University of Alberta

An Integrated Computational Intelligence Framework for Construction Performance Diagnosis

by

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ABSTRACT

Construction performance diagnosis (CPD), the process of finding and explaining performance problems, is a vital part of the project control process. Generally in construction, a diagnostic problem arises if there is a discrepancy between the actual performance of resource(s) and the planned performance. The diagnostic task is to determine the cause(s) of this discrepancy. Understanding what caused an event to occur enables the construction manager to predict, to plan for, to prevent, and to explain the occurrence of the event. Automating the performance diagnosis process to detect, diagnose, and report results within a time frame that permits prompt field response can significantly enhance the project control process.

This thesis investigates the advantages of introducing computational intelligence tools to develop automated performance diagnostic models to explain construction performance. The integrated diagnostic system has advantages of both fuzzy systems (e.g., the use of expert knowledge representation and the ability of explaining generated decisions) and neural-network systems (e.g., ability of learning, adaptation, optimization, and high fault tolerance). Additionally, the powerful global-optimization technique of genetic algorithms effectively optimizes the network structure to provide the best solution.

In this thesis, several key issues and challenges of developing robust performance diagnostic models for construction-related problems are discussed. The essential features of the model are described in detail. The efficiency and effectiveness of the techniques and methods developed in this thesis are tested in the domain of industrial construction labor productivity and implemented in a computer system called XCOPE.

The main contributions of this work are twofold. One contribution is the development of a unified integrated computationally intelligent framework to diagnose construction performance. Another contribution is in the acquisition and representation of a construction expert's knowledge. Several different techniques, such as Nominal Group Technique (NGT), Semantic Differential (SD) Approach, and Fuzzy Membership Functions, are explored to select the most suitable knowledge acquisition and representation techniques for construction performance modeling.

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CHAPTER ONE

1. INTRODUCTION

1.1 BACKGROUND AND PROBLEM STATEMENT

Performance monitoring and analysis are integral parts of planning and controlling construction projects. During the course of project execution, performance is measured using different indices and reviewed periodically (e.g., daily, weekly, or monthly). Generally, a diagnostic problem arises if there is a discrepancy between the actual behaviour (of a resource, e.g., production rate of a welder) and the planned behavior; in other words, when the expected behavior does not correspond with reality. The diagnostic task is to determine the best explanation of observed abnormal behavior of a system under study, to decide on appropriate interventions and facilitate rapid response. Figure 1-1 presents a graphical illustration of diagnostic process as an interaction of observation and prediction.

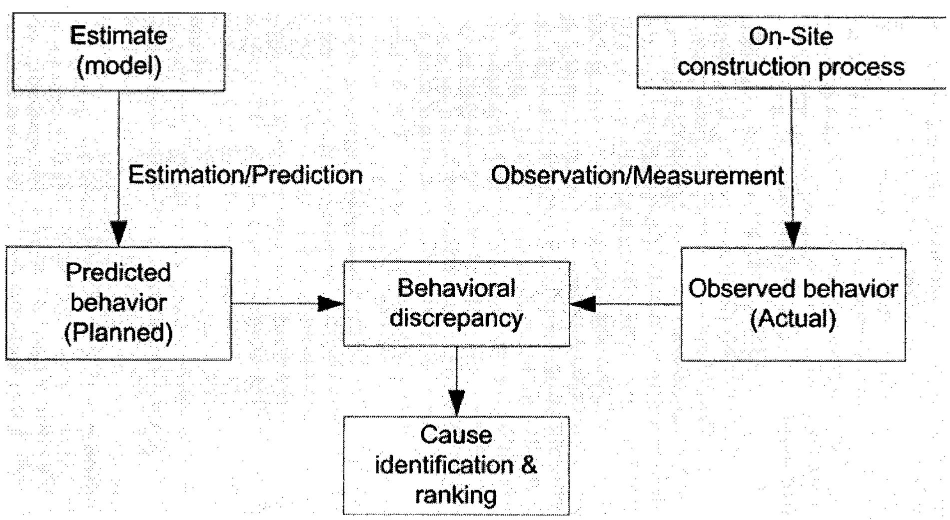

Figure 1-1. Diagnosis as the interaction of observation and prediction

Typically, the construction manager uses his or her intuition and expert causal knowledge combined with relevant data (if available) to find explanations for performance failures. Finding a reliable explanation depends on factors such as the complexity of the issue at hand, the expert's experience and knowledge, the nature of the project, and the quality of available data. It is crucial that the construction manager(s) analyze performance to determine possible causes of performance deviations in a timely manner. Due to the increasing complexity and fast nature of the construction process, in most cases, by the time the construction manager obtains the necessary information to improve performance, the task may have already been completed (Maloney 1990). Generally, since management's extremely limited time resources are often allocated to future tasks rather than to past completed tasks, managers do not get a chance to review and analyze performance-related information generated.

Additionally, research related to construction performance management (e.g., (Fayek et al. 2004; Kagioglou et al. 2001; Tang and Ogunlana 2003; Ward et al. 1991)) emphasized that traditional performance parameters measured on projects, namely costs, schedule, and quality, are not appropriate for continuous improvement because they are not effective in identifying causes of performance failures. These parameters do not provide satisfactory revelation of the potential for improvement, and the information obtained usually arrives too late to take corrective actions.

Construction-related problems are mostly unstructured in nature, which makes it difficult to apply algorithmic methods based on mathematical models to the process of performance analysis and reasoning. The relentless pressures of shorter project life cycles and increased design complexity place construction contractors in an exigent position. Complexity due to non-linearity and subjectivity are two main challenges of construction performance modeling.

In light of the above observations, this thesis assumes that determining in a scientific manner, the impact and the contributing effect of each cause to the performance indicators should assist in improving performance management in the construction industry.

1.2 RESEARCH OBJECTIVES

The objective of this study is to develop a unified framework and approach to find the best explanation for the observed abnormal behavior of key performance indicators at different levels of abstraction.

This thesis addresses three problems. The first is the construction performance diagnosis problem, in particular the problem of efficiently identifying multiple root causes of performance deviations. The second is the knowledge acquisition problem, particularly the problem of acquiring (1) causal domain knowledge from a group of construction experts, and (2) obtaining subjective assessments of (daily) working conditions that potentially impact construction performance. The third is the problem of representing such domain knowledge in a manner that can be used as inputs for a diagnostic model.

The methods described in this thesis seek to achieve robust construction performance diagnosis by simultaneously considering the importance and interrelation of all three problems. The goal is to make the solution of the complex construction performance diagnostic problem more robust and efficient.

1.3 RESEARCH SCOPE

The efficiency and effectiveness of the techniques and methods developed in this thesis are tested in the domain of industrial construction labour productivity, more specifically, pipe module fabrication, and are implemented a computer system called XCOPE (eXplaining COnstruction PErformance). Construction workforce performance, as measured in terms of labour productivity is chosen as a test domain for the following reasons:

1. Since construction is a labour-intensive process, manpower (workforce) is the key productive resource in construction (Lauter and Jenkins 1982); therefore, construction performance greatly depends upon labour productivity;
2. Labour productivity is commonly accepted as a key performance indicator (Cox et al. 2003);
3. Multiple root causes are common in labour productivity related issues;
4. The presence of a comparatively high number of qualitative (subjective) variables (i.e., causal factors) affect labour productivity;
5. Labour productivity is directly related to cost and schedule performance, i.e., a major contributor to other performance variations.

The proposed methodologies and developed systems are intended to be used by construction managers who work for general contracting firms, construction management firms, and owners.

1.4 THESIS ORGANIZATION

The rest of this thesis is organized as follows. Chapter 2 provides an overview on performance diagnostic models, describes previous research related to the work described in this thesis, and discusses the key issues and challenges of developing robust construction performance diagnostic models. Chapter 3 introduces the concept of computational intelligence and defines its key components: Fuzzy Set Theory, Artificial

Neural Networks, and Genetic Algorithms. A comparative study is made on the computational characteristics of key components of CI for performance diagnosis models and relates them to the issues identified in Chapter 2. Chapter 4 presents a construction performance modeling framework that is based on AND-OR fuzzy neural networks. Experiments conducted using data collected from an industrial construction project are also presented along with results. Having identified several limitations of the AND-OR neuron model for construction performance modeling, Chapter 5 proposes an alternative performance diagnostic modeling framework that is based on a Generalized Neural Network. The learning and inference modes of the network are discussed and the results are compared with the model presented in Chapter 4. In an effort to augment the capabilities of the Generalized Regression Neural Network model (presented in Chapter 5), Chapter 6 investigates membership function determination techniques and proposes more suitable membership function determination techniques for construction performance modeling. Chapter 6 also proposes a novel approach for representing and acquiring expert knowledge to construct membership functions. The results of experiments conducted to test the effectiveness of the proposed membership function determination, knowledge acquisition, and representation techniques are also presented. Chapter 7 illustrates the integrated computationally intelligent framework for construction performance diagnosis along with the software system (XCOPE) developed based on the concepts proposed in this thesis. Chapter 8 summarizes this thesis, drawing conclusions based on the results of this work, highlighting the contributions made, and suggesting prospective new research directions.

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CHAPTER TWO

2. PERFORMANCE DIAGNOSTIC MODELS: ISSUES AND CHALLENGES

The purpose of this chapter is two-fold: (1) to review system diagnosis research, and to examine its application, particularly in the area of construction performance diagnosis, and (2) to identify the issues and challenges to be addressed to develop robust construction performance diagnostic models.

2.1 INTRODUCTION TO PERFORMANCE DIAGNOSTICS

A decision support system that makes it possible to diagnose root causes of performance deviations in a timely manner is an attractive way to improve project performance in order to meet or exceed project performance goals. The diagnostic context investigated in this thesis is construction performance reasoning. Performance deviations are detected when one or more key performance indicators (KPI) (e.g., labour productivity factor, cost variance, rework index) go outside a given range or change significantly from their planned values. Performance diagnosis aims to isolate the cause(s) of a performance deviation by collecting and analyzing information on performance indicators using field measurements, subjective judgments, and other information sources (e.g., time-cards, weather data, etc.). A construction manager often performs diagnosis. A decision support system that makes it possible to diagnose root causes of performance deviations in a timely manner is an attractive way to improve project performance in order to meet or exceed project performance goals. A few sample construction performance diagnostic problem scenarios are given below:

> *[1] Poor productivity: "Today's labour productivity performance (measured as earned vs. actual man-hours) of structural steel erection is low (e.g., 0.65)." Why?*
>
> *[2] Schedule delay: "Activity duration of pipe-fabrication for module # PM 324 is extended by two days." Why?*
>
> *[3] Cost overrun: "This week's labour cost of hydro-testing is 12 percent higher than the budgeted value." Why?*

Identifying relevant causes to such a performance deviation in a timely manner is a key task in construction project control. However, due to the complex dynamic nature of construction projects, the diagnosis of construction performance has become a complicated undertaking. An early attempt on identifying causes of labour productivity is reported by Chang and Borcherding (1986) using a technique called Craftsmen Questionnaire Sampling (CQS). The administrator of CQS walks around the site, randomly selects craftsmen, and collect data from them regarding sources of delay and amount of rework. CQS's time consuming nature, disruption to workflow, inconsistencies caused due to random selection of time, place and crew, unstructured responses via open ended questions, and inability to rank causes where multiple causes exists hinder the usability of the CQS technique as an effective way to identify causes of performance deviations. Maloney (1990) reported that it is crucial to respond promptly to evidence of poor performance and take corrective actions to eliminate its causes. According to Maloney (1990), there are two key factors that hinder construction managers (CM) from taking actions in a timely manner: (1) the CM's extremely demanding schedule of routine work, and (2) the short duration of activities and/or construction projects. Maloney proposed a performance analysis framework that guides an individual through a flowchart, which analyzes causes of unacceptable performance. Unfortunately, his framework does not provide a quick response; instead, it requires an individual to go through the entire process, repetitively, and it also does not facilitate identifying the root causes of the problem. In a comprehensive review of construction performance models, Li et al. (2005) identified that there is no "definitive model for either predicting or explaining performance; most of the models described are more research than practice oriented; and, strong consensus as to the most important factors to use, what their definition should be, how best to express outcomes for them, or what the relationship amongst factors is, if any".

A number of different approaches to diagnosis have been explored over the years by other research communities, mainly in the chemical and power industries (e.g., Corea et al. 1992; Milne and Trave-Massuyes 1995; Patton et al. 1994; Sugeno and Yasukawa 1993; Vinson and Ungar 1995), where definitive process models comprised of physical and readily measurable variables exist. It is useful to establish the appropriate circumstances for their use, and specifically to identify suitable approaches for construction performance diagnosis.

The remainder of this chapter is organized into three sections. The following section reviews a range of diagnosis techniques to identify a suitable model/s that can be applied to the construction management domain for performance diagnostic reasoning. It will be followed by a discussion on key issues and challenges of construction performance modeling. A summary providing a match between the issues identified and techniques that can be used to solve these issues, in order to develop a robust diagnostic model for reasoning about construction performance, concludes the chapter.

2.2 DIAGNOSIS TECHNIQUES: A REVIEW

Over the last two decades, diagnosis has been an active research area in which the larger part of the work has been concerned with the diagnosis of man-made artifacts such as electronic devices, or medical diagnosis. A comprehensive review of the literature suggests that different diagnosis techniques can be categorized into four approaches: (1) control theory approach, (2) Artificial Intelligence approach, (3) Computational intelligence approach, and (4) Hybrid approach. Figure 2-1 graphically illustrates the taxonomy of diagnosis techniques.

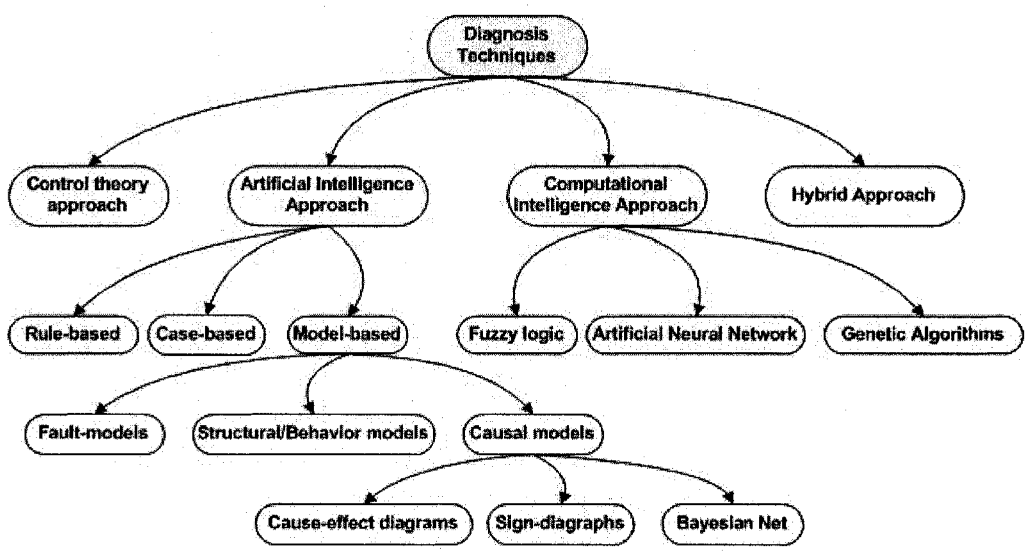

Figure 2-1: Taxonomy of diagnosis techniques

In control theory, the diagnostic model is numerical, generally represented as a set of differential algebraic equations. Anomaly detection and cause identification is conducted using a specification of the different failure modes (problem scenarios) of the system along with a description of how these problems are manifest within the behavior of the system (Clancy 1998). A strictly numerical representation of the construction performance problem is not possible due to the nature of the construction work in a dynamic, uncontrolled, and labour-intensive manner with numerous interacting qualitative and quantitative variables. Furthermore, due to the dynamic nature (i.e., changing state of the measurable parameters at every step of time) of performance factors, specifying all of the possible problem scenarios that may be encountered becomes impractical.

In contrast, an artificial intelligence (AI) approach considers diagnosis as a reasoning process and tries to reproduce human reasoning (Gentil et al. 2004). Several AI diagnostic techniques are available, such as rule-based reasoning (e.g., Chou et al. 1994; McDonald et al. 1997), case-based reasoning (e.g., Derere 2000; Breese and Heckerman 1996; Sharma and Sleeman 1993), and model-based reasoning (e.g., Clancy 1998; Druzovec and Sostar 1998; Shen and Leitch 1992).

In rule-based systems, the empirical information and experience is encoded in rules that generally take the form "IF symptom(s) THEN diagnose(s)." Overall, rule-based diagnosis is only feasible for problems for which any and all knowledge in the problem area can be written in the form of if-then rules, and for which the problem area is not large. Depending on the problem, it may require hundreds, or even thousands of rules. If there are too many rules, the system can become difficult to maintain. Furthermore, the difficulty of acquiring the knowledge to build the rule-base – known as the knowledge acquisition bottleneck – is the main limitation of this approach.

Case-based reasoning (CBR) is a powerful approach when much experimental data describing faults/deviations are available. A case-based reasoner works by matching new problems to "cases" from a historical database and then adapting successful solutions from the past to current situations. The most challenging part of implementing a CBR model is the capturing of historical information to form the cases. In other words, CBR also suffers from the impact of the knowledge acquisition bottleneck. In construction, however, historical information related to construction performance indicators and other variables are available. If a systematic methodology to collect data in the form of input-output pairs is employed, the CBR approach can be a viable approach to assist construction performance modeling.

Model-based diagnosis, also referred to as consistency-based diagnosis (Reiter 1987), provides an alternative "implicit behavioral approach" to system modeling. They are appropriate when an abstraction of the quantitative modeling is sought in order to facilitate interaction with a human reasoner. Poole (1992) identifies two extremes of the model-based diagnostic problem: (1) the consistency-based approach in which normal-operation-oriented diagnosis is carried out based on the knowledge about how components are structured and work normally, and (2) the adductive approach in which abnormal-operation-oriented diagnosis is carried out using knowledge about how the components are affected by specific faults.

Fault models (or fault dictionaries) anticipate the type of faults that may occur, and only model these. Model simulation provides a list of fault/symptom pairs, which produce the fault dictionary. According to Fenton (2001a), this method has primarily been applied to the diagnosis of digital circuits. In contrast, models based on structure and behaviour (e.g., Dague 1994; Davis 1984) model correct behaviour. "The structure representation lists all the components and interconnections within the modeled system. The behaviour representation describes the correct behaviour pattern for each component. Both representations are often created using logical formulae, such as first order predicate calculus" (Fenton et al. 2001b).

Causal modeling (e.g. Montmain and Gentil 2000; Peng and Cheng 2000; Gentil et al. 2004) is another AI diagnostic approach that focuses on representing qualitative knowledge. As cited in (Rasmussen 1993), " diagnostic judgment implies the perception of a causal relation between a state, an action, and the ultimate effect, as related to the current objective". Causal reasoning is an important approach in the diagnostic task. Causal graph-based diagnosis is appropriate where it is usually difficult and costly to develop precise mathematical models. Cause-effect diagrams (Ishikawa 1985), influence graphs (e.g., Linkens and Wang 1994; Gentil et al. 2004; Xia et al. 2004), and Bayesian networks (e.g., Kirsch 1993) are a few categories of causal models that found applications in diagnosis. Moselhi et al. (2004) proposed a construction performance diagnostic method based on predefined causal models; the use of the causal model concept, however, is limited to showing the relationship between quantitative performance indicators.

Cause-effect diagrams, otherwise known as fishbone diagrams, are very useful in analyzing and describing cause and effect relations in a qualitative way. In a pilot study to identify and classify causes of construction field rework, Fayek et al. (2004) used cause-effect diagrams as the framework for diagnosing causes of field rework with the assistance of field construction personnel's input. The required extent of manual user input and the subjective nature of assessments restrict the feasibility of this approach for daily performance diagnosis on large-scale projects.

Influence graphs are another type of causal approach for reasoning about the way in which normal or abnormal changes propagate. The graph nodes represent the system variables; the directed arcs symbolize the relations among variables. Relations can be quantitative or qualitative. The simplest influence graph is the signed diagraph (SGD) where relations are represented by signs: "+" or "-". Iri et al. (1980) used SGD as the basic data structure for diagnosis. According to Gentil et al. (2004), over the years, this approach has been considerably enhanced. For example, Yu and Lee (1991) symbolized the variables as fuzzy sets to incorporate the continuous nature of the variables.

In Bayesian networks, entities are defined probabilistically, using prior knowledge and statistical data, in acyclic graphs where nodes are random variables and the relationships between them are represented by arcs. Even though the concepts (or variables) can be represented with greater ease than by using rules, the knowledge acquisition bottleneck is a primary shortcoming. McCabe et al. (2001) used Bayesian networks to assess productivity of construction operations; however, in most of the real-life problem scenarios, uncertainties encountered cannot be described exclusively by statistical means.

Diagnostic systems based on Computational Intelligence (CI) tools such as fuzzy sets (Zadeh 1965), artificial neural networks (ANN) (Meireles et al. 2003), and genetic algorithms (GA) (Holland 1975) are emerging as more realistic approaches due to their unique characteristics. Fuzzy set theory-based diagnostic systems provide a good alternative for reasoning under uncertainty (e.g., Dexter 1995; Dexter and Benouarets 1997; Miyata et al. 1995; Sauter et al. 1994; Sugeno and Yasukawa 1993; Ulieru and Isermann 1993; Ulieru 1996). These systems are becoming popular because they provide human-like and intuitive ways of representing and reasoning with incomplete and imprecise information. However, fuzzy logic-based systems do not have the ability to learn from experience (previous cases). In contrast, diagnostic systems based on Artificial Neural Networks (e.g., Bernieri et al. 1994; Bernieri et al. 1995; Maki and Loparo 1997; Marcu and Mirea 1997; Penedo et al. 1998; Sorsa et al. 1991; Vemuri and Polycarpou 1997) exploit self-learning capabilities using historical data. Additionally, ANN-based systems provide a mathematical tool for modeling dynamic nonlinear relationships. The primary shortcoming of ANN systems is that they need a significant amount of historical quantitative data for their training.

As described above, each individual technique has its own advantages and disadvantages. Hybrid solutions can significantly enhance the robustness of a diagnostic system by capitalizing on the advantages of combining supplementary techniques. For example, Breese et al. (1996) combined case-based reasoning and Bayesian networks for diagnosis and troubleshooting applications, while Ariton et al. (1999) used a fuzzy-neuro architecture for modular fault isolation in complex systems. Liu and Yan (1997) combined fuzzy logic, neural networks and case-based reasoning to develop a system for diagnosing symptoms in electronic systems.

The selection of the appropriate technique or a hybrid combination of several techniques depends primarily on the diagnostic problem at hand. Each problem domain has its distinctiveness, for example, in terms of availability of data, problem complexity, and dynamic nature. Hence, the following section provides a detailed discussion on the issues and challenges of developing robust construction performance models with the intention of assisting in the selection of an appropriate diagnostic technique(s) for explaining construction performance.

2.3 ISSUES AND CHALLENGES

This section describes a list of key issues that need to be addressed in order to develop robust construction performance diagnostic models. These issues are categorized into four different areas: (1) data and information related issues, (2) knowledge acquisition and representational issues, (3) modeling issues, and (4) reasoning issues. Key challenges are identified, as are prerequisites and desired properties of a diagnostic model. Table 2-1 provides a summary of the issues and their challenges. Each issue is detailed further in this section.

2.3.1 Data and information-related issues

Establishing practical and economical data collection procedures have a significant impact on the successful implementation of a diagnostic model. A contractor should be able to collect (daily) data on the values of the variables at the individual project/activity level, either in quantitative or qualitative form. Current information management systems available to contractors are limited to storing quantitative information compared to qualitative information (e.g., the complexity of a task, the level of site congestion). This is mainly due to a lack (or absence) of systematic procedures to collect, process, and store qualitative data. However, both qualitative and categorical variables play a major role in construction performance. Hence, any robust diagnostic tool should be able to utilize both quantitative and qualitative information.

Achieving planned performance depends on establishing planned conditions of factors that affect performance. A formal procedure is required in order to derive planned values from different sources such as the master schedule, manpower estimates, past project records, and industry standards (handbooks).

Table 2-1. Issues and Challenges of Construction Performance Diagnostic Models

ISSUES	CHALLENGES	PROPERTIES/PREREQUISITES OF A DIAGNOSTIC MODEL
Data and information related issues	Field data collection and reporting	Practical and economical data collection procedures to capture both quantitative and qualitative data.
	Establishing normal functional parameters (performance baselines)	A formal procedure needs to be established to derive planned values from different sources.
	Uncertainty in data	Ability to compute with incomplete, qualitative, and subjective data.
Knowledge acquisition and representational issues	Non-verifiability of critical causal factors	Ability to use expert (causal) knowledge
	Incompleteness in the relation between key performance indicators and related causes	Ability to determine the strength of causal factors using historical data
Modeling issues	Complex non-linear system	Non-linear modeling capability
	Capturing dynamics	Adaptability via learning from past data
	Model transparency	Explanation capability of the model
Reasoning issues	Identification of multiple root causes	Identifying the significance of each causal factor in cases where multiple factors contributed to the performance deviation.
	Identifying contributing vs. counteracting factors	Identifying whether a certain causal factor is contributing towards or counteracting performance.
	Different levels of abstraction	Reasoning at multiple levels of abstraction.

The vast majority of the information related to construction performance modeling is characterized by uncertainty. Identifying the nature of uncertainty is crucial in selecting appropriate methods to manage it effectively and even to use it profitably. Two kinds of uncertainty are encountered in construction performance modeling: ambiguity and vagueness. Ambiguity can be caused by the presence of random variables or approximate estimates. Vagueness arises from "a lack of precision (whose boundaries are not sharply defined) or a lack of understanding of an event, a proposition, a value, or a system (Ayyub 1991)". Vagueness can result from (1) qualitative (instead of quantitative) information, (2) incomplete or vague expert knowledge, and (3) subjectivity in the information obtained from an expert. As an example, the suitability of a particular crane to hoist a pipe spool can be assessed by a crane operator as "fairly good". A robust diagnostic system should be able to represent and manipulate vagueness and statistical uncertainties.

Additionally, it is noteworthy to highlight the fact that obtaining a dataset with reasonable accuracy is challenging in construction. Incomplete and imprecise data due to measurement uncertainties and approximation are common. Thus it is always preferable to have a less data-hungry approach for diagnostic modeling in construction.

2.3.2 Knowledge Acquisition and Representation Issues

Due to the absence of explicit mathematical relationships between performance factors, expert (domain) knowledge has to be exploited to identify the possible causes of performance deviations in construction. In other words, experts' mental models (causal maps) of the problem scenarios have to be used as the first step in identifying possible causal relationships. Based on the construction manager's expertise, a representation of the behavior of the performance indicator in causal terms is very effective in describing complex phenomena, such as construction labour productivity deviation. In addition, since the majority of variables are qualitative, subjective measurement of each variable in predefined time intervals (e.g., daily) is also required for effective diagnosis.

Complex relationships between performance factors frequently exceed the construction manager's ability to identify conceptually causal relationships amongst them. Normally, there can be more than a handful of factors that can cause a given observation of deviation (e.g., low productivity). Judging the degree of relatedness (contribution) of each factor is always challenging, especially due to the dynamic nature of construction projects.

Hence, domain expert knowledge (from those who have had years of experience working in construction) has to be acquired and presented in a way that enables a system to utilize the knowledge for its reasoning tasks. In construction, frontline supervisors (i.e., foremen) usually have a comprehensive knowledge of the activities that they supervise; accordingly, eliciting the knowledge from frontline supervisors to identify plausible causes of performance deviations related to the activities they supervise is a viable option. One expert or a number of experts can be utilized as the primary source of domain expertise. McGraw and Warbison-Briggs (1989) identified four primary problems with knowledge acquisition from a single expert: (1) difficulty in allocating adequate time by an "already-busy" individual; (2) problems caused by different biases of human experts; (3) limitation to a single line of reasoning; and (4) incomplete domain expertise (the available knowledge in many practical situations is often incomplete and imprecise). In contrast, even though multiple experts can create a synergy, the involvement of multiple experts increases the complexity of the knowledge acquisition process. This is mainly due to the difficulty of merging each individual expert's knowledge structures into one group knowledge structure. A systematic procedure is therefore required to combine multiple experts' knowledge in order to make the diagnostic process efficient.

2.3.3 Modeling Issues

Successful diagnostic modeling requires a close match between the diagnostic model and the true underlying problem scenario associated with the model. In construction, obtaining a quality dataset that can be used for input-output mapping is limited; hence, the diagnostic models should have the capability to model with limited amounts of data. Additionally, the following key modeling issues need to be addressed. Identifying the underlying dynamics of construction performance is extremely challenging due to complex nonlinear behavior of the causal relationships among variables. As shown in Figure 2, most of the construction performance indicators and related factors display the characteristics of a nonlinear system. Thus modeling for construction performance requires a methodology that is capable of mapping these complex nonlinear systems. Note that in the Figure 2, the variation is calculated by taking the difference between daily value and average value.

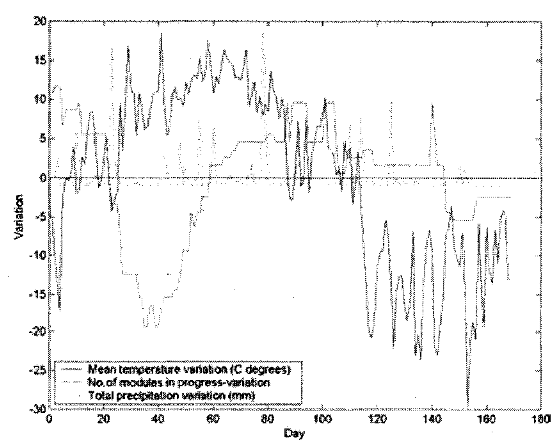

Figure 2-2. Example of non-linear behavior of performance variables (temperature, precipitation, and the number of modules in progress variation)

2.3.4 Reasoning Issues

In addition to the above issues, construction performance diagnosis reasoning attempts to address a number of the following reasoning issues:

1. Identification of multiple root causes: The most likely cause of a deviation cannot be determined by looking at its immediate cause in isolation, since it generally depends on the relative strength of multiple causes that occur simultaneously. Most construction performance diagnostic problems have several root causes; hence, identifying the significance (i.e., relative contribution) of each cause is important, so that corrective actions can be prioritized accordingly. Complex interrelationships between factors make it difficult to identify their individual impact on performance.
2. Identifying contributing vs. counteracting factors: Diagnostic models should have the ability to differentiate and identify contributing vs. counteracting factors during the course of inference. For example, low hydro-testing productivity may occur mainly because of {lack of supervision, high precipitation} despite {below average workload, average pipe-fitters availability, and no rework hours}. It is also noteworthy to highlight the fact that the same cause can act as both a contributing as well as a counteracting cause, depending on its activation status. For example, both low and high temperature variation can possibly impact labour productivity negatively, while an average temperature can make the process efficient.
3. Issues related to different levels of abstraction: Another important issue of diagnostic modeling is the selection of an appropriate level of abstraction based on user requirements. Different stakeholders (e.g., client, construction managers, superintendents, and foremen) demand different perspectives (such as project level, work package, or activity) on the same issue. Hence data must be clustered into multiple groups to represent the hierarchical structure of a problem scenario. One of the key challenges here is how to aggregate information (both objective and subjective). A robust diagnostic model, therefore, should not only possess capabilities to process subjective information, but also aggregate subjective data to provide meaningful representation at different levels of abstraction.

2.4 DISCUSSION

These issues all suggest that implementing a performance diagnostic reasoning system is non-trivial. In an attempt to deal with the above key diagnostic modeling issues, characteristic properties of different techniques discussed above are compared, as shown in Table 2-2.

Based on the summary given in Table 2-2, it can be concluded that a single technique does not solve all of the issues identified in the construction performance diagnosis. Fuzzy set theory can be used to compute incomplete, approximate, and qualitative data; to manage uncertainty caused by vagueness; and to identify contributing vs. counteracting causes. Causal models can be used to represent expert knowledge while Artificial Neural Networks can be used to capture the nonlinearity and to identify the significance of multiple root causes. Case-based reasoning approaches and Artificial Neural Networks can be used to learn from previous data.

Table 2-2. Key Modeling Issues and Possible Solutions

	KEY MODELING ISSUES	POSSIBLE SOLUTION(S)
1	Computing with incomplete, approximate and qualitative data	Fuzzy set theory
2	Uncertainty modeling caused by vagueness	Fuzzy set theory
3	Expert knowledge representation	Rule-based approach, Causal models
4	Non-linear and dynamic system modeling capability	Artificial Neural Networks (ANN)
5	Learning from previous data/ adaptive capability	Case-based reasoning approach (CBR) Artificial Neural Networks (ANN)
6	Identification of multiple root cause and relative significance of each cause	Artificial Neural Networks (ANN)
7	Identifying contributing vs. counteracting causes	Fuzzy sets (membership functions)

2.5 SUMMARY

This chapter identifies the issues and challenges that need to be addressed in terms of developing a robust diagnostic model for reasoning about construction performance. Key issues are categorized into four different aspects: (1) data and information related issues, (2) knowledge acquisition and representational issues, (3) input-output mapping issues, and (4) reasoning issues. This chapter concludes with a summary providing a match between issues identified and techniques that can possibly be used to solve the issues by developing a robust diagnostic model for reasoning about construction performance.

The next chapter presents a detailed discussion on supplementary techniques that can be used to develop a unified-hybrid framework for creating robust construction performance diagnostic model(s). It is assumed that the development of a technique capable of diagnosing a nonlinear dynamic system, which will address the above-mentioned issues, will be a significant contribution to the state-of-the-art in establishing robust performance diagnostic models.

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CHAPTER THREE

3. COMPUTATIONAL INTELLIGENCE TECHNIQUES FOR CONSTRUCTION PERFORMANCE DIAGNOSIS

3.1 INTRODUCTION TO COMPUTATIONAL INTELLIGENCE

The term "Computational Intelligence" (CI) (Bezdek 1994; Pedrycz 1997), encompasses three key technological components: (1) artificial neural networks, (2) methods of granular information processing (in particular, fuzzy sets and fuzzy logic), and (3) methods of evolutionary computations (in particular, genetic algorithms). The key difference between traditional Artificial Intelligence (AI) systems and CI is that AI systems adopt symbolic processing as their main paradigm while CI systems use sub-symbolic representation. AI systems are designed to deal with problems characterized by exact and complete knowledge representation. In contrast, CI systems are designed to deal with problems characterized by imprecise, uncertain, and incomplete data, and by information which significantly contributes to the description of real-world problems (Gorzalczany 2002).

Furthermore, CI methods are intended to mimic the approximate problem solving capacities of living systems, algorithmically. Adaptability, fault tolerance, low error rates, and high performance are some common properties among CI methods. CI methods can be successfully applied in cases where conventional AI concepts fail or where exact solutions that might be gained with particular methods are by far too expensive and where approximate solutions are acceptable. In other words, CI methods provide robust solutions at low cost for problems that would be intractable with traditional AI systems.

3.1.1 Computational Intelligence Tools for Construction Performance Diagnosis

As shown in Figure 3-1, CI methods possess several information processing capabilities that are vital to construction performance diagnosis. As identified previously (Section 2.3 of Chapter 2), construction performance-related data and knowledge are imprecise, incomplete, and uncertain; granular information processing and fault tolerance are therefore some key capabilities of a robust diagnostic system. The complex (e.g., nonlinear and dynamic) nature of the diagnostic problem also demands learning, generalization, and adaptation capabilities. Parametric and structural optimization of the diagnostic model can augment the robustness of the model.

INFORMATION PROCESSING SYSTEM	PROPERTY	CI Method
Granular information processing	Imprecise, uncertain and incomplete data and information processing, high-level reasoning	Fuzzy sets and fuzzy logic
Parallel and distributed information processing	Learning generalization adaptation Fault tolerance	Artificial Neural Networks
Evolutionary computations	Parameter and structure optimization	Genetic Algorithms

Figure 3-1. Information processing capabilities and properties of CI methods.

3.1.2 Hybrid Systems

Each CI method has its own advantages and disadvantages. Neural networks approach the modeling representation by using numerical inputs and outputs that are used to "train" a network so that it can formulate a good approximation of the complex nonlinear relationship between inputs and outputs. Precise numerical input-output pairs, however, are limited. In contrast, fuzzy systems address the imprecision of the input and output variables directly by defining them as fuzzy sets expressed in linguistic terms. The domain knowledge is coded in an explicit manner; the explanation capabilities of the resulting system are therefore excellent. Unfortunately, a lack of training and learning ability makes the fuzzy system unable to automatically acquire knowledge and to automatically build its representation as it is in neural systems. An appropriate synergistic combination of these methodologies could lead to robust diagnostic solutions. Their combination within one system significantly reduces their shortcomings and amplifies their merits.

In a synergistic combination of CI methods (as shown in Figure 3-2), a fuzzy system can contribute by: (1) accommodating imprecise, ambiguous, common sense knowledge, (2) employing human-like reasoning mechanisms, (3) implementing universal approximation techniques, and (4) retaining a low cost of development and maintenance.

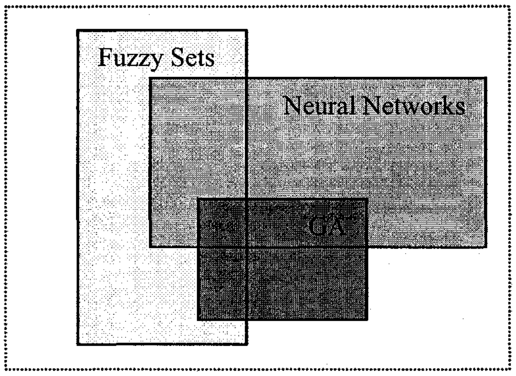

Figure 3-2. Synergistic combination of CI methods

Neural networks can contribute by: (1) extracting knowledge and learning from data, (2) making good generalizations, (3) implementing methods for data analysis, (4) coordinating massive parallelism, and (5) ensuring fault tolerance and robustness. Genetic algorithms can contribute by optimizing network parameters, such as weight values, using parallel techniques that include the ability to search the entire space versus a localized search in the weight space via a gradient decent technique.

Commonly, such hybridization is typically done in a sequential manner (method A as a pre-processing step of method B) (Gorzalczany 2002). For example, in a diagnostic reasoning system, input data pre-processing can be handled via fuzzy sets, and learning from input-output data can be done using artificial neural networks. Also, the network parameter (and structure) can be optimized using genetic algorithms, as shown in Figure 3-3.

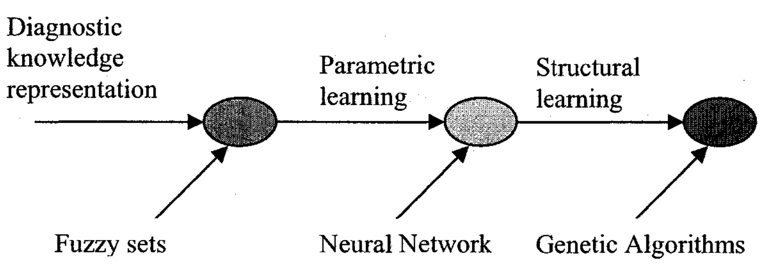

Figure 3-3. Sequential hybridization of CI methods for performance diagnostic reasoning

The following sections elaborate on the main conceptual and fundamental components of CI that will be used to develop a unified framework for construction performance modeling.

3.2 FUZZY SET THEORY

The notion of the fuzzy set was introduced by Zadeh (1965) as a means of handling linguistic uncertainty.

The traditional way of representing elements of X of a set A is through a *characteristic function*:

$$X_A(x) = \begin{cases} 1 \; for \; x \in A \\ 0 \; for \; x \notin A \end{cases}$$

That is, the characteristic function maps the element of X to elements of the set $\{0,1\}$.

In fuzzy sets an element can belong partially to a set. The degree of belongingness (i.e., membership degree) is defined through a generalized characteristic function called the *membership function* (μ), and the set defined by it a "fuzzy set". It can be expressed as:

$$\mu_A : X \rightarrow [0,1]$$

Fuzzy sets are uniquely specified by their membership functions.

3.2.1 Linguistic Variables

Linguistic variables are variables whose values are not numbers but words or sentences in natural language (Zadeh 1975). Linguistic variable can be characterized by a quintuple $(X, T(X), U, G, M)$ in which X is the name of the variable, $T(X)$ is the term set of X (i.e., the values of the linguistic variable X), U is the universe of discourse which is associated with base variable, G is a syntactic rule for generating the term set $T(X)$, and M is the semantic rule for associating meaning with the linguistic values of X.

For example, consider a composite linguistic variable such as "daily site working condition". As shown in Figure 3-4, working condition can be represented by linguistic variables (X) such as crew-size, task complexity, and temperature. Values of "crew-size", that is the term set of linguistic variable crew-size, can be represented as

$$T(Crewsize) = \text{small} + \text{average} + \text{large}$$

The universe of discourse could be $U = [2,12]$ where the minimum size the crew is 2-person and the maximum is 12-person.

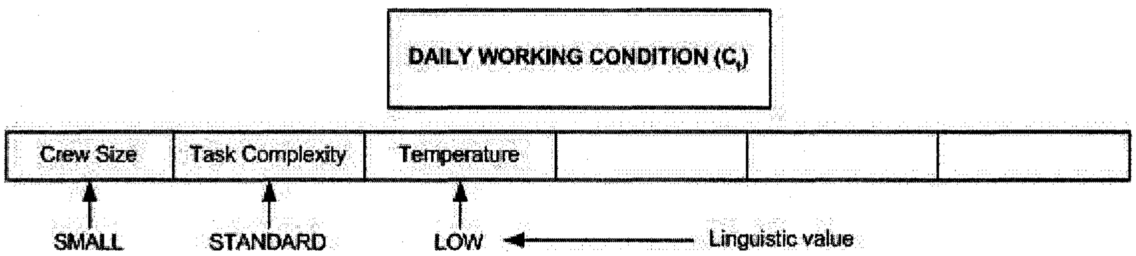

Figure 3-4. Assignment of linguistic values to attributes of "daily working condition".

This can also be written as follows:

$$\text{Crew-Size } (C_t) = \text{Small}$$
$$\text{Task-Complexity } (C_t) = \text{Standard}$$
$$\text{Temperature } (C_t) = \text{Low}$$

Figure 3-5 shows the hierarchical structure of the relation between the linguistic variable "temperature", its linguistic values (i.e., term set), and the base variable temperature, which is measured in degrees Celsius. Each of the basic linguistic terms is assigned a "fuzzy number" by a semantic rule, whose membership functions have the usual trapezoidal shapes on the interval [-15, 30], the range of the base variable.

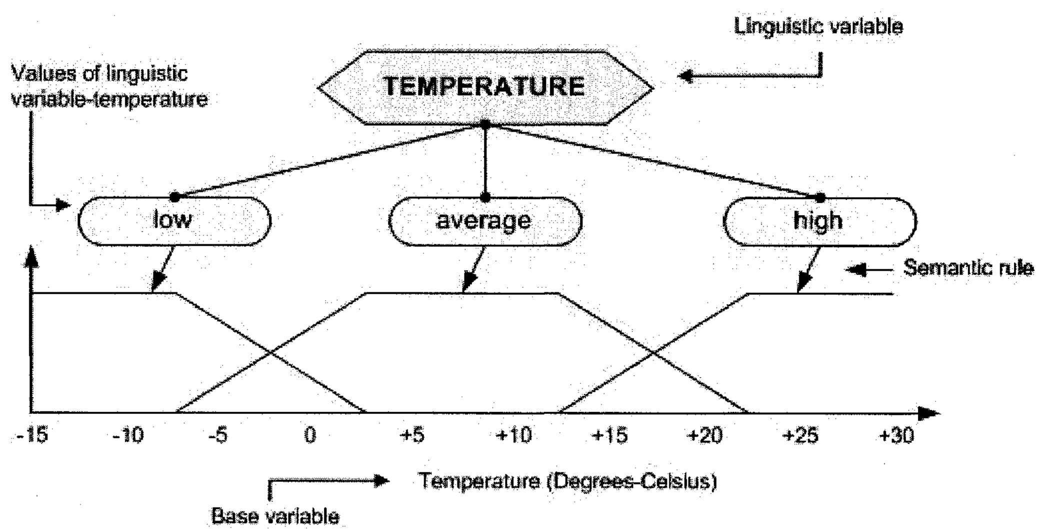

Figure 3-5. Hierarchical structure of linguistic variable-temperature.

The membership degrees associated with each value represented in the universe of discourse is subjective as well as context dependent. For example, a tradesperson working in the field may assess the temperature differently compared to a tradesperson working in the shop. The assessment also varies across different seasons, countries, and climates.

Another important issue is that some linguistic variables (e.g., temperature, crew size) have well-defined base variables (e.g., degrees Celsius, and number of tradesmen, respectively) while variables such as task complexity, equipment suitability, and ground condition do not have well-defined bases variables. In latter case, obtaining the grade of membership is challenging compared to the cases where some physical measurements are available. Choosing a surrogate-physical measure (e.g., number of bends representing "task complexity" of pipe module fabrication) or selecting a scale (e.g., 0-10, zero being the low extreme and 10 being the high extreme) are commonly used to address this challenge.

3.2.2 Membership Function Development Techniques

The construction of a fuzzy set depends on two things (Gorzalczany 2002): (1) the identification of a suitable universe of discourse and (2) the specification of appropriate membership functions. How best to determine the membership functions is one of the main questions that have to be tackled. The determination of membership functions can be categorized as either being manual or automatic.

Manual methods utilize expert opinion to design and develop membership functions. Some examples are: (1) the horizontal method, which is the use of frequencies by measuring the percentage of experts in a group who answer yes to a question about whether an object belongs to a particular set; (2) direct estimation by asking experts to grade an event on a scale; (3) the vertical method, which involves interviewing expert to identify plausible intervals; and (4) through pairwise comparison (rank ordering), which consists of identifying an experts level of preference of objects(Pedrycz 1995). Generally, all these manual methods suffer from knowledge acquisition problems.

Several automatic methods of membership generation are found in literature: (1) training examples (Hong and Lee 1996; Pedrycz and Vukovich 2002), (2) artificial neural networks (Takagi and Hayashi 1991; Wang 1994), and (3) genetic algorithms (Karr and Gentry 1993). What makes the automatic MBF construction methods differ from manual methods is the fact that experts are totally or partially eliminated from the elicitation process. Hong (1996) uses a method that eliminated experts totally from the process while Pedrycz (2002) proposes an expert-initiated process of MBF elicitation.

Section 2 of Chapter 6 discusses suitable alternative methodologies in detail for developing a practically feasible (compared to theoretically possible) approach for designing membership functions for construction performance modeling.

3.3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural networks are biologically inspired, massively parallel, distributed information processing systems. They are characterized by a computational power, fault tolerance, as well as learning and generalization capabilities.

An artificial neuron is the basic building block of a Neural Network. As shown in Figure 3-6, a neuron is a processing element that consists of two parts: (1) summation and (2) activation function. As shown in Figure 3.6, the input variables are represented by input vector $\mathbf{x} = x_0, x_1, x_2, ..., x_n$. Each of these inputs is modified by a weight (w_{ij}). The first part of the neuron simply aggregates (sums) the weighted inputs ($w_{ij}.x_i$) results in quantity I. The second part is an activation (squashing) function that transforms I into a value between the two asymptotes, keeping the output of the neuron within a reasonable dynamic range.

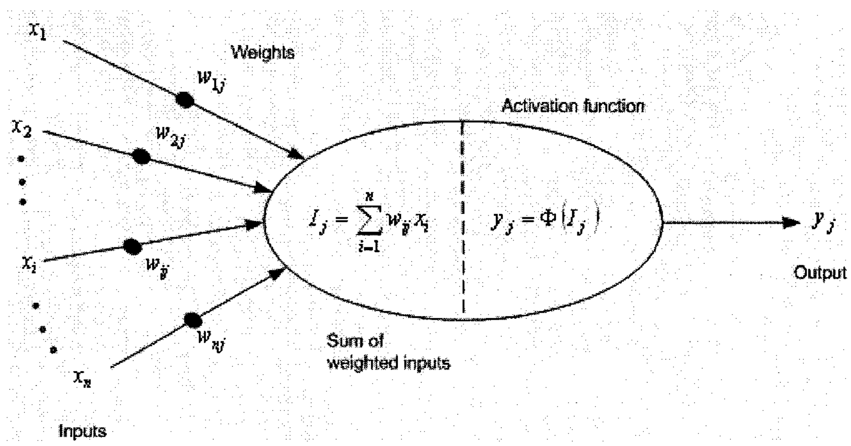

Figure 3-6. The Artificial Neuron

Neural Networks are made of interconnected neurons, usually organized in a sequence of layers with full or random connections between layers. Figure 3-7 illustrates a network that is fully connected. These multilayer networks have been proven to have capabilities to map any complex nonlinear systems.

The input layer represents input variables that a network uses to make a prediction (or classification). The output layer represents the values(s) of the network predict. Layers in between input and output layers are called hidden layers. Both hidden and output layers are made of groups of neurons. The input layer is not a neuron-computing layer; it merely presents the example data to the network. Neurons in the hidden layer process the sum of weighted values, usually using a nonlinear transfer function, then the hidden layer passes the values to the output layer in the same fashion and the output layer produces the desired results. Typically, the network constitutes a model that represents the relationship between input and output variables. The network "learns" by adjusting the interconnection weights between layers during training process. Training algorithms are generally categorized as supervised and unsupervised (Wasserman 1989).

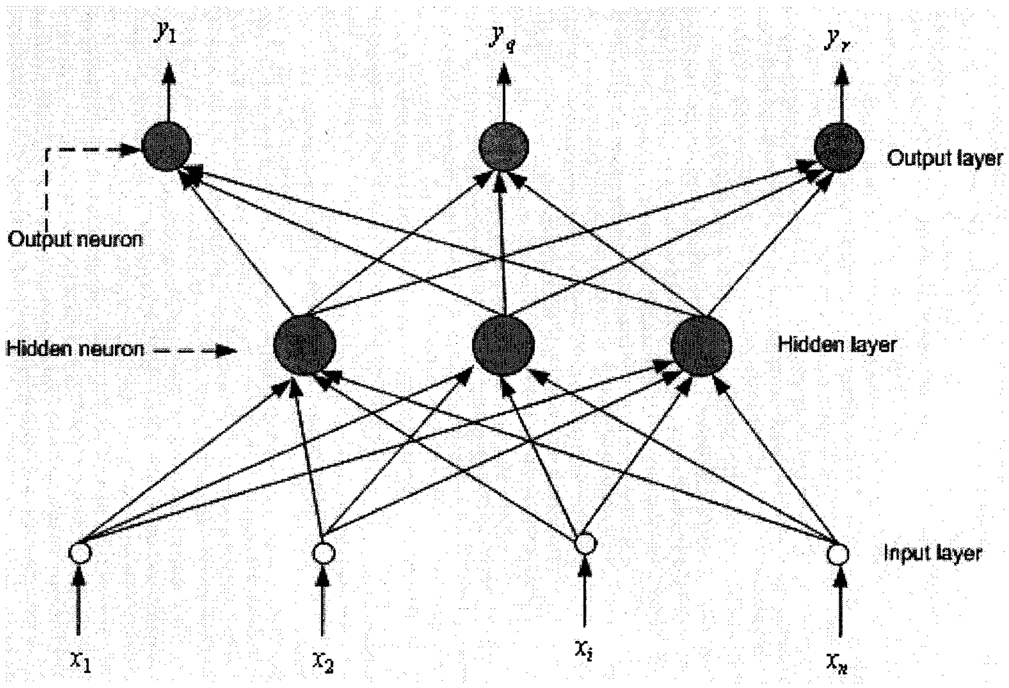

Figure 3-7. Multilayer Artificial Neural Network

In supervised learning, the network is trained over a number of training pairs (i.e., input vector with a target vector representing the desired output). An input vector is applied, the output of the network is calculated and compared to the corresponding target vector, and the difference (error) is fed back through the network. Weights are then changed according to an algorithm (e.g., Hebbian learning), which tends to minimize the error. Back-propagation multilayer neural networks, Probabilistic Neural Networks

(PNN) (Specht 1990) and generalized regression neural networks (GRNN) (Specht 1991) are supervised network types. Supervised learning can be employed for construction performance modeling as follows: construction performance variables can be represented as an input vector at the input layer, and key performance indicator(s) in question can be represented at the output layer, representing the desired output. The difference between the actual value of key performance indicator and network output constitutes an error, which is used to adjust the connection weights. Even though back-propagation networks are commonly used, they suffer from "local minima" problem, i.e., the training process easily trapped in a local minimum solution instead a global solution. Both multi-layer back propagation networks and GRNNs are generally used for predicting, evaluating, and generalization while PNN provides a general technique for pattern classification problems.

In contrast, unsupervised learning requires no target vector for the outputs; the training set consists solely of input vectors. It classifies a set of training input data into a predefined number of categories. Kohonen networks (Kohonen 1984) are unsupervised.

According to Bailey and Thompson (Bailey and Thompson 1990), neural network solutions are appropriate when;

- A problem requires complex quantitative (or qualitative) reasoning and an approximate solution is sufficient,
- Parameters are highly interdependent (multiple interactions) and have no precise quantification, or
- Data are available from specific examples, and some of the data may be erroneous or missing.

To apply neural networks in construction performance diagnostic reasoning, the appropriate choice of the type of neural network paradigm is crucial. Creating a multilayer neural network model that provides the most accurate, consistent, and robust model possible requires iterative building, training, and testing to refine the neural network. The selection of the size of the network (i.e., number of layers and number of neurons in each layer) and the neuron activation functions (e.g., linear, step, hyperbolic tangent) are to be carried out in trial-and-error fashion; it can be a tedious, and time-consuming task.

Additionally, in an analysis to explain a particular event (or effect) such as "low (labour) productivity", the nature of causal reasoning will require backtracking to critical causes. However, the distributed character of the computations (i.e., acquire knowledge from a family of learning patterns and distribute it along the connections in the structure during the learning process) make it almost impossible to reasonably interpret the overall structure of the network and to explain the results generated by the network in the form of transparent, logical constructs (such as conditional rules and frames) (Gorzalczany 2002). In construction performance modeling, more often than not, backtracking can lead to multiple causes, thus identifying the order-of-magnitude (i.e., the relative significance) of each factor is a necessity.

3.4 GENETIC ALGORITHMS (GA)

The underlying principles of genetic algorithms (GA) were first formulated by Holland (Holland 1975). Genetic algorithms have been very effective at function optimization, efficiently searching large and complex spaces to find nearly global optima. The advantages of using genetic algorithms include the ability to search the entire smoothing factor space, rather than a localized search via a gradient descent technique such as backpropagation (Tsoukalas and Uhrig 1997).

In this study, a GA's optimization capabilities are utilized as an important supportive tool in parameter (e.g., weights) learning of network processing module. The major components of GA are presented below (on the basis of (Gorzałczany 2002; Jain and De Wilde 2001; Tsoukalas and Uhrig 1997)). As identified in Konar and Jain (2001), GA operates through a simple cycle of stages, as shown below in Figure 3-8.

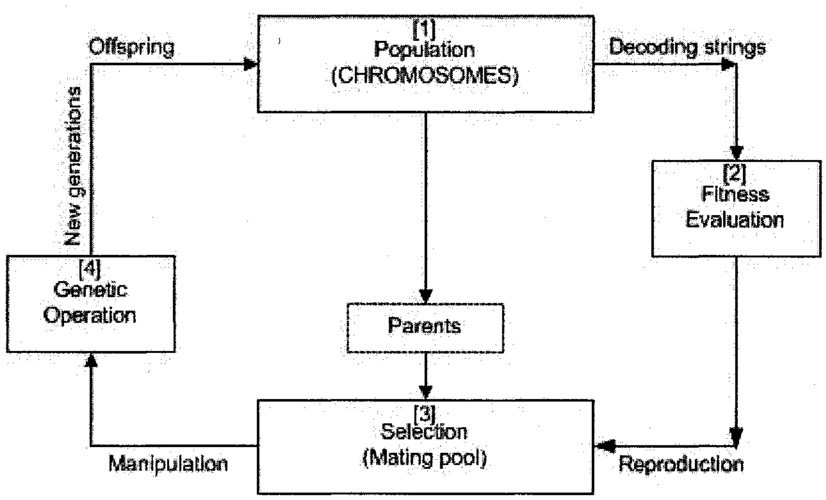

Figure 3-8. The cycle of genetic algorithm (Konar and Jain 2001)

In the first phase, an initial population of "individuals" is created to initiate the search process. Each individual (named as chromosomes) represents a potential solution to the problem at hand. A chromosome can be represented using both binary and real-value encodings with binary being the more prevalent method. The performance of the chromosome, often called the "fitness value", is then evaluated using a fitness function. This function must be established for each specific problem. In a network parameter learning problem, for example, the fitness function (Θ) can be represented as follows. Given N training data $[\mathbf{x}, y_i]$ (i=1,…,N), the learning algorithm's target is to find best parameters values to keep the difference between predicted value $\hat{y}_i$ and the real output y_i as small as possible. In other words, the target is to find the best network parameters to keep the network performance index Q defined in Equation 3-1 as small as possible.

$$Q = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{3-1}$$

Where $\hat{y}_i$ is a predicted value with input vector $\mathbf{x}_i$. Accordingly, the fitness function can be defined as in Equation 3-2.

$$\Theta = \frac{1}{1+Q} \tag{3-2}$$

The fitness value Q is the quantity that guides the reproduction process for creating the next generation. Chromosomes with higher fitness values tend to reproduce more often than those with lower fitness values. Several alternative selection mechanisms are reported in the literature, among the roulette-wheel parent selection, which is commonly applied. Once the selection of the population is over, the resulting new population is subject to the two main mechanisms of genetic algorithms such as *cross-over* (in general, a recombination) and a *mutation*.

The crossover operation generates new chromosomes that possibly retain good features from previous generations. Once the chromosomes are selected from the pool for the crossover operation, the selected chromosomes are mated randomly, and for each pair of coupled chromosomes (parents) a random integer number *pos* from the set $\{1,2,\ldots,l-1\}$ (l is the total length of a chromosome) is chosen. The number *pos* indicates the position of the crossover point. Two chromosomes representing network weights, for example, can be represented as:

$w_{pos}\, w_{pos+1} \ldots w$

$$\langle w_1 w_2 \ldots w_{pos} w_{pos+1} \ldots w_l \rangle \text{ and } \langle v_1 v_2 \ldots v_{pos} v_{pos+1} \ldots v_l \rangle \tag{3-3}$$

After the crossover, a pair of their offspring can be represented as

$$\langle w_1 w_2 \ldots w_{pos} v_{pos+1} \ldots v_l \rangle \text{ and } \langle v_1 v_2 \ldots v_{pos} w_{pos+1} \ldots w_l \rangle \tag{3-4}$$

In equation 3-3 and 3-4, the crossover operation is one point since one crossover position is chosen. In general, n-point crossover can be identified.

The second genetic operation is mutation, where the single components of the chromosomes (called bit strings) at one or more randomly selected positions are altered. Mutation represents an abrupt change in the nature of the chromosome. After selection, crossover and mutation, the currently worst chromosomes are replaced with the best chromosomes and the new population is formed for a new evaluation. The rest of the evolution process is just a cyclic repetition of the above steps until a stopping criterion is satisfied. The best chromosome, for example, provides the optimal weights of network connections.

3.5 HYBRID SYSTEMS FOR CONSTRUCTION PERFORMANCE MODELING

Two hybrid system architectures have been considered in this thesis that combines fuzzy set theory as possible solutions to assist construction performance diagnosis: neural networks and genetic algorithms, in a sequential manner, as previously shown in Figure 3.3. The selection of these two frameworks was based on several properties of a diagnostic system, as shown in Table 3-1.

Table 3-1. A rough comparative analysis of alternative computational intelligence systems.

REQUIRED PROPERTIES OF PERFORMANCE DIAGNOSTIC SYSTEMS	*ARTIFICIAL NEURAL NETWORKS*	*RULE-BASED FUZZY SYSTEMS*	*GENETIC ALGORITHMS*	*NEURO FUZZY SYSTEMS: RULE-BASED (+GA)*	*FUZZY NEURAL NETWORKS: AND-OR (+ GA)*	*GENETIC ADAPTIVE-GRNN (+ FUZZY NEURONS)*
Transparency (Explanation ability)	Very Low	Very High	Very Low	High	Very High	High
Learning ability	Very High	None	High	Very High	High	Very High
Generalization capability	Very High	High	High	Very High	High	Very High
Using Experts' knowledge	None	Very High	None	Very High	Medium	Medium
Using numerical data sets	Very High	Very Low	High	Very High	Very High	Very High
Using qualitative linguistic information	None	Very High	Very Low	Very High	Very High	Very High
Fault tolerance	Very High	High	High	Very High	Very High	Very High
Limited data	Low	Very High	Very High	High	Low	High
Knowledge representation	Unstructured	Structured	Unstructured	Structured	Unstructured	Unstructured
Type of Inference	Approximate	Approximate	Approximate	Approximate	Approximate	Approximate

Adapted from (Gorzalczany 2002; Holland 1975; Pedrycz 1995; Specht 1991; Specht and Romsdahl 1994)

From a diagnostic reasoning perspective, *transparency* is a paramount feature desired in any diagnostic system. In general, transparency means the ability to trace the process of inferring a solution. While most fuzzy systems have transparent structures (based on if-then rules), massively parallel inference systems such as neural networks have a very limited ability to explain the inference process. In construction performance diagnostic reasoning applications, an explanation ability is expected to be at least at the level that can identify the relative significance of each variable that can possibly impact the performance indicator(s) in question. Both fuzzy neural networks based on AND/OR neurons and Generalized Regression Neural Networks possess the characteristics that facilitate interpretation of connection weights. Chapters Four and Five provide detailed descriptions of these two networks, respectively.

Learning ability is another key attribute that a diagnostic system should posses. It is the process of knowledge acquisition that results in adaptation to the complex dynamic nature of the problem. While neural networks have excellent ability to learn from data samples, fuzzy systems do not posses a learning ability.

Generalization capability is what makes a diagnostic system respond correctly to a new situation. In other words, it is the process of inferring a solution based on previously unknown data to the system (network). Both neural networks and fuzzy systems have a good generalization capability.

Both fuzzy systems and neuro-fuzzy systems use structured *knowledge representation* such as conditional rules of the IF-THEN type, while neural networks and fuzzy neural networks use unstructured knowledge representation (e.g., input-output data pairs) to transform the available problem knowledge in order to process it by standard knowledge engineering methods. For construction performance diagnostic systems, unstructured knowledge representation in the form of input-output data pairs is more appropriate, mainly due to well-known knowledge acquisition problems, especially in the form of rules from multiple experts. The remaining properties of performance diagnostic systems, as shown in Table 3-1, are self-explanatory.

The first approach presented in this thesis is based on Pedrycz's OR/AND neuron model (Pedrycz 1995) of fuzzy neural networks. It can be considered as a tightly coupled fuzzy-neural system, as the basic elements in the network have the composite characteristics of both neural nets and fuzzy sets (Konar and Jain 2001). The second approach (i.e., Generalized Regression Neural Networks (GRNN)-based processing module) can be considered as a weakly coupled fuzzy-neural system. This model preserves the basic properties and general architecture of Specht's GRNN (Specht 1991), while introducing fuzzy input neurons for comprehensive improvement of the performance of the network in terms of accuracy and knowledge representation. A schematic description of the general configuration of both approaches (i.e., AND-OR neuron model and GRNN-based model) is illustrated in Figure 3-9.

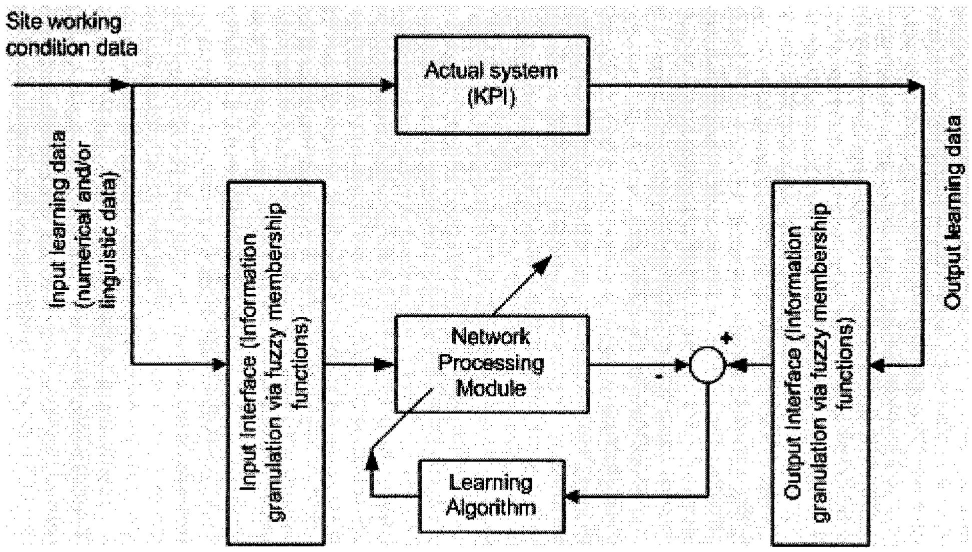

Figure 3-9. Configuration of the System Architecture.

At the front end, a user interface allows the user to represent input variables (i.e., causal factors) and linguistic values to represent the selected variables. Each linguistic value is represented as a fuzzy set. The input interface transforms input information into membership values. The network processing module (i.e., inference engine) represents both AND/OR neuron model and the GRNN-based model. The membership values of input learning data are used as input to the inference engine. The inference engine is trained using different learning algorithms (e.g., gradient decent, genetic algorithms) to reveal and quantify logical relationships between input and output variables.

Both approaches are used to model the normal functional structure of selected key performance indicators (KPI). Both models characterize the possible performance of the construction process using quantitative numerical data as well as qualitative linguistic information that reflect actual behaviour.

3.6 SUMMARY

This chapter provides a brief introduction to Computational Intelligence (CI) and describes the main constituents of CI. The advantages of synergistic links between key constituents are identified. Two potential CI systems based on Fuzzy-neural systems are identified and a system architecture is proposed to exploit the benefits of CI systems to assist construction performance diagnostic reasoning. Detailed descriptions and empirical analysis of AND/OR neuron processing module and GRNN based processing module are given in Chapter 4 and Chapter 5, respectively.

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CHAPTER FOUR

4. FUZZY NEURAL NETWORKS: AND/OR NEURON MODEL

4.1 INTRODUCTION

This chapter presents a network processing module based on Pedrycz's AND-OR neuron model (Pedrycz 1993; Pedrycz 1995). This fuzzy set-based neuron model incorporates fuzzy logic elements into the neural network. The resulting topology can perform diagnostic inference functions by analyzing the values of the connection weights. The logic operations of the AND-OR neuron model are discussed and a learning algorithm is presented. To assess the effectiveness of the proposed fuzzy neural network in construction performance modeling, experiments are conducted using data collected from an industrial construction project; these results are also presented.

This chapter contains some of the results of the author's prior research (Dissanayake et al. 2004), recast in light of later developments.

4.2 FUZZY NEURAL NETWORKS

The underlying topology of the proposed schema is based on fuzzy neural networks. Fuzzy neural networks are processing structures with an explicit form of knowledge representation due to the well-defined semantics of its neurons (Pedrycz and Gomide 1998). Liu and Yan (1997) demonstrated that fuzzy neural network based on AND/OR neurons can be interpreted by revealing the connection weights; furthermore, the network size can be optimized by pruning out those connections with weak (insignificant) weights. Several successful implementations of the AND/OR neuron-based models can be found in the literature (e.g., Gobi and Pedrycz 2004; Myung-Geun Chun et al. 1997), in which both gradient decent learning and GA-based learning are employed. In this section, an OR/AND neuron model of fuzzy neural networks (FNNs) with fuzzy input variables is presented, and a learning algorithm is discussed.

4.2.1 OR/AND Fuzzy Neurons

The key functional element forming a core of the proposed fuzzy neural network is Pedrycz's OR/AND fuzzy neuron (Pedrycz 1995). As shown in Figure 4-1, the proposed network has four layers, namely:

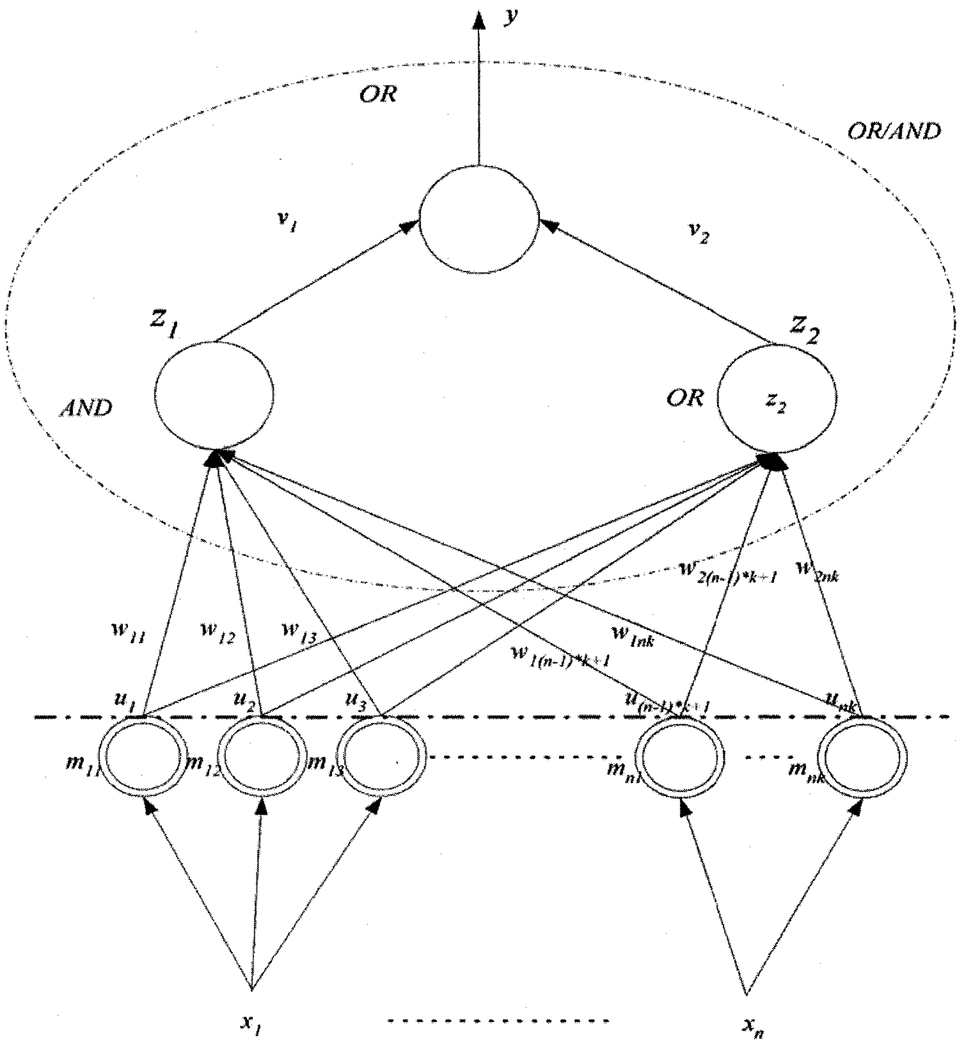


Figure 4-1. Topology for the Fuzzy Neural Network based on AND-OR Neurons

(1) Input layer: represents the input variables and simply channels the values of input variables (x_i, i=1,2,…,n.) to the next layer. n is the total number of input variables.

(2) Membership function layer: represents the membership functions of each input variable and transforms input values to the corresponding membership values m_{ij}, i=1,2,…,n, j=1,2,…,k where k equals the total number of terms (i.e., linguistic values) that belong to each input variable.

The membership values, m_{ij}, are combined into a vector of single input $\boldsymbol{u}=[m_{11},\ldots,m_{1k},\ldots,m_{i1},\ldots,m_{ik},\ldots,m_{n1},\ldots,m_{ik}]=[u_1, u_{2,},\ldots u_p]$ where the total dimension of $\boldsymbol{u}$ is p=n*k.

(3) AND-OR neuron layer: represents the AND neuron (z_1) and the OR neuron (z_2). This layer transforms membership values, m_{ij}, AND-wise (i.e., by the AND neuron) and OR-wise (i.e., by the OR neuron) into two separate computing channels, and sends them to the output layer.

(4) Output layer: represents the output OR-neuron, which merges the inputs from the previous layer and produces the output y.

The connections of the neurons (weights) distributed in the unit hypercube are denoted by **w**, **v**. More specifically, the AND neuron is described as $z_1 = \text{AND}(\boldsymbol{u};\mathbf{w}_1)$, which, using the notation of triangular norm (t-norm), is expressed as:

$$z_1 = \mathop{T}_{i=1}^{p}(u_i s w_{1i}), \tag{4-1}$$

Where w_{1i} summarizes a collection of the AND neuron's connections ($\mathbf{w}_1$). The OR neuron is produced using the expression $z_2 = \text{OR}(\boldsymbol{u};\mathbf{w}_2)$, which, using the notation of triangular norm (s-norm), is expressed as:

$$z_2 = \mathop{S}_{i=1}^{p}(u_i t w_{2i}). \tag{4-2}$$

The role of the OR neuron (output layer) is to combine the results of AND and OR aggregation. Depending on the values of the connections (v_1 and v_2), the overall OR/AND neuron exhibits mixed characteristics of both these two logic operations. This aggregation is expressed as:

$$y = \text{OR/AND}(\boldsymbol{u};\mathbf{w},\mathbf{v}), \tag{4-3}$$

which using the t and s norms, is expressed as:

$$y = (z_1 t v_1) s (z_2 t v_2). \tag{4-4}$$

In boundary cases, If v_1=1 v_2=0, the OR/AND neuron operates as a pure OR neuron; if v_1=0 and v_2=1, the structure functions as a pure AND neuron. For example, if the above t and s norms are realized by product and probabilistic sum operators using the following expressions:

$$atb = ab;\ a,\ b \in [0,1] \tag{4-5}$$

$$asb = 1-(1-a)(1-b) = a+b-ab;\ a,b \in [0,1] \tag{4-6}$$

the input-output mapping will be:

$$y = z_1 v_1 + z_2 v_2 - z_1 v_1 z_2 v_2, \tag{4-7}$$

$$\text{Where } z_1 = \prod_{i=1}^{p}(u_i + w_{1i} - u_i w_{1i}),\ z_2 = 1 - \prod_{i=1}^{p}(1 - u_i w_{2i}). \tag{4-8}$$

If the above t and s norms are realized by the min and max operators that follow:

$$atb = \min(a,b)\,;\ a,\ b \in [0,1] \tag{4-9}$$

$$asb = \max(a,b)\,;\ a,\ b \in [0,1] \tag{4-10}$$

the input-output mapping will be:

$$y = \max(\min(z_1, v_1), \min(z_2, v_2))\ , \text{ where } z_1 = \min_{i=1}^{p}(\max(u_i, w_{1i}))\ ,\ z_2 = \max_{i=1}^{p}(\min(u_i, w_{2i})) \tag{4-11}$$

4.2.2 Learning/Optimization Mode of the AND-OR Neuron Model

The learning and optimization processes of the AND-OR neuron model consist in finding the connection weights (**w**, **v**) from the input-output training pairs. Results of the learning mode also determine the network topology by eliminating insignificant connections. The resulting network topology provides a logical construct that illustrates the logical causal relationship between the input causal factors and output variable(s) (i.e., key performance indicators). The two main elements of any supervised training exercise comprise a network performance index (Q) and the learning scheme. The learning algorithm adjusts the weights **w**, **v** so that the performance index (Q) is optimized.

4.2.2.1 Network Performance Index (Q)

Assume that we have T datasets for learning; $[u_1(r),\ldots,u_p(r),y_r]$ r=1,…,T; y_r as target and $\hat{y}_r$ as the FNN's output with respect to its inputs $[u_1(r),\ldots,u_p(r)]$.

Accordingly, the performance index (Q) is expressed as:

$$Q = \frac{1}{T}\sum_{i=1}^{T}(y_r - \hat{y}_r)^2 \tag{4-12}$$

which is the mean square error of the prediction. The objective is to minimize the performance index (Q) with regard to the structure of the model and its parameters.

4.2.2.2 Learning Algorithm -Gradient Descent Learning

The learning algorithm will update **w, v** through gradient-based learning as follows:

$$w_{1i} = w_{1i} - \frac{1}{2}\alpha\frac{\partial Q}{\partial w_{1i}}, \qquad w_{2i} = w_{2i} - \frac{1}{2}\alpha\frac{\partial Q}{\partial w_{2i}} \tag{4-13}$$

$$v_1 = v_1 - \frac{1}{2}\alpha\frac{\partial Q}{\partial v_1}, \qquad v_2 = v_2 - \frac{1}{2}\alpha\frac{\partial Q}{\partial v_2} \tag{4-14}$$

Where $\alpha \in [0,1]$ is the learning rate.

The updating process is stopped when there is no further improvement in the output error for a certain consecutive number of training epochs (user-defined, e.g., 1000).

4.2.3 Interpretation of the Network via Connection Weights

Pedrycz (1995) identified that, because of the triangular norm's boundary conditions, the values for the connections in the OR neuron ensure that the corresponding input exerts a stronger influence on the neuron's output. By contrast, the opposite weighting effect takes place in the case of the AND neuron: the values of connections closer to 1 make the influence of corresponding input almost negligible.

Initial values of the connections of the network can be assigned randomly or based on expert judgment. Once the network is trained using (4-13) and (4-14), the values of **v** are compared. Since aggregative AND and OR neurons are connected via the OR neuron, the corresponding neuron with the highest value of **v** has the strongest influence on network output. For example, if v_1=0.35 and v_2=0.80, the values of connections leading to OR neuron to derive explanations can be analyzed.

In an OR neuron, those connections with weights close to zero (or below a certain threshold) can be eliminated. Conversely, in an AND neuron, those connections with weights close to one or above a certain threshold can be eliminated.

4.3 EMPIRICAL VALIDATION OF THE AND-OR NEURON MODEL

To assess the effectiveness of the model, several experiments were conducted. A description of the experimental data is given, followed by a description and the results of four different cases conducted to assess the validity of the proposed FNN.

4.3.1 Description of Case Data

A dataset from the industrial construction sector was chosen to demonstrate how the proposed system could be used for reasoning about construction performance. Specifically, the "labour productivity in hydrotesting (HT)" of pipe fabrication in a pipe module fabrication yard was considered. The PF is calculated as follows:

$$PF = \frac{Earned\ manhours}{Actual\ manhours} = \frac{quantity\ installed * (Estimated\ Manhours / unit\ quantity)}{Actual\ manhours}$$

The daily values of key performance indicators are considered as outputs and the daily values of possible causes that affect the KPI as inputs to the network.

Table 4-1 shows the identified plausible causal factors of "low HT productivity" by a group of experts who manage the job. A total of seven causal factors were identified. Once possible causes were identified, relevant (daily) data were extracted from the contractor's Information Management System (IMS) for a period of 169 working days covering the period of April 2003 to February 2004. Figure 4-2 graphically illustrates the variation of the key performance indicator (KPI) studied, i.e., the pipe hydrotesting productivity, over the duration of the study.

Table 4-1. Causal factors that impact labour productivity in Pipe Hydro-testing

	Causal Factor		Description
1	WKL	Work Load	No. of pipe modules in progress
2	EQA	Equipment availability	No. of cranes available
3	MAV	Manpower availability	No. of pipefitters available
4	TEM	Mean Temperature	The mean temperature of the air in degrees Celsius.
5	PRE	Total precipitation	The sum of the total rainfall and the water equivalent of the total snowfall
6	RWK	Rework	Pipe fabrication rework (work force hours spent on repairs)
7	QAC	Quality Assurance/ Quality Control input	Number of hours spent on QA/QC work.

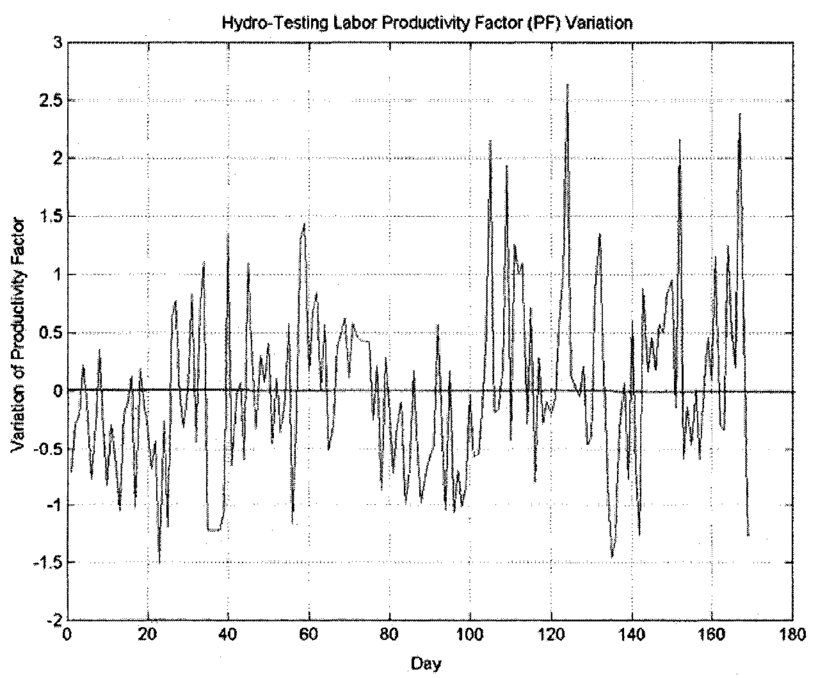


Figure 4-2. Variation of pipe hydrotesting productivity

One of the main objectives of this study is to develop a reliable model that can map the type of non-linearity shown in Figure 4-3. Interviewing a group of experts has identified linguistic measures of each cause. Accordingly, membership functions were developed using the expert knowledge of the same group by the heuristic method (see section 6.2.4.1 of Chapter 6 for further details of heuristic method). The parameters of the membership functions are given in Figure 4-3.

The construction of the fuzzy neural network model is completed using 100 data points treated as a training set. The rest of the data (i.e., 69 data points) are retained for testing purposes.

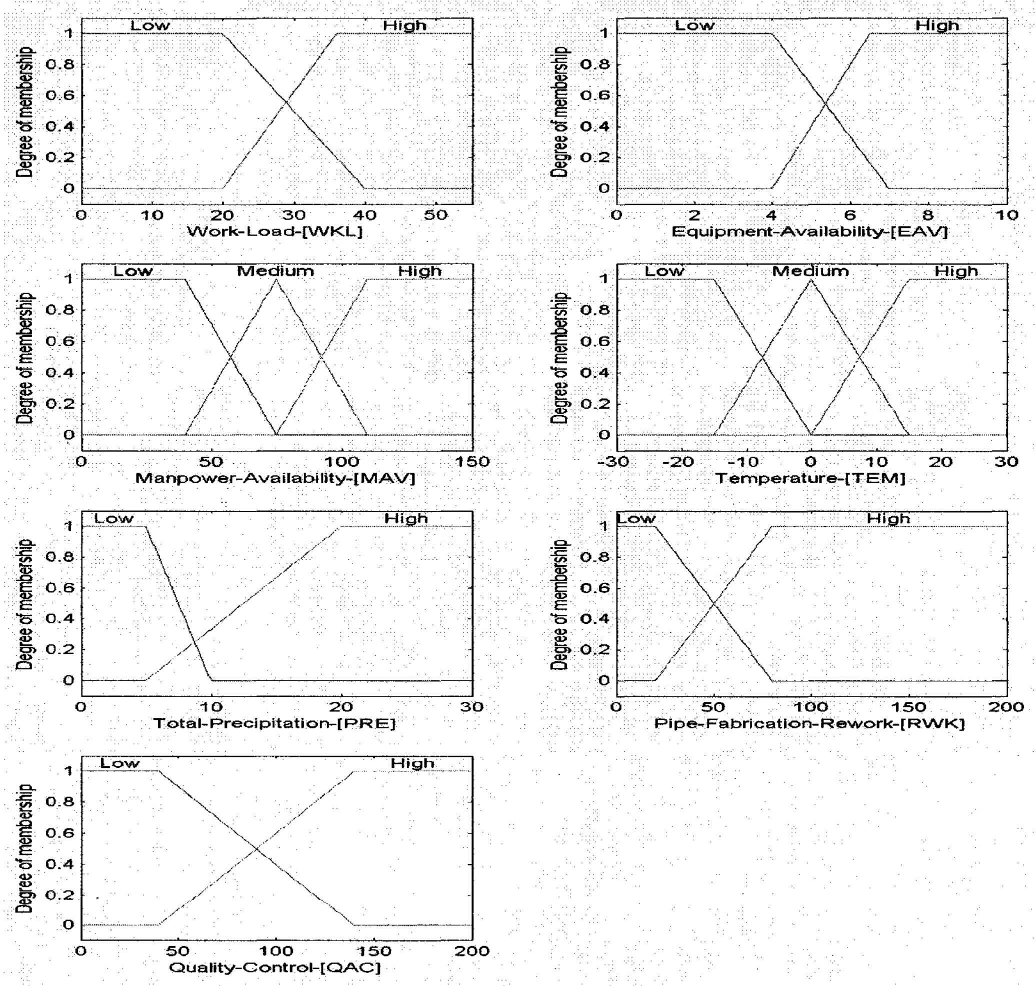


Figure 4-3. Membership functions

4.3.2 Case 1: AND-OR Neuron Model

In this case, the model is trained with gradient decent learning algorithm (Equation 4-13 and 4-14). The learning rate (α) is experimentally adjusted and set to 0.01. Initial values of the connections of the network (**w**) were assigned using two methods: (1) using random weights, and (2) using a normalized principal eigenvector, i.e., a vector of priorities. An AHP comparison of causal factors made by the construction manager is shown in Table 4-2. The initial connections of the aggregation operation (**v**) were assigned randomly.

4.3.2.1 Initial Weight Assignment by AHP Method

The AHP organizes and quantifies those relative measurements concerned with deriving dominance priorities from paired comparisons of homogeneous elements (or variables) with respect to a common criterion (Saaty 1980.). The process consists mainly of two phases: the first phase involves setting priorities based on subjective judgment using pairwise comparison, and the second phase checks for the consistency of the comparison.

Pairwise Comparison: The method of deriving the vector of priorities from a pairwise comparison matrix is as follows:

Assume the vector of priorities $\boldsymbol{a}=[a_1,a_2,\ldots,a_n]^{\mathrm{T}}$, and let A be the positive pairwise comparison matrix with respect to n criteria.

$$A=\begin{bmatrix} a_{11} \; a_{12} \; \ldots\ldots a_{1i} \; \ldots\ldots a_{1n} \\ a_{21} \; a_{22} \; \ldots\ldots a_{2i} \; \ldots\ldots a_{2n} \\ . \\ . \\ a_{n1} \; a_{n2} \; \ldots\ldots a_{ni} \; \ldots\ldots a_{nn} \end{bmatrix} \tag{4-15}$$

Where a_{ij} represents the relative importance of the i^{th} element over j^{th} element. A is usually referred to as a reciprocal matrix. Note that:

(1) All diagonal elements of A are equal to unity, $a_{ij}=1$;

(2) A satisfies the property of reciprocity, since $a_{ij}.a_{ji}=1$;

(3) A is transitive in the sense that $a_{ik}.(a_{kj})=a_{ij}$

Multiplying A by the vector of priorities $\boldsymbol{a}=[a_1,a_2,\ldots,a_n]^{\mathrm{T}}$, one obtains $A\boldsymbol{a}=n\boldsymbol{a}$, namely $(A-n\boldsymbol{I})\boldsymbol{a}=0$ where $\boldsymbol{I}$ is the identity matrix; n denotes the largest Eigenvalue of A (Saaty 1980.). Thus the vector of priorities is simply equal to the corresponding normalized eigenvector associated with A.

Consistency Measure: In general, the user subjectively provides the value of a_{ij}; hence the transitivity property cannot always be strictly enforced. A consistency index (CI) has been introduced (Saaty 1980.) to estimate the departure from consistency by $C.I. = (\lambda - n)/(n-1)$, where λ is the maximal eigenvalue, and n is the number of elements (variables) being compared.

For each matrix of size n, random matrices were generated (Saaty 1980.) and their mean CI value, called the random index (RI), was computed. Using these values, the consistency ratio (CR) is defined as the ratio of the CI to the RI; it concluded that a consistent reciprocal matrix should have a CR < 0.1 [10]. When the CR>0.1, it is recommended that the user revisit his or her pairwise comparison.

The priority vector for identified variables obtained by AHP comparison, as made by the construction manager, is as follows:

$$\mathbf{w}=[0.062\ 0.462\ 0.164\ 0.162\ 0.172\ 1.000\ 0.816] \qquad (4\text{-}16)$$

According to Equation 4-16, the construction manager's opinion is that RWK, QAC and EQA have the highest impact on the issue concerned, while WKL, MPA, TEM, and PRE have a minimal impact. Two distinct operators for t-norms and s-norms are used to build two separate models. Model-A uses product and probabilistic sum as t and s norms, respectively; in the case of Model-B, min and max terms are used as t and s norms, respectively.

The value of the normalized performance index ($\bar{Q}$) (i.e., average value of Q per data point) of the optimal structure of Model A is equal to 0.02 and the value of Model B is equal to 0.03. Model A is therefore considered for further analysis.

The values of the normalized performance index vis-à-vis successive learning epochs for Model A are shown in Figure 4-4. The dashed lines represent five experiments initialized with random weights, and the solid lines represent the AHP-based initial weight assignment. Figure 4-4 shows that the AHP-based initialization always converges to a sub-optimal solution while random initialization converges away from a sub-optimal solution in certain instances.

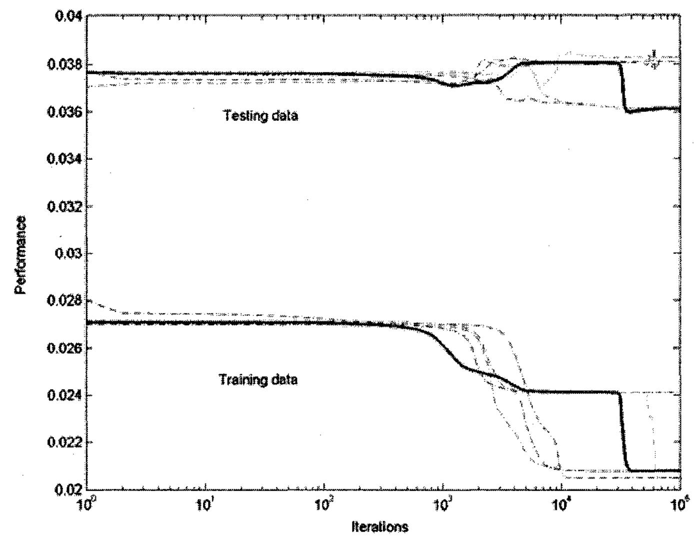


Figure 4-4. Normalized performance index in successive learning epochs

The above findings highlight that when expert causal knowledge is available with respect to an observed event, we can use the Analytic Hierarchy Process to capture the causal knowledge and the intuition of the expert so that a simple yet efficient fuzzy logic model can be developed to identify plausible explanations.

4.3.2.2 Interpretation of AND-OR Neuron Model Results

After optimization, the final value of the connection between the AND neuron and the OR neuron (v_1) is equal to 0.42, and the final value of the connection between the OR and the OR neuron (v_2) is equal to 1, making OR-wise connection of inputs to the network more significant.

Table 4-2 shows the comparison of initial and final weights of the connections of the AND and the OR neurons. Initial weight of the OR neuron ($\mathbf{w}_2$) is assigned using a normalized eigenvector, and the initial weight of the AND neuron is calculated as:

$$w_{1i} = 1 - w_{2i} \tag{4-17}$$

Since the OR neuron became significant in this particular instance, we analyze the final weights derived from the OR-wise connection (see highlighted column in Table 4-2). For OR neurons, the higher values for the connections emphasize that the corresponding inputs exert a stronger influence on the neuron's output. Accordingly, Low QAC, High RWK, and Low EAV were identified as significant contributors, compared to the seven variables identified that impact on labour productivity in HT. The comparison of the initial and final values of connections provides insight regarding how the optimization process changes the initial perception of the expert.

Table 4-2. Weight comparison of causal factors

			OR NEURON		AND NEURON	
		AHP-priority	Initial Weight	Final Weight	Initial Weight	Final Weight
WKL	Low	0.0618	0.0618	0.2441	0.9382	1.0000
	High		0.0618	0.0000	0.9382	0.9391
EAV	Low	**0.4616**	0.4616	**0.5627**	0.5384	1.0000
	High		0.4616	0.0000	0.5384	1.0000
MAV	Low	0.1637	0.1637	0.0000	0.8363	1.0000
	Medium		0.1637	0.0000	0.8363	1.0000
	High		0.1637	0.0000	0.8363	0.0000
TEM	Low	0.1623	0.1623	**0.3092**	0.8377	1.0000
	Medium		0.1623	0.0000	0.8377	0.0000
	High		0.1623	**0.4194**	0.8377	0.5455
PRE	LOW	0.1714	0.1714	0.0000	0.8287	0.0000
	High		0.1714	0.0000	0.8287	1.0000
RWK	Low	**1.0000**	1.0000	0.0000	0.0000	0.1850
	High		1.0000	**0.7513**	0.0000	1.0000
QAC	Low	**0.8162**	0.8162	**1.0000**	0.1838	1.0000
	High		0.8162	**0.4713**	0.1838	0.0000

Interestingly, this finding largely agrees with the expert's judgment given as a vector of priorities (Equation 4-16). The FNN model has the further advantage of identifying the significant linguistic terms, e.g., whether the *low* QAC or the *high* QAC has the greater impact on labour productivity of HT.

4.3.2.3 Accuracy of the AND-OR Neuron Model

Figure 4-4 illustrates graphically the FNN's output vs. target output. Figure 4-5 shows the corresponding network performance index over successive learning epochs. Both graphs indicate that the FNN network does not have sufficient non-linear modeling capabilities. Accordingly, several augmentations were made to the FNN model, and discussed in the following sections.

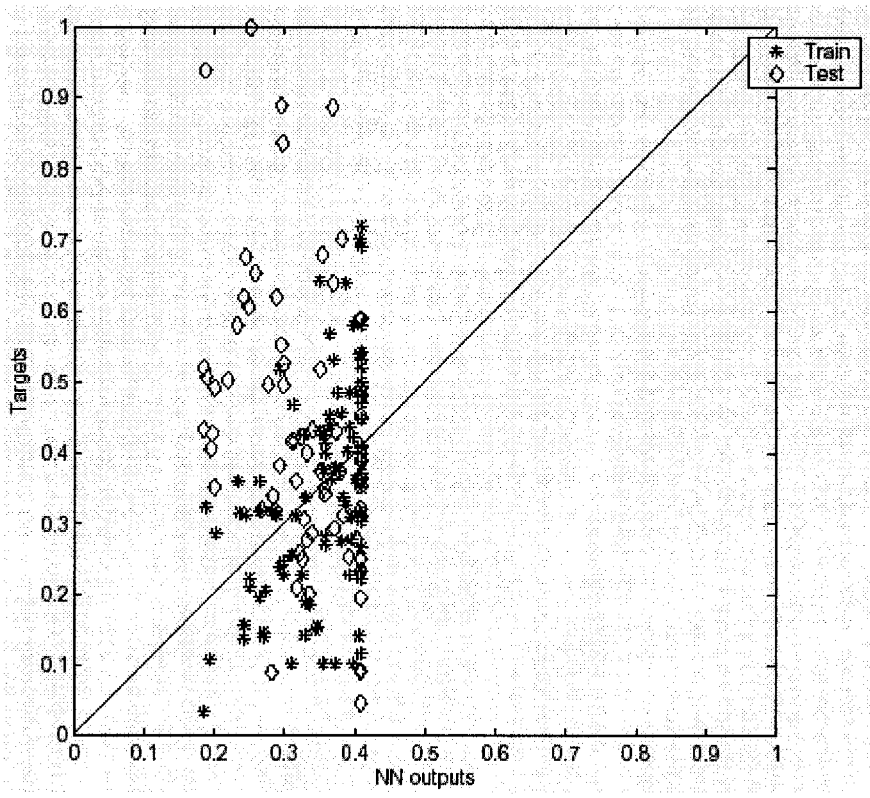


Figure 4-5. Plot of FNN output vs. target

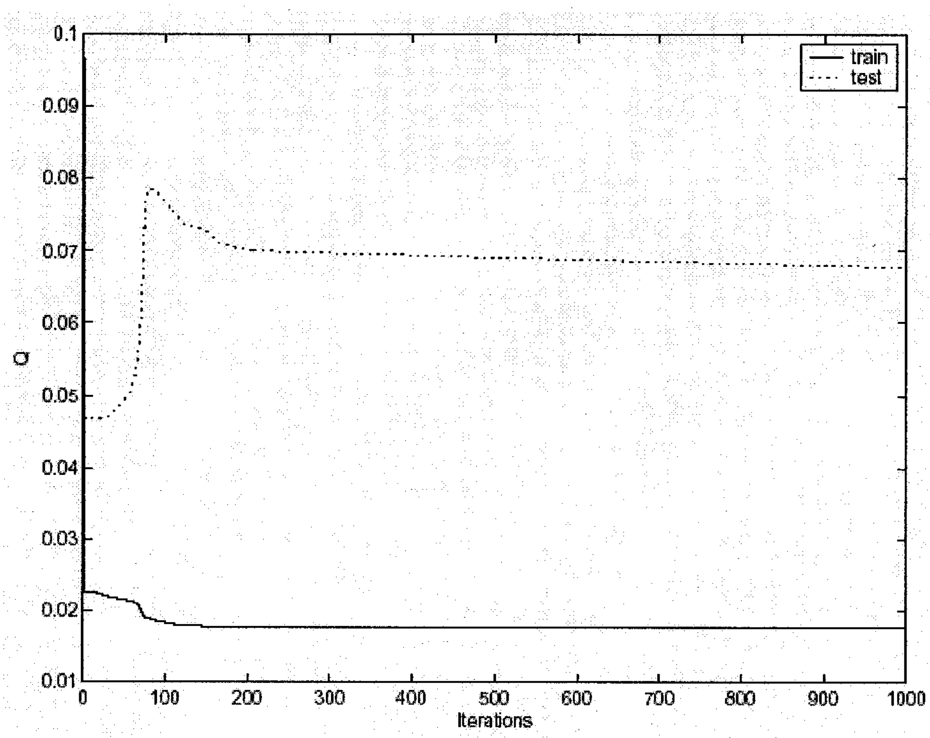


Figure 4-6. Network performance index in successive learning epochs.

4.3.3 Case 2: Using a Nonlinear Transfer Function

To improve the neurons' approximation capability, while keeping the characteristics of the AND-OR neuron model, a monotonic sigmoidal transfer function is applied at the output of the AND-OR neuron, as shown below in Figure 4-6.

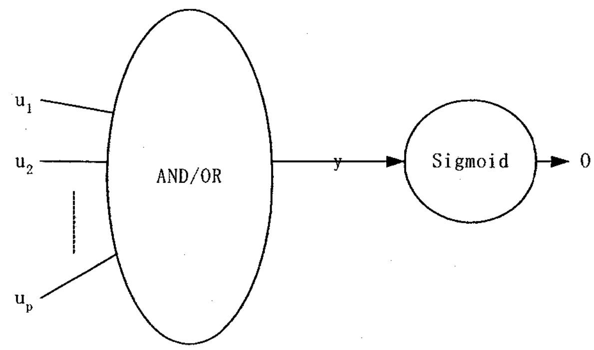


Figure 4-7. AND-OR neuron model augmented with sigmoidal transfer function

As a result, the new network output can be represented as follows:

$$y' = \frac{1}{1+\exp[-(y-m)*\sigma]} \tag{4-18}$$

Where y' is the output of the network (with sigmoidal function), m and σ are tunable parameters of the sigmoidal transfer function and y is the output of the AND-OR neuron model.

4.3.3.1 Learning/Optimization with Gradient Descending

Accordingly the performance index (4-12) is modified as follows:

$$Q = \frac{1}{T}\sum_{i=1}^{T}\left(y_r - y'\right)^2 \tag{4-19}$$

Where the y_r is target and y' as augmented FNN's output based on Equation (4-18) with respect to inputs $[u_1(r),...,u_p(r)]$. The parameters of Sigmoid function are adjusted as follows:

$m{=}m{-}\frac{1}{2}\alpha\frac{\partial Q}{\partial m}$, $\sigma = \sigma - \frac{1}{2}\alpha\frac{\partial Q}{\partial \sigma}$ where $\alpha \in [0,1]$ is the learning rate. (4-20)

4.3.3.2 Accuracy of the AND-OR Neuron Model with Sigmoidal Transfer Function

The network is trained and tested with the same data set. As shown in Figure 4-7, the resulting network (with Sigmoidal transfer function) still does not possess the ability to model the nonlinear characteristics of the problem at hand.

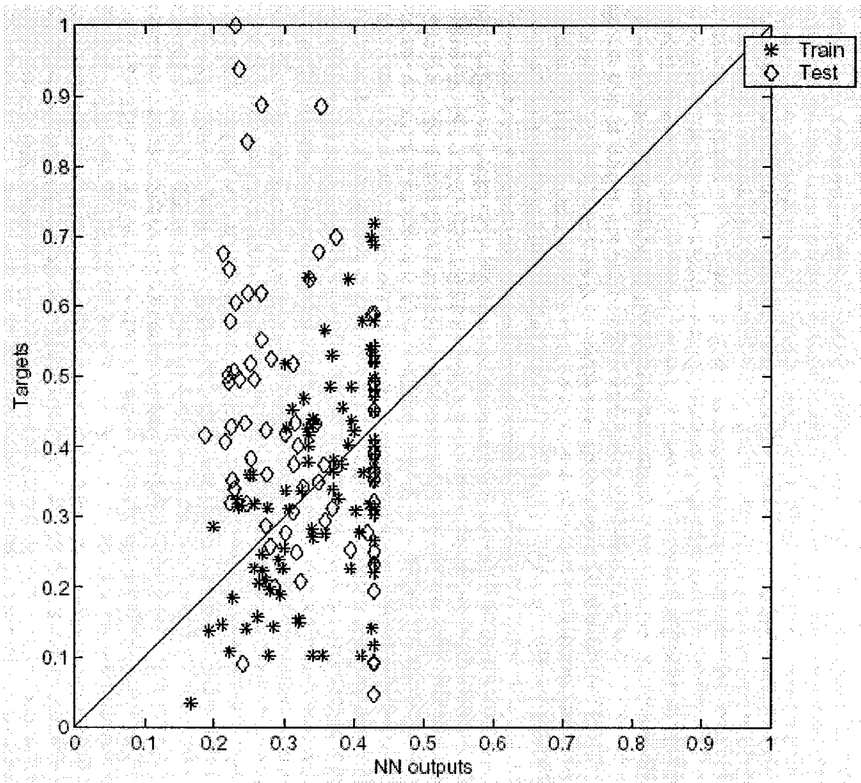


Figure 4-8. Target vs. AND-OR neuron model augmented with Sigmoidal transfer function

4.3.4 Case 3: Genetic Adaptive Learning

In this case, gradient descent learning is replaced by genetic algorithms, and the model discussed in Case 2 is optimized using genetic algorithms, as described in Section 3.4 of Chapter 3. The tunable parameters of the network are represented in a chromosome coded with a real vector, as shown in Figure 4-8.

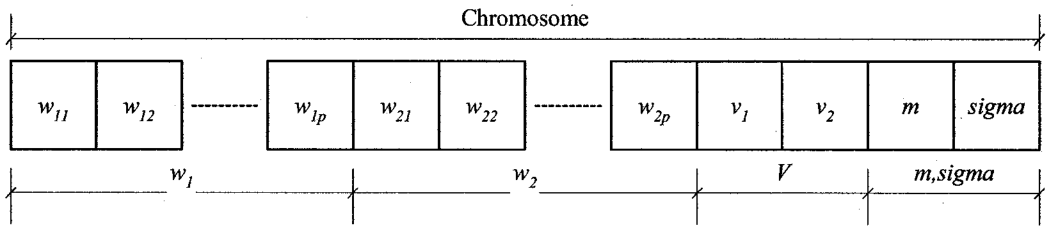


Figure 4-9. Chromosome representation

The network is trained with the most widely used genetic operators such as roulette-based selection, one point crossover and uniform mutation. The fitness function is defined as follows:

$$\Theta = \frac{1}{1+Q} \tag{4-20}$$

Where the Q is the performance index defined in Equation 4-19. The Probability of Crossover is set to 0.9; the probability of mutation is set to 0.01; and the initial size of the population is set to 50.

The network performance index in successive generations is shown in Figure 4-9. Albeit the training performance is better if compared to Case 1, the training performance is still not acceptable. The average and best fitness value of individuals is shown in Figure 4-10. As shown in Figure 4.11, the input-output mapping capability of the network has significantly improved with learning based on genetic algorithms, especially with the training dataset (final test Q=5.915x10^{-2}).

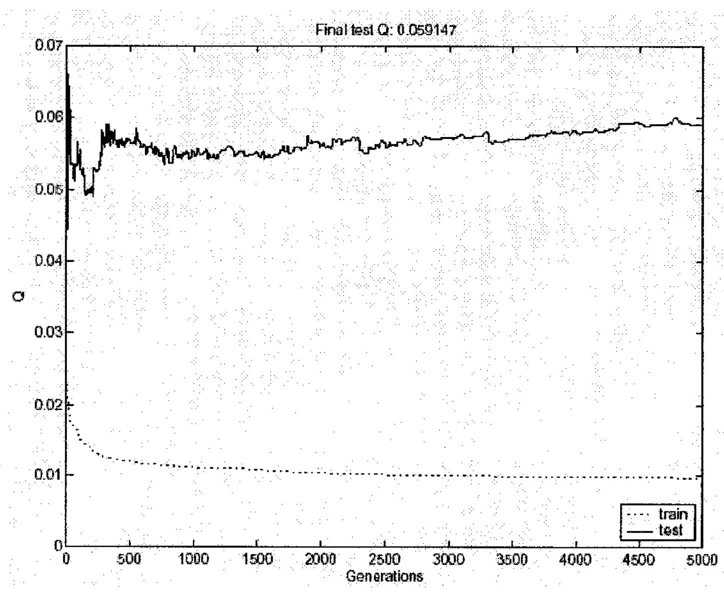


Figure 4-10. The values of network performance index (Q) in successive generations.

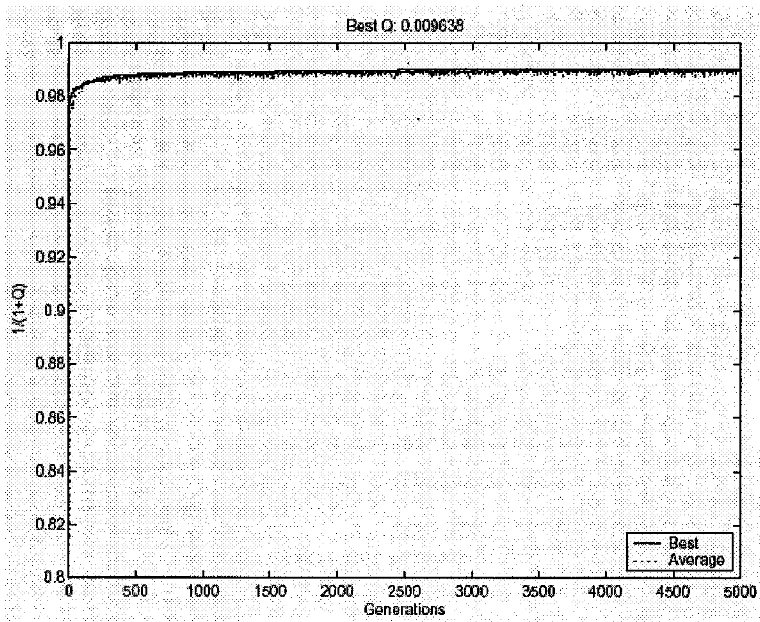


Figure 4-11. The average and best fitness value of individuals in successive generations.

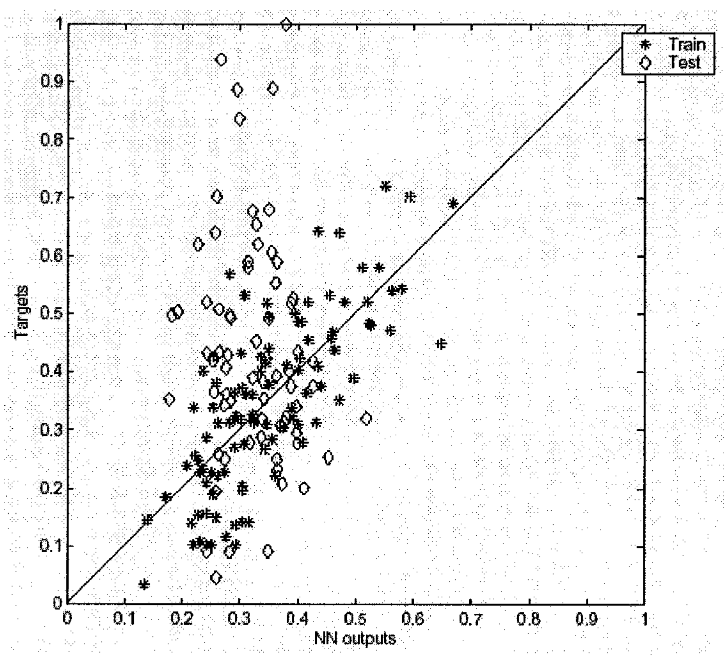


Figure 4-12. Target output vs. network output (trained using genetic algorithm)

4.3.5 Case 4: Genetic Adaptive Learning with Cumulative Impact Values

In this case, an assumption is made that there can be a cumulative impact of the input causal factor. For example, today's productivity is low not only because it rained today, but also due to the rain yesterday and the day before. To capture this cumulative impact, instead of using the input value at time *t*, a weighted average value is used as follows:

$$\hat{x} = \left(x_t + a * x_{t-1} + b * x_{t-2} + ... + k * x_d\right) / (1 + a + b + ... + k) \quad (4\text{-}21)$$

If a three day period is considered to assess the cumulative impact, and the corresponding weights for three days can be represented as a=0.8, b=0.6, c=0.4, the corresponding membership values can be represented as:

$$\bar{u}_i(t) = (u_i(t) + 0.8 * u_i(t-1) + 0.6 * u_i(t-2) + 0.4 * u_i(t-3)) / 2.8 \quad (4\text{-}21)$$

Accordingly, the most recent value (at time t) of the input causal factor gets a higher weight. While keeping the rest of the model characteristics the same as in Case 3, the FNN is trained and tested using the same dataset. As shown in Figure 4-11, the network performance is slightly improved (final test Q=5.334x10^{-2}); however, as illustrated in Figure 4-12, the network still does not demonstrate good generalization capabilities.

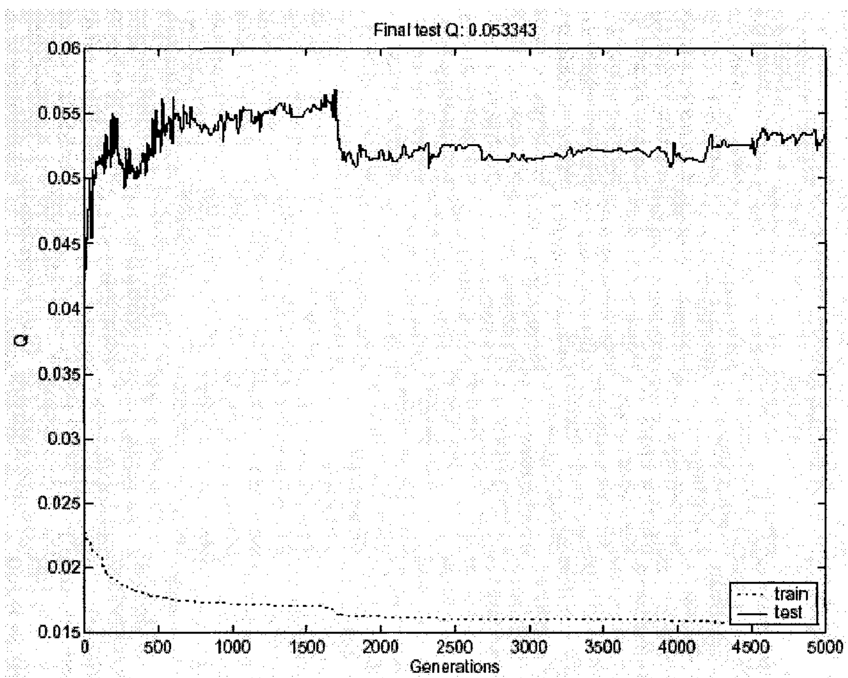


Figure 4-13. Network performance index on successive learning epochs (with cumulative input values)

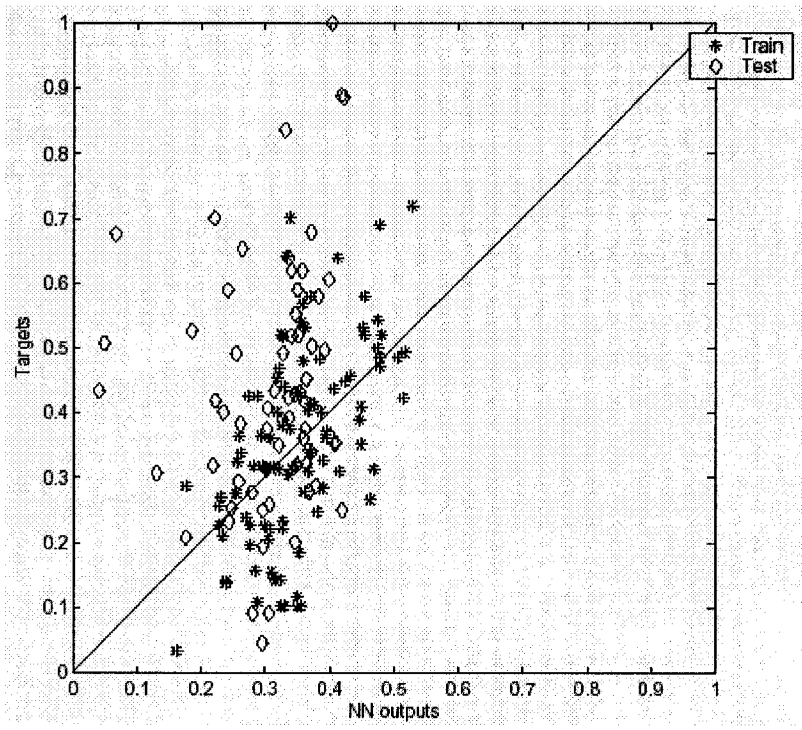
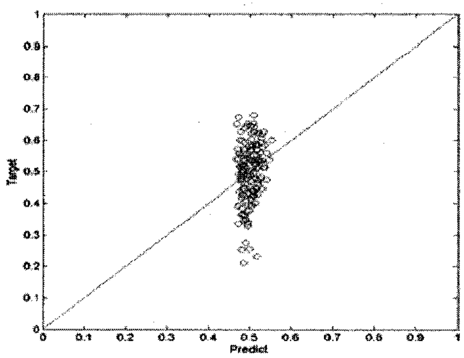


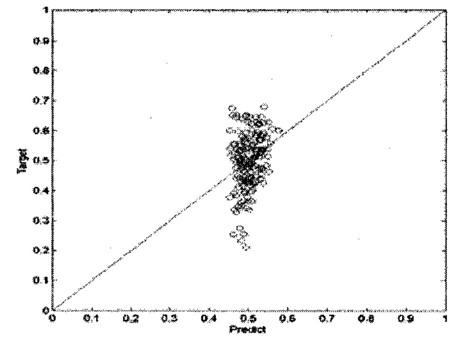
Figure 4-14.Target vs. Network Output (with cumulative input values)

4.4 AN ADDITIONAL TEST FOR NONLINEARITY

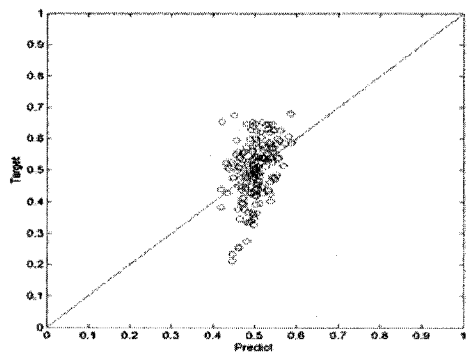
Having identified the limitations of the model in terms of generalization, to discover the underlying complexity of the problem, several high-order polynomial regression models were created, and the results are illustrated in Figure 4-13. It is clearly evident from the plots that the higher the order of the polynomial model, the higher the generalization capability. These high order polynomial regression models, however, have too many parameters to be easily determined; hence, the interpretation of the model becomes practically impossible. At the same time, it involves the predefined specification of the form of the regression equation. In construction performance modeling, the specification of the form of the regression equation is infeasible.



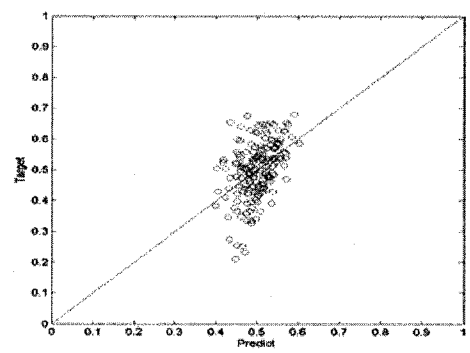
(a) linear relationship



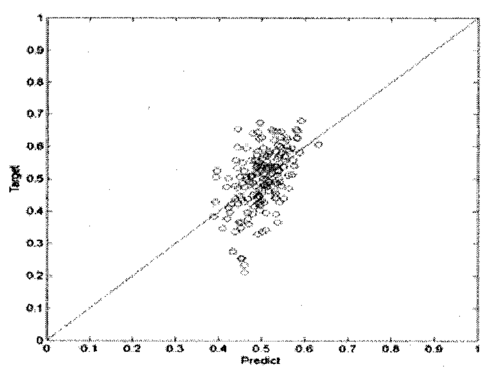
(b) quadratic



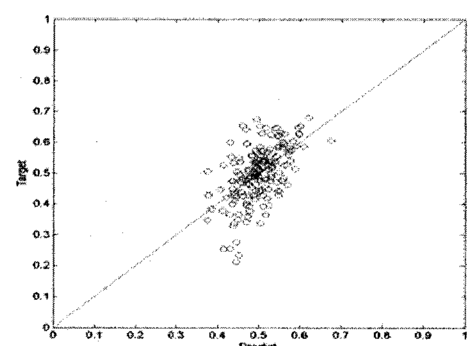
(c) third order



(d) fourth order



(e) fifth order



(f) sixth order

Figure 4-15. Target vs. high-order polynomial regression model output.

4.5 SUMMARY

This chapter describes a logical modeling framework based on AND-OR fuzzy neural networks. The simple yet efficient structure of the AND-OR neuron model provides the flexibility to identify the significance of input causal factors on key performance indicators in construction performance modeling. Based on four experimental cases, as shown in a summary Table 4-3, it can be concluded that the AND-OR Neuron model based on genetic adaptive learning with cumulative input values has, comparatively, the highest generalization, i.e., input-output mapping capability. The explanation capability of each model remains the same; however, the generalization capability of the model is fairly low (compared to a 6^{th} order polynomial regression model). All four AND-OR neuron models display considerable scatter and inconsistency between the target and the network output (see Figures 4-4, 4-7, 4-10, and 4-12). This can be considered an exemplary case of dichotomy between the generalization and explanation of a model.

The dataset used to test the AND-OR neuron model can be considered a representative sample of the construction performance data. Based on the experiments described above, it can be concluded that the underlying problem has a complex nonlinear character. Thus, to get a reasonably accurate input matting capability, a model that has greater generalization capabilities is required.

The next chapter presents an alternative network architecture that focuses on mapping the complex non-linear problem at hand at a greater level of accuracy. The main objective of the alternative system architecture is to enhance the generalization capability while maintaining the explanation capability that is available with the AND-OR neuron model in terms of interpreting connection weights.

Table 4-3. Summary results of AND-OR Neuron models

			AND				OR			
	Membership	AHP Weight	Basic Model	with Sigmoidal function	with GA	with Dynamic data	Basic Model	with Sigmoidal function	with GA	with Dynamic data
Initial v1			1	1	1	1	1	1	1	1
Initial v2			1	1	1	1	1	1	1	1
Final v1			0.999999	1	0.99765	0.99842	0.999999	1	0.99765	0.99842
Final v2			0.408605	0.952967	0.94072	0.72934	0.408605	0.952967	0.94072	0.72934
Work load	Low	0.061844	0.93815	0.938197	0.99934	0.99838	0	0	0.15128	0.72065
	Medium	0.061844	0.938152	0.938203	0.99772	0.99993	0	0.262776	0.9876	8.82E-04
	High	0.061844	0.938166	0.938183	0.0009528	0.48303	0	0	0.15246	0.00047505
Equipment availability	Low	0.46156	0.538429	0.538529	0.99865	0.99048	0.617717	0.50906	0.12547	0.99938
	Medium	0.46156	0.538434	0.538519	0.15781	0.34948	0	0	0.000264	0.0003907
	High	0.46156	0.538447	0.538442	0.99986	0.99976	0	0	0.59353	0.0010322
Manpower availability	Low	0.163688	0.83631	0.836362	0.99863	0.99944	0	0	0.8474	0.0020526
	Medium	0.163688	0.836317	0.836331	0.99975	0.42225	0	0	0.10747	0.80279
	High	0.163688	0.836312	0.836374	9.61E-05	0.8317	0.35765	0.29063	0.63813	0.75058
Mean tempereture	Low	0.16227	0.83773	0.837794	0.99905	0.99935	1	1	0.95932	0.21315
	Medium	0.16227	0.83773	0.837764	0.0011585	0.52217	0.450552	0.744908	0.92895	1.35E-06
	High	0.16227	0.83773	0.837756	0.99956	0.99968	1	1	0.56065	0.00010123
Total Precipitation	Low	0.171348	0.828652	0.828652	0.97459	0.0022023	0	0.378654	0.37025	0.00050449
	Medium	0.171348	0.828652	0.828717	0.99967	0.99775	0	0	0.084054	0.00027176
	High	0.171348	0.828652	0.828717	0.99861	0.99959	0	0	0.99947	0.59473
Rework	Low	1	0	0	0.99369	0.054153	0	0	0.64198	0.00090474
	Medium	1	7.89E-06	0	0.17794	0.99989	0	0.00339298	0.71803	0.002056
	High	1	0	0.0103447	0.99881	0.9996	0.19438	0.371263	0.002645	0.65103
QA/QC	Low	0.81617	0.183837	0.183888	0.10401	0.67953	0	0	0.009764	0.46068
	Medium	0.81617	0.183733	0.183656	0.99686	0.9995	0.466896	0.532425	0.74245	0.00051952
	High	0.81617	0.183852	0.184178	0.9996	0.99754	0	0	0.15187	0.70547
Final Q- Training (100 data points)			0.0177551	0.0167294	0.009638	0.015693	0.0177551	0.0167294	0.009638	0.015693
Final Q- Testing			0.067774	0.0715309	0.059147	0.053343	0.067774	0.0715309	0.059147	0.053343
m			x	1	0.92067	0.76864	x	1	0.92067	0.76864
sigma			x	6.03942	-74.899	10.679	x	6.03942	-74.899	10.679

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CHAPTER FIVE

5. FUZZY ADAPTIVE GENERALIZED REGRESSION NEURAL NETWORK (FA-GRNN)

5.1 INTRODUCTION

This chapter demonstrates the utility of applying an alternative network processing module based on a synergistic combination of neural networks (specifically, Generalized Regression Neural Networks), Fuzzy Sets, and Genetic Algorithms (GA). Fuzzy neurons are introduced to the classical GRNN architecture as a means of handling granulated information. The learning and inference modes of the network are discussed and its application to construction performance modeling is presented. This chapter contains many of the author's earlier results (Dissanayake et al. 2005), recast in light of later developments.

5.2 GENERALIZED REGRESSION NEURAL NETWORKS (GRNN)

A generalized regression neural network (Specht 1991; Specht and Romsdahl 1994) is a memory-based network capable of fitting multidimensional surfaces through data via a one-pass learning algorithm; it provides estimates of its variables and converges with an underlying linear or nonlinear regression surface. Since Specht's (1991) work on GRNN, the methodology has been successfully applied in several cases (Kiefa 1998; Seng et al. 1999). The incentives to using a GRNN model in construction performance modeling, relative to other nonlinear modeling techniques, are as follows:

- The network instantly defines a very reasonable regression surface, even with sparse data in a multidimensional measurement space, that is, in a real-time environment (Specht 1991; Seng et al. 1999);
- The network can be used to rank input variables using (local) smoothing factors (Specht and Romsdahl 1994) ;
- Since the network is not based on the gradient descent algorithm, it does not face the local minima problems, which results in rapid training;
- The network provides a mechanism for updating new knowledge (data) to the network and forgetting old data (Specht 1991; Seng et al. 1999);
- The network can be optimized/calibrated easily using genetic algorithms (Ward Systems Group, Inc. 2003).

5.3 FUZZY ADAPTIVE GENERALIZED REGRESSION NEURAL NETWORK (FA-GRNN)

This section presents the proposed network architecture. It differs from Sprecht's classical GRNN (Specht 1991) in three ways. First, an additional layer of (fuzzy) neurons is introduced to capture and represent expert knowledge on causal factors. Additionally, since fuzzy neurons transform input values to a unit interval, this additional layer also facilitates as the input scaling step. Secondly, both the transparency and the accuracy of the classical GRNN are enhanced by adapting separate smoothing parameters, or "local smoothing factors", as suggested by Specht and Romsdahl (1994). Thirdly, the network is trained using real-coded genetic algorithms, making the network optimization procedure more efficient and accurate. The pertinent details of the proposed fuzzy adaptive generalized regression neural network (FA-GRNN) are presented below.

The proposed FA-GRNN architecture is illustrated in Figure 5-1. It consists of five layers, namely: input, fuzzy neurons, pattern, summation, and output.

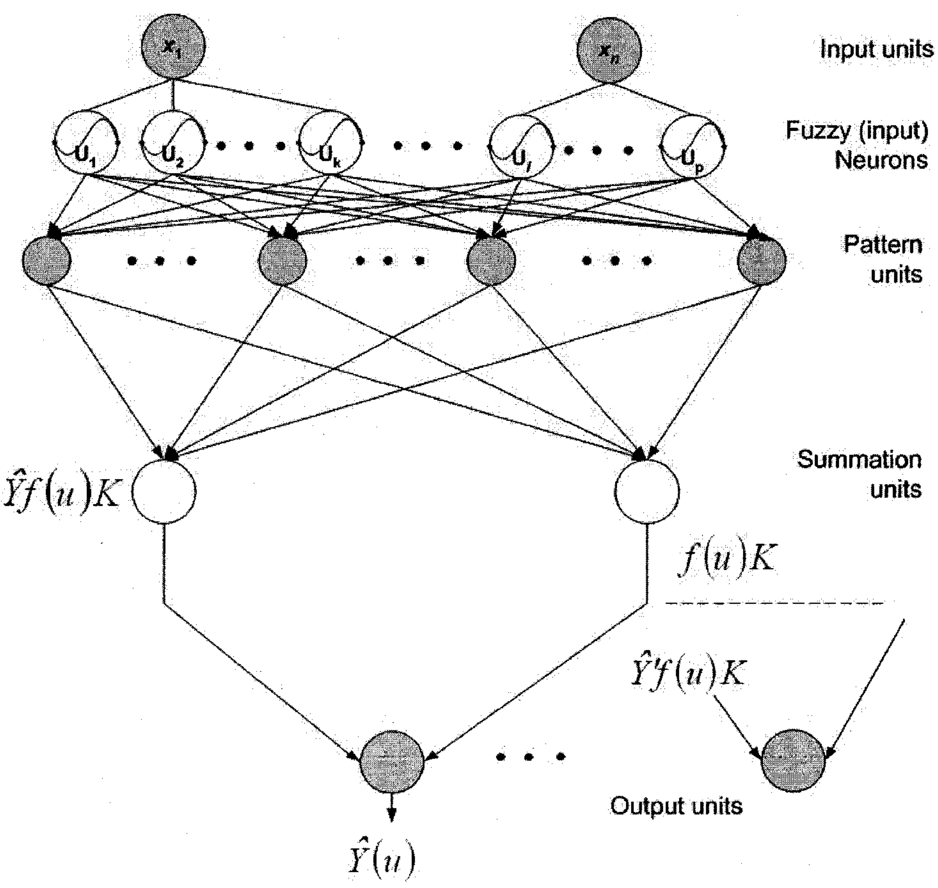

Figure 5-1. Fuzzy Adaptive Generalized Regression Neural Network Architecture

The input layer consists of input units that represent causal factors (of KPIs). Input units are merely distribution units. Input units channel the values of causal factors, **x** (i.e., input variables), to the fuzzy neurons in the second layer. The fuzzy input neuron layer represents the respective linguistic values as fuzzy sets of each input causal factor. Fuzzy neurons calculate the corresponding membership values and transfer them to the pattern layer.

The pattern layer consists of pattern units representing each data pattern (one exemplar, i.e., values of input vector **u** in day *t*) by one pattern unit. Hence the number of pattern units of a FA-GRNN model is equal to the number of observed data patterns (i.e., total number of days, *T*, represented in training dataset). Pattern units sum the squared values of the difference between the new and stored data patterns and feed this information into a nonlinear activation function (e.g., exponential). The pattern unit outputs are then passed to the summation units. The summation unit that generates *f*(u)K sums the outputs from the pattern units weighted by the number of observations each cluster center represents. (K is a data-dependant constant). The summation unit that generates Y*f*(u)K multiplies each value from a pattern unit by the sum of sample Y, which is associated with cluster-centre X. The function of the output neuron consists in a simple division of Y*f*(u)K by *f*(u)K. In general, the direct mapping between inputs and output of the system is given in Equation 5-1:

$$\hat{y} = \frac{\sum_{t=1}^{T} y_t \exp\left[-\frac{D^2}{2\sigma^2}\right]}{\sum_{t=1}^{T} \exp\left[-\frac{D^2}{2\sigma^2}\right]} \tag{5-1}$$

Where
$$D^2 = \sum_{l=1}^{p} \sigma_l \left(u_l - u_l^t\right)^2 \tag{5-2}$$

x_i	Input variable, i.e., causes (e.g., crew skill level, temperature)
y	Output variable, i.e., Key Performance Indicator (KPI) (e.g. Labour Productivity)
$\hat{y}$	Network output (e.g. predicted Performance Factor)
n	Number of factors
T	Number of data patterns
m_{ij}	Membership functions of input variable x_i
u	Input vector
k	Number of membership functions of each input variable
p	Total number of input membership functions

c	Center of the sigmoidal transfer function
σ_s	Sigmoid
σ	Global smoothing factor
σ_l	Individual (local) smoothing factor
i, j, t, l	Index

The interested reader is referred to the further research of Specht (1991) for a more detailed methodology and for the process of implementing this formula.

5.3.1 Smoothing Factors

As shown in Equation 5-1 and Equation 5-2, the only parameters of the FA-GRNN are the global smoothing factor (σ) and the local (individual) smoothing factors σ_l. Both σ and σ_l are automatically calculated using the genetic algorithm (GA)-based optimization procedure, which is described in Section 5.3.2. The global smoothing factor determines how tightly the network matches its prediction to the training data patterns. A higher global smoothing factor causes more relaxed surface fits through data. The local smoothing factor σ_l is a positive value representing the relative significance of the l^{th} input variable to the distance measurement D (e.g., city block distance, Euclidean distance).

5.3.2 Learning and Optimization Mode of the FA-GRNN Model

The learning and optimization of the FA-GRNN network is the process of finding the smoothing factors (σ, σ_l) through supervised learning. The results of the learning can also be used to prune the network and finally determine the best network topology. The learning mode of the proposed FA-GRNN architecture is presented in Figure 5-2.

Consider a multi-input and a single-output (MISO) scenario, with n inputs $x_1, x_2, \ldots, x_n \; (x_i \in X_i, i = 1,2,\ldots,n)$ and the single output y. The learning data, which are the basis for the construction of a fuzzy neural network, have the form of T input-output pairs, as given below:

$$L = \{\mathbf{x}_t, \mathrm{y}_t\}_{t=1}^{T} \tag{5-3}$$

The learning data set $\boldsymbol{L}$ consists in finding the mapping $M{:}\, \boldsymbol{X} \rightarrow y$, provided its restrictions on learning data $\boldsymbol{L}$. In general, the learning data set (5-3) may contain purely quantitative numerical data samples or mixed qualitative and quantitative samples of data.

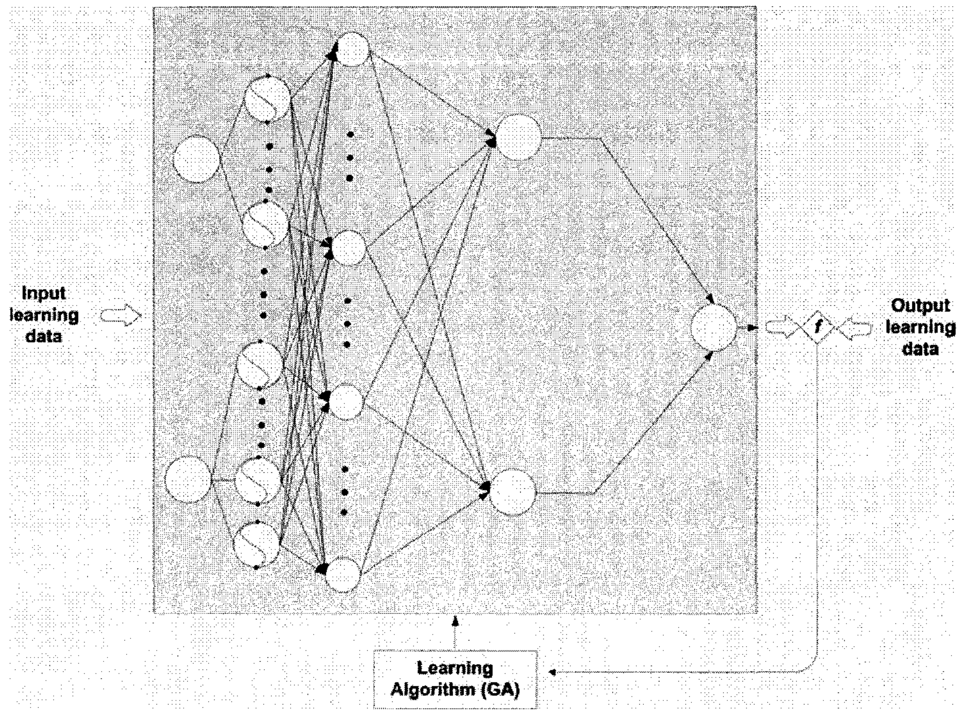

Figure 5-2. Learning mode of the FA-GRNN

Accordingly, to characterize the mix of quantitative and qualitative data, we represent each input factor using fuzzy membership functions, as shown below:

$$m_{ij}, (i = 1,2,...,n; j = 1,2,...,k) \tag{5-4}$$

Where m_{ij} is membership functions of input variable x_i, n is the number of input factors and k is the number of membership functions for each factor. Vector **u** represents the combined membership grades (m_{ij}) in a single input vector in Equation (5-5) below:

$$\mathbf{u} = [m_{11}, m_{12}, ..., m_{1k}, m_{21}, m_{22}, ..., m_{2k}, ..., m_{n1}, m_{n2}, ..., m_{nk}] = [u_1, u_2, ..., u_p] \tag{5-5}$$

Where total dimension of u is $p = n.k$. Thus the learning dataset is a comprehensive representation of the data and knowledge describing the behaviour of complex systems.

When the desired output (i.e., key performance indicator) is best represented by quantitative measures, such as labour performance factors, target output values can be represented as in Equation 5-6.

$$y_t' = \frac{1}{[1 + \exp\{-(y_t - c)\sigma_s\}]} \tag{5-6}$$

5.3.3 Parametric Optimization via Genetic Algorithms

To avoid getting trapped in a local optimal solution, the genetic algorithm's robust optimization capabilities are utilized to calibrate the proposed FA-GRNN model.

5.3.3.1 Network Performance Index

The learning algorithm's target is to find the best parameter values for retaining the smallest possible difference between the predicted value $\hat{y}_t$ and the real output y_t'. In other words, the goal is to find the best smoothing factors to keep the network performance index(Q), i.e., mean squared errors, defined in Equation 5-7, as small as possible.

$$Q = \frac{1}{T}\sum_{t=1}^{T}\left(y_t' - \hat{y}_t\right)^2 \tag{5-7}$$

Where $\hat{y}_t$ is a predicted value computed using Equation (5-3) with input vector **x**.

Additionally, the coefficient of a multiple determination (R^2) provides an estimate of the accuracy of the model. R^2 is calculated as follows:

$$R^2 = 1 - \frac{\sum\left(y_t' - \hat{y}_t\right)}{\sum\left(y_t' - \bar{y}\right)} \tag{5-8}$$

Where $\bar{y}$ is the mean of y_t''s values. According to Equation 5-8, a very good fit would result in an R^2 value of near 1 and a very poor fit less than 0.

5.3.3.2 Learning Based on Genetic Algorithm

To minimize the performance index (Q), a real coded genetic algorithm is applied, as described in Section 3.4 of Chapter 3. The tunable parameters of the FA-GRNN network are represented in a chromosome coded with a real vector. The first n real number represents the n local smoothing factors σ_j (j=1,..., n), and the $(n+1)^{th}$ real number represents the global smoothing factor σ.

The network is trained with the most widely used genetic operators, such as roulette-based selections, one-point crossover, and uniform mutation. The fitness function is defined as follows:

$$\Theta = \frac{1}{1+Q} \tag{5-9}$$

Where Q is the performance index as defined in Equation (5-7). The Probability of Crossover is set to 0.9; the probability of mutation is set to 0.01; and the initial size of the population is set to 50.

5.3.4 Interpretation of the Network via Smoothing Factors

According to Equation 5-1, the larger the value of the individual (local) smoothing factor σ_l, the higher the impact the input variable j will have on the distance measurement and on the final output $\hat{y}$. In other words, when sample data points for one variable have a greater smoothing factor than sample data points for a second variable, the first variable is said to be more important in predicting an outcome than the second variable. An examination of the relative ranking of individual smoothing values σ_l reveals which input variables are most important in determining the output. This property is used to identify the strength between causal factors and related key performance indicators in construction performance modeling.

5.4 EMPIRICAL VALIDATION OF THE FA-GRNN MODEL

5.4.1 Description of Data

The same dataset described in Chapter 4 (Section 4.3.1) is used to conduct the experiments to train and validate the FA-GRNN model. For the reader's convenience, Table 4-1, which described the causal factors studied, is here reproduced as Table 5-1. A simple, cluster-based approach (Hong and Lee 1996) is used for designing membership functions for input fuzzy neurons based on the sample data.

Table 5-1. Causal factors that impact labour productivity in Pipe Hydro-testing

	Causal Factor		Description
F1	WKL	Work Load	No. of pipe modules in progress
F2	EQA	Equipment availability	No. of cranes available
F3	MAV	Manpower availability	No. of pipefitters available
F4	TEM	Mean Temperature	The mean temperature of the air in degrees Celsius.
F5	PRE	Total precipitation	The sum of the total rainfall and the water equivalent of the total snowfall
F6	RWK	Rework	Pipe fabrication rework (work force hours spent on repairs)
F7	QAC	Quality Assurance/ Quality Control input	No. of hours spent on QA/QC work.

Figure 5-3 shows the membership function for Factors F1-F3 and F5-F7. Data for Factor F4 (i.e., temperature) are categorized into four respective seasons (due to a highly seasonal dependant nature) and membership functions are derived accordingly (see Figure 5-4).

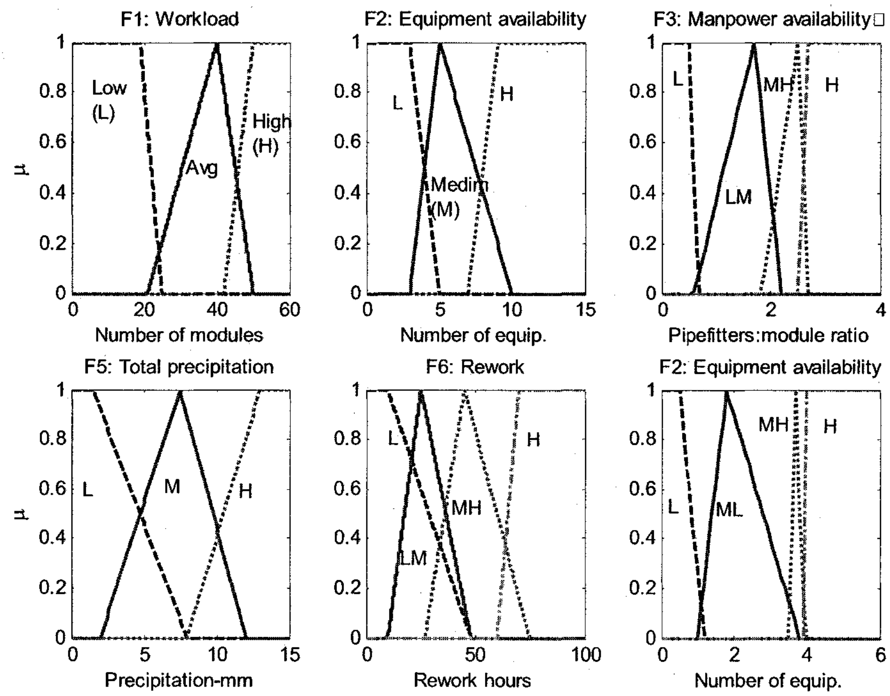

Figure 5-3. Membership functions.

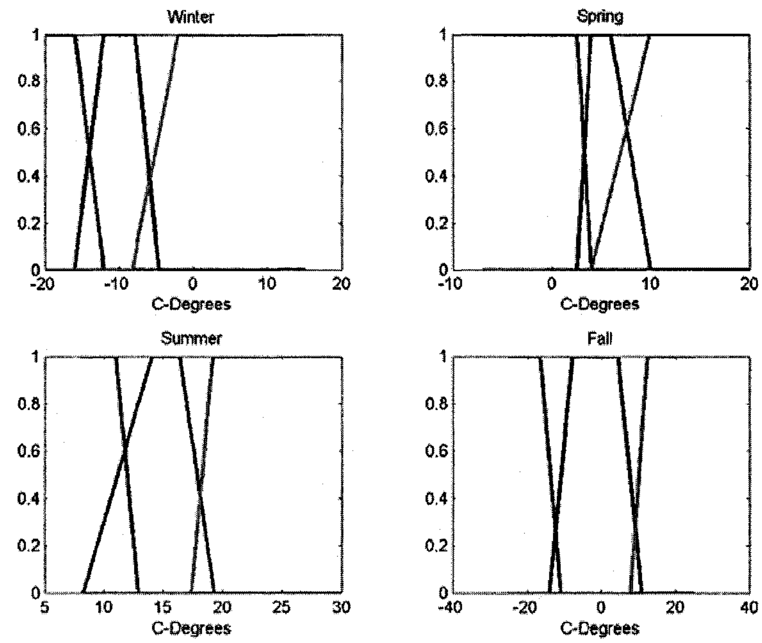

Figure 5-4. Membership functions for temperature (cold, average and warm).

5.4.2 Case 1: FA-GRNN Model Validation using Full Data Set

In this case, the proposed FA-GRNN architecture is realized using genetic algorithms, beginning with 132 *training* data patterns and tested with 32 data patterns. Figure 5-5 shows the performance of the network in terms of a comparison between the actual (i.e., target) and network outputs, both in the training and testing data sets. The Mean Squared Error (MSE), i.e., Q of the FA-GRNN network is 0.002, may be compared to the best performance of the AND-OR neuron model (i.e., 0.0533), as presented in Chapter 4. The coefficient of determination (R^2) of the FA-GRNN network is equal to 0.67. This is a comparatively significant improvement, and based on the visual analysis of the scatter plot shown in Figure 5-5a, one can conclude that this preliminary investigation into possible applications of the FA-GRNN model in modeling the complexity and the dynamics of the construction performance proves very promising. Figure 5-6 shows the corresponding test-error elapsed over several generations, which shows that the FA-GRNN model converges to an acceptable error smoothly. Appendix C presents a summary of the actual output (i.e., measured labour productivity factor) and the results predicted by the FA-GRNN model for all 164 records included in both the training and the testing datasets.

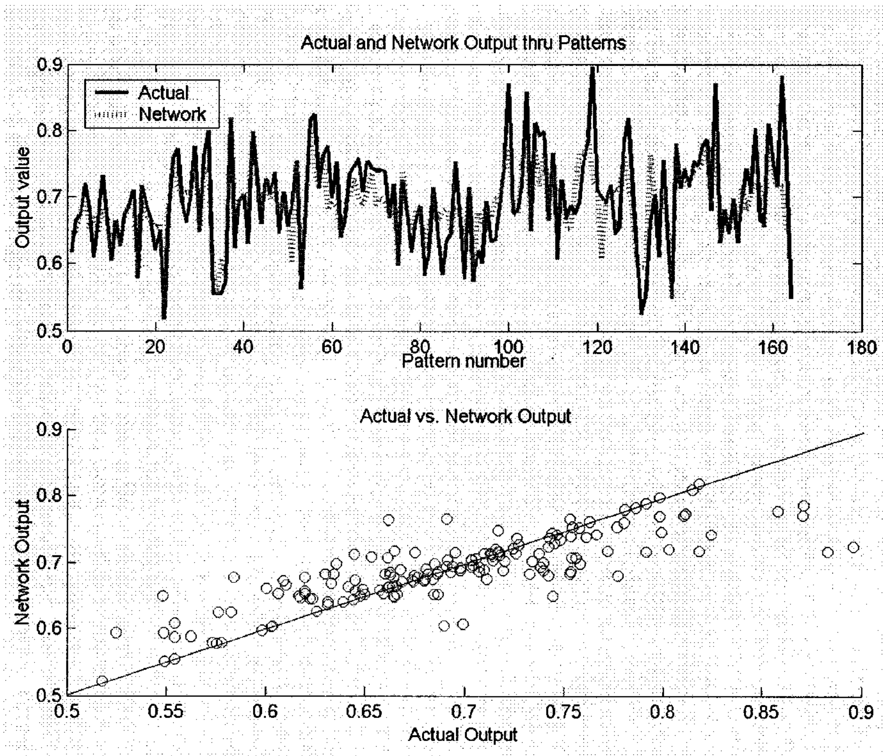

Figure 5-5. FA-GRNN Network performance (based on full dataset): (a) comparison of actual and network output through patterns, (b) Comparison of actual vs. network output.

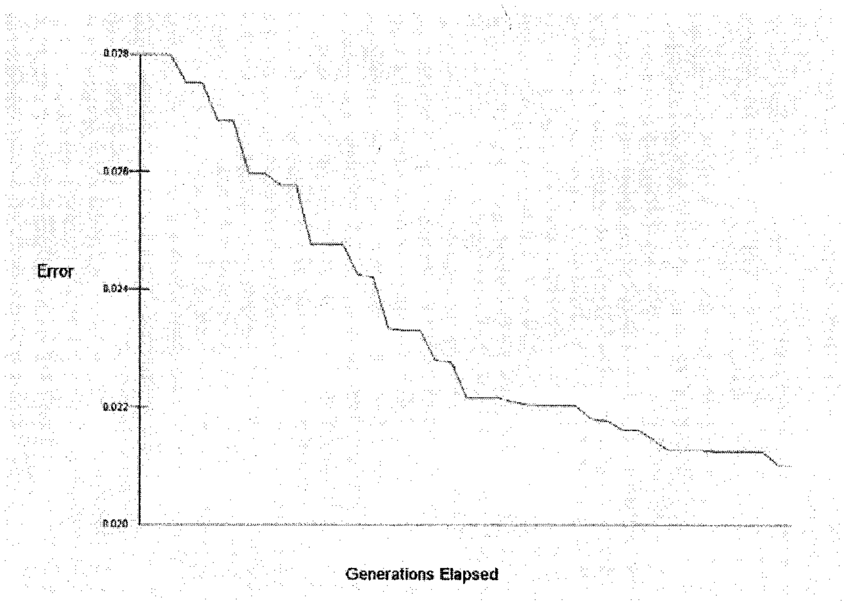

Figure 5-6. FA-GRNN test error in successive generations.

For comparison purposes, the same data set is fed into a multilayer back propagation artificial neural network (ANN). The test error (Q) in successive learning epochs is shown in Figure 5-7, which shows that the average error level is somewhat similar to the FA-GRNN network, but it is highly unstable.

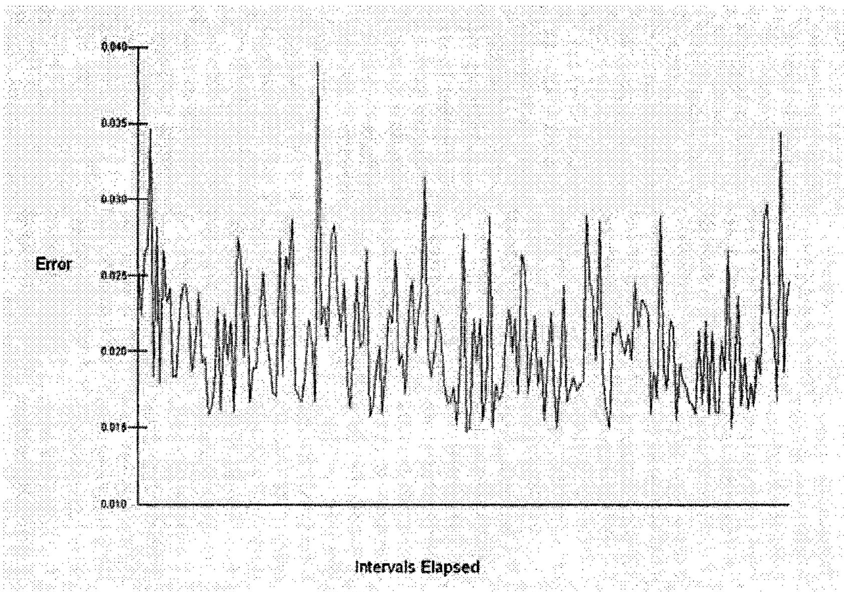

Figure 5-7. Traditional ANN test error in successive generations.

Comparison of Figure 5-6 and Figure 5-7 indicates that FA-GRNN model outperforms not only the AND-OR neuron model, but also the traditional ANNs.

5.4.2.1 Interpretation of FA-GRNN Results

During the training phase, the FA-GRNN model is trained adaptively with 132 data patterns, and the network's robustness is tested with 32 data patterns. The resulting FA-GRNN network has the following local smoothing factors, as shown in Table 5-2. Accordingly, it can conclude that low manpower availability, low workload, and medium to high rework have the highest impact on pipe hydro-testing productivity for the time period represented by the dataset.

The above model was trained and tested with 169 data patterns representing 169 working days. To exploit GRNN's capability of modeling with sparse data, the following changes were made to the data pattern set: first, the patterns were categorized according to their respective months and 11 models were trained and tested; second, the patterns were categorized into respective (four) seasons, and 4 models were trained and tested.

The rationale in developing models using data sets representing months and seasons is that most of the possible causal factors of construction performance indicators will change dynamically as the construction project unfolds. For example, from season to season, changes in weather parameters can be observed; manpower and equipment availability will change based on the scope of the work scheduled; and more fabrication rework can be expected at the early and latter stages of the project due to the learning-curve effect and compressed schedules, respectively. Both monthly and seasonal data pattern sets can be considered as natural clusters of data for construction performance modeling.

Table 5-2. Local smoothing factors and rankings from FA-GRNN model

	CAUSAL FACTOR	FUZZY INPUT	SMOOTHING FACTOR	RANK
F1	Workload	Low	2.96	**2**
		Average	0.14	19
		High	0.21	17
F2	Equipment availability	Low	2.48	9
		Medium	2.39	10
		High	0.15	18
F3	Manpower availability	Low	2.99	**1**
		Low-Medium	2.62	8
		Medium-High	0.00	24
		High	0.01	22
F4	Mean Temperature	Low	1.73	13
		Average	0.01	23
		High	2.65	**5**
F5	Total precipitation	Low	0.35	16
		Medium	2.15	11
		High	2.06	12
F6	Rework	Low	2.64	7
		Low-Medium	2.85	**3**
		Medium-High	2.73	**4**
		High	2.65	**5**
F7	Quality Assurance/ Quality Control input	Low	1.24	15
		Low-Medium	0.08	21
		Medium-High	0.08	20
		High	1.28	14

5.4.3 Case 2: FA-GRNN Models Trained with Monthly Data Pattern Sets

To validate the proposed FA-GRNN model described above for sparse data, the model was trained and tested with eleven (11) data pattern sets, which were created by categorizing the original dataset (162 patterns) according to respective months. Summarized in Table 5-3 are the performance results of the model based on 11 data pattern sets. Comparisons between the actual output and FA-GRNN model outputs are shown in Figure 5-8.

As shown in Table 5-3, the number of training data patterns for each new data set varies from 8 to 16. Even though a significant reduction in the number of training data patterns (i.e., 132→16) were made, in 54% of the cases (6 out of 11), the accuracy of the model (based on both Q and R^2) is greater than the FA-GRNN model trained with the full dataset. In both cases, however, where training data patterns were less than 10, the accuracy of the model decreases, indicating insufficient pattern data. Conversely, in cases where numbers of training data patterns were higher than 15, model accuracy was increased by 43%. A possible explanation may be that with sufficient data patterns representing similar clusters of data, the proposed FA-GRNN model can produce better results, even with sparse datasets. As shown in Figure 5-9, the mean squared error of all 11 different models converged smoothly to an acceptable error level.

Table 5-3. Summary statistics of FA-GRNN model trained with monthly datasets.

	NUMBER OF TRAINING PATTERNS	NUMBER OF TEST PATTERNS	R^2	MEAN SQUARED ERROR:Q	CORRELATION COEFFICIENT r:
All	132	32	0.667	0.002	0.829
April	16	3	0.962	0.000	0.981
May	8	2	0.257	0.004	0.705
June	12	2	1.000	0.000	1.000
July	15	3	0.722	0.001	0.853
August	12	3	0.947	0.000	0.978
September	13	3	0.577	0.001	0.825
October	16	3	0.969	0.000	0.986
November	12	2	0.660	0.001	0.862
December	8	2	0.596	0.004	0.792
January	10	2	0.976	0.000	0.991
February	14	3	0.446	0.003	0.687

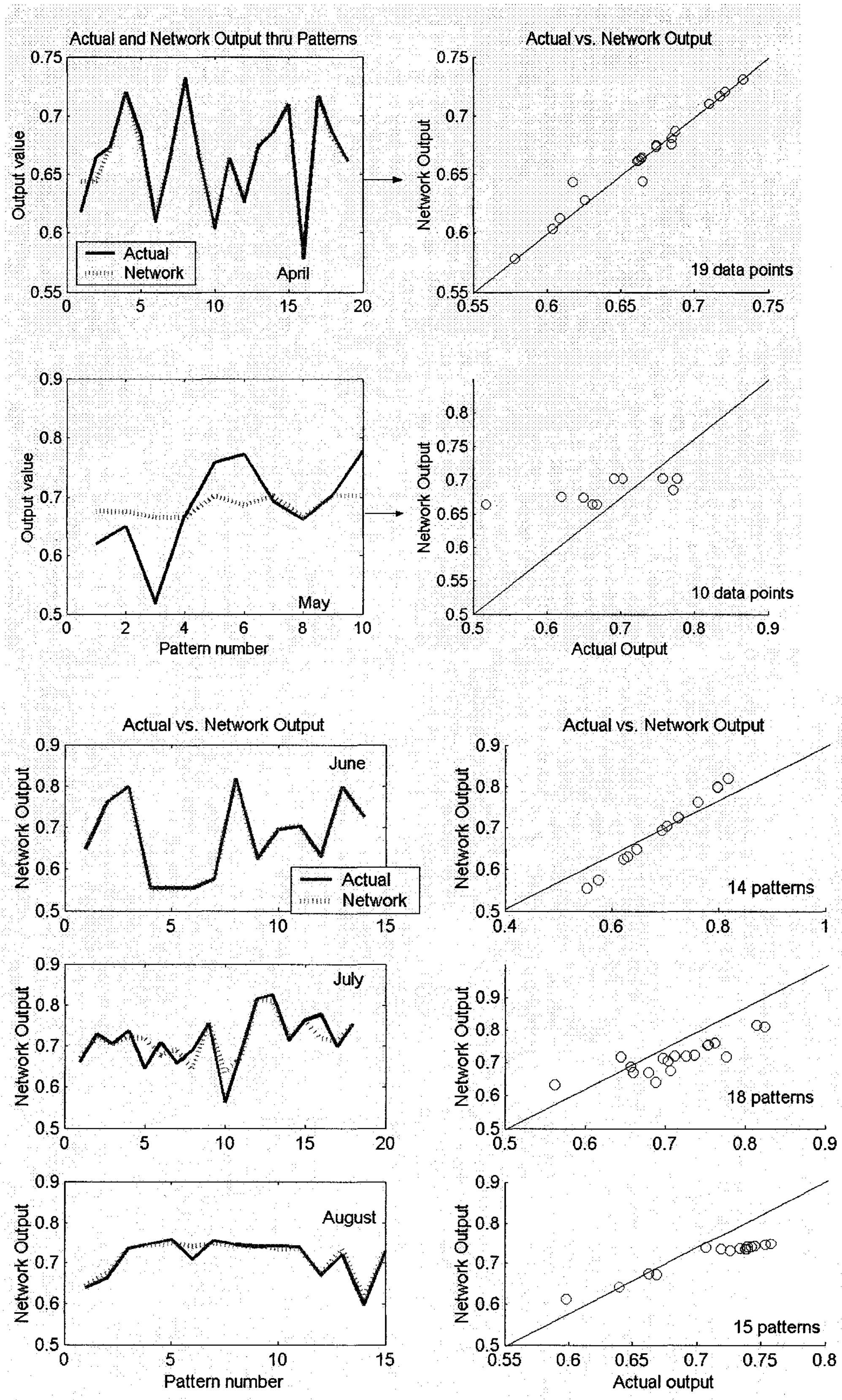

Figure 5-8. a. Actual vs. network output comparison for April 2003 through August 2003.

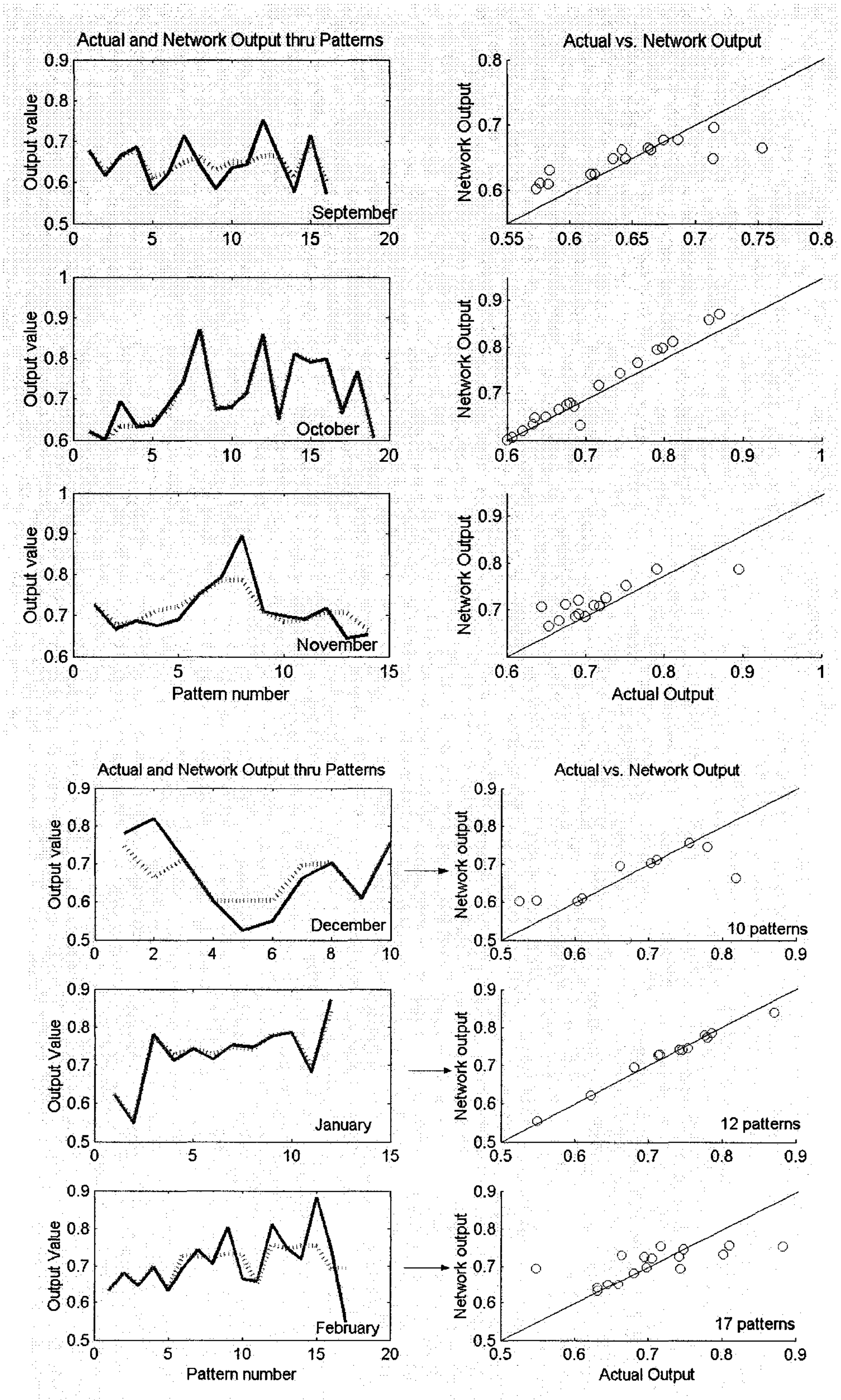

Figure 5-8b. Actual vs. network output comparison for September 2003 through February 2004.

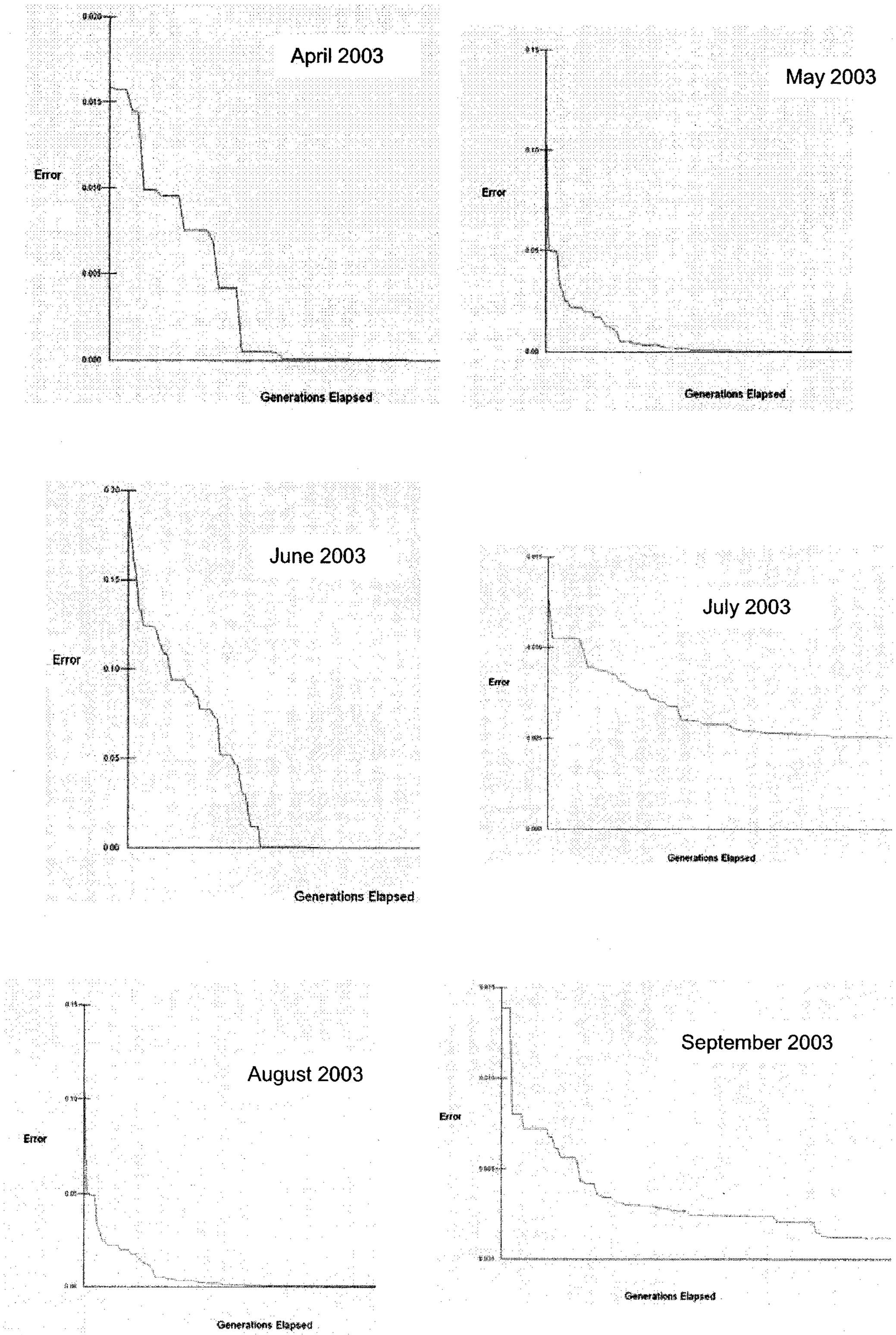

Figure 5-9.a. Mean squared error on test datasets over generations elapsed (from April 2003 to September 2003)

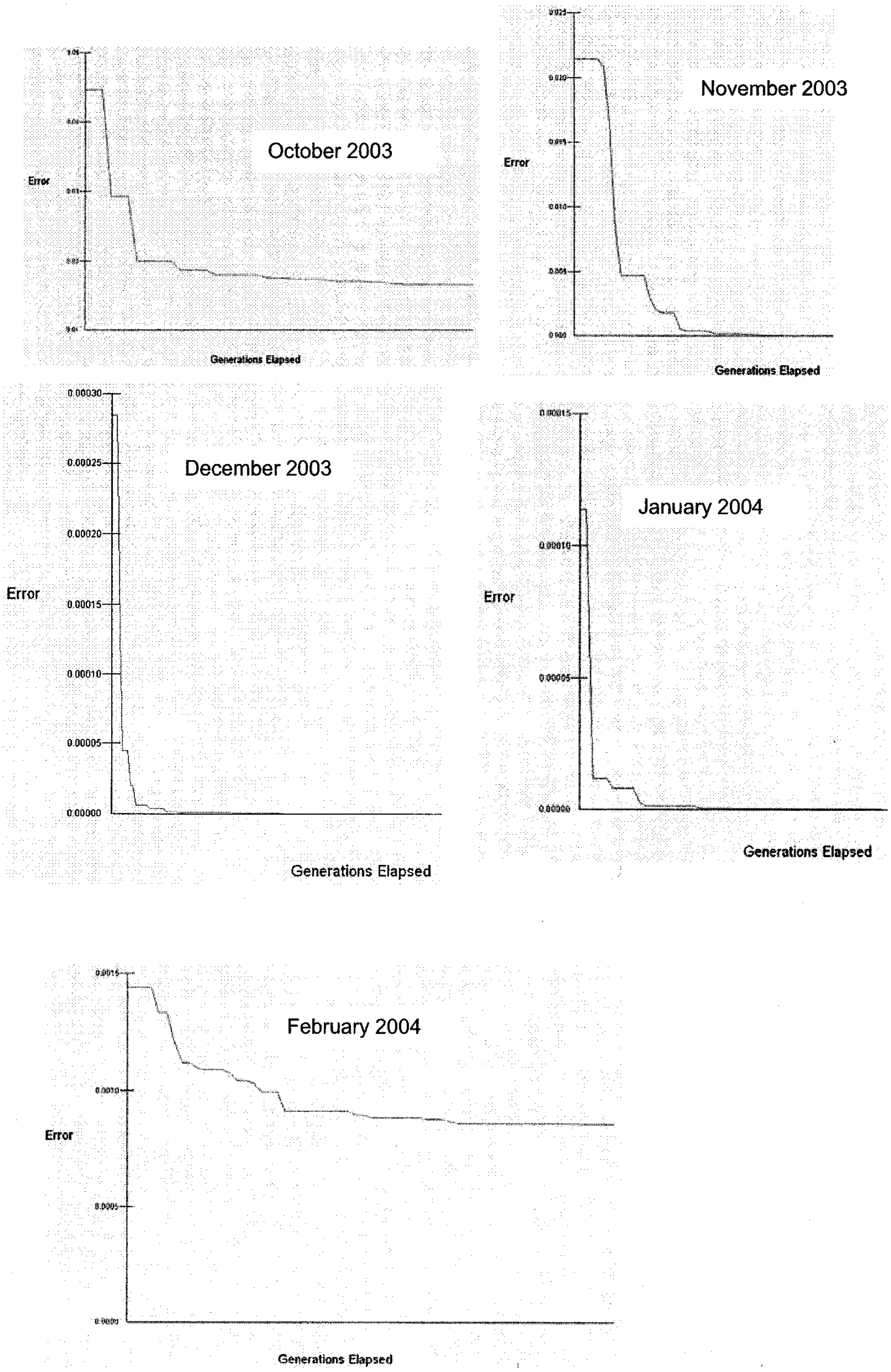

Figure 5-9b. Mean squared error on test datasets over generations elapsed (from October 2003 to February 2004)

5.4.3.1 Smoothing factor analysis

Table 5-4 presents the normalized (local) smoothing factors for each dataset (representing 11 different months) from April 2003 to February 2004. The highlighted values in Table 5-4 indicate the most significant causal factors for each dataset. An analysis of smoothing factors reveals that the significance of each causal factor to the prediction of KPI (labour performance) varies across datasets; however, several causal factors appear prominently across the data sets. For example, manpower availability is a significant causal factor in 73% of (8 out of 11) cases. Both rework and workload are also significant causal factors. These results are consistent with the results obtained from the FA-GRNN model trained with the full dataset (169 data patterns), described in Section 5.4.2.1.

Table 5-4. Normalized smoothing factors representing the significance of causal factors in monthly datasets.

CAUSAL FACTOR	FUZZY INPUT	INDIVIDUAL SMOOTHING FACTOR (NORMALIZED)										
		April	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb
Workload	Low	0.08	0.53	0.01	0.00	0.59	0.73	0.49	0.27	0.87	0.13	0.67
	Average	0.76	0.00	**1.00**	0.00	**1.00**	0.00	0.06	0.44	0.54	**0.87**	**1.00**
	High	0.45	0.15	0.50	0.61	0.22	0.00	0.02	0.16	0.42	0.76	0.47
Equipment availability	Low	0.12	0.00	0.06	**0.99**	0.00	0.85	0.53	0.02	0.64	0.65	0.29
	Medium	0.59	0.29	0.62	0.72	0.08	0.44	0.06	0.38	0.63	0.50	0.54
	High	0.17	0.00	0.09	0.00	0.00	0.87	0.00	0.07	0.60	0.28	0.53
Manpower availability	Low	0.73	**0.98**	**0.96**	0.34	0.59	**0.93**	0.04	0.10	**0.89**	0.04	**0.90**
	Low-Medium	**0.98**	0.00	0.02	0.00	0.02	0.89	0.29	**1.00**	0.81	**1.00**	0.50
	Medium-High	0.60	0.40	0.86	0.01	0.63	**0.97**	0.49	**0.91**	0.60	0.40	0.37
	High	0.11	**1.00**	0.32	0.19	0.12	0.41	0.11	0.03	0.38	**0.87**	0.56
Mean Temperature	Low	0.32	0.00	0.01	0.84	0.15	0.65	0.68	0.01	0.04	0.62	0.07
	Average	0.70	0.32	0.03	0.01	**0.87**	0.49	**1.00**	**1.00**	0.85	0.47	0.50
	High	0.06	0.10	0.40	0.69	0.00	0.00	**0.86**	0.26	**1.00**	0.51	0.07
Total precipitation	Low	0.33	0.00	0.71	0.08	0.00	0.09	0.33	0.57	0.63	0.12	0.55
	Medium	0.86	0.09	**0.99**	0.17	0.01	0.74	**0.94**	0.33	0.74	0.80	0.76
	High	0.78	0.81	0.28	0.69	0.21	**0.93**	0.00	0.41	0.69	0.39	0.60
Rework	Low	**0.97**	0.56	0.54	0.00	0.00	0.00	0.21	0.24	0.69	0.76	0.28
	Low-Medium	**0.98**	0.49	0.15	**1.00**	0.00	0.13	0.56	0.00	0.99	0.83	0.65
	Medium-High	0.18	0.02	0.11	0.98	0.64	0.11	0.73	0.72	0.64	0.27	0.63
	High	0.37	0.26	0.63	0.85	**0.85**	0.30	0.54	0.13	0.21	0.30	0.19
Quality Assurance/ Quality Control input	Low	0.83	0.00	0.25	0.54	0.02	**1.00**	0.12	0.44	0.85	0.36	0.39
	Low-Medium	**1.00**	0.00	0.00	0.00	0.34	0.00	0.23	0.04	0.43	0.83	**0.83**
	Medium-High	0.84	0.88	0.00	0.85	0.04	0.00	0.10	0.00	**0.98**	0.06	0.22
	High	0.84	0.16	0.18	0.90	**0.80**	0.53	0.25	0.02	**0.96**	0.70	0.15

5.4.4 Case 3: FA-GRNN Models Trained with Seasonal Data

In this case, four datasets were formed by grouping the full dataset into respective seasons (spring, summer, fall and winter), hypothesizing that data grouped into respective seasons have similar and unique characteristics that can possibly impact the labour performance. Summarized in Table 5-5 is a comparison of the performances of FA-GRNNs trained using four datasets based on seasonal data. Figure 5-10 illustrates the comparison of actual vs. network prediction.

Table 5-5. Summary statistics of FA-GRNN model trained with seasonal datasets.

	NUMBER OF TRAINING PATTERNS	NUMBER OF TESTING PATTERNS	R^2	MEAN SQUARED ERROR:Q
All	132	32	0.667	0.002
Spring	24	5	0.8879	0.0005
Summer	38	9	0.9444	0.000
Fall	40	9	0.9334	0.0002
Winter	32	7	0.8061	0.001

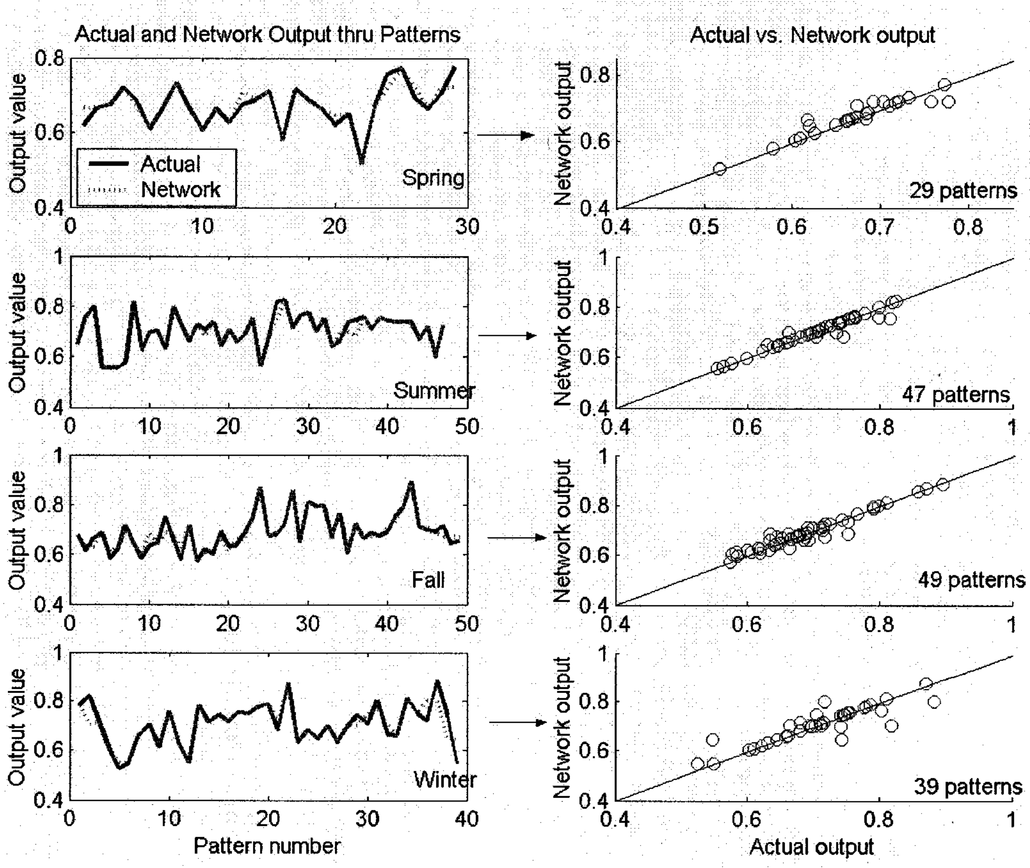

Figure 5-10. Actual vs. network output comparison for seasonal data categories

Based on the results shown in Table 5-5 and on the visual analysis of Figure 5-10, one can conclude that the models trained with seasonal data sets have a better overall performance. Table 5-5 shows that all four seasonal dataset-based models outperformed the original model trained with the full dataset. As shown in Figure 5-10, mean squared error in test data sets smoothly converged into a very reasonable state.

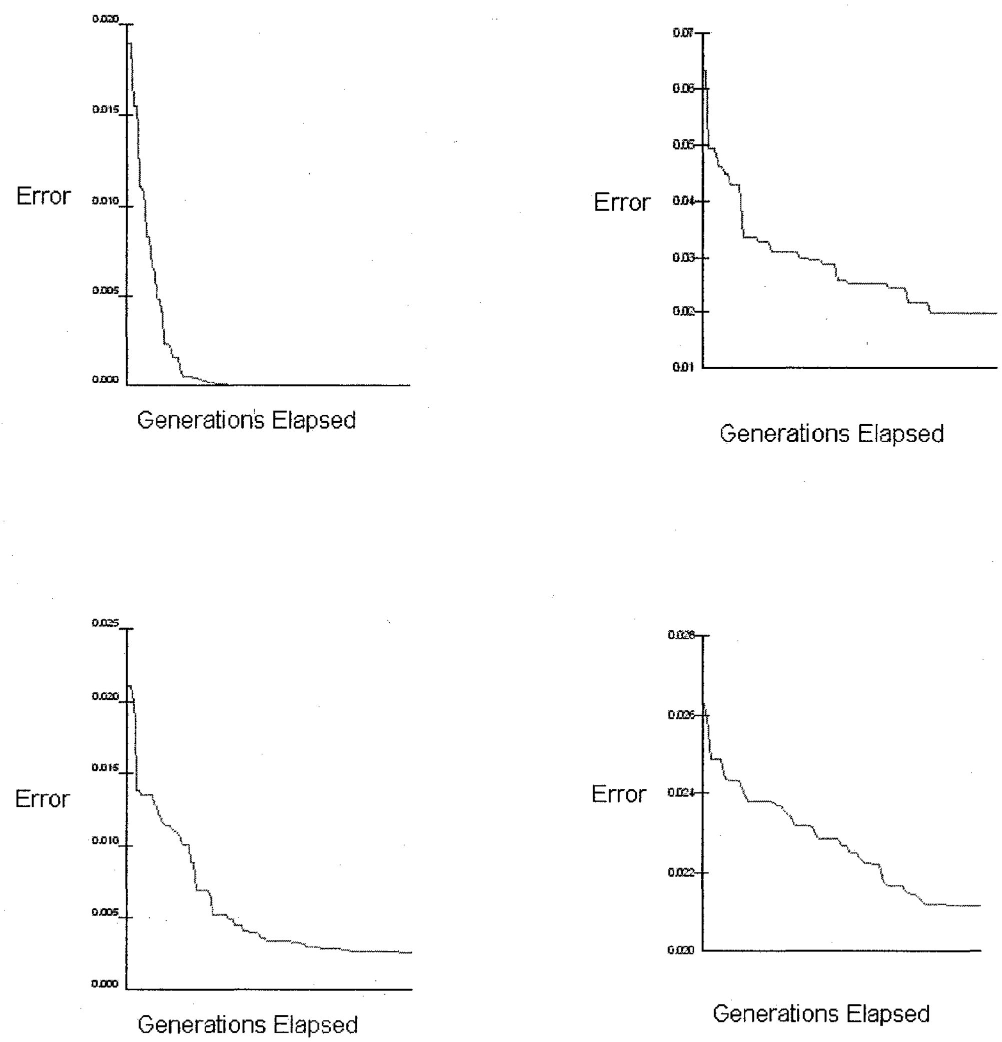

Figure 5-11. Mean squared error (MSE) of test data patters of seasonal data

5.4.4.1 Smoothing Factor Analysis for Seasonal Datasets

Summarized in Table 5-6 are the normalized individual (local) smoothing factors representing the significance of each causal factor in the four datasets formed based on particular construction seasons. The highlighted figures indicate the most significant causal factors in each dataset. An analysis of the smoothing factors reveals that results are consistent with Case 1 as well as Case 2.

Table 5-6. Normalized individual smoothing factors representing significance of causal factors in seasonal datasets.

		INDIVIDUAL SMOOTHING FACTOR (NORMALIZED)			
CAUSAL FACTOR	FUZZY INPUT	spring	summer	fall	winter
Workload	Low	0.69	0.20	0.57	**0.96**
	Average	0.07	0.53	**1.00**	0.82
	High	0.00	0.34	0.00	**1.00**
Equipment availability	Low	**0.95**	0.04	0.72	0.56
	Medium	0.01	0.62	0.21	0.24
	High	0.00	**0.91**	0.80	0.82
Manpower availability	Low	**0.92**	0.57	0.14	0.78
	Low-Medium	0.22	0.08	0.00	0.04
	Medium-High	0.76	0.45	0.71	0.00
	High	0.33	0.05	0.26	**0.91**
Mean Temperature	Low	0.31	0.09	0.06	0.86
	Average	**1.00**	**0.96**	0.00	0.72
	High	0.01	0.24	0.23	0.10
Total precipitation	Low	**0.98**	0.96	0.22	0.73
	Medium	0.41	0.98	0.72	0.47
	High	**0.93**	0.58	0.57	0.19
Rework	Low	**0.98**	0.42	0.54	0.24
	Low-Medium	**0.98**	**1.00**	0.02	0.05
	Medium-High	**0.89**	0.71	0.55	0.55
	High	0.79	0.24	0.80	0.55
Quality Assurance/ Quality Control input	Low	0.09	0.01	0.00	**0.97**
	Low-Medium	0.08	0.06	0.03	0.23
	Medium-High	**0.89**	0.38	**0.96**	**0.86**
	High	0.51	0.85	0.00	0.47

5.5 SUMMARY

This chapter introduced a novel fuzzy neural network, the Fuzzy Adaptive Generalized Regression Neural Network (FA-GRNN), for mapping input-output data with greater accuracy (as compared to the model presented in Chapter 4) for construction performance modeling. The proposed FA-GRNN automatically extracts the underlying nonlinear regression surface from available sample data. FA-GRNN is a nonlinear and nonparametric method (i.e., no assumptions are made regarding the distribution of the data in the model). Prediction (input output mapping) accuracy of the model is tested with 16 data sets; it was shown that the model provides better overall performance when it is trained with data representing seasonal characteristics.

The proposed FA-GRNN model introduced fuzzy neurons to the classical GRNN architecture. By doing so, the user of the model (i.e., construction managers) is provided with a mechanism for incorporating linguistic values as causal factors. This added level of information granularity enables better capturing and representation of the qualitative knowledge of the system user.

By introducing local smoothing factors to the classical GRNN, the transparency of the proposed FA-GRNN model is enhanced up to a level that the model can be used to identify the relative significance of each input causal factor. This important feature of the FA-GRNN model is later used as the foundation of performance diagnostic inference, which is described in Chapter 7.

It is noted at this stage that significant improvements can be made to the accuracy of the FA-GRNN model, through further development of: (1) the input causal factor selection using expert knowledge, (2) the qualitative data collection from construction projects on daily basis, and (3) the efficient and practical membership function estimation using quantitative and qualitative data collected from the field (i.e., from experts). In view of this, Chapter 6 presents the efforts made to enhance the proposed FA-GRNN model using several knowledge representation and acquisition techniques to condition the input causal factors.

5.6 REFERENCES

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CHAPTER SIX

6. DATA–DRIVEN MEMBERSHIP FUNCTION ESTIMATION

"A very widespread question about fuzzy set theory is: from what kind of data and how can membership functions actually be derived? Answering this question is very important for practical applications" Dubios and Prade 1980

6.1 INTRODUCTION

To ensure the efficient performance of a diagnostic reasoning system, the acquisition and representation of knowledge from domain experts become the most essential tasks in the development process. Construction projects are managed by a group of experts, ranging from frontline supervisors, representing each trade, to the construction manager who oversees the entire project operations. Each individual possesses a certain amount of causal knowledge regarding the task they supervise based on his or her on-the-job experience, previous experience on similar jobs, and the training and education he or she has received. This study is designed to reason about construction productivity from the construction activity-level and upwards. Thus knowledge acquisition is carried out at the front-line supervision level, in two stages:

(i) Causal knowledge representation to identify possible causal factors of key performance indicators (i.e., finding out what is likely to be causing performance deviations); and

(ii) Daily quantitative and qualitative (subjective) judgments about the causal factors.

This study uses fuzzy set theory, more specifically membership functions, to process knowledge elicited from (a group of) experts. The representation of causal knowledge and of developing membership functions is a very under-researched area, but is nevertheless a vital aspect if fuzzy sets are to be used in construction performance modeling.

This chapter first reviews membership function determination techniques, and then suggests suitable development techniques for construction performance modeling. A pragmatic approach to causal knowledge acquisition (i.e., to identify the causal factors) using a modified version of the nominal group technique is presented. Next, a parsimonious approach to collect and analyze both objective and fuzzy-linguistic assessments on the causal factors is presented along with validation using data collected from an actual construction project. Subsequently, a systematic procedure is presented to transform linguistic values into numerical values that are ultimately used for developing membership functions, thereby developing a fuzzy-logic-based construction performance diagnostic reasoning system.

6.2 MEMBERSHIP FUNCTIONS

A membership function ($\mu_A(x)$) is a function that defines the degree of an element's (x) membership in a fuzzy set A. The degree of membership to a concept is indicated by a number in the interval [0,1]. A membership function maps every element of the universe of discourse X to the interval [0,1]. This can be formally represented as:

$$\mu_A(x): X \to [0,1]$$

Figure 6-1 shows sample membership functions defined for three fuzzy sets, named Cold, Average, and Warm, of the linguistic variable 'temperature'. The construction of the membership function is fundamental work in real-world applications of fuzzy set theory. There is, however, no unified form of membership function(s) available that can be readily applied in practical applications, due to the context-dependent nature of fuzzy sets. Piecewise-linear (e.g., triangular or trapezoidal) membership functions are commonly used due to factors such as mathematical simplicity, good interpretability, and a minimal amount of domain knowledge requirement.

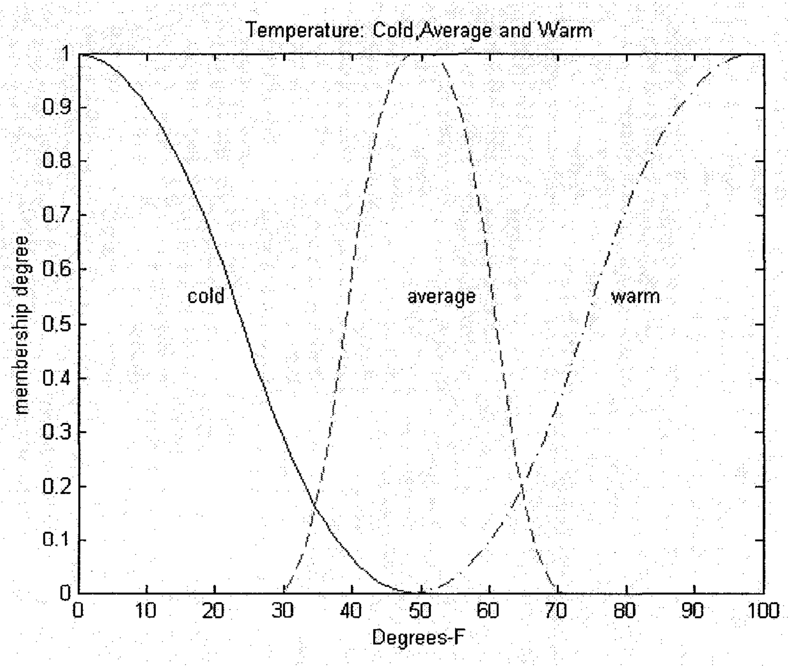


Figure 6-1. Sample Membership functions

6.2.1 Properties of Membership Functions

Although there is little consensus among membership function development techniques, the majority of the membership functions used in practical applications have the following properties:

(i) Membership functions map μ[a, b] to [0,1] or to [1,0] on an arbitrary interval [a, b].

(ii) Continuous and monotonic: All membership functions are continuously increasing or decreasing functions or can be divided into a monotonically increasing or decreasing part.

(iii) Boundary condition: Membership functions satisfy boundary conditions μ(a)=0 and μ(b)=1 (for increasing functions), or μ(a)=1 and μ(b)=0 (for decreasing functions), simply put, membership functions are bounded in [0,1].

(iv) Fuzzy convexity: Typically membership functions are convex (with a convex curve).

(v) Normal: At least one member has a membership degree of 1.

Some of these membership function properties are shown in Figure 6-2.

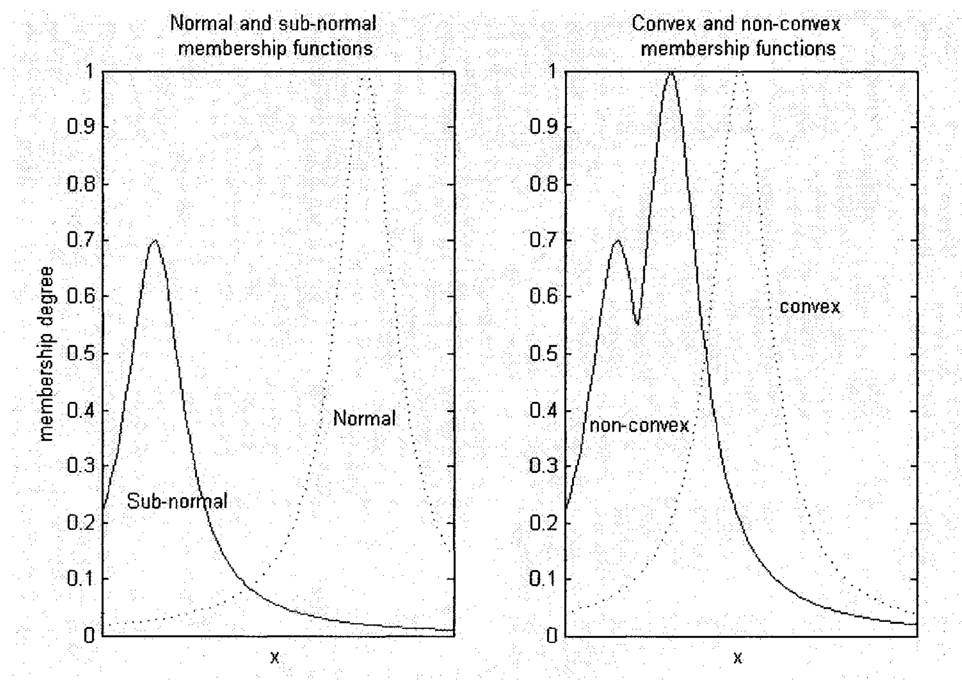


Figure 6-2. Properties of membership functions: (a) normal vs. subnormal, (b) convex vs. nonconvex.

6.2.2 Desirable Characteristics of Generation of Membership Functions

In construction performance modeling, the following characteristics are desirable for an efficient membership function generation mechanism:

(i) **Accurate:** The representing membership function should reflect the multiple records of expert knowledge (where available) contained in the sample data points in the most accurate way possible.

(ii) **Easy** to collect necessary data: The type of data required should be easy to collect without disrupting the already-busy frontline supervisor's schedule. In other words, the methodology should require only a limited set of training samples.

(iii) **Flexible:** The methodology should provide a broad family of membership functions, both linear and non-linear, to represent simple and complex causal factors, respectively. The number of parameters in the functional representation should be as small as possible. A free functional form that preserves the shape of the sample data would be a better choice.

(iv) **Dynamic:** The methodology should be able to capture and represent the time variant nature of the causal factors. For example, the parameters of the membership function should be easily adjusted to represent the different stages of construction and or seasonal impacts where applicable, i.e., changing contexts.

(v) **Computationally inexpensive**: The methodology should be easy and inexpensive to implement.

6.2.3 Interpretation of Membership Functions

Several different interpretations of the meaning of membership functions (i.e., what does graded membership mean?) can be found in the current literature. Consider the vague predicate "Today's temperature (x) is Cold (C)."

What does it mean to say $\mu_A(x) = 0.8$?

Pedrycz and Vukovich (2002) categorized the interpretations into three main views as follow:

(i) **Likelihood view:** 80% of a given population of experts declared that today's temperature is cold. This corresponds to the frequency-driven statistical methods (e.g., Yes/No experiments) and implicitly assumes that there is a pool of experts available.

(ii) **Random set view:** 80% of a given population of experts described "cold" as an interval containing today's temperature. This corresponds to the interval estimation and implicitly assumes that there is a pool of experts available.

(iii) **Typicality view:** Today's temperature is away from the "seasonal average" (i.e., prototypical object/value) by a degree of 0.8 (a normalized distance).

Each view is associated with different membership function elicitation methods. For example, the likelihood view is associated with a horizontal approach to membership estimation while the random set view is associated with vertical method and interval estimation. Hence, the interpretation that membership functions shall have in construction performance modeling must first be decided, and only then can an elicitation method be implemented. As identified in Zadeh's (1965; 1975) original work on fuzzy sets, membership functions are subjective and context dependent. Fuzziness arises mainly due to subjectivity based on the context, and not because of errors and inconsistencies of measurement. Hence, neither the likelihood nor random set views are qualified for the practical problem under study. In this study, the fuzzy membership was elicited by adopting the typicality/similarity view. Related membership function elicitation methods are reviewed and suitable methods are proposed and tested in the subsequent sections.

6.2.4 A Review of Membership Function Determination Techniques

The membership function determination techniques are developed to answer the practical need of designing membership functions. As Bilgic identified (Bilgic and Turksen 1997), each elicitation method is developed with a "specific (sometimes implicit) interpretation of the membership function in mind." It is crucial to identify an appropriate elicitation method that matches with the requisite interpretation, i.e., similarity view in this study.

This section reviews membership function determination techniques, which depend upon sample data points. (The review is mainly based on (Medasani et al. 1998; Ross 1995; Sancho and Verdegay 1999; Turksen 1991).)

Figure 6-3 illustrates different membership function elicitation techniques, categorized into four groups: (1) heuristic methods, (2) statistical methods, (3) clustering-based methods, and (4) exemplification methods (i.e., experimental acquisition of membership values).

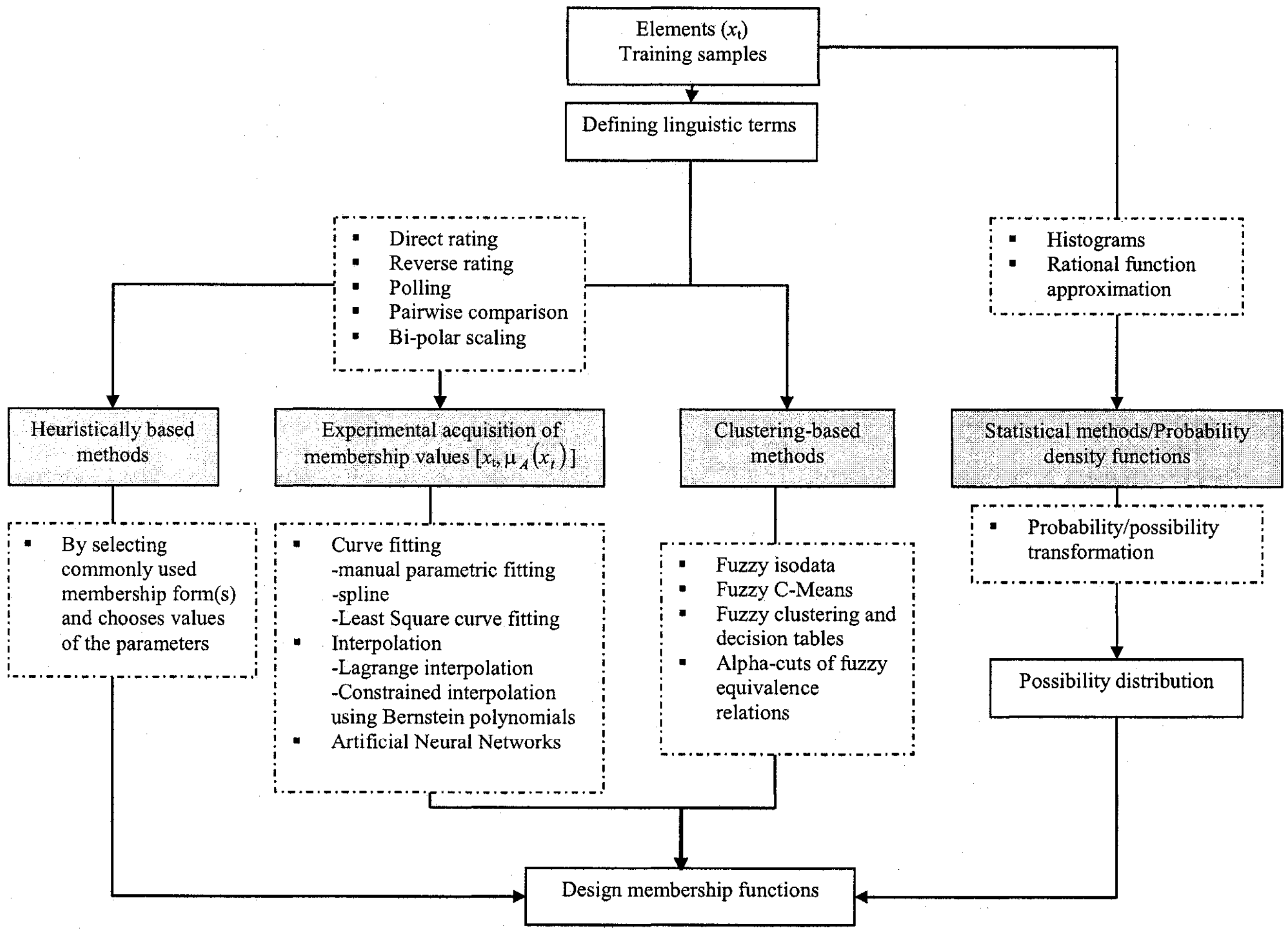


Figure 6-3. Different membership function determination techniques

6.2.4.1 Heuristic Methods

The heuristically based membership function development consists of selecting shapes and parameters of membership functions in accordance with previous experience, rules-of-thumb and often-used shapes. This can be considered a purely subjective technique.

In this case, the general approach is to first select the shape of the membership function from a list of families, and then to fine-tune the values of the parameters of the function. The most frequently used shapes for membership functions are: (1) Piecewise linear functions (e.g., triangular and trapezoidal shapes), and (2) Piecewise monotonic functions (e.g., the *S*-functions, exp) (Dombi 1990; Hisdal 1988; Medasani et al. 1998). Due to its simplicity, the heuristic method is commonly applied in construction management applications (e.g., (Ayyub and Halder 1984; Fayek and Oduba 2005; Liu and Ling 2005; Singh and Tiong 2005)). Unfortunately, the disadvantages of this method are several. For example, a lack of understanding about the complex nature of some variables limits the proper selection of shapes, the parameters associated with the membership functions must therefore be provided by experts and, for a large number of input variables, it is impractical to estimate the parameters with a reasonable accuracy level. Applications of this method to membership function determination in a poorly understood phenomenon such as construction performance modeling can lead to inaccurate models (via inaccurate values of various parameters).

6.2.4.2 Pairwise Comparison

As explained in (Pedrycz and Gomide 1998), membership functions can be estimated by the pairwise comparison method proposed by Saaty (1980). This procedure involves a series of pairwise comparisons (using a ratio scale, usually involves 7 quantization levels) of the elements pertaining to the description of fuzzy set A in a finite universe of discourse.

The membership values at sample elements ($x_1, x_2, \ldots, x_i, \ldots, x_n \ , x \in X$) from a pairwise comparison matrix are obtained in two steps, as described below. First, select a pair of elements (x_i , x_j) and choose the level of preference of x_i over x_j satisfying the concept A. Prioritize the preference of x_i over x_j, and prioritize the numerical value associated with this pair (μ_{ij}). The results of the pairwise comparison process are arranged in a matrix form P. The eigenvector ($(\mu_1, \mu_2, \ldots, \mu_n)^T$) associated with the largest eigenvalue is the desired vector of membership values. The elements of matrix P satisfy

$$p_{ij} > 0, \quad p_{ij} = \frac{1}{p_{ji}}, \quad i.j = 1,2,...,n$$

Additionally, all diagonal elements of A are equal to unity, $p_{ij}=1$; furthermore, A satisfies the property of reciprocality since $p_{ij}.p_{ji}=1$; A is also transitive in the scene that $p_{ik}.(p_{kj})=p_{ij}$

Consistency Measure

In general, user subjectively has the value of a_{ij}. Hence the transitivity property cannot always be strictly enforced. A consistency index (CI) has been introduced (Saaty 1980) to estimate the departure from consistency by $C.I. = (\lambda - n)/(n-1)$, where λ is the maximal eigenvalue, and n is the number of elements (variables) being compared.

For each matrix of size n, random matrices were generated (Saaty 1980) and their mean CI value, called the random index (RI), was computed. Using these values, the consistency ratio (CR) is defined as the ratio of the CI to the RI. It was concluded that a consistent reciprocal matrix should have the CR <0.1 (Saaty 1980). When the CR>0.1, the user is requested to review his or her pairwise comparison.

Weighted Least-Square Method

Chu et al. (1979) proposed an alternative method to eigenvalue problem to estimate membership values using pairwise comparison, using a weighted least-square method. It aims to determine the membership values μ_i, such that, given $p_{ij} \approx \mu_i / \mu_j$. The membership values can be obtained by solving the constrained optimization problem

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} \left(p_{ij}\mu_j - \mu_i\right)^2$$

Subject to constraint $\sum_{i=1}^{n} \mu_i = 1$

A normalized fuzzy set can be obtained by normalizing μ_i. The reader is referred to the work of Chu et al. (1979) for the mathematical details of solving the above nonlinear problem. Compared to the eigenvector method, the weighted least-square method is much easier to understand.

The main disadvantage of these methods of membership value estimation via pairwise comparison is that when the number of elements of the universe of discourse is large (e.g., more than 10), the pairwise comparison procedure becomes cumbersome, thereby dampening the consistency of comparison. However, these methods can be used in cases where a slightly low amount of sample elements represent the context.

6.2.4.3 Statistical Methods

Statistical methods based on probability theory are used to determine membership functions for fuzzy sets when the elements have a defining feature with a known probability density function (Civanlar and Trussell 1986). Statistical based methods of membership determination involve two steps: (1) the determination of probability density function, and (2) the transformation of probability distributions into possibility distributions. Generally, histograms of elements provide information regarding the distribution of the input (and output) values and probability distributions are modeled by a mixture of parameterized functions such as Gaussian and exponential. The problems in converting probability distributions to possibility distributions have been examined by several authors (e.g., Civanlar and Trussell 1986; Devi and Sharma 1985; Dubois and Prade 1986). In a construction management-related application, Oliveros and Fayek (2005) used the statistical based method proposed by Dubois (Dubois and Prade 1986) to determine the membership function of construction activity duration for activity delay analysis. However, statistical based methods can be applied only when sufficient data is available to substantiate such distributions by statistical analysis. Furthermore, membership functions derived based on probabilistic distributions theoretically represent the frequency of occurrence instead of subjective opinion(s) based on different contexts. This technique is suitable to determine membership functions when experts are not available to provide subjective assessments and sufficiently large number of experimental data is available to derive probability-possibility distributions.

6.2.4.4 Methods Based on Clustering

According to Pedrycz (1995), "fuzzy clustering forms another important avenue of methods of membership function estimation. The primary objective of fuzzy clustering is to partition a set of numerical data into a series of overlapping clusters whose degrees of belongings are treated as membership functions. The method is concerned with a fuzzy partition (a family of fuzzy sets) of the universe of discourse rather than a single membership function."

As Medasani et al. (1998) states, the Fuzzy C-Means (FCM) (Bezdek 1981) algorithm is one of the most popular fuzzy clustering algorithms. The FCM algorithm partitions a collection of n vectors (X={x1, x2, ..., xn}) into c fuzzy groups such that the weighted within groups sum of squared error objective function is minimized. The interested reader is referred to (Bezdek 1981) for detail description of the algorithms. As identified in various literature (Chen and Wang 1999; Medasani et al. 1998), the FCM algorithm must have the following features:

- The number of classes must be provided to run the algorithm. There is no standard procedure to determine the optimal number of clusters.
- The membership values generated do not typically represent degrees of belonging, but rather "degrees of sharing".
- The memberships cannot distinguish between a moderate outlier and an extreme outlier. That makes the algorithm sensitive to outliers.

Another important factor in the FCM algorithm is the fuzzy exponent m. The parameter m is selected according to the problem under consideration. When m→1, the fuzzy c-means converges classical c-means. When m→ infinity, all cluster centers tend towards the centroid of the dataset. Currently, there is no theoretical basis for an optimal choice for the value m.

Several alternative clustering-based techniques to determine membership functions and fuzzy rules (as a joint exercise) from numerical data (training samples) can be found in the literature (e.g., Hong and Chen 1999; Hong and Chen 2000; Hong and Lee 1996; Wu and Chen 1999). Hong and Lee (1996) proposed an approach based on fuzzy clustering and decision tables. After identifying its computational limitations in cases where the numbers of variables become larger (hence the complexity of the decision table), Hong and Chen (1999; 2000) proposed some augmentations to Hong and Lee's (1996) method, namely the "merging-decision-table-first" method and the "merging-membership-functions-first" method. However, all three methods (Hong and Chen 1999; Hong and Chen 2000; Hong and Lee 1996) need to predefine the membership functions of the input linguistic variables. Having identified the limitations of Hong and Lee's (1996) work, Wu and Chen (1999) proposed an alternative method to construct membership functions and fuzzy rules through training examples using α-cuts of fuzzy equivalence relations and α-cuts of fuzzy sets. Results were compared with

Hong and Lee's (1996) work and highlighted the main advantages as (1) better average accuracy, (2) fewer rules, and (2) no need to predefine membership functions or partition the input/output space.

The clustering-based membership function determination techniques discussed above have few common characteristics such as (1) algorithmic nature, (2) depends on a large amount of numerical data (training samples), and (3) computational complexity, which makes them less candidates for construction performance modeling applications.

6.2.4.5 Exemplification

As described in Zadeh (1972), exemplification is a method of membership degree estimation with partial information about the concept using finite number of samples in the universe of discourse. Dubois explains (Dubois and Prade 1980) that in order to build a membership function, A= "Cold" temperature, we may ask the frontline supervisor whether today's temperature is "Cold". To answer, the frontline supervisor has to use one among several possible linguistic truth-values, e.g., *true, more or less true, borderline, more or less false, false*. The simplest method is then to translate these linguistic levels into numerical ones: respectively, 1, 0.75, 0.5, 0.25, and 0. A discrete representation of the membership function is thus obtained by repeating the query for several temperature values. The result is given as a set of discrete data points on a plane. Two key methods to determine continuous membership functions using acquired sample membership values are (Klir and Yuan 1995): (1) interpolation, and (2) curve fitting. Discussions on selected curve fitting and interpolation techniques are given in subsequent sections.

From the above review, it can be concluded that to use exemplification for any practical application, both the sample membership value estimation and membership function determination method should be tailored to suit the application. This study exploits membership function exemplification as a means of obtaining sample membership values. A detail discussion on a novel approach to elicit membership values from a group of construction experts is presented in Section 6.4 of this chapter.

6.2.5 Curve Fitting Techniques

The intent of curve fitting is to find a mathematical function that fits the sample data points, which are collected from expert opinion. Generally, selecting the function of a certain form (e.g., Gaussian) is based on theoretical reasons. The curve fit finds the specific coefficients (parameters) that make that function match the data as closely as possible. The process of finding the coefficients for the fitting function is called curve fitting. The curve with a minimal deviation from all data points is obtained by the method of least squares.

In construction performance modeling, however, the behavior of causal factors does not necessarily follow a particular functional form, or a family of known functional forms; hence the applicability of curve fitting for the problem under review is less appropriate. In contrast, the interpolation methods (i.e., the process of estimating the outcomes in between sampled data points) become a practical solution to the problem.

6.2.6 Interpolation Techniques

In contrast to the curve fitting approach, the aim of interpolation is to find a polynomial that goes exactly through the sample data points. Klir and Yuan (1995) proposed using Lagrange (polynomial) interpolation for constructing membership functions from sample data. Klir and Yuan also identified that the complexity of the function increases with the number of data points and the risk of over fitting data. Farin (1990) noted that although "Lagrange interpolation is simple, unique, and has a nice geometric interpretation, nobody uses it in a design situation" because it exhibits "wild wiggles that are not inherent in the data". This problem is called as "Runge phenomenon." This problem is commonly resolved using piecewise polynomial curves, a.k.a. splines (Farin 1990). Nevertheless, Chen and Otto (1995) argued that neither of these least-squares or spline methods satisfy the constraints of membership functions, i.e., mainly the monotonic and convex property and the condition that membership functions are bounded in [0,1]. For example, using a sample dataset presented in (Chen and Otto 1995), Figure 6-4 illustrates the Runge phenomenon and also shows why unconstrained interpolation cannot be used for membership function determination (unnecessary "wiggles" that make the function overshoot beyond the [0,1] range).

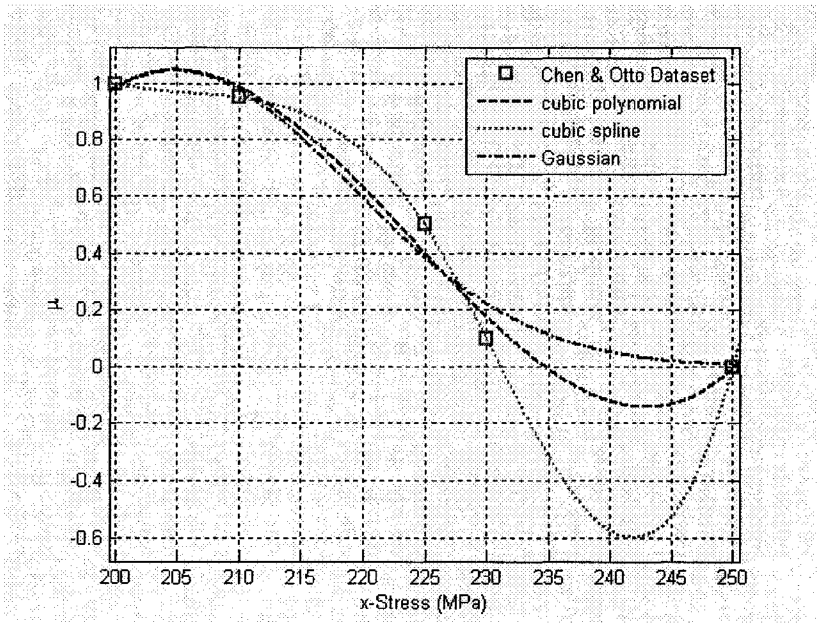


Figure 6-4. Unconstrained interpolation of sample data

There is therefore a need for algorithms that preserve the monotonicity or convexity properties of the data, to determine membership functions from interpolation methods. Two noteworthy competitive methods that preserve the monotonicity or convexity properties of the data type are as follows:

1. The monotone piecewise cubic interpolation method, developed by Fritsch and Carlson (1980), and
2. Quadratic Bernstein polynomial interpolation method developed by McAllister and Roulier (1981):

It is noteworthy to mention that these two constrained interpolation methods demand monotonic data assumed to be sufficiently accurate to warrant interpolation, not approximation, i.e., curve fitting. These methods do not work for scattered data points. The methodology proposed in Section 6.4, using a semantic differential approach to obtain sample membership values guarantees monotone datasets. A description of each algorithm is given below.

6.2.6.1 The monotone piecewise cubic interpolation

The monotone piecewise cubic interpolation method developed by Fritsch and Carlson (1980) or its improved version by Fritsch and Butland (1984) claims that it preserves the properties, such as monotonocity and convexity, that are presented in the data.

The algorithm for constructing a piecewise cubic interpolant $p(x)$ to $\{(x_i, \mu_i): i = 1,2,\ldots,n\}$ can be represented as follows:

$$p(x) = \left[\frac{d_i + d_{i+1} - 2\Delta_i}{h_i^2}\right](x - x_i)^3 + \left[\frac{-2d_i - d_{i+1} + 3\Delta_i}{h_i}\right](x - x_i)^2 + d_i(x - x_i) + \mu_i$$

where $d_j = p'(x_j), j = i, i+1$; $\Delta_i = \mu_{i+1} - \mu_i; h_i = x_{i+1} - x_i$

The conditions necessary for the above cubic interpolant to be monotone in a subinterval $I = [x_i, x_{i+1}]$ are given in (1980). The slopes at x_i are chosen in such a way that $p(x)$ is shape preserving. This means that on intervals where the data is monotonic, so is $p(x)$. At points where the data have a local extremum, so does $p(x)$.

6.2.6.2 McAllister and Roulier Algorithm

Chen and Otto (1995) proposed to use a constrained interpolation technique based on the McAllister and Roulier algorithm (Mcallister and Roulier 1981) to determine membership functions. Chen and Otto's method produces a monotonocity and convexity preserving the quadratic Bernstein polynomial, which qualifies as a membership function. The method is fast and efficient to implement.

Because of the algorithm's importance as one of the most suitable techniques for determining membership functions from sample membership values, a detailed description of the algorithm is presented below.

6.2.6.3 Bernstein Polynomial

The Bernstein polynomial, defined explicitly by

$$B_i^n(x) = \binom{n}{i} x^i (1 - x)^{n-i}$$

Where the binomial coefficients are given by

$$\binom{n}{i} = \begin{cases} \dfrac{n!}{i!(n-i)!} & \text{if } 0 \le i \le n \\ 0 & \text{else} \end{cases}$$

As shown in Figure 6-5, the Bernstein polynomial $B_{i,n}(x)$ has the following useful properties that make it an ideal candidate for membership function determination:

(i) Normalization between 0 and 1,

(ii) Single unique local maximum at x=i/n, and

(iii) Positive (i.e., *y* values greater than zero always).

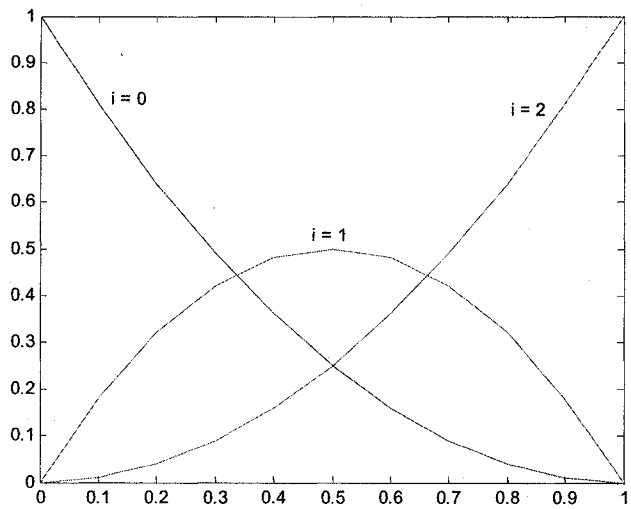


Figure 6-5. Bernstein polynomials: the quadratic case

6.2.6.4 McAllister and Roulier Algorithm

The shape-preserving piecewise interpolation algorithm proposed by McAllister and Roulier (1981) is constructed based on quadratic Bernstein polynomials.

Let $\vec{d}_0 = (x_0, \mu_0)$ and $\vec{d}_1 = (x_1, \mu_1)$ be two non-decreasing data points ($x_0 < x_1$). Let $\vec{o} = (a, b)$ be an arbitrary data point with $a = (x_0 + x_1)/2$. Let g be the first-degree spline passing through the points $\vec{d}_0$, $\vec{d}_1$, and $\vec{o}$, with a single knot at a.

Let $B_2(g)$ be the second-degree Bernstein polynomial of g on [a,b]

$$\begin{aligned} B_2\{d_0, o, d_1\} &= B_2(g)(x) \\ &= (x_1 - x_0)^{-2}\left\{g(x_0)(x_1 - x)^2 + 2b(x - x_0)(x_1 - x) + g(x_1)(x - x_0)^2\right\} \end{aligned} \quad (6.1)$$

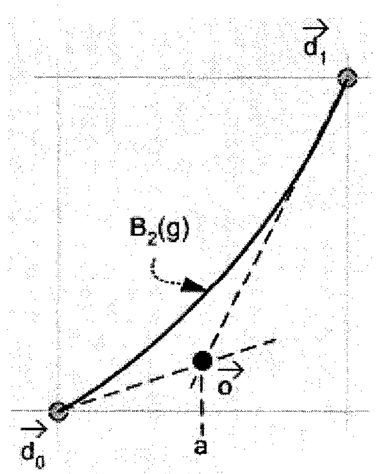


Figure 6-6. Second degree Bernstein polynomial

The interpolation algorithm has two key steps: (1) slope calculation and (2) knot point insertion.

STEP 1. Slope Calculation: The first step is to calculate the slopes (m_i) at each known data point $\vec{d}_i$ $\{(x_i, \mu_i)\}_{i=0}^{N}$. To maintain the condition that the slope at the end-points of the membership function (i.e., when $\mu(x) = 0 \text{ or } 1$) equals zero, we set $m_i = 0$ when $i = \{0, n\}$.

Otherwise, for non-decreasing data points (i.e., $\mu_i < \mu_{i+1}$), to calculate m_i at each intermediate data points, first define $s_i = (\mu_i - \mu_{i-1})/(x_i - x_{i-1})$ for $1 < i < N$. Note that a similar algorithm can be used for non-increasing data points.

(i). If $s_i \cdot s_{i+1} \leq 0$, set $m_i = 0$ to guarantee that local extrema of data (i.e., height of the membership function) has a zero slope. This also segments the data into monotonically increasing and monotonically decreasing (or vise versa) subsets.

(ii). Otherwise, if $|s_i| > |s_{i+1}|$, extend the line through $\vec{d}_i$ of slope s_i until it intersects the horizontal line through $\vec{d}_{i+1}$ at the point $\vec{b} = (x_b, \mu_{i+1})$. Refer to Figure 6-7.

Then define

$$x_c = (x_{i+1} + x_b)/2 \tag{6.2}$$

Which is the abscissa of point c shown in Figure 6-7. The slope m_i at (x_i, μ_i) is defined as

$$m_i = (\mu_{i+1} - \mu_i)/(x_c - x_i) \tag{6.3}$$

Note that $c_x > \dfrac{x_i + x_{i+1}}{2}$.

(iii). If, on the other hand, $|s_i| \leq |s_{i+1}|$, the above procedure is reversed by extending the line through $\vec{d}_i$ of slope s_{i+1} until it intersects the horizontal line through $\vec{d}_{i-1}$. Then set

$$x_c = (x_{i-1} + x_b)/2 \tag{6.4}$$

and

$$m_i = (\mu_i - \mu_{i-1})/(x_i - x_c) \tag{6.5}$$

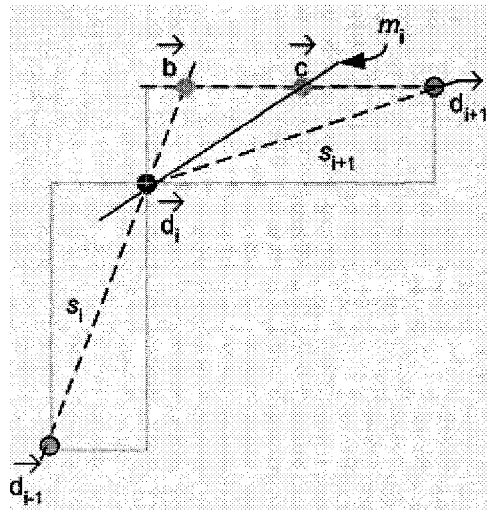


Figure 6-7. Determination of slope m_i

STEP 2. Calculate Knot Points: Insert a point in between each point $\vec{d}_i$ and $\vec{d}_{i+1}$, and then fit a quadratic Bernstein polynomial to the 2n-1 data points.

Let R_i be the rectangle determined by the points $\vec{d}_i$ (x_i, μ_i) and $\vec{d}_{i+1}$ (x_{i+1}, μ_{i+1}) and let the midpoint segment of it be a line segment that bisects R_i vertically and is bounded within each R_i. Refer to the Figure 6-8. Let L_i be the line that passes through $\vec{d}_i$ (x_i, μ_i) with slope m_i. There are two distinct cases related to the neighboring slope lines L_i and L_{i+1} depending on whether the knots change the local convexity of the spline or not. Even though the knot point calculation procedure described in (Chen and Otto 1995) is a general method for all the knot points, there are nevertheless slight modifications that have been made to the algorithm for the first and last knot (i.e., end knot) points. They are described below.

(i). Knot point calculation (general case)

Case 1. L_i and L_{i+1} intersect at a point $\vec{z} = (x_z, \mu_z)$ in R_i. Refer to Figure 6-8a. Note that this case happens when $s_i < s_{i+1}$.

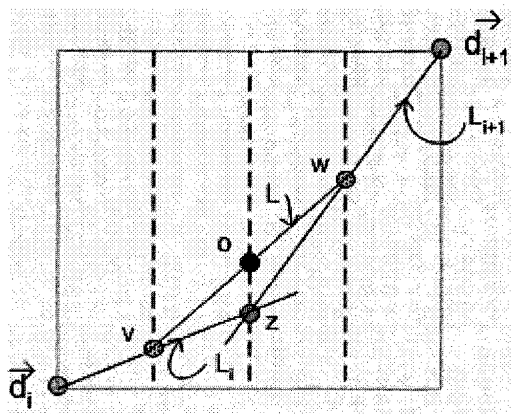


Figure 6-8.a. Knot point determination- Case 1

Accordingly in this general case,

$$x_z = \frac{m_{i+1}x_{i+1} - m_i x_i + \mu_i - \mu_{i+1}}{m_{i+1} - m_i} \tag{6. 6}$$

Let

$$\vec{v} = \left(\frac{x_i + x_z}{2}, L_i\left(\frac{x_i + x_z}{2} \right) \right) \tag{6. 7}$$

$$\vec{w} = \left(\frac{x_z + x_{i+1}}{2}, L_{i+1}\left(\frac{x_z + x_{i+1}}{2} \right) \right) \tag{6. 8}$$

Let L be the line joining $\vec{v}$ and $\vec{w}$ and define $\tilde{\mu} = L(x_z)$. Let $\vec{o}_i = (x_z, \tilde{\mu})$ be the knot point

$$\vec{o}_i = (x_z, L(x_z)) = \left(x_z,\ \mu_v + \frac{(\mu_w - \mu_v)(x_z - x_v)}{x_w - x_v} \right) \tag{6. 9}$$

Thus, the interpolation function $\mu(x)$ can be defined on $[x_i, x_{i+1}]$ as follows:

$$\mu(x) = \begin{cases} B_2\left[\vec{d}_i, \vec{v}_i, \vec{o}_i\right](x) & on[x_i, x_z] \\ B_2\left[\vec{o}_i, \vec{w}_i, \vec{d}_{i+1}\right](x) & on[x_z, x_{i+1}] \end{cases}$$

Case 2. L_i and L_{i+1} do not intersect at a point $\vec{z} = (x_z, \mu_z)$ in R_i. Refer to Figure 6-8b. Note that this case happens when $s_i > s_{i+1}$. The knot $\vec{o}$ is determined similarly as in case 1, but in this case

$$x_z = \left(\frac{x_0 + x_1}{2} \right) \tag{6.10}$$

All equations (6.7- 6.9) remain valid for points $\vec{v}$, $\vec{w}$ and $\vec{o}$.

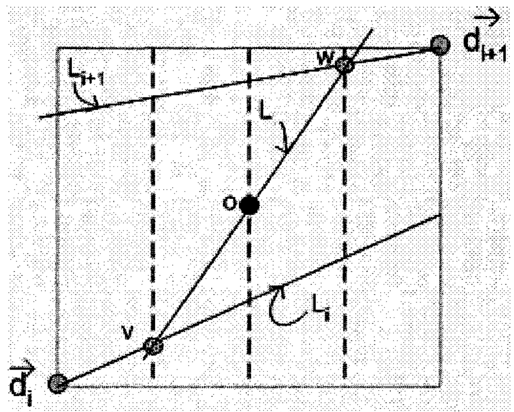


Figure 6.8.b. Knot point determination- Case 2

Both first and last knot point calculations follow the same algorithm described above, but can be simplified, as shown below, to include the zero slope conditions.

(ii). First Knot Point Calculation

First knot point is in between $\vec{d}_0$ and $\vec{d}_1$ where $m_0 = 0$.

Case 1. L_i and L_{i+1} intersect at a point $\vec{z} = (x_z, \mu_z)$ in R_i. Refer to Figure 6-9a. Note that this case happens when $s_i < s_{i+1}$. Accordingly,

$$x_z = x_1 - \frac{\mu_1 - \mu_0}{m_1} \tag{6.11}$$

Let

$$\vec{v} = \left(\frac{x_0 + x_z}{2}, L_0\left(\frac{x_0 + x_z}{2}\right)\right) = \left(\frac{x_0 + x_z}{2}, \mu_0\right) \tag{6.12}$$

$$\vec{w} = \left(\frac{x_z + x_1}{2}, L_1\left(\frac{x_z + x_1}{2}\right)\right) = \left(\frac{x_z + x_1}{2}, \mu_1 - m_1\left(\frac{3x_1 - x_z}{2}\right)\right) \tag{6.13}$$

Let L be the line joining $\vec{v}$ and $\vec{w}$ and define $\tilde{\mu} = L(x_z)$. Let $\vec{o}_i = (x_z, \tilde{\mu})$ be the knot point

$$\vec{o}_i = (x_z, L(x_z)) = \left(x_z,\ \mu_v + \frac{(\mu_w - \mu_v)(x_z - x_v)}{x_w - x_v}\right) = \left(x_z,\ \mu_v + \frac{(\mu_w - \mu_0)(x_z - x_v)}{x_w - x_v}\right) \tag{6.14}$$

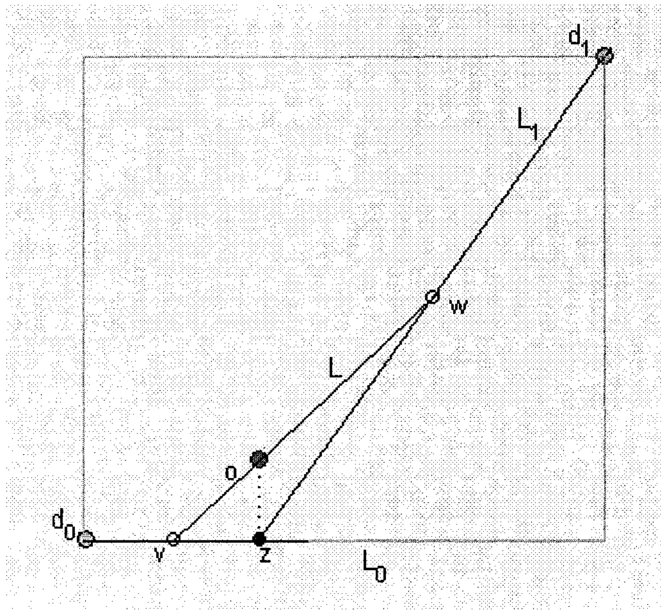


Figure 6-9.a. First knot point determination - Case 1

Case 2. L_i and L_{i+1} do not intersect at a point $\vec{z} = (x_z, \mu_z)$ in R_i. Refer to the Figure 6-9b. Note that this case happens when $s_i > s_{i+1}$. The knot $\vec{o}$ is determined similarly as in case 1, but in this case

$$x_z = \left(\frac{x_0 + x_1}{2} \right) \tag{6.15}$$

All equations (6.12- 6.14) remain valid for points $\vec{v}$, $\vec{w}$ and $\vec{o}$.

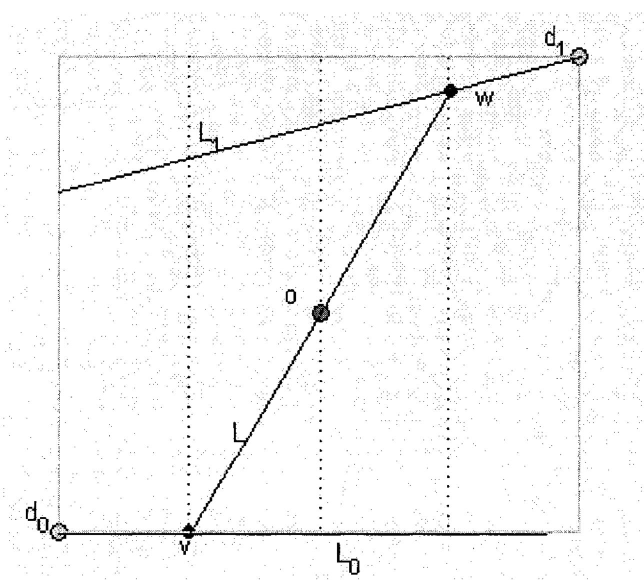


Figure 6-9.b. First knot point determination – Case 2.

(iii). Last knot point calculation

Last knot point is in between $\vec{d}_{N-1}$ and $\vec{d}_N$ where $m_0 = 0$.

Case 1. L_{N-1} and L_N intersect at a point $\vec{z}=(x_z,\mu_z)$ in R_i, refer to Figure 6-10. In this case,

$$x_z = x_{N-1} + \frac{\mu_N - \mu_{N-1}}{m_{N-1}} \tag{6.16}$$

Let

$$\vec{v}=\left(\frac{x_{N-1}+x_z}{2}, L_{N-1}\left(\frac{x_{N-1}+x_z}{2}\right)\right)=\left(\frac{x_{N-1}+x_z}{2}, \mu_{N-1}+m_{N-1}\left(\frac{x_z-x_{N-1}}{2}\right)\right) \tag{6.17}$$

$$\vec{w}=\left(\frac{x_z+x_N}{2}, L_N\left(\frac{x_z+x_N}{2}\right)\right)=\left(\frac{x_z+x_N}{2}, \mu_N\right) \tag{6.18}$$

and

$$\vec{o}_i=(x_z, L(x_z))=\left(x_z,\ \mu_v+\frac{(\mu_w-\mu_v)(x_z-x_v)}{x_w-x_v}\right)=\left(x_z,\ \mu_v+\frac{(\mu_N-\mu_v)(x_z-x_v)}{x_w-x_v}\right) \tag{6.19}$$

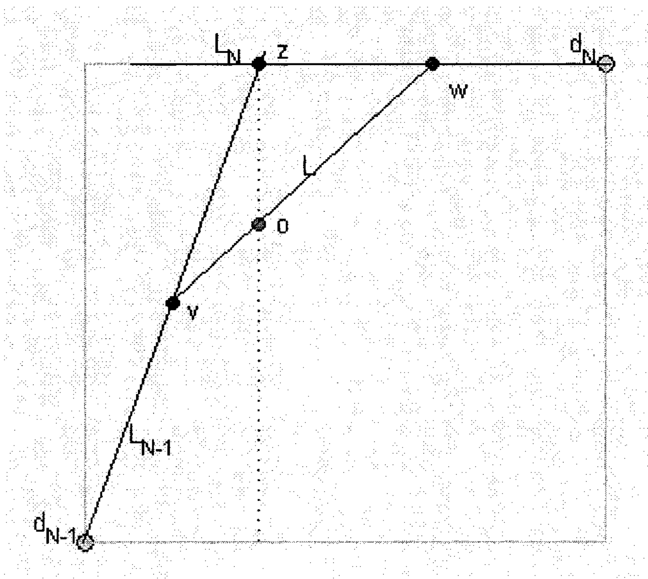


Figure 6-10. Last knot point determination – Case 1.

Case 2. In the case where L_{N-1} and L_N do not intersect at a point $\vec{z}=(x_z,\mu_z)$ in R_i, as shown in Figure 6-11,

$$x_z = \left(\frac{x_{N-1}+x_N}{2}\right) \tag{6.20}$$

All equations (6.17- 6.19) remain valid for points $\vec{v}$, $\vec{w}$ and $\vec{o}$.

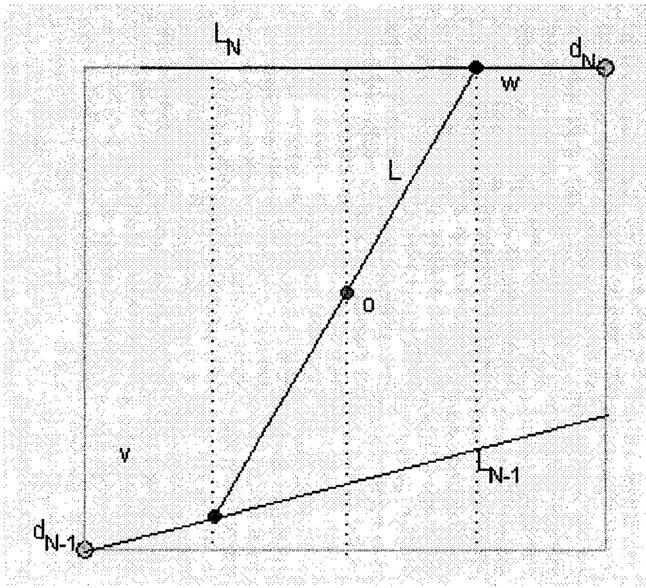


Figure 6-11. Last knot point determination – Case 2.

6.2.6.5 Comparison of "Fritsch and Carlson Algorithm" and "McAllister and Roulier Algorithm"

The ability of the above shape-preserving quadratic interpolation algorithm is demonstrated using three different data sets. The first dataset, used in Figure 6-8, is a monotonically decreasing dataset from (Chen and Otto 1995), namely:

Maximum Stress (MPa) (x)	200	210	225	230	250
Membership degree (μ)	1	0.95	0.5	0.1	0

As shown in Figure 6-12 (b), an unconstrained cubic spline interpolation introduces unwanted oscillations that make the curve overshoot beyond boundary conditions, i.e., [0,1]. However, as shown in Figure 6-12 (c) and (d), both a monotone piecewise cubic interpolant and a quadratic Bernstein interpolant maintain the shape implicit in the data set and also satisfy the constraints imposed by membership functions. Also note that the results produced by the two selected constrained interpolation algorithms are almost identical for this particular dataset.

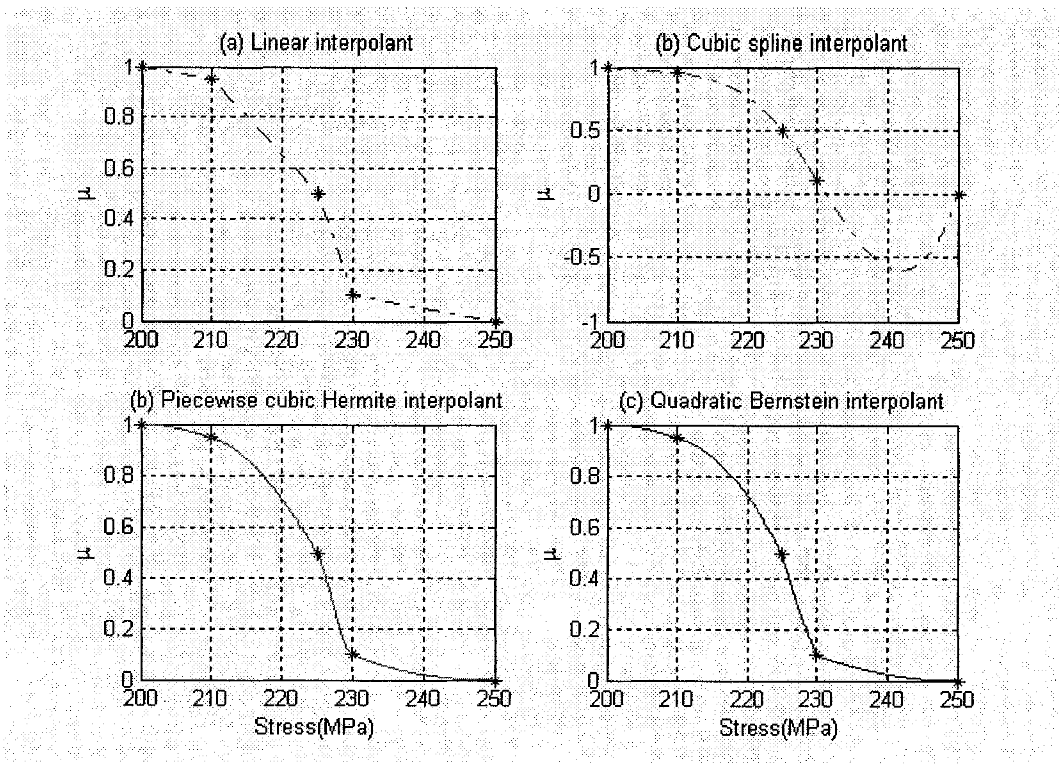


Figure 6-12. Results on monotonically decreasing dataset from (Chen and Otto 1995).

The second dataset, used in Figure 6-13, the membership values of which are monotonically increasing and then monotonically decreasing, for increasing values of elements of the set, is from ((Klir and Yuan 1995), p290), namely:

x	0	0.5	0.8	1.0	1.2	1.5	0
Membership degree (μ)	1.0	0.2	0.9	1.0	0.9	0.2	0

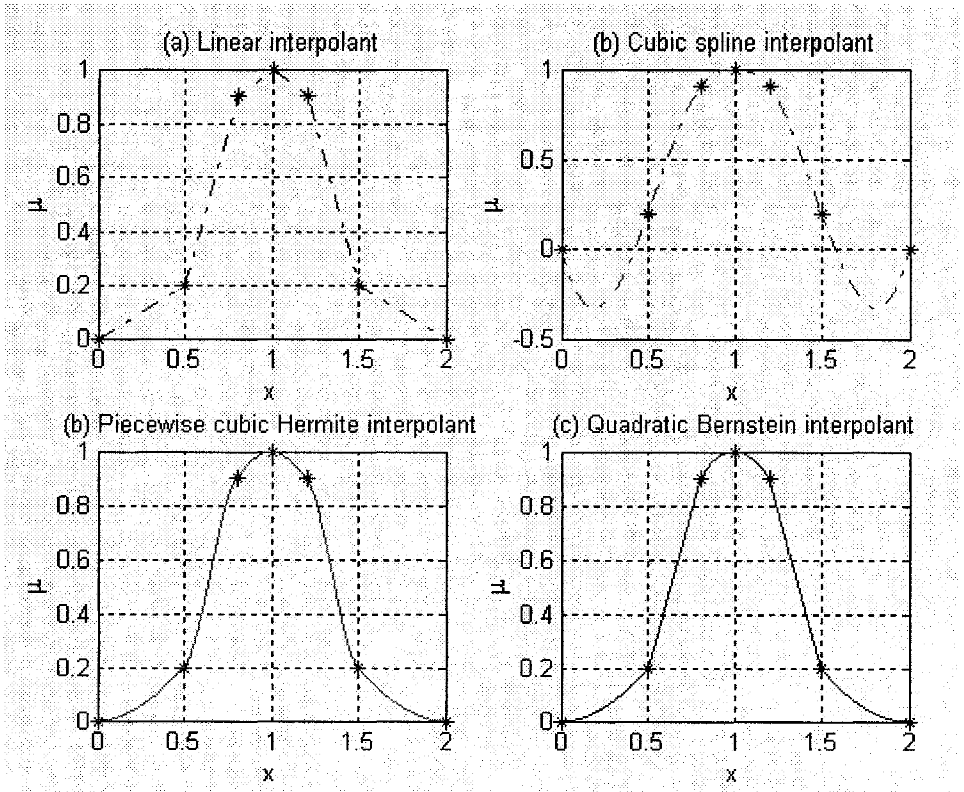


Figure 6-13. Results on monotonically increasing and then monotonically decreasing dataset from (Klir and Yuan 1995).

Results shown in Figure 6-13 also indicate that both constrained interpolation methods produce acceptable results while an unconstrained cubic spline shows excessive undulations.

Thirdly, a more 'complex' dataset, used in Figure 6-14, is a representative of a real-life construction data. These are actual data obtained from the causal factor, "medium temperature".

Temperature-x	6	9	13	14	17	20	24	26	30
Membership degree (μ)	0	0.33	0.77	1	0.83	0.77	0.43	0.33	0

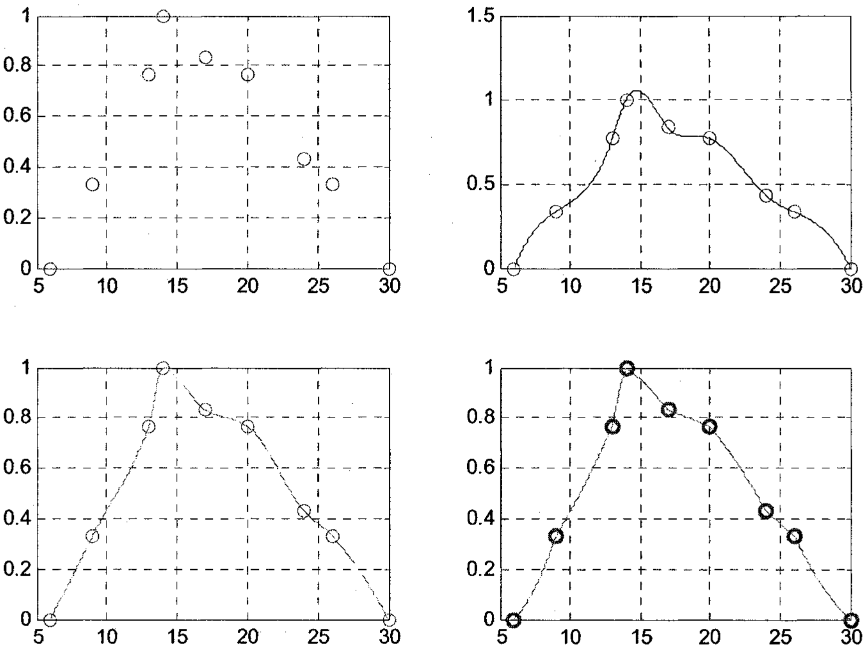


Figure 6-14. Results on monotonically increasing and then monotonically decreasing dataset for causal factor "medium temperature".

Figure 6-14 also demonstrates results similar to previous datasets, proving that both algorithms can preserve the monotonocity and convexity of the sample data. It can therefore be concluded that both the monotone piecewise cubic interpolation method proposed by Fritsch and Carlson and Chen and Otto's method, which is based on quadratic Bernstein polynomial method, are suitable constrained interpolation methods to determine membership functions from sample membership values.

6.3 INTRODUCTION TO THE FIELD STUDY

The field study presented in this section is designed and conducted to obtain subjective opinions on daily working condition(s), and subsequently transforming them into sample membership values in a structured manner in order to construct membership functions to use in reasoning about construction performance (with fuzzy-neural networks).

This field study is carried out at a pipe module fabrication yard located in Edmonton, Alberta. A total number of fifteen (15) frontline supervisors representing five trades (i.e., iron workers, pipe fitters, equipment operators, electricians, and carpenters) and nine different activities (i.e., steel erection, pipe fitting and installation, welding, hydrotesting, glycol tracing, material handling, equipment operation, carpentry/scaffolding, and electrical) completed the study over a sixty (60) workday period, during summer 2005. Figure 6-15 illustrates the pipe module fabrication process. Graphical illustration of the pipe fabrication process is given in Appendix A. The experience of the group of experts (frontline supervisors, otherwise known as foremen) ranges from 6 to 32 years in trade, averaging 20 years.

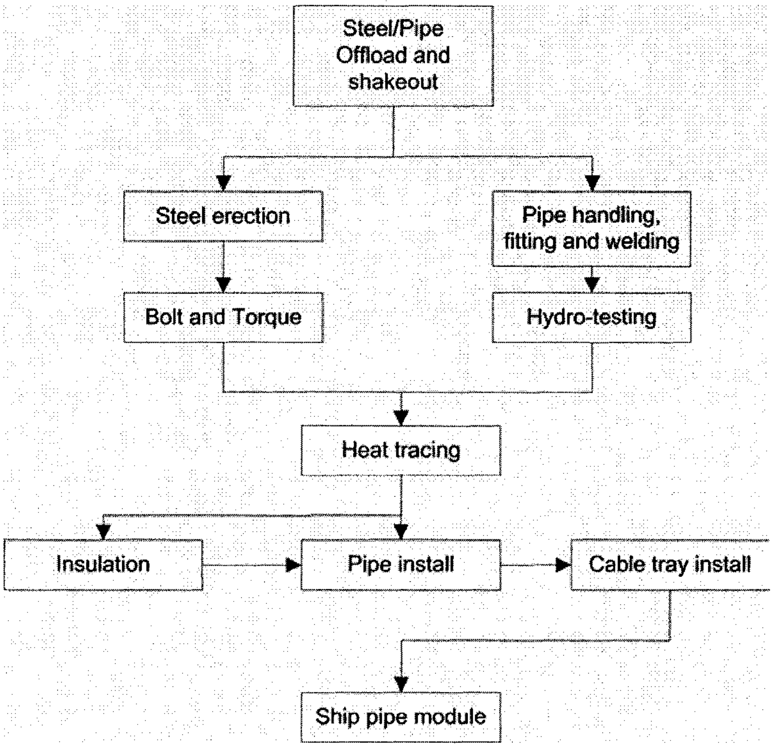


Figure 6-15. Activities in pipe module fabrication process

6.4 CAUSAL KNOWLEDGE REPRESENTATION

Knowledge acquisition from construction experts, taking place in a systematic manner, remains one of the challenges of using fuzzy set theory effectively. This section presents a systematic methodology to elicit and represent qualitative construction performance knowledge from a group of construction experts.

The most common techniques used to identify the causes (factors) in construction literature is based on a review of past studies, postal questionnaire surveys, and face-to-face interviews, or a combination of these techniques (e.g., (Liu and Ling 2005)). Low response rate, out-dated information, and the validity of the responses and disagreements are common criticisms of the above techniques.

Additionally, both the Nominal Group Technique (NGT) and the Delphi technique provide a structured format that helps to increase the quantity and quality of participant responses. Rowe et al. (1991) concluded that the Delphi technique is generally inferior to the NGT, but state that the degree of inferiority is small, arising more from practical than from theoretical difficulties. Singh (2005) used the fuzzy Delphi technique to achieve group consensus in defining decision criteria in the assessment of contractors' performance for the selection of contractors. However, Singh and Tiong (2005) identified that the fuzzy Delphi technique is very time-consuming.

This study proposes a causal knowledge acquisition method based on the NGT to find a more representative causal factor, and to establish a pair of polar adjectives for each causal factor. A brief description and a review of the NGT is given below.

6.4.1 Nominal Group Technique

The Nominal Group Technique (NGT) was first introduced by Delbecq et al. (1975) as a method for structuring group meetings which would allow individual judgments to be pooled effectively while providing opportunities for all participants to contribute equally. This is a proven technique that is helpful in identifying problems, establishing priorities, and exploring solutions in many areas such as medicine, health care, education, engineering, information systems, and management. NGT also found several applications related to project management (e.g., Garbarini 1984; Kolano 1991; Yiu et al. 2005)). Yiu et al. (2005) used NGT in identifying the decision criteria for consultant selection; Kolano (1991) applied NGT in a value engineering project, assisting a group in selecting among many ideas and ranking ideas in order of importance; Garbarini (1984) used NGT to identify productivity improvement opportunities in construction projects.

NGT typically includes four steps: (1) silent generation of ideas in writing; (2) round-robin feedback session to record concisely each idea; (3) serial discussion of the list of ideas to obtain clarification and evaluation; and (4) voting on ideas. This procedure is known to produce balanced participation across members, to generate more creative ideas within a limited meeting time, and results in greater satisfaction for participants. The two key limitations noted commonly in literature are (1) extensive advance preparation, which means that it cannot be a spontaneous technique, and (2) tends to be limited to a single-purpose, single-topic meeting; it is difficult to change topics in the middle of the meeting.

The procedure can be adapted and has been used in different formats. For example, Hegedus and Rasmussen (1986) proposed a modified version of the NGT, avoiding the last step of standard NGT, i.e., the voting on ideas, to encourage participants to arrive at a consensus by means of group decision; Trickey et al. (1998) conducted the idea generation via a series of reviews of recent literature, semi-structured interviews, and questionnaire survey (conducted by post).

6.4.2 Modified NGT Protocol to Identify Causal Factors

A modified version of the standard NGT is used in this study as the formal consensus development method for identifying causal factors of selected key performance indicators by a group of experts in construction project supervision and management. The objective is to identify a minimum number of causal factors that can measure reliably and sufficiently the multidimensional semantic space. The overall process of identifying causal factors and arriving at a consensus is shown in Figure 6-16.

Broadly speaking, the process starts by identifying the key performance indicators (KPIs). Once KPIs are identified, a detailed literature review is conducted to identify a list of causal factors that can possibly impact on selected construction activities. The expert panel should then be selected to represent the expertise in those construction activities selected for diagnosis. It is assumed that the frontline supervisors possess the required expertise. Additionally, frontline supervisors are selected because they will be the individuals most suitable to collect and report daily working conditions (along with work progress) based on the causal factors identified. Once the teams of experts are identified, the session can be arranged at a suitable convenient location (e.g., site office meeting room) minimizing the interruption to the routine work schedule. The estimated timeline for the actual session is approximately one and a half hours. As noted in (Potter et al.), generally, a standard NGT session can range between 45 minutes and 2 hours. Table 6-1 outlines the protocol used in identifying the causal factors via a modified NGT.

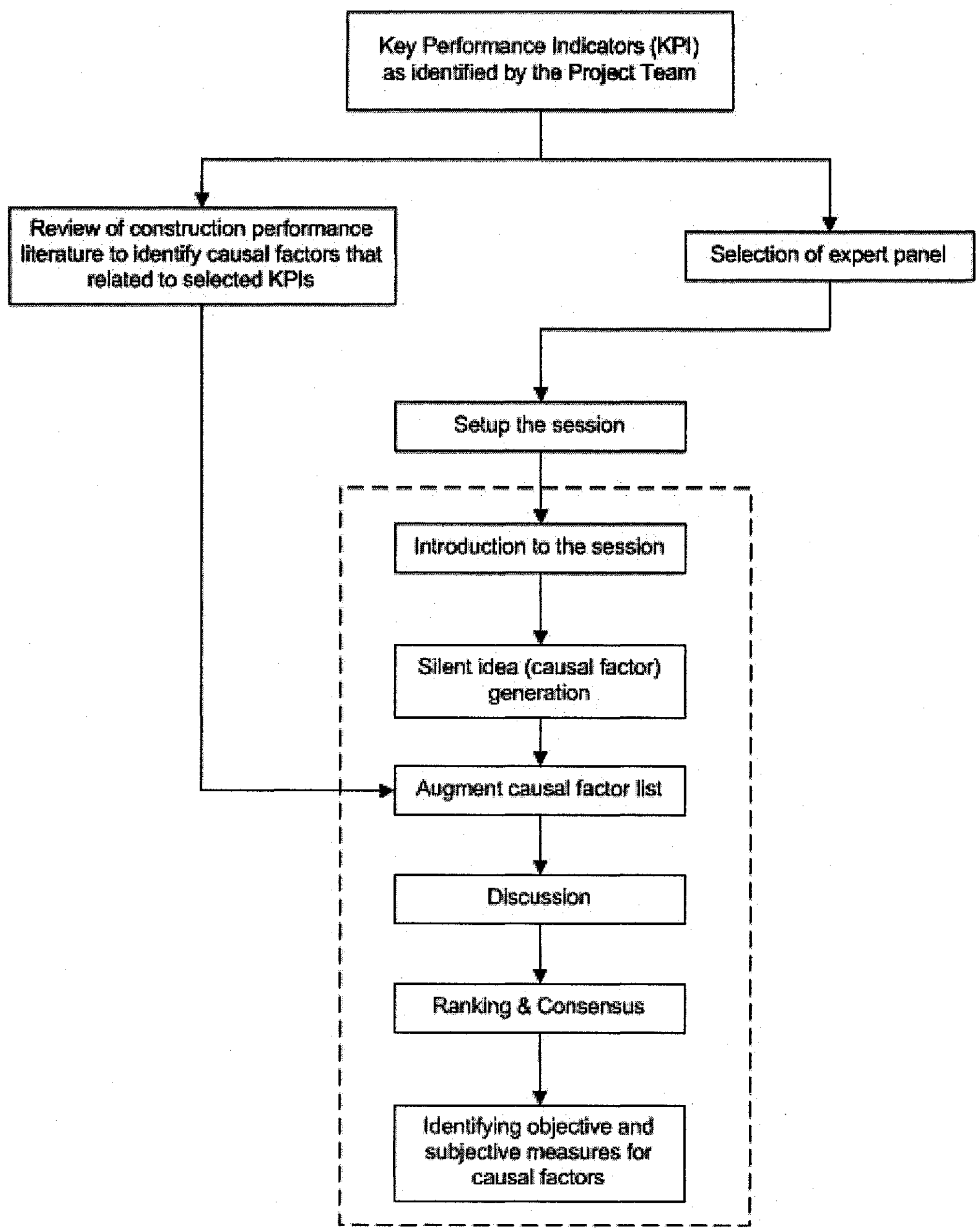


Figure 6-16. Causal factor identification and consensus development process.

Table 6-1. The modified NGT protocol for identifying causal factors of construction performance.

1.	**Review of literature:** Conduct a detailed review of literature as background material for the topic under discussion.
2.	**Setup the meeting:** Inform selected participants about (1) the purpose of the session, (2) venue, and (3) time, at least a day in advance.
3.	**Introduction**: Welcome the participants, and reiterate the purpose of the session. Explain the procedure.
4.	**Silent idea generation**: provide each participant with a sheet of paper (see Appendix-C(a)) that can be used to write down their pertinent related personal details (e.g., trade, activity supervised, experience in number of years) and ask them to write down all causal factors that come to mind with respect to the activity they supervise. During this phase, participants are not supposed to consult or discuss their ideas with others.
5.	**List augmentation**: the session organizer to present the results of review of literature and ask to augment (if necessary) the list of causal factors identified in above step.
6.	**Listing and discussion of ideas**: The session organizer list all the casual factors generated by each member of each group in a flip chart (or white board) and discuss each factor to clarify and elaborate.
7.	**Ranking of ideas**: Each member of the group chose the 10 (or less) causal factors that they consider most important based on the list (Step 5) and the discussion at Step 6. Factors are ranked in order of priority, giving 10 points to the most important factor and 1 point for the least important factor.
8.	**Discussion of rankings**: The group's top 10 factors were listed on a new flip chart by the session organizer and provide a discussion about the content of the selected factors, together with details about the items included and excluded. This is to initiate and facilitate a discussion about each member's concern on factors included/excluded from the list, providing them a chance to defend or dispute the factors and, arrive at a consensus. The number of causal factors selected for the model can be higher or lower than 10, based on this final discussion.
9.	**Selecting objective and subjective measures:** For each factor identified in the above step, an objective and subjective (where applicable) measure is identified, so that relevant values can be collected on regular time intervals (e.g., daily, weekly). Subjective measures are selected using bipolar terms that are most familiar yet most representative.

Note that the ranking (discussed in the NGT protocol) is used solely for selecting a suitable number of causal factors for the model. Unless the findings can be tested against the observed data, we can never be sure that the NGT session has produced the "correct list" of causal factors. Nonetheless, this study uses a computational intelligence approach, as described in Chapter 5, to model the diagnostic problem scenario and by pruning the network (by analyzing the trained networks connection weights), insignificant causal factors can be removed from the model.

6.4.3 Results of the NGT Session

A summary of the results of the session conducted at the pipe module fabrication facility is shown in Table 6-2. Graphical illustrations of the factors that affect pipe module fabrication crew productivity are shown in Figure 6-17. This figure highlights a key issue, i.e., multi-levels of factors, which is worthy of further discussion.

Causal factors can be represented as (1) root causes (e.g., task complexity, equipment condition), (2) intermediate causes (e.g., crew size, equipment breakdown), and (3) composite causes (e.g., precipitation, wind-chill). For example, consider the following chain of cause-effect relationships:

Equipment condition → equipment breakdown → equipment availability →crew productivity

The above relationship can be interpreted as follows: poor equipment condition may cause equipment breakdown that may lead to equipment unavailability, which results in low crew productivity due to idle time. The group has to decide up to what level of detail information is required for diagnosing construction performance. In the above case, for example, the group has to decide whether they need to know why equipment was unavailable, or do they need to know why equipment would break down. If the group merely wants to know whether crew productivity is low due to equipment unavailability, it is not required to include "equipment breakdown" and "equipment condition" as causal factors for the reasoning process. Additionally, the above causal chain does not necessarily indicate that equipment breakdown can be caused only by poor equipment condition. For example, equipment can breakdown due to misuse. In that case, "misuse of the equipment" has to be included in the list of factors.

Another important point to notice in Figure 6-17 is when labour productivity is considered as the hub, the reasoning process can easily be extend to other performance indicators such as cost and schedule.

Table 6-2. Summary results of the session based on the modified Nominal Group Technique

PERFORMANCE FACTOR	Steel Erection	Pipefitting & installation	Hydro testing	Glycol tracing	Welding	Mat. Handling	Equip.oper'n	Carpentry	Electrical	PROPOSED PHYSICAL MEASURE	PROPOSED BIPOLAR SCALE
Crew size	√	√								No of workers/crew	Small, Large
Absenteeism	√	√	√	√						No of workers absent	Low, High
Crew experience				√						No of years in the trade	Low, High
Rework	√	√	√	√						Rework hours	Low, High
Incomplete/unclear drawings		√	√						√	No of RFIs	Low, High
Temperature (day time average)	√	√		√		√			√	Celsius degrees	Cold, Warm
Total Precipitation	√	√	√						√	Millimetres	Low, High
Wind speed (day time average)	√	√							√	km/hr	Low, High
Manpower availability						√				No of workers/trade	Low, High
Equipment availability	√	√		√	√	√			√	Total number of key equipment	Poor, Good
Equipment suitability	√	√			√	√			√	Equipment capacity	Improper, , Ideal
Tools condition	√				√				√		Poor, Good
Consumables availability	√				√						Poor, Good
Material availability	√	√	√		√				√		Poor, Good
Congestion on work location	√		√	√	√				√	Men/Area	Low, High
Access to work location	√	√		√					√		Restricted, Excellent
Time to await inspections			√							No of hours	Low, High
Waiting for other trades		√		√	√				√	No of hours	Low, High
Task complexity				√							Below normal, Above N
Safety equipment availability		√									Low, High
Right tool availability		√									Low, High
Crew attitude/morale			√								Poor, Good

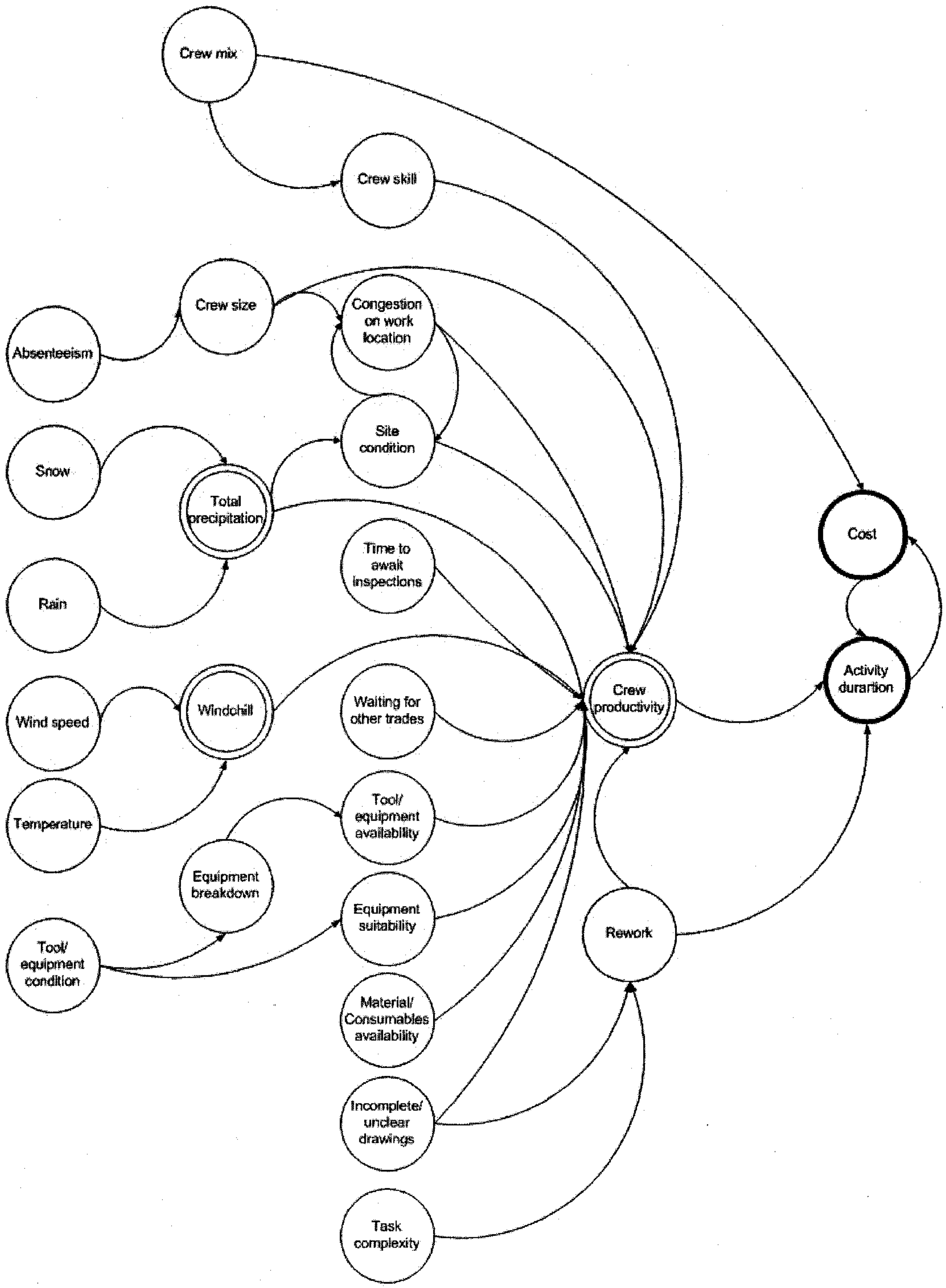


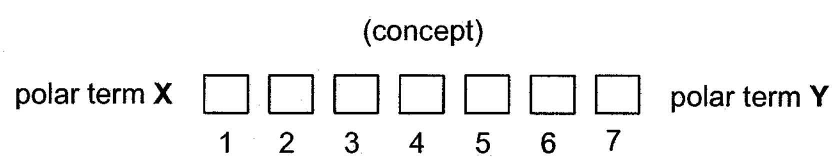
Figure 6-17. Causal factors that affect pipe module fabrication crew productivity.

Once the causal factors are identified, the next step is to collect the objective and subjective values of the selected variables on predefined time intervals (e.g., on a daily basis). As described in Section 3.2.2, since there are variables that do not have well defined objective measures, a structured approach is required to obtain subjective assessments (i.e., soft estimates) of daily working conditions from multiple experts. Furthermore, this approach should facilitate the aggregation of subjective assessments across multiple experts and across different time intervals as well.

Generally, in most studies, a unipolar scale (e.g., zero to 10, zero being the lowest and 10 being the highest) is selected to represent the individual judgment. This study exploits a measurement technique based on bipolar scales, i.e., semantic differential, for structuring the subjective assessment of construction performance variables. The rationale in selecting a bipolar scale, rather than a traditional unipolar scale, is presented in the next section.

6.4.4 Semantic Differential Analysis

The method of Semantic Differential Analysis (Osgood et al. 1957) offers a simple, reliable, and widely used method to measure the connotative meaning of objects, events, and concepts. It is a type of rating scale defined using bipolar adjectives (e.g., cold-warm, light-heavy, etc.). The adjectives are usually scaled in seven steps, represented by seven linguistic hedges, as shown in Figure 6-18.



1. extremely X
2. quite X
3. slightly X
4. neither X nor Y; equally X and Y
5. slightly Y
6. quite Y
7. extremely Y

Figure 6-18. Bipolar scale.

The subject's placement of the concept on the adjectival scale indicates the connotative meaning of the concept. Studies carried out by Osgood et al. (Osgood et al. 1957) on a large number of different subjects in many different experiments, found that "with seven alternatives all of them tend to be used and with roughly, if not exactly, equal frequencies. When nine alternatives were used, where "quite" is broken into "considerably" and "somewhat" on both sides of the neutral position, it was found that all three discriminative positions on each side had much lower frequencies." This finding is consistent with Saaty's (1980) seven-point scale. To each of the seven positions on the bipolar scales, a digit is assigned arbitrarily. These digits may be either 1,2,3,4,5,6,7 or -3,-2,-1,0,1,2,3. For mathematical descriptions (described later), the choice makes no difference. In a 1 to 7 scale, as shown in Figure 1, 4 corresponds to the neutral point, in -3 to +3 scale, 0 represents the neutral point.

The choice of bipolar scales to represent the experts' evaluation (i.e., fuzzy linguistic estimates) has several advantages:

1. **Intensity and Direction:** Bipolar scales represent intensity as well as the direction of the fuzzy estimate while a traditional unipolar only provides the intensity.
2. **Multidimensionality**: If we use a unipolar scale, we presume that the factor in question can be represented as unidimensional. In other words, the best reason to use unidimensional scaling is because we believe the concept we are measuring really is unidimensional in reality. Factors such as site congestion, for example, can be represented by both manpower density and equipment mobility. In such situations, we can use bipolar scales to capture the multidimensionality of such factors.
3. **Planned conditions**: In some cases, the neutral values of the bipolar scale (i.e., number 4) represent the planned conditions of the causal factors (e.g., temperature, wind), which can be used to identify implicit planned working conditions. This information can be useful in conducting variance analysis using fuzzy linguistic estimates.

6.5 DAILY WORKING CONDITION ASSESSMENT

This section provides a well-defined methodology for construction managers to assess (daily) working condition using fuzzy linguistic estimates based on semantic differentials.

Figure 6-19 shows a sample daily working condition report. "Steel erection" is selected as the activity, R, for illustration. This working condition report, C_R, represents the multidimensional space of the concept: the daily working conditions for steel erection. The list of causal factors (L_k, k=1 to m, where m is the total number of causal factors in C_R) represent the dimensions of the semantic space. Each dimension (i.e., each causal factor) is represented using a bipolar scale assumed to represent a straight line function that passes through the origin of the space. A sample of such scales then represents a multidimensional space. Raw data obtained from a "daily working condition report" are a collection of checkmarks against bipolar scales, S_p^k , where

$p \in \{1,2,3,4,5,6,7\}$. As shown in Figure 6-19, the scale values are labeled using seven linguistic hedges to help experts make adequate distinctions amongst them.

Activity: STEEL ERECTION

GF/Foreman: **Date:**

DAILY WORKING CONDITION REPORT

			Extremely	Quite	Slightly	Both/ N.A	Slightly	Quite	Extremely	
★ Today's Crew Productivity		Low	1	2	3	4	5	6	7	High
1. Crew size (no. of workers/crew)	(___)	Small	1	2	3	4	5	6	7	Large
2. Absenteeism (no. of crew members absent)	(___)	Low	1	2	3	4	5	6	7	High
3. Rework (Rework hours)	(___)	Low	1	2	3	4	5	6	7	High
4. Temperature		Cold	1	2	3	4	5	6	7	Warm
5. Total precipitation		Low	1	2	3	4	5	6	7	High
6. Wind speed		Low	1	2	3	4	5	6	7	High
7. Equipment availability (no. of cranes available)	(___)	Poor	1	2	3	4	5	6	7	Good
8. Equipment suitability		Improper	1	2	3	4	5	6	7	Ideal
9. Tools condition		Poor	1	2	3	4	5	6	7	Good
10. Consumables availability		Poor	1	2	3	4	5	6	7	Good
11. Material availability		Poor	1	2	3	4	5	6	7	Good
12. Congestion on work location		Low	1	2	3	4	5	6	7	High
13. Access to work location		Restricted	1	2	3	4	5	6	7	Unrestri -cted

Example

Crew Size (Average 10, Today 9)
(No. of crew members)

Small	1	2	✓3	4	5	6	7	Large

1. *extremely* Small
2. *quite* Small
3. *slightly* Small
4. *Neither* Small nor High; *equally* Small and Large
5. *slightly* Large
6. *quite* Large
7. *extremely* Large

Figure 6-19. Sample working condition report.

Assume that n frontline supervisors representing C_R reported their objective (where applicable) and linguistic estimates on L_k (k= 1 to m, where m is total number of causal factors) on day t. This results in a set of pairs $\langle x_{L_k}, S_{i,p}^k \rangle$, where x_{L_K} represents the corresponding objective measure of the causal factor L_k during the period concerned (e.g., daily). $S^k_{i,p}$ represents the fuzzy linguistic estimate provided by expert i on variable L_k, ($p \in \{1,2,3,4,5,6,7\}$, fuzzy linguistic estimate).

As illustrated in Figure 6-20, for a given activity on a certain day, the working condition report C_R provides a $n*m$ matrix of data points. An alternative representation of the n*m matrix is shown in Figure 6-21.

Each of the fifteen experts were asked to record their subjective judgment of the (daily) working conditions based on selected causal factors in activity specific working condition reports, at the end of each workday. The primary objective here is to obtain a fairly accurate assessment of the daily working condition from group of experts who were exposed to different working condition during a defined shift.

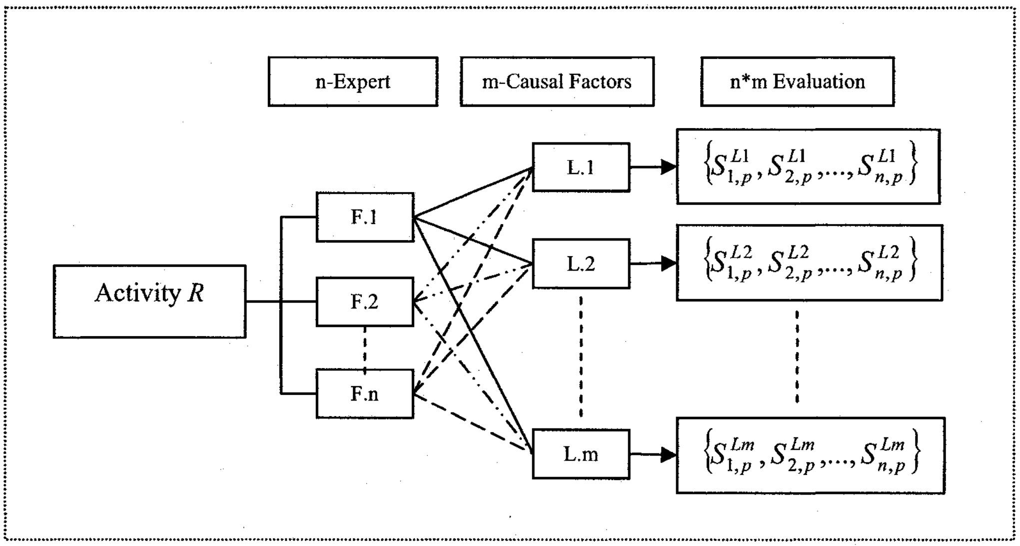


Figure 6-20. Multiple fuzzy linguistic estimates from daily working condition report.

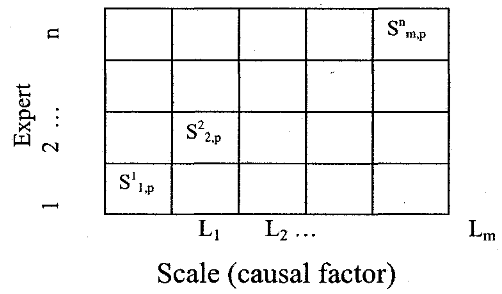


Figure 6-21. Matrix representation of multiple fuzzy linguistic estimates.

When the fuzzy linguistic estimates are obtained over a period of time, T, the resulting matrix of data (n*m*T) can be represented as shown in Figure 6-22.

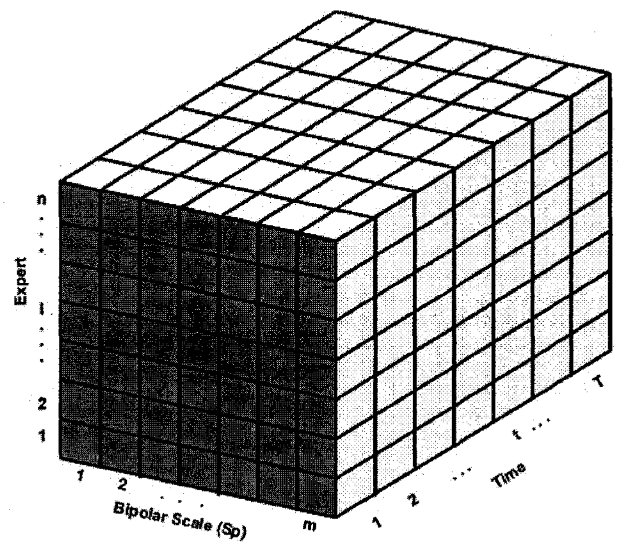


Figure 6-22. Rectangular solid of data representing experts' assessment over a period of T.

Each cell in this matrix of data represents the judgment of a particular causal factor by a particular expert on day *t*; each of the *n* slices represents the complete judgment of a single expert (i.e., one daily working condition report. Each of the m slices represents the assessment of a particular causal factor over the duration T.

6.5.1 Aggregation of Data

There are three possible scenarios that may require an aggregation of estimates:

Mean response of group of experts: This is a case where the group estimate is required. Assume that we have *n* number of experts providing fuzzy linguistic estimates on causal factor L_k.

$$\text{Let } S_p^k = \frac{1}{n}\sum_{i=1}^{n} S_{ip}^k \tag{6.15}$$

S_p^k represents the mean response of the group of experts. It may be viewed as a probabilistic interpretation of the (mean) bipolar score. Consider that 3 steel-erection foremen (n=3) were asked evaluate "today's equipment availability" (L_k). Assume that their responses were as follows:

Foreman	Today's equipment availability	
1	*Slightly poor*	3
2	*Neither poor/good*	4
3	*Quite good*	6

The mean response of the group can be calculated as $S_p^k = \frac{1}{3}(3+4+6) = 4.33$, which indicates that the assessment of today's equipment availability for steel erection lies in between "*slightly good*" and "*neither good or poor*".

Equation 6.15 can be generalized by allowing one to distinguish degrees of competence, c_i, of the individual experts {{939 Klir, G.J. 1995; }}. This results in the formula

$$S_p^k = \sum_{i=1}^{n} c_i \cdot S_{ip}^k \qquad (6.16)$$

Where $\sum_{i=1}^{n} c_i = 1$

For example, assume that the competency of each foremen is estimated as follows;

Foreman	Competency
1	0.5
2	0.3
3	0.2

Accordingly, the mean response of the group can be calculated as $S_p^k = [(3\times 0.5)+(4\times 0.3)+(6\times 0.2)] = 3.9 \approx 4.0$, indicating that the assessment of today's equipment availability for steel erection lies close to "*neither good or poor*".

Weekly (or monthly) averages: This is a case where data need to be aggregated across time (e.g., in the case where weekly average is obtained by daily values). In this case,

$$S_p^k = \frac{1}{T}\sum_{i=1}^{T} S_p^k \qquad (6.17)$$

Where T is total number of days across the time period concerned.

For example, consider that it is required to obtain weekly (T=5) assessment of equipment availability. Assume that the daily assessment of equipment availability as given in the table below.

Foreman	Competency	Equipment availability				
		Day 1	Day 2	Day 3	Day 4	Day5
1	0.5	3	4	6	3	7
2	0.3	4	3	5	2	6
3	0.2	6	2	4	5	2
Mean		3.9	3.3	5.3	3.1	5.7

The mean response shown in the above table is calculated using Equation 6-16. based on the Equation 6-17, the weekly average assessment of equipment availability for the steel erection can be calculated as $S_p^k = \frac{1}{5}(3.9 + 3.3 + 5.3 + 3.1 + 5.7) = 4.26$, indicating the equipment availability of that week for steel erection was close to ""*neither good or poor*".

Composite causal factor scores: In cases where hierarchical representations are required and composite factors are identified, to obtain composite causal factor scores, the (root) causal factor scores are summed and averaged over the scales. The composite causal factor score is

$$S_p^{\hat{k}} = \sum_{i=1}^{q} c_q \cdot S_p^k \tag{6.18}$$

Where c_q represent the significance of each (sub) causal factor.

Consider that it is required to represent three weather related causal factors (i.e., precipitation, wind speed and temperature" as a single causal factor: "weather". Also assume that among those three causal factors, precipitation has a higher influence compared to other two, and significance of each causal factor is as follows:

Causal Factor	*Significance*	*Mean Response of week (using Eq.6-17)*
Precipitation	0.6	5.8
Wind speed	0.2	4.5
Temperature	0.2	3.9

In such a case, the composite causal factor score can be calculated as follows:

$S_p^{\hat{k}} = [(0.6 \times 3.9) + (0.2 \times 4.5) + (0.2 \times 5.8)] = 5.16$, indicating that the weekly *weather* condition was close to "*slightly good*".

The above equations provide a strategy to aggregate linguistic assessments when necessary.

Notation

C_R	=	working condition report of Activity R.
i	=	expert;
L_k	=	causal factor
m	=	total number of causal factors
n	=	total number of experts
$p \in \{1,2,3,4,5,6,7\}$	=	values that represent the linguistic hedges of bipolar scale S.
q	=	total number of sub causal factors consists in the composite factor
R	=	activity
S	=	bipolar scale
$S^{k}_{i,p}$	=	linguistic assessment of causal factor L_k by expert i
$S^{\hat{k}}_{p}$	=	composite causal factor score
x_{L_K}	=	objective measurement of causal factor L_k

6.5.2 Interim Analysis of Fuzzy Linguistic Estimates

To determine the effectiveness of the proposed semantic differential scales to obtain fuzzy linguistic estimates, an interim analysis was carried out on selected causal factors. The purpose of this analysis was as follows:

- To identify the limits of the base variable, where applicable;
- To identify the factors that have variability, in order to limit the number of input variables;
- To identify threshold values; and
- To assist in selecting the appropriate number of fuzzy sets (linguistic variables) to represent each factor.

6.5.2.1 Causal Factor: Daytime Average Temperature

Results related to the causal factor "temperature" are discussed in this section. Figure 6-23 shows how daytime average temperature varied over the period of study. Weather-related data such as temperature, wind speed, precipitation, and humidity were collected at the site by setting up a professional wireless mini-weather station (Model: WS-2315AL by La Crosse Technology).

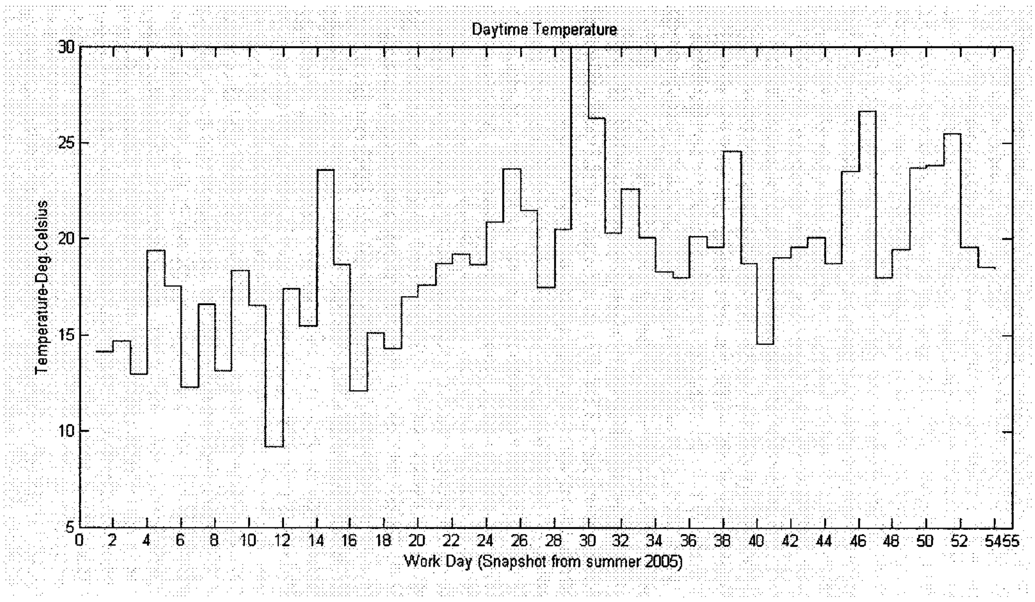


Figure 6-23. Daytime average temperature (degrees Celsius).

Figure 6-24 shows the average fuzzy estimates aggregate from all experts (assuming equal competency levels) against the daytime average temperature. Note that multiple dots for the same x-axis values (i.e., degrees Celsius) indicate that (i) the same daytime average temperature was recorded on multiple days, and (ii) different aggregated expert evaluations were obtained for the same value of temperature (on different days of the month/season) , during the period studied.

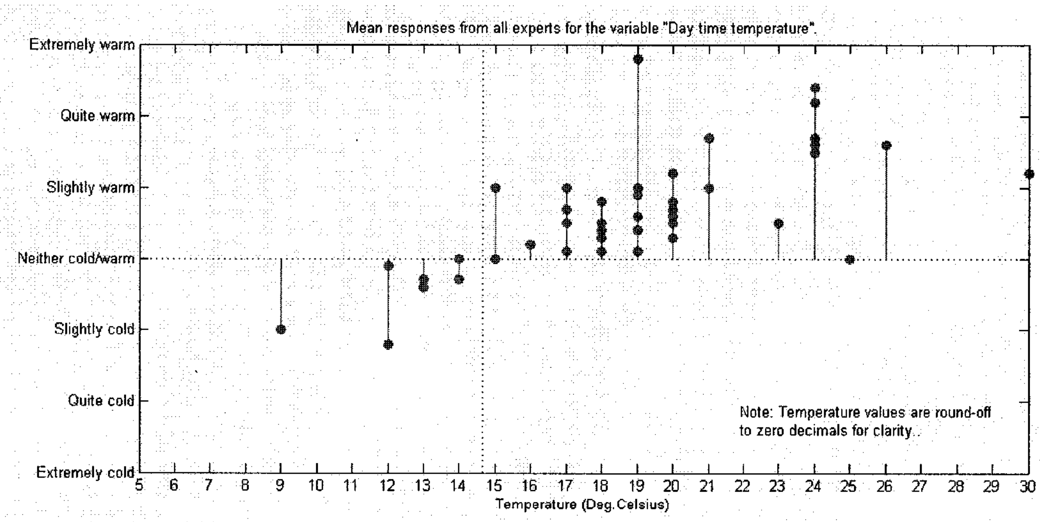


Figure 6-24. Mean estimated values for temperature.

However, as shown in Figure 6-24, in most cases, the variation of the fuzzy estimates is low and remained in between two linguistic values. For example, the value of 18 degrees Celsius is recorded 5 times during the study period. The mean value of fuzzy linguistic estimates for all five days remained in between "neither cold/warm" and "slightly warm". Similar results were observed for the temperature values, 12, 13, 14, 15, 17, 21, and 24. This indicates that, for the period studied (i.e., summer 2005), the mean estimates (of the group) are nearly consistent.

A sample activity level analysis (for structural steel erection) for the same causal factor (i.e., temperature) is shown in Figure 6-25. The subjectivity of the individual assessments is clearly visible in the Figure 6-25. Nonetheless, the assessments are still in between two linguistic values in 85% (18 out of 25) of the cases. Similar results related to the pipefitting and fabrication activities are shown in Figure 6-26.

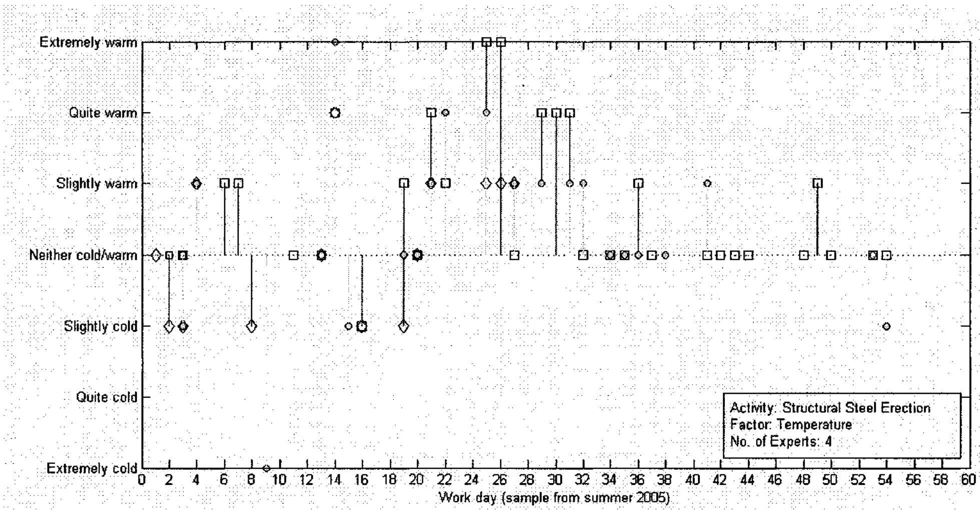


Figure 6-25. Individual estimated values for temperature by steel erection experts.

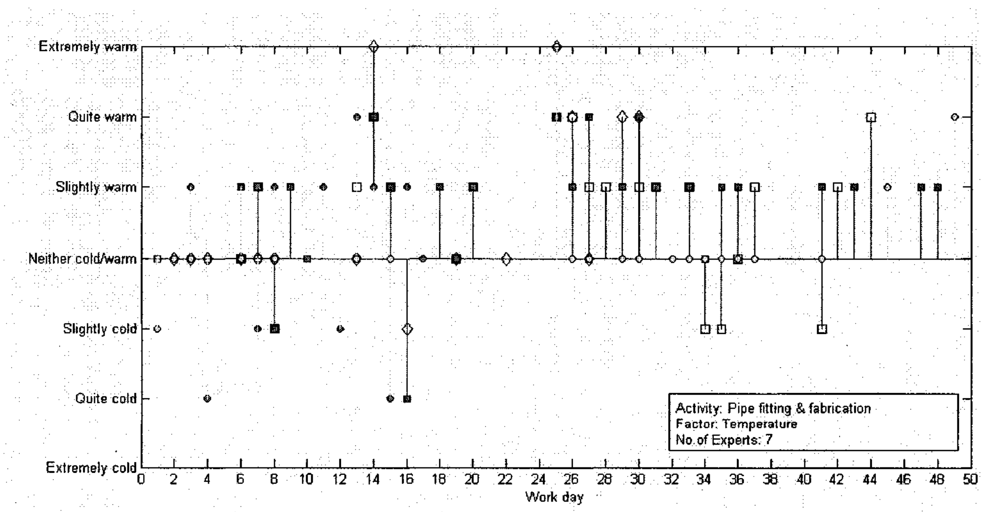


Figure 6-26. Individual estimated values for temperature by pipefitting and fabrication experts.

It is also noteworthy to highlight the fact that assessments of the variables such as temperature and precipitation (rain and snow) can vary significantly from season to season. These time-varying (i.e., temporal) dynamics of such causal factors can be captured using time-dependent membership functions. This study addresses this issue by constructing membership functions for each season for such causal factors by categorizing data into respective seasons.

6.5.2.2 Causal Factor: Daytime-Average Wind Speed

Figure 6-27 shows how daytime average wind-speed (km/hr) varies over the period of study. Figure 6-28 shows the average estimated values for daytime average wind speed (km/hr) by ironworkers (assuming equal competency levels). Estimates of the same data obtained from pipefitting experts are shown in Figure 6-29.

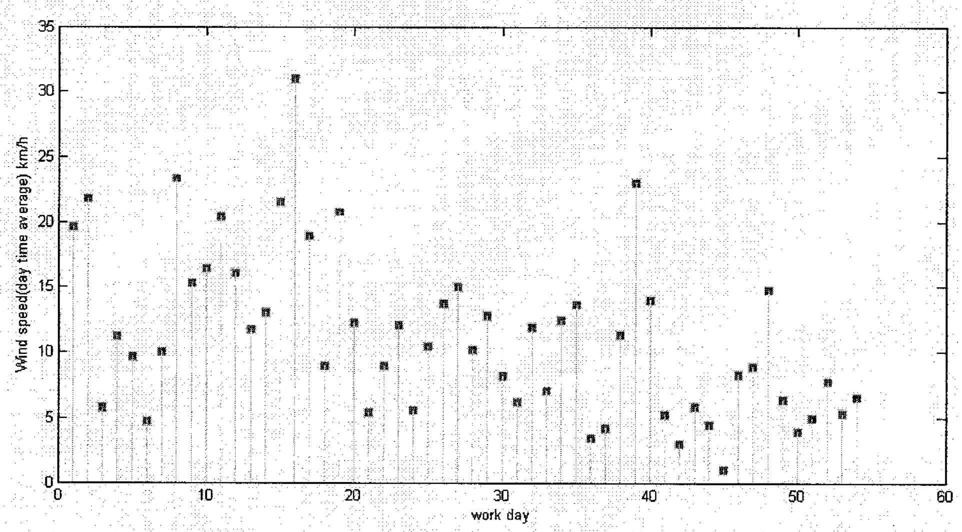


Figure 6-27. Daytime average wind speed (km/hr).

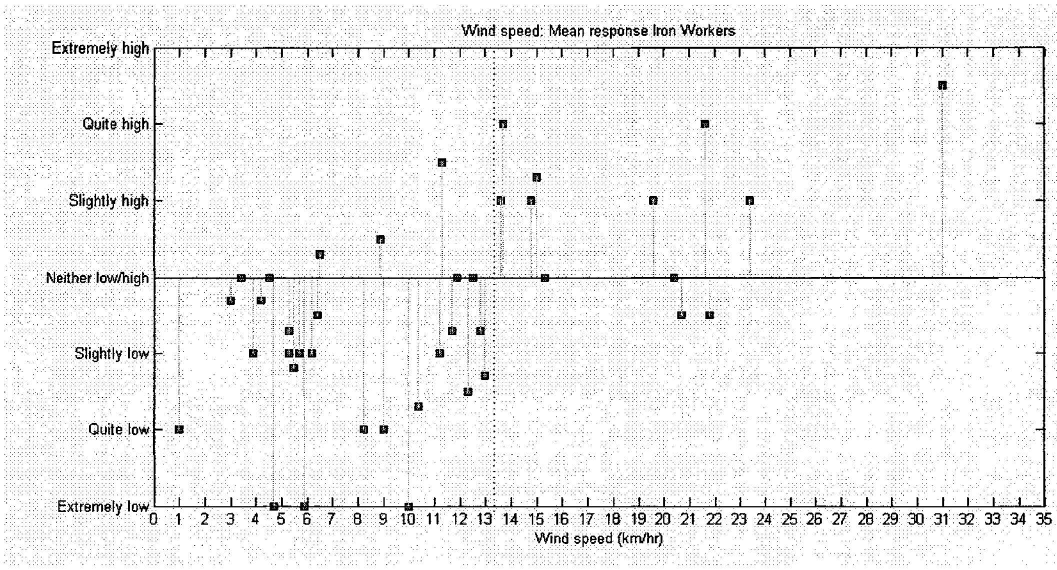


Figure 6-28.Mean estimated values for daytime average wind speed (km/hr) by ironworkers.

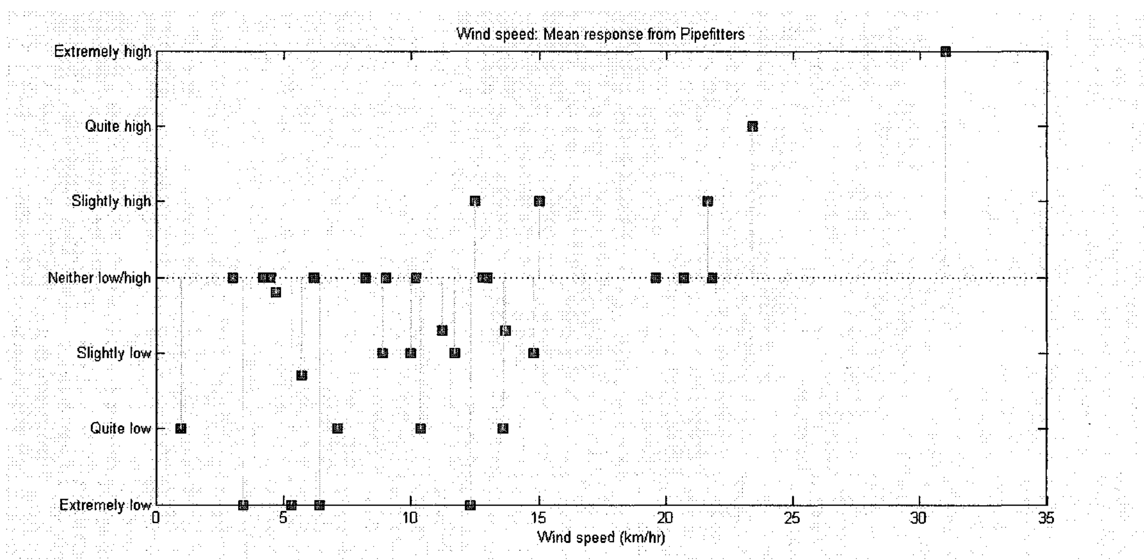


Figure 6-29. Mean estimated values for daytime average wind speed (km/hr) by pipefitters.

A few key observations can be made from Figures 6-28 and 6-29. First, it is clear that linguistic assessments can be divided into two groups as follows: when the wind speed is less than 13-15km/hr, the average estimated values by both ironworkers and pipe-fitters belong to "low" part of the bipolar scale. When the average wind speed is greater than 13-15km/hr, average estimates remained in the "high" side of the bipolar scale. This assessment helps to identify threshold values (of wind speed), which can be effectively used in performance diagnostic reasoning. The analysis also helps to identify the boundaries of the variable that can be used to define the universe of discourse of the variable. Additionally, when compared with the causal factor discussed in the previous section, i.e., temperature, the causal factor *wind speed* behaves different. In the case of *temperature*, both extreme polar conditions (i.e., extremely/quite-cold and -warm) can have a negative impact on project performance while in the case of *wind speed*, only one polar condition, i.e., high, can have the negative impact. It can be argued that if the wind speed is below the threshold value, there will not be impact of wind speed on activity performance.

6.5.2.3 Causal Factor: Crew Size

Compared to the causal factors discussed before, the "crew size", measured as the number of workers per crew, has its unique characteristics. For example, both "temperature" and "wind speed" are factors that change continuously, while crew size changes intermittently due to factors such as absenteeism, turnover, and crew reallocation, or splits due to changes in scope of work. It is a common practice in construction that multiple crews are assigned to the same activity. In most of the cases, each individual crew carries out a sub-activity. For example, in the "steel erection" activity, there can be two crews working simultaneously on two sub-activities, such as "steel handling" and "bolt-and-torque" of steel members. Thus the linguistic assessments made for same crew size by different crew supervisors can vary considerably. Figure 6-30 shows assessments made by five experts on different crew sizes.

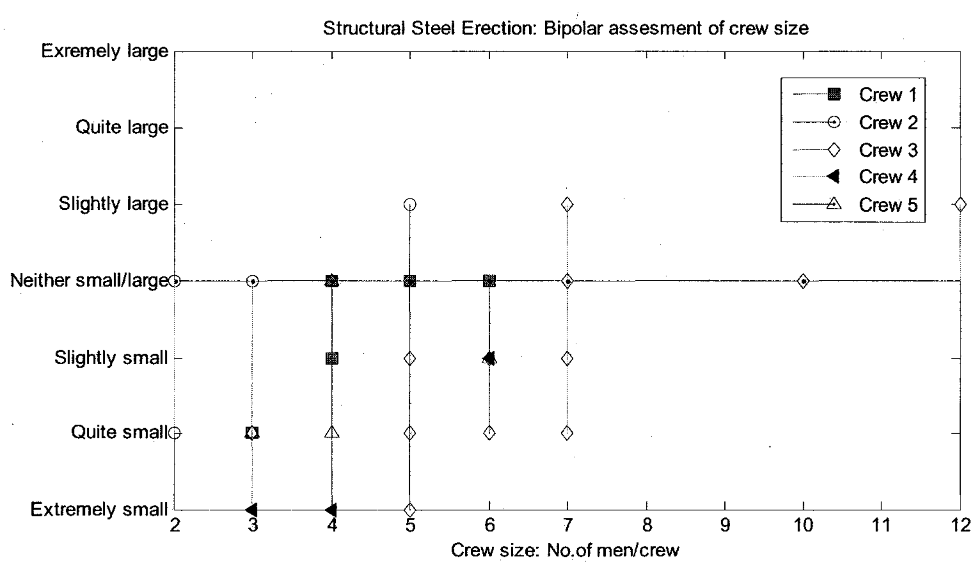


Figure 6-30. Linguistic assessments of crew size.

As shown in Figure 6-30, the size of Crew #3 has taken the values {5, 6, 7, 10, 12}. The linguistic assessments also vary considerably, for example, in the case where the crew size is 7, linguistic assessments relevant to Crew #3 vary from quite small to slightly large. Further analysis of this issue has indicated that the same crew has been assigned for different sub-activities of steel erection (e.g., steel handling, bolt-and-torque steel members), which contributes to the varied assessment. For example, in the case of handling steel, a crew size of 7 will be "slightly small" while for bolt-and-torque, it will be "slightly large".

However, since the main focus of this study is to explain construction performance at activity level (instead sub-activity level), linguistic assessments made by each crew supervisor (at sub-activity level) should be aggregated to represent the assessment of crew-size at the activity level. The linguistic assessment at the activity level can be obtained using the following aggregation operation:

$$S_p^k = \left(\sum_{k'=1}^{m'} x_i' * S_{i,p}^{k'} \right)^{1/m'} \tag{6.19}$$

Where m' is the total number of sub-activities, x_i' is the size of crew, and $S_{i,p}^{k'}$ is the linguistic assessment of crew size of sub-activity k'. For example, consider that activity D has 3 sub-activities: A, B, and C that are carried out by Crew A, Crew B and Crew C, respectively. Following table shows the size of each crew and respective bipolar assessment of each crew size:

Crew	A	B	C
Size (no.of workers)	6	8	10
Bipolar assessment	Neither small/ large (4)	Quite large (6)	Slightly large (5)

Accordingly, the aggregated value of the linguistic assessments at activity level, D, can be calculated as follows: $S_i^p = [(6 \times 4) + (8 \times 6) + (10 \times 5)]^{1/3} = 4.96$.

A graphical illustration of the variability of the linguistic assessments across different crew sizes over the study period is shown in Figure 6-31. In general, the crew size of 5 to 7 is considered as average (i.e., neither small or large) while a crew size above 10 is considered as quite large. Certain crew sizes have not changed over the period (e.g., Crew #2) while certain crew sizes vary considerably (e.g., Crew #3).

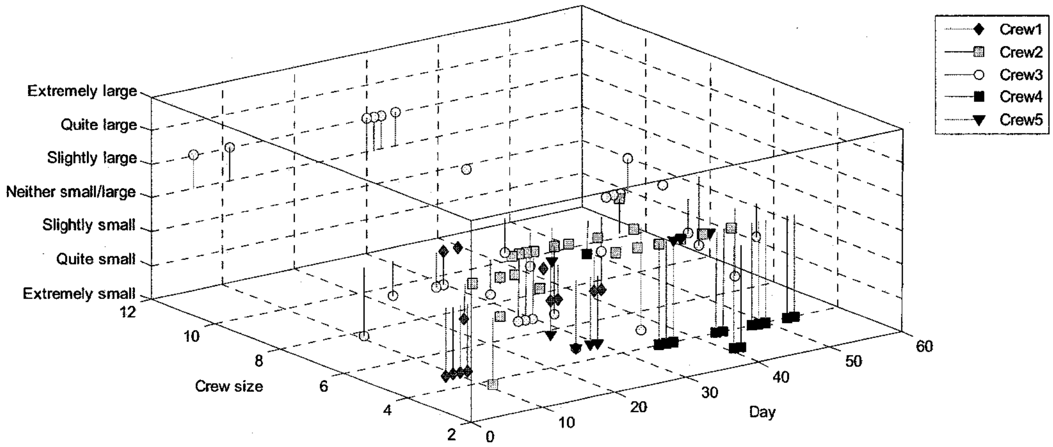


Figure 6-31. Linguistic assessments of crew size over the study period.

This high variability of the size of the same crew over the project duration is mainly due to change of scope of activity. This insight leads to the conclusion that the measure for crew size may need to modify in future studies, to reflect scope of activity. Additionally, Figure 6-31 also illustrates the usability of linguistic assessments to model the appropriateness of the crew size, in an explicit way, in contrast to the current practice of implicit modeling with multiplication factor(s).

6.5.2.4 Causal Factor: Field Rework

As shown in Figure 6-32, generally any amount of field rework hours are estimated at the "high" side of the bipolar scale. If the amount of rework hours spent on a particular day by the crew is greater than 10 hours, it is estimated as "extremely high" while rework hours ranging from 2-10 are estimated in between "slightly high" to "quite high". Similar to the factor "wind speed", this analysis also helps to identify threshold values and boundaries of the causal factor "field rework".

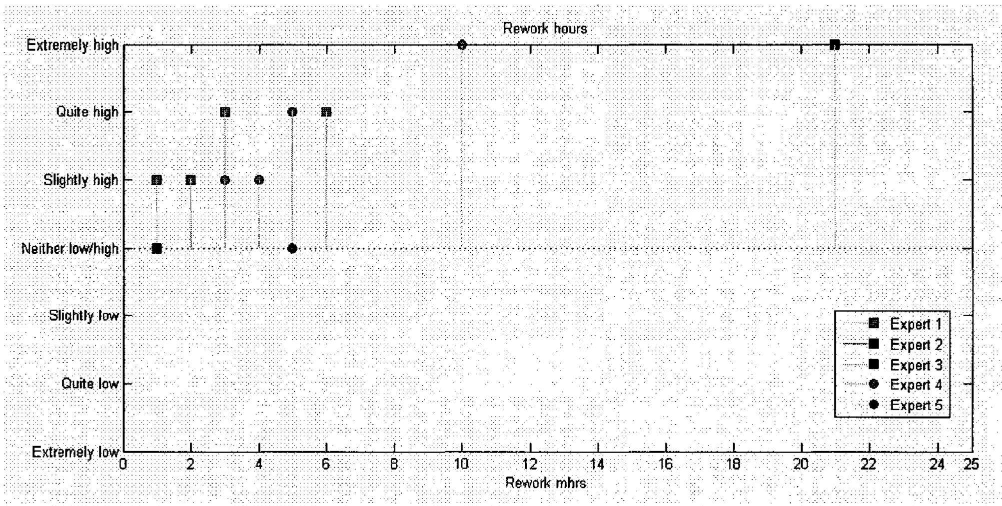


Figure 6-32. Linguistic assessments of rework hours.

6.5.2.5 Causal Factor: Equipment Availability

Compared to variables such as temperature, wind speed, or field rework, the variability of the equipment availability (measured as the number of cranes available for pipe handling, for example) is very low, thus the linguistic assessments do not vary much over a period. One main reason for this lack of variability is that compared to most of the other causal factors, equipment availability is a cost-significant factor thus closely monitored and controlled. The number of equipment needed for construction is planned ahead and a change to the equipment fleet occurs only if there is a significant change to the scope of the work. With respect to defining membership functions using sample membership values across the limited universe of discourse (e.g., number of cranes, ranges from 3-5) is inappropriate for causal factors such as equipment availability. In such cases, a pairwise comparison method is a more suitable approach to construct membership functions.

Similar to equipment availability, considerably less variability in linguistic estimates is observed for variables such as equipment suitability, tool condition, consumables availability, and materials availability.

6.5.3 Summary and Discussion on Interim Analysis

In addition to the causal factors described above, linguistic assessments made on the 21 causal factors shown in Table 6-2 across four different activities are analyzed. The consistency (measured in terms of variation of linguistic assessments on bipolar scale) of the experts' linguistic assessments was above 72 percent in all cases, which indicates that the proposed methodology is a practical tool for acquiring and representing subjective assessments from a group of individuals for construction performance diagnosis. The approximate time taken to complete the daily assessment ranged from 1 to 2 minutes, depending on the number of causal factors listed under the activity concerned. The accuracy of the linguistic estimates on working condition can be considered fairly accurate compared to any interview-based technique, since the expert is exposed to the particular working condition all day and the proposed methodology is considerably structured compared to the alternative approaches.

Additionally, the above analysis also helps to set the directions on how to select a particular type of membership function determination technique for each variable. As shown in Figure 6-33, when the variable have a well-defined base variable (i.e., objective measure for x-axis), if it is practically and economically possible to collect relevant objective measurements, and if there are more than a handful of different measurements to be obtained, the method of constrained interpolation can be used as a means to define membership functions.

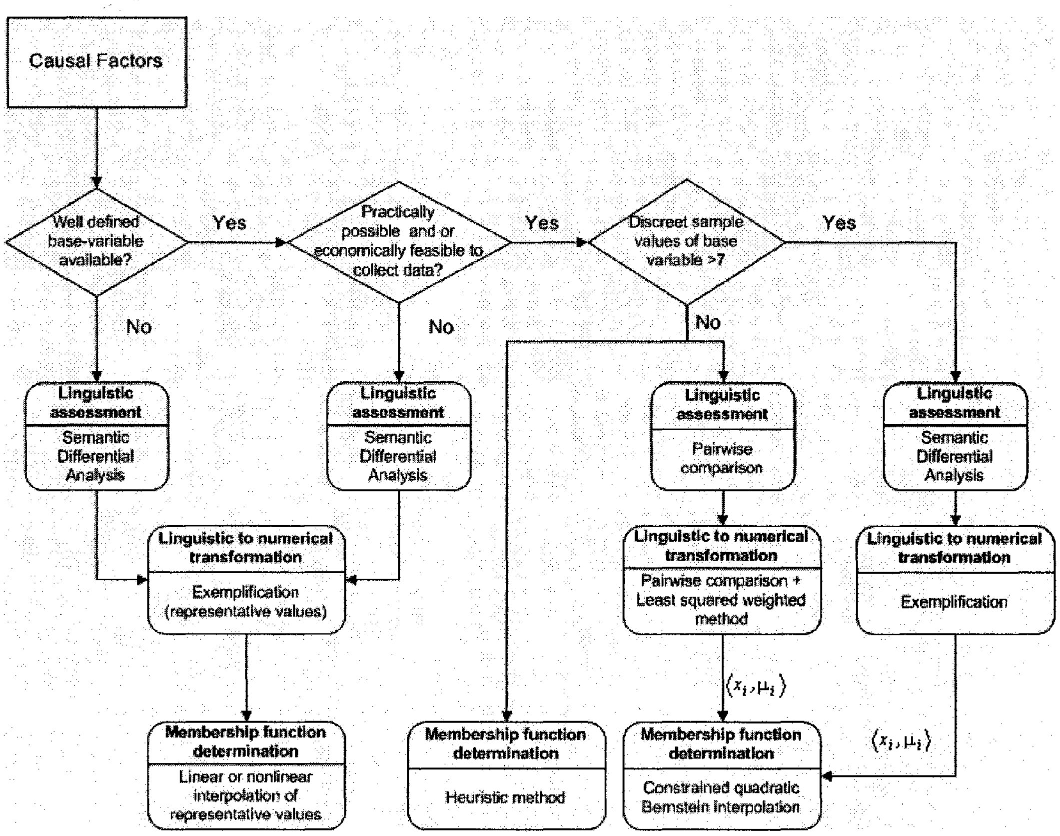


Figure 6-33. Protocol to select suitable techniques to determine linguistic assessments and membership function.

Causal factors such as temperature, wind speed, precipitation, manpower availability, and rework hours, belong to this category. In cases where there are no more than 7 sample objective measurements that can be taken (e.g., crew size, absenteeism, equipment availability), the user can opt for a pairwise comparison method to elicit sample membership values, instead of the semantic differential method, and subsequently determine the membership function using constrained interpolation methods. Conversely, when well-defined objective measures are not available (e.g., access to work location, equipment suitability, tools condition, crew attitude), or if it is practically and economically impossible to collect objective measurements (e.g., congestion on work location, task complexity, incomplete/unclear drawings), the user can opt for the membership function exemplification method.

As presented in the above discussions, these fuzzy linguistic assessments can be used directly for a number of purposes. For example, (1) to identify and evaluate implicit planned working conditions, and (2) to identify the causal factors that vary most considerably. The causal factors that do not show variability across a time period can be excluded from the inputs to the diagnostic model, making the reasoning process more efficient. Most importantly, these linguistic assessments can be transformed into membership values so that they can be used as inputs to the fuzzy logic based diagnostic systems. The next section describes a methodology to transform the linguistic assessments obtained via a semantic differential approach to numerical membership values.

6.6 LINGUISTIC TO NUMERICAL TRANSFORMATION

Once the fuzzy linguistic estimates are obtained using bipolar scales, the next step is to translate these linguistic values into numerical ones. Through this translation, a discrete representation of the membership function can be obtained. This process involves two key steps: first, a set of terms has to be selected (i.e., level of information granularity), and, second, the predefined representative values for the selected fuzzy linguistic terms should be defined.

6.6.1 Information Granulation

The proposed methodology enables the user to select the level of information granularity to suit the problem under consideration. At the highest level of granularity, the user can select the seven linguistic hedges that represent the bipolar scale as the term set. For example, for the causal factor temperature, the corresponding term set can be represented as < *extremely cold, quite cold, slightly cold, neither cold nor warm, slightly warm, quite warm, extremely warm*>. However, for practical purposes, the user may want to limit the granularity to fewer terms (e.g., 5, 3, or 2). For example, the causal factor, "temperature", may need to be represented by three term sets, such as <cold, average, warm>. Once the term set is selected, the next step is to predefine representative values for the chosen level of granularity.

6.6.2 Predefined Representative Values and Functions

As suggested in (Dubois and Prade 1980), a simple yet meaningful method to translate selected linguistic hedges to numerical values is to select representative values for selected linguistic hedges. This method works similar to a look-up table. Table 6-3 shows a set of sample representative values for three terms <low, medium, high>. Likewise, for each level of granularity, a different look-up table can be created.

Table 6-3. Representative values for bipolar scale X-Y.

	EXTREMELY X *(1)*	QUITE X *(2)*	SLIGHTLY X *(3)*	BOTH-X&Y *(4)*	SLIGHTLY Y *(5)*	QUITE Y *(6)*	EXTREMELY Y *(7)*
Low	1	0.6667	0.3333	0	0	0	0
Medium	0	0.3333	0.6667	1	0.6667	0.3333	0
High	0	0	0	0	0.3333	0.6667	1

However, it should be noted that these look-up tables can be used only for those sample values identified in the Table, i.e., for the values 1,2,3,4,5,6,7 in Table 6.3. Intermediate values (e.g., 2.5, 5.85) can also be obtained, for example, in cases where multiple fuzzy linguistic estimates are aggregated to represent group judgments. To obtain the representative values for such intermediate values, a set of continuous (transfer) functions, instead of a set of discrete representative values, need to be defined to represent the selected term set. One of the simplest methods for obtaining a continuous transfer function is to interpolate linearly the discrete representatives. Figure 6-34 shows the piecewise linear transfer function generated by the linear interpolation of the representative values shown in Table 6-3 for three term sets.

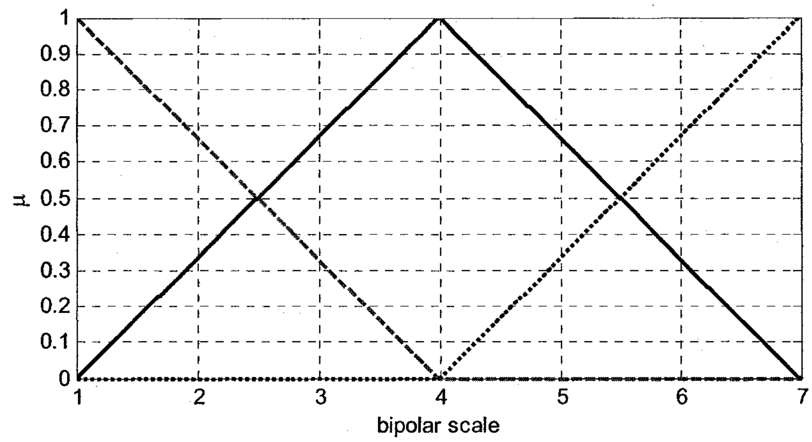


Figure 6-34. Predefined piecewise linear transfer functions based on linear interpolation of representative membership values.

Alternatively, as illustrated in Figure 6-35, the user can choose nonlinear representative transfer functions to transform fuzzy linguistic estimates into sample (numerical) membership values, at different granularity levels. It is noteworthy to mention here that these representative functions are not specific to any causal factor, instead they are specific to the level of granularity.

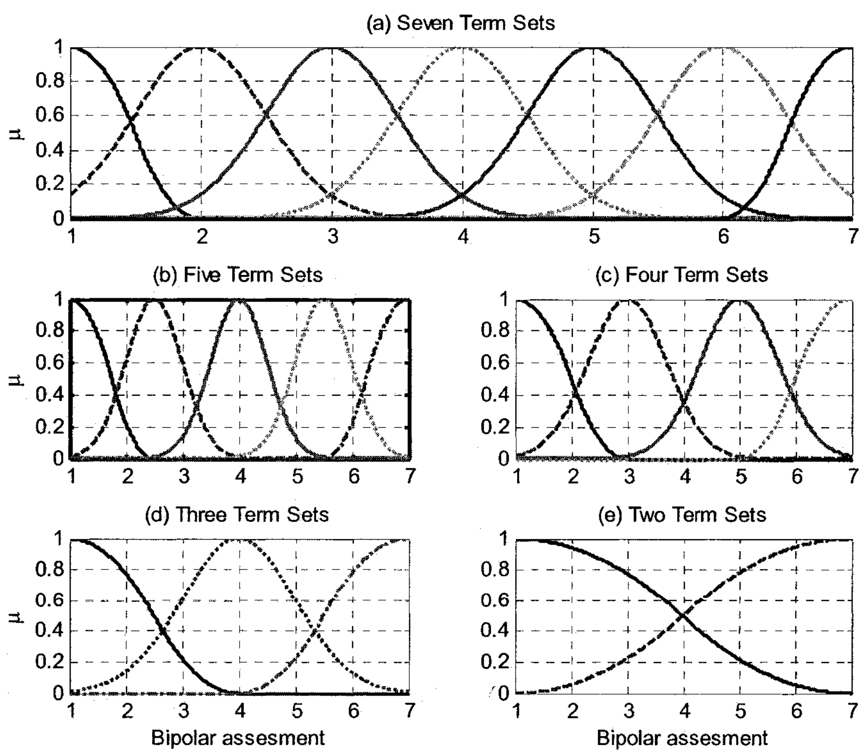


Figure 6-35. Predefined representative transfer functions to transform linguistic assessments to sample membership values.

Once the transfer functions are identified for the selected term sets, these functions can be used to obtain membership values for fuzzy linguistic assessments. This procedure of linguistic estimates for numerical (membership value) transformation is graphically illustrated in Figure 6-36.

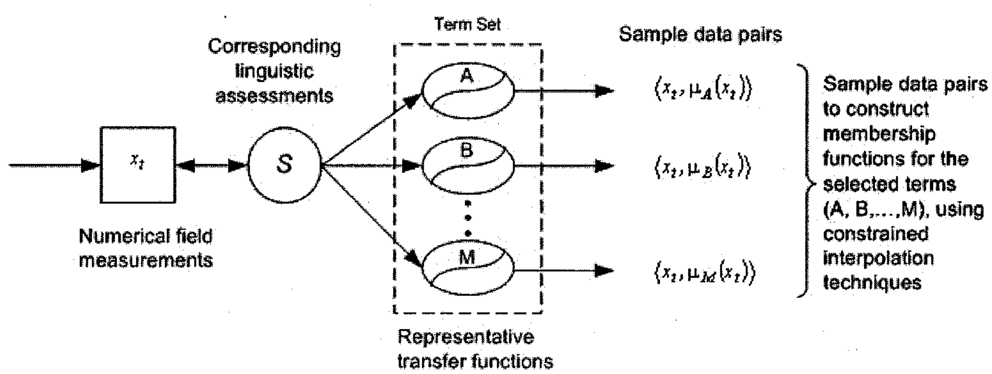
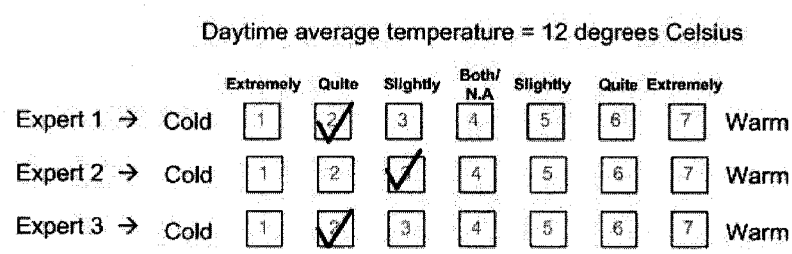


Figure 6-36. The procedure of obtaining sample membership values from representative function.

Consider the causal factor, daytime average temperature, as an example. If one assumes that on day t, the daytime average temperature at site was 12 degrees Celsius and three experts provided their assessments of day t's temperature condition using the bipolar scale Cold-Warm, as follows:



The mean value of above judgments can be obtained using Equation 6.15, as follows:

$$\bar{S} = \frac{1}{3}\sum_{i=1}^{3} S_{ip}^{k} = \frac{1}{3}(2+3+2) = 2.33$$

Now, to obtain the respective membership values of each term A, B,…,K, representative functions have to be evaluated at $\bar{S}$. Assume, for example, three terms are selected (i.e., cold, average, and warm) to represent the causal factor, daytime average temperature. Corresponding representative functions are shown in Figure 6-35 (d). The procedure of obtaining corresponding membership values for the mean linguistic assessment $\overline{S}$ is shown in Figure 6-37.

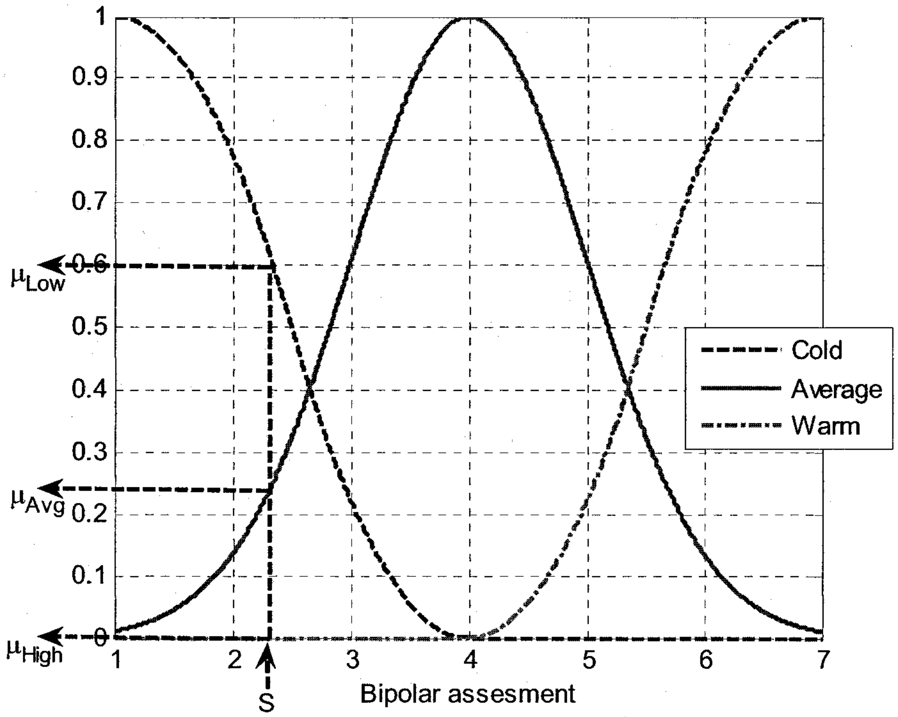


Figure 6-37. Example of obtaining sample membership values from representative functions of three terms.

The membership values for the temperature value of 12 degrees Celsius, as shown in Figure 6-36, are as follows:

	Cold	Average	Warm
Membership degree	0.6	0.233	0.0

These membership values can also be represented as sample data pairs, as follows: Cold <12, 0.6>, Average <12, 0.23>, Warm <12, 0>.

As presented above, in cases where there is a corresponding numerical measurement (e.g., 12 degrees Celsius) is available for the causal factor under consideration, membership values that obtained from the procedure described above can be associated with the numerical measurement, x_t, to represent sample data pairs $< x_t, \mu_A(x_t) >$. Once a set of discrete data pairs are obtained for several elements of the universe of discourse, they can be used to construct membership functions using interpolation methods described in Section 6.2.6. Once the membership functions are constructed, it is only necessary to collect numerical measurements of the causal factors, on a daily basis.

Conversely, for causal factors that do not have a well-defined base variable (i.e., a numerical measurement), membership values are obtained directly from evaluating the respective representative transfer function at $\overline{S}$. For example, consider the causal factor, access to work location, which does not have a well-defined numerical measure. Linguistic assessments of daily condition of access to work location can be obtained using bipolar scale: unrestricted–restricted. Assume that a mean linguistic assessment of S is obtained for day *t*. Figure 6-38 graphically illustrates the procedure to be followed to obtain the respective membership values.

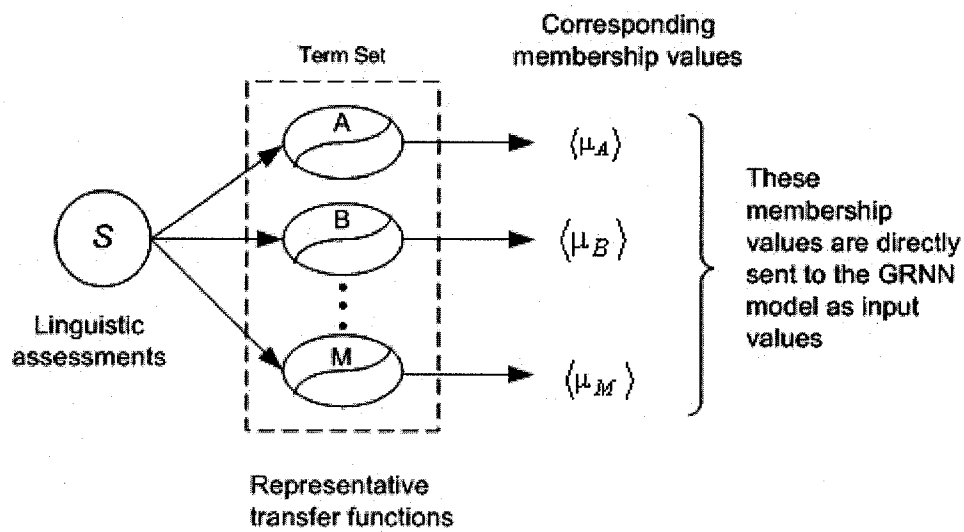


Figure 6-38. Procedure to transform linguistic assessments of causal factors (that do not have a well defined numerical measurement) to membership values.

If "restricted" and "unrestricted" are selected as two terms to represent the causal factor, access to work location, membership values related to *S* can be obtained, as shown in Figure 6-39. It is worthy to mention that, in cases where there are no well-defined numerical measurements, fuzzy linguistic assessments need to be collected on a daily basis.

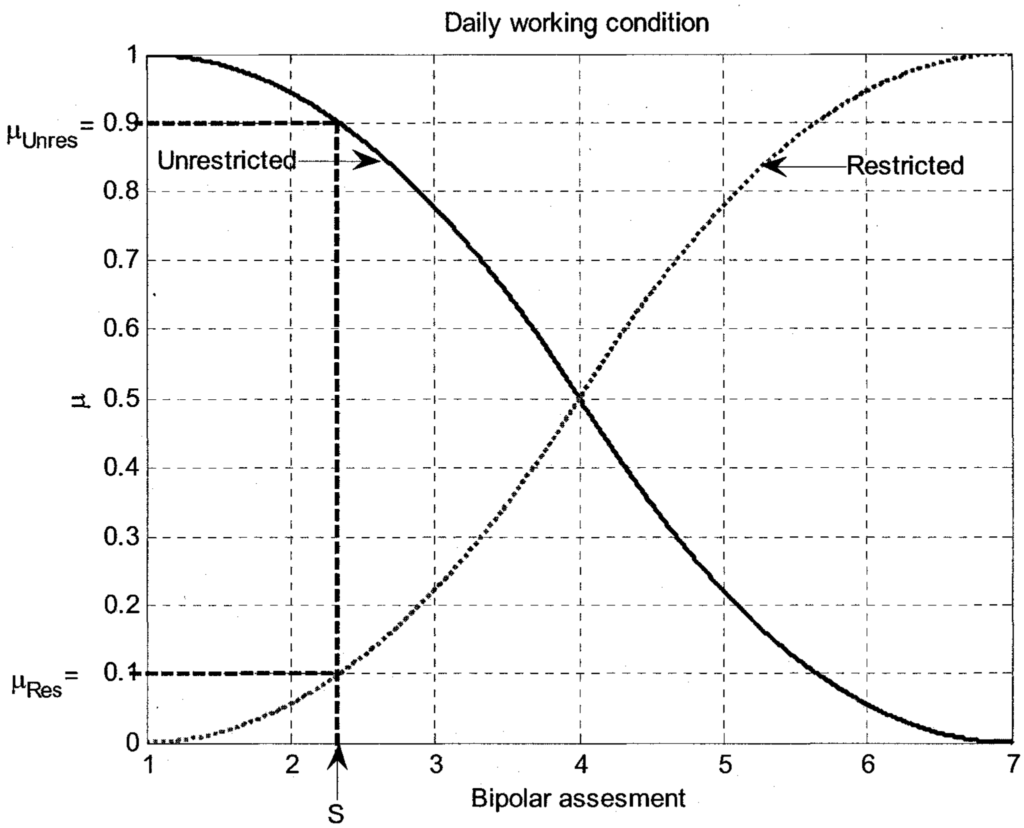


Figure 6-39. Example of obtaining sample membership values from representative transfer functions for causal factor: access to work location.

In summary, two distinctive types of causal factors are identified. The first type has well-defined numerical (objective) measures, and the second type does not have well-defined numerical measures. Two different approaches to obtaining membership values for each type are discussed above. Figure 6-40 illustrates how membership values are obtained and transformed as inputs to the proposed Generalized Regression Neural Network model (presented in Chapter 5).

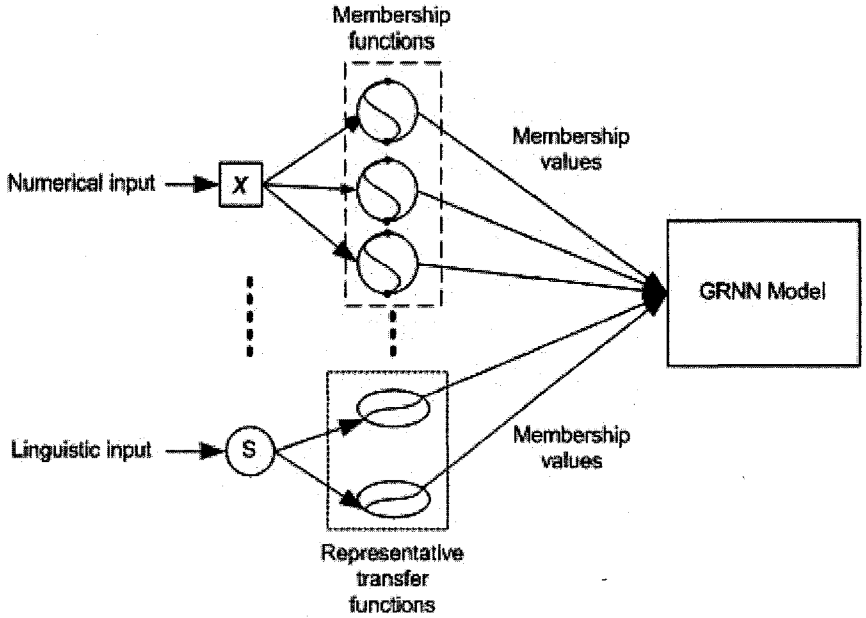


Figure 6-40. Illustration of how different types of inputs are transformed to the proposed GRNN model.

6.6.3 Experimental Results

The procedures described above to determine membership functions are further illustrated in this section with real data, for several causal factors that have well-defined numerical measurements. Table 6-4 shows the factors selected to demonstrate the membership function determination techniques proposed above.

Table 6-4. Selected causal factors to demonstrate membership function determination via proposed techniques.

CAUSAL FACTOR	NUMERICAL MEASURE	COMMENT
Daytime average temperature	Degrees Celsius	Represent a causal factor that has a site wide impact
Daytime average wind speed	Kilometers per hour	Represent a causal factor that has activity specific impact
Crew size	Number of crew members	Represent a causal factor that has sub-activity specific impact
Absenteeism	Number of crew members absent	Another causal factor that has sub-activity specific impact
Rework hours	man-hours	Represent a causal factor that has activity specific impact

6.6.3.1 Causal Factor: Day time average temperature

Table 6-5 shows the group judgment (mean *S*) about the causal factor, daytime average temperature, over a period of 54 working days by a group of 19 experts representing 7 activities related to pipe module fabrication.

Table 6-5. Linguistic assessments and representative membership values for day time average temperature.

Temperature (Degrees Celsius)	Mean-S	Term Set		
		Cold	Average	Warm
9	3	0.2222	0.6065	0
12	3.35	0.0939	0.8096	0
13	3.65	0.0272	0.9406	0
14	3.85	0.0050	0.9888	0
15	4.2	0	0.9802	0.0089
16	4.4	0	0.9231	0.0356
17	4.47	0	0.8954	0.0491
18	4.58	0	0.8452	0.0748
19	4.68	0	0.7936	0.1028
20	4.96	0	0.6308	0.2048
21	4.98	0	0.6187	0.2134
23	5	0	0.6065	0.2222
24	5.1	0	0.5461	0.2689
25	5.35	0	0.4020	0.4050
26	5.6	0	0.2780	0.5644
30	5.88	0	0.1708	0.7212

The membership values are obtained for three terms (cold, average, and warm), as shown in Table 6-5, using the representative function shown in Figure 6-35 (d). Figure 6-41 shows the corresponding membership functions constructed using the quadratic Bernstein polynomial interpolation algorithm using sample membership values of each term.

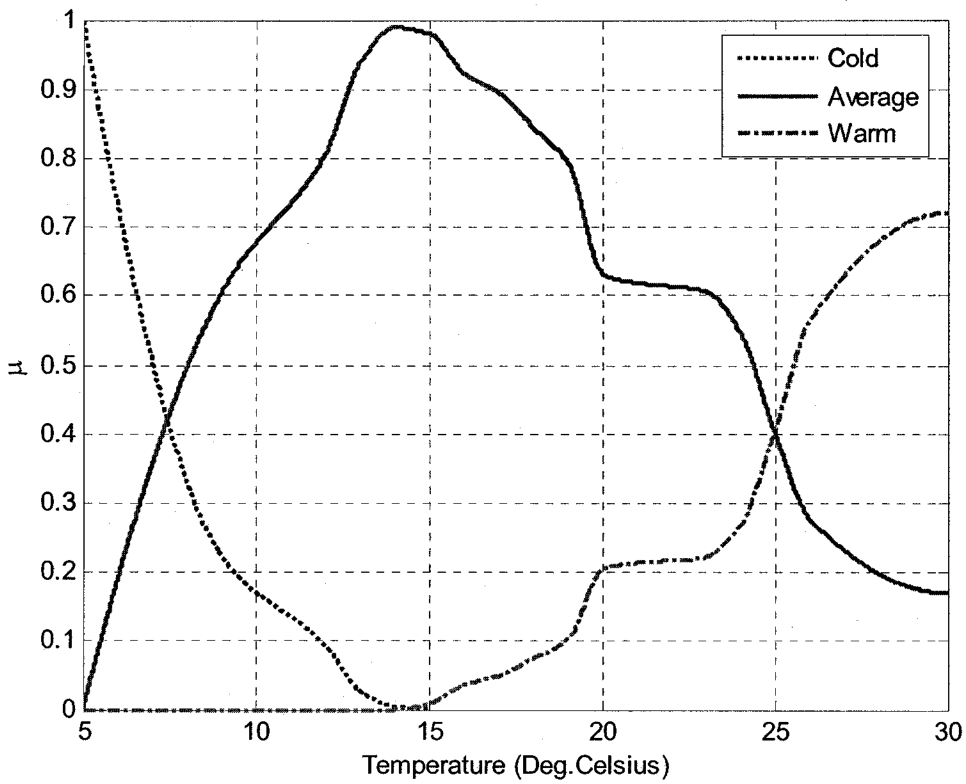


Figure 6-41. Membership function for Cold, Average and Warm daytime average temperature.

6.6.3.2 Causal Factor: Daytime average wind speed

The effect of wind speed can be considered activity-specific as some activities have a minimal impact from wind (e.g., hydrotesting) while activities such as pipe handling and erection of structural steel members can be affected significantly by the wind. The mean values of the linguistic assessments about daytime average wind speed provided by 4 structural steel erection experts are shown in Table 6-6. Assessments made by 5 pipefitting and fabrication experts on the same causal factor are shown in Table 6-7. The corresponding membership functions for three terms (low, medium and high wind speed) are shown in Figure 6-42.

Table 6-6. Linguistic assessments by structural steel erection experts and representative membership values for day time average wind speed.

Wind Speed	Mean-B	Term Set		
		Low	Medium	High
1	1.00	1.0000	0.0111	0
5	2.50	0.5000	0.3247	0
9	3.30	0.1089	0.7827	0
11	4.30	0	0.9560	0.0200
14	5.00	0	0.6065	0.2222
20	5.50	0	0.3247	0.5000
23	6.00	0	0.1353	0.7778
31	6.50	0	0.0439	0.9444

Table 6-7. Linguistic assessments by pipefitting and fabrication experts and representative membership values for day time average wind speed.

Wind Speed	Mean-B	Term Set		
		Low	Medium	High
1	1.00	1.0000	0.0111	0
3	2.38	0.5768	0.2692	0
5	2.50	0.5000	0.3247	0
6	2.56	0.4608	0.3546	0
10	3.00	0.2222	0.6065	0
11	3.30	0.1089	0.7827	0
14	4.00	0	1.0000	0
20	4.50	0	0.8825	0.0556
22	5.00	0	0.6065	0.2222
23	6.00	0	0.1353	0.7778
31	7.00	0	0.0111	1.0000

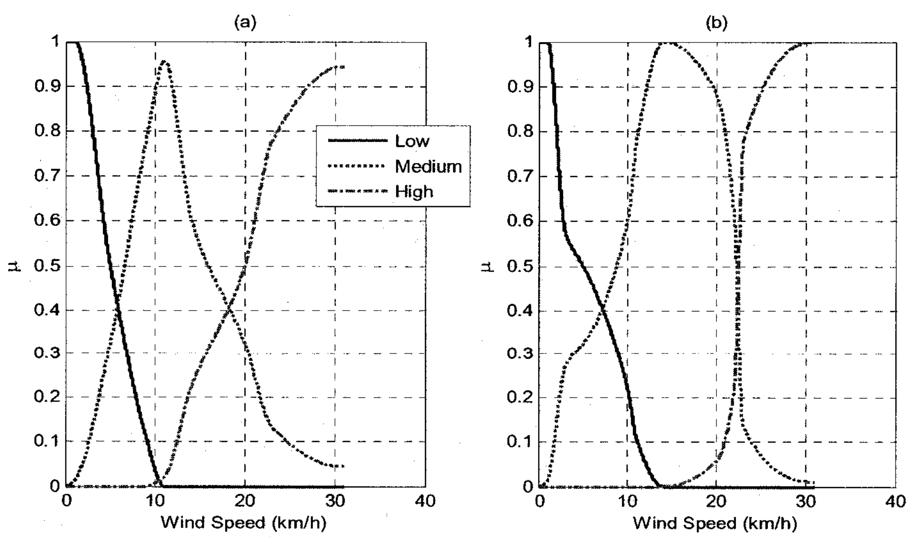


Figure 6-42. Membership functions of Low-, Medium- and High- wind speed: (a) for structural steel erection activity, (b) pipe fitting and fabrication activity.

6.6.3.3 Causal Factor: Crew Size (number of members in the crew)

The following table shows the crew size (CS) and corresponding linguistic assessments provided by structural steel erection expert, over a period of 21 workdays.

day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
CS	6	12	6	12	6	6	5	3	5	5	5	5	6	7	12	12	12	12	10	6	5
S	2	5	3	5	3	3	3	2	2	2	2	2	3	3	5	5	5	4	3	1	4

CS=crew size, S=bipolar assessment

This table indicates that the crew size has taken the following g values: 3,5,6,7,10, and 12 over a period of 21 days. Linguistic assessments indicate that the crew size was never considered as quite- or extremely- large, in any of the days. It indicates that usually oversize crews were not used in the project. Table 6-8 shows the crew sizes, corresponding mean linguistic assessments, and representative membership values for three terms (i.e., small, average and large crew).

Table 6-8. Linguistic assessments (by a structural steel erection expert) and representative membership values for Crew Size.

CS	MEAN S	TERM SET		
		Small	Average	Large
3	2.0	0.7778	0.1353	0
5	2.125	0.7188	0.1724	0
6	2.857	0.2903	0.5204	0
7	3.71	0.0187	0.9588	0
10	4.0	0	1.0000	0
12	5.0	0	0.6065	0.2222

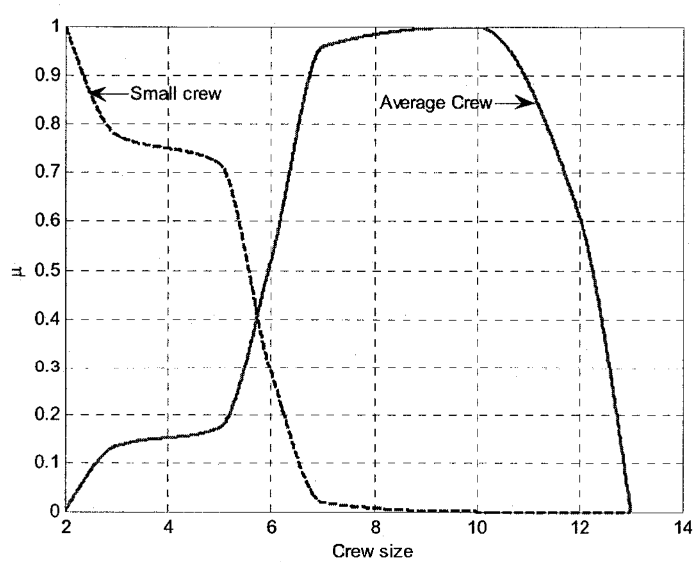


Figure 6-43. Membership functions of *Small* and *Average* crew sizes.

6.6.3.4 Causal Factor: Absenteeism of crew member(s)

Linguistic assessments obtained for the causal factor: absenteeism of crew members are shown below.

Number of crew members absent	0	1	2	3
S	1	4	6	7

It is quite obvious from the above assessments that experts believe that on any given day, the absenteeism of one crew member is expected. Any number of absentees more than one is considered as *quite* or *extremely* high. As shown in the above assessment, this causal factor does have a very limited amount of representative values (i.e., 1, 2 or 3 absentees); an interpolation method is therefore not suitable for constructing membership functions. Representation of membership values in a tabular form is sufficient in these cases. A sample representation of membership values for two term sets (Low and High absenteeism) is shown in Table 6-9.

Table 6-9. Example of membership function representation in tabular form.

NUMBER OF ABSENTEES IN A CREW	TERM SET	
	Low	High
0	1.0	0
1	0.6	0.2
2	0.2	0.6
3	0	1.0
4	0	1.0

6.6.3.5 Causal Factor: Rework Hours

Representative values of rework hours and corresponding linguistic assessments on bipolar scale, *low-high*, made by a group of experts are shown below:

Rework hours	1	2	3	5	6	10	21
Mean-S	4	5	5	5	6	7	7

Similar to the causal factor, absenteeism of crew members, rework hours also has very limited representative values. The corresponding linguistic assessments indicates that any amount of rework hours that are higher than 1 are considered as a variation of *high,* i.e., either *slightly high*, *quite high* or *extremely high.* When the rework hours are greater than 10 (which represent a day's worth of work by an individual crew member), it is considered as *extremely high.*

Since almost all the linguistic assessments are concentrated on one side of the bipolar scale, the method of representative transfer functions is not suitable to obtain membership values for the causal factor, crew size. However, the above linguistic assessments indicate that a simple heuristic-based method of membership function construction is sufficient in this case. Sample membership functions for two terms (low and high) are shown in Figure 6-44.

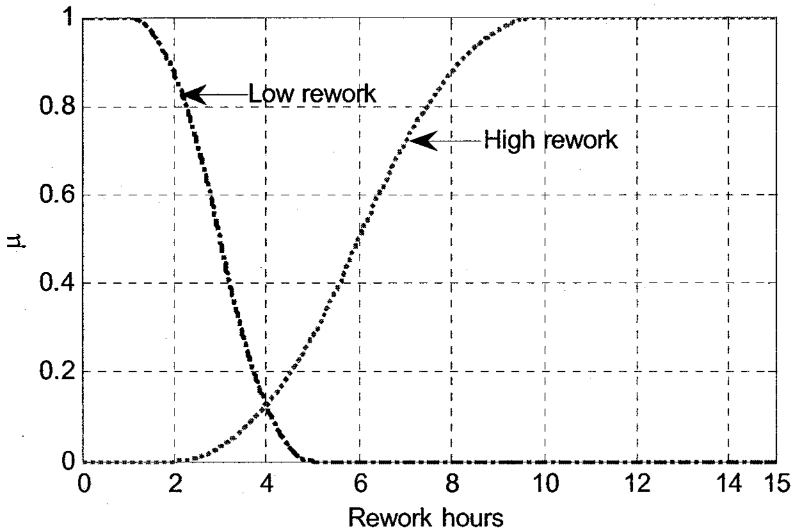


Figure 6-44. Membership functions of *low* and *high* rework.

Based on the above discussion and the protocol presented in Figure 6-33, suitable membership function development techniques are identified for the variables listed in Table 6-2. The results are shown in Table 6-10.

6.7 DISCUSSION AND SUMMARY

In this chapter, the membership function determinations techniques that are based on sample membership values are first reviewed and methods most suitable for applications in construction performance modeling are identified. Constrained interpolation methods that are identified as potential membership function determination techniques are tested using illustrative examples. A pragmatic approach is then proposed for qualitative knowledge acquisition and representation. The proposed causal knowledge representation methodology was a combination of the nominal group technique (NGT) and semantic differential (SD) approach. The proposed methods are tested and validated using an actual dataset collected from an industrial construction project.

Table 6-10. Suitable membership function determination techniques for the causal factors identified in this study.

CAUSAL FACTOR	SAMPLE MEMBERSHIP VALUE DETERMINATION TECHNIQUE(S)	MEMBERSHIP FUNCTION DEVELOPMENT TECHNIQUE(S)
Crew size	Semantic Differential Approach	Constrained interpolation
Absenteeism	Semantic Differential Approach/ Pairwise comparison	Tabular form/ Heuristic method
Crew experience	Semantic Differential Approach	Heuristic method
Rework	Pairwise comparison/ Semantic Differential Approach	Constrained interpolation
Incomplete/unclear drawings	Semantic Differential Approach	Membership values from transfer functions
Temperature (day time average)	Semantic Differential Approach	Constrained interpolation
Total Precipitation	Semantic Differential Approach	Constrained interpolation
Wind speed (day time average)	Semantic Differential Approach	Constrained interpolation
Manpower availability	Semantic Differential Approach	Membership values from transfer functions
Equipment availability	Semantic Differential Approach	Membership values from transfer functions
Equipment suitability	Semantic Differential Approach	Membership values from transfer functions
Tools condition	Semantic Differential Approach	Membership values from transfer functions
Consumables availability	Semantic Differential Approach	Membership values from transfer functions
Material availability	Semantic Differential Approach	Membership values from transfer functions
Congestion on work location	Semantic Differential Approach	Membership values from transfer functions
Access to work location	Semantic Differential Approach	Membership values from transfer functions
Time to await inspections	Semantic Differential Approach	Membership values from transfer functions
Waiting for other trades	Semantic Differential Approach	Membership values from transfer functions
Task complexity	Semantic Differential Approach	Membership values from transfer functions
Safety equipment availability	Semantic Differential Approach	Membership values from transfer functions
Right tool availability	Semantic Differential Approach	Membership values from transfer functions
Crew attitude/morale	Semantic Differential Approach	Membership values from transfer functions

The results indicate that the proposed methodology for representing experts' knowledge is effectual and generates fairly accurate results. Finally, a linguistic-to-numerical transformation process is proposed. These numerical values represent the sample membership values, [0,1]. They can be used to define membership functions or can be used as direct inputs to the FA-GRNN model described in Chapter 5.

Chapter 7 describes the overall diagnostic reasoning development strategy, combining the knowledge representation and acquisition methods presented in this chapter and the FA-GRNN model proposed in Chapter 5. It also presents the software (XCOPE, explaining **co**nstruction **pe**rformance) developed based on the principles discussed in this thesis. Chapter 8 will draw conclusions based on the research and identify the future research directions.

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CHAPTER SEVEN

7. INTEGRATED CONSTRUCTION PERFORMANCE DIAGNOSTIC FRAMEWORK

7.1 INTRODUCTION

This chapter presents an overall description of an integrated construction performance diagnostic framework capable of predicting construction performance and diagnosing performance deviations based on a combination of expert opinion and daily measures of performance-related factors. The proposed integrated system has the advantage of neural network systems (e.g., learning, fault tolerance, generalization, and adaptation abilities), fuzzy systems (capturing the subjectivity of expert assessments, processing linguistic information at different levels of granularity) and genetic algorithms (parametric and structural optimization of the system). The integrated framework is implemented in a Microsoft® Visual Studio® platform in order to validate the effectiveness of the proposed system.

The following sections provide an overview about the proposed integrated framework and identify its key modules. A descriptive, step-by-step guide for developing each module is presented. It is followed by a discussion on the framework validation strategies used. Finally, an example case is presented validating the overall framework to obtain high degree of confidence of the proposed framework.

7.2 PROPOSED INTEGRATED FRAMEWORK FOR DIAGNOSING CONSTRICTION PERFORMANCE

The proposed framework consists with two key modules: the prognostic module and the diagnostic module, as illustrated in Figure 7-1. In its functional form (i.e., after the model is designed, trained, and tested), inputs to the model are daily values of causal factors that represent the working condition of an activity. The model has three key outputs. In its predictive form, the model allows the user to estimate construction performance based on different conditions/states of causal factors. This estimation provides the user an efficient methodology to execute a what-if analysis, so that construction managers can identify the expected performance of construction activities based on different scenarios. Additionally, as an output of the prognostic module, the model identifies the relative-significance of each input causal factor (in terms of smoothing factors). This characteristic of the proposed network provides the construction manager an effective way to keep focus on the most important and significant factors to control the performance of the activity. In its diagnostic form, the model let the construction manager to identify the root causes of performance deviation(s).

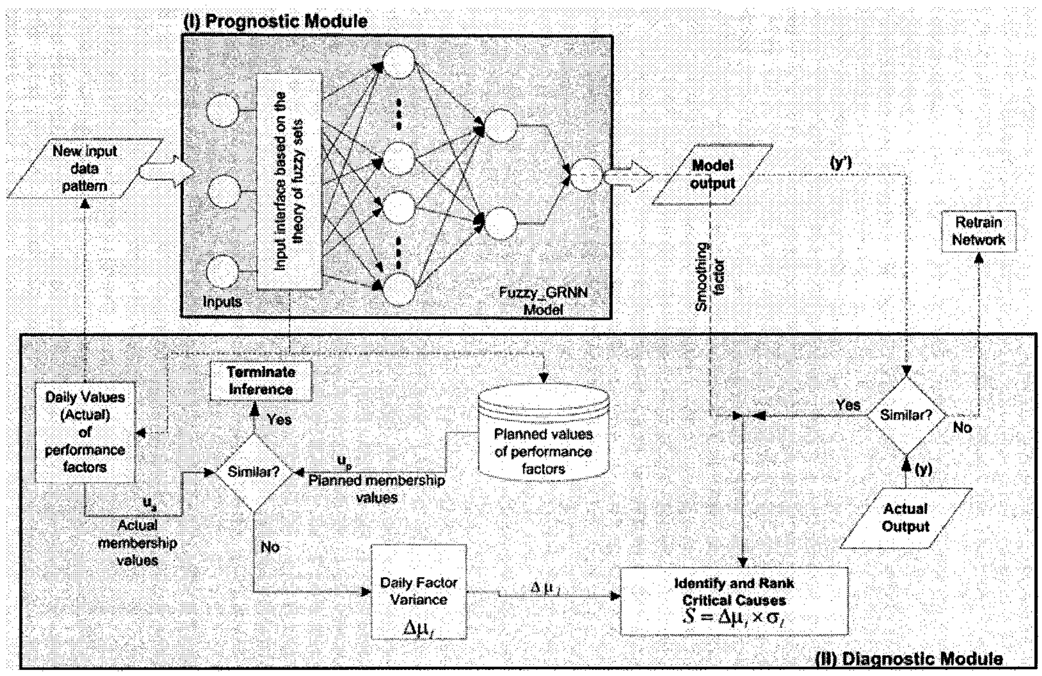


Figure 7-1. Proposed integrated framework

A summary description of each module along with a step-by-step guide to develop the framework is presented in the following sections.

7.2.1 The Prognostic Module

The prognostic module comprises a user interface and the fuzzy adaptive generalized regression neural network (FA-GRNN) model. The user interface facilitates the knowledge representation and data preprocessing, which is designed using the concepts presented in Chapter 6. The FA-GRNN model provides the nonlinear-dynamic input-output mapping capabilities, which are described in detail in Chapter 5. This module is designed to perform several key tasks. A description of each task along with a step-by-step guide to implement each task is described below.

(a). Allows the user to define project performance goals and related key performance indicators (KPIs), and to represent causal knowledge about the KPI. The following steps can be performed at this stage:

1. Identify key performance indicators (KPIs) for activity performance.

2. Identify a list of causal factors for each KPI (via modified nominal group technique). This list of factors serves as input variables ($x_i \in X, i = 1,2,\ldots,n$) to the proposed model, where n equals total number of causal factors associated with the selected KPI. The output variable is the KPI, which is represented by y. Since, generally, the KPI is a numerical measure such as the productivity factor, the proposed model is designed as a Multi-Input-Single-Output (MISO) system.

3. Identify numerical measures and subjective measures (i.e., bipolar scales) for causal factors identified in the above step.

4. Identify planned values (i.e., baseline parameters) of each input variable x_i (i.e., x_p) for each KPI. These planned values are used to calculate the performance deviation, later in the diagnostic reasoning process.

5. Select linguistic values (i.e., term sets) for each causal factor identified. This allows experts to represent the level of information granularity that they expect in the reasoning process.

(b). Allow experts to assess and report qualitative and quantitative assessments on daily working conditions (represented by list of causal factors). A methodology is proposed in Section 6.5 of the Chapter 6 for assessing working condition using linguistic estimates. Steps for determining this are as follows:

1. Collect daily values $x_{,t}$ (i.e., numerical measurements and or linguistic assessments) of causal factors and respective key performance indicators (y_t) over a time period (or extract data from the project database for previous similar project/s).

2. For cases in which multiple expert assessments are available, assessments need to be aggregated, using procedures described in Section 6.5.1 of the Chapter 6.

3. Categorize collected daily values, if necessary, into different groups based on user requirements (e.g., seasonal data, work package, etc). Models specific to each data category must be developed.

These daily values form the learning data of the model: $L = \{\mathrm{x}_t, \mathrm{y}_t\}_{t=1}^{T}$.

(c) Input Fuzzification. This facilitates transforming qualitative and quantitative input data into membership degrees of selected linguistic values of input causal factors. Input

Fuzzification can also be considered as an input preprocessing process. This process not only enables one to capture the subjectivity of an individual expert's assessment of daily working conditions but also allows one to transform the input values to a form (i.e., between 0 and 1) that can be used as a direct input to a neural network model. Input Fuzzification is carried out in two different ways, based on the characteristic of the causal factors. For causal factors that do not have well-defined numerical measures, representative transfer functions are used (as described in Section 6.6.2) to obtain membership values that are directly used as input to the FAGRNN model. For causal factors that have well-defined numerical measures, membership functions are constructed by interpolating sample membership values (as described in Section 6.2.6). Once the membership functions are developed for those causal factors, corresponding membership values of daily assessments can be obtained by sending the quantitative measurement through the membership function. It is recommended that once the membership functions are constructed that they are crosschecked with the construction management team to make sure that the shapes of the functions constructed are meaningful. A step-by-step guide for input fuzzification is as follows:

1. Select representative transfer functions for each linguistic value (refer to Section 6.6.2 for detail description).

2. Construct membership functions (for factors that have numerical measures) using sample data by a constrained interpolation technique (refer to Section 6.2.6 for a detailed description).

3. Combine the membership functions (and representative transfer functions for factors that do not have numerical measurements), m_{ij}, into a vector of a single input vector, $\mathbf{u} = [m_{11}, m_{12},..., m_{1k}, m_{21}, m_{22},..., m_{2k},..., m_{n1}, m_{n2},..., m_{nk}] = \lfloor u_1, u_2,..., u_p \rfloor$ where the total dimension of $\mathbf{u}$ is p=n*k, where n is the number of factors and k is the number of membership functions (or transfer functions) for each factor (i.e., input vector of the model).

(d). Training and testing FA-GRNN model. This phase focuses on training and testing the FA-GRNN model (presented in Chapter 5) that is capable in mapping complex phenomena, such as construction labour productivity. Once an accurate predictive model is developed, as described in the following phase III, the model can be used for diagnostic inference, with further extensions to the same network. Necessary steps for training and testing the FA-GRNN model are described below:

1. Obtain sample training input-output data pairs, ($\mathbf{x}_t$, y_t), which represent the values of causal factors and the corresponding KPI values, respectively.

2. Transform sample values of causal factors ($\mathbf{x}_t$) into membership degrees ($\mathbf{u}_t$) by sending $\mathbf{x}_t$ through vector $\mathbf{u}$.

3. To obtain the corresponding output values, y'_t which are numerical measurements, a nonlinear transfer function (e.g., sigmoidal function) can be used to transform actual daily output, y_t (i.e., KPI) values into a unit interval, i.e., [0,1], to feed into the FA-GRNN model.

4. Combine sample input ($\mathbf{u}_t$) and output (y'_t) data to create the learning data set (input and output data pairs) that can be represented as $L = \{\mathrm{u}_t, \mathrm{y}'_t\}_{t=1}^{T}$, where T is total number of days.

5. Divide the sample dataset L into two sets (for training and testing).

5. Train the FA-GRNN model with *training* data patterns using genetic algorithms.

6. Analyze the individual (local) smoothing factors, and crosscheck with construction management team.

7. Test and validate the model using *testing* data.

8. Feed the planned values ($\mathbf{x}_p$) into the FA-GRNN model, and obtain the planned (*output*) KPI estimate (y'_p), thereby establishing a baseline estimate of the KPI. By applying the planned values ($\mathbf{x}_p$) to the network, we can obtain the *normal functional state* of the system under study. This will be considered as the baseline for diagnostic inference, which is presented in Section 7.2.2.

7.2.2 The Diagnostic Module

Once the learning phase is successfully completed, the FA-GRNN model can be employed as an approximate inference and forecasting engine. Essentially, the diagnostic process can be defined as a root cause identification using information collected from daily working condition reports, established baseline parameters, and values of key performance indicators. The sequence that should be followed to perform a diagnosis can be summarized as follows:

1. Diagnostic inference starts with selecting a new data pattern, and then comparing the observed (field measurement) KPI value, y, with planned KPI value, y^p. If y is equal or similar to y^p, one can presume that the planned conditions of factors have prevailed during that particular day, making the diagnosis not required.
2. Otherwise, feed the new data pattern ($\mathbf{x}_a$) into the network and get the network output ($\hat{y}$). Compare y and $\hat{y}$. If the prognostic model is accurate, y should be equal or similar to $\hat{y}$. Otherwise, the prognostic model is inappropriate for diagnostic reasoning. This conflict can be caused by: (1) measurement errors in the actual KPI (e.g., hours were incorrectly charged to calculate productivity factor) and/or (2) incomplete or inaccurate model. A simple protocol to identify and evaluate an incorrect model is shown in Figure 7-2.

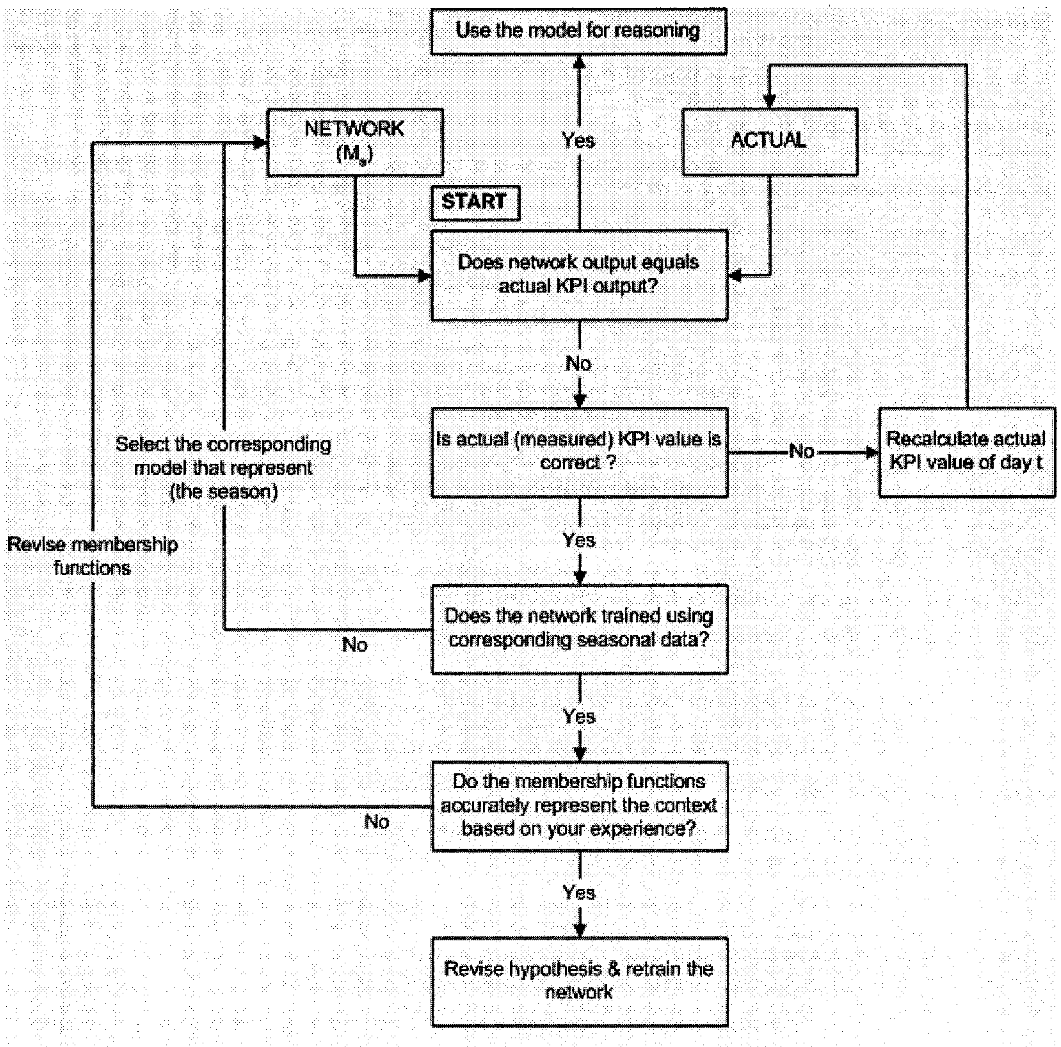


Figure 7-2. A protocol for identifying and evaluating inaccurate models.

3. If y is equal or similar to $\hat{y}$ (or within an acceptable range), then calculate difference between u_a and u_p ($\Delta\mu_l$); a critical cause for abnormal behavior of KPI comes from an unexpected variation of a performance factor, the difference between the actual and planned condition ($\Delta\mu_l$) of each linguistic values of causal factors is thereby calculated.
4. Multiply $\Delta\mu_l$ by smoothing factor σ_l, $S = \Delta\mu_i \times \sigma_l$. The inference should be based on multiplication of degree of membership of cause variance and associated weight. In order to become the most significant cause of an effect, both the variation should be high and the weight should be comparatively high. In cases where the weight is comparatively high but if the variation is low, the

impact will not be significant. Hence both the cause variance and the associated weight should be considered while making the inference.

5. Rank S and identify critical factors of performance variation.

7.2.3 Example of a Performance Diagnostic Inference

This section presents an example to further explain the diagnostic inference process discussed above. A FA-GRNN model was developed for reasoning hydro-testing activity. A data pattern (representing the day of June 12, 2003) that has not been seen by the FA-GRNN model (developed based on summer 2003 data; see Section 5.4.4 for model details) was selected for diagnostic reasoning. The actual output value (PF) for the day of June 12, 2003 was 0.4380. The objective here is to identify the causes of low productivity of hydrotesting on that day. The absolute error of the network output for the same data pattern was 0.006. The model was therefore considered pertinent for diagnostic inference. Summary results of the diagnostic inference for that particular data pattern are shown in Table 7-1.

Column 1 shows factors that identified by the construction management team and possible causes of low hydro-testing productivity. Membership functions for each factor, which were derived from collected daily data, are shown in column 2. Respective individual smoothing factors (σ_l) that represent the relative importance of individual factors to the selected network output is given in column 3. Membership values of the *planned* (estimated) value of each factor are shown in column 4. Membership values of *actual* daily value of each factor are given in column 5. The variance ($\Delta\mu_l = \mu_l^a - \mu_l^p$) of membership values (of actual and planned values) of the selected day is shown in column 6. Column 7 shows the multiplication of individual smoothing factor and the variance ($S = \Delta\mu_i \times \sigma_l$). The value S indicates the significance of the particular linguistic term (e.g., low work load, high manpower availability) as a combination of variance of the particular day and the relative importance of the particular term in the network. For example, as shown in Table 7-1, on June 12, 2003, among the seven factors identified, the mean-temperature had the largest variation. Based on linguistic terms, "medium" mean-temperature had a negative variation of 1.0 and "high" mean-temperature had a positive variation of 1.0 indicating that on the particular summer day, the mean-temperature was higher than the average value. The respective σ_l value of "medium" and "high" temperatures are 2.882 and 0, respectively. 718 indicate that a "medium" mean-temperature has a higher influence, compared to a "high" temperature, in the selected network. As shown in the column 8, the summation of S values indicates the overall significance of mean-temperature, compared to other factors on the particular day. In this case, the corresponding negative sign indicates that mean-temperature has a contributing impact on productivity deviation. Similar types of analysis have been carried out for the rest of the factors and ranked accordingly, based on the summation of *S* values, as shown in column 9.

Table 7-1. Diagnostic inference for low hydro-testing productivity on June 12, 2003*.

(1) Factor	(2) Membership function	(3) Smoothing Factor- σ_l (for summer)	(4) Planned values (for Summer)	(5) Actual Value (for 12June 03)	(6) Variance Δ (Act-Planned)	(3)X(6) $S = \Delta\mu_i \times \sigma_l$	(7) $\sum S$	(8) Contributing (C+) Counteracting (C-) Neutral (N)	(9) C+ Rank	(10) Comment
Work Load	Low	0.588		0.500	0.500	0.29				Actual work load was less than planned on this day
	Medium	1.576	0.909		-0.909	-1.43				
	High	1.024					-1.14	C-		
Equipment availability	Low	0.106								Equipment availability was as planned.
	Medium	1.847	0.500	0.500						
	High	2.741						N		
Manpower availability (ratio)	Low	1.718								Manpower availability was less than planned.
	Med-Low	0.235		0.770	0.770	0.18				
	Med-High	1.341	0.893		-0.893	-1.20				
	High	0.165					-1.02	C+	2	
Mean temperature	Low	0.259								Mean temperature was higher than planned.
	Medium	2.882	1.000		-1.000	-2.88				
	High	0.718		1.000	1.000	0.72	-2.16	C+	1	
Total precipitation	Low	2.871	0.342	1.000	0.658	1.89				
	Medium	2.953	0.772		-0.772	-2.28				
	High	1.753					-0.39	C+	3	
Rework (hours)	Low	1.247	1.000	1.000						Zero rework.
	Med-Low	3.000								
	Med-High	2.118								
	High	0.729						N		
QC hours (ratio)	Low	0.035								Actual QC input is less than planned.
	Med-Low	0.176	0.263	0.096	-0.167	-0.03				
	Med-High	1.129								
	High	2.565					-0.03	C+	4	

*Cells with zero values were left blank to increase the brevity.

7.2.4 Visual Representation of Diagnostic Inference

Results shown in the Table 7-1 are transformed into a visual form, using the tree-map approach (Johnson and Shneiderman 1991) enabling the construction manager to observe, browse, and understand the comparison of significance between different factors of each KPI. Technically, the tree-map is used to convert numerical and symbolic results into a graphical representation. As shown in Figures 7-3 and 7-4, the tree-map presents diagnostic information at several levels of detail, making extensive data comparisons coherent. It helps to answer basic questions that a construction manager has about his project performance.

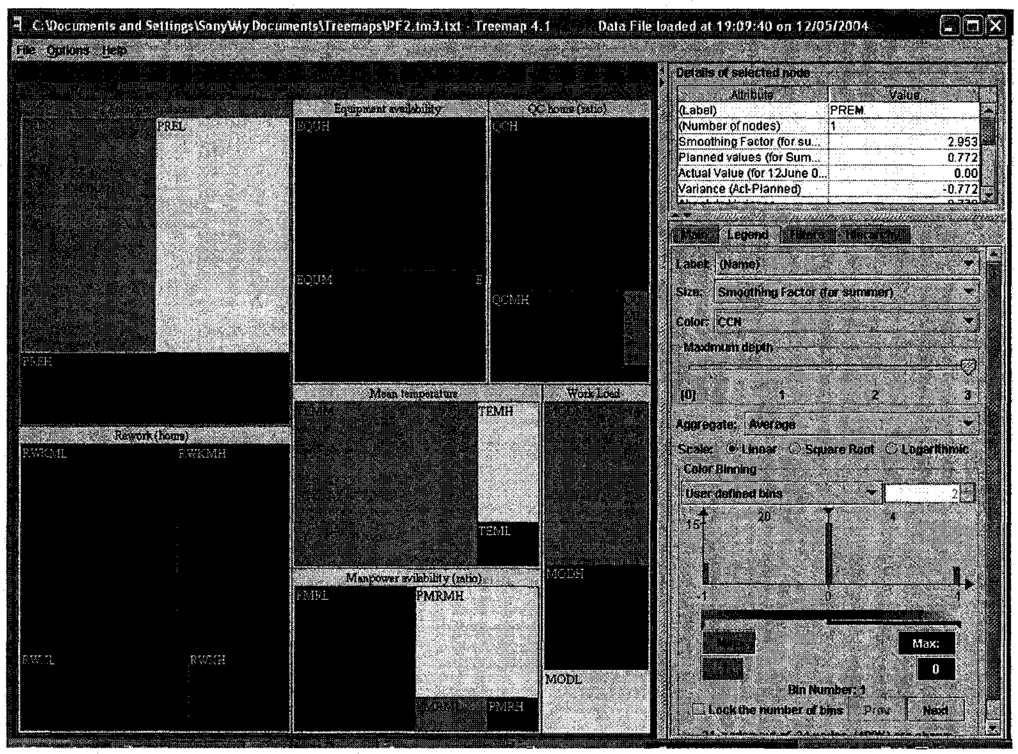


Figure 7-3. Size based on Smoothing factor and the color based on contributing (red) and counteracting (green) causes.

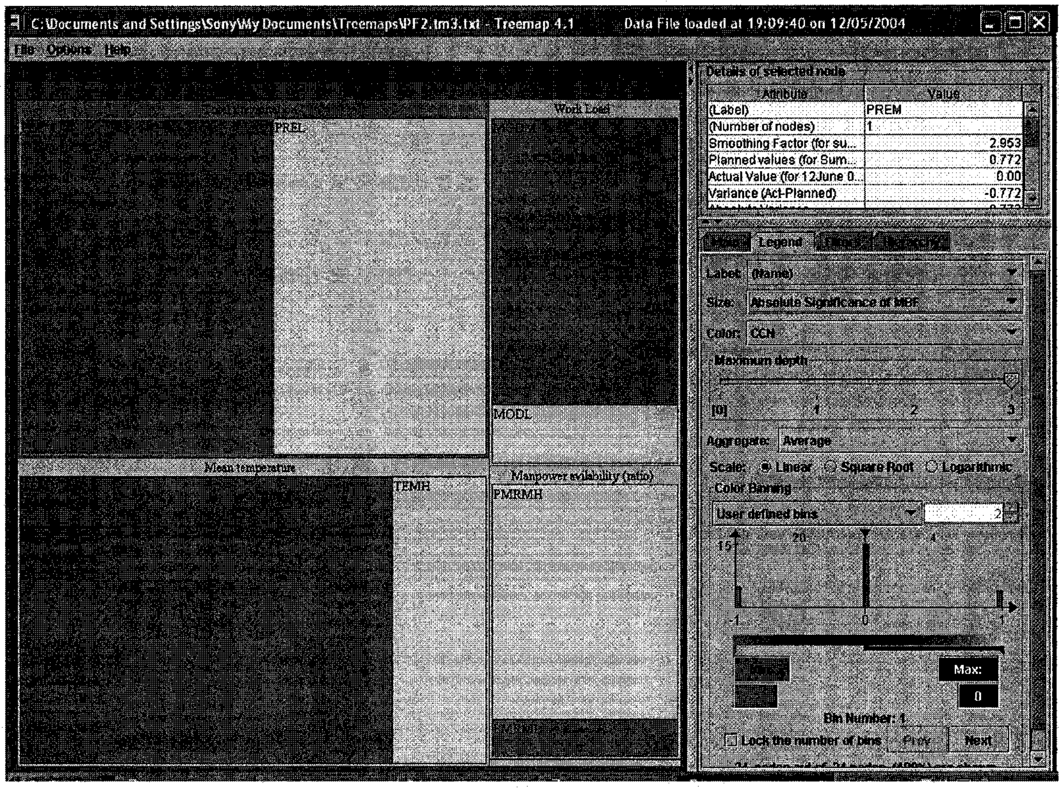


Figure 7-4.Size based on significance of significance of factor and color based on contributing (red) and counteracting (green) causes.

7.3 FRAMEWORK VALIDATION

The proposed framework, which is capable of predicting and diagnosing construction performance, integrates several concepts that are designed and developed in this thesis. A bottom-up approach of framework validation, i.e., validating the sub-modules first and then the overall framework, is used. As described in Section 7.2, the proposed framework has two key sub-modules: the prognostic module and diagnostic module. Several objectives as well as subjective model validation techniques have been used to ensure that the proposed framework possesses a satisfactory range of accuracy for predicting and diagnosing construction performance. This section summarize the efforts put forth to substantiate the accuracy of the proposed framework.

7.3.1 Conceptual Model Validation

In the proposed framework, designing the conceptual model is limited to identifying the most representative causal factors of key performance indicators by a group of experts and constructing membership functions using the membership values obtained from the expert judgment of representative values of causal factors. (Note that the strength of input-output relationship is calculated via neural network training by providing input-output sample data of the network). The process of causal knowledge representation depends on the experience and knowledge of a group of construction personnel. A structured methodology based on a modified version of the Nominal Group Technique (NGT) is proposed (see Section 6.4.2) to guide the group of experts to identify an appropriate and "reasonable" list of causal factors that can affect the performance indicator. Membership functions constructed based on sample membership values are validated using face-validation, i.e., by asking construction experts about the membership function and whether they are reasonably able to represent the selected linguistic concepts.

7.3.2 Validity of Working Condition Assessment Data

Proposed framework utilizes both quantitative and qualitative working condition assessment data for three purposes: training the FA-GRNN model, testing the FA-GRNN model, and for performing prognostic and diagnostic experiments with the validated model. Data is collected in terms of input-output pairs (**x**,y) representing daily values of selected causal factors (as input, x) and the corresponding measurements of the key performance indicator (y). The input vector, x, consists of both quantitative and qualitative measurements while output values are represented as a quantitative value. A structured procedure is proposed (in Section 6.4.4) that is based on a semantic differential approach to achieve a reasonable accuracy in qualitative expert assessments on qualitative variables. Internal consistency checks were carried out, as described in Section 6.5.2, to determine whether the individual expert judgments were within a reasonable accuracy level. The quantitative measurements on working condition are automated where possible (e.g., weather data is collected by setting up a mini-wireless weather station at site) to collect accurate field measurements. Additionally, data transformation procedure is also structured (see Section 6.5.1) by developing data aggregation procedures to combine expert qualitative assessments and/or to combine assessments in order to represent data in a different time scale. Furthermore, a database is designed, developed and maintained to collect and store both quantitative and qualitative data.

7.3.3 Prognostic Validation

The operational validity of the proposed framework is determined in Section 5.4 by comparing the actual system behaviour with the model's behaviour. In the prognostic module, the model is used to predict the construction performance based on input working conditions. Comparisons are then made between the actual output (i.e., daily actual KPI value) and the model's estimate to determine if they are same (or within reasonable level of accuracy, e.g., 10%). A statistical technique and a graph-based comparison approach are used to validate the prognostic model. The coefficient of multiple determinations, R^2, (see Equation 5.4) is used as a means of statistical validation, to determine the FA-GRNN model's accuracy. Additionally, scatter plots (see Figures 5-5, 5-8, and 5-10) and error graphs (See Figures 5-6, 5-9, and 5-11) are used to visualize the comparison of the actual vs. FA-GRNN model behaviour. Sixteen experiments were conducted (in Section 5. 4) using datasets that represent different time intervals (e.g., months, seasons) and found that models trained using seasonal data have the highest accuracy levels.

7.3.4 Diagnostic Validation

The purpose of the diagnostic module is to explain construction performance deviations by identifying the relative significance of causal factors. The operational validity of the diagnostic module is determined before each time the diagnostic inference is conducted. As described in Section 7.2.2, diagnostic inference is carried out only if the FA-GRNN prognostic model has the reasonable accuracy to predict the actual performance level of the activity based on the actual working conditions of a particular day. In other words, the FA-GRNN model is the foundation of the diagnostic inference. Additionally, the user always has the option to crosscheck the accuracy of the diagnostic inference by analyzing the variance of identified root causes of performance deviations manually. A protocol is also developed (in Section 7.2.2) to identify the accuracy of the model or diagnostic inference.

7.4 CASE EXAMPLE OF REASONING INDUSTRIAL CONSTRUCTION LABOUR PRODUCTIVITY

To obtain a high degree of confidence in the proposed framework, a set of actual data (collected using the proposed data collection methods) is used in this section to validate and verify the overall framework. For project related details, the reader is referred to the Section 6.3 of Chapter 6. This section presents the results of the experiments conducted on industrial construction activity: pipe handling and fabrication (hereinafter referred as pipe fabrication), to demonstrate the validity of the overall framework.

The labour productivity factor (PF) of the pipe fabrication activity was selected as the performance indicator, representing the output variable y. Causal factors that represent the daily working condition of pipe fabrication is identified by 4 frontline-supervisors who belong to the pipe-fitter trade. The average experience of this group of experts was 22 years in the same trade.

7.4.1 Causal knowledge representation and daily working condition assessments

The list of causal factors identified (using the proposed modified nominal group technique) to represent the daily working conditions of the pipe fabrication, their numerical and or bipolar measures, and selected linguistic values of each causal factor is shown in Table 7-2.

Table 7-2. Causal factors of pipe fabrication, their measures, and selected linguistic values.

FACTORS		NUMERICAL MEASURE	BIPOLAR MEASURE	SELECTED LINGUISTIC VALUES (TERM SET FOR REASONING)		
Crew size	CSZ	Number of crew members	Small - Large	Small	Average	Large
Absenteeism	ABS	Number of crew members absent	Low - High	Low	High	
Rework	RWK	Workforce hours	Low - High	Low	High	
Temperature (day time average)	TEM	Degrees Celsius	Cold - Warm	Cold	Average	Warm
Total Precipitation	PRE	mm	Low – Heavy	Low	Heavy	
Wind speed (day time average)	WSD	km/hr	Low - High	Low	Medium	High
Equipment availability	EQA	-	Low - High	Low	High	
Equipment suitability	EQS	-	Improper - Ideal	Improper	Ideal	
Material availability	MTA	-	Poor - Good	Poor	Good	
Access to work location	AWL	-	Restricted - unrestricted	Restricted	Unrestricted	
Waiting for other trades	WOT	-	Short- long	Short	Long	
Incomplete/Unclear Drawings	IUD	-	Few -many	Few	Many	
Right tool availability	RTA	-	Low - High	Low	High	

Once the causal factors and their quantitative and/or qualitative measures were identified, daily assessments of each causal factor are obtained by the same group of experts over the period from 6th June 2005 to 28th August 2005. The reader is referred to the Appendix A for complete details of the assessment data for the above causal factors. Figure 7-5 and Figure 7-6 show the screen captures of the XCOPE, the system developed to facilitate the above knowledge representation and collection of expert assessments.

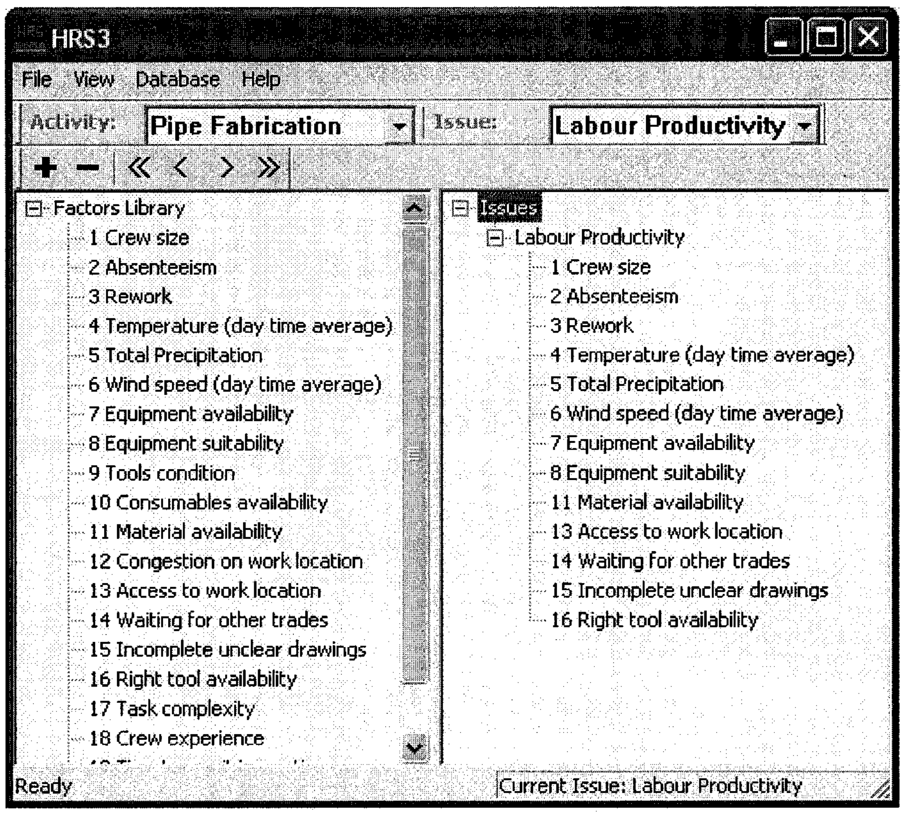


Figure 7-5. XCOPE representation of causal factors that affect steel erection productivity

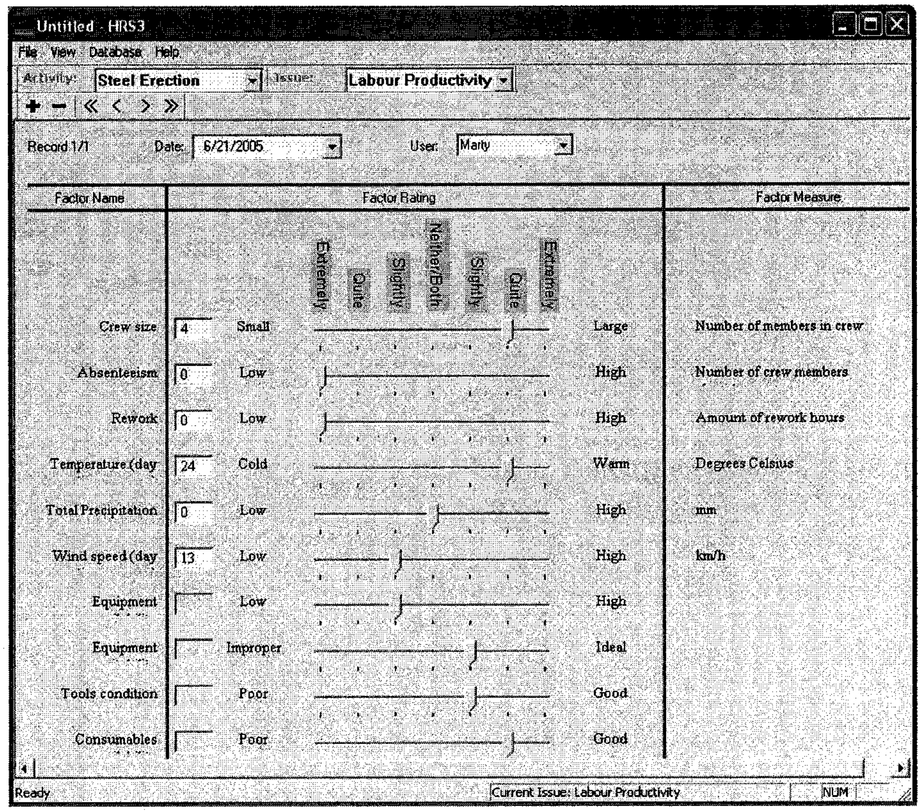


Figure 7-6. XCOPE representation of daily expert assessments

The variability of the labour productivity (PF) of pipe fabrication during the period concerned is illustrated in Figure 7-7. Technically, one of the proposed framework's key objectives is to map the complex variability of performance that is based on related working conditions.

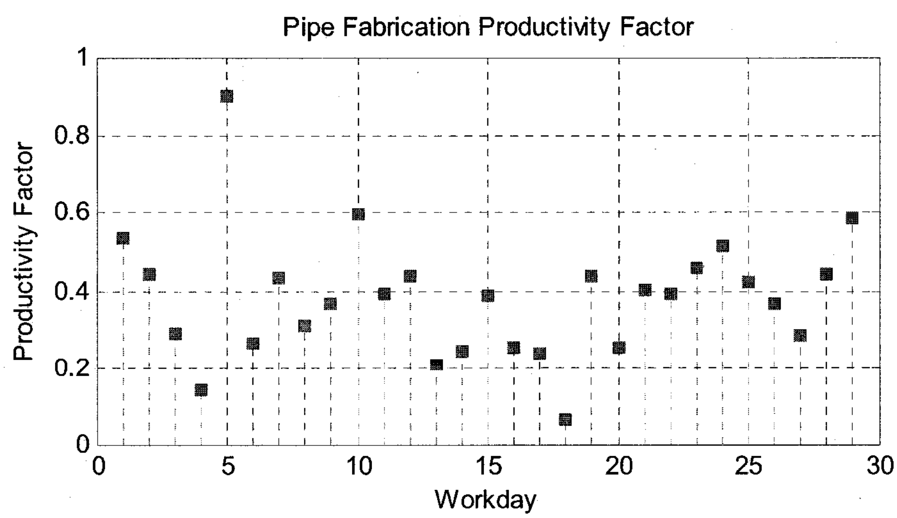


Figure 7-7. Productivity factor variation of structural steel erection

Figure 7-8 shows the average crew size and the number of crew members absent over the period concerned. Figure 7-9 shows the numerical measurements of the weather-related causal factors for the same period concerned.

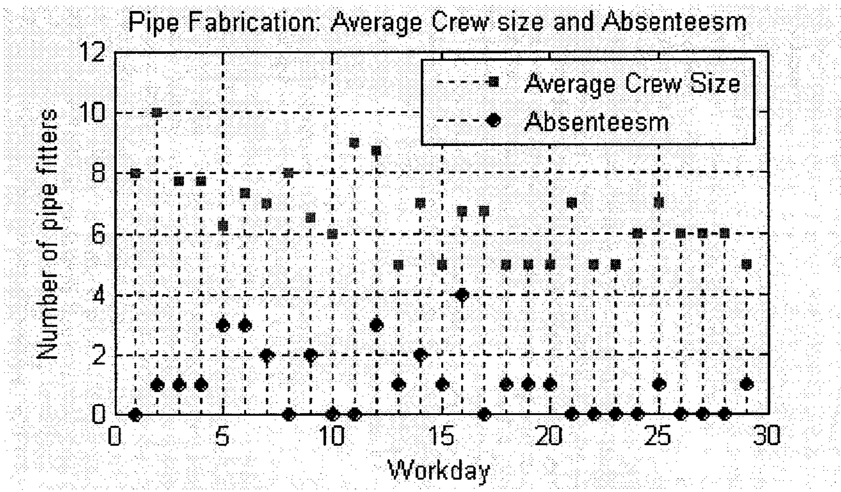


Figure 7-8.The average crew size and numbers of absent crew members

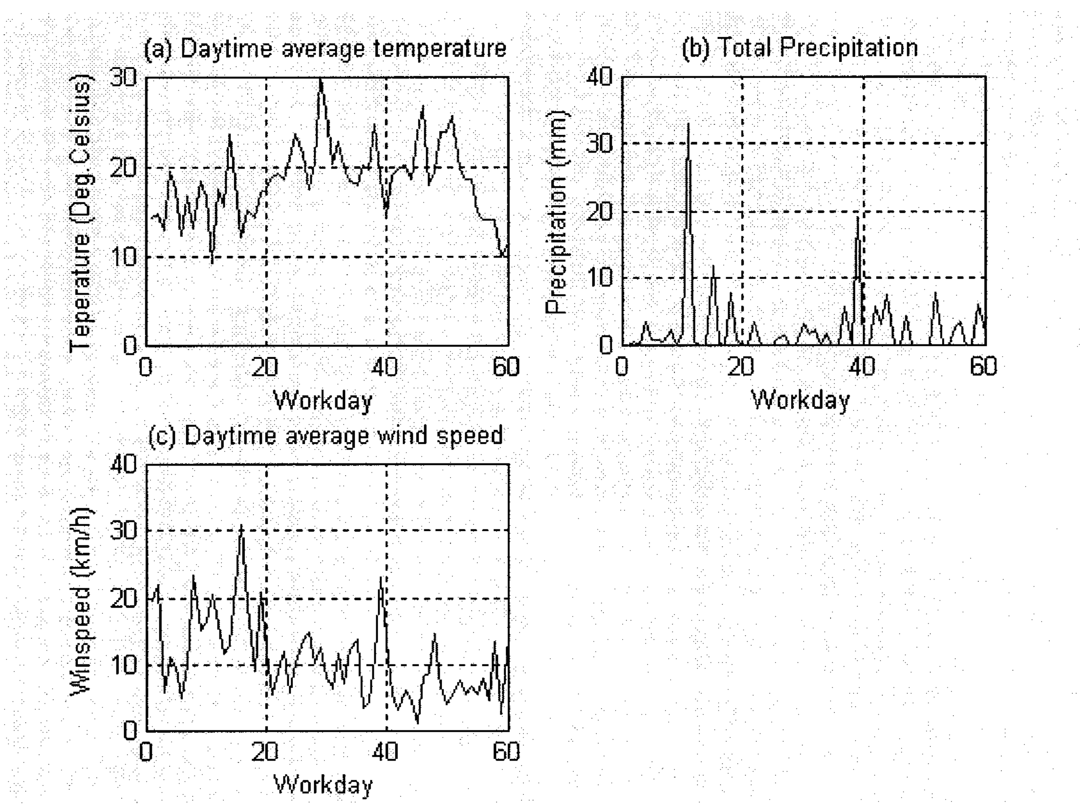


Figure 7-9. Daily values of weather related causal factors: (a) daytime average temperature, (b) precipitation during last 24 hours, and (3) daytime average wind speed.

Figure 7-10 shows the aggregated expert assessments (obtained via the semantic differential approach) about the causal factors that do not have well-defined numerical measures. An equal competence level is assumed among all four experts.

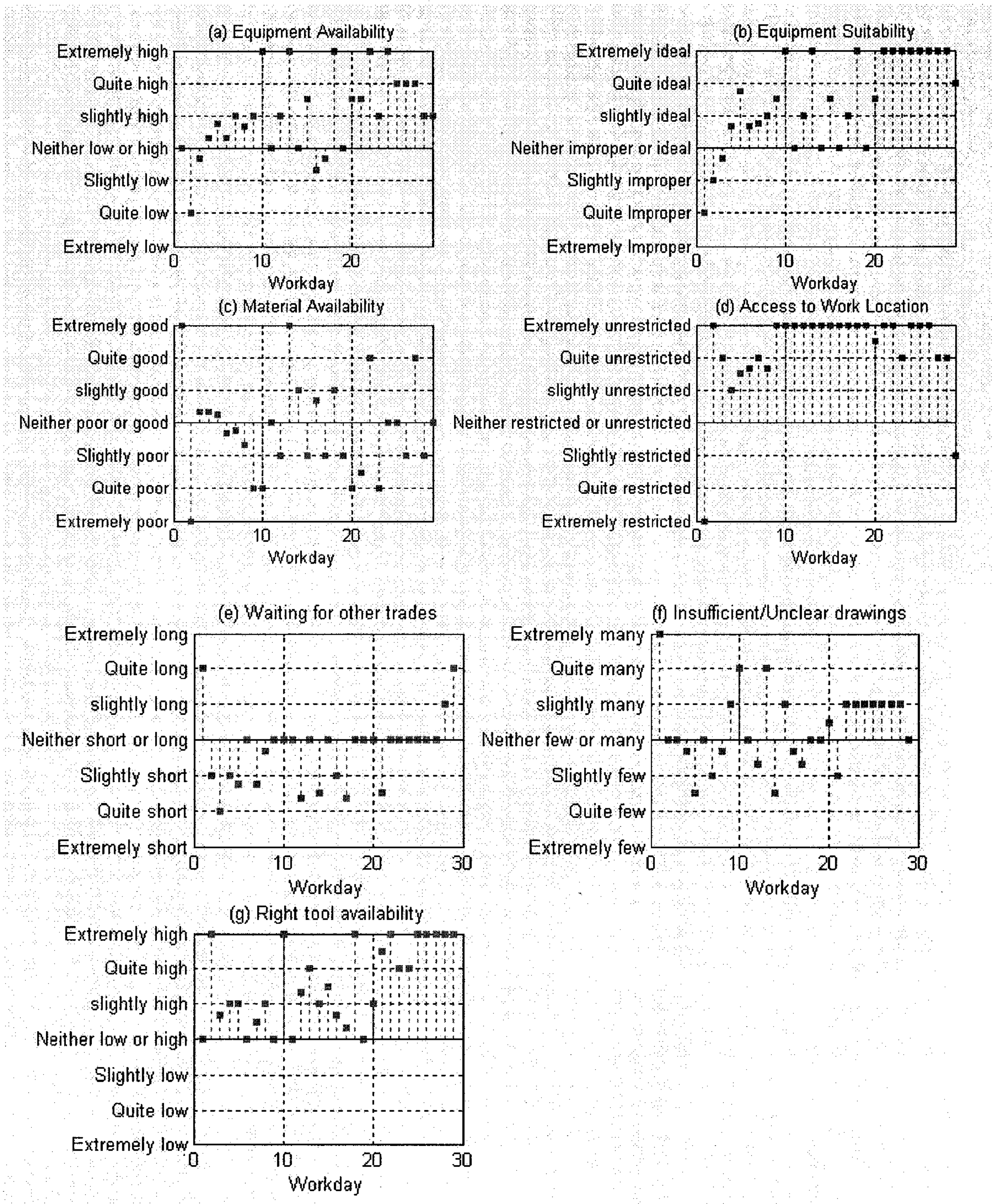


Figure 7-10. Aggregated pipe fabrication expert assessments about daily working condition

7.4.2 Input Fuzzification

The input fuzzification is carried out based on the proposed protocol (described in Section 6.5.3) for selecting suitable techniques to determine membership functions. The Figure 7-11 shows the selected nonlinear representative transfer functions to obtain (sample) membership values for the list of causal factors. By following the procedure described in Section 6.6.3, membership functions are constructed for causal factors {CSZ, TEM, PRE, and WSD} by a constrained interpolation of sample membership values obtained from the proposed linguistic-to-numerical transformation procedure (see Figures 7-12 to 7-15).

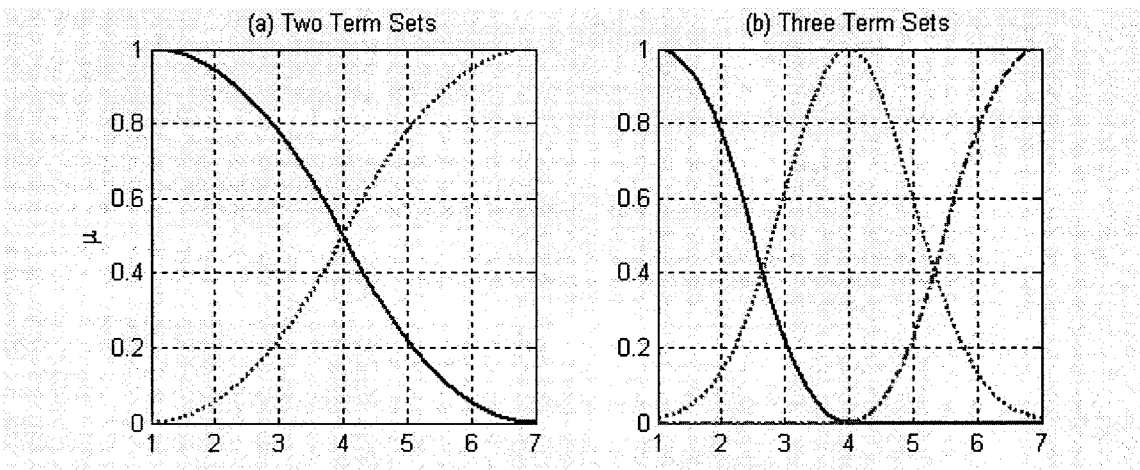


Figure 7-11. Selected representative transfer functions: (a) Two terms sets for causal factors {ABS, RWK, PRE, EQA, EQS, MTA, AWL, WOT, IUD, RTA}, and (b) Three term sets for causal factors {CSZ, TEM, WSD}.

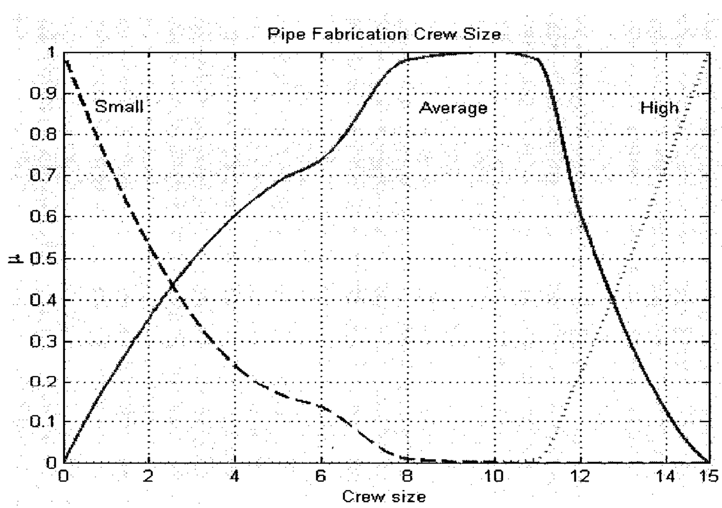


Figure 7-12. Membership functions of pipe fabrication crew size (small, average and large)

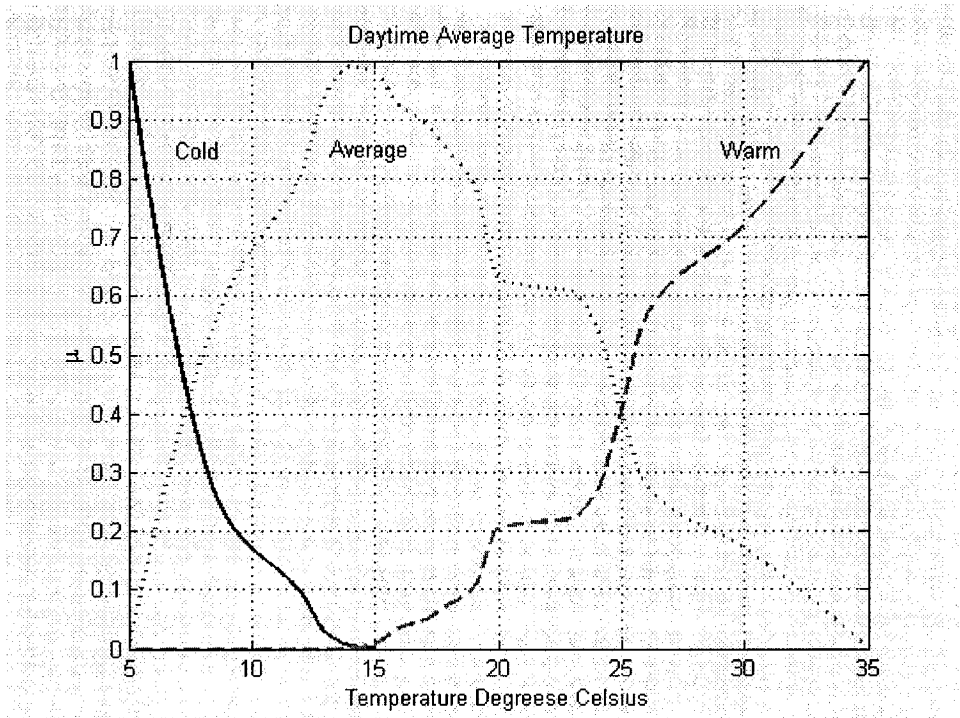


Figure 7-13. Membership functions of daytime average temperature (cold, average and warm)

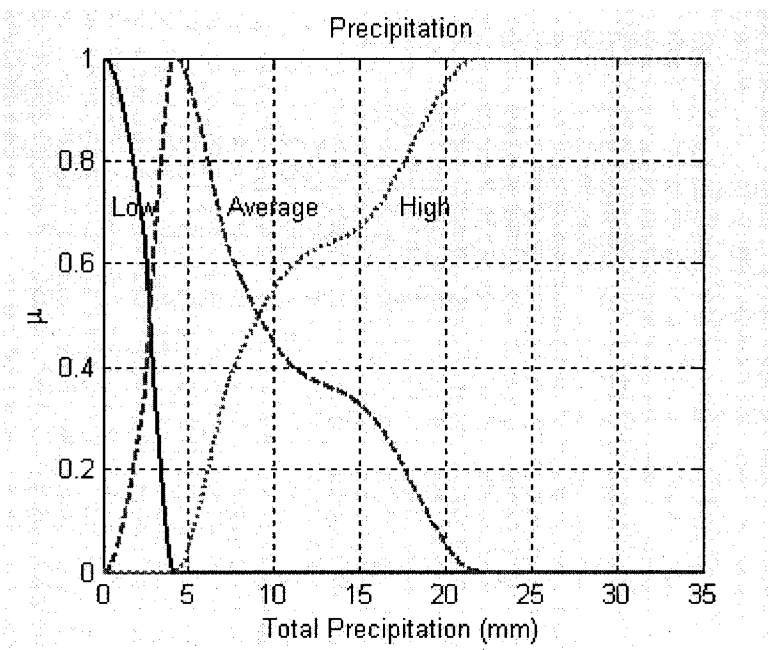


Figure 7-14.Membership functions of total precipitation (low, average and high)

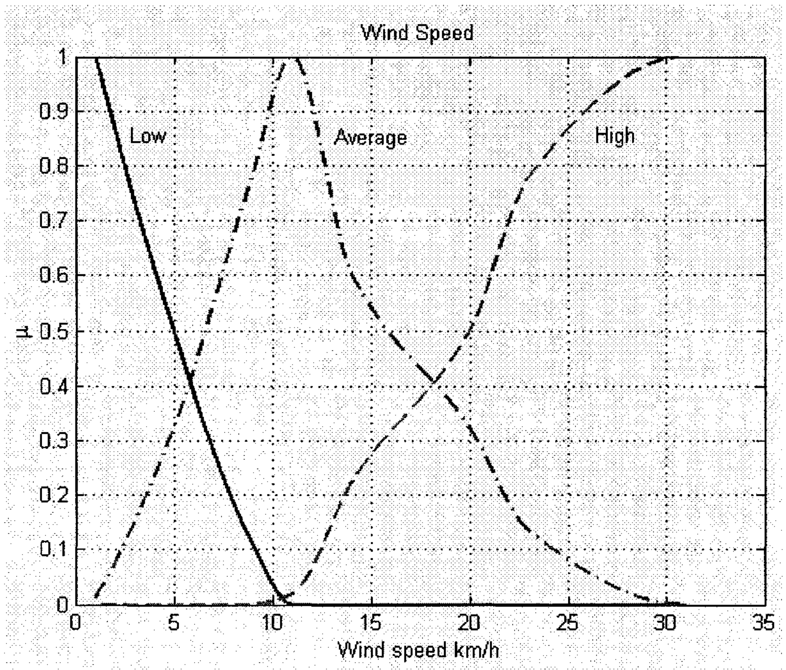


Figure 7-15. Membership functions of daytime average wind speed (low, average, high)

Due to the simplicity and limited number of discrete sample values, membership functions for causal factors {ABS and RWK} are constructed using heuristic method, as shown in Figure 7-16 and Figure 7-17, respectively. Membership values for causal factors { EQA, EQS, MTA, AWL, WOT, IUD, RTA } are obtained directly from respective transfer functions.

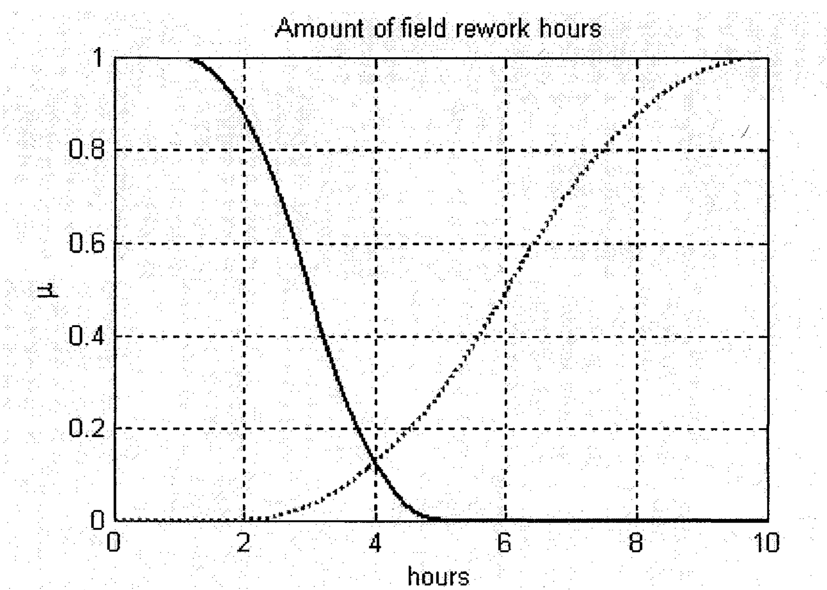


Figure 7-16. Membership function of field rework (low, high)

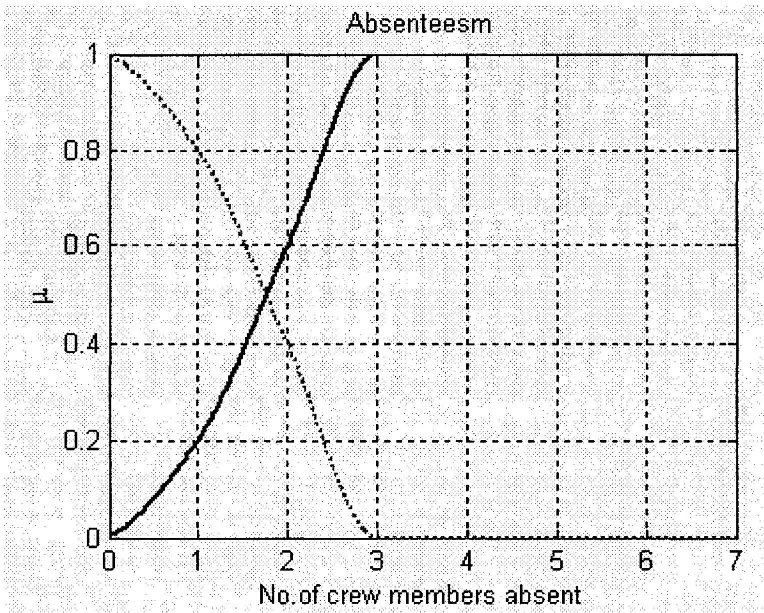


Figure 7-17. Membership function of Absenteeism (low and high)

7.4.3 Training and testing the FA-GRNN model

The dataset collected over the period of the summer 2005 (graphically shown in Figures 7-8 to 7-10) consists of 29 data patterns that could be used for training and testing the proposed FA-GRNN model for modeling structural steel erection productivity performance. Two data patterns were set aside for diagnostic reasoning. The remaining 27 data patterns were divided into two sets. 22 data patterns (i.e., 80%) were assigned for training the FA-GRNN model while the remaining five data patterns (i.e., 20%) are used for testing the model. The model is trained and optimized adaptively using a genetic algorithm, as described in Section 5.3.3. The adaptive training and optimization step of the FA-GRNN model is automatically stopped when there have been 20 successive reproductions of the whole population, but none has produced an individual that improved the mean squared error by at least 1 percent. The accuracy of the trained network is tested using several statistical and graph-based techniques.

The coefficient of multiple determinations, R^2, of the trained model was equal to 0.958 while the mean squared error (MSE) is equal to 0.001. Figure 7-18 shows the test error over generations elapsed while Figure 7-19 illustrates a comparison of actual output vs. FA-GRNN model output of training and testing data.

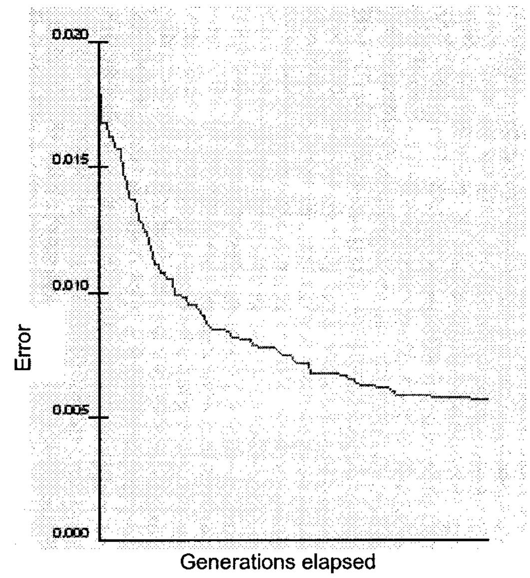


Figure 7-18. Test error of the FA-GRNN model over generations elapsed.

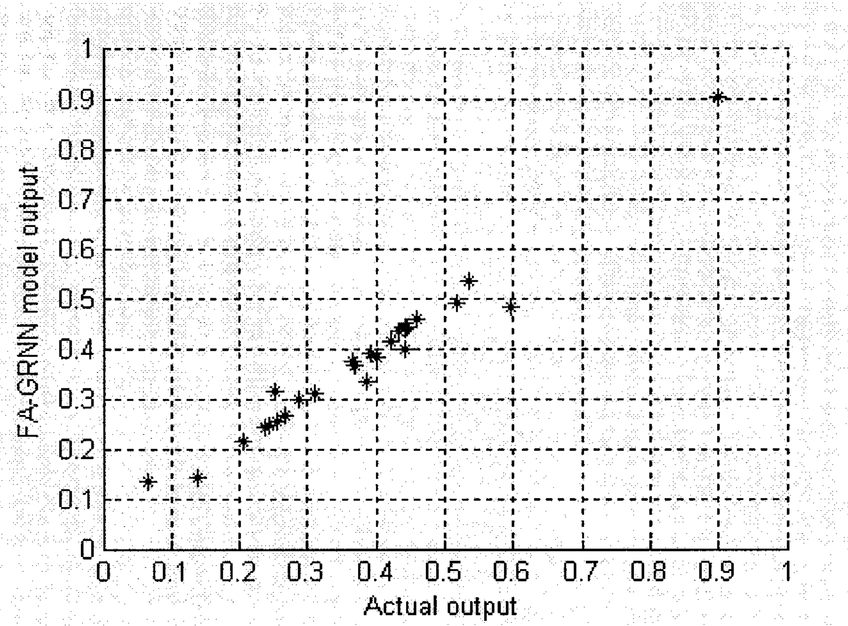


Figure 7-19. Actual vs. FA-GRNN network output comparison

Based on the analysis of statistical results and a visual inspection of Figures 7-18 and 7-19, one can conclude that the FA-GRNN model developed for reasoning structural steel erection productivity has a high level of accuracy in mapping input-output data.

To identify the sensitivity of the shape of representative transfer functions (in Figure 7-11) on FA-GRNN model accuracy, the experiment is repeated using linear representative transfer functions (see Figure 6-35). The corresponding value of the coefficient of multiple determinations, R2, is 0.960 and the mean squared error (MSE) remains the same. The comparison of actual vs. FA-GRNN network output is shown in

Figure 7-20. Accordingly, one can conclude that the shape of the representative transfer function has a very minimal impact on FA-GRNN model accuracy.

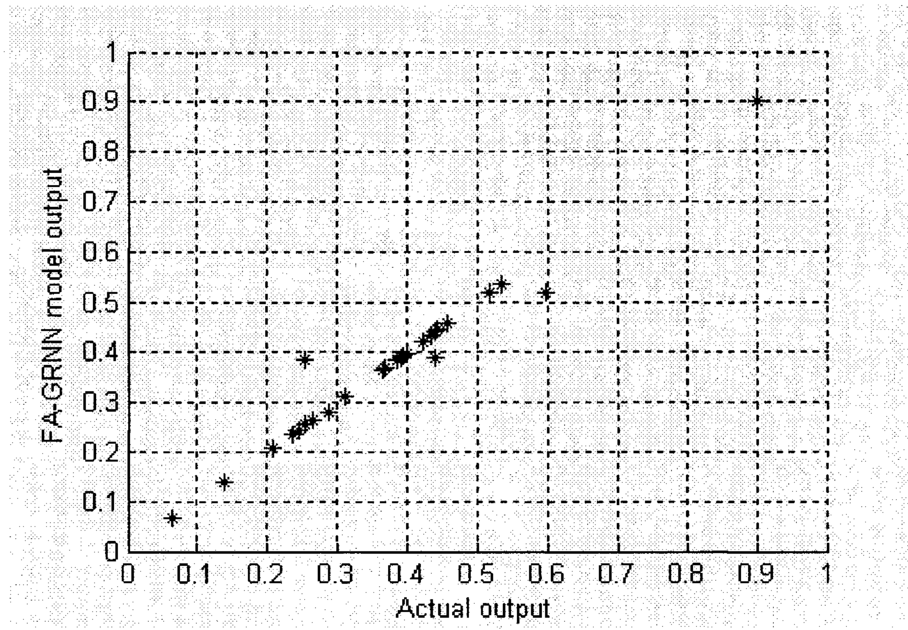


Figure 7-20. Actual vs. FA-GRNN network output comparison: Linear transfer functions

Table 7-3 shows the individual smoothing factors produced as an output of the above FA-GRNN model, which represent the relative significance of each fuzzy input neuron.

Table 7-3. Normalized individual smoothing factors representing significance of causal factors of pipe fabrication productivity.

INPUT NAME	LINGUISTIC VALUE	INDIVIDUAL SMOOTHING FACTOR	INPUT NAME	LINGUISTIC VALUE	INDIVIDUAL SMOOTHING FACTOR
CSZ	small	0.70	EQA	low	0.76
	average	**1.00**		high	0.62
ABS	low	0.40	EQS	improper	**1.00**
	high	0.21		ideal	**0.92**
RWK	low	0.00	MTA	poor	0.04
	high	0.64		good	0.63
TEM	cold	0.52	AWL	restricted	0.75
	average	**0.97**		unrestricted	0.43
	warm	0.53	WOT	short	0.19
PRE	low	0.03		long	0.61
	average	0.02	IUD	few	**0.99**
WSD	low	**0.97**		many	0.04
	average	0.12	RTA	low	0.00
	high	0.05		high	0.15

Smoothing factor results shown in Table 7-3 indicates that among 13 causal factors listed, CSZ, TEM, WSD, EQS and IUD have the highest impact on pipe fabrication labour productivity for the period concerned. Moreover, one can also conclude (at a different level of detail) that any change to *average* CSZ, *average* TEM, *low* WSD, *improper*- and *ideal*- EQS or *few* IUD may have considerable impact on pipe fabrication productivity.

7.4.4 The Diagnostic Inference

A data pattern that represents the day of July 28th, 2005 is used for diagnostic inference purpose. The labour productivity factor of pipe fabrication on that particular day was 0.589, which is considered as quite low productivity. The objective of the diagnostic inference is to identify the root cause(s) of low pipe fabrication productivity. As suggested in Section 7.2.2, the FA-GRNN model is realized by the data that represent actual working condition assessment. The absolute error of the FA-GRNN model for the particular data pattern was 0.002, thus the model is considered as accurate for diagnostic reasoning.

As shown in Table 7-4, planned conditions related to that day are identified. The size of the crews are assigned generally during a 1-week look ahead planning stage and generally no absenteeism is expected. Similarly, zero amount of field rework is expected. Planned values of weather-related causal factors are obtained by weekly weather forecasts. Planned values for the remaining causal factors shown in Table 7-4 are implied (assumed) conditions.

Table 7-4. Planned values (numerical and bipolar assessments)

CAUSAL FACTOR	PLANNED VALUE
CSZ	6
ABS	Zero
RWK	Zero
TEM	16 degrees Celsius
PRE	2 mm
WSD	Calm
EQA	Quite high
EQS	Quite sutable
MTA	Quite good
AWL	Quite unrestricted
WOT	Quite short
IUD	Extremely few
RTA	Extremely High

The Table 7-5 shows the diagnostic inference identifying the root causes (as well as their relative significance) of the low labour productivity for pipe fabrication on July 28, 2005. Results indicate that a high amount of rework hours, unclear drawings, and long waiting time for other trades contributed for the low labour productivity on the given day.

7.5 SUMMARY

This chapter presented an overall description of a proposed integrated computationally intelligent framework for predicting and diagnosing construction performance. Detailed descriptions about each key module of the system are given along with a step-by-step guide to implement each module. The functionally of the proposed framework is tested using a real-life industrial construction dataset. Results indicate that the proposed framework has greater capabilities in mapping complex relationships between causal factors and related construction performance indicator.

Table 7-5. Diagnostic inference for pipe fabrication productivity on July 28, 2005.

(1) Factor	(2) Membership function	(3) Smoothing Factor- σ_l (for summer)	(4) Planned value	(5) Actual Value (for 28 July 05)	(6) Variance Δ (Act-Planned)	(3)X(6) $S = \Delta\mu_i \times \sigma_l$	(7) $\sum S$	(8) Contributing (C+) Counteracting (C-) Neutral (N)	(9) Rank	(10) Comment
CSZ	small	0.70	0.14	0.17	0.03	0.02				Actual average crew size was slightly less than the planned crew size
	average	1.00	0.74	0.68	-0.05	-0.05	-0.03	C+		
ABS	low	0.40	1.00	0.80	-0.20	-0.08				1 crew member was absent
	high	0.21	0.00	0.20	0.20	0.04	-0.04	C+		
RWK	low	0.00	1.00	0.00	-1.00	0.00				10 hours of field rework
	high	0.54	0.00	1.00	1.00	0.54	**0.54**	C+	1	
TEM	cold	0.52	0.00	0.00	0.00	0.00				
	average	0.97	0.92	0.81	-0.11	-0.10				
	warm	0.53	0.04	0.09	0.05	0.03	-0.08	C+		
PRE	low	0.03	0.92	0.15	-0.77	-0.02				
	average	0.02	0.04	0.50	0.46	0.01	-0.01	C-		
WSD	low	0.97	1.00	0.52	-0.48	-0.47				
	average	0.12	0.00	0.31	0.31	0.04				
	high	0.05	0.00	0.00	0.00	0.00	-0.43	C-		
EQA	low	0.76	0.17	0.33	0.17	0.13				
	high	0.62	0.83	0.67	-0.17	-0.10	0.02	C-		
EQS	improper	1.00	0.17	0.17	0.00	0.00				
	ideal	0.92	0.83	0.83	0.00	0.00	0.00	N		

Table 7.5. Contd.

(1) Factor	(2) Membership function	(3) Smoothing Factor- σ_l (for summer)	(4) Planned value	(5) Actual Value (for 28 July 05)	(6) Variance Δ (Act-Planned)	(3)X(6) $S = \Delta\mu_i \times \sigma_l$	(7) $\sum S$	(8) Contributing (C+) Counteracting (C-) Neutral (N)	(9) Rank	(10) Comment
MTA	poor	0.04	0.17	0.50	0.33	0.01				
	good	0.63	0.83	0.50	-0.33	-0.21	-0.20	C+	4	
AWL	restricted	0.75	0.17	0.67	0.50	0.37				
	unrestricted	0.43	0.83	0.33	-0.50	-0.21	0.16	C+	5	
WOT	short	0.19	1.00	0.17	-0.83	-0.16				
	long	0.61	0.00	0.83	0.83	0.51	**0.35**	C+	3	
IUD	few	0.99	1.00	0.50	-0.50	-0.50				
	many	0.04	0.00	0.50	0.50	0.02	**-0.48**	C+	2	
RTA	low	0.00	0.00	0.00	0.00	0.00				
	high	0.15	1.00	1.00	0.00	0.00	0.00	N		

7.6 REFERENCE

Johnson, B., and Shneiderman, B. (1991). "Treemaps: a space-filling approach to the visualization of hierarchical information structures." *Proc. of the 2nd International IEEE Visualization Conference,* IEEE, San Diego, 284-291.

CHAPTER EIGHT

8. CONCLUSION

In this chapter, the details of the research discussed in the previous chapters are summarized, and recommendations for future research are given.

8.1 SUMMARY OF WORK

Continuous performance improvement is vital for construction contractors to be competitive in the marketplace. Identifying root causes of performance deviations, and quantifying them in a systematic manner both play a major role in continuous performance improvement. It is vital to identify causes of construction performance deviations, the results of which are to increase profit, and to meet schedule, quality, and safety requirements. Therefore it is important to consider how project performance is measured and how plausible explanations for performance deviations can be generated.

Performance deviations are detected when one or more key performance indicators go outside a given range or change significantly from their normal values. Performance diagnosis is to isolate the cause(s) of a performance deviation by collecting and analyzing information on performance indicators using field measurements, subjective judgments, and other information sources. Often, it is performed by the construction manager; it is an important function of construction project control. A decision support system that makes it possible to diagnose the root causes of performance deviations, in a timely manner, would be an attractive way to improve project performance and meet or exceed project performance goals.

Currently, there is no standard system to reason about construction performance. This is mainly because construction-related problems are mostly unstructured in nature, which makes it difficult to apply algorithmic methods based on mathematical models to the process of performance analysis and diagnostic reasoning. The process of diagnostic reasoning makes this application more difficult due to modeling requirements, such as a capability in computing with incomplete, approximate, and qualitative data; non-linear and dynamic system modeling capability; and the identification of multiple root causes and the relative significance of each cause.

This research is an effort to address most of the above-mentioned issues in the proposed construction performance diagnostic framework. The proposed methodology is a step towards developing an application of computational intelligence tools in predicting and diagnosing construction performance. This research provides an integrated framework for predicting and reasoning construction performance during the construction process using three key computational intelligence (CI) tools: Fuzzy Sets, Generalized Regression Neural Network (GRNN), and Genetic Algorithms. The advantages of synergistic links between key constituents are identified. Two potential CI systems based on fuzzy-neural systems are identified (i.e., of AND/OR neuron processing module and GRNN based processing module) and a system architecture is proposed to exploit the benefits of CI systems to assist construction performance diagnostic reasoning.

First, a logic modeling framework based on AND/OR fuzzy neural networks is explored. The transparent structure of the AND/OR neuron model provides the flexibility needed to identify the significance of input causal factors. Irrespective of the high explanatory capabilities of the model, the results of the experiments carried out using a representative sample of construction performance data collected from a industrial construction project showed that the generalization capability of the AND/OR network is inadequate. Experimental results indicated that the underlying problem has a complex nonlinear character.

Having identified the limitations and importance of accurate mapping capabilities for construction performance diagnostic reasoning, an alternative fuzzy neural network architecture (i.e., fuzzy adaptive generalized regression neural network, FA-GRNN) is designed, developed, and tested with the same dataset that was used to test the AND/OR neuron model. The objective of the FA-GRNN model was to map the complex non-linear problem at hand at a greater level of accuracy, while maintaining the explanation capability that is available with AND-OR neuron model in terms of interpreting connection weights. FA-GRNN is a nonlinear and nonparametric method, i.e., no assumptions are made about the distribution of the data in the model. This nonparametric nature of the model suits the construction performance reasoning application well because of its inability to identify an *a priori* distribution function due to the complex nature of the problem. The FA-GRNN model's accuracy is tested with 16 data (sub) sets and the results indicate that the model has a greater accuracy level. Experimentation results also demonstrate that the model provides better overall performance when it is trained with data representing seasonal characteristics.

In an effort to further enhance the modeling capabilities of the proposed model, a pragmatic-structured approach is developed to acquire and represent construction experts' knowledge on daily working conditions. The proposed causal knowledge representation methodology was a combination of a nominal group technique (NGT) and a semantic differential (SD) approach.

A practically possible approach (compared to theoretically feasible) for determining membership functions based on sample membership values is explored. Constrained interpolation methods that are identified as potential membership function determination techniques are tested with data collected from detailed case studies that were carried out at an industrial construction project.

Finally, the description of the overall diagnostic reasoning development strategy, combining the knowledge representation and acquisition methods and proposed FA-GRNN architecture is given. The outcome of the research assists construction managers identifying possible causes of construction performance deviations, on a daily basis. It prioritizes the causes so that construction managers can take suitable corrective actions, in a timely manner. In addition to using the model to identify root causes of daily performance deviations, the same model can be used as a prognostic model to predict construction performance (e.g., predict labour productivity). A computer system named XCOPE (e**X**plaining **CO**nstruction **PE**rformance) is developed based on the concepts and methodologies developed in this research.

8.2 RESEARCH CONTRIBUTIONS

Developing a technique capable of diagnosing a nonlinear dynamic system is a significant contribution to the state-of-the-art in establishing robust performance diagnostic models. After identifying the key issues and challenges in developing construction performance diagnostic models, this study proposed a novel approach that includes techniques developed to acquire and represent the construction experts' knowledge and the diagnostic schema based on computational intelligence techniques. Described below are the three key contributions made by this study.

(1). Integrated reasoning framework: The major outcome of this research is the integrated computationally intelligent framework that is capable of predicting and diagnosing construction performance. The proposed framework is based on three key computationally intelligent tools: fuzzy sets, generalized regression neural networks, and genetic algorithms. This hybrid architecture is named the Fuzzy Adaptive Generalized Regression Neural Network (FA-GRNN). The application of fuzzy set theory, more specifically, membership functions, as the input interface facilitates computing with linguistic terms, which represent subjective knowledge of construction experts. The proposed FA-GRNN model introduced fuzzy neurons to the classical GRNN architecture. By doing so, the user of the model (i.e., construction managers) is provided with a mechanism to incorporate linguistic values for causal factors. This added level of information granularity allows for the capturing and representing qualitative knowledge of the system user. This fuzzy neurons allows explicit modeling of each causal factor impacting construction performance, where in current practice, from tradition unit-rate estimating to construction simulation models, this function is handled implicitly using a multiplication factor to suite to the context. The proposed methodology also allows the user to modify the individual causal factors and assess the sensitivity of the impact on construction performance.

Generalized Neural Networks provides the vehicle for complex input-output mapping, and genetic algorithms are used to optimize the proposed network. By introducing local smoothing factors to the classical GRNN, the transparency of the proposed FA-GRNN model is enhanced up to a level that the model can be used to identify the relative significance of each input causal factor (i.e., identification of multiple root causes). This important feature of the FA-GRNN model is used as the foundation of performance diagnostic inference. Additionally, FA-GRNN model also capable in identifying whether a certain causal factor is contributing towards or counteracting performance.

The FA-GRNN is the only integrated framework currently exists that has both prediction and diagnosis capabilities whilst utilizing quantitative and qualitative data. Based on a series of experiments carried out using real data, it is proved that the FA-GRNN model is capable in highly accurate predictions and diagnosis of construction performance with sparse data.

(2) Expert knowledge acquisition and representation method: The special feature of the model is that it allows for capturing the expertise of construction managers and utilizing it in the diagnostic reasoning process. This is the first ever effort in construction

management domain to acquire construction experts' qualitative knowledge (along with quantitative data) in a systematic and economical manner. A unique methodology is proposed, using a semantic differential technique to represent the construction expert's qualitative knowledge on daily working conditions. Additionally, a novel approach is proposed to aggregate expert qualitative assessments to represent multiple expert opinion on causal factors across different time intervals (e.g., weekly, monthly), and across different levels of abstractions (e.g., sub-activity level , activity level, work package level) for the purpose of reasoning performance at multiple levels of abstractions. Furthermore, a fast and efficient mechanism (a group consensus methodology) for identifying lists of potential causal factors of construction performance deviations, in a structured manner, is proposed using a modified nominal group technique. This list forms the basis of diagnostic model, i.e., identifies input and outputs of the diagnostic model.

(3). Membership function development technique(s): Another major contribution of this research is the identification and development of appropriate techniques to obtain membership values and to develop membership functions, for causal factors. The main objective here was to identify a practically possible membership function determination technique, compared to a theoretically feasible technique. It has been discovered that each causal factor has its unique characteristics and there is no one single membership function construction technique that can apply for all causal factors. A protocol is developed to guide the users to identify suitable membership function development techniques depending on factors and conditions. The proposed membership function development technique using constrained interpolation of sample membership values preserve the need of the context dependent nature of membership functions while making it easy to reproduce when the context changes (e.g., in different projects, locations, climates). This proposed membership function development technique can be applied in any other domain where sample qualitative assessments can be obtained from multiple experts.

8.3 RECOMMENDATIONS FOR FUTURE RESEARCH

An opportunity exists to enhance significantly the potential for a greater adoption of computational intelligence techniques by the construction industry, because of the novel approach proposed as compared to previous performance modeling approaches in the construction domain. The methodology and findings of this research have opened up certain issues that need to be investigated further to build upon the findings of this research. They are summarized below and may serve to guide future research related to the construction performance diagnosis.

1. This proposed framework is tested and validated for modeling construction productivity in industrial construction domain at activity level (and then aggregating up to the trade level). To generalize the applicability, the framework should be tested for different key performance indicators, in various other industries (e.g., commercial, civil construction) for different activities and trades.

2. This study focused on assisting construction managers to identify root causes of daily performance deviations. One can exploit the possibilities of using the proposed framework at more abstract level so that the output can be used for top-level decision making.

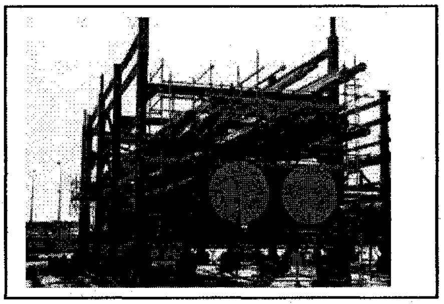
3. The proposed system can be significantly benefited by building a supplement to the output interface to suggest corrective actions based on identified causes. Developing a rule-based fuzzy expert system would be an appropriate choice.

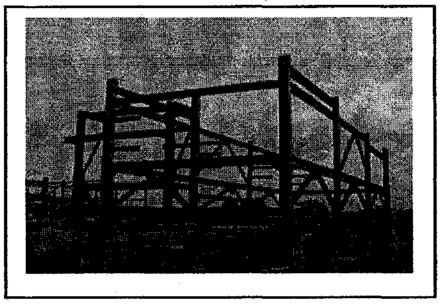
4. The efficiency of the proposed system can be greatly enhanced by automating the daily working condition reporting process using constantly developing wireless technology.

5. One can experiment with automated membership function construction techniques so that the expert knowledge-based membership functions developed in this study can be validated.

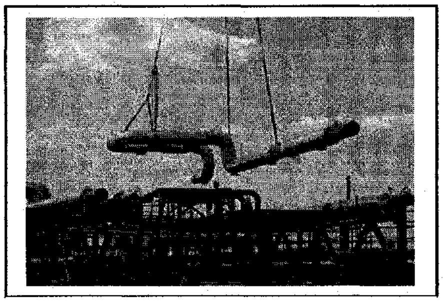
APPENDIX- A

Pipe Module Fabrication Process

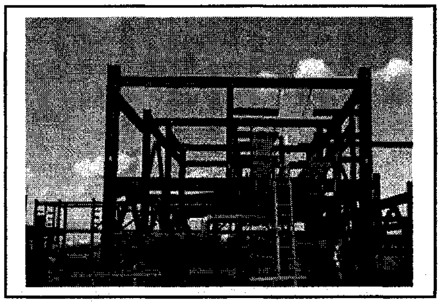




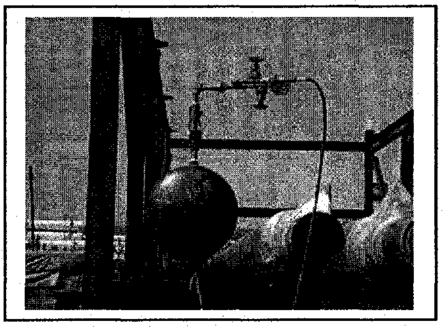
(b). Steel erection



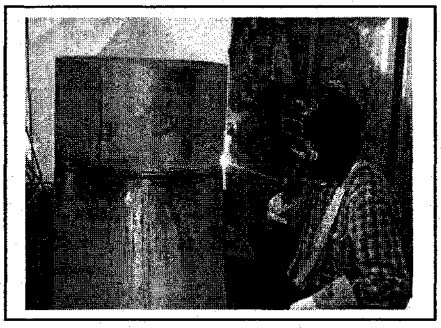
(c). Pipe handling



(c). Cable tray installation

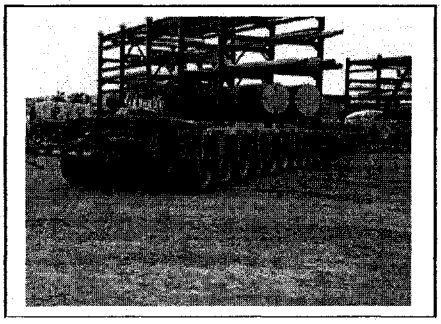


(d). Pipe hydro-testing



(e). Pipe welding

(f). Pipe insulation



(g). Shipping pipe module