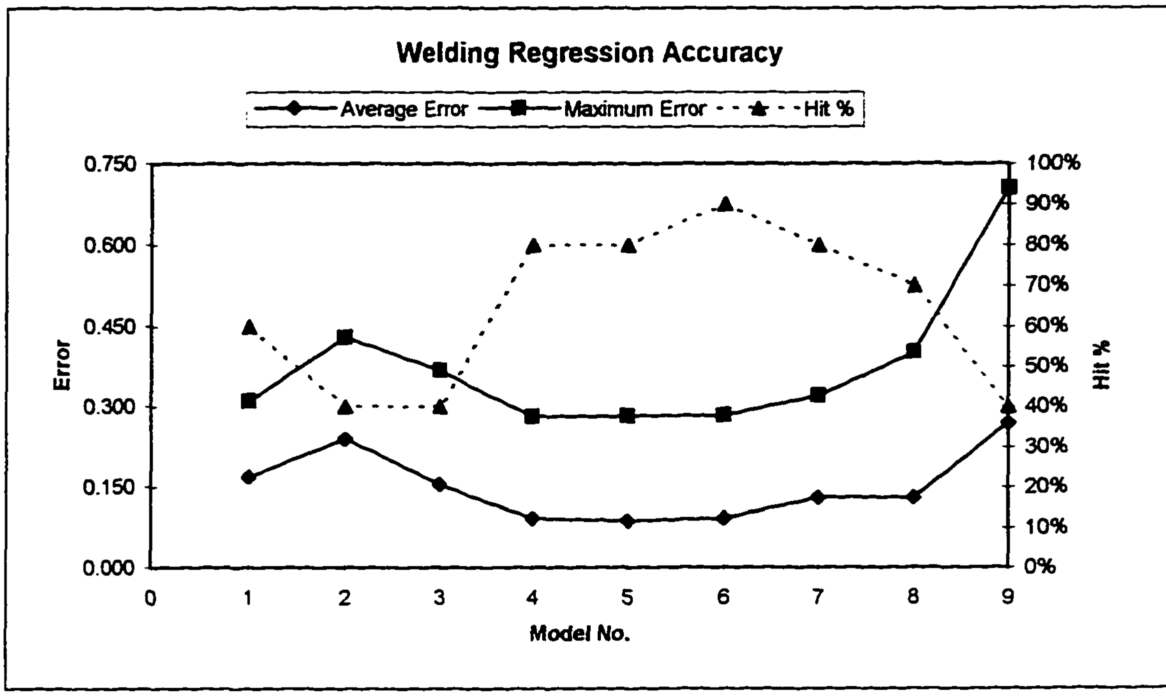
$$Multiplier = 0.440 + 0.252 * MaterialType + 0.064 * PeakCrew - 0.085 * Difficulty + 0.182 * Extra$$

Model 6:

$$Multiplier = 0.512 + 0.243 * MaterialType + 0.075 * PeakCrew - 0.090 * Difficulty + 0.163 * Extra - 0.077 * DesignerIndex$$

The ability of these three regression models to predict is slightly better in average error than the defined accuracy of the neural networks (0.087 versus 0.099). The maximum error of the regression models, however, is slightly worse than that achieved by the neural network (0.283 versus 0.228). Therefore, the regression models essentially match the ability of the neural networks for the pipe welding data. This ability to match, however, is expected to be short-lived. Training of the neural networks revealed that many more than five or six variables contribute to the value of the multiplier. However, the regression model breaks down as more variables are included (see Figure 5.18 - the accuracy increases as more factors are added, but only to a point, and then accuracy decreases). As more records are added to the database, the effect of more than just the five or six factors will be present in the multiplier value. Unless the regression models are able to increase the number of inputs that can be accurately account for, the accuracy expressed here will not be maintained. Furthermore, the ability of the regression models to successful account for a large number of factors is doubtful. This is because a regression technique does not learn as a neural network does, and therefore, it requires every possible combination to be exposed during training or the system will fail. As the number of factors increase, however, the number of required training records grows at an exponential, and unrealistic, rate.

Figure 5.18 Welding Regression Model Accuracy

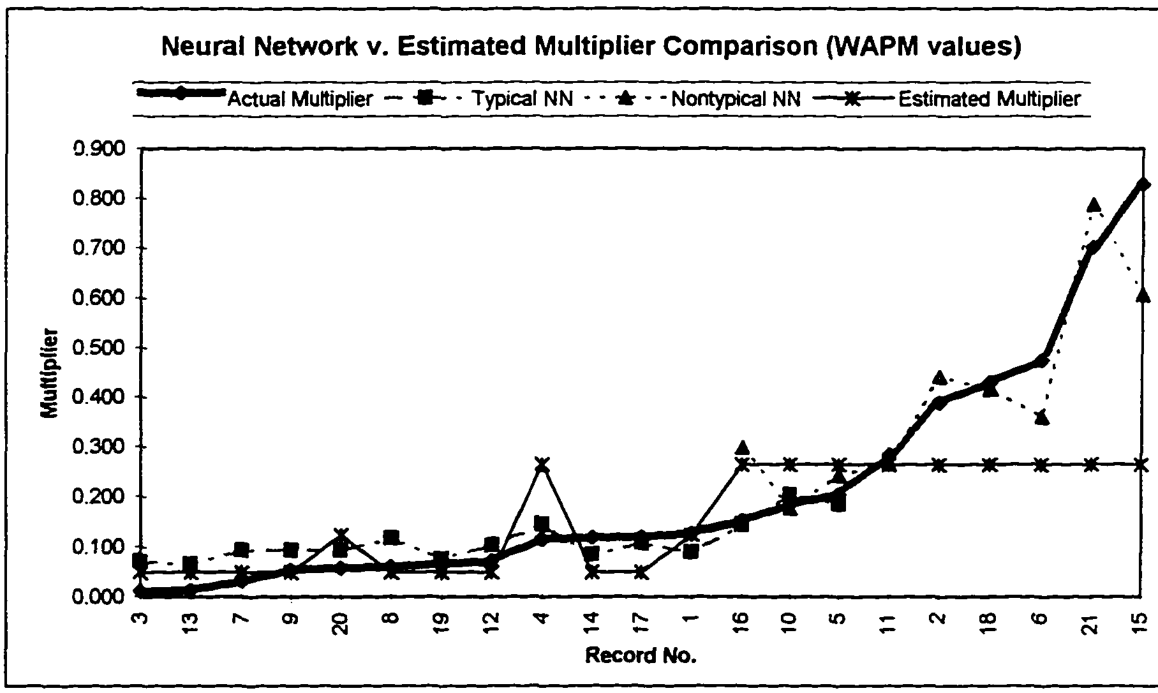


5.7 Summary of Results

The objective of the research in industrial construction productivity was to reveal the factors that influence labour productivity and use neural networks as means of determining the effect of the factors. In doing so, pipe handling and welding activities were researched in detail. Data limitations, however, prevented a traditional approach of directly predicting a productivity, so with the use of industry derived base productivity, a productivity multiplier was manipulated in order to reveal the effects of all the defined productivity factors.

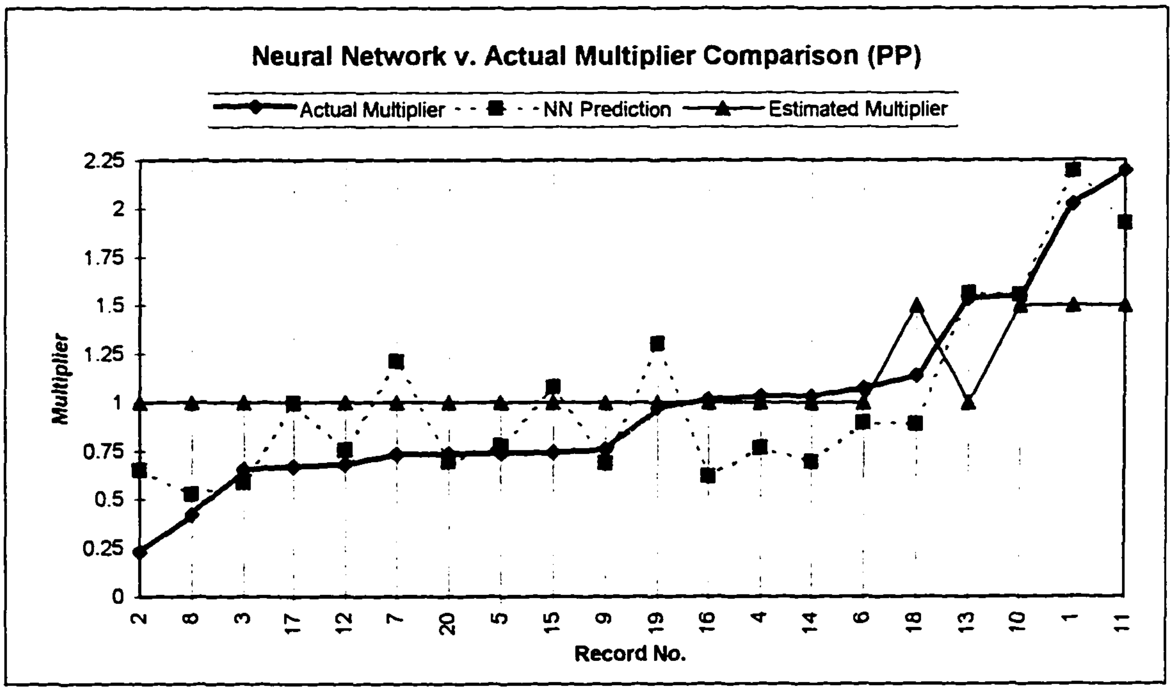
For pipe handling 33 influencing factors were identified and a data search collected these factors for 37 historic activities. Neural network and statistical analysis revealed that the use of classification neural networks is necessary to properly capture the effects of each factor. This technique is proven applicable through its application to the formwork models addressed by this research, and again proven successful for pipe handling. The developed model first defines an activity as typical or nontypical using a LVQ classification network. A typical activity is a pipe handling duty which possesses the characteristics of a normal activity that has been historically estimated within a defined range of multiplier values. A nontypical activity, on the other hand, possesses characteristics that prevent the activity from falling within the historic multiplier range. The model is capable of predicting to an average of 0.03 and a maximum of 0.06 multiplier error for a typical activity and an average of 0.08 and maximum of 0.22 multiplier error for a nontypical activity. Figure 5.19 shows the prediction abilities of the neural network system. Within the figure, it can be seen that the neural network predictions correlate to the actual multiplier much better than the historical estimated multipliers are able to.

Figure 5.19 Handling Neural Network Versus Estimated Multiplier Comparison



For pipe welding 30 influencing factors were identified and a data search collected factors for 30 historic activities. Only a single feed forward back propagation neural network is necessary for pipe welding as the status and quantity of the collected data makes this a valid and practical solution. Furthermore, the accuracy of the network model proves to meet that obtained by the classification method required for pipe handling. The pipe welding neural network predicts to 0.1 average and 0.23 maximum multiplier error. Furthermore, the predictions set forth by the network prove to match the achieved value better than the multipliers actually used for historic activities for extreme multiplier activities (see Figure 5.20). The extreme multiplier activities are those that land outside the possible range of historic estimators multipliers. The neural network was more accurate 70% of the time when the actual multiplier was below the designated range and 100% more accurate when it exceed the designated rate. Within the historic range, however, it can be seen that the network does not yet out predict the historic estimated multiplier. This is attributed to the data limitations of the training set.

Figure 5.20 Welding Neural Network Versus Estimated Multiplier Comparison



Multi-linear regression was tested for both the pipe handling and pipe welding activities with low level of success. Although the regression models proved to match the abilities of the neural network in the case of pipe welding, many limitations of regression models for this scale of modeling were identified. The large number of input factors essentially makes regression an unfeasible option as the possible combination of inputs make memorization of all combinations impossible. Furthermore, the inability of the technique to account for the combined effects of inputs will inevitably reduce the attainable accuracy.

Both PP and WAPM values were carried throughout this analysis in order to determine which value is more accurate. Although formwork models consistently used the weighted value, as it was the more accurate value, slightly different findings were uncovered by comparing accuracy achievements of the PP and WAPM values. For the pipe handling neural networks, the WAPM value tended to be only slightly more accurate. The nature of each prediction type, however, tended to vary slightly. The PP, in most cases, fluctuates to a greater degree than the WAPM. This is essentially due to the averaging of the prediction zones for the WAPM producing a more conservative prediction. As a result, the weighted prediction value, WAPM, as with the formwork models is the area of focus for the pipe handling data so that a more conservative and safer multiplier is recommended by the neural network model. For the pipe welding neural networks, the PP predicted to a significantly higher accuracy than did the WAPM value. Furthermore, no significant difference in the fluctuation tendencies of either value was identified. Therefore, for the pipe welding neural networks the PP is recommended.

6. Final Discussion

6.1 Summarized Findings

The focus of this research has been predicting construction labour productivity in two distinct types of construction using neural network artificial intelligence. The following defines the findings reached and developments achieved for the commercial formwork and industrial productivity research.

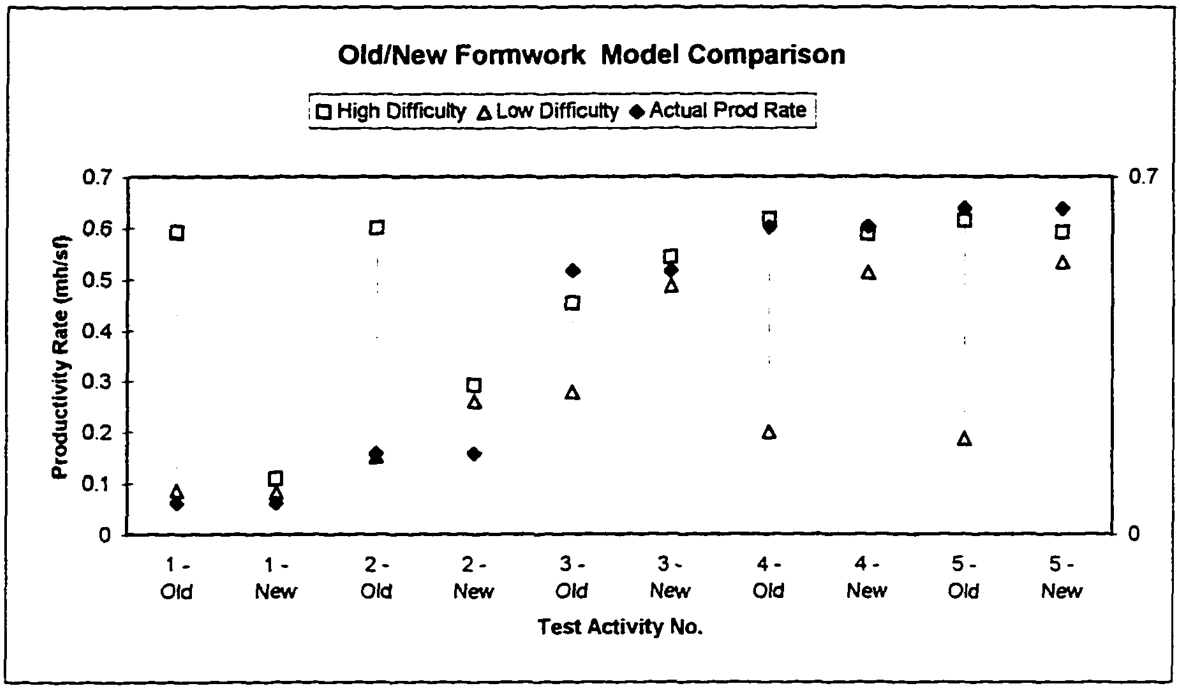
6.1.1 Commercial Formwork Project

Formwork neural network models designed for the purpose of predicting labour productivity were developed by previous research. Two properties of these models, however, limited the successful implementation of the models. These two properties were instability and the inability of the models to accurately predict extreme, very high or very low, productivity.

6.1.1.1 Stability Enhancement

The formwork neural network models were incorrectly distributing influences affecting productivity among input factors because of limited training data, missing input factors, and inadequate conversion of subjective data. The addition of more training records and the collection of a number of new input factors eliminated part of this effect. A breakdown of the, neural network controlling, "subjective" factor into a number of more descriptive factors served to eliminate the remainder of the effect. Figure 6.1 depicts this increase in stability by examining the effect of difficulty on a formwork activity. The range bars shown for each of the five test activities show that the effect within the new models is considerably more reasonable than that in the old models. Furthermore, this graph shows that differing estimator opinions on what level at which to rank individual factors will no longer cause the prediction to drastically drift from the actual value. Therefore, the new test activity model bars indicate a much more stable network.

Figure 6.1 Increased Formwork Neural Network Model Stability



6.1.1.2 Accuracy Enhancement

An inability to adequately predict formwork activities which achieve productivity outside the 10th and 90th percentiles was a major concern of the models developed by previous research. The intent of the models is to expose and provide an idea of the order of magnitude for extreme activities. Instead, the models' best accuracy occurs on average activities, the types of activities which are also typical to the estimator, and thus, easily estimated without the aid of a productivity model. The cause of this characteristic is the normalization tendency of neural networks. A neural network is more likely to predict towards the average side of an actual rate than to the extreme side. This is because a network is primarily trained on near average activities, and in order to obtain the lowest attainable error for a trained neural network, it will oblige to the average rather than the extreme records.

The use of classification neural networks was found to minimize this effect to a level at which it was insignificant. For this method, a Kohonen classification network, Linear Vector Quantization, is used to classify formwork records to high, medium, and low classifications. Three feed forward back propagation neural networks are then trained on limited size ranges. The average neural network acted very similarly to the single feed forward back propagation network of the original models, on a slightly decreased range of productivity. The high and low neural networks, however, now trained only upon extreme ranges of records and, as a result, the testing of an extreme record is no longer biased by the high population of near average records.

The use of three feed forward back propagation neural networks greatly increased the ability of a formwork activity to predict within +/-15% of the total productivity range for an activity. The models developed in previous research for walls formwork and slabs formwork were only accurate to +/-15%, 80% of the time. Furthermore, walls formwork were only accurate on extreme activities to +/-15%, 67% of the time and slabs formwork to +/-15%, 54% of the time.

The high, medium, and low neural networks of the new models are accurate to +/-15%, 100%, 94% and 100% of the time, respectively, for walls formwork and 100%, 100%, 83% of the time, respectively, for slabs formwork. The ability of the classification network to properly classify proves to be essentially the only source of error in the new formwork models. Classification attained an accuracy of 80% for slabs formwork, and 85% for walls formwork. However, a technique of overlapping the training boundaries between the low and medium and the medium and high neural networks accounted for many of the classification errors. By combining the accuracy achievements of both the classification and feed forward back propagation neural networks the accuracy improved for both walls formwork and slabs formwork, as shown in Figure 6.2 and Figure 6.3 respectively.

Figure 6.2 Accuracy Comparison - Walls Formwork

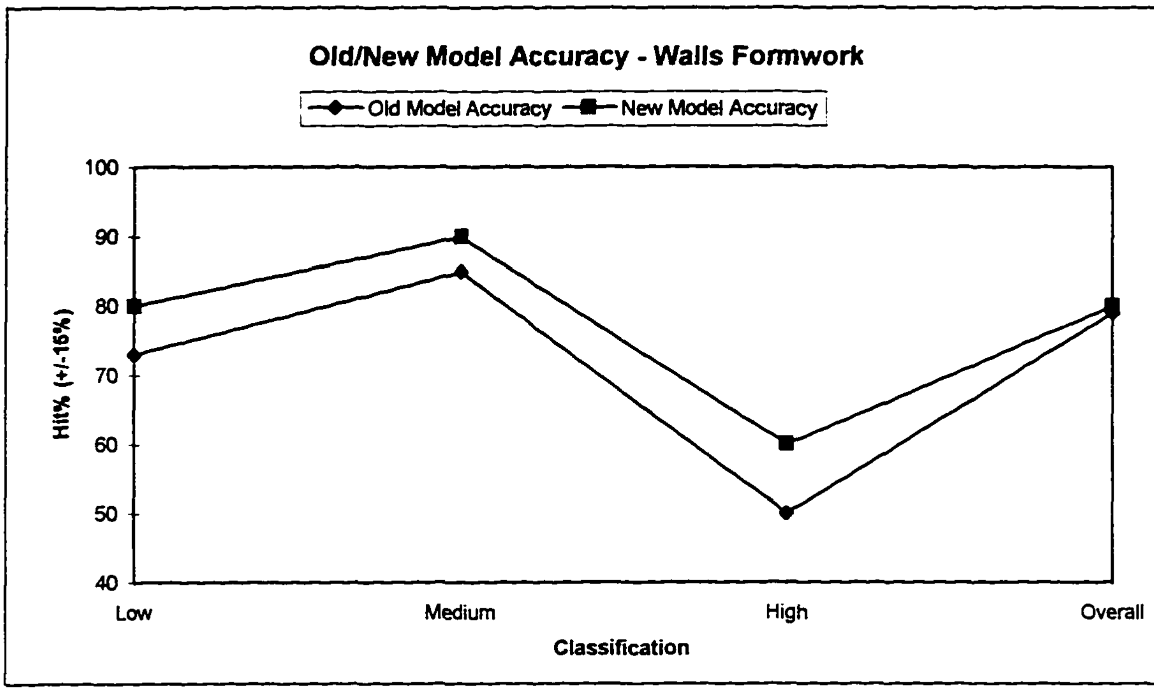
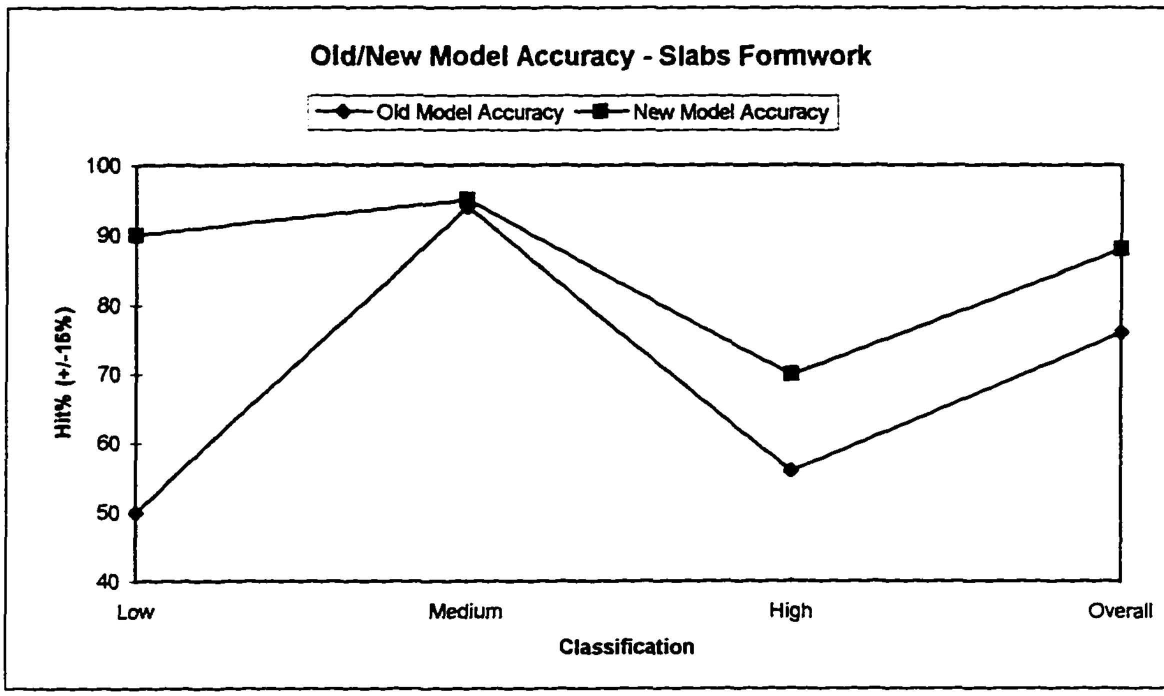


Figure 6.3 Accuracy Comparison - Slabs Formwork



The most significant achievement shown in Figure 6.2 and Figure 6.3 is the ability of the new models to more accurately capture the extreme activities more accurately.

The adjustment of the stability and accuracy properties of the formwork neural network models has essentially produced a more stable and accurate application. Estimator use of the application should now be much less difficult to implement as it better reflects the common sense aspect of the neural network predictions.

6.1.2 Industrial Construction Project

Industrial pipe handling and pipe welding neural network models designed for the purpose of predicting labour productivity were developed as part of this research. In doing so, two major accomplishments were attained.

1. the identification of the factors on an industrial project that may affect the rate at which a pipe handling or pipe welding activity can be completed

2. the development of a productivity prediction tool capable of aiding an estimator during examination of a new project.

Identification of factors affecting productivity for industrial construction was accomplished through interviews with experienced personnel in the field and the utilization of the knowledge gained through the identification of formwork productivity factors. An initiative taken that varies from the technique used by the commercial formwork project is the replacement of descriptive or qualitative factors with quantitative inputs. This is accomplished through the use of a number of general expenses and administrative ratios as a means of identifying a factor rather than basing the status of a factor on the opinion of a site superintendent. This technique was successful, as successful neural network training was accomplished for the industrial activities without the need for any of the subjective data conversion techniques used by the formwork models. Table 6.1, Table 6.2, and Table 6.3 summarize the productivity factors identified for industrial construction. For neural network training, the pipe handling models used both the global and pipe handling factors, and pipe welding models used the global and pipe welding factors.

Table 6.1 Global Productivity Factors

Global Factors	
• location	• project type
• province	• location of work scope
• administrative requirements	• average crew size
• year of construction	• peak crew size
• client	• unionized
• engineering firm	• equipment and material cost
• superintendent	• extra work
• project manager	• change orders
• project definition	• drawing and specifications quality
• prefab, modulatization, and field work characteristics	

Table 6.2 Pipe Handling Productivity Factors

Pipe Handling Factors	
• learning rate	• boltups quantity
• location classification	• valves quantity
• installation quantities	• screwed joints quantity
• material type	• season
• method of installation	• crew ability
• pipe support quantity	• working conditions
• owner inspection, safety, and quality requirements	• overall degree of difficulty

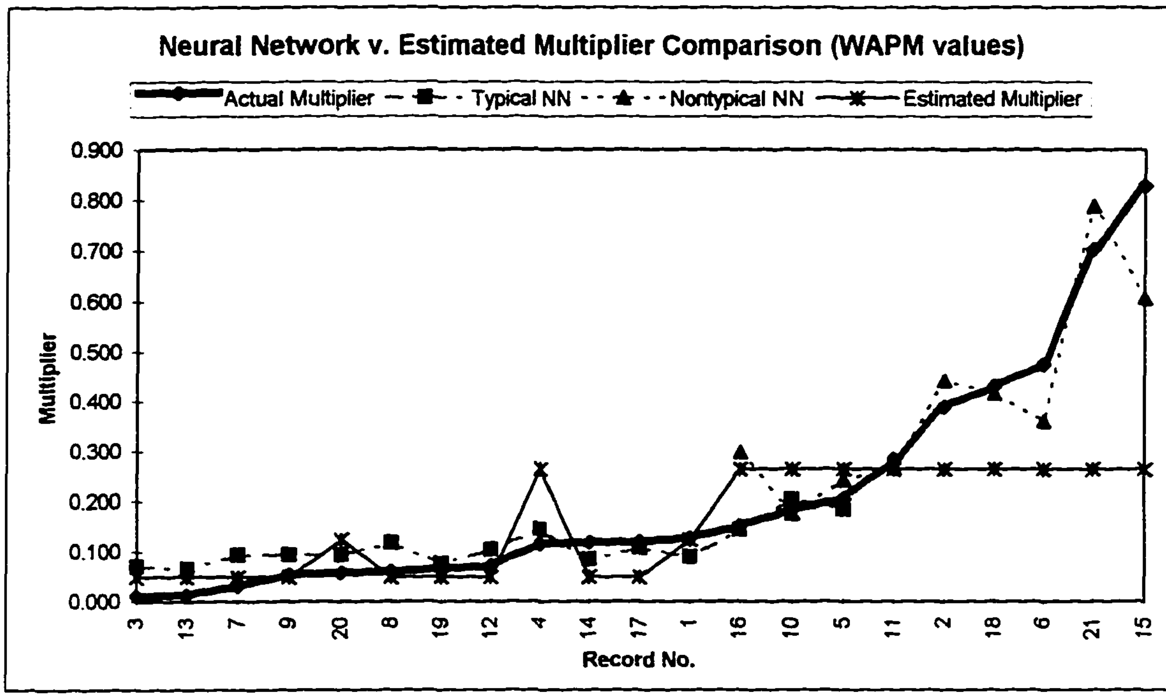
Table 6.3 Pipe Welding Productivity Factors

Pipe Welding Factors	
• learning rate	• season
• location classification	• crew ability
• rig welders	• working conditions
• material type	• proximity of equipment
• welding quantities	• overall degree of difficulty
• owner inspection, safety, and quality requirements	

The application of similar neural network models for both commercial and industrial productivity estimation was limited due to both industry and contractor differences. As a result, an estimator multiplier value is the focus of the study for the industrial project. This multiplier is simply applied to base productivity to account for varying activity conditions. Historically, however, the multiplier has only accounted for one factor for pipe handling and pipe welding activities. The developed neural networks models account for numerous project and activity factors.

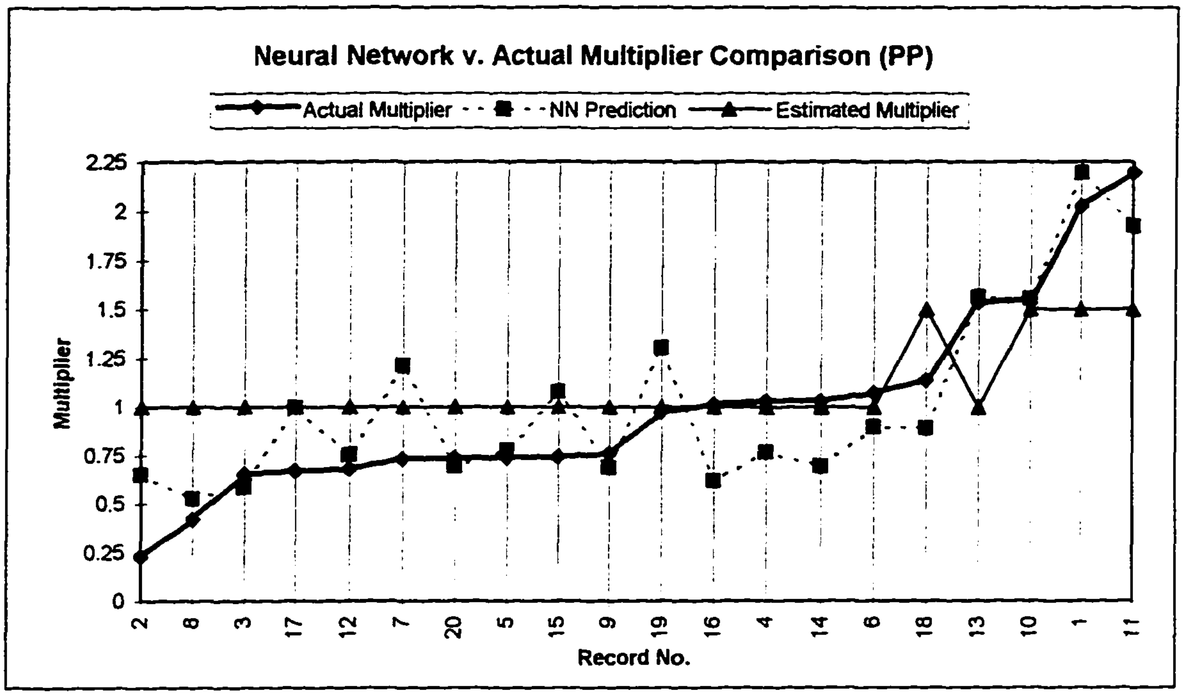
The knowledge gained by the implementation of classification neural networks into a training method for the formwork models is applied to the pipe handling data. An abnormal distribution of collected pipe handling data required this technique in order for the normalizing effect of a neural network's predictions to be minimized. As a result, the developed neural network model, based on 32 factors, is capable of predicting to a much better level of accuracy than the historic multiplier was able to predict based on only one factor (see Figure 6.4).

Figure 6.4 Pipe Handling Neural Network Accuracy



Classification networks are not applied to the pipe welding data for a number of reasons. Most important of the reasons is the ability of a single feed forward back propagation neural network to accurately predict. The reasoning for this is the normal distribution that the pipe welding data represents. The entire range of the pipe welding multipliers were adequately represented so that the normalizing effect of the neural networks was minimal. Figure 6.5 shows that the neural network is capable of predicting beyond the strict boundaries of the one-factor historic multiplier to account for 29 factors.

Figure 6.5 Pipe Welding Neural Network Accuracy



6.2 Final Comments

This research has proven the relevance of neural network artificial intelligence to the construction industry as demonstrated by the ability of neural networks to model construction productivity based on a large number of input factors. Furthermore, the flexibility of the technology has been proven through its ability to be applied to two distinctly different types of construction and to predict to a high level of confidence.

Two issues were primarily the focus of this neural networks research. Initial stability and accuracy measures were developed and implemented within models capable of predicting formwork labour productivity, then these measures were verified through their implementation within successful industrial productivity prediction models. The use of descriptive, and where possible quantitative, data collection techniques proved to increase neural network stability. Furthermore, the development of a dual neural network system using both classification and prediction proved to produce very good accuracy not only in the bulk of the training data found the average, but throughout the range of the training data.

Future research in the development of neural network modeling for the purposes of predicting labour productivity should investigate a generic neural network structure. Both the commercial formwork and industrial activities were successfully built with very similar network structures. This indicates that the developed neural network structure may potentially have the ability to be rapidly applied to other types of construction activities, given sufficient available training. If a generic structure is possible, such an application would have unlimited use in a construction industry rich in unique types of work.

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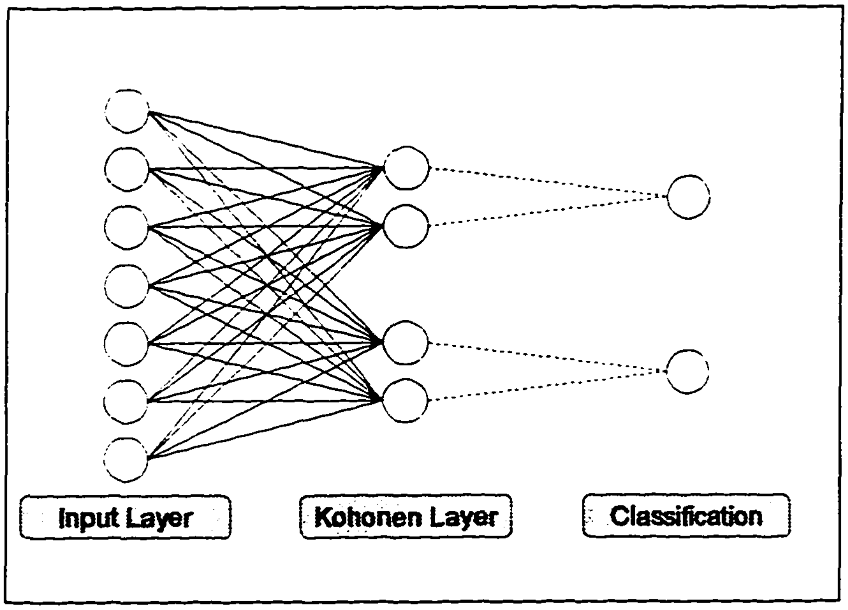
Appendix 1: Linear Vector Quantization (LVQ) Neural Networks

LVQ neural networks are a branch of Kohonen neural network technology. LVQ neural networks act to classify the outcome of a problem by means of a supervised learning technique. In other words, training records for a LVQ neural network would specify the location to which they are to be classified. The structure of a LVQ neural network involves three layers (see Figure A1). The first layer is the input layer and simply contains nodes for each input factor. The second layer ,called the Kohonen layer, contains a number of nodes entitled processing elements (PEs). Each PE in the Kohonen layer is connected to each input node in the input layer. Connections consist of weights which define the relationship between PEs and the input nodes. The third layer contains the output, or classification, nodes. Connection weights between PE nodes and classification nodes do not exist, however, as the classification node simply acts to define classes of a PEs. In Figure A1, the sample LVQ neural network has two output classification nodes. These two classification nodes act to define two classes of PE nodes, each of which contain two PEs. The number of PEs per class is a constant that is determined experimentally.

Figure A1: Sample LVQ Neural Network



LVQ neural network training uses both unsupervised and supervised learning techniques in order the adjust the weights of a neural network structure. As supervised learning, LVQ training first calculates a global distance to each PE as a summation of the distance from the PE to each input node. The following equation defines the calculation:

$$d_i = \left\{ \sum_{j=1}^{N} \left(w_{ij} - x_j \right)^2 \right\}^{1/2} \qquad \text{(Equation 1)}$$

d_i = global distance of PE i

w_{ij} = weight connecting input j and PE i

x_j = input j

N = number of inputs

The PE with the minimum global distance is the global winner. If the class of the global winning PE is not in the class represented by the actual classification for the testing record, the PE is punished according to the following formula:

$$w_{ij}' = w_{ij} - \gamma(x_j - w_{ij})$$ (Equation 2)

w_{ij}' = new weight connecting input j with the winning PE i

w_{ij} = old weight connecting input j with the winning PE i

γ = repulsion rate

x_j = input j

If the class of the global winning PE is in the same class as that represented by the actual classification then no operation is performed on the weights connected to the winning PE.

As unsupervised learning, LVQ training act to determine an in-class winner based only on biased distances. This stage of training, however, is still somewhat supervised as the class in which this analysis takes place is only the actual classification defined class. The unsupervised training stage recalculates a distance but adds a bias to the previous calculation. Therefore the following equation defines the in-class distance:

$$d_i' = d_i + b_i$$ (Equation 3)

where $b_i = \mu * d_{i\max}(N * p_i - 1)$ (Equation 4)

b_i = bias value for PE i

μ = conscience factor

d_{imax} = maximum global distance

N = number of PEs per class

p_i = winfrequency

The PE with the minimum in-class distance is declared the in-class winner and is rewarded according to the following equation:

$$w_{ij}' = w_{ij} - \alpha\left(x_j - w_{ij}\right)$$ (Equation 5)

α = learning rate

other variables same as defined by Equation 2

The presence of the winfrequency variable is the key to successful unsupervised training. The winfrequency is updated following training of each record such that the winfrequency of the winning in-class PE is increased and for all the losing PEs is decreased. The following equations define the winfrequency adjustments:

If PE i is the in-class winner:

$$p_i = (1-\varphi)p_i$$ (Equation 6)

If PE i is not the in-class winner:

$$p_i = (1-\varphi)p_i + \varphi$$ (Equation 7)

p_i = winfrequency

φ = frequency estimate

The win frequency value for a PE acts to increase the bias value. Therefore, a PE that wins for one record has its winfrequency increased and will not have as good a chance at winning the for the next record as its increased in-class distance will less likely be the minimum value. This procedure is called conscience learning and simply acts to prevent one PE from always winning.

LVQ training repeats the process of defining global and in-class winners, punishing incorrect global winners, and rewarding in-class winners for each record in a training set and then repeats training the set for a defined number of iterations. The learning, repulsion, conscience, and frequency estimate rates are continually reduced such that the magnitudes of punishing and rewarding becomes less as the network becomes more trained. As a result of reducing network constants, once the data set has had a efficient period of training to determine in-class winners, an in-class winner from each class will eventually pull away from the other PEs and dominantly become the winner in each class. Each of these dominant PEs, therefore, essentially become the output, or classification, node in which its class is represented by.

The following flowchart, Figure A2, defines the training procedure, described above, for a LVQ neural network.

Figure A2: LVQ Training Flowchart