University of Alberta

Predicting Industrial Construction Productivity Using Fuzzy Expert Systems

By

Ayodele Olugbenga Oduba ©

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Ayodubz

Ayodele Olugbenga Oduba
#1A, 10745-106 Street,
Edmonton, Alberta T5H 2Y1.

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University of Alberta

Faculty of Graduate Studies and Research

The undersigned persons certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled **Predicting Industrial Construction Productivity Using Fuzzy Expert Systems** submitted by **Ayodele Olugbenga Oduba** in partial fulfillment of the requirements for the degree of **Master of Science** in **Construction Engineering and Management**.

A Robinson

Dr. Aminah Robinson

Dr. Hamid Soleymani

Dr. John Whittaker

Date: Sept 27/02

Abstract

This research studies the use of fuzzy expert system to predict the productivities of industrial rig pipe and weld pipe activities. Three models were developed, one for rig pipe and two for weld pipe.

Context variables and factors influencing the productivity of each activity were identified. A fuzzy expert system that comprises membership functions, a fuzzy rulebase containing If-Then rules, a fuzzy inference system, and a defuzzification module, was generated for each model, in a computer environment. Correlation analysis was used to determine the factors that significantly affect productivity. The models were calibrated to improve their accuracies, and validated using productivity data. All the models have high linguistic accuracies. Sensitivity analysis was performed for each model to improve its numerical and linguistic accuracies.

The study demonstrates the use of fuzzy expert system in predicting the productivity of industrial construction activities, given limited data and a large number of input factors.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

AB: Alloy and Butt Weld

Avg.: Average

CB: Carbon Steel and Butt Weld

Dia.: Diameter

e.g.: Example

i.e.: That is

Km/hr: Kilometer per Hour

mm: Millimeter

No.: Number

^{o} C: Degree Celsius

1. Introduction

1.1 Introduction

Construction labor productivity is very crucial to the successful completion of any construction project. Since labor constitutes a large portion of the entire project cost, it is of utmost importance that labor is fully and effectively utilized on a construction project. The ability of the estimating team to accurately determine labor productivities for different activities will have a significant impact on the labor cost component of a project. Most studies on construction labor productivity have focused on commercial construction. There has not been significant study of this topic in the area of industrial construction, therefore necessitating the focus of this research on this sector of the construction industry.

Barrie and Paulson (1992) stated that industrial construction involves the execution of construction projects, such as petroleum refineries and petrochemical plants, synthetic fuel plants, fossil fuel and nuclear power plants, offshore oil and gas production facilities, cryogenic plants, etc. They also observed that industrial construction generally features large amounts of highly complex process piping, mechanical, electrical, and instrumentation work, and that industrial design and construction require the highest level of engineering expertise from multiple disciplines. Knowles (1997) defined industrial construction as the construction of piping systems, typically for oil and gas, petrochemical, mining, or other industrial-related fields.

This research studies the use of fuzzy expert system to develop models that predict industrial productivity, for two pipefitting activities, namely rig pipe and weld pipe. Construction productivity models were developed for these activities. The development of the models were done by defining the factors that affect productivity for each activity, developing the models based on the proposed model structures, and finally testing the models with previously published construction productivity data, in order to determine the accuracy of the models.

1.2 Thesis Objectives

The main purpose of this research is to present a methodology for developing fuzzy expert system models for predicting industrial construction labor productivity for two major pipefitting activities, namely rig pipe and weld pipe. The study seeks to develop a methodology for the development of productivity models that are realistic and accurate for predicting productivity. These models, which are applicable to crew-level operations, can help estimators in the industrial construction sector to estimate productivities for different activities based on the several factors that affect the activities. Three models were developed in this study, one for rig pipe and the others for weld pipe. The model for each activity accounts for many factors that may influence crew productivity and also overcome the rigidity problem associated with existing productivity models. The major idea behind this study is that if the productivity of a crew can be accurately predicted, then it would be easy to determine appropriate crew ratios (apprentice to journeyman ratios) required to achieve certain desired levels of productivity.

This research set out to identify factors that affect industrial construction labor productivity for the chosen activities. A variety of factors that affect industrial construction productivity were closely examined and subsequently reduced to a manageable few that can be used in the models to be developed. This was necessary since it would be difficult to consider all the possible factors affecting construction productivity in the models. This difficulty arises from the fact that it is hard to implement a productivity model, based on a fuzzy expert system, if the model comprises a large number of input and output factors. The factors included in the models developed in this study were determined by the availability of data for each factor. This is because the data published in Fayek et al. (2002), were used in this study, and the data do not cover all the possible factors affecting industrial construction productivity. The published data were collected at a major industrial construction site in Alberta in 2001.

The factors included in the models were reduced based on the statistical significance of each factor with respect to the prediction of productivity values. In order to achieve the objectives of this research, two statistical techniques, namely correlation and regression analyses, were examined in order to determine their degrees of applicability. Eventually, correlation analysis was used to reduce the factors affecting productivity to a significant, manageable subset of factors. Multiple linear regression could not be used because it was assumed that the relationships between some of the input factors and productivity are not linear, but polynomial or exponential. Correlation analysis was used in this study because it is more appropriate in situations where uncontrolled experiments have been conducted.

The objectives of this research can be summarized as follows:

- To identify and classify all the possible factors that affect the productivity of rig pipe and weld pipe activities.
- To identify the most significant factors affecting labor productivity for these two activities.
- To develop membership functions and fuzzy rulebases for the input factors and productivity (output factor) based on objective and subjective data.
- To develop fuzzy expert system models for predicting the productivities of the rig pipe and weld pipe activities.
- To validate the developed models using the rig pipe and weld pipe productivity data published in Fayek et al. (2002).

1.3 Expected Contributions

This study is expected to generate models that can be used to predict industrial construction productivity. The models will be able to determine the effects of changing project conditions on productivity and predict the most appropriate crew ratios for different combinations of factors affecting productivity. The study will involve the development of a technique for determining the significant factors influencing productivity. The technique will involve the use of statistical methods and field knowledge. A flexible model structure that will facilitate easy prediction of productivity will be developed. Techniques for generating membership functions and fuzzy expert rules will also be developed, using the available data set. The models will be able to predict productivity from incomplete and inconsistent data sets.

The use of the models is expected to result in savings in cost of construction and savings in the cost of the overall project since labor constitutes a significant proportion of the total construction costs. The models will enable the construction estimating team to determine the amounts of labor required to complete different quantities of an activity, while taking into consideration the other factors that affect productivity. Using the models, the estimating team will also be able to determine the adequacy of the crew size and will be able to suggest the right mix of apprentices and journeymen for each activity. This will facilitate effective use of available manpower, and it will enhance the use of apprentices on industrial projects.

This study will determine the applicability of a neuro-fuzzy technique, namely, the Adaptive Neuro-Fuzzy Inference System (ANFIS), and, a neural network technique, namely, Neuroshell 2, towards predicting the productivities of industrial construction activities.

1.4 Research Methodology

A thorough review of existing literature is done in this study in order to identify factors relevant to industrial construction productivity estimation. A review of existing literature is also important so as to identify existing techniques for predicting labor productivity and if possible, to suggest ways of improving on the existing models.

Apart from fuzzy logic, this study examines the application of ANFIS and Neuroshell 2, to the process of modeling industrial construction data with respect to the factors affecting productivity. This was done in order to determine if more feasible models could be developed using those techniques. However, the two techniques were found to be unsuitable. This is because the two techniques do not work well with many input and output factors and they require substantial data sets for training, testing and checking the model developed.

Fayek et al. (2002) carried out a three-month survey of two trades, namely the pipefitting and electrical trades, at a major industrial construction site in Alberta. Objective numerical and subjective linguistic data on both the quantities of work done and the amounts of manhours used to do the work, and data on some of the factors affecting productivity of the two chosen activities, were collected during the survey. The data were obtained using the Work Improvement techniques of Work Sampling and Five-Minute Rating, the information contained in structured questionnaires that were completed by the foremen, journeymen and apprentices on the crews studied, and in the productivity forms completed by the survey's researchers in conjunction with the crew foremen.

The factors affecting the productivity of each activity were identified and classified based on previous research and existing literature. The factors included in the models developed in this study are those for which data were available. These factors were categorized into context variables, activity-level input factors, and project-level input factors. The context variables are the factors that are used to classify the other factors based on how the objective data of each factor relate to subjective linguistic descriptors for different activities in different contexts. Membership functions and expert rules were generated for the models based on expert opinions. The membership functions were developed for each of the input factors and productivity included in each model and they were used to represent factors that are subjective in nature. The membership functions for a factor are used to define the extent, which is defined in terms of a membership value between 0 and 1, to which different levels of the factor fits different linguistic concepts (such as low, average, and high).

In order to reduce the number of factors to be included in the productivity models to a manageable number, correlation analysis, which provides a greater understanding of the relationships in the data being studied, was used to determine the most important factors affecting crew productivity based on data already collected. The correlation analysis was done after the development of membership functions for all the input and output factors, and, using the Statistical Package for Social Sciences (SPSS) for Windows, Version 9 (SPSS Inc., 2001).

The fuzzy rules were developed to provide the models with the logical reasoning necessary to infer the output (productivity) of the models. The membership functions and fuzzy rules were developed in MS Excel spreadsheets and later implemented in the Fuzzy Logic Toolbox of MATLAB 6.1 (The Mathworks, Inc., 2001).

Construction of membership functions was primarily based on information elicited from structured questionnaires that were completed by experts. The information obtained was used to determine the range of membership values corresponding to the linguistic concepts of the membership functions. The rulebases were developed using logical reasoning skills. The existing data were then used to test the models so as to determine their levels of accuracy, that is, how far the predicted productivity values are from the actual productivity values. The models developed were calibrated in order to improve their accuracy. The model calibration was done by adjusting the productivity membership functions used in building the models. This was done using MS Excel spreadsheets. A sensitivity analysis of the fuzzy inference system was carried out to determine the sensitivity of the system to fuzzy operators, and to implication, aggregation and defuzzification methods. This analysis helped to improve the accuracy of the developed models.

1.5 Thesis Outline

Chapter 2 describes a detailed review of topics related to construction labor productivity and fuzzy logic. The chapter gives a brief overview of the previous research efforts in the area of modeling labor productivity with the use of neural network techniques, fuzzy logic techniques, and, other techniques.

Chapter 3 describes the process of developing the models for predicting industrial construction labor productivity. It consists of a detailed description of the factors affecting construction labor productivity with respect to the activities that were chosen for this study. This chapter also consists of the graphical structure of the models, as well as the flowchart indicating how the models work.

Chapter 4 gives a description of the process of developing the expert systems employed in the models. This chapter comprises the development of the membership functions, simplification of the models using correlation analysis, development of the If-Then rules, as well as the sensitivity and linguistic error distribution analyses performed on the models.

Chapter 5 comprises the conclusions and contributions of this research study, as well as the recommendations for future work.

2. Literature Review

2.1 Introduction

The relationship that exists between the inputs to a production or construction system and the output from the system is defined by productivity. According to Liou and Borcherding (1986), productivity can be defined as the ratio of the outputs from a system, which may be goods and/or services, to the inputs to the system, which may be resources, such as, labor, capital, technology, materials, and/or energy. In its simplest form, productivity can be mathematically expressed as:

$$\text{Productivity} = \text{input(s)}/\text{output(s)} \tag{2-1}$$

From the mathematical expression in the equation shown above, it appears that one can easily increase productivity either by increasing the output(s) of the production or construction system while keeping the input(s) constant, reducing the input(s) to the system while keeping the output(s) constant, or by reducing the input(s) and increasing the output(s) simultaneously.

It is not easy to represent productivity as a ratio because there are certain variables that cannot be easily quantified, such as, reputation, credibility, quality, and achievement. Most of the available methods of measuring productivity do not measure productivity completely. Using fuzzy logic, inputs and outputs that are not easily quantifiable can be quantified in the form of linguistic variables. For example, although quality is not an objective measure of productivity, it can be described in terms of low, average or high quality. This subjective quantification can further be translated to objective values by assigning numerical values to subjective ratings.

In construction terms, an input to the system may be in the form of the number of manhours used to complete a unit of work. The unit of work completed is quantified and it represents the output from the system. An example is the amount of earth moved by an excavator in an earthmoving activity, in terms of cubic yards of earth material. In the construction industry, the commonly used index for calculating productivity is manhours per unit of work done.

Relatively, more research has been done on construction productivity in the commercial and institutional construction sectors than in the industrial sector. Therefore, there is a great need for more research to be carried out in the industrial construction sector. This chapter reviews existing literature on productivity, productivity models, the application of fuzzy logic in construction, and, the existing techniques of developing membership functions and fuzzy expert rules.

2.2 Previous Studies of Labor Productivity

It is difficult to study construction productivity because of the variable nature of the factors that affect productivity from one job to the other (Logcher and William, 1978).

Hinze and Kuechenmeister (1981) observed that one of the major problems of productivity studies is the determination of a convenient and feasible approach to measuring productivity. They noted that profitability is probably the most frequently used measure, although it assumes perfect estimates and that work conditions do not vary from job to job. Other measures of productivity include work hours and average direct activity ratings on jobs, which is an indirect measure. The work hour measure assumes that there are no changes in work conditions during the comparison of different project units. Hancher and Abd-Elkhalek (1998) observed that for most projects, productivity is more difficult to estimate and control than any other cost component. According to Halligan et al. (1994), in construction, productivity is taken to mean labor productivity. It is work defined as the units of work placed or produced per manhour. This measure of productivity is believed to have several advantages: the meaning of the term labor productivity is relatively easy to comprehend; labor productivity is frequently the greatest source of variation in overall construction productivity; and the productivity of other inputs can often be determined with respect to labor productivity. The inverse of labor productivity, manhours per unit of work placed or produced (i.e., unit rate), is also commonly used.

Although labor productivity rate is sometimes measured using other rates, such as installation rate (or units of work placed per unit time), and manhours used per week or month, these rates do not directly measure productivity and can therefore give false results if not carefully applied. For example, manhours per week or month indicates only the intensity of effort, not productivity. Labor productivity for a particular activity is often treated as a single, discrete value. However, productivity is better understood as a quantity that varies throughout the duration of an activity. A single-valued estimate is typically used in preparing a bid but in contrast, the measured value of productivity varies throughout the duration of the job. However, at any given time during the duration of the activity, the measured productivity may be close to or far from the estimated productivity.

Efforts have been made to determine the relationship between productivity and direct work. Liou and Borcherding (1986) studied the relationship between direct work and unit rate productivity of concrete pouring activity and they developed several equations for predicting productivity. Liou and Borcherding (1986); Thomas et al. (1984); and Handa and Abdalla (1989), reported that the percentage of time spent in direct work activities is correlated to labor productivity, that is, labor productivity improves as more time is spent on direct work activities. Thomas (1991) used seven databases, collected primarily from nuclear power plant construction projects, to determine the relationship between labor productivity and direct work. In the study, linear regression models were developed, and these models proved that direct work is not related to productivity, contrary to previous studies. This conclusion is based on the following three assumptions (Thomas et al., 1990):

- By reducing the wait time, the direct work time is increased.
- By increasing the direct work time, the productivity is improved.
- If the two assumptions stated above are true, reducing wait time leads to improved productivity.

Each assumption was tested, and the model statistics showed very poor correlations and predictive capabilities between direct work and productivity. The study concluded that work sampling studies show how busy trades are, and the results cannot be used to predict labor productivity or to estimate the number of work hours that is wasted. This result is contrary to previously published articles that suggest that labor productivity is related to work sampling.

A subsequent study of the relationship between labor productivity and work sampling by Thomas (1991), on reviewing the work done by Liou and Borcherding (1986), observed that rather than correlate monthly unit rates with work sampling point estimates, Liou and Borcherding (1986) correlated cumulative unit rates to work sampling data. This type of correlation is incorrect because, while a typical work sampling study spans two weeks, the unit rate may span three to five years. Thomas et al. (1984) used a seven-day moving average data to develop a mathematical relationship between direct work and performance. Although the derived relationship had a high correlation, the standard error of the estimate was not reported. Thomas (1991) re-derived the relationship using un-averaged data. The results obtained indicated that the variable direct work is a random variable and the relationship derived by Thomas et al. (1984) suffered from a narrow definition of direct work, the measurement of crew output by concentrating on only certain crews, and the moving average data.

An understanding of the relationship between the manning levels of projects and the productivity of trades can aid construction project managers in the area of project planning, scheduling and management. Jansma (1988) studied the relationship that exists between project manning levels and trade productivity for a nuclear power construction plant. However, no attempt was made to estimate the industry optimum manning level.

Jansma (1998) stated that the peak manning level could only be determined on a project by project basis by comparing the costs associated with a longer schedule duration and the costs due to productivity losses. In order to determine the extent of overmanning of a construction activity and to minimize productivity losses, it is necessary to establish a peak manning level. The factors affecting construction trade productivity were grouped under five main categories of unproductive time, namely: waiting or idle, traveling, working slowly, doing ineffective work, and doing rework. The main causes of loss of productivity as they relate to the five main categories are listed in the study in the form of an influence diagram. It may not be straightforward to relate a factor to a category because of the inter-relationships that exist among the factors. Therefore, a factor may be identified with more than one category.

According to Jansma (1988), the factors include: "overtime, time of day and day of week, remote location, outdated equipment, unclear technical information, adverse weather, fatigue, low craftsmen skills, pacing, low morale and no motivation, lack of visible work, negative labor influences, lack of respect, poor site access, lack of eating or toilet facilities, pay inequalities, lack of communication, protesters at the site, public opinion, workforce observation and measurement, poor quality craftsmanship, damage, engineering errors, poor drawings, scope and design changes, conservative design, alcohol and drugs, poor lighting and poor ventilation, accelerated schedule, cumbersome procedures, slow drawing revision and distribution, engineering errors and poor drawings, paperwork, survey alignment, elevation, and markings, unclear, poorly marked walkways, housekeeping, lack of pre-planning, logistics of tools and materials, absenteeism turnover, poor quality of supervision, inexperienced quality control inspectors, late quality control inspectors, regulatory changes, cumbersome procedures, late starts and early quits, inadequate consumables, tool repair, crew coordination, unbalanced crews, overcrowding, materials, tools, and equipment, accidents, poor safety, shift coordination, mobilization and re-mobilization, contract coordination, jurisdictional disputes, strikes, temporary installation, quality control hold points, start, stop, move, and restart, lack of engineering information, lack of communication, phase of the project, joint occupancy, work sequencing, make-work, restrictive work practice and featherbedding".

These factors make it difficult to accurately measure craft productivity. This is because the factors exert many influences on one another and on productivity. Jansma (1988) used multiple regression analysis to account for the numerous factors that affect productivity, with the exception of scheduled acceleration. The multiple regression analysis was also used to control for project specific characteristics. The study concluded that the results of the regression analysis carried out in the study may be applicable to large industrial construction projects.

Borcherding et al. (1979) listed materials availability, tool availability, work redone, overcrowded work areas and delays due to interference with other crews, and, inspection delays, as the major factors influencing craftsman productivity. Maloney (1983) listed the design of the construction facility, management of the construction firm, government regulation, and, labor, as the major factors that affect construction labor productivity.

Borcherding and Alarcon (1991) classified productivity factors under the following groups:

- **Factors associated with scheduled acceleration:** These include materials shortage, tools and equipment shortage, late inspection, increased craft population overcrowding, competition for facilities, equipment, and space; shortage of skilled labor, and, scheduled overtime.
- **Factors associated with poor coordination:** These include stacking of trades, congestion, inability to locate tools and materials, damage to other trades' work, and, the presence of additional safety hazards.
- **Factors associated with changes:** These include re-assignment of manpower, engineering errors and ommisions, inaccurate drawings and unclear technical instructions.
- **Factors associated with resources and site management:** These include site conditions and organization, materials and tools availability, limited materials handling space, access to the site, interferences, poor lighting and housekeeping, size and dispersion of tasks, poor methods and equipment, poor management of labor, and, crew size.
- **Factors associated with management characteristics:** These include management control and dilution of supervision.
- **Factors associated with project characteristics:** These include project size, work force size, fast-track construction, and sub-contracting.
- **Factor associated with labor and morale:** These include poor training, low payment, and scarce labor, quality control and quality assurance practices, non-

availability of inspectors, craft absenteeism and turnover, long periods of overtime, morale and attitude, wages, and incentives.

- **Factors associated with project location and external conditions:** These include economical activity, availability of skilled labor, commuting time, support community size, and, adverse weather.

They observed that previous attempts to evaluate the complex interactions among the factors affecting productivity have been concentrated on measuring the effect of one factor on productivity while disregarding the effects of other factors on productivity. They also mentioned that no standards exist for identifying, categorizing, or measuring productivity factors. Although Horner et al. (1987), Thomas and Yiakoumis (1987), and, Tucker et al (1986), tried to solve this problem, no acceptable standards have been produced.

Tucker et al. (1999) in their review of the factors affecting construction labor productivity, identified project uniqueness, technology, management, labor organization, real wage trends, and, construction training, as the factors affecting productivity. Borcherding (1976) stated that very large construction projects, predominantly industrial construction projects, experience decreasing productivities, due mainly to labor and construction time and costs. The following factors were stated as having adverse effects on the productivities of large projects:

- Effects of union attitudes
- Effects of workman selection practices
- Effects of workman motivation
- Effects of inflexible bureaucratic structures

- Effects of scheduled overtime
- Effects of change orders

The following recommendations were made to improve labor productivity:

- Organizational change
- Open shop challenge
- Motivation of workmen
- Overtime and change order strategies

The scope of the study by Borcherding (1976) is narrow because it only considered a limited number of factors having adverse effects on productivities. Future work along this line of study should consider several other factors that are known to affect the productivities of large construction projects.

Thomas and Oloufa (1995) quantified the effect of disruptions on labor productivity. They collected and analyzed data from 19 international construction sites on crew size, crew composition and absenteeism; quantity measurement, work content, site conditions, management practices, construction methods, project organization, and, project features. The construction sites studied include masonry, concrete formwork, and, structural steel erection; electrical conduit and cable installation; fabrication of precast concrete segments for a segmental bridge; and, caisson drilling. It was observed that for projects that have a low frequency of disruptions (i.e., reasonably good projects), the average weekly labor performance is reduced by about 9% for every disrupted workday, as indicated by the regression model that was generated.

Thomas and Daily (1983) stated that in order to achieve better construction productivity at the crew level, methods of measuring performance, other than unit productivity rate should be used. They illustrated the use of three methods of sampling activities, namely: work sampling, group timing technique, and, the five-minute rating, and concluded that the work sampling and group timing methods are better than the five-minute rating method.

Tucker et al. (1999) observed that productivity increased substantially in the construction industry of the United States between 1970 and 1998. They concluded that the two major reasons for the increase are depressed real wages and technological advances. They also concluded that based on the data used in the study, management practices were not a leading contributor to construction productivity changes over time. The conclusions were based on the results derived by monitoring and recording the labor cost and output productivity trends for tasks that represent different trades and differing levels of technological intensity within the building construction sector. A wide range of specific tasks was chosen and R.S. Means cost manuals were used to trace the benchmark values for these tasks. These benchmark values were found to give a good description of productivity trends. The researchers recommended that the construction industry needs to expand benchmarking efforts and additional research should be conducted to determine productivity trends. They observed that a major problem associated with conducting studies on productivity trends in the construction industry is the lack of data.

Hanna et al. (2002) developed benchmark productivity indicators for labor-intensive industries, specifically the mechanical and electrical industries. The benchmark productivity indicators include relationships developed using regression analysis, between the percent complete or percent time and cumulative work hours or cost. They also include project size and duration, project size and average manpower, project size and peak manpower, and, average manpower and peak manpower. Manpower loading charts and S-curves were used to compare actual project values with the benchmark values. The benchmark data can only be used for projects that vary in size between 2,000 and 100,000 work hours.

2.3 Productivity Models

Lu (2001) observed that it is difficult to create a conventional analytical model that incorporates the impacts of numerous factors on productivity. An estimator requires years of site experience and estimating practice in order to develop a model mentally. The decision making process attaches a lot of weight to the estimator's experience and the results may be inconsistent. Lu et al. (2000) noted that when the estimator determines industrial productivity, he or she usually over-estimate or under-estimate labor rates (manhours per unit quantity). This is done by using a difficulty multiplier to indicate overall favorable or unfavorable conditions. In order to determine the difficulty multiplier, the estimator only considers the factors that are believed to have great impact on job productivity as being significant.

For the purpose of this research, the existing labor productivity models are classified into two categories, namely: Neural Network Productivity Models, and Other Productivity Models. These models are reviewed in the following sub-sections.

2.3.1 Neural Network Productivity Models

Portas and AbouRizk (1997) developed a feed forward back propagation neural network model for estimating the productivity rates of formwork. The model generates a single point productivity rate that has an equal chance of occurring in a number of symmetrically and equally divided productivity zones that are generated by the model within the possible range of productivity rates. A score of 1.0, representing high certainty, is assigned to the output zone containing the predicted productivity rate, which coincides with the actual productivity rate. The two adjacent output zones are also assigned a score of 0.5 each while the other zones are assigned a score of zero, representing low certainty. The shortcoming of the model is that it requires substantial amounts of accurate data.

The productivity of two pipeline activities, namely: trenching and welding, were predicted using neural networks (McCabe et al., 1996). Using a feed forward back propagation neural network training algorithm, the effects of certain factors that affect trenching and welding activities on productivity were determined. For the trenching activity, historic data from two projects, on weather characteristics, equipment type, hours worked per day, and, the cumulative percentage of the trenching activity that is completed, are used to train the neural network. The output from the network was the daily productivity. For the welding activity, the neural network was trained with data on crew size, hours of work per day, air temperature, and, the cumulative percentage of the welding activity that is completed. The output from the network was the number of joints welded daily.

The network for the trenching activity predicted with a better accuracy than has ever been obtained but the training data was noisy. This was attributed to poor reporting of daily production and poor documentation of equipment failures. The variability in the training data was eliminated by training the network using five-day averages of the productivity rates. However, little improvement was achieved in the accuracy of the trained network. The network for the welding activity was used to determine the appropriate crew size and then trained using data on the input and output factors. A high level of accuracy was achieved by the network but the training data was noisy. This was traced to poor reporting of daily production. In order to overcome this problem, average project productivity rates were used. Adequate training of the network could not be done due to lack of sufficient data.

A feed forward back propagation neural network training algorithm was used by Wales and AbouRizk (1993) to determine the effects of three major environmental site factors, namely: daily average temperature, precipitation, and cumulative precipitation, on labor productivity. The temperature, precipitation and, cumulative precipitation data served as inputs to the algorithm while the output was a productivity factor. A productivity factor less than one indicates that the environmental conditions produce a productivity that is less than the average value, while a productivity factor greater than one indicates that the environmental conditions produce a productivity that is greater than average value.

Regression analysis was used to determine the effects of job complexity, crew size and composition, repetition, weather, equipment, and, motivation and fatigue, on concrete construction productivity (Sonmez, 1996). This was done with respect to four concrete construction tasks: concrete pouring, formwork, concrete finishing, and, granular filling. Neural network models were used to predict productivity rates for these activities. Feed forward back propagation neural network models were trained for each of the four tasks. Sonmez (1996) also attempted to predict productivity rates using regression analysis, and observed that the neural network models produce more accurate results. This is because neural networks have the ability to account for the effects of interactions among factors.

Portas (1996) studied the use of neural network to predict formwork productivity for two formwork activities: loose or non-repetitive walls and loose or non-repetitive slabs. Data were collected for project factors such as staff (administrative) characteristics, size, location, and, site characteristics, and activity factors such as crew characteristics, formwork design aspects, quantity, repetition, and, working conditions. A complex feed forward back propagation neural network structure comprising 40 inputs, 35 hidden nodes, and 14 output nodes was used to estimate productivity rates. Thirteen of the 14 output nodes composed a fuzzy output format while the last node composed a point prediction. During 80% of the time the model was tested, it proved to be accurate to within 15% of the actual productivity rates.

A two-stage neural network model for predicting the productivity of pipe installation activity was developed by Knowles (1997). A Linear Vector Quantization (LVQ) classification procedure was developed using the input factors. A predictive procedure was also developed. The LVQ classification procedure models the productivity output and estimates its range. This enables the proper feed forward back propagation network to be implemented. However, the technique accumulates errors if classification failure occurs.

Chao and Skibniewski (1994) provided an approach to estimating construction operation productivity using neural networks and observed data. This was done in order to perform complex mapping from environment and management conditions to operation productivity. The neural networks were trained with samples of observation data and the trained networks performed the required estimation. The methodology used includes identifying the factors affecting productivity, breaking down the productivity analysis into several simpler modules, and, defining the inputs and outputs of each module, as well as collecting real data representing the model. An example of excavation-hauling operation was given for which an automated experiment was used to simulate the hauling process.

Data were then collected and applied into two networks: excavator cycle-time estimate network and excavator efficiency network. In both cases, a neural network is trained and tested using 16 hidden nodes, a learning rate of 0.7, and, a momentum of 0.9. More testing was subsequently done to minimize the error generated. This study shows that neural networks can be used to model complex relationships between job conditions and the productivity of a construction operation with an acceptable level of accuracy in estimation. The authors recommended further model validation using real-job data.

Murtaza and Fisher (1994) examined the feasibility of using modularization instead of conventional methods in construction and observed that the feasibility is affected by the project specifics such as the organizations involved, social, legal, and, environmental conditions. A neural networks-based modularization approach that can handle inexact and incomplete inputs in order to obtain results, Neuromodex, was used in this study based on five major factors namely: plant location, labor considerations, environmental and organizational factors, plant characteristics, and, project risks. A multi-layered, self-organizing neural network was designed and implemented for the purpose of performing the decision making or classification process for the construction modularization problem.

The multi-layered network consisted of two neural network paradigms which are based on unsupervised learning, namely, Kohonen's self-organizing feature maps and competitive learning. The input data vector consisted of up to 40 components, corresponding to problem attributes for decision making. The architecture of the network is parallel, multi-layered, self-organizing, and, hierarchichal. This network was developed in order to decrease system complexity, to increase classification accuracy, to reduce learning and recall times, and, to achieve a high degree of robustness and fault tolerance. A self-organizing feature map (unsupervised learning), was used to train each Kohonen layer. Forty cases were run several hundred times while the learning rate was continuously reduced until the connection weights stabilized. Three comparison tests were carried out on the system in order to validate it after completion of the network training process. Statistical tests were carried out to validate the system and the tests' results showed that the probability distributions of the actual decisions and the neural network decisions were identical.

Lu et al. (2000) developed a probabilistic neural network classification model and studied its applicability to the construction industry. They developed a Probability Inference Neural Network (PINN) model that has a structure similar to the General Regression Neural Network/Probabilistic Neural Network (GRPNN/PNN) that was generated by Sprecht (1991), by combining statistical regression and a trained neural network. The GRPNN/PNN is a feed forward neural network model that is based on memory, and uses less time for network training. The PINN model combines LVQ with probabilistic inferencing, and it also combines classification and prediction networks. The PINN model was trained using 300 iterations with 101 records and tested with 18 records, and using Microsoft Access 97 and Visual Basic Applications. The 119 records were obtained from the historical productivity for three piping activities, namely pipe installation, pipe welding, and pipe hydro-testing, and from 66 projects. The structure of the PINN model consists of an input layer, a Kohonen layer, a Bayesian layer, and, an output layer. The Kohonen and Bayesian layers are the middle layers while the output is described by a probability density function (PDF).

For the pipe installation activity, 81 input nodes were used and the output range had 20 output zones, each containing 10 elements, and each having a width of 0.72. An average absolute error of 0.57 and a maximum absolute error of 2.02 were obtained for the mode value, when the model was tested, and on comparison with the actual output values obtained from the test data. An average absolute error of 0.75 and a maximum absolute error of 2.23 were obtained for the weighted average value, when the model was tested, and on comparison with the actual output values obtained from the test data.

2.3.2 Other Productivity Models

Sanvido (1988) proposed a conceptual model to describe how job site organization affects the productivity of a construction process. His study provided a conceptual framework under which the complexity of the problem of construction productivity can be understood. A causal model was proposed by Shaddad and Pilcher (1984). This model involved the development of a concept for the effects that different management sub-systems have on construction productivity.

Thomas et al. (1990) described three work-study-based productivity models. These are the delay, activity, and task models. The delay model relates delays and worker productivity. The activity model, which is based on the work-measurement method of activity sampling, measures the time engaged in various activities. The delay model is most applicable to closed systems that have few external influences. The task model is an extension of the delay and activity models and it introduces the concept that some activities are basic or necessary, some are additional but necessary, and others are not necessary. The three models indicate the time required to carry out various tasks that define the work method. However, the degree of their applicability to other activities is limited and the models have limited abilities to model other factors.

The Factor Model proposed by Thomas and Yiakoumis (1987) is a statistical model that accounts for the effect of different factors on construction productivity. Factors affecting productivity are divided into the following groups: manpower or labor, design features and work content, environment and site conditions, management practices and control, construction methods, and, project organizational structure. The factors are quantified using statistical analysis of crew productivity and factors that are related to it.

Maloney and Fillen (1985) developed the Expectancy Theory model which models individual performance. The model is based on the theory that if a worker has sufficient knowledge, skills, and, abilities; applies effort on a job; and, he or she receives adequate job directions and there are no job constraints, the worker's performance is expected to be high. The theory can also be applied to a group such as a construction crew. The members of a group are motivated to produce greater output if they know that they would receive better rewards.

Halligan et al. (1994) developed an Action-Response model for evaluating loss of productivity in construction. This model identifies the factors and processes that result in productivity loss. The factors and processes include the following:

- Owner actions
- Force majeure or third party actions
- Environmental conditions
- Contractor's initial actions
- Management-level constraints

- Crew-level constraints
- Consequences of management actions
- Contractor's management actions
- Crew responses

Using three case studies, they developed a model that graphically depicts how a variety of factors may interact to cause a loss of productivity; how a crew is influenced by these factors; and, how management of crews can mitigate, eliminate, initiate, or exacerbate any particular loss of productivity.

Unlike previously developed similar models that are general in nature, the Action-Response model can be applied to any particular project. This is very important because by applying the model on individual projects, the framework for evaluating the causes of productivity loss on the specific project is provided. This makes it possible for the project managers to take appropriate management actions to reduce or eliminate the occurrence of a loss of productivity. If the cause of the loss of productivity is unknown, any remedial actions taken may be ineffective or may worsen the situation.

In a situation in which a loss cannot be eliminated, the model facilitates the identification of the party responsible for the loss in productivity, by first facilitating an understanding of the cause of the loss. This party will then have to bear the cost of the loss. It recognizes the importance of focusing on the crew in any discussion of productivity, and it indicates the extent to which productivity loss at the crew level may be eliminated from initiating events. The model also shows the contractor's active role in influencing productivity through management decisions, and it clearly illustrates the two ways in which a contractor becomes aware of the need for management decisions: either specifically in response to constraints resulting from external conditions or in response to an observed loss of productivity at the crew level. The model shows how productivity can go into a downward spiral if inappropriate management actions are taken. The model provides a practical tool for evaluating the loss of productivity that can accompany unanticipated conditions in construction. It takes into account the complex nature of interactions or non-interactions of factors affecting productivity.

An additive linear regression model that takes into consideration factors that are not previously accounted for by existing models in forecasting labor productivity rates, such as weather and changing work requirements, was developed by Sanders and Thomas (1993). The model is represented mathematically as follows:

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

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

The model evaluates the combined effects of factors on the labor productivity rate of masonry construction. The model is easily implemented in a database or spreadsheet program and it can be used to forecast daily labor productivity rates.

Based on a historical data search of masonry projects between 1984 and 1986, Sanders and Thomas (1991) identified six factors, namely, work type, building elements, construction method, design requirement, weather zone, and, crew size, as the factors that have the greatest effects on masonry labor productivity. After determining a standard condition for each factor, the coefficients of impact of each factor on productivity rate was evaluated using the historical data and subsequently compared, in the form of a ratio, to the range of productivity values for the standard condition.

Based on the research focus of Sanders and Thomas (1993), Thomas and Sakarcan (1994) developed a factor model that recognizes that labor productivity predictably varies with time. They stated that two classes of factors affect labor productivity, namely, organizational and executional continuities. Organizational continuity represents the work content and physical components of the work, and these factors affect masonry productivity by as much as 15%. Executional continuity includes the work environment, and organization and management factors. These factors affect masonry productivity by as much as 25%. The factor model concentrates on only organizational continuity because the factors in this class, unlike those in executional continuity, are predictable. In order to achieve accurate predictions, the productivity rates predicted by the model must be factored based on the productivity rates obtained during the first few days after the commencement of construction activities. The factor model, which is also based on the results of a two-year historical study, is expressed mathematically as shown below:

$$E_t = I_s + \sum_{i=1}^{m} a_i x_i + \sum_{j=1}^{n} f(y)_j, \tag{2-3}$$

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 (present = 1, absent = 0)

m = Number of variables in the problem

$\sum_{j=1}^{n} f(y)_j$ = Submodels effect (e.g., the effect of crew size)

A similar factor model, which models crew-level productivity, had earlier been developed by Thomas and Yiakoumis (1987). The model uses statistical analysis to quantify factors and it is represented mathematically as:

$$AUR_t = IUR(q) + \sum_{i=1}^{m} a_i x_i + \sum_{j=1}^{n} f(y)_j, \tag{2-4}$$

where

AUR = The actual or predicted crew productivity for time period t

IUR = The ideal productivity for a wide range of classifications of work performed under standard conditions

q = Number of quantities installed

a_i = A constant representing the change in productivity caused by factor i

x_i = A variable whose value is either zero or one, and which denotes the presence of the factor i

$f(y)_j$ = Submodel j

y = The factors in submodel j

IUR is a function of the number of quantities installed q. The factors can be expressed as binary integer (that is, with a value of zero or one), or continuous variables. The submodels consist of integer and continuous variable factors and they describe factors such as weather, crew size, and, absenteeism. Unlike work study models, the factor model determines productivity as a function of output and not as a function of time. The model considers the crew and not the individual members of the crew as the basic unit of work and it comprises the major factors that affect productivity. It is flexible because it allows factors to be added or removed from it easily. The model can also be validated easily using statistical techniques, such as regression. The model can be validated using data that are measured daily, such as the daily data including the productivity of the crew (Horner et al., 1989).

Hendrickson et al. (1987) used expert system knowledge to develop MASON, a two-stage expert system whose function is to estimate activity durations for masonry construction. They estimated the maximum expected productivity rate and then adjusted the rate for job and site characteristics, based on the knowledge acquired from interviewing a professional mason and his supporting laborer. An expert system for predicting the production rates for concrete pouring was developed by Christian and Hachey (1995). The expert system is based on the knowledge obtained from concrete experts and from data collected on seven construction sites where concrete pouring activities were observed. The expert system is user-friendly, and the user is allowed to query the expert system for an estimate by asking questions to which answers are provided by the system. The two expert systems described above estimate productivity based on rules that have been previously defined by experts. This may introduce inconsistency into the system since rule generation by the experts is subjective. Furthermore, the expert systems cannot evaluate the effects of changing job conditions on productivity.

Herbsman and Ellis (1990) proposed a model based on statistical analysis to relate certain identified factors affecting construction productivity to productivity. The model was developed in order to predict highly accurate estimates of unit productivity rates on construction projects. Statistical models that evaluate the effects of weather on productivity were developed by Yiakoumis (1986) and Thomas (1987). Three building project activities, namely, masonry construction, structural steel erection, and, formwork erection, were chosen for the study. Hancher and Abd-Elkhalek (1998) used a hot-weather productivity model to generate a group of productivity curves. The productivity curves were validated using questionnaires that were completed by contractors in warm weather areas. The equations of the curves can be used to determine productivity for construction processes in different temperatures.

An expert-simulation model that simulates the expected occurrence of productivity factors, and analyzes and quantifies their combined effects on a productivity rate was developed by Boussabaine and Duff (1996). The model is based on rules set by experts and the prototype system is very specific; it only applies to reinforced concrete buildings that are not more than five storeys tall.

2.3.3 Discussion of Previous Productivity Models

Some models, such as the Mansonry Productivity Forecasting Model and the Factor Model are simply rigid, and therefore cannot be applied beyond the project on which the model is based (Knowles, 1997). The structure and rules of the models are only applicable to the construction activity and to the factors for which the models are constructed. This makes it difficult to apply the models to other activities. The models developed in this study are more flexible because the factors in the model structures can easily be substituted with other factors and the same process of model building can then be carried out.

The inability of most models to predict productivity accurately arises from the various factors that affect the final results. Other reasons that limit the application of existing models include the quantification of input factors, limited number of inputs, and the effects of incomplete or inconsistent data. The present study overcomes the problem associated with having a multitude of factors by identifying all the factors that affect productivity, for which data are available, and then reducing the factors to a manageable number by correlation analysis, such that only the factors that are found to contribute significantly to the models are included in the process of model development. The problems of factor quantification, and incomplete or inconsistent data were solved through the use of fuzzy logic techniques, which are described in subsequent chapters of this research.

2.4 Use of Fuzzy Logic in Construction

Fuzzy logic is growing rapidly to become one of the most useful modeling techniques available in construction and other areas (Knight, 2001). Fuzzy logic and fuzzy set theory are applied to the data in order to account for the qualitative and quantitative factors that affect productivity. Fuzzy logic is a branch of artificial intelligence that provides a method of representing human language in mathematical form. It has the capability to generate solutions to problems through the use of subjective data. In this study, a fuzzy logic approach is developed, and it can be used by estimators to estimate industrial construction productivity when there is lack of sufficient data. This approach makes linguistic or qualitative assertions about the relationships between productivity and the factors affecting it.

Fuzzy logic is a technique that can be used to model systems in situations in which there is insufficient data (Mason and Kahn, 1997). The fuzzy approach is used to model several problems because it produces simple models in little time, and because of its easy and cheap implementation in a computer environment. Fuzzy logic provides a clear representation of the state of activities and events and it introduces fuzziness into systems which facilitates easy modeling with insufficient data. In fuzzy logic, a statement is true to various degrees, ranging from totally true to totally false. Elements or objects belong to a fuzzy set to different degrees, called grades of membership. The use of grades of membership in a fuzzy set facilitates the easy construction of expert systems.

Fuzzy techniques can be used to assess productivity factors in qualitative terms in order to capture and reduce the degree of subjectivity that may be present in the collected data. The use of fuzzy techniques is especially appropriate in construction since large data sizes are hard to collect. Membership functions and expert rules can be generated based on the collected data. The membership functions can assume shapes that are based on the frequency plots generated for the relevant data sets.

In order to apply fuzzy techniques on the input factors efficiently so as to develop fuzzy logic models, correlation and/or regression analysis is and/or sometimes used to determine the relationship of the input factors to the output factor. This is done to reduce the size of the rulebase since it increases exponentially with the number of input factors. The correlation and/or regression analysis determine(s) the factors that mostly affect the output factor. Fuzzy expert rules can be generated for the model based on the factors that are correlated to the output factor. These expert rules can relate input factors to the output factor.

Fayek and Sun (2001) developed a complex fuzzy expert system which models design project performance based on the techniques of fuzzy logic. Several factors that affect design project performance were identified and classified based on literature search and professional guidelines. A technique was generated for developing membership functions based on the data that was gathered through a mail out survey of actual completed design projects in the industrial construction sector in Alberta and British Columbia. An expert rule method was developed to relate the factors affecting design project performance in a logical manner. The fuzzy expert system was developed in the MATLAB Fuzzy Logic Toolbox (Mathworks, Inc., 1998), and the model was trained and validated using the collected data. The model does not account for the impact of context variables and the data set was small. This affected the performance of some of the model's membership functions and consequently, the numerical accuracy of the model. However, the model achieved a high linguistic accuracy.

A flexible model that uses fuzzy logic techniques to assist decision makers in building and civil engineering companies in selecting the right margin or markup to add to the estimated project cost was developed by Fayek (1998). This model improves the quality of the decision making process employed in setting a margin, thereby giving contractors using the model an edge over the competition. The model implementation was done using a user-friendly prototype software called PRESTTO (PRoject EStimating and Tendering Tool). The model employs fuzzy binary relations to link data related to a company's objectives in bidding with data related to the factors that affect the margin size with which the company chooses to bid. The relationship between the company's objectives in bidding and the factors affecting margin sizes is generated by fuzzy composition operations. The model was validated using real-life bids whose data were collected from the Australian construction industry.

Knight (2001) developed a model for predicting design cost overruns and underruns on commercial building construction projects. The model, which is applicable during the design stage of commercial building projects, employs fuzzy binary relations to relate project characteristics with potential risk events, in order to predict a percentage cost overrun or underrun above or below the estimated fee respectively. The data used in developing the model were collected by interviewing the project managers of a local consulting engineering firm in Edmonton, Alberta. Two types of interview questionnaires were used to obtain the data. The first questionnaire was used to obtain expert opinions on the standard strengths to be used in the model. The second questionnaire was used to collect data that were used in testing the developed model. The application of fuzzy logic in building the model facilitated the easy description of input and output data in subjective terms. However, only a limited number of project characteristics and risk events were considered in the study. Furthermore, the standard strengths used in the model require more refinement and the project ratings should be evaluated on the same scale.

Cost estimating relationships were used by Mason and Kahn (1997), to describe the process of estimating construction excavation costs, in a situation where there is insufficient data. The process of model building involves:

- Defining the fuzzy sets that describe the cost drivers.
- Defining the fuzzy sets that describe the excavation costs.
- Defining and constructing the membership functions and rules for the expert system.
- Applying the inferencing procedure to estimate costs.

The advantage of applying fuzzy logic in estimating cost is that linguistic or qualitative inferences about the relationships between costs and the project factors that affect costs can be made, when there are insufficient data. However, it is difficult to predict the cost surface that will be obtained when there are more than two input factors involved.

Kangari and Riggs (1989) proposed a model for evaluating construction risks using a linguistic approach. The model employs the extension principle for construction risk analysis in a situation in which numerical and detailed information are not available. A problem that a user of this model faces is how to assign realistic membership values of a fuzzy set to represent a linguistic variable. The present research overcame this problem by eliciting expert opinions on what can be considered as realistic membership values. This was done by using structured questionnaires. The effects of varying the membership values of fuzzy sets may be determined by doing a sensitivity analysis.

2.5 Methods of Developing Membership Functions and Expert Rules

Several methods exist in literature for developing membership functions. However, very few methods have been used to build fuzzy expert rules. The existing techniques of developing membership functions and expert rules are reviewed in this section.

According to Musilek (2001), the horizontal approach of developing membership functions involves arbitrarily choosing the shape of the membership functions and asking experts to assign values to elements in the universal set, U, based on the linguistic concepts specified for the membership functions. A membership function plot is then constructed based on the ratio of the number of positive responses to the total number of responses. The vertical approach of constructing membership functions involves asking experts to identify alpha cuts, which are intervals of values that fit a concept with a specific level of confidence associated with them, and which are used to develop fuzzy sets. The horizontal and vertical approaches are easy to use and are easily adapted for constructing membership functions for isolated experiments dealing with single elements of the universal set. In order to use these techniques, numerous expert responses are required.

Bobrowicz et al. (1990) proposed a method of building membership functions, using a semantic definition module, which enables the construction of membership functions of three dependent linguistic descriptors, for example, low, normal, and high, which are defined on the same universe of discourse, U. The method uses fuzzy set theory to develop membership functions that represent the opinion of experts. The membership in a set U is defined by the grades of membership whose values range between 0 and 1 and there is a gradual transition from membership to non-membership. It is possible to compare a fuzzy descriptor, A, to a fuzzy set and in order to assign meaning to the fuzzy descriptor, a membership function μ_A, must be defined on the universe of discourse U. The parameters of the membership functions are determined from the knowledge about semantic links joining the three fuzzy descriptors that are to be represented on the same universe of discourse, and from the expert knowledge representing the meaning the experts assign to the fuzzy descriptors. In order to determine the membership functions that best represent the fuzzy descriptors, numerical parameters that describe the membership functions have to be determined. The determination of the parameters is done by calculations that are based on the knowledge of the experts and by successive parameter approximations within the boundaries of the semantic links.

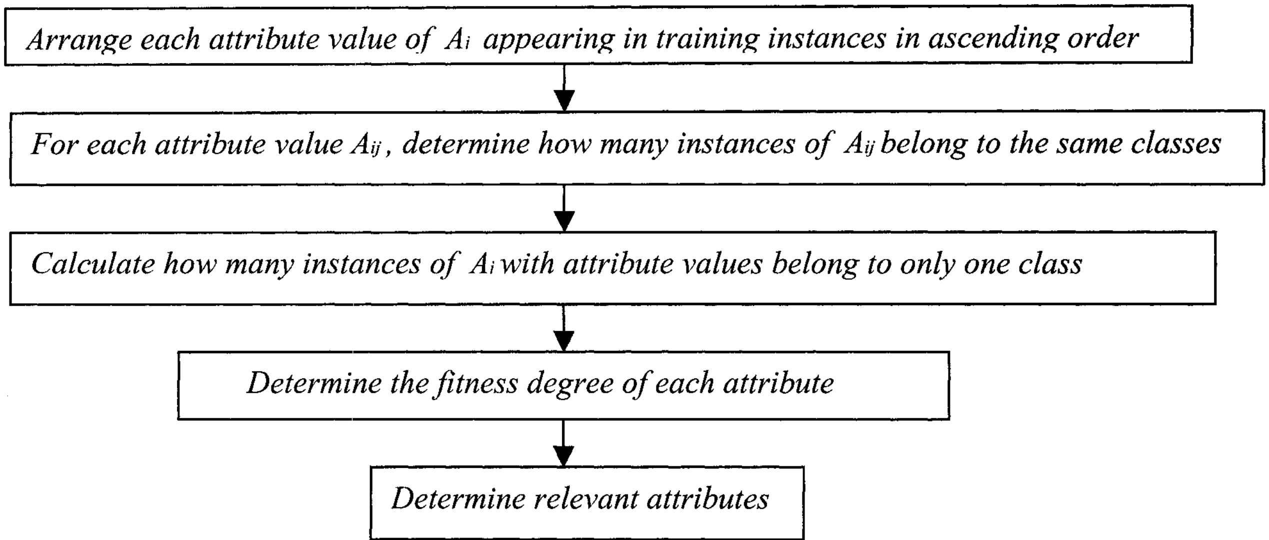
Civanlar and Trussel (1986) presented a technique for developing membership functions from probability density function (PDF). The PDF is generated from a histogram which has been constructed based on collected data. This technique of generating membership functions require the use of large data sets and a high frequency of responses from experts to questionnaires. Therefore, the technique could not be used in the present study.

Hong and Chen (1999) used a training data set to develop membership functions and fuzzy If-Then rules. This was done by determining the attributes that are important and using these attributes to develop preliminary membership functions. The attributes and preliminary membership functions are then used in a decision table to generate final fuzzy if-then rules and membership functions. The learning algorithm, proposed for automatically inducing membership functions and fuzzy rules from training instances, is illustrated below:

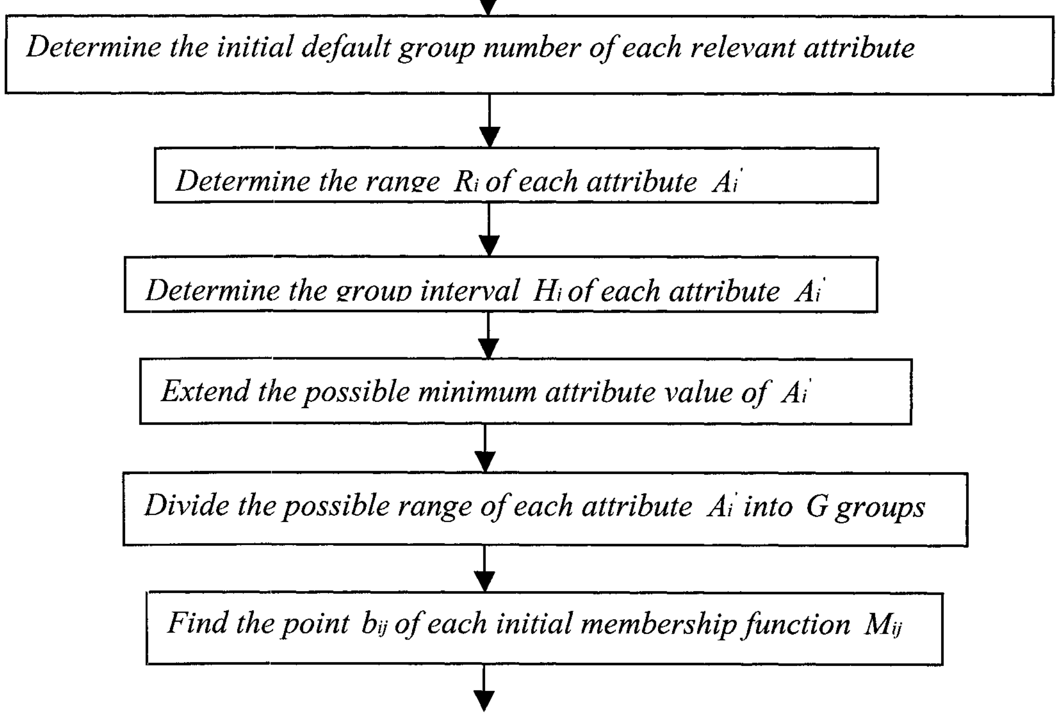
1. Find relevant attributes
2. Build initial membership functions
3. Derive decision rules

The architecture of the learning algorithm is shown in Figure 2-1:

Part 1: Find Relevant Attributes



Part 2: Build Initial Membership Functions



Part 3:Derive Decision Rules

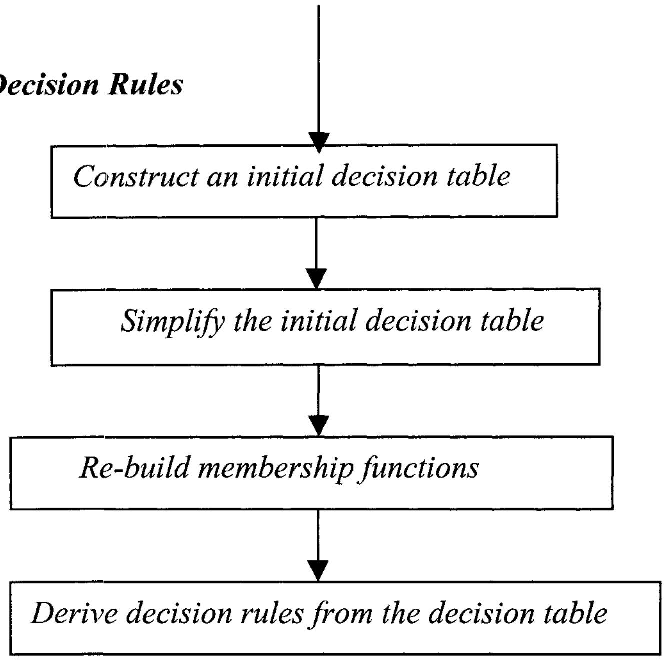


Figure 2-1: Learning Algorithm for Developing Membership Functions and Fuzzy Rules (Hong and Chen, 1999).

The algorithm is useful when developing membership functions and when faced with uncertainty. However, interactions between attributes reduce the accuracy of the learning algorithm.

Mabuchi (1997) constructed membership functions for attributes in a universal set U, by finding a membership grade of a particular element, x, associated with an attribute of the domain. Membership grade values are determined through the knowledge of a person, facts and reasons, or the knowledge of many persons. In the present study, membership grade values were determined through the knowledge of many persons. This was done by using structured questionnaires to elicit information on membership values for membership functions of factors from industry experts.

The pairwise comparison method involves the development of membership functions by comparing the individual objects, in pairs, in the universal set, within the context of the membership values, which are organized as a reciprocal matrix (Musilek, 2001).

The method of determining membership functions as a problem of parametric optimization uses procedures such as the mean squared errors to estimate the vector, *p*, of the parameters of a membership function (Pedrycz and Gomide, 1998). This technique is based on the availability of experimental data:

$$(X_K, M(X_K)), K = 1,2,\ldots, N$$

Where X_k and $M(X_k)$ denote the k^{th} values of an ordered pair of element and membership value, respectively, and X is an element of the universal set, U. The method determines the optimum values given the parametized membership function $A(X, p)$ in order to fit the experimental data:

$$\min \sum_{K=1}^{N} (M(X_K) - A(X_K, p))^2$$

Chen and Otto (1995) used interpolation and measurement theory to construct membership functions. This was done by fitting a membership function to a finite number of known membership values. In order to specify a complete membership function, membership values are determined at a finite subset of a set of points and constrained interpolation is smoothly applied on the remaining part of the set to determine the remaining membership values. This technique does not require a lot of data. However, the problem associated with the technique is that the x-axis of the membership function must have a limit.

Sun (2000) developed a technique for generating membership functions from the available data set. She divided the data set into training and testing sets and used the training set to construct membership functions based on the frequency of responses to questions by industry experts in Alberta and British Columbia. The assumption behind using the frequency of responses is that the frequency of responses can reasonably approximate membership values of a given fuzzy set (Li and Yen, 1995).

Membership functions can be developed by using fuzzy clustering technique (Pedrycz and Gomide, 1998). This technique involves segregating the data into clusters and interpreting the extent to which the data points belong to the clusters as membership values. According to Musilek (2001), given an experimental data set

$X_{k}, K = 1,2,\ldots, N$

Data points can be grouped or clusterered into "c" categories of fuzzy sets

$A_{i}, i = 1,2,\ldots\ldots, c$

The fuzzy set is derived through the process of optimization. The fuzzy set A_i can be obtained by finding a solution to the following optimization problem:

$$\min_{A} Q$$

subject to:

$$\sum_{i=1}^{c} A_i(x) = 1$$

Krishnapuram (1994) used the possibilistic clustering technique to develop membership functions. He demonstrated how to use the calculated distances between clusters to determine the parameters that approximate the shape of membership functions that can be derived from the clusters. The clusters are naturally formed through the attraction of similar prototypes and the number of clusters involved are easily determined.

Runkler and Bezdek (1999) developed a method to generate parameters of piecewise quadratic membership functions, by determining the parameters that can be used to approximately calculate the left hand side parameters and the right hand side parameters of the membership functions. They observed that if the center and directions of clusters could be precisely determined, membership functions could be precisely generated from the clusters.

Yager and Filev (1994) used a mountain clustering technique to determine the structure and preliminary parameters of the rule base of fuzzy expert system models. This technique gives a clear picture of input regions where there is insufficient data and it facilitates the use of multiple rules in a given region. This technique could not be used in this study because of its complex nature.

Sun (2000) developed a technique for generating fuzzy rules from the available data set. She divided the data set into training and testing sets and used the training set to elicit linguistic relationships while maintaining a complete and consistent rulebase. The magnitudes and directions of correlation among the input and output variables were used to determine the nature of the rules. The rules derived were tested using the test data.

Araki et al. (1991) stated that fuzzy rules could be generated by determining fuzzy partitions and parameters of a model and by adjusting the parameters and the steps necessary to develop the rules, while keeping track of the inference error, and changes in it. The process of generating fuzzy rules is iterative and it involves increasing the number of membership functions in the fuzzy partition with the highest inference error. The process of generating rules involves determining the rule generating region, generating the membership function of the antecedent part, and generating real numbers of the consequent part. This technique has been used to study the ability of a moving robot to avoid obstacles. Its effectiveness in determining rules for construction data is yet to be proved.

None of the techniques of constructing membership functions and fuzzy rules that are described above could be used in the present study. The major reason for this inapplicability is the size of the available data set, which does not lend itself to these techniques. Most of the techniques of developing membership functions require a large data set, and, a high frequency of response to questionnaires, in order to be able to cluster the data and subsequently determine the parameters that approximate the shape of the membership functions, or train the data set and subsequently elicit membership values, based on frequencies of response, or, as may be approximated by a histogram or a PDF.

The existing techniques for constructing fuzzy rules also require extensive data sets to train data sets, or partition data sets, or cluster the data set so as to determine the structure and parameters of the rulebase.

2.6 Summary

Several models of labor productivity have been reviewed in this chapter. Only few of the previous research work have been in the area of industrial construction. Neural network models require a large data set for model training and testing, which is difficult and time-consuming to obtain in most construction applications. The data sets available for use in this study are small, therefore neural network models could not be used to achieve the modeling objectives. The other types of productivity model can accommodate only a few input variables. However, this research involves the development of many-inputs-productivity fuzzy expert system models. In order to use these fuzzy logic techniques in this study, many of the input variables available in the data sets would have to be eliminated. This was not done because of the belief that most of the factors are important, and, failure to use most of them in modeling productivity of construction activities would result in incomplete models being developed. A solution to this problem, which was applied in this study, is to simplify the models by reducing the input variables to obtain a subset of factors, all of which are important in determining the output factor. This also made it possible to develop manageable rulebases for the models.

3. Factors Affecting Industrial Construction Labor Productivity

3.1 Factors Affecting Industrial Construction Labor Productivity

Construction labor productivity, whether it is in the commercial, residential, or industrial sector, is a complex topic, and it is not straightforward to determine the effects of factors that affect it. Fayek and Knight (2000) observed that there are many factors affecting construction labor productivity and these factors include those affecting the productivity of the project and those affecting the productivity of the individual worker or crew. Every construction project is unique because it is affected differently by a combination of productivity factors. Factors affecting the productivity of the project include factors such as weather, landscape and physical location. It is important that the various factors affecting labor productivity are considered within the contexts in which they operate. This is because different factors, in different contexts, can combine to have different effects on productivity.

The productivity of projects is also affected by the availability, ability, and quality of skilled labor, availability and time of delivery of material, availability and level of technology employed in the project, breakdown or lack of equipment, and the nature of managerial direction. Worker motivation affects the productivity of the individual worker or crew and it depends on the level of planning, communication, work environment, discipline for poor performance or rewards for exemplary performance, overtime work, overstaffing, trade stacking, crowding on site, and other factors. Labor productivity is also affected by poor labor organization, lack of training, absenteeism, disruptions, and turnover. Job conditions such as poor planning, poor management or supervision, inadequate tools, and, equipment will increase both absenteeism and turnover.

Productivity is a complex topic and there are numerous factors that affect it. These factors affect different activities in different trades. Knowles (1997) stated that industrial construction involves the construction of piping systems, typically for oil and gas, petrochemical, mining, or other industrial-related fields. Industrial construction activities include rig pipe, rig equipment, weld pipe, bolt up, install cable trays, install basket trays, pull electrical cable, cut electrical cable, terminate electrical cable, install boiler, erect steel, construct and install scaffold, carpentary, and, install, repair, and maintain machinery. These varieties of activities are carried out by different trades namely: the pipefitters, electricians, boilermakers, steel workers, scaffolders and carpenters, and, millwrights, respectively (Fayek and Knight, 2000). The productivity of each activity is affected by a wide variety of factors.

Two pipefitting activities, namely rig pipe and weld pipe, were chosen for this study because data were collected on them in a case study carried out at a major industrial construction site in Alberta in 2001. One of the objectives of this study is to identify the various factors that affect the productivities of the chosen activities. The factors identified in this study were determined from existing literature, and from the data published in Fayek et al. (2002). Adequate identification of these input factors is very important because improper use or exclusion of certain factors may lead to inadequate modeling of the rig pipe and weld pipe productivities.

3.2 Classification of Variables and Factors

3.2.1 Type of factors

The major factors affecting construction labor productivity, as obtained from the data published in Fayek et al. (2002), were used in this study to model labor productivity. The factors considered in this study can be classified into context variables, input factors, and the output factor (productivity). The three categories of factors are described in the following sub-sections.

3.2.1.1 Context Variables

Context variables are fixed input factors whose values are constant and are used to categorize activities. They affect the shape and range of the membership function and are not used as input factors in the productivity model because their values are fixed. However, if these factors, which specify different conditions or contexts for membership functions change, the membership functions will also change. For example, in order to properly determine the membership functions for temperature different membership functions have to be constructed for different seasons and locations. Since context variables are usually fixed, they are used in this study to categorize activities, and therefore models. The total number of the context variables and input factors, for rig and weld pipe activities, are shown in Table 3-1 below.

The context variables that were identified for rig and weld pipe activities in this study, and their corresponding categories, are indicated in Tables 3-2 and 3-3 respectively below. These context variables were identified for activity-level and project-level factors. Activity-level context variables such as material type and weld type, affect the productivity of an activity, while project-level factors context variables, such as project location and contract type, affect the productivity of an entire project. Eleven context variables were identified for rig pipe while 14 context variables were identified for weld pipe. While activity-level and project-level context variables could be identified for weld pipe, only project-level context variables could be identified for the rig pipe activity because none of the activity-level input factors could be easily categorized based on its characteristics.

Table 3-1: Total Number of Factors and Variables for Rig and Weld Pipe Activities

Activity	Number of context variables	Number of input factors	Total number of factors and variables
Rig pipe	11	41	52
Weld pipe	14	43	57

Table 3-2: Project-Level Context Variables for Rig Pipe and Weld Pipe

Name of Context Variable	Category of Context Variable
Project location	Urban, rural
Province	e.g., Alberta, British Columbia, Saskatchewan
Year of construction	e.g., 2001, 2002
Client	e.g., Shell, Mobil-Exxon, Syncrude, Suncor
Contract type	Cost re-imbursable, lump sum, unit price, negotiated
Project definition	New construction, new construction with some upgrading, plant upgrade where a shutdown is required
Project type	e.g., refinery, pipeline, mining, water treatment plant
Union status	Union job, open-shop job
Project sector	Industrial, commercial, institutional, residential
Season	Summer, spring, winter, fall
Location of work scope	Confined, scattered

Table 3-3: Activity-Level Context Variables for Weld Pipe

Name of Context Variable	Category of Context Variable
Material type	Carbon steel, stainless steel, alloy
Weld type	Butt weld, socket weld, fillet weld
Filler material type	Tig, stick, flux core

Project-Level Context Variables for Rig Pipe and Weld Pipe:

- **Project Location:** This factor describes the location of the project. The location of the project may affect the skill level and morale of the worker, as well as the availability of resources necessary to carry out construction tasks. The weather conditions may also vary with location.
- **Province:** This factor is important because different provinces have different weather conditions and varying availability or supply of labor, and this may affect the productivity of the workers on a project. Furthermore, different provinces have different working conditions, attitudes, practices, and, regulations.
- **Year of Construction:** This factor addresses the differences in the times in which projects take place. Productivity may differ on a yearly basis if different years have different work ethics, regulations, and, standards. Furthermore, the supply of skilled workers may vary from year to year, and this is bound to affect labor productivity.
- **Client:** The productivity of workers may be affected by the policies, missions, and visions, of the client with regard to work quality, safety practices, and, work conditions such as working hours, work schedules, and workers' incentive or bonus system.

- **Contract Type:** The type of contract under which a project is being executed may determine the level of management's or outside interference, and this may influence construction productivity.
- **Project Definition:** This factor describes the nature of the project being undertaken. The nature of the project may affect construction productivity. For example, whether the project is a plant upgrade where a shutdown is required, a plant upgrade where no shut down is required, or the project is a new construction, may affect the productivity of the project.
- **Project Type:** This involves describing the type of the project a firm is currently undertaking. The project may fall into the oil and gas, petrochemical, mining, water treatment or other industrial-related fields. This may have a significant impact on construction productivity because different projects have different safety requirements, work hours, work conditions, or, other conditions.
- **Union Status:** Labor supply and job rules and regulations differ between union and non-union projects.
- **Project Sector:** Industrial construction projects differ from commercial and residential projects in terms of quality requirements, safety requirements, and, supply of labor.
- **Season:** The pace of rig pipe activities becomes reduced during harsh weather conditions, especially during the winter season. This has a negative effect on crew productivity.
- **Location of Work Scope:** This factor describes the crew arrangement within the project's workspace or site.

Activity-Level Context Variables for Weld Pipe:

- **Material Type:** This factor describes the type of pipe material to be welded. It may be carbon steel pipe, stainless steel pipe, or alloy pipe.
- **Weld Type:** This factor describes the type of welding used. It may be butt weld, socket weld, or, fillet weld.
- **Type of Filler Material:** This factor describes the type of filler material that is used in welding. The filler material type can be classified based on the welding process involved, such as, tig, stick, and flux core.

3.2.1.2 Input Factors

As stated in the previous section, the ability to properly model the chosen industrial construction activities depends on the proper identification of the factors that influence industrial construction productivity, as well as the proper use of input factors (Knowles, 1997). Depending on individual project circumstances, any particular factor may or may not result in a loss of productivity (Halligan et al., 1994). Unanticipated conditions on a construction project, such as adverse weather, scheduled overtime, and, material shortages, sometimes result in a significant loss of productivity. When such losses are observed, their magnitudes vary from project to project, from activity to activity, and, from crew to crew.

The focus of this research is on two major pipefitting activities, namely: rig pipe and weld pipe. These activities are typically two of the major cost items on an industrial construction project. The factors that affect industrial construction productivity for the two activities can be categorized as rig pipe productivity factors, and weld pipe productivity factors. These factors, their linguistic descriptors, and, the numerical scales of their membership functions, are shown in Tables 3-4 to 3-7. The factors are highly variable and their effects change from time to time and from context to context. Activity-level factors are factors that affect the productivity of an activity such as pipe diameter and crew ratio. Project-level factors are factors that affect the productivity of an entire project such as the extent of fast tracking and the criticality of schedule.

Table 3-4: Activity-Level Input Factors Influencing Productivity for Rig Pipe

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 1	Pipe length	small, average, large	Real numbers (feet)
Input 2	Pipe diameter	small, average, large	Real numbers (inches)
Input 3	Efficiency of rigging method	low, average, high	Percentage (%) of hand vs. crane rigging
Input 4	Crew ratio	small, average, large	Ratio of apprentices to journeymen
Input 5	Task crew size	small, average, large	Real numbers (numbers)
Input 6	Overall crew size	small, average, large	Real numbers (numbers)
Input 7	Elevation	small, average, large	Real numbers (feet)
Input 8	Complexity of shape of pipe	low, average, high	1-10 ratings
Input 9	Scaffold requirement	yes, no	0-1 ratings
Input 10	Impact of weather conditions	poor, fair, good	1-10 ratings
Input 11	Ground conditions	poor, fair, good	1-10 ratings
Input 12	Access to work area	poor, fair, good	1-10 ratings
Input 13	Crowding of work area	poor, fair, good	1-10 ratings
Input 14	Adequacy of site storage	poor, fair, good	1-10 ratings
Input 15	Sufficiency of number of crew members	low, medium, high	1-10 ratings
Input 16	Crew's skill level	low, medium, high	1-10 ratings
Input 17	Crew turnover	low, medium, high	1-10 ratings
Input 18	Average temperature	low, average, high	Real numbers (°C)
Input 19	Average windspeed	low, average, high	Real numbers (km/h)
Input 20	Average precipitation	low, average, high	Real numbers (mm)
Input 21	Average relative humidity	low, average, high	Percentage (%)
Input 22	Crew experience in terms of learning	low, average, high	Real numbers (total number months of crew working together)
Input 23	Crew experience in terms of seniority	low, average, high	Real numbers (total number of years of crew members working in the trade)
Input 24	Amount of rework	low, average, high	1-10 ratings
Input 25	Amount of change orders	low, average, high	1-10 ratings
Input 26	Drawings and specifications quality	poor, fair, good	1-10 ratings
Input 27	Extent and quality of training	low, average, high	1-10 ratings
Input 28	Extent and quality of supervision	low, average, high	1-10 ratings
Input 29	Number of disruptions per day	low, average, high	1-10 ratings
Input 30	Percentage overtime per week	low, average, high	Percentage (%)

Table 3-4: Activity-Level Input Factors Influencing Productivity for Rig Pipe (Continued)

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 31	Frequency and extent of material shortages	low, average, high	1-10 ratings
Input 32	Magnitude of organizational constraints	small, average, large	1-10 ratings
Input 33	Number of consecutive days worked	low, average, high	1-10 ratings
Input 34	Inspection requirements	detailed, average, tolerant	1-10 ratings
Input 35	Safety requirements	detailed, average, tolerant	1-10 ratings
Input 36	Quality requirements	detailed, average, tolerant	1-10 ratings
Input 37	Percentage of prefabricated or modularized work	low, average, high	Percentage (%)
Input 38	Equipment availability	poor, fair, good	1-10 ratings

Table 3-5: Project-Level Input Factors Influencing Productivity for Rig Pipe

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 39	Extent of fast tracking	Low, average, high	1-10 ratings
Input 40	Criticality of schedule	Low, average, high	1-10 ratings
Input 41	Tightness of budget	Low, average, high	1-10 ratings

Table 3-6: Activity-Level Input Factors Influencing Productivity for Weld Pipe

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 1	Pipe diameter	small, average, large	Real numbers (inches)
Input 2	Wall thickness or schedule	small, average, large	Real numbers (inches)
Input 3	Crew ratio	small, average, large	Ratio of apprentices to journeymen
Input 4	Task crew size	small, average, large	Real numbers (number)
Input 5	Overall crew size	small, average, large	Real numbers (number)
Input 6	Elevation	small, average, large	Real numbers (feet)
Input 7	Shelter requirement	yes, no	0-1 ratings
Input 8	Scaffold requirement	yes, no	0-1 ratings
Input 9	Purge requirement	yes, no	0-1 ratings
Input 10	Pre-heat requirement	yes, no	0-1 ratings
Input 11	Bevel dimension or joint configuration	small, average, large	1-10 ratings
Input 12	Impact of weather conditions	poor, fair, good	1-10 ratings
Input 13	Ground conditions	poor, fair, good	1-10 ratings
Input 14	Access to work area	poor, fair, good	1-10 ratings
Input 15	Crowding of work area	poor, fair, good	1-10 ratings
Input 16	Adequacy of site storage	low, medium, high	1-10 ratings
Input 17	Sufficiency of number of crew members	low, medium, high	1-10 ratings
Input 18	Crew's skill level	low, medium, high	1-10 ratings
Input 19	Crew turnover	low, medium, high	1-10 ratings
Input 20	Average temperature	low, average, high	Real numbers (°C)
Input 21	Average windspeed	low, average, high	Real numbers (km/h)
Input 22	Average precipitation	low, average, high	Real numbers (mm)
Input 23	Average relative humidity	low, average, high	Percentage (%)
Input 24	Crew experience in terms of learning	low, average, high	Real numbers (total number months of crew working together)
Input 25	Crew experience in terms of seniority	low, average, high	Real numbers (total number of years crew members have worked in the trade)
Input 26	Amount of rework	low, average, high	1-10 ratings
Input 27	Amount of change orders	low, average, high	1-10 ratings
Input 28	Drawings and specifications quality	poor, fair, good	1-10 ratings
Input 29	Extent and quality of training	low, average, high	1-10 ratings
Input 30	Extent and quality of supervision	low, average, high	1-10 ratings
Input 31	Number of disruptions per day	low, average, high	1-10 ratings

Table 3-6: Activity-Level Input Factors Influencing Productivity for Weld Pipe (Continued)

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 32	Percentage of overtime per week	low, average, high	1-10 ratings
Input 33	Frequency and extent of material shortages	low, average, high	1-10 ratings
Input 34	Magnitude of organizational constraints	small, average, large	1-10 ratings
Input 35	Number of consecutive days worked	low, average, high	1-10 ratings
Input 36	Inspection requirements	detailed, average, tolerant	1-10 ratings
Input 37	Safety requirements	detailed, average, tolerant	1-10 ratings
Input 38	Quality requirements	detailed, average, tolerant	1-10 ratings
Input 39	Percentage of prefabricated or modularized work	low, average, high	Percentage (%)
Input 40	Equipment availability	poor, fair, good	1-10 ratings

Table 3-7: Project-Level Input Factors Influencing Productivity for Weld Pipe

Factor Number	Name of Factor	Linguistic Descriptors	Numerical Scale
Input 41	Extent of fast tracking	Low, average, high	1-10 ratings
Input 42	Criticality of schedule	Low, average, high	1-10 ratings
Input 43	Tightness of budget	Low, average, high	1-10 ratings

The input factors that affect each of the pipefitting activities mentioned above are compiled for use in the proposed models. The data for each activity are converted into fuzzy data sets and membership functions are consequently generated based on the completed expert questionnaires that were filled by some industrial construction personnel. For each activity, each of the input factors is described using linguistic terms (e.g., low, medium, high) or using numerical ratings (e.g., from 1 to 10, for example, crew turnover may be assigned a rating of zero, five or ten). The models generated in this study can be used to predict activity productivities prior to the start of construction. This will involve a consideration of the factors that affect that activity. A detailed description of each activity, and the factors that affect the productivity of each activity considered in this study, are illustrated below:

- **Rig Pipe**: Rig pipe describes the process of installing a piping system within a construction plant site. Rig pipe involves preparing the pipe for rigging by tying it to the hook of a crane, signaling the crane operator, helping the crane operator to spot the final location of the pipe, and, rigging the pipe in place (Fayek et al., 2002). This type of rigging is called crane rigging. The activity may also be carried out without the use of the crane, in which case, it is called hand rigging. The activity is mainly performed by pipefitters, although in some cases, the welders on the pipefitting crew are involved. Both journeymen and apprentices can be involved in the rig pipe activity.

A comprehensive investigation of literature and the data published in Fayek et al. (2002), revealed 41 input factors for the rig pipe activity, which are described below. Some of these factors affect productivity at the activity level, while others affect productivity at the project level.

Activity-Level Input Factors:

- **Pipe Length:** The longer the pipe to be rigged, the more difficult is the rigging process, and consequently, the lower the productivity of the crew.
- **Pipe Diameter:** The larger the diameter of a pipe, the bigger is its size, and the more difficult it is to rig the pipe.
- **Efficiency of Rigging Method:** A rigging task that is carried out using a crane may be more effective than a rigging task that is carried out using hands.

- **Crew Ratio:** The composition of a crew may determine the crew's level of output. A crew that has a high ratio of inexperienced workers may not be as productive as a crew that has a high ratio of experienced workers.
- **Task Crew Size:** Construction productivity at the task level may be affected by the size of the crew unit carrying out the rigging task. Obtaining the optimum task crew size depends on the work quantity and work space requirements.
- **Overall Crew Size:** Construction productivity at the task level may be affected by overall crew sizes, especially during periods when some crew members may have to be moved from one task to another.
- **Elevation:** The higher the point of installation of a pipe, the more difficult is the rigging process, and therefore, the lower is the rigging crew's productivity.
- **Complexity of Shape of Pipe:** It may be easier to rig straight pipes than curved pipes, especially when the point of pipe installation is not easy to access.
- **Scaffold Requirement:** The quality of scaffold provided and the performance of the scaffolding team in quickly erecting the scaffold will either slow down or improve the performance of the rigging team if the use of scaffolds is required to carry out the rig pipe activity.
- **Impact of Weather Conditions:** The more severe the weather conditions are, the greater their impacts are on productivity.
- **Ground Conditions:** If ground conditions are bad, for example, wet and marshy, the mobility of the rigging crew may be reduced, and this may have a negative impact on productivity.

- **Access to Work Area:** The easier it is to access the area where pipes are to be installed, the easier is the rigging process, and the shorter the time that will be spent by the rigging crew on the activity. This will have a direct impact on the crew's productivity.
- **Crowding of Work Area:** If the work area is crowded with materials, equipment, tools, or, other trades, the rigging process may be more difficult to carry out, and the rigging crew may have to spend more time on the activity. This will have a direct impact on the crew's productivity.
- **Adequacy of Site Storage:** If adequate storage facilities are provided for materials on the site, the crowding of work area will be reduced and the access to work area will be improved. This will have a positive impact on crew productivity.
- **Sufficiency of Number of Crew Members:** If a crew is sufficiently staffed, as determined by the optimum crew size, the crew's productivity will be high.
- **Crew's Skill Level:** Crews having high skill levels tend to perform better than crews having low skill levels.
- **Crew Turnover:** Crews having low labor turnovers have high learning experiences and know the job better.
- **Average Temperature:** Variations in temperature may affect workers' performances. In this part of the world, workers tend to perform better when the temperature is moderately cold than when the temperature is hot.
- **Average Windspeed:** A rigging crew's productivity will be reduced in windy conditions. If the weather condition is too windy, the entire work may be disrupted or delayed for long periods.

- **Average Precipitation:** A rigging crew's productivity will be reduced in rainy conditions. If there is heavy rainfall, the entire work may be disrupted or delayed for long periods.
- **Average Relative Humidity:** Crew performance may be reduced if the relative humidity of the work environment is very high.
- **Crew Experience in terms of Learning:** The longer the time a worker spends on a particular type of activity, the greater will be his or her learning curve, and the greater will be his or her productivity.
- **Crew Experience in terms of Seniority:** The longer the time a worker spends in a particular trade, the greater will be his or her learning curve, and the greater will be his or her productivity.
- **Amount of Rework:** If rework is to be done by a crew, the morale of the crew may be negatively affected.
- **Amount of Change Orders:** Change orders may also affect workers' morale and consequently productivity, because additional time is required to carry out necessary job adjustments.
- **Drawings and Specifications Quality:** The quality of drawings and specifications will affect the time spent on activities and consequently, this will affect construction productivity.
- **Extent and Quality of Training:** Adequate and continuous exposure of workers to training will increase their skill levels and safety awareness levels. This will increase the productivity of the workers.

- **Extent and Quality of Supervision:** The quality of crew supervision has a significant impact on the crew's performance. Undue interference, untimely supervision, and lack of leadership qualities in the supervision, may affect the morale of the crew. This may reduce the productivity of the crew.
- **Number of Disruptions per Day:** Frequent disruptions caused by management interference, weather, and union disputes will reduce the time spent on activities by crews. This will have a negative impact on the crew's productivity.
- **Percentage of Overtime per Week:** This factor may positively or negatively affect the performance of a crew. A crew's productivity level may reduce if the workers believe that they will make more money while working at reduced levels of performance. A crew may not be keen on completing the activities assigned to it on time if it believes that the work can be completed during the overtime period. On the contrary, a crew may see overtime as a morale booster and this may enhance its productivity. Instead of increasing the crew size, project managers sometimes allow crews to work overtime in order to meet the date planned for the completion of the project. Overtime may also be allowed in order to remove undesirable float from a schedule. This facilitates the compression of the duration of activities. However, as the number of days of the week and the number of weeks during which overtime is allowed increase, the productivity of a crew decreases (RS Means, 2002).
- **Frequency and Extent of Material Shortages:** Improper or inadequate planning may result in delays due to non-arrival or late arrival of materials to the construction site. A rigging crew may be delayed or may have to be re-assigned to

another activity if rigging items do not arrive on the construction site on time. This may negatively affect the crew's productivity.

- **Magnitude of Organization Constraints:** The more organized the management team is, the better the quality of supervision, training, and resources, provided to the workers on the site.
- **Number of consecutive days worked:** This factor describes the number of consecutive days in the week during which a crew work without a break. This may have a positive effect on the productivity of the crew because of the learning effect it has on the crew.
- **Inspection Requirements:** The productivity of a project may be affected by the extent of the client's inspection requirements.
- **Safety Requirements:** The productivity of a project may be affected by the extent of the client's safety requirements.
- **Quality Requirements:** The productivity of a project may be affected by the extent of the client's quality requirements.
- **Percentage of Prefabricated or Modularized Work:** The higher the percentage of the prefabrication that is done in the shop, or modularized work that a crew does, the lower is the amount of physical exertion that is required. This should improve the crew's performance.
- **Equipment Availability:** The performance of a crew may be reduced if the equipment the crew requires to perform its tasks, such as the crane or manlift, is not available at the right time.

Project-Level Input Factors:

- **Extent of Fast Tracking:** This factor represents the amount of overlap that exists between the commencement of design and the commencement of construction. The greater the overlap, the greater the likelihood of delays and problems occurring due to incomplete design and specifications, which may adversely affect productivity.
- **Criticality of Schedule:** This factor describes the extent to which the job schedule is critical. A very critical job schedule will result in more job pressures and overtime, which may have a negative effect on productivity.
- **Tightness of Budget:** This factor describes the criticality and tightness of the budget on a project. A tight budget will result in more job pressures and less allowance for overtime, which may have a negative effect on productivity.

- **Weld Pipe:** Weld pipe describes the process of performing welding on a pipe section. It comprises pipefitting, which is usually carried out by a pipefitter or a welder who has pipefitting experience, and welding pipe, which is usually carried out by a journeyman welder (Fayek et al., 2002). Pipefitting is the process of joining different components of a piping system, such as pipe, elbow, or, flange, to form one pipe unit. Weld pipe is usually performed by two crew members, who work as a team by assisting each other in their respective roles. The welding process involves joining different pipe components by welding and it is always performed by a journeyman welder. The pipefitting process involves aligning the pipe components in order to prepare them for welding and it is usually carried out by a journeyman or apprentice pipefitter, who basically assists the welder in fitting the pipe under close supervision.

A comprehensive investigation of literature and the data published in Fayek et al. (2002), revealed 43 input factors for the weld pipe activity, which are described in below. Some of these factors affect productivity at the activity level, while the others affect productivity at the project level.

Activity-Level Input Factors:

- **Pipe Diameter:** A pipe with a large diameter takes more time to weld, than a pipe with a smaller diameter.
- **Pipe Thickness or Schedule:** A pipe with a greater wall thickness or schedule takes more time to weld, than a pipe with a smaller wall thickness or schedule.
- **Shelter Requirement:** The productivity of a welding crew will be enhanced if adequate shelter is provided. This is important since many welding procedures have to be carried out in an enclosed unit.
- **Scaffold Requirement:** The quality of scaffold provided and the performance of the scaffolding team in quickly erecting the scaffold will either slow down or improve the performance of the welding team.
- **Purge Requirement:** The welding team may spend more hours on the same task if purging is required.
- **Pre-heat Requirement:** The welding team may spend more hours on the same task if pre-heating is required.

- **Bevel Dimension or Joint Configuration:** The simpler the joint configuration, the greater the productivity of a welding crew, and vice versa.

The other activity-level input factors listed in Table 3-6 and the project-level input factors listed in Table 3-7, have the same descriptions as those of the rig pipe activity.

3.2.1.3 Output Factor

Defining the output factor, productivity is not a simple task. The definition of productivity depends on the perspective of the user of the productivity data (Thomas et al., 1990). Productivity can be defined in many ways. In the construction industry, productivity is usually taken to mean labor productivity. For the purpose of this study, productivity definition is based on the activity-oriented model unit rate definitions outlined in Thomas et al. (1990):

Labor productivity = Labor cost / Unit Quantity and,

Labor productivity = Manhours / Unit Quantity

In the definitions stated above, labor cost and manhours are the input parameters while the quantity of work done is the output parameter. The input parameter may be in dollars (that is, labor cost), or manhours, while the output quantity is measured in inches, feet, kilogram, or numbers, depending on the type of task carried out by the crew involved.

3.3 Structure, Description and Flowchart of the Models

The structure of the many-inputs-single-output models used to evaluate the impact of the input factors on construction productivity of rig pipe and weld pipe activities is shown in Figure 3-1. Three models were developed, one for rig pipe activity and the other two for weld pipe activities. This is because, while no context variable was used as part of the model development process for rig pipe activity, two context variables, namely: material type and weld type, were used in developing the models for the weld pipe activity. The weld pipe models predict productivity by the combination of different numbers of input factors under different contexts.

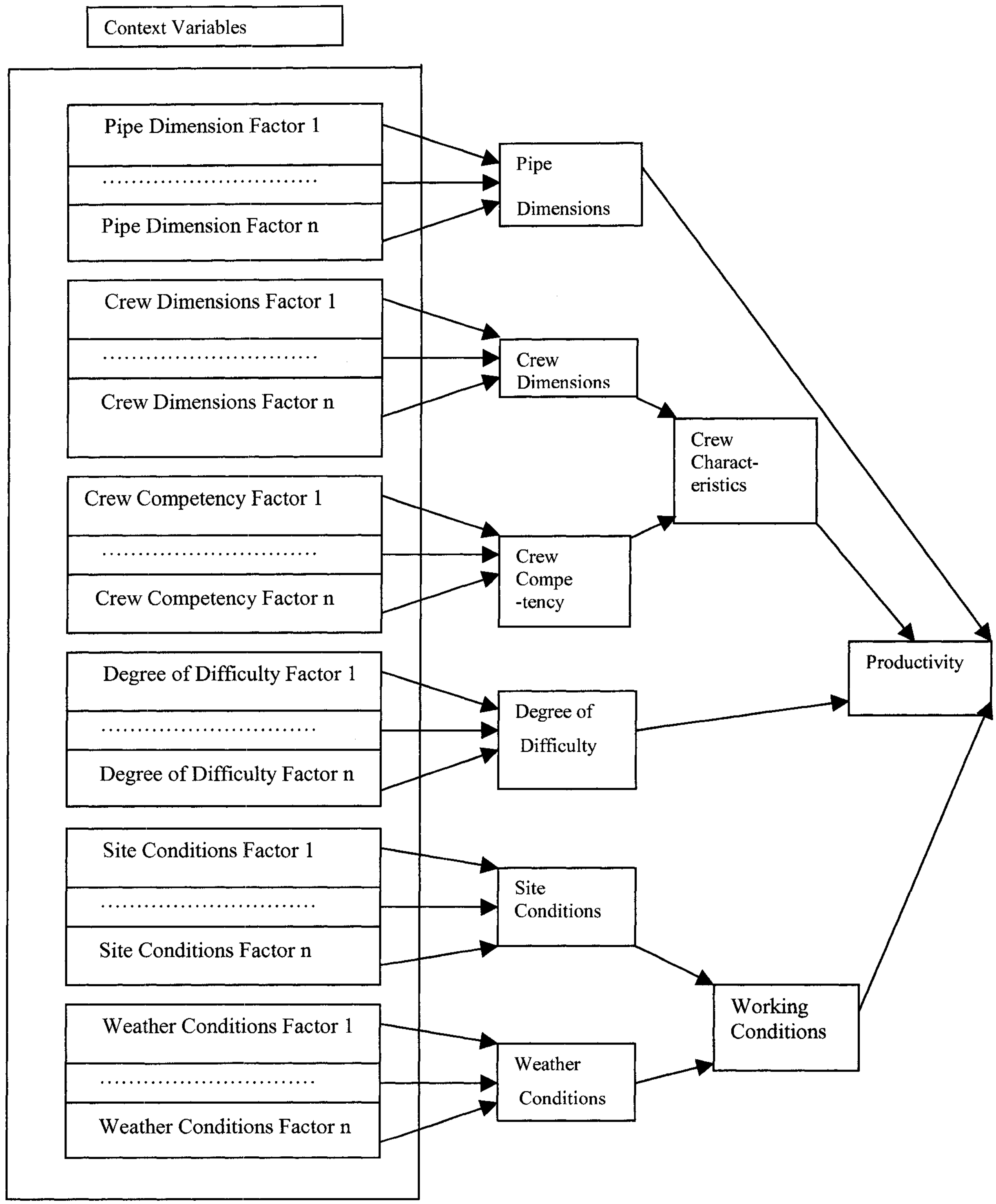


Figure 3-1: Structure of the Models for Predicting Productivity of Rig Pipe and Weld Pipe.

The rig pipe and weld pipe models are four-layered in structure. This is necessary because of the large number of input factors that were eventually used to test the models. The structure of each model was broken down into four layers in order to reduce the sizes of the rulebases to be developed for the models. If all the factors are included in a single-layer structure, this would result in a very large rulebase, which would be tedious and time consuming to develop. The first layer of each model consists of all 21 input factors that were used in each of the models. The second layer consists of six sub-models, namely, pipe dimensions, crew dimensions, crew competency, degree of difficulty, site conditions, and, weather conditions. These sub-models serve as input factors for the sub-models in the third layer. The 21 original inputs of each model were categorized within these second layer sub-models. The third layer consists of two additional sub-models, namely, crew characteristics and working conditions, which were used to categorize four of the sub-models in the second layer. The two sub-models in the third layer serve as input factors for the fourth layer, together with the two remaining sub-models in the second layer. The fourth layer consists of the output factor, that is, productivity. The components of the models are illustrated in tabulated form in Tables 3-8 and 3-9 below.

The basis of categorization throughout the models is the functions of the factors. For example, crew dimensions and crew competency sub-models were categorized under the crew characteristics sub-model because both sub-models deal with the crew-related input factors in the first layer. Some of the factors in the sub-models in the first layer are objective factors while others are subjective factors. All the factors in the sub-models in the second and third layers were made subjective because data were not collected for them by Fayek et al. (2002). In order to convert the subjective factors into objective ones during the model development process, numerical ratings on a scale of 1 to 10 were given to the linguistic variables (for example, poor, fair, and good) used to describe the factors in the sub-models.

Table 3-8: Rig Pipe Model Structure

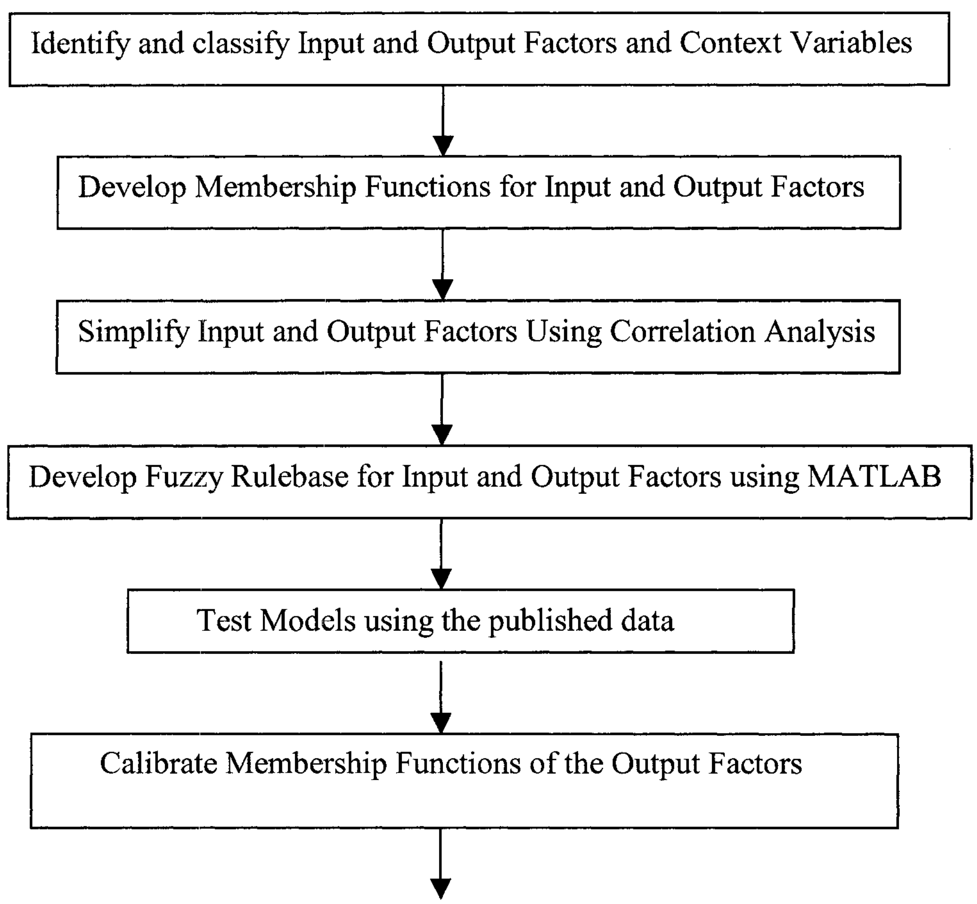
Factors in First Layer	Factors in Second Layer	Factors in Third Layer
Pipe length Pipe diameter	Pipe Dimensions	None
Crew ratio Task crew size Crew sufficiency Overall crew size	Crew Dimensions	Crew Characteristics
Skill level Crew turnover Crew experience in terms of learning Crew experience in terms of seniority Number of consecutive days	Crew Competency	
Elevation Complexity of shape of pipe	Degree of Difficulty	None
Ground conditions Access to work area Crowding of work area Adequacy of site storage	Site Conditions	Working Conditions
Impact of weather conditions Average temperature Average windspeed Average precipitation	Weather Conditions	

Table 3-9: Weld Pipe Models Structure

Factors in First Layer	Factors in Second Layer	Factors in Third Layer
Pipe diameter Wall thickness or schedule	Pipe Dimensions	None
Crew ratio Task crew size Crew sufficiency Overall crew size	Crew Dimensions	Crew Characteristics
Skill level Crew turnover Crew experience in terms of learning Crew experience in terms of seniority Number of consecutive days	Crew Competency	
Elevation Shelter requirement	Degree of Difficulty	None
Ground conditions Access to work area Crowding of work area Adequacy of site storage	Site Conditions	Working Conditions
Impact of weather conditions Average temperature Average windspeed Average precipitation	Weather Conditions	

The flowchart for developing the rig pipe and weld pipe models are illustrated in Figure 3-2 below. This flowchart describes the steps and methods that were used in order to build the models. The first step involves the identification of the context variables, input and output factors, and the classification of the input factors using the context variables as the basis for classification. The second step is the development of membership functions for the input and output factors, using the information obtained from experts, while the third step is the simplification of the models by using correlation analysis to reduce the number of factors to be used in the models to a manageable but significant number.

The fourth step involves developing fuzzy rulebases for the models in MATLAB using logical reasoning, while taking into consideration the directions and magnitudes of correlation between the factors. In the fifth step, the numerical and linguistic accuracies of the models were tested using the data published in Fayek et al. (2002), and, in the sixth step the membership functions of the output factor were calibrated by shifting the legs of the productivity membership functions in order to achieve higher accuracies. The seventh step involves re-testing the models after calibration using the published data, while the eight and last step involves the performance of sensitivity analysis on the models in order to improve their accuracies.



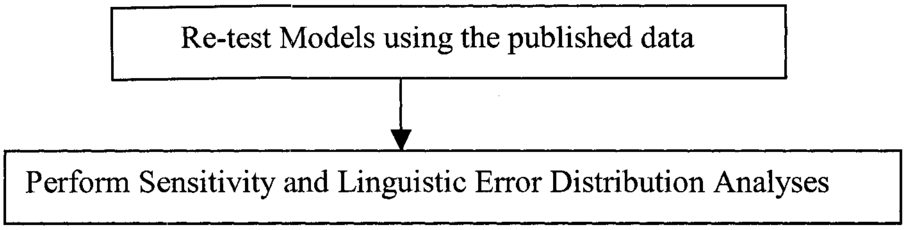


Figure 3-2: Steps in the Development of the Models Predicting Productivity for Rig Pipe and Weld Pipe.

3.4 Summary

This chapter describes the factors employed in the proposed fuzzy logic models, the structure of the models, and the steps taken in developing the models. The context variables and the factors affecting industrial construction productivity were identified for two pipefitting activities, namely: the rig pipe and weld pipe activities. The linguistic descriptors and numerical scales corresponding to each factor were also determined. The structure of the models developed in this study were described in this chapter and the basis for using this structure was also explained in detail. The steps and the methods used to develop the models were outlined in this chapter. The next section describes the methods that were used to simplify, develop, test, and calibrate the models in this study.

4. Development of Fuzzy Expert System

4.1 Introduction

This chapter describes the development of the fuzzy expert systems used to model the productivity prediction of rig pipe and weld pipe. It describes the development of membership functions, fuzzy rules, and, the fuzzy inference mechanisms for the rig pipe productivity model and the two weld pipe productivity models that were developed in this study. The chapter also covers the procedures used to test and calibrate the models, and the procedures used to perform sensitivity analysis on the models. Two other techniques, namely ANFIS and Neuroshell 2, that were explored in the process of model building, are also discussed in this chapter.

The major problem that was encountered in trying to develop the models in this study was the fact that there were not sufficient data sets with which to develop and validate membership functions, and with which to develop the fuzzy rules. The rig pipe data set had only 32 original data points while the weld pipe data set had 102 original data points. The number of data points for weld pipe was reduced when context variables were applied. While no context variable was applied to the rig pipe data, two context variables, namely material type and weld type, were applied to the weld pipe data. The material types that were used in the data categorization are carbon steel and alloy, while the weld type that was used in the categorization is butt weld. This is because on carrying out a statistical analysis of the weld pipe productivities for all the different context variable combinations, the combinations of carbon steel and butt weld and that of alloy and butt weld were found to have reasonably wide ranges of productivity and close median productivities. The average productivity of carbon steel and butt weld productivities is about 68% of the average productivities of alloy and butt weld.

Carbon steel and socket weld ranges of productivity and average productivity are also close to those of carbon steel and butt weld, and, alloy and butt weld. However, the carbon steel and socket weld data had to be discarded because of insufficient data points (only five data points). These explanations are illustrated in Table 4-1. The 102 weld data points were categorized on the basis of the combination of material type and weld type context variables. Eventually, two sets of weld pipe data were created, with one having 63 data points (for carbon steel and butt weld) and the other having 32 data points (for alloy and butt weld).

Table 4-1: Context Variable Statistics for Weld Pipe

Context Variable Combination	Range of Productivity (Manhours/Dia.-inch)	Median Productivity (Manhours/Dia.-inch)	Average Productivity (Manhours/Dia.-inch)
Carbon steel and Butt weld	0.25 - 4.00	1.20	1.35
Carbon steel and Socket weld	1.50 - 2.50	2.00	2.00
Alloy and Butt weld	0.56 - 6.67	1.67	1.99
Alloy and Socket weld	18.87 - 26.67	22.67	22.67

Another problem that was encountered was the large number of input factors that had to be considered in the productivity models. Twenty-one original input factors were considered in each of the three models. The selection of the 21 input factors was based on the input factors for which objective and subjective data were published in Fayek et al. (2002). At the early stage of model development, all the 21 factors were used to develop the fuzzy expert system. However, it was found that this is not a feasible procedure due to the problem of exponential growth of rules and consequently, generation of a very large rulebase. For example, if a rulebase is to be created for an expert system having 21 input factors, with each input factor having three membership functions, the number of rules that would have to be generated is 3^{21} or 1.05×10^{10} (i.e., approximately 10 billion rules). Attempts were made to overcome the rule growth problem by using ANFIS and Neuroshell 2 techniques to develop the models. However, these techniques gave results that were not satisfactory because they only work well with a small number of input and output factors, and a large data set. Furthermore, ANFIS may not provide a complete rulebase for model development.

Eventually, each model structure was readjusted to include sub-models. This was done in order to reduce the number of input factors that had to be considered in any rulebase and to solve the problem of growth of rules. The models were developed based on this new structure.

4.2 Data Extraction

The data used in this study are published in Fayek et al. (2002). The data were collected using productivity forms, work sampling, five-minute rating, and, interview questionnaires. For this study, the types of data required to model construction productivity are those pertaining to productivity input and output factors.

Prior to developing membership functions, the necessary data for all the input and output factors were extracted from the data set in Fayek et al. (2002). The data were extracted for each of the 21 input factors for all the days during which the chosen activities, that is rig pipe and weld pipe, were studied. Consequently, there are 32 data points for the rig pipe activity while 102 data points were obtained for the weld pipe activity. Each data point consists of data for all the 21 input factors and the output factor, that is, productivity, for each of the two activities.

The productivity form used by Fayek et al. (2002) to collect productivity data, was structured to collect subjective and objective data. Therefore, for input factors such as pipe diameter, pipe length, and, elevation, objective data, such as pipe diameter values in inches, pipe length values in feet, and, elevation values in feet, were collected. For input factors such as crew turnover, access to work area, and, crowding of work area, subjective data, in the form of linguistic variables, such as low, average, and, high, were collected on the productivity forms. The only exceptions are the data for the weather-related input factors, namely, average temperature, average windspeed, and, average precipitation. Data for these factors were obtained from the weather data provided by a major oil company located adjacent to the industrial construction site where the data were collected (Fayek et al., 2002). Objective data were also collected for the output factor, that is, productivity, in manhours per foot of pipe (for rig pipe activity), and manhours per diameter-inch of pipe (for weld pipe activity).

For each of the input factors and the output factor (productivity), three membership functions were developed, such as poor, fair, and, good, with the exception of the input factor named shelter requirement, used in only in the weld pipe models. Shelter requirement has only two membership functions (low and high). This is because the data collected for this factor were in terms of either a "no" or a "yes" which was translated to "low" and "high" respectively, for the purpose of membership function generation. The purpose of developing the membership functions is to convert raw data into membership values, which can be applied in fuzzy sets using the fuzzy rules and fuzzy inference mechanisms. The membership value, μ_x, corresponding to a particular element, x, in the universe of discourse U, depends on the shape of the membership function and varies between 0 and 1. The degree of belief that an element x, in the universe of discourse, U, is well represented by a linguistic concept, is depicted by the membership function. This degree of belief is measured in terms of the membership value, μ_x.

The extracted data was used to test the fuzzy expert systems that were developed. The tests were done in four trials for the rig pipe fuzzy expert system and the two weld pipe fuzzy expert systems. The trials were carried out to obtain the best fuzzy expert systems, in terms of numerical and linguistic accuracies of the output from each system. Some key adjustments were made to the raw data during the trials:

- In the second trial, the raw data ratings of all subjective factors were adjusted from 0, 1, 2 descriptors (for example, 0=poor, 1=fair, 2=good) to 0, 5, 10 descriptors (0=poor, 5=fair, 10=good).
- In the fourth trial, the average lengths of pipe were used in the rig pipe model and because of this, three of the 32 data points had to be removed because their average lengths could not be determined.
- In the fourth trial, the crew ratio was changed from journeyman to apprentice ratio to apprentice to journeyman ratio for all models.

4.3 Development of Membership Functions

4.3.1 Introduction

Model development using fuzzy logic involves the generation of membership functions for all the input and output factors in the models. In this study, the next procedure in the development of the fuzzy expert systems, after the identification and categorization of the factors using context variables, is the development of membership functions for all the input and output factors, as well as for all the factors in the sub-models, used in developing the models.

The review of existing literature on the study of the modeling of construction labor productivity reveals that no fuzzy logic model exists for modeling industrial construction labor productivity. The development of membership functions depends on the availability of large data sets that are not easy to obtain in the construction industry. In this study, both subjective and objective data sets published in Fayek et al. (2002), were used to model industrial construction labor productivity, for the rig pipe and weld pipe activities. The review of existing literature revealed the different techniques that are available for developing membership functions. Most of these techniques require the use of a small number of input factors and large data sets in order to train, test, and, validate the membership functions (Sun, 2000).

As an example, Sun used a technique that is based on the frequency of numerical responses to structured interview questions about the linguistic descriptors (such as low, average and high) of the factors that affect design performance in the industrial construction sector. This technique could not be applied in this study because a large number of responses from industry experts were not available through structured questionnaires. Furthermore, the technique requires that objective (numerical) and subjective (linguistic) data should be collected simultaneously, for all the input and output factors. This type of data was not available for use in this study because the data published in Fayek et al. (2002) were either objective or subjective. The two types of data were not collected simultaneously.

4.3.2 Assumptions Used in Developing Membership Functions

The following assumptions were used to develop the membership functions used in this study.

- Only triangular and trapezoidal membership functions are developed for the input and output factors. In order to achieve as much overlap as possible among the membership functions, most of the membership functions, especially membership functions of subjective factors such as crew turnover, access to work area, and, adequacy of site storage, are trapezoidal in shape.
- Each input factor, with the exception of shelter requirement, is assumed to have three membership functions. The three membership functions are low, average, high; short, average, long; small, average, large; low, medium, high; poor, fair, good; and, tolerant, average, detailed. Shelter requirement is represented by two membership functions, namely low and high. The output factor, productivity, has three membership functions, namely, good, average, and, poor.

- All subjective factors have the same triangular or trapezoidal membership function shapes (depending on the trial involved). Furthermore, each subjective factor has three membership functions. The only exception is shelter requirement that has two triangularly shaped membership functions.
- All input sub-models, such as crew characteristics, crew dimensions, and, crew competency, have the same trapezoidal membership function shapes. Furthermore, each sub-model has three membership functions.

4.3.3 Method of Developing Membership Functions

The development of membership functions was based on the expert questionnaires that were completed by two industrial construction researchers (including the author of this study) and two industrial construction personnel. Four questionnaires were sent out to the construction personnel, but only two questionnaires were completed and returned.

An expert questionnaire was developed for each of the two activities that were studied in this research. This was done in order to generate membership functions for each input and output factors. The questionnaire was developed for the rig pipe and the weld pipe activities in the industrial construction context. The questionnaire addressed each of the factors affecting productivity for which membership functions have been developed in this study. A sample of the expert questionnaire is shown in Appendix A. For each question asked, the respondents were required to provide answers based on their knowledge of the concerned topic.

The respondents were provided with a range of values or ratings (such as 0 to 10) that describe a particular factor or productivity, and were asked to determine which values or ratings they considered as appropriate for linguistic variables such as small, average, and, large. The responses were used to determine the linguistic ratings and membership values that define the membership functions of each input factor and the output factor (productivity).

The technique used to define the membership functions for the factors is simple but subjective. The completed questionnaires were used to construct the initial membership functions for both input and output factors. The weather-related membership functions were developed using the questionnaires, information obtained from Chilldex (which is a software for predicting weather information), and, information obtained from the weather-related websites located in Appendix B.

The overall range of x-axis values for the membership functions of any factor is determined by the range of values for that factor as contained in the raw data. For example, if the range of raw data values for elevation is from zero to 60 feet, then the range of x-axis values for elevation is between zero and greater than 70 feet. The range of a particular membership function is defined by the average of the respondents' values. The respondents were asked to circle on the questionnaires (refer to Appendix A), that is, numerical values or subjective values (on a scale of zero to 10), of a particular factor which they believe belong to a certain linguistic variable. For example, on a scale of zero to greater than 70 feet, that is, x-axis values, the respondents were asked to define the range of elevation values which they believe could be described as low elevation. The membership value μ_x is determined by the average degree of belief that the respondents have in their chosen responses. For example, if the respondent believes that an elevation of zero belongs to the variable low more than an elevation of 10 feet, then in the membership function "low", an elevation of zero on the x-axis is assigned a greater membership value on the y-axis than an elevation of 10 feet. The membership value assigned to an elevation value on the x-axis would depend on the number of elevation values on the x-axis, for the range of any linguistic descriptor. For example, if on the x-axis, for the membership function "low", the value of elevation corresponding to low elevation ranges from 0 to 30 feet, then zero may be assigned a membership value of 1, 10 feet may be assigned a value of 0.75, 20 feet may be assigned a value of 0.5, 30 feet may be assigned a value of 0.25, and, 40 feet may be assigned a value of zero, assuming the membership function is triangular in shape.

The four trials carried out for each of the three models are illustrated using the membership functions for pipe diameter as an example for the rig pipe model, and the membership functions for pipe wall thickness for the weld pipe models. The examples are illustrated as follows:

Rig Pipe Model, Pipe Diameter

The membership functions developed for pipe diameter of the rig pipe model are as shown in Figure 4-1. For this factor, the same membership functions were used in all the four trials.

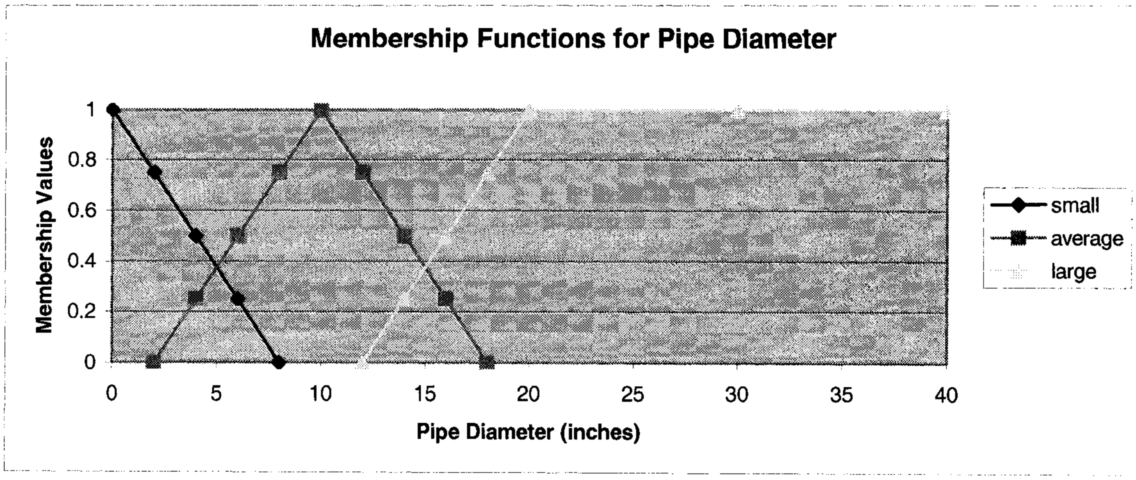


Figure 4-1: Membership Functions for Pipe Diameter (Rig Pipe Model)-Trials 1, 2, 3, and 4.

Weld Pipe Models, Pipe Wall Thickness or Schedule

The membership functions developed for wall thickness (schedule) of the weld pipe models are as shown in Figure 4-2. For this factor, the same membership functions were used in all the four trials.

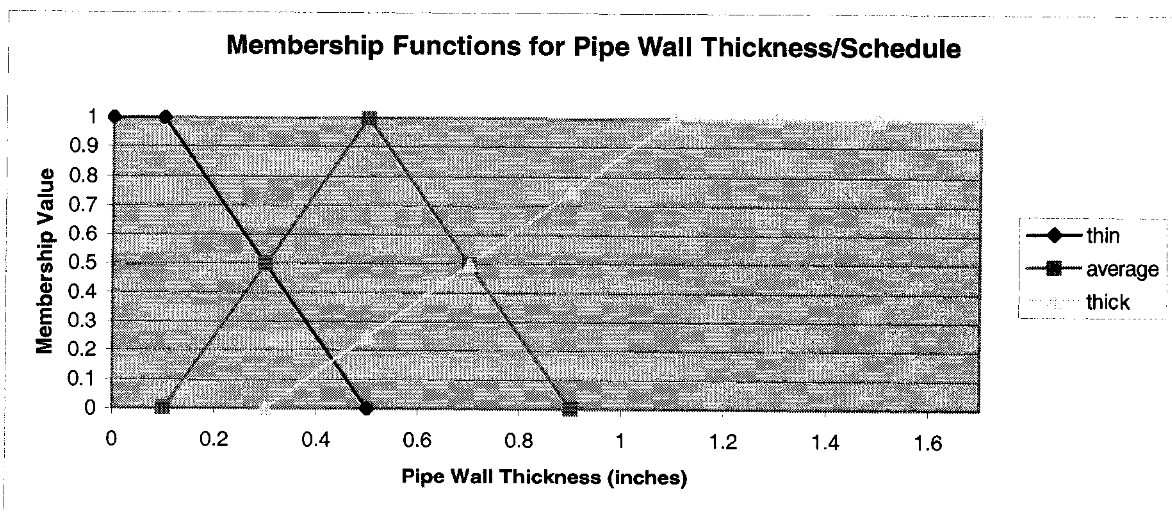


Figure 4-2: Membership Functions for Wall Thickness (Weld Pipe Models)-Trials 1, 2, 3, and 4.

All the membership functions that were developed in the four trials and used in this study to develop the three fuzzy expert systems are found in Appendix C.

Adjustments were made by changing the shapes of the membership functions, by increasing the degree of overlap among the membership functions, and, by increasing the extreme membership functions beyond the limits described in the questionnaires.

4.3.4 Discussion of Trials

The process of developing the models was carried out four times, that is, in four trials. This was done in order to obtain the most numerically and linguistically accurate models. At the end of each trial, the membership functions were adjusted, either in terms of shape or the range of values on the x-axis. The cumulative or incremental changes in the membership functions for the four steps are described as follows:

- In the first trial, all the input factors of both rig pipe and weld pipe have three membership functions each. The membership functions have both triangular and trapezoidal shapes. The only exception is the input factor called shelter requirement, of the weld pipe models, which has two trapezoidal membership functions. In this trial, the subjective factors also have three membership functions each, including both triangular and trapezoidal shapes. However, each objective factor in the sub-models has three triangular membership functions. The output factor, productivity, also has three membership functions, all trapezoidal in shape. For the weld pipe activity, the carbon steel and butt weld membership functions are the same as those of the alloy and butt weld membership functions.

- In the second trial, shelter requirement has two symmetrical triangular membership functions and its x-axis values were changed from 0-10 to 0-1. The peak membership value, μ_x=1.0, is located at the extreme ends of the x-axis, that is, x=0 and x=1. Each factor in the sub-models has three symmetrical, triangular membership functions, with x-axis values ranging between zero and 10, and with the peak membership value of the membership function in the middle, that is μ_x=1.0, corresponding to an x-axis value, x=5. For the weld pipe activity, the x-axis values of the carbon steel and butt weld output membership functions are adjusted to be 60 % (based on the approximation of the ratio of the average productivity of carbon steel and butt weld to the average productivity of alloy and butt weld expressed as a percentage) of the x-axis values of the alloy and butt weld membership functions.

- In the third trial, and for the weld pipe activity, the x-axis values of the carbon steel and butt weld membership functions are adjusted to be 68 % (based on the exact ratio of the average productivity of carbon steel and butt weld to the average productivity of alloy and butt weld expressed as a percentage) of the x-axis values of the alloy and butt weld membership functions.

- In the fourth trial, the membership functions of seniority, overall crew size, and, precipitation, were adjusted by increasing the degrees of overlap between them.

For all the models, the crew ratio was changed from journeyman to apprentice ratio to apprentice to journeyman ratio. The subjective factors and the factors in the sub-models all have symmetrical trapezoidal membership functions.

4.4 Correlation Analysis

4.4.1 Introduction

Each of the three models built in this study originally had 21 input factors and one output factor. An attempt was made to develop rulebases for each model which would include all the 21 input factors. There is exponential growth of rules, since the number of rules for a complete rulebase is given by Equation 4-1.

$$Number\ of\ rules = (number\ of\ membership\ functions)^{number\ of\ factors} \tag{4-1}$$

This would lead to a very large number of unmanageable rules for each model. Besides, it would be difficult to input and implement such a large rulebase in the Fuzzy Logic Toolbox in MATLAB or any other existing computer software. For example, if a rulebase is to be created for an expert system having 21 input factors, with each input factor having three membership functions, the number of rules that would have to be generated is 3^{21} or 1.05×10^{10} (that is, approximately 10 billion rules). In order to solve this problem, the models were broken down into sub-models. However, it was still necessary to determine which factors actually contributed positively and negatively towards determining the models' outputs.

An attempt was made to simplify the models using a combination of correlation analysis and simple linear regression analysis, specifically the Backward Elimination method.

However, the linear regression technique was considered infeasible because some of the input factors may not have a linear relationship with productivity. The other alternative was to use non-linear regression, but this technique was discarded because it requires that the relationships between the input variables (such as exponential, or polynomial) and the output factor should be assumed. This technique could easily be applied only in a situation where a small number of variables are involved.

Furthermore, the objective of this research is not to develop regression models, but to develop fuzzy expert systems for predicting productivity. However, prior to developing the expert systems, it was necessary to quantify the relationships between the input and output variables. Therefore, correlation analysis is used in this study to determine how the input and output factors vary together. It is convenient to use correlation analysis in preference to regression analysis because the variables involved are measurable and none of the variables is a controlled variable (GraphPad Software Inc., 1999). Consequently, only correlation analysis was used to determine the input factors that make significant contributions towards determining the productivity of the models. The factors found to be significant were included in the sub-models described in Chapter 3.

It was convenient to use correlation analysis because it presents a clear picture of the type, significance, and direction of the relationship that exists among the input factors and between the input factors and productivity. Correlation analysis was used to determine if there is a linear relationship between the input factors and productivity. The level of importance of an input factor with respect to the output factor can be determined by either the significance value (i.e., p value), or the Pearson Correlation Coefficient, determined during the correlation. The significance value is associated with the hypothesis test that the correlation is zero. If the significance value obtained for two variables in a correlation test is less than the significance level, then the null hypothesis stating that the correlation is zero is rejected. In other words, this implies that there is correlation between the variables or that they are correlated. In this study, the significance value, which is used in statistics to test whether or not the correlation is significantly different from zero, is used as the basis for determining the level of importance of each input factor (Sun, 2001).

This significance value varies between 0.0 and 1.0, and the closer the value is to 0.0, the higher is the significance of the factor. A factor having a significance value that is greater than 0.1 is considered insignificant. Two-tailed significance values were obtained and used in this study because the direction of the correlation could either be positive or negative. Most of the correlation results obtained in this study were achieved at the 99% confidence level, that is, the results obtained have a 1% or 0.01 significance level or chance of not being true. The significance level measures the error tolerance allowed in the correlation analysis. In this study, for the purpose of determining the factors to be included in the models, the significance level was taken to be 0.1 (that is, 90% confidence level), thereby increasing the error tolerance level in the correlation results.

The direction of correlation is determined by the Pearson Correlation Coefficient, denoted by γ, and it is described in Norusis (1993). The value of γ can vary between -1 and $+1$ and a γ value of zero implies that there is no relationship between variables x and y, a γ value of -1 implies that there is a complete indirect relationship between variables x and y, while a γ value of +1 implies that there is a complete direct relationship between the two variables. The strength of the linear relationship between variables x and y is determined by the magnitude of γ. If the magnitude of γ is greater than or equal to 0.8, then both variables x and y are highly correlated or multi-collinear (Jalal, 1999). When two variables are perfectly multi-collinear, they have equal ability to predict the output, thereby creating redundancy. In a situation where two variables are found to be multi-collinear, either one of the variables is excluded from the rule joining the two variables, or the two variables are joined by the "OR" operator instead of the "AND" operator. This is because the two variables are highly dependent on each other. The equation below shows Norusis' formula for determining the relationship between two variables x and y.

$$\gamma = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{(N-1)S_x S_y} \tag{4-2}$$

where

γ = Pearson correlation coefficient

x_i = ith value of variable x

y_i = ith value of variable y

$\bar{x}$ = the average of N values of variable x

$\bar{y}$ = the average of N values of variable y

N = Number of cases

S_x = Standard deviation of variable x

S_y = Standard deviation of variable y

Although the purpose of doing correlation analysis in this study is to simplify the productivity models, the major problem that was encountered was how flexible to be in determining the factors that should be included in the models. Under normal circumstances, factors should be included in the models based on their statistical significances. However, when this was done, it was observed that certain factors that are believed to be important based on field experience were found to be insignificant by the correlation analysis.

This problem was solved by introducing more flexibility into the process of factor selection. This was done by selecting the factors that were found to be statistically significant and those that were believed to be important based on field experience. In the case of the weld pipe models, the significance of the factors were determined by their significance in their weld pipe correlation (that is, carbon steel and butt weld correlation, and, alloy and butt weld correlation) and in a preliminary correlation analysis done for all 95 butt weld data points.

4.4.2 Models' Simplification Using Correlation Analysis

The correlation analysis was done using the Statistical Package for Social Sciences (SPSS) for Windows, Version 9 (SPSS Inc., 2001), which is a data management and analysis software. The correlation analysis was done for each of the three models in two steps which are as explained below. Step 1 comprises the first three trials while step 2 involves the fourth trial.

Step 1

In the first three trials, the correlation analysis was done as follows:

- Correlation analysis was done for all of the original 32 data points of the rig pipe activity.
- Correlation analysis was done for all of the 95 data points of the butt weld, weld pipe activity. Originally, there were 102 data points for the weld pipe activity.
- Correlation analysis was done for the 63 data points of the carbon steel and butt weld, weld pipe activity.
- Correlation analysis was done for the 32 data points of the alloy and butt weld, weld pipe activity.

Step 2

In the fourth trial, the correlation analysis was done as follows:

- Correlation analysis was done for the 29 data points remaining after the application of average pipe lengths, in the rig pipe model. In the first three trials, the total pipe length obtained by adding the individual lengths of the pipe pieces rigged by a crew was used, while in the fourth trial, the total pipe length was divided by the quantity of pipes that were rigged by the crew involved, in order to obtain the average pipe length.
- The factor called access to work area was replaced with the factor called crowding of work area, in the alloy and butt weld, weld pipe model. This was done because the correlation analysis done for the 95 data points for butt weld, and the 63 data points for carbon steel and butt weld, in step 1, found access to work area to be multi-collinear with crowding of work area and adequacy of site storage.

The models' simplification using correlation analysis is demonstrated in Tables 4-2 and 4-3, with the use of the crew competency sub-model for carbon steel and butt weld, weld pipe from step 1. The correlations were determined to be significant at the 90% confidence level, that is, at the 10% significance level. If the two-tailed Pearson correlation coefficient of two variables have an absolute value that is greater than, or equal to 0.8, the two variables are considered to be multi-collinear. Therefore, if the significance value of a particular factor, in a model, is greater than 10% or 0.10, the factor is considered as not contributing significantly to the output of the model and would be rejected after the correlation is done (Sun, 2001). However, in situations in which a factor is found to be insignificant by statistical correlation but is believed to be significant based on field experience, the factor is included in the model. All the tables showing the rig pipe and weld pipe data that were input into the SPSS environment, and the results of the correlation analysis, can be found in Appendix D. The example is illustrated in Tables 4-2 and 4-3.

The crew competency sub-models for carbon steel and butt weld, weld pipe model, before and after simplification, are shown below:

(Sub-model before simplification)		(Sub-model after simplification)
Input 7: Skill level Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked	→	Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked

All the simplified sub-models derived using correlation analysis can be found in Appendix E.

Table 4-2: Results of Correlation Analysis for Crew Competency Sub-model of the Carbon Steel and Butt Weld, Weld Pipe Model.

Correlations							
		Productivity	Skill level	Crew turnover	Crew experience (learning)	Crew experience (seniority)	No. of consecutive days worked
Productivity	Pearson Correlation	1	-0.04818	0.30268	0.001682	0.219882	0.101035
	Sig. (2-tailed)	.	0.707657	0.0159	0.989562	0.08335	0.430755
	N	63	63	63	63	63	63
Skill level	Pearson Correlation	-0.04818	1	-0.28201	-0.00631	-0.82659	0.220264
	Sig. (2-tailed)	0.707657	.	0.025143	0.96086	7.23E-17	0.082802
	N	63	63	63	63	63	63
Crew turnover	Pearson Correlation	0.30268	-0.28201	1	-0.05051	0.404341	-0.33958
	Sig. (2-tailed)	0.0159	0.025143	.	0.694219	0.001014	0.006474
	N	63	63	63	63	63	63
Crew experience (learning)	Pearson Correlation	0.001682	-0.00631	-0.05051	1	-0.09353	0.275002
	Sig. (2-tailed)	0.989562	0.96086	0.694219	.	0.465953	0.029162
	N	63	63	63	63	63	63
Crew experience (seniority)	Pearson Correlation	0.219882	-0.82659	0.404341	-0.09353	1	-0.30312
	Sig. (2-tailed)	0.08335	7.23E-17	0.001014	0.465953	.	0.015741
	N	63	63	63	63	63	63
No. of consecutive days worked	Pearson Correlation	0.101035	0.220264	-0.33958	0.275002	-0.30312	1
	Sig. (2-tailed)	0.430755	0.082802	0.006474	0.029162	0.015741	.
	N	63	63	63	63	63	63
*	Correlation is significant at the 0.05 level (2-tailed).						
**	Correlation is significant at the 0.01 level (2-tailed).						

Table 4-3: Summary of Correlation Results for Crew Competency Sub-model of the Carbon Steel and Butt Weld, Weld Pipe Model.

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/Reject	Basis for acceptance/rejection
Skill level	-0.048	0.708	4	63	Reject	High significance value, and factor is multi-collinear with crew experience (seniority)
Crew turnover	0.303	0.016	1	63	Accept	Low significance value
Crew experience (learning)	0.002	0.990	5	63	Accept	High significance value, factor is considered important based on field experience
Crew experience (seniority)	0.219	0.083	2	63	Accept	Low significance value, but factor is multi-collinear with skill level
No. of consecutive days worked	0.101	0.431	3	63	Accept	High significant value, but factor is considered important based on field experience

The development of the fuzzy rulebase of each model became easier after model simplification using correlation analysis. This is because a fewer number of input factors had to be considered in each rulebase. Table 4-4 summarizes the number of input factors that remained in each model after model simplification. In Table 4-4, step 1 denotes correlation analysis that was done for trials 1, 2, and 3, while step 2 denotes correlation analysis that was done for trial 4. Eventually, only the correlation results for rig pipe, weld pipe (carbon steel and butt weld), and weld pipe (alloy and butt weld), were used. The results for weld pipe (butt weld) was discarded. In fact, no correlation analysis was done for weld pipe (butt weld) in step 2.

Table 4-4: Summary of Input Factors Remaining After Model Simplification

Step	Rig Pipe Model	Weld Pipe Model (Butt Weld)	Weld Pipe Model (Carbon Steel and Butt Weld)	Weld Pipe Model (Alloy and Butt Weld)
1	15	16	16	16
2	16	Not applicable	16	16

4.5 Development of Fuzzy Expert Rules

4.5.1 Introduction

Fuzzy expert system development involves the creation of a fuzzy rule base, which consists of If-Then rules that relate the input factors to the output factors. The If-Then rules are composed of fuzzy antecedents or premises (represented by the membership functions of the input factors) and fuzzy consequents or conclusions (represented by the membership functions of the output factor). The If-Then rules provide the logical reasoning framework for determining the output, based on values of the input factors. Various fuzzy inference mechanisms are used for reasoning.

For a two-input-one output fuzzy expert system, the following example can be used to illustrate a fuzzy If-Then rule. Assuming that crew skill level and crew experience level are the input factors and productivity is the output factor, a fuzzy If-Then rule can be expressed as follows:

If *crew skill level* is high and *crew experience level* is high, then *productivity* is good

The input and output factors are represented in the fuzzy expert system by membership functions such as low, average, and, high for each input factor, and, good, average, and, poor for the output factor. The fuzzy inference mechanism in this example is denoted by "and", which assumes that the input factors exert equal but independent effects on the output factor.

4.5.2 Fuzzy Inference Mechanisms

The fuzzy inference mechanisms of a fuzzy expert system consists of the mechanisms for carrying out the fuzzification, implication, aggregation, and, defuzzification procedures necessary to generate outputs from a system, given the inputs to the system. These procedures are implemented with the use of fuzzy operators. The fuzzy operator is used to combine the membership values of the input variables in the premise of a rule when more than one variable exists in the premise. The fuzzy operators that are commonly used are "AND" and "OR".

The fuzzy operator "AND" is used when the input variables are believed to have equal and independent effects on the output of the system. The operator "AND" performs its operation process in either of two ways: as a "MIN" operator, or as a "PRODUCT" operator. The former operator determines the minimum of the membership values of the input variables while the latter calculates the product of the membership values of the input variables. The operator "OR" performs its operation process as a "MAX" operator, or as a "PROBOR" operator. The former determines the maximum of the membership values of the input variables while the latter calculates the algebraic sum of the membership values of the input variables. All the input factors exert equal but independent effects on the output factor of each model. This necessitated the use of the "AND" operator in the fuzzy rules.

However, in situations where the factors are highly correlated (i.e., multi-collinear), they are joined using the "OR" operator. For example, in the pipe dimensions sub-model for carbon steel and butt weld, weld pipe model, the two input variables in the sub-model, namely pipe diameter and wall thickness, were found to be multi-collinear. This necessitated the use of the operator "OR" in joining the rules linking the two variables. Furthermore, all the rules developed in this study are assumed to have the same weights. If two factors are believed to be dependent on each other as determined by a high correlation between them (multi-collinearity), then the two variables should be joined in the rule by "OR".

The different steps of the fuzzy inference mechanisms are explained below:

- **Fuzzification** is the process of converting the crisp input variables to fuzzy data by determining the membership values or the degrees of belief that elements of the input variables belong to fuzzy sets that are defined by membership functions.
- **Application of fuzzy operator** If there is more than one input variable in the antecedent of the rule, the membership values of the input variables are combined using a fuzzy operator such as "AND" and "OR", to obtain a single value in the consequent of the rule. The "AND" operator has two operating methods, including the "MIN" operator, which uses the minimum of the membership values in the antecedent. The other operation method is the "PRODUCT" operator, which uses the product of the membership values in the antecedent. The "OR" operator also has two operation methods, including the "MAX" operator, which uses the maximum of the membership values in the antecedent. The other

operating method is the "PROBOR" operator, which uses the algebraic sum of the membership values in the antecedent.

- **Implication** is the process of applying the single membership value obtained after combining membership values in the antecedent of the rule, to the fuzzy set of the output variable in the consequent of the rule. The membership function in the consequent part of the rule is truncated (using "MIN"), or squashed down (using "PRODUCT").
- **Aggregation** which is a process that occurs once for all rules in a rulebase, involves combining the fuzzy output of each rule in the rulebase to obtain a single fuzzy set. This occurs when an aggregation operator ("MAX" or "PROBOR") combines the output fuzzy set of each rule to obtain a single fuzzy set. The fuzzy operator "MAX" combines the maximum value from the output of each rule, while the operator "PROBOR" combines the algebraic sum of the output from each rule, in order to determine the single output fuzzy set.
- **Defuzzification** is the process of generating a crisp value from the fuzzy set obtained by the aggregation method. This can be achieved using defuzzification methods such as "CENTROID", "BISECTOR", Largest of Maximum or "LOM", Middle of Maximum or "MOM", and, Smallest of Maximum or "SOM". The operator "CENTROID" is used to determine the single value related to the center of gravity of the output membership function, while the operator "BISECTOR" is used to calculate a defuzzified value obtained by bisecting the area under the curve of the aggregate output set. The operators "LOM", "MOM", and "SOM", are used to determine the largest value, the mean value, and, the smallest value,

respectively, from the range of elements in the output membership function that have the maximum membership value.

4.5.3 Method of Developing Fuzzy Rules

The rulebases were developed by iteratively combining the input variables in a logical manner. The development of complete and consistent fuzzy rules for the models was done in four trials. In each trial, If-Then rules were developed for each of the three productivity models. The method used in developing the rules are explained below:

- The minimum number of rules required to obtain a rulebase that is complete was determined using Equation 4-1.
- The results obtained from the correlation analysis were used to determine whether or not the input factors are independent of one another. If they are independent, the operator "AND" is used to join the factors, while the operator "OR" is used to join the factors if the factors are dependent on one another, that is, if they are multi-collinear.
- The rules were constructed based on the author's logical reasoning about the way different combinations of varying degrees of input factors affect the output factor. This iterative process was carried out in the four trials.

4.5.4 An Example of Fuzzy Rules Development

The fuzzy rules used in this study were developed for the four trials described in Section 4.2 (Data Extraction), for the rig pipe fuzzy expert system and the two weld pipe fuzzy expert systems, according to the method described in section 4.5.3 above. The trials were carried out to obtain the best fuzzy expert systems, in terms of numerical and linguistic accuracies of the output from each system. The process of developing the rules was carried out in two steps. The rules developed in the first step were used in the first and second trials while the rules developed in the second step were used in the third and fourth trials. The fuzzy rules were developed for the sub-models that make up the models. The technique used is strictly an iterative procedure based on the logical reasoning of the author. The four trials carried out for the pipe dimensions sub-model for the rig pipe model are described in this section. The example is illustrated as follows:

The procedures used to develop the rulebase for the pipe dimensions sub-models, for rig pipe, are outlined below. The rules developed for the sub-model in the first step (i.e., the rules that were used in trials 1 and 2), and, in the second step (i.e., the rules that were used in trials 3 and 4), are shown in Table 4-5.

- The minimum number of rules required to develop a complete rulebase for each of the pipe dimension sub-models, was determined. Since there are two input factors in each sub-model and each factor has three membership functions, the minimum number of rules used in each sub-model is equal to $3^2 = 9$ rules.

- The correlation analysis of the sub-model showed that there is no multi-collinearity between the two factors. Therefore, the rules were joined using the operator "AND".
- The rules were developed based on logical reasoning, while maintaining a complete rulebase.

Table 4-5: Fuzzy Rules for Pipe Dimensions Sub-model, Rig Pipe Model for Step1 (Trials 1 and 2) and Step 2 (Trials 3 and 4)

Pipe Dimensions		
pipe length	**pipe diameter**	**pipe dimensions**
short	small	small
short	average	small
short	large	average
average	small	average
average	average	average
average	large	large
long	small	large
long	average	large
long	large	large

The rules used in step 2 (trials 3 and 4) are the same as those used in step 1(trials 1 and 2). No change was made to the rules between steps 1 and 2.

4.5.5 Development of Fuzzy Rulebases in MATLAB

The fuzzy rulebases for the three models were developed in a MATLAB environment using the Mamdani Fuzzy Inference System (FIS) located in the Fuzzy Logic Toolbox of MATLAB (Mathworks Inc., 1998). The following procedures were carried out to implement the fuzzy inference system in MATLAB. The procedures are illustrated using the Graphical User Interfaces (GUIs) for the pipe dimensions sub-model, rig pipe model. For this sub-model, the FIS is the same for all the four trials.

- Open a new Mamdani Fuzzy Inference System (FIS), and specify all the input and output variables in the FIS. This is illustrated in Figure 4-3.
- Use the Membership Function Editor to specify all the membership functions for all the input and output variables in the FIS. This is illustrated in Figure 4-4.
- Use the Rule Editor to specify all the rules in the FIS, using the appropriate fuzzy operator. This is illustrated in Figure 4-5.
- Use the Rule Viewer to inspect the results generated by the FIS. This is illustrated in Figure 4-6. Otherwise use the "readfis" function to load the FIS from disk, and use the "evalfis" function to carry out the fuzzy inference calculations necessary to determine the outputs from the FIS.

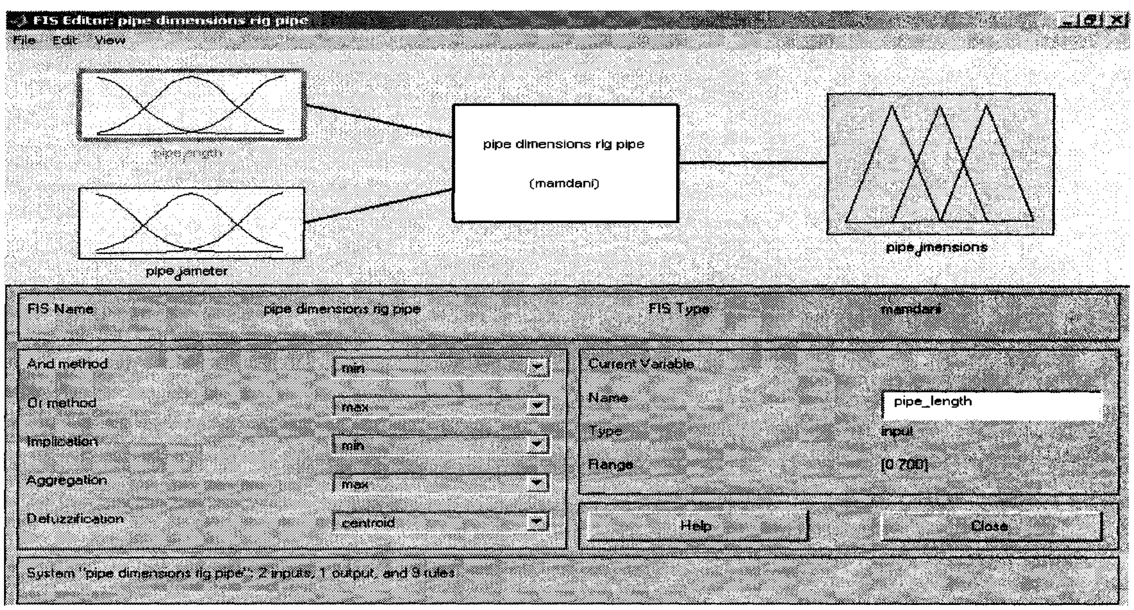


Figure 4-3: GUI Showing the Input and Output Variables of the Pipe Dimensions Sub-model, Rig Pipe, in MATLAB.

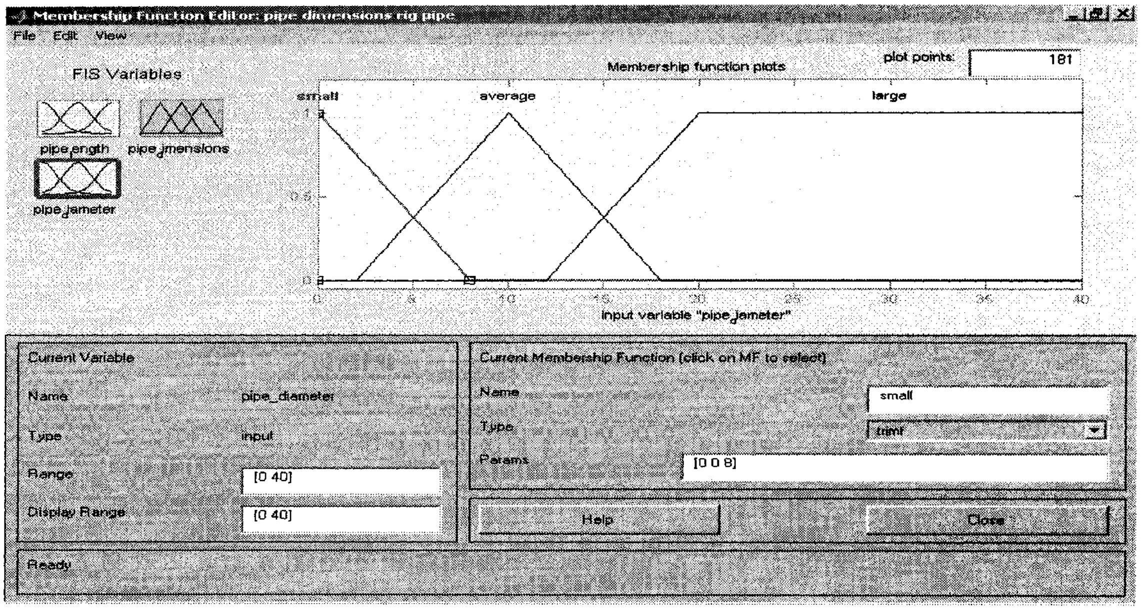


Figure 4-4: GUI Showing the Membership Functions of the Input and Output Variables of the Pipe Dimensions Sub-model, Rig Pipe, in MATLAB.

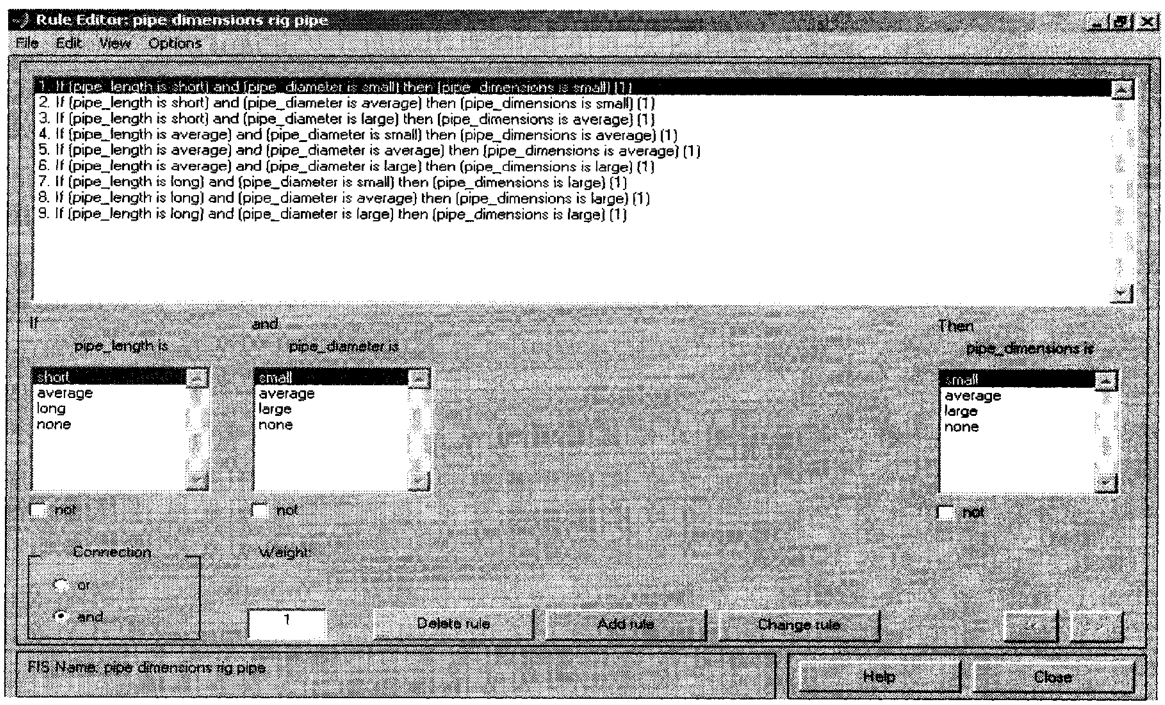


Figure 4-5: GUI Showing the Rules of the Input and Output Variables of the Pipe Dimensions Sub-model, Rig Pipe, in MATLAB.

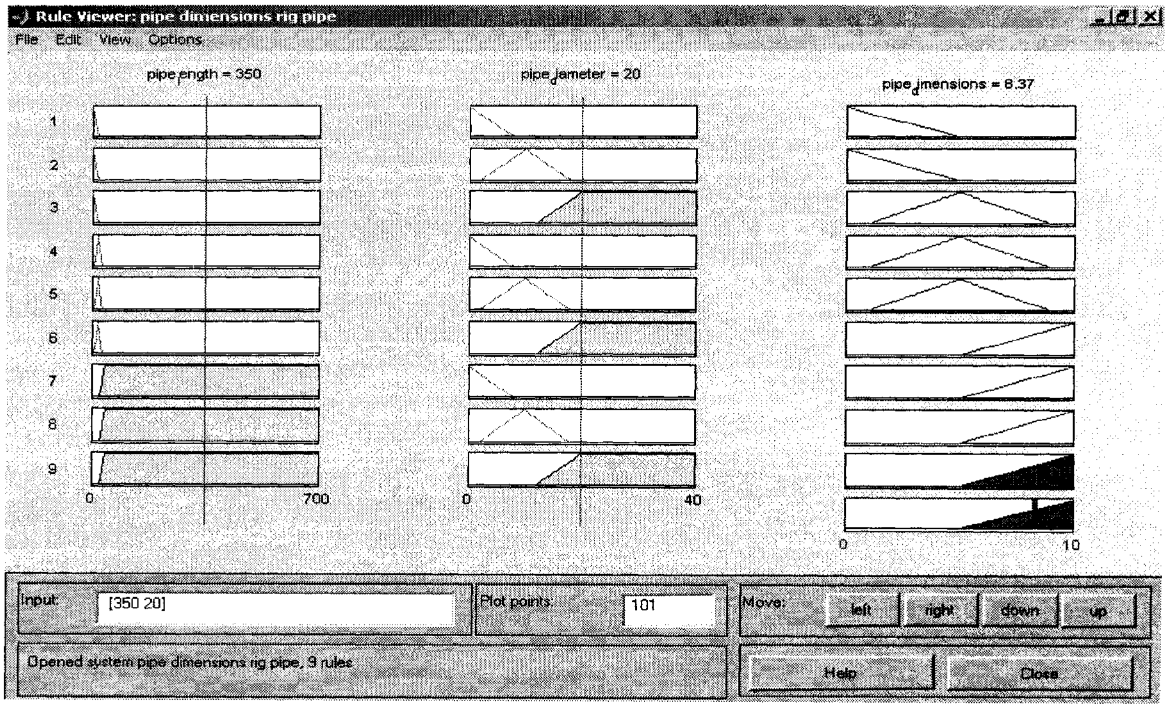


Figure 4-6: GUI Showing the Membership Functions and the Rules of the Input and Output Variables of the Pipe Dimensions Sub-model, Rig Pipe, in MATLAB.

The complete rulebase for each model is shown in Appendix F.

4.6 Testing and Calibration of Models

4.6.1 Method of Testing Models

The accuracies of the models developed were determined by testing the models with the existing data sets. In the base case, the "AND" method used is min, the "OR" method used is max (i.e., in cases where multi-collinearity existed between the input factors), the implication method used is min, the aggregation method used is max, and the defuzzification method used is centroid. The crisp output obtained for each data point is compared to the actual output of the existing data. The percentage error is then calculated using the following formula:

$$\text{Percentage Error} = (\text{Predicted Output-Actual Output})/\text{Actual Output} * 100 \qquad (4\text{-}3)$$

For the rulebase to be considered adequate, the percentage error for each data point must be less than or equal to 33% (Sun, 2001). Therefore, a numerical match is achieved if the percentage error is not more than 33%. If the linguistic term of the defuzzified output is the same as that of the actual output, then the data point has a linguistic match. For the model to be considered successful, the percentage of numerical or linguistic matches over the total number of data points should be greater than or equal to 50% (Sun, 2001).

The testing process was done on the base case models. The numerical and linguistic accuracies of each model developed in each of the four trials were determined. The models with the best linguistic accuracies were then selected for calibration and sensitivity and linguistic error distribution analyses. Linguistic accuracy was used as the basis for model selection because the purpose of fuzzy expert system is to provide linguistic output based on input to the system. For the rig pipe model, all the different sensitivity methods used have high linguistic matches. The numerical and linguistic matches for all the models are as shown in Tables 4-6, 4-7, and, 4-8.

Table 4-6: Rig Pipe Model Selection Table (Base Case)

Trial Number	1	2	3	4
Numerical match (%)	3.13	9.40	37.50	37.93
Linguistic match (%)	12.50	21.90	62.50	70.00
Selected model	Trial 4			

Table 4-7: Weld Pipe, Carbon Steel and Butt Weld Model Selection Table (Base Case)

Trial Number	1	2	3	4
Numerical match (%)	3.17	39.70	47.62	42.86
Linguistic match (%)	15.87	63.50	68.25	60.32
Selected model	Trial 3			

Table 4-8: Weld Pipe, Alloy and Butt Weld Model Selection Table (Base Case)

Trial Number	1	2	3	4
Numerical match (%)	15.63	21.90	40.63	21.88
Linguistic match (%)	21.88	40.60	50.00	34.38
Selected model	Trial 3			

The results of the model trials show that the most acceptable model for rig pipe is the model in trial 4 with a numerical accuracy of 37.93% and a linguistic accuracy of 70%. The best model for weld pipe, carbon steel and butt weld model is the model in trial 3 with a numerical accuracy of 47.62% and a linguistic accuracy of 68.25%. The best model for weld pipe, alloy and butt weld model is the model in trial 3 with a numerical accuracy of 40.63% and a linguistic accuracy of 50%. These three models were selected for model calibration in order to obtain more accurate models. The model testing results are located in Appendix G.

4.6.2 Method of Calibrating Models

The models obtained after initial testing using the existing raw data generally had numerical accuracies that were less than 50% and linguistic accuracies greater than 50%. In order to improve the accuracies of the models, the most accurate model was selected for each model type and then calibrated. The output membership functions of the selected models were calibrated by shifting the right leg of each membership function, first to the right, by increasing the x-axis value by 20%; then to the left, by reducing the x-axis values by 20%; and finally by shifting both legs of the membership functions in either direction, by 20%. The predicted productivity values were then determined. The entire results of the calibration of the models are as shown in Appendix H. The calibration process was carried out on the base case models. The summary of the results obtained after the model calibration carried out for the base case of each of the three chosen models are shown in Tables 4-9, 4-10, and 4-11.

Table 4-9: Calibration Results for Rig Pipe Model (Base Case)

Match Type	20% Shift to Right	20% Shift to Left	20% Shift in both Directions
Numerical match (%)	25.79	34.48	37.93
Linguistic match (%)	62.07	62.07	86.21

Table 4-10: Calibration Results for Weld Pipe, Carbon Steel and Butt Weld Model (Base Case)

Match Type	20% Shift to Right	20% Shift to Left	20% Shift in both Directions
Numerical match (%)	47.62	42.86	49.21
Linguistic match (%)	61.90	65.08	74.60

Table 4-11: Calibration Results for Weld Pipe, Alloy and Butt Weld Model (Base Case)

Match Type	20% Shift to Right	20% Shift to Left	20% Shift in both Directions
Numerical match (%)	34.38	25.00	40.63
Linguistic match (%)	50.00	37.50	50.00

The results obtained before and after calibration of the models selected from each model type are shown in Tables 4-12, 4-13, and 4-14.

Table 4-12: Rig Pipe Model Comparison (Base Case)

Match Type	Before Calibration	After Calibration
Numerical match (%)	37.93	37.93
Linguistic match (%)	70.00	86.21

Table 4-13: Weld Pipe, Carbon Steel and Butt Weld Model Comparison (Base Case)

Match Type	Before Calibration	After Calibration
Numerical match (%)	47.62	49.21
Linguistic match (%)	68.25	74.60

Table 4-14: Weld Pipe, Alloy and Butt Weld Model Comparison (Base Case)

Match Type	Before Calibration	After Calibration
Numerical match (%)	40.63	40.63
Linguistic match (%)	50.00	50.00

The tables shown above indicate that calibration of the three models selected after initial testing by shifting the two legs of the membership functions of the output factor by 20%, prior to determining the predicted outputs, numerically and linguistically improved the results of the rig pipe model and the weld pipe, carbon steel and butt weld model. This is probably due to the increase in the overlap between the membership functions. However, there was neither an improvement nor a deterioration in the results obtained for the weld pipe, alloy and butt weld model. Therefore, a sensitivity analysis was done for each model to see if better results could be obtained.

4.7 Model Sensitivity Analysis

Model sensitivity analysis was performed for each of the three calibrated models in order to improve the accuracies of the models The sensitivity analysis was carried out on the calibrated models and it involves the determination of the changes in the accuracy of the models, resulting from changing all the methods in the fuzzy inference mechanism of the base case.

The sensitivity analysis was done by first varying the defuzzification methods, followed by the implication-aggregation method. The "and" and "or" operator methods were also varied. The results of the analysis are shown in Appendix I. The analysis was carried out in the following steps or methods. The results obtained by using all the methods listed below are shown in Tables 4-15, 4-16, and 4-17.

4.7.1 Bisector Defuzzification Method

The bisector defuzzification method improved the numerical accuracy of the rig pipe and weld pipe, alloy and butt weld models, to 41.38% and 44.82% respectively.

4.7.2 LOM Defuzzification Method

The LOM defuzzification method was only able to improve the numerical accuracy of the weld pipe, alloy and butt weld model, to 43.75%.

4.7.3 SOM Defuzzification Method

The SOM defuzzification method was only able to improve the linguistic accuracy of the weld pipe, alloy and butt weld model, to 56.25%.

4.7.4 MOM Defuzzification Method

The MOM defuzzification method was only able to improve the numerical accuracy of the weld pipe, carbon steel and butt weld model, to 52.38%.

4.7.5 Prod-Probor Implication-Aggregate Method

The prod-probor implication-aggregation method is used when there is interaction between variables (on the contrary, the min-max method is used when there is no interaction between variables). The method did not improve the accuracies of any of the three models.

4.7.6 "and"-Product Operation Method

The "and"-product operation method changes the "and" operator from min, in the base case, to product. The method was only able to improve the numerical accuracy of the weld pipe, carbon steel and butt weld model, to 50.79%.

4.7.7 “or”-Probor Operation Method

The “or”-probor operation method improved the numerical accuracy of the rig pipe model, to 48.28%.

Table 4-15: Sensitivity Results for the Rig Pipe Model

Method	Modified Operator	Numerical match(%)	Linguistic match(%)	Ranking
Base case	None	37.93	86.21	3
Bisector	Defuzzification	41.38	86.21	2
MOM	Defuzzification	34.48	86.21	6
LOM	Defuzzification	27.59	17.24	8
SOM	Defuzzification	0.00	86.21	7
Prod-Probor	Implication-aggregation	37.93	86.21	3
"and"-product	"and"	37.93	86.21	3
"or"-probor	"or"	48.28	86.21	1

Table 4-16: Sensitivity Results for the Weld Pipe, Carbon Steel and Butt Weld Model

Method	Modified Operator	Numerical match(%)	Linguistic match(%)	Ranking
Base case (centroid)	None	49.21	74.60	1
Bisector	Defuzzification	42.86	57.14	7
MOM	Defuzzification	52.38	73.02	2
LOM	Defuzzification	31.75	71.42	4
SOM	Defuzzification	22.22	12.70	8
Prod-Probor	Implication-aggregation	49.21	69.84	5
"and"-product	"and"	50.79	71.43	3
"or"-probor	"or"	42.86	63.49	6

Table 4-17: Sensitivity Results for the Weld Pipe, Alloy and Butt Weld Model

Method	Modified Operator	Numerical match(%)	Linguistic match(%)	Ranking
Base case (centroid)	None	40.63	50.00	4
Bisector	Defuzzification	44.82	50.00	2
MOM	Defuzzification	37.50	50.00	8
LOM	Defuzzification	43.75	50.00	3
SOM	Defuzzification	25.00	56.25	1
Prod-Probor	Implication-aggregation	40.63	50.00	4
"and"-product	"and"	40.63	50.00	4
"or"-probor	"or"	40.63	50.00	4

The analysis shows that the models achieved better linguistic accuracy than numerical accuracy. While sensitivity analysis caused some positive and negative changes in the numerical accuracies of the models, it did not change their linguistic accuracies. The only exception is the weld pipe model for alloy and butt weld, which had a linguistic accuracy improvement from 50.00% to 56.25%. The sensitivity analysis done on the calibrated rig pipe model improved the numerical accuracy of the base case, but there was no improvement in the linguistic accuracy. The "or"-probor operation method produced the best result for this model, that is, numerical and linguistic accuracies of 48.28% and 86.21% respectively, followed by the bisector method, which produced numerical and linguistic accuracies of 41.38% and 86.21% respectively.

The sensitivity analysis done on the calibrated weld pipe, carbon steel and butt weld model, resulted in numerical accuracy improvements over the base case, for the model through the MOM method (52.38%) and "and"-product methods (50.79%). However, greater linguistic accuracy could not be obtained. Rather, the other methods produced linguistic accuracies that are lower than that of the base case. Based primarily on the linguistic matches and secondarily on the numerical matches, the best method is the base case method.

The sensitivity analysis done on the calibrated weld pipe, alloy and butt weld model, resulted in numerical accuracy improvement over the base case, through the bisector method (44.82%) and the LOM method (43.75%), and linguistic accuracy improvement for the model through the SOM method (56.25%), the latter of which produced the lowest numerical accuracy among the methods (25.00%). Based primarily on the linguistic matches and secondarily on the numerical matches, the best method is the SOM method.

4.7.8 Linguistic Error Distribution Analysis

In order to determine the accuracies of the linguistic outputs from the models, an error distribution matrix was developed. This matrix helps to determine the percentage of the linguistic outputs of a model that constitutes a match, or that are one term off or two terms off. One term off means that the actual and predicted outputs are one term apart. For example, if the predicted output is "average" and the actual term is "large", the error is a 1-term error. Two terms off means that the actual and predicted output are two linguistic terms apart. For example, if the predicted output is "low" and the actual term is "large", the error is a 2-term error. These explanations are illustrated in Table 4-18.

Table 4-18: Linguistic Error Distribution Matrix

		Actual Linguistic Term		
		small	average	large
Predicted Linguistic Term	small	match	1 term off	2 terms off
	average	1 term off	match	1 term off
	large	2 terms off	1 term off	match

The results of the linguistic term matching are shown in Table 4-19. The linguistic error distribution analysis was done to determine the nature and degree of the linguistic errors that are present in the developed models. This is necessary since the function of fuzzy expert systems is primarily to provide linguistic output based on linguistic input. For the rig pipe model, all the different sensitivity methods used have high linguistic matches. The only exception is the LOM method which has a very low linguistic match (17.24%). For the weld pipe model (carbon steel and butt weld), all the different sensitivity methods used except the bisector method (57.14%), and the SOM method (12.70%), have high linguistic matches. For the weld pipe model (alloy and butt weld), all the different sensitivity methods used have average linguistic matches.

Table 4-19: Linguistic Error Distribution Table for Rig Pipe and Weld Pipe Models

Testing Method	match/no match	Rig Pipe Model	Weld Pipe, Carbon Steel and Butt Weld Model	Weld Pipe, Alloy and Butt Weld Model
Base case	match (%)	86.21	74.60	50.00
	1-term off (%)	10.34	22.22	50.00
	2-term off (%)	3.45	3.17	0.00
Bisector	match (%)	86.21	57.14	50.00
	1-term off (%)	10.34	39.68	50.00
	2-term off (%)	3.45	3.17	0.00
MOM method	match (%)	86.21	73.02	50.00
	1-term off (%)	10.34	26.98	50.00
	2-term off (%)	3.45	0.00	0.00
LOM method	match (%)	17.24	71.42	50.00
	1-term off (%)	79.31	28.57	50.00
	2-term off (%)	3.45	0.00	0.00
SOM method	match (%)	86.21	12.70	56.25
	1-term off (%)	10.34	71.43	37.50
	2-term off (%)	3.45	15.87	6.25
Prod-Probor method	match (%)	86.21	69.84	50.00
	1-term off (%)	10.34	28.57	50.00
	2-term off (%)	3.45	1.59	0.00
"and"-product method	match (%)	86.21	71.43	50.00
	1-term off (%)	10.34	28.57	50.00
	2-term off (%)	3.45	0.00	0.00
"or"-probor method	match (%)	86.21	63.49	50.00
	1-term off (%)	10.34	33.33	50.00
	2-term off (%)	3.45	3.17	0.00

Although the models do not have good numerical accuracies (i.e., they mostly have numerical accuracies less than 50%), their linguistic accuracies are satisfactory (i.e., they mostly have linguistic accuracies greater than 50%). All the different methods in the fuzzy inference mechanism affected the model accuracies to different extents. Therefore, a conclusion cannot be drawn with regard to the best method. There is no clear-cut method for improving the accuracies of the models, using sensitivity analysis. The results obtained from the error distribution analysis show that all the models have a high linguistic accuracy and a low 2-term error.

4.8 Conclusions

In conclusion, even though the models have high linguistic accuracies, the numerical accuracy of the models is low. Several reasons contribute to these results:

- The models suffered from lack of sufficient data and responses to interview questionnaires. Some of the available data were subjective, and had to be converted into numerical data, and this may have introduced errors in the models. It was difficult to build membership functions and fuzzy rules by using any of the existing methods. This is because of lack of significant size data set, which is a common problem in modeling construction operations. Although the data set available for use in this study, that is, the data set published in Fayek et al. (2002), is not a large data set, significant effort was required to collect it over a period of three months. The data available does not exist in the form required for model development. The membership functions could not be validated since data for validation does not exist in this form while the fuzzy rules were developed using an iterative logical reasoning approach.

- Selecting all of the significant factors that affect productivity of tasks is a complex problem. A large number of factors affect industrial construction productivity and it is difficult to determine which factors should be included in a productivity model. In this study, two important considerations were the factors for which data was available and the factors that were identified in Fayek et al. (2002) as being important.

- The problems of lack of sufficient data and the presence of a large number of input variables made it difficult to use the other two techniques for model development that were explored in this research, namely, ANFIS, and Neuroshell 2. These two methods could not be implemented because they require substantial amounts of data to train the models, as well as to test and check the models for errors. Furthermore, these techniques work well with a limited number of input variables. Twenty-one input variables were considered for use in this study, for each model, and this number is too large for the ANFIS and Neuroshell 2 techniques, therefore rendering the techniques infeasible. It is also difficult to implement a fuzzy expert system to model productivity with a large number of input variables, because of the problem associated with building a large rulebase to accommodate all the factors. This is why the models' structures were modified to accommodate sub-models, which may have introduced inaccuracies.

The study demonstrated that fuzzy logic and fuzzy expert systems could be used to develop models for predicting the productivity of industrial construction activities to a high degree of linguistic accuracy. The study also illustrated how to use incomplete data, especially in situations where objective and/or exact data are not available, to model productivity, as well as how to model a many-input system, using statistical techniques. However, several issues have to be addressed before a very complete model can be developed. These issues are discussed in the next chapter.

5. Conclusions and Recommendations

5.1 Conclusions

The main objective for carrying out this research was to develop models for predicting industrial construction labor productivity with the use of fuzzy logic techniques. In order to achieve this objective, the factors that affect industrial construction labor productivity, at the activity and project levels, were identified, along with their context variables. Membership functions were generated for these factors, as well as for the output factor, that is, productivity, and, fuzzy rulebases were developed for the models. The models were tested and calibrated for numerical and linguistic accuracies in MATLAB.

A comprehensive list of factors affecting industrial construction productivity was identified through a review of existing literature, and through the use of information obtained from the study done by Fayek et al. (2002). All the factors that were identified were categorized into three classes, namely: context variables, activity-level factors, and project-level factors. The context variables were identified based on their degrees of variation on a project while the activity-level and project-level factors were identified based on the scope within which they affect the productivity of an activity. Two context variables, namely: material type and weld type, were used to partition the data set for the weld pipe activity. Two model types were generated for this activity, namely: the weld pipe model based on carbon steel material and butt weld process, and, the weld pipe model based on alloy material and butt weld process. Carbon steel and alloy were chosen because they were the most frequently occurring pipe material types during the period of data collection at the industrial construction site where the data published in Fayek et al. (2002) were obtained. Butt weld was the only welding process that was selected because it constituted over 93% of the data collected for weld pipe activity (that is, 95 out of 102 data points). No context variable was applied on the rig pipe data and therefore, this activity had only one model.

The factors that were included in the productivity models that were developed in this study were selected based on the availability of raw data. The raw data that were used to test the numerical and linguistic accuracies of the models were extracted from the data published in Fayek et al. (2002). Expert questionnaires were also completed by industrial construction researchers and personnel. The data on 21 input factors affecting industrial construction productivity, as well as data on the productivity of the two activities, namely rig pipe and weld pipe, were extracted from the data records of the industrial construction study.

Membership functions were developed for the fuzzy expert systems used to build the productivity models. The development process incorporated both objective and subjective input data. The development of membership functions was done using logical reasoning and interview responses. The membership functions were subsequently fine-tuned by increasing the extent of overlap between the legs of the membership functions, thereby increasing their fuzziness. However, the accuracy of the membership functions could not be tested because of a lack of data that exists in the required form.

The input factors that were used to model rig pipe and weld pipe productivities in this study are quite considerable in number, and this presented a problem regarding model development using the Mamdani-type fuzzy expert system. Therefore, the feasibility of one neuro-fuzzy technique, that is, the Sugeno-type ANFIS, and, a neural network technique, that is, Neuroshell 2, was explored, with the main objective of modeling productivity using all the input factors. However, it was observed that the two techniques do not work well with many input factors and limited data sets. Therefore, it became necessary to modify the modeling process in order to be able to use the Mamdani fuzzy expert technique in MATLAB. This was achieved in two stages: firstly, the structures of the three models were modified to accommodate sub-models, and, secondly, using correlation analysis, the models were simplified by determining the factors that contributed significantly towards determining the productivity output. This statistical technique also provided a clear picture of the relationships that existed among the input variables, and, between the variables and productivity. This reduced the number of input factors to a manageable number, for each model, and helped in the development of the rulebases.

The relationships existing among the input variables and between the input variables and productivity were used to develop the fuzzy rulebases that were used to provide the logical reasoning component of the fuzzy expert systems. The rulebases were developed based on the simplification of the input factors done using correlation analysis. This facilitated the development of manageable rulebases, therefore avoiding the exponential growth of rules that could arise from having to use a large number of input factors in the models. The fuzzy If-Then rules were developed based on logical reasoning, and subsequently fine-tuned to achieve better model accuracies. The rulebases were implemented in MATLAB using the Mamdani fuzzy expert system technique. Each of the three models was developed in four trials, and each of the models developed in each trial was initially tested using the data published in Fayek et al. (2002). The best trial was selected for each model type, based on the degree of linguistic and numerical accuracies achieved. The selected models were calibrated to improve their performances and were re-tested with the published data.

The models developed were tested using the extracted raw data for rig pipe and weld pipe activities. The results predicted by the models are acceptable, with the three models having generally low numerical accuracies, but high linguistic accuracies. Only the weld pipe model based on carbon steel and butt weld, had a numerical accuracy that is greater than 50%. However, this acceptable numerical accuracy was achieved only after performing a sensitivity analysis on the model. No concrete conclusion could however be drawn based on the sensitivity analysis. A linguistic error distribution analysis was also carried out for each model to determine the margin of error generated by the linguistic outputs of the models. The models were observed to have performed at low linguistic error margins. Since the intent of the fuzzy expert system is to provide linguistic output based on linguistic input, these results indicate that the performance of the productivity prediction models is acceptable.

In conclusion, this study demonstrated the use of fuzzy logic and fuzzy expert system in modeling industrial construction productivity. The study also highlighted the problems that would be faced by researchers carrying out other similar studies. More work remains to be done in order to be able to use fuzzy logic and fuzzy expert systems to accurately model industrial construction labor productivity, especially since little research has been carried out in this area using these techniques.

5.2 Contributions

Significant contributions were made by this study in advancing the field of industrial construction productivity research. The main contribution of this research is in developing a methodology for the development of realistic models for predicting industrial construction productivity. Other contributions were made in terms of highlighting the appropriateness of using fuzzy logic and fuzzy expert system techniques to model productivity, despite facing different problems, and, using these techniques to model objective and subjective data that were extracted from an actual productivity study. Since the data collected in the productivity study represent the type of data that would be available within organizations, this research demonstrates how such data can be used for predicting productivity.

This study shows how fuzzy set theory and fuzzy expert system could be used to build productivity models based on realistic data. A large number of factors affecting two industrial construction activities were identified. A subset of these factors was used in building the productivity models in this study. This study shows how a subset of factors could be chosen based on the availability of data. A process of converting subjective data into objective data was also developed. This process involves translating subjective linguistic variables, such as low, average, and, high, into objective numbers, such as 0, 5, and 10, in a realistic manner.

Membership functions and fuzzy rulebases were developed based on logical reasoning, without the availability of large data sets required to train, test, and, validate the membership functions and fuzzy rules, and without a large number of expert opinions. This study demonstrates how to incorporate flexibility by using basic model structuring and statistical correlation analysis to simplify productivity models that would otherwise have had to incorporate a large number of input factors.

Finally, this research provides a basis for future work in predicting the productivity of different industrial construction activities, given the numerous factors affecting productivity. Since this problem is largely a subjective one, with non-mathematical relationships, fuzzy logic is an appropriate technique for modeling. This research has illustrated its usefulness in modeling the productivity prediction problem, and has laid the foundation for future research in this area.

5.3 Limitations and Recommendations for Future Research

This research study was faced with several limitations, which may have affected the performance of the productivity models developed. If these limitations could be overcome in future studies, better productivity models could be developed. The limitations are as follows:

- **Survey Data:** The study was done using productivity data collected for a study on the effective integration of apprentices into the industrial construction sector. While such data illustrates what data is realistically available, future research can improve on these models by including a data collection process that is well structured and conducted specifically for the purpose of collecting the required data for the models. The survey should be structured with the main objective of collecting both subjective and objective data for factors affecting industrial construction labor productivity of the chosen activities. For each factor, both objective and linguistic data should be obtained from as many industry sources as possible, within the time and cost budget of the research study. This would help provide sufficient data sets and a sufficient number of responses necessary for the development of fuzzy expert systems. It may also improve the accuracy of the resultant models.

- **Model Design and Structure:** A limited number of context variables were used to develop the weld pipe models, while no context variable was used to develop the rig pipe model. This limits the classification of the activities and their models, as well as the models' outputs. The models' structures include factors in the sub-models, for which no raw data exist. The only data used in the sub-models were those resulting from the membership functions, which were based on subjective logical reasoning. This may have introduced errors into the models and consequently reduced the models' accuracies. Future studies should involve the acquisition of data for these sub-models, and more data related to the context variables.

- **Statistical Techniques:** Correlation analysis was used in this study to simplify the models through the determination of the input factors that most significantly contribute to the models' output. However, in order not to leave out certain factors that were considered as important based on field experience, greater flexibility was introduced into the factor-selection process by the inclusion of certain input factors that were not found to be statistically significant. This may have introduced errors into the models. Future research should devise a method of factor selection that reduces the errors introduced through the selection of factors. Future research should also consider the possibility of using multiple non-linear regression as a preliminary factor selection technique. The benefit of doing this is that factors will be selected not only on the basis of their linear relationship with productivity, but also on the basis of other possible relationships, such as exponential or polynomial relationship. This requires that the relationships between the input variables (such as exponential or polynomial) and the output factor should be assumed. This technique could easily be applied only in a situation where a small number of variables are involved.

- **Development of Fuzzy Expert Systems:** The membership functions and fuzzy rules could not be developed and validated using existing techniques because of the lack of sufficient data and limited interview responses. Consequently, the membership functions and fuzzy rules had to be developed using iterative logical reasoning. This may have introduced errors in the models. Future data collection techniques should take into consideration the techniques to be used to develop the membership functions and fuzzy rules to be used in the fuzzy expert systems. With respect to the development of membership functions, greater research should be done to determine how the shape and degree of overlap of membership functions affect the model performance.

- **Fuzzy Logic Techniques:** The models in this study were developed using the Mamdani fuzzy expert system. Although the feasibility of neuro-fuzzy and neural network techniques was studied in this research, future work should examine the feasibility of these and other fuzzy logic techniques, such as binary relations, to model industrial construction productivity. Furthermore, although significant studies have been done in this area using artificial neural networks, more work should be done to determine how fuzzy logic techniques could perform better when faced with the problem of insufficient data, especially since it is difficult to obtain large data sets in the field of construction.

This study is one of the few that has been done in the area of industrial construction labor productivity modeling using fuzzy logic and fuzzy expert systems. It is hoped that future studies will improve on the techniques used in this study, while taking into consideration the difficulties encountered in this study.

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Appendix A (Expert Questionnaire)

General Information

This survey questionnaire is being used to obtain information for the development of a university thesis. Its main purpose is to gather information from an expert's point of view, which will be used to model certain factors affecting industrial construction productivity with respect to two tasks: Rig Pipe and Weld Pipe. Please fill out the questionnaire as accurately as you can by circling the chosen response(s). If you are not sure of an exact value for any particular question, you can estimate an approximate value.

*For the purpose of ensuring **confidentiality**, your company information and identity will not be linked in any way to the project information in subsequent sections. Kindly answer the following questions based on your general knowledge and experience. If in your opinion, the questions can have more than one answer, you may circle more than one answer.*

The terms "average", "fair", and " medium" imply that the condition is standard in the experience of the respondent.

General Instruction: Kindly circle the most appropriate options. You may circle more than one value for each term.

A. Rig Pipe

I. Questions related to Input Factors:

1. What sizes or diameters would you consider as small, average and large, respectively for a rigged pipe? The pipe sizes or diameters are in inches.

   Small: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

   Average: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

   Large: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

2. What lengths would you consider as short, average and long, respectively for a rigged pipe? The pipe lengths are in feet.

   Short: <2, 2, 6, 10, 14, 18, 22, 26, 30, 40, >40

   Average: <2, 2, 6, 10, 14, 18, 22, 26, 30, 40, >40

   Long: <2, 2, 6, 10, 14, 18, 22, 26, 30, 40, >40

3. The efficiency of rigging a pipe is to be determined by the percentage of crane rigging involved. What percentage of crane rigging would you consider as low, average and high, respectively, for a rigged pipe?

   Low: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

   Average: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

   High: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

4. What crew ratios (journeymen : apprentice) would you consider as small, average, and high, respectively, for a rigging task?

   Small: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Average: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Large: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Note:

   1:1 = one journeyman for every one apprentice on the crew
   2:1 = two journeymen for every one apprentice on the crew
   3:1 = three journeymen for every one apprentice on the crew
   4:1 = four journeymen for every one apprentice on the crew
   5:1 = five journeymen for every one apprentice on the crew
   6:1 = six journeymen for every one apprentice on the crew
   7:1 = seven journeymen for every one apprentice on the crew

5. What task crew sizes would you consider as small, average, and large, respectively, for a rigging task? The task crew sizes are in terms of number of crew members, excluding the foreman.

   Small: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

   Average: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

   Large: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

6. What overall crew sizes would you consider as small, average, and large, respectively, for a rigging task? The overall crew sizes are in terms of number of crew members, excluding the foreman.

   Small: <4, 8, 12, 16, 20, 24, 28, >28

   Average: <4, 8, 12, 16, 20, 24, 28, >28

   Large: <4, 8, 12, 16, 20, 24, 28, >28

7. What final elevations above the ground would you consider as low, average and high, for a rigging task? The elevations are in feet above the ground level.

   Low: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

   Average: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

   High: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

8. How would you rate the experience of a crew working together on a rigging task? The times shown below are in terms of number of months that the crew has worked together.

   Low: <1, 1, 2, 4, 6, 8, 10, 12, >12

   Average: <1, 1, 2, 4, 6, 8, 10, 12, >12

   High: <1, 1, 2, 4, 6, 8, 10, 12, >12

9. How would you rate the experience of a crew in terms of seniority, on a rigging task? Ratings are in terms of average number of years of crew members' experience (e.g. total number of crew members divided by total number of years of experience of all crew members combined).

   Low: <1, 1, 2, 4, 6, 8, 10, 12, >12

   Average: <1, 1, 2, 4, 6, 8, 10, 12, >12

   High: <1, 1, 2, 4, 6, 8, 10, 12, >12

10. How would you rate the following average temperatures as they affect productivity of a rigging task? The temperature values are in ° C.

    Low: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

    Average: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

    High: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

11. How would you rate the following average windspeeds as they affect the productivity of a rigging task? The windspeed values are in km/hr.

Low: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

Average: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

High: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

12. How would you rate the following average precipitations as they affect the productivity of a rigging task? The precipitation values are in mm.

Low: <10, 10, 20, 30, 40, 50, 60, >60

Average: <10, 10, 20, 30, 40, 50, 60, >60

High: <10, 10, 20, 30, 40, 50, 60, >60

13. How would you rate the following average relative humidities as they affect the productivity of a rigging task? The average relative humidity values are in percentages.

Low: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Average: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

High: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

14. On a scale of 1-100 %, what percentage of overtime per week would you consider as low, average and high respectively, for a rigging task?

Low: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

Average: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

High: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

15. On a scale of 1-100 %, what percentage of prefabricated work ratings would you consider as low, average and high respectively, for a rigging task?

    Low: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    Average: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    High: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

16. On a scale of 1-10, what is the impact of the access to the work area on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

17. On a scale of 1-10, what is the impact of ground condition on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

18. On a scale of 1-10, what is the impact of crowding of work area on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

19. On a scale of 1-10, what is the impact of drawing and specification quality on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

20. On a scale of 1-10, what is the impact of the crew's skill level on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

21. On a scale of 1-10, what impact of weather conditions on work progress and productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

22. On a scale of 1-10, what is the impact of the adequacy of site storage on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

23. On a scale of 1-10, what is the impact of crew turnover on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

24. On a scale of 1-10, how would you rate the level of inspection required for a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

25. On a scale of 1-10, how would you rate the level of safety required for a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

26. On a scale of 1-10, how would you rate the level of quality required for a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

27. On a scale of 1-10, what is the impact of the sufficiency of number of crew members on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

28. On a scale of 1-10, what is the impact of the complexity of the shape of pipe on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

29. On a scale of 1-10, what is the impact of training on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

30. On a scale of 1-10, what is the impact of field supervision on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

31. On a scale of 1-10, what is the impact of disruptions on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

32. On a scale of 1-10, what is the impact of material shortages on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

33. On a scale of 1-10, what is the impact of rework on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

34. On a scale of 1-10, what is the impact of change orders on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

35. On a scale of 1-10, what is the impact of organizational constraint on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

36. On a scale of 1-10, what is the impact of the availability of equipment on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

37. On a scale of 1-10, what is the impact of equipment breakdowns on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

38. On a scale of 1-10, what is the impact of project management on the productivity of a rigging task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

II. Question(s) related to the Output Factor (Productivity):

1. For carbon steel pipe, what are the productivity ranges for rigging? Productivity values are in manhours/foot.

   Good: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Average: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Poor: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

2. For stainless steel pipe, what are the productivity ranges for rigging? Productivity values are in manhours/foot.

   Good: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Average: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Poor: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

3. For alloy pipe, what are the productivity ranges for rigging? Productivity values are in manhours/foot.

   Good: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Average: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Poor: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

4. For a typical rigging task, what productivity ranges would you consider as good, average and poor? Productivity values are in manhours/foot.

   Good: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Average: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

   Poor: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, >3.1

B. Weld Pipe

I. Questions related to Input Factors:

1. What sizes or diameters would you consider as small, average and large, respectively for a welded pipe? The pipe sizes or diameters are in inches.

   Small: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

   Average: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

   Large: <2, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, >20

2. What wall thicknesses would you consider as thin, average, thick, respectively for a welded pipe? The wall thicknesses are in inches.

   Thin: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, >1.7

   Average: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, >1.7

   Thick: <0.1, 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, 1.5, 1.7, >1.7

3. What crew ratios (journeymen: apprentice) would you consider as small, average, and high, respectively, for a welding task?

   Small: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Average: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Large: 1:1, 2:1, 3:1, 4:1, 5:1, 6:1, 7:1

   Note:

   1:1 = one journeyman for every one apprentice on the crew
   2:1 = two journeymen for every one apprentice on the crew
   3:1 = three journeymen for every one apprentice on the crew
   4:1 = four journeymen for every one apprentice on the crew
   5:1 = five journeymen for every one apprentice on the crew
   6:1 = six journeymen for every one apprentice on the crew
   7:1 = seven journeymen for every one apprentice on the crew

4. What task crew sizes would you consider as small, average, and large, respectively, for a rigging task? The task crew sizes are in terms of number of crew members, excluding the foreman.

   Small: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

   Average: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

   Large: <2, 2, 4, 6, 8, 10, 12, 14, 16, >16

5. What overall crew sizes would you consider as small, average, and large, respectively, for a rigging task? The overall crew sizes are in terms of number of crew members, excluding the foreman.

   Small: <4, 8, 12, 16, 20, 24, 28, >28

   Average: <4, 8, 12, 16, 20, 24, 28, >28

   Large: <4, 8, 12, 16, 20, 24, 28, >28

6. What final elevations above the ground would you consider as low, average and high, for a welding task? The elevations are in feet above the ground level.

   Low: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

   Average: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

   High: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

7. How would you rate the experience of a crew working together on a welding task? The times shown below are in terms of number of months that the crew has worked together.

   Low: <1, 1, 2, 4, 6, 8, 10, 12, >12

   Average: <1, 1, 2, 4, 6, 8, 10, 12, >12

   High: <1, 1, 2, 4, 6, 8, 10, 12, >12

8. How would you rate the experience of a crew in terms of seniority, on a welding task? Ratings are in terms of average number of years of crew members' experience (e.g. total number of crew members divided by total number of years of experience of all crew members combined).

   Low: <1, 1, 2, 4, 6, 8, 10, 12, >12

   Average: <1, 1, 2, 4, 6, 8, 10, 12, >12

   High: <1, 1, 2, 4, 6, 8, 10, 12, >12

9. How would you rate the following average temperatures as they affect productivity of a welding task? The temperature values are in ° C.

   Low: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

   Average: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

   High: <-40, -40, -30, -20, -10, 0, 10, 20, 30, >30

10. How would you rate the following average windspeeds as they affect the productivity of a welding task? The windspeed values are in km/hr.

    Low: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

    Average: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

    High: <5, 5, 10, 15, 20, 25, 30, 35, 40, >40

11. How would you rate the following average precipitations as they affect the productivity of a welding task? The precipitation values are in mm.

    Low: <10, 10, 20, 30, 40, 50, 60, >60

    Average: <10, 10, 20, 30, 40, 50, 60, >60

    High: <10, 10, 20, 30, 40, 50, 60, >60

12. How would you rate the following average relative humidities as they affect the productivity of a welding task? The average relative humidity values are in percentages.

    Low: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    Average: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    High: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

13. On a scale of 1-100 %, what percentage of overtime per week would you consider as low, average and high respectively, for a welding task?

    Low: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    Average: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    High: <10, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

14. On a scale of 1-100 %, what percentage of prefabricated work ratings would you consider as low, average and high respectively, for a welding task?

    Low: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    Average: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

    High: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100

15. On a scale of 1-10, what is the impact of the access to the work area on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

16. On a scale of 1-10, what is the impact of ground condition on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

17. On a scale of 1-10, what is the impact of crowding of work area ratings on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

18. On a scale of 1-10, what is the impact of drawing and specification quality on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

19. On a scale of 1-10, what is the impact of the crew's skill level on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

20. On a scale of 1-10, what impact of weather conditions on work progress and productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

21. On a scale of 1-10, what is the impact of the adequacy of site storage on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

22. On a scale of 1-10, what is the impact of crew turnover on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

23. On a scale of 1-10, how would you rate the level of inspection required for a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

24. On a scale of 1-10, how would you rate the level of safety required for a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

25. On a scale of 1-10, how would you rate the level of quality required for a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

26. On a scale of 1-10, what is the impact of the sufficiency of number of crew members on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

27. On a scale of 1-10, what is the impact of the complexity of the shape of pipe on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

28. On a scale of 1-10, what is the impact of training on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

29. On a scale of 1-10, what is the impact of field supervision on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

30. On a scale of 1-10, what is the impact of disruptions on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

31. On a scale of 1-10, what is the impact of material shortages on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

32. On a scale of 1-10, what is the impact of rework on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

33. On a scale of 1-10, what is the impact of change orders on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

34. On a scale of 1-10, what is the impact of organizational constraint on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

35. On a scale of 1-10, what is the impact of the availability of equipment on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

36. On a scale of 1-10, what is the impact of equipment breakdowns on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

37. On a scale of 1-10, what is the impact of project management on the productivity of a welding task?

    1, 2, 3, 4, 5, 6, 7, 8, 9, 10

III. Question(s) related to the Output Factor (Productivity):

1. For carbon steel pipe and a butt weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

2. For carbon steel pipe and a socket weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

3. For carbon steel pipe and a fillet weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

4. For stainless steel pipe and a butt weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

5. For stainless steel pipe and a socket weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

6. For stainless steel pipe and a fillet weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

7. For alloy pipe and a butt weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

8. For alloy pipe and a socket weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

9. For alloy pipe and a fillet weld, what are the productivity ranges for welding? Productivity values are in manhours/dia.-inch.

   Good: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Average: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

   Poor: <0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, >7.5

Appendix B (Weather-Related Websites)

http://www.washingtonpost.com/wp-srv/weather/longterm/historical/data/edmonton_alberta.htm (July, 2002).

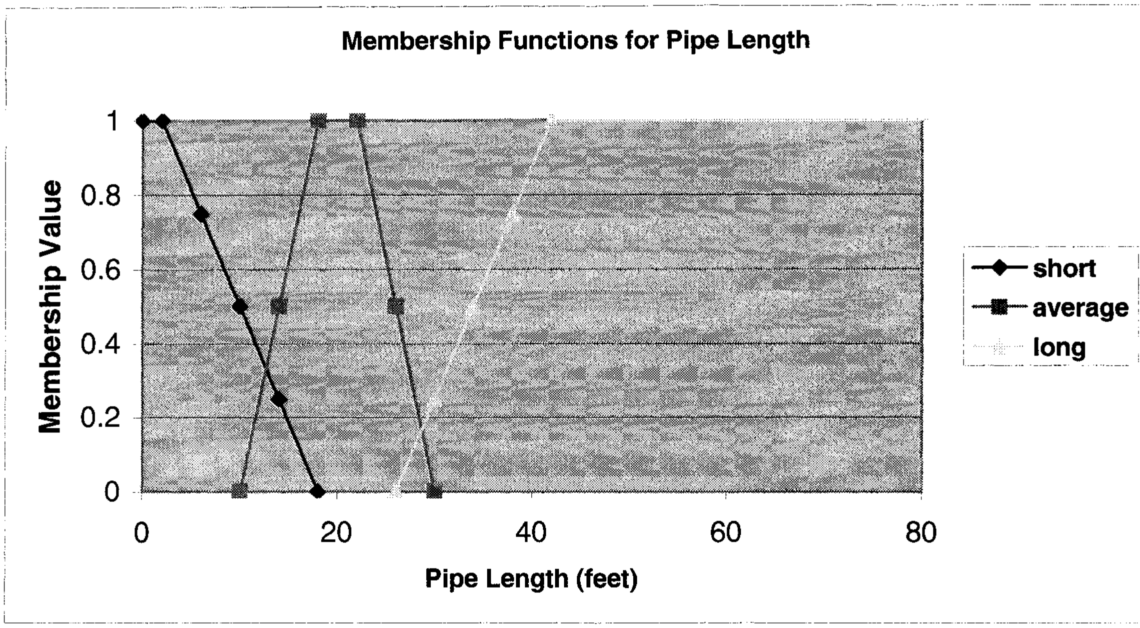
http://www.discoveredmonton.com/Edmonton/TravelEssentials/WeatherInformation/8-106.html (July, 2002).

http://parkscanada.pch.gc.ca/parks/alberta/elk_island/English/weather_e.htm (July, 2002).

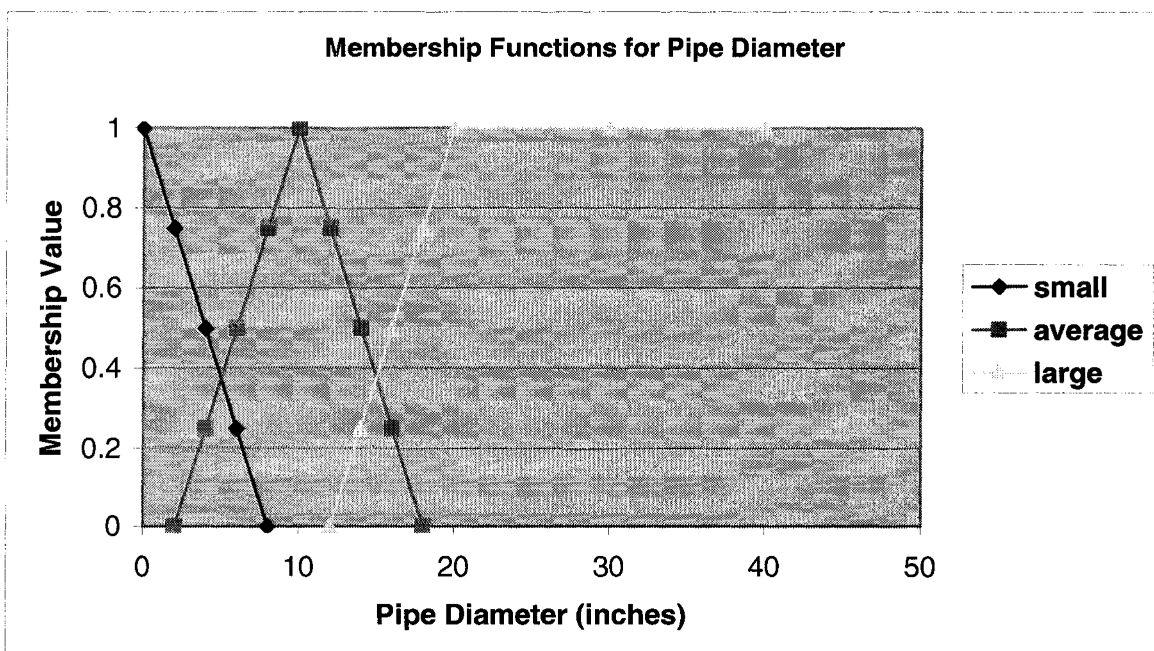
http://envweb.env.gov.ab.ca/env/forests/fpd/htit.html (July, 2002).

Appendix C (Membership Functions)

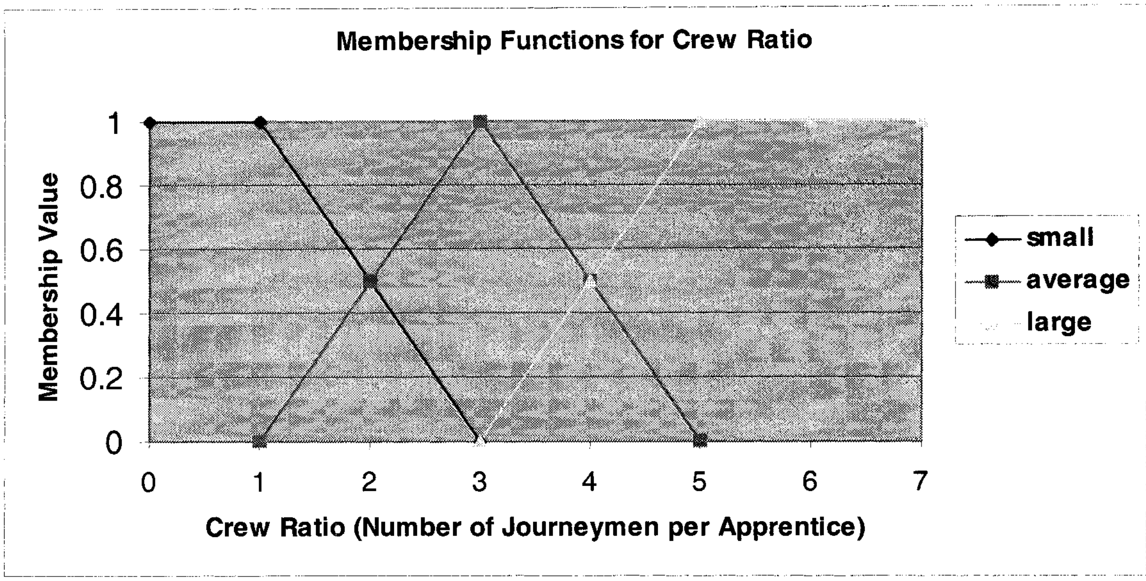
(I) Membership Functions for Rig Pipe Model



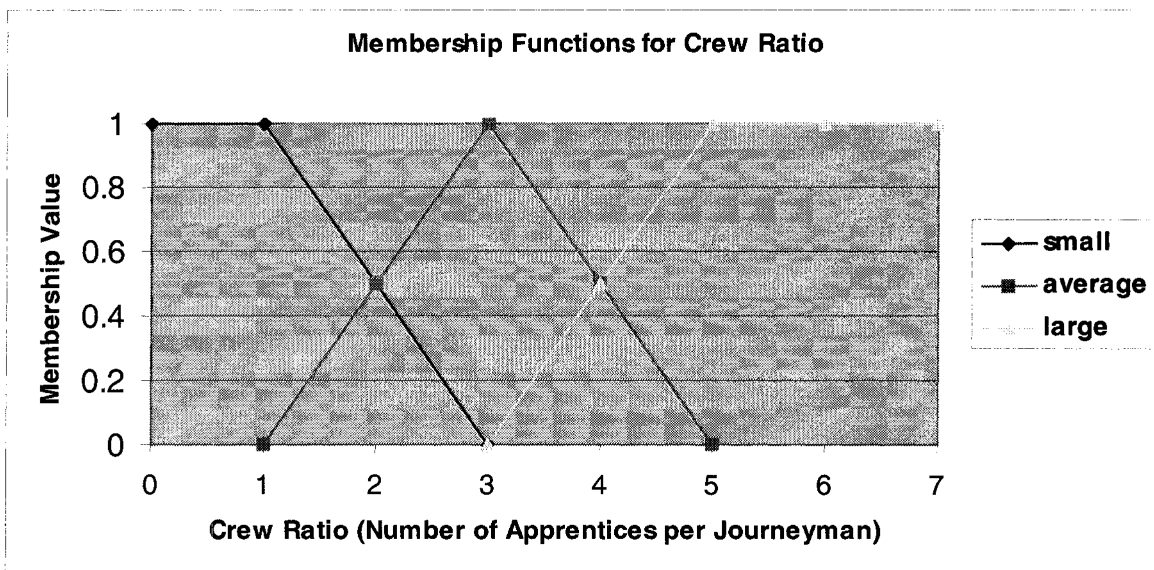
Membership Functions for Pipe Length (Trials 1,2,3, and, 4)



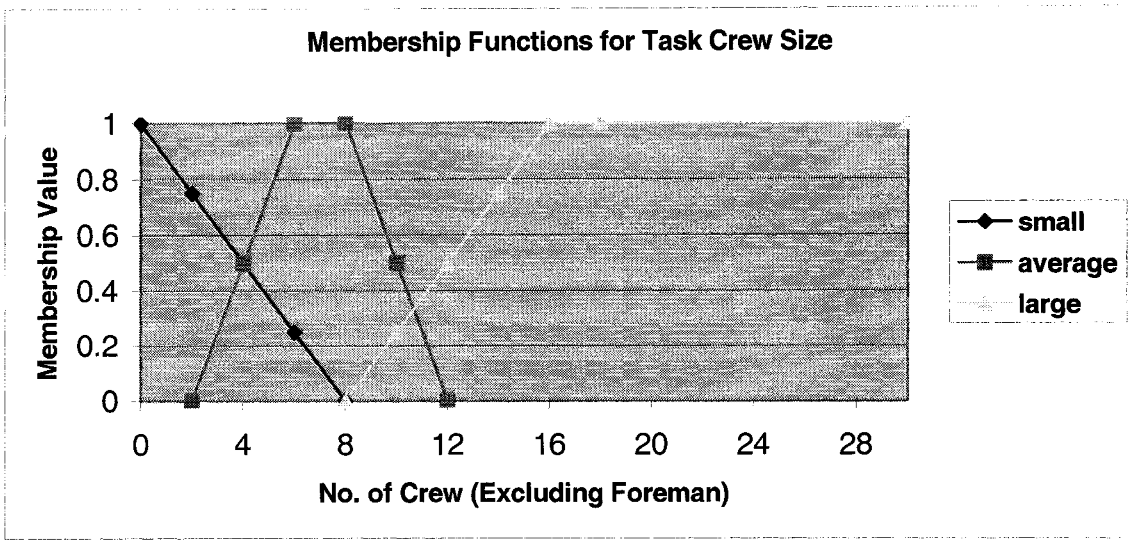
Membership Functions for Pipe Diameter (Trials 1,2,3, and, 4)



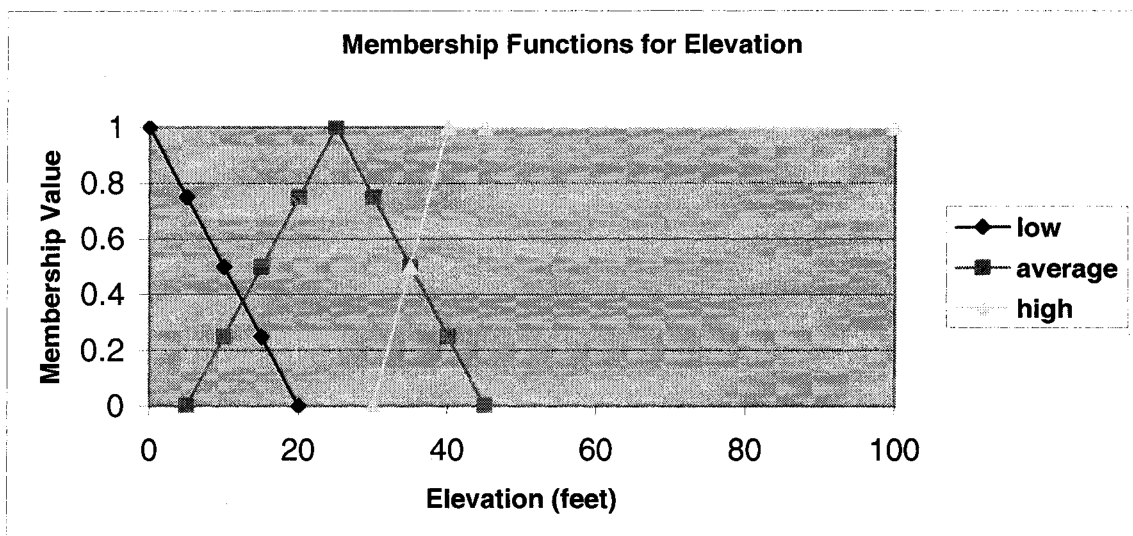
Membership Functions for Crew Ratio (Trials 1,2, and, 3)



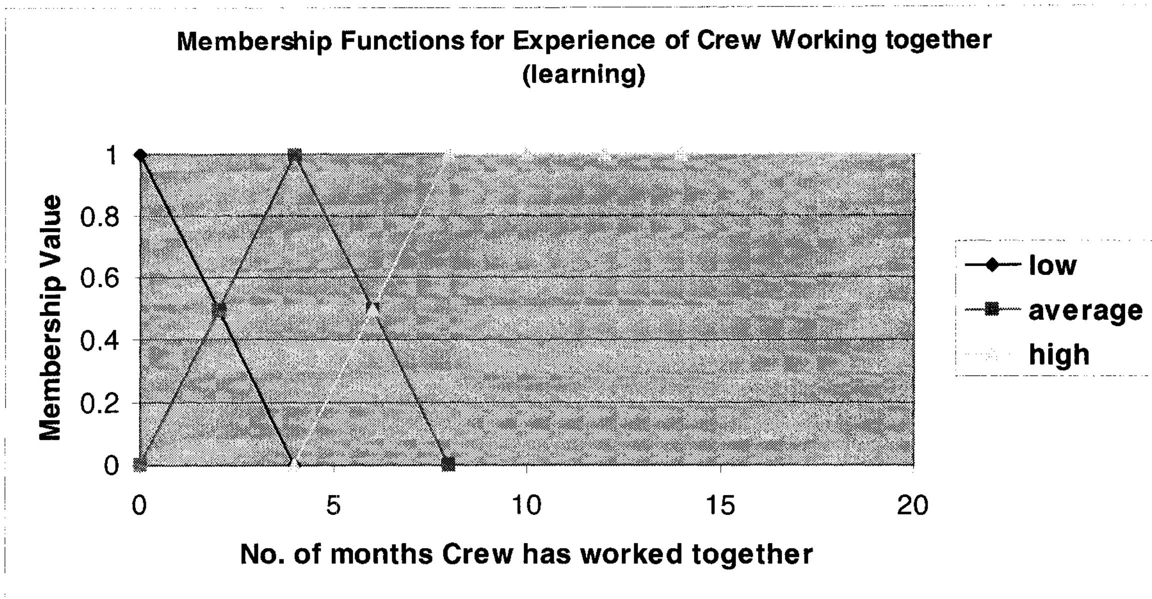
Membership Functions for Crew Ratio (Trial 4)



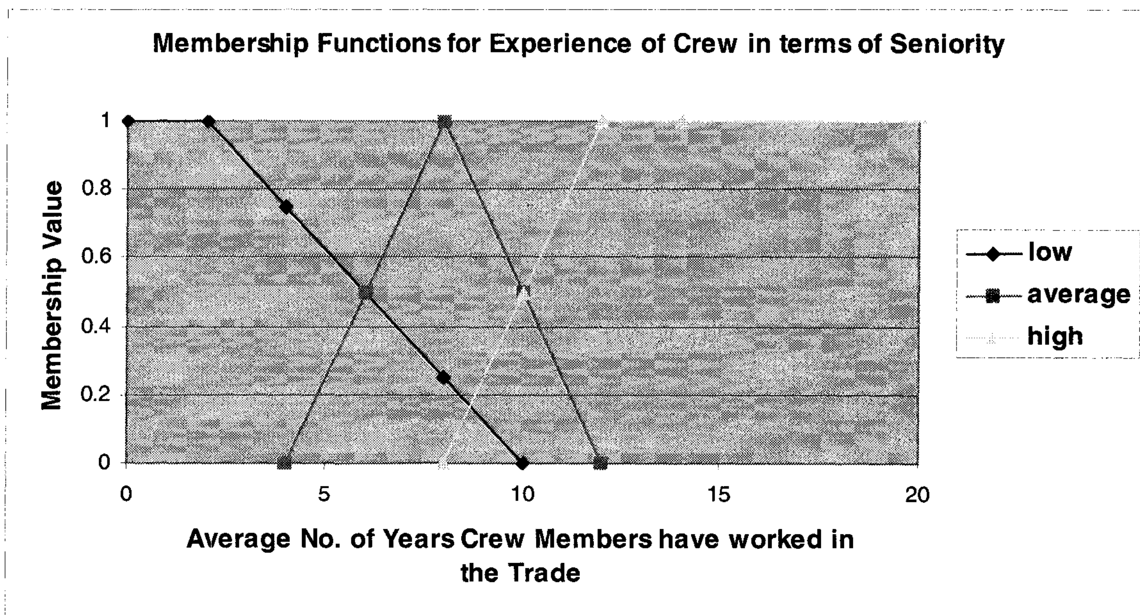
Membership Functions for Task Crew Size (Trials 1,2,3,and, 4)



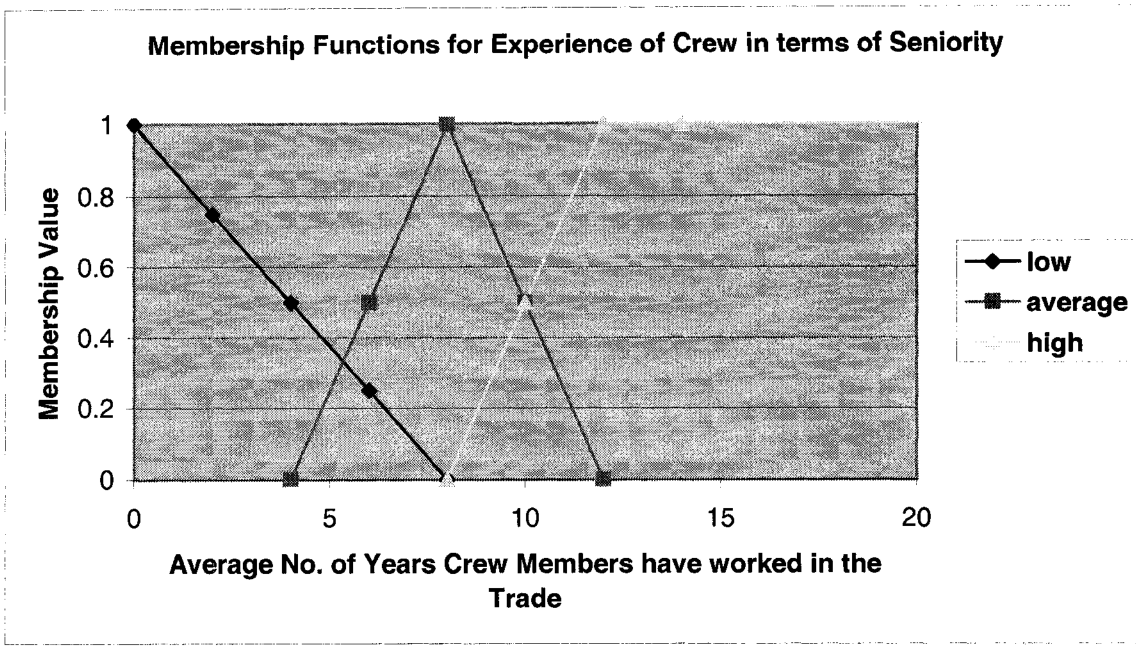
Membership Functions for Elevation (Trials 1,2,3, and, 4)



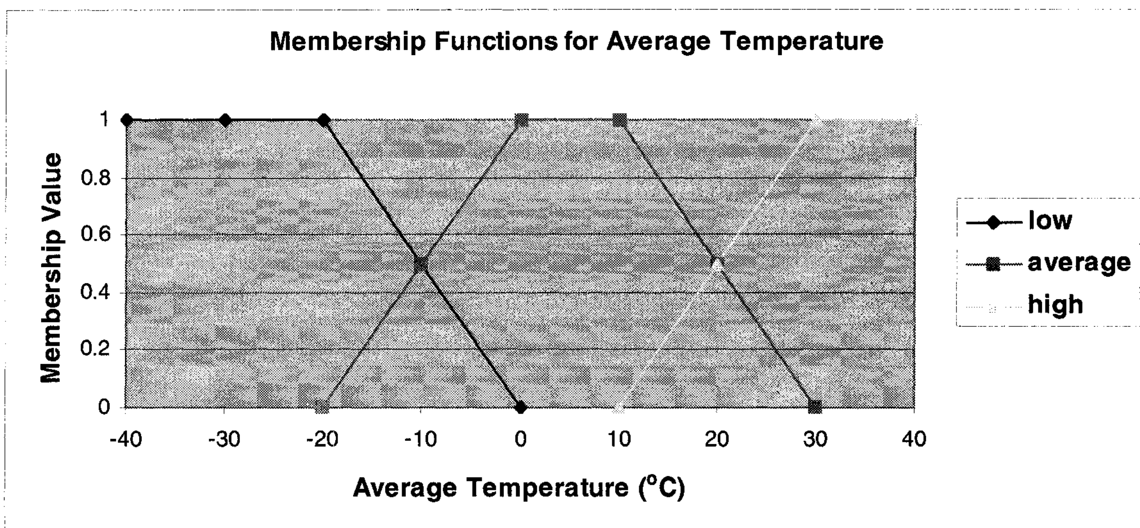
Membership Functions for Crew Experience-Learning (Trial 1,2,3,and, 4)



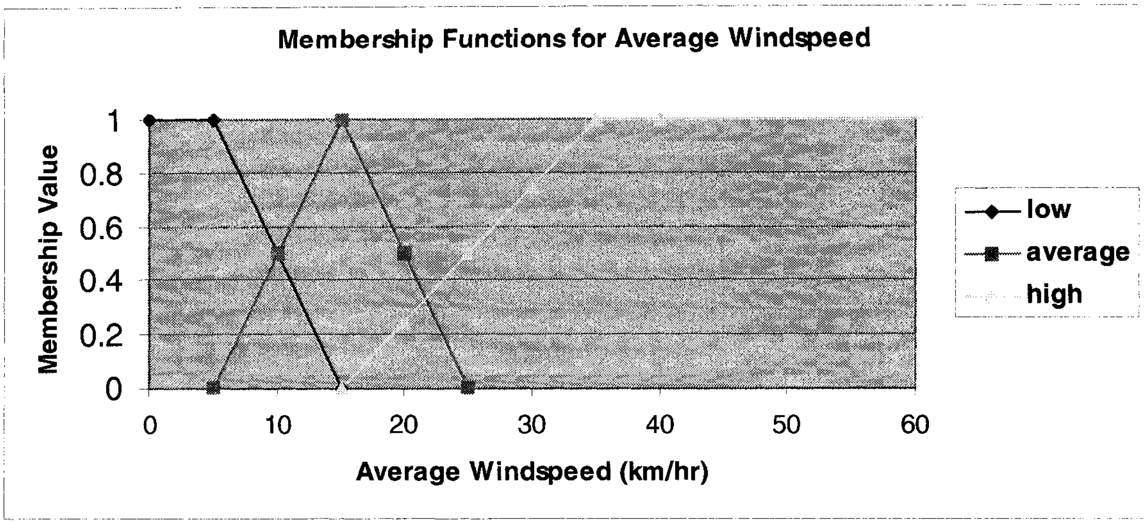
Membership Functions for Crew Experience-Seniority (Trial 1,2, and, 3)



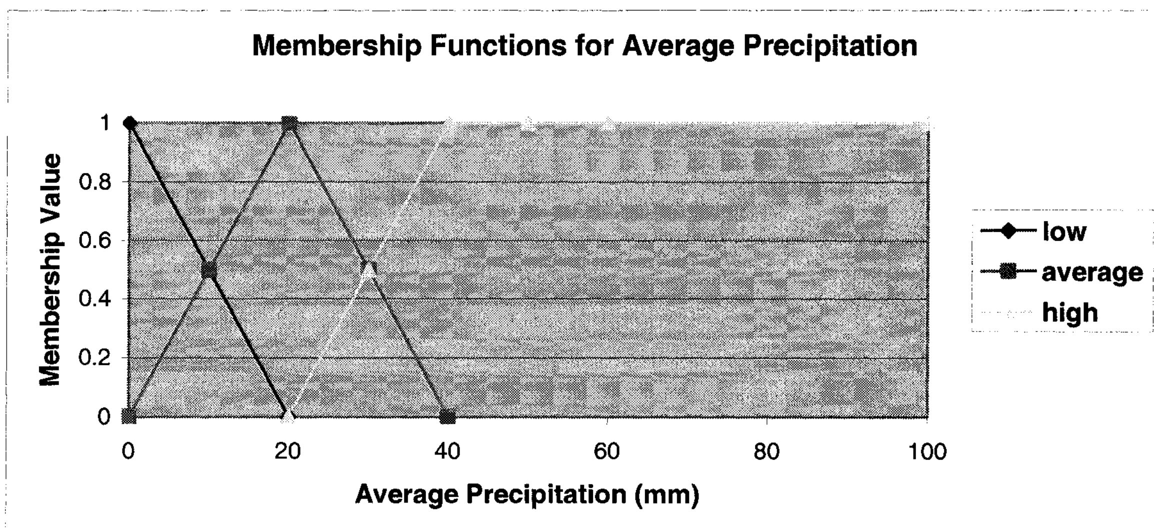
Membership Functions for Crew Experience-Seniority (Trial 4)



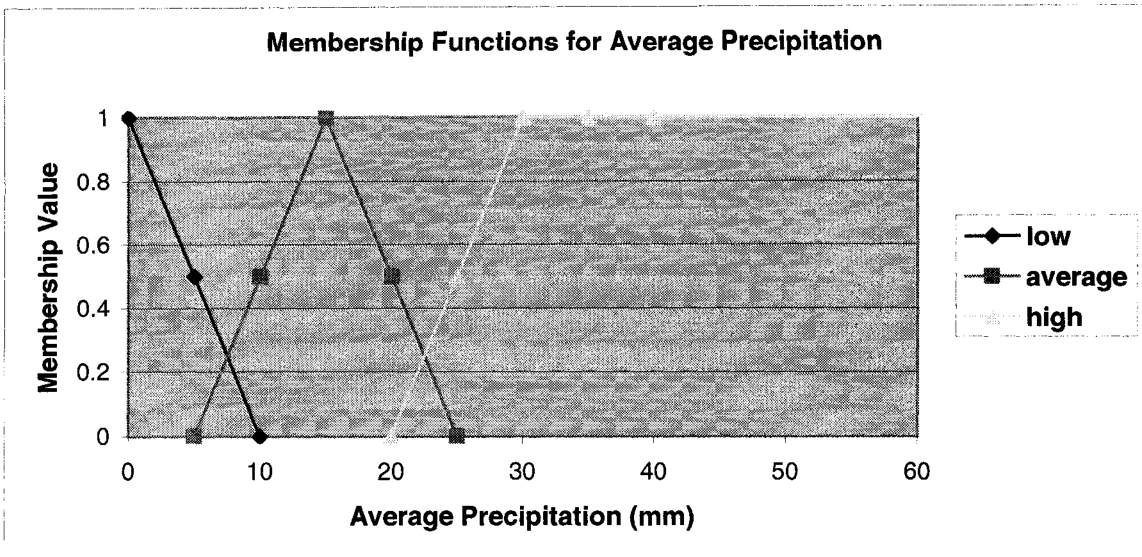
Membership Functions for Average Temperature (Trials 1,2,3, and, 4)



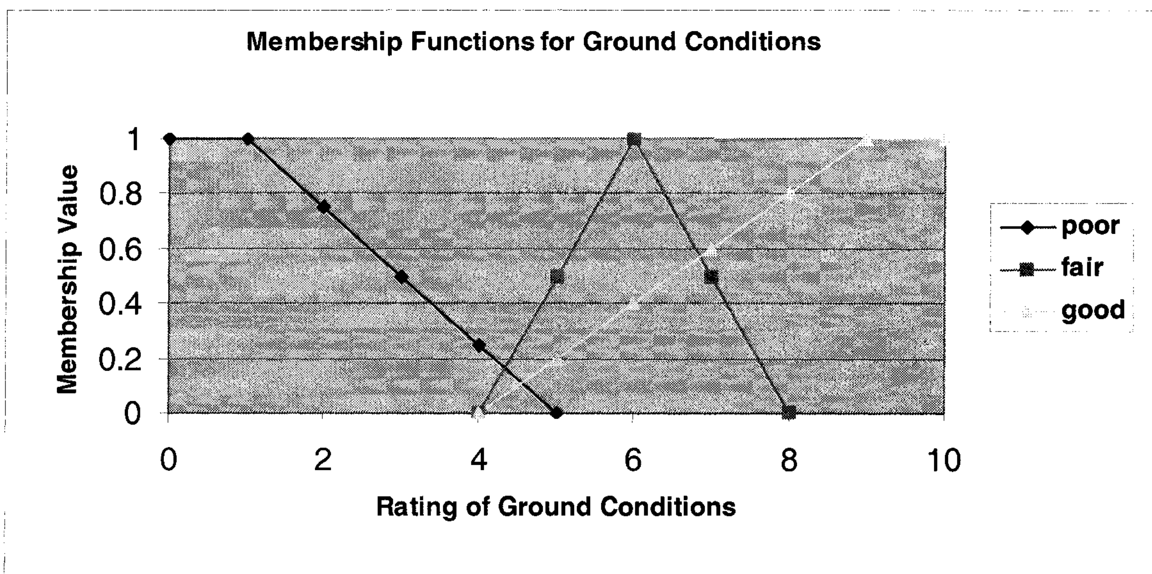
Membership Functions for Average Windspeed (Trials 1,2,3, and, 4)



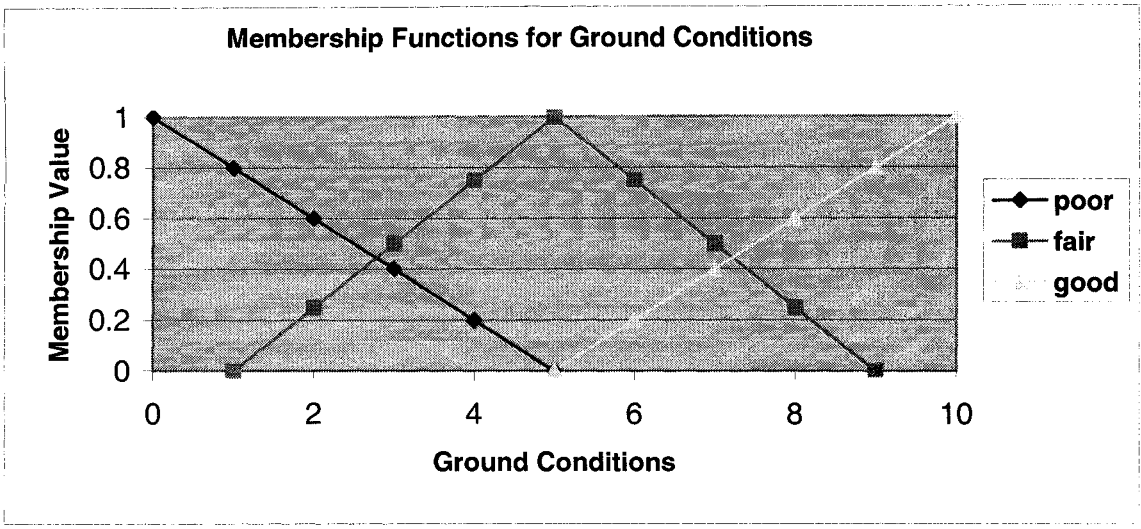
Membership Functions for Average Precipitation (Trials 1,2, and, 3)



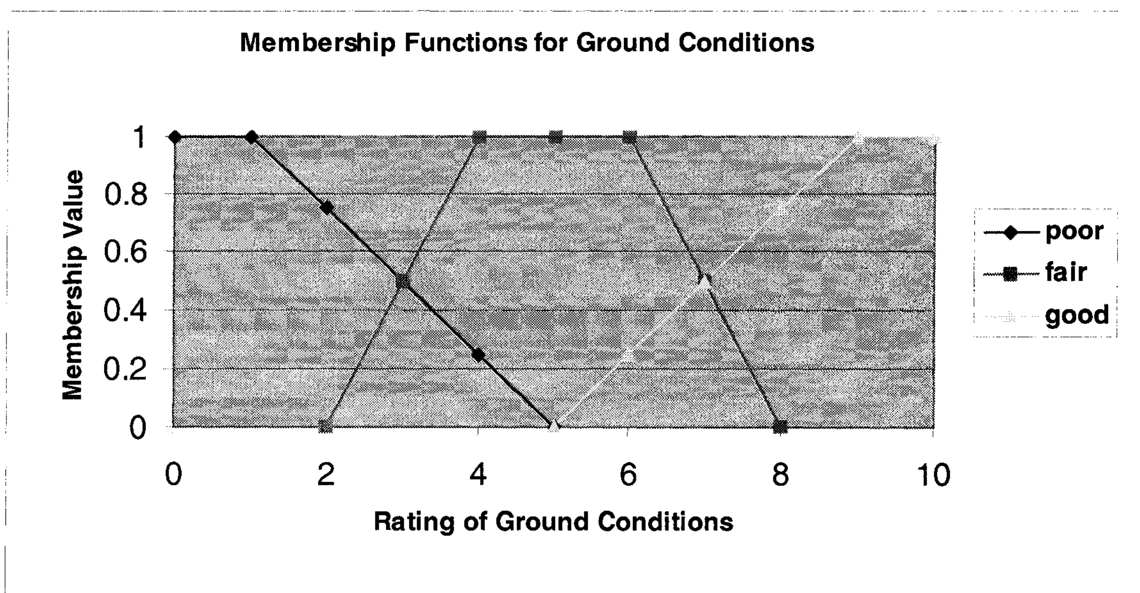
Membership Functions for Average Precipitation (Trial 4)



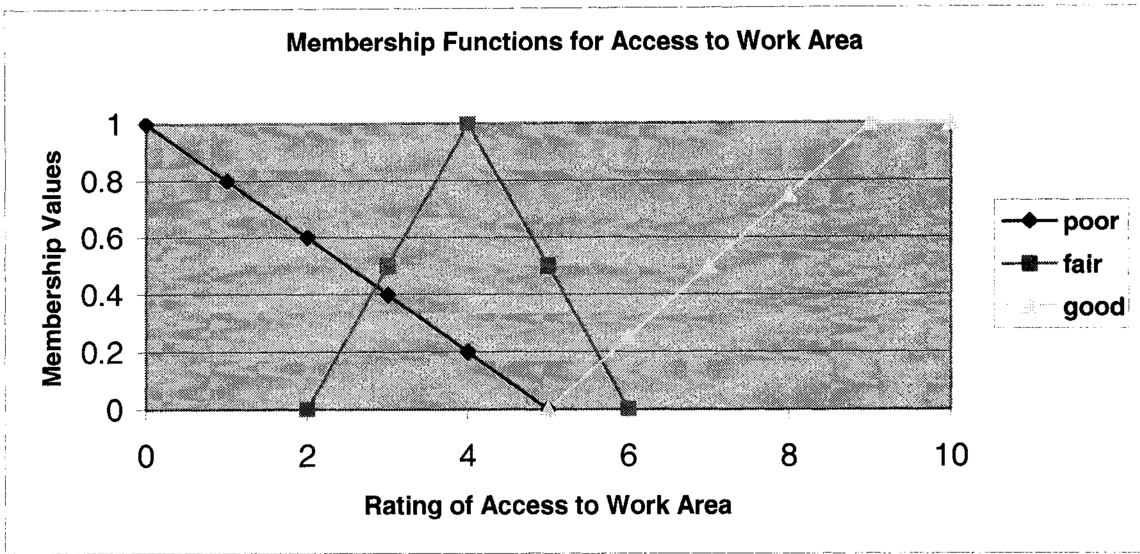
Membership Functions for Ground Conditions (Trials 1 and 2)



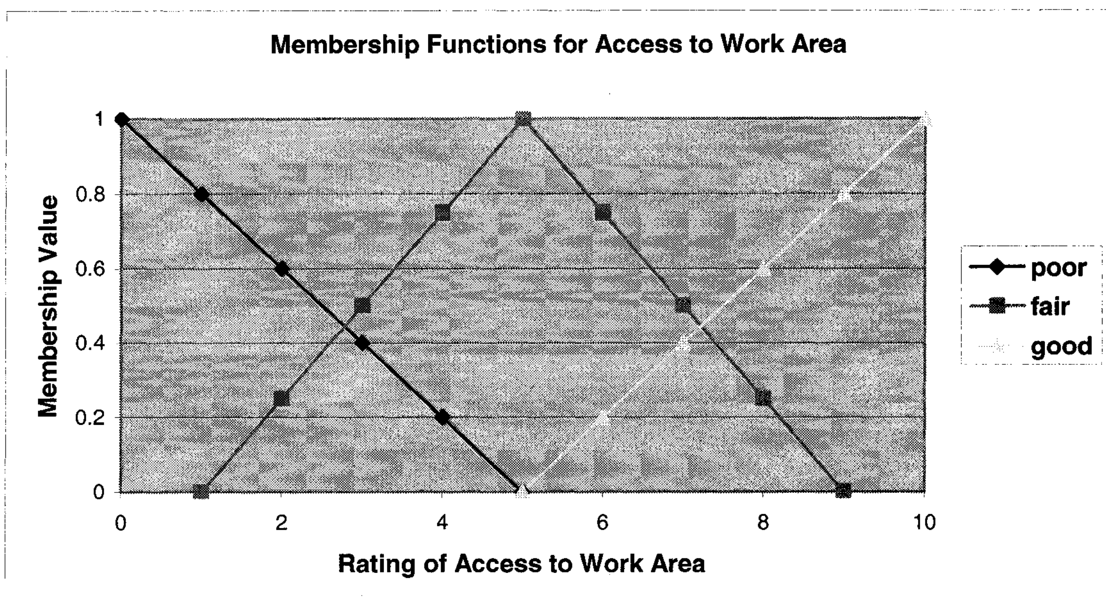
Membership Functions for Ground Conditions (Trial 3)



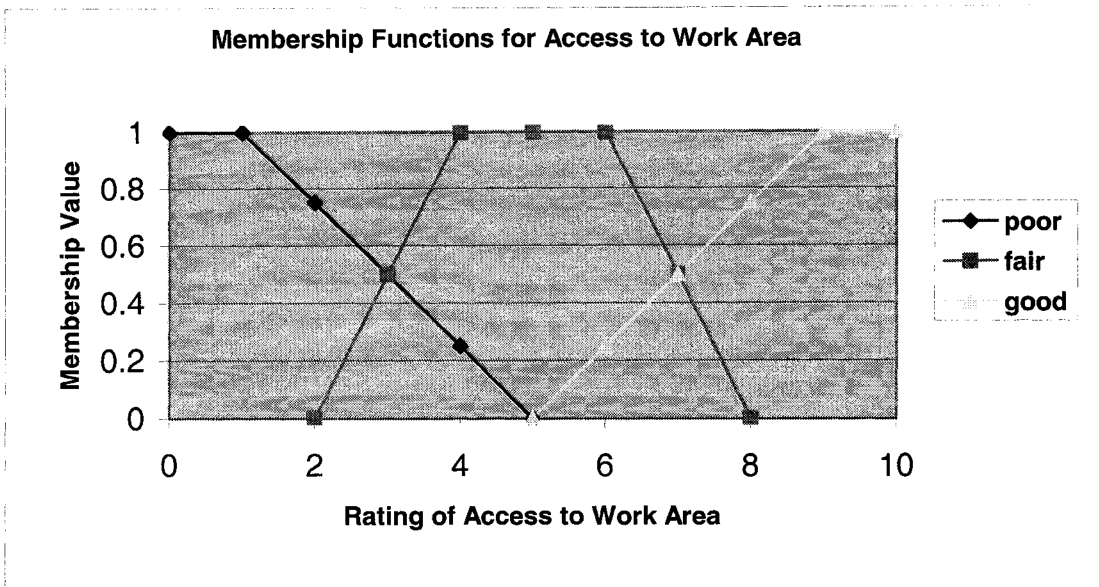
Membership Functions for Ground Conditions (Trial 4)



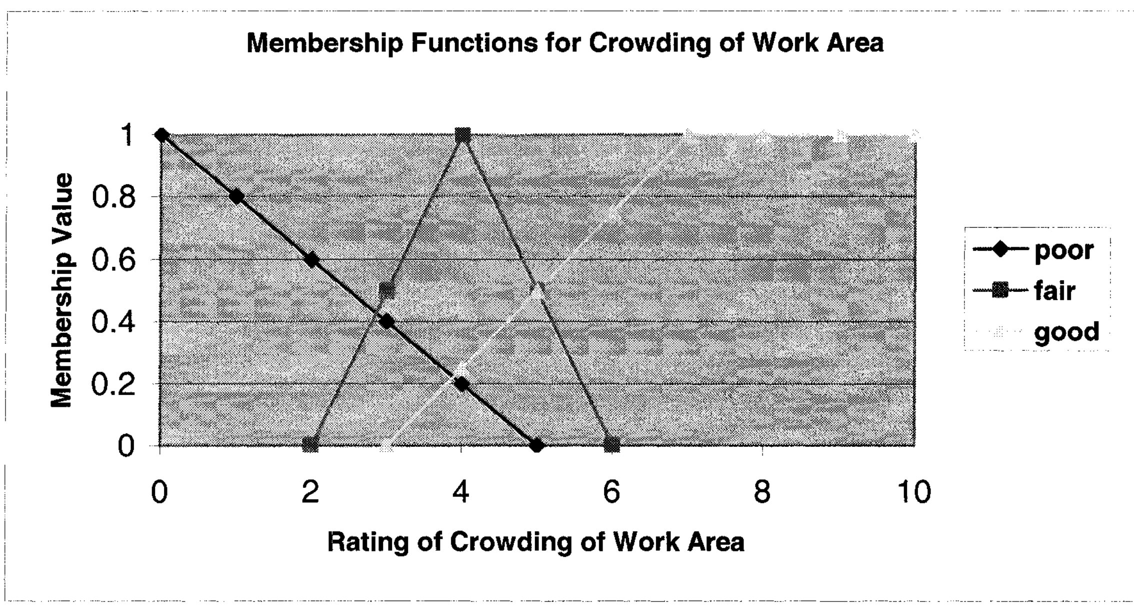
Membership Functions for Access to Work Area (Trials 1 and 2)



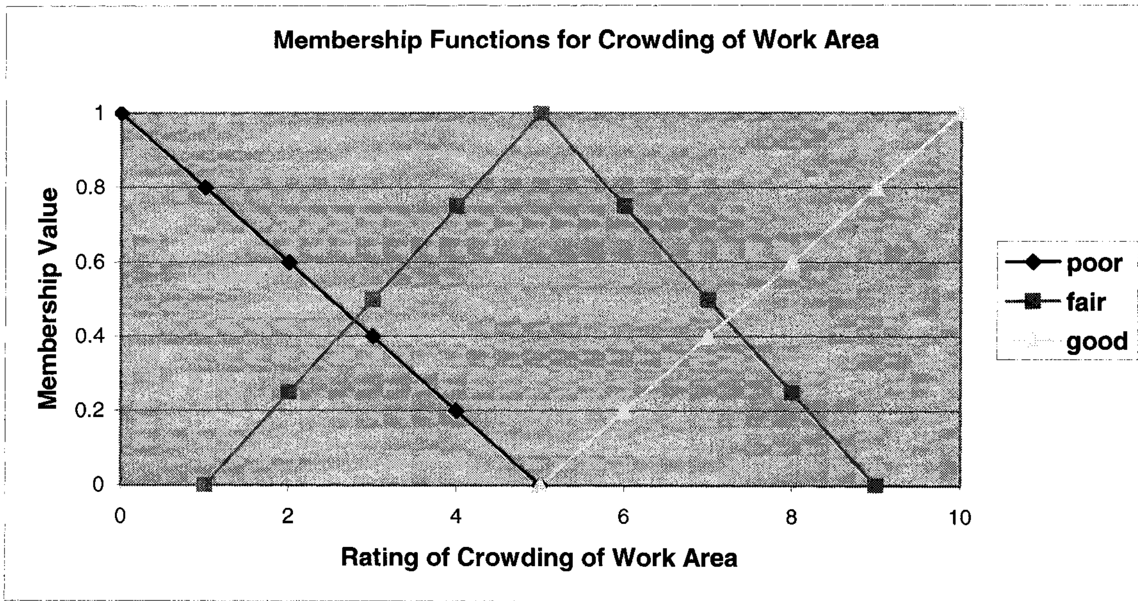
Membership Functions for Access to Work Area (Trial 3)



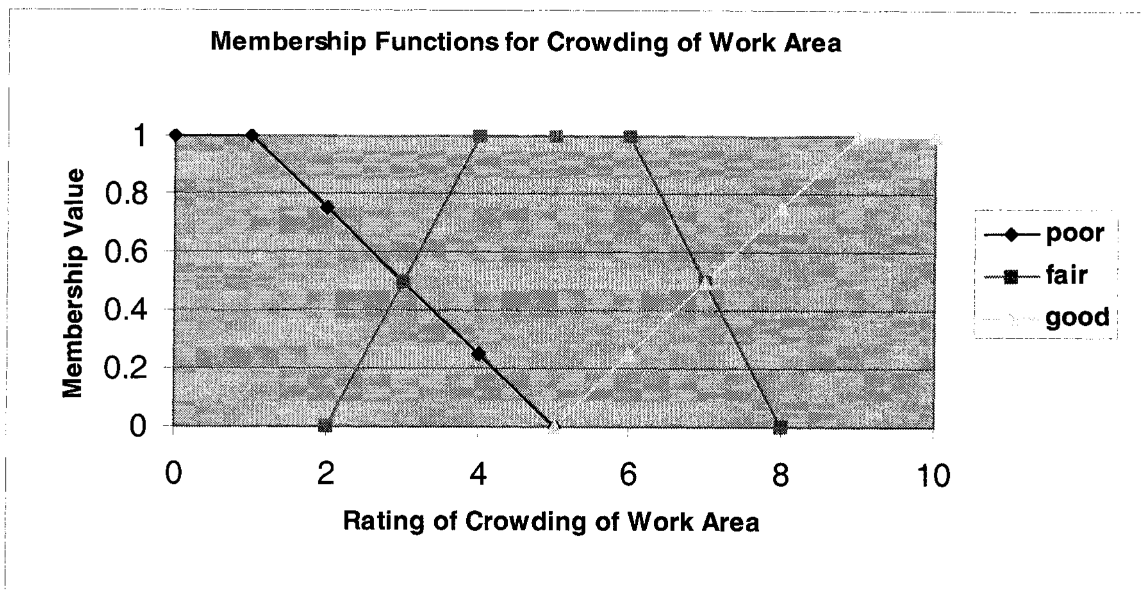
Membership Functions for Access to Work Area (Trial 4)



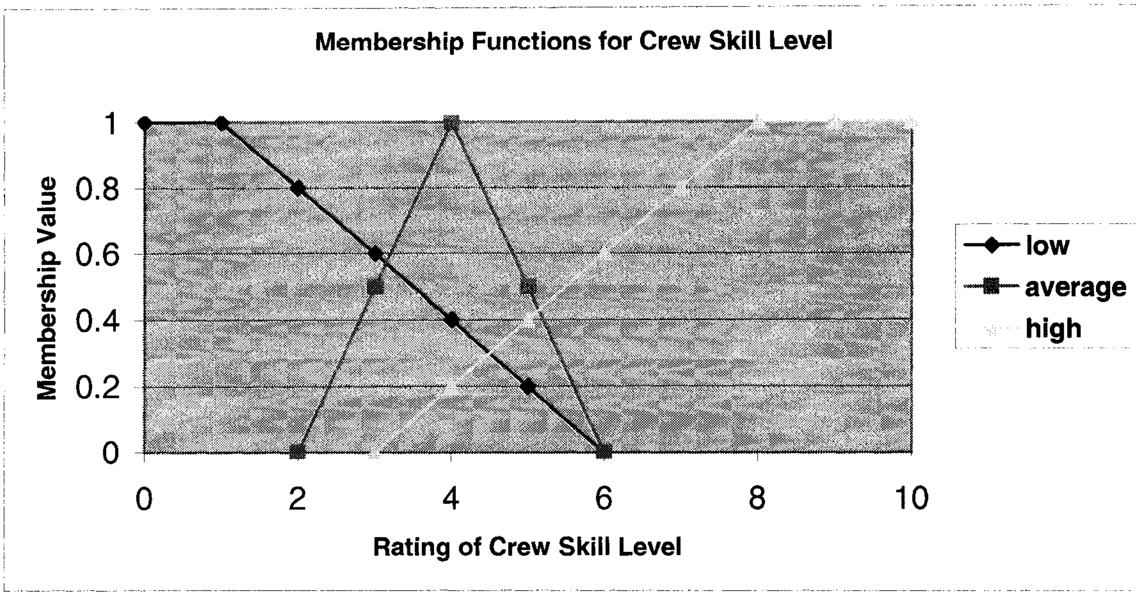
Membership Functions for Crowding of Work Area (Trials 1 and 2)



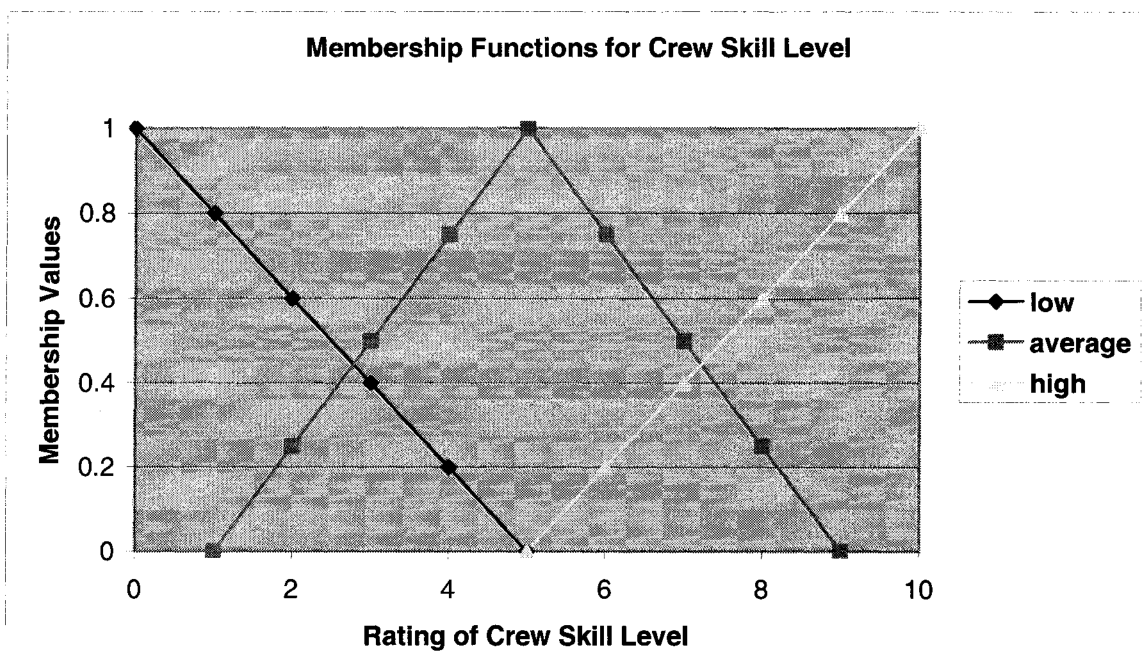
Membership Functions for Crowding of Work Area (Trial 3)



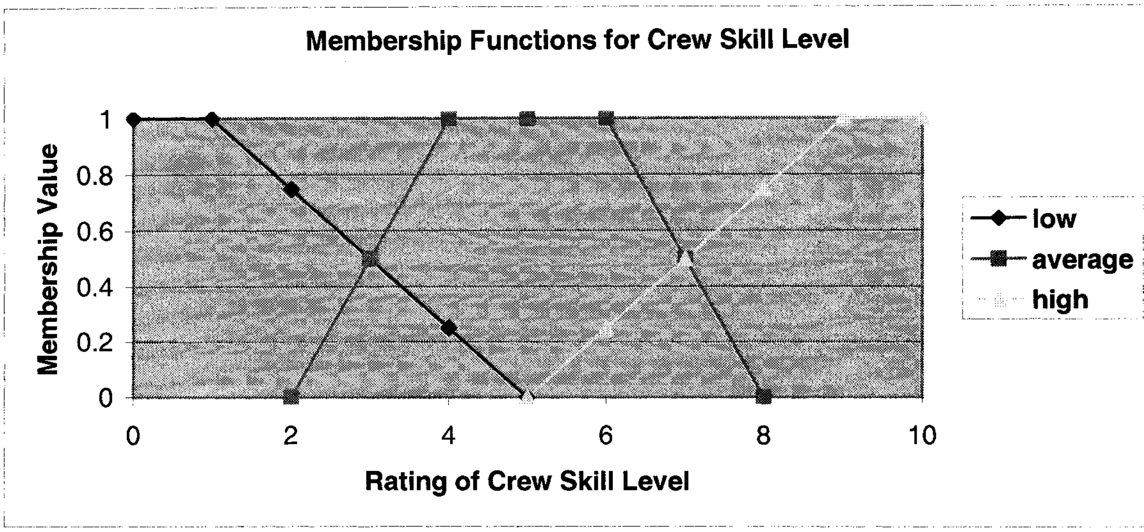
Membership Functions for Access to Work Area (Trial 4)



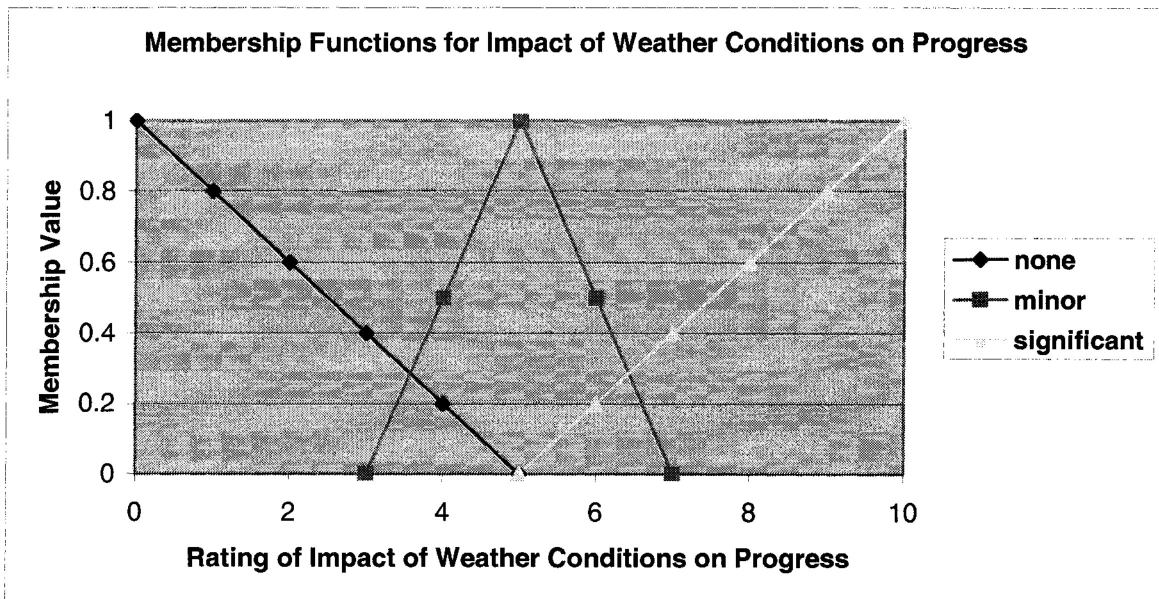
Membership Functions for Crew Skill Level (Trials 1 and 2)



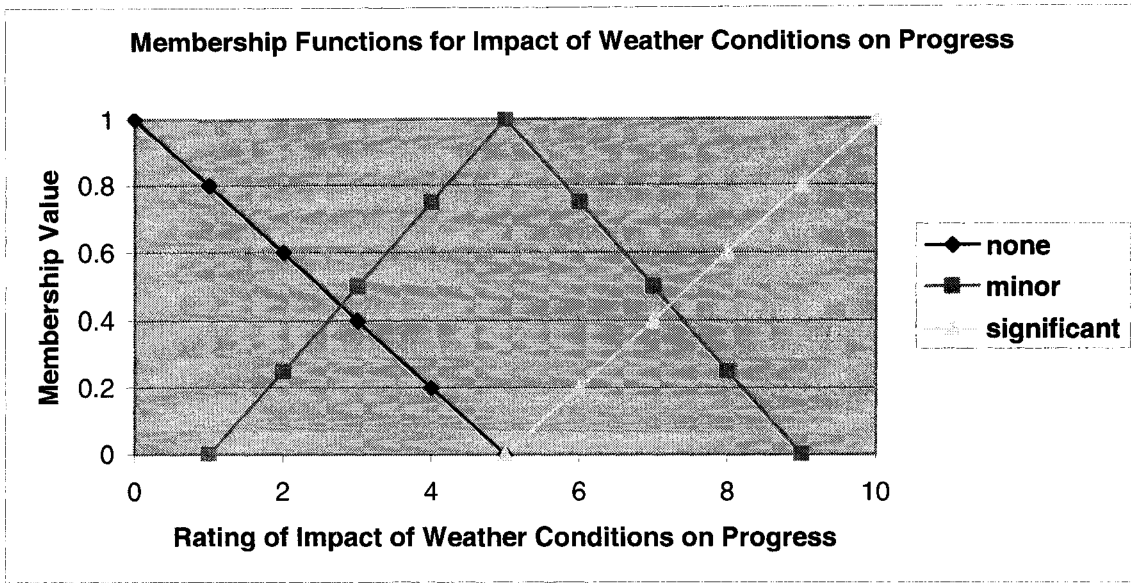
Membership Functions for Crew Skill Level (Trial 3)



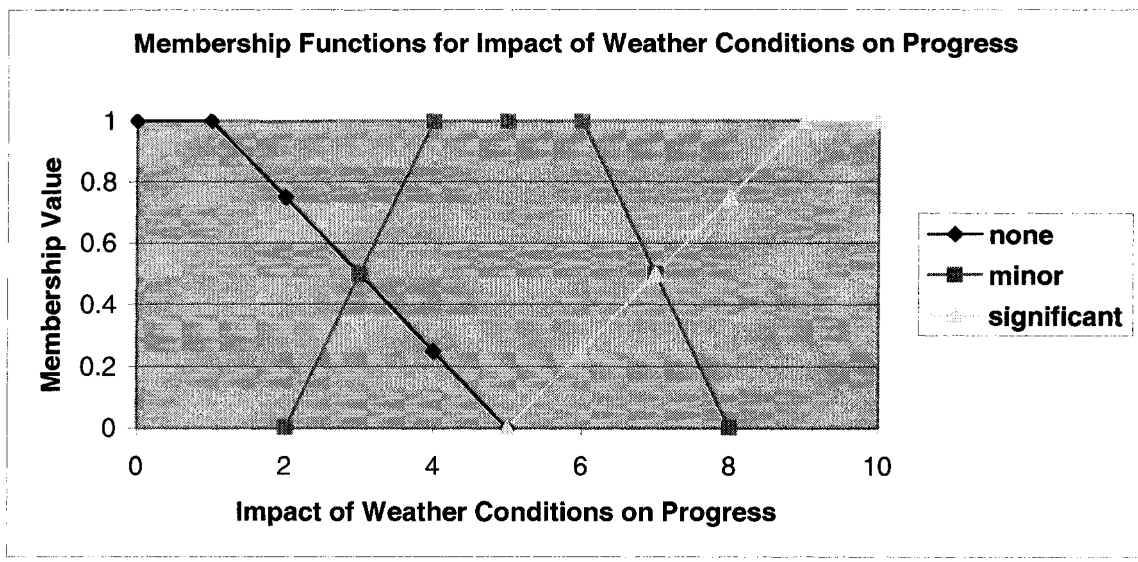
Membership Functions for Crew Skill Level (Trial 4)



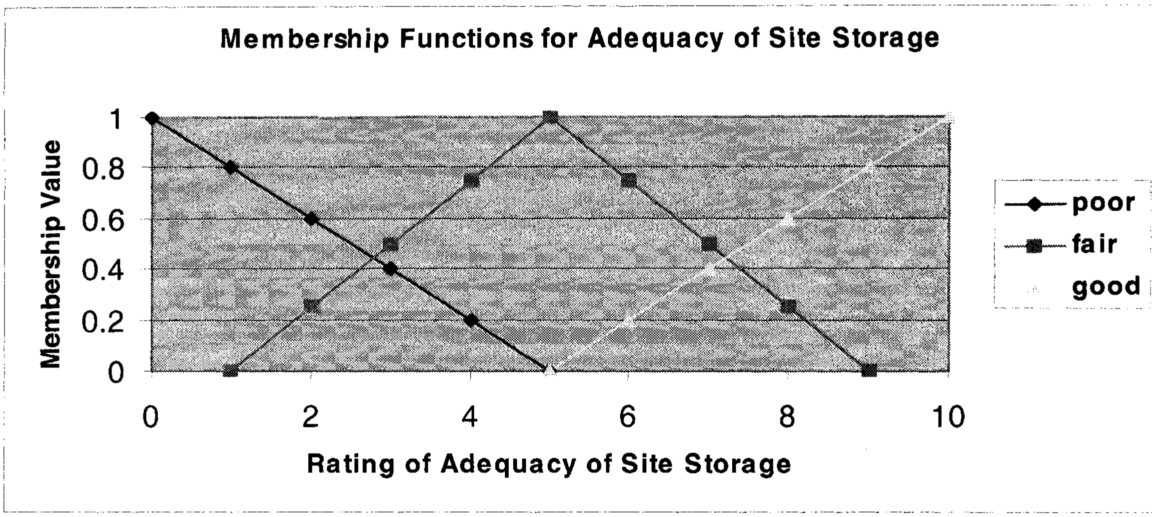
Membership Functions for Impact of Weather Conditions on Progress (Trials 1 and 2)



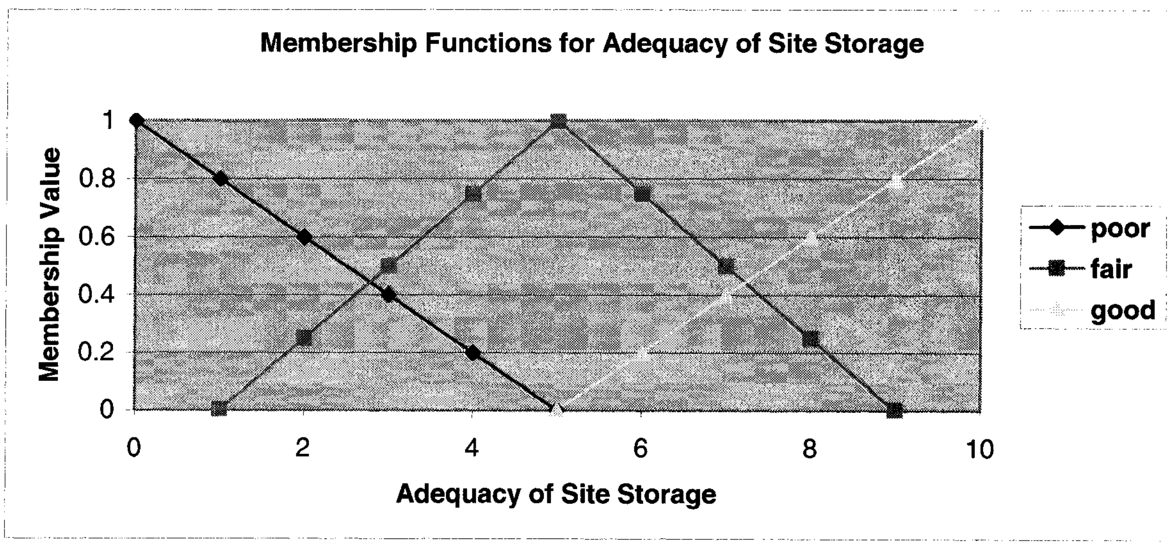
Membership Functions for Impact of Weather Conditions on Progress (Trial 3)



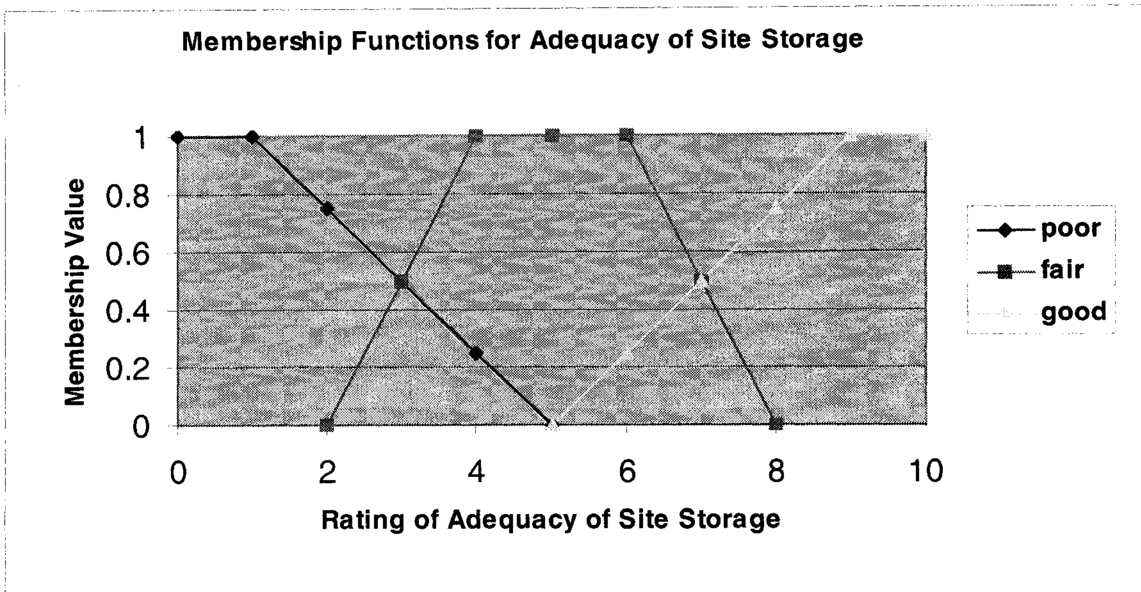
Membership Functions for Impact of Weather Conditions on Progress (Trial 4)



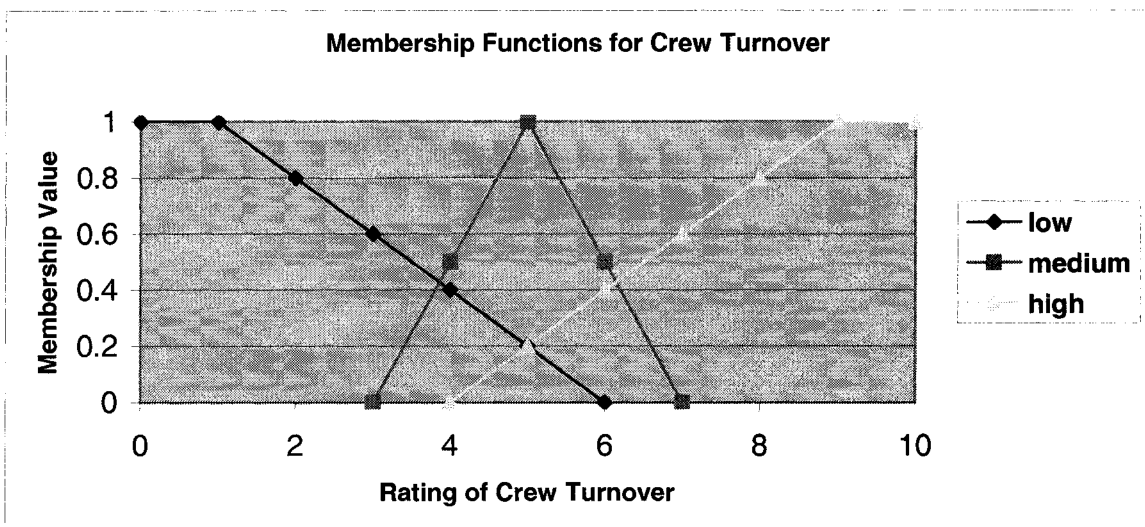
Membership Functions for Adequacy of Site Storage (Trials 1 and 2)



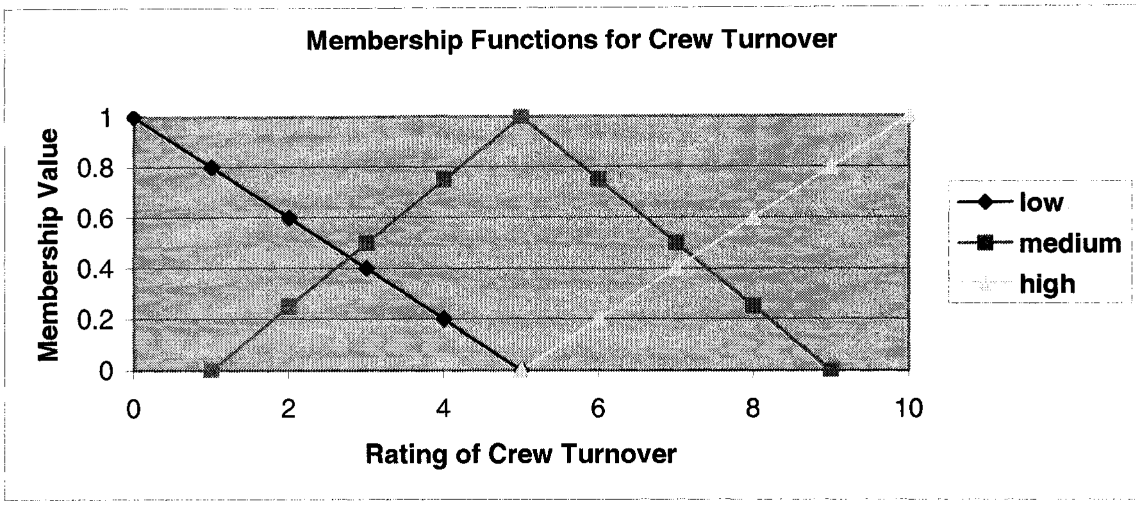
Membership Functions for Adequacy of Site Storage (Trial 3)



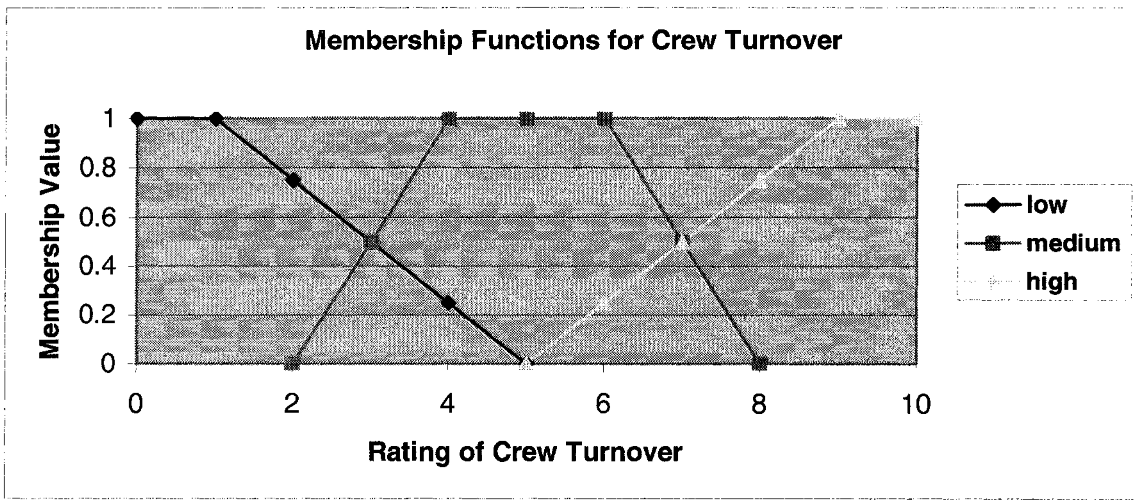
Membership Functions for Adequacy of Site Storage (Trial 4)



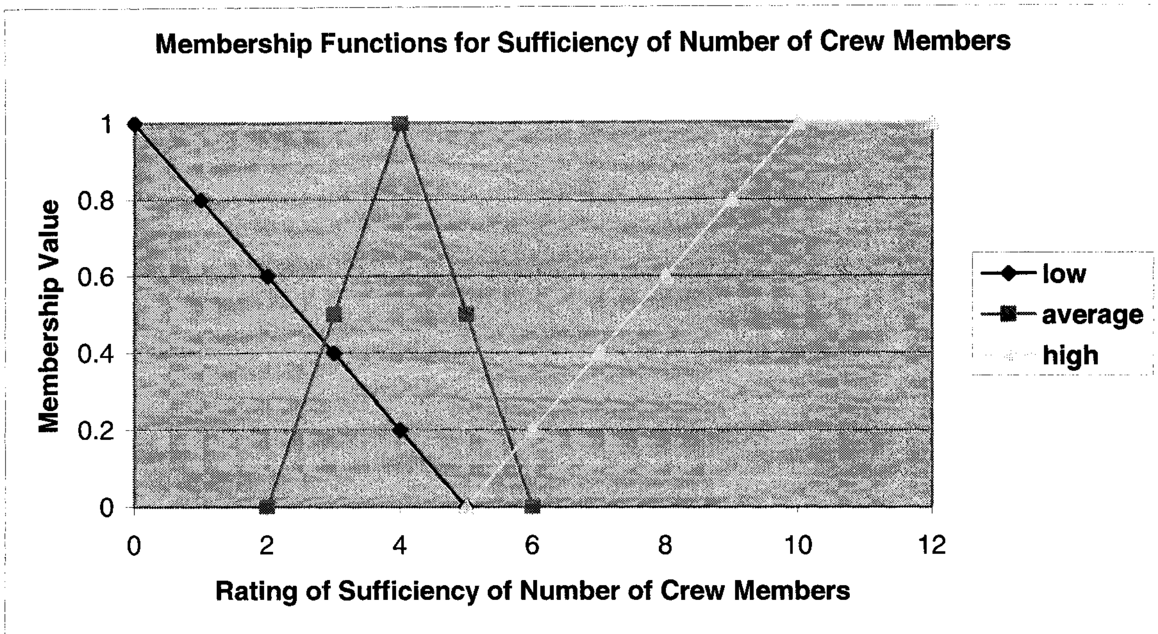
Membership Functions for Crew Turnover (Trials 1 and 2)



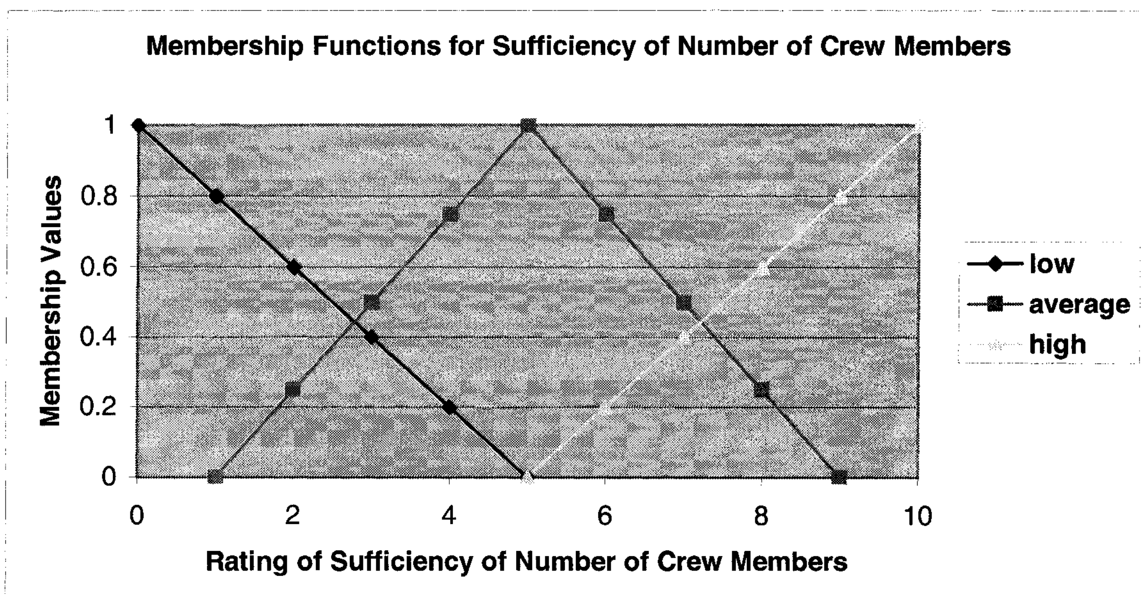
Membership Functions for Crew Turnover (Trial 3)



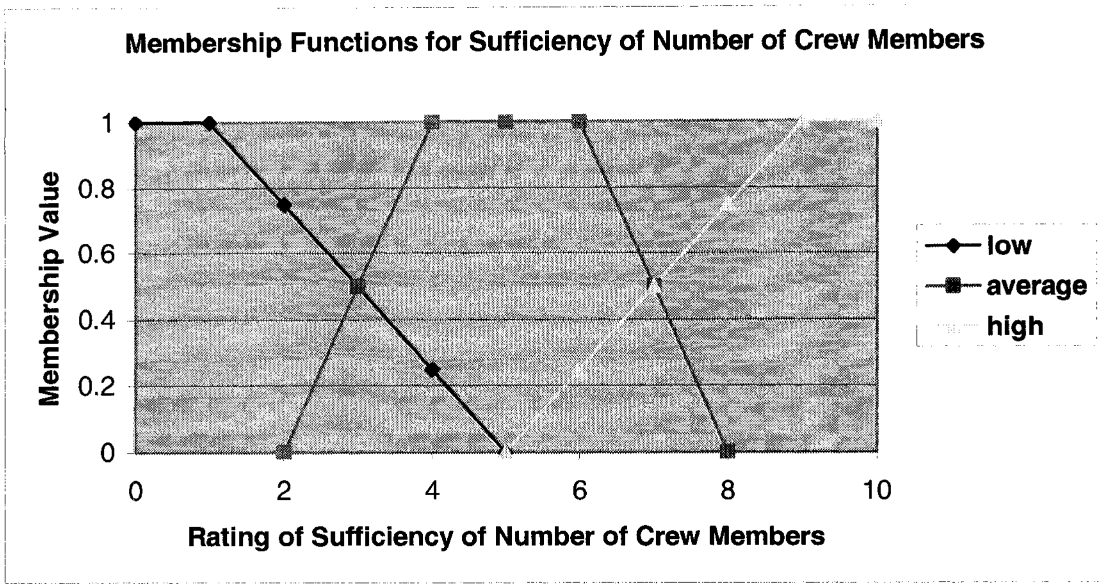
Membership Functions for Crew Turnover (Trial 4)



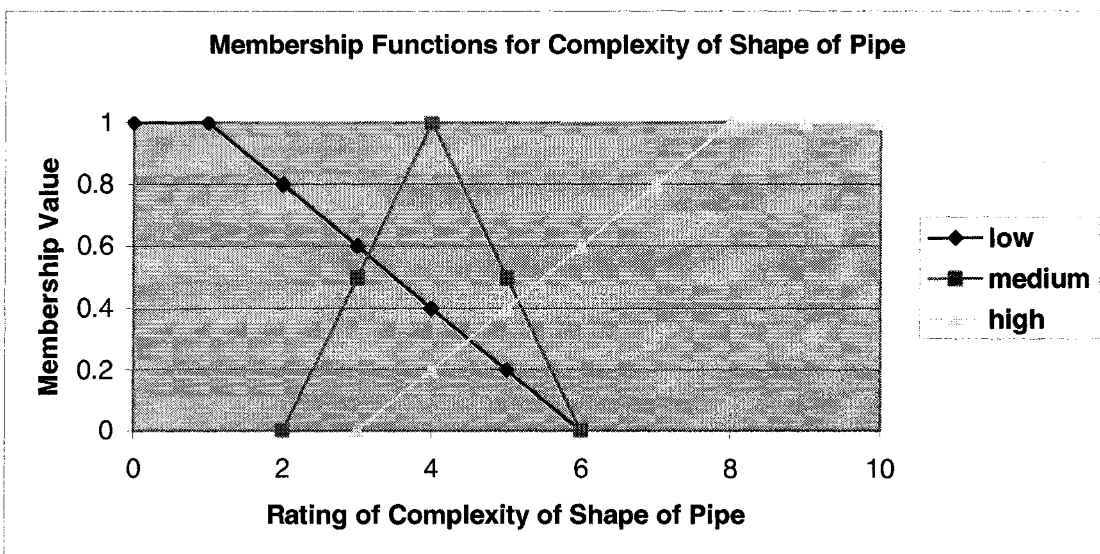
Membership Functions for Sufficiency of Number of Crew Members (Trials 1 and 2)



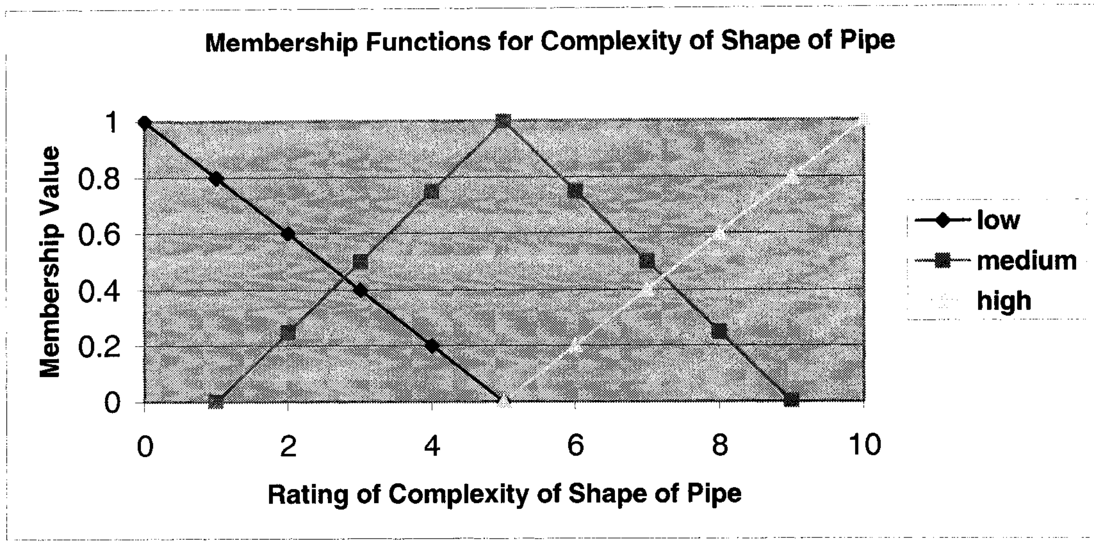
Membership Functions for Sufficiency of Number of Crew Members (Trial 3)



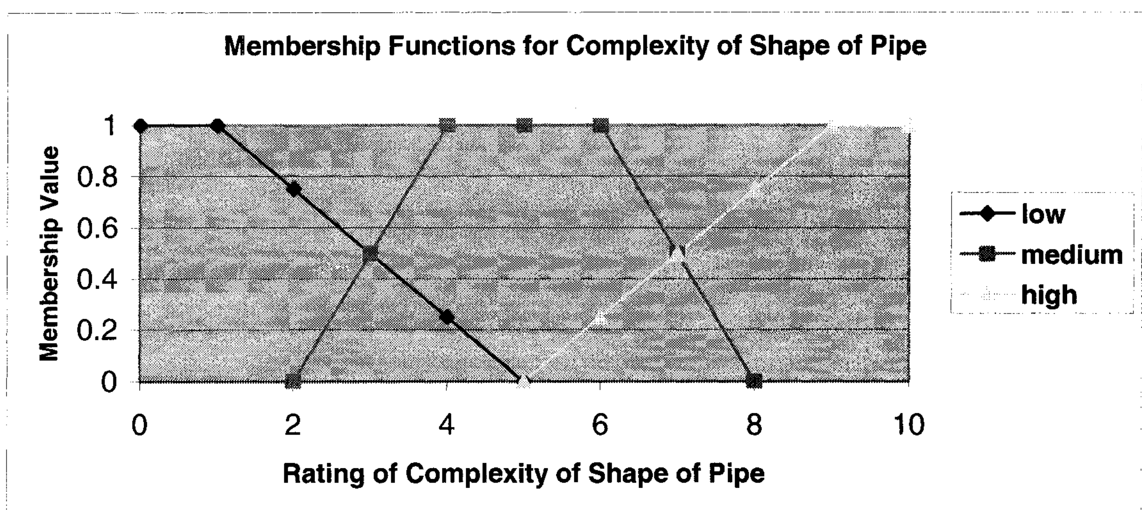
Membership Functions for Sufficiency of Number of Crew Members (Trial 4)



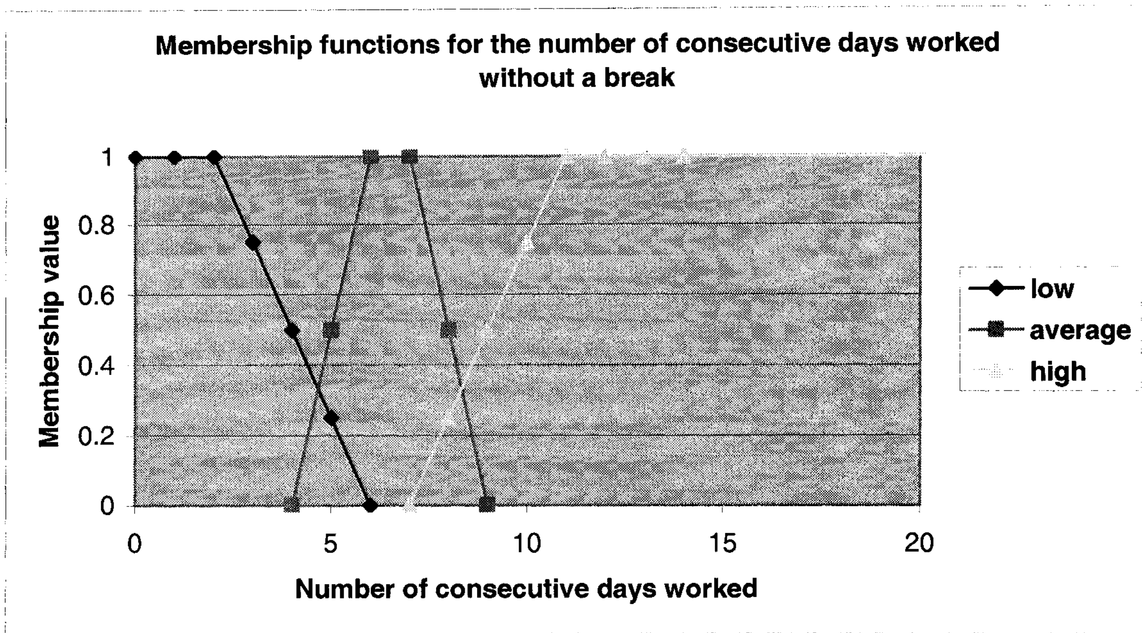
Membership Functions for Complexity of Shape of Pipe (Trials 1 and 2)



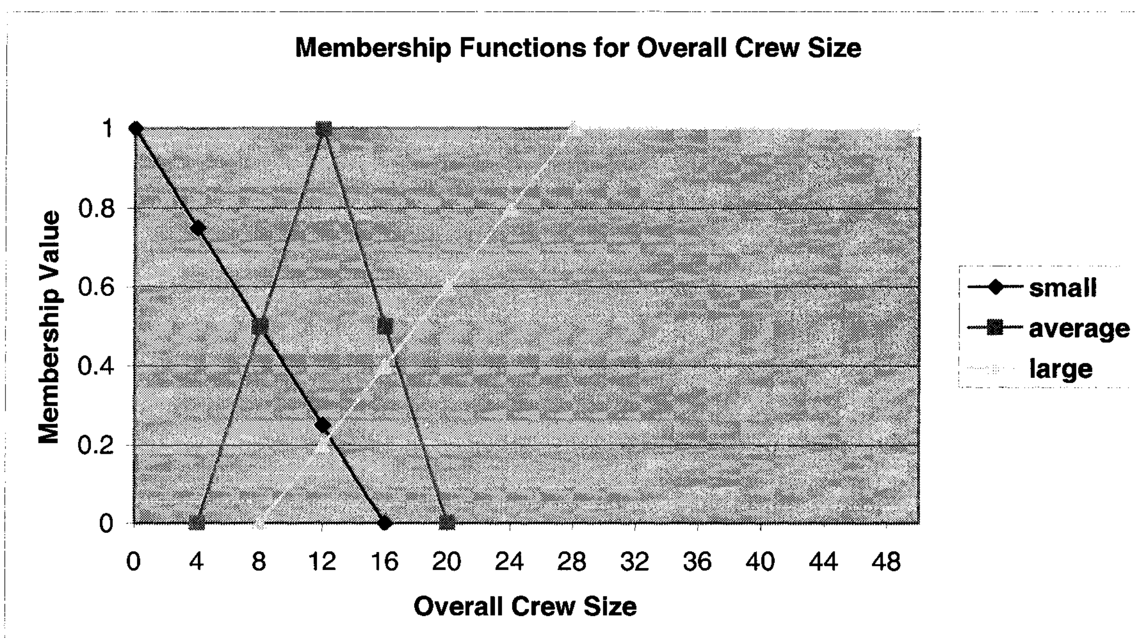
Membership Functions for Complexity of Shape of Pipe (Trial 3)



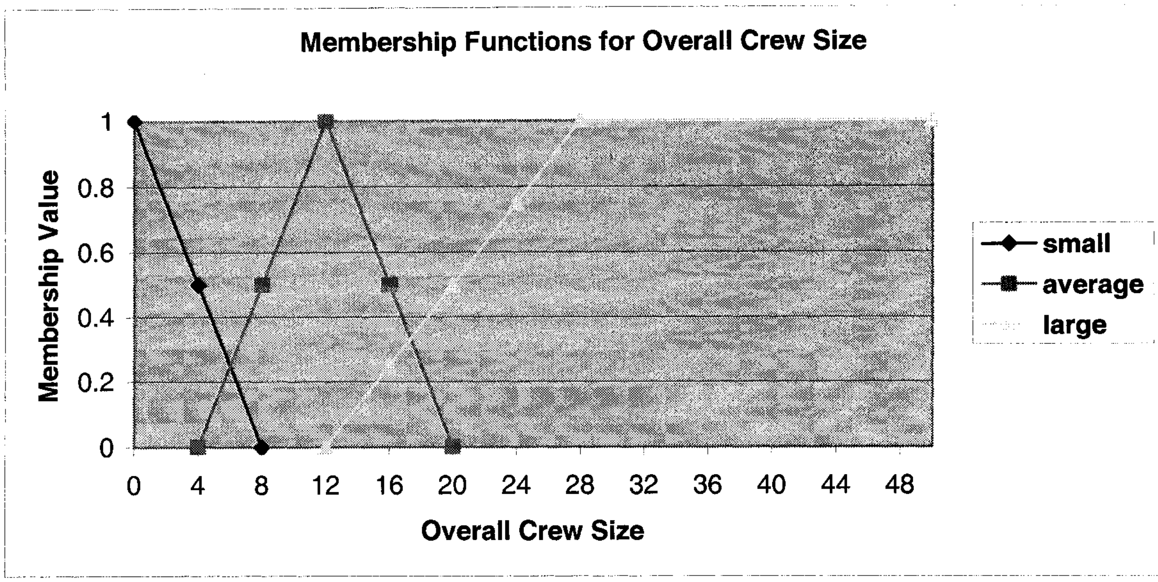
Membership Functions for Complexity of Shape of Pipe (Trial 4)



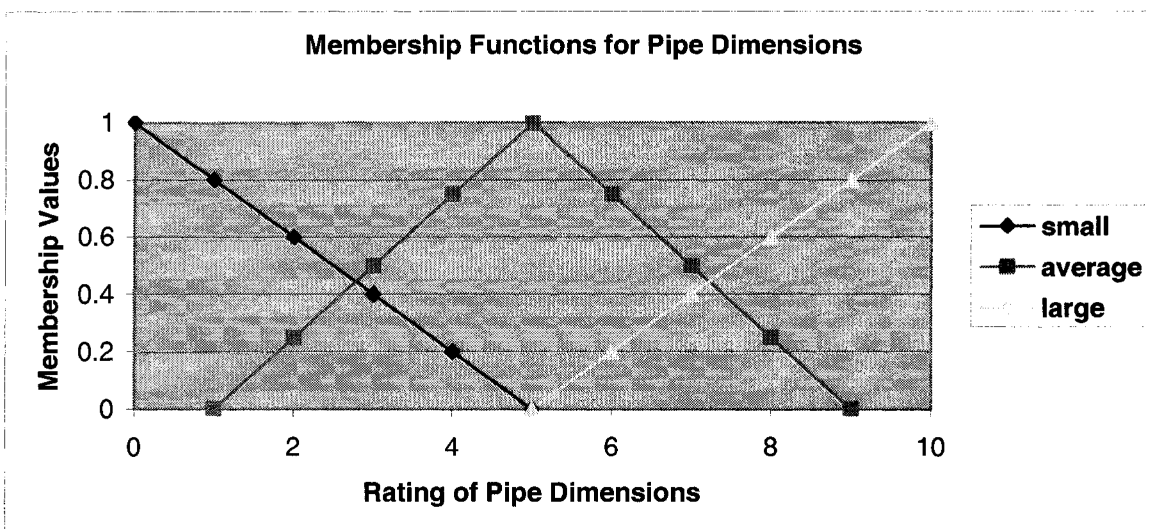
Membership Functions for Number of Consecutive Days worked without a break (Trials 1, 2, 3, and, 4)



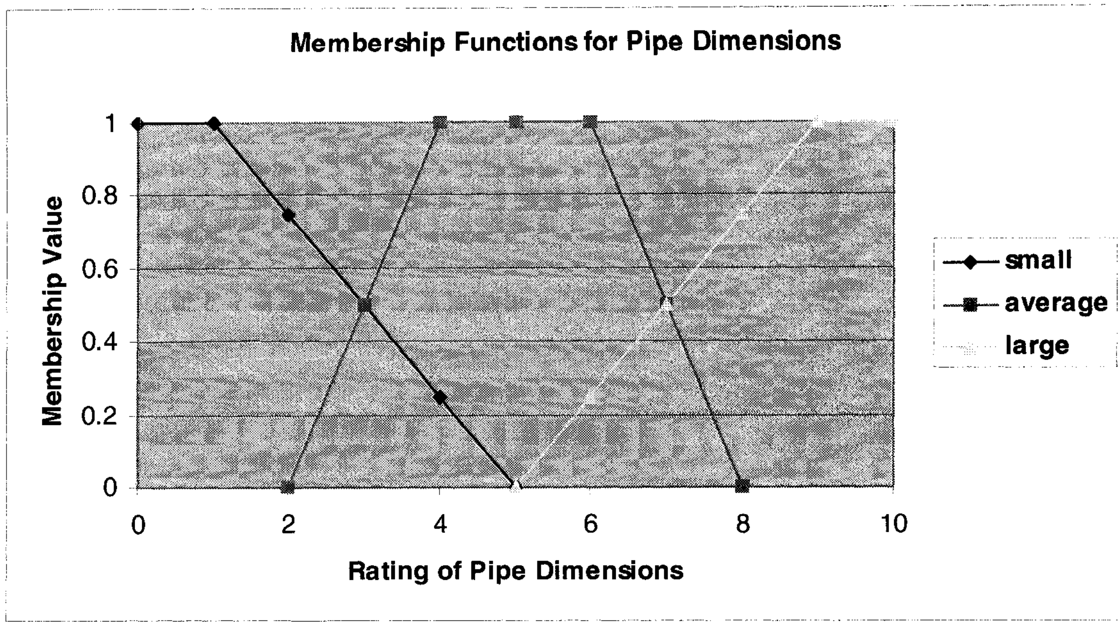
Membership Functions for Overall Crew Size (Trials 1, 2, and, 3)



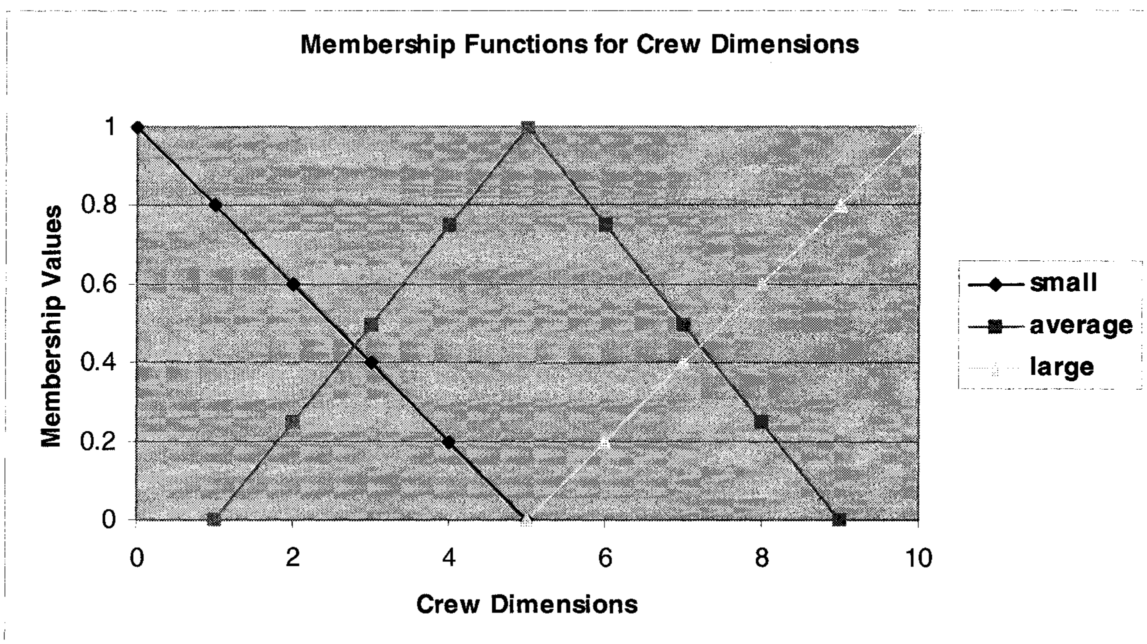
Membership Functions for Overall Crew Size (Trial 4)



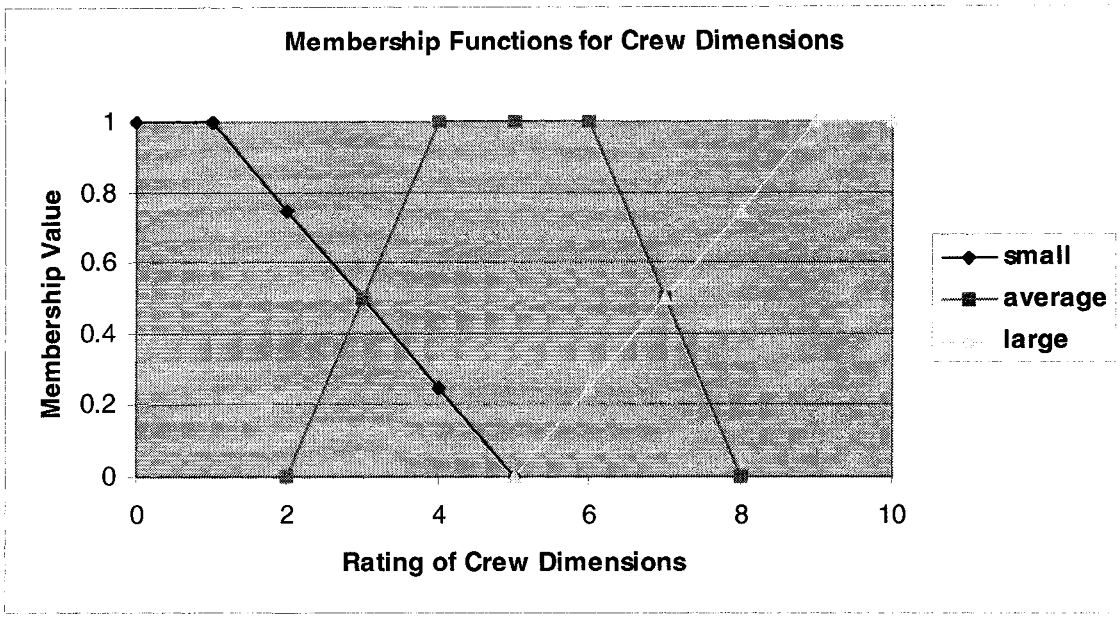
Membership Functions for Pipe Dimensions (Trials 1, 2, and, 3)



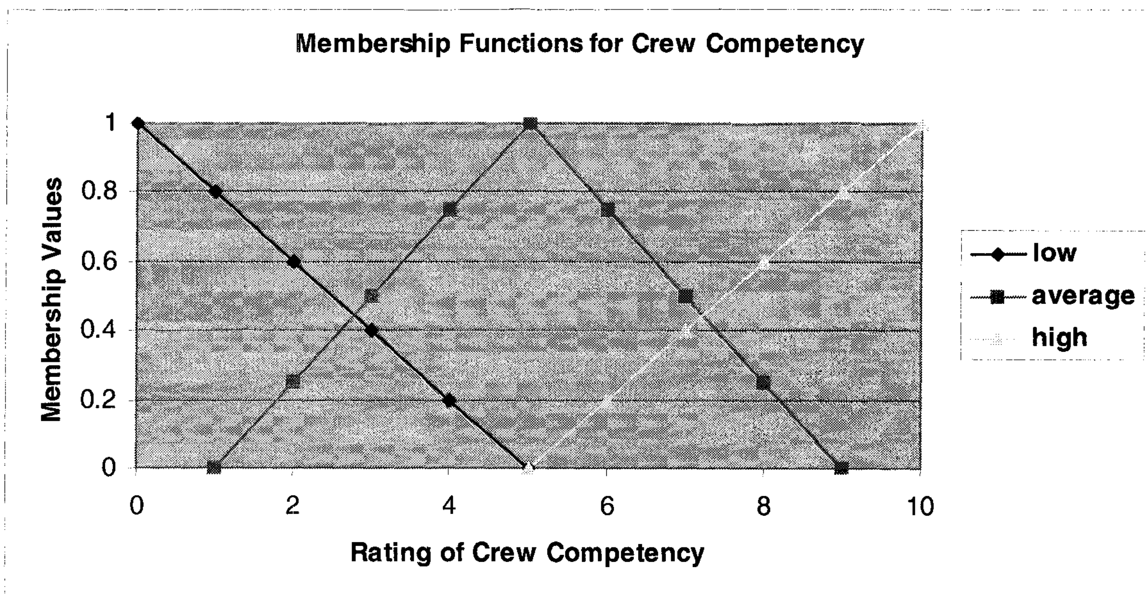
Membership Functions for Ground Conditions (Trial 4)



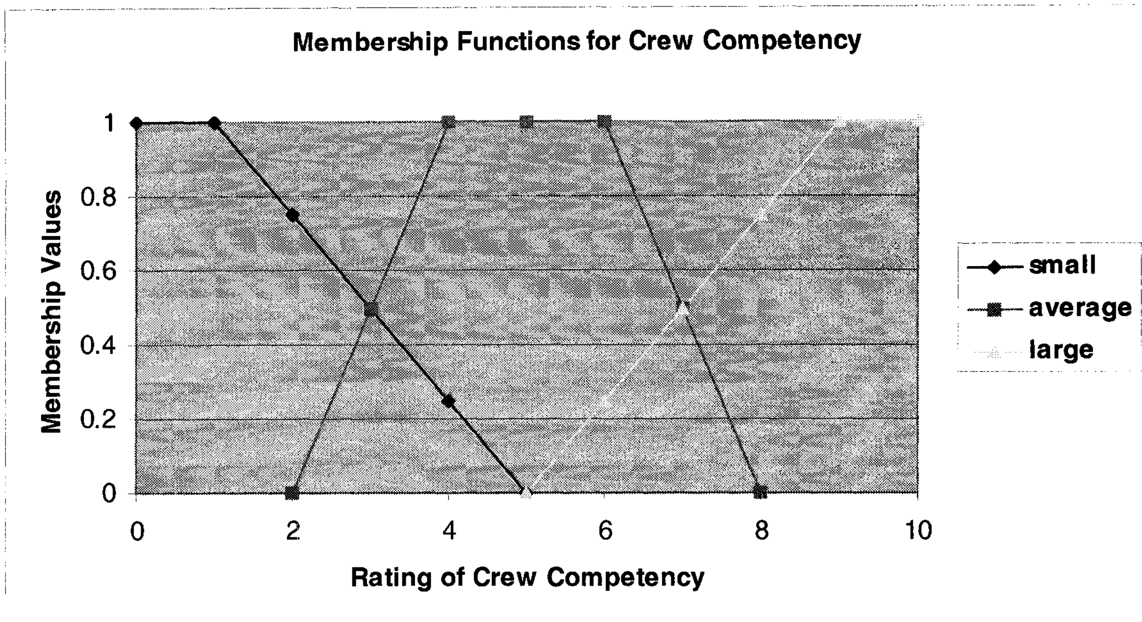
Membership Functions for Crew Dimensions (Trials1, 2, and, 3)



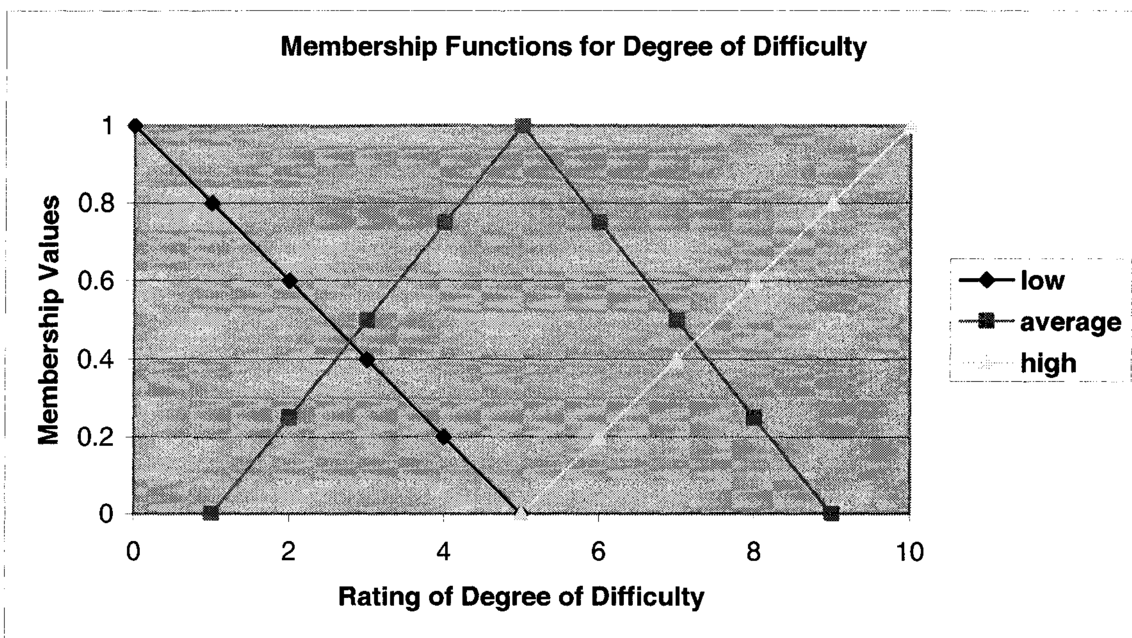
Membership Functions for Crew Dimensions (Trial 4)



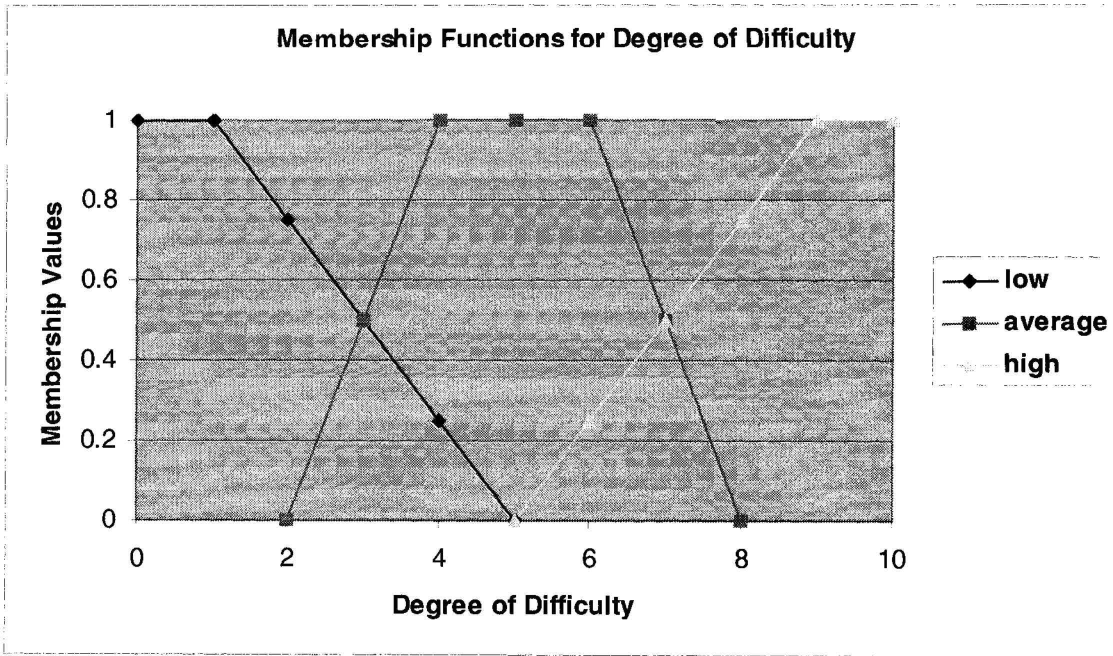
Membership Functions for Crew Competency (Trials 1, 2, and, 3)



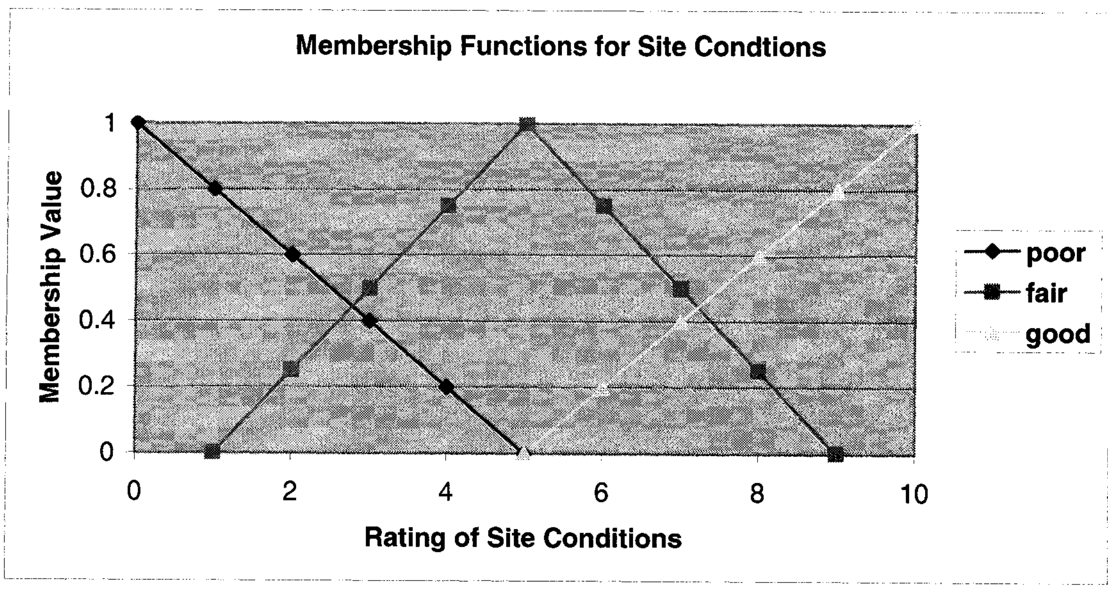
Membership Functions for Crew Competency (Trial 4)



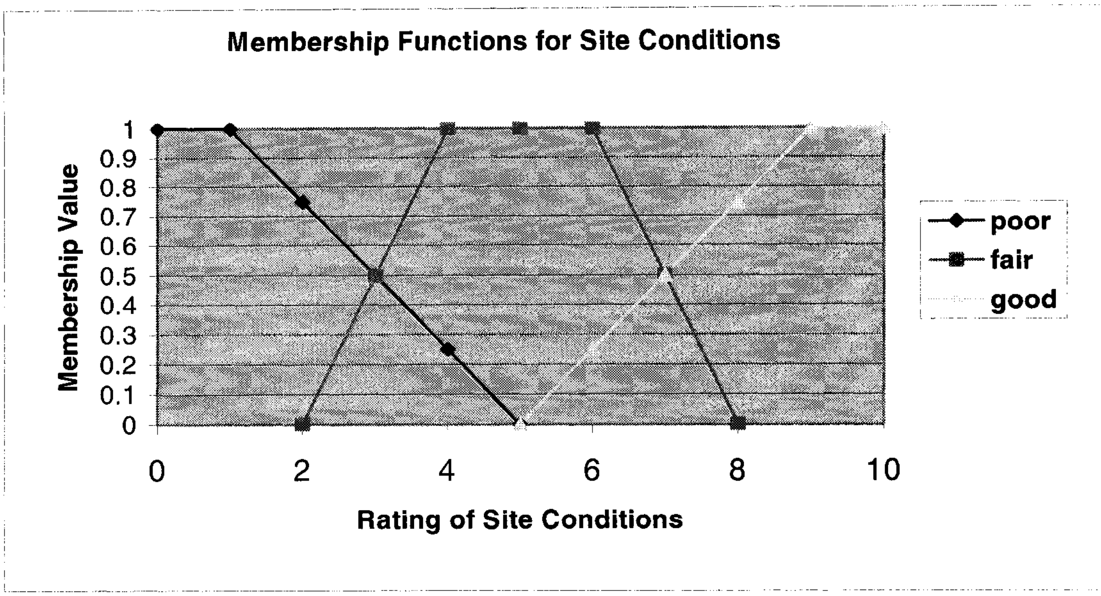
Membership Functions for Degree of Difficulty (Trials 1, 2, and, 3)



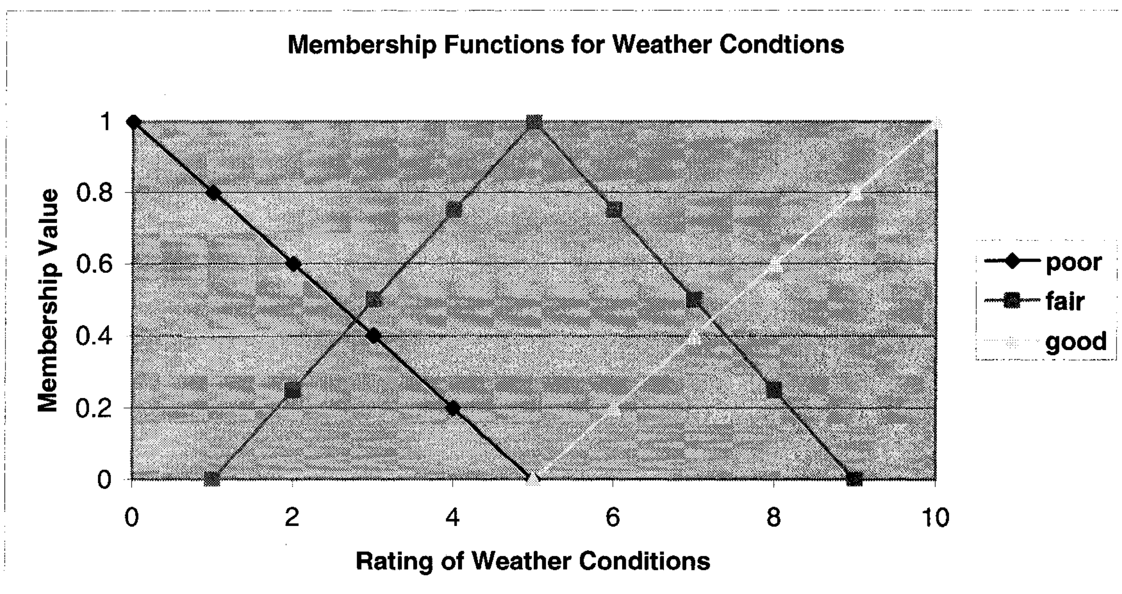
Membership Functions for Degree of Difficulty (Trial 4)



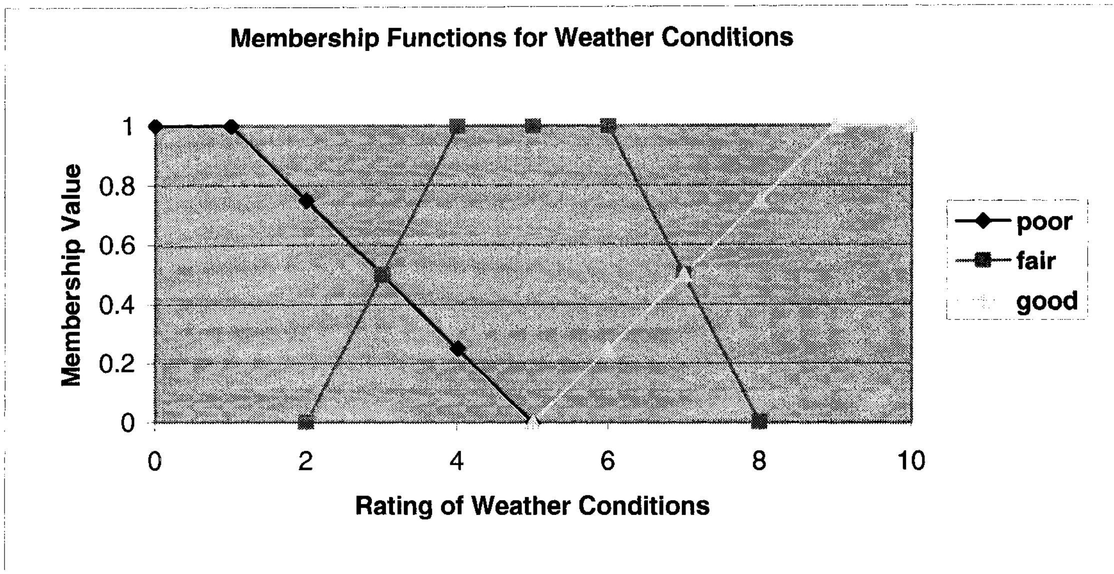
Membership Functions for Site Conditions (Trials 1, 2, and, 3)



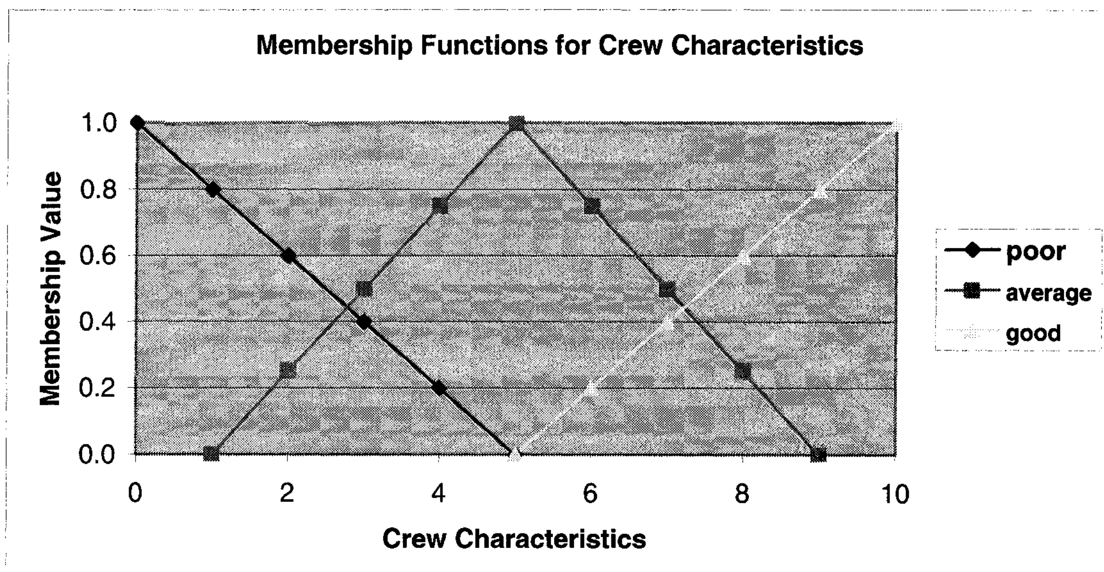
Membership Functions for Site Conditions (Trial 4)



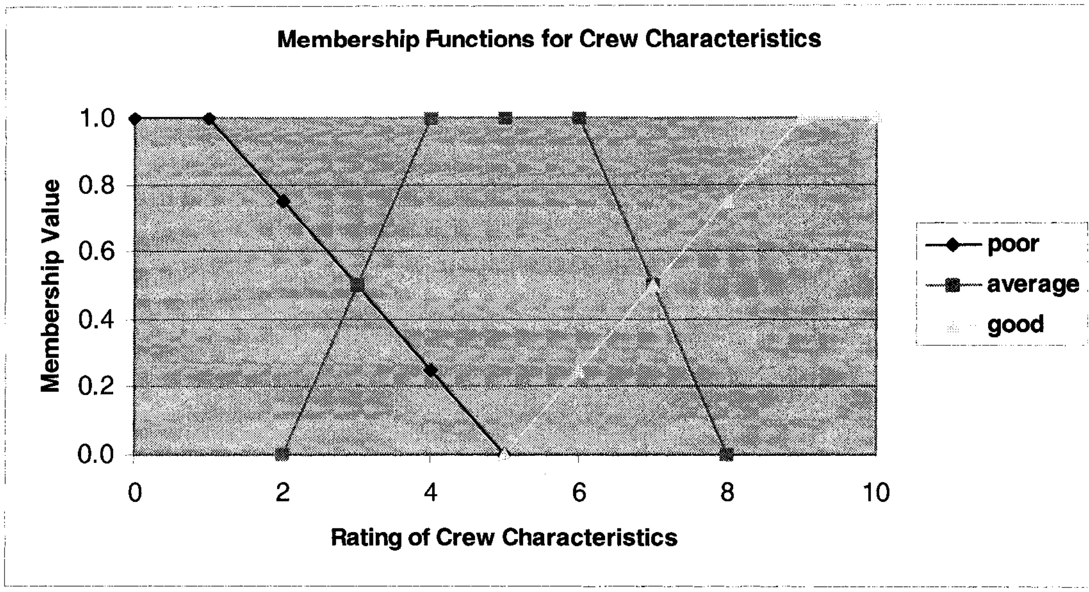
Membership Functions for Weather Conditions (Trials 1, 2, and, 3)



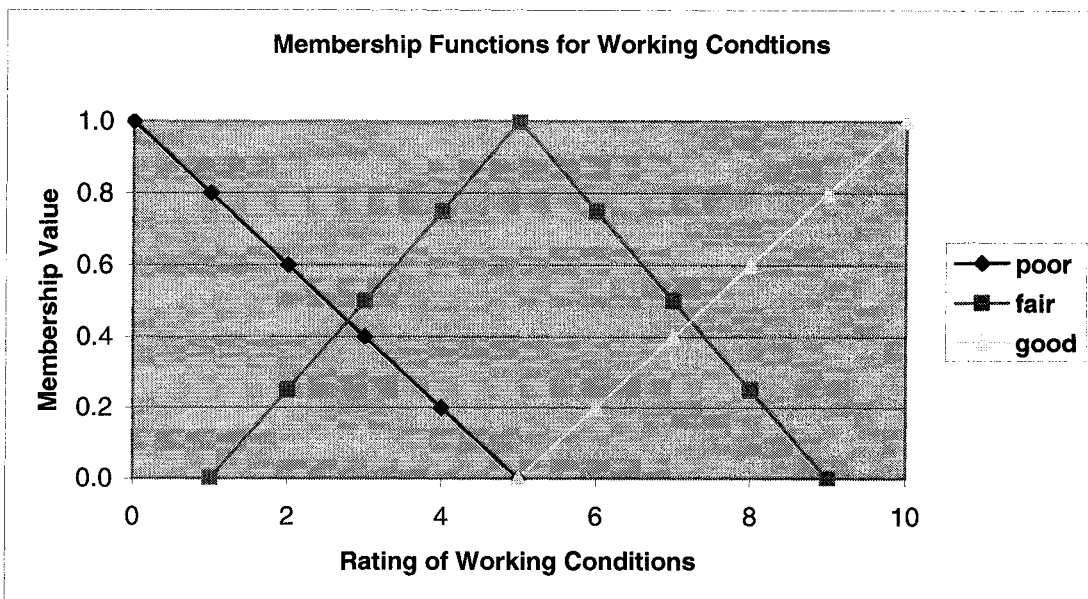
Membership Functions for Weather Conditions (Trial 4)



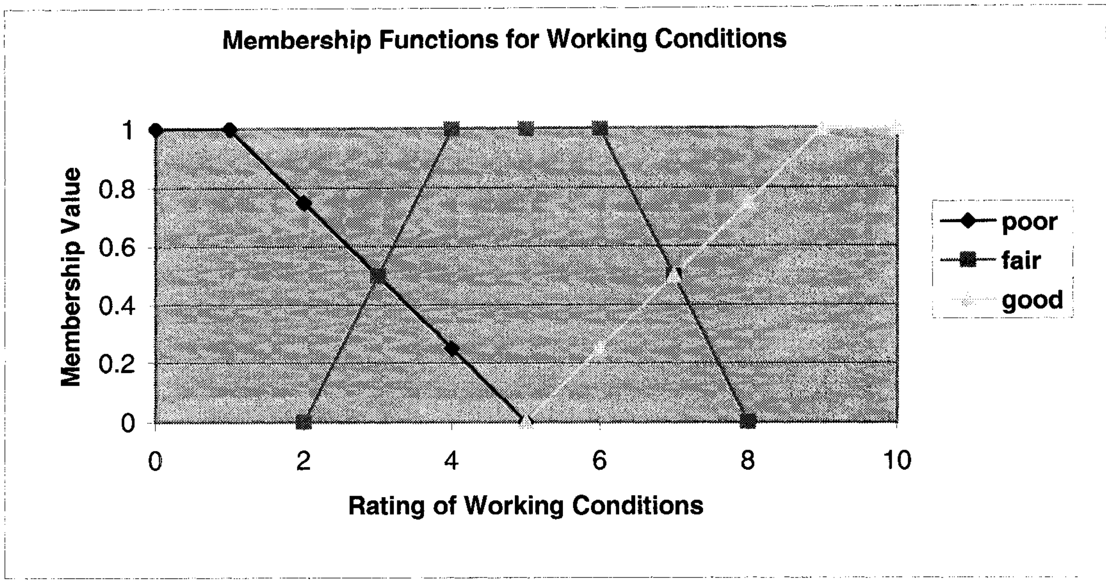
Membership Functions for Crew Characteristics (Trials 1, 2, and, 3)



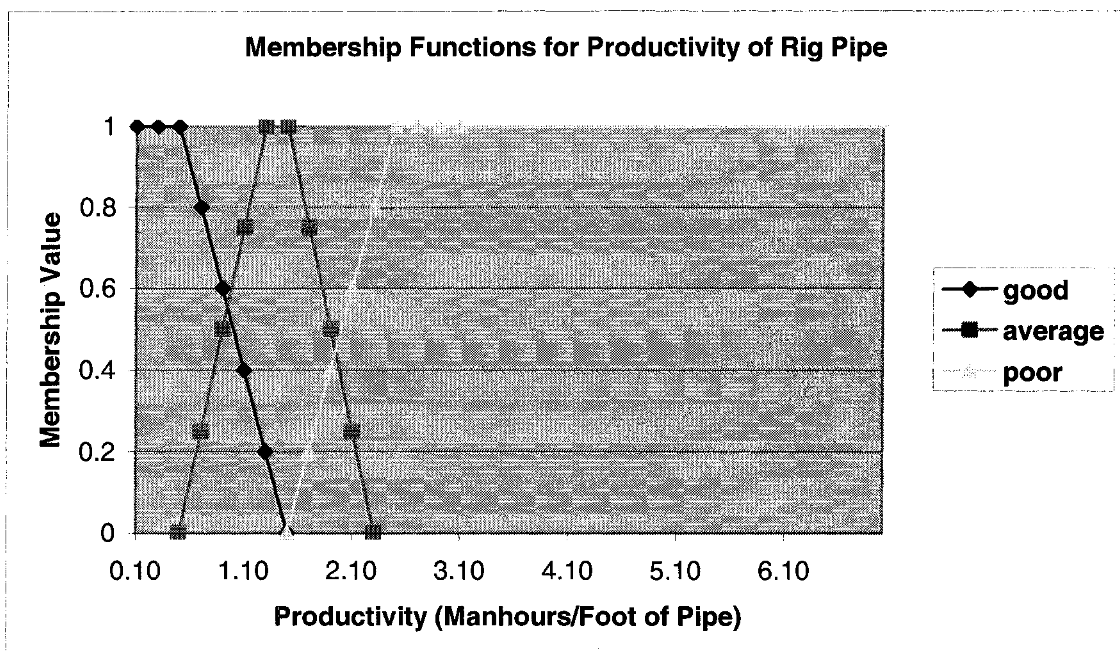
Membership Functions for Crew Characteristics (Trial 4)



Membership Functions for Working Conditions (Trials 1, 2, and, 3)



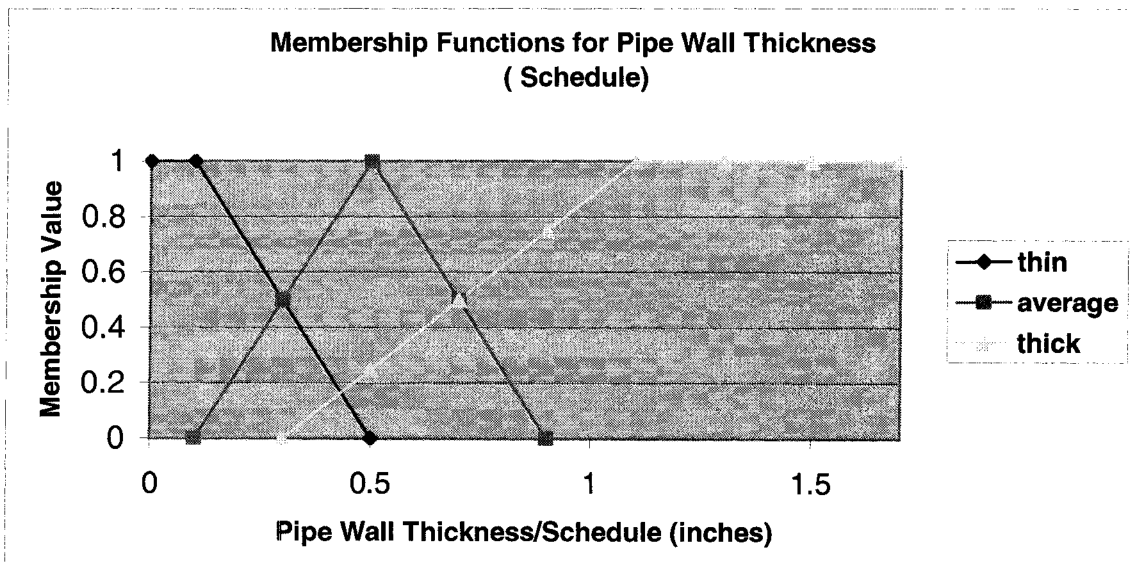
Membership Functions for Working Conditions (Trial 4)



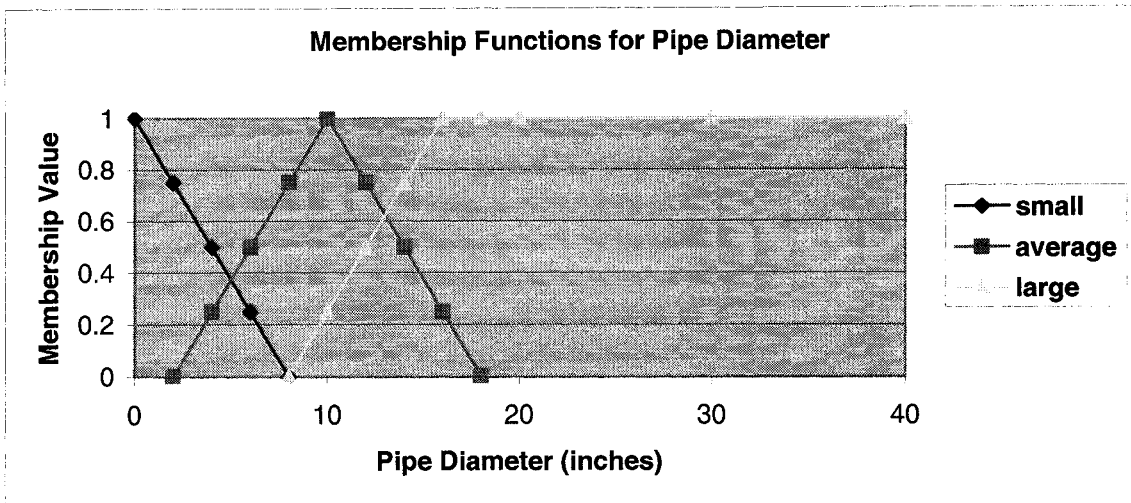
Membership Functions for Productivity of Rig Pipe (Trials 1, 2, 3, and, 4)

(II) Membership Functions for Weld Models (Applies to both Weld Pipe Models, except in cases where it is stated otherwise)

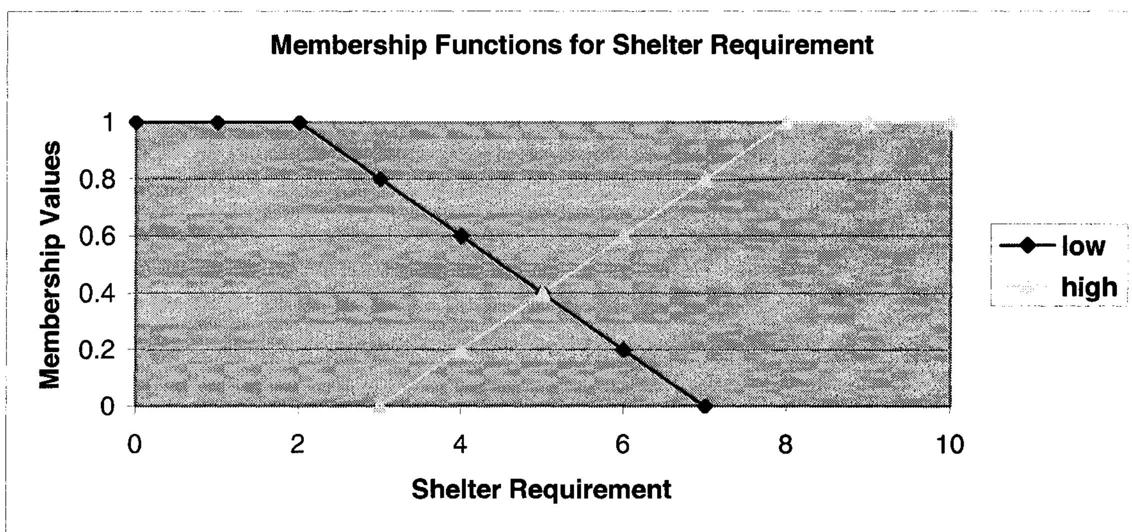
The same membership functions exist for the weld pipe models as the ones for the rig pipe model. The only exceptions are the membership functions for pipe wall thickness or schedule, pipe diameter, shelter requirement, and productivity. These membership functions are illustrated below:



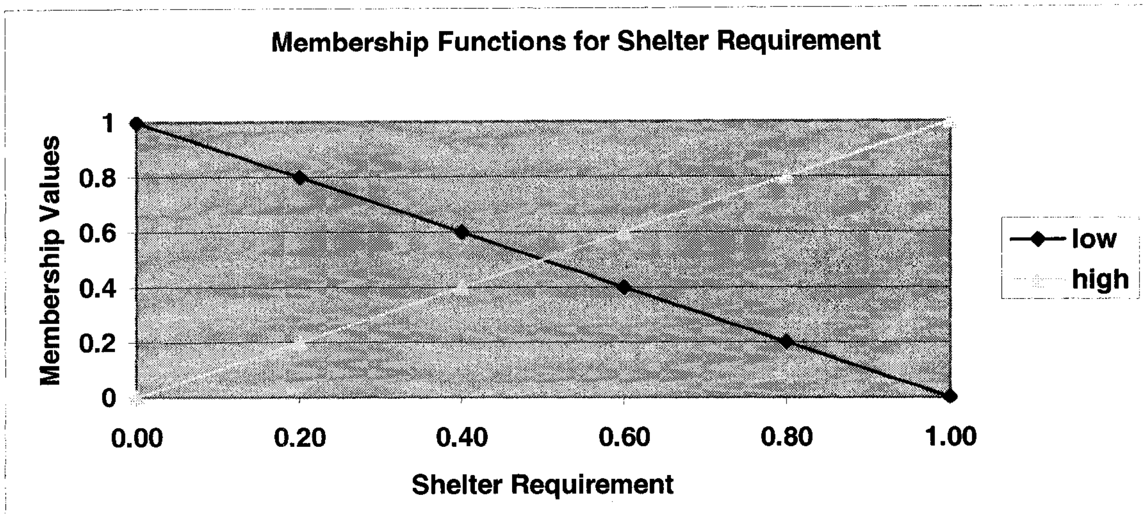
Membership Functions for Pipe Wall Thickness or Schedule (Trials 1, 2, 3, and, 4)



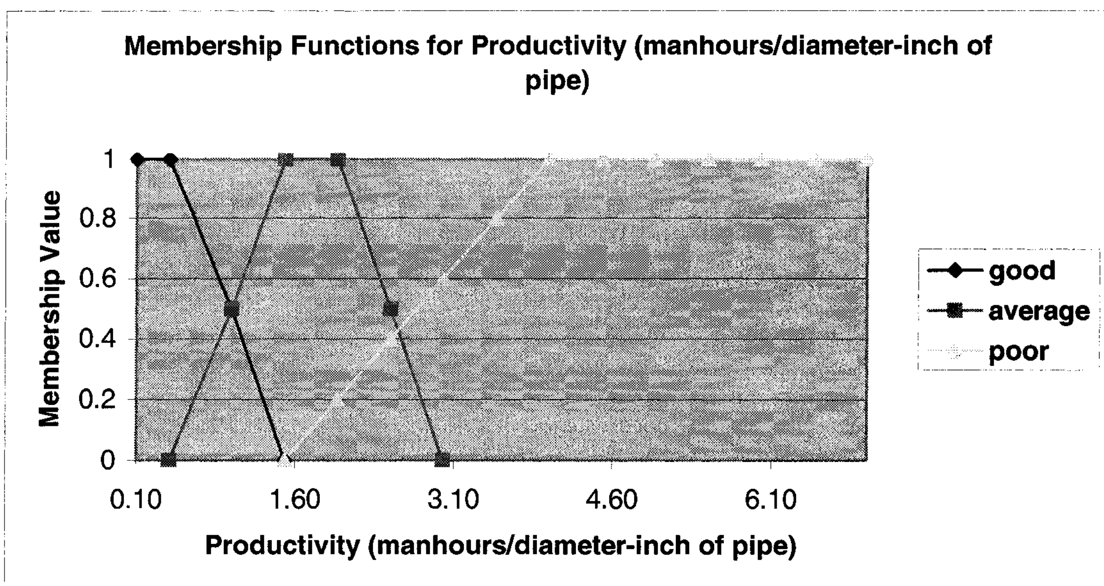
Membership Functions for Pipe Diameter (Trials 1, 2, 3, and, 4)



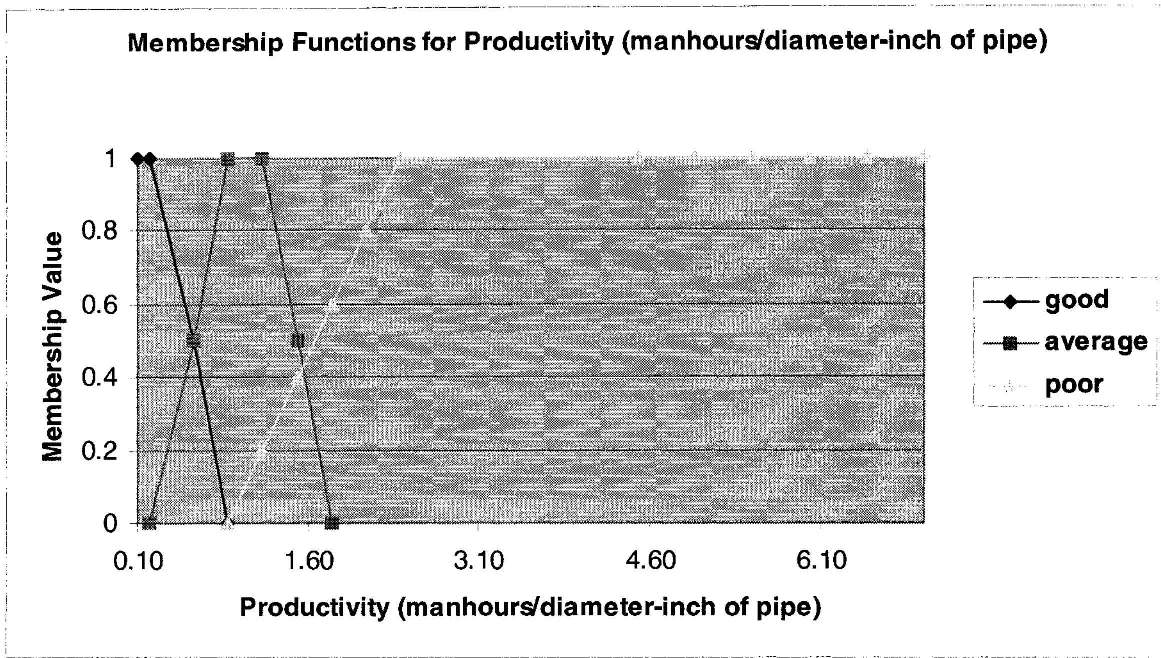
Membership Functions for Shelter Requirement (Trial 1)



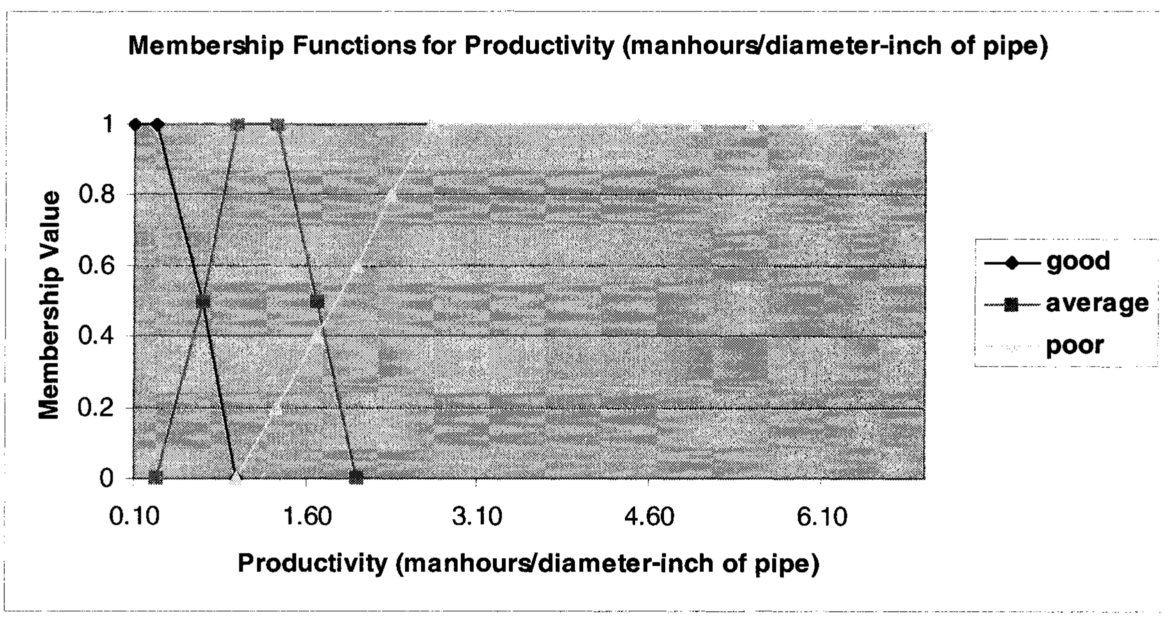
Membership Functions for Shelter Requirement (Trials 2, 3, and, 4)



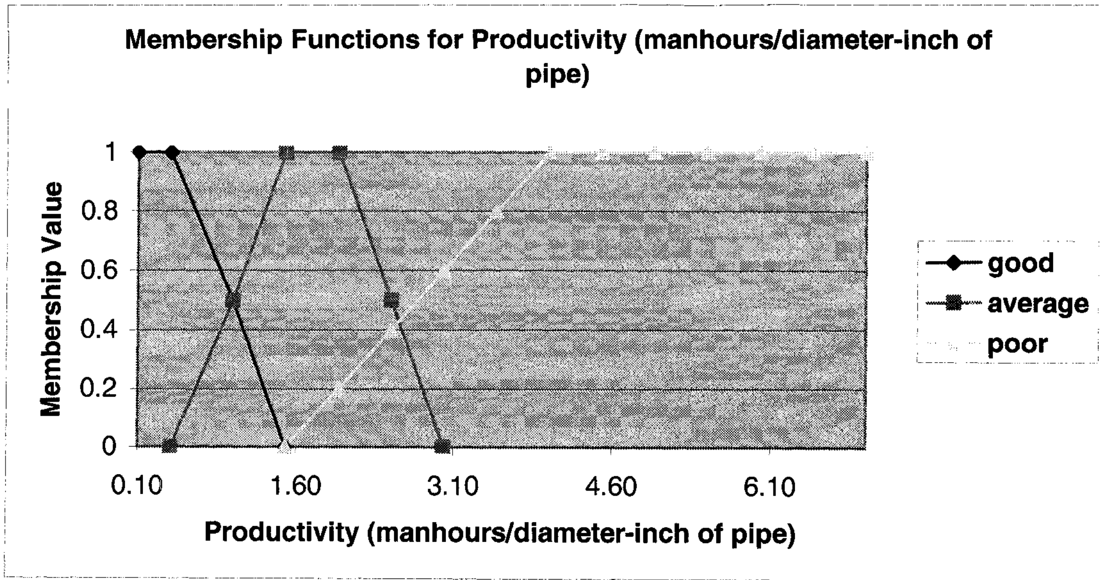
Membership Functions for Productivity, Carbon Steel and Butt Weld (Trial 1)



Membership Functions for Productivity, Carbon Steel and Butt Weld (Trial 2)



Membership Functions for Productivity, Carbon Steel and Butt Weld (Trials 3 and 4)



Membership Functions for Productivity, Alloy and Butt Weld (Trials 1, 2, 3, and, 4)

Appendix D (Correlation Analysis Results)

Correlation Results for Rig Pipe Model (Trials 1, 2, and, 3)

Summary of Correlation Results for Input Sub-model 1 for Rig Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe length	-0.522	0.002	2	32	Accept	Low significance value
Pipe diameter	0.548	0.001	1	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 2 for Rig Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	0.136	0.459	2	32	Accept	High significance value, but factor is considered important based on field experience
Task crew size	-0.007	0.969	4	32	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	0.096	0.601	3	32	Reject	High significance value
Overall crew size	0.383	0.030	1	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 3 for Rig Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	-0.603	0.000	1	32	Accept	Low significance value
Crew turnover	0.118	0.522	4	32	Reject	High significance value, and only subjective data is available for this factor
Crew experience (learning)	-0.026	0.890	5	32	Accept	High significance value, but factor is considered important based on field experience
Crew experience (seniority)	0.217	0.234	3	32	Accept	High significance value, but factor is considered important based on field experience
No of consecutive days	-0.249	0.170	2	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 4 for Rig Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	0.520	0.002	1	32	Accept	Low significance value
Complexity of shape of pipe	-0.446	0.010	2	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 5 for Rig Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	0.265	0.142	2	32	Reject	High significance value, tasks were carried out above the ground level, and only subjective data is available for this factor
Access to work area	-0.235	0.195	3	32	Reject	High significance value, factor is multi-collinear with adequacy of site storage, and only subjective data is available for this factor
Crowding of work area	-0.140	0.443	4	32	Reject	High significance value, and only subjective data is available for this factor
Adequacy of site storage	-0.470	0.007	1	32	Accept	Low significance value, but factor is multi-collinear with access to work area

Summary of Correlation Results for Input Sub-model 6 for Rig Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.130	0.478	4	32	Reject	High significance value, and only subjective data is available for this factor
Avg. temperature	0.496	0.004	1	32	Accept	Low significance value
Avg. windspeed	0.216	0.235	3	32	Accept	High significance value, but factor is considered important based on field experience
Avg. precipitation	-0.308	0.086	2	32	Accept	Low significance value

Correlation Results for Weld Pipe Model (Trial 1)

Summary of Correlation Results for Input Sub-model 1 for Weld Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe diameter	-0.588	0.000	1	95	Accept	Low significance value
Wall thickness	-0.086	0.408	2	95	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 2 for Weld Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	-0.148	0.153	1	95	Accept	High significance value, but factor is considered important based on field experience
Task crew size	-0.136	0.190	2	95	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	-0.005	0.960	4	95	Reject	High significance value, and only subjective data is available for this factor
Overall crew size	0.060	0.564	3	95	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 3 for Weld Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	-0.142	0.169	4	95	Reject	High significance value, and only subjective data is available for this factor
Crew turnover	0.345	0.001	1	95	Accept	Low significance value
Crew experience (learning)	-0.164	0.113	3	95	Accept	High significance value, but factor is considered important based on field experience
Crew experience (seniority)	0.332	0.001	2	95	Accept	Low significance value
No. of consecutive days	-0.02	0.849	5	95	Accept	High significant value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 4 for Weld Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	-0.117	0.259	1	95	Accept	High significance value, but factor is considered important based on field experience
Shelter requirement	0.067	0.519	2	95	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 5 for Weld Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	-0.035	0.733	4	95	Reject	High significance value, all tasks were carried out on or above the ground level, and only subjective data is available for this factor
Access to work area	-0.324	0.001	2	95	Reject	Low significance value, but factor is multi-collinear with crowding of work area and adequacy of site storage
Crowding of work area	-0.226	0.027	3	95	Accept	Low significance value, but factor is multi-collinear with access to work area
Adequacy of site storage	-0.368	0.000	1	95	Accept	Low significance value, but factor is multi-collinear with access to work area

Summary of Correlation Results for Input Sub-model 6 for Weld Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.105	0.310	4	95	Reject	High significance value, and only subjective data is available for this factor
Avg. temperature	-0.153	0.139	2	95	Accept	High significance value, but factor is considered important based on field experience
Avg. windspeed	0.195	0.058	1	95	Accept	Low significance value
Avg. precipitation	0.132	0.202	3	95	Accept	High significance value, but factor is considered important based on field experience

Correlation Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trials 1, 2, and, 3)

Summary of Correlation Results for Input Sub-model CB1 for Weld Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe diameter	-0.602	0.000	1	63	Accept	Low significance value, but factor is multi-collinear with pipe thickness
Wall thickness	-0.455	0.000	2	63	Accept	Low significance value, but factor is multi-collinear with pipe diameter

Summary of Correlation Results for Input Sub-model CB2 for Weld Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	0.366	0.003	1	63	Accept	Low significance value
Task crew size	-0.134	0.293	3	63	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	0.150	0.240	2	63	Reject	High significance value
Overall crew size	-0.096	0.452	4	63	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model CB3 for Weld Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	-0.048	0.708	4	63	Reject	High significance value, but factor is multi-collinear with crew exp. (seniority)
Crew turnover	0.303	0.016	1	63	Accept	Low significance value
Crew experience (learning)	0.002	0.990	5	63	Accept	High significance value, but factor is considered important based on field experience
Crew experience (seniority)	0.219	0.083	2	63	Accept	Low significance value, but factor is multi-collinear with skill level
No of consecutive days	0.101	0.431	3	63	Accept	High significant value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model CB4 for Weld Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	-0.357	0.004	2	63	Accept	Low significance value
Shelter requirement	0.420	0.001	1	63	Accept	Low significance value

Summary of Correlation Results for Input Sub-model CB5 for Weld Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	0.076	0.552	4	63	Reject	High significance value, and all tasks were carried out on or above the ground level
Access to work area	-0.149	0.244	3	63	Reject	High significance value, and factor is multi-collinear with crowding of work area and adequacy of site storage
Crowding of work area	-0.198	0.120	1	63	Accept	Slightly high significance value, and factor is multi-collinear with access to work area
Adequacy of site storage	-0.196	0.124	2	63	Accept	Slightly high significance value, and factor is multi-collinear with access to work area

Summary of Correlation Results for Input Sub-model CB6 for Weld Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.046	0.719	4	63	Reject	High significance value
Avg. temperature	-0.082	0.521	3	63	Accept	High significance value, but factor is considered important based on field experience
Avg. windspeed	0.101	0.429	2	63	Accept	High significance value, but factor is considered important based on field experience
Avg. precipitation	0.254	0.044	1	63	Accept	Low significance value

Correlation Results for Weld Pipe Model, Alloy and Butt Weld (Trials 1, 2, and, 3)

Summary of Correlation Results for Input Sub-model AB1 for Weld Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe diameter	-0.747	0.000	1	32	Accept	Low significance value
Wall thickness	-0.159	0.384	2	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB2 for Weld Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	-0.253	0.163	1	32	Accept	High significance value, but factor is considered important based on field experience
Task crew size	-0.120	0.512	3	32	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	0.006	0.973	4	32	Reject	High significance value
Overall crew size	0.187	0.305	2	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB3 for Weld Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	0.095	0.603	4	32	Reject	High significance value
Crew turnover	0.297	0.099	3	32	Accept	Low significance value
Crew experience (learning)	-0.433	0.013	1	32	Accept	Low significance value
Crew experience (seniority)	0.429	0.014	2	32	Accept	Low significance value
No. of consecutive days	-0.030	0.870	5	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB4 for Weld Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	0.669	0.000	1	32	Accept	Low significance value
Shelter requirement	-0.336	0.060	2	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model AB5 for Weld Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	-0.137	0.455	3	32	Reject	High significance value, and all tasks were carried out on or above the ground level
Access to work area	-0.338	0.058	2	32	Accept	Low significance value
Crowding of work area	0.021	0.909	4	32	Reject	High significance value
Adequacy of site storage	-0.346	0.052	1	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model AB6 for Weld Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.231	0.204	3	32	Reject	High significance value
Avg. temperature	-0.254	0.161	2	32	Accept	High significance value, but factor considered important based on field experience
Avg. windspeed	0.305	0.090	1	32	Accept	Low significance value
Avg. precipitation	-0.036	0.846	4	32	Accept	High significance value, but factor is considered important based on field experience

Correlation Results for Rig Pipe Model (Trial 4)

Summary of Correlation Results for Input Sub-model 1 for Rig Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe length	-0.466	0.011	2	29	Accept	Low significance value
Pipe diameter	0.546	0.002	1	29	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 2 for Rig Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	-0.031	0.872	4	29	Accept	High significance value, but factor is considered important based on field experience
Task crew size	0.121	0.532	2	29	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	0.059	0.760	3	29	Reject	High significance value
Overall crew size	0.271	0.155	1	29	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 3 for Rig Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	-0.507	0.005	1	29	Accept	Low significance value
Crew turnover	0.010	0.959	5	29	Reject	High significance value, and only subjective data is available for this factor
Crew experience (learning)	0.054	0.782	4	29	Accept	High significance value, but factor is considered important based on field experience
Crew experience (seniority)	0.174	0.368	3	29	Accept	High significance value, but factor is considered important based on field experience
No of consecutive days	-0.192	0.317	2	29	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model 4 for Rig Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	0.505	0.005	1	29	Accept	Low significance value
Complexity of shape of pipe	-0.448	0.015	2	29	Accept	Low significance value

Summary of Correlation Results for Input Sub-model 5 for Rig Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	0.290	0.127	4	29	Reject	High significance value, tasks were carried out above the ground level, and only subjective data is available for this factor
Access to work area	-0.249	0.192	3	29	Reject	High significance value, factor is multi-collinear with site storage, and only subjective data is available for this factor
Crowding of work area	-0.345	0.067	2	29	Reject	Low significance value, and factor is multi-collinear with access to work area
Adequacy of site storage	-0.378	0.043	1	29	Accept	Low significance value, and factor is multi-collinear with access to work area

Summary of Correlation Results for Input Sub-model 6 for Rig Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.007	0.971	4	29	Reject	High significance value, and only subjective data is available for this factor
Avg. temperature	0.455	0.013	1	29	Accept	Low significance value
Avg. windspeed	0.121	0.532	3	29	Accept	High significance value, and factor is considered important based on field experience
Avg. precipitation	-0.362	0.053	2	29	Accept	Low significance value

Correlation Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 4)

Summary of Correlation Results for Input Sub-model CB1 for Weld Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe diameter	-0.602	0.000	1	63	Accept	Low significance value, and factor is multi-collinear with pipe thickness
Wall thickness	-0.455	0.000	2	63	Accept	Low significance value, and factor is multi-collinear with pipe diameter

Summary of Correlation Results for Input Sub-model CB2 for Weld Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	-0.338	0.007	1	63	Accept	Low significance value
Task crew size	-0.134	0.294	3	63	Accept	High significance value, and factor is considered important based on field experience
Sufficiency of No. of Crew	0.150	0.240	2	63	Reject	High significance value
Overall crew size	-0.097	0.452	4	63	Accept	High significance value, and factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model CB3 for Weld Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	-0.048	0.708	4	63	Reject	High significance value, and factor is multi-collinear with crew experience (seniority)
Crew turnover	0.303	0.016	1	63	Accept	Low significance value
Crew experience (learning)	0.002	0.990	5	63	Accept	High significance value, and factor is considered important based on field experience
Crew experience (seniority)	0.219	0.083	2	63	Accept	Low significance value, and factor is multi-collinear with skill level
No. of consecutive days	0.101	0.431	3	63	Accept	High significant value, and factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model CB4 for Weld Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	-0.357	0.004	2	63	Accept	Low significance value
Shelter requirement	0.420	0.001	1	63	Accept	Low significance value

Summary of Correlation Results for Input Sub-model CB5 for Weld Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	0.076	0.552	4	63	Reject	High significance value, and all tasks were carried out on or above the ground level
Access to work area	-0.149	0.244	3	63	Reject	High significance value, and factor is multi-collinear with crowding of work area and site storage
Crowding of work area	-0.198	0.120	1	63	Accept	Slightly high significance value, and factor is multi-collinear with access to work area
Adequacy of site storage	-0.196	0.124	2	63	Accept	Slightly high significance value, and factor is multi-collinear with access to work area

Summary of Correlation Results for Input Sub-model CB6 for Weld Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.046	0.719	4	63	Reject	High significance value
Avg. temperature	-0.082	0.521	3	63	Accept	High significance value, but factor is considered important based on field experience
Avg. windspeed	0.101	0.429	2	63	Accept	High significance value, but factor is considered important based on field experience
Avg. precipitation	0.254	0.044	1	63	Accept	Low significance value

Correlation Results for Weld Pipe Model, Alloy and Butt Weld (Trial 4)

Summary of Correlation Results for Input Sub-model AB1 for Weld Pipe (Pipe Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Pipe diameter	-0.747	0.000	1	32	Accept	Low significance value
Wall thickness	-0.159	0.384	2	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB2 for Weld Pipe (Crew Dimensions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Crew ratio	0.262	0.148	1	32	Accept	High significance value, but factor is considered important based on field experience
Task crew size	-0.120	0.512	3	32	Accept	High significance value, but factor is considered important based on field experience
Sufficiency of No. of Crew	0.006	0.973	4	32	Reject	High significance value
Overall crew size	0.187	0.305	2	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB3 for Weld Pipe (Crew Competency)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Skill level	0.095	0.603	4	32	Reject	High significance value
Crew turnover	0.297	0.099	3	32	Accept	Low significance value
Crew experience (learning)	-0.433	0.013	1	32	Accept	Low significance value
Crew experience (seniority)	0.429	0.014	2	32	Accept	Low significance value
No. of consecutive days	-0.030	0.870	5	32	Accept	High significance value, but factor is considered important based on field experience

Summary of Correlation Results for Input Sub-model AB4 for Weld Pipe (Degree of Difficulty)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Elevation	0.669	0.000	1	32	Accept	Low significance value
Shelter requirement	-0.336	0.060	2	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model AB5 for Weld Pipe (Site Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Ground conditions	-0.137	0.455	3	32	Reject	High significance value, and all tasks were carried out on or above the ground level
Access to work area	-0.338	0.058	2	32	Accept	Low significance value
Crowding of work area	0.021	0.909	4	32	Reject	High significance value
Adequacy of site storage	-0.346	0.052	1	32	Accept	Low significance value

Summary of Correlation Results for Input Sub-model AB6 for Weld Pipe (Weather Conditions)

Factor	Pearson Correlation	Significance (2-tailed)	Ranking of Factors	Sample Size at alpha = 0.01	Accept/ Reject	Basis for acceptance/rejection
Impact of weather conditions	0.231	0.204	3	32	Reject	High significance value
Avg. temperature	-0.254	0.161	2	32	Accept	High significance value, but factor considered important based on field experience
Avg. windspeed	0.305	0.090	1	32	Accept	Low significance value
Avg. precipitation	-0.036	0.846	4	32	Accept	High significance value, but factor is considered important based on field experience

Appendix E (Simplified Models)

Rig Pipe Model Before and After Simplification (Trials 1, 2, and, 3)

Pipe Dimensions Sub-model:

Input 1: Pipe length Input 2: Pipe diameter	→	Input 1: Pipe length Input 2: Pipe diameter

Crew Dimensions Sub-model:

Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size Input 6: Sufficiency of number of crew	→	Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked	→	Input 7: Crew Skill level Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation Input 13: Complexity of shape of pipe	→	Input 12: Elevation Input 13: Complexity of shape of pipe

Site Conditions Sub-model:

Input 14: Ground conditions
Input 15: Access to work area
Input 16: Crowding of work area
Input 17: Adequacy of site storage

→

Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions
Input 19: Avg. temperature
Input 20: Avg. windspeed
Input 21: Avg. precipitation

→

Input 19: Avg. temperature
Input 20: Avg. windspeed
Input 21: Avg. precipitation

Weld Pipe Model (Carbon Steel and Butt Weld) Before and After Simplification (Trials 1, 2, and, 3)

Pipe Dimensions Sub-model:

Input 1: Pipe diameter
Input 2: Wall thickness

→

Input 1: Pipe diameter
Input 2: Wall thickness

Crew Dimensions Sub-model:

Input 3: Crew ratio
Input 4: Task crew size
Input 5: Overall crew size
Input 6: Sufficiency of number of crew

→

Input 3: Crew ratio
Input 4: Task crew size
Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked	→	Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation Input 13: Shelter requirement	→	Input 12: Elevation Input 13: Shelter requirement

Site Conditions Sub-model:

Input 14: Ground conditions Input 15: Access to work area Input 16: Crowding of work area Input 17: Adequacy of site storage	→	Input 16: Crowding of work area Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation	→	Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation

Weld Pipe Model (Alloy and Butt Weld) Before and After Simplification (Trials 1, 2, and, 3)

Pipe Dimensions Sub-model:

Input 1: Pipe diameter
Input 2: Wall thickness

Input 1: Pipe diameter
Input 2: Wall thickness

Crew Dimensions Sub-model:

Input 3: Crew ratio
Input 4: Task crew size
Input 5: Overall crew size
Input 6: Sufficiency of number of crew

Input 3: Crew ratio
Input 4: Task crew size
Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level
Input 8: Crew turnover
Input 9: Crew experience (learning)
Input 10: Crew experience (seniority)
Input 11: No. of consecutive days worked

Input 8: Crew turnover
Input 9: Crew experience (learning)
Input 10: Crew experience (seniority)
Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation
Input 13: Shelter requirement

Input 12: Elevation
Input 13: Shelter requirement

Site Conditions Sub-model:

Input 14: Ground conditions Input 15: Access to work area Input 16: Crowding of work area Input 17: Adequacy of site storage	Input 15: Access to work area Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation	Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation

Rig Pipe Model Before and After Simplification (Trial 4)

Pipe Dimensions Sub-model:

Input 1: Pipe length Input 2: Pipe diameter	Input 1: Pipe length Input 2: Pipe diameter

Crew Dimensions Sub-model:

Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size Input 6: Sufficiency of number of crew	Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked	→	Input 7: Crew Skill level Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation Input 13: Complexity of shape of pipe	→	Input 12: Elevation Input 13: Complexity of shape of pipe

Site Conditions Sub-model:

Input 14: Ground conditions Input 15: Access to work area Input 16: Crowding of work area Input 17: Adequacy of site storage	→	Input 16: Crowding of work area Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation	→	Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation

Weld Pipe Model (Carbon Steel and Butt Weld) Before and After Simplification (Trial 4)

Pipe Dimensions Sub-model:

Input 1: Pipe diameter Input 2: Wall thickness	→	Input 1: Pipe diameter Input 2: Wall thickness

Crew Dimensions Sub-model:

Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size Input 6: Sufficiency of number of crew	→	Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked	→	Input 8: Crew turnover Input 9: Crew experience (learning) Input 10: Crew experience (seniority) Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation Input 13: Shelter requirement	→	Input 12: Elevation Input 13: Shelter requirement

Site Conditions Sub-model:

Input 14: Ground conditions Input 15: Access to work area Input 16: Crowding of work area Input 17: Adequacy of site storage	Input 16: Crowding of work area Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation	Input 19: Avg. temperature Input 20: Avg. windspeed Input 21: Avg. precipitation

Weld Pipe Model (Alloy and Butt Weld) Before and After Simplification (Trial 4)

Pipe Dimensions Sub-model:

Input 1: Pipe diameter Input 2: Wall thickness	Input 1: Pipe diameter Input 2: Wall thickness

Crew Dimensions Sub-model:

Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size Input 6: Sufficiency of number of crew	Input 3: Crew ratio Input 4: Task crew size Input 5: Overall crew size

Crew Competency Sub-model:

Input 7: Crew Skill level
Input 8: Crew turnover
Input 9: Crew experience (learning)
Input 10: Crew experience (seniority)
Input 11: No. of consecutive days worked

Input 8: Crew turnover
Input 9: Crew experience (learning)
Input 10: Crew experience (seniority)
Input 11: No. of consecutive days worked

Degree of Difficulty Sub-model:

Input 12: Elevation
Input 13: Shelter requirement

Input 12: Elevation
Input 13: Shelter requirement

Site Conditions Sub-model:

Input 14: Ground conditions
Input 15: Access to work area
Input 16: Crowding of work area
Input 17: Adequacy of site storage

Input 15: Access to work area
Input 17: Adequacy of site storage

Weather Conditions Sub-model:

Input 18: Impact of weather conditions
Input 19: Avg. temperature
Input 20: Avg. windspeed
Input 21: Avg. precipitation

Input 19: Avg. temperature
Input 20: Avg. windspeed
Input 21: Avg. precipitation

Appendix F (Fuzzy Rulebases)

Rules for Rig Pipe Model (Trials 1 and 2)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe length	pipe diameter	pipe dimensions
short	small	small
short	average	small
short	large	average
average	small	average
average	average	average
average	large	large
long	small	large
long	average	large
long	large	large

Rules for Crew Dimensions Sub-model			
Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
skill level	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low
medium	average	low	average	average
medium	average	low	high	average
medium	average	average	low	average
medium	average	average	average	average
medium	average	average	high	average
medium	average	high	low	average

Rules for Crew Competency Sub-model (Continued)				
Crew Competency				
skill level	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
complexity of shape	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
medium	low	average
medium	average	high
medium	high	high
high	low	average
high	average	high
high	high	high

Rules for Site Conditions Sub-model	
Site Conditions	
adequacy of site storage	site conditions
poor	poor
fair	fair
good	good

Rules for Weather Conditions Sub-model			
Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	good
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	average
small	poor	average	good	good
small	poor	high	poor	poor
small	poor	high	fair	average
small	poor	high	good	average
small	average	low	poor	average
small	average	low	fair	good
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	average
small	average	average	good	good
small	average	high	poor	average
small	average	high	fair	average
small	average	high	good	average
small	good	low	poor	average
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	average
small	good	average	fair	good
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	good
small	good	high	good	good
average	poor	low	poor	poor
average	poor	low	fair	average
average	poor	low	good	good
average	poor	average	poor	poor
average	poor	average	fair	average
average	poor	average	good	average
average	poor	high	poor	poor
average	poor	high	fair	poor
average	poor	high	good	average
average	average	low	poor	average
average	average	low	fair	good
average	average	low	good	good
average	average	average	poor	poor
average	average	average	fair	average
average	average	average	good	good
average	average	high	poor	poor
average	average	high	fair	average

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	high	good	average
average	good	low	poor	average
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	average
average	good	average	fair	average
average	good	average	good	good
average	good	high	poor	poor
average	good	high	fair	average
average	good	high	good	good
large	poor	low	poor	poor
large	poor	low	fair	average
large	poor	low	good	good
large	poor	average	poor	poor
large	poor	average	fair	poor
large	poor	average	good	average
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	average
large	average	low	good	good
large	average	average	poor	poor
large	average	average	fair	average
large	average	average	good	average
large	average	high	poor	poor
large	average	high	fair	poor
large	average	high	good	average
large	good	low	poor	average
large	good	low	fair	good
large	good	low	good	good
large	good	average	poor	average
large	good	average	fair	average
large	good	average	good	good
large	good	high	poor	poor
large	good	high	fair	average
large	good	high	good	average

Rules for Weld Pipe Model, Carbon Steel and Butt Weld (Trials 1 and 2)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe diameter	wall thickness	pipe dimensions
small	thin	small
small	average	small
small	thick	average
average	thin	average
average	average	average
average	thick	large
large	thin	large
large	average	large
large	thick	large

Rules for Crew Dimensions Sub-model			
Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low
medium	average	low	average	average
medium	average	low	high	average
medium	average	average	low	average
medium	average	average	average	average

Rules for Crew Competency Sub-model-Continued				
Crew Competency				
crew turnover	crew experience(seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	average	high	average
medium	average	high	low	average
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
shelter requirement	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
high	low	average
high	average	average
high	high	high

Rules for Site Conditions Sub-model		
Site Conditions		
crowding of work area	adequacy of site storage	site conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for Weather Conditions Sub-model			
Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	good
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	average
small	poor	average	good	good
small	poor	high	poor	poor
small	poor	high	fair	average
small	poor	high	good	average
small	average	low	poor	average
small	average	low	fair	good
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	average
small	average	average	good	good
small	average	high	poor	average
small	average	high	fair	average
small	average	high	good	average
small	good	low	poor	average
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	average
small	good	average	fair	good
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	good
small	good	high	good	good
average	poor	low	poor	poor
average	poor	low	fair	average
average	poor	low	good	good
average	poor	average	poor	poor
average	poor	average	fair	average
average	poor	average	good	average
average	poor	high	poor	poor
average	poor	high	fair	poor
average	poor	high	good	average
average	average	low	poor	average
average	average	low	fair	good
average	average	low	good	good
average	average	average	poor	poor
average	average	average	fair	average
average	average	average	good	good
average	average	high	poor	poor
average	average	high	fair	average

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	high	good	average
average	good	low	poor	average
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	average
average	good	average	fair	average
average	good	average	good	good
average	good	high	poor	poor
average	good	high	fair	average
average	good	high	good	good
large	poor	low	poor	poor
large	poor	low	fair	average
large	poor	low	good	good
large	poor	average	poor	poor
large	poor	average	fair	poor
large	poor	average	good	average
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	average
large	average	low	good	good
large	average	average	poor	poor
large	average	average	fair	average
large	average	average	good	average
large	average	high	poor	poor
large	average	high	fair	poor
large	average	high	good	average
large	good	low	poor	average
large	good	low	fair	good
large	good	low	good	good
large	good	average	poor	average
large	good	average	fair	average
large	good	average	good	good
large	good	high	poor	poor
large	good	high	fair	average
large	good	high	good	average

Rules for Weld Pipe Model, Alloy and Butt Weld (Trials 1 and 2)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe diameter	wall thickness	pipe dimensions
small	thin	small
small	average	small
small	thick	average
average	thin	average
average	average	average
average	thick	large
large	thin	large
large	average	large
large	thick	large

Rules for Crew Dimensions Sub-model			
Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low
medium	average	low	average	average
medium	average	low	high	average
medium	average	average	low	average
medium	average	average	average	average
medium	average	average	high	average

Rules for Crew Competency Sub-model-Continued				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	high	low	average
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
shelter requirement	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
high	low	average
high	average	average
high	high	high

Rules for Site Conditions Sub-model		
Site Conditions		
access to work area	adequacy of site storage	site conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for Weather Conditions Sub-model			
Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	good
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	average
small	poor	average	good	good
small	poor	high	poor	poor
small	poor	high	fair	average
small	poor	high	good	average
small	average	low	poor	average
small	average	low	fair	good
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	average
small	average	average	good	good
small	average	high	poor	average
small	average	high	fair	average
small	average	high	good	average
small	good	low	poor	average
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	average
small	good	average	fair	good
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	good
small	good	high	good	good
average	poor	low	poor	poor
average	poor	low	fair	average
average	poor	low	good	good
average	poor	average	poor	poor
average	poor	average	fair	average
average	poor	average	good	average
average	poor	high	poor	poor
average	poor	high	fair	poor
average	poor	high	good	average
average	average	low	poor	average
average	average	low	fair	good
average	average	low	good	good
average	average	average	poor	poor
average	average	average	fair	average
average	average	average	good	good
average	average	high	poor	poor

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	high	fair	average
average	average	high	good	average
average	good	low	poor	average
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	average
average	good	average	fair	average
average	good	average	good	good
average	good	high	poor	poor
average	good	high	fair	average
average	good	high	good	good
large	poor	low	poor	poor
large	poor	low	fair	average
large	poor	low	good	good
large	poor	average	poor	poor
large	poor	average	fair	poor
large	poor	average	good	average
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	average
large	average	low	good	good
large	average	average	poor	poor
large	average	average	fair	average
large	average	average	good	average
large	average	high	poor	poor
large	average	high	fair	poor
large	average	high	good	average
large	good	low	poor	average
large	good	low	fair	good
large	good	low	good	good
large	good	average	poor	average
large	good	average	fair	average
large	good	average	good	good
large	good	high	poor	poor
large	good	high	fair	average
large	good	high	good	average

Rules for Rig Pipe Model (Trials 3 and 4)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe length	pipe diameter	pipe dimensions
short	small	small
short	average	small
short	large	average
average	small	average
average	average	average
average	large	large
long	small	large
long	average	large
long	large	large

Rules for Crew Dimensions Sub-model

Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
skill level	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low

Rules for Crew Competency Sub-model-Continued				
Crew Competency				
skill level	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	low	average	average
medium	average	low	high	average
medium	average	average	low	average
medium	average	average	average	average
medium	average	average	high	average
medium	average	high	low	average
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
complexity of shape	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
medium	low	average
medium	average	high
medium	high	high
high	low	average
high	average	high
high	high	high

Rules for Site Conditions Sub-model	
Site Conditions (Trial 3)	
adequacy of site storage	site conditions
poor	poor
fair	fair
good	good

Rules for Site Conditions Sub-model		
Site Conditions (Trial 4)		
crowding of work area	adequacy of site storage	site conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for Weather Conditions Sub-model			
Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	good
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	good
small	poor	average	good	good
small	poor	high	poor	poor
small	poor	high	fair	good
small	poor	high	good	good
small	average	low	poor	good
small	average	low	fair	good
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	good
small	average	average	good	good
small	average	high	poor	average
small	average	high	fair	good
small	average	high	good	good
small	good	low	poor	good
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	good
small	good	average	fair	good
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	good
small	good	high	good	good
average	poor	low	poor	average
average	poor	low	fair	good
average	poor	low	good	good
average	poor	average	poor	average
average	poor	average	fair	good
average	poor	average	good	good
average	poor	high	poor	poor
average	poor	high	fair	good
average	poor	high	good	good
average	average	low	poor	good
average	average	low	fair	good
average	average	low	good	good
average	average	average	poor	average
average	average	average	fair	good

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	average	good	good
average	average	high	poor	average
average	average	high	fair	good
average	average	high	good	good
average	good	low	poor	good
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	good
average	good	average	fair	good
average	good	average	good	good
average	good	high	poor	average
average	good	high	fair	good
average	good	high	good	good
large	poor	low	poor	poor
large	poor	low	fair	good
large	poor	low	good	good
large	poor	average	poor	poor
large	poor	average	fair	good
large	poor	average	good	good
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	good
large	average	low	good	good
large	average	average	poor	average
large	average	average	fair	good
large	average	average	good	good
large	average	high	poor	poor
large	average	high	fair	good
large	average	high	good	good
large	good	low	poor	good
large	good	low	fair	good
large	good	low	good	good
large	good	average	poor	average
large	good	average	fair	good
large	good	average	good	good
large	good	high	poor	average
large	good	high	fair	good
large	good	high	good	good

Rules for Weld Pipe Model, Carbon Steel and Butt Weld (Trials 3 and 4)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe diameter	wall thickness	pipe dimensions
small	thin	small
small	average	small
small	thick	average
average	thin	average
average	average	average
average	thick	large
large	thin	large
large	average	large
large	thick	large

Rules for Crew Dimensions Sub-model

Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low
medium	average	low	average	average
medium	average	low	high	average

Rules for Crew Competency Sub-model

Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	average	low	average
medium	average	average	average	average
medium	average	average	high	average
medium	average	high	low	average
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
shelter requirement	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
high	low	average
high	average	average
high	high	high

Rules for Site Conditions Sub-model		
Site Conditions		
crowding of work area	adequacy of site storage	site conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for Weather Conditions Sub-model

Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	average
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	average
small	poor	average	good	average
small	poor	high	poor	poor
small	poor	high	fair	average
small	poor	high	good	average
small	average	low	poor	average
small	average	low	fair	good
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	average
small	average	average	good	good
small	average	high	poor	average
small	average	high	fair	average
small	average	high	good	average
small	good	low	poor	average
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	average
small	good	average	fair	good
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	average
small	good	high	good	good
average	poor	low	poor	poor
average	poor	low	fair	average
average	poor	low	good	average
average	poor	average	poor	poor
average	poor	average	fair	average
average	poor	average	good	average
average	poor	high	poor	poor
average	poor	high	fair	poor
average	poor	high	good	average
average	average	low	poor	average
average	average	low	fair	average
average	average	low	good	good
average	average	average	poor	average

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	average	fair	average
average	average	average	good	average
average	average	high	poor	average
average	average	high	fair	average
average	average	high	good	average
average	good	low	poor	average
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	average
average	good	average	fair	average
average	good	average	good	good
average	good	high	poor	average
average	good	high	fair	average
average	good	high	good	average
large	poor	low	poor	poor
large	poor	low	fair	average
large	poor	low	good	average
large	poor	average	poor	poor
large	poor	average	fair	average
large	poor	average	good	average
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	average
large	average	low	good	average
large	average	average	poor	average
large	average	average	fair	average
large	average	average	good	average
large	average	high	poor	poor
large	average	high	fair	average
large	average	high	good	average
large	good	low	poor	average
large	good	low	fair	average
large	good	low	good	average
large	good	average	poor	average
large	good	average	fair	average
large	good	average	good	average
large	good	high	poor	poor
large	good	high	fair	average
large	good	high	good	average

Rules for Weld Pipe Model, Alloy and Butt Weld (Trials 3 and 4)

Rules for Pipe Dimensions Sub-model		
Pipe Dimensions		
pipe diameter	wall thickness	pipe dimensions
small	thin	small
small	average	small
small	thick	average
average	thin	average
average	average	average
average	thick	large
large	thin	large
large	average	large
large	thick	large

Rules for Crew Dimensions Sub-model			
Crew Dimensions			
crew ratio	task crew size	overall crew size	crew dimensions
small	small	small	small
small	small	average	small
small	small	large	average
small	average	small	small
small	average	average	average
small	average	large	average
small	large	small	average
small	large	average	average
small	large	large	large
average	small	small	small
average	small	average	average
average	small	large	large
average	average	small	average
average	average	average	average
average	average	large	large
average	large	small	average
average	large	average	average
average	large	large	large
large	small	small	small
large	small	average	average
large	small	large	large
large	average	small	average
large	average	average	average
large	average	large	large
large	large	small	average
large	large	average	large
large	large	large	large

Rules for Crew Competency Sub-model				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
low	low	low	low	low
low	low	low	average	average
low	low	low	high	average
low	low	average	low	average
low	low	average	average	average
low	low	average	high	average
low	low	high	low	average
low	low	high	average	average
low	low	high	high	high
low	average	low	low	average
low	average	low	average	average
low	average	low	high	average
low	average	average	low	average
low	average	average	average	average
low	average	average	high	high
low	average	high	low	average
low	average	high	average	average
low	average	high	high	average
low	high	low	low	average
low	high	low	average	average
low	high	low	high	high
low	high	average	low	average
low	high	average	average	average
low	high	average	high	high
low	high	high	low	high
low	high	high	average	high
low	high	high	high	high
medium	low	low	low	low
medium	low	low	average	low
medium	low	low	high	average
medium	low	average	low	low
medium	low	average	average	average
medium	low	average	high	average
medium	low	high	low	average
medium	low	high	average	average
medium	low	high	high	average
medium	average	low	low	low
medium	average	low	average	average
medium	average	low	high	average

Rules for Crew Competency Sub-model-Continued				
Crew Competency				
crew turnover	crew experience (seniority)	crew experience (learning)	no. of consecutive days	crew competency
medium	average	average	low	average
medium	average	average	average	average
medium	average	average	high	average
medium	average	high	low	average
medium	average	high	average	average
medium	average	high	high	high
medium	high	low	low	average
medium	high	low	average	average
medium	high	low	high	average
medium	high	average	low	average
medium	high	average	average	average
medium	high	average	high	high
medium	high	high	low	average
medium	high	high	average	high
medium	high	high	high	high
high	low	low	low	low
high	low	low	average	low
high	low	low	high	low
high	low	average	low	low
high	low	average	average	low
high	low	average	high	average
high	low	high	low	low
high	low	high	average	average
high	low	high	high	average
high	average	low	low	low
high	average	low	average	low
high	average	low	high	average
high	average	average	low	average
high	average	average	average	high
high	average	average	high	high
high	average	high	low	high
high	average	high	average	high
high	average	high	high	high
high	high	low	low	high
high	high	low	average	high
high	high	low	high	high
high	high	average	low	high
high	high	average	average	high
high	high	average	high	high
high	high	high	low	high
high	high	high	average	high
high	high	high	high	high

Rules for Degree of Difficulty Sub-model		
Degree of Difficulty		
shelter requirement	elevation	degree of difficulty
low	low	low
low	average	average
low	high	high
high	low	average
high	average	average
high	high	high

Rules for Site Conditions Sub-model		
Site Conditions		
crowding of work area	adequacy of site storage	site conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for Weather Conditions Sub-model

Weather Conditions			
avg. temperature	avg.precipitation	avg.windspeed	weather conditions
low	low	low	good
low	low	average	good
low	low	high	fair
low	average	low	fair
low	average	average	fair
low	average	high	poor
low	high	low	poor
low	high	average	poor
low	high	high	poor
average	low	low	good
average	low	average	good
average	low	high	poor
average	average	low	fair
average	average	average	poor
average	average	high	poor
average	high	low	poor
average	high	average	poor
average	high	high	poor
high	low	low	fair
high	low	average	fair
high	low	high	poor
high	average	low	fair
high	average	average	fair
high	average	high	poor
high	high	low	poor
high	high	average	poor
high	high	high	poor

Rules for Crew Characteristics Sub-model		
Crew Characteristics		
crew dimensions	crew competency	crew characteristics
small	low	poor
small	average	average
small	high	good
average	low	poor
average	average	average
average	high	good
large	low	poor
large	average	average
large	high	good

Rules for Working Conditions Sub-model		
Working Conditions		
site conditions	weather conditions	working conditions
poor	poor	poor
poor	fair	poor
poor	good	fair
fair	poor	poor
fair	fair	fair
fair	good	good
good	poor	fair
good	fair	good
good	good	good

Rules for the Output Factor (Productivity)				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
small	poor	low	poor	average
small	poor	low	fair	good
small	poor	low	good	good
small	poor	average	poor	average
small	poor	average	fair	average
small	poor	average	good	good
small	poor	high	poor	poor
small	poor	high	fair	good
small	poor	high	good	average
small	average	low	poor	average
small	average	low	fair	average
small	average	low	good	good
small	average	average	poor	average
small	average	average	fair	average
small	average	average	good	average
small	average	high	poor	average
small	average	high	fair	average
small	average	high	good	good
small	good	low	poor	good
small	good	low	fair	good
small	good	low	good	good
small	good	average	poor	good
small	good	average	fair	average
small	good	average	good	good
small	good	high	poor	average
small	good	high	fair	good
small	good	high	good	good
average	poor	low	poor	average
average	poor	low	fair	average
average	poor	low	good	good
average	poor	average	poor	average
average	poor	average	fair	average
average	poor	average	good	average
average	poor	high	poor	poor
average	poor	high	fair	average
average	poor	high	good	good
average	average	low	poor	average
average	average	low	fair	average
average	average	low	good	average
average	average	average	poor	average

Rules for the Output Factor (Productivity)-Continued				
Productivity				
pipe dimensions	crew characteristics	degree of difficulty	working conditions	productivity
average	average	average	fair	average
average	average	average	good	good
average	average	high	poor	average
average	average	high	fair	average
average	average	high	good	good
average	good	low	poor	good
average	good	low	fair	good
average	good	low	good	good
average	good	average	poor	average
average	good	average	fair	average
average	good	average	good	good
average	good	high	poor	average
average	good	high	fair	average
average	good	high	good	good
large	poor	low	poor	poor
large	poor	low	fair	good
large	poor	low	good	good
large	poor	average	poor	poor
large	poor	average	fair	average
large	poor	average	good	good
large	poor	high	poor	poor
large	poor	high	fair	poor
large	poor	high	good	average
large	average	low	poor	average
large	average	low	fair	average
large	average	low	good	good
large	average	average	poor	average
large	average	average	fair	average
large	average	average	good	average
large	average	high	poor	poor
large	average	high	fair	average
large	average	high	good	good
large	good	low	poor	good
large	good	low	fair	good
large	good	low	good	good
large	good	average	poor	average
large	good	average	fair	average
large	good	average	good	good
large	good	high	poor	average
large	good	high	fair	good
large	good	high	good	good

Appendix G (Model Test Results)

Test Results for Rig Pipe Model (Trial 1)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	3.8733	919.2895	N	good	poor	N
0.81	3.4751	329.0247	N	good	poor	N
0.38	0.8579	125.7632	N	good	good	Y
0.76	0.8335	9.671053	Y	good	good	Y
0.41	0.8335	103.2927	N	good	good	Y
0.64	1.1738	83.40625	N	good	average	N
0.05	1.1193	2138.6	N	good	average	N
0.08	3.4191	4173.875	N	good	poor	N
0.83	1.2053	45.21687	N	good	average	N
0.41	1.2053	193.9756	N	good	average	N
0.58	4.9497	753.3966	N	good	poor	N
0.63	1.9542	210.1905	N	good	poor	N
2.00	4.9927	149.635	N	poor	poor	Y
0.13	3.1678	2336.769	N	good	poor	N
0.42	3.1678	654.2381	N	good	poor	N
0.40	3.9953	898.825	N	good	poor	N
1.28	5.3128	315.0625	N	average	poor	N
2.05	5.3128	159.161	N	average	poor	N
0.89	4.0565	355.7865	N	good	poor	N
0.52	5.3097	921.0962	N	good	poor	N
0.62	5.3097	756.4032	N	good	poor	N
0.04	3.9892	9873	N	good	poor	N
0.28	5.2326	1768.786	N	good	poor	N
0.14	3.9745	2738.929	N	good	poor	N
0.03	4.118	13626.67	N	good	poor	N
1.52	4.9582	226.1974	N	average	poor	N
0.49	4.666	852.2449	N	good	poor	N
0.89	4.2866	381.6404	N	good	poor	N
0.38	5.09	1239.474	N	good	poor	N
0.89	4.1407	365.2472	N	good	poor	N
0.56	3.9667	608.3393	N	good	poor	N
0.67	4.8317	621.1493	N	good	poor	N

numerical match % (base case) =3.13%
linguistic match % (base case) =12.5%

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 1)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	4.9797	298.376	N	average	poor	N
2.00	5.0309	151.545	N	poor	poor	Y
1.00	4.9797	397.97	N	average	poor	N
1.00	4.9797	397.97	N	average	poor	N
0.67	4.9797	643.2388	N	good	poor	N
0.75	4.0045	433.9333	N	average	poor	N
1.50	4.0045	166.9667	N	average	poor	N
1.25	4.9797	298.376	N	average	poor	N
1.67	4.0566	142.9102	N	average	poor	N
1.56	4.0566	160.0385	N	average	poor	N
2.50	3.9574	58.296	N	poor	poor	Y
1.67	3.9646	137.4012	N	average	poor	N
1.67	3.9646	137.4012	N	average	poor	N
1.13	4.8338	327.7699	N	average	poor	N
1.39	4.0501	191.3741	N	average	poor	N
0.61	4.0084	557.1148	N	good	poor	N
1.33	4.0501	204.5188	N	average	poor	N
1.67	3.3075	98.05389	N	average	poor	N
0.81	3.2964	306.963	N	average	poor	N
1.33	4.9577	272.7594	N	average	poor	N
1.00	4.9577	395.77	N	average	poor	N
0.86	4.9571	476.407	N	average	poor	N
1.11	4.0386	263.8378	N	average	poor	N
0.73	5.1375	603.7671	N	average	poor	N
2.50	4.0106	60.424	N	poor	poor	Y
1.08	4.0545	275.4167	N	average	poor	N
0.83	4.9793	499.9157	N	average	poor	N
0.75	1.9804	164.0533	N	average	poor	N
1.17	2.245	91.88034	N	average	poor	N
0.80	4.5145	464.3125	N	average	poor	N
1.33	4.2137	216.8195	N	average	poor	N
1.20	4.1968	249.7333	N	average	poor	N
0.25	4.1968	1578.72	N	good	poor	N
0.56	4.1406	639.3929	N	good	poor	N
2.00	4.0667	103.335	N	poor	poor	Y
1.33	4.9327	270.8797	N	average	poor	N
0.70	4.9327	604.6714	N	average	poor	N
1.67	3.8726	131.8922	N	average	poor	N
1.25	3.8726	209.808	N	average	poor	N
0.67	4.5112	573.3134	N	good	poor	N
3.00	4.0265	34.21667	N	poor	poor	Y
1.00	5.0166	401.66	N	average	poor	N
1.20	5.0166	318.05	N	average	poor	N
0.67	5.1499	668.6418	N	good	poor	N
1.67	4.6185	176.5569	N	average	poor	N

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 1)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.94	4.6239	391.9043	N	average	poor	N
0.67	4.7414	607.6716	N	average	poor	N
1.67	4.746	184.1916	N	average	poor	N
0.38	4.746	1148.947	N	good	poor	N
0.88	4.746	439.3182	N	average	poor	N
2.50	4.7722	90.888	N	poor	poor	Y
1.00	4.7937	379.37	N	average	poor	N
0.83	4.7944	477.6386	N	average	poor	N
0.63	4.7938	660.9206	N	good	poor	N
2.33	5.0114	115.0815	N	poor	poor	Y
2.50	5.0527	102.108	N	poor	poor	Y
0.83	4.1535	400.4217	N	average	poor	N
1.67	4.0938	145.1377	N	average	poor	N
1.67	2.6332	57.67665	N	average	poor	N
3.33	4.0545	21.75676	Y	poor	poor	Y
1.67	3.9162	134.503	N	average	poor	N
4.00	4.1642	4.105	Y	poor	poor	Y
1.67	3.9313	135.4072	N	average	poor	N

numerical match % (base case) =3.17%
linguistic match % (base case) =15.87%

Test Results for Weld Pipe Model, Alloy and Butt Weld (Trial 1)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	3.575	358.3333	N	good	poor	N
2.50	3.4881	39.524	N	average	poor	N
1.00	3.4953	249.53	N	good	poor	N
2.00	3.8261	91.305	N	average	poor	N
1.75	3.8331	119.0343	N	average	poor	N
1.67	2.2222	33.06587	Y	average	average	Y
1.67	4.0581	143	N	average	poor	N
1.67	4.0939	145.1437	N	average	poor	N
1.67	3.8455	130.2695	N	average	poor	N
0.56	3.8201	582.1607	N	good	poor	N
0.63	1.1668	85.20635	N	good	average	N
1.25	3.8311	206.488	N	average	poor	N
1.67	3.9765	138.1138	N	average	poor	N
0.89	3.8201	329.2247	N	good	poor	N
1.67	3.8035	127.7545	N	average	poor	N
1.67	3.8035	127.7545	N	average	poor	N
2.33	5.1048	119.0901	N	average	poor	N
6.67	5.2198	-21.7421	Y	poor	poor	Y
2.50	4.1226	64.904	N	average	poor	N
3.33	5.0908	52.87688	N	poor	poor	Y
3.33	5.1199	53.75075	N	poor	poor	Y
3.33	4.1232	23.81982	Y	poor	poor	Y
1.67	4.1015	145.5988	N	average	poor	N
1.67	4.0131	140.3054	N	average	poor	N
3.33	4.0827	22.6036	Y	poor	poor	Y
1.00	3.8081	280.81	N	good	poor	N
1.00	1.6953	69.53	N	good	average	N
3.33	3.8331	15.10811	Y	poor	poor	Y
1.00	3.8331	283.31	N	good	poor	N
1.00	4.1204	312.04	N	good	poor	N
2.50	4.3085	72.34	N	average	poor	N
0.50	4.1061	721.22	N	good	poor	N

numerical match % (base case) =15.63%
linguistic match % (base case) =21.88%

Test Results for Rig Pipe Model (Trial 2)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.8786	131.2105263	N	good	good	Y
0.81	0.8851	9.271604938	Y	good	good	Y
0.38	0.8659	127.8684211	N	good	good	Y
0.76	0.8718	14.71052632	Y	good	good	Y
0.41	0.8718	112.6341463	N	good	good	Y
0.64	1.1256	75.875	N	good	average	N
0.05	1.1026	2105.2	N	good	average	N
0.08	1.1035	1279.375	N	good	average	N
0.83	1.1703	41	N	good	average	N
0.41	1.1703	185.4390244	N	good	average	N
0.58	1.2118	108.9310345	N	good	average	N
0.63	1.1078	75.84126984	N	good	average	N
2.00	4.9368	146.84	N	poor	poor	Y
0.13	1.9601	1407.769231	N	good	poor	N
0.42	1.149	173.5714286	N	good	average	N
0.40	3.9742	893.55	N	good	poor	N
1.28	5.6809	343.8203125	N	average	poor	N
2.05	5.6809	177.1170732	N	average	poor	N
0.89	4.2156	373.6629213	N	good	poor	N
0.52	5.3097	921.0961538	N	good	poor	N
0.62	5.3097	756.4032258	N	good	poor	N
0.04	3.9719	9829.75	N	good	poor	N
0.28	5.1495	1739.107143	N	good	poor	N
0.14	3.9745	2738.928571	N	good	poor	N
0.03	4.0918	13539.33333	N	good	poor	N
1.52	1.3513	-11.09868421	Y	average	average	Y
0.49	1.323	170	N	good	average	N
0.89	1.2953	45.53932584	N	good	average	N
0.38	1.3918	266.2631579	N	good	average	N
0.89	4.8111	440.5730337	N	good	poor	N
0.56	1.3259	136.7678571	N	good	average	N
0.67	4.7161	603.8955224	N	good	poor	N

numerical match % (base case) = 9.4%
linguistic match % (base case) =21.9%

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 2)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	0.9799	-21.608	Y	average	average	Y
2.00	0.9704	-51.48	N	poor	average	N
1.00	0.9799	-2.01	Y	average	average	Y
1.00	0.9799	-2.01	Y	average	average	Y
0.67	0.9799	46.25373134	N	good	average	N
0.75	0.7731	3.08	Y	average	average	Y
1.50	0.7532	-49.78666667	N	average	average	Y
1.25	0.9368	-25.056	Y	average	average	Y
1.67	0.7605	-54.46107784	N	average	average	Y
1.56	0.7605	-51.25	N	average	average	Y
2.50	0.7729	-69.084	N	poor	average	N
1.67	0.7731	-53.70658683	N	average	average	Y
1.67	0.7731	-53.70658683	N	average	average	Y
1.13	0.9105	-19.42477876	Y	average	average	Y
1.39	0.7731	-44.38129496	N	average	average	Y
0.61	0.7731	26.73770492	Y	good	average	N
1.33	0.7731	-41.87218045	N	average	average	Y
1.67	0.7232	-56.69461078	N	average	average	Y
0.81	0.7609	-6.061728395	Y	average	average	Y
1.33	0.9978	-24.97744361	Y	average	average	Y
1.00	0.9978	-0.22	Y	average	average	Y
0.86	0.9978	16.02325581	Y	average	average	Y
1.11	3.654	229.1891892	N	average	poor	N
0.73	4.6036	530.630137	N	average	poor	N
2.50	0.7558	-69.768	N	poor	average	N
1.08	1.658	53.51851852	N	average	average	Y
0.83	0.9336	12.48192771	Y	average	average	Y
0.75	0.924	23.2	Y	average	average	Y
1.17	0.7362	-37.07692308	N	average	average	Y
0.80	4.3196	439.95	N	average	poor	N
1.33	0.9302	-30.06015038	Y	average	average	Y
1.20	0.9317	-22.35833333	Y	average	average	Y
0.25	0.9317	272.68	N	good	average	N
0.56	0.751	34.10714286	N	good	average	N
2.00	0.7731	-61.345	N	poor	average	N
1.33	0.9105	-31.54135338	Y	average	average	Y
0.70	0.9105	30.07142857	Y	average	average	Y
1.67	0.9483	-43.21556886	N	average	average	Y
1.25	0.9483	-24.136	Y	average	average	Y
0.67	4.4192	559.5820896	N	good	poor	N
3.00	0.7402	-75.32666667	N	poor	average	N
1.00	1.0152	1.52	Y	average	average	Y
1.20	1.0152	-15.4	Y	average	average	Y
0.67	5.0964	660.6567164	N	good	poor	N
1.67	0.9131	-45.32335329	N	average	average	Y
0.94	0.9131	-2.861702128	Y	average	average	Y

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 2)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.67	4.2682	537.0447761	N	average	poor	N
1.67	0.9105	-45.47904192	N	average	average	Y
0.38	0.9105	139.6052632	N	good	average	N
0.88	0.9105	3.465909091	Y	average	average	Y
2.50	0.9105	-63.58	N	poor	average	N
1.00	0.9105	-8.95	Y	average	average	Y
0.83	0.9105	9.698795181	Y	average	average	Y
0.63	0.9105	44.52380952	N	good	average	N
2.33	4.9085	110.6652361	N	poor	poor	Y
2.50	5.093	103.72	N	poor	poor	Y
0.83	3.9237	372.7349398	N	average	poor	N
1.67	3.9411	135.994012	N	average	poor	N
1.67	0.7663	-54.11377246	N	average	average	Y
3.33	0.8243	-75.24624625	N	poor	average	N
1.67	4.1436	148.1197605	N	average	poor	N
4.00	4.3119	7.7975	Y	poor	poor	Y
1.67	4.1989	151.4311377	N	average	poor	N

numerical match % (base case) = 39.7%
linguistic match % (base case) =63.5%

Test Results for Weld Pipe Model, Alloy and Butt Weld (Trial 2)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	1.4967	91.8846154	N	good	average	N
2.50	1.5227	-39.092	N	average	average	Y
1.00	1.5227	52.27	N	good	average	N
2.00	3.5921	79.605	N	average	average	Y
1.75	1.7591	0.52	Y	average	average	Y
1.67	1.1334	-32.131737	Y	average	average	Y
1.67	1.1663	-30.161677	Y	average	average	Y
1.67	1.1235	-32.724551	Y	average	average	Y
1.67	1.1776	-29.48503	Y	average	average	Y
0.56	1.529	173.035714	N	good	average	N
0.63	1.1668	85.2063492	N	good	average	N
1.25	3.8226	205.808	N	average	poor	N
1.67	1.085	-35.02994	N	average	average	Y
0.89	3.8201	329.224719	N	good	poor	N
1.67	3.8023	127.682635	N	average	poor	N
1.67	3.8022	127.676647	N	average	poor	N
2.33	4.9769	113.600858	N	average	poor	N
6.67	5.0481	-24.316342	Y	poor	poor	N
2.50	3.9186	56.744	N	average	poor	N
3.33	4.9043	47.2762763	N	poor	poor	Y
3.33	5.056	51.8318318	N	poor	poor	Y
3.33	1.0288	-69.105105	N	poor	good	N
1.67	1.085	-35.02994	N	average	average	Y
1.67	1.085	-35.02994	N	average	average	Y
3.33	3.8321	15.0780781	Y	poor	poor	Y
1.00	3.8739	287.39	N	good	poor	N
1.00	1.492	49.2	N	good	average	N
3.33	1.7619	-47.09009	N	poor	average	N
1.00	1.7619	76.19	N	good	average	N
1.00	1.8988	89.88	N	good	average	N
2.50	4.4127	76.508	N	average	poor	N
0.50	1.6063	221.26	N	good	average	N

numerical match % (base case) =21.9%
linguistic match % (base case) =40.6%

Test Results for Rig Pipe Model (Trial 3)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.6636	74.63157895	N	good	good	Y
0.81	0.6666	-17.7037037	Y	good	good	Y
0.38	0.6581	73.18421053	N	good	good	Y
0.76	0.6608	-13.05263158	Y	good	good	Y
0.41	0.6608	61.17073171	N	good	good	Y
0.64	0.6608	3.25	Y	good	good	Y
0.05	0.6666	1233.2	N	good	good	Y
0.08	0.6666	733.25	N	good	good	Y
0.83	0.6503	-21.65060241	Y	good	good	Y
0.41	0.6503	58.6097561	N	good	good	Y
0.58	0.6466	11.48275862	Y	good	good	Y
0.63	0.6654	5.619047619	Y	good	good	Y
2.00	0.941	-52.95	N	poor	good	N
0.13	0.6666	412.7692308	N	good	good	Y
0.42	0.6666	58.71428571	N	good	good	Y
0.40	1.027	156.75	N	good	average	N
1.28	5.1115	299.3359375	N	average	poor	N
2.05	5.1115	149.3414634	N	average	poor	N
0.89	1.0607	19.17977528	Y	good	average	N
0.52	1.0656	104.9230769	N	good	average	N
0.62	1.0656	71.87096774	N	good	average	N
0.04	1.0087	2421.75	N	good	average	N
0.28	1.019	263.9285714	N	good	average	N
0.14	1.019	627.8571429	N	good	average	N
0.03	1.0306	3335.333333	N	good	average	N
1.52	0.5865	-61.41447368	N	average	good	N
0.49	0.6249	27.53061224	Y	good	good	Y
0.89	0.6441	-27.62921348	Y	good	good	Y
0.38	0.6366	67.52631579	N	good	good	Y
0.89	0.6653	-25.24719101	Y	good	good	Y
0.56	0.6437	14.94642857	Y	good	good	Y
0.67	0.6547	-2.28358209	Y	good	good	Y

numerical match % (base case) =37.5 %
linguistic match % (base case) =62.5%

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 3)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	1.0586	-15.312	Y	average	average	Y
2.00	1.0783	-46.085	N	poor	average	N
1.00	1.0586	5.86	Y	average	average	Y
1.00	1.0586	5.86	Y	average	average	Y
0.67	1.0586	58	N	good	average	N
0.75	1.0118	34.90666667	N	average	average	Y
1.50	1.063	-29.13333333	Y	average	average	Y
1.25	1.0419	-16.648	Y	average	average	Y
1.67	1.0309	-38.26946108	N	average	average	Y
1.56	1.0309	-33.91666667	N	average	average	Y
2.50	1.0554	-57.784	N	poor	average	N
1.67	1.0555	-36.79640719	N	average	average	Y
1.67	1.0555	-36.79640719	N	average	average	Y
1.13	1.0125	-10.39823009	Y	average	average	Y
1.39	1.0125	-27.15827338	Y	average	average	Y
0.61	1.0125	65.98360656	N	good	average	N
1.33	1.0125	-23.87218045	Y	average	average	Y
1.67	1.2015	-28.05389222	Y	average	average	Y
0.81	1.0309	27.27160494	Y	average	average	Y
1.33	1.0367	-22.05263158	Y	average	average	Y
1.00	1.0367	3.67	Y	average	average	Y
0.86	1.0367	20.54651163	Y	average	average	Y
1.11	1.0586	-4.630630631	Y	average	average	Y
0.73	3.8882	432.630137	N	average	poor	N
2.50	1.062	-57.52	N	poor	average	N
1.08	1.0422	-3.5	Y	average	average	N
0.83	1.0385	25.12048193	Y	average	average	Y
0.75	1.0285	37.13333333	N	average	average	Y
1.17	1.0685	-8.675213675	Y	average	average	Y
0.80	1.1355	41.9375	N	average	average	Y
1.33	1.0173	-23.5112782	Y	average	average	Y
1.20	1.0231	-14.74166667	Y	average	average	Y
0.25	1.0231	309.24	N	good	average	N
0.56	1.0458	86.75	N	good	average	N
2.00	1.0281	-48.595	N	poor	average	N
1.33	1.0125	-23.87218045	Y	average	average	Y
0.70	1.0125	44.64285714	N	average	average	Y
1.67	1.0538	-36.89820359	N	average	average	Y
1.25	1.0538	-15.696	Y	average	average	Y
0.67	1.1355	69.47761194	N	good	average	N
3.00	1.1957	-60.14333333	N	poor	average	N
1.00	1.0622	6.22	Y	average	average	Y
1.20	1.0622	-11.48333333	Y	average	average	Y
0.67	4.5484	578.8656716	N	good	poor	N
1.67	1.0158	-39.17365269	N	average	average	Y
0.94	1.0158	8.063829787	Y	average	average	Y

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 3)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.67	1.2009	79.23880597	N	average	average	Y
1.67	1.0125	-39.37125749	N	average	average	Y
0.38	1.0125	166.4473684	N	good	average	N
0.88	1.0125	15.05681818	Y	average	average	Y
2.50	1.0539	-57.844	N	poor	average	N
1.00	1.0125	1.25	Y	average	average	Y
0.83	1.0125	21.98795181	Y	average	average	Y
0.63	1.0125	60.71428571	N	good	average	N
2.33	1.2008	-48.46351931	N	poor	average	N
2.50	1.2018	-51.928	N	poor	average	N
0.83	1.2014	44.74698795	N	average	average	Y
1.67	1.2009	-28.08982036	Y	average	average	Y
1.67	1.0627	-36.36526946	N	average	average	Y
3.33	1.2018	-63.90990991	N	poor	average	N
1.67	1.2014	-28.05988024	Y	average	average	Y
4.00	1.0622	-73.445	N	poor	average	N
1.67	1.2018	-28.03592814	Y	average	average	Y

numerical match % (base case) =47.619 %
linguistic match % (base case) =68.25%

Test Results for Weld Pipe Model, Alloy and Butt Weld (Trial 3)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	1.4967	91.8846154	N	good	average	N
2.50	1.556	-37.76	N	average	average	Y
1.00	1.5227	52.27	N	good	average	N
2.00	1.5496	-22.52	Y	average	average	Y
1.75	1.5664	-10.491429	Y	average	average	Y
1.67	1.5707	-5.9461078	Y	average	average	Y
1.67	1.529	-8.4431138	Y	average	average	Y
1.67	1.529	-8.4431138	Y	average	average	Y
1.67	1.5149	-9.2874251	Y	average	average	Y
0.56	1.5243	172.196429	N	good	average	N
0.63	1.6711	165.253968	N	good	average	N
1.25	1.7891	43.128	N	average	average	Y
1.67	1.78	6.58682635	Y	average	average	Y
0.89	1.789	101.011236	N	good	average	N
1.67	1.5667	-6.1856287	Y	average	average	Y
1.67	1.5667	-6.1856287	Y	average	average	Y
2.33	1.5458	-33.656652	N	average	average	Y
6.67	1.5277	-77.095952	N	poor	average	N
2.50	1.7906	-28.376	Y	average	average	Y
3.33	1.5466	-53.555556	N	poor	average	N
3.33	1.7891	-46.273273	N	poor	average	N
3.33	1.7861	-46.363363	N	poor	average	N
1.67	1.7848	6.8742515	Y	average	average	Y
1.67	1.7863	6.96407186	Y	average	average	Y
3.33	1.7861	-46.363363	N	poor	average	N
1.00	1.7861	78.61	N	good	average	N
1.00	1.5927	59.27	N	good	average	N
3.33	1.492	-55.195195	N	poor	average	N
1.00	1.7901	79.01	N	good	average	N
1.00	1.7901	79.01	N	good	average	N
2.50	1.5114	-39.544	Y	average	average	Y
0.50	1.5537	210.74	N	good	average	N

numerical match % (base case) =40.625 %
linguistic match % (base case) =50.00%

Test Results for Rig Pipe Model (Trial 4)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.7251	90.81578947	N	good	good	Y
0.81	0.7013	-13.41975309	Y	good	good	Y
0.38	0.7323	92.71052632	N	good	good	Y
0.76	0.7298	-3.973684211	Y	good	good	Y
0.41	0.7494	82.7804878	N	good	good	Y
0.64	0.7293	13.953125	Y	good	good	Y
0.83	0.742	-10.60240964	Y	good	good	Y
0.41	0.7354	79.36585366	N	good	good	Y
0.58	0.7307	25.98275862	Y	good	good	Y
0.63	0.7506	19.14285714	Y	good	good	Y
2.00	0.9438	-52.81	N	poor	good	N
0.13	0.7388	468.3076923	N	good	good	Y
0.42	0.7501	78.5952381	N	good	good	Y
0.40	1.0675	166.875	N	good	good	Y
1.28	5.0316	293.09375	N	average	poor	N
2.05	5.0316	145.4439024	N	average	poor	N
0.89	0.8512	-4.359550562	Y	good	good	Y
0.52	1.0851	108.6730769	N	good	average	N
0.62	1.0656	71.87096774	N	good	average	N
0.04	1.0485	2521.25	N	good	average	N
0.28	1.039	271.0714286	N	good	average	N
0.14	1.0485	648.9285714	N	good	average	N
1.52	0.6018	-60.40789474	N	average	good	N
0.49	0.848	73.06122449	N	good	good	Y
0.89	0.7878	-11.48314607	Y	good	good	Y
0.38	0.6796	78.84210526	N	good	good	Y
0.89	0.7515	-15.56179775	Y	good	good	Y
0.56	0.7033	25.58928571	Y	good	good	Y
0.67	0.7321	9.268656716	Y	good	good	Y

numerical match % (base case) =37.93 %
linguistic match % (base case) =70.00%

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 4)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	0.9872	-21.024	Y	average	average	Y
2.00	1.0843	-45.785	N	poor	average	N
1.00	0.9872	-1.28	Y	average	average	Y
1.00	0.9872	-1.28	Y	average	average	Y
0.67	0.9872	47.34328358	N	good	average	N
0.75	0.6699	-10.68	Y	average	average	Y
1.50	1.0839	-27.74	Y	average	average	Y
1.25	0.9872	-21.024	Y	average	average	Y
1.67	0.6428	-61.50898204	N	average	good	N
1.56	0.6429	-58.78846154	N	average	good	N
2.50	1.0667	-57.332	N	poor	average	N
1.67	1.0667	-36.1257485	N	average	average	Y
1.67	1.0667	-36.1257485	N	average	average	Y
1.13	0.9865	-12.69911504	Y	average	average	Y
1.39	0.6226	-55.20863309	N	average	good	N
0.61	0.6094	-0.098360656	Y	good	good	Y
1.33	0.6226	-53.18796992	N	average	good	N
1.67	0.8372	-49.86826347	N	average	average	Y
0.81	0.6638	-18.04938272	Y	average	average	Y
1.33	0.987	-25.78947368	Y	average	average	Y
1.00	0.987	-1.3	Y	average	average	Y
0.86	0.987	14.76744186	Y	average	average	Y
1.11	0.6712	-39.53153153	N	average	average	Y
0.73	3.9603	442.5068493	N	average	poor	N
2.50	1.0841	-56.636	N	poor	average	N
1.08	0.6293	-41.73148148	N	average	good	N
0.83	0.9866	18.86746988	Y	average	average	Y
0.75	0.6128	-18.29333333	Y	average	good	N
1.17	0.6128	-47.62393162	N	average	good	N
0.80	0.7234	-9.575	Y	average	average	Y
1.33	0.9581	-27.96240602	Y	average	average	Y
1.20	0.9581	-20.15833333	Y	average	average	Y
0.25	0.9581	283.24	N	good	average	N
0.56	0.6257	11.73214286	Y	good	good	Y
2.00	1.0705	-46.475	N	poor	average	N
1.33	0.987	-25.78947368	Y	average	average	Y
0.70	0.987	41	N	average	average	Y
1.67	0.925	-44.61077844	N	average	average	Y
1.25	0.925	-26	Y	average	average	Y
0.67	0.925	38.05970149	N	good	average	N
3.00	1.0845	-63.85	N	poor	average	N
1.00	1.0845	8.45	Y	average	average	Y
1.20	1.0845	-9.625	Y	average	average	Y
0.67	4.5818	583.8507463	N	good	poor	N
1.67	0.987	-40.89820359	N	average	average	Y
0.94	0.9861	4.904255319	Y	average	average	Y

Test Results for Weld Pipe Model, Carbon Steel and Butt Weld (Trial 4)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.67	4.4424	563.0447761	N	average	poor	N
1.67	0.987	-40.89820359	N	average	average	Y
0.38	0.987	159.7368421	N	good	average	N
0.88	0.987	12.15909091	Y	average	average	Y
2.50	1.0544	-57.824	N	poor	average	N
1.00	0.9866	-1.34	Y	average	average	Y
0.83	0.9866	18.86746988	Y	average	average	Y
0.63	0.9866	56.6031746	N	good	average	N
2.33	1.0841	-53.472103	N	poor	average	N
2.50	1.0843	-56.628	N	poor	average	N
0.83	0.9856	18.74698795	Y	average	average	Y
1.67	0.955	-42.81437126	N	average	average	Y
1.67	0.7312	-56.21556886	N	average	average	Y
3.33	1.0842	-67.44144144	N	poor	average	N
1.67	0.9965	-40.32934132	N	average	average	Y
4.00	0.9406	-76.485	N	poor	average	N
1.67	0.9796	-41.34131737	N	average	average	Y

numerical match % (base case) =42.86 %
linguistic match % (base case) =60.32%

Test Results for Weld Pipe Model, Alloy and Butt Weld (Trial 4)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	0.6897	-11.576923	Y	good	good	Y
2.50	0.975	-61	N	average	good	N
1.00	0.6568	-34.32	N	good	good	Y
2.00	0.6347	-68.265	N	average	good	N
1.75	0.6347	-63.731429	N	average	good	N
1.67	0.638	-61.796407	N	average	good	N
1.67	0.6505	-61.047904	N	average	good	N
1.67	0.6505	-61.047904	N	average	good	N
1.67	0.6536	-60.862275	N	average	good	N
0.56	0.6536	16.7142857	Y	good	good	Y
0.63	1.5005	138.174603	N	good	average	N
1.25	1.7853	42.824	N	average	average	Y
1.67	1.7036	2.01197605	Y	average	average	Y
0.89	1.789	101.011236	N	good	average	N
1.67	0.6756	-59.54491	N	average	good	N
1.67	0.6756	-59.54491	N	average	good	N
2.33	1.6113	-30.845494	Y	average	average	Y
6.67	1.3145	-80.292354	N	poor	average	N
2.50	1.784	-28.64	Y	average	average	Y
3.33	1.6111	-51.618619	N	poor	average	N
3.33	1.7837	-46.435435	N	poor	average	N
3.33	1.7837	-46.435435	N	poor	average	N
1.67	1.7828	6.75449102	Y	average	average	Y
1.67	1.7871	7.01197605	Y	average	average	Y
3.33	1.7837	-46.435435	N	poor	average	N
1.00	1.7837	78.37	N	good	average	N
1.00	0.6377	-36.23	N	good	good	Y
3.33	0.636	-80.900901	N	poor	good	N
1.00	1.7837	78.37	N	good	average	N
1.00	1.7837	78.37	N	good	average	N
2.50	1.5317	-38.732	N	average	average	Y
0.50	1.5317	206.34	N	good	average	N

numerical match % (base case) =21.88 %
linguistic match % (base case) =34.38%

Appendix H (Model Calibration Results)

Calibration Results for Rig Pipe Model (Selected from Trial 4)-First Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.8168	114.9473684	N	good	good	Y
0.81	0.7896	-2.518518519	Y	good	good	Y
0.38	0.8298	118.3684211	N	good	good	Y
0.76	0.8252	8.578947368	Y	good	good	Y
0.41	0.8432	105.6585366	N	good	good	Y
0.64	0.8244	28.8125	Y	good	good	Y
0.83	0.8385	1.024096386	Y	good	good	Y
0.41	0.8344	103.5121951	N	good	good	Y
0.58	0.8268	42.55172414	N	good	good	Y
0.63	0.8468	34.41269841	N	good	good	Y
2.00	1.1574	-42.13	N	poor	average	N
0.13	0.8365	543.4615385	N	good	good	Y
0.42	0.8443	101.0238095	N	good	good	Y
0.40	1.3278	231.95	N	good	average	N
1.28	4.9192	284.3125	N	average	poor	N
2.05	4.9192	139.9609756	N	average	poor	N
0.89	1.0098	13.46067416	Y	good	average	N
0.52	1.3493	159.4807692	N	good	average	N
0.62	1.3197	112.8548387	N	good	average	N
0.04	1.3015	3153.75	N	good	average	N
0.28	1.2882	360.0714286	N	good	average	N
0.14	1.3015	829.6428571	N	good	average	N
1.52	0.6693	-55.96710526	N	average	good	N
0.49	1.0209	108.3469388	N	good	good	Y
0.89	0.9395	5.561797753	Y	good	good	Y
0.38	0.7648	101.2631579	N	good	good	Y
0.89	0.8514	-4.337078652	Y	good	good	Y
0.56	0.7923	41.48214286	N	good	good	Y
0.67	0.8293	23.7761194	Y	good	good	Y

numerical match % (base case) =27.59 %
linguistic match % (base case) =62.07%

Calibration Results for Rig Pipe Model (Selected from Trial 4)-Second Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.5375	41.44736842	N	good	good	Y
0.81	0.5186	-35.97530864	N	good	good	Y
0.38	0.544	43.15789474	N	good	good	Y
0.76	0.5417	-28.72368421	Y	good	good	Y
0.41	0.5593	36.41463415	N	good	good	Y
0.64	0.5413	-15.421875	Y	good	good	Y
0.83	0.5526	-33.42168675	N	good	good	Y
0.41	0.5468	33.36585366	N	good	good	Y
0.58	0.5425	-6.465517241	Y	good	good	Y
0.63	0.5595	-11.19047619	Y	good	good	Y
2.00	0.7699	-61.505	N	poor	good	N
0.13	0.5497	322.8461538	N	good	good	Y
0.42	0.5594	33.19047619	Y	good	good	Y
0.40	0.8759	118.975	N	good	average	N
1.28	5.0728	296.3125	N	average	poor	N
2.05	5.0728	147.4536585	N	average	poor	N
0.89	0.6645	-25.33707865	Y	good	average	N
0.52	0.899	72.88461538	N	good	average	N
0.62	0.883	42.41935484	N	good	average	N
0.04	0.8573	2043.25	N	good	average	N
0.28	0.8531	204.6785714	N	good	average	N
0.14	0.8573	512.3571429	N	good	average	N
1.52	0.4392	-71.10526316	N	average	good	N
0.49	0.6765	38.06122449	N	good	good	Y
0.89	0.6213	-30.19101124	Y	good	good	Y
0.38	0.5023	32.18421053	Y	good	good	Y
0.89	0.5595	-37.13483146	N	good	good	Y
0.56	0.5206	-7.035714286	Y	good	good	Y
0.67	0.5437	-18.85074627	Y	good	good	Y

numerical match % (base case) =34.48 %
linguistic match % (base case) =62.07%

Calibration Results for Rig Pipe Model (Selected from Trial 4)-Third Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.38	0.5413	42.44736842	N	good	good	Y
0.81	0.5261	-35.04938272	N	good	good	Y
0.38	0.5486	44.36842105	N	good	good	Y
0.76	0.546	-28.15789474	Y	good	good	Y
0.41	0.5594	36.43902439	N	good	good	Y
0.64	0.5455	-14.765625	Y	good	good	Y
0.83	0.5583	-32.73493976	Y	good	good	Y
0.41	0.5517	34.56097561	N	good	good	Y
0.58	0.5469	-5.706896552	Y	good	good	Y
0.63	0.5595	-11.19047619	Y	good	good	Y
2.00	0.7174	-64.13	N	poor	good	N
0.13	0.5551	327	N	good	good	Y
0.42	0.5594	33.19047619	Y	good	good	Y
0.40	0.7917	97.925	N	good	good	Y
1.28	5.0549	294.9140625	N	average	poor	N
2.05	5.0549	146.5804878	N	average	poor	N
0.89	0.6285	-29.38202247	Y	good	good	Y
0.52	0.8344	60.46153846	N	good	good	Y
0.62	0.8225	32.66129032	Y	good	good	Y
0.04	0.7774	1843.5	N	good	good	Y
0.28	0.7721	175.75	N	good	good	Y
0.14	0.7774	455.2857143	N	good	good	Y
1.52	0.4541	-70.125	N	average	good	N
0.49	0.6282	28.20408163	Y	good	good	Y
0.89	0.5829	-34.50561798	N	good	good	Y
0.38	0.5122	34.78947368	N	good	good	Y
0.89	0.5595	-37.13483146	N	good	good	Y
0.56	0.5283	-5.660714286	Y	good	good	Y
0.67	0.5483	-18.1641791	Y	good	good	Y

numerical match % (base case) =37.93 %
linguistic match % (base case) =86.21%

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-First Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	1.2835	2.68	Y	average	average	Y
2.00	1.2883	-35.585	N	poor	average	N
1.00	1.2835	28.35	Y	average	average	Y
1.00	1.2835	28.35	Y	average	average	Y
0.67	1.2835	91.56716418	N	good	average	N
0.75	0.9354	24.72	Y	average	average	Y
1.50	1.2361	-17.59333333	Y	average	average	Y
1.25	1.2361	-1.112	Y	average	average	Y
1.67	0.9158	-45.16167665	N	average	average	Y
1.56	0.9158	-41.29487179	N	average	average	Y
2.50	1.2029	-51.884	N	poor	average	N
1.67	1.2029	-27.97005988	Y	average	average	Y
1.67	1.2029	-27.97005988	Y	average	average	Y
1.13	1.2029	6.451327434	Y	average	average	N
1.39	0.9347	-32.75539568	Y	average	average	N
0.61	0.9347	53.2295082	N	good	average	N
1.33	0.935	-29.69924812	Y	average	average	Y
1.67	1.2551	-24.84431138	Y	average	average	Y
0.81	0.942	16.2962963	Y	average	average	Y
1.33	1.3253	-0.353383459	Y	average	average	Y
1.00	1.3253	32.53	Y	average	average	Y
0.86	1.3253	54.10465116	N	average	average	Y
1.11	3.95	255.8558559	N	average	poor	N
0.73	4.3039	489.5753425	N	average	poor	N
2.50	1.2383	-50.468	Y	poor	average	Y
1.08	1.865	72.68518519	N	average	poor	N
0.83	1.2383	49.19277108	N	average	average	Y
0.75	1.224	63.2	N	average	average	Y
1.17	0.8846	-24.39316239	Y	average	average	Y
0.80	3.9254	390.675	N	average	poor	N
1.33	1.2337	-7.240601504	Y	average	average	Y
1.20	1.2337	2.808333333	Y	average	average	Y
0.25	1.2337	393.48	N	good	average	N
0.56	0.9316	66.35714286	N	good	average	N
2.00	1.2029	-39.855	N	poor	average	N
1.33	1.2029	-9.556390977	Y	average	average	Y
0.70	1.2029	71.84285714	N	average	average	Y
1.67	1.259	-24.61077844	Y	average	average	Y
1.25	1.259	0.72	Y	average	average	Y
0.67	4.1507	519.5074627	N	good	poor	N
3.00	1.4449	-51.83666667	N	poor	average	N
1.00	1.3494	34.94	N	average	average	Y
1.20	1.3494	12.45	Y	average	average	Y
0.67	5.1392	667.0447761	N	good	poor	N

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-First Calibration (Base Case)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.67	1.2071	-27.71856287	Y	average	average	Y
0.94	1.2071	28.41489362	Y	average	average	Y
0.67	3.9184	484.8358209	N	average	poor	N
1.67	1.2029	-27.97005988	Y	average	average	Y
0.38	1.2029	216.5526316	N	good	average	N
0.88	1.2029	36.69318182	N	average	average	Y
2.50	1.2029	-51.884	N	poor	average	N
1.00	1.2029	20.29	Y	average	average	Y
0.83	1.2029	44.92771084	N	average	average	Y
0.63	1.2029	90.93650794	N	good	average	N
2.33	5.1566	121.3133047	N	poor	poor	Y
2.50	5.2216	108.864	N	poor	poor	Y
0.83	4.2334	410.0481928	N	average	poor	N
1.67	3.9472	136.3592814	N	average	poor	N
1.67	1.2322	-26.21556886	Y	average	average	Y
3.33	4.0701	22.22522523	Y	poor	poor	Y
1.67	4.6382	177.7365269	N	average	poor	N
4.00	4.1935	4.8375	Y	poor	poor	Y
1.67	4.5239	170.8922156	N	average	poor	N

numerical match % (base case) =47.62 %
linguistic match % (base case) =61.90%

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-Second Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	0.8662	-30.704	Y	average	average	Y
2.00	0.8686	-56.57	N	poor	average	N
1.00	0.8662	-13.38	Y	average	average	Y
1.00	0.8662	-13.38	Y	average	average	Y
0.67	0.8662	29.28358209	Y	good	average	N
0.75	0.6434	-14.21333333	Y	average	average	Y
1.50	0.8378	-44.14666667	N	average	average	Y
1.25	0.8378	-32.976	Y	average	average	Y
1.67	0.63	-62.2754491	N	average	average	Y
1.56	0.63	-59.61538462	N	average	average	Y
2.50	0.8183	-67.268	N	poor	average	N
1.67	0.8183	-51	N	average	average	Y
1.67	0.8183	-51	N	average	average	Y
1.13	0.8183	-27.5840708	Y	average	average	Y
1.39	0.6429	-53.74820144	N	average	average	Y
0.61	0.6429	5.393442623	Y	good	average	N
1.33	0.6431	-51.64661654	N	average	average	Y
1.67	0.8489	-49.16766467	N	average	average	Y
0.81	0.6479	-20.01234568	Y	average	average	Y
1.33	0.8886	-33.18796992	Y	average	average	Y
1.00	0.8886	-11.14	Y	average	average	Y
0.86	0.8886	3.325581395	Y	average	average	Y
1.11	4.2382	281.8198198	N	average	poor	N
0.73	4.365	497.9452055	N	average	poor	N
2.50	0.8392	-66.432	N	poor	average	N
1.08	2.035	88.42592593	N	average	poor	N
0.83	0.8392	1.108433735	Y	average	average	Y
0.75	0.8306	10.74666667	Y	average	average	Y
1.17	0.6096	-47.8974359	N	average	average	Y
0.80	4.107	413.375	N	average	poor	N
1.33	0.8365	-37.10526316	N	average	average	Y
1.20	0.8365	-30.29166667	Y	average	average	Y
0.25	0.8365	234.6	N	good	average	N
0.56	0.6408	14.42857143	Y	good	average	N
2.00	0.8183	-59.085	N	poor	average	N
1.33	0.8183	-38.47368421	N	average	average	Y
0.70	0.8183	16.9	Y	average	average	Y
1.67	0.8512	-49.02994012	N	average	average	Y
1.25	0.8512	-31.904	Y	average	average	Y
0.67	4.2772	538.3880597	N	good	poor	N
3.00	0.9485	-68.38333333	N	poor	average	Y
1.00	0.9022	-9.78	Y	average	average	Y
1.20	0.9022	-24.81666667	Y	average	average	Y

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-Second Calibration (Base Case)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.67	5.0664	656.1791045	N	good	poor	N
1.67	0.8207	-50.85628743	N	average	average	Y
0.94	0.8207	-12.69148936	Y	average	average	Y
0.67	4.0401	503	N	average	poor	N
1.67	0.8183	-51	N	average	average	Y
0.38	0.8183	115.3421053	N	good	average	N
0.88	0.8183	-7.011363636	Y	average	average	Y
2.50	0.8183	-67.268	N	poor	average	N
1.00	0.8183	-18.17	Y	average	average	Y
0.83	0.8183	-1.409638554	Y	average	average	Y
0.63	0.8183	29.88888889	Y	good	average	N
2.33	5.0782	117.9484979	N	poor	poor	Y
2.50	5.1343	105.372	N	poor	poor	Y
0.83	4.3146	419.8313253	N	average	poor	N
1.67	4.048	142.3952096	N	average	poor	N
1.67	0.8356	-49.96407186	N	average	average	Y
3.33	4.1511	24.65765766	Y	poor	poor	Y
1.67	4.656	178.8023952	N	average	poor	N
4.00	4.3365	8.4125	Y	poor	poor	Y
1.67	4.5604	173.0778443	N	average	poor	N

numerical match % (base case) =42.86 %
linguistic match % (base case) =65.08%

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-Third Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
1.25	1.216	-2.72	Y	average	average	Y
2.00	1.2154	-39.23	N	poor	average	N
1.00	1.216	21.6	Y	average	average	Y
1.00	1.216	21.6	Y	average	average	Y
0.67	1.216	81.49253731	N	good	good	Y
0.75	1.1649	55.32	N	average	average	Y
1.50	1.1825	-21.16666667	Y	average	average	Y
1.25	1.1825	-5.4	Y	average	average	Y
1.67	1.1766	-29.54491018	Y	average	average	Y
1.56	1.1766	-24.57692308	Y	average	average	Y
2.50	1.194	-52.24	N	poor	poor	Y
1.67	1.194	-28.50299401	Y	average	average	Y
1.67	1.194	-28.50299401	Y	average	average	Y
1.13	1.194	5.663716814	Y	average	average	Y
1.39	1.1654	-16.15827338	Y	average	average	Y
0.61	1.1654	91.04918033	N	good	good	Y
1.33	1.1652	-12.39097744	Y	average	average	Y
1.67	1.2901	-22.74850299	Y	average	average	Y
0.81	1.1604	43.25925926	N	average	average	Y
1.33	1.2336	-7.248120301	Y	average	average	Y
1.00	1.2336	23.36	Y	average	average	Y
0.86	1.2336	43.44186047	N	average	average	Y
1.11	1.1634	4.810810811	Y	average	average	Y
0.73	3.6747	403.3835616	N	average	poor	N
2.50	1.1938	-52.248	N	poor	average	N
1.08	1.1737	8.675925926	Y	average	average	Y
0.83	1.1954	44.02409639	N	average	average	Y
0.75	1.1943	59.24	N	average	average	Y
1.17	1.1979	2.384615385	Y	average	average	Y
0.80	1.2086	51.075	N	average	average	Y
1.33	1.183	-11.05263158	Y	average	average	Y
1.20	1.183	-1.416666667	Y	average	average	Y

Calibration Results for Weld Pipe Model, Carbon Steel and Butt Weld (Selected from Trial 3)-Third Calibration (Base Case)-Continued

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.25	1.183	373.2	N	good	average	N
0.56	1.1675	108.4821429	N	good	average	N
2.00	1.1786	-41.07	N	poor	average	N
1.33	1.1786	-11.38345865	Y	average	average	Y
0.70	1.1786	68.37142857	N	average	average	Y
1.67	1.1971	-28.31736527	Y	average	average	Y
1.25	1.1971	-4.232	Y	average	average	Y
0.67	1.2513	86.76119403	N	good	poor	N
3.00	1.2857	-57.14333333	N	poor	average	N
1.00	1.2426	24.26	Y	average	average	Y
1.20	1.2426	3.55	Y	average	average	Y
0.67	4.0743	508.1044776	N	good	poor	N
1.67	1.1714	-29.85628743	Y	average	average	Y
0.94	1.1703	24.5	Y	average	average	Y
0.67	1.2721	89.86567164	N	average	average	Y
1.67	1.1786	-29.4251497	Y	average	average	Y
0.38	1.1786	210.1578947	N	good	average	N
0.88	1.1786	33.93181818	N	average	average	Y
2.50	1.1746	-53.016	N	poor	average	N
1.00	1.1939	19.39	Y	average	average	Y
0.83	1.1939	43.84337349	N	average	average	Y
0.63	1.1939	89.50793651	N	good	average	N
2.33	1.2974	-44.31759657	N	poor	average	N
2.50	1.2955	-48.18	N	poor	average	N
0.83	1.2704	53.06024096	N	average	average	Y
1.67	1.2656	-24.21556886	Y	average	average	Y
1.67	1.182	-29.22155689	Y	average	average	Y
3.33	1.2953	-61.1021021	N	poor	average	N
1.67	1.2915	-22.66467066	Y	average	average	Y
4.00	1.2211	-69.4725	N	poor	average	N
1.67	1.2953	-22.43712575	Y	average	average	Y

numerical match % (base case) =49.21 %
linguistic match % (base case) =74.60%

Calibration Results for Weld Pipe Model, Alloy and Butt Weld (Selected from Trial 3)-First Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	1.7527	124.705128	N	good	average	N
2.50	1.7964	-28.144	Y	average	average	Y
1.00	1.7582	75.82	N	good	average	N
2.00	3.6603	83.015	Y	average	average	Y
1.75	1.9335	10.4857143	Y	average	average	Y
1.67	1.3616	-18.467066	Y	average	average	Y
1.67	1.433	-14.191617	Y	average	average	Y
1.67	1.3813	-17.287425	Y	average	average	Y
1.67	3.7617	125.251497	N	average	average	Y
0.56	3.7876	576.357143	N	good	average	N
0.63	1.9523	209.888889	N	good	average	N
1.25	5.1516	312.128	N	average	average	Y
1.67	2.0222	21.0898204	Y	average	average	Y
0.89	4.9942	461.146067	N	good	average	N
1.67	3.8243	129	N	average	average	Y
1.67	3.8243	129	N	average	average	Y
2.33	5.0348	116.085837	N	average	average	Y
6.67	4.9904	-25.181409	Y	poor	average	N
2.50	5.2997	111.988	N	average	average	Y
3.33	5.1286	54.012012	N	poor	average	N
3.33	5.0227	50.8318318	N	poor	average	N
3.33	3.7317	12.0630631	Y	poor	average	N
1.67	3.9808	138.371257	N	average	average	Y
1.67	4.4899	168.856287	N	average	average	Y
3.33	3.7146	11.5495495	Y	poor	average	N
1.00	3.9426	294.26	N	good	average	N
1.00	1.7923	79.23	N	good	average	N
3.33	3.8185	14.6696697	Y	poor	average	N
1.00	3.9804	298.04	N	good	average	N
1.00	3.9804	298.04	N	good	average	N
2.50	4.3316	73.264	N	average	average	Y
0.50	4.0989	719.78	N	good	average	N

numerical match % (base case) =34.38 %
linguistic match % (base case) =50.00%

Calibration Results for Weld Pipe Model, Alloy and Butt Weld (Selected from Trial 3)-Second Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	1.1943	53.1153846	N	good	average	N
2.50	1.2324	-50.704	N	average	average	Y
1.00	1.1993	19.93	Y	good	average	N
2.00	3.9083	95.415	N	average	poor	N
1.75	1.8373	4.98857143	Y	average	average	Y
1.67	0.9288	-44.383234	N	average	average	Y
1.67	0.9766	-41.520958	N	average	average	Y
1.67	0.9427	-43.550898	N	average	average	Y
1.67	3.9316	135.42515	N	average	poor	N
0.56	3.9416	603.857143	N	good	poor	N
0.63	1.3856	119.936508	N	good	average	N
1.25	5.2518	320.144	N	average	poor	N
1.67	1.4801	-11.371257	Y	average	average	Y
0.89	5.1161	474.842697	N	good	poor	N
1.67	4.0021	139.646707	N	average	poor	N
1.67	4.0021	139.646707	N	average	poor	N
2.33	5.1106	119.339056	N	average	poor	N
6.67	5.0392	-24.449775	Y	poor	poor	Y
2.50	5.3583	114.332	N	average	poor	N
3.33	5.1935	55.960961	N	poor	poor	Y
3.33	5.1144	53.5855856	N	poor	poor	Y
3.33	4.0033	20.2192192	Y	poor	poor	Y
1.67	4.317	158.502994	N	average	poor	N
1.67	4.7549	184.724551	N	average	poor	N
3.33	3.9792	19.4954955	Y	poor	poor	Y
1.00	4.2532	325.32	N	good	poor	N
1.00	1.2283	22.83	Y	good	average	N
3.33	4.068	22.1621622	Y	poor	poor	Y
1.00	4.238	323.8	N	good	poor	N
1.00	4.238	323.8	N	good	poor	N
2.50	4.5128	80.512	N	average	poor	N
0.50	4.3032	760.64	N	good	poor	N

numerical match % (base case) =25.00 %
linguistic match % (base case) =37.50%

Calibration Results for Weld Pipe Model, Alloy and Butt Weld (Selected from Trial 3)-Third Calibration (Base Case)

Productivity (actual)	Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)
0.78	1.1922	52.8461538	N	good	average	N
2.50	1.2245	-51.02	N	average	average	Y
1.00	1.1964	19.64	Y	good	average	N
2.00	1.1892	-40.54	N	average	average	Y
1.75	1.2103	-30.84	Y	average	average	Y
1.67	1.2562	-24.778443	Y	average	average	Y
1.67	1.197	-28.323353	Y	average	average	Y
1.67	1.197	-28.323353	Y	average	average	Y
1.67	1.2237	-26.724551	Y	average	average	Y
0.56	1.197	113.75	N	good	average	N
0.63	1.3465	113.730159	N	good	average	N
1.25	1.4391	15.128	Y	average	average	Y
1.67	1.4097	-15.586826	Y	average	average	Y
0.89	1.441	61.9101124	N	good	average	N
1.67	1.2145	-27.275449	Y	average	average	Y
1.67	1.2145	-27.275449	Y	average	average	Y
2.33	1.3258	-43.098712	N	average	average	Y
6.67	1.2032	-81.961019	N	poor	average	N
2.50	1.441	-42.36	N	average	average	Y
3.33	1.3269	-60.153153	N	poor	average	N
3.33	1.4391	-56.783784	N	poor	average	N
3.33	1.4366	-56.858859	N	poor	average	N
1.67	1.4345	-14.101796	Y	average	average	Y
1.67	1.4366	-13.976048	Y	average	average	Y
3.33	1.4366	-56.858859	N	poor	average	N
1.00	1.4366	43.66	N	good	average	N
1.00	1.2213	22.13	Y	good	average	N
3.33	1.2057	-63.792793	N	poor	average	N
1.00	1.4408	44.08	N	good	average	N
1.00	1.4408	44.08	N	good	average	N
2.50	1.2889	-48.444	N	average	average	Y
0.50	1.2929	158.58	N	good	average	N

numerical match % (base case) =40.63 %
linguistic match % (base case) =50.00%

Appendix I (Sensitivity and Error Distribution Analyses)

Results of Sensitivity Analysis

Rig Pipe Model (Third Calibrated Model)

Base Case

Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.5413	42.44736842	N	good	good	Y	match
0.5261	-35.04938272	N	good	good	Y	match
0.5486	44.36842105	N	good	good	Y	match
0.546	-28.15789474	Y	good	good	Y	match
0.5594	36.43902439	N	good	good	Y	match
0.5455	-14.765625	Y	good	good	Y	match
0.5583	-32.73493976	Y	good	good	Y	match
0.5517	34.56097561	N	good	good	Y	match
0.5469	-5.706896552	Y	good	good	Y	match
0.5595	-11.19047619	Y	good	good	Y	match
0.7174	-64.13	N	poor	good	N	2-term
0.5551	327	N	good	good	Y	match
0.5594	33.19047619	Y	good	good	Y	match
0.7917	97.925	N	good	good	Y	match
5.0549	294.9140625	N	average	poor	N	1-term
5.0549	146.5804878	N	average	poor	N	1-term
0.6285	-29.38202247	Y	good	good	Y	match
0.8344	60.46153846	N	good	good	Y	match
0.8225	32.66129032	Y	good	good	Y	match
0.7774	1843.5	N	good	good	Y	match
0.7721	175.75	N	good	good	Y	match
0.7774	455.2857143	N	good	good	Y	match
0.4541	-70.125	N	average	good	N	1-term
0.6282	28.20408163	Y	good	good	Y	match
0.5829	-34.50561798	N	good	good	Y	match
0.5122	34.78947368	N	good	good	Y	match
0.5595	-37.13483146	N	good	good	Y	match
0.5283	-5.660714286	Y	good	good	Y	match
0.5483	-18.1641791	Y	good	good	Y	match

numerical match % (base case) =37.93 %
linguistic match % (base case) =86.21%
1-term off = 10.34%
2-term off = 3.45%

Bisector Method

Productivity (bisector method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.5095	34.07895	N	good	good	Y	match
0.5095	-37.0988	N	good	good	Y	match
0.5095	34.07895	N	good	good	Y	match
0.5095	-32.9605	Y	good	good	Y	match
0.5095	24.26829	Y	good	good	Y	match
0.5095	-20.3906	Y	good	good	Y	match
0.5095	-38.6145	N	good	good	Y	match
0.5095	24.26829	Y	good	good	Y	match
0.5095	-12.1552	Y	good	good	Y	match
0.5095	-19.127	Y	good	good	Y	match
0.6094	-69.53	N	poor	good	N	2-term
0.5095	291.9231	N	good	good	Y	match
0.5095	21.30952	Y	good	good	Y	match
0.7093	77.325	N	good	good	Y	match
5.1049	298.8203	N	average	poor	N	1-term
5.1049	149.0195	N	average	poor	N	1-term
0.6094	-31.5281	Y	good	good	Y	match
0.8092	55.61538	N	good	good	Y	match
0.8092	30.51613	Y	good	good	Y	match
0.7093	1673.25	N	good	good	Y	match
0.7093	153.3214	N	good	good	Y	match
0.7093	406.6429	N	good	good	Y	match
0.4096	-73.0526	N	average	good	N	1-term
0.6094	24.36735	Y	good	good	Y	match
0.5095	-42.7528	N	good	good	Y	match
0.5095	34.07895	N	good	good	Y	match
0.5095	-42.7528	N	good	good	Y	match
0.5095	-9.01786	Y	good	good	Y	match
0.5095	-23.9552	Y	good	good	Y	match

numerical match % (bisector method) =41.38%
linguistic match % (bisector method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

MOM Method

Productivity (MOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error istribution
0.5095	34.07894737	N	good	good	Y	match
0.4596	-43.25925926	N	good	good	Y	match
0.5095	34.07894737	N	good	good	Y	match
0.5095	-32.96052632	Y	good	good	Y	match
0.5595	36.46341463	N	good	good	Y	match
0.5095	-20.390625	Y	good	good	Y	match
0.5095	-38.61445783	N	good	good	Y	match
0.5095	24.26829268	Y	good	good	Y	match
0.5095	-12.15517241	Y	good	good	Y	match
0.5595	-11.19047619	Y	good	good	Y	match
0.3597	-82.015	N	poor	good	N	2-term
0.5095	291.9230769	N	good	good	Y	match
0.5595	33.21428571	Y	good	good	Y	match
0.5595	39.875	N	good	good	Y	match
0.5095	-60.1953125	N	average	good	N	1-term
0.5095	-75.14634146	N	average	good	N	1-term
0.5095	-42.75280899	N	good	good	Y	match
0.4596	-11.61538462	Y	good	good	Y	match
0.4096	-33.93548387	N	good	good	Y	match
0.5595	1298.75	N	good	good	Y	match
0.5095	81.96428571	N	good	good	Y	match
0.5595	299.6428571	N	good	good	Y	match
0.3097	-79.625	N	average	good	N	1-term
0.4096	-16.40816327	Y	good	good	Y	match
0.3597	-59.58426966	N	good	good	Y	match
0.4596	20.94736842	Y	good	good	Y	match
0.5595	-37.13483146	N	good	good	Y	match
0.4596	-17.92857143	Y	good	good	Y	match
0.5095	-23.95522388	Y	good	good	Y	match

numerical match % (MOM method) =34.48%
linguistic match % (MOM method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

LOM Method

Productivity (LOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.009	165.5263158	N	good	average	N	1-term
0.9091	12.2345679	Y	good	average	N	1-term
1.009	165.5263158	N	good	average	N	1-term
1.009	32.76315789	Y	good	average	N	1-term
1.1089	170.4634146	N	good	average	N	1-term
1.009	57.65625	N	good	average	N	1-term
1.009	21.56626506	Y	good	average	N	1-term
1.009	146.097561	N	good	average	N	1-term
1.009	73.96551724	N	good	average	N	1-term
1.1089	76.01587302	N	good	average	N	1-term
0.7093	-64.535	N	poor	good	N	2-term
1.009	676.1538462	N	good	average	N	1-term
1.1089	164.0238095	N	good	average	N	1-term
1.1089	177.225	N	good	average	N	1-term
1.009	-21.171875	Y	average	average	Y	match
1.009	-50.7804878	N	average	average	Y	match
1.009	13.37078652	Y	good	average	N	1-term
0.9091	74.82692308	N	good	average	N	1-term
0.8092	30.51612903	Y	good	good	Y	match
1.1089	2672.25	N	good	average	N	1-term
1.009	260.3571429	N	good	average	N	1-term
1.1089	692.0714286	N	good	average	N	1-term
0.6094	-59.90789474	N	average	good	N	1-term
0.8092	65.14285714	N	good	good	Y	match
0.7093	-20.30337079	Y	good	good	Y	match
0.9091	139.2368421	N	good	average	N	1-term
1.1089	24.59550562	Y	good	average	N	1-term
0.9091	62.33928571	N	good	average	N	1-term
1.009	50.59701493	N	good	average	N	1-term

numerical match % (LOM method) =27.59%
linguistic match % (LOM method) =17.24%
1-term off = 79.31%
2-term off = 3.45%

SOM Method

Productivity (SOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.01	-97.36842105	N	good	good	Y	match
0.01	-98.7654321	N	good	good	Y	match
0.01	-97.36842105	N	good	good	Y	match
0.01	-98.68421053	N	good	good	Y	match
0.01	-97.56097561	N	good	good	Y	match
0.01	-98.4375	N	good	good	Y	match
0.01	-98.79518072	N	good	good	Y	match
0.01	-97.56097561	N	good	good	Y	match
0.01	-98.27586207	N	good	good	Y	match
0.01	-98.41269841	N	good	good	Y	match
0.01	-99.5	N	poor	good	N	2-term
0.01	-92.30769231	N	good	good	Y	match
0.01	-97.61904762	N	good	good	Y	match
0.01	-97.5	N	good	good	Y	match
0.01	-99.21875	N	average	good	N	1-term
0.01	-99.51219512	N	average	good	N	1-term
0.01	-98.87640449	N	good	good	Y	match
0.01	-98.07692308	N	good	good	Y	match
0.01	-98.38709677	N	good	good	Y	match
0.01	-75	N	good	good	Y	match
0.01	-96.42857143	N	good	good	Y	match
0.01	-92.85714286	N	good	good	Y	match
0.01	-99.34210526	N	average	good	N	1-term
0.01	-97.95918367	N	good	good	Y	match
0.01	-98.87640449	N	good	good	Y	match
0.01	-97.36842105	N	good	good	Y	match
0.01	-98.87640449	N	good	good	Y	match
0.01	-98.21428571	N	good	good	Y	match
0.01	-98.50746269	N	good	good	Y	match

numerical match % (SOM method) =0%
linguistic match % (SOM method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

Prod-Probor Method

Productivity (prod-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.5413	42.44736842	N	good	good	Y	match
0.5261	-35.04938272	N	good	good	Y	match
0.5486	44.36842105	N	good	good	Y	match
0.546	-28.15789474	Y	good	good	Y	match
0.5594	36.43902439	N	good	good	Y	match
0.5455	-14.765625	Y	good	good	Y	match
0.5583	-32.73493976	Y	good	good	Y	match
0.5517	34.56097561	N	good	good	Y	match
0.5469	-5.706896552	Y	good	good	Y	match
0.5595	-11.19047619	Y	good	good	Y	match
0.7174	-64.13	N	poor	good	N	2-term
0.5551	327	N	good	good	Y	match
0.5594	33.19047619	Y	good	good	Y	match
0.7917	97.925	N	good	good	Y	match
5.0549	294.9140625	N	average	poor	N	1-term
5.0549	146.5804878	N	average	poor	N	1-term
0.6285	-29.38202247	Y	good	good	Y	match
0.8344	60.46153846	N	good	good	Y	match
0.8225	32.66129032	Y	good	good	Y	match
0.7774	1843.5	N	good	good	Y	match
0.7721	175.75	N	good	good	Y	match
0.7774	455.2857143	N	good	good	Y	match
0.4541	-70.125	N	average	good	N	1-term
0.6282	28.20408163	Y	good	good	Y	match
0.5829	-34.50561798	N	good	good	Y	match
0.5122	34.78947368	N	good	good	Y	match
0.5595	-37.13483146	N	good	good	Y	match
0.5283	-5.660714286	Y	good	good	Y	match
0.5483	-18.1641791	Y	good	good	Y	match

numerical match % (prod-probor method) =37.93%
linguistic match % (prod-probor method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

“and”-Product Method

Productivity ("and"-product method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.5413	42.44737	N	good	good	Y	match
0.5261	-35.0494	N	good	good	Y	match
0.5486	44.36842	N	good	good	Y	match
0.546	-28.1579	Y	good	good	Y	match
0.5594	36.43902	N	good	good	Y	match
0.5455	-14.7656	Y	good	good	Y	match
0.5583	-32.7349	Y	good	good	Y	match
0.5517	34.56098	N	good	good	Y	match
0.5469	-5.7069	Y	good	good	Y	match
0.5595	-11.1905	Y	good	good	Y	match
0.7174	-64.13	N	poor	good	N	2-term
0.5551	327	N	good	good	Y	match
0.5594	33.19048	Y	good	good	Y	match
0.7917	97.925	N	good	good	Y	match
5.0549	294.9141	N	average	poor	N	1-term
5.0549	146.5805	N	average	poor	N	1-term
0.6285	-29.382	Y	good	good	Y	match
0.8344	60.46154	N	good	good	Y	match
0.8225	32.66129	Y	good	good	Y	match
0.7774	1843.5	N	good	good	Y	match
0.7721	175.75	N	good	good	Y	match
0.7774	455.2857	N	good	good	Y	match
0.4541	-70.125	N	average	good	N	1-term
0.6282	28.20408	Y	good	good	Y	match
0.5829	-34.5056	N	good	good	Y	match
0.5122	34.78947	N	good	good	Y	match
0.5595	-37.1348	N	good	good	Y	match
0.5283	-5.66071	Y	good	good	Y	match
0.5483	-18.1642	Y	good	good	Y	match

numerical match % ("and"-product method) =37.93%
linguistic match % ("and"-product method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

“or”-Probor Method

productivity ("or"-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.4979	31.02632	Y	good	good	Y	match
0.5023	-37.9877	N	good	good	Y	match
0.5005	31.71053	Y	good	good	Y	match
0.4977	-34.5132	N	good	good	Y	match
0.4977	21.39024	Y	good	good	Y	match
0.4977	-22.2344	Y	good	good	Y	match
0.4908	-40.8675	N	good	good	Y	match
0.4908	19.70732	Y	good	good	Y	match
0.4942	-14.7931	Y	good	good	Y	match
0.5014	-20.4127	Y	good	good	Y	match
0.7159	-64.205	N	poor	good	N	2-term
0.5023	286.3846	N	good	good	Y	match
0.5023	19.59524	Y	good	good	Y	match
0.7874	96.85	N	good	good	Y	match
5.0856	297.3125	N	average	poor	N	1-term
5.0856	148.078	N	average	poor	N	1-term
0.6526	-26.6742	Y	good	good	Y	match
0.8225	58.17308	N	good	good	Y	match
0.8225	32.66129	Y	good	good	Y	match
0.7805	1851.25	N	good	good	Y	match
0.7805	178.75	N	good	good	Y	match
0.7805	457.5	N	good	good	Y	match
0.4421	-70.9145	N	average	good	N	1-term
0.6381	30.22449	Y	good	good	Y	match
0.5724	-35.6854	N	good	good	Y	match
0.4798	26.26316	Y	good	good	Y	match
0.5013	-43.6742	N	good	good	Y	match
0.4918	-12.1786	Y	good	good	Y	match
0.4935	-26.3433	Y	good	good	Y	match

numerical match % ("or"-probor method) =48.28%
linguistic match % ("or"-probor method) =86.21%
1-term off = 10.34%
2-term off = 3.45%

Weld Pipe Model, Carbon Steel and Butt Weld (Third Calibrated Model)

Base Case

Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.216	-2.72	Y	average	average	Y	match
1.2154	-39.23	N	poor	average	N	1-term
1.216	21.6	Y	average	average	Y	match
1.216	21.6	Y	average	average	Y	match
1.216	81.49253731	N	good	good	Y	match
1.1649	55.32	N	average	average	Y	match
1.1825	-21.16666667	Y	average	average	Y	match
1.1825	-5.4	Y	average	average	Y	match
1.1766	-29.54491018	Y	average	average	Y	match
1.1766	-24.57692308	Y	average	average	Y	match
1.194	-52.24	N	poor	poor	Y	match
1.194	-28.50299401	Y	average	average	Y	match
1.194	-28.50299401	Y	average	average	Y	match
1.194	5.663716814	Y	average	average	Y	match
1.1654	-16.15827338	Y	average	average	Y	match
1.1654	91.04918033	N	good	good	Y	match
1.1652	-12.39097744	Y	average	average	Y	match
1.2901	-22.74850299	Y	average	average	Y	match
1.1604	43.25925926	N	average	average	Y	match
1.2336	-7.248120301	Y	average	average	Y	match
1.2336	23.36	Y	average	average	Y	match
1.2336	43.44186047	N	average	average	Y	match
1.1634	4.810810811	Y	average	average	Y	match
3.6747	403.3835616	N	average	poor	N	1-term
1.1938	-52.248	N	poor	average	N	1-term
1.1737	8.675925926	Y	average	average	Y	match
1.1954	44.02409639	N	average	average	Y	match
1.1943	59.24	N	average	average	Y	match
1.1979	2.384615385	Y	average	average	Y	match
1.2086	51.075	N	average	average	Y	match
1.183	-11.05263158	Y	average	average	Y	match
1.183	-1.416666667	Y	average	average	Y	match
1.183	373.2	N	good	average	N	1-term
1.1675	108.4821429	N	good	average	N	1-term
1.1786	-41.07	N	poor	average	N	1-term
1.1786	-11.38345865	Y	average	average	Y	match
1.1786	68.37142857	N	average	average	Y	match
1.1971	-28.31736527	Y	average	average	Y	match
1.1971	-4.232	Y	average	average	Y	match
1.2513	86.76119403	N	good	poor	N	2-term
1.2857	-57.14333333	N	poor	average	N	1-term
1.2426	24.26	Y	average	average	Y	match

Base Case-Continued

Productivity (base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2426	3.55	Y	average	average	Y	match
4.0743	508.1044776	N	good	poor	N	2-term
1.1714	-29.85628743	Y	average	average	Y	match
1.1703	24.5	Y	average	average	Y	match
1.2721	89.86567164	N	average	average	Y	match
1.1786	-29.4251497	Y	average	average	Y	match
1.1786	210.1578947	N	good	average	N	1-term
1.1786	33.93181818	N	average	average	Y	match
1.1746	-53.016	N	poor	average	N	1-term
1.1939	19.39	Y	average	average	Y	match
1.1939	43.84337349	N	average	average	Y	match
1.1939	89.50793651	N	good	average	N	1-term
1.2974	-44.31759657	N	poor	average	N	1-term
1.2955	-48.18	N	poor	average	N	1-term
1.2704	53.06024096	N	average	average	Y	match
1.2656	-24.21556886	Y	average	average	Y	match
1.182	-29.22155689	Y	average	average	Y	match
1.2953	-61.1021021	N	poor	average	N	1-term
1.2915	-22.66467066	Y	average	average	Y	match
1.2211	-69.4725	N	poor	average	N	1-term
1.2953	-22.43712575	Y	average	average	Y	match

numerical match % (base case) =49.21 %
linguistic match % (base case) =74.60%
1-term off = 22.22%
2-term off = 3.17%

Bisector

Productivity (bisector method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.892	-28.64	Y	average	average	Y	match
0.892	-55.4	N	poor	average	N	1-term
0.892	-10.8	Y	average	average	Y	match
0.892	-10.8	Y	average	average	Y	match
0.892	33.13433	Y	good	average	N	1-term
0.496	-33.8667	Y	average	good	N	1-term
0.892	-40.5333	N	average	average	Y	match
0.892	-28.64	Y	average	average	Y	match
0.496	-70.2994	N	average	good	N	1-term
0.496	-68.2051	N	average	good	N	1-term
0.793	-68.28	N	poor	average	N	1-term
0.793	-52.515	N	average	average	Y	match
0.793	-52.515	N	average	average	Y	match
0.793	-29.823	Y	average	average	Y	match
0.496	-64.3165	N	average	good	N	1-term
0.496	-18.6885	Y	good	good	Y	match
0.496	-62.7068	N	average	good	N	1-term
0.892	-46.5868	N	average	average	Y	match
0.496	-38.7654	N	average	good	N	1-term
0.892	-32.9323	Y	average	average	Y	match
0.892	-10.8	Y	average	average	Y	match
0.892	3.72093	Y	average	average	Y	match
3.961	256.8468	N	average	poor	N	1-term
4.258	483.2877	N	average	poor	N	1-term
0.892	-64.32	N	poor	average	N	1-term
0.793	-26.5741	Y	average	average	Y	match
0.892	7.46988	Y	average	average	Y	match
0.892	18.93333	Y	average	average	Y	match
0.496	-57.6068	N	average	good	N	1-term
3.664	358	N	average	poor	N	1-term
0.892	-32.9323	Y	average	average	Y	match
0.892	-25.6667	Y	average	average	Y	match
0.892	256.8	N	good	average	N	1-term
0.496	-11.4286	Y	good	good	Y	match
0.793	-60.35	N	poor	average	N	1-term
0.793	-40.3759	N	average	average	Y	match
0.793	13.28571	Y	average	average	Y	match
0.892	-46.5868	N	average	average	Y	match
0.892	-28.64	Y	average	average	Y	match
4.06	505.9701	N	good	poor	N	2-term
0.991	-66.9667	N	poor	average	N	1-term

Bisector-Continued

Productivity (bisector method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.991	-0.9	Y	average	average	Y	match
0.991	-17.4167	Y	average	average	Y	match
5.149	668.5075	N	good	poor	N	2-term
0.793	-52.515	N	average	average	Y	match
0.793	-15.6383	Y	average	average	Y	match
3.664	446.8657	N	average	poor	N	1-term
0.793	-52.515	N	average	average	Y	match
0.793	108.6842	N	good	average	N	1-term
0.793	-9.88636	Y	average	average	Y	match
0.793	-68.28	N	poor	average	N	1-term
0.793	-20.7	Y	average	average	Y	match
0.793	-4.45783	Y	average	average	Y	match
0.793	25.87302	Y	good	average	N	1-term
5.149	120.9871	N	poor	poor	Y	match
5.248	109.92	N	poor	poor	Y	match
4.159	401.0843	N	average	poor	N	1-term
3.763	125.3293	N	average	poor	N	1-term
0.892	-46.5868	N	average	average	Y	match
3.862	15.97598	Y	poor	poor	Y	match
4.654	178.6826	N	average	poor	N	1-term
4.159	3.975	Y	poor	poor	Y	match
4.555	172.7545	N	average	poor	N	1-term

numerical match % (bisector method) =42.86%
linguistic match % (bisector method) =63.49%
1-term off = 39.68%
2-term off = 3.17%

MOM Method

Productivity (MOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2385	-0.92	Y	average	average	Y	match
1.189	-40.55	N	poor	average	N	1-term
1.2385	23.85	Y	average	average	Y	match
1.2385	23.85	Y	average	average	Y	match
1.2385	84.8507463	N	good	average	N	1-term
1.2385	65.1333333	N	average	average	Y	match
1.2385	-17.433333	Y	average	average	Y	match
1.2385	-0.92	Y	average	average	Y	match
1.2385	-25.838323	Y	average	average	Y	match
1.2385	-20.608974	Y	average	average	Y	match
1.2385	-50.46	N	poor	average	N	1-term
1.2385	-25.838323	Y	average	average	Y	match
1.2385	-25.838323	Y	average	average	Y	match
1.2385	9.60176991	Y	average	average	Y	match
1.2385	-10.899281	Y	average	average	Y	match
1.2385	103.032787	N	good	good	Y	match
1.2385	-6.8796992	Y	average	average	Y	match
1.2385	-25.838323	Y	average	average	Y	match
1.2385	52.9012346	N	average	average	Y	match
1.2385	-6.8796992	Y	average	average	Y	match
1.2385	23.85	Y	average	average	Y	match
1.2385	44.0116279	N	average	average	Y	match
1.2385	11.5765766	Y	average	average	Y	match
1.189	62.8767123	N	average	average	Y	match
1.2385	-50.46	N	poor	average	N	1-term
1.189	10.0925926	Y	average	average	Y	match
1.2385	49.2168675	N	average	average	Y	match
1.189	58.5333333	N	average	average	Y	match
1.2385	5.85470085	Y	average	average	Y	match
1.2385	54.8125	N	average	average	Y	match
1.189	-10.601504	Y	average	average	Y	match
1.189	-0.9166667	Y	average	average	Y	match
1.189	375.6	N	good	average	N	1-term
1.2385	121.160714	N	good	average	N	1-term
1.2385	-38.075	N	poor	average	N	1-term
1.2385	-6.8796992	Y	average	average	Y	match
1.2385	76.9285714	N	average	average	Y	match
1.2385	-25.838323	Y	average	average	Y	match
1.2385	-0.92	Y	average	average	Y	match
1.2385	84.8507463	N	good	average	N	1-term
1.2385	-58.716667	N	poor	average	N	1-term
1.2385	23.85	Y	average	average	Y	match
1.2385	3.20833333	Y	average	average	Y	match

MOM Method-Continued

Productivity (MOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2385	84.8507463	N	good	average	N	1-term
1.2385	-25.838323	Y	average	average	Y	match
1.2385	31.7553191	Y	average	average	Y	match
1.189	77.4626866	N	average	average	Y	match
1.2385	-25.838323	Y	average	average	Y	match
1.2385	225.921053	N	good	average	N	1-term
1.2385	40.7386364	N	average	average	Y	match
1.2385	-50.46	N	poor	average	N	1-term
1.2385	23.85	Y	average	average	Y	match
1.2385	49.2168675	N	average	average	Y	match
1.2385	96.5873016	N	good	average	N	1-term
1.2385	-46.845494	N	poor	average	N	1-term
1.189	-52.44	N	poor	average	N	1-term
1.1395	37.2891566	N	average	average	Y	match
1.1395	-31.766467	Y	average	average	Y	match
1.189	-28.802395	Y	average	average	Y	match
1.189	-64.294294	N	poor	average	N	1-term
1.2385	-25.838323	Y	average	average	Y	match
1.2385	-69.0375	N	poor	average	N	1-term
1.189	-28.802395	Y	average	average	Y	match

numerical match % (MOM method) =52.38%
linguistic match % (MOM method) =73.02%
1-term off = 26.98%
2-term off = 0.00%

LOM Method

Productivity (LOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.981	58.48	N	average	average	Y	match
1.882	-5.9	Y	poor	average	N	1-term
1.981	98.1	N	average	average	Y	match
1.981	98.1	N	average	average	Y	match
1.981	195.671642	N	good	average	N	1-term
1.981	164.133333	N	average	average	Y	match
1.882	25.4666667	Y	average	average	Y	match
1.882	50.56	N	average	average	Y	match
1.882	12.6946108	Y	average	average	Y	match
1.882	20.6410256	Y	average	average	Y	match
1.981	-20.76	Y	poor	average	N	1-term
1.981	18.6227545	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	75.3097345	N	average	average	Y	match
1.981	42.5179856	N	average	average	Y	match
1.981	224.754098	N	good	average	N	1-term
1.981	48.9473684	N	average	average	Y	match
1.882	12.6946108	Y	average	average	Y	match
1.981	144.567901	N	average	average	Y	match
1.882	41.5037594	N	average	average	Y	match
1.882	88.2	N	average	average	Y	match
1.882	118.837209	N	average	average	Y	match
1.981	78.4684685	N	average	average	Y	match
1.882	157.808219	N	average	average	Y	match
1.882	-24.72	Y	poor	average	N	1-term
1.882	74.2592593	N	average	average	Y	match
1.882	126.746988	N	average	average	Y	match
1.882	150.933333	N	average	average	Y	match
1.882	60.8547009	N	average	average	Y	match
1.882	135.25	N	average	average	Y	match
1.882	41.5037594	N	average	average	Y	match
1.882	56.8333333	N	average	average	Y	match
1.882	652.8	N	good	average	N	1-term
1.981	253.75	N	good	average	N	1-term
1.981	-0.95	Y	poor	average	N	1-term
1.981	48.9473684	N	average	average	Y	match
1.981	183	N	average	average	Y	match
1.882	12.6946108	Y	average	average	Y	match
1.882	50.56	N	average	average	Y	match
1.882	180.895522	N	good	average	N	1-term
1.882	-37.2666667	N	poor	average	N	1-term
1.882	88.2	N	average	average	Y	match
1.882	56.8333333	N	average	average	Y	match
1.882	180.895522	N	good	average	N	1-term
1.981	18.6227545	Y	average	average	Y	match
1.981	110.744681	N	average	average	Y	match

LOM Method-Continued

Productivity (LOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.684	151.343284	N	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	421.315789	N	good	average	N	1-term
1.981	125.113636	N	average	average	Y	match
1.981	-20.76	Y	poor	average	N	1-term
1.981	98.1	N	average	average	Y	match
1.981	138.674699	N	average	average	Y	match
1.981	214.444444	N	good	average	N	1-term
1.981	-14.9785408	Y	poor	average	N	1-term
1.882	-24.72	Y	poor	average	N	1-term
1.585	90.9638554	N	average	average	Y	match
1.585	-5.08982036	Y	average	average	Y	match
1.882	12.6946108	Y	average	average	Y	match
1.882	-43.4834835	N	poor	average	N	1-term
1.882	12.6946108	Y	average	average	Y	match
1.882	-52.95	N	poor	average	N	1-term
1.882	12.6946108	Y	average	average	Y	match

numerical match % (LOM method) =31.75%
linguistic match % (LOM method) =71.42%
1-term off = 28.57%
2-term off = 0.00%

SOM Method

Productivity (SOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.496	-60.32	N	average	good	N	1-term
0.496	-75.2	N	poor	good	N	2-term
0.496	-50.4	N	average	good	N	1-term
0.496	-50.4	N	average	good	N	1-term
0.496	-25.9701	Y	good	good	Y	match
0.496	-33.8667	N	average	good	N	1-term
0.595	-60.3333	N	average	good	N	1-term
0.595	-52.4	N	average	good	N	1-term
0.595	-64.3713	N	average	good	N	1-term
0.595	-61.859	N	average	good	N	1-term
0.496	-80.16	N	poor	good	N	2-term
0.496	-70.2994	N	average	good	N	1-term
0.496	-70.2994	N	average	good	N	1-term
0.496	-56.1062	N	average	good	N	1-term
0.496	-64.3165	N	average	good	N	1-term
0.496	-18.6885	Y	good	good	Y	match
0.496	-62.7068	N	average	good	N	1-term
0.595	-64.3713	N	average	good	N	1-term
0.496	-38.7654	N	average	good	N	1-term
0.595	-55.2632	N	average	good	N	1-term
0.595	-40.5	N	average	good	N	1-term
0.595	-30.814	Y	average	good	N	1-term
0.496	-55.3153	N	average	good	N	1-term
0.496	-32.0548	Y	average	good	N	1-term
0.595	-76.2	N	poor	good	N	2-term
0.496	-54.0741	N	average	good	N	1-term
0.595	-28.3133	Y	average	good	N	1-term
0.496	-33.8667	N	average	good	N	1-term
0.595	-49.1453	N	average	good	N	1-term
0.595	-25.625	Y	average	good	N	1-term
0.496	-62.7068	N	average	good	N	1-term
0.496	-58.6667	N	average	good	N	1-term
0.496	98.4	N	good	good	Y	match
0.496	-11.4286	Y	good	good	Y	match
0.496	-75.2	N	poor	good	N	2-term
0.496	-62.7068	N	average	good	N	1-term
0.496	-29.1429	Y	average	good	N	1-term
0.595	-64.3713	N	average	good	N	1-term
0.595	-52.4	N	average	good	N	1-term
0.595	-11.194	Y	good	good	Y	match
0.595	-80.1667	N	poor	good	N	2-term
0.595	-40.5	N	average	good	N	1-term
0.595	-50.4167	N	average	good	N	1-term
0.595	-11.194	Y	good	good	Y	match

SOM Method-Continued

Productivity (SOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.496	-70.2994	N	average	good	N	1-term
0.496	-47.234	N	average	good	N	1-term
0.694	3.58209	Y	average	good	N	1-term
0.496	-70.2994	N	average	good	N	1-term
0.496	30.52632	Y	good	good	Y	match
0.496	-43.6364	N	average	good	N	1-term
0.496	-80.16	N	poor	good	N	2-term
0.496	-50.4	N	average	good	N	1-term
0.496	-40.241	N	average	good	N	1-term
0.496	-21.2698	Y	good	good	Y	match
0.496	-78.7124	N	poor	good	N	2-term
0.496	-80.16	N	poor	good	N	2-term
0.694	-16.3855	Y	average	good	N	1-term
0.694	-58.4431	N	average	good	N	1-term
0.496	-70.2994	N	average	good	N	1-term
0.496	-85.1051	N	poor	good	N	2-term
0.595	-64.3713	N	average	good	N	1-term
0.595	-85.125	N	poor	good	N	2-term
0.496	-70.2994	N	average	good	N	1-term

numerical match % (SOM method) =22.22%
linguistic match % (SOM method) =12.70%
1-term off = 71.43%
2-term off = 15.87%

Prod-Probor Method

Productivity (prod-probor) method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.1374	-9.008	Y	average	average	Y	match
1.1932	-40.34	N	poor	average	N	1-term
1.1335	13.35	Y	average	average	Y	match
1.1335	13.35	Y	average	average	Y	match
1.1124	66.02985	N	good	average	N	1-term
1.0392	38.56	N	average	average	Y	match
1.1654	-22.3067	Y	average	average	Y	match
1.1348	-9.216	Y	average	average	Y	match
1.0319	-38.2096	N	average	average	Y	match
1.0321	-33.8397	N	average	average	Y	match
1.1704	-53.184	N	poor	average	N	1-term
1.1704	-29.9162	Y	average	average	Y	match
1.1704	-29.9162	Y	average	average	Y	match
1.1112	-1.66372	Y	average	average	Y	match
1.0243	-26.3094	Y	average	average	Y	match
1.021	67.37705	N	good	average	N	1-term
1.0252	-22.9173	Y	average	average	Y	match
1.2603	-24.5329	Y	average	average	Y	match
1.0478	29.35802	Y	average	average	Y	match
1.1145	-16.203	Y	average	average	Y	match
1.1401	14.01	Y	average	average	Y	match
1.1145	29.59302	Y	average	average	Y	match
1.1509	3.684685	Y	average	average	Y	match
3.6842	404.6849	N	average	poor	N	1-term
1.1705	-53.18	N	poor	average	N	1-term
1.1259	4.25	Y	average	average	Y	match
1.1511	38.68675	N	average	average	Y	match
1.1118	48.24	N	average	average	Y	match
1.0575	-9.61538	Y	average	average	Y	match
1.2476	55.95	N	average	average	Y	match
1.1111	-16.4586	Y	average	average	Y	match
1.1312	-5.73333	Y	average	average	Y	match
1.1111	344.44	N	good	average	N	1-term
1.0658	90.32143	N	good	average	N	1-term
1.1636	-41.82	N	poor	average	N	1-term
1.1105	-16.5038	Y	average	average	Y	match
1.1306	61.51429	N	average	average	Y	match
1.1131	-33.3473	N	average	average	Y	match
1.1363	-9.096	Y	average	average	Y	match
1.267	89.10448	N	good	average	N	1-term
1.2558	-58.14	N	poor	average	N	1-term
1.2071	20.71	Y	average	average	Y	match
1.2058	0.483333	Y	average	average	Y	match

Prod-Probor Method-Continued

Productivity (prod-probor) method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
4.0172	499.5821	N	good	poor	N	2-term
1.1104	-33.509	N	average	average	Y	match
1.1103	18.11702	Y	average	average	Y	match
1.2746	90.23881	N	average	average	Y	match
1.1105	-33.503	N	average	average	Y	match
1.1105	192.2368	N	good	average	N	1-term
1.1105	26.19318	Y	average	average	Y	match
1.1728	-53.088	N	poor	average	N	1-term
1.1317	13.17	Y	average	average	Y	match
1.1111	33.86747	N	average	average	Y	match
1.1111	76.36508	N	good	average	N	1-term
1.2757	-45.2489	N	poor	average	N	1-term
1.2768	-48.928	N	poor	average	N	1-term
1.2572	51.46988	N	average	average	Y	match
1.256	-24.7904	Y	average	average	Y	match
1.1651	-30.2335	Y	average	average	Y	match
1.2667	-61.961	N	poor	average	N	1-term
1.2706	-23.9162	Y	average	average	Y	match
1.2216	-69.46	N	poor	average	N	1-term
1.2693	-23.994	Y	average	average	Y	match

numerical match % (prod-probor method) =49.21%
linguistic match % (prod-probor method) =69.84%
1-term off = 28.57%
2-term off = 1.59%

"and"-Product Method

Productivity ("and"-product method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2853	2.824	Y	average	average	Y	match
1.2769	-36.155	N	poor	average	N	1-term
1.2849	28.49	Y	average	average	Y	match
1.2849	28.49	Y	average	average	Y	match
1.283	91.49254	N	good	average	N	1-term
1.2326	64.34667	N	average	average	Y	match
1.258	-16.1333	Y	average	average	Y	match
1.2671	1.368	Y	average	average	Y	match
1.2477	-25.2874	Y	average	average	Y	match
1.2477	-20.0192	Y	average	average	Y	match
1.2602	-49.592	N	poor	average	N	1-term
1.2602	-24.5389	Y	average	average	Y	match
1.2602	-24.5389	Y	average	average	Y	match
1.2697	12.36283	Y	average	average	Y	match
1.2375	-10.9712	Y	average	average	Y	match
1.2399	103.2623	N	good	average	N	1-term
1.2373	-6.96992	Y	average	average	Y	match
1.2901	-22.7485	Y	average	average	Y	match
1.221	50.74074	N	average	average	Y	match
1.2931	-2.77444	Y	average	average	Y	match
1.2951	29.51	Y	average	average	Y	match
1.2931	50.36047	N	average	average	Y	match
1.2116	9.153153	Y	average	average	Y	match
1.4645	100.6164	N	average	average	Y	match
1.2664	-49.344	N	poor	average	N	1-term
1.2114	12.16667	Y	average	average	Y	match
1.2798	54.19277	N	average	average	Y	match
1.2752	70.02667	N	average	average	Y	match
1.2611	7.786325	Y	average	average	Y	match
1.2947	61.8375	N	average	average	Y	match
1.2647	-4.90977	Y	average	average	Y	match
1.2646	5.383333	Y	average	average	Y	match
1.2647	405.88	N	good	average	N	1-term
1.2189	117.6607	N	good	average	N	1-term
1.2495	-37.525	N	poor	average	N	1-term
1.2566	-5.5188	Y	average	average	Y	match
1.2566	79.51429	N	average	average	Y	match
1.2809	-23.2994	Y	average	average	Y	match
1.2832	2.656	Y	average	average	Y	match
1.3073	95.1194	N	good	average	N	1-term
1.2881	-57.0633	N	poor	average	N	1-term
1.2878	28.78	Y	average	average	Y	match
1.2872	7.266667	Y	average	average	Y	match
2.0308	203.1045	N	good	average	N	1-term
1.2506	-25.1138	Y	average	average	Y	match

"and"-Product Method-Continued

Productivity ("and"-product method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2496	32.93617	Y	average	average	Y	match
1.292	92.83582	N	average	average	Y	match
1.2566	-24.7545	Y	average	average	Y	match
1.2566	230.6842	N	good	average	N	1-term
1.2566	42.79545	N	average	average	Y	match
1.25	-50	N	poor	average	N	1-term
1.2695	26.95	Y	average	average	Y	match
1.2696	52.96386	N	average	average	Y	match
1.2696	101.5238	N	good	average	N	1-term
1.3233	-43.206	N	poor	average	N	1-term
1.325	-47	N	poor	average	N	1-term
1.2704	53.06024	N	average	average	Y	match
1.2656	-24.2156	Y	average	average	Y	match
1.2556	-24.8144	Y	average	average	Y	match
1.3052	-60.8048	N	poor	average	N	1-term
1.3087	-21.6347	Y	average	average	Y	match
1.2911	-67.7225	N	poor	average	N	1-term
1.3089	-21.6228	Y	average	average	Y	match

numerical match % ("and"-product method) =50.79%
linguistic match % ("and"-product method) =71.43%
1-term off = 28.57%
2-term off = 0.00%

“or”-Probor Method

Productivity ("or"-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.8819	-29.448	Y	average	average	Y	match
0.8862	-55.69	N	poor	average	N	1-term
0.8819	-11.81	Y	average	average	Y	match
0.8819	-11.81	Y	average	average	Y	match
0.8819	31.62687	Y	good	average	N	1-term
0.6434	-14.2133	Y	average	average	Y	match
0.8457	-43.62	N	average	average	Y	match
0.8457	-32.344	Y	average	average	Y	match
0.63	-62.2754	N	average	average	Y	match
0.63	-59.6154	N	average	average	Y	match
0.8212	-67.152	N	poor	average	N	1-term
0.8212	-50.8263	N	average	average	Y	match
0.8212	-50.8263	N	average	average	Y	match
0.8212	-27.3274	Y	average	average	Y	match
0.6429	-53.7482	N	average	average	Y	match
0.6429	5.393443	Y	good	average	N	1-term
0.6431	-51.6466	N	average	average	Y	match
0.859	-48.5629	N	average	average	Y	match
0.6479	-20.0123	Y	average	average	Y	match
0.9137	-31.3008	Y	average	average	Y	match
0.9137	-8.63	Y	average	average	Y	match
0.9137	6.244186	Y	average	average	Y	match
4.2382	281.8198	N	average	poor	N	1-term
4.4951	515.7671	N	average	poor	N	1-term
0.8473	-66.108	N	poor	average	N	1-term
2.035	88.42593	N	average	poor	N	1-term
0.8473	2.084337	Y	average	average	Y	match
0.837	11.6	Y	average	average	Y	match
0.6096	-47.8974	N	average	average	Y	match
4.1619	420.2375	N	average	poor	N	1-term
0.8436	-36.5714	N	average	average	Y	match
0.8436	-29.7	Y	average	average	Y	match
0.8436	237.44	N	good	average	N	1-term
0.6408	14.42857	Y	good	average	N	1-term
0.8212	-58.94	N	poor	average	N	1-term
0.8212	-38.2556	N	average	average	Y	match
0.8212	17.31429	Y	average	average	Y	match
0.8618	-48.3952	N	average	average	Y	match
0.8618	-31.056	Y	average	average	Y	match
4.3627	551.1493	N	good	poor	N	2-term
1.0076	-66.4133	N	poor	average	N	1-term
0.932	-6.8	Y	average	average	Y	match
0.932	-22.3333	Y	average	average	Y	match
5.1446	667.8507	N	good	poor	N	2-term
0.8243	-50.6407	N	average	average	Y	match

“or”-Probor Method-Continued

Productivity ("or"-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.8243	-12.3085	Y	average	average	Y	match
4.1907	525.4776	N	average	poor	N	1-term
0.8212	-50.8263	N	average	average	Y	match
0.8212	116.1053	N	good	average	N	1-term
0.8212	-6.68182	Y	average	average	Y	match
0.8212	-67.152	N	poor	average	N	1-term
0.8212	-17.88	Y	average	average	Y	match
0.8212	-1.06024	Y	average	average	Y	match
0.8212	30.34921	Y	good	average	N	1-term
5.1524	121.133	N	poor	poor	Y	match
5.2054	108.216	N	poor	poor	Y	match
4.4755	439.2169	N	average	poor	N	1-term
4.2345	153.5629	N	average	poor	N	1-term
0.8425	-49.5509	N	average	average	Y	match
4.2914	28.87087	Y	poor	poor	Y	match
4.7679	185.503	N	average	poor	N	1-term
4.4027	10.0675	Y	poor	poor	Y	match
4.6773	180.0778	N	average	poor	N	1-term

numerical match % ("or"-probor method) =42.86%
linguistic match % ("or"-probor method) =63.49%
1-term off = 33.33%
2-term off = 3.17%

Weld Pipe Model, Alloy and Butt Weld (Third Calibrated Model)

Base Case

Productivity (actual)	output(base case)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.78	1.1922	52.8461538	N	good	average	N	1-term
2.50	1.2245	-51.02	N	average	average	Y	match
1.00	1.1964	19.64	Y	good	average	N	1-term
2.00	1.1892	-40.54	N	average	average	Y	match
1.75	1.2103	-30.84	Y	average	average	Y	match
1.67	1.2562	-24.778443	Y	average	average	Y	match
1.67	1.197	-28.323353	Y	average	average	Y	match
1.67	1.197	-28.323353	Y	average	average	Y	match
1.67	1.2237	-26.724551	Y	average	average	Y	match
0.56	1.197	113.75	N	good	average	N	1-term
0.63	1.3465	113.730159	N	good	average	N	1-term
1.25	1.4391	15.128	Y	average	average	Y	match
1.67	1.4097	-15.586826	Y	average	average	Y	match
0.89	1.441	61.9101124	N	good	average	N	1-term
1.67	1.2145	-27.275449	Y	average	average	Y	match
1.67	1.2145	-27.275449	Y	average	average	Y	match
2.33	1.3258	-43.098712	N	average	average	Y	match
6.67	1.2032	-81.961019	N	poor	average	N	1-term
2.50	1.441	-42.36	N	average	average	Y	match
3.33	1.3269	-60.153153	N	poor	average	N	1-term
3.33	1.4391	-56.783784	N	poor	average	N	1-term
3.33	1.4366	-56.858859	N	poor	average	N	1-term
1.67	1.4345	-14.101796	Y	average	average	Y	match
1.67	1.4366	-13.976048	Y	average	average	Y	match
3.33	1.4366	-56.858859	N	poor	average	N	1-term
1.00	1.4366	43.66	N	good	average	N	1-term
1.00	1.2213	22.13	Y	good	average	N	1-term
3.33	1.2057	-63.792793	N	poor	average	N	1-term
1.00	1.4408	44.08	N	good	average	N	1-term
1.00	1.4408	44.08	N	good	average	N	1-term
2.50	1.2889	-48.444	N	average	average	Y	match
0.50	1.2929	158.58	N	good	average	N	1-term

numerical match % (base case) =40.63 %
linguistic match % (base case) =50.00%
1-term off = 50.00%
2-term off = 0.00%

Bisector

Productivity (bisector method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.189	52.4358974	N	good	average	N	1-term
1.288	-48.48	N	average	average	Y	match
1.189	18.9	Y	good	average	N	1-term
1.189	-40.55	N	average	average	Y	match
1.189	-32.057143	Y	average	average	Y	match
1.288	-22.874251	Y	average	average	Y	match
1.189	-28.802395	Y	average	average	Y	match
1.189	-28.802395	Y	average	average	Y	match
1.288	-22.874251	Y	average	average	Y	match
1.189	112.321429	N	good	average	N	1-term
1.387	120.15873	N	good	average	N	1-term
1.486	18.88	Y	average	average	Y	match
1.387	-16.946108	Y	average	average	Y	match
1.486	66.9662921	N	good	average	N	1-term
1.189	-28.802395	Y	average	average	Y	match
1.189	-28.802395	Y	average	average	Y	match
1.387	-40.472103	N	average	average	Y	match
1.189	-82.173913	N	poor	average	N	1-term
1.486	-40.56	N	average	average	Y	match
1.387	-58.348348	N	poor	average	N	1-term
1.486	-55.375375	N	poor	average	N	1-term
1.387	-58.348348	N	poor	average	N	1-term
1.387	-16.946108	Y	average	average	Y	match
1.387	-16.946108	Y	average	average	Y	match
1.387	-58.348348	N	poor	average	N	1-term
1.387	38.7	N	good	average	N	1-term
1.189	18.9	Y	good	average	N	1-term
1.189	-64.294294	N	poor	average	N	1-term
1.486	48.6	N	good	average	N	1-term
1.486	48.6	N	good	average	N	1-term
1.288	-48.48	N	average	average	Y	match
1.288	157.6	N	good	average	N	1-term

numerical match % (bisector method) =44.82%
linguistic match % (bisector method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

MOM Method

Productivity (MOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.4365	84.16666667	N	good	average	N	1-term
1.4365	-42.54	N	average	average	Y	match
1.387	38.7	N	good	average	N	1-term
1.4365	-28.175	Y	average	average	Y	match
1.387	-20.74285714	Y	average	average	Y	match
1.4365	-13.98203593	Y	average	average	Y	match
1.387	-16.94610778	Y	average	average	Y	match
1.387	-16.94610778	Y	average	average	Y	match
1.4365	-13.98203593	Y	average	average	Y	match
1.387	147.6785714	N	good	average	N	1-term
1.4365	128.015873	N	good	average	N	1-term
1.4365	14.92	Y	average	average	Y	match
1.4365	-13.98203593	Y	average	average	Y	match
1.387	55.84269663	N	good	average	N	1-term
1.4365	-13.98203593	Y	average	average	Y	match
1.4365	-13.98203593	Y	average	average	Y	match
1.387	-40.472103	N	average	average	Y	match
1.387	-79.2053973	N	poor	average	N	1-term
1.387	-44.52	N	average	average	Y	match
1.387	-58.34834835	N	poor	average	N	1-term
1.4365	-56.86186186	N	poor	average	N	1-term
1.4365	-56.86186186	N	poor	average	N	1-term
1.4365	-13.98203593	Y	average	average	Y	match
1.4365	-13.98203593	Y	average	average	Y	match
1.4365	-56.86186186	N	poor	average	N	1-term
1.4365	43.65	N	good	average	N	1-term
1.387	38.7	N	good	average	N	1-term
1.387	-58.34834835	N	poor	average	N	1-term
1.387	38.7	N	good	average	N	1-term
1.387	38.7	N	good	average	N	1-term
1.4365	-42.54	N	average	average	Y	match
1.4365	187.3	N	good	average	N	1-term

numerical match % (MOM method) =37.5%
linguistic match % (MOM method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

LOM Method

Productivity (LOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
2.08	166.666667	N	good	average	N	1-term
1.981	-20.76	Y	average	average	Y	match
1.981	98.1	N	good	average	N	1-term
2.08	4	Y	average	average	Y	match
1.981	13.2	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	253.75	N	good	average	N	1-term
1.981	214.444444	N	good	average	N	1-term
1.981	58.48	N	average	average	Y	match
1.783	6.76646707	N	average	average	Y	match
1.981	122.58427	N	good	average	N	1-term
1.981	18.6227545	Y	average	average	Y	match
1.981	18.6227545	Y	average	average	Y	match
1.981	-14.978541	Y	average	average	Y	match
1.981	-70.29985	N	poor	average	N	1-term
1.981	-20.76	Y	average	average	Y	match
1.981	-40.510511	N	poor	average	N	1-term
1.981	-40.510511	N	poor	average	N	1-term
1.882	-43.483483	N	poor	average	N	1-term
1.783	6.76646707	Y	average	average	Y	match
1.882	12.6946108	Y	average	average	Y	match
1.882	-43.483483	N	poor	average	N	1-term
1.882	88.2	N	good	average	N	1-term
1.981	98.1	N	good	average	N	1-term
1.981	-40.510511	N	poor	average	N	1-term
1.981	98.1	N	good	average	N	1-term
1.981	98.1	N	good	average	N	1-term
1.981	-20.76	Y	average	average	Y	match
1.981	296.2	N	good	average	N	1-term

numerical match % (LOM method) =43.75%
linguistic match % (LOM method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

SOM Method

Productivity (SOM method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
0.793	1.66666667	Y	good	good	Y	match
0.892	-64.32	N	average	average	Y	match
0.793	-20.7	Y	good	good	Y	match
0.793	-60.35	N	average	good	N	1-term
0.793	-54.685714	N	average	good	N	1-term
0.892	-46.586826	N	average	average	Y	match
0.793	-52.51497	N	average	good	N	1-term
0.793	-52.51497	N	average	good	N	1-term
0.892	-46.586826	N	average	average	Y	match
0.793	41.6071429	N	good	good	Y	match
0.892	41.5873016	N	good	average	N	1-term
0.892	-28.64	Y	average	average	Y	match
1.09	-34.730539	N	average	average	Y	match
0.793	-10.898876	Y	good	good	Y	match
0.892	-46.586826	N	average	average	Y	match
0.892	-46.586826	N	average	average	Y	match
0.793	-65.965665	N	average	good	N	1-term
0.793	-88.110945	N	poor	good	N	2-term
0.793	-68.28	N	average	good	N	1-term
0.793	-76.186186	N	poor	good	N	2-term
0.892	-73.213213	N	poor	average	N	1-term
0.991	-70.24024	N	poor	average	N	1-term
1.09	-34.730539	N	average	average	Y	match
0.991	-40.658683	N	average	average	Y	match
0.991	-70.24024	N	poor	average	N	1-term
0.991	-0.9	Y	good	average	N	1-term
0.793	-20.7	Y	good	good	Y	match
0.793	-76.186186	N	poor	good	Y	match
0.793	-20.7	Y	good	good	Y	match
0.793	-20.7	Y	good	good	Y	match
0.892	-64.32	N	average	average	Y	match
0.892	78.4	N	good	average	N	1-term

numerical match % (SOM method) =25.00%
linguistic match % (SOM method) =56.25%
1-term off = 37.50%
2-term off = 6.25%

Prod-Probor Method

Productivity (prod-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.1087	42.1410256	N	good	average	N	1-term
1.2034	-51.864	N	average	average	Y	match
1.1014	10.14	Y	good	average	N	1-term
1.2	-40	N	average	average	Y	match
1.2038	-31.211429	Y	average	average	Y	match
1.1379	-31.862275	Y	average	average	Y	match
1.1252	-32.622754	Y	average	average	Y	match
1.1245	-32.664671	Y	average	average	Y	match
1.198	-28.263473	Y	average	average	Y	match
1.1937	113.160714	N	good	average	N	1-term
1.2438	97.4285714	N	good	average	N	1-term
1.4391	15.128	Y	average	average	Y	match
1.3976	-16.311377	Y	average	average	Y	match
1.4386	61.6404494	N	good	average	N	1-term
1.1985	-28.233533	Y	average	average	Y	match
1.1985	-28.233533	Y	average	average	Y	match
1.2866	-44.781116	N	average	average	Y	match
1.3011	-80.493253	N	poor	average	N	1-term
1.4395	-42.42	N	average	average	Y	match
1.2889	-61.294294	N	poor	average	N	1-term
1.4362	-56.870871	N	poor	average	N	1-term
1.4354	-56.894895	N	poor	average	N	1-term
1.4348	-14.083832	Y	average	average	Y	match
1.4351	-14.065868	Y	average	average	Y	match
1.4355	-56.891892	N	poor	average	N	1-term
1.4343	43.43	N	good	average	N	1-term
1.2096	20.96	Y	good	average	N	1-term
1.2051	-63.810811	N	poor	average	N	1-term
1.4361	43.61	N	good	average	N	1-term
1.437	43.7	N	good	average	N	1-term
1.2426	-50.296	N	average	average	Y	match
1.245	149	N	good	average	N	1-term

numerical match % (prod-probor method) =40.63%
linguistic match % (prod-probor method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

“and”-Product Method

Productivity ("and"-product method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.2624	61.8461538	N	good	average	N	1-term
1.3173	-47.308	N	average	average	Y	match
1.2659	26.59	Y	good	average	N	1-term
1.2343	-38.285	N	average	average	Y	match
1.2545	-28.314286	Y	average	average	Y	match
1.3125	-21.407186	Y	average	average	Y	match
1.25	-25.149701	Y	average	average	Y	match
1.2483	-25.251497	Y	average	average	Y	match
1.2906	-22.718563	Y	average	average	Y	match
1.2669	126.232143	N	good	average	N	1-term
1.3896	120.571429	N	good	average	N	1-term
1.4466	15.728	Y	average	average	Y	match
1.4162	-15.197605	Y	average	average	Y	match
1.4482	62.7191011	N	good	average	N	1-term
1.2829	-23.179641	Y	average	average	Y	match
1.2829	-23.179641	Y	average	average	Y	match
1.3926	-40.23176	N	average	average	Y	match
1.3035	-80.457271	N	poor	average	N	1-term
1.4517	-41.932	N	average	average	Y	match
1.3988	-57.993994	N	poor	average	N	1-term
1.4434	-56.654655	N	poor	average	N	1-term
1.4398	-56.762763	N	poor	average	N	1-term
1.4385	-13.862275	Y	average	average	Y	match
1.4391	-13.826347	Y	average	average	Y	match
1.441	-56.726727	N	poor	average	N	1-term
1.439	43.9	N	good	average	N	1-term
1.3106	31.06	Y	good	average	N	1-term
1.2496	-62.474474	N	poor	average	N	1-term
1.4436	44.36	N	good	average	N	1-term
1.4456	44.56	N	good	average	N	1-term
1.378	-44.88	N	average	average	Y	match
1.3896	177.92	N	good	average	N	1-term

match % ("and"-product method) =40.63%
match % ("and"-product method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

“or”-Probor Method

Productivity ("or"-probor method)	error %	match(y/n)	actual term	defuzzified term	match(y/n)	error distribution
1.1922	52.8461538	N	good	average	N	1-term
1.2245	-51.02	N	average	average	Y	match
1.1964	19.64	Y	good	average	N	1-term
1.1892	-40.54	N	average	average	Y	match
1.2103	-30.84	Y	average	average	Y	match
1.2562	-24.778443	Y	average	average	Y	match
1.197	-28.323353	Y	average	average	Y	match
1.197	-28.323353	Y	average	average	Y	match
1.2237	-26.724551	Y	average	average	Y	match
1.197	113.75	N	good	average	N	1-term
1.3465	113.730159	N	good	average	N	1-term
1.4391	15.128	Y	average	average	Y	match
1.4097	-15.586826	Y	average	average	Y	match
1.441	61.9101124	N	good	average	N	1-term
1.2145	-27.275449	Y	average	average	Y	match
1.2145	-27.275449	Y	average	average	Y	match
1.3258	-43.098712	N	average	average	Y	match
1.2032	-81.961019	N	poor	average	N	1-term
1.441	-42.36	N	average	average	Y	match
1.3269	-60.153153	N	poor	average	N	1-term
1.4391	-56.783784	N	poor	average	N	1-term
1.4366	-56.858859	N	poor	average	N	1-term
1.4345	-14.101796	Y	average	average	Y	match
1.4366	-13.976048	Y	average	average	Y	match
1.4366	-56.858859	N	poor	average	N	1-term
1.4366	43.66	N	good	average	N	1-term
1.2213	22.13	Y	good	average	N	1-term
1.2057	-63.792793	N	poor	average	N	1-term
1.4408	44.08	N	good	average	N	1-term
1.4408	44.08	N	good	average	N	1-term
1.2889	-48.444	N	average	average	Y	match
1.2929	158.58	N	good	average	N	1-term

match % ("or"-probor method) =40.63%
match % ("or"-probor method) =50.00%
1-term off = 50.00%
2-term off = 0.00%

Sensitivity Results for the Rig Pipe Model

Method	Modified Operator	Numerical match (%)	Linguistic match (%)	Ranking
Base case	None	37.93	86.21	3
Bisector	Defuzzification	41.38	86.21	2
MOM	Defuzzification	34.48	86.21	6
LOM	Defuzzification	27.59	17.24	8
SOM	Defuzzification	0.00	86.21	7
Prod-Probor	Implication-aggregation	37.93	86.21	3
"and"-product	"and"	37.93	86.21	3
"or"-probor	"or"	48.28	86.21	1

Sensitivity Results for the Weld Pipe, Carbon Steel and Butt Weld Model

Method	Modified Operator	Numerical match (%)	Linguistic match (%)	Ranking
Base case (centroid)	None	49.21	74.60	1
Bisector	Defuzzification	42.86	57.14	7
MOM	Defuzzification	52.38	73.02	2
LOM	Defuzzification	31.75	71.42	4
SOM	Defuzzification	22.22	12.70	8
Prod-Probor	Implication-aggregation	49.21	69.84	5
"and"-product	"and"	50.79	71.43	3
"or"-probor	"or"	42.86	63.49	6

Sensitivity Results for the Weld Pipe, Alloy and Butt Weld Model

Method	Modified Operator	Numerical match (%)	Linguistic match (%)	Ranking
Base case (centroid)	None	40.63	50.00	4
Bisector	Defuzzification	44.82	50.00	2
MOM	Defuzzification	37.50	50.00	8
LOM	Defuzzification	43.75	50.00	3
SOM	Defuzzification	25.00	56.25	1
Prod-Probor	Implication-aggregation	40.63	50.00	4
"and"-product	"and"	40.63	50.00	4
"or"-probor	"or"	40.63	50.00	4

Results of Linguistic Error Distribution Analysis

Linguistic Error Distribution Table for Rig Pipe and Weld Pipe Models

Testing Method	match/no-match	Rig Pipe Model	Weld Pipe, Carbon Steel and Butt Weld Model	Weld Pipe, Alloy and Butt Weld Model
Base case	match (%)	86.21	74.60	50.00
	1-term off (%)	10.34	22.22	50.00
	2-term off (%)	3.45	3.17	0.00
Bisector	match (%)	86.21	57.14	50.00
	1-term off (%)	10.34	39.68	50.00
	2-term off (%)	3.45	3.17	0.00
MOM method	match (%)	86.21	73.02	50.00
	1-term off (%)	10.34	26.98	50.00
	2-term off (%)	3.45	0.00	0.00
LOM method	match (%)	17.24	71.42	50.00
	1-term off (%)	79.31	28.57	50.00
	2-term off (%)	3.45	0.00	0.00
SOM method	match (%)	86.21	12.70	56.25
	1-term off (%)	10.34	71.43	37.50
	2-term off (%)	3.45	15.87	6.25
Prod-Probor method	match (%)	86.21	69.84	50.00
	1-term off (%)	10.34	28.57	50.00
	2-term off (%)	3.45	1.59	0.00
"and"-product method	match (%)	86.21	71.43	50.00
	1-term off (%)	10.34	28.57	50.00
	2-term off (%)	3.45	0.00	0.00
"or"-probor method	match (%)	86.21	63.49	50.00
	1-term off (%)	10.34	33.33	50.00
	2-term off (%)	3.45	3.17	0.00