University of Alberta

Intelligent Contractor Default Prediction Model for Surety Bonding in the Construction Industry

By

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Dedication

This thesis is dedicated with love, admiration, and respect

to my kind mother, dear father, my lovely wife

and my beloved children: Pola and Mayven.

Abstract

Construction is a risk-filled, uncertain, and dynamic environment. Contractor default is a critical risk that can influence the outcome of projects in the construction industry. Construction project owners and other stakeholders look for methods to predict the potential of contractors to default, in order to avoid awarding contracts to high-risk contractors. One of the most effective tools for project owners to mitigate the risk of contractor failure is to transfer the risk of project completion to a surety company. The surety company conducts a comprehensive prequalification (underwriting) process to assess the possibility of contractor default. The prequalification process is done to evaluate any contractor, project, and contractual risks that may affect the contractor's performance. The prequalification process involves evaluating various qualitative and quantitative evaluation criteria, many of which contain uncertainty and require subjective judgment.

This thesis demonstrates how fuzzy logic and expert systems techniques are integrated to develop a model able to help surety professionals in contractor default prediction for a specific construction project for bonding purposes. Building the contractor default prediction model (CDPM) included identifying, classifying, and providing a comprehensive, detailed list of the evaluation criteria for contractor and project prequalification. Numerical scales were defined for the quantitative evaluation criteria, and rating scales, using reference variables, were developed to quantify the qualitative criteria. An important evaluation category, "contractor's organizational practices," was incorporated as input to the CDPM.

The CDPM was built using the expertise of surety practitioners across Canada, and several different knowledge acquisition techniques were used. A novel methodology for finding a group consensus function that aggregates experts' judgment scores to represent a common opinion was applied, in order to aggregate the experts' inputs for the CDPM development. A methodology to apply two different optimization techniques, genetic algorithms and artificial neural network back-propagation, for the CDPM's adaptation is presented. Finally, software for contractor default prediction, SuretyQualification, is developed.

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I would like to express my deepest gratitude and sincere thanks to my lovely parents for their never ending support. Although I have been away from you, your prayers have always paved my road to success. This journey could not be finished successfully without the help, support, and warm companionship of my dearest lovely wife Heba. Thank you for your continuous love, inspiration, and patience. Words cannot express my gratitude and everlasting love toward you.

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I would like to take this opportunity to thank all the individuals, colleagues and friends who assisted me during this research project. I extend my sincere thanks to Mr. Andre Giasson, Mr. Brian Davidson, Mr. Jason Smith, Ms. Betty Shellnutt, Mr. Greg Forsythe, and the Board and members of the Surety Association of Canada (SAC) for their time, knowledge, and expertise in providing input to the research.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

SIO	The Surety Information Office
SAA	The Surety Association of America
DSS	Decision Support System
FES	Fuzzy Expert System
MBF	Fuzzy Membership Function
DoS	Rules' Degree of Support
CPDM	Contractor Default Prediction Model
MAUF	Multi-Attribute Utility Function
ANNs	Artificial Neural Networks
MOORA	Multi-Objective Optimization by Ratio Analysis
SVM	The Support Vector Machine
PCA	Principal Component Analysis
MKL	Multiple Kernel Learning
AHP	Analytical Hierarchy Process
CSC	Contractor Selection Criteria
GAs	Genetic Algorithms
WC	Working Capital
TNW	Tangible Net Worth
GPM	Gross Profit Margin
NPM	Net Profit Margin
MIN	Minimum
PROD	Product
MAX	Maximum
CoM	Centre Of Maximum
AVG	Average
BSUM	Bounded Sum
COA	Centre of Area
MOM	Middle of Maximum
GCS	Group Consensus System
CWF	Consensus Weight Factor

IS^n	Individual Expert's Score
RIW	Relative Importance Weight
ESC	Experience in Surety for Construction
CR	Current Role
ECP	Experience in Contractor Prequalification
EPE	Experience in Project Evaluation
SL	Size Limit
LP	Largest Project Evaluated
L_L	Lower Limit
U_L	Upper limit
λ_{max}	Largest Eigenvalue
ν	Consistency Index
DoA	Degree of Attainment
μ	Membership Value
RV	Ranking Value
SVM	Support Vector Machine
KB	Knowledge Base
F_w	Windowing Scaled Fitness Value
MS	Mutation Step
Pc	Crossover Probability
P_m	Mutation Probability

CHAPTER 1. - Introduction[1]

1.1 Background

Construction is risky and dynamic business, full of uncertainties and always changing. It is almost impossible to find two construction projects that are completely the same (Marsh 2008; Chao and Skibniewski 1998). Contractor failure is always possible, even for capable and well-established contractors, and happens when the contractor fails to fulfill the contractual obligations (Surety Information Office 2007; Russell 1991). According to the Office of the Superintendent of Bankruptcy Canada (2008, 2010, 2011), between 2007 and 2011, the highest frequency of the bankruptcy cases in Canada were related to the construction sector. Of 20 economic sectors, the bankruptcy cases in the construction sector represent 17.4%, 15.4%, 20.2%, and 24.3% in 2008, 2009, 2010, and 2011 respectively.

The Surety Information Office (SIO) (2007) presented the following questions: How can public agencies using the low-bid policy in awarding public works contracts be sure the lowest bidder is dependable? How can private sector construction project owners manage the risk of contractor failure? In construction, owners always search for the ways by which the risk of contractor failure can be mitigated. Surety bonding in the construction industry is a very useful tool for

[1]Parts of this chapter have been published in Journal of Automation in Construction, Volume 21, January 2012, and accepted for publication in Canadian Journal of Civil Engineering, 2012.

project owners to mitigate the risk of contractor failure by transferring the risk of project completion to a surety company (Maxwell 2005). Surety bonds provide financial security and construction assurance by assuring project owners that contractors will perform the work and will pay their specified subcontractors, laborers, and material suppliers (Surety Association of Canada [SAC)] 2009).

The Surety Association of America (SAA) (2009) defined surety bonds as an agreement providing for monetary compensation should there be a failure to perform specified acts within a stated period. That means that the surety company guarantees to the owner of the construction project that the project will be constructed within the required time and according to the specifications and contract documents (Kangari and Bakheet 2001). Many owners require surety bonds from their contractors to protect their company and shareholders from the enormous cost of contractor failure.

It is a very important and critical decision for the surety company to accept bonding a contractor for a specific construction project. Due to the huge risk that the surety company carries, that risk must be estimated and reduced as much as possible, and that reduction comes by conducting a comprehensive evaluation (i.e., prequalification) of the contractor. In other words, the surety company should assess/predict the possible risk of the contractor defaulting on performing the construction project. This contractor default prediction process is complex, not only because there are many criteria that should be taken into consideration, but also because the evaluation criteria are both qualitative and quantitative.

Furthermore, some are uncertain and subjective, making them difficult to assess. The construction bond underwriting (i.e., prequalification) process requires expert knowledge and judgment, and many times, experts incorporate their instinct or intuition without explaining a logical rationale.

1.2 Problem Statement

Construction project owners and other stakeholders look for methods to predict the potential of contractors to default, in order to avoid awarding contracts to high-risk contractors. Owners request a contractor to be bonded so that the surety company can provide a guarantee to the owner that the project will be constructed, and that contractual obligations will be fulfilled. Therefore, the risk of project completion is transferred to the surety company (Al-Sobiei et al. 2005). When the surety company accepts the request to provide a contractor with the bonding for a specific project, many of the project risks are transferred to the surety company. These risks include the contractor prequalification process, macroeconomic changes that can occur in the construction industry over a very short period, and the uncertainty of a project (Russell 1990). To mitigate the possible risk of a contractor defaulting on completing a specific project, a comprehensive and detailed prequalification process should be done to quantify the contractor's competency to perform the proposed construction project. The contractor prequalification process occurs in two phases (as presented in detail in chapter 2).

The objective of the first prequalification stage is to build a relationship between the contractor and the surety company. At this stage, the evaluation criteria that are considered to prequalify the contractor and his/her organization are mainly grouped under three categories: character, capacity, and capital (Surety Information Office 2011). Several models have been developed for the first stage of contractor prequalification for surety bonding, such as the model created by Bayraktar and Hastak (2010), who developed a conceptual scoring-based contractor evaluation system to assist sureties in evaluating the contractor's character, capacity, and capital; and SuretyAssist, a decision support system designed by Marsh (2008) and Marsh and Fayek (2009) to assist surety underwriters and brokers in evaluating general contractors in the construction industry.

The second bonding prequalification stage is done when the contractor requests bonding for a specific construction project. At this point, the surety company conducts a more comprehensive prequalification (surety underwriting) process that focuses not only on evaluating the contactor, but also on the proposed project aspects, the contractual risk, and the contractor's organizational practices. A system or methodology to conduct the second surety bonding prequalification process to provide prediction of the possible risk of contractor default in a specific construction project has not been presented.

Having identified contractor prequalification from different perspectives and provided several techniques to represent contractor prequalification, the previous research in the area of construction contractor prequalification and surety underwriting provides a point of departure for the research presented in this thesis. A model or methodology for the second phase in the underwriting (i.e., prequalification) process has not been addressed in previous research; no study has integrated contractor-specific risk, project-specific risk, contract-specific risk, and contractor's organizational practices evaluation criteria in the underwriting process. In the construction industry, there is a need for a structured system to assess/predict the risk of contractor default to enhance the surety practitioner's decision-making in providing bonding to a contractor for a specific project.

1.3 Research Objectives

The overall aim of this thesis is to present a methodology to integrate fuzzy set theory with expert systems to create a decision support system (DSS) for contractor prequalification for surety bonding, and to investigate the appropriateness of a fuzzy expert system (FES) for contractor prequalification for a specific construction project. Additionally, this thesis seeks to explore and present new techniques to build the main FES's components (fuzzy membership function and fuzzy rule base). One final aim is to fill the gap in existing contractor prequalification models by presenting a suitable way (i.e., model) to integrate all the evaluation criteria required for the surety prequalification process, and provide a comprehensive assessment tool to assist surety experts in their decision-making. Many of the evaluation criteria for the underwriting process contain uncertainty and depend upon expert knowledge and subjective judgment. Therefore, incorporating expert judgment into the model is highly important. The detailed objectives of this research are as follows:

- To combine fuzzy logic with an expert system to create a model that has the ability to include expert knowledge and subjective judgment, or intuition, in the decision-making process. The model can handle uncertainty and subjectivity, and incorporate both quantitative and qualitative criteria that are considered in the prequalification process. The integration of expert knowledge with prequalification cases (i.e., data) to build a FES is a relatively new research area.
- To apply and present a new approach for fuzzy rule base development that combines two methods: (1) learning from examples, using contractor default prediction cases; and (2) using the inputs' relative importance weights to develop fuzzy rules. Also, to present an approach for fuzzy membership function (MBF) estimation that integrates a traditional estimation technique with set of contractor prequalification cases.
- To present a methodology to integrate a FES with two adaptation/optimization approaches (genetic algorithms and neural network back-propagation) to applying the data-based adaptive learning concept. The optimization process focuses on adaptation of fuzzy MBF and rules' degree of support (DoS) to determine the most suitable technique to adapt the FES.
- To identify and classify the major evaluation criteria that should be considered for general contractor prequalification for a specific

construction project from the surety industry's perspective, and to develop a comprehensive contractor default prediction model (CPDM) that enhances the previously-developed models for contractor prequalification, evaluation, and default prediction, and provides a structured contractor default prediction method to enhance the surety practitioner's decision-making process in providing bonding to a contractor for a specific project. Furthermore, this research incorporates a very important evaluation category (contractor's organizational practices) that has not been addressed in previous models.

- To incorporate knowledge from several surety experts across Canada with different levels of experience and various roles in the surety industry into the model development. Therefore, a group consensus system/approach to aggregate the experts' knowledge and obtain collective values for their inputs for the model development is needed.
- To present a contractor default prediction model that accurately reflects participating surety experts' assessments by applying a methodology for FES adaptation. The optimized model is used to develop a software tool to enhance the practical benefits of the contractor default prediction model, and to allow interaction between the user and the model by providing a means of storing the user input criteria and designating the system's output.

1.4 Expected Contributions

This thesis presents several contributions, some of which are relevant to researchers and classified as academic contributions, and others that are industrial contributions to the construction industry, as follows:

1.4.1 Academic Contributions

- Presenting a methodology to integrate fuzzy logic with an expert system to create a fuzzy expert decision support system (DSS) for contractor prequalification for surety bonding.
- Presenting a novel approach for fuzzy membership function (MBF) estimation that incorporates the Horizontal MBF estimation technique, which depends on experts' knowledge (knowledge-based) and contractor prequalification cases (data integration).
- Developing a proposed group consensus approach to incorporate experts' inputs as a collective single opinion for building a fuzzy experts system. The proposed approach uses the multi-attribute utility function (MAUF) approach.
- Exploring and implementing a novel approach for fuzzy rule base development that combines two methods: (1) learning from examples, and (2) using the inputs' relative importance weights.
- Presenting a methodology to integrate a FES with two adaptation/optimization approaches (genetic algorithms and neural network back-propagation) separately to adapt the developed FES.

- Presenting and applying several experts' knowledge acquisition techniques for building FESs.

1.4.2 Industrial Contributions

- Compiling a comprehensive, detailed list of the evaluation criteria for contractor and project prequalification.
- Offering numerical scales for the quantitative evaluation criteria, and developing rating scales using reference variables to quantify the qualitative criteria.
- Incorporating the evaluation of all the project aspects, the project team, contractual risks, and project management evaluation criteria into the proposed comprehensive model to predict the possibility of a contractor's default on a specific construction project. The proposed CDPM provides several application contributions, as follows:

A. Providing a structured, organized, and objective approach for surety underwriters to use in the evaluation of subjective criteria and criteria that are difficult to quantify in contractor qualification for a specific project, which helps formalize this complex decision process while making its logic easy to trace.

B. Decreasing the subjectivity of the evaluation process by identifying the important factors that should be considered for a comprehensive assessment of the contractor and the project.

C. Providing the required documentation that summarizes the prequalification process, whether for upper management levels or for the contractor, in any case where a certain bonding request for a construction project has been rejected.

D. Providing a method for assisting the construction contractors to discover areas that need improvement in order to obtain bonding for a construction project.

E. Advancing the state-of-the-art of the surety underwriting process by including evaluation criteria related to the project and contractual risks, in addition to the contractor-related criteria.

- Developing the proposed SuretyQualification software for contractor default prediction; it can be used for contractor evaluation/prequalification by surety underwriters, surety brokers, and owners in the construction industry.
- Advancing the state-of-the-art of contractor evaluation/prequalification for a specific construction project by automating the surety underwriting process using the proposed SuretyQualification.

1.5 Research Methodology

The research study presented in this thesis is conducted in four main stages, as follows:

1.5.1 The First Stage

The decision support system (DSS) development process starts with identifying and classifying the most relevant evaluation criteria that surety underwriters and brokers consider when evaluating a specific construction project for bonding purposes. Several data collection techniques (questionnaires, one-on-one interviews, and interactive group meetings with highly experienced surety experts) are used to compile a comprehensive and detailed list of the evaluation criteria. Both fuzzy logic and expert systems are combined to develop the proposed DSS. For estimating the inputs' MBFs, a new approach for fuzzy MBF estimation is applied, by integrating the Horizontal MBF estimation technique with contractor prequalification cases.

1.5.2 The Second Stage

The developed DSS is used to build a more comprehensive contractor default prediction model (CDPM). One important evaluation component, contractor's organizational practices, is incorporated. A group consensus system (GCS) is developed first to determine the consensus weight factor (CWF) for surety experts working in the construction industry, to incorporate their input as a collective opinion. The multi-attribute utility function (MAUF) methodology is used to develop the proposed group consensus system based on six attributes (experience measures). The Analytical Hierarchy Process (AHP) is used to determine the experts degrees of "liking" (i.e., preference) of the experience attributes. Fuzzy logic and expert systems techniques are integrated to develop the CDPM. The proposed CDPM is built using the expertise of surety practitioners across Canada, and several different knowledge acquisition techniques are used (web-based surveys, and one-on-one and interactive group meetings). A new approach for developing fuzzy rules is applied to generate and complete the rule base.

1.5.3 The Third Stage

Two different optimization techniques, genetic algorithms and artificial neural network back-propagation, are applied separately to adapt the FES knowledge base (membership function and rules' degrees of support). The two trained FESs are being validated using unseen contractor default prediction cases to select the most accurate FES for building the SuretyQualification software.

The validation process of the optimized model was conducting against the participating surety experts' assessments (i.e., the experts' judgment was the baseline for measuring the model accuracy). A number of hypothetical contractor prequalification cases, in which experts' judgments were used to provide the cases' output, have been developed for the model validation process. Hypothetical rather than actual cases were required for validation for the following reasons:

- Surety professionals do not currently document all evaluation (input) criteria used for the developed model; therefore, actual cases of such data do not exist.
- Due to the large number of the model inputs, collecting actual cases would require a large amount of time and commitment from the experts; collection of the hypothetical cases was a very difficult and time consuming process, which took about 12 months.

- To collect actual case data would require the surety experts to change the prequalification assessment process they currently use, which would take some time and decision-making at higher levels within each organization.

1.5.4 The Fourth Stage

A user interface for the CDPM is developed. The proposed CDPM model is implemented using FuzzyTECH® Professional Version 5.78, which has the ability to create an executable, stand-alone system that is connected to the user interface.

1.6 Thesis Organization

Chapter 1 provides background, a brief literature review, and a statement of the problem. This chapter also explains the expected contribution and the methodology of this research.

Chapter 2 presents a detailed methodology to combine both fuzzy logic and expert systems to create a decision support system (DSS) for contactor prequalification. A new approach for fuzzy membership function (MBF) estimation is also presented in this chapter.

Chapter 3 describes the use of the multi-attribute utility function (MAUF) approach integrated with the Analytical Hierarchy Process (AHP) to establish the surety experts' group consensus system.

Chapter 4 presents the steps of developing the contractor default prediction model as a FES. This chapter also presents a new approach for fuzzy rule base development.

Chapter 5 demonstrates the methodology and application of two optimization approaches (genetic algorithms and neural network back-propagation) for adaptation in the FES, to increase the accuracy of the developed CDPM.

Chapter 6 presents the development of a software tool called SuretyQualification through an easy-to-use, Excel-based interface connected with the developed CDPM.

Chapter 7 describes the conclusions, the contribution, and the limitations of this research, as well as recommendations for future research.

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CHAPTER 2. - Contractor Prequalification Decision Support System for Surety Bonding[2]

2.1 Introduction

Construction is a risk-filled, uncertain, and dynamic environment, where contractor failure is always possible. For that reason, owners search for ways to mitigate the risk of contractor failure. One such technique is surety bonding, where the risk of project completion is transferred to the surety company (Russell 1990; Marsh and Fayek 2009). Therefore, it is a critical decision for a surety company to bond a contractor for a construction project (Surety Information Office 2011). The risk must be estimated and reduced as much as possible via a complex evaluation (prequalification) process for the contractor. Many quantitative and qualitative evaluation criteria must be taken into consideration in the contractor prequalification process (Surety Information Office 2011).

This chapter presents a decision support system (DSS) for surety brokers and underwriters that helps them to prequalify a contractor to perform a specific project in the construction industry. The DSS was developed in close collaboration with major surety broker and surety underwriting companies in Canada. With this tool, surety professionals can better decide whether or not to bond a contractor for a specific construction project, and contractors can identify

[2] Parts of this chapter have been published in Journal of Automation in Construction, Volume 21, January 2012, pp. 89–98; and the Proceedings, ASCE Construction Research Congress, Banff, AB, May 8-10, Vol. 2: 899–908.

areas that need improvement in order to obtain bonding for construction projects. In this chapter, the major evaluation criteria were identified and classified, including project specifics and contractual risks, necessary to advance the state of the art in surety underwriting.

The developed DSS combines both fuzzy logic and expert systems to create a more structured, organized, and objective approach to use in contractor/project risk evaluation for surety underwriting purposes. This fuzzy expert DSS decreases subjectivity in the evaluation criteria by creating predefined rating scales for the quantitative criteria, and defining reference variables used to quantify values on the rating scales of the qualitative criteria. This chapter describes the methodology used to create the fuzzy expert DSS, and focuses, in particular, on a new approach for fuzzy membership function (MBF) estimation, which combines both knowledge-based (using the Horizontal Method) and data-integration approaches. A validation of the system with hypothetical cases of contractor/project bonding evaluation is presented.

2.2 Background and Previous Research

2.2.1 Surety Bonding in Construction

In the construction industry, a surety company assumes the risks associated with contractor prequalification by agreeing to bond a contractor for a construction project (Russell 1990). Figure 2-1 shows a summary of the steps for obtaining the bonding facility. Most surety companies work through surety brokers or a surety professional agent. Therefore, to obtain a bond, a contractor must first contact a construction surety broker and provide the required business information. The broker organizes an information file on the contractor and submits it to the appropriate surety company according to the contractor's profile and needs (Russell 1990). The surety underwriter then conducts a new contractor prequalification process that may require more in-depth information about the contractor's business. The underwriter's objective in this process is to quantify the ability of the contractor to complete the construction project (Awad, Fayek 2010).

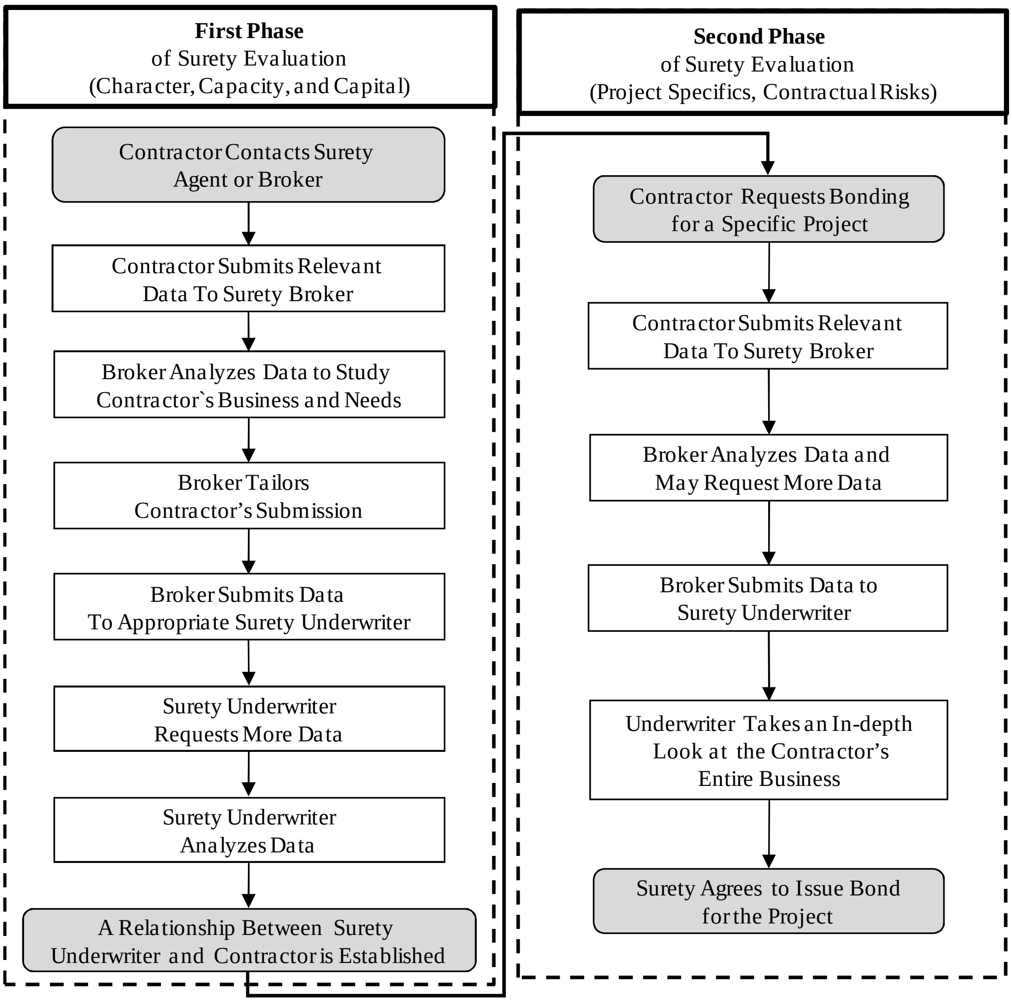


Figure 2-1 Summary of Bonding Process (Awad and Fayek 2012)

The contractor prequalification process occurs in two phases. The first phase (contractor prequalification) begins when the contractor seeks a relationship with the surety company. The evaluation criteria considered by the surety company during this phase can be placed in three categories: character, capacity, and capital. The second phase begins when the contractor requests bonding for a specific construction project, and the surety underwriter conducts a second, more comprehensive prequalification (surety underwriting) process. The second surety underwriting process includes evaluation of the project specifics and the contractual risks.

2.2.2 Contractor Prequalification and Surety Underwriting Studies

2.2.2.1 Contractor Prequalification

Many studies exist on the topic of contractor prequalification. Diekmann (1981) created a multi-criteria decision model that uses the utility theory to incorporate subjective judgments of the contractor's performance. He presented a range of criteria for use in contractor selection of cost-plus contracts. Nguyen (1985) presented a method for contractor prequalification that uses fuzzy set theory to incorporate subjective criteria inherent in the evaluation process. The developed method depended on three categories of evaluation criteria: cost, experience, and performance. Each category has sub-criteria that have weights that reflect the order of importance. The evaluation criteria, and the assigned weights that reflect their importance, were predetermined based on the opinion of surety professionals. Russell and Skibniewski (1990a) developed "Qualifier-1," which is a computer-based model for contractor evaluation based on a linear combination of decision factors to determine the weighting rate for contractors. The candidates (i.e., contractors) are ranked based on the aggregated rating value using the evaluation criteria, which are quantified based on a 10-point rating scale. Using a 1–10 rating scale increases the subjectivity in the evaluation process and the need for highly experienced users to conduct the prequalification process.“Qualifier-1” was then improved by developing “Qualifier-2,” a knowledge-based expert system to deal with some of Qualifier-1’s limitations (Russell and Skibniewski 1990b). Qualifier-2 was developed in a hierarchal structure of five levels: references/reputation/past performance, financial stability, status of current workload, technical expertise, and project-specific criteria, which is evaluated individually. The outcome of each evaluation process could be: disqualify contractor, qualify contractor and proceed to next level, or no decision—more data required. Russell and Jaselskis (1992a) identified the causes of contractor failure in construction. Then, Russell and Jaselskis (1992b) developed a model to calculate the probability of contractor failure prior to contract award using discrete choice modeling as a regression technique. Two questionnaire surveys were developed to investigate different characteristics for failed and non-failed projects. The characteristics consisted of three groups: (1) project characteristics, (2) owner characteristics, and (3) contractor characteristics. After conducting a numerical analysis for the collected data, the developed model included two variables within the control of project owner: (1) the owner’s effort in the evaluation of the contractor before the contract award, and (2) the owner’s cost monitoring involvement during the construction phase. The outcome of the model is to predict whether the project failed or non-failed. Ng and Skitmore (1995) proposed a multi-criteria contractor prequalification model that integrates seven expert systems to evaluate the contractor's performance, management capability, reputation, resources, progress, competitiveness, and activeness (Russell and Skibniewski 1988). The support system was found to be a practical tool after it was tested by industry experts; however, it was not tested or validated with real case data and/or statistical analyses. Elton et al. (1994) presented a method to rate contractors (i.e., prequalification) depending on nine evaluation criteria, using fuzzy set theory to deal with prequalification factors that are difficult to quantify numerically. Holt (1996) developed a model using cluster analysis for contractor prequalification. Two cluster analysis approaches were found to be suitable for this application: hierarchical clustering and k-means clustering. The cluster analysis classifies the candidate contractors into a number of clusters to determine the best contractors to perform a certain project. One problem with using clustering techniques is not considering the relative importance of the evaluation criteria in the decision-making process. Hatush and Skitmore (1998) used the multi-criteria utility theory in developing a model to determine the overall utility of a contractor. A rating scale of 1–20 is used to quantify several evaluation criteria. There are several limitations for the developed model, such as: (1) using a scale of 1–20 for criteria quantification makes the evaluation process very subjective, (2) it does not account for the uncertainty in subjective judgment, and (3) it is unable to capture linguistic uncertainty and uncertainty inherent in the collected input data. Khosrowshahi (1999) used ANNs to develop a model to predict the suitability of contractors to tender for public clients' projects (i.e., qualified or disqualified). Khosrowshahi first developed a list of 21 prequalification attributes. That list was then reduced to the 11 most important attributes, using the responses of 42 local authorities in England, based on a five-scale rating system (for determining attributes' relative importance weight). Although the model presented a high degree of viability, the quantification method of the attributes is subjective, based on the scoring system. Palaneeswaran and Kumaraswamy (2000) presented a methodology for contractor prequalification for design/build projects using a scoring system. This methodology depends first on classifying the project into either "simple" or "complex." If the project is simple, a single-stage prequalification process is done; however, if the project is complex, a two-stage prequalification process will be done. The evaluation criteria have not been introduced and the model has not been validated. Lam et al. (2001) developed a fuzzy neural network model for contractor prequalification that consisted of five layers that functionally work as a fuzzy model interface: an input layer, a fuzzification layer, a base rule layer, a normalizing layer, and a defuzzification layer. The model inputs (i.e., contractor evaluation criteria) are: experience, response to the brief, approach to cost-effectiveness, methodology, and staffing. The model was validated using 83 case studies, and it was found to outperform the general feedforward neural network it was tested against. Sonmez et al. (2002) used an evidential reasoning approach to develop a model for the multi-criteria contractor prequalification process. The model was developed in a hierarchical structure that contains five main categories: contractor's organization, financial considerations, management resources, past experience, and past performance. Each one of these categories has a number of sub-criteria for contractor prequalification. The model was not validated. Wong (2004) developed a model to predict the contractor performance using a logistic regression approach. A total of 31 tender evaluation criteria were considered for the developed model, based on the collected information of about 48 projects. The 31 evaluation criteria were grouped under 8 evaluation categories: staff quality and experience, plant and equipment resources, contractor site management/execution capability, health and safety, past performance records in similar projects, contractor reputation/image, contractor proposal, and other evaluation criteria. The model was validated using 20 cases and showed accuracy of 75%. The developed methodology considered the relative importance of the evaluation criteria, but did not present the quantification method for the criteria or how the qualitative criteria can be integrated. Topcu (2004) presented a study for a model for construction contractor selection in the Turkish public sector, and provided a critical review for the practices for contractor selection. The proposed model depended on the analytical hierarchy process (AHP), and included two evaluation stages: (1) contractor prequalification and (2) selecting the eligible bidder among the prequalified contractors. The model has not been validated. Brauers et al. (2008) applied the MOORA (multi-objective optimization by ratio analysis) approach for contractor selection. The presented methodology was applied to rank 15 maintenance contractors. However, validation results were not presented. The model considered 9 evaluation criteria, which did not include any evaluation criteria related to the contractors' financial status and/or organizational practices. Plebankiewicz (2009) developed a fuzzy model for contractor prequalification from the owner's perspective. The model considered different contractor evaluation criteria and objectives that the owner wants to achieve in the project. Five groups of evaluation criteria were included: financial standing, technical ability, management capability, health and safety, and reputation. The model was not validated. Lam et al. (2009, 2010) investigated the suitability of using the support vector machine (SVM) method in contractor prequalification for construction project procurement, and presented an SVM-based decision support framework for contractor prequalification. The efficacy of the SVM model was validated in a case study, and the results were compared with the results of using ANNs and principal component analysis (PCA) for the same case study. The results showed that the SVM model was more effective than ANNs and PCA. Lam and Yu (2010) used the principle of multiple kernel learning (MKL) for decision support in contractor prequalification. Their study measured the accuracy and efficiency of the SVM method versus that of the MKL using a case study. The results showed that MKL performed slightly better than SVM. All the evaluation criteria were quantified using a rating scale of 1–5. Trivedi et al. (2011) presented an approach for contractor prequalification for a housing project. The approach presented there integrates the analytical hierarchy process (AHP) to deal with the multiple prequalification criteria, and the fuzzy set theory to include the fuzziness and vagueness characteristics of the prequalification criteria. Six evaluation criteria were considered to apply the proposed approach. However, the evaluation criteria quantification method was not presented, and the model's results were not tested and/or validated. Plebankiewicz (2011) proposed a schema of contractor prequalification that considers the owner's main objectives: time, cost, and quality of the work. The schema presents the evaluation process in two stages: "on the standing list" and "per project." In the same paper, a fuzzy model was presented for the evaluation of the "per project" contractors. The model Plebankiewicz (2011) developed allows for the evaluators to present the evaluation values in linguistic terms, and includes evaluations of several evaluators as well. No specific evaluation criteria for contractor prequalification were presented for the developed model. Furthermore, the model was not validated.

2.2.2.2 Contractor Prequalification Criteria

Several studies, such as Russell and Skibniewski (1988), Holt et al. (1994a), and Russell (1988), have been conducted to present evaluation criteria that can be used for contractor prequalification. Some additional studies, such as Russell (1992), Holt et al. (1994b), and Ng and Skitmore (1999), were conducted to rank the prequalification criteria according to the importance of each criterion. Ng and Skitmore (2001) used a cost-benefit analysis to identify the appropriate evaluation criteria for contractor prequalification. Furthermore, the North American Development Bank (2009) presented a note prepared for owners to provide information about the criteria that should be considered in contractor prequalification, and included a definition for each criterion. Egemen and

Mohamed (2005) presented a study showing different clients' and consultants' approaches and perceptions of the contractor during the prequalification process. The study concluded that consultants' needs and expectations regarding contractor prequalification are significantly different from clients'. Banaitienė and Banaitis (2006) provided a study that presents the most important contactor evaluation criteria to improve the prequalification/selection process from the perspective of the Lithuanian construction industry. Singh and Tiong (2005) developed a study for identifying the most important contractor selection criteria (CSC) from the perspective of Singaporean construction industry practitioners. It was observed that the importance of CSC differs not only between contractors and owners, but also between private and public owners. Plebankiewicz (2010) presented analysis of the main criteria and methods used for contractor prequalification from a Polish owner's perspective. The study did not provide any methodology for contractor prequalification. However, it presented important information for future contractor prequalification models. Idrus et al. (2011) identified and ranked 17 criteria used by owners for contractor selection in Malaysia. The study showed that "track performance" was the most important criterion, which includes an indication that the contractor has the ability to perform the project, and includes an evaluation of a contractor's past experience. No specific model and/or methodology for contractor prequalification was presented.

2.2.2.3 Surety Underwriting

Few studies have been done on the topic of surety underwriting. Kangari et al. (1992) presented a quantitative model to prequalify the performance of construction companies from a financial perspective. The model was not validated. Kangari and Bakheet (2001) developed a list of the major factors that impact surety underwriting, in addition to five evaluation forms to support the process. However, their study did not provide a method to predict the outcome of the contractor's performance based on the data gathered from the forms. Severson et al. (1994) investigated discrete choice modeling to predict the likelihood of a claim occurrence on a construction surety bond. Their research considered only financial evaluation criteria, and was validated using 40 projects. The discrete choice model was found to have an accuracy of 87.5%. The study concluded that other criteria such as experience, past performance, and size and type of project must also be included in the contractor prequalification process. Al-Sobiei et al. (2005) developed a decision-making mechanism to assist owners in predicting the likelihood of contractor default and in selecting the most suitable risk management method. Their research also compared two artificial intelligence techniques (artificial neural networks [ANNs] and genetic algorithms [GAs]) that can be used for contractor evaluation models. Eight cases were used for validation, yielding a prediction accuracy of 75% based on NN training and 88% based on GA training. Data used to test and validate the models were collected from surety companies. Bayraktar and Hastak (2010) developed a conceptual, scoring-based contractor evaluation system that considers contractor-specific criteria in the three categories of character, capacity, and capital. Further research by Marsh and Fayek (2008, 2009, 2006, 2010a, 2010b) focused on the first phase of the underwriting process (Sub-section 2.2.2.1); they developed SuretyAssist, a decision support model that incorporates contractor-specific evaluation criteria (character, capacity, and capital). SuretyAssist was validated in thirty-one historical cases, and a sensitivity analysis was conducted to select the best system configuration. The model yielded an accuracy of 81.0%.

Having identified contractor evaluation from different perspectives, the previous research in the area of construction contractor prequalification and surety underwriting provides a point of departure for the developed DSS presented in this chapter. A model or a methodology for the second phase in the underwriting process has not been addressed in previous research; no study has integrated contractor-specific, project-specific, and contract-specific risk evaluation criteria in the underwriting process. There remains a need for a more structured and organized contractor/project prequalification decision-support system, not to replicate the surety practitioner's decisions, but to enhance them. This chapter focuses on the more advanced contractor evaluation process during surety underwriting (the second evaluation phase) when seeking bonding for a construction project.

The DSS presented in this chapter fills an important gap in existing models by presenting a suitable way to integrate the evaluation criteria required for the second phase of the surety underwriting process and provides a comprehensive assessment tool to assist surety experts in their decision-making. Moreover, the integration of expert knowledge with prequalification cases (data) to build a surety DSS (as presented in this chapter) is a relatively new research area. Many of the crucial evaluation criteria for the underwriting process depend upon expert knowledge, many of which contain uncertainty and require subjective judgment. Therefore, incorporating expert judgment into the DSS is highly important. Many criteria are qualitative and some are quantitative. Combining all of these criteria into a single assessment tool becomes a complex process, especially since the relationships between the criteria are non-linear and difficult to determine. Fuzzy logic, an artificial intelligence technique, can handle uncertainty and subjectivity, and incorporate both quantitative and qualitative criteria into decision-making models. Combining fuzzy logic with an expert system to create a DSS that has the ability to include expert knowledge and subjective judgment, or intuition, into the decision-making process advances the state of the art in the surety underwriting process (Marsh and Fayek 2010b).

2.3 Development of the Prequalification Decision Support System

2.3.1 Surety Underwriting/Prequalification Criteria

The process of preparing the contractor prequalification criteria, which are the DSS's inputs, was performed in two main steps, as illustrated in Figure 2-2. The first step was to develop an initial list that included all the evaluation (prequalification) criteria to be considered in surety underwriting. The second step was to refine the initial list to include only the most important evaluation criteria.

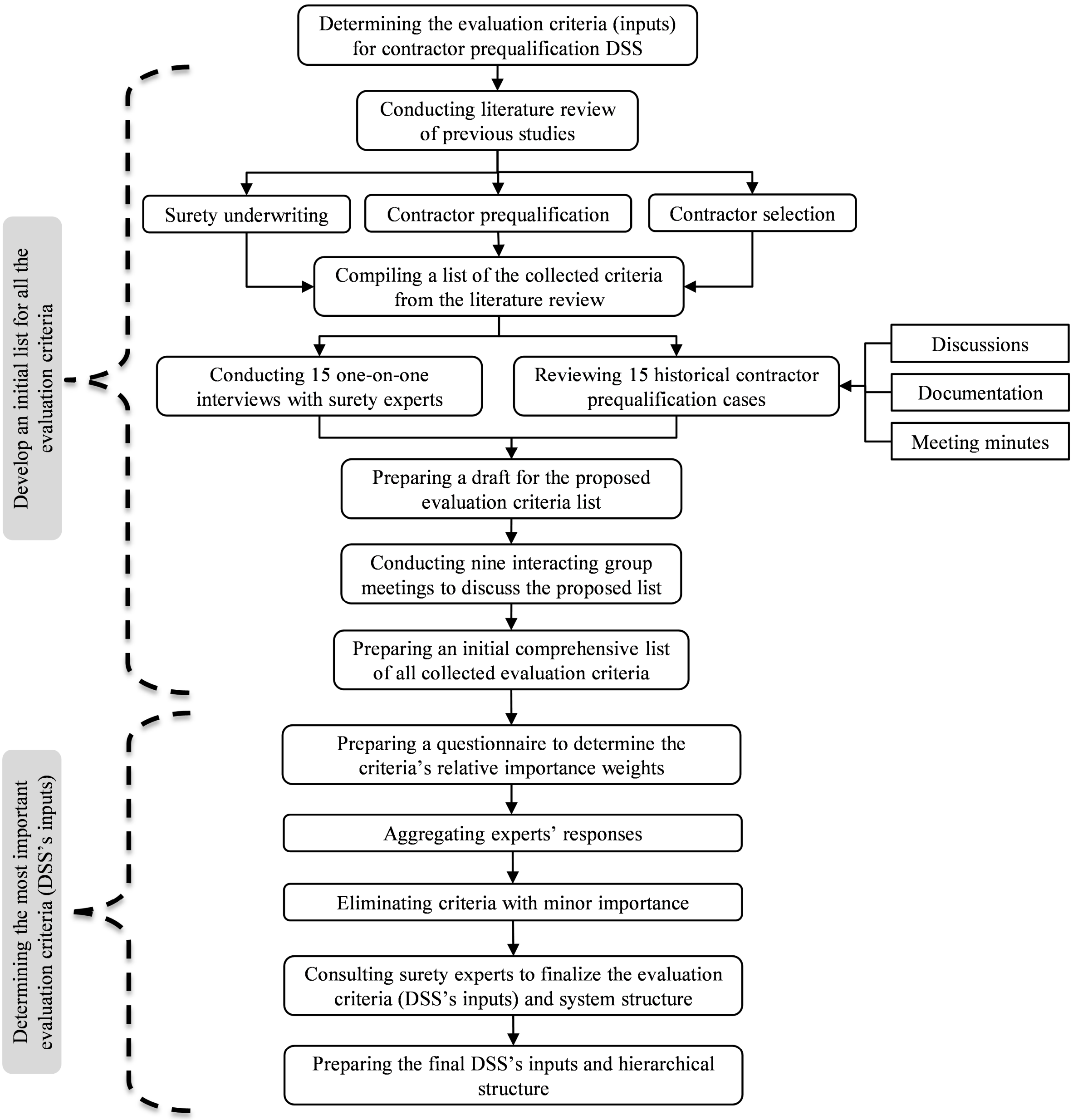


Figure 2-2 The Process for Determining the Contractor Prequalification Criteria (DSS's Inputs)

2.3.1.1 Initial List of Evaluation Criteria

As presented in Figure 2-2, the first step to determine contractor evaluation criteria involved conducting a thorough literature review on previous studies that related to contractor evaluation in the construction industry. A comprehensive list was developed to include all the evaluation criteria that should be considered for bonding a contractor for a specific project. All the criteria presented in the previous studies that related to contactor and project evaluation on surety underwriting (Marsh 2008; Marsh and Fayek 2009; Nguyen 1985), contractor prequalification (Russell and Skibniewski 1988; Singh and Tiong 2006; Holt et al. 1994a; Russell 1988 and 1992), and contractor selection models (Plebankiewicz 2009; Lam et al. 2010; Kangari and Bakheet 2001; Brauers et al. 2008; Zavadskas et al. 2008; Abudayyeh et al. 2007; Li et al. 2007; Singh and Tiong 2005; Wong 2004; Mahdi et al. 2002; Lam et al. 2001; Holt et al. 1994b) were included in the list. Then, several interviews and meetings with experts in the surety industry were held, and historical contractor prequalification cases were reviewed. Fifteen historical contractor prequalification cases from the participating surety underwriting and broker companies were used to generate additional evaluation criteria. For the historical cases, all the documentation, information, and minutes of meetings between surety professionals and contractor representatives were reviewed and discussed with the surety experts, to determine the importance of the collected information in the prequalification process and how it might impact their bonding decision.

A group of five surety experts (with no less than ten years' experience each) were selected to participate in the research: two experts came from underwriting companies, and three experts came from surety broker companies. One of the participating broker companies is one of the top Canadian surety broker companies, and handles the accounts for thirteen of Canada's top fifteen construction companies. The company has over 500 offices in more than 120 countries. The two underwriters had 23 and 10 years of experience in the surety industry, and the three brokers had 26, 15, and 10 years of experience in the surety industry, specifically in construction. The last stage in developing the initial list of criteria was to hold fifteen one-on-one interviews (three meetings each) with the five surety experts. Each expert was asked to incorporate his or her thought process when evaluating general contractors and projects for surety bonding. After these one-on-one interviews and meetings, nine group meetings, in which the experts could interact with each other, were held to discuss the proposed list of evaluation criteria, and add any helpful notes (Hallowell and Gambatese 2010). The result of this step was a comprehensive list that documented factors, found in the literature and determined during interviews (104 in total), that pertained to contractor and project evaluation.

The criteria were divided into three main categories: contractual risks, project specifics, and contractor's organizational practices. Each category had several criteria and sub-criteria along with questions and other notes to assist the surety underwriter/broker. Tables 2-1, 2-2 and 2-3 show the contractor prequalification criteria (under each category) that were included in the initial list (at this stage). Surety underwriters must be satisfied towards all the project aspects. Therefore, project aspects included two categories: (1) the project team, and (2) project specifics/scope. The project team category included the evaluation of the owner's experience in construction, funding, and type (public or private). The project team category also incorporated the evaluation of the subcontractors and contractor. The periodic evaluation of the contractor was included, particularly the financial situation or updated financial statements of the contractor. Recent evaluation of the contractor capacity and financial arrangements for the current work load were also considered.

Table 2-1 Initial Project Aspects Evaluation Criteria

Project Aspects	
Project Team	Contractor Current Cash Flow
Owner	Contractor Funding
Owner Type	Dividends
Owner Funding	Contractor Capacity Background
Owner Experience	Organizational capacity
Architect/Engineer	Key Employee Experience
Architect/Engineer Experience	Resources Availability
Architect/Engineer Reputation	Equipment Availability
Architect/Engineer Liability Insurance	Materials Availability
Subcontractors	Labour Availability
Subcontractors Bonding or Security	Subcontractors Availability
Assigned or Nominated Subcontractors	Contractor Experience
Owner Conditions about Subcontractors	Contractor Capacity
Scope Gaps between Subcontractors	Character/Past Performance
Contractor	Current Work on Hand
Year End evaluation	**Project Specifics/Scope**
Working Capital Trend	Scope of Work for the Proposed Project
Tangible Net Worth Trend	Project Type Experience
Profitability Trends	Project Size Experience
Gross Profit Margin Trend	Project Location Experience
Net Profit Margin Trend	Project Cost Breakdown
Debt to Equity Ratio Trend	Mobilization/Demobilization

Project Aspects	
Project Profitability	Project Schedule Flexibility
Gross Profit Margin	Expected Project Duration
Net Profit Margin	Project Risk
Debt to Equity Ratio	Project Identified Risk
	Risk Assessment Analyses
Current evaluation	Risk Mitigated Plan
Financial Aspects	

Table 2-2 Initial Contractual Risk Evaluation Criteria

Contractual Risk	
Contract	Toxic and Hazardous Substance and Materials Clauses
Form of Contract	Disputes/Arbitration Clauses
Type of Contract - Bid/Proposal	Assignment of Contract
Consultants	Termination of Contract by Contractor Clauses
Insurance	Termination of Contract by Owner Clauses
Subcontractors	Design Concerns Clauses
Contract Clauses	Taxes/Duties Clauses
Payment Clauses	Bonding/Security
Warranty Clauses	Insurance by Contractor
Indemnity Clauses	Insurance by Contractor Builders Risk
Changes to Work Clauses	General Liability Clauses
Schedule Extensions and Price Adjustment Clauses	Automobile Clauses
Concealed or Unknown Conditions Clauses	Partial Occupancy Clauses
Damages/Penalties/Bonuses Clauses	Completion Definition Clauses

Table 2-3 Initial Contractor's Organizational Practices Evaluation Criteria

Contractor's Organizational Practices	
Constructability	Expense Form
Constructability Overview	Expense Register
Applying the Constructability Principles	**Communications Management**
Constructability Coordinator	Communications Process
Constructability Documentation	Communications Roles
Constructability Tracking Method	Communications Register
Change Management	Project Status Report
Change process	**Procurement Management**
Change roles	Procurement Process
Change register	Procurement Roles
Change request form	Procurement Register
Past Change Management Performance	Purchase Order Form
Documentation	**Quality Management**
Justification Procedure	Quality Process
Authorization	Quality Management Roles
Communication Time	Deliverables Register

Contractor's Organizational Practices	
Project Contract	Quality Review Form
Identification	**Past Quality Management Performance**
Evaluation	Implementation
Timely Manner	Project Reimbursement
Impacts Mitigation	Budgeting
Overall Assess	Formality
Zero Accident Techniques	Communication to Key Person
Proposed Safety Performance	QA/QC Manager
Past Safety Performance	Corrective Actions
Cost Management	Sources of Problems
Cost Management Process	Overall Assess
Cost Management Roles	
Cost Management Documents	

The second main category is contractual risks, which is also evaluated by the broker and underwriter to ensure that the contractor is familiar with the project delivery method and that the clauses in the contract are acceptable from the contractor’s side. Contractual risks include an assessment of the contract form (standard verses owner wording) and the contract type. Contractual risk factors also include the assessment of different contractual aspects, such as payment, warranty, toxic and hazardous substances and materials, and many more that assess the contactor’s obligations and responsibilities according to the contract. The contractor’s organizational practices evaluate several project management areas, including constructability, cost management, zero accident techniques, change management, procurement management, communication management, and quality management. The contractor’s organizational practices include assessment of the contractor preparation for different management practices for the proposed project. The contractor`s organizational practices factor was not evaluated in the first phase of surety underwriting because it is related to what will be done for a specific project.

2.3.1.2 Relative Importance of Contractor Prequalification Criteria

Due to the large number of evaluation criteria (104 criteria) included in the compiled list, a filtering process was done for the list by finding the most important evaluation criteria in the decision-making process. As presented in Figure 2-2, a questionnaire was developed to determine the relative importance of the evaluation criteria (i.e., inputs), meaning their influence at a lower level in the model on the criteria (i.e., outputs) at a higher level. The following are samples of the questions included in the questionnaire:

- What is the influence of the "Owner Type," "Owner Funding," and "Owner/Owner Agent Experience" on the "Owner" evaluation?
- What is the influence of the "Owner" evaluation, "Subcontractors" evaluation, and "Contractor" evaluation on the "Project Team" evaluation"?

Figure 2-3 shows a part of the questionnaire that was developed to determine the relative importance weight of the evaluation criteria. A sample of the questionnaire is presented in Appendix A. The questionnaire was distributed among the five participating surety experts, but only four experts responded. Experts were asked to evaluate the importance of each criterion on a scale of 1–7, with 1 being the least important and 7 being the most important. The seven-point scale was selected on the basis of its efficiency, and its ability to capture variations in experts' opinion, without presenting too many or too few choices (leading to vacillation or lost data) (Osgood et al. 1957). The questionnaire results were used to identify the most important criteria, and to eliminate those with a minor impact on the bonding broker's or underwriter's judgment. The score from each participant for each criterion was given equal weight to calculate an average rating. Equal weight was given to all the participants' scores, because they all have substantial experience (ten years or more) in the process of contractor prequalification.

Project Aspects							
1.0 Project Team – Which criterion is more/less important?							
1.1 Owner	1	2	3	4	5	6	7
Owner Type	1	2	3	4	5	6	7
Funding	1	2	3	4	5	6	7
Experience	1	2	3	4	5	6	7
1.2 Architect / Engineer	1	2	3	4	5	6	7
1.2.1 Experience	1	2	3	4	5	6	7
1.2.2 Reputation	1	2	3	4	5	6	7
1.2.3 Liability Insurance	1	2	3	4	5	6	7
1.3 Subcontractors	1	2	3	4	5	6	7
1.3.1 Bonding or Security	1	2	3	4	5	6	7
1.3.2 Assigned or Nominated	1	2	3	4	5	6	7
1.3.3 Owner Conditions	1	2	3	4	5	6	7
1.3.4 Scope Gaps	1	2	3	4	5	6	7
1.4 Contractor	1	2	3	4	5	6	7
Year end evaluation							
1.4.1 WC/TNW Trends	1	2	3	4	5	6	7
1.4.1.1 Working Capital Trend	1	2	3	4	5	6	7
1.4.1.2 Tangible Net Worth Trend	1	2	3	4	5	6	7
1.4.2 Profitability Trends	1	2	3	4	5	6	7
1.4.2.1 Gross Profit Margin Trend	1	2	3	4	5	6	7
1.4.2.2 Net Profit Margin Trend	1	2	3	4	5	6	7
1.4.2.3 Debt to Equity Ratio Trend	1	2	3	4	5	6	7

Figure 2-3 Part of the Questionnaire for the Relative Importance Weight of the Evaluation Criteria

The average ratings were then used to reduce the number of criteria, and to generate the fuzzy rules that logically relate each input variable (i.e., the evaluation criteria) to the output variable (i.e., contractor/project overall prequalification). Generation of the fuzzy rules is explained later in this chapter. Due to the large number of evaluation criteria and to the practical limitations of fuzzy expert systems, a hierarchical organizational structure was created for the input criteria, and their number was reduced. The criteria that had an average importance value of less than 4.0 (a cutoff value recommended by the surety experts) on the questionnaire were eliminated. Also, some calculations were done to provide an indication for the consensus in expert's responses. A total of 86 criteria, 1% had one difference in rating, 76% of the criteria had differences of only two ratings, and 22% of the criteria had differences of three ratings, which indicates non-existence of dispersion in experts' responses. Only 1% had differences of four ratings, and there were no criteria that had differences of 5 or 6 ratings. A sample of the questionnaire results is presented in Table 2-4.

The number of criteria was reduced, leaving 32 of the original 104 criteria to have a high influence on the surety underwriting decision. According to the surety experts who participated in the study, the evaluation criteria that address both project and contractual risks are the most important evaluation criteria to be used in the evaluation of general contractors when they request bonding for specific projects. Therefore, the evaluation criteria were grouped under two main categories: project aspects and contractual risk. As recommended by surety professionals, evaluation criteria under 'contractor's organizational practices' were dropped from further consideration (at this stage of research). Also, experts had some recommendations about the hierarchical structure of the evaluation criteria; they suggested including some criteria under a different category. Figure 2-4 illustrates the hierarchical structure that was developed through consultations with the surety industry professionals.

Table 2-4 Sample of the Criteria's Relative Importance Questionnaire Results and Calculations

	1	2	3	4	5	6	7	No Answer	Responses	Average Rating	Minimum Rate	Maximum Rate	Spread
Project Aspects													
Project Team						2	2	0	4	6.5	6	7	1
Owner						2	2	0	4	6.5	6	7	1
Owner Type						3	1	0	4	6.25	6	7	1
Owner Funding						3	1	0	4	6.25	6	7	1
Owner Experience				1	2	1		0	4	5	4	6	2
Architect / Engineer			1	3				0	4	3.75	3	5	2
Architect /Engineer Experience			1	3				0	4	3.75	3	4	1
Architect /Engineer Reputation			2	2				0	4	3.5	3	4	1
Architect /Engineer Liability Insurance			1	3				0	4	3.75	4	1	3
Subcontractors					3	1		0	4	5.25	5	6	1
Bonding or Security						3	1	0	4	6.25	6	7	1
Assigned or Nominated			1	3				0	4	3.75	3	4	1
Owner Conditions			1	3				0	4	3.75	3	4	1
Scope Gaps				2	2			0	4	4.5	5	6	1
Contractor						2	2	0	4	6.5	6	7	1
Year End evaluation													
WC/TNW Trends						2	2	0	4	6.5	6	7	1
Working Capital Trend						2	2	0	4	6.5	6	7	1
Tangible Net Worth Trend						2	2	0	4	6.5	6	7	1
Profitability Trends						4		0	4	4	6	6	0
Gross Profit Margin Trend						3	1	0	4	6.25	6	7	1
Net Profit Margin Trend						4		0	4	4	6	6	0
Debt to Equity Ratio Trend				2	2			0	4	4.5	4	5	1
Project Profitability				1	1	2		0	4	5.25	4	6	2
Gross Profit Margin						3	1	0	4	6.25	6	7	1
Net Profit Margin						4		0	4	4	6	6	0
Debt to Equity Ratio	2	1	1					0	4	1.75	1	3	2
Current evaluation													
Financial Aspects						1	3	0	4	6.75	6	7	1

	1	2	3	4	5	6	7	No Answer	Responses	Average Rating	Minimum Rate	Maximum Rate	Spread
Cash Flow							4	0	4	7.0	7	7	0
Operating Line				3	1			0	4	4.25	4	5	1
Dividends	3	1						0	4	1.25	1	2	1
Capacity Background	2	2						0	4	1.5	1	2	1
Organizational capacity	3	1						0	4	1.25	1	2	1
Key Employee Experience	2	2						0	4	1.5	1	2	1
Resources	1	2	1					0	4	2	1	3	2
Equipment	1	3						0	4	1.75	1	2	1

2.3.1.3 Quantification and Description of the Evaluation Criteria (DSS's Inputs)

The final list of the contractor and project evaluation criteria is presented in Table 2-5. The first main category, "Project Aspects," includes the "Project Team" ("Owner Evaluation, Subcontractor Evaluation, and Contractor Evaluation) and the "Project Specifics/Scope" (Project Type/Complexity, Project Size, Project Location, Cost Breakdown, Schedule, and Project Risk). Each subcategory is divided into one or two more levels of detail. For example, the "Contractor" evaluation is divided into two categories: Year-End evaluation and Current evaluation. Current evaluation, in turn, has three subdivisions: Cash Flow, Operating Line, and Work on Hand.

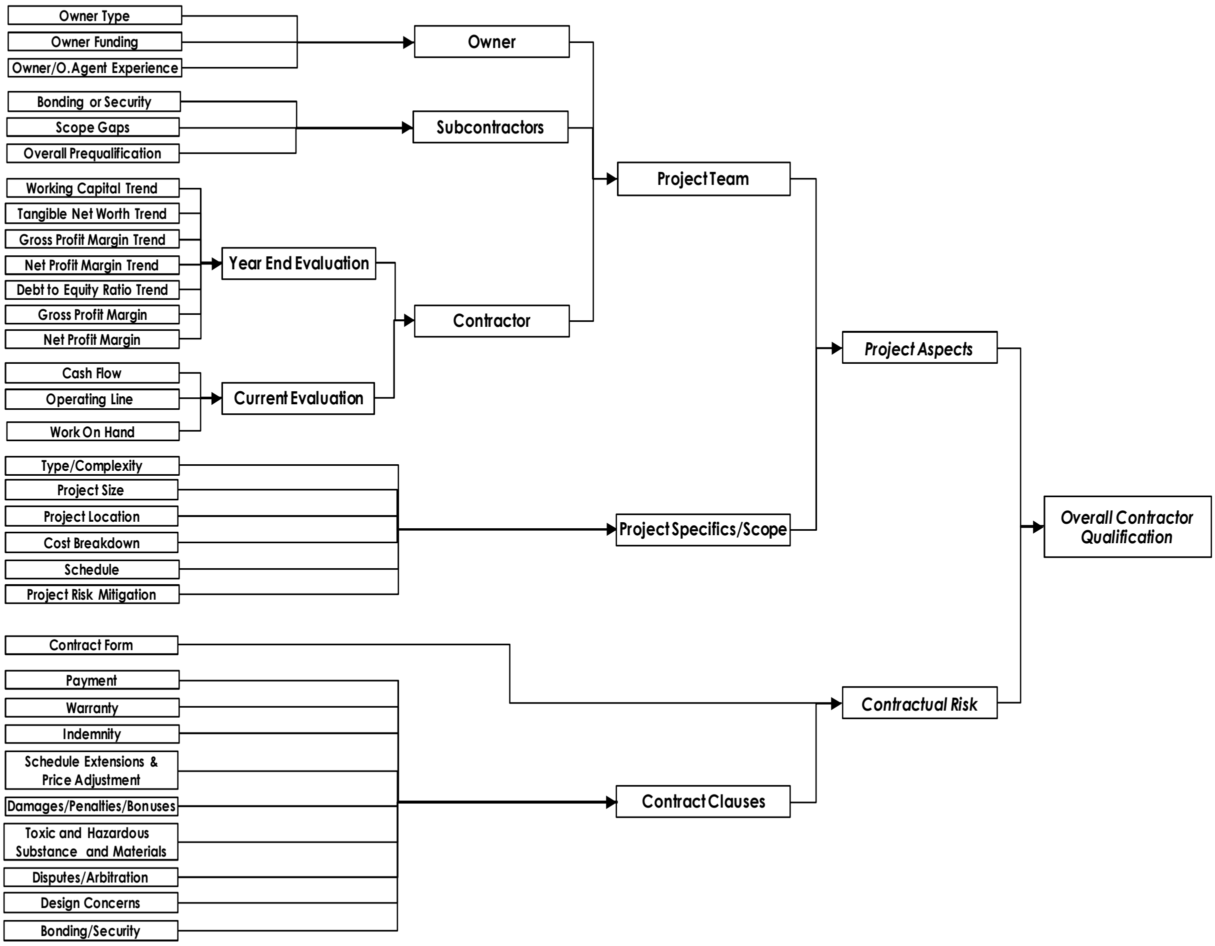


Figure 2-4 Contractor Evaluation Criteria Hierarchy

Table 2-5 Evaluation Criteria and Method of Assessment (Awad and Fayek 2012)

Criterion Name	Quantification	Sub-models	Red Flags	Favourable If
PROJECT ASPECTS EVALUATION				
Owner Evaluation				
Owner Type	(Public or Private)	Owner sub-model	If private	Public
Owner Funding	Rating Scale of 1-7		< 4	Higher
Owner/Owner Agent Experience	Real Numbers(years)		< 4	Higher
Subcontractors Evaluation				
Bonding/Security (Subcontractors)	Rating Scale of 1-7	Subcontractors sub-model	< 4	Higher

Criterion Name	Quantification	Sub-models	Red Flags	Favourable If
Scope Gaps	Rating Scale of 1-7		< 4	Higher
Overall (Subcontractors) Prequalification	Rating Scale of 1-7		< 4	Higher
Contractor Evaluation				
Year End Evaluation				
Working Capital Trend	Real Numbers (percent)	Year End Evaluation sub-model	< 10%	Higher
Tangible Net Worth Trend	Real Numbers (percent)		< 10%	Higher
Gross Profit Margin Trend	Real Numbers (percent)		< 0%	Higher
Net Profit Margin Trend	Real Numbers (percent)		< 0%	Higher
Debt to Equity Ratio	Real Numbers (ratio)		> 2:1	Lower
Gross Profit Margin	Real Numbers (percent)		< 5%	Higher
Net Profit Margin	Real Numbers (percent)		< 2%	Higher
Current Evaluation				
Cash Flow	Rating Scale of 1-7	Current Evaluation sub-model	< 4	Higher
Operating Line	Rating Scale of 1-7		< 4	Higher
Work on Hand	Rating Scale of 1-7		< 4	Higher
Project Specifics/Scope Evaluation				
Type/Complexity	Rating Scale of 1-7	Project Specifics/Scope sub-model	< 4	Higher
Project Size	Rating Scale of 1-7		< 4	Higher
Project Location	Rating Scale of 1-7		< 4	Higher
Project Cost Breakdown	Rating Scale of 1-7		< 4	Higher
Project Schedule	Rating Scale of 1-7		< 4	Higher
Project Risk	Rating Scale of 1-7		< 4	Higher
CONTRACTUAL RISK EVALUATION				
Contract Form	Standard, Owner Wording, or Combined		If Owner Wording	Standard
Contract Clauses Evaluation				
Payment Clauses	Rating Scale of 1-7	Contract Clauses sub-model	< 4	Higher
Warranty Clauses	Rating Scale of 1-7		< 4	Higher
Indemnity Clauses	Rating Scale of 1-7		< 4	Higher
Schedule Extensions and Price Adjustment Clauses	Rating Scale of 1-7		< 4	Higher
Damages/Penalties/Bonuses Clauses	Rating Scale of 1-7		< 4	Higher
Toxic and Hazardous Substance and Materials Clauses	Rating Scale of 1-7		< 4	Higher
Disputes/Arbitration Clauses	Rating Scale of 1-7		< 4	Higher
Design Concerns Clauses	Rating Scale of 1-7		< 4	Higher
Bonding/Security Clauses	Rating Scale of 1-7		< 4	Higher

The second main category, “Contractual Risk,” includes specific criteria to analyze the contract documents, such as the form of contract (Standard, Combined [which is “Standard” with some modifications], or Owner-Worded), and the specific contract clauses (payment, warranty, indemnity, schedule extensions and price adjustment, damages/penalties/bonuses, toxic and hazardous substances and materials, disputes/arbitration, design concerns, and bonding/security). The hierarchical structure of the fuzzy expert DSS presented in Table 2-5 was used for three purposes: (1) to reduce the required number of rules, because rules in fuzzy expert systems grow exponentially according to the number of input criteria for a single rule block; (2) to divide the fuzzy expert DSS into six smaller systems (sub-models) to apply the proposed approach for membership function (MBF) estimation, explained later in this chapter; and (3) to provide intermediate assessments of criteria categories to help identify specific areas for improvement. In the six smaller systems, groups of lower level criteria provide inputs into separate rule blocks whose output is higher-level, intermediate variables. These intermediate variables then form the input for the next layer of intermediate criteria, until a single output (i.e., overall prequalification) is obtained. Table 2-5 also presents the scales used to quantify the evaluation criteria; the threshold values (red flags), below which there is a cause for concern for the variable; and the favourable trends, as suggested by surety experts. The red flags were created to enable the broker or underwriter to conduct further research regarding the variable that creates a red flag. The DSS considers thirty-two evaluation criteria: eight are quantitative, twenty-two are qualitative, and two are categorical, such as owner type (i.e., public or private). Table 2-5 presents the system's quantitative criteria, which appear as a percentage (e.g., working capital trend), a ratio (e.g., debt to equity ratio), or a number of years (e.g., owner/owner agent experience).

A rating scale of 1–7 was created for all the qualitative criteria. To reduce subjective interpretation during the rating of the qualitative criteria, four group meetings were held, with the participating surety experts interacting with each other to determine how the values for the qualitative criteria could be objectively evaluated. The outcome of these meetings was a set of reference variables, used to objectively quantify the qualitative criteria and to define each scale value (1 to 7) for each of the qualitative criteria. For example, a set of six reference variables were used to define the predetermined rating scale for the "Project Risk" criterion: (1) prepared project risk profile, (2) quality of project risk assessment (3) effect on the project cost and time, (4) contingency assignment, (5) prepared risk mitigation plan, and (6) existence of a risk management team.

Project Aspects

There are 22 evaluation criteria to evaluate project aspects; 9 of these categories are quantitative and 13 are qualitative. The first subcategory under project team category is project owner, which includes three evaluation factors to evaluate risk related to the project owner. The Owner type factor can be public or private, while the Owner funding factor indicates the level of satisfaction towards the owner's funding ability. A seven-point rating scale is used to rate the owner funding. Using rating scales to quantify criteria does not reduce the subjectivity unless the scales are predefined and relative bases for the decision are provided (Marsh 2008). By creating predetermined rating scales and providing sub-variables or reference points, the decision process would be modeled the most accurately. For instance, to evaluate the owner funding criterion, there are five reference points to decide the rate: (1) funding ability, (2) the existence of a financial responsibility clause on the bid document, (3) confirmation of project financing, (4) type of confirmation provided, and (5) the surety underwriter's/broker's overall satisfaction regarding the owner's ability to fund the project. Then, the predetermined rating scale for owner funding can be used as described in Table 2-6.

Owner/ Owner agent experience is an example of the quantitative criteria under the owner sub-subcategory. "Owner/Owner agent experience" refers to the number of years of experience that the owner or owner agent has in the construction industry.

Table 2-6 Predetermined Rating Scale for Owner Funding

Rating	Description
1	INADEQUATE funding ability, No financial responsibility clause on bid document, No confirmation of project financing, and LOW surety underwriter/broker satisfaction
2	ADEQUATE funding ability, No financial responsibility clause on bid document, No confirmation of project financing, and LOW surety underwriter/broker satisfaction
3	ADEQUATE funding ability, AVERAGE financial responsibility clause on bid document, No confirmation of project financing, and LOW surety underwriter/broker satisfaction
4	ADEQUATE funding ability, GOOD financial responsibility clause on bid document, POOR confirmation of project financing, and LOW surety underwriter/broker satisfaction

Rating	Description
5	ADEQUATE funding ability, GOOD financial responsibility clause on bid document, AVERAGE confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction
6	ADEQUATE funding ability, GOOD financial responsibility clause on bid document, GOOD confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction
7	VERY ADEQUATE funding ability, GOOD financial responsibility clause on bid document, GOOD confirmation of project financing, and HIGH surety underwriter/broker satisfaction

Under the subcontractor sub-subcategory there are three qualitative evaluation criteria: “Bonding or Security,” which is an average rating given to describe the bonding and security for subcontractors involved on the proposed project; “Scope Gaps,” which indicates if the general contractor ensured that there are no scope gaps on the assigned subcontracts; and “Overall Subcontractors’ Prequalification,” which indicates the assigned subcontractors’ evaluation. Table 2-7 presents the predetermined rating scale used to quantify the “Overall Subcontractors’ Prequalification” criterion. The following five reference points were used for defining each rating point: (1) experience, (2) capacity (availability of the required resources), (3) relationship with the contractor, (4) the policy around prequalifying subcontractors, and (5) bonding.

Table 2-7 Predetermined Rating Scale for Overall (Subcontractors) Prequalification

Rating	Description
1	POOR experience, POOR capacity, POOR relationship with the contractor, POOR prequalifying policy, and No bonding
2	AVERAGE experience, POOR capacity, POOR relationship with the contractor, POOR prequalifying policy, and No bonding

Rating	Description
3	AVERAGE experience, AVERAGE capacity, POOR relationship with the contractor, POOR prequalifying policy, and have bonding
4	AVERAGE experience, AVERAGE capacity, AVERAGE relationship with the contractor, AVERAGE prequalifying policy, and have bonding
5	GOOD experience, AVERAGE capacity, AVERAGE relationship with the contractor, GOOD prequalifying policy, and have bonding
6	GOOD experience, GOOD capacity, AVERAGE relationship with the contractor, AVERAGE prequalifying policy, and have bonding
7	GOOD experience, GOOD capacity, GOOD relationship with the contractor, GOOD prequalifying policy, and have bonding

As noted above, the contractor sub-subcategory was divided into two categories "year-end evaluation" and "current evaluation." The year-end evaluation category is used to evaluate the latest contractor's yearly financial performance, and includes seven quantitative criteria, as follows: (1) "Working Capital Trend," which is the percentage of increase or decrease of working capital (i.e., assets minus liabilities) over a given time period; (2) "Tangible Net Worth Trend," which is the percentage of increase or decrease of tangible net worth (i.e., reduction in net worth) over a given time period; (3) "Gross Profit Margin Trend," which is the percentage of increase or decrease of the gross profit margin ([revenue - cost of sales] / revenue) over a given time period (i.e. the previous year); (4) "Net Profit Margin Trend," which is the percentage of increase or decrease of the net profit margin (net profit after sales / net sales) over a given time period; (5) "Debt to Equity Ratio Trend," which is the percentage of increase or decrease of the debt to equity ratio (total debt / equity) over a given time period; (6) "Gross Profit Margin," which assesses profitability ([revenue - cost of sales] / revenue); and 7) “Net Profit Margin,” which assesses profitability (net profit after sales / net sales).

The contractor evaluation category includes another sub-category which is “current evaluation”. The “current evaluation” evaluates the current situation of the contractor regarding (1) cash flow, (2) operating line, and (3) work on hand. “Cash flow” is used as a measure of the contractor company's financial health, which equals cash receipts minus cash payments over a given period of time. The contractor should provide cash flow for the proposed project and all projects on hand. “Operating line” reflects the funding ability of the contractor, while “work on hand” is a factor that indicates the evaluator’s level of satisfaction with the current contractor`s workload.

The last category to evaluate the project aspects is “Project Specifics/Scope.” Six evaluation criteria are used to reflect the risk around the project scope. “Type/Complexity” is a factor that reflects the extent of differences and similarities (in type and complexity) between projects that the contractor carried out in the past and for the proposed project. “Project Size” is a factor that reflects the extent of differences and similarities (in size) between projects that the contractor carried out in the past and for the proposed project. “Project Location” is a factor that reflects the contractor’s familiarity with the proposed project’s location and environment. “Cost Breakdown” is a factor that reflects the surety broker’s/underwriter’s satisfaction toward the project cost breakdown (i.e., labour, material, equipment, and subcontract). “Schedule” is a factor that reflects the surety broker's/underwriter's satisfaction toward the project schedule. "Project Risk" is a factor that reflects satisfaction toward project risk aspects (risk identification, risk assessment analyses, and risk mitigation plan). To define the predetermined rating scale for "Project Risk" criterion, six reference points are used: (1) prepared project risk profile, (2) goodness of project risks assessment, (3) effect on the project cost and time, (4) contingencies assignment, (5) prepared risk mitigation plan, and (6) existence of risk management team. Table 2-8 presents the predetermined rating scale used to quantify the "Project Risk" criterion.

Table 2-8 Predetermined Rating Scale for Project Risk

Rating	Description
1	POOR risk profile, POOR risks assessment, HIGH effect on the project cost and time, POOR contingencies assignment, POOR risk mitigation plan, NO existence of risk management team and LOW surety underwriter/broker satisfaction
2	AVERAGE risk profile, AVERAGE risks assessment, HIGH effect on the project cost and time, POOR contingencies assignment, POOR risk mitigation plan, NO existence of risk management team and LOW surety underwriter/broker satisfaction
3	AVERAGE risk profile, AVERAGE risks assessment, AVERAGE effect on the project cost and time, AVERAGE contingencies assignment, POOR risk mitigation plan, NO existence of risk management team and LOW surety underwriter/broker satisfaction
4	AVERAGE risk profile, AVERAGE risks assessment, AVERAGE effect on the project cost and time, AVERAGE contingencies assignment, AVERAGE risk mitigation plan, existence of risk management team and AVERAGE surety underwriter/broker satisfaction
5	GOOD risk profile, GOOD risks assessment, LOW effect on the project cost and time, AVERAGE contingencies assignment, AVERAGE risk mitigation plan, existence of risk management team and AVERAGE surety underwriter/broker satisfaction
6	GOOD risk profile, GOOD risks assessment, LOW effect on the project cost and time, GOOD contingencies assignment, GOOD risk mitigation plan, existence of risk management team and AVERAGE surety underwriter/broker satisfaction
7	GOOD risk profile, GOOD risks assessment, LOW effect on the project cost and time, GOOD contingencies assignment, GOOD risk mitigation plan, existence of GOOD risk management team and GOOD surety underwriter/broker satisfaction

Contractual Risks

There are ten evaluation criteria to evaluate the contractual risks. Nine of these categories are qualitative, and the remaining one, referred to as “contract form,” is categorical, and can be either standard, owner-worded, or combined. The nine qualitative evaluation criteria are used to quantify the risk in the contract clauses. “Payment” is a factor used to reflect the evaluator’s satisfaction towards the conditions under which payment will be made for work completed during a portion of a construction period. “Warranty” is a factor that reflects satisfaction toward project warranty (i.e., a guarantee of the integrity of the project and of the contractor`s responsibility for the replacement or repair of deficiencies) terms and clauses. “Indemnity” is a factor that reflects satisfaction toward project indemnity (i.e., possible exemption or compensation claimed for damage, loss, or injury suffered by the other party) terms and clauses. “Schedule Extensions and Price Adjustment” is a factor to reflect satisfaction toward project schedule extensions and price adjustment conditions, in case of delays outside of the contractor’s responsibility. “Damages/Penalties/Bonuses” is a factor that reflects satisfaction toward terms and clauses related to project-liquidated damages, penalties, and bonuses “Toxic and Hazardous Substances and Materials” is a factor that reflects satisfaction toward the responsibility of using any toxic and hazardous substances and materials during project construction. “Disputes/Arbitration” is a factor that reflects satisfaction toward the conditions and procedures to be followed in case of disputes and/or arbitration during project construction. “Design Concerns” is a factor that reflects satisfaction toward any contractor design responsibilities included in the contractual clauses or terms. “Bonding/Security” is a factor that reflects satisfaction toward bonding and security included in the contractual clauses or terms. An example for developing the predetermined rating scale for the criteria under the contract clauses category is “Payment.” To define the predetermined rating scale for the “Payment” criterion, there are eight reference points used: (1) payment terms; (2) the architect’s/engineer's role to make changes in the work, payment approval, substantial completion, and completion; (3) owner approval in the payment process; (4) the entire payment process and timing; (5) payment for materials on site; (6) holdback amount; (7) holdback releasing; and (8) in the case of a project requiring several phases, receiving holdback upon completion of each phase. Table 2-9 presents the predetermined rating scale used to quantify the “Payment” criterion. Appendix B presents sample of the description, definition, and quantification of the evaluation criteria considered here within the questionnaire developed for membership function estimation.

Table 2-9 Predetermined Rating Scale for Payment

Rating	Description
1	POOR payment terms; POOR payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is NOT CLEARLY defined; UNREASONABLE holdback amount; NOT INCORPORATED payment for materials on site; if project makes up several phases, the contractor NOT ABLE TO receive holdback upon completion of each phase; and LOW surety underwriter/broker satisfaction
2	AVERAGE payment terms; AVERAGE payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is NOT CLEARLY defined; UNREASONABLE holdback amount; NOT INCORPORATED payment for materials on site; if project makes up several phases, the contractor NOT ABLE TO receive holdback upon completion of each phase; and AVERAGE surety underwriter/broker satisfaction

Rating	Description
3	AVERAGE payment terms; AVERAGE payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is SOMEWHAT CLEARLY defined; REASONABLE holdback amount; NOT INCORPORATED payment for materials on site; if project makes up several phases, the contractor NOT ABLE TO receive holdback upon completion of each phase; and AVERAGE surety underwriter/broker satisfaction
4	GOOD payment terms; GOOD payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is SOMEWHAT CLEARLY defined; SOMEWHAT REASONABLE holdback amount; NOT INCORPORATED payment for materials on site; if project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase; and AVERAGE surety underwriter/broker satisfaction
5	GOOD payment terms; GOOD payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is SOMEWHAT CLEARLY defined; REASONABLE holdback amount; INCORPORATED payment for materials on site; if project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase; and AVERAGE surety underwriter/broker satisfaction
6	VERY GOOD payment terms; GOOD payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is CLEARLY defined; REASONABLE holdback amount; INCORPORATED payment for materials on site; if project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase; and AVERAGE surety underwriter/broker satisfaction
7	VERY GOOD payment terms; VERY GOOD payment process and timing; architect/engineer's role to changes in the work, payment approval, substantial completion, and completion is VERY CLEARLY defined; VERY REASONABLE holdback amount; INCORPORATED payment for materials on site; if project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase; and HIGH surety underwriter/broker satisfaction

2.3.2 Membership Function Estimation

Membership functions (MBF) describe and represent the fuzzy expert DSS input and output evaluation criteria, and the linguistic terms used for each criterion. The membership value indicates the degree of belonging of an element on the relevant scale to the linguistic terms. Membership values are between 0 and 1, where a value of 0 indicates non-membership, and a value of 1 indicates full membership. Estimating MBF is a vital step in creating any fuzzy system, and the success of the system depends on it. However, MBF estimation is one of the most challenging aspects in designing fuzzy systems. It is difficult to evaluate the correctness of the MBF by using any particular method. In addition, the techniques used for estimation need to be flexible so that the MBF can be easily adjusted, or tuned, to optimize the system's performance. Moreover, the choice of the MBF estimation method depends on the nature of the problem and the type of data available (Medasani et al. 1998; Pedrycz and Gomide 1998; Civanlar and Trussell 1986; Klir and Yuan 1995). Medasani et al. (1998) pointed out that, for most applications, several methods must be incorporated to construct MBF, because many methods are difficult to use in practical applications, and because, generally, the applications are unique. Developing the context in which these methods will be applied is crucial (Klir and Yuan 1995), and must be considered before deciding on which method is appropriate.

In building predictive models, such as a fuzzy expert DSS, and especially for MBF estimation, there are two approaches that can be followed. The first approach is to use expert knowledge, if a group of subject matter experts is available. For example, in fuzzy membership function estimation, the membership values are assigned subjectively by experts, based on their knowledge and past experience. The second approach is to use a set of research-related data to build the model. The design of the model components is governed by using historical and documented data that represent the research problem domain. For example, in fuzzy MBF, the fuzzy membership values are calculated from collected data (i.e., cases).

Surety professionals do not currently document all evaluation (input) criteria used for the proposed DSS. Therefore, there are no data that can be used for MBF estimation. In order to consider the issue of evaluation of MBF quality or correctness, a number of hypothetical contractor prequalification cases were developed to be used in the estimation of MBFs. Estimation of the MBF for the proposed DSS occurred in two steps. The first step used expert knowledge (knowledge-based initial estimation step) to initially estimate the MBF, and the second step used the developed contractor prequalification cases (data integration step) to evaluate the quality of the estimated MBFs. Before the MBF estimation process began, the participating experts were consulted on the most appropriate linguistic terms to describe the input and output variables, and on the numerical values used to quantify the variables.

2.3.2.1 The Knowledge-Based Initial Estimation Step

The first step in the process of MBF estimation used the Horizontal Method, a traditional MBF estimation technique that depends on expert knowledge. During this step, a second questionnaire was created to estimate the initial membership functions for the input evaluation criteria. The questionnaire contained questions about the proposed values of the elements of each fuzzy set and the degree of membership of each value in the linguistic terms for the input evaluation criteria. Figure 2-5 shows a sample of the developed questionnaire for membership function estimation using the Horizontal Method. Another sample of the questionnaire is presented in Appendix B.

2. Owner / Owner Agent Experience

"Owner / Owner Agent Experience" is the years of experience that the owner or owner agent has in construction industry.

1. How many YEARS of experience would classify an Owner as having **POOR** Construction Experience? Please check all applicable boxes.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

2. How many YEARS of experience would classify an Owner as having **AVERAGE** Construction Experience? Please check all applicable boxes.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

3. How many YEARS of experience would classify an Owner as having **GOOD** Construction Experience? Please check all applicable boxes.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Comments:

Figure 2-5 Part of the Membership Function Estimation Questionnaire

After being asked to identify a collection of elements in the universe of discourse for each criterion, the experts were then asked to answer some yes or no questions in the form "Does x_i belong to the concept of fuzzy set A?" (Pedrycz and Gomide 2007). For each value (x_i) the number of positive (yes) answers was counted, and the ratio of the positive answers to the total number of replies was computed using Equation 2-1.

$$A(x_i) = \frac{P(x_i)}{N} \qquad [2\text{-}1]$$

where $P(x_i)$ is the number of positive replies of the total number N responses, and $A(x_i)$ is the membership value for the element x_i. This ratio was treated as a membership degree of the concept, at the given point of the universe of discourse. Figure 2-6 shows an example of the estimated MBF for the "Owner/Owner Agent Experience" evaluation criterion using the horizontal method. The x-axis represents the scale used to quantify the evaluation criterion (i.e., number of years), and the y-axis represents the corresponding membership value.

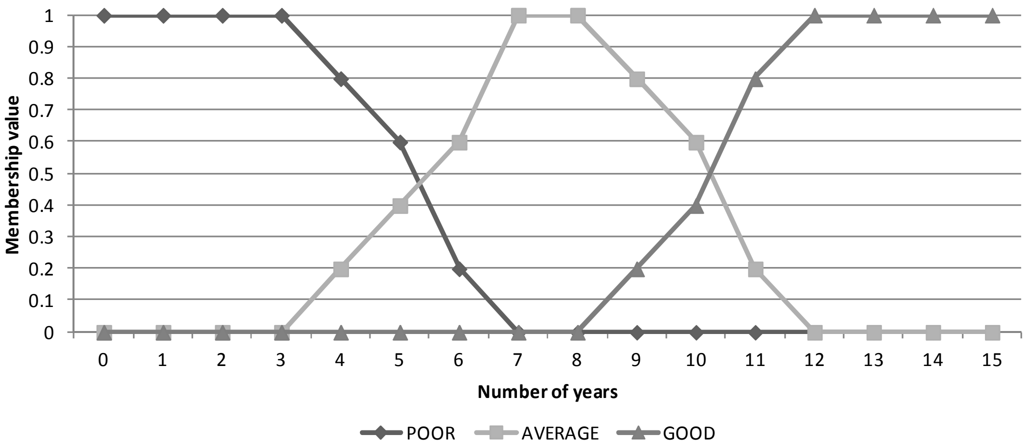


Figure 2-6 Example of Estimated Membership Function (Owner/Owner Agent Experience Evaluation) Using the Horizontal Method

2.3.2.2 Data Integration Step

The second step in the MBF estimation process used sixty-three hypothetical contractor prequalification cases to select the best solution from the previously calculated MBFs, as will be explained later in this chapter. The evaluation criteria representing the input to the DSS were divided into six groups representing the inputs of six sub-models, as presented in Table 2-5 and illustrated in Figure 2-7. Each sub-model was named according to its output (evaluation), and contains a number of input criteria. The evaluation criteria for the six sub-models represent all the evaluation criteria presented in Table 2-5, except for the contract form criterion, which has no level of evaluation criteria below it. The contract form criterion is also represented by crisp (discrete) values, so it does not need membership functions for its linguistic terms.

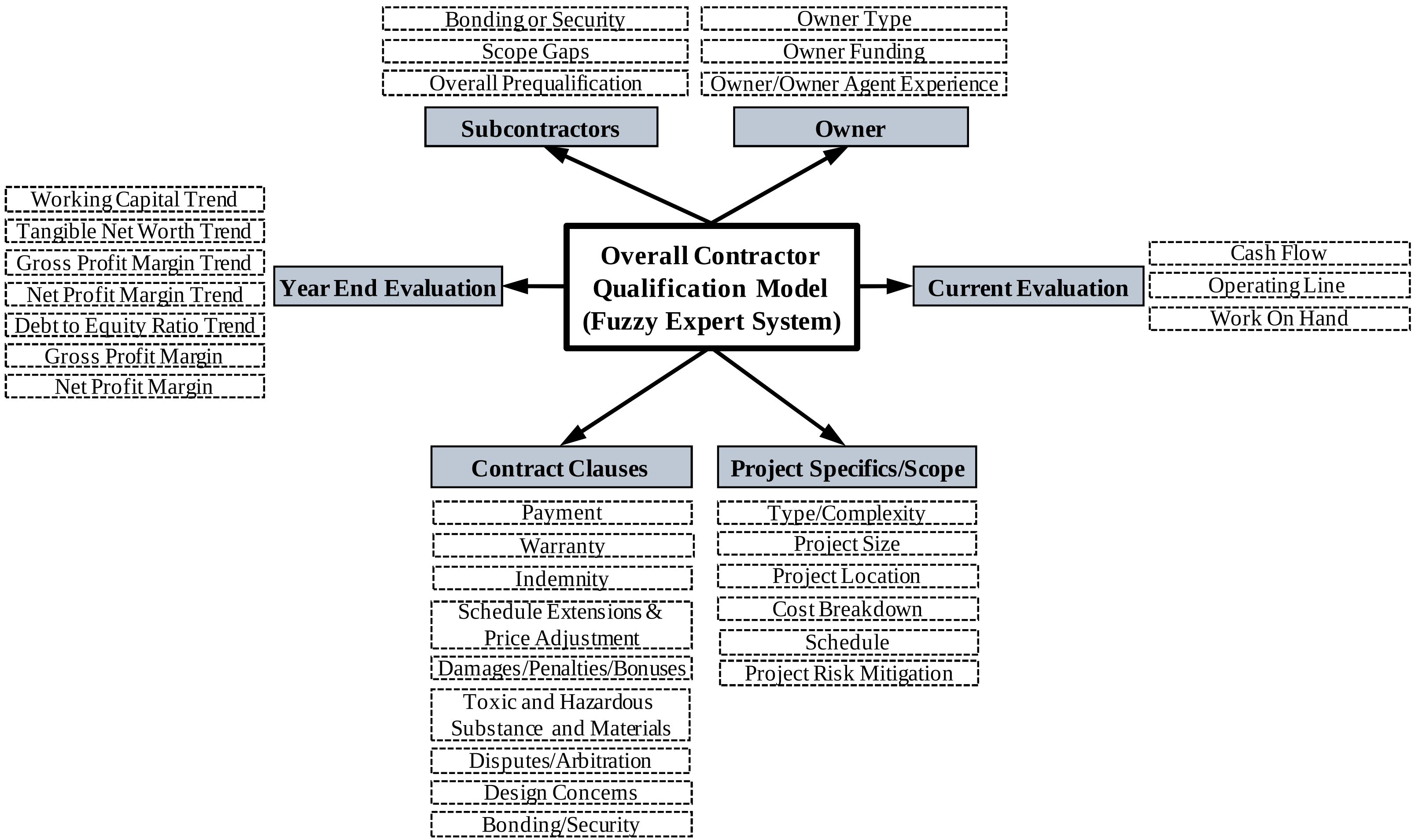


Figure 2-7 Six Sub-Models of Overall Contractor Prequalification DSS

2.3.2.2.1 Membership Function Interpolation

After the initial MBFs' estimation using the Horizontal Method, the estimated MBFs were then transformed (interpolated) to two of the most practical and commonly used shapes: triangular and trapezoidal (Singh and Tiong 2006). Figures 2-8(a) and (b) illustrate an example of the MBF interpolation process (linear approximation). According to the approximation process, several solutions were found to represent the calculated membership functions for each linguistic term. All approximated shapes (whether triangular or trapezoidal) for the actual data were considered as alternative solutions. The target of this step was to select the most appropriate shapes and parameters for input's MBFs for developing the DSS. The selection process depended on the production of an objective value to measure the performance status for each solution.

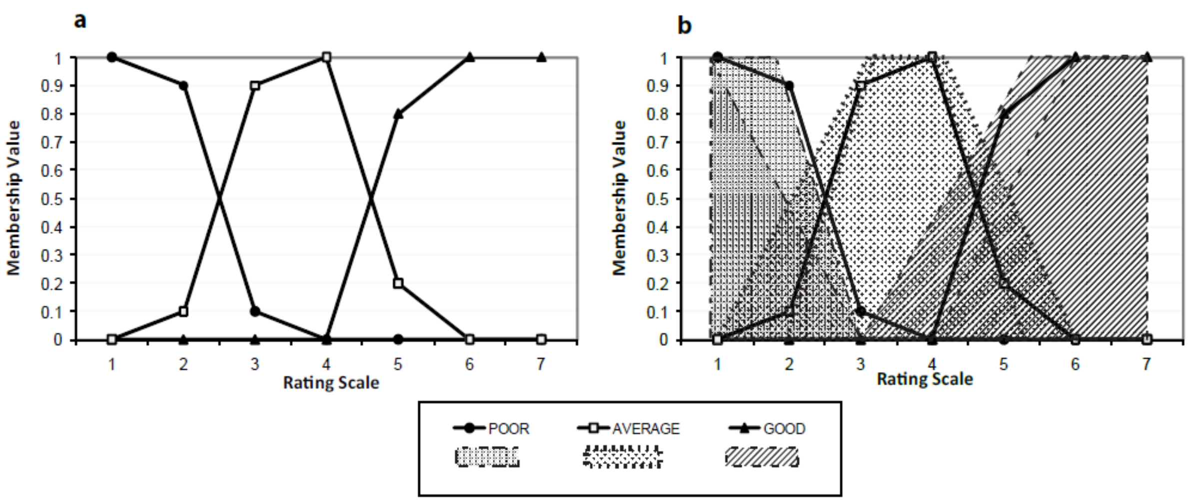


Figure 2-8 (a) Project Type/Complexity Initial Membership Function Estimated by Horizontal Method; (b) Interpolation of Project Type/Complexity Membership Function (Awad and Fayek 2012)

The triangular and trapezoidal MBF were described using four parameters, a, b, c, and d; in triangular functions $b = c$. All the possible linear approximations for the MBFs were investigated. Table 2-10 shows an example of ten different possible solutions for the “Owner” sub-model. For example, in the first solution, under the “Owner Funding” criterion, the “POOR” linguistic term is represented by a trapezoidal MBF with the parameters 1, 1, 2.5, and 5; the “AVERAGE” linguistic term is represented by a triangular MBF with the parameters 2, 5, 5, and 7; and the “GOOD” linguistic term is represented by a trapezoidal MBF with the parameters 5, 6.75, 7, and 7. In the “Owner” sub-model, the solutions represented only two sub-criteria: “Owner funding” and “Owner/Owner Agent Experience.” The third sub-criterion, “Owner Type,” was represented using discrete values.

2.3.2.2.2 Testing Alternative Solutions for Sub-models

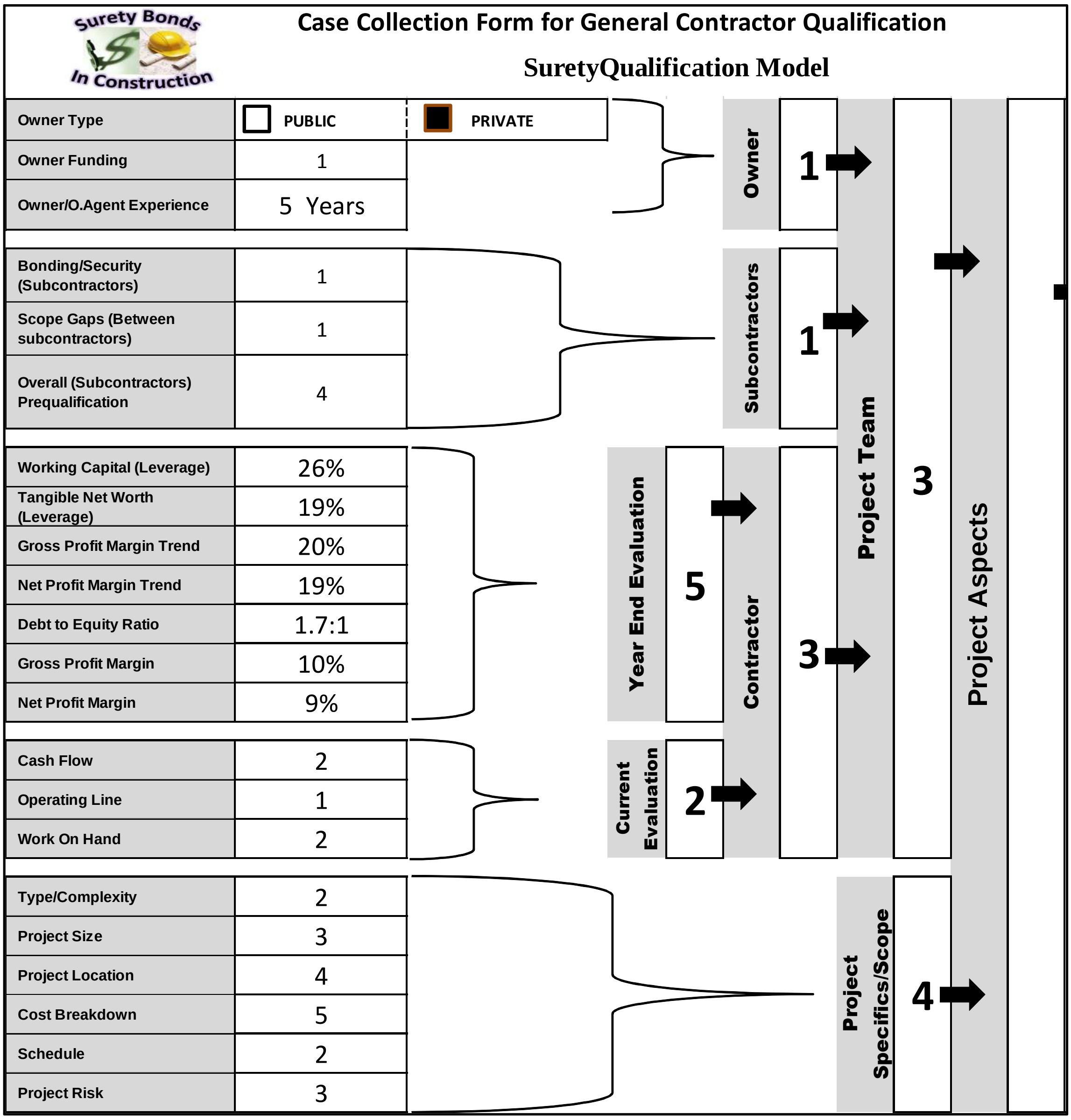
Linear approximations for the calculated MBFs were performed for each sub-model; some had ten solutions, such as “Subcontractors” and “Year-End Evaluation,” while other sub-models had only six solutions. Each sub-model was investigated as a separate model, in order to select the best MBF representation for the sub-model input criteria. All of the different solutions for each sub-model were implemented using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005).

Table 2-10 Membership Function Solutions for Owner Sub-Model (Awad and Fayek 2012)

Solution No.				1	2	3	4	5	6	7	8	9	10
Owner Evaluation	**Owner Funding**	POOR	**a**	1	1	1	1	1	1	1	1	1	1
			b	1	1	1	1	1	1	1	1	1	1
			c	2.5	2	2.5	2	2.5	2	2.5	2	2.5	2
			d	5	5	5	5	5	5	5	5	5	5
		AVERAGE	**a**	2	2	2.5	2.5	2	2	2.5	2.5	2	2.5
			b	5	5	5	5	5	5	5	5	5	5
			c	5	5	5	5	5	5	5	5	5	5
			d	7	7	6.7	6.7	6.7	6.7	7	7	6.7	7
		GOOD	**a**	5	4.5	5	4.5	5	4.5	5	4.5	4.5	5
			b	6.75	7	6.75	7	6.75	7	6.75	7	7	6.75
			c	7	7	7	7	7	7	7	7	7	7
			d	7	7	7	7	7	7	7	7	7	7
	Owner/Owner Agent Experience	POOR	**a**	0	0	0	0	0	0	0	0	0	0
			b	0	0	0	0	0	0	0	0	0	0
			c	3	3.5	2.5	3	4	3.5	3	4	3	2.5
			d	7	7	7	8	6.5	7	8	6.5	8	7
		AVERAGE	**a**	3	3	3	3	4.5	4.5	4.5	3	4.5	3
			b	7	8	7	7	7	7	7	7	7	7
			c	8	8.75	7	8.75	8	8.75	7	8	8	9
			d	12	12	12	12	12	12	12	13	13	11.5
		GOOD	**a**	8	8	8	9	8	8	8	8	8	9
			b	12	12.75	11.7	11.5	12	11.7	12.75	12	11.7	11.5
			c	15	15	15	15	15	15	15	15	15	15
			d	15	15	15	15	15	15	15	15	15	15

Surety underwriters and brokers do not currently document all evaluation criteria (inputs) that were established in this study. Therefore, ninety-five hypothetical cases were created, to cover the full range of possible contractor evaluation scenarios. Figure 2-9 shows part of the developed form to collect the hypothetical contractor prequalification cases. Two-thirds (63) of the cases were used for the DSS development stage, while one-third (32) was used for the validation and sensitivity analysis stage. Each of the participating experts was asked to develop input values for cases he or she believed would most likely happen in reality.

The cases were distributed among the experts, who were asked to provide the appropriate output values according to the input values. As a result of this process, each of the hypothetical cases contained the values of each input evaluation criterion, and the corresponding sub-model output value, in addition to the corresponding overall prequalification value. Table 2-11 presents a sample of the contractor prequalification cases (5 cases). Each case includes values for each evaluation criteria, and surety experts provided the assessment for all the intermediate outputs in addition to the overall contractor prequalification. For example, in the “Current Evaluation” sub-model, if the “Cash Flow,” “Operating Line,” and “Work On Hand” values are 2, 5, and 3, respectively, then the “Current Evaluation” output value is 4 (as determined by surety experts according to the input values).



Case Collection Form for General Contractor Qualification

SuretyQualification Model

Owner Type	PUBLIC ☐ / PRIVATE ■
Owner Funding	1
Owner/O.Agent Experience	5 Years
Bonding/Security (Subcontractors)	1
Scope Gaps (Between subcontractors)	1
Overall (Subcontractors) Prequalification	4
Working Capital (Leverage)	26%
Tangible Net Worth (Leverage)	19%
Gross Profit Margin Trend	20%
Net Profit Margin Trend	19%
Debt to Equity Ratio	1.7:1
Gross Profit Margin	10%
Net Profit Margin	9%
Cash Flow	2
Operating Line	1
Work On Hand	2
Type/Complexity	2
Project Size	3
Project Location	4
Cost Breakdown	5
Schedule	2
Project Risk	3

Figure 2-9 Part of the Developed Form to Collect the Hypothetical Contractor Prequalification Cases

Table 2-11 Sample of the Developed Contractor Prequalification Cases Including Experts' Evaluation

Case Number	**1**	**2**	**3**	**4**	**5**
Owner Type	Private	Public	Public	Public	Private
Owner Funding	1	6	6	2	4
Owner/Owner Agent Experience	5	9	11	0	10
Owner	**1**	**6**	**6**	**2**	**5**
Bonding/Security (Subcontractors)	1	5	6	2	3
Scope Gaps	1	3	6	1	5
Overall (Subcontractors) Prequalification	4	4	6	2	2
Subcontractors	**1**	**4**	**6**	**2**	**5**
Working Capital Trend	-15	26	8	5	10
Tangible Net Worth Trend	-15	19	26	5	-15
Gross Profit Margin Trend	-50	20	19	-25	25
Net Profit Margin Trend	-50	19	18	-25	-25
Debt to Equity Ratio	4:1	1.7:1	1.6:1	3.5:1	3:1
Gross Profit Margin	15	10	18	3	12
Net Profit Margin	6	9	10	2	4
Year End Evaluation	**1**	**5**	**6**	**2**	**4**
Cash Flow	1	5	5	2	2
Operating Line	1	5	5	1	5
Work On Hand	3	5	4	2	3
Current evaluation	**1**	**5**	**5**	**2**	**4**
Contractor	**1**	**5**	**6**	**2**	**4**
Project Team	**1**	**5**	**6**	**2**	**5**
Type/Complexity	1	5	6	2	2
Project Size	1	6	5	1	3
Project Location	1	5	5	2	4
Cost Breakdown	1	5	5	1	5
Schedule	1	5	5	2	2
Project Risk	4	6	6	1	3
Project specifics/scope	**1**	**5**	**6**	**2**	**4**
Project Aspects	**1**	**5**	**6**	**2**	**5**
Payment	1	5	3	2	3
Warranty	1	5	5	1	4
Indemnity	1	5	3	2	5
Schedule Extensions and Price Adjustment	1	5	5	1	2
Damages / Penalties / Bonuses	1	7	4	3	4
Toxic and Hazardous Substance and Materials	4	3	3	1	6
Disputes / Arbitration	1	5	5	2	3
Design Concerns	1	5	5	1	2
Bonding/Security	4	5	3	2	4
Contract Clauses	**1**	**5**	**6**	**2**	**5**
Contract Form	Combined	Standard	Combined	Standard	Owner Wording
Contractual Risk	**1**	**6**	**5**	**3**	**5**
Overall Contractor Qualification	**1**	**5**	**6**	**2**	**5**

All the alternative solutions for each sub-model were developed using the same configuration (rule base, rules' degrees of support, fuzzy operator, implication method, rule aggregation method, defuzzification method). The only difference between each solution for the same sub-model was in the MBFs that represent the input criteria. Each sub-model was implemented using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005). The structures of the sub-models in FuzzyTECH® are presented in Figures 2-10 to 2-15. A comparison between the accuracy of the different solutions therefore reflects the quality of the membership functions.

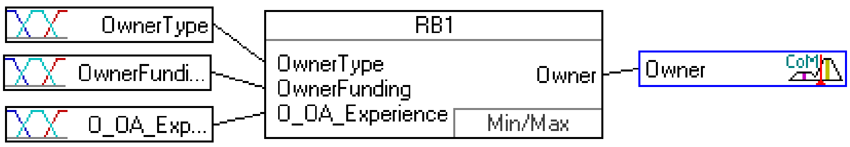


Figure 2-10 The Structure of Owner Evaluation System (Sub-Model)

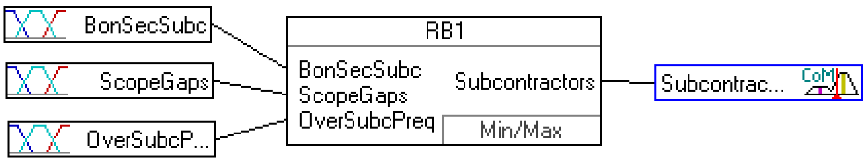


Figure 2-11 The Structure of Subcontractors Evaluation System (Sub-Model)

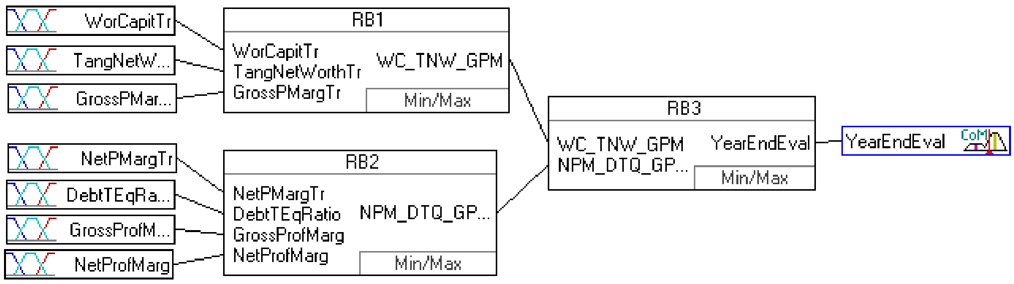


Figure 2-12 The Structure of Year-End Evaluation System (Sub-Model)

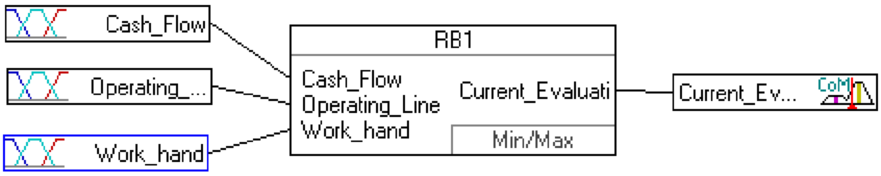


Figure 2-13 The Structure of Current Evaluation System (Sub-Model)

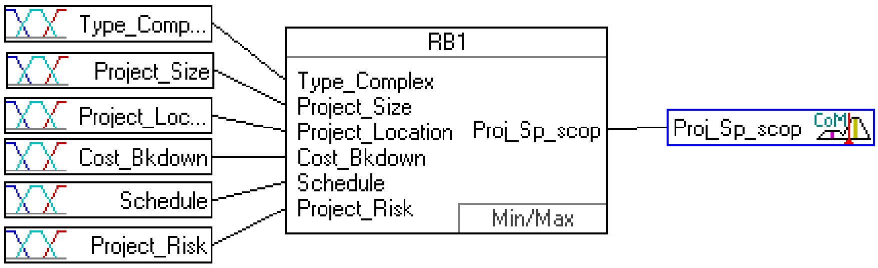


Figure 2-14 The Structure of Project Specifics/Scope Evaluation System (Sub-Model)

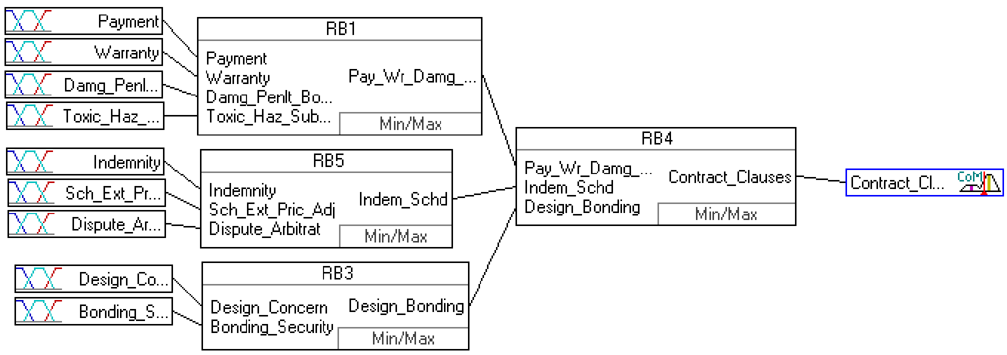


Figure 2-15 The Structure of Contractual Risk Evaluation System (Sub-Model)

The values of the input evaluation criteria were presented to each sub-model to predict the output value. For example, sixty-three hypothetical cases containing values for "Cash Flow," "Operating Line," and "Work On Hand" were presented to the "Current Evaluation" sub-model to predict the value of "Current Evaluation." A comparison was made between the predicted output values and actual output values (developed by participating experts). The average percent error of each solution for each sub-model configuration was calculated using Equation 2-2 (Marsh 2008).

$$\text{Average Percent Error} = \frac{\left(\sum_{i=1}^{n}\left|\frac{Predicted\ Output_i - \text{Actual Value}_\text{i}}{Actual\ Value_i}\right|\right)}{n} \times 100 \qquad 2\text{-}2$$

where "Predicted Output" is the output value provided by the model according to the inputs values for each case, "Actual Value" is the output value by the underwriter or broker for each case, *i* is the individual case number, and *n* is the total number of cases. A sample of the average percent error calculated for three alternative solutions for the "Owner Evaluation" sub-model is presented in Table 2-12, as an example.

Table 2-12 Samples for Testing the Alternative Solutions for the Owner Evaluation Sub-model

Case Number	Owner	Alt_1	Error Percentage	Alt_2	Error Percentage	Alt_3	Error Percentage
1	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
2	**5**	4.00	20.00%	4.50	10.00%	4.00	20.00%
3	**3**	3.97	32.45%	3.37	12.45%	3.97	32.45%
4	**7**	6.22	11.10%	6.22	11.19%	6.22	11.10%
5	**2**	1.75	12.50%	2.13	6.31%	1.75	12.50%
6	**5**	5.21	4.21%	5.22	4.47%	6.22	24.47%
7	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
8	**5**	4.00	20.00%	4.00	20.00%	4.00	20.00%
9	**5**	3.97	20.53%	3.97	20.53%	3.97	20.53%
10	**7**	6.22	11.10%	6.22	11.19%	6.22	11.10%
11	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
12	**6**	5.00	16.67%	5.00	16.67%	4.00	33.33%
13	**3**	3.96	32.01%	3.35	11.67%	3.97	32.45%
14	**7**	6.22	11.10%	6.22	11.10%	6.22	11.10%

Case Number	Owner	Alt_1	Error Percentage	Alt_2	Error Percentage	Alt_3	Error Percentage
15	**4**	4.00	0.00%	4.00	0.00%	4.00	0.00%
16	**5**	6.21	24.21%	5.22	4.47%	6.22	24.47%
17	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
18	**4**	4.00	0.00%	4.00	0.00%	4.00	0.00%
19	**3**	3.97	32.45%	3.89	29.67%	3.97	32.45%
20	**5**	5.22	4.47%	5.22	4.34%	6.22	24.47%
21	**3**	1.75	41.67%	2.13	29.13%	1.75	41.67%
22	**7**	4.00	42.86%	6.00	14.29%	4.00	42.86%
23	**5**	6.21	24.21%	6.22	24.47%	6.22	24.34%
24	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
25	**5**	4.00	20.00%	5.00	0.00%	4.00	20.00%
26	**3**	3.97	32.45%	3.97	32.45%	3.97	32.23%
27	**6**	6.22	3.72%	6.22	3.72%	6.22	3.72%
28	**2**	1.75	12.50%	1.75	12.50%	1.75	12.50%
29	**6**	6.20	3.40%	6.21	3.44%	6.20	3.40%
30	**6**	6.20	3.40%	6.21	3.44%	6.20	3.40%
31	**3**	2.88	4.17%	2.58	14.04%	2.39	20.24%
32	**3**	2.88	4.17%	2.58	14.04%	2.39	20.24%
33	**6**	2.65	55.84%	5.00	16.67%	2.20	63.34%
34	**3**	3.75	25.00%	2.75	8.33%	1.75	41.67%
35	**4**	1.75	56.25%	2.75	31.25%	2.75	31.25%
36	**5**	1.75	65.00%	3.50	30.00%	1.75	65.00%
37	**6**	3.10	48.33%	5.95	0.83%	4.98	16.94%
38	**6**	3.32	44.74%	5.27	12.10%	3.37	43.83%
39	**7**	6.20	11.37%	6.21	11.34%	6.20	11.37%
40	**4**	3.97	0.67%	3.97	0.67%	3.97	0.67%
41	**7**	5.22	25.43%	6.00	14.29%	5.00	28.57%
42	**4**	4.53	13.23%	4.48	12.04%	4.48	12.04%
43	**5**	6.21	24.21%	6.22	24.34%	6.22	24.47%
44	**3**	3.97	32.45%	3.97	32.45%	3.97	32.45%
45	**5**	3.01	39.73%	4.22	15.64%	3.04	39.14%
46	**6**	4.00	33.33%	4.00	33.33%	4.00	33.33%
47	**5**	4.84	3.26%	4.71	5.71%	4.42	11.64%
48	**5**	6.20	23.95%	6.20	24.08%	6.20	23.95%
49	**1**	1.75	75.00%	1.50	50.00%	1.75	75.00%
50	**5**	4.00	20.00%	4.00	20.00%	2.00	60.00%
51	**3**	3.97	32.45%	3.97	32.45%	3.97	32.23%
52	**6**	6.22	3.72%	6.22	3.72%	6.22	3.72%
53	**3**	1.75	41.67%	1.75	41.67%	1.75	41.67%
54	**6**	4.00	33.33%	4.99	16.83%	4.00	33.33%
55	**6**	6.21	3.51%	6.22	3.61%	6.22	3.72%

Case Number	Owner	Alt_1	Error Percentage	Alt_2	Error Percentage	Alt_3	Error Percentage
56	**1**	1.75	75.00%	1.35	35.00%	1.00	0.00%
57	**5**	4.00	20.00%	4.00	20.00%	4.00	20.00%
58	**7**	6.22	11.10%	6.22	11.10%	6.22	11.10%
59	**3**	1.75	41.67%	2.13	29.13%	1.75	41.67%
60	**5**	4.00	20.00%	4.00	20.00%	4.00	20.00%
61	**3**	3.97	32.45%	3.97	32.45%	3.97	32.45%
62	**7**	6.22	11.10%	6.22	11.19%	6.22	11.10%
63	**4**	1.75	56.25%	3.13	21.85%	1.75	56.25%
Average Percent Error			**23.62%**		**16.03%**		**24.12%**

Figure 2-16 shows the graphical representation of the average error percentage obtained from testing each solution for each of the six sub-models. The x-axis represents the alternative solution number, and the y-axis represents the corresponding average percent error for each solution. For example, for the "Subcontractor" sub-model, ten alternative solutions for MBFs were investigated, and the average percent error for the solutions ranged from 20.8% to 23.6%. In each case, the solution with the lowest average percent error was selected to build the final fuzzy expert DSS. For the "Subcontractor" sub-model, the third solution was the best one, having an average error of 20.8%. For the "Owner" sub-model, the best solution had an average error of 16.0%. For "Year End Evaluation," the best solution had an average error of 19.4%. For "Current Evaluation," the best solution had an average error of 12.4%. For "Contract Clauses," the best solution had an average error of 18.4%; and for "Project Specifics/Scope," the best solution had an average error of 17.3%. Samples of the final input's membership functions that were used for developing the final fuzzy expert DSS are presented in Appendix C.

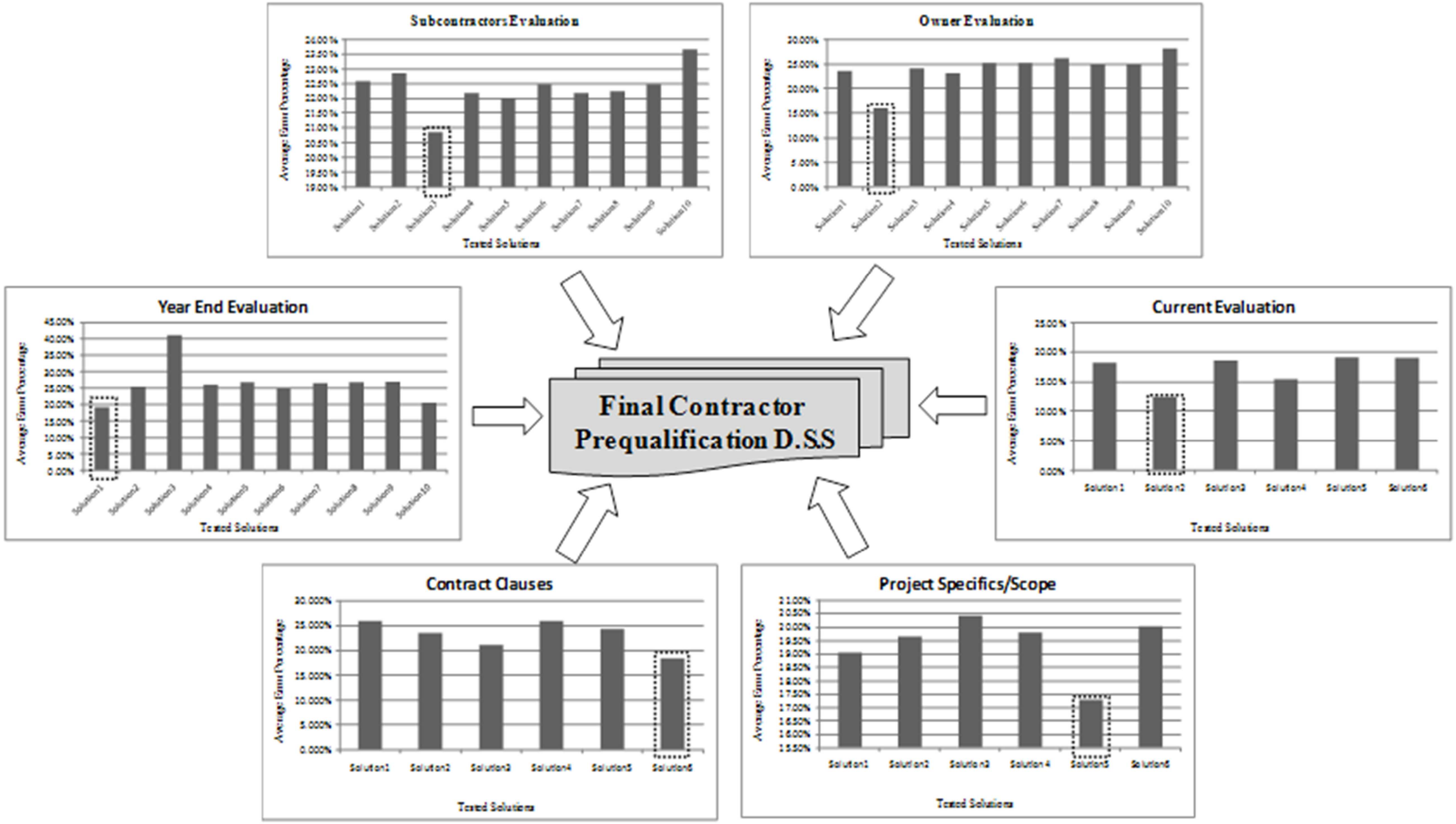


Figure 2-16 Results of Testing of Sub-Models' Alternative Solutions

2.3.3 Rule Base Development

Fuzzy rules consist of a condition ('If' part) and a conclusion ('Then' part), and represent the experts' reasoning process in the fuzzy expert system. In developing the fuzzy expert DSS, the data obtained from the first questionnaire (Sub-section 2.3.1.2) was used to create a rule base for the system. The average relative importance weights of the input criteria were used to determine the rule base that represents the relation between the inputs and the output. Three influence levels (based on the average relative importance weights on a scale of 1 to 7) were defined for each input criterion: < 5, 5 to 6, or > 6. Corresponding influence levels were defined as: "minor influence," "moderate influence," or "high influence," respectively. Table 2-13 presents the influence levels for the input criteria and the intermediate variables that were used to generate the rule base. The three levels of influence were chosen due to the way input variables and rules are entered into FuzzyTECH® (March 2008). The rule base was then created according to the influence levels of the inputs. As an example, the "Current Evaluation" sub-model contains three inputs ("Cash Flow," "Operating Line," and "Work on Hand") that have average importance weights equal to 7.0, 4.25, and 6.25, respectively. These average importance weights translate to influence levels of "high influence," "minor influence," and "high influence," respectively. According to the influence level for each input, the rules were generated. If "Cash Flow" is "Good"; "Operating Line" is "Unacceptable"; and "Work On Hand" is "High," then the output ("Current Evaluation") is "Average." Because "Cash

Flow” has a higher influence level, it is given greater weight than “Operating Line” or “Work on Hand” in the determination of the output level. All possible combinations between the inputs’ linguistic terms were considered to generate a complete rule base; i.e., if there are N inputs, each with Z membership functions, then the complete rule base contains Z^N rules. The FuzzyTECH® rule wizard generates a complete rule base based on the input variable’s influence on the output variables. These influences are entered for each variable before the wizard generates the rule base. An example of the developed rule bases for the “Current Evaluation” sub-model is illustrated in Figure 2-17, and a sample of developed rule blocks is included in Appendix C. For the DSS, all developed rules are weighted equally (DoS = 1.0), which means that all rules have the same importance in the overall output.

Table 2-13 Input Criteria and Intermediate Variables' Level of Influence on the Corresponding Outputs

Input Criteria and Intermediate Variable	Influence Level	Output
Project Aspects	High Influence	Overall Contractor Prequalification Rating
Contractual Risk	Moderate Influence	
Project Team	High Influence	Project Aspects
Project Specifics/Scope	High Influence	
Owner	High Influence	Project Team
Subcontractors	Moderate Influence	
Contractor	High Influence	
Owner Type	High Influence	Owner
Owner Funding	High Influence	
Owner/Owner Agent Experience	Moderate Influence	
Bonding or Security	High Influence	Subcontractors
Scope Gaps	Minor Influence	
Overall Prequalification	Moderate Influence	
Year End Evaluation	High Influence	Contractor
Current Evaluation	Moderate Influence	
Working Capital Trend	High Influence	Year End Evaluation
Tangible Net Worth Trend	High Influence	
Gross Profit Margin Trend	High Influence	
Net Profit Margin Trend	Moderate Influence	
Debt to Equity Ratio	Minor Influence	
Gross Profit Margin	High Influence	
Net Profit Margin	Moderate Influence	
Cash Flow	High Influence	Current Evaluation
Operating Line	Minor Influence	
Work On Hand	High Influence	
Type/Complexity	High Influence	Project Specifics/Scope
Project Size	High Influence	
Project Location	Minor Influence	
Cost Breakdown	Minor Influence	
Schedule	Minor Influence	
Project Risk Mitigation	High Influence	
Contract Form	High Influence	Contractual Risk
Contract Clauses	High Influence	
Payment	Moderate Influence	Contract Clauses
Warranty	Moderate Influence	
Indemnity	Minor Influence	
Schedule Extensions and Price Adjustment	Minor Influence	
Damages / Penalties / Bonuses	Moderate Influence	
Toxic and Hazardous Substance and Materials	Moderate Influence	
Disputes / Arbitration	Minor Influence	
Design Concerns	High Influence	
Bonding/Security	High Influence	

#	IF Cash_Flow	Operating_Line	Work_hand	THEN DoS	Current_Evaluati
4	Unacceptable	Acceptable	High	1.00	Low
5	Unacceptable	Acceptable	Average	1.00	Average
6	Unacceptable	Acceptable	Low	1.00	Average
7	Unacceptable	Good	High	1.00	Low
8	Unacceptable	Good	Average	1.00	Average
9	Unacceptable	Good	Low	1.00	Average
10	Acceptable	Unacceptable	High	1.00	Low
11	Acceptable	Unacceptable	Average	1.00	Average
12	Acceptable	Unacceptable	Low	1.00	Average
13	Acceptable	Acceptable	High	1.00	Average
14	Acceptable	Acceptable	Average	1.00	Average
15	Acceptable	Acceptable	Low	1.00	High
16	Acceptable	Good	High	1.00	Average
17	Acceptable	Good	Average	1.00	Average
18	Acceptable	Good	Low	1.00	High
19	Good	Unacceptable	High	1.00	Average
20	Good	Unacceptable	Average	1.00	Average
21	Good	Unacceptable	Low	1.00	High
22	Good	Acceptable	High	1.00	Average
23	Good	Acceptable	Average	1.00	High
24	Good	Acceptable	Low	1.00	High
25	Good	Good	High	1.00	Average
26	Good	Good	Average	1.00	High
27	Good	Good	Low	1.00	High

Figure 2-17 Example of the Developed (Current Evaluation) Rule Base

2.4 DSS Validation and Sensitivity Analysis

The final fuzzy expert DSS (including all the contractor/project evaluation criteria and sub-models described previously) was implemented using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005), as shown in Figure 2-18.

The fuzzy expert system shell consists of three parts: fuzzification, inference engine, and defuzzification. In fuzzification, the system calculates the degree of membership for each linguistic term that defines each criterion value. Then, it applies a fuzzy operator to the membership values from each evaluation criterion to link the combinations of evaluation criteria to overall contractor/project prequalification as a single value for each rule. The MIN (minimum) fuzzy operator was initially used as the fuzzy operator in this step. In the next step, the inference engine applies an implication method for each rule to the output variable's membership function. The PROD (product) operator was used as an implication method. The last step in the inference engine is rule aggregation. Rule aggregation is the process of combining the output sets from each rule into a single output fuzzy set. The MAX (maximum) rule aggregation method was initially used. Defuzzification, the last step, determines a crisp value from the output fuzzy set. The CoM (centre of maximum) method was initially selected as a defuzzification method.

A base case model was built using all the initial operators described previously, along with piecewise linear membership functions (e.g., triangular or trapezoidal), estimated during the MBF estimation step. The base case model and thirty-eight alternative system configurations were developed to determine which system configuration produced the most accurate results. The configurations considered the different input aggregation methods (MIN [minimum], MAX [maximum], AVG [average], PROD [product], MIN/AVG [minimum/average], and MIN/MAX [minimum/maximum]), different rule aggregation methods (MAX [maximum] and BSUM [bounded sum]), and different defuzzification methods (COM [centre of maximum], MOM [middle of maximum], Fast COA [fast centre of area], and Hyper COM [hyper centre of maximum]). The product method (PROD [product]) was used for rule implication, as it is the only available method in FuzzyTECH for implication.

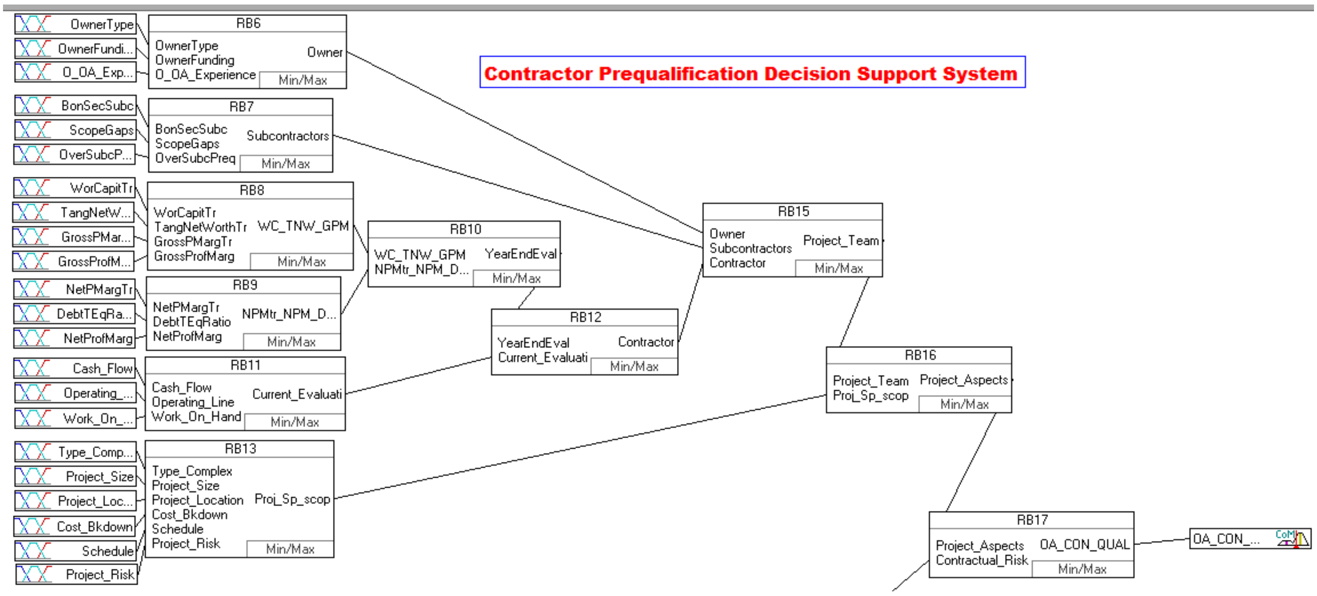


Figure 2-18 Part of the Structure of the Fuzzy Expert DSS

The fuzzy expert DSS was validated using the 32 hypothetical contractor/project prequalification cases. Each case contained a value for all the evaluation criteria and the corresponding output (overall contractor/project prequalification) based on the participating surety experts' opinions. The average percent error of each system configuration was calculated using Equation 2-2. In

Equation 2-2, the fuzzy expert DSS output is the crisp rating provided by the system's defuzzification process. The actual rating is the rating given to the contractor by the underwriter or broker. A sample of the calculations for validation and sensitivity analysis are shown in Table 2-14. As illustrated in Table 2-14, the error for each system was calculated according to the variation between the actual output value and the value presented by each alternative system for all 32 contractor prequalification cases.

Table 2-15 presents the 38 different system configurations that were tested, along with the average percent error and 95% confidence intervals from evaluating the hypothetical contractor/project prequalification cases. The most accurate system configuration, number 24, consists of piecewise linear membership functions, MIN (minimum) for input aggregation, PROD (product) for implication, MAX (maximum) for rule aggregation, and Fast CoA (fast centre of area) for defuzzification. This system configuration has an average percent error of 16.0% (i.e., 84.0% accuracy), with a 95% confidence interval between 12.0% and 20.1% (i.e., 88.0% and 79.9% accuracy).

Table 2-14 Sample of Validation and Sensitivity Analysis Calculations for Three Configurations

Case Number	Overall Contractor Prequalification	System 1	Error 1	System 2	Error 2	System 3	Error 3	System 4	Error 4
1	**4**	4.50	12.50%	4.00	0.00%	4.05	1.14%	5.50	37.50%
2	**5**	5.50	10.00%	4.00	20.00%	4.03	19.34%	5.50	10.00%
3	**3**	2.87	4.17%	4.00	33.33%	3.97	32.30%	2.75	8.34%
4	**7**	5.50	21.43%	4.00	42.86%	4.07	41.88%	5.50	21.43%
5	**5**	5.50	10.00%	4.00	20.00%	4.04	19.24%	5.50	10.00%
6	**3**	4.00	33.33%	4.00	33.33%	4.02	33.95%	4.00	33.33%
7	**4**	4.75	18.75%	4.00	0.00%	4.00	0.01%	4.75	18.75%
8	**4**	3.58	10.56%	4.00	0.00%	4.00	0.11%	3.67	8.33%
9	**4**	3.25	18.75%	4.00	0.00%	4.00	0.00%	3.45	13.64%
10	**4**	4.00	0.00%	4.00	0.00%	4.00	0.00%	4.00	0.00%
11	**5**	3.91	21.73%	4.00	20.00%	3.99	20.11%	3.62	27.50%
12	**6**	4.00	33.33%	4.00	33.33%	4.00	33.33%	1.00	83.33%
13	**6**	4.41	26.55%	4.00	33.33%	4.01	33.22%	4.90	18.34%
14	**3**	3.17	5.70%	4.00	33.33%	3.97	32.28%	3.00	0.00%
15	**5**	4.00	20.00%	4.00	20.00%	4.00	20.01%	1.00	80.00%
16	**4**	4.00	0.00%	4.00	0.00%	4.00	0.06%	4.75	18.75%
17	**5**	4.00	20.00%	4.00	20.00%	4.01	19.89%	1.00	80.00%
18	**6**	3.25	45.83%	4.00	33.33%	5.98	0.25%	3.25	45.83%
19	**7**	5.50	21.43%	4.00	42.86%	6.06	13.47%	1.00	85.71%
20	**4**	4.00	0.00%	4.00	0.00%	4.00	0.08%	3.89	2.71%
21	**2**	2.50	25.00%	4.00	100.00%	2.98	49.15%	2.50	25.00%
22	**2**	2.50	25.00%	4.00	100.00%	3.98	99.11%	2.50	25.00%
23	**3**	2.50	16.67%	4.00	33.33%	3.98	32.54%	2.50	16.67%
24	**4**	5.50	37.50%	4.00	0.00%	4.06	1.54%	5.50	37.50%
25	**3**	4.12	37.24%	4.00	33.33%	3.03	1.15%	5.20	73.33%
26	**2**	2.50	25.00%	4.00	100.00%	1.96	1.89%	2.50	25.00%
27	**5**	4.00	20.00%	4.00	20.00%	5.00	0.02%	3.40	32.00%
28	**3**	2.50	16.67%	4.00	33.33%	3.98	32.52%	2.50	16.67%
29	**3**	3.50	16.67%	4.00	33.33%	4.03	34.25%	5.50	83.33%
30	**3**	2.50	16.67%	4.00	33.33%	4.00	33.21%	2.50	16.67%
31	**5**	5.50	10.00%	4.00	20.00%	4.07	18.69%	5.50	10.00%
32	**4**	5.50	37.50%	4.00	0.00%	4.06	1.60%	5.50	37.50%
Average Percent Error			**19.3%**		**27.9%**		**19.6%**		**31.3%**

According to the input values for each case, the DSS provides the user with the contractor prequalification for both intermediate variables and the final output (i.e., overall contractor and project prequalification) on a defuzzified scale of 1to 7. For the final output, this rating scale is represented by five MBF. Each defuzzified value on the 1 to 7 rating scale for the final output is described by the following linguistic terms, respectively: “Not Qualified,” “Somewhat Qualified,” “Below Average Qualified,” “Average Qualified,” “Above Average Qualified,” “Very Qualified,” and “extremely qualified.”

Table 2-15 System Configuration for Validation and Sensitivity Analysis (Awad and Fayek 2012)

Scenario #	MF Shape	Fuzzy Operator	Inference Method	Aggregation Method	Defuzzification Method	Average Percent Error	95% Confidence Interval
Base	Piece Linear	MIN	PROD	MAX	COM	19.3%	15.1% - 23.5%
1	Piece Linear	MAX	PROD	MAX	COM	27.9%	17.9% - 37.9%
2	Piece Linear	AVG	PROD	MAX	COM	19.6%	11.9% - 27.3%
3	Piece Linear	PROD	PROD	MAX	COM	31.3%	21.7% - 40.9%
4	Piece Linear	MIN/AVG	PROD	MAX	COM	24.5%	16.3% - 32.6%
5	Piece Linear	MIN/MAX	PROD	MAX	COM	25.6%	17.0% - 34.2%
6	Piece Linear	MIN	PROD	BSUM	COM	23.7%	17.5% - 29.9%
7	Piece Linear	MAX	PROD	BSUM	COM	27.9%	17.9% - 37.9%
8	Piece Linear	AVG	PROD	BSUM	COM	27.9%	17.9% - 37.9%
9	Piece Linear	PROD	PROD	BSUM	COM	24.2%	17.7% - 30.6%
10	Piece Linear	MIN/AVG	PROD	BSUM	COM	27.9%	17.9% - 37.9%
11	Piece Linear	MIN/MAX	PROD	BSUM	COM	27.9%	17.9% - 37.9%
12	Piece Linear	MIN	PROD	MAX	MOM	28.6%	20.6% - 36.5%
13	Piece Linear	MAX	PROD	MAX	MOM	37.5%	31.8% - 43.2%
14	Piece Linear	AVG	PROD	MAX	MOM	24.5%	16.6% - 32.4%
15	Piece Linear	PROD	PROD	MAX	MOM	30.9%	20.4% - 41.4%
16	Piece Linear	MIN/AVG	PROD	MAX	MOM	24.5%	16.6% - 32.4%
17	Piece Linear	MIN/MAX	PROD	MAX	MOM	25.7%	17.9% - 33.4%
18	Piece Linear	MIN	PROD	BSUM	MOM	24.7%	17.1% - 32.3%
19	Piece Linear	MAX	PROD	BSUM	MOM	37.5%	31.8% - 43.2%
20	Piece Linear	AVG	PROD	BSUM	MOM	37.5%	31.8% - 43.2%
21	Piece Linear	PROD	PROD	BSUM	MOM	22.6%	15.1% - 30.1%
22	Piece Linear	MIN/AVG	PROD	BSUM	MOM	37.5%	31.8% - 43.2%
23	Piece Linear	MIN/MAX	PROD	BSUM	MOM	37.5%	31.8% - 43.2%
24	**Piece Linear**	**MIN**	**PROD**	**MAX**	**Fast COA**	**16.0%**	**12.0% - 20.1%**
25	Piece Linear	MAX	PROD	MAX	Fast COA	27.9%	17.9% - 37.9%
26	Piece Linear	AVG	PROD	MAX	Fast COA	27.7%	17.9% - 37.6%
27	Piece Linear	PROD	PROD	MAX	Fast COA	30.8%	21.0% - 40.6%
28	Piece Linear	MIN/AVG	PROD	MAX	Fast COA	27.0%	17.9% - 36.1%
29	Piece Linear	MIN/MAX	PROD	MAX	Fast COA	27.6%	17.9% - 37.4%
30	Piece Linear	MIN	PROD	BSUM	Fast COA	23.7%	17.5% - 29.9%
31	Piece Linear	MAX	PROD	BSUM	Fast COA	27.9%	17.9% - 37.9%

Scenario #	MF Shape	Fuzzy Operator	Inference Method	Aggregation Method	Defuzzification Method	Average Percent Error	95% Confidence Interval
32	Piece Linear	AVG	PROD	BSUM	Fast COA	27.9%	17.9% - 37.9%
33	Piece Linear	PROD	PROD	BSUM	Fast COA	24.1%	17.6% - 30.5%
34	Piece Linear	MIN/AVG	PROD	BSUM	Fast COA	27.9%	17.6% - 37.9%
35	Piece Linear	MIN/MAX	PROD	BSUM	Fast COA	26.1%	19.3% - 32.8%
36	Piece Linear	MIN	PROD	MAX	Hyper COM	17.1%	13.0% - 21.1%
37	Piece Linear	PROD	PROD	BSUM	Hyper COM	23.6%	16.1% - 30.1%
38	Piece Linear	MIN/MAX	PROD	BSUM	Hyper COM	28.2%	17.5% - 38.9%

If the overall contractor prequalification is “Average Qualified” (i.e., 4) or higher, the contractor will likely be accepted for bonding. A report consisting of the input and output values can then be printed to document the contractor’s prequalification case.

2.5 Concluding Remarks

In the construction bonding business, a complex comprehensive prequalification or assessment process is done to evaluate contractor, project, and contractual risks. The underwriting process incorporates the subjective judgment or intuition of experts, without an easily explained or transparent logical rationale, and involves various qualitative and quantitative evaluation criteria, many of which contain uncertainty and require subjective judgment. This chapter identifies, classifies, and provides a comprehensive, detailed list of the evaluation criteria for contractor and project prequalification that was compiled following a thorough literature review, a review of contractor prequalification cases, fifteen one-on-one interviews, and nine group meetings in which participating surety experts interacted. Numerical scales were defined for the quantitative evaluation criteria, and rating scales, using reference variables, were developed to quantify the qualitative criteria. For all criteria, critical threshold values and favourable trends were determined.

In this chapter, both fuzzy logic and expert systems are combined to develop a decision support system (DSS) for use in contractor and project evaluation to help surety underwriters and brokers in the second phase of the surety underwriting process and to provide a systematic and structured approach to this complex process. Thirty-eight alternative system configurations were investigated to determine the most accurate configuration. The system is validated using 32 prequalification cases, and the accuracy of the fuzzy expert DSS is found to be 84%. Five senior surety professionals provided input to the determination of the contractor evaluation criteria and the model development.

Through this research, a new approach for fuzzy membership function estimation was developed. The new approach incorporates the Horizontal MBF estimation technique, which depends on expert knowledge, as well as some prequalification cases (data integration). Finally, the fuzzy expert DSS was validated with a number of hypothetical cases of project bonding evaluation.

The fuzzy expert DSS developed here offers several advantages to surety professionals who conduct surety underwriting. The system improves surety underwriters' and brokers' reliance on judgment and experience to validate their underwriting decisions. It also provides a structured, organized, and objective approach to evaluate subjective—and difficult to quantify—criteria in contractor qualification for a specific project, to formalize and quantify complex decision-making, and make its logic easy to trace. Finally, the proposed system can assist construction contractors to self-assess and to discover areas for improvement to better obtain bonding for construction projects.

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CHAPTER 3. Surety Experts Weighting (Group Consensus) System[1]

3.1 Introduction

Inputs from many surety experts across Canada are considered in several stages throughout the development of the contractor default prediction model (CDPM) (presented in Chapter 5). To incorporate their input as a collective opinion, a group consensus system (GCS) is needed to aggregate the experts' assessments into collective single values to compile the required data for CDPM development.

Finding a group consensus function of aggregation of experts' judgmental scores to represent a common opinion is an important issue (Hsu and Chen 1996), as each expert (broker or underwriter) has his/her own perspective for providing a certain assessment score. The purpose of this chapter is to establish an overall weighting system to determine the consensus weight factor (CWF) of each surety expert. The CWF of the participating experts is a key aspect in aggregating their inputs or assessments into a collective assessment. Experts with higher CWFs will have more impact on the collective assessment of the experts' opinions than those with lower CWFs.

[1] Parts of this chapter have been accepted for publication in Canadian Journal of Civil Engineering, Awad, A. and Fayek, A. Robinson. (2012) "Contractor default prediction model for surety bonding," Canadian Journal of Civil Engineering, in press.

The developed experts' CWFs were used to combine the individual scores to form a group consensus opinion in two stages: (1) to determine the relative importance/influence weights for the CDPM input variables, and (2) to evaluate the output values for the contractor default prediction hypothetical cases (as presented in Chapter 5).

The multi-attribute utility function (MAUF) is a methodology that can be used to represent a rational decision-making process (Nishizaki et al. 2009). MAUF is effective in resolving decision-making problems in which the decision-maker considers preferences (liking/worth) of multiple criteria or attributes for making the final decision. In this chapter, the determination of an overall importance weight for the surety expert, depending on a number of different experience measures, is expressed as a decision-making problem that can be represented by the MAUF approach. Using MAUF for the assessment of several attributes and providing a collective total assessment is not new; however, the application of that concept for the aggregation of experts' opinion is. Two validation approaches have been applied to validate the developed GCS: face validation and numerical validation.

3.2 Aggregation of Experts' Opinions

In the context of group decision-making problems, there are many factors that may influence experts' opinions, such as differences in their personalities, perception, and level of expertise (Karamouz and Mostafavi 2010; Pedrycz et al. 2011). Predd et al. (2008) pointed out that aggregation or combining experts' subjective opinions is one of the major problems that may affect the decision-making process.

Many approaches have been presented to solve the problem of aggregating experts' opinions (Elbarkouky 2010). One of the most common and simple approaches is the simple linear averaging method. In this method, the experts' opinions are given equal weights/probabilities to determine an average value, which is expressed as the sum of the expert's assessments divided by the number of experts. For example, if we have 3 scores/assessments then the average is calculated as follows: [Score 1 + Score 2 + Score 3] / [1+1+1] = [Summation of the Scores]/3. The simple linear averaging method has been used for aggregating experts' opinions collected using surveys (Genest and Zidek 1986; Clemen and Winkler 1999). The main assumption in applying the simple linear averaging method is that there is no bias in the experts' opinions. To consider the effect of expertise on the experts' opinions for the aggregation process, the weighted averaging approach is followed (Ter Braak and Barendregt 1986; Javier et al. 2002). For the same example, if the scores have different weights or probabilities, the weighted averaging approach is applied as follows: [(Weight of Score 1 x Score 1) + (Weight of Score 2 x Score 2) + (Weight of Score 3 x Score 3)] / [(Weight of Score 1 x 1) + (Weight of Score 2 x 1) + (Weight of Score 3 x 1)] = [Summation of (Weight x Score)] / [Summation of (Weights)].

The objective of developing a group consensus system (GCS) in this chapter is to determine a consensus weighting factor (CWF) for all the participating surety experts to determine one aggregate value for each input relative importance weight (RIW), where the summation of each individual expert's score (IS^n) is multiplied by the expert's consensus weighting factor (CWF^n) and divided by the summation of all experts' CWFs, as in Equation 3-1.

$$Aggregated\ Input\ RIW = \frac{\sum_{n=1}^{N} IS^n * Expert's\ CWF^n}{\sum_{n=1}^{N} Expert's\ CWF^n} \qquad [3\text{-}1]$$

where $Aggregated\ Input\ RIW$ is the aggregated assessment of the experts' assessments, and N is the number of participating experts. For example, if three experts with CWFs of 0.852, 0.427, and 0.952 provided scores of 4, 5, and 3 respectively, then the aggregated relative importance weight is calculated as shown in Equation 3-2.

$$Aggregated\ Input\ RIW = \frac{(4\times0.852)+(5\times0.427)+(3\times0.952)}{0.852+0.427+0.952} = 3.8 \qquad [3\text{-}2]$$

3.3 Group Consensus System (GCS) Development Methodology

Figure 3-1 illustrates the group consensus system (GCS) development process. The first step was to determine the surety experts' experience measures. One-on-one meetings followed by an interactive group meeting were held to determine the experience measure attributes. Then, a questionnaire was developed to collect the required knowledge to build the surety experts' GCS. The questionnaire was divided into two parts in addition to the introductory part. The introduction provided all the required information about the group consensus system, the questionnaire content, the objective of the system and the questionnaire, and finally, a detailed explanation of all the experience measures. The first part contained questions to develop the individual utility functions for the experience measures. The second part was designed for conducting the pairwise comparisons between the six experience measures. Sample of the developed questionnaire is presented in Appendix D. The overall utility function (for all six experience measures) was then established and validated using the experience measures values for 10 experts. The final stage involved implementing the developed GCS to determine the overall experience weight (CWF) for all 33 surety experts participating in developing the contractor default prediction model.

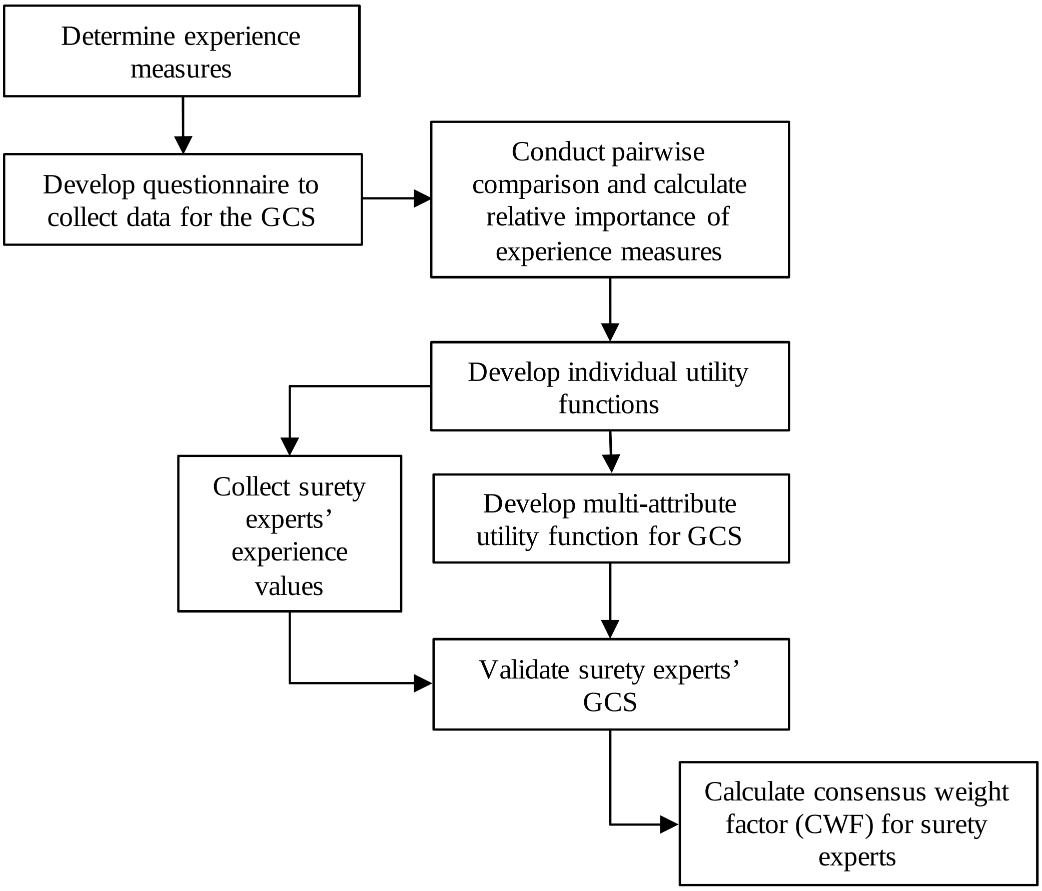

Figure 3-1 The Group Consensus System Development Process (Awad and Fayek 2012)

3.4 Experience Measures

The first step in building the surety experts weighing system was defining the attributes that should be considered to evaluate the surety experts' experience. Five one-on-one meetings with highly experienced surety experts (with no less than ten years' experience each), plus an additional group meeting in which the surety experts could interact with each other, were held to determine the experience measure attributes. In the end, the experts agreed upon six attributes as the most important criteria to measure the experience for any surety expert working in the field of contractor prequalification for the construction industry. These criteria, listed in Table 4-1, are: (1) experience in surety for construction (ESC), (2) current role (CR), (3) experience in contractor prequalification (ECP), (4) experience in project evaluation (EPE), (5) size limit (SL), and (6) largest project evaluated (LP). Table 3-1 also provides the definition of each experience measure and its quantification method.

Table 3-1 The Surety Group Consensus System Attributes (Awad and Fayek 2012)

Experience Measure Attribute	Definition	Quantification Method (units) and Range of Scale
Experience in Surety for Construction (ESC)	The number of years the expert has been working in the surety industry for construction	Numerical value (number of years) From 2 to 20 years
Current Role (CR)	The expert's current role in the surety/brokerage organization	Broker/underwriter (under training) Junior broker/underwriter Intermediate broker/underwriter Senior surety broker/underwriter Surety/brokerage manager
Experience in Contractor Prequalification (ECP)	Number of contractors that the expert has been involved in evaluating during his/her entire career	Numerical value (number of contractors) From 20 to 350 contractors
Experience in Project Evaluation (EPE)	Number of projects the expert has been involved in evaluating during his/her entire career	Numerical value (number of projects) From 0 to 100 projects
Size Limit (SL)	The value of the largest aggregate work program that the surety expert managed for a single contractor	Numerical value (dollar value) From $10,000,000 to $300,000,000
Largest Project Evaluated (LP)	The value of the largest project the expert has been involved in evaluating	Numerical value (dollar value) From $1,000,000 to $80,000,000

3.5 The GCS Development Approach

The process of evaluating the surety experts' experience based on the six experience measures was approached as a multi-criteria assessment process. The multi-attribute utility function (MAUF) was used to determine a consensus weighting factor (CWF) for each surety expert, depending on a number of different experience measures. The determination of the CWF was expressed as a decision-making problem, where the decision-maker considers preferences (worth) of multiple criteria or attributes for making the CWF assessment.

The first step in developing the MAUF was to develop individual utility functions for each experience measure. Then the MAUF was used to integrate the individual utility functions into a single function. Integrating the individual utility functions required determining the surety expert's relative preference (importance) of the experience measures.

The Analytical Hierarchy Process (AHP), introduced by Saaty (1980) and described in Zio (1996), is one of the most systematic and popular techniques for determining relative preference among various attributes (Mollaghasemi and Pet-Edward 1997; Zeleny 1982). The AHP has been successfully used in construction engineering and management research (Abourizk et al. 1994; Chua et al. 1999; Dias and Ioannou 1996). The GCS was developed by integrating the AHP and the multi-attribute utility function (Georgy 2000).

3.6 Development of the Individual Utility Functions

To determine the multi-attribute utility function $U(y_1, y_2, \dots, y_m)$, first it was decomposed into m individual utility functions for each attribute. Each of the individual utility functions, $y_j = u_j(x_j)$, $j = 1,2, \dots\dots, m$, is used to quantify the worth value according to the values of the attribute j. In other words, the individual utility function represents the relationship between the attribute value and its worth (i.e., utility value). The individual utility function can be established by determining two values: upper limit (U_L) and lower limit (L_L), in addition to the risk attitude as illustrated in Figure 3-2 (Georgy et al 2005; Georgy 2000).

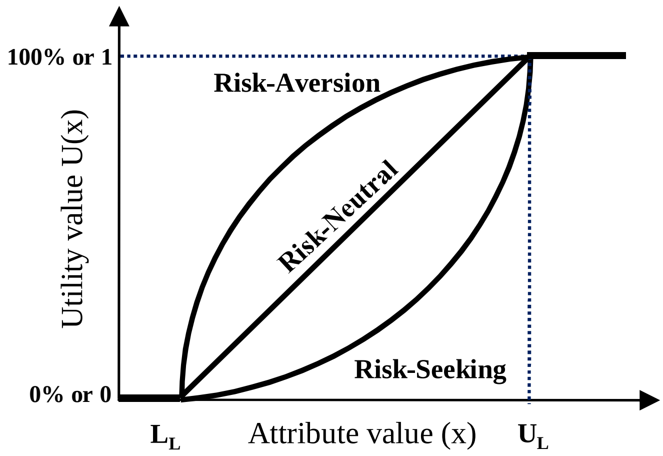

Figure 3-2 The Risk Attitudes for Individual Utility Function (Georgy 2000)

The "lower limit" (or less) will have 0% (no) utility/worth value and the "upper limit" (or more) will have 100% (full) utility/worth value. This can be represented by Equations (3-3a) and (3-3b) (Georgy et al 2005).

$$u_j(L_L) = 0.0 \quad [3\text{-}3a]$$

$$u_j(U_L) = 1.0 \quad [3\text{-}3b]$$

The worth values between the L_L and U_L varies from 0.0 to 1.0 according to the shape of the utility function, which depends on the evaluator's risk attitude. For deriving individual attribute utility functions in this chapter, the L_L and U_L were defined in addition to intermediate values on the utility function.

Each of the six experience measures is quantified by a certain range of experience values (Table 3-1). For instance, the measure 'experience in surety for construction' (ESC) has a range of 0–20 years. Its degree of worth is determined according to the experience value in this possible range, i.e., the surety expert who has a higher number of years of experience would have a higher degree of worth or utility value.

The purpose of the first section of the questionnaire developed for this research was to derive the individual utility function for each experience measure. In that section, the participating surety experts were asked to provide their inputs regarding the degree of liking for each experience measure. The questions were developed to identify the upper limit (U_L), lower limit (L_L) and three intermediate values, in order to construct a function for each experience measure, as illustrated in Table 3-2.

Table 3-2 Sample of the Questionnaire for Constructing the Single Utility Functions

Experience in surety for construction (ESC)	Quantification method (numerical, e.g., 10 years)				
	Lower Limit (L_L)	Intermediate values			Upper limit (U_L)
Years of experience					
Worth value/percentage	0%				100%

Experts were asked to provide the numerical or linguistic limits (according to the nature of the attribute) for each measure. The evaluation was limited to surety underwriters and brokers who were working in surety bonding in the construction industry.

Example:

If the expert considers, for instance, that 2 years of experience or less in surety for construction has no value (0%); that 20 years or more has a total value (100%) in context of surety underwriters and brokers in construction; and that the three intermediate values of 6, 10, and 15 have worth values of 0.4, 0.7, and 0.9 respectively, the expert should fill the table for experience in surety for construction as shown in Table 3-3.

Table 3-3 Experts' Responses to Construct the Individual Utility Function for the ESC

Experience in surety for construction (ESC)	Quantification method (numerical, e.g., 10 years)				
	Lower Limit (L_L)	Intermediate values			Upper limit (U_L)
Years of experience	2	6	10	15	20
Worth value/percentage	0%	0.4	0.7	0.9	100%

All of the participating surety experts provided their individual inputs for that part of the questionnaire during the one-on-one meetings. Then, to reach a consensus about their responses, an interactive group meeting was held. Table 3-4 presents the final common assessment of the U_L, L_L, and three intermediate values to construct the single utility functions.

Table 3-4 Experts' Responses to Construct the Individual Utility Functions (Awad and Fayek 2012)

1. Experience in Surety for Construction (ESC)					
Years of Experience	2	6	10	15	20
Worth/Utility Value	0.00	0.40	0.70	0.90	1.00
2. Current Role (CR)					
Expert Role	1. Broker/Underwriter (Under Training)	2. Junior Broker/Underwriter	3. Intermediate Broker/Underwriter	4. Senior Surety Broker/Underwriter	5. Surety/Brokerage Manager
Worth/Utility Value	0.00	0.00	0.65	0.85	1.00
3. Experience in Contractor Prequalification (ECP)					
Number of Contractors	20	100	150	250	350
Worth/Utility Value	0.00	0.55	0.80	0.90	1.00
4. Experience in Project Evaluation (EPE)					
Number of Projects	0	20	60	80	100
Worth/Utility Value	0.00	0.25	0.60	0.90	1.00
5. Size Limit (SL)					
Dollar Value	10,000,000	25,000,000	90,000,000	165,000,000	300,000,000
Worth/Utility Value	0.00	0.25	0.65	0.90	1.00
6. Largest Project Evaluated (LP)					
Dollar Value	1,000,000	10,000,000	30,000,000	60,000,000	80,000,000
Worth/Utility Value	0.00	0.25	0.65	0.80	1.00

The values presented in Table 3-4 were used to initially develop the utility functions for the six attributes. Then, curve-fitting was done using Microsoft Excel© to determine the best representation for each individual utility function. The best-fitting functions were selected depending on the R-squared value: a statistical measure of how well a regression line approximates real data points. It is a descriptive measure between 0 and 1.0, indicating how good one term is at predicting another. Figure 3-3 illustrates the graphical representation for the utility functions. Table 3-5 presents the final individual utility functions, in addition to their corresponding R-squared values. As shown, all the R-squared values are very close to 1.0, which means the developed functions adequately reflect the actual data.

Figure 3-3 Graphical Representation of the Experience Measures Utility Functions

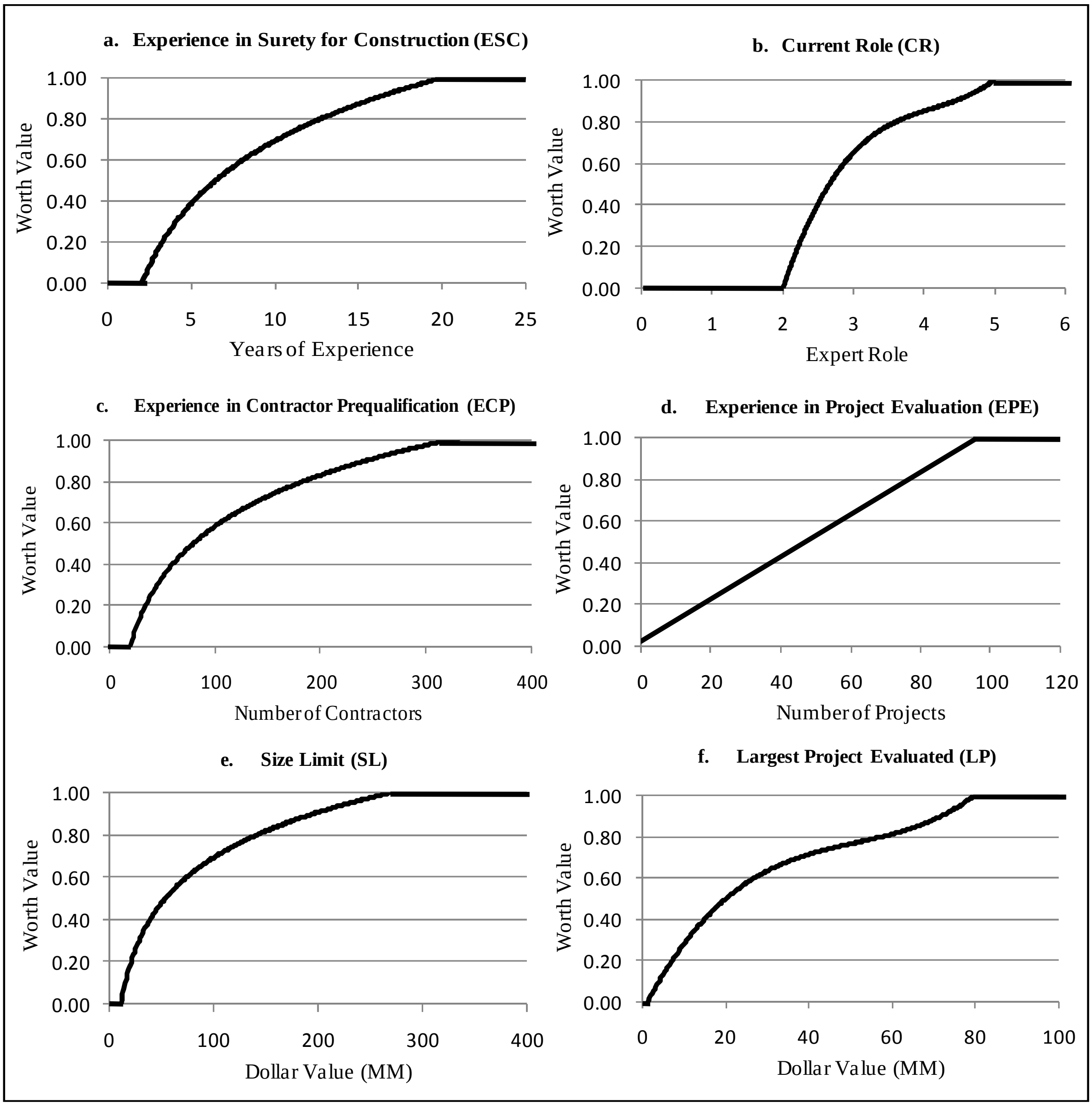

Table 3-5 Individual Utility Functions of the Surety Experts' Experience Measures (Awad and Fayek 2012)

Experience Measure Attribute	Individual Attribute Utility Function	R-Squared Value
Experience in Surety for Construction (ESC)	$u_1(x_1) = \begin{cases} 0, & x_1 \leq 2\ years \\ 0.4462\ \ln(x_1) - 0.3362, & 2\ years < x_1 < 20\ years \\ 1.0, & x_1 \geq 20\ years \end{cases}$	0.992
Current Role (CR)	$u_2(x_2) = \begin{cases} 0, & x_2 \leq 2 \\ 0.0667x_2{}^3 - 0.825x_2{}^2 + 3.5083x_2 - 4.25, & 2 < x_2 < 5 \\ 1.0, & x_2 \geq 5 \end{cases}$ Where 1= Broker/Underwriter (Under Training), 2= Junior Broker/Underwriter, 3= Intermediate Broker/Underwriter, 4= Senior Surety Broker/Underwriter, 5= Surety/Brokerage Manager	1.000
Experience in Contractor Prequalification (ECP)	$u_3(x_3) = \begin{cases} 0, & x_3 \leq 20\ contractors \\ 0.3453\ \ln(x_3) - 1.0159, & 20\ contractors < x_3 < 350\ contractors \\ 1.0, & x_3 \geq 350\ contractors \end{cases}$	0.983
Experience in Project Evaluation (EPE)	$u_4(x_4) = \begin{cases} 0, & x_4 \leq 0\ projects \\ 0.0102x_4 + 0.0209, & 0\ projects < x_4 < 100\ projects \\ 1.0, & x_4 \geq 100\ projects \end{cases}$	0.989
Size Limit (SL)	$u_5(x_5) = \begin{cases} 0, & x_5 \leq \$10\ Million \\ 0.2957\ln(x_5) - 0.681, & \$10 Million < x_5 < \$300\ Million \\ 1.0, & x_5 \geq \$300\ Million \end{cases}$	0.989
Largest Project Evaluated (LP)	$u_5(x_6) = \begin{cases} 0, & x_6 \leq \$1\ Million \\ 4\text{E} - 06x_6{}^3 - 0.0007x_6{}^2 + 0.0391x_6 - 0.0518, & \$1\ Million < x_6 < \$80\ Million \\ 1.0, & x_6 \geq \$80\ Million \end{cases}$	0.998

3.7 The Analytical Hierarchy Process (AHP)

The goal of using the AHP as a multiple criteria decision-making technique is to quantify the relative importance of the six experts' experience evaluation attributes A_1, A_2, …, A_6 that represent the ESC, CR, ECP, EPE, SL, and LP respectively. The main concept of the AHP (i.e., pairwise comparison) approach involves conducting a comparative judgement (comparison) between each two of the evaluation attributes.

The second section of the questionnaire contained 15 questions to conduct a pairwise comparison between the experts' six experience measures. The comparison was simply taking the form: "How important is measure A_1 when compared to measure A_2 in evaluating the surety expert's experience?" Experts were provided with a finite scale with values between 1 and 5 to compare between two values or attributes (A_i and A_j). The higher the value, the more A_i is preferred over A_j (Pedrycz and Gomide 2007). In other words, each expert was asked to provide one of pre-specified responses in either numeric or linguistic format, as shown in Table 3-6.

Table 3-6 Decision Aids for Pairwise Comparison of the AHP (Saaty 1980)

Numerical Rating	Importance
1	EQUALLY IMPORTANT
2	SLIGHTLY MORE IMPORTANT
3	STRONGLY MORE IMPORTANT
4	VERY STRONGLY MORE IMPORTANT
5	EXTREMELY MORE IMPORTANT

For example, if the two attributes to be considered in the pairwise comparison are 'current role' and 'experience in surety for construction,' the pairwise comparison was conducted as illustrated in Table 3-7:

Table 3-7 Sample for the Pairwise Comparison Question

Current Role Verses Experience in Surety for Construction	Current role	Experience in surety for construction

If the expert considers, for instance, that 'experience in surety for construction' is STRONGLY MORE IMPORTANT than "current role," the expert would assign "3" below 'current role,' as illustrated in Table 3-8:

Table 3-8 Sample for the Pairwise Comparison Value

Current Role Verses Experience in Surety for Construction	Current role	Experience in surety for construction
		3

Each surety expert provided his/her input individually, then an interactive group meeting allowed all of the participating experts to provide overall collective values (presented In Table 3-9) for the 15 pairwise comparison questions.

Table 3-9 Questionnaire Results of the Pairwise Comparisons

No.	**Attributes A_i**	**Attributes A_j**
Q1	Experience in surety for construction	Current role
	4	
Q2	Experience in surety for construction	Experience in contractor prequalification
		1
Q3	Experience in surety for construction	Experience in project evaluation
		3
Q4	Experience in surety for construction	Size limit
		4
Q5	Experience in surety for construction	Largest project evaluated
		2
Q6	Current role	Experience in contractor prequalification
		3
Q7	Current role	Experience in project evaluation
		3
Q8	Current role	Size limit
		2
Q9	Current role	Largest project evaluated
		5
Q10	Experience in contractor prequalification	Experience in project evaluation
		2
Q11	Experience in contractor prequalification	Size limit
		4
Q12	Experience in contractor prequalification	Largest project evaluated
		3
Q13	Experience in project evaluation	Size limit
		2
Q14	Experience in project evaluation	Largest project evaluated
		3
Q15	Size limit	Largest project evaluated
	1	

The results of the pairwise comparisons were then placed into a so-called reciprocal matrix $[R]_{n \times n}$ (where n is the number of attributes) of the form presented in Equation 3-4.

$$[R]_{n\times n} = \begin{bmatrix} A_{11} & A_{12} & A_{13} & \cdots & \cdots & A_{1n} \\ A_{21} & A_{22} & A_{23} & \vdots & \vdots & A_{2n} \\ A_{31} & A_{32} & A_{33} & \vdots & \vdots & A_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & A_{n3} & \cdots & \cdots & A_{nn} \end{bmatrix} = \begin{bmatrix} 1 & A_{12} & A_{13} & \cdots & \cdots & A_{1n} \\ A_{21} & 1 & A_{23} & \vdots & \vdots & A_{2n} \\ A_{31} & A_{32} & 1 & \vdots & \vdots & A_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{n1} & A_{n2} & A_{n3} & \cdots & \cdots & 1 \end{bmatrix}_{n\times n} \quad [3\text{-}4]$$

The values of the matrix diagonal are equal to 1. This matrix is reciprocal because the entire values are symmetrically positioned with respect to the diagonal. Using the developed comparison matrix, the attribute's priorities are determined by calculating the normalized version of the eigenvector associated with the largest eigenvalue, which is the desired vector of the attributes' relative weights (Pedrycz and Gomide 2007). Based on the expert assessment in Table 3-9, the priority matrix $[R]_{6\times 6}$ is developed as shown in Equation 3-5.

$$[\mathrm{R}]_{6\times 6} = \begin{bmatrix} 1.00 & 4.00 & 1.00 & 0.33 & 0.25 & 0.50 \\ 0.25 & 1.00 & 0.33 & 0.33 & 0.50 & 0.20 \\ 1.00 & 3.00 & 1.00 & 0.50 & 0.25 & 0.33 \\ 3.00 & 3.00 & 2.00 & 1.00 & 0.50 & 0.33 \\ 4.00 & 2.00 & 4.00 & 2.00 & 1.00 & 1.00 \\ 2.00 & 5.00 & 3.00 & 3.00 & 1.00 & 1.00 \end{bmatrix} \quad [3\text{-}5]$$

Then, according to Mollaghasemi and Pet-Edwards (1997) and Pedrycz and Gomide (2007), the following steps are followed to determine the priorities of the attributes. The first step is normalizing the developed matrix $[\mathrm{R}]_{6\times 6}$ by dividing the values of each column by the sum of this column, as shown in Equation 3-6.

$$[\mathrm{R}_{\mathrm{normalized}}]_{6\times 6} = \begin{bmatrix} 0.0889 & 0.2222 & 0.0882 & 0.0465 & 0.0714 & 0.1485 \\ 0.0222 & 0.0556 & 0.0294 & 0.0465 & 0.1429 & 0.0594 \\ 0.8889 & 0.1667 & 0.0882 & 0.0698 & 0.0714 & 0.0990 \\ 0.2667 & 0.1667 & 0.1765 & 0.1395 & 0.1429 & 0.0990 \\ 0.3556 & 0.1111 & 0.3529 & 0.2791 & 0.2857 & 0.2970 \\ 0.1778 & 0.778 & 0.2647 & 0.4186 & 0.2857 & 0.2970 \end{bmatrix} \quad [3\text{-}6]$$

Then, the eigenvector (measures' weights) is calculated by averaging each row of the normalized matrix, as presented in Equations 3-7 and 3-8.

$$[\text{Weight}]_{3\times1} = \begin{bmatrix} (0.8889 + 0.2222 + 0.0882 + 0.0465 + 0.0714 + 0.1485)/6 \\ (0.0222 + 0.0556 + 0.0294 + 0.0465 + 0.1429 + 0.0594)/6 \\ (0.8889 + 0.1667 + 0.0882 + 0.0698 + 0.0714 + 0.0990)/6 \\ (0.2667 + 0.1667 + 0.1765 + 0.1395 + 0.1429 + 0.0990)/6 \\ (0.3556 + 0.1111 + 0.3529 + 0.2791 + 0.2857 + 0.2970)/6 \\ (0.1778 + 0.778 + 0.2647 + 0.4186 + 0.2857 + 0.2970)/6 \end{bmatrix} \text{[3-7]}$$

$$[\text{Weight}]_{3\times1} = \begin{bmatrix} K_1 \\ K_2 \\ K_3 \\ K_4 \\ K_5 \\ K_6 \end{bmatrix} = \begin{bmatrix} 0.1109 \\ 0.0593 \\ 0.0973 \\ 0.1652 \\ 0.2802 \\ 0.2869 \end{bmatrix} \text{[3-8]}$$

The ability to measure consistency between experts' responses is an important advantage of using AHP. The lack of consistency is measured by comparing the largest eigenvalue (λ_{max}), that was computed for $[R]_{6\times6}$, with the dimensionality of the reciprocal matrix (n). $\lambda_{\max}$ is always greater than n. Full consistency accrues when $\lambda_{\max}$= n. Calculating the matrix's largest eigenvalue (λ_{max}) is done by multiplying the original matrix ($[R]_{6\times6}$) with the calculated weights ($[\text{Weight}]_{3\times1}$) then dividing the resulting matrix by the weights matrix as in Equations 3-9, 3-10, 3-11, and 3-12.

$$[R]_{6\times6} \,.\, [\text{Weight}]_{3\times1} = [RK]_{3\times1} = \begin{bmatrix} KR_1 \\ RK_2 \\ RK_3 \\ RK_4 \\ RK_5 \\ RK_6 \end{bmatrix} \quad \text{[3-9]}$$

$$[\mathrm{RK}]_{3\times1} = \begin{bmatrix} 0.8889 & 0.2222 & 0.0882 & 0.0465 & 0.0714 & 0.1485 \\ 0.0222 & 0.0556 & 0.0294 & 0.0465 & 0.1429 & 0.0594 \\ 0.8889 & 0.1667 & 0.0882 & 0.0698 & 0.0714 & 0.0990 \\ 0.2667 & 0.1667 & 0.1765 & 0.1395 & 0.1429 & 0.0990 \\ 0.3556 & 0.1111 & 0.3529 & 0.2791 & 0.2857 & 0.2970 \\ 0.1778 & 0.778 & 0.2647 & 0.4186 & 0.2857 & 0.2970 \end{bmatrix} \cdot \begin{bmatrix} 0.1109 \\ 0.0593 \\ 0.0973 \\ 0.1652 \\ 0.2802 \\ 0.2869 \end{bmatrix} = \begin{bmatrix} 0.7142 \\ 0.3721 \\ 0.6346 \\ 1.1065 \\ 1.8494 \\ 1.8733 \end{bmatrix} \quad [3\text{-}10]$$

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n} {}^{\mathrm{RK_i}}/_{\mathrm{K_i}} \quad [3\text{-}11]$$

$$\lambda_{\max} = \frac{1}{6}\sum_{i=1}^{6} \frac{0.7142}{0.1109} + \frac{0.3721}{0.0593} + \frac{0.6346}{0.0973} + \frac{1.1065}{0.1652} + \frac{1.8494}{0.2802} + \frac{1.8733}{0.2869} = 6.5089 \quad [3\text{-}12]$$

where $[\mathrm{R}]_{6\times6}$ is the priority matrix, $[\mathrm{Weight}]_{3\times1}$ is the weights matrix, and $[\mathrm{RK}]_{3\times1}$ is the resulting matrix of multiplying $[\mathrm{R}]_{6\times6}$ and$[\mathrm{Weight}]_{3\times1}$. k_i is the experts` experience measure weight and n is the matrix size.

The next step is to check the consistency of the expert responses by calculating the consistency index (ν), as presented in Equation 4-13.

$$\nu = \frac{\lambda_{\max} - \mathrm{n}}{(\mathrm{n}-1)(\mathrm{R.I.})} = \frac{6.5089 - 6}{(6-1)(1.24)} = 0.0821 \quad [3\text{-}13]$$

where R.I. is a random index determined according to the matrix size. According to Georgy (2000), the R.I. has been approximated by Saaty (1980), based on simulation runs, as presented in Table 3-10.

Table 3-10 Approximated Random Indices (R.I.) (Saaty 1980)

n	1	2	3	4	5	6	7	8	9	10
R.I.	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The lower the consistency index (lower than 0.1), the higher the consistency. To increase the consistency index, a smaller rating scale can be used, e.g., using a 7-point scale instead of a 9-point scale, or using a 5-point scale instead of a 7-point scale, and so on. According to the size of the $[\mathrm{R}]_{6\times6}$ matrix (n=6), the R.I. value is equal to 1.24 for the table developed by Saaty (1980). If the consistency index (ν) is less than 0.1, then the expert responses are consistent (Saaty 1980; Pedrycz and Gomide 2007). The calculated consistency index (ν) in Equation 4-13, which is equal to 0.0821 (i.e., <0.1), indicates that the experts' responses were consistent.

3.8 Development of the Multi-Attribute Utility Function (MAUF)

There are two approaches to determine the overall utility function. Fishburn (1965) presented the additive approach for the utility-independent attributes, as shown in Equation 3-14.

$$U(x_1, x_2, \dots, x_m) = \sum_{i=1}^{m} k_i\, u_i\,(x_i) = k_1u_1(x_1) + k_2u_2(x_2) + \dots + k_mu_m(x_m) \quad [3\text{-}14]$$

where *i*= 1,2,...; *m* is the number of attributes; and x_i, is the value of attribute *i*; While, $u_i(x_i)$, is the utility function value for attribute *i* corresponding to x_i, and K_i is the weight of attribute *i*.

Keeney (1974) developed the multiplicative approach to consider the dependency between the attributes. The multiplicative MAUF is illustrated in Equation 3-15.

$$1 + Ku(x_1, x_2, \ldots, x_m) = \prod_{i=1}^{m}[1 + Kk_i u_i(x_i)] \text{ [3-15]}$$

where every variable has the same meaning previously introduced (for Equation 3-14) and K is a scaling constant that is chosen to satisfy Equation 3-16.

$$1 + K = \prod_{i=1}^{m}[1 + Kk_i] \text{ [3-16]}$$

The main condition for the validity of applying the additive MAUF is that mutual independence exists between the attributes, or that the summation of the relative preference values is equal to 1.0 (Georgy 2000; Keeney 1974). A very weak correlation (i.e., mutual independence) was found between the experience measures (i.e., using the data from the participating 33 surety experts, all Pearson correlation coefficients were found to be less than 0.45), and the summation of the relative preference values of the six experience measures was equal to 1.0 (as a result of using the AHP). Consequently, the additive utility function, presented by Fishburn (1965), was used, as shown in Equation 3-17.

$$U(x_1, x_2, \ldots, x_m) = \sum_{i=1}^{m} WV_i\, u_i\,(x_i) = WV_1 u_1(x_1) + WV_2 u_2(x_2) + \ldots + WV_m u_m(x_m) \text{ [3-17]}$$

where *i* = 1,2,...; *m* is the number of attributes (experience measures); x_i is the value of the attribute *i*; $u_i(x_i)$ is the utility function value for attribute *i* corresponding to x_i; and WV_i is the preference value of the attribute *i*.

Example:

Assume for a surety expert the following values (as in Table 3-11) are his/her experience measures. Then, according to the developed individual utility functions and the expert's values, the corresponding utility values are determined as follows:

Table 3-11 Surety Expert Experience Measures and Utility Values

Experience Measures	Actual Value (x)	Utility Value u(x)	Weights (k_i)
Experience In Surety for Construction (ESC)	10 Years	0.691	0.220
Current Role (CR)	(3) Intermediate broker/underwriter	0.650	0.104
Experience in Contractor Prequalification (ECP)	50 Contractors	0.335	0.206
Experience in Project Evaluation (EPE)	70 Projects	0.720	0.220
Size Limit (SL)	50 MM	0.473	0.084
Largest Project Evaluated (LP)	120 MM	1.000	0.166

Using the expert utility values and the relative weights obtained for the experience measures, the overall surety expert weight can be determined as in Equation 3-18:

CWF $[u(x_1, x_2, \dots, x_6)]$ = (0.220 * 0.691) + (0.104*0.650) + (0.206*0.335) + (0.220*0.720) + (0.084*0.473) + (0.1664*1.000) = 0.641 [3-18]

Data on the six experience measures for each of the participating 33 surety experts were collected using a web-based survey. Table 3-12 illustrates sample experience measure values for the participating surety experts, their calculated worth value (WV) for each experience measure, and their overall consensus weight factor (CWF).

Table 3-12 Sample of the Attributes' Values, Worth Values, and Consensus Weight Factors for the Participating Experts

Values of Experience Attributes for the Surety Experts						Corresponding Worth/Utility Values						Overall Consensus Weight Factor
CR	ESC (years)	ECP (contractors)	EPE (projects)	SL (MM$)	LP (MM$)	CR_WV	ESC_WV	ECP_WV	EPE_WV	SL_WV	LP_WV	CWF
Manager	11	750	5000	60	55	1.000	0.733	1.000	1.000	0.527	0.796	0.781
Manager	22	500	3000	4000	60	1.000	1.000	1.000	1.000	1.000	0.815	0.965
Senior	23	300	1500	200	45	0.850	1.000	0.953	1.000	0.882	0.751	0.901
Manager	12	250	700	580	65	1.000	0.733	0.890	1.000	1.000	0.832	0.919
Senior	15	200	3000	50	35	0.850	0.872	0.813	1.000	0.473	0.696	0.731
Senior	24	100	200	30	30	0.850	1.000	0.574	1.000	0.322	0.662	0.666
Senior	19	10	30	25	15	0.850	0.977	0.000	0.320	0.269	0.510	0.426
Senior	15	30	100	2.5	40	0.850	0.872	0.158	1.000	0.000	0.726	0.511
Senior	10	20	200	1000	25	0.850	0.733	0.000	1.000	1.000	0.622	0.759
Intermediate	3	5	20	10	5	0.650	0.154	0.000	0.220	0.000	0.268	0.156
Manager	25	500	10000	1300	50	1.000	1.000	1.000	1.000	1.000	0.775	0.958
Senior	11	50	100	3000	47	0.850	0.733	0.335	1.000	1.000	0.761	0.827
Manager	24	500	1000	300	50	1.000	1.000	1.000	1.000	1.002	0.775	0.958
Manager	20	150	1000	130	80	1.000	1.000	0.714	1.000	0.755	1.000	0.847
Senior	20	1000	300	300	60	0.850	1.000	1.000	1.000	1.002	0.815	0.955
Senior	20	50	100	240	57	0.850	1.000	0.335	1.000	0.936	0.803	0.851
Intermediate	7	100	100	65	54	0.650	0.532	0.574	1.000	0.550	0.792	0.683
Manager	22	1000	5000	130	48	1.000	0.977	1.000	1.000	0.755	0.766	0.878
Junior	3	150	400	20	31	0.000	0.154	0.714	1.000	0.203	0.669	0.474
Intermediate	7	350	3000	80	35	0.650	0.532	1.006	1.000	0.612	0.696	0.737

3.9 Validation of the Surety Experts Weighting (Group Consensus) System

The surety experts' GCS was validated using two approaches: (1) face validation and (2) numerical validation. Face validation, as presented by Lucko and Rojas (2010), was conducted to get the approval of non-researchers (experts) regarding the validity of the study. The face validation process began with a presentation to the surety experts of the concept, the proposed methodology, and the objective of developing a group consensus system. All the participating experts agreed with the proposed methodology, indicated the suitability of the methodology to determine experience weights for the surety practitioners, and noted the advantage of using the group consensus system for developing the contractor prequalification fuzzy expert system. Also, the face validation was considered during all of the system's development stages, starting with defining the experience attributes that should be considered and the quantification method for each one. Then, the responses that were provided to the developed questionnaire helped to build the individual utility functions and determine the attributes' relative importance weights. Each one of these stages has been conducted in two rounds. The first round was done by obtaining the experts' feedback and inputs individually. Then, the second round was done by conducting a group meeting, wherein the participating experts interacted to achieve a common approval regarding the collected information. All participating surety experts noted their acceptance with all of the collected data. The last stage of the face validation was done by presenting the results of the system to the experts by providing them with the 33 surety experts' experience values and the corresponding calculated overall experience weights. The experts completely agreed with the system's results.

Following these stages of applying the face validation approach, a numerical validation was performed for further validation of the developed surety experts' group consensus system.

From the 33 surety experts' cases that were collected, 10 cases were randomly chosen for the validation process. The experience measure values for these cases (in Table 3-13) were presented to the participating surety experts to provide a score for overall experience weight (CWF) for each case from 0 to 1.0, according to their own opinion. Then the developed system was used to calculate the CWF for each case. Table 3-13 presents the CWF values provided by the surety experts and the calculated values by the GCS as well.

Table 3-13 GCS Validation Cases (Awad and Fayek 2012)

Expert ID	CR	ESC (years)	ECP (contractors)	EPE (projects)	SL (MM$)	LP (MM$)	Given CWF	Calculated CWF	Error %
1	Manager	25	500	3000	4000	55	1.00	0.962	3.84%
2	Senior	19	10	30	25	15	0.60	0.426	29.01%
3	Senior	11	20	200	1000	25	0.80	0.759	5.07%
4	Manager	22	500	1000	300	55	1.00	0.962	3.79%
5	Manager	19	150	1000	130	55	0.90	0.848	5.75%
6	Intermediate	7	100	100	65	55	0.70	0.684	2.28%
7	Junior	3	100	1000	25	25	0.50	0.468	6.31%
8	Junior	3	300	2250	31.5	15	0.60	0.515	14.18%
9	Intermediate	7	250	2000	100	55	0.70	0.762	8.84%
10	Senior	22	300	5000	200	45	1.00	0.901	9.93%

The average percent error between the experts' and the GCS's scores were calculated using Equation 3-19.

$$\text{Average Percent Error} = \frac{\left(\sum_{i=1}^{z}\left|\frac{\text{GCS Score}_i - \text{Experts' Score}_i}{\text{Experts' Score}_i}\right|\right)}{z} \times 100 \quad [3\text{-}19]$$

where "GCS score" is the CWF provided by the GCS according to the experience measure values for each of the 10 expert cases, "experts' score" is the CWF provided by the five surety experts (collectively agreed) for each case, *i* is the individual case number, and *z* is the total number of cases (10).

Table 3-14 shows the experience measure values provided by the surety experts, the GCS for the validation cases, and the calculated percent error. The GCS has an average percent error (calculated using Equation 3-16) of 8.9% (i.e., 91.1% accuracy), with a 95% confidence interval between 14.5% and 3.3% (i.e., 85.5% and 96.7% accuracy).

Table 3-14 Experts' GCS Validation Results (Awad and Fayek 2012)

Case No.	Experts scores	GCS scores	Error Percentage
Case 1	1.00	0.962	3.84%
Case 2	0.60	0.426	29.01%
Case 3	0.80	0.759	5.07%
Case 4	1.00	0.962	3.79%
Case 5	0.90	0.848	5.75%
Case 6	0.70	0.684	2.28%
Case 7	0.50	0.468	6.31%
Case 8	0.60	0.515	14.18%
Case 9	0.70	0.762	8.84%
Case 10	1.00	0.901	9.93%
Average error percentage			**8.90%**

3.10 Concluding Remarks

This chapter presents a novel methodology for finding a group consensus function that aggregates experts' judgment scores to represent a common opinion. A group consensus system (GCS) has been developed to determine the consensus weight factor (CWF) of experts working in surety within the construction industry, in order to incorporate their input as a collective opinion. The multi-attribute utility function (MAUF) methodology, which considers the preferences (liking) of six experience attributes in order to determine the CWF for surety experts, was used. The Analytical Hierarchy Process (AHP) was used to determine the liking of the experience attributes. The consistency index showed that the experts' responses were consistent. Two validation approaches have been applied to validate the developed GCM: face validation and numerical validation. The GCS was validated against the experts' assessment, and showed 91.1% accuracy, with a 95% confidence interval between 85.5% and 96.7%.

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CHAPTER 4. Contractor Default Prediction Model for Surety Bonding[1]

4.1 Introduction

Contractor default is a critical risk that can influence the outcome of projects in the construction industry. Contractor default occurs when a contractor is unable to complete the project according to the contractual obligations (Zhai and Russell 1999). Thousands of contractors face failures in the construction industry every year. According to the Office of the Superintendent of Bankruptcy Canada (2008, 2010, 2011), between 2007 and 2011, the highest frequency of the bankruptcy cases in Canada were related to the construction sector. Between 2006 and 2008, 235,397 general contractors and operative builders, heavy construction contractors, and special trade contractors in the U.S. construction industry faced business failure (Surety Information Office 2009). As a result, construction project owners and other stakeholders look for methods to predict the potential of contractors to default, in order to avoid awarding contracts to high-risk contractors. Owners commonly safeguard against the risk of contractors defaulting on the completion of a construction project by transferring this risk to surety companies (Al-Sobiei et al. 2005; Awad and Fayek 2012a). The construction industry needs, therefore, a structured contractor default prediction model to enhance the surety practitioner's decision-making in providing bonding to a contractor for a specific project.

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This chapter presents a contractor default prediction model (CDPM) that facilitates evaluation of the risk of contractor default on a specific construction project. The CDPM integrates both fuzzy set theory and expert systems, making it suitable for the appraisal of complex decisions based on expert judgment. Fuzzy set theory can incorporate uncertainty and subjectivity into the assessments of both quantitative and qualitative contractor and project-related evaluation criteria, while expert systems include the experts' knowledge and subjective judgment necessary to determine the risk of contractor default.

Russell and Jaselskis (1992) noted that previously-developed models for the evaluation of business failure are focused mainly on financial factors; however, other factors, including contractors' project management practices, should be considered in evaluating the performance of construction contractors and their probability of failure. In Severson et al. (1994), the accuracy of their classification model, developed to predict claim and non-claim contracts, increased from 70% to 87.5% when they included management-related variables (e.g., cost monitoring). Tserng et al. (2011) noted that the contractor's management capability (practices) and technical expertise are essential factors for construction contractors' success. As a result, the CDPM contains an important new evaluation category to enhance the evaluation process. This new category, "contractor's organizational practices," includes a comprehensive list of contractor default evaluation criteria to measure a contractor's competency for a specific construction project. These criteria include safety management, quality management, time management, cost management, and other practices that contribute to project success.

Inputs from at least 20 surety experts across Canada were considered in several stages throughout the development and testing of the CDPM. To incorporate their input as a collective opinion, the group consensus system (GCS) (presented in chapter 4) was used to aggregate the experts' assessments into collective single values, in order to compile the required data for CDPM development.

This chapter also presents a new approach for fuzzy rule base development that combines two methods: (1) learning from examples, using hypothetical contractor default prediction cases; and (2) using the inputs' relative importance weights to develop fuzzy rules.

4.2 Background and Previous Research

When a surety company agrees to provide bonding to a contractor for a construction project, it demonstrates assurance of the contractor's financial security and project completion to the project owner by verifying that the contractor is capable of meeting the contractual obligations, and will pay its subcontractors and suppliers (Surety Information Office 2009; Russell 1990). The surety company, which could be a broker or an underwriter, conducts a comprehensive evaluation (prequalification) process to assess (predict) the possibility of contractor default by evaluating many quantitative and qualitative evaluation criteria that may affect the contractor's performance.

Previous research into predicting contractor default in the construction industry has provided a point of departure for the research presented in this chapter. Abidali and Harris (1995) presented a methodology to predict the probability of construction contractor failure that includes managerial performance variables. Russell and Zhai (1996, 1999) used stochastic modeling to predict contractor failure according to the evaluation of both macroeconomic variables and contractor financial variables. Russell and Jaselskis (1992) developed a predictive contractor failure model using a discrete choice approach based on four inputs: (1) owner-contractor effort, (2) cost monitoring effort, (3) level of support for the project manager, and (4) early involvement of the project manager. Al-Sobiei et al. (2005) used both artificial neural networks and genetic algorithms to predict the risk of contractor default. Tserng et al. (2011) presented a methodology that employs three previously-developed option-based models: (1) the Black, Scholes, and Merton (BSM) contingent claims model, (2) the Crosbie and Bohn (CB) refined option-based model, and (3) the Bharath and Shumway (BS) naive model, to measure contractor default risk.

These previous models helped identify several contractor evaluation criteria from different perspectives; however, a model that integrates the contractor's organizational practices with contractor-, project-, and contract-specific risk evaluation criteria had not been developed.

The CPDM presented in this chapter enhances previous models for contractor prequalification, evaluation, and default prediction. Firstly, the proposed model includes a more comprehensive set of contractor- and project-related evaluation criteria (120 in total). Secondly, knowledge from numerous surety experts across Canada with different levels of experience and various roles in the surety industry is incorporated into the model development. A data-based approach that uses input-output cases has been used for the development of the model's membership functions and fuzzy rule base. Additionally, the model incorporates a very important evaluation category (contractor's organizational practices), which has not been addressed in previous models. The CPDM enhances previous models and provides a structured contractor default prediction method to enhance the surety practitioner's decision-making process in providing bonding to a contractor for a specific project.

4.3 Participating Surety Experts and Data Collection

In order to collect the data required to develop the CDPM, previous research conducted by Awad and Fayek (2012a) on developing a decision support system for general contractor prequalification for surety bonding (presented in chapter 3) was presented to the Surety Association of Canada (SAC). From SAC, forty-two surety experts (underwriters and brokers), with various levels of experience in contractor prequalification and different roles in surety companies across Canada, expressed an interest in providing their expertise, and were invited to join the CDPM development process. The data required to develop the CDPM was collected from the participating surety experts in a series of six steps. Several different collection techniques were used. Figure 4-1 illustrates, in a step-by-step process, the research and model development methodology, as explained in the following sections.

In the first step, a group of five (out of the 42) highly-experienced surety experts (with no less than 10 years of experience each) participated in one-on-one and interactive group meetings: two experts came from two underwriting companies, and three experts came from two surety broker companies. These meetings yielded a comprehensive list of contractor default prediction (input) criteria for the CDPM.

In the next step, a web-based questionnaire was sent to all the participating surety experts (42 in total) to determine the relative importance weights (RIW) for the input criteria. Of the 42 experts, 33 responded (for a response rate of 78.6%). Then, another web-based questionnaire was sent to the 33 experts who responded to the RIW questionnaire, in order to estimate the initial membership functions (MBF) for the CDPM input evaluation criteria. Of the 33 experts, 21 responded to the MBF estimation questionnaire.

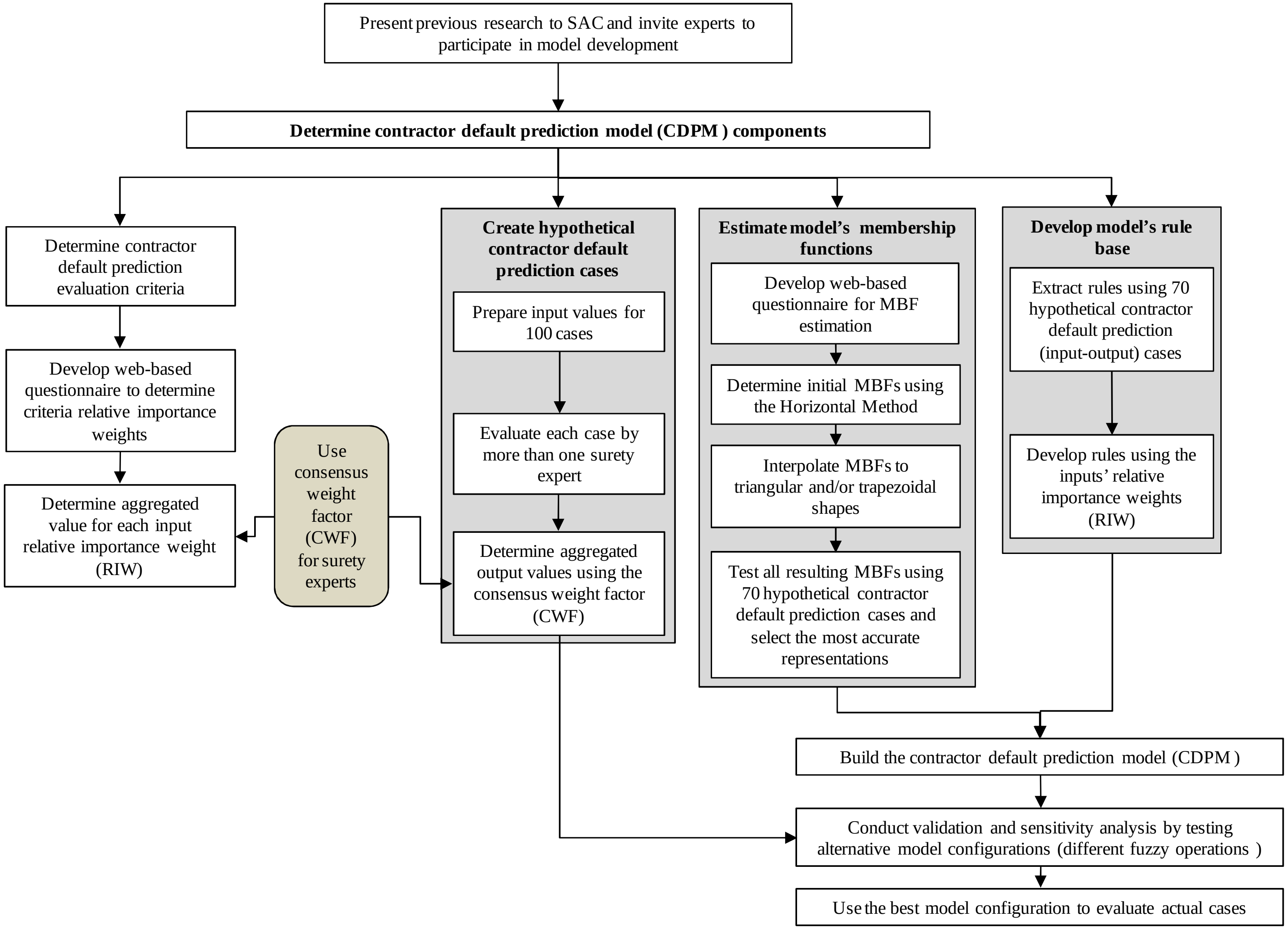

Figure 4-1 Model Development Methodology (Awad and Fayek 2012b)

Surety underwriters and brokers do not currently document all the contractor evaluation criteria (model inputs) that were established in this study. Therefore, in order to develop the model components and validate the CPDM, 27 experts (out of 33) participated in developing 100 hypothetical cases to cover the full range of possible scenarios of contractor default risk evaluation. For the development stage, 70% of the hypothetical cases were used to apply the learning-from-examples approach to extract the fuzzy rules and to estimate the fuzzy membership functions (MBF). The remaining 30% of the cases were used to validate the CDPM.

4.4 Developing the Contractor Default Prediction Model

The following subsections provide a description of the model development process, as illustrated in Figure 4-1. The development process started by preparing the model inputs, and included: (1) determining the contractor evaluation criteria, (2) developing a web-based questionnaire to determine the criteria's relative importance weights, and (3) aggregating the experts' responses using the experts' consensus weights (determined in chapter 4) to get the final relative importance weights (RIW) of the criteria. The second stage involved developing the hypothetical contractor default predication cases (as explained in subsection 4.4.3) to be used for membership function (MBF) estimation, fuzzy rule extraction, and model validation. The next stage involved developing the model components' MBFs and rule base. The MBF estimation process was done in 4 steps: (1) developing a web-based questionnaire to collect the required knowledge for MBF estimation using the horizontal method, (2) determining the initial MBFs, (3) interpolating the initially-estimated MBFs to linear shapes, and (4) developing models using all the alternative MBF representations, and testing them to determine the most accurate MBFs to be used. The final stage of the model development was rule base extraction, which was conducted in two steps: (1) rule extraction from input-output contractor default cases, and (2) rule development using the inputs' relative importance weights.

4.4.1 The Input Criteria for the CDPM

Awad and Fayek (2012a) developed a fuzzy decision support system (DSS) for surety underwriters and brokers to use in contractor prequalification for bonding a specific construction project (presented in chapter 2). The CDPM presented in this chapter enhances this DSS in three ways: by incorporating more surety experts in the development stage; by including and modifying more criteria and to predict contractor default on a specific construction project, particularly contractor's organizational practices; and by applying a new approach for fuzzy rule base extraction.

The process of adding and modifying the input criteria to enhance the developed DSS (Awad and Fayek 2012a) can be divided into three categories: (1) adding new evaluation criteria under the previously-prepared categories or subcategories, (2) modifying some criteria to improve their quantification method, and (3) adding new evaluation categories.

Many evaluation criteria that were not included in the DSS were added to the new CDPM, such as evaluation of the architect/engineer (design consultant), which has been added as a subcategory under the project team evaluation. There are three evaluation criteria to evaluate the project architect/engineer: (1) “A/E experience,” which evaluates the A/E’s experience in the construction industry; (2) “A/E reputation,” which evaluates the A/E’s reputation in the construction industry and his/her past experience with the contractor (if any); and (3) “A/E liability insurance,” which evaluates the level of errors and omissions that A/E carry and the claims history.

Some evaluation criteria were modified to make their quantification method reduce the subjectivity in the evaluation process. For instance, the contractor’s experience regarding the proposed project size was previously evaluated using a predefined rating scale from 1 to 7. Three numerical evaluation criteria were added to evaluate the project size experience of the contractor: (1) “past projects experience in size,” which is measured as the number of projects done in the past within the same size; (2) “ratio to largest project,” which is the ratio to the largest project done in the past; and (3) “project manager size experience,” which is the number of projects within the same size that the project manager has participated in. There are many criteria that have been added in the same way to reduce the subjectivity in the evaluation process, under the following subcategories: “project type/complexity experience,” “project location experience,” “project cost breakdown evaluation,” “payment clauses,” “warranty clauses,” “indemnity clauses,” “schedule extensions and price adjustment clauses,” “liquidated damages/bonuses,” “toxic and hazardous substances and materials clauses," "disputes/arbitration clauses," "design concerns clauses," and "bonding/security" evaluation.

One important evaluation component, "contractor's organizational practices," was identified by all five experts as significant in predicting contractor default. It was therefore incorporated in the CDPM. Each contractor's organizational practice was evaluated using a number of evaluation criteria, as shown in Table 4-1. This evaluation component measures how well the contractor is prepared to manage the proposed project, according to 11 project management knowledge areas that contribute to project success, 9 of which are based on the PMBOK® (Project Management Institute 2009). The 11 key areas of project management knowledge are: integration management, scope management, time management, cost management, quality management, human resource management, communications management, risk management, procurements management, safety management, and change management.

Table 4-1 Sample of Contractor Default Prediction Model (CDPM) Sub-models and Evaluation Criteria (Inputs) (Awad and Fayek 2012b)

Project Aspects Evaluation	**Contractual Risk Evaluation**	**Contractor's Organizational Practices**
"Owner Evaluation" Sub-model • Owner Type • Owner Funding Ability • Owner/Owner Agent Experience • Owner/Owner Agent Reputation **"Subcontractors Evaluation" Sub-model** • Subcontractors Bonds Value • Subcontractors Experience	**"Contract Wording/Type" Sub-model** • Contract Form Wording • Contract Type **"Payment Clauses Evaluation" Sub-model** • Architect/Engineer Role • Materials Payment • Payment Process Timing • Billing Requirement	**"Project Time Management" Sub-model** • Project Administrator Experience • Time Management Process • Time Management Documents **"Project Cost Management" Sub-model** • Cost Management Roles • Cost Management Process • Cost Management Documents

Project Aspects Evaluation	**Contractual Risk Evaluation**	**Contractor's Organizational Practices**
• Overall Subcontractors Qualification • Scope Gaps between Subcontracts **"Contractor Current Evaluation" Sub-model** • Working Capital Trend • Tangible Net Worth Trend • Gross Profit Margin Trend • Net Profit Margin Trend • Debt to Equity Ratio • Gross Profit Margin • Net Profit Margin **"Contractor Work on Hand Evaluation" Sub-model** • Contractor`s Cash Flow • Contractor`s Operating Line • Work on Hand to Aggregation Limit • Overbilled – for Contracts Under Construction • Underbilled – for Contracts Under Construction **"Project Type/Complexity Experience Evaluation" Sub-model** • Past Similar (Type/Complexity) Projects • Key Employee Type/Complexity Experience • Project Manager Type/Complexity Experience **"Project Size Experience Evaluation" Sub-model** • Past Projects Experience in Size • Ratio to Largest Project • Project Manager Size Experience **"Project Schedule Evaluation" Sub-model** • Expected Project Duration • Overall Schedule Evaluation	• Holdback Amount • Holdback Releasing **"Warranty Clauses Evaluation" Sub-model** • Warranty Periods Clauses Evaluation • Performance Warranties • Manufacture Warranties • Clear Definition of Defective Work **"Indemnity Clauses Evaluation" Sub-model** • Contractor's Negligence • Indemnity List • Liability Cap • Architect/Engineer Errors **"Schedule Extensions and Price Adjustment Clauses Evaluation" Sub-model** • Acts/Omissions Extension Clauses • Stop Orders Extension Clauses • Delays Events Extension Clauses • Acts/Omissions Price Clauses • Stop Orders Price Clauses • Delays Events Price Clauses • Notification Time Clauses **"Liquidated Damages / Bonuses" Sub-model** • Liquidated Damages Cap • Phased Completion – Liquidated Damages • Bonus Value **"Disputes /Arbitration Clauses Evaluation" Sub-model** • Dispute Resolution Method • Resolution Time Frame • Architect/Engineer Role for Documents Resolution and Interpretation	**"Project Quality Management" Sub-model** • Quality Management Plans • Quality Management Responsibilities • Quality Manager Experience • Quality Management Documents **"Project Human Resource Management" Sub-model** • Developing Human Resource Plan • Acquiring and Developing Project Team • Managing Project Team **"Project Communications Management" Sub-model** • Communication Management Process • Number/Types of Communication Roles • Communications Management Documents **"Project Risk Management" Sub-model** • Risk Plan/Identification/ Quantification • Risk Responses/Monitor/Control • Risk Management Team Experience • Procurement Responsibilities **"Project Procurement Management" Sub-model** • Procurements Manager Experience • Procurements Management Documents • Procurements Plan/Administer/Close **"Project Safety Management" Sub-model** • Safety Preplanning Meetings • Safety Toolbox Meetings • Site Safety Supervision • Number of Workers per Safety Person (on site) • Safety Incentives

Several evaluation criteria were considered to evaluate each knowledge area. For instance, in order to evaluate how prepared the contractor is to perform quality management for the proposed project, the following 4 evaluation criteria should be measured:

- Evaluation of the "quality management plans," using the following predefined 5-point scale (Table 4-2);

Table 4-2 Predetermined Rating Scale for Quality Management Plans

Rating	Description
1	NO prepared quality plan, NO process to perform quality assurance, and NO process to perform quality control
2	INADEQUATE prepared quality plan, INADEQUATE process to perform quality assurance, and INADEQUATE process to perform quality control
3	ADEQUATE prepared quality plan, AVERAGE process to perform quality assurance, and AVERAGE process to perform quality control
4	ADEQUATE prepared quality plan, ADEQUATE process to perform quality assurance, and ADEQUATE process to perform quality control
5	VERY ADEQUATE prepared quality plan, GOOD process to perform quality assurance, and GOOD process to perform quality control

- Evaluation of the "quality management responsibilities." This criterion is quantified using categorical values (yes/no) to answer the following question: "Are the roles and responsibilities for all resources (both internal and external to the project) involved with the assurance and control of quality on the project well-defined?" If the answer is "yes," the contractor should provide a copy of the responsibilities distribution chart.

- Evaluation of the "quality manager experience." This criterion is quantified as the number of years that the quality manger worked in the construction industry.
- Evaluation of the "quality management documents," using the following predefined 5-point scale (Table 4-3):

Table 4-3 Predetermined Rating Scale for Quality Management Documents

Rating	Description
1	NO prepared log/database (deliverables register), NO pre-prepared project quality review form, and NO pre-prepared project quality documentation process
2	POOR prepared log/database (deliverables register), POOR pre-prepared project quality review form, and NO pre-prepared project quality documentation process
3	AVERAGE prepared log/database (deliverables register), AVERAGE pre-prepared project quality review form, and INADEQUATE pre-prepared project quality documentation process
4	GOOD prepared log/database (deliverables register), GOOD pre-prepared project quality review form, and INADEQUATE pre-prepared project quality documentation process
5	GOOD prepared log/database (deliverables register), GOOD pre-prepared project quality review form, and GOOD pre-prepared project quality documentation process

The contractor should provide a demonstration for the deliverables register and quality review form to show how the quality of deliverables will be recorded and how quality reviews will be documented on the proposed project. Samples of the definitions of all the predetermined rating scales are presented Appendix H.

The one-on-one meetings held with the five surety experts (2 meetings each) to determine the criteria for evaluating the risk of contractor default on a specific project resulted in a total of 120 CPDM inputs. The inputs were divided into three main categories: (1) project aspects evaluation, (2) contractual risk evaluation, and (3) contractor's organizational practices (as illustrated in Figures

4-2, 4-3, and 4-4). These three categories include 31 sub-models to provide the evaluator with an assessment of the intermediate outputs, such as “owner evaluation” and “subcontractors evaluation,” in addition to an assessment of the overall contractor default risk on a specific project. Table 4-1 contains examples of the sub-models and the evaluation criteria contained in each sub-model. Appendix E presents sample definitions; quantification scales used to quantify the evaluation criteria; threshold values (red flags), below which there is a cause for concern for the variable; and favourable values, as suggested by surety experts. The red flags were created to enable the broker or underwriter to conduct further research regarding the variable that creates a red flag.

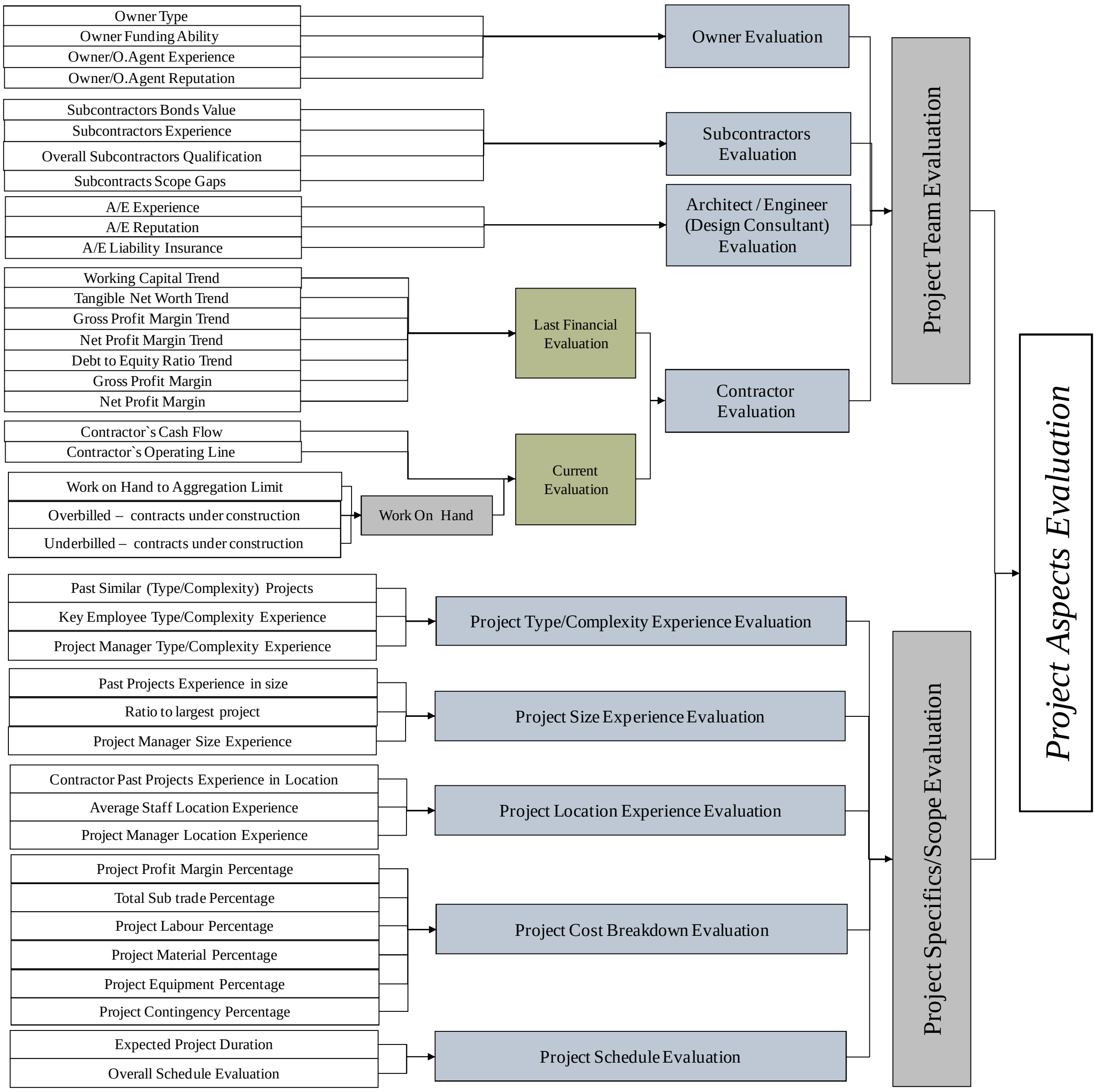

Figure 4-2 Project Aspects Evaluation

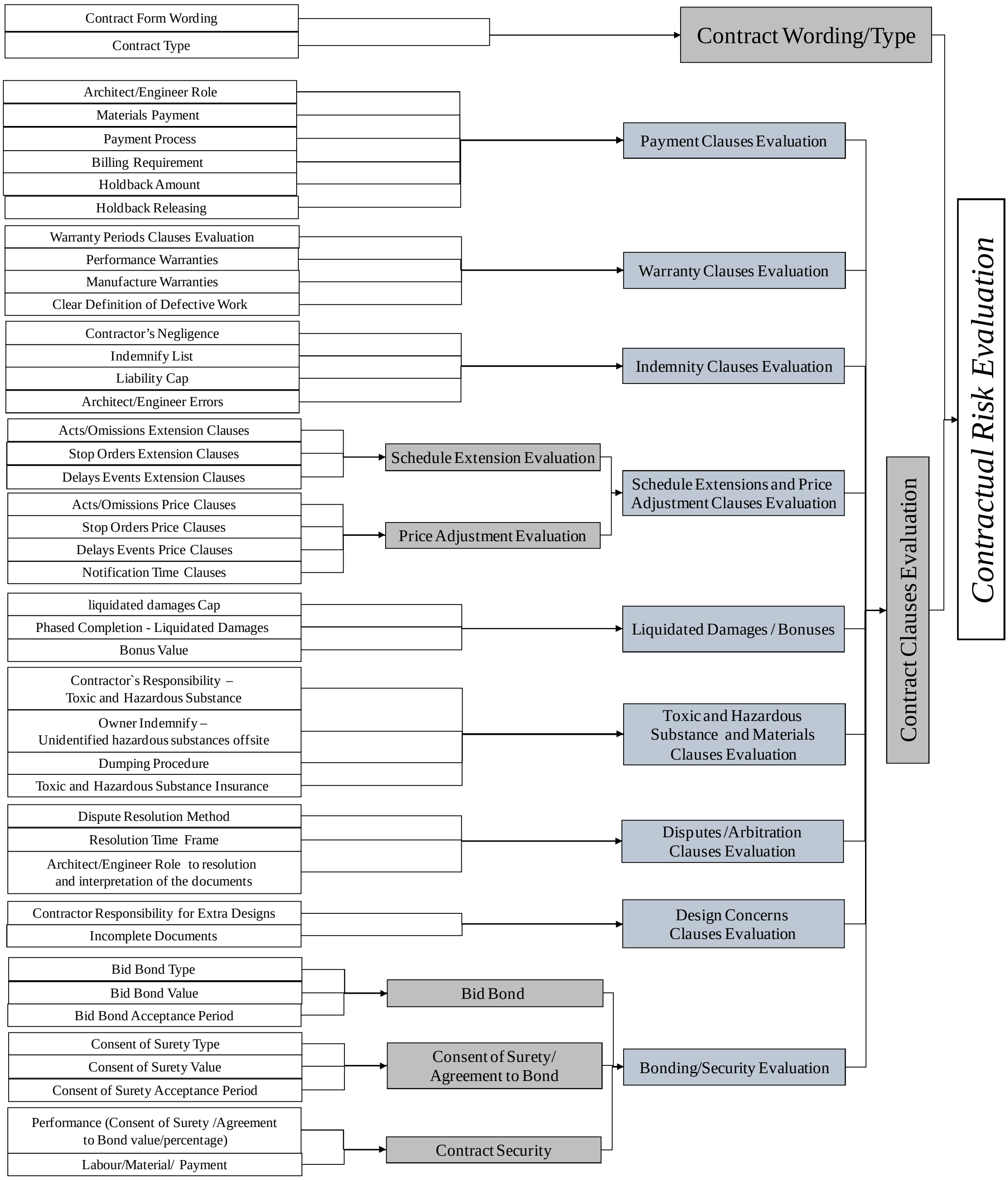

Figure 4-3 Contractual Risk Evaluation

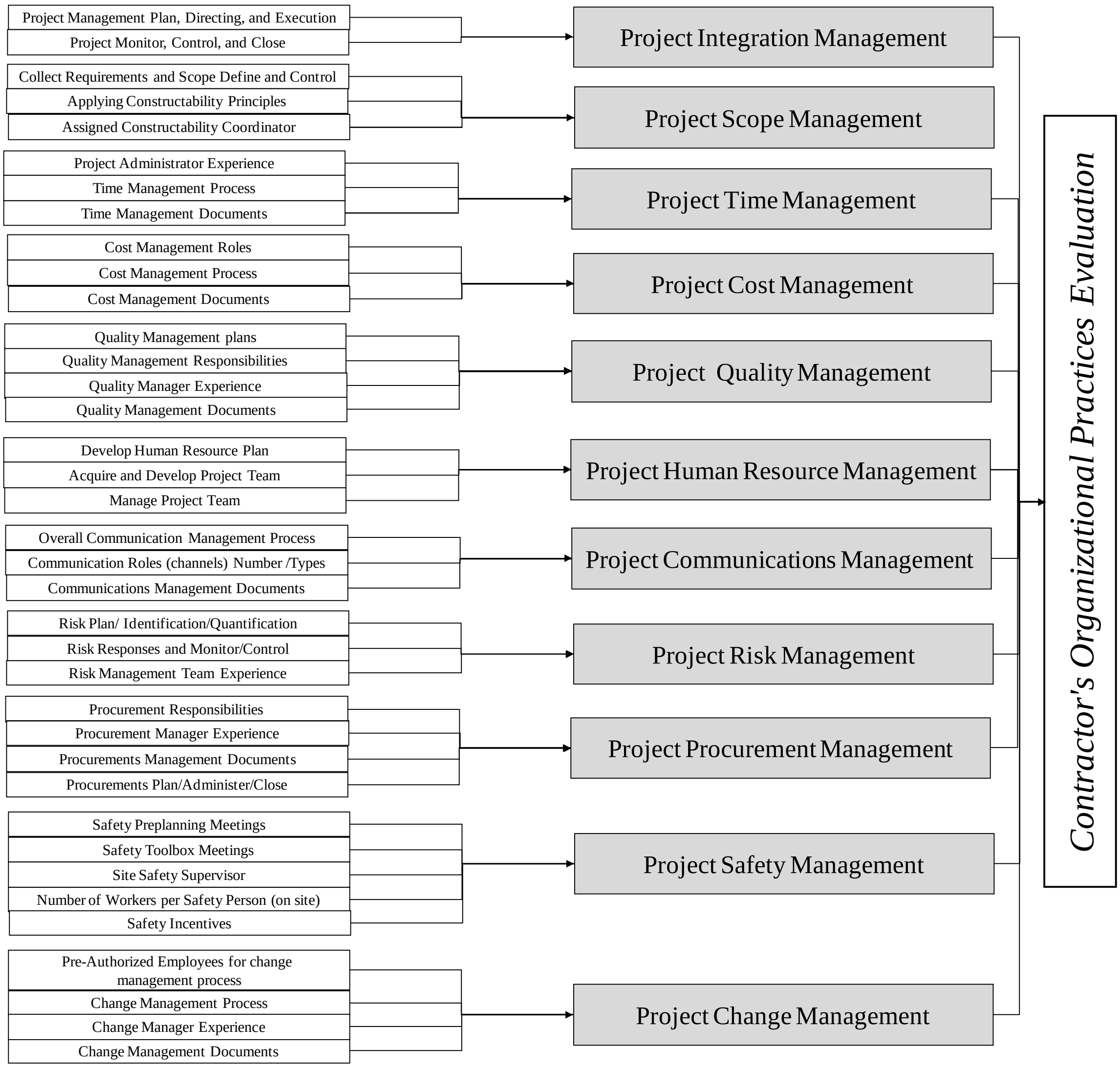

Figure 4-4 Contractor's Organizational Practices

4.4.2 Relative Importance Weight of the CDPM Input Criteria

In fuzzy expert systems, the fuzzy rules represent the experts' reasoning process, by combining the inputs ('If' part) to determine the outputs ('Then' part). One of the approaches used for developing the rule base for the CDPM depends on determining the relative importance weights (RIW) of the input evaluation criteria. The inputs' weights reflect the influence of the inputs on the corresponding output.

A web-based questionnaire was developed to determine the extent to which surety experts perceive each of the evaluation criteria to affect the output in the CDPM. Experts were asked to provide the RIW using a rating scale ranging from 1 ("minor influence") to 5 ("significant influence"). The experts were asked to weight the importance of each criterion relative to the other criteria in the same category, subcategory, or sub-subcategory. Figure 4-5 shows an example of the question included in that questionnaire. A sample of the questionnaire is presented in Appendix F.

An invitation to fill the questionnaire was sent to 42 surety experts, and 33 responded, resulting in a response rate of 78.6%. The participating experts were both brokers and underwriters, which helped achieve diversity in the acquired knowledge. Figure 4-6 illustrates the classification of participating experts according to the type of entity to which they belong. The roles of participating surety experts varied between surety underwriter/broker (11), surety manager (10), vice president (3), senior account executive (1), and senior surety underwriter/broker (8). The experience of participating experts was quantified in two ways: years in current role (average of 5.6 years), and years of experience in surety for construction (average of 13.9 years). The experience of participating experts was quantified in two ways: years in current role, and years of experience in surety for construction. Table 4-4 shows the percentage of surety experts in each category according to the number of years in their current role and in surety for construction.

***1. Specify the influence of the following input variables on the Owner Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Owner Type (Private Unknown - Private Known - Public)						
Owner funding ability						
Owner or owner agent experience						
Owner or owner agent reputation						

Comment:

***2. Specify the influence of the following input variables on the Subcontractors Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Obtaining bonds from subcontractors and total value of Bonds obtained						
Subcontractors Experience						
Overall Subcontractors Qualification						
Scope Gaps between subcontractors						

Comment:

Figure 4-5 Sample of the Input's Relative Importance Weights Questionnaire

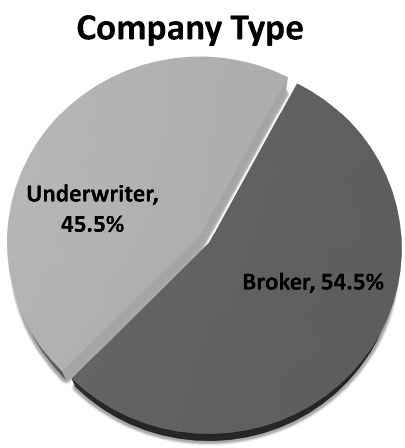

Figure 4-6 Classification of Participating Surety Experts With Respect to Company Type

Table 4-4 Levels of Experience of Participating Surety Experts

	Level of Experience						
Experience Category	**<1**	**1–4**	**5–8**	**9–12**	**13–16**	**17–20**	**>20**
Years in Current Role	0	33.5%	39.5%	9%	9%	9%	0%
Years of Experience in Surety for Construction	0	18%	15.3%	15.3%	9%	12.1%	30.3%

4.4.2.1 Questionnaire Results

To reach consensus regarding the assessment of the relative importance weights of the model input criteria, two approaches are followed. The Delphi technique was used, first by conducting two rounds of experts' feedback, then the developed group consensus system (presented in chapter 4) was used to finalize the common scores.

As presented by Yousuf (2007) and Hsu and Sandford (2007), the Delphi technique is a process to collect the opinions and judgments of experts and to achieve convergence on experts' opinions regarding a certain topic. The Delphi technique is useful when it is unlikely or impossible to collect the participating experts together in the same physical location. The main concept in applying the Delphi involves conducting more than one round of research, and providing the participating experts with feedback regarding the opinion of the other experts in order to reduce the variance in the experts' responses (Hallowell and Gambatese 2010). The Delphi technique involves an interaction between the researcher and experts to obtain highly reliable data (Yousuf 2007; Hallowell and Gambatese

2010). After collecting the experts' responses for the developed questionnaire, a detailed report has been developed containing the first round results. Only aggregate findings were revealed, and no individual data was associated with an individual respondent. Experts were asked to review the results presented in the report and provide the researcher with their comments and/or any changes in their opinions. Table 4-5 presents a sample of the final inputs from participating experts. Each expert selected the level of influence of each input on the corresponding output. The influence level was either "NO influence," or an influence rate given using a 1 to 5 rating scale, where 1 is "minor influence" and 5 is "significant influence." The input's influence rate was determined compared with the other inputs in the same category (not absolute rate). The percentages presented in Table 4-5 are the percentages of the numbers of experts who selected a certain influence level, compared to the total number of experts who responded (33). The shaded numbers represent the highest percentages.

Table 4-5 The Relative Importance Weight of The "Owner Evaluation" Criteria

Input variables for Owner Evaluation	**Influence Level**					
	No Influence	**1 "Minor Influence"**	**2**	**3**	**4**	**5 "Significant Influence"**
Owner Type	0%	0%	0%	15%	52%	33%
Owner Funding Ability	0%	0%	0%	0%	6%	94%
Owner/O. Agent Experience	0%	0%	0%	73%	27%	0%
Owner/O. Agent Reputation	0%	0%	75%	25%	0%	0%

The questionnaire results were used to identify the most important criteria, and to screen out those with a minor impact on the bonding broker's or underwriter's judgment. After getting the feedback and changes from all the participating experts, the final experts' assessments were provided to the developed group consensus system to reach one value for each importance value. The final ratings were then used to generate the rules that logically relate each input variable (i.e., the evaluation criteria) to the output variable. This activity is explained later in this chapter. Due to the large number of evaluation criteria, and to the practical limitations of fuzzy expert systems, a hierarchical organizational structure was created for the input criteria.

4.4.2.2 Using the Group Consensus System to Aggregate the Questionnaire Results

Using Equation 4-1, the CWFs for the surety experts were used to reach one aggregate value for each input relative importance weight (*RIW*), where the summation of each individual expert's score (IS_k^n) is multiplied by the expert's consensus weighting factor (CWF_k^n) and divided by the summation of all experts' CWFs.

$$Aggregated\ Input\ RIW\ _k^N = \frac{\sum_{n=1}^{N} IS_k^n * Expert's\ CWF^n}{\sum_{n=1}^{N} Expert's\ CWF^n} \quad [4\text{-}1]$$

where $Aggregated\ Input\ RIW$ is the aggregated assessment of the CDPM's input (evaluation criteria) importance weights, and N is the number of participating experts who provided their inputs for the k^{th} evaluation criterion weight. For example, if three experts with CWFs of 0.852, 0.427, and 0.952 provided importance scores of 4, 5, and 3 respectively, then the aggregated relative importance weight is calculated as shown in Equation 4-2.

$$Aggregated\ Input\ RIW\ = \frac{(4\times 0.852)+(5\times 0.427)+(3\times 0.952)}{0.852+0.427+0.952} = 3.8 \quad [4\text{-}2]$$

Table 4-6 presents the experts' assessment scores collected for the input criteria to evaluate the owner of the proposed construction project. Under each evaluation criteria, there are two columns. The first column includes the scores provided by each surety expert (the influence level), while the second column includes the experts processed score (multiplied by the expert's CWF). Using Equation 4-1, the final importance values for "owner type," "owner funding ability," "owner or owner agent experience," and "owner or owner agent reputation" on "owner evaluation" are 4.0, 5.0, 3.0, and 2.0 respectively.

Table 4-6 Owner Evaluation Criteria Importance Weights

Owner Type		Owner Funding Ability		Owner or Owner Agent Experience		Owner or Owner Agent Reputation	
Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score
3	0.0945	5	0.1575	4	0.1260	2	0.0630
4	0.1551	5	0.1938	3	0.1163	2	0.0775
4	0.1453	5	0.1816	3	0.1089	2	0.0726
4	0.1471	5	0.1839	3	0.1104	2	0.0736
5	0.1473	5	0.1473	4	0.1178	2	0.0589
5	0.1355	5	0.1355	4	0.1084	2	0.0542
4	0.0687	5	0.0859	3	0.0515	2	0.0343
4	0.0815	5	0.1019	3	0.0611	2	0.0407
4	0.1225	5	0.1531	3	0.0919	2	0.0612
4	0.0252	5	0.0315	3	0.0189	2	0.0126
5	0.1938	5	0.1938	3	0.1163	2	0.0775
3	0.1008	4	0.1344	2	0.0672	3	0.1008
4	0.1552	5	0.1939	3	0.1164	2	0.0776
3	0.1026	5	0.1710	3	0.1026	2	0.0684

Owner Type		Owner Funding Ability		Owner or Owner Agent Experience		Owner or Owner Agent Reputation	
Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score	Experts Scores	Experts Processed Score
5	0.1918	5	0.1918	4	0.1534	2	0.0767
5	0.1712	5	0.1712	3	0.1027	2	0.0685
5	0.1379	5	0.1379	1	0.0276	2	0.0552
4	0.1425	5	0.1781	3	0.1069	3	0.1069
3	0.0580	4	0.0773	4	0.0773	3	0.0580
4	0.1219	5	0.1524	4	0.1219	3	0.0914
4	0.1486	5	0.1857	3	0.1114	2	0.0743
5	0.1536	5	0.1536	4	0.1229	2	0.0614
5	0.0944	5	0.0944	3	0.0567	2	0.0378
5	0.1763	5	0.1763	4	0.1411	2	0.0705
4	0.0830	5	0.1038	3	0.0623	2	0.0415
5	0.0950	5	0.0950	4	0.0760	2	0.0380
4	0.1478	5	0.1848	3	0.1109	3	0.1109
4	0.1485	5	0.1857	3	0.1114	2	0.0743
3	0.0922	5	0.1536	2	0.0614	3	0.0922
5	0.1894	5	0.1894	3	0.1137	2	0.0758
4	0.1392	5	0.1740	3	0.1044	3	0.1044
4	0.0762	5	0.0953	3	0.0572	2	0.0381
4	0.1453	5	0.1816	3	0.1089	3	0.1089
Aggregated Score	**4.0**	Aggregated Score	**5.0**	Aggregated Score	**3.0**	Aggregated Score	**2.0**

4.4.3 Creating the Hypothetical Contractor Default Prediction Cases

Surety underwriters and brokers do not currently document all evaluation criteria (inputs) that were established in this study. Therefore, the 33 surety experts that participated in determining the relative importance weights for the CDPM input criteria were invited to participate in the evaluation of 100 hypothetical contractor default prediction cases for MBF and rule base estimation, and 27 responded. Many hypothetical cases were developed to cover the full range of possible contractor default prediction scenarios. The cases were distributed among the experts, who were asked to provide the appropriate output values according to the given input values. Evaluation of each case included assessment of the output value for each sub-model, in addition to the output value for the overall contractor default risk, based on the given input values (120 criteria). Due to the experts' time limitations, only 100 hypothetical contractor default prediction cases were created and evaluated, and these were sufficient to cover all possible contractor default prediction cases. The participating surety experts were classified according to their CWF into three experience categories: "low experience" if the CWF was less than 0.5, "intermediate experience" if the CWF was more than 0.5 and up to 0.8, and "high experience" if the CWF was more than 0.8. Surety experts were consulted to set the rules to select the surety experts for the contractor default prediction cases as follows: (1) each case would be evaluated by a group of three surety experts, (2) each group of experts should include the two surety roles (broker and underwriter), and (3) each group should include experts with different levels of experience (if it is possible). According to the group formulation rules, 10 surety expert groups were developed as presented in Table 4-7.

Table 4-7 Surety Experts Groups for Developing the Contractor Default Prediction Cases

Group No.	Surety Role	CWF	Experience Level
Group 1	Broker	0.962	High Experience
	Underwriter	0.684	Intermediate Experience
	Underwriter	0.471	Low Experience
Group 2	Broker	0.833	High Experience
	Broker	0.731	Intermediate Experience
	Underwriter	0.473	Low Experience
Group 3	Underwriter	0.962	High Experience
	Broker	0.762	Intermediate Experience
	Broker	0.426	Low Experience
Group 4	Broker	0.921	High Experience
	Underwriter	0.759	Intermediate Experience
	Broker	0.156	Low Experience
Group 5	Broker	0.951	High Experience
	Underwriter	0.756	Intermediate Experience
	Underwriter	0.468	Low Experience
Group 6	Broker	0.940	High Experience
	Broker	0.672	Intermediate Experience
	Underwriter	0.479	Low Experience
Group 7	Broker	0.849	High Experience
	Broker	0.505	Intermediate Experience
	Underwriter	0.962	High Experience
Group 8	Broker	0.848	High Experience
	Underwriter	0.515	Intermediate Experience
	Underwriter	0.884	High Experience
Group 9	Underwriter	0.912	High Experience
	Underwriter	0.762	Intermediate Experience
	Broker	0.875	High Experience
Group 10	Underwriter	0.901	High Experience
	Underwriter	0.781	Intermediate Experience
	Broker	0.863	High Experience

Special forms were developed using Microsoft Excel® to evaluate the contractor default prediction cases. These forms were designed in a way to make the evaluation process easy and to enable the expert to provide the evaluation assessment score to the final output in addition to the values of the intermediate outputs. When the expert provided the assessment score for the outputs, these output scores became inputs for the higher level. Then, the expert provides the corresponding higher output assessment score. The forms also included an explanation of every input factor and the meaning of every scaling point in the rating scale. All the instructions, explanations, and illustrated graphical examples regarding the evaluation process and how to use the developed forms were developed and sent to all the participating experts with the cases. Each group of surety experts were asked to evaluate 10 hypothetical cases. Each case contained proposed values for each input evaluation criterion. The experts were required to provide the corresponding appropriate output assessment score from their own perspective. All the output criteria are quantified using a 5-point rating scale (as recommended by the surety experts), except for the final overall contractor default prediction value, in which a 7-point rating scale (1 to 7) is used. For scoring the output values, experts were informed that they could use integer values (i.e., 1, 2, 3…) or fractions (e.g., 1.2, 3.5, 4.7…). As a result of this process, each of the hypothetical cases contained the values of each input evaluation criterion, and the corresponding sub-model output value, in addition to the corresponding overall prequalification value. Table 4-8 presents samples of the owner evaluation input and output values for 10 cases (evaluated by first group of experts). After obtaining the output values from each group of three experts, the assessments were aggregated using Equation 4-3, according to the CWF for the experts (aggregated values presented in Table 4-8).

$$Aggregated\ Output\ Value\ _k^N = \frac{\sum_{n=1}^{N} Expert\ Assessment\ _k^n * Expert's\ CWF^n}{\sum_{n=1}^{N} Expert's\ CWF^n} \quad [4\text{-}3]$$

where $Aggregated\ Output\ Value_k^N$ is the aggregated CDPM output value, and N is the number of participating experts who provided their output assessment for the k^{th} contractor default prediction case. Of the 100 hypothetical contractor default prediction cases developed, 70 were selected randomly for membership function estimation and rule base development for the CDPM, and the remaining cases were used for CDPM validation and sensitivity analysis. A sample of the developed cases is presented in Appendix G.

Table 4-8 Sample of the Collected Cases for the Owner Evaluation Sub-Model (Awad and Fayek 2012b)

Case No.	Owner Evaluation							
	Owner Type	Owner Funding	Owner/Owner Agent Experience	Owner/ Owner Agent Reputation	Output Expert 1	Output Expert 2	Output Expert 3	Aggregated Score
Group1 (Experts' CWF)					**0.962**	**0.684**	**0.471**	
1	Public	1	1	1	2.5	1.5	1.0	**1.84**
2	Public	3	0	3	4.0	2.5	3.0	**3.29**
3	Public	5	0	5	4.5	3.5	4.0	**4.07**
4	PrivateKnown	1	6	2	1.5	2.0	1.5	**1.66**
5	PrivateKnown	3	6	3	2.5	3.5	3.0	**2.93**
6	PrivateKnown	5	5	5	4.3	4.6	4.0	**4.33**
7	PrivateUnknown	1	9	1	1.0	2.5	1.5	**1.60**
8	PrivateUnknown	3	11	3	2.5	3.0	4.0	**3.00**
9	PrivateUnknown	5	15	5	4.5	4.0	4.6	**4.36**
10	Public	1	5	5	3.6	2.0	3.0	**2.95**

4.4.4 Membership Function Estimation

In fuzzy expert systems, the input criteria are described by linguistic terms, which are represented by membership functions (MBFs). The MBFs for the CDPM were estimated by integrating both knowledge-based and data-integration approaches, as presented by Awad and Fayek (2012a) (in chapter 2, subsection 2.3.2). The MBFs were initially estimated with the horizontal method, using the expert knowledge that was collected via the MBF estimation web-based questionnaire. A sample of the MBF estimation questionnaire is presented in Appendix H. For each input criterion, several values on the quantification scale (universe of discourse) for each fuzzy set were presented to the surety experts to assess which values correspond to which linguistic terms used to describe the criterion. The experts' responses were used to determine the membership degree of each value in the fuzzy set representing each linguistic term for each criterion. Next, the estimated membership functions were interpolated to the most practical and commonly used shapes (triangular and trapezoidal). The interpolation process resulted in more than one solution representing each membership function. A sample of the interpolation process results are presented in Appendix I. Finally, all the possible MBF representations were tested using 70 of the hypothetical contractor default predication cases. The input values for each case were presented to the sub-model to determine the corresponding predicted output as a crisp value. The variation between the predicted output value and actual output value (provided by the underwriter or broker) was calculated. The only difference between each solution for the same sub-model was the MBFs that represent the input linguistic terms. The comparison between the accuracy of the different solutions therefore reflects the accuracy of the MBFs. The best MBFs were used to build the CDPM (see chapter 3, subsection 3.3.2 for more details).

4.4.5 Rule Base Development

Fuzzy rules can be developed using one of two methods: (1) extraction using input-output, historical cases, or databases; or (2) using an expert or a group of experts with knowledge of the research topic (Del Campo 2004; Chen and Tsai 2005). Using the first approach helps in developing rules that reflect actual cases, but it is often not enough to cover all possible scenarios of input-output (Wang and Mendel 1992). To cover all possible scenarios, this research used both methods: input-output cases and experts' knowledge, both of which are described next.

4.4.5.1 Rule Extraction Using Input-Output Cases

The learning-from-examples approach was initially followed for fuzzy rule extraction from the available contractor default prediction (input-output) cases. In fuzzy expert systems, the relationships between the inputs and outputs are expressed using linguistic terms. Figure 4-7 shows the steps of applying learning from examples for fuzzy rule extraction. The process started with selecting a contractor default prediction case that contains crisp input values and the corresponding output score. Then the cases' input and output values are transformed to the best linguistic terms. As presented by Wang and Mendel (1992) and Ross (2004), the transformation was done in two steps: (1)

determining the membership degree of the input and output values in each linguistic term, then (2) selecting the linguistic terms with the maximum membership degree for the input and output variables to generate the fuzzy rule. The detailed algorithm for fuzzy rules extraction from contractor default prediction cases was performed according to the following detailed steps:

- Select a contractor default prediction case/instance.
- Select an input value.
- Determine the membership degree of the input in each linguistic term and the corresponding membership value.
- Select the linguistic term that has the highest membership value for the input.
- Repeat steps 2, 3, and 4 for all the input values.
- Determine the linguistic terms for the output and the corresponding membership values.
- Select the linguistic term that has the highest membership value for the output.
- Construct the fuzzy rule, where the "If" part contains the all the inputs' linguistic terms and the "Then" part contains the output's linguistic term.
- Determine the "degree of attainment."
- Repeat all the steps from 1 to 9 for all the available prequalification cases/instances.
- Review all the extracted rules for any conflicts.
- For any conflicts, select the rule with the highest degree of attainment and eliminate the other conflicting rules.

Each of the 70 cases is used in a similar way to generate the rule base. In fuzzy rules extraction using learning from examples, it is always possible to have conflicting rules. Conflicting rules are rules with the same linguistic terms for the inputs but different linguistic terms for the output (Wang and Mendel 1992). To resolve the problem of conflicting rules, a value is calculated for each rule. This value depends on inputs' and the output's membership degrees and is called the "degree of attainment" (DoA) (Ross 2004).

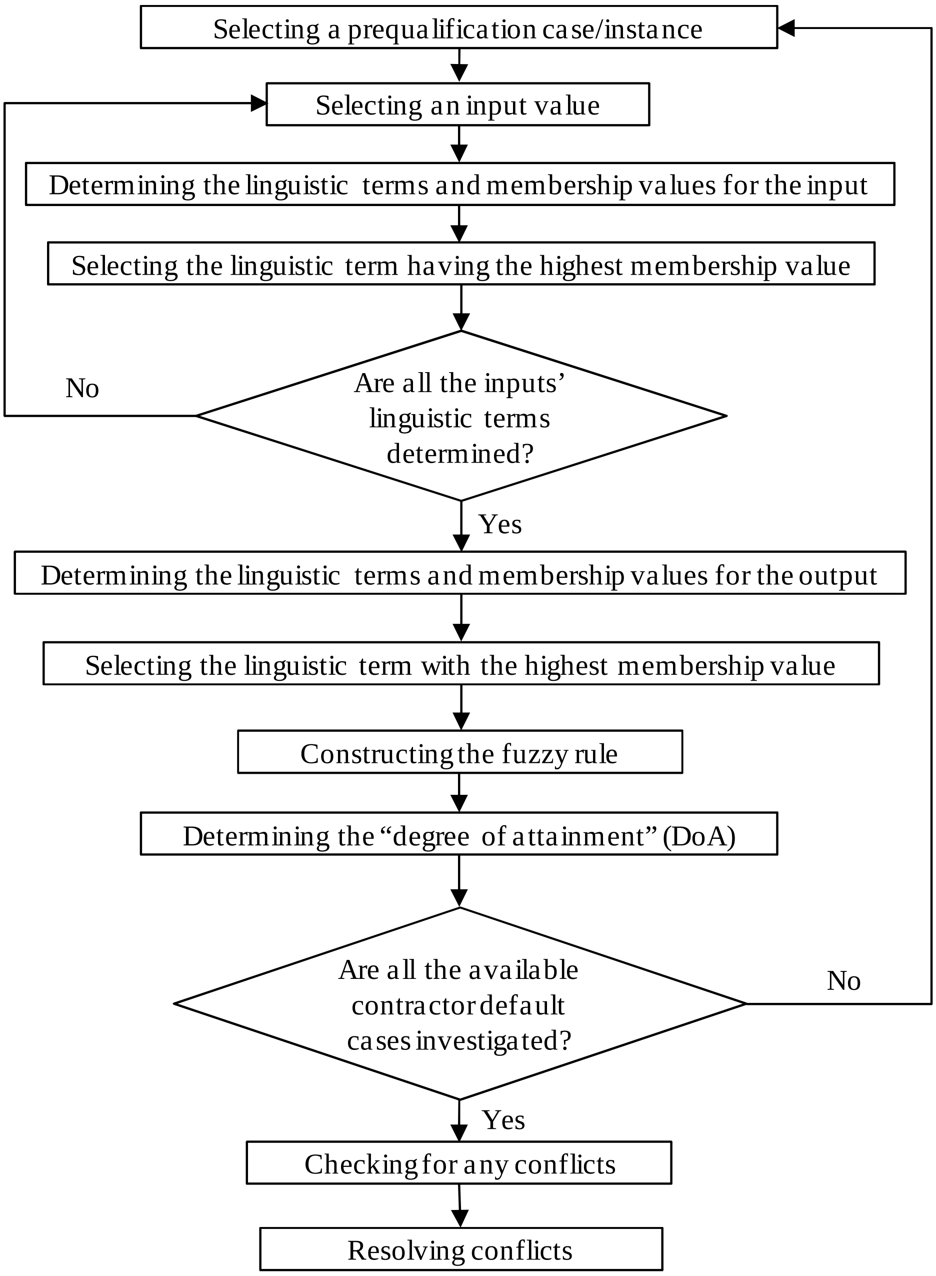

Figure 4-7 Fuzzy Rule Extraction by Learning from Examples (Awad and Fayek 2012b)

The DoA is calculated as in Equation 4-4, where $\mu_{x_t^l}$ is the membership degree of the inputs according to the inputs' values for the contractor default predication cases, and μ_{y^l} is the membership degree of the corresponding output value, where, t is the number of inputs in the l^{th} case. Then, only the rule that has the maximum DoA is retained from the conflicting group of rules.

$$DoA^l = \mu_{x_1^l} \times \mu_{x_2^l} \times \dots \dots \dots \mu_{x_t^l} \times \mu_{y^l} \quad [4\text{-}4]$$

Table 4-9 illustrates an example for the application of learning from examples for rule extraction on the "owner evaluation" sub-model. In this case, there are 4 inputs for "owner evaluation": (1) "owner type" (a categorical criterion), which was "private known" (i.e., there is previous experience between the project owner and the contractor); (2) "owner funding," with a rate equal to 3 (average) on a 1–5 rating scale; (3) "owner/owner agent experience," with 6 years (medium) of experience in the construction industry; and (4) "owner/owner agent reputation," with a rate equal to 3 (average) on a 1–5 rating scale. Three surety experts, with CWFs of 0.962, 0.684, and 0.471, assessed the "owner evaluation" as follows: 2.5, 3.5, and 3.0 respectively. Using Equation 4-3, the aggregated output ("owner evaluation") value is equal to 2.9 (average). The resulting rule is as follows: **"If** 'owner type' is 'private known,' 'owner funding' is 'average,' 'owner/owner agent experience' is 'medium,' and 'owner/owner agent reputation' is 'average,' **THEN** 'owner evaluation' is 'average.'" The DoA of this rule is equal to 0.778. Table 4-10 illustrates an example of two conflicting rules with two different values of DoA.

Table 4-9 Example for Rule Extraction by Learning from Examples (Awad and Fayek 2012b)

Owner Type		Owner Funding		Owner/Owner Agent Experience		Owner/Owner Agent Reputation		Owner Evaluation	
Private Known		3 (rating)		6 (years)		3 (rating)		2.9 (rating)	
Linguistic terms	μ_{x1l}	Linguistic terms	μ_{x2l}	Linguistic terms	μ_{x3l}	Linguistic terms	μ_{x4l}	Linguistic terms	μ_{yl}
Public	0.00	Poor	0.00	Low	0.10	Poor	0.05	Poor	0.09
Private Known	**1.00**	**Average**	**1.00**	**Medium**	**0.90**	**Average**	**0.95**	**Average**	**0.91**
Private Unknown	0.00	Good	0.00	High	0.00	Good	0.00	Good	0.00
N/A	0.00	N/A	0.00	N/A	0.00	N/A	0.00	N/A	0.00
Degree of Attainment	$DoA = 1.0 \times 1.0 \times 0.9 \times 0.95 \times 0.91 = \mathbf{0.778}$								

The example illustrates (in Table 4-10) the input values of two cases of the "owner evaluation" sub-model, the corresponding output assessment of three experts with three different CWFs, and the aggregation of the three assessment values to obtain one output value. The rule with the higher DoA (case 1) was retained. Table 4-11 presents a sample of the extracted rules for "owner evaluation" and the corresponding calculated DoA.

Table 4-10 Example of Two Extracted Conflicting Rules (Awad and Fayek 2012b)

	Input Evaluation Criteria				Output				DoA
	Owner Type	Owner Funding	Owner/Owner Agent Experience	Owner/Owner Agent Reputation	Expert 1	Expert 2	Expert 3	Aggregation of the "Owner Evaluation" Assessment	
				Experts' CWFs	0.833	0.731	0.473	(2*0.883) + (3.5*0.731) + (2.8*0.473) = 2.7	0.713
Case 1					Experts' Assessment				
Input/Output Values	Public	1	2	3	2	3.5	2.8		
Membership Degrees	1.00	1.00	1.00	0.95				0.75	
Linguistic Terms	Public	Poor	Low	Average				Average	
				Experts' CWFs	0.849	0.505	0.962	(4*0.849) + (4*0.505) + (3.5*0.962) = 3.8	0.248
Case 2					Experts' Assessment				
Input/Output Values	Public	2	2	4	4	4	3.5		
Membership Degrees	1.00	0.75	1.00	0.60				0.55	
Linguistic Terms	Public	Poor	Low	Average				Good	

Table 4-11 Examples of the Extracted Rules for "Owner Evaluation" by Learning from Examples

Inputs				Output	Rules' DoA
Owner Type	Owner Funding	Owner/Owner Agent Experience	Owner/Owner Agent Reputation	Owner Evaluation	
Public	Poor	Low	Poor	Poor	1.000
Public	Average	Low	Average	Average	0.713
Public	Good	Medium	Poor	Average	0.730
Public	Poor	Low	Good	Average	0.850
Public	Good	High	Poor	Good	1.000
Public	Average	Medium	Poor	Average	0.770
Private Known	Poor	Medium	Poor	Poor	1.000
Private Known	Poor	Medium	Average	Average	0.720
Private Known	Average	High	Poor	Average	0.650
Private Known	Good	Low	Poor	Average	0.970
Private Known	Average	High	Average	Average	0.713
Private Known	Average	Medium	Poor	Average	0.880
Private Known	Good	Medium	Good	Good	0.800
Private Unknown	Poor	High	Good	Average	0.900
Private Unknown	Poor	Low	Average	Poor	0.950
Private Unknown	Average	Low	Poor	Poor	1.000
Private Unknown	Average	Low	Average	Poor	0.950
Private Unknown	Good	Medium	Poor	Average	0.740
Private Unknown	Good	Medium	Average	Average	0.941
Private Unknown	Good	Medium	Good	Average	0.980

4.4.5.2 Rule Development Using Experts' Knowledge for Inputs' Relative Importance Weights

Fuzzy sets in the condition part of a rule must cover the entire universe of discourse, i.e., all combinations of input criteria should be represented in the rules. The rules created using the input-output cases do not cover all possible combinations of input variables. Therefore, a new technique for developing fuzzy rules was applied to generate the required rules to complete the rule base. The fuzzy rules represent the relationship between the inputs and the outputs. The proposed technique considers the relative importance/influence of the input evaluation criteria on the determination of the resulting output. The results of the relative importance web-based questionnaire (subsection 4.4.2) were used for the development of the proposed approach.

The steps for fuzzy rule development are illustrated in Figure 4-8. The process starts with determining the inputs' relative importance/influence weights (RIW) on the output of all sub-models and the overall CDPM, for all possible combinations of the inputs' linguistic terms. The proposed approach converts the input linguistic terms of each combination to numerical ranking values to be mathematically processed (using Equation 4-5) to determine an output ranking value (as illustrated in the following example) that is finally transformed into the appropriate linguistic term.

The relationships between the inputs and their corresponding outputs can be positive/direct or negative/inverse. The positive/direct relationship means that the change in the input associated with a change in the output is in the same direction, i.e. when the input increases, the output increases and vice versa. In the negative/inverse relationship, when the input increases, the output decreases and vice versa. Then, for each combination of inputs, the inputs' linguistic terms in the IF part(s) are transformed into ranking values (RV) according to the number of membership functions representing each input and the type of relationship between the input and the output. For example, if the input has three linguistic terms (low, medium, and high) and has a positive/direct relationship with the output, then the input linguistic terms are transformed to 1, 2, and 3 (ascending), respectively. If the relationship is negative/inverse, the linguistic terms are transformed to 3, 2, and 1 (descending), respectively. The output value for the THEN part is calculated using Equation 4-5.

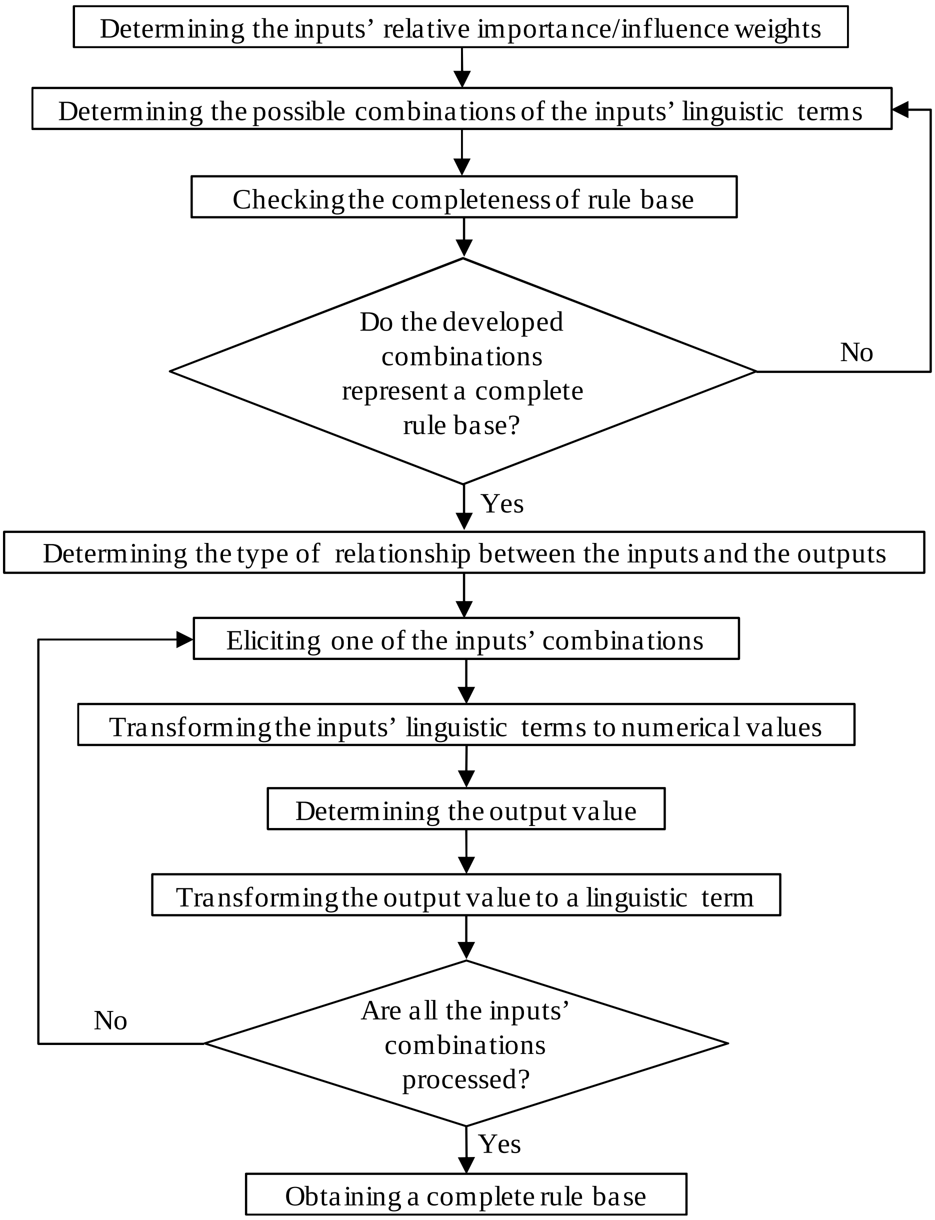

Figure 4-8 Fuzzy Rule Development based on the Inputs' Importance Weights (Awad and Fayek 2012b)

$$Output\ Ranking\ Value = \frac{\sum_{i=1}^{S} RV_i \times RIW_i}{\sum_{i=1}^{S} RIW_i} \quad [4\text{-}5]$$

where RV is the ranking value for the i^{th} input linguistic term in the IF part, RIW is the relative importance weight for the input (resulting from Equation 4-1), and S is the number of inputs. The result of Equation 4-5 is mathematically rounded to the closest integer value (1, 2, or 3), based on three linguistic terms for all the outputs. The resulting output value is then transformed into a linguistic term. According to the previous example, the output value can be 1, 2, or 3, which is transformed to poor, average, or good, respectively. All of the previous steps are done for all the inputs' combinations to determine the corresponding output (THEN) part for each missing rule in the rule base, to yield a complete rule base.

Table 4-12 presents some of the developed rules for the "owner evaluation" rule base. For example, for the second case shown in Table 4-12, the first input ("owner type") is "public," which is the third linguistic term (i.e., the ranking value [RV] is 3). The second input is "average," which is the second linguistic term (i.e., the ranking value is 2). All the linguistic terms in the IF part of the rules are transformed numerically in the same way. The inputs' relative importance weights (RIW) are 4.1, 5.0, 3.1, and 2.2 (from the web-based questionnaire, as explained in subsection 4.4.2). The corresponding "owner evaluation" ranking value is calculated as in Equation 4-6, and the output ranking value is rounded to 3, which corresponds to the third linguistic term ("good").

$$"Owner\ Evaluation"\ Ranking\ Value = \frac{(3\times4.1)+(2\times5.0)+(3\times3.1)+(2\times2.2)}{(4.1+5.0+3.1+2.2)} = 2.5 \quad [4\text{-}6]$$

Table 4-12 Examples of the Rules Developed for "Owner Evaluation" Using Inputs' Weights

Inputs' Relative Importance Weights (RIW)				4.1	5.0	3.1	2.2	Calculated Output Value	Transformed Output Linguistic Term
Inputs' Linguistic Term Combinations (IF part)				Inputs' Linguistic Terms Transformed into Numerical Ranks					
Owner Type	Owner Funding	Owner/ Owner Agent Experience	Owner/ Owner Agent Reputation	Owner Type	Owner Funding	Owner/ Owner Agent Experience	Owner/ Owner Agent Reputation	Owner Evaluation	Owner Evaluation
Public	Poor	High	Average	3	1	3	2	2	Average
Public	Average	High	Average	3	2	3	2	3	Good
Public	Average	NA	Good	3	2	0	3	3	Good
Public	Average	NA	NA	3	2	0	0	2	Average
Public	Good	Low	Poor	3	3	1	1	2	Average
Public	Good	NA	NA	3	3	0	0	3	Good
Public	NA	Low	Poor	3	0	1	1	2	Average
Private Known	Poor	Low	Poor	2	1	1	1	1	Poor
Private Known	Average	Low	Average	2	2	1	2	2	Average
Private Known	Good	Low	Poor	2	3	1	1	2	Average
Private Known	NA	Low	Poor	2	0	1	1	1	Poor
Private Unknown	Poor	Low	Poor	1	1	1	1	1	Poor
Private Unknown	Poor	High	Average	1	1	3	2	2	Average
Private Unknown	Average	Medium	Poor	1	2	2	1	2	Average
Private Unknown	Good	Medium	Poor	1	3	2	1	2	Average
Private Unknown	Good	Medium	NA	1	3	2	0	2	Average
Private Unknown	NA	Medium	Average	1	0	2	2	2	Average
NA	Poor	Low	Poor	0	1	1	1	1	Poor
NA	Average	Low	Poor	0	2	1	1	2	Average
NA	Good	Low	Poor	0	3	1	1	2	Average
NA	NA	Low	Poor	0	0	1	1	1	Poor
NA	NA	High	NA	0	0	3	0	3	Good
NA	NA	NA	Poor	0	0	0	1	1	Poor
NA	NA	NA	Good	0	0	0	3	3	Good
NA	NA	NA	NA	0	0	0	0	0	NA

The "owner evaluation" sub-model contains four input evaluation criteria, and each one has four MBFs that represent three linguistic terms (e.g., poor, average, and good), as well as the crisp N/A (not applicable) MBF. So, if there are H inputs, each with F membership functions, then the complete rule base contains H^F rules, consisting of 4^4 or 256 rules. Sample of the final developed rule bases are presented in Appendix J.

4.5 Model Validation and Sensitivity Analysis

The CDPM development process was completed by constructing the MBFs that represent the inputs and outputs, and by developing a complete rule base that represents the experts' reasoning process. The CDPM was validated using the 30 hypothetical contractor default prediction cases that were not used in the CDPM development process. Each case contained values for all the input evaluation criteria and the corresponding output (overall contractor default risk assessment), based on the participating surety experts' assessment. The CDPM was implemented using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005).

A base case model was developed using the MIN (minimum) fuzzy operator to combine the fuzzified values of the input variables, the PROD (product) implication method to determine the output fuzzy set from each rule, MAX (maximum) for rule aggregation, and the CoM (centre of maximum) for output defuzzification. The base case model and thirty-five alternative system configurations were developed to determine which system configuration produced the most accurate results. The configurations considered different input aggregation methods (minimum, maximum, average, product, minimum/average, and minimum/maximum), different rule aggregation methods (maximum, bounded sum), and different defuzzification methods (centre of maximum, middle of maximum, centre of area, centre of maximum). The product method was used for rule implication as it is the only available implication method in FuzzyTECH®. The characteristics of each system configuration are shown in Table 4-13.

Table 4-13 Model Configuration for Validation and Sensitivity Analysis (Awad and Fayek 2012b)

Scenario #	MBF Shape	Fuzzy Operator	Inference Method	Aggregation Method	Defuzzification Method	Average Percent Error	95% Confidence Interval
1	Piecewise Linear	MIN	PROD	MAX	COM	20.5%	16.8% - 24.9%
2	Piecewise Linear	MAX	PROD	MAX	COM	31.4%	20.5% - 39.4%
3	Piecewise Linear	AVG	PROD	MAX	COM	19.5%	12.4% - 28.6%
4	Piecewise Linear	PROD	PROD	MAX	COM	33.2%	23.0% - 42.1%
5	Piecewise Linear	MIN/AVG	PROD	MAX	COM	23.8%	15.3% - 33.2%
6	Piecewise Linear	MIN/MAX	PROD	MAX	COM	26.3%	18.0% - 35.1%
7	Piecewise Linear	MIN	PROD	BSUM	COM	24.4%	18.5% - 31.9%
8	Piecewise Linear	MAX	PROD	BSUM	COM	28.2%	17.3% - 38.9%
9	Piecewise Linear	AVG	PROD	BSUM	COM	23.0%	15.9% - 34.9%
10	Piecewise Linear	PROD	PROD	BSUM	COM	25.0%	16.5% - 29.4%
11	Piecewise Linear	MIN/AVG	PROD	BSUM	COM	28.1%	16.3% - 36.0%
12	Piecewise Linear	MIN/MAX	PROD	BSUM	COM	26.5%	17.0% - 38.1%
13	Piecewise Linear	MIN	PROD	MAX	MOM	28.9%	20.0% - 37.2%
14	Piecewise Linear	MAX	PROD	MAX	MOM	41.3%	30.2% - 45.3%
15	Piecewise Linear	AVG	PROD	MAX	MOM	27.3%	15.9% - 33.4%
16	Piecewise Linear	PROD	PROD	MAX	MOM	34.6%	21.5% - 44.7%
17	Piecewise Linear	MIN/AVG	PROD	MAX	MOM	25.1%	17.5% - 33.2%
18	Piecewise Linear	MIN/MAX	PROD	MAX	MOM	24.3%	16.2% - 35.2%
19	Piecewise Linear	MIN	PROD	BSUM	MOM	24.5%	17.9% - 32.8%
20	Piecewise Linear	MAX	PROD	BSUM	MOM	37.3%	31.0% - 44.5%
21	Piecewise Linear	AVG	PROD	BSUM	MOM	37.8%	30.4% - 45.2%
22	Piecewise Linear	PROD	PROD	BSUM	MOM	23.4%	16.1% - 29.9%
23	Piecewise Linear	MIN/AVG	PROD	BSUM	MOM	41.5%	30.8% - 43.8%
24	Piecewise Linear	MIN/MAX	PROD	BSUM	MOM	43.2%	31.0% - 44.2%
25	**Piecewise Linear**	**MIN**	**PROD**	**MAX**	**COA**	**13.5%**	**10.5% - 18.6%**
26	Piecewise Linear	MAX	PROD	MAX	COA	28.5%	16.9% - 37.9%
27	Piecewise Linear	AVG	PROD	MAX	COA	27.9%	18.2% - 38.1%
28	Piecewise Linear	PROD	PROD	MAX	COA	32.4%	24.2% - 43.5%
29	Piecewise Linear	MIN/AVG	PROD	MAX	COA	28.1%	17.4% - 37.2%
30	Piecewise Linear	MIN/MAX	PROD	MAX	COA	26.4%	18.2% - 38.6%
31	Piecewise Linear	MIN	PROD	BSUM	COA	24.0%	17.5% - 30.0%
32	Piecewise Linear	MAX	PROD	BSUM	COA	26.0%	17.4% - 38.4%
33	Piecewise Linear	AVG	PROD	BSUM	COA	29.4%	17.6% - 40.1%
34	Piecewise Linear	PROD	PROD	BSUM	COA	26.2%	16.3% - 30.5%
35	Piecewise Linear	MIN/AVG	PROD	BSUM	COA	29.5%	18.5% - 36.3%
36	Piecewise Linear	MIN/MAX	PROD	BSUM	COA	27.0%	21.6% - 34.7%

When the user enters the input values in the CDPM, the CDPM processes the input evaluation data and provides the user with the contractor default risk assessment for both intermediate criteria (expressed on a scale of 1 to 5) and the final output (i.e., overall contractor default risk assessment), which is expressed on a scale of 1 to 7.

For the final output, this rating scale represents seven contractor default risk levels: (1) extremely high risk, (2) very high risk, (3) high risk, (4) average risk, (5) low risk, (6) very low risk, and (7) extremely low risk. A report consisting of the input and output values can then be printed to document the contractor's default risk assessment process.

For the surety bonding decision-making process, if the predicted contractor default risk assessment is 4 (average risk) or higher, the contractor will likely be accepted for bonding. The CDPM has the ability to create "red flags" (i.e., warnings) if any of the input and/or the output values is below a certain threshold value (suggested by the five participating surety experts). The red flags are used to highlight particularly risky areas that may lead to contractor default.

The CDPM was provided with the input values for the 30 hypothetical cases to predict the possible risk of contractor default. The predicted risk values provided by the CDPM were then compared with the experts' assessment in the hypothetical cases to measure the model's accuracy. The average percent error for all the validation cases was calculated using Equation 4-6.

$$\text{Average Percent Error} = \frac{\left(\sum_{i=1}^{n}\left|\frac{CDPM\ Value_i - \text{Actual Value}_i}{ActualValue_i}\right|\right)}{n} \times 100 \qquad [4\text{-}6]$$

"CDPM Value" is the crisp output value provided by the CDPM defuzzification process according to the input values for each case; "Actual Value" is the output value provided by the underwriter or broker for each case; i is the individual case number; and, n is the total number of cases. Table 4-13 presents the thirty-six different system configurations that were tested, along with the average percent error and 95% confidence intervals. The most accurate model configuration, number 25 (shown bolded in Table 4-13), consists of piecewise linear membership functions: "minimum" for input aggregation, "product" for implication, "maximum" for rule aggregation, and "centre of area" for defuzzification. This CDPM configuration has an average percent error of 13.5% (i.e., 86.5% accuracy) with a 95% confidence interval between 10.5% and 18.6% (i.e., 89.5% and 81.4% accuracy).

4.6 Concluding Remarks

This chapter demonstrates how fuzzy logic and expert systems techniques were integrated to develop a model able to help surety professionals in contractor default prediction for specific construction project for bonding purposes. An important evaluation category, contractor's organizational practices, was incorporated as input to the CDPM. The CDPM was built using the expertise of surety practitioners across Canada, and several different knowledge acquisition techniques were used. The group consensus system (GCS) was applied to aggregate the experts' inputs for the CDPM development. A new approach for developing fuzzy rules was presented to generate a complete the rule base. The

CDPM was validated using 30 of the 100 contractor default prediction cases, and the accuracy was found to be 86.5%.

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CHAPTER 5. - Optimization of the Contractor Default Prediction Model (CDPM) for Surety Bonding[1]

5.1 Introduction

The performance of a fuzzy expert system (FES) is significantly affected by the accuracy of its knowledge base parameters (membership functions and rule bases). This chapter presents a methodology to integrate an FES with adaptation/optimization techniques and apply the data-based adaptive learning concept to increase the accuracy of the developed FES for contractor default prediction (CDPM) for surety bonding. Two optimization approaches (genetic algorithms and neural network back-propagation) were investigated for adaptation of the fuzzy membership function (MBF) and rules' degree of support (DoS) to determine the most suitable technique to adapt the FES. The optimized FES was validated using 30 hypothetical contractor default prediction cases, and the highest accuracy of the system (adapted using neural networks) was found to be 91.83%. The optimization approaches presented here address FES context adaptation using any changing information conveyed by the input-output data, and provide a methodology for continuous adaptation of the FES parameters, using practical cases to adjust the FES according to any changes in context.

[1] Parts of this chapter have been published in the Proceedings, CSCE Annual General Conference, Ottawa, ON, June 14–17, and submitted for publication in Journal of Construction Engineering and Management, ASCE, 30 manuscript pages, submitted February 17, 2012.

5.2 Background and Previous Research

Different techniques have been used to develop models for contractor prequalification, contractor default prediction, and surety underwriting. Lam et al. (2009 and 2010) used the support vector machine (SVM) approach to develop a decision support framework for contractor prequalification, and compared the SVM system with neural networks (NNs) and principal component analysis systems. Plebankiewicz (2009) used fuzzy set theory to develop a model for contractor prequalification, but the model was not validated. A decision support for contractor prequalification was developed by Lam and Yu (2010) using the principle of multiple kernel learning (MKL), and had better accuracy than an SVM system using a case study. Al-Sobiei et al. (2005) investigated building a classification model for contractor default prediction using NNs and genetic algorithms (GAs), but the GAs presented better results. Marsh and Fayek (2010) developed a fuzzy expert system (FES) for surety underwriting to evaluate a contractor's character, capacity, and capital. Bayraktar and Hastak (2010) developed a scoring-based system for contractor prequalification for surety bonding. Awad and Fayek (2012a) developed a contractor default prediction model (presented in chapter 4) to assist in the surety bonding decision-making process by providing an FES for evaluating the possible risk of contractor default on a specific construction project.

There is a need for a specific methodology for systematic tuning of the fuzzy systems' knowledge base. Adaptation has not been addressed in the previously developed models for contractor default prediction and/or contractor prequalification. This chapter takes FES-adaptation into consideration to increase the accuracy of the contractor default prediction FES previously developed by Awad and Fayek (2012a).

The fuzzy expert system (FES) is a context-oriented system. One of the main challenges in developing decision support systems (especially fuzzy systems) for the construction environment is context adaptation, which involves being tuned to any changes in the development context and making appropriate adjustments. Construction of the suitable membership functions (MBFs) and estimation of the fuzzy rule base are the most vital and challenging issues in designing an FES (Masoud et al. 2003). Kangrang and Chaleeraktrakoon (2007) mentioned that adaptation of the fuzzy model's knowledge base (MBF and rules) is usually done manually. However, Pedrycz et al. (1997) pointed out that generic MBFs for a fuzzy model can be adapted using a data set to modify the model in response to any contextual changes. In this chapter, the adaptation methodology is presented using input-output (contractor default prediction) cases to adjust the originally-developed (generic) MBFs and rule base (Awad and Fayek 2012a) to any new environment (context) information conveyed by available data.

Adaptation of fuzzy systems has been presented in several studies: (1) Kasabov et al. (1997) introduced the architecture of a fuzzy NN for applying adaptive learning for fuzzy rule extraction; (2) Kangrang and Chaleeraktrakoon (2007) applied GAs for MBF adaptation for a fuzzy system to estimate irrigation efficiency; (3) Abraham (2005) presented several structures for fuzzy systems adaptation using NNs, but no specific model was presented; and (4) Pedrycz et al. (1997) presented a framework for nonlinear context adaptation for fuzzy MBFs using experimental data. However, investigation of more than one adaptation/optimization technique applied to the same problem to determine the most suitable technique has not been presented. In this chapter, GAs and artificial NN back-propagation, integrated with the FES separately, are both explored to determine the best MBFs and the degrees of support (DoS) for the fuzzy rules. Figure 5-1 illustrates the FES optimization/adaptation process by integrating an optimization technique with the FES to adapt the FES's components to reduce the error between the FES evolution and the expert's evaluation.

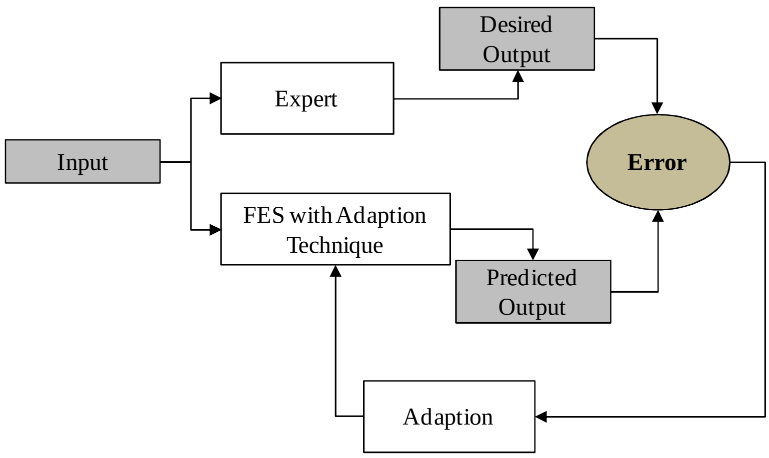


Figure 5-1 General Scheme for the FES Adaptation

Awad and Fayek's (2012a) previously-developed FES (presented in chapter 4) was used as the base model to develop two optimized/adapted models; the optimized model that had the highest accuracy was used to develop the contractor default prediction software, called SuretyQualification (as presented in chapter 6).

5.2.1 Development of the Fuzzy Expert System Base Model

Developing the FES was done in three steps: (1) determining the model input criteria and system structure, (2) estimating input membership functions, and (3) developing the fuzzy rule base (see chapter 4 for more details). The following sub-sections provide a brief description for the FES developed as a base model to apply the proposed adaptation process.

5.2.1.1 Input Criteria and System Structure

The contractor default prediction FES development process started by compiling a comprehensive list of the most important evaluation criteria that surety brokers and underwriters consider for general contractor and project prequalification for surety bonding in the construction industry. Several data collection techniques (one-on-one meetings, interactive group meetings, and web-based questionnaires) were used to collect the relevant evaluation criteria. At least 20 surety experts across Canada participated in the different stages of the FES development stages (see chapter 4 for more details). The final list consists of a total of 120 critera for evaluating the risk of contractor default on a specific project. The evaluation criteria were grouped into three main categories: (1) project aspects evaluation, (2) contractual risk evaluation, and (3) contractor's organizational practices, as presented in Figure 5-2.

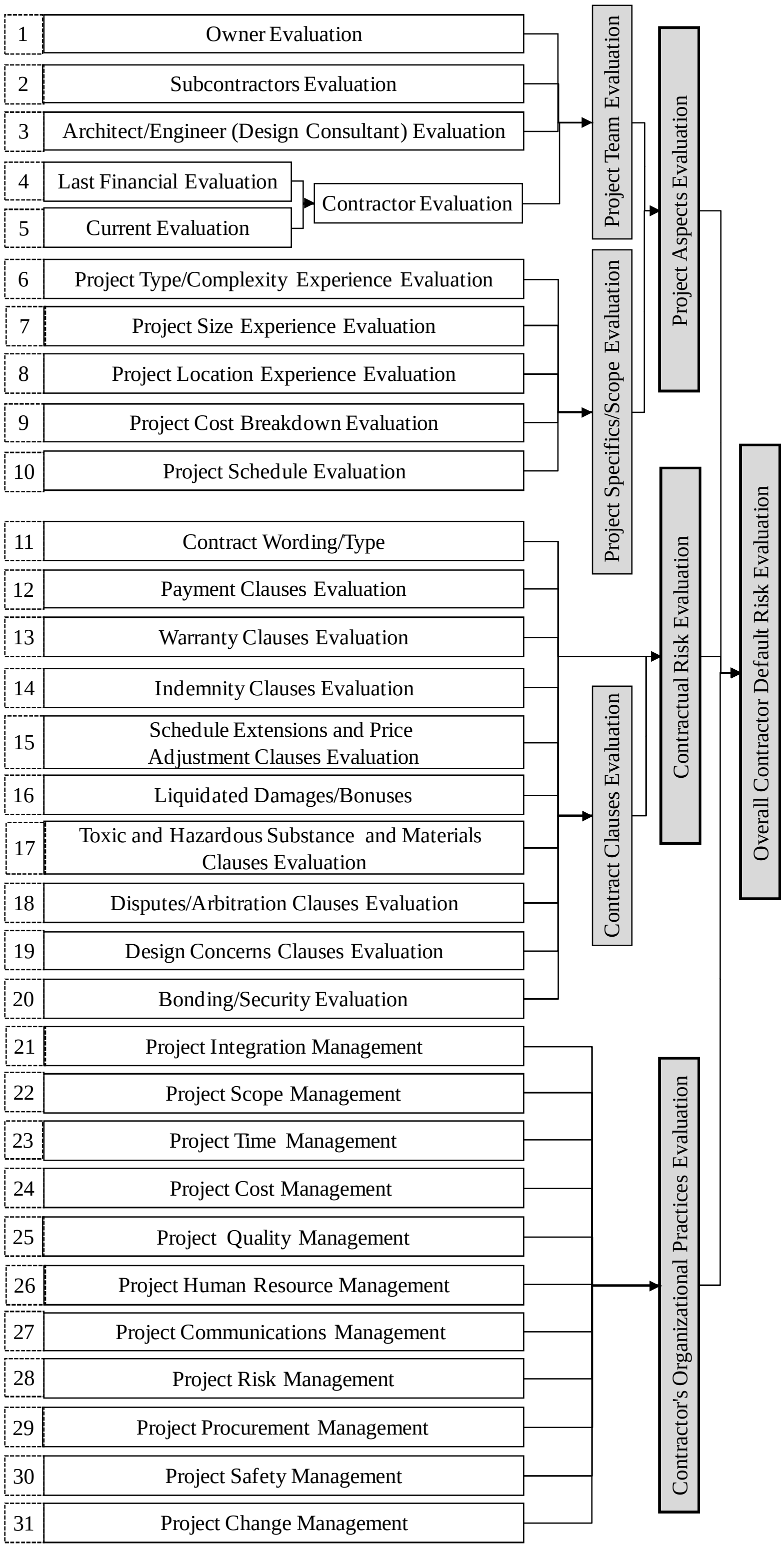


Figure 5-2 Thirty-one Sub-models of Contractor Default Prediction FES (Awad and Fayek 2012b)

These three categories included 31 sub-models to provide the evaluator with an assessment of the intermediate outputs, such as “owner evaluation” and “contractor’s evaluation,” in addition to an assessment of the possible risk of contractor default on a specific project. Each sub-model contains a number of input criteria.

5.2.1.2 Initial Estimation of FES Membership Functions

Initial estimation of the membership functions (MBFs) was done in two steps: (1) using the horizontal method and (2) interpolating the resulting MBFs to linear representations. A web-based questionnaire (Appendix H) was developed to estimate the initial MBFs for the input evaluation criteria. The questionnaire was sent to the 33 surety experts, and 21 responded. The questions included several values for the elements in each fuzzy set for each criterion, and surety experts were asked to assess which values of a given factor belong to which linguistic terms used to describe the criterion. Then, the experts’ responses were used to determine the membership degree of the concept at the given point of the universe of discourse in each fuzzy set (Pedrycz and Gomide 2007). After determining the membership values for all the points of each fuzzy set, the initial MBFs were determined. Then, the estimated membership functions were interpolated to determine linear shape approximations (triangular or trapezoidal) for each linguistic term in each input criterion.

The interpolation process resulted in more than one solution representing each membership function (Appendix I). Table 5-1 shows an example of the resulting

10 alternative solutions (from the interpolation process) for the percentage of the "contractors' work on hand to aggregation limit." The triangular and trapezoidal membership functions, for each linguistic term in the input criteria, were described using four parameters: a, b, c, and d. In triangular functions, $b = c$.

Table 5-1 Membership Function Solutions for Contractor's Work on Hand to Aggregation Limit

Solution No.			1	2	3	4	5	6	7	8	9	10
Work on Hand to Aggregation Limit	Low	*b*	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		c	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		d	28.0	25.0	22.0	20.0	20.0	20.0	28.0	25.0	22.0	20.0
		a	40.0	40.0	40.0	40.0	50.0	47.0	40.0	40.0	40.0	40.0
	Medium	*b*	20.00	28.0	23.0	22.5	20.0	28.0	23.00	22.50	20.0	28.0
		c	40.0	40.0	43.5	40.0	40.0	40.0	43.50	40.0	40.0	40.0
		d	59.0	59.0	59.0	59.00	50.0	50.0	50.0	50.0	56.0	56.0
		a	70.0	70.0	70.0	70.0	75.0	75.0	75.0	75.0	70.0	70.0
	High	*b*	50.0	55.0	60.0	50.00	55.0	60.0	50.0	55.0	60.0	50.0
		c	75.0	80.0	72.0	75.00	80.0	72.0	75.0	80.0	72.0	75.0
		d	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
		a	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Of the 120 evaluation criteria, 80 were quantified numerically or using a rating scale. The remaining 40 were quantified using crisp (i.e., categorical) values, and although not fuzzified, were also represented by membership functions in order to be included in the fuzzy expert system (March 2008). For example, in Figure 5-3, the membership function for the input variable “owner type” is presented. Each x-axis value, “N/A”, “private_unknown,” “private_known,” and “public,” has a crisp membership with degrees of belonging of 0 or 1 only. The x-axis value “private_unknown” refers to a private owner who has never dealt with the contractor before, whereas “private_known” is a private owner who has experience with the contractor in the past, and “public” refers to a public project owner. N/A indicates “not applicable” or “not available.” These crisp MBFs were excluded from the training/adoption process.

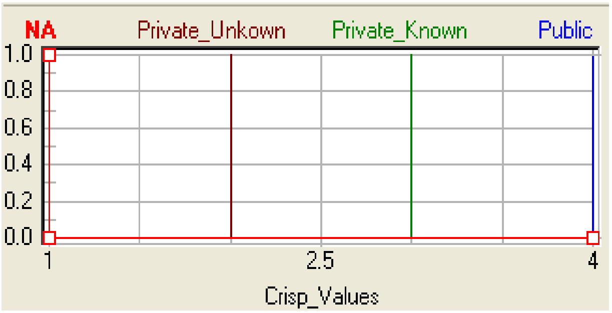


Figure 5-3 Owner Type Membership Functions

MBFs for the intermediate and final output variables did not need extensive expert knowledge to be constructed. However, the linguistic terms used to describe these variables were discussed with the participating surety experts to ensure terms typical to the industry were used for all variables. For all the intermediate output variables, participating experts recommended using rating scales from 1–5, as illustrated in Figure 5-4. The “average” membership function was given full membership at value 3 on the rating scale, and zero at values 1 and 5. The membership function for the linguistic variable “poor” is considered anything less than average, so at the value 3, the degree of membership is equal to zero. Similarly, "good" could be considered anything greater than average.

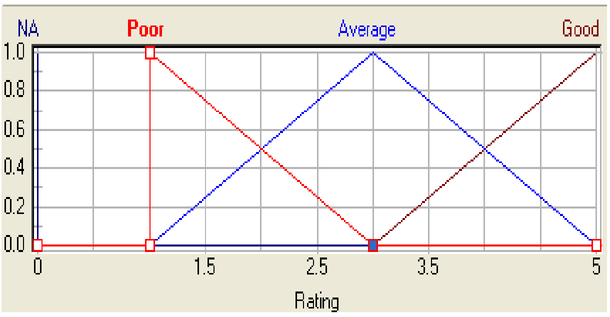


Figure 5-4 Example for the Intermediate Output Rating Membership Functions

The output "contractor default prediction rate" was created using a 1 to 7 rating scale, and five linguistic terms instead of three, in order to increase the overlap of membership functions and to improve the consistency and accuracy of the rule base. The five linguistic terms used are "very critical risk," "somewhat critical risk," "average risk," "low risk," and "very low risk." Figure 5-5 illustrates the output variable "contractor default prediction rate."

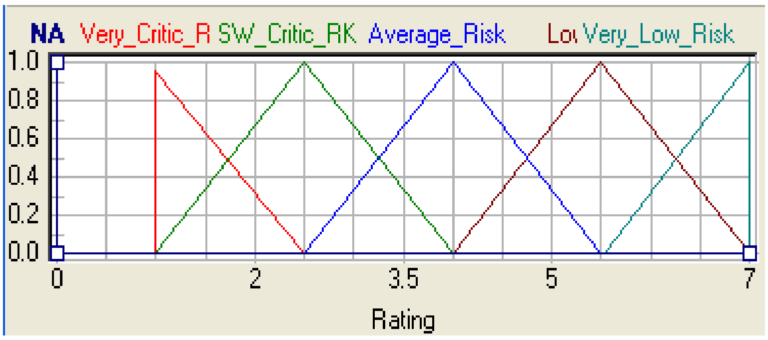


Figure 5-5 Overall Contractor Default Prediction Rate Membership Function

The membership function “N/A” was added to each input, intermediate, and output variable to provide the option of not including any given input criterion into the evaluation process. Commonly, some criteria are not available or not applicable to the case being evaluated. Without these criteria, leaving an input variable blank would automatically default it to the lowest x-axis value, which would create inaccurate results (Marsh 2008). By selecting the “N/A” for any evaluation criterion, the FES takes out the influence of that criterion on the output.

5.2.1.3 Initial development of the FES rule base

In fuzzy expert systems, the relationships between the inputs and outputs are expressed using linguistic terms and represented by fuzzy rules. To determine the rule base, two approaches were followed: (1) using input-output contractor default prediction cases, and (2) using the relative importance weights of the input evaluation criteria. The learning-from-examples approach was initially followed for fuzzy rule extraction from 70 contractor default prediction (input-output) cases (chapter 4). To develop a rule base that covers the entire universe of discourse for all the fuzzy sets, all combinations of input criteria should be represented in the rules. Another technique was applied for developing fuzzy rules, using the relative importance/influence of the input evaluation criteria on the output (see chapter 4 for more details).

5.3 Fuzzy Expert System Adaptation

In the FES, the input evaluation criteria were decomposed into sub-models in the hierarchal structure (as presented in Figure 5-2) to avoid adaptation of multi-layers, which produces inaccurate results (Von Altrock 1997). Each sub-model contains a number of input criteria. The evaluation criteria are on the first-level inputs for the sub-models, while the outputs of the sub-models are the inputs of the higher level in the FES hierarchical structure. This structure provides the evaluator with an assessment of the intermediate outputs (sub-models), such as "owner evaluation" and "contractors evaluation" (under the "project aspects evaluation" category); and higher levels of intermediate outputs (e.g., "team evaluation"), which are an evaluation of a group of sub-models, in addition to an assessment of the overall risk of contractor default.

Figure 5-6 illustrates the roadmap of the FES adaptation process using the hypothetical contractor default prediction cases, as described in chapter 4 (Appendix G). Surety underwriters and brokers do not currently document all the evaluation criteria that are the inputs of the FES. Therefore, 100 hypothetical contractor default prediction cases were developed for the FES adaptation and validation processes. Each case contained proposed values for all the evaluation criteria. The experts were asked to provide the corresponding output values (intermediate and overall) of contractor default risk according to the FES hierarchical structure (see chapter 4 for more details).

The adaptation process started after determining all the possible representations (i.e., solutions) for input MBFs from linear interpolation of the results of the horizontal method. In the GA adaptation process, all the alternative solutions for MBFs were used to build alternative fuzzy models (for each sub-model). Then 70 contractor default prediction cases (training set) were used to measure the fitness for the individuals in each generation during the training process. At the end of the training process, the best solution was selected for validation using 30 unseen cases (validation set). In the NN back-propagation adaptation process, 20 contractor default prediction cases (testing set) were used to measure the accuracy of the previously-developed alternative fuzzy models (MBF solutions). The best solution was selected to apply adaptation using 50 contractor default prediction cases (training set). At the end of the optimization process, the resulting solution was validated using the validation set. The validation results from the two optimization processes were compared to select the best-trained FES to build SuretyQualification.

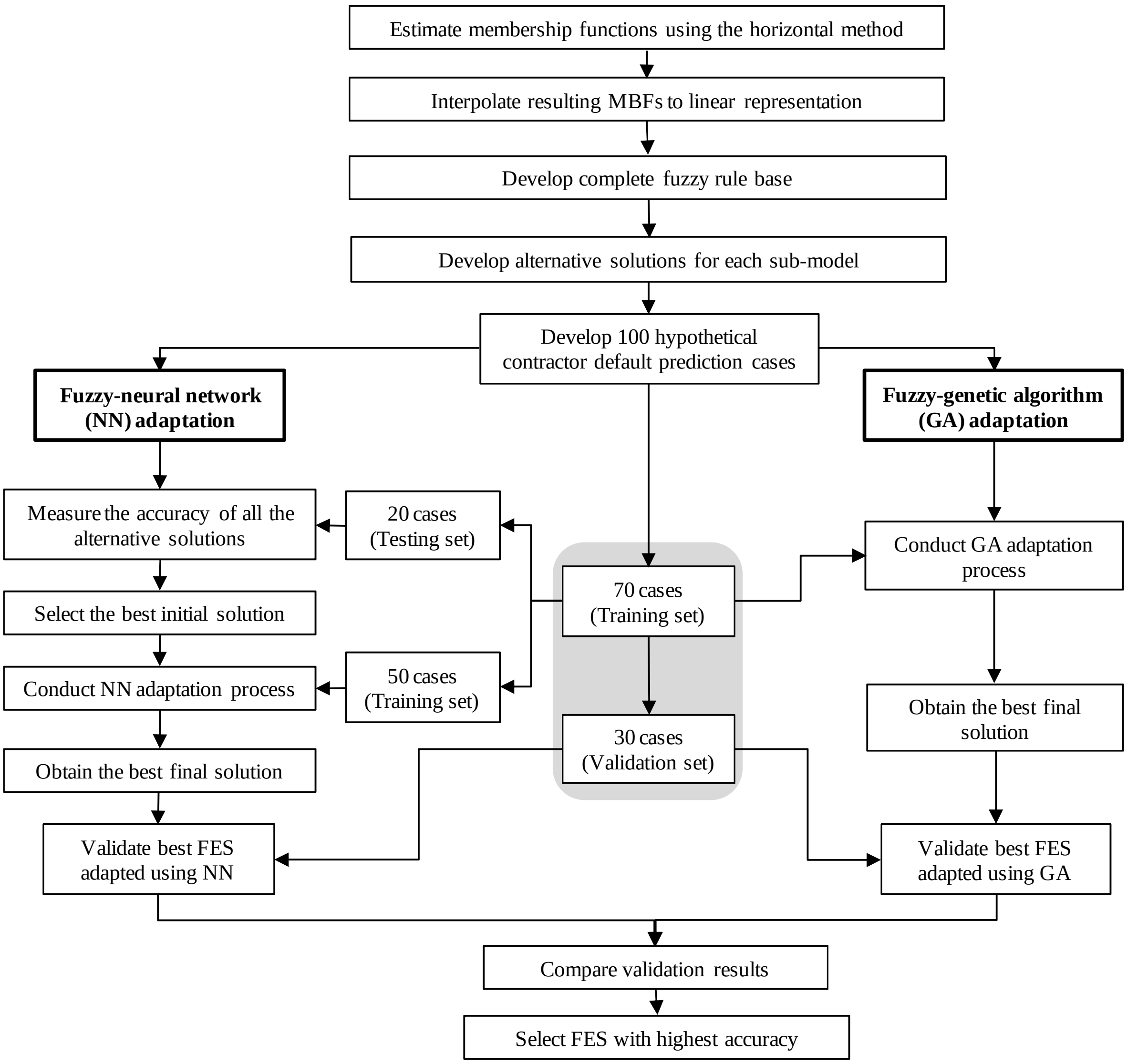


Figure 5-6 The Roadmap for FES Optimization Process Using Contractor Default Prediction Cases (Awad and Fayek 2012b)

5.3.1 Adaptation of the Fuzzy Expert System Using Genetic Algorithms

Genetic algorithms (GAs) are iterative searching algorithms based on principles inspired from natural genetics. GAs are optimization and/or adaptive algorithms to find the optimal or near-optimal solution for a given search space, and can be used for a wide range of optimization and learning problems, such as modifying and/or learning the parameters and improving the accuracy of fuzzy systems (Cordon et al. 2004; Arun et al. 2007; Cordon and Herrera 2001; Varkonyi-Koczy et al. 1999; John et al. 1996; Cao and Wu 1999; Palade et al. 1998; Goldberg 1989 and 2002; Holland 1975).

The typical GAs cycle is shown in Figure 5-7. The first step in applying the GAs is defining the initial population or alternative solutions for the problem where each solution, that includes a set of variables being optimized, is encoded and called chromosome (John et al. 1996). For the proposed FES adaptation, the proposed solutions contain the inputs' membership functions and the rules' degree of support (DoS) values. Then each solution is evaluated and ranked according to a fitness function. Of the proposed solutions, "parents" with high performance are selected to develop a new "generation." Then the two GAs operations (crossover and mutation) are applied to produce new "children" from selected "parents." The evaluation of the produced "generations" (solutions) is done according to the evaluation of the training cases using a fitness function. The previous steps are done iteratively until the problem criterion is satisfied to reach the optimal or near-optimal solution.

The detailed algorithm followed for applying GAs for the adoption of the contractor default prediction FES is illustrated in Figure 5-8 and explained in the following sub-sections.

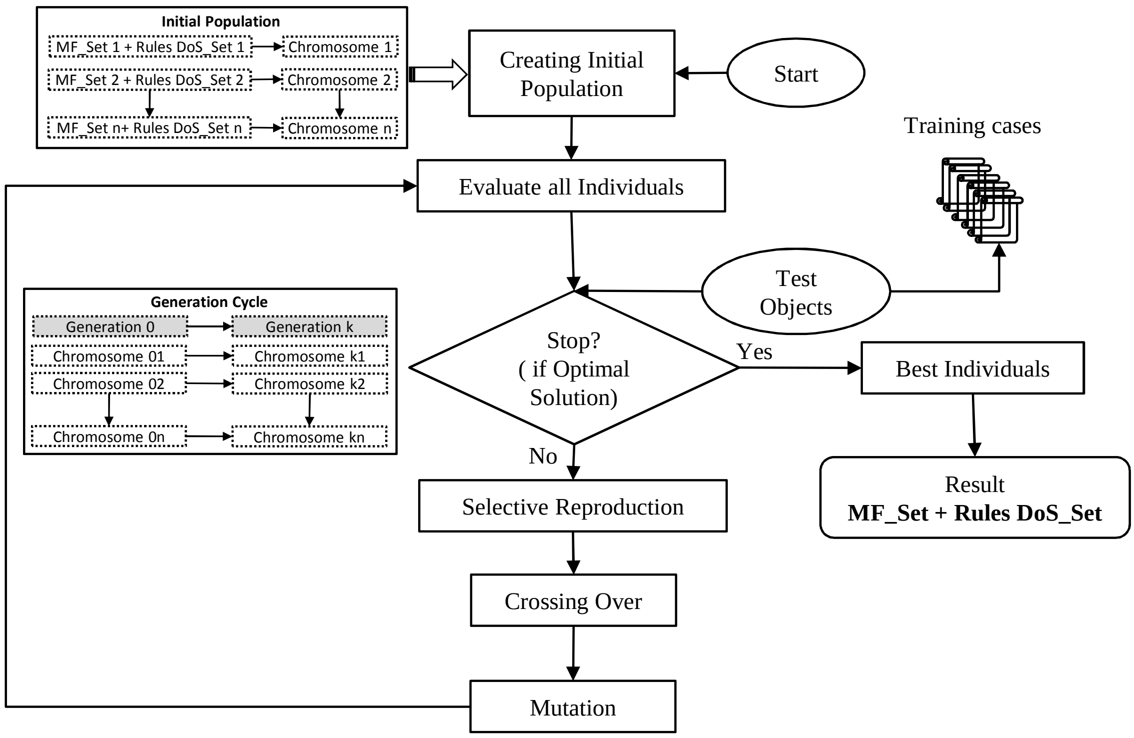


Figure 5-7 Genetic Algorithms (GAs) Adaptation Flow Chart

5.3.1.1 Encoding Scheme

GAs, as a global search and optimization technique, work with a population of chromosomes. A chromosome is generally a sequence of the variables that represent the problem-related information. Every variable sequenced to construct the chromosome is called a “gene.” The organization and transformation of the required problem-related information into a structured chromosome is known as “the encoding process” (John et al. 1996; Arslan and Kaya 2001).

The first step in applying genetic algorithms is finding the suitable representation and structure for the possible problem solutions. The optimization process for the proposed FES included optimization of the MBFs for the input variables and the DoS for the entire rule base. Therefore, each chromosome that represents the optimization problem should include the information about MBFs and the rules’ DoS. The linear MBF can be triangular (either isosceles [Karr 1991; Park et al. 1994] or asymmetrical [Cordon and Herrera 1997; Kinzel et al. 1994]) or trapezoidal (Herrera et al. 1995; Karr and Gentry 1993).

The GA-based optimization process for the FES included optimization of the MBFs for the input variables and the DoS for the entire rule base. As presented in Table 5-2, each chromosome that represents the optimization problem consists of two parts: the MBF part and the rules’ DoS part. The MBF part includes the parameters that describe the linear (triangular or trapezoidal) MBFs for all input criteria. The rules’ DoS part includes the importance values for all the fuzzy rules in each sub-model’s rule base.

Table 5-2 Chromosomes Coding Structure (Awad and Fayek 2012b)

Problem Solutions "Chromosomes"	MFB Part				Rules’ DoS Part			
	Linguistic Term “1”	Linguistic Term “2”	Linguistic Term “---“	Linguistic Term "U"	Rule 1 "DoS"	Rule 2 "DoS"	Rule -- "DoS"	Rule q "DoS"
Solution 1	$a_{11}\ b_{11}\ c_{11}\ d_{11}$	$a_{12}\ b_{12}\ c_{12}\ d_{12}$	--- --- --- ---	$a_{1u}\ b_{1u}\ c_{1u}\ d_{1u}$	R_{11}	R_{12}	------	R_{1q}
Solution 2	$a_{21}\ b_{21}\ c_{21}\ d_{21}$	$a_{22}\ b_{22}\ c_{22}\ d_{22}$	--- --- --- ---	$a_{2u}\ b_{2u}\ c_{2u}\ d_{2u}$	R_{21}	R_{22}	------	R_{2q}
---	--- --- --- ---	--- --- --- ---	--- --- --- ---	--- --- --- ---	---	---	---	---
Solution n	$a_{n1}\ b_{n1}\ c_{n1}\ d_{n1}$	$a_{n2}\ b_{n2}\ c_{n2}\ d_{n2}$	--- --- --- ---	$a_{nu}\ b_{nu}\ c_{nu}\ d_{nu}$	R_{n2}	R_{n2}	------	R_{nq}

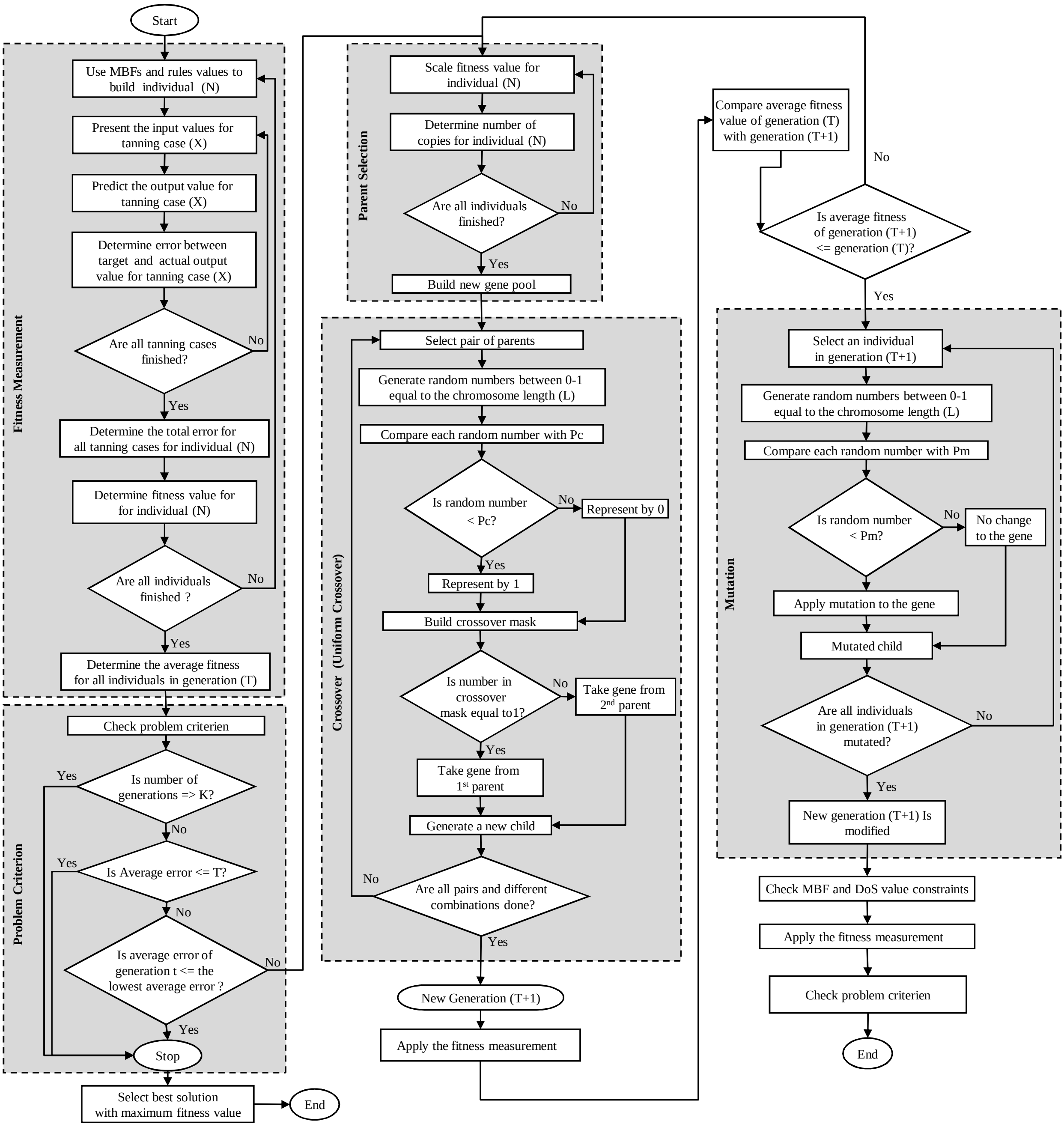


Figure 5-8 The Detailed Algorithm for FES Adaptation Using Genetic Algorithms

The values that describe the problem parameters (MBF or DoS) can be represented in two ways: either binary (Chien et al. 2002) or real coded (Chi et al. 1996; Myung et al. 1997; Aleksandra 1998; Goldberg 1989). The real coding approach was followed. In real coding there is no difference between the genotype (i.e., the real values of problem's parameters) and the phenotype (i.e., search space). In other words, real coding means the real values of the problem are used for building the chromosomes and the GA operators are applied to the real values without any intermediate transformation process. Real coding is very effective (Varkonyi-Koczy et al. 1999; Goldberg 1989; Aleksandra 1998), especially for continuous optimization problems and in avoiding the repeated conversion from genotype to phenotype for fitness evaluation (Varkonyi-Koczy et al. 1999; Cordon et al. 2004). The coding and optimization of the MBFs and rules' DoS were conducted on the basis of the following assumptions and constraints (Awad and Fayek 2012b and 2011):

- A fixed number of linguistic terms, MBF parameters, and rules were used for all solutions for the same sub-model, to avoid any changes to the chromosome structure.
- Each MBF in the input criterion was represented by four numeric values (*a*, *b*, *c*, and *d*).
- The complete rule base was considered, such that all possible combinations of input linguistic terms of all the input variables were used for rule formulation.

5.3.1.2 Initial Population

The initial population to apply the GAs optimization can be developed by one of the following methods (Jarmo 2006): (1) randomly-generated solutions (Cordon and Herrera 2001; John et al. 1996), (2) approximate solutions (using knowledge from experts), (3) solutions of similar problems, or (4) a mixture of three methods. The initial population was developed by integrating knowledge from experts and randomly-generated solutions. For the MBF part, all the linear approximations for the calculated MBFs were considered as the initial population. For the DoS part, the DoS for all the rules in the rule base were initially randomly generated.

5.3.1.3 Fitness Technique

The real challenge when implementing GAs is finding the appropriate method to measure the status of performance of each chromosome (solution) at the beginning of each generation. This measure is called the "fitness function," by which each solution is selected or rejected for replication in the next generation. According to the fitness value, the high-performing problem solutions (chromosomes) are accepted and produce several copies of themselves, while the poorly-performing solutions will be rejected and not produce any copies (Palade et al. 1998).

The MBFs parameters and rules' DoS were used to build the individuals/solutions for each sub-model using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005). Then the input values for 70 contractor default prediction cases (training set) were presented to each individual/solution to predict the corresponding output value. The fitness value for each solution chromosome was determined according to the error between the target output values (provided by the surety experts) and the predicted output values (provided by the FES). The fitness value was used to determine if the problem solution was rejected (poor-performing solution) or produced several copies (high-performing solution) (Ross 2004; Arslan and Kaya 2001; Palade et al. 1998). In each generation, the two solutions with the lowest performance were rejected, and the two highest performing solutions were doubled. The fitness value for each chromosome (i.e., solution) was calculated as follows:

- Calculating the total error for each individual using Equation 5-1 (Ross 2004 and Arslan and Kaya 2001),

$$Total\ Error = \sum_{i=1}^{n} (y_i - y_{GAi})^2 \qquad [5\text{-}1]$$

where n is the number of cases used for fitness evaluation, y_i is the given output value (by the surety experts) for the i^{th} input case, and y_{GAi} is the output value for the i^{th} input case that is obtained by the model.

- Calculating the fitness function value using Equation 5-2 (Ross 2004 and Arslan and Kaya 2001),

$$Fitness\ Value = BV - Total\ Error \qquad [5\text{-}2]$$

BV refers to a big value (more than the maximum error that can be reached) that will be used to convert the minimization process to a maximization process and to prevent the fitness value from getting negative values. For the final output, a 7-point rating scale was used to quantify the predicted risk of contractor failure. According to Equation 5-3, the maximum total error value could be equal to 3430.

$$\text{Maximum } Total\ Error = \sum_{i=1}^{70}(7 - 0)^2 = 3430 \quad [5\text{-}3]$$

- Scaling the fitness value using Windowing scaling, as in Equation 5-4 (Arslan and Kaya 2001),

$$F_{wi} = f_i - f_{lowest} \quad [5\text{-}4]$$

where F_{wi} is the windowing scaled fitness value of the ith chromosome, f_i is the unscaled fitness value of the ith chromosome, and f_{lowest} is the lowest fitness value.

5.3.1.4 Parent Selection

Although there are several different methods to carry out the parent selection procedure, the proportional selection method is used here. As presented by Arslan and Kaya (2001), Equation 5-5 was used to determine the number of copies of each individual in the next generation.

$$Number\ of\ Copies = \frac{(Scaled\ Fitness * Population\ Size)}{Total\ Scaled\ Fitness} \quad [5\text{-}5]$$

As an example, Table 5-3 presents the total average error, fitness, and scaled values for the 10 solutions (the initial population) of the “owner evaluation” sub-model. The “number of copies” column shows that the best solutions (solutions 1 and 4) were doubled, and solutions with the lowest accuracy (solutions 3 and 7) were eliminated.

Table 5-3 Initial Population (Generation 0) for “Owner Evaluation” Sub-model (Awad and Fayek 2012b)

Solution Number	Owner Evaluation Sub-model				
	Total Error	Fitness	Scaled Value	Number of Copies	Average Error/Solution
Solution 1	98.56	3331.44	105.50	2	42.05%
Solution 2	162.35	3267.65	41.71	1	45.32%
Solution 3	201.55	3228.45	2.51	0	47.08%
Solution 4	86.55	3343.45	117.51	2	39.90%
Solution 5	142.91	3287.09	61.15	1	43.90%
Solution 6	132.74	3297.26	71.32	1	43.65%
Solution 7	204.06	3225.94	0.00	0	48.61%
Solution 8	108.38	3321.62	95.68	1	42.17%
Solution 9	167.44	3262.56	36.62	1	46.31%
Solution 10	128.95	3301.05	75.11	1	43.26%

5.3.1.5 Genetic Algorithms Operations

The next step is generating new children from the selected parents. The genetic operators were applied in order to obtain new chromosomes from the selected chromosomes. There are two basic genetic operators: crossover and mutation. The crossover swaps parts of two chromosomes according to a crossover probability, in order to create new chromosomes. Mutation is the process of reinjecting any information that may have been lost in previous generations (Goldberg 1989).

5.3.1.5.1 Crossover

Crossover is the most important operator in GAs. As presented by Munakata (2008), Arslan and Kaya (2001), and Cao and Wu (1999), crossover is the process of information exchange of two ‘parent’ chromosomes to produce a new chromosome, as shown in Figure 5-9.

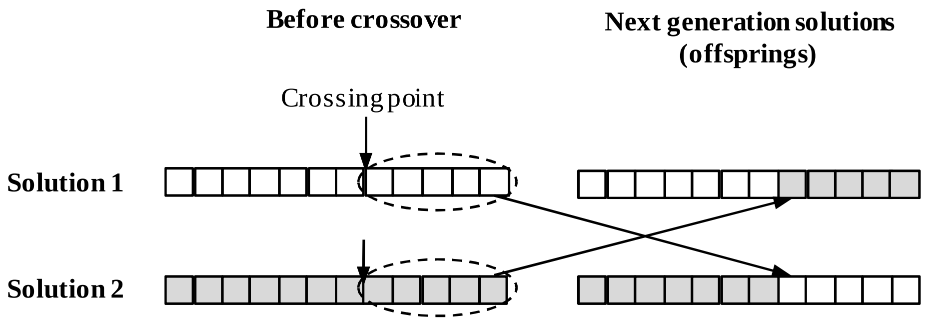


Figure 5-9 Crossover Operators to Generate New Generations

Crossover in GAs can be performed in several ways, as follows:

- One-point Crossover

The main concept of one-point crossover is randomly selecting a crossover position. Then, keep the bits before that position and swap the bits after the crossover position between the two parents (as illustrated in Figure 5-9).

- Two-point Crossover

The procedure of two-point crossover is similar to that of one-point crossover except that two positions are selected, and only the bits between the two positions are swapped.

- Uniform Crossover

In this type of crossover operator, many crossover positions are selected to perform the crossover. Because the chromosomes representing the MBF and rules' DoS values were long, the uniform crossover was used by randomly selecting many crossover positions to perform the crossover between parents and to produce new children. This crossover process was done in the following steps:

- Parent selection: two individuals from the gene pool (the selected parents) were randomly selected.
- Selection of crossover points: for each position, a number between 0 and 1 was randomly generated. If the number generated for a given position was less than the Pc (crossover probability = [0.5… 0.8]), then child #1 got the gene from parent #1, and child #2 got the gene from parent #2. Otherwise, vice versa. In other words, from the generated random numbers the crossover mask was constructed. In the crossover mask, if the number generated is less than the Pc, then it is represented by 1; otherwise, it is represented by 0. Where there is a 1 in the crossover mask, the gene is copied from the first parent, and where there is a 0 in the mask, the gene is copied from the second parent. Offspring therefore contain a mixture of genes from each parent. The number of effective crossing points is not fixed. The process was repeated with all parents to produce the second offspring. A new crossover mask is randomly generated for each pair of parents (Beasley et al. 1993).

5.3.1.5.2 Mutation

According to Arslan and Kaya (2001), after producing a new generation, a comparison between the old and new generations was conducted according to the average fitness. If the average fitness of the new generation was smaller than the average fitness of the previous generation, a random change in the information of the new generation was done, and that is known as mutation.

Each component of every individual was modified with probability P_m, and P_m was usually small (0.001… 0.01) (Beasley et al. 1993; Cao and Wu 1999). To implement the mutation process, another mask was developed from random numbers, with a length equal to the chromosome length, using values between “0” and “1.” In the mutation mask, if the number generated was less than the P_m, then it was represented by “1”; otherwise, it was represented by “0.” Where there was a “0” in the mutation mask, there was no mutation, and where there was a “1” in the mask, mutation was performed.

Since the problem attributes were represented by real coding, the mutation changed the value of a real number randomly, as in Equation 5-6:

$$x_{i\,old} \rightarrow x_{i\,new} = x_{i\,old} + rand() \times \big(MS - (-MS)\big) + (-MS) \quad [5\text{-}6]$$

where $x_{i\,old}$ is the attribute value before mutation, $x_{i\,new}$ is the attribute value after mutation, and *MS* is the mutation step which is selected to be 10% of the maximum scale value (X_{max}). For example, if the element that will be mutated is in a 5-point scale MBF, then the *MS* will be 0.5.

Figure 5-10 illustrates the MBF representation for GAs optimization (MBF_{qk}), where q is the number of the input variable in the sub-model and k is the number of the linguistic term in the input criterion. After each training step, the MBF values were checked according to the constraints presented in Table 5-4. For example, for each MBF, the "*b*" value could not be less than the "*a*" value or more than the "*c*" value.

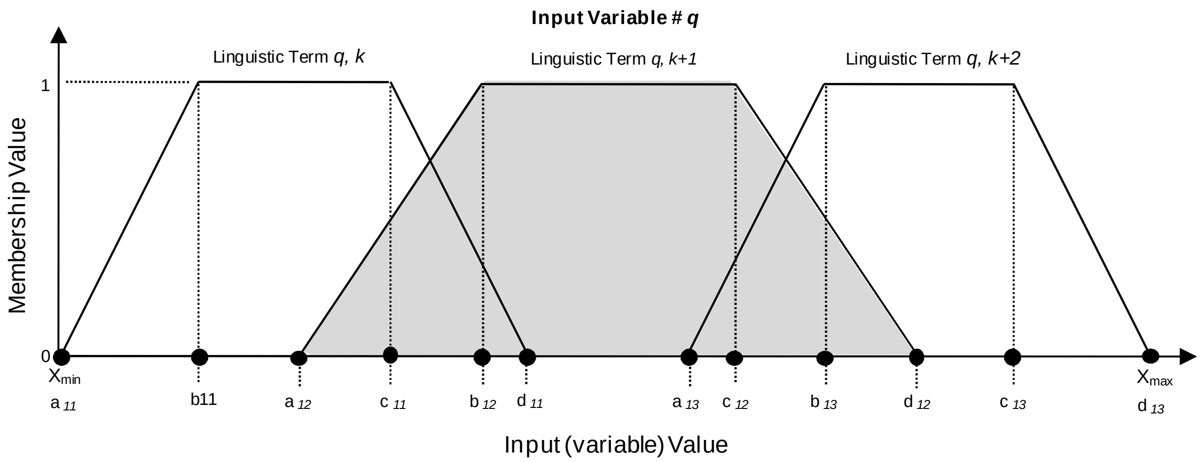


Figure 5-10 Membership Functions Representation in GAs Optimization (Awad and Fayek 2011)

Table 5-4 MBF Value Constraints for Linguistic Terms for Each Input Variable (Awad and Fayek 2012b)

Linguistic Term No. $_{11}$	Linguistic Term No. $_{12}$	Linguistic Term No. $_{13}$
$a_{11} = X_{min}$ $b_{11} >= a_{11}$ $c_{11} >= b_{11}$ $d_{11} >= c_{11}$	$a_{12} > X_{min}$ $b_{12} >= a_{12}$ $c_{12} >= b_{12}$ $d_{12} >= c_{12}$	$a_{13} > X_{min}$ $b_{13} >= a_{13}$ $c_{13} >= b_{13}$ $d_{13} = X_{max}$
b_{11}, c_{11}, d_{11}, a_{12}, b_{12}, c_{12}, d_{12}, a_{13}, b_{13}, $c_{13} < X_{max}$		
The only constraint for rules' DoS value (S) is 0<=S=>1.		
X_{min} and X_{max} are the minimum and maximum values for the evaluation criterion quantification range, respectively.		

5.3.1.6 Stopping Conditions

In GAs, there are several ways to define the stopping conditions to decide whether to continue the optimization process or stop the process, such as: number of iterations, time limit, and fitness limit. The stopping conditions were checked after each generation. If one of these conditions has occurred, the optimization process stops. In the applied algorithm, the three stopping conditions described below were applied.

5.3.1.6.1 Generation Number

As the number of generations (iterations) increased, the resulting fitness values also increased and finally converged to a specific value. When the chromosomes subjected to evaluation gave fitness values that were almost the same (with a difference less than or equal to 5%), and the average error between three successive generations did not change, a random mutation was used to examine whether the population has reached its optimum solution. If a mutated population evolves to the same solution after generations, this solution is assumed to be optimum. The best value for the number of iterations was found to be 40 generations. As an example, Figure 5-11 shows a representation of the average error percentage for 3 sub-models, “owner evaluation,” “subcontractor evaluation,” and “architect/engineer evaluation,” through 40 iterations. At the end of the GAs training process, the best solution (with the lowest average error percentage) for each sub-model was selected to build the overall optimized contractor default prediction model.

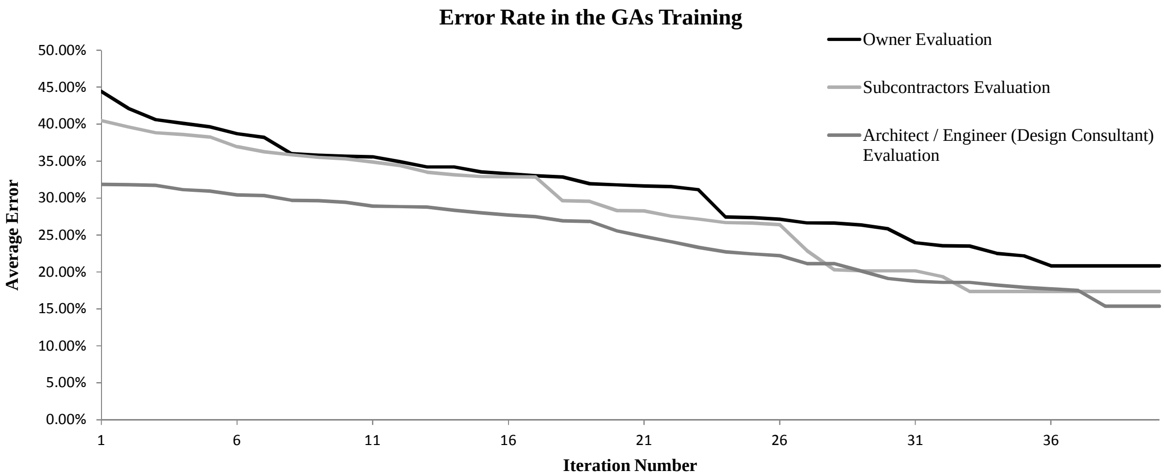


Figure 5-11 Average Percentage Error for 3 Sub-Models for 40 Iterations Using the GAs Adaptation

5.3.1.6.2 Average error limit

One of the stopping conditions was defining a specific average error threshold. When the best average error (calculated by Equation 5-7) in the current population becomes less than or equal to 10%, the algorithm stops.

$$\text{Average Percent Error} = \frac{\left(\sum_{i=1}^{n}\left|\frac{Predicted\ Output_i - \text{Actual Value}_\text{i}}{Actual\ Value_i}\right|\right)}{n} \times 100 \qquad [5\text{-}7]$$

where “predicted output” is the output value provided by the model (i.e., solution) according to the inputs’ values for the contractor default prediction case, “actual value” is the output value by the underwriter or broker for each case, *i* is the individual case number, and *n* is the total number of cases.

5.3.1.6.3 Population Convergence

The population is deemed to be “converged” when the average error across the current population is less than or equal to a specified percentage (5%) away from the best solution (that has the lowest average error) of the current population.

5.3.1.7 Genetic Algorithm Implementation Results

The GA adaptation process was applied to the contactor default prediction sub-models (separately) to adapt the input MBFs and rules’ DoS. The results of applying the GAs depended on the GA parameters: crossover probability, mutation probability, population size, and number of generations. The population sizes were determined according to the interpolation of the initially-estimated MBFs (considering all the linear piecewise MBF representations), and the initial

DoS for a complete rule base were generated randomly with values between 0.0 and 1.0. Several values were tested for each parameter. The best values were 0.6 for crossover probability, 0.01 for mutation probability, and 40 for the number of generations. As an example, Table 5-5 presents the average error percentages at the end of the optimization process for the "project aspects evaluation" sub-models. The results show that the model accuracy increased significantly after the training process. For example, the average percent error for the initial population (the first solutions before the optimization process) for the "owner evaluation" sub-model was 44.43% (accuracy of 55.57%), and, after conducting the GA optimization, the average percent error became 20.82% (accuracy of 79.18%), with 42.49% accuracy enhancement over the untrained "owner evaluation" sub-model. The accuracy of the trained FES (using GAs) to predict the overall contractor default risk was found to be 88.54%. Figure 5-12 presents the lowest achieved average error percentages for the optimized sub-models. The resulting FES was validated and compared with the FES trained by the neural network technique (as explained later in this chapter).

Table 5-5 Testing Results of the "Project Aspects Evaluation" Sub-models Before and After the GAs Adaptation Processes (Awad and Fayek 2012b)

"Project Aspects Evaluation" Sub-models	Average Error (GA Adaptation)	
	Before Training	After Training
Owner Evaluation	44.43%	20.82%
Subcontractors Evaluation	40.48%	17.37%
Architect/Engineer (Design Consultant) Evaluation	31.83%	15.36%
Last Financial Evaluation	40.72%	22.12%
Current Evaluation	34.69%	12.54%
Project Type/Complexity Experience Evaluation	39.84%	19.83%
Project Size Experience Evaluation	43.91%	19.98%
Project Location Experience Evaluation	27.85%	12.41%
Project Cost Breakdown Evaluation	34.97%	17.00%
Project Schedule Evaluation	27.78%	12.14%

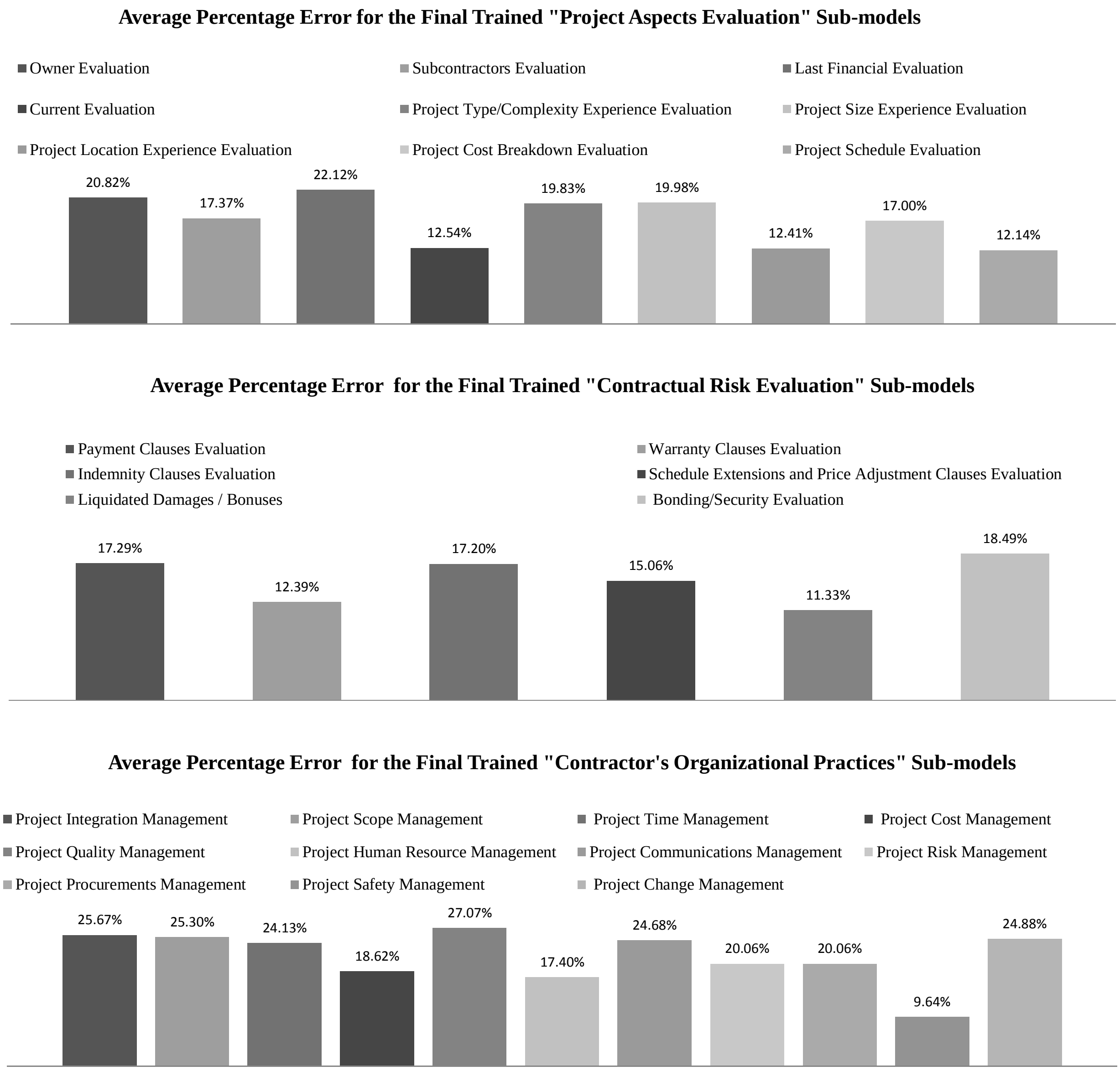


Figure 5-12 The Lowest Achieved Average Error Percentages for the Optimized Sub-models

5.3.2 Adaptation of the Fuzzy Expert System Using Neural Networks

The neural network (NN) technique has the ability to determine the non-linear relationships between input and output factors, and to incorporate data into the model. NNs are generally introduced into fuzzy expert systems to extract rule weights and identify membership functions to adapt fuzzy systems using case data (Tsoukalas and Uhrig 1997; Marsh 2008). The NN back-propagation technique was investigated as an alternative technique to adapt the originally-developed (base) FES. The 100 contractor default prediction cases were divided as follows: (1) 20 cases for testing, (2) 50 cases for training, and (3) 30 cases for final validation, shown in Figure 5-6. As mentioned previously in this chapter, the interpolation process of the initially-estimated MBFs resulted in several solutions for the input MBFs for each sub-model. All the alternative solutions for each sub-model were implemented through an FES shell, FuzzyTECH® (Inform GmbH 2005), using the same configuration (rule base, rules' DoS, fuzzy operator, implication method, rule aggregation method, defuzzification method); the only differences between solutions for the same sub-model were the MBFs that represent the input criteria. Twenty contractor default prediction cases were used for testing different solutions for each sub-model (the same approach presented in chapter 2, subsection 2.3.2.2.2). The input values for each case were presented to the sub-model to determine the corresponding predicted output as a crisp value. The variation between the predicted output value and actual value (given by the underwriter/broker) was calculated for the 20 cases. The solution that had the lowest average percent error for each sub-model was selected to apply the NN adaptation algorithm using 50 contractor default prediction cases.

5.3.2.1 Architecture of the NN for Fuzzy Model Adaptation

The reasoning process in fuzzy systems depends on a set of fuzzy (IF-THEN) rules. The "IF" part contains linguistic terms for the input evaluation criteria. Each evaluation criterion includes a number of linguistic terms (A_i^j), where i is the number of the evaluation input criterion, i = 1,2,...,n_i; and j indicates the number of linguistic term of the *i*-th input criterion, j = 1,2,..., m_i. Each linguistic term is described by a MBF μ_i^j, and each crisp value of the linguistic term has a degree of membership V_i^j.

Adaptation of a fuzzy system using NNs means training the NN while it works, similar to a fuzzy inference model. The general structure of the NN for fuzzy model adaptation consists of input and output layers, and three hidden layers that represent MBFs and fuzzy rules (Kasabov et al. 1997), as illustrated in Figure 5-13. Each layer is associated with a particular step in the fuzzy inference process, as explained in the following sub-subsections with an illustrative example (Sewilam 2002; Kasabov et al. 1997).

5.3.2.1.1 Input Layers

<u>Layer 1:</u>

Layer #1 represents the values of the input evaluation criteria. Each neuron in this layer does not introduce any change to the received values; it just transmits external crisp signals directly to the next layer. Figure 5-14 shows an illustrative example for one of the inputs for the “subcontractor evaluation” sub-model. The role of the first layer is simply to receive the “subcontractors bonds value” (85%) and transmit it to the second layer.

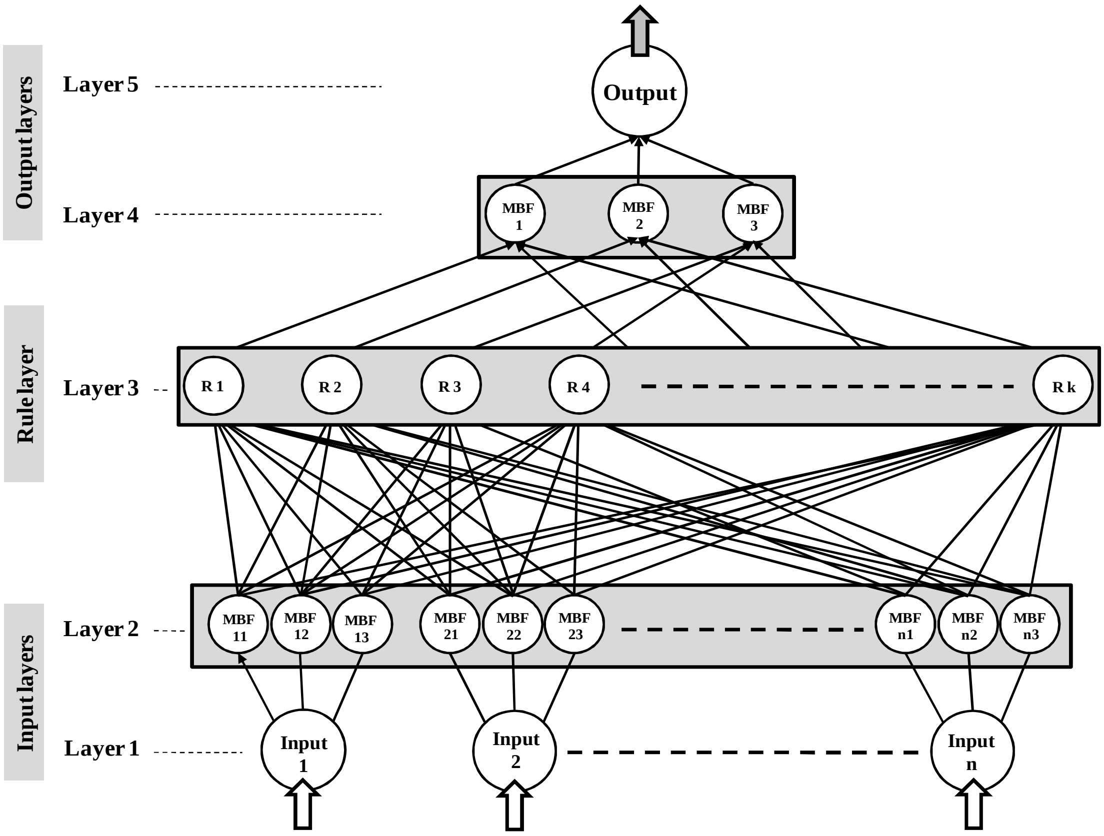
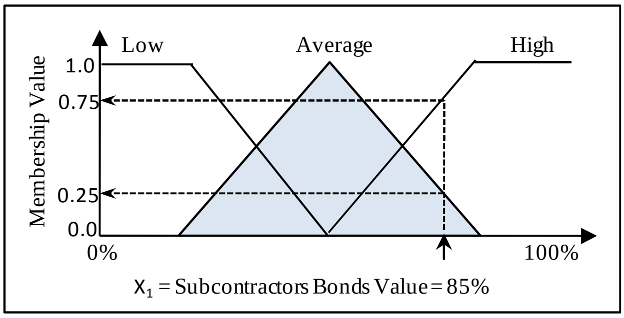


Figure 5-13 Structure of the NN for Fuzzy Model Adaptation

Layer 2

Layer #2 represents the fuzzification process in the fuzzy system. Neurons in this layer represent fuzzy MBFs used in the antecedents (IF part) of fuzzy rules. A fuzzification neuron receives a crisp input and determines the degree to which this input belongs to the neuron’s fuzzy MBF. The activation function of a membership neuron is set to the function that specifies the neuron's fuzzy MBF. In other words, the fuzzification process is conducted according to the MBF or each linguistic term for the input criteria. In the same example (Figure 5-14), the 85% "subcontractors bonds value" has membership values of 0.0, 0.25, and 0.75 for the "low," "average," and "high" linguistic terms, respectively.



Input variable	Input crisp value	Linguistic term	Membership degree
Subcontractors Bonds Value	85%	Low	0.0
		Average	0.25
		High	0.75

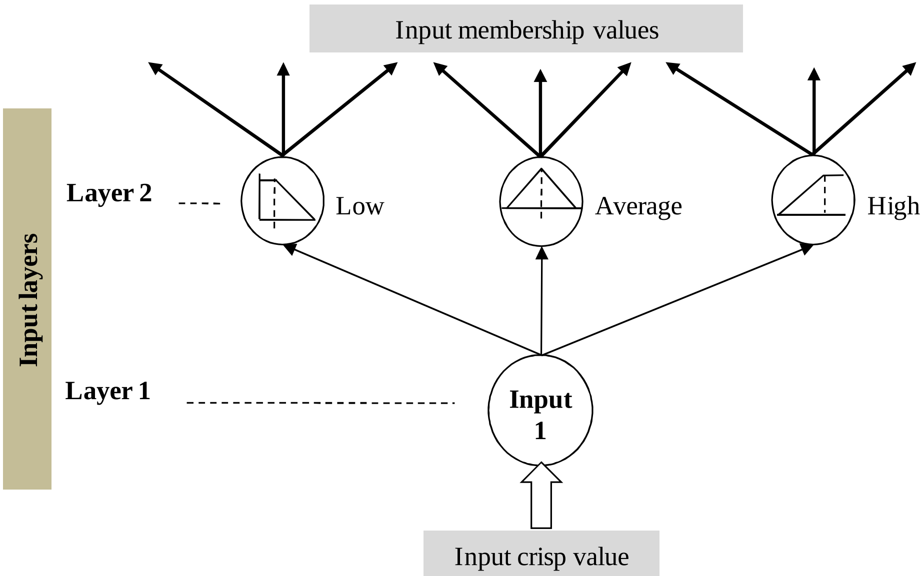
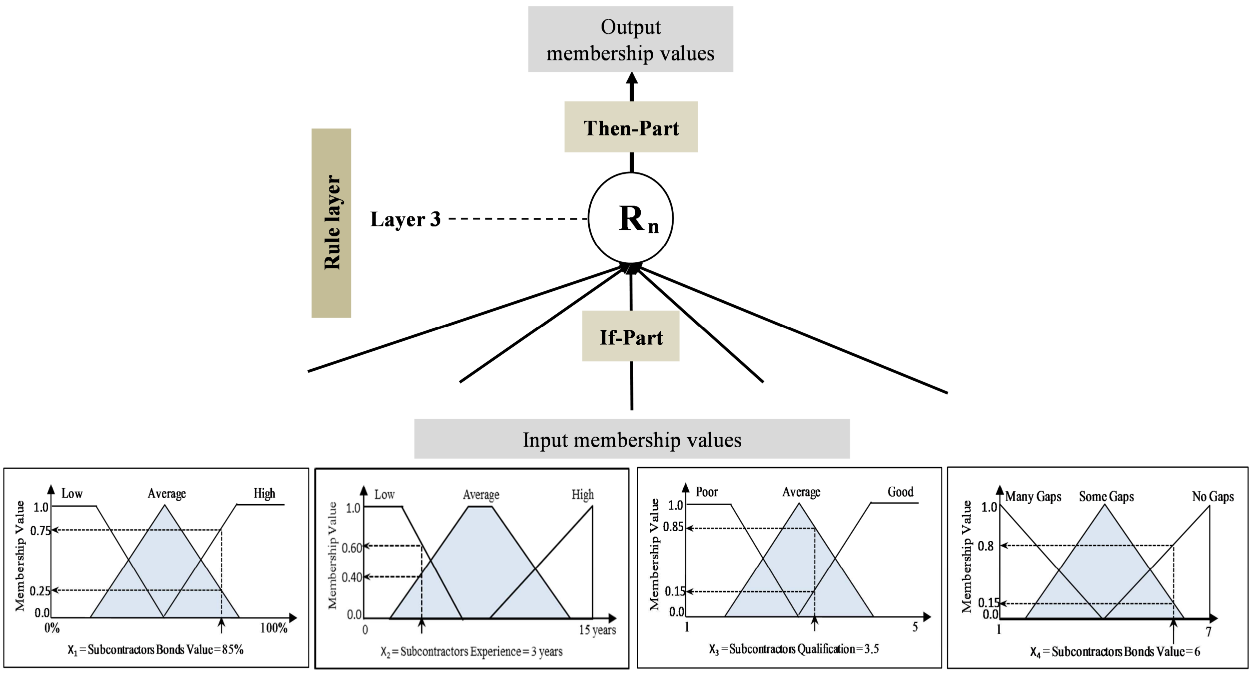


Figure 5-14 Example for the Input Layers

5.3.2.1.2 Rule Layer

Layer 3

Layer #3 represents the rule block, where each node represents a single fuzzy rule. The connection weights between the second layer and the third layer represent the rules' DoS. As in Figure 5-15, after receiving the membership values for each input (4 inputs in the illustrative example) with the corresponding linguistic terms, the output linguistic term with the corresponding membership value is determined in this layer.



Rule R_n

If........Then	Variable		Linguistic term	Membership value	DoS
If	X_1	Is	High	0.75	
and	X_2	Is	Average	0.40	
and	X_3	Is	Average	0.85	0.825
and	X_4	Is	No Gaps	0.80	
Then	Y_1	Is	Very Qualified	0.40	

Figure 5-15 Example for the Rule Layer

The output value in this example was determined using the ‘minimum’ operator from the four input values.

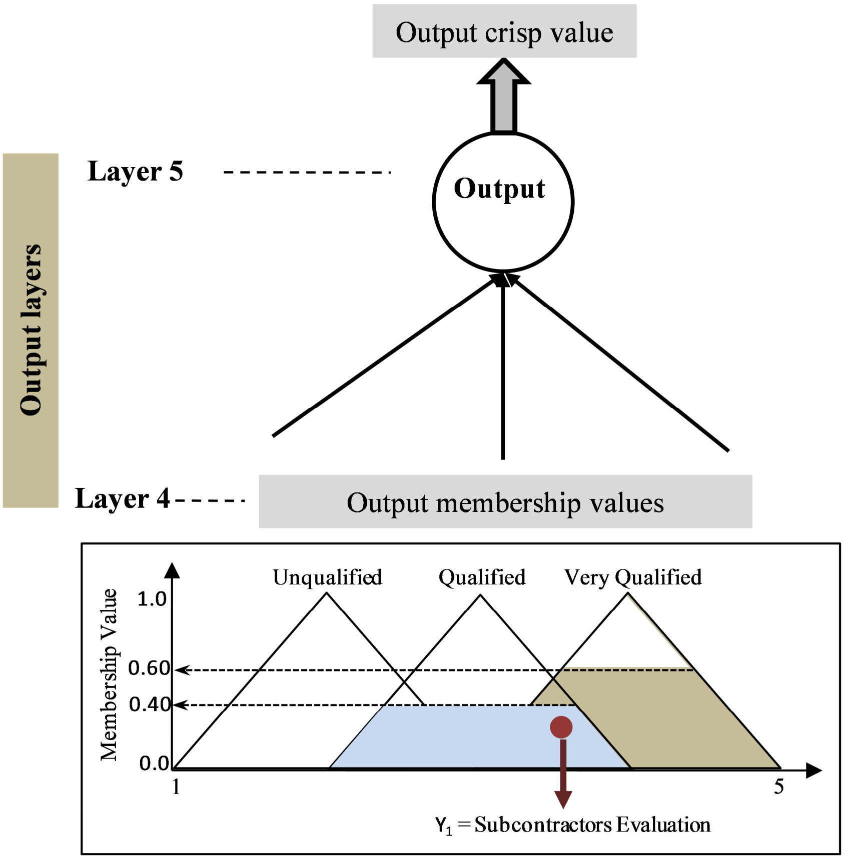
5.3.2.1.3 Output Layers

***Layer* 4**

Layer #4 represents the MBF for the output of the model. Neurons in this layer represent fuzzy sets used in the consequent part of fuzzy rules. An output membership neuron combines all its inputs by using the fuzzy operation union.

***Layer* 5**

Layer #5 performs the defuzzification process to provide a crisp output value. Each neuron in this layer represents a single output of the model. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set. As presented in Figure 5-16, this layer has received the output membership values 0.0, 0.4, and 0.6 for the three output linguistic terms, “unqualified,” “qualified,” and “very qualified,” respectively, as a result for applying fuzzy rules (Layer #4). Then, using the specified aggregation operator (centre of area) and the output MBF, the output value is determined (i.e., 3.6).



Output variable	Linguistic term	Membership degree	Output crisp value
Subcontractors Evaluation	Unqualified	0.0	3.6
	Qualified	0.40	
	Very Qualified	0.60	

Figure 5-16 Example for the Output Layers

5.3.2.2 Fuzzy Model Adaptation Approach Using NN

Adaptation of a fuzzy model using NNs can be done by following one of two approaches (Kasabov et al. 1997): (1) applying the back-propagation algorithm to adapt either the rules' DoS or the MBFs (partially adaptive approach), or (2) applying the back-propagation algorithm to adapt both the rules'

DoS and the MBFs (fully adaptive approach). The fully adaptive approach was applied for the contractor default prediction FES, as illustrated in Figure 5-17.

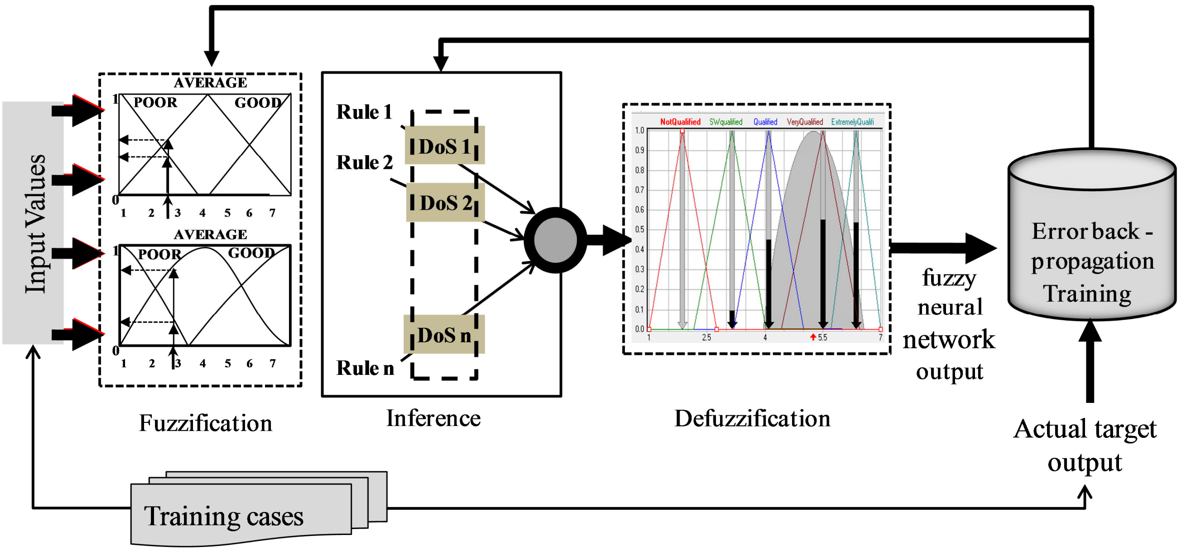


Figure 5-17 Fully Fuzzy Model Adaptive Approach Using NN

The input values for the training cases were presented to each sub-model to predict the output values. Then the network was trained in an iterative process by adjusting both the rules' DoS and input MBFs. The adaptation process for the neuro-fuzzy system can be summarized in the following steps (Sewilam 2002; Awad and Fayek 2011):

- A training set that contains crisp input values and the corresponding output score is elicited.
- The training set is propagated forward, starting from the first layer until the predicted crisp output value is determined.
- Error or variation between the actual/target output value and the system's predicted output value is determined.

- If the error is within the acceptable range (as defined by the developer), another training set is presented to the system, and forward propagating is applied.
- If the error is not acceptable, then the winner neuron is identified (according to the unsupervised learning approach).
- The connection weight of the winner neuron is adjusted.

5.3.2.3 NN Learning Algorithm

The NN training process was done in two phases: (1) the feed-forward pass and (2) the error back-propagation pass (a detailed explanation of the NN training algorithm is presented in Appendix S). The feed-forward pass started by propagating a training case forward through the FES system to determine the predicted output value. The error back-propagation pass started by determining error/variation between the actual/desired output value and the system's predicted output value. If the error was within the acceptable range (up to 5%), another training case was presented to the system. If the error was not acceptable, then the "winner-takes-all" algorithm was applied (Inform GmbH 2005). If the winner neuron represented a MBF, then its parameters were modified, or the rule DoS was modified if the winner neuron represented a rule, according to the predefined learning parameters. Two important parameters influenced the adaptation process: (1) the MBF step learning width and (2) the DoS step learning width. These two values governed the changing values of the MBF parameters and rules' DoS as a percentage of the value before training. The training process ceased automatically when the average error was less than or equal to 5%, or after conducting 100 training iterations.

5.3.2.4 NN Implementation Results

The NN adaptation process was applied to the 31 sub-models to adapt the input MBFs and rules' DoS. All the MBF linear piecewise representations for the input MBFs were considered to select the best solution for optimization. The initial DoS was set at 1.0 for each of the rules. The optimization process depends on the selected fuzzy operators (input aggregation, implication, rule aggregation, and defuzzification) and/or the learning rates (for DoS and MBF) (Boussabine 2001). Awad and Fayek (2012a) conducted a sensitivity analysis to investigate the best fuzzy operators for the original (base) FES. The sensitivity analysis results showed that the MIN (minimum) for input aggregation, PROD (product) for implication, MAX (maximum) for rule aggregation, and CoA (centre of area) for defuzzification were the best operators. Therefore, these operators were used during the optimization process. Different values for the learning parameters (0.1, 0.2, 0.3, and 0.4) were used. Higher learning parameters were not tried because the FES accuracy declined when the learning parameter values increased. The best step learning width for the DoS training was 0.1, and the best step learning width for the MBFs training was 5%. Figure 5-18 presents the final average error percentages for the optimized sub-models using NNs.

Table 5-6 presents the average error percentages at the end of the optimization process for "project aspects evaluation" sub-models as an example.

The results showed that the average error percentages for all the sub-models have reduced significantly after the training process. For example, the average percent error for the "subcontractors evaluation" sub-model before training was 15.36% (accuracy of 84.64%), and, after performing the NN optimization, the average percent error was 6.58% (accuracy of 93.42%), resulting in a 57.16% decrease in error. The accuracy of the trained FES (using NNs) to predict the overall contractor default risk was 90.02%.

Figure 5-18 The Lowest Achieved Average Error Percentages for the Optimized Sub-models

Table 5-6 Testing Results of the "Project Aspects Evaluation" Sub-models Before and After the NN Adaptation Processes (Awad and Fayek 2012b)

"Project Aspects Evaluation" Sub-models	Average Error (NN Adaptation)	
	Before Training	After Training
Owner Evaluation	22.34%	15.46%
Subcontractors Evaluation	15.36%	6.58%
Architect/Engineer (Design Consultant) Evaluation	14.21%	5.82%
Last Financial Evaluation	13.65%	4.35%
Current Evaluation	18.22%	9.25%
Project Type/Complexity Experience Evaluation	21.35%	9.25%
Project Size Experience Evaluation	17.88%	7.27%
Project Location Experience Evaluation	13.22%	5.93%
Project Cost Breakdown Evaluation	35.55%	17.00%
Project Schedule Evaluation	26.41%	10.56%

At the end of the two optimization processes (using the GAs and NNs), all the resulting sub-models optimized by NNs presented lower error percentages than the sub-models optimized using the proposed GA adaptation approach. The higher accuracy obtained from applying the NN approach rather than the GA approach could be due to the following:

- GA adaptation started with all the possible alternative solutions (i.e., training several solutions) for each sub-model. However, in NN adaptation, the best solution from the alternative solutions was selected, and then the optimization process focused on optimizing only the best solution.
- GA adaptation started with random values for the rules' DoS, which were far from the accurate values; some rules that had DoS equal to 0.0 may be lost, and there were no cases (in the training set) to change these values

during the optimization process. On the other hand, the NN adaptation process started with 1.0 for all rules' DoS, so there were no missed rules.

5.4 Model Validation and Results

Conducting the two optimization processes for the FES resulted in two optimized FESs, one from GA adaptation and the other from NN adaptation. A set of 30 contractor default prediction cases that were not used in the development process was used to validate each FES. Every case contained values for all the input evaluation criteria and the corresponding output (overall contractor default risk value), based on the participating surety experts' evaluation. The predicted risk values provided by the FES were then compared with the experts' evaluation in the contractor default prediction cases to measure the FES accuracy. Tables 5-7 and 5-8 show some of the validation results for the adapted FESs (using GAs and NNs) for the higher level of the intermediate outputs: "team evaluation," "project specific," "project aspects," "contract clauses," "contractual risk," and "contractor's organizational practices," as well as the final "overall contractor default risk value" output. The average percent error for evaluating the validation (30 unseen) cases was calculated. The results showed that the optimization process (whether using the GAs or NNs) significantly increased the accuracy of the FES in evaluation of both the intermediate and final outputs. However, the FES optimized by the NNs presented better validation results.

Table 5-7 Validation Results for the FES Adapted Using GAs (Awad and Fayek 2012b)

	Average Percent Error		95% Confidence Interval			
Outputs	Error Percentage	Accuracy	Error Percentage		Accuracy	
Team Evaluation	20.65%	79.35%	8.60%	32.70%	91.40%	67.30%
Project Specific	14.06%	85.94%	7.48%	20.64%	92.52%	79.36%
Project Aspects	18.29%	81.71%	9.74%	26.84%	90.26%	73.16%
Contract Clauses	27.26%	72.74%	13.04%	41.48%	86.96%	58.52%
Contractual Risk	19.22%	80.78%	7.26%	31.18%	92.74%	68.82%
Contractor's Organizational Practices	10.33%	89.67%	5.07%	15.59%	94.93%	84.41%
Overall Contractor Default Prediction	12.46%	87.54%	6.22%	18.69%	93.78%	81.31%

Table 5-8 Validation Results for the FES Adapted Using NNs

	Average Percent Error		95% Confidence Interval			
Outputs	Error Percentage	Accuracy	Error Percentage		Accuracy	
Team Evaluation	13.05%	86.95%	7.59%	18.51%	92.41%	81.49%
Project Specific	6.95%	93.05%	3.70%	10.20%	96.30%	89.80%
Project Aspects	11.07%	88.93%	6.81%	15.33%	93.19%	84.67%
Contract Clauses	25.98%	74.02%	13.76%	38.19%	86.24%	61.81%
Contractual Risk	18.78%	81.22%	7.87%	29.69%	92.13%	70.31%
Contractor's Organizational Practices	3.29%	96.71%	2.03%	4.54%	97.97%	95.46%
Overall Contractor Default Prediction	8.17%	91.83%	5.75%	10.59%	94.25%	89.41%

Table 5-9 presents the structure, configuration, and development of the base (untrained) FES (Awad and Fayek 2012a), the optimized FES using GAs, and the optimized FES using NNs. The highest accuracy for the FES was achieved by applying the NN back-propagation training algorithm. The average accuracy of the (untrained) FES for evaluating the final output (overall contractor default risk) was 82.5%. The optimized FES accuracy (after the NN training) was increased to 91.83%, with 11.31% accuracy enhancement over the untrained FES.

The validation results (calculated according to the final output) showed that the FES adapted using the GAs had an average percent error of 12.46% (i.e., 87.54% accuracy), with a 95% confidence interval between 6.22% and 18.69% (i.e., 93.78% and 81.31% accuracy). The FES adapted using NNs had an average percent error of 8.17% (i.e., 91.83% accuracy), with a 95% confidence interval between 5.75% and 10.59% (i.e., 94.25% and 89.41% accuracy). The highest accuracy for the FES was achieved by applying the NN back-propagation training algorithm, which was the most suitable approach to optimize/adapt the contractor default prediction FES. Sample of the final trained MBFs and rule bases that are used to develop the final FES are presented in Appendix K.

.

Table 5-9 The Base (Untrained) FES, FES Adapted by GAs, and FES Adapted by NNs: Structure and Configuration (Awad and Fayek 2012b)

System's Components and Operators	**Base (Untrained) FES**	**Adapted FES Using GAs**	**Adapted FES Using NNs**
Membership Function Shape	Linear Piecewise	Linear Piecewise	Linear Piecewise
Input Aggregation Operator	MIN	MIN	MIN
Implication Method	PROD	PROD	PROD
Rule Aggregation Operator	MAX	MAX	MAX
Defuzzification Method	CoA	CoA	CoA
Initial Estimation of MBF	Estimated using the Horizontal Method, then interpolated to triangular and trapezoidal shapes		
Rule Base	Covers the entire universe of discourse, i.e., all combinations of input criteria were represented in the rules base		
Rules' DoS	Set at 1.0 for all the rules	Generated randomly with values between 0.0 and 1.0 then trained	Set at 1.0 for all the rules then trained
Membership Function Estimation	All the possible MBF representations were tested, and the best MBFs were used.	All the possible MBF representations were used as initial population for the adaptation process.	All the possible MBF representations were tested, and the best MBFs were used for the adaptation process.
Accuracy	82.5%	87.54%	91.83%
95% Confidence Interval	85.6% to 79.4%	93.78% to 81.3%	94.25% to 89.41%

5.5 Contractor Default Prediction Model Implementation

The final FES that includes all the contractor default prediction criteria and contains all the sub-models, described previously, was implemented using the fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005).

The fuzzy expert system consists of three parts: fuzzification, inference engine, and defuzzification, as illustrated in Figure 5-18. After the values of the contractor default prediction criteria (inputs) are entered into the model, the fuzzification process begins. In fuzzification, the system calculates the degree of membership for each linguistic term defining each criterion. The fuzzification is done according to the membership functions that were constructed previously. Then, the fuzzy operators are applied to the membership values from each evaluation criterion to link the combinations of evaluation criteria to overall contractor default prediction as a single value for each rule. The MIN (minimum) fuzzy operator was initially used. The next step is applying an implication method for each rule to the output variable's membership function. The PROD (product) was used as an implication method. The last step in the inference engine is rule aggregation. Rule aggregation is the process of combining the output sets from each rule into a single output fuzzy set. The MAX (maximum) rule aggregation method was initially used. Defuzzification is the last step, in which a crisp value from the output fuzzy set is determined. The CoM (centre of maximum) method was initially selected as a defuzzification method.

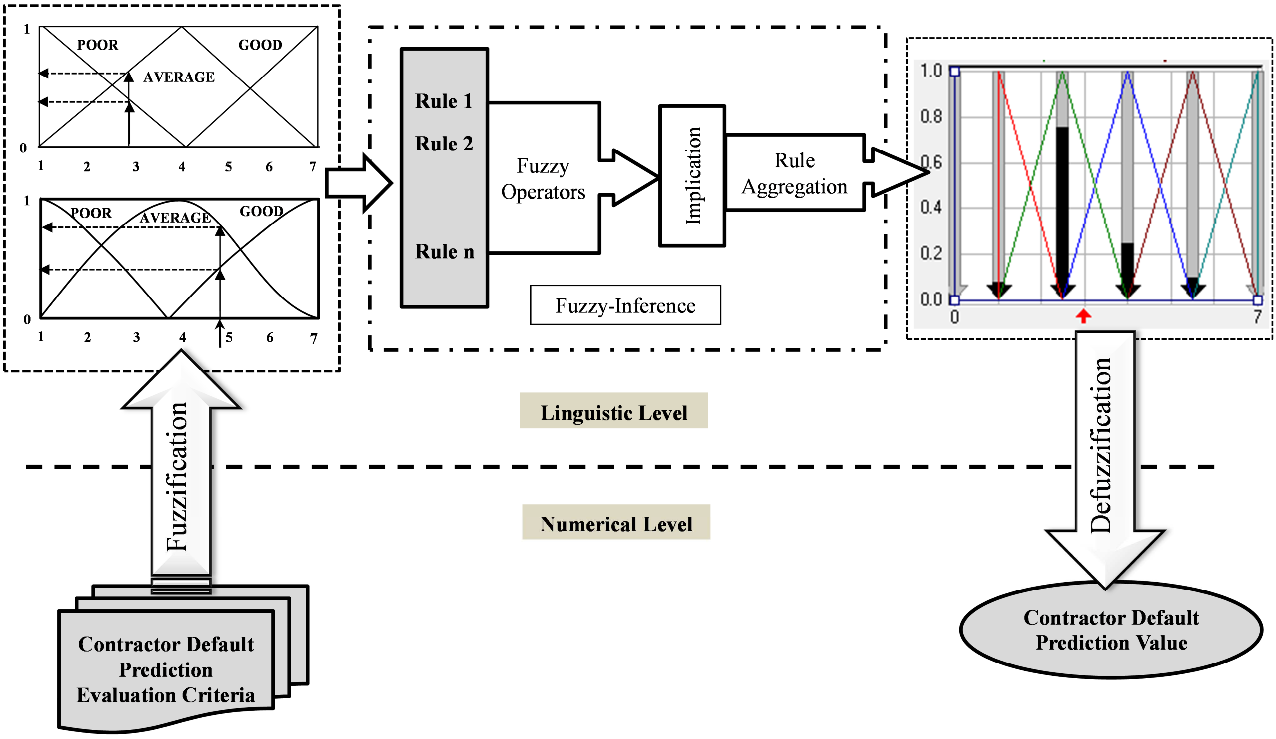


Figure 5-19 FES for Contractor Default Prediction

5.6 Concluding Remarks

This chapter provides a methodology for fuzzy expert system (FES) adaptation to increase the accuracy of a previously-developed FES for contractor default prediction. Two different optimization techniques, genetic algorithms and artificial neural network back-propagation, were applied separately to adapt the FES knowledge base (membership function and rules' degrees of support). The adaptation process enhanced the accuracy of the previously-developed contractor default prediction FES by providing results that are close to the surety experts' evaluation. The two adapted FESs were validated using the same unseen 30 of the 100 contractor default prediction cases, and the best accuracy was found to be 91.38% using the NN back-propagation algorithm. The research presented in this chapter also provides the contribution of determining the most suitable approach (from the investigated techniques) for data-based adaptive learning of an FES knowledge base. The NN adaptation approach, which achieved better training results than GA adaptation, can be used for future adaptation of the FES, to adjust the MBFs and rule base to any new environmental (contextual) information conveyed using input-output (contractor default prediction) cases.

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CHAPTER 6. - SuretyQualification Software[1]

6.1 Introduction

Awad and Fayek's previously-developed fuzzy expert system (FES), presented in chapter 4, was used as the base model to apply two optimization approaches (genetic algorithms and neural network back-propagation) to adapt fuzzy membership function (MBF) and rules' degree of support (DoS) (presented in chapter 5). The two optimized contractor default prediction FESs were validated to determine the one that has the highest accuracy. The validation process (using 30 hypothetical contractor default prediction cases) showed that the system adapted using neural networks has the highest accuracy, at 91.83%.

To enhance the practical benefits of the contractor default prediction FES, a user interface needed to be developed to enable interaction between the evaluator and the FES itself. This chapter presents the development of a software tool called SuretyQualification that provides a comprehensive and systematic evaluation process to evaluate contractors and their risk of default in performing construction projects. The optimized FES that had the highest accuracy was used to develop SuretyQualification. Through an easy-to-use, Excel-based interface, SuretyQualification provides the evaluator with contractor default risk values (overall and intermediate), as well as other decision-making aids such as "Level of Contractor Default Risk" and "Red Flags" (as explained later in this chapter).

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[1]Parts of this chapter have been submitted for publication in Journal of Management in Engineering, ASCE, Awad A. and Fayek A. Robinson. (2012). "Adaptive learning of contractor default prediction model for surety bonding." Manuscript, 30 pages.

SuretyQualification can be used for contractor prequalification by surety practitioners, as well as project owners, and can also assist contractors in conducting self-assessments to discover the areas that may cause default when performing a specific construction project.

6.2 SuretyQualification Development

SuretyQualification was created to allow interaction between the user and the optimized FES by providing a means of storing the user input (120) criteria and designating the system's output. The SuretyQualification user interface was created in Microsoft Excel®, using the Visual Basic editor macro. The trained FES was implemented using a fuzzy expert system shell, FuzzyTECH® (Inform GmbH 2005). The developed FES could not be implemented using FuzzyTECH® in one single file, because FuzzyTECH® allows for a limited number of the variables (inputs, intermediate, and outputs) to be generated in each file. Therefore, the overall contractor default prediction FES was divided into four FESs and implemented in FuzzyTECH®, as illustrated in Figure 6-1. The three models in the lower level are created to evaluate the main categories of the FES: (1) project aspects evaluation, (2) contractual risk evaluation, and (3) contractor's organizational practices. These three FESs' outputs are the inputs to the FES in the higher level, which provides the evaluation of the overall contractor default prediction risk. A brief description for building the four FESs in FuzzyTECH® are presented in Appendix K.

The contractor default prediction model (CDPM) that was used for developing SuretyQualification was built in a hierarchical structure with three categories of variables: input, intermediate output, and final overall output. The evaluation criteria on the first-level of input provide intermediate outputs, which become inputs for the next level. The input variables are the 120 evaluation criteria that the user enters into the model to assess the possible risk of contractor default. The intermediate output variables exist in different levels in the model hierarchical structure. The final overall output is the predicted value of the contractor default risk.

For example, the "owner evaluation" sub-model includes four input variables: "owner type", "owner funding ability", "owner/owner agent experience", and "owner/owner agent reputation". These input variables provide one of sub-models' (intermediate) output values (i.e. "owner evaluation"). The sub-models' intermediate output values (e.g. "owner evaluation", and "subcontractors evaluation") then become inputs to evaluate "project team evaluation". Then the "project team evaluation" with the "project specifics/scope evaluation" (which are also intermediate output variables) become inputs to evaluate the "project aspects evaluation" which is one of the FESs presented in Figure 6-1.

The imprecision/uncertainty (i.e., "fuzziness") of intermediate output variables of the FES are carried through until determining the (intermediate) output of each of the three FESs' in Figure 6-1 (i.e., "project aspects evaluation", “contractual risk evaluation”, and “contractor’s organizational practices”). However, the (intermediate) output values of these three FESs are provided to the fourth FES (“overall contractor default prediction”) as “crisp” (i.e., discrete) numbers (with no imprecision in these numbers).

The approach that was followed to develop the CDPM consisted of building sub-models (Chapter 4 – Sub-section 4.4.1) that provide the intermediate outputs in different levels of the model hierarchical structure, which were then used as inputs for the higher levels to get the final overall output. Each collected contractor default prediction case contained the input values for all 120 evaluation criteria, values for all the intermediate outputs (as crisp values) in all the model`s levels, and a value for the final overall output of the contractor default risk Chapter 4 – Sub-section 4.4.3). This approach was followed for two reasons: (1) to overcome the limitations of FuzzyTECH® in terms of the number of variables, rule blocks, and operations that can be handled in a single model and (2) to allow for future calibration or adaptation of each sub-model, which can be treated as a separate model, since calibration/adaptation of a model with many variables (e.g., 120) and multiple layers produces inaccurate results (Von Altrock 1997). This approach provides the added advantage of being able to use each sub-model as a standalone model for contractor evaluation.

Executable, standalone instances of the four FESs were developed in FuzzyTECH® and connected to the interface to facilitate the use of the overall FES by practitioners in the construction industry.

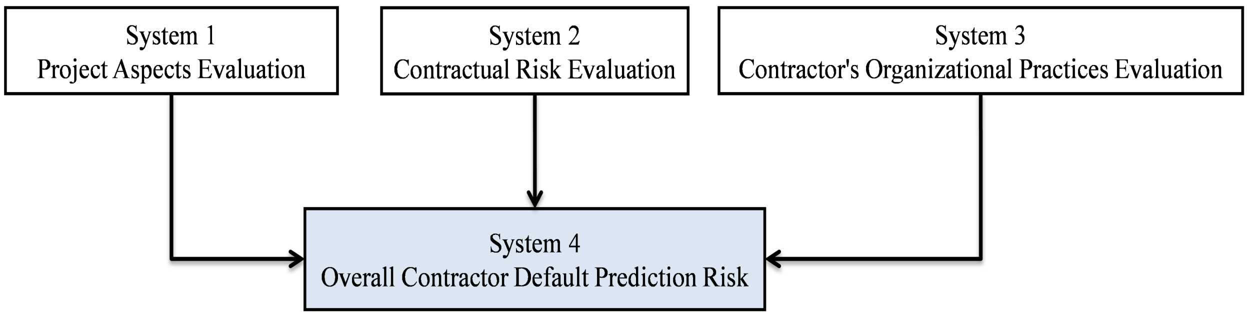


Figure 6-1 The Hierarchical Structure of the FES Implementation

6.3 SuretyQualification Interface

The SuretyQualification interface contains six Excel worksheets: “Input,” “Output,” “Actual Input,” “Red Flags,” “Lists,” and “Input Definitions” (Marsh 2008). The input worksheet prompts the user to assess the 120 input criteria by posing appropriate questions and providing predetermined rating scales. The output worksheet displays the model’s outputs. Red flags are indicated on the input worksheet if an assessment value beyond an acceptable threshold is entered. The “Lists” and “Actual Input” worksheets are for software organizational purposes only.

6.3.1 Input Worksheet

The Input worksheet is where the user enters all of the input data. It has been divided into three main sections: (1) project aspects evaluation, (2) contractual risk evaluation, and (3) contractor’s organizational practices evaluation. There are three types of evaluation criteria according to their quantification method: (1) criteria that are quantified using real numbers (e.g., years, percentages, or number of projects); (2) criteria that are quantified using predefined rating scales of 1–5, which provide guidelines for decision-makers to assist them in their decision-making process; and (3) categorical criteria that are given discrete choices. When the user selects a specific criterion to quantify, an information box containing detailed explanation about the scalar value (i.e., a description of what that value represents) shows up, as illustrated in Figure 6-2.

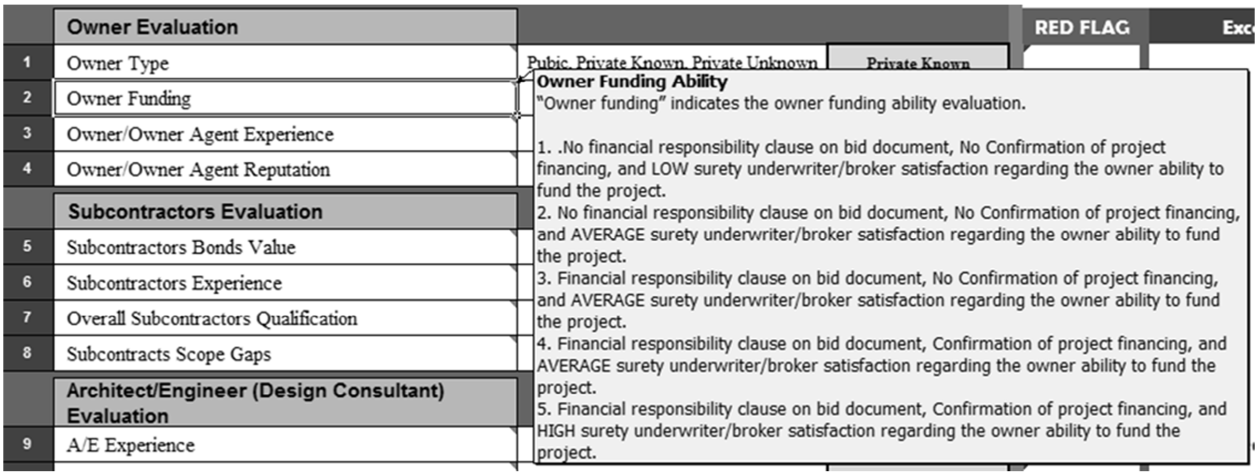


Figure 6-2 Example of an Information Box for Predefined Rating Scale Guidelines

For the categorical input criteria, drop-down menus are available to select the appropriate value or input. “Not applicable” or “not available” (“N/A”) can also be selected from the drop-down menus. N/A can also be entered into cells that do not have a drop-down menu; however, if a cell is left blank, it will automatically be considered as N/A. The membership function “not applicable” or “not available” (N/A) was added to each input variable to accommodate users who do not want to incorporate particular variables into the final output, or who do not have the input data available. A portion of the “Input” worksheet is illustrated in Figure 6-3.

General Contractor Default Prediction

Contractor Name/ID: ABC Construction

Project Name/ID: A012012

Date: March 20, 2012

Project Aspects Evaluation

Evaluation of two categories; Project Team and Project Specifics/Scope

1. Project Team Evaluation (Owner, Architect/Engineer, Subcontractors, and Contractor)

Evaluation of project stakeholders (Owner, Subcontractors, Architect / Engineer (Design Consultant), and Contractor)

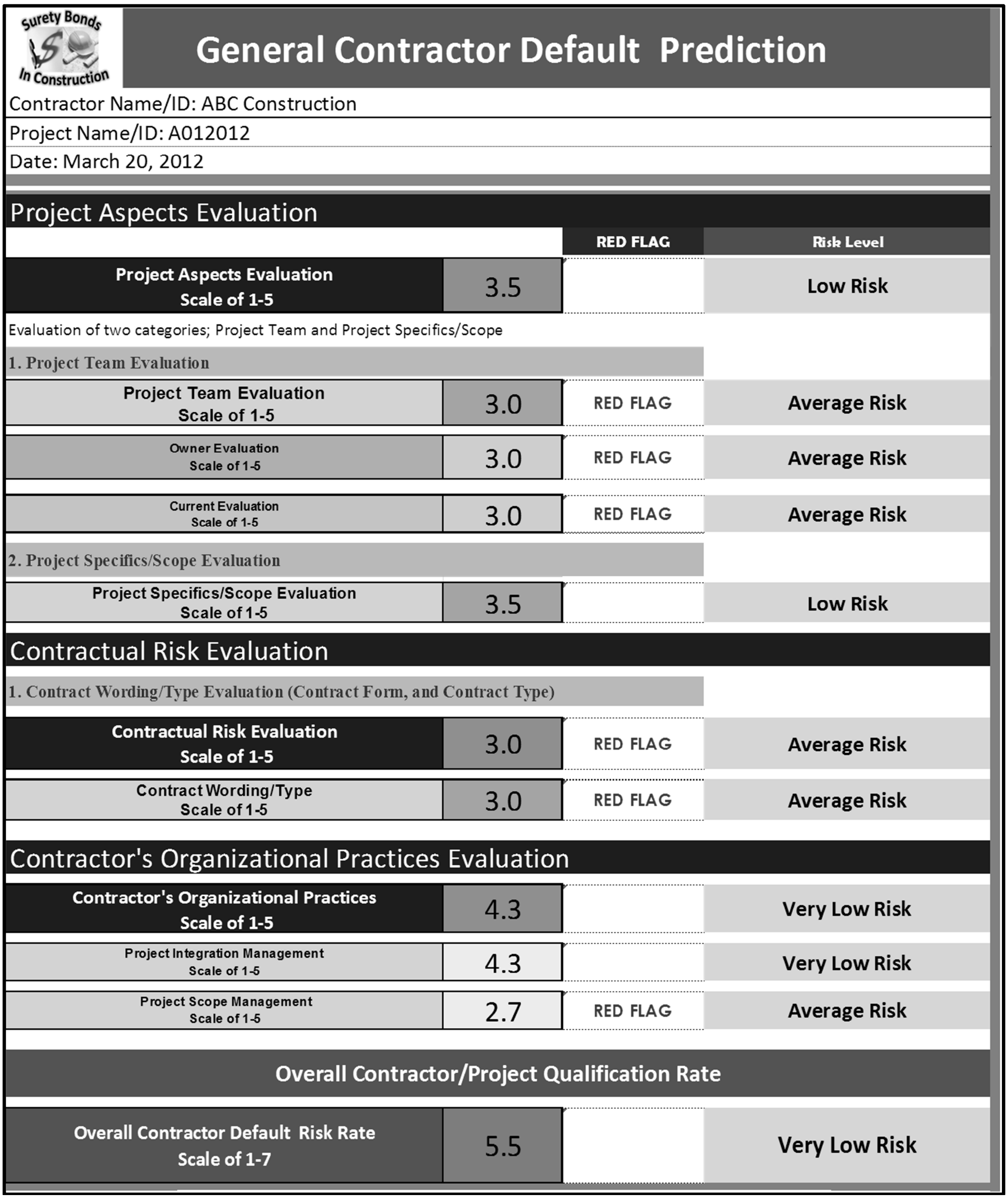
	Owner Evaluation			**RED FLAG**
1	Owner Type	Pubic, Private Known, Private Unknown	Private Known	
2	Owner Funding Ability	Scale of 1-5	2	RED FLAG
3	Owner/Owner Agent Experience	# years (0 -15)	12	
4	Owner/Owner Agent Reputation	Scale of 1-5	3	
	Subcontractors Evaluation			
5	Subcontractors Bonds Value	% Percent (0% - 100%)	50	
6	Subcontractors Experience	# years (0 - 15)	10	
7	Overall Subcontractors Qualification	Scale of 1-5	NA	
8	Subcontracts Scope Gaps	Scale of 1-5	3	
	Architect/Engineer (Design Consultant) Evaluation			
9	A/E Experience	# years (0 - 15)	20	
10	A/E Reputation	Scale of 1-5	NA	
11	A/E Liability Insurance	Scale of 1-5	3	
	Contractor Evaluation			
	Last Financial Evaluation			
12	Working Capital (Leverage)	% Percent (-30 % - 30%)	-20	RED FLAG
13	Tangible Net Worth (Leverage)	% Percent (-30 % - 30%)	10	
14	Gross Profit Margin Trend	% Percent (-50 % - 50%)	20	
15	Net Profit Margin Trend	% Percent (-50 % - 50%)	30	
16	Debt to Equity Ratio	Ratio 1: (0 - 4)	2	
17	Gross Profit Margin	% Percent (0 % - 25%)	10	
18	Net Profit Margin	% Percent (0% - 15%)	10	
	Current Evaluation			
19	Work on Hand to Aggregation Limit	% Percent (0% - 100%)	20	
20	Overbilled - contracts under construction	% Percent (0 % - 25%)	15	
21	Underbilled - contracts under construction	% Percent (0 %- 25%)	10	
22	Contractor's Cash Flow	Scale of 1-5	3	
23	Contractor's Operating Line	Scale of 1-5	4	

Figure 6-3 Sample of SuretyQualification Interface – Input

The input numerical values are limited to the range of values presented in the "Input Definitions" worksheet and beside each criterion, according to the x-axis value for each criterion. If the value entered is outside of the specified range, a message will appear that says "Input exceeds limits, defaulted to 'Maximum' (or 'Minimum') value." For example, for the factor "owner/owner agent experience," the minimum and maximum values of the x-axis are 0 and 15 years, respectively. If the user enters experience equal to 20 years, the user will receive a message that says "Input exceeds limits, defaulted to 15 years," and SuretyQualification will deal with this value as the maximum value (15 years).

6.3.2 Output Worksheet

Once the user enters the evaluation data, he/she can review the "Output" worksheet (a portion of the "Output" worksheet is illustrated in Figure 6-4). The "Output" worksheet provides the user with the contractor default risk values for all the sub-models, as well as the final overall contractor default risk value (39 outputs are generated). The sub-model outputs allow the user to discover areas that need improvement or that should be investigated further. The "Red Flag" designations are also given on the "Output" worksheet to inform the user of any critical values (i.e., values not within the acceptable range).



General Contractor Default Prediction

Surety Bonds In Construction

Contractor Name/ID: ABC Construction

Project Name/ID: A012012

Date: March 20, 2012

Project Aspects Evaluation			
		RED FLAG	Risk Level
Project Aspects Evaluation Scale of 1-5	3.5		Low Risk
Evaluation of two categories; Project Team and Project Specifics/Scope			
1. Project Team Evaluation			
Project Team Evaluation Scale of 1-5	3.0	RED FLAG	Average Risk
Owner Evaluation Scale of 1-5	3.0	RED FLAG	Average Risk
Current Evaluation Scale of 1-5	3.0	RED FLAG	Average Risk
2. Project Specifics/Scope Evaluation			
Project Specifics/Scope Evaluation Scale of 1-5	3.5		Low Risk
Contractual Risk Evaluation			
1. Contract Wording/Type Evaluation (Contract Form, and Contract Type)			
Contractual Risk Evaluation Scale of 1-5	3.0	RED FLAG	Average Risk
Contract Wording/Type Scale of 1-5	3.0	RED FLAG	Average Risk
Contractor's Organizational Practices Evaluation			
Contractor's Organizational Practices Scale of 1-5	4.3		Very Low Risk
Project Integration Management Scale of 1-5	4.3		Very Low Risk
Project Scope Management Scale of 1-5	2.7	RED FLAG	Average Risk
Overall Contractor/Project Qualification Rate			
Overall Contractor Default Risk Rate Scale of 1-7	5.5		Very Low Risk

Figure 6-4 Sample SuretyQualification Interface – Output

According to the output values, the interface provides the user with the "Level of Contractor Default Risk" for the intermediate (i.e., sub-model) and overall contractor default risk value (as shown in Tables 6-1 and 6-2). “Level of Contractor Default Risk” is a linguistic description of the contractor default risk value.

Table 6-1 Intermediate SuretyQualification Output Value and Level of Contractor Default Risk

Intermediate Contractor Default Risk Assessment*	Contractor Default Risk levels
Less than or equal to 1.0	Very High Risk
More than 1.0 but less than or equal to 2.0	High Risk
More than 2.0 but less than or equal to 3.0	Average Risk
More than 3.0 but less than or equal to 4.0	Low Risk
More than 4.0 but less than or equal to 5.0	Very Low Risk

*Intermediate ratings are based on the following scale from 1–5

Table 6-2 Final SuretyQualification Output Value and Level of Contractor Default Risk

Overall Contractor Default Risk Assessment*	Contractor Default Risk levels
Less than or equal to 1.0	Extremely Risk
More than 1.0 but less than or equal to 2.0	Very High Risk
More than 2.0 but less than or equal to 3.0	High Risk
More than 3.0 but less than or equal to 4.0	Average Risk
More than 4.0 but less than or equal to 5.0	Low Risk
More than 5.0 but less than or equal to 6.0	Very Low Risk
More than 6.0 but less than or equal to 7.0	Extremely Low Risk

*Overall ratings are based on the following scale from 1–7

6.3.3 Actual Input Worksheet

The “Actual Input” worksheet was developed to format the input values in a way that can be entered into the FES. For example, the “owner type” is a categorical input evaluation criterion, which is described by four linguistic terms (values): “private unknown,” “private known,” “public,” and “N/A.” The linguistic descriptions are represented by crisp (discrete) values, as illustrated in Figure 6-5, and 1, 2, 3, and 4 represent “N/A,” “private unknown,” “private known”, and “public,” respectively. When the user enters his or her linguistic choice, it should be converted to the corresponding numerical value that the FES can deal with. So, in the “Actual Input” worksheet, the following “IF” statement structure is used:

If the entered value is equal to “N/A” **Then** enter “1” or

If the entered value is equal to “ ” (empty) **Then** enter “1” or

If the entered value is equal to “Private Unknown” **Then** enter “2” or

If the entered value is equal to “Private Known” **Then** enter “3” or

If the entered value is equal to “Public” **Then** enter “4”

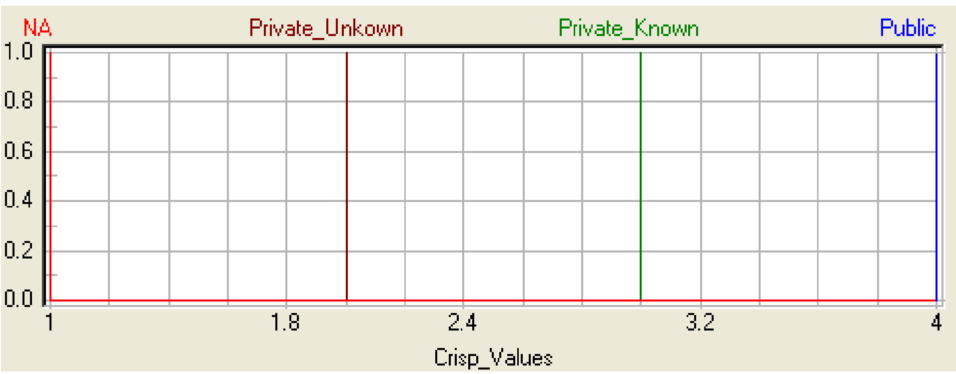


Figure 6-5 Membership Function of "Owner Type"

6.3.4 Red Flags Worksheet

The “Red Flag” worksheet indicates the threshold values given for each criterion. Threshold values are used as red flags that indicate to the user that a value has been entered that is outside the desirable range. If a value entered is greater or less than a user-specified threshold, it will automatically receive a red flag designation to prompt the user to investigate that particular criterion further. These “red flag” indicators are given on the input and the output worksheets as soon as the value has been entered for that criterion, as shown in Figures 6-3 and 6-4. The user can change threshold values as needed through the “Red Flags” worksheet. A sample of the default values for each input criterion’s threshold are listed in Table 6-1.

6.3.5 Lists Worksheet

The “Lists” worksheet includes all lists that are used in the drop-down menus on the “Input” worksheet. The information in the “Lists” worksheet cannot be altered by the user.

6.3.6 Input Definitions Worksheet

The “Input Definitions” worksheet provides the user with detailed information about all the evaluation criteria, such as definitions, quantification methods, and threshold values.

Table 6-3 Sample of the Threshold Values of the Input Criteria

Input Variable	Red Flag	Threshold
Owner Type	If	Private Unknown
Owner Funding Ability	Less Than	3.0
Owner/Owner Agent Experience	Less Than	5.0
Owner/Owner Agent Reputation	Less Than	3.0
Subcontractors Bonds Value	Less Than	25.0
Subcontractors Experience	Less Than	2.0
Overall Subcontractors Qualification	Less Than	3.0
Subcontracts Scope Gaps	Less Than	3.0
A/E Experience	Less Than	5.0
A/E Reputation	Less Than	3.0
A/E Liability Insurance	Less Than	3.0
Working Capital (Leverage)	Less Than	-10.0
Tangible Net Worth (Leverage)	Less Than	-10.0
Gross Profit Margin Trend	Less Than	-10.0
Net Profit Margin Trend	Less Than	-10.0
Debt to Equity Ratio	Greater Than	2.2
Gross Profit Margin	Less Than	2.0
Net Profit Margin	Less Than	2.0
Work on Hand to Aggregation Limit	Greater Than	50.0
Overbilled - contracts under construction	Less Than	5.0
Underbilled - contracts under construction	Greater Than	10.0
Contractor`s Cash Flow	Less Than	3.0
Contractor`s Operating Line	Less Than	3.0
Past Similar (Type/Complexity) Projects	Less Than	3.0
Key Employee Type/Complexity Experience	Less Than	4.0
Project Manager Type/Complexity Experience	Less Than	5.0
Past Projects Experience in size	Less Than	3.0
Ratio to largest project	Less Than	80.0
Project Manager Size Experience	Less Than	5.0
Contractor Past Projects Experience in Location	Less Than	3.0
Average Staff Location Experience	Less Than	5.0

6.4 Steps in Applying SuretyQualification

The steps to apply SuretyQualification are illustrated in Figure 6-6. For a new contractor default prediction case, the process starts with collecting all of the required data to quantify the input evaluation criteria. The required evaluation includes the contractor's financial situation, the proposed project characteristics (size, type, schedule, etc.), and the contractual clauses. The evaluator should verify the threshold values for the evaluation criteria to ensure that the threshold values reflect the tolerance for acceptable values of the evaluation criteria. Then the evaluator enters the input values into SuretyQualification's "Input" worksheet. If any evaluation criterion has a "red flag," the broker or underwriter conducts further research regarding that criterion and investigates with the contractor how to reduce the risk in this area. Finally, SuretyQualification processes the input evaluation data and provides the evaluator with the contractor default risk (intermediate and overall) values. A report consisting of the input and output values can then be printed to document the contractor's default risk prediction process.

Table 6-4 presents an example for a hypothetical contractor default risk prediction case. The example shows in detail the calculations and the assumptions to quantify the 120 evaluation criteria. Table 6-5 presents the output report that includes the contractor default risk (intermediate and overall) values according to the input values from Table 6-4. The output report also presents the decision-making aids: "Level of Contractor Default Risk" and "Red Flags".

For example, there is a red flag for the current evaluation of the contractor, which means further investigation is needed for this category. If we looked back (in Table 6-4) for this category to discover the source of risk, we would find that this category includes three factors. These factors are: (1) work on hand to aggregation limit, (2) overbilled, and (3) underbilled. The first factor value is equal to 80%, which means the contractor is currently involved in projects that are equal to 80% of his aggregation limit. That means the contractor is very close to reaching his financial capacity. Therefore, further investigation with the contractor should be done to figure out how to increase the aggregation limit (i.e., capacity). The second factor, overbilled, is equal to zero, which means that the contractor has not billed for more than the amount actually earned (i.e., performed). That means that particular situation is not risky. For the third factor, underbilled, the value is equal to 4%. That means that in some projects, the contractor performed work but did not bill for it, which will affect the cash flow and may lead to shortage in the contactor's financial ability. The contractor is required to provide an explanation for this underbilling problem, in addition to providing a corrective plan to mitigate the possible financial shortage and a description of how that will help mitigate the risk on the overall cash flow.

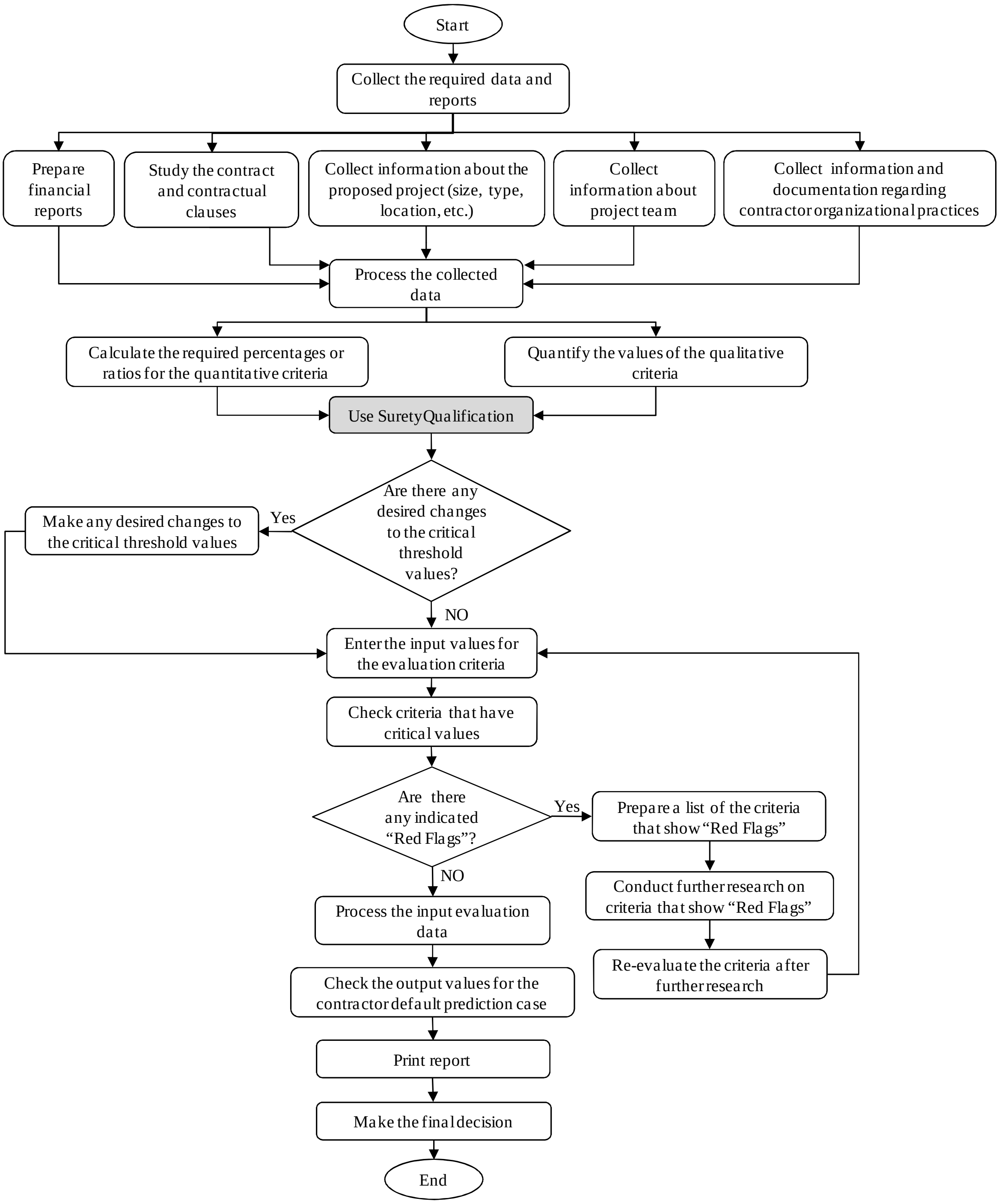


Figure 6-6 Steps in Applying SuretyQualification (Awad and Fayek 2012)

Table 6-4 Hypothetical Contractor Default Risk Prediction Case: Input Criteria Quantification

Input Evaluation Criteria		Case Description and Quantification	Input Value
Project Aspects Evaluation			
1. Project Team Evaluation			
Owner Evaluation			
1	Owner Type	There is previous experience between the project owner and the contractor	Private Known
2	Owner Funding Ability	There is no financial responsibility clause on bid document, no confirmation of project financing, and average surety underwriter/broker satisfaction regarding the owner ability to fund the project	2
3	Owner/Owner Agent Experience	The owner or owner agent has 12 years of experience in construction industry	12
4	Owner/Owner Agent Reputation	Owner/owner agent has good character, and has good relationship with general contractor	5
Subcontractors Evaluation			
5	Subcontractors Bonds Value	Subcontractors provided bonding value of 50% of the subcontracting work value	50
6	Subcontractors Experience	The average years of experience that the assigned subcontractors have in construction industry = 10 years	10
7	Overall Subcontractors Qualification	Subcontractors are prequalified informally, general contractor has no past relationship with subcontractors, and there is no check for subcontractor's availability of resources	2
8	Subcontracts Scope Gaps	Scope for each subcontractor is somewhat well-defined, average procedure to ensure that there is not any scope gapes, few meetings between subcontractors, and poor overall review for all subcontractors' roles	3
Architect/Engineer (Design Consultant) Evaluation			
9	A/E Experience	Architect/Engineer has 20 years of experience in construction industry	20
10	A/E Reputation	A/E has a good character, and has good relationships with general contractor	5
11	A/E Liability Insurance	A/E carries a medium level of errors and omissions, and has average claims history	3
Contractor Evaluation			
Last Financial Evaluation			
12	Working Capital Trend	According to the updated financial report: Current Assets = \$1,500,000; Current Liabilities = \$200,000 According to the previous financial report: Current Assets = \$1,000,000; Current Liabilities = \$150,000 Working Capital = Current Assets - Current Liabilities Current TNW = \$1,500,000 - \$200,000 = \$1,300,000 Previous TNW = \$1,000,000 - \$150,000 = \$850,000 Working Capital Trend = (Updated WC - Previous WC) / Updated WC Working Capital Trend = (\$1,300,000 - \$850,000) / \$1,300,000 = 0.346 = 34.6%	34.6

Input Evaluation Criteria		Case Description and Quantification	Input Value
13	Tangible Net Worth Trend	According to the updated financial report: Total Assets = $20,000,000; Liabilities = $300,000; Intangible Assets = $50,000 According to the previous financial report: Total Assets = $18,500,000; Liabilities = $375,000; Intangible Assets = $50,000 Tangible Net Worth = Total Assets - Liabilities - Intangible Assets Current TNW = $20,000,000 - $300,000 - $50,000 = $19,650,000 Previous TNW = $18,500,000 - $375,000 - $50,000 = $18,075,000 Tangible Net Worth Trend = (Updated TNW - Previous TNW) / Updated TNW Tangible Net Worth Trend = ($19,650.000 - $18,075,000) / $19,650.000 = 0.08 = 8%	8
14	Gross Profit Margin Trend	According to the updated financial report: Current GPM = 20% According to the previous financial report: Previous GPM = 18.7% Gross Profit Trend = (Current GPM - Previous GPM) / Current GPM Gross Profit Trend = (20 - 18.7) / 20 = 0.065 = 6.5%	6.5
15	Net Profit Margin Trend	According to the updated financial report: Current NPM = 16.7% According to the previous financial report: Previous NPM = 17.2% Net Profit Trend = (Current NPM - Previous NPM) / Current NPM Gross Profit Trend = (16.7 - 17.2) / 16.7 = -0.0299 = -3.0%	-3.0
16	Debt to Equity Ratio	According to the updated financial report: Current Debt = $300,000; Current Equity = $850,000 Debt to Equity Ratio = Current Debt / Current Equity Debt to Equity Ratio = $300,000 / $850,000 = 1:2.83	2.83
17	Gross Profit Margin	According to the updated financial report: Revenue = $3,500,000; Cost of delivered work = $2,800,000 Gross Profit Margin = (Revenue - Cost of Goods Sold) / Revenue Gross Profit Margin = ($3,500,000 - $2,800,000) / $3,500,000 = 0.2 = 20%	20
18	Net Profit Margin	According to the updated financial report: Net Profit = $500,000; Net Sales = $3,000,000 Net Profit Margin = Net Profit after Sales (i.e., net income) / Net Sales Net Profit Margin = $500,000 / $3,000,000 = 0.1667 = 16.7%	16.7
Current Evaluation			
19	Work on Hand to Aggregation Limit	Total Work on Hand = $100,000,000, and Aggregation Limit = $80,000,000 Ratio = (80,000,000 / 100,000,000)*100 = 60	80
20	Overbilled—contracts under construction	To date, there are no billings to owner more than the amount actually earned by the contractor for any projects under construction	0

	Input Evaluation Criteria	Case Description and Quantification	Input Value
21	Underbilled—contracts under construction	In one of the projects under construction: Billing to owner = $1,300,000 Amount actually earned by the contractor = $1,250,000 Underbilled Ratio = Absolute (Billed Amount - Earned Amount) / Earned Amount Underbilled Ratio = Absolute ($1,300,000 - $1,250,000) / 1,250,000 = 0.04 = 4%	4
22	Contractor`s Cash Flow	Average established cash flow, somewhat readable cash flow, average ability to handle the anticipated volume of work, average anticipated shortage of cash, somewhat reasonable actions to face shortage of cash, and average impact on the balance sheet in terms of liquidity and debt	3
23	Contractor`s Operating Line	Good expenditure requirements, good expected changes to the overall banking facility, average performance balance sheet and income statement for next year, and average backlog runoff report of projects for next 12 months	4
2. Project Specifics/Scope Evaluation			
Project Type/Complexity Experience Evaluation			
24	Past Similar (Type/Complexity) Projects	The contractor has performed 8 similar projects, in terms of type and complexity, in the past	8
25	Key Employee Type/Complexity Experience	Key employees have, on average, participated in 5 similar projects in terms of type and complexity	5
26	Project Manager Type/Complexity Experience	The project manager has been involved in 10 similar projects, in terms of type and complexity	10
Project Size Experience Evaluation			
27	Past Projects Experience in size	The contractor has performed 10 projects similar in size in the past	10
28	Ratio to largest project	The proposed project value = $200,000,000 The largest project that the contractor has performed to date = $150,000,000 Ratio to largest project = largest performed project value / proposed project value Ratio to largest project = $150,000,000 / $200,000,000 = 0.75 = 75%	75
29	Project Manager Size Experience	The project manager has been involved in 6 projects similar in size	6
Project Location Experience Evaluation			
30	Contractor’s Past Projects Experience in Location	The contractor has performed 15 projects in the past within the same location/environment	15
31	Average Staff Location Experience	The staff have participated in 4 projects (on average) within the same location/environment	4
32	Project Manager Location Experience	The project manager has been involved in 8 projects within the same location/environment	8
Project Cost Breakdown Evaluation			
33	Project Profit Margin Percentage	Total contract amount = $200,000,000 The Estimated Profit Margin = $10,000,000 Profit Margin Percentage = The Estimated Profit Margin / Total contract amount	5

Input Evaluation Criteria		Case Description and Quantification	Input Value
		Profit Margin Percentage = $10,000,000 / $200,000,000 = 0.05 = 5%	
34	Total Subtrade Percentage	Total contract amount = $200,000,000 Total Subtrade work = $40,000,000 Total Subtrade Percentage = Subtrade work / Total contract amount Total Subtrade Percentage = $40,000,000 / $200,000,000 = 0.20 = 20% The value of subtrade works to the total contract amount	20
35	Project Labour Percentage	Total contract amount = $200,000,000 Estimated labour costs = $46,000,000 Project Labour Percentage = Estimated labour costs / Total contract amount Project Labour Percentage = $46,000,000 / $200,000,000 = 0.23 = 23%	23
36	Project Material Percentage	Total contract amount = $200,000,000 Estimated Material costs = $58,000,000 Project Material Percentage = Estimated Material costs / Total contract amount Project Material Percentage = $58,000,000 / $200,000,000 = 0.27 = 27%	27
37	Project Equipment Percentage	Total contract amount = $200,000,000 Estimated Equipment Costs = $30,000,000 Project Equipment Percentage = Estimated Equipment Costs / Total contract amount Project Equipment Percentage = $30,000,000 / $200,000,000 = 0.15 = 15%	15
38	Project Contingency Percentage	Total contract amount = $200,000,000 Estimated Contingency = $16,000,000 Project Contingency Percentage = Estimated Contingency / Total contract amount Project Contingency Percentage = $16,000,000 / $200,000,000 = 0.08 = 8%	8
Project Schedule Evaluation			
39	Expected Project Duration	The estimated project duration = 30 months	30
40	Overall Schedule Evaluation	Well-prepared project schedule, average flexibility (floats) in project duration, average effect on payment cycle, and schedule has low impact on projects on hand	4
		Contractual Risk Evaluation	
1. Contract Wording/Type Evaluation			
Contract Wording/Type			
41	Contract Form Wording	The Owner used his/her wording for developing the contract	Owner Wording
42	Contract Type	A Unit Price contract is used	Unit Price
2. Contract Clauses Evaluation			
Payment Clauses Evaluation			
43	Architect/Engineer Role	The Architect/Engineer role is not clearly defined as to changes in the work, payment approval, substantial completion, and completion	NO
44	Materials Payment	Payment will be made for materials on site even if not	YES

Input Evaluation Criteria		Case Description and Quantification	Input Value
		incorporated yet	
45	Payment Process Timing	The timing period for the payment process = 10 days	10
46	Billing Requirement	The billing paper work requirement is reasonable	YES
47	Holdback Amount	The holdback amount = 15%	15
48	Holdback Releasing	Holdback will be released at substantial completion Holdback will be received upon completion of each phase of the project	YES
Warranty Clauses Evaluation			
49	Warranty Periods Clauses Evaluation	Warranty period = 20 months	20
50	Performance Warranties	There are performance warranties	YES
51	Manufacture Warranties	There are manufacture warranties	YES
52	Clear Definition of Defective Work	Defective work is clearly defined as being distinct from warranty items	YES
Indemnity Clauses Evaluation			
53	Contractor's Negligence	Liability is expressly limited to the contractor's negligence	YES
54	Indemnify List	There is not a reasonable limited list of parties that the contractor has to indemnify	NO
55	Liability Cap	Total contract amount = $200,000,000 Liability Cap Value = $15,000,000 Liability Cap Percentage = Liability Cap Value / Total contract amount Liability Cap Percentage = $15,000,000 / $200,000,000 = 0.075 = 7.5%	7.5
56	Architect/Engineer Errors	There is not any exclusion for Architect/Engineer design errors and/or instructions	NO
Schedule Extensions and Price Adjustment Clauses Evaluation			
57	Acts/Omissions Extension	Time will be extended for delays caused by acts or omissions of the owner, the architect/engineer, other contractors, or anyone employed or engaged by them	YES
58	Stop Orders Extension Clauses	Time will be extended for delays caused by stop orders, other than contractor`s fault	YES
59	Delays Events Extension Clauses	Time will be extended for delays caused by all events that are beyond contractor`s control (e.g., Force Major)	YES
60	Acts/Omissions Price Clauses	No additional money will provided for omissions of the owner, the architect/engineer, other contractors, or anyone employed or engaged by them	NO
61	Stop Orders Price Clauses	Additional money will provided for delays caused by stop orders, other than contractor`s fault	YES
62	Delays Events Price Clauses	No additional money will provided for delays caused by all events that are beyond contractor`s control	NO
63	Notification Time Clauses	Time to notify the owner or architect/engineer when contractor is delayed = no more than 20 days	20
Liquidated Damages / Bonuses			
64	Liquidated Damages Cap	Total contract amount = $200,000,000 Liquidated Damages Cap Value = $50,000,000 Liquidated Damages Cap Percentage = Liquidated Damages Cap Value / Total contract amount	25

Input Evaluation Criteria		Case Description and Quantification	Input Value
		Liquidated Damages Cap Percentage = $50,000,000 / $200,000,000 = 0.25 = 25%	
65	Phased Completion – Liquidated Damages	There are phased completion dates and the liquidated damages do not apply to each phase	NO
66	Bonus Value	Total contract amount = $200,000,000 Bonus Value = $2,000,000 Bonus Value Percentage = Bonus Value / Total contract amount Bonus Value Percentage = $2,000,000 / $200,000,000 = 0.01 = 1%	1
Toxic and Hazardous Substance and Materials Clauses Evaluation			
67	Contractor`s Responsibility – Toxic and Hazardous Substance	The wording of contractor`s responsibility for toxic and hazardous substances and materials under his/her care and control is clear	YES
68	Owner Indemnify – Unidentified hazardous substances offsite	The owner does not indemnify the contractor from claims or actions as a result of the contractor encountering unidentified hazardous substances offsite	NO
69	Dumping Procedure	There is a procedure to identify and monitor where waste is being dumped	YES
70	Toxic and Hazardous Substance Insurance	The contractor has no insurance for toxic and hazardous substances and Materials	NO
Disputes/Arbitration Clauses Evaluation			
71	Dispute Resolution Method	The method of dispute resolution (courts, arbitration, administrative procedure) is reasonable	YES
72	Resolution Time Frame	Time frame for resolution of dispute is reasonable	YES
73	Architect/Engineer Role to resolution and interpretation of the documents	The architect/engineer role is not clearly defined as to resolution and interpretation of the documents	NO
Design Concerns Clauses Evaluation			
74	Contractor Responsibility for Extra Designs	Contractor is responsible for some designs in addition to formwork, shoring, and false work	YES
75	Incomplete Documents	Contractor is not responsible for incomplete or inconsistent documents (drawings and specifications) beyond notification	NO
Bonding/Security Evaluation			
76	Bid Bond Type	Standard bid bond form is used	Standard
77	Bid Bond Value	Bid Bond value = 50% of the contract value	50
78	Bid Bond Acceptance Period	Bid Bond acceptance period = 60 days	60
79	Consent of Surety Type	Standard Consent of Surety/Agreement to Bond form is used	Standard
80	Consent of Surety Value	Percentage of Consent of Surety value = 50% of the contract value	20
81	Acceptance Period	Consent of Surety/Agreement to Bond acceptance period = 80 days	80

Input Evaluation Criteria		Case Description and Quantification	Input Value
82	Performance (Consent of Surety/Agreement to Bond percentage)	Performance Bond value = 20% of the contract value	20
83	Labour/Material/Payment	Labour/Material/Payment value = 80% of the Bond value	80
Contractor's Organizational Practices Evaluation			
Project Integration Management			
84	Project Management Plan/Directing and Execution/Configuration Management System	Very adequate project management plan is developed, the performance measurement baselines (scope baseline, schedule baseline, and cost baseline) are well-defined, the process for performing the work is well-defined in the project management plan to achieve the project`s objectives, and a good configuration management system is developed	5
85	Project Monitor, Control, and Close	Average process for tracking, reviewing, and regulating the progress to meet the performance objectives defined in the project management plan, and average process for finalizing all activities to formally complete the project	3
Project Scope Management			
86	Collect Requirements and Scope Define and Control	Good process for defining and documenting stakeholders' needs, good process for developing a detailed description of the project and product, and average process for monitoring the status of the project and product scope	4
87	Applying Constructability Principles	No effort for applying and emphasizing constructability principles	1
88	Assigned Constructability Coordinator	No constructability coordinator assigned to the proposed project	No coordinator
Project Time Management			
89	Project Administrator Experience	The Project Administrator (who manages the day-to-day timesheet process) has 10 years of experience in construction	10
90	Time Management Process	Project activities and activities' attributes are adequately defined, an average milestone list is developed, the required activity resources are adequately estimated, the three generic processes of time management are somewhat defined and understood, and a good process for control schedule is prepared	4
91	Time Management Documents	No prepared central log/database (timesheet register), no pre-prepared project timesheet form, and no pre-prepared project time management documentation process.	1
Project Cost Management			
92	Cost Management Roles	The roles and responsibilities for all resources involved with the request, approval, and payment of expenses within the project are not defined	NO
93	Cost Management Process	Adequate approximation of the monetary resource needed to complete project activities, good process for monitoring the status of the project to update the project budget and managing changes to the cost baseline, and the three generic processes of cost management are adequately defined and understood	4
94	Cost Management Documents	Good prepared expense form, good pre-prepared expense register (log/database), and inadequate pre-prepared project expenses documentation process	4

Input Evaluation Criteria		Case Description and Quantification	Input Value
Project Quality Management			
95	Quality Management plans	Inadequate prepared quality plan, inadequate process to perform quality assurance, and inadequate process to perform quality control	2
96	Quality Management Responsibilities	The contractor provided a good overview of the proposed cost management process. The three generic processes (document expense form, approve expense form, and register expense form) of cost management are well-defined and understood.	YES
97	Quality Manager Experience	The Quality Manger has 9 years of experience in construction	9
98	Quality Management Documents	Good prepared log/database (deliverables register), good pre-prepared project quality review form, and inadequate pre-prepared project quality documentation process	4
Project Human Resource Management			
99	Develop Human Resource Plan	Average identification for the project roles and responsibilities, average identification of the required skills, and inadequate staffing management plan is created	3
100	Acquire and Develop Project Team	Adequate confirmation of human resource availability, somewhat adequate plan for obtaining the team necessary to complete project assignments, average plan for improving project team competencies and team interaction	4
101	Manage Project Team	Inadequate process for tracking team member performance and providing feedback, and no prepared process for resolving issues and managing changes	2
Project Communications Management			
102	Overall Communication Management Process	Inadequate communication plan; communication roles/ responsibilities are not well-defined; stakeholders are inadequately identified; average process of collecting and distributing performance information, including status reports, progress measurements, and forecasts; average process of making relevant information available to project stakeholders	3
103	Communication Roles (channels) Number/Types	The number and types of communications roles are reasonable regarding the size and complexity of the project	YES
104	Communications Management Documents	Good prepared log/database (procurement register), good pre-prepared project purchase order form, and inadequate pre-prepared project purchase documentation process	4
Project Risk Management			
105	Risk Plan/ Identification/ Quantification	Very adequate risk management plan, good process of determining which risks may affect the project, and good qualitative and quantitative risk analysis	5
106	Risk Responses and Monitor/Control	Very good process for developing options and actions to enhance opportunities and to reduce threats to project objectives, very adequate process to monitor and control risks	5
107	Risk Management Team Experience	The risk management team has an average of 5 years of experience in risk management in construction	15
Project Procurements Management			
108	Procurements Responsibilities	The roles and responsibilities for all resources (both internal and external to the project) involved with the procurement of product and management of supplier relationships are well-defined. The contactor provided a copy of the responsibilities	YES

Input Evaluation Criteria		Case Description and Quantification	Input Value
		distribution chart.	
109	Procurements Manager Experience	The procurement manager/officer has 15 years of experience in construction	15
110	Procurements Management Documents	Average prepared log/database (procurement register), average pre-prepared project purchase order form, and inadequate pre-prepared project purchase documentation process	3
111	Procurements Plan/Administer/Close	Adequate procurements plan; good process for managing procurement relationships, monitoring contract performance, and making changes and corrections as needed; and good process for completing project procurement	4
Project Safety Management			
112	Safety Preplanning Meetings	Safety was a priority topic at preplanning meetings	YES
113	Safety Toolbox Meetings	Safety toolbox meetings will be held regularly	YES
114	Site Safety Supervisor	There will be a part-time site safety supervisor for the proposed project working	Part-Time
115	Number of Workers per Safety Person (on site)	There will be a safety person for every 35 on-site workers	35
116	Safety Incentives	No safety incentives will be used	NO
Project Change Management			
117	Pre-Authorized Employees	There are pre-authorized employees in charge of the different responsibilities of the change management process (change requester, change manager, change feasibility group, change approval group, change implementation group)	YES
118	Change Management Process	The contactor provided a good proposal for applying the change management process in the proposed project. The five key processes of change management (submit change request, review change request, identify change feasibility, approve change request, implement change request) are well-defined and understood.	NO
119	Change Manager	The Change Manager has 10 years of experience in construction	10
120	Change Documents	Good prepared log/database (change register), good pre-prepared change request form, and good pre-prepared change management documentation process	5

Table 6-5 SuretyQualification Evaluation for the Hypothetical Contractor Default Risk Prediction Case

Output Evaluation Criteria	Output Value	Red Flag	Risk Level
Project Aspects Evaluation			
Project Aspects Evaluation	3.6		Low Risk
1. Project Team Evaluation			
Project Team Evaluation	3.4		Low Risk
Owner Evaluation	3.3		Low Risk
Subcontractors Evaluation	3.0		Average Risk
Architect/Engineer (Design Consultant) Evaluation	4.3		Very Low Risk
Contractor Evaluation	3.6		Low Risk
Last Financial Evaluation	4.1		Very Low Risk
Current Evaluation	2.7	RED FLAG	Average Risk
2. Project Specifics/Scope Evaluation			
Project Specifics/Scope Evaluation	3.6		Low Risk
Project Type/Complexity Experience Evaluation	3.6		Low Risk
Project Size Experience Evaluation	4.3		Very Low Risk
Project Location Experience Evaluation	4.0		Very Low Risk
Project Cost Breakdown Evaluation	3.6		Low Risk
Project Schedule Evaluation	3.3		Low Risk
Contractual Risk Evaluation			
1. Contract Wording/Type Evaluation (Contract Form and Contract Type)			
Contractual Risk Evaluation	3.0		Average Risk
Contract Wording/Type	1.6	RED FLAG	Somewhat Critical Risk
2. Contract Clauses Evaluation			
Contract Clauses Evaluation	4.3		Very Low Risk
Payment Clauses Evaluation	4.3		Very Low Risk
Warranty Clauses Evaluation	3.0		Average Risk
Indemnity Clauses Evaluation	4.3		Very Low Risk
Schedule Extensions and Price Adjustment Clauses Evaluation	3.6		Low Risk
Liquidated Damages/Bonuses Evaluation	3.1		Low Risk
Toxic and Hazardous Substances and Materials Clauses Evaluation	3.0		Average Risk
Disputes/Arbitration Clauses Evaluation	3.0		Average Risk
Design Concerns Clauses Evaluation	3.0		Average Risk
Bonding/Security Evaluation	2.9	RED FLAG	Average Risk
Contractor's Organizational Practices Evaluation			

Output Evaluation Criteria	Output Value	Red Flag	Risk Level
Contractor's Organizational Practices	3.4		Low Risk
Project Integration Management	3.5		Low Risk
Project Scope Management	1.6	RED FLAG	Somewhat Critical Risk
Project Time Management	3.4		Low Risk
Project Cost Management	3.0		Average Risk
Project Quality Management	3.2		Low Risk
Project Human Resource Management	3.1		Low Risk
Project Communications Management	3.8		Low Risk
Project Risk Management	4.3		Very Low Risk
Project Procurements Management	4.3		Very Low Risk
Project Safety Management	3.0		Average Risk
Project Change Management	4.3		Very Low Risk
Overall Contractor Default Risk Rate	**5.5**		**Very Low Risk**

6.5 Concluding Remarks

The SuretyQualification software was developed for contractor default prediction; it can be used for contractor evaluation/prequalification by surety underwriters, surety brokers, and owners in the construction industry. The software can also be used by contractors to conduct self-assessments to discover the areas that may cause them to default when performing a project, and therefore may need improvement. SuretyQualification’s interface was developed to allow easy interaction between the evaluator and the software, and to provide a comprehensive report for the contractor default prediction risk values (overall and intermediate), with additional decision-making process aids such as “Level of Contractor Default Risk” and “Red Flags.” SuretyQualification advances the state-of-the-art of contractor evaluation/prequalification for a specific construction project by automating and enhancing the surety underwriting process.

6.6 References

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CHAPTER 7. - Conclusions and Recommendations[1]

This chapter provides a review of the work conducted in this research, and summarizes the contributions. Limitations of the developed model and recommendations for future research are also outlined.

7.1 Research Summary

In the construction bonding business, a complex and comprehensive prequalification or assessment process is done to evaluate contractor, project, and contractual risks. Previous studies have focused mainly on contractor prequalification from the owner's or consultant's perspective, considering the evaluation of the contractor's financial aspects to predict contractor default. Contractor default is one of the major risks that may threaten a project's success in the construction industry.

The main motivation of this research was to introduce a structured methodology and develop a system to predict the possible risk of contractor default in a construction project. In construction, contractor default occurrence depends not only on the contractor but also on many other aspects. Therefore, the intention was to develop a system that focused on the contractor evaluation in addition to other aspects that may influence the success of project completion, such as the construction contract and the project team.

[1]Parts of this chapter have been published in Journal of Automation in Construction, Volume 21, January 2012, and accepted for publication in Canadian Journal of Civil Engineering, 2012.

The research in this thesis was conducted mainly in four stages: (1) developing an initial contractor prequalification DSS, (2) enhancing the developed DSS to present a comprehensive contractor default prediction model (CDPM), (3) optimizing the developed CDPM to increase its accuracy, and (4) developing the SuretyQualification software for the optimized CDPM.

7.1.1 The First Stage

The second chapter identifies and classifies the most relevant evaluation criteria that surety underwriters and brokers consider when evaluating a specific construction project for bonding purposes. Several data collection techniques (questionnaires, one-on-one interviews, and interactive group meetings) with highly experienced surety experts were conducted to compile a comprehensive and detailed list of the evaluation criteria. Both fuzzy logic and expert systems are combined to develop a decision support system (DSS) for use in contractor and project evaluation.

A new approach for fuzzy membership function estimation was presented. The new approach incorporates the Horizontal MBF estimation technique, which depends on expert knowledge and contractor prequalification cases (data integration). Several alternative system configurations are investigated to determine the most accurate one. Finally, the fuzzy expert DSS was validated with hypothetical project- contractor prequalification cases.

7.1.2 The Second Stage

Further improvements to the developed fuzzy expert DSS were needed. One important evaluation component, contractor’s organizational practices, needed to be incorporated. Contractor’s organizational practices have not been evaluated in the surety underwriting process, but their inclusion might enhance decision-making, and allow the evaluation of a contractor’s plans regarding practices—such as safety management, quality management, time management, cost management, and many other practices that can contribute to project success—to be considered. However, this evaluation component required more research before being incorporated into the developed DSS, and more surety experts from across Canada were needed to contribute to the development process.

To include the experts’ input for the next stage of the contractor evaluation model, there was a need for a methodology to determine a group consensus function of the aggregation of experts’ judgmental scores to represent a common opinion. In the third chapter, a group consensus system was developed to determine the consensus weight factor (CWF) for surety experts working in the construction industry, to incorporate their input as a collective opinion. The system uses the multi-attribute utility function (MAUF) methodology, which determines the CWF for surety experts by considering their preferences (liking) of six experience measures. The Analytical Hierarchy Process (AHP) was used to determine the degree of liking of the experience attributes. Two validation approaches have been applied to validate the developed GCM: face validation and numerical validation.

The fourth chapter presented a contractor default prediction model (CDPM) from the surety bonding perspective that incorporates the evaluation of all the project aspects, the project team, contractual risks, and project management evaluation criteria to predict the possibility of a contractor defaulting on a specific construction project. Fuzzy logic and expert system techniques were integrated to develop the CDPM. An important evaluation category, contractor's organizational practices, was incorporated as input to the CDPM. The CDPM was built using the expertise of surety practitioners across Canada, and several different knowledge acquisition techniques were used. A new approach for developing fuzzy rules was presented to generate a complete rule base. The CDPM was validated using contractor default prediction cases.

7.1.3 The Third Stage

The performance of a fuzzy expert system (FES) is significantly affected by the accuracy of its knowledge base parameters (membership functions and rule bases). The fifth chapter presents a methodology to integrate an FES with adaptation/optimization techniques and to apply the data-based adaptive learning concept to increase the accuracy of an FES developed for contractor default prediction for surety bonding. Two different optimization techniques, genetic algorithms and artificial neural network back-propagation, were applied separately to adapt the FES knowledge base (membership function and rules' degrees of support). The adaptation process enhanced the accuracy of the previously-developed contractor default prediction FES by providing results that are close to the surety experts' evaluation. The two adapted FESs were validated using the same unseen contractor default prediction cases, and the best accuracy was obtained using the NN back-propagation algorithm.

7.1.4 The Fourth Stage

In the sixth chapter, the SuretyQualification software was developed for contractor default prediction. SuretyQualification's interface was developed to allow easy interaction between the evaluator and the software, and to provide a comprehensive report for the contractor default prediction risk values (overall and intermediate), with additional decision-making process aids such as "Level of Contractor Default Risk" and "Red Flags."

7.2 Research Contributions

This thesis presents approaches that are relevant to researchers. Additionally, it makes various academic and industrial contributions to the construction industry, in addition to some practical applications for surety bonding and contractor prequalification. The details of these contributions are as follow.

7.2.1 Academic Contributions

The main academic contributions offered by this research can be summarized as follows:

- An exploration and proof of the appropriateness of the FES for contractor evaluation (underwriting) for surety bonding for a specific construction project. The use of fuzzy expert systems in decision-making is not new;

however, applying it to surety underwriting for a specific project is. The methodology used to create the fuzzy expert decision support system (DSS) for contractor prequalification for surety bonding has been described. For developing the DSS, a novel approach for fuzzy membership function (MBF) estimation was developed. The new approach incorporates the Horizontal MBF estimation technique, which depends on experts' knowledge (knowledge-based) and contractor prequalification cases (data integration). Also, a novel approach for fuzzy rule base development that combines two methods—learning from examples, using hypothetical contractor default prediction cases; and using the inputs' relative importance weights to develop fuzzy rules—has been presented. Several experts` knowledge acquisition techniques for building FESs have been applied.

- A new approach to incorporate experts' inputs as a collective single opinion for building a fuzzy experts system. The new approach depends mainly on the weighted averaging approach, with bias to the experts' level of expertise. Applying this approach included developing a surety group consensus system (GCS) to determine consensus weight factor (CWF) for surety experts. This is a key aspect in aggregating the participating experts' inputs or assessments into a collective assessment. The process of developing the GCS included investigating and proofing the suitability of the multi-attribute utility function (MAUF) methodology, to solve the problem of aggregating experts' opinions.

- A description of a methodology to integrate a fuzzy expert system (FES) with adaptation/optimization techniques, and apply the data-based adaptive learning concept to increase the accuracy of an FES developed for contractor default prediction for surety bonding. Two optimization approaches (genetic algorithms and neural network back-propagation) were investigated to adapt fuzzy MBF and rules' degree of support (DoS). Each optimization technique has been integrated with the contractor default prediction model separately, to determine the most suitable technique to adapt the FES to any new environmental (contextual) information conveyed using input-output (contractor default prediction) cases.

7.2.2 Industrial Contributions

In addition to the academic contributions, this research also offers several industrial contributions, which can be summarized as follows:

- A fuzzy expert DSS, which was developed to help surety underwriters and brokers in the second phase of the surety underwriting process and to provide a systematic and structured approach to this complex process. To determine the DSS's inputs, a comprehensive, detailed list of the evaluation criteria for contractor and project prequalification was compiled. In addition, numerical scales for the quantitative evaluation criteria and rating scales to quantify the qualitative criteria were defined.

For all contactor evaluation criteria, critical threshold values and favourable trends were determined.

- A comprehensive model that has been developed with the ability to incorporate the evaluation of all the project aspects, the project team, contractual risks, and project management evaluation criteria to predict the possibility of a contractor's default on a specific construction project. The contractor default prediction model (CDPM) was built from the surety bonding perspective that incorporates these criteria and uses a fuzzy inference system for reasoning.
- The SuretyQualification software, which was developed for contractor default prediction, and can be used for contractor evaluation/prequalification by surety underwriters, surety brokers, and owners in the construction industry. SuretyQualification's interface was developed to allow easy interaction between the evaluator and the software, and to provide a comprehensive report for the contractor default prediction risk values (overall and intermediate), with additional decision-making process aids such as "Level of Contractor Default Risk" and "Red Flags." SuretyQualification advances the state-of-the-art of contractor evaluation/prequalification for a specific construction project by automating and enhancing the surety underwriting process.

7.2.3 Practical Applications

The developed CDPM and SuretyQualification software provide several practical applications for surety bonding and contractor prequalification, as follows:

- An improved method for surety underwriters and brokers to validate their underwriting decision versus the current method that they are using (expert's judgment or experience), in addition to a structured, organized, and objective approach for surety underwriters to use in the evaluation of subjective criteria and criteria that are difficult to quantify in contractor qualification for a specific project, which helps in formalizing this complex decision process while making its logic easy to trace. Using the developed model will also decrease the subjectivity of the evaluation process by identifying all of the important factors that should be considered for a comprehensive assessment of the contractor and the project.
- The required documentation that summarizes the prequalification process, whether for upper management levels or for the contractor, in any case where a certain bonding request for a construction project is rejected. Also, the surety underwriter or broker can use the documentation provided by the CDPM to show an owner, the true customer and beneficiary of the surety product, how they "prequalified" the contractor for their project, which is the main service of the surety product.

- A structure to the underwriting process, by guiding the evaluator through a series of questions to systematically evaluate each factor that contributes to the contractor evaluation, leading to more thorough and improved decision-making. That can help in succession planning by capturing senior surety experts` knowledge and assisting with the training of new or inexperienced (junior) surety underwriters or brokers who may not know which questions to ask to evaluate a contractor, or in what range the values for each variable should fall.
- An advancement of the state-of-the-art of the surety underwriting process, by including evaluation criteria related to the project and contractual risks, in addition to the contractor-related criteria. The CDPM and developed software also provide a method for assisting the construction contractors to discover areas that need improvement in order to obtain bonding for a construction project.

7.3 Research Limitations and Recommendations for Future Research and Development

This research has provided a basis for future research in contractor default prediction and contractor prequalification by compiling a complete and comprehensive list of evaluation criteria, and applying fuzzy set theory to deal with subjective and uncertain factors in the evaluation of the possible risk of contractors' default in construction projects. Despite the contributions presented in this research, the research has certain limitations. The following steps are recommended to be applied for future research, in order to cover the current research limitations:

7.3.1 Model Validation

- The developed CDPM was validated against the participating surety experts' assessments. In other words, the experts' judgment was the baseline for measuring the accuracy of the CDPM. Notwithstanding the high level of experience of the participating experts, it is recommend that future work identify the quality of their decisions by comparing the number of claims for bonded (prequalified) and unbonded work. The potential improvements that could be gained by using the CDPM (presented in this research) could then be better assessed.
- Surety professionals did not document all evaluation (input) criteria used for the developed model. Therefore, hypothetical contractor default prediction cases were used for the model's development, optimization, and validation stages. The model was developed to provide an evaluation that simulates the surety experts' evaluation (assessment). Actual contractor default prediction cases need to be collected to conduct more optimization for the developed contractor default prediction model (CDPM). The collected cases can also be used to conduct more validation and sensitivity analysis for the CDPM. In the actual cases, the contractor performance after the project completion can be compared with the pre-project evaluation conducted by the developed model.

- It is suggested that another model or system be developed that has the ability to measure contractor performance after project completion. To further validate the developed CDPM, a comparison between the CDPM evaluation (before the project) should be done against the contractor performance evaluation (after the project). The model could consider several contractor performance indicators such as: type, number, and value of the claims that have been issued during project execution; the planned and actual budget; the planned and actual schedule; feedback from project stakeholders, etc.).
- Due to the large number of the model inputs, experts will not be able to provide the evaluation for many cases. However, many cases will be needed for the optimization process. Therefore, it is advisable to connect as many as possible experts to provide their input for the future development of the model. It is important to prepare a plan to meet with surety organizations in construction and provide an explanation of the developed model, in addition to the expected benefits from the further improvements. It is also important to provide the experts with the developed model and ask them to use it for future contractor prequalification. That way, they can document all contractor default prediction or contractor prequalification cases in the future according to the structure of the developed model. The experts should also provide the assessment for all the model outputs (intermediate and final overall).

7.3.2 Model Optimization

- Optimization of the developed model (i.e., CDPM) using the GAs was conducted for one trial using the predetermined initial solutions. However, it is recommended to conduct several GA optimization trials (not less than 10 trials) for the same model. The initial population for these trials can be randomly generated and/or developed as a mix between the predetermined solutions presented in this study and random solutions.
- Different approaches should be investigated to perform the different GA processes (i.e., parent selection, crossover, and mutation). A sensitivity analysis should be conducted using the optimization results from each approach to determine the most suitable approach for CDPM adaptation.
- Only the most common optimization techniques (genetic algorithms and artificial neural networks) that can be integrated with fuzzy systems were investigated for the model optimization. More optimization techniques that can be integrated with fuzzy models, such as the “Ant Colony” and/or the “Particle Swarm” optimization algorithms, can be investigated to increase the model accuracy.

7.3.3 Model Context Variables

Since economic conditions can have a significant effect on contractor default, it is recommended that a variety of economic and market conditions be incorporated as context variables for future work in the CDPM model.

7.3.4 Model Scope

- Only surety experts provided the knowledge required for the contractor default prediction model development. However, to improve the versatility of the model, more construction parties (e.g., owners, consultants, and suppliers) need to be invited to provide their inputs for improvements to the model. Their contributions may add more evaluation criteria that make the model suitable for everyone who is concerned with contractor prequalification and/or contractor default prediction.
- The contractor default prediction model presented in this research was developed to evaluate general contractors; it could be enhanced by including more evaluation criteria in order to evaluate subcontractors and heavy equipment contractors.

Appendix A – Sample of the Relative Importance Weights Questionnaire for the DSS

Criteria Weighting for General Contractors

The purpose of this document is to weight evaluation criteria used in the prequalification process of **General Contractors for a specific project**. The prequalification criteria was subdivided into 3 categories; Project Aspects, Contractual Risks, and Contractor`s Organizational Practices. Each of these categories is divided into subcategories, some of which are also divided into sub-subcategories. Please weight the importance of each criterion relative to the other criteria in that category, subcategory, or sub-subcategory by circling **1 for the LEAST Important and 7 for the MOST important**. For more clarification of different levels of categories and subcategories and sub-subcategories, each category colored with certain color and each color represents a certain level of evaluation factors as indicated below.

First level	**Second level**	**Third level**	**Fourth level**

If you have any questions regarding this document please contact me (Adel Awad) by email, Alawad@ualberta.ca, or by telephone, 780.492.9131, and I will be happy to answer them. Thank you very much for your time and helpful insight.

Project Aspects

1.0 Project Team – 7	1	2	3	4	5	6	
1.1 Owner	1	2	3	4	5	6	7
1.1.1Owner Type	1	2	3	4	5	6	7
1.1.2Funding	1	2	3	4	5	6	7
1.1.3Experience	1	2	3	4	5	6	7
Quarterly evaluation							
1.4.1 WC/TNW Trends	1	2	3	4	5	6	7
1.4.1.1 Working Capital Trend	1	2	3	4	5	6	7
1.4.1.2 Tangible Net Worth Trend	1	2	3	4	5	6	7

2.0 Project Specifics	1	2	3	4	5	6	7
2.1 Scope of Work	1	2	3	4	5	6	7
2.1.2Type	1	2	3	4	5	6	7
2.1.3Size	1	2	3	4	5	6	7

2.1.4Location	1	2	3	4	5	6	7
2.1.5Cost Breakdown	1	2	3	4	5	6	7
2.1.6Mobilization/Demobilization	1	2	3	4	5	6	7
2.2 Schedule	1	2	3	4	5	6	7
2.2.1Project Duration	1	2	3	4	5	6	7
2.2.2Flexibility	1	2	3	4	5	6	7

3.0 Project Risk	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3.1 Risk Identification	1	2	3	4	5	6	7
3.2 Risk Assessment Analyses	1	2	3	4	5	6	7
3.3 Risk Mitigated Plan	1	2	3	4	5	6	7

Contractual Risk

1.0 Contract – Which criterion is more/less important?							
1.1 Form of Contract	1	2	3	4	5	6	7
1.2 Type of Contract - Bid/Proposal	1	2	3	4	5	6	7
1.2.1Consultants	1	2	3	4	5	6	7
1.2.2Insurance	1	2	3	4	5	6	7
1.2.3Subcontractors	1	2	3	4	5	6	7

2.0 Contract Clauses	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2.1 Payment	1	2	3	4	5	6	7
2.2 Warranty	1	2	3	4	5	6	7
2.3 Indemnity	1	2	3	4	5	6	7
2.4 Changes to Work	1	2	3	4	5	6	7
2.5 Schedule Extensions & Price Adjustment	1	2	3	4	5	6	7
2.6 Concealed or Unknown Conditions	1	2	3	4	5	6	7
2.7 Damages / Penalties / Bonuses	1	2	3	4	5	6	7
2.8 Toxic, Hazardous Substance & Materials	1	2	3	4	5	6	7
2.9 Disputes / Arbitration	1	2	3	4	5	6	7
2.10 Assignment of Contract	1	2	3	4	5	6	7

Appendix B – Sample of the Membership Function Estimation Questionnaire for the DSS

PART (1) - Project Aspects

1. Owner Funding

"Owner funding" indicates the owner funding ability evaluation. There are several points related to this issue, such as;

1. Funding ability.
2. The existence of financial responsibility clause on bid document.
3. Confirmation of project financing.
4. Type of confirmation provided.
5. The surety underwriter/broker satisfaction regarding the owner ability to fund the project.

Using 1-7 rating scale to evaluate the owner funding situation as;

1. INADEQUATE Funding ability, No financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction.

2. ADEQUATE Funding ability, No financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction.

3. ADEQUATE Funding ability, AVERAGE financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction.

4. ADEQUATE Funding ability, GOOD financial responsibility clause on bid document, POOR Confirmation of project financing, and low surety underwriter/broker satisfaction.

5. ADEQUATE Funding ability, GOOD financial responsibility clause on bid document, AVERAGE Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction.

6. ADEQUATE Funding ability, GOOD financial responsibility clause on bid document, GOOD Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction.

7. VERY ADEQUATE Funding ability, GOOD financial responsibility clause on bid document, GOOD Confirmation of project financing, and HIGH surety underwriter/broker satisfaction.

1. What would you consider to be POOR Owner Funding situation?

Please check all applicable boxes.

Average						
○	○	○	○	○	○	○
1	2	3	4	5	6	7

2. What would you consider to be **AVERAGE** Owner Funding situation?

Please check all applicable boxes.

Average						
○	○	○	○	○	○	○
1	2	3	4	5	6	7

3. What would you consider to be GOOD Owner Funding situation?

Please check all applicable boxes.

Average						
○	○	○	○	○	○	○
1	2	3	4	5	6	7

Comments:

----

6. Working Capital Trend

"Working Capital (WC)

A measure of both a company's efficiency and its short-term financial health.

Working Capital = Current Assets – Current Liabilities

Working Capital Trend

The percentage of increase or decrease of working capital

Working Capital Trend = (Current WC – Last WC)/Current WC"

1. What would you consider **LOW** in Working Capital to be?

Please check all applicable boxes.

-16%	-14%	-12%	-10%	-8%	-6%	-4%	-2%	0	2%	4%	6%	8%	10%	12%

14%	18%	20%	22%	24%	26%	28%	30%

2. What would you consider **AVERAGE** in Working Capital to be?

Please check all applicable boxes.

-16%	-14%	-12%	-10%	-8%	-6%	-4%	-2%	0	2%	4%	6%	8%	10%	12%

14%	18%	20%	22%	24%	26%	28%	30%

3. What would you consider **HIGH** in Working Capital to be?

Please check all applicable boxes.

-16%	-14%	-12%	-10%	-8%	-6%	-4%	-2%	0	2%	4%	6%	8%	10%	12%

14%	18%	20%	22%	24%	26%	28%	30%

PART (2) - Contractual Risk

"Payment" is a factor reflects satisfaction towards the conditions under which payment will be made for work completed during a portion of a construction period.

Points that can be used for rating the Payment factor, such as;

- Payment terms.
- Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion.
- Owner approval in the payment process.
- Entire payment process and timing.
  - Payment will be made for materials on site.
- Holdback amount.
- Holdback releasing.
  - In case of several phases project, receiving holdback upon completion of each phase.

Using 1-7 rating scale to evaluate Payment factor as;

- POOR payment terms, POOR payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is NOT CLEARLY defined, UNREASONABLE holdback amount, NOT INCORPORATED payment for materials on site, If project makes up several phases, the contractor NOTABLE TO receive holdback upon completion of each phase and LOW surety underwriter/broker satisfaction.
- AVERAGE payment terms, AVERAGE payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is NOT CLEARLY defined, UNREASONABLE holdback amount, NOT INCORPORATED payment for materials on site, If project makes up several phases, the contractor NOTABLE TO receive holdback upon completion of each phase and AVERAGE surety underwriter/broker satisfaction.
- AVERAGE payment terms, AVERAGE payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is SOMEWHAT CLEARLY defined, REASONABLE holdback amount, NOT INCORPORATED payment for materials on site, If project makes up several phases, the contractor NOTABLE TO receive holdback upon completion of each phase and AVERAGE surety underwriter/broker satisfaction.
- GOOD payment terms, GOOD payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is SOMEWHAT CLEARLY defined,

SOMEWHAT REASONABLE holdback amount, NOT INCORPORATED payment for materials on site, If project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase and AVERAGE surety underwriter/broker satisfaction.

- GOOD payment terms, GOOD payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is SOMEWHAT CLEARLY defined, REASONABLE holdback amount, INCORPORATED payment for materials on site, If project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase and AVERAGE surety underwriter/broker satisfaction.

- VERY GOOD payment terms, GOOD payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is CLEARLY defined, REASONABLE holdback amount, INCORPORATED payment for materials on site, If project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase and AVERAGE surety underwriter/broker satisfaction.

- VERY GOOD payment terms, VERY GOOD payment process and timing, Architect/Engineer's role to changes in the work, payment approval, substantial completion and completion is VERY CLEARLY defined, VERY REASONABLE holdback amount, INCORPORATED payment for materials on site, If project makes up several phases, the contractor ABLE TO receive holdback upon completion of each phase, and HIGH surety underwriter/broker satisfaction.

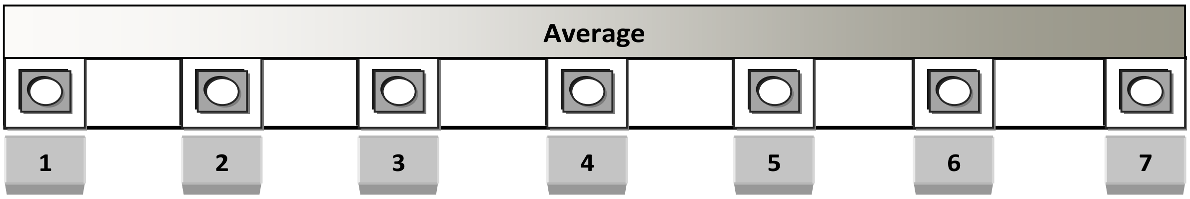
1. Which rate would you consider **POOR** Payment to be? Please check all applicable boxes.

Average						
☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7

2. Which rate would you consider **AVERAGE** Payment to be? Please check all applicable boxes.

Average						
☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7

3. Which rate would you consider **GOOD** Payment to be? Please check all applicable boxes.



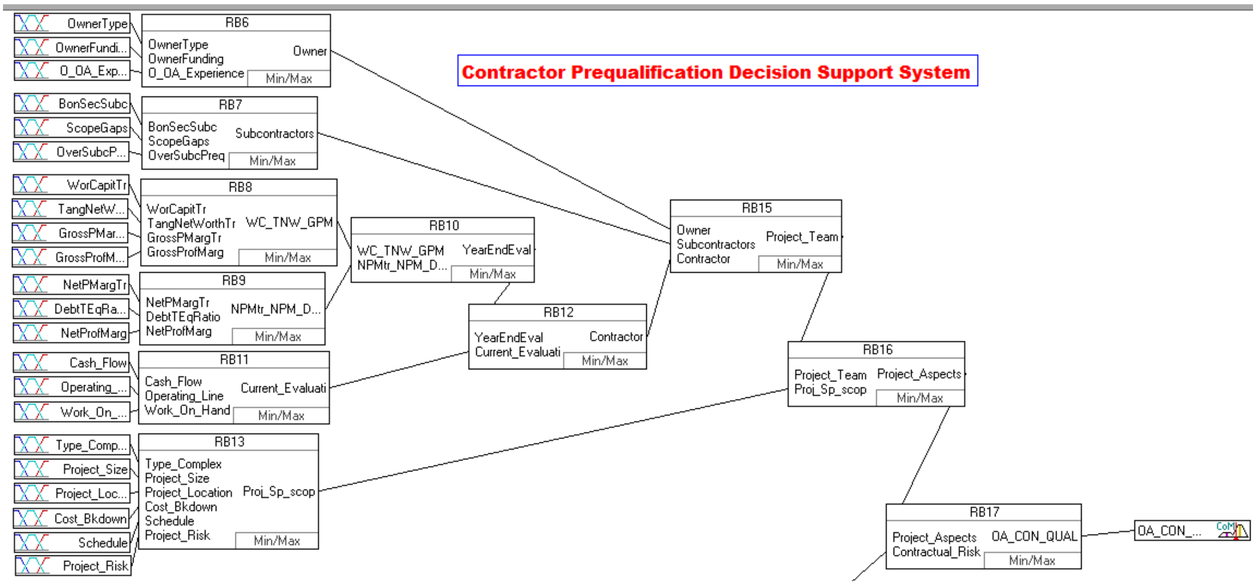
Appendix C – DSS Description and Sample of the MBFs, and Rule Base

DSS Description

Input Variables	32
Output Variables	1
Intermediate Variables	15
Rule Blocks	16
Rules	1134
Membership Functions	143

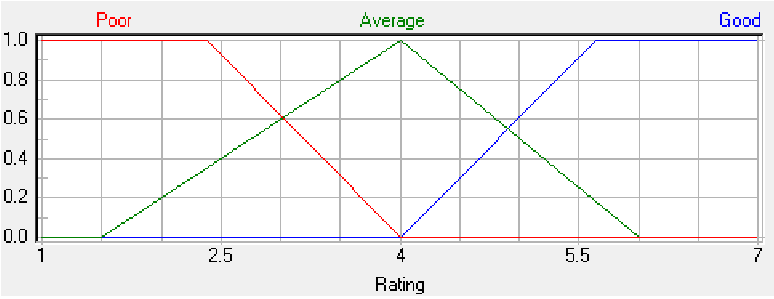
Part of the System Structure

The system structure identifies the fuzzy logic inference flow from the input variables to the output variables.



Sample of the input' MBFs

Input Variable "Bonding_Security"

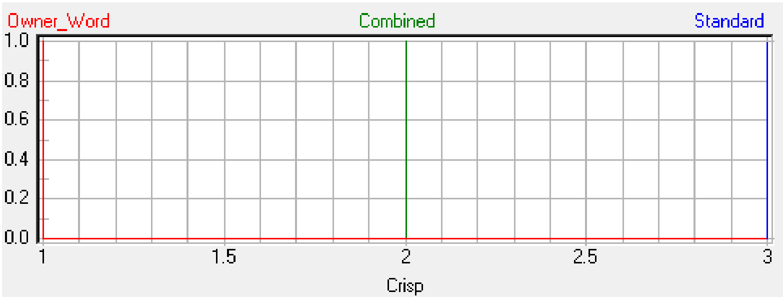


MBF of "Bonding_Security"

Term Name	**Shape/Par.**	**Definition Points (x, y)**		
Poor	linear	(1, 1) (7, 0)	(2.38, 1)	(4, 0)
Average	linear	(1, 0) (6, 0)	(1.5, 0) (7, 0)	(4, 1)
Good	linear	(1, 0) (7, 1)	(4, 0)	(5.65, 0.99804)

Definition Points of MBF "Bonding_Security"

Input Variable "Contract_Form"

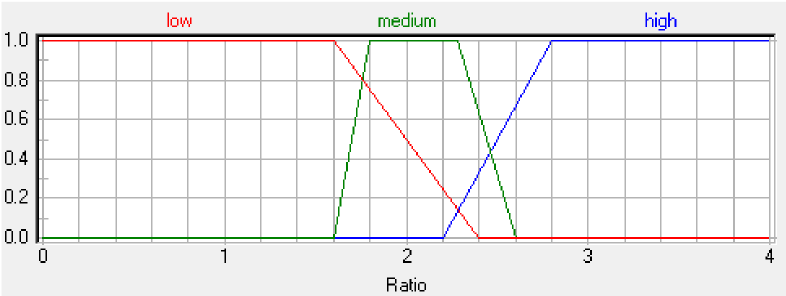


MBF of "Contract_Form"

Term Name	**Shape/Par.**	**Definition Points (x, y)**		
Owner_Word	linear	(1, 1)	(1, 0)	(3, 0)
Combined	linear	(1, 0) (2.001, 0)	(2, 0.00196) (3, 0)	(2, 1)
Standard	linear	(1, 0)	(3, 0)	(3, 1)

Definition Points of MBF "Contract_Form"

Input Variable "DebtTEqRatio"



MBF of "DebtTEqRatio"

Term Name	**Shape/Par.**	**Definition Points (x, y)**		
low	linear	(0, 1) (4, 0)	(1.6, 1)	(2.4, 0)
medium	linear	(0, 0) (2.28, 1)	(1.6, 0) (2.6, 0)	(1.8, 1) (4, 0)
high	linear	(0, 0) (4, 1)	(2.2, 0)	(2.8, 1)

Definition Points of MBF "DebtTEqRatio"

Sample of the Rule Blocks

Rule Block "RB1"

Parameter

Aggregation:	MIN
Parameter:	0.00
Result Aggregation:	MAX
Number of Inputs:	4
Number of Outputs:	1
Number of Rules:	81

IF					**THEN**
Payment	**Warranty**	**Damg_Penlt_Bonus**	**Toxic_Haz_SubMat**	**DoS**	**Pay_Wr_Damg_Toxi**
Poor	Poor	Poor	Poor	1.00	low
Poor	Poor	Poor	Average	1.00	low
Poor	Poor	Poor	Good	1.00	low
Poor	Poor	Average	Poor	1.00	low
Poor	Poor	Average	Average	1.00	low
Poor	Poor	Average	Good	1.00	medium
Poor	Poor	Good	Poor	1.00	low
Poor	Poor	Good	Average	1.00	medium

IF				THEN	
Poor	Poor	Good	Good	1.00	medium
Poor	Average	Poor	Poor	1.00	low
Poor	Average	Poor	Average	1.00	low
Poor	Average	Poor	Good	1.00	medium
Poor	Average	Average	Poor	1.00	low
Poor	Average	Average	Average	1.00	medium
Poor	Average	Average	Good	1.00	medium
Poor	Average	Good	Poor	1.00	medium
Poor	Average	Good	Average	1.00	medium
Poor	Average	Good	Good	1.00	medium
Poor	Good	Poor	Poor	1.00	low
Poor	Good	Poor	Average	1.00	medium
Poor	Good	Poor	Good	1.00	medium
Poor	Good	Average	Poor	1.00	medium
Poor	Good	Average	Average	1.00	medium
Poor	Good	Average	Good	1.00	medium
Poor	Good	Good	Poor	1.00	medium
Poor	Good	Good	Average	1.00	medium
Poor	Good	Good	Good	1.00	high
Average	Poor	Poor	Poor	1.00	low
Average	Poor	Poor	Average	1.00	low
Average	Poor	Poor	Good	1.00	medium
Average	Poor	Average	Poor	1.00	low
Average	Poor	Average	Average	1.00	medium
Average	Poor	Average	Good	1.00	medium
Average	Poor	Good	Poor	1.00	medium
Average	Poor	Good	Average	1.00	medium
Average	Poor	Good	Good	1.00	medium
Average	Average	Poor	Poor	1.00	low
Average	Average	Poor	Average	1.00	medium
Average	Average	Poor	Good	1.00	medium
Average	Average	Average	Poor	1.00	medium
Average	Average	Average	Average	1.00	medium
Average	Average	Average	Good	1.00	medium
Average	Average	Good	Poor	1.00	medium
Average	Average	Good	Average	1.00	medium
Average	Average	Good	Good	1.00	high
Average	Good	Poor	Poor	1.00	medium
Average	Good	Poor	Average	1.00	medium
Average	Good	Poor	Good	1.00	medium
Average	Good	Average	Poor	1.00	medium
Average	Good	Average	Average	1.00	medium
Average	Good	Average	Good	1.00	high
Average	Good	Good	Poor	1.00	medium
Average	Good	Good	Average	1.00	high
Average	Good	Good	Good	1.00	high
Good	Poor	Poor	Poor	1.00	low
Good	Poor	Poor	Average	1.00	medium
Good	Poor	Poor	Good	1.00	medium
Good	Poor	Average	Poor	1.00	medium
Good	Poor	Average	Average	1.00	medium

IF				THEN	
Good	Poor	Average	Good	1.00	medium
Good	Poor	Good	Poor	1.00	medium
Good	Poor	Good	Average	1.00	medium
Good	Poor	Good	Good	1.00	high
Good	Average	Poor	Poor	1.00	medium
Good	Average	Poor	Average	1.00	medium
Good	Average	Poor	Good	1.00	medium
Good	Average	Average	Poor	1.00	medium
Good	Average	Average	Average	1.00	medium
Good	Average	Average	Good	1.00	high
Good	Average	Good	Poor	1.00	medium
Good	Average	Good	Average	1.00	high
Good	Average	Good	Good	1.00	high
Good	Good	Poor	Poor	1.00	medium
Good	Good	Poor	Average	1.00	medium
Good	Good	Poor	Good	1.00	high
Good	Good	Average	Poor	1.00	medium
Good	Good	Average	Average	1.00	high
Good	Good	Average	Good	1.00	high
Good	Good	Good	Poor	1.00	high
Good	Good	Good	Average	1.00	high
Good	Good	Good	Good	1.00	high

Rules of the Rule Block "RB1"

Appendix D – Sample of the Questionnaire for Quantifying the Relative Experience of Surety Experts

Part A:

Relative Importance of Quantification Attributes

This section requires you to conduct a pairwise comparison between the expert` six experience measures identified earlier. The comparison would simply take the form: "How important is measure 1 when compared to measure 2 in evaluating surety expert experience?" The expert is asked to provide one of the following responses in either numeric or linguistic fashion, as shown in the following table.

Decision aids for Pairwise Comparison

Numerical Rating	Importance
1	EQUALLY IMPORTANT
2	SLIGHTLY MORE IMPORTANT
3	STRONGLY MORE IMPORTANT
4	VERY STRONGLY MORE IMPORTANT
5	EXTREMELY MORE IMPORTANT

	Experience in surety for construction	Current role
Experience In Surety For Construction Vs. **Current Role**		

	Experience in surety for construction	Experience in Contractor Prequalification
Experience In Surety For Construction Vs. **Experience In Contractor Prequalification**		

	Experience in surety for construction	Experience in Project Evaluation
Experience In Surety For Construction Vs. **Experience In Project Evaluation**		

	Experience in surety for construction	Size Limit
Experience In Surety For Construction Vs. **Size Limit**		

	Experience in surety for construction	Largest Project Evaluated
Experience In Surety For Construction Vs. **Largest Project Evaluated**		

	Current role	Experience in Contractor Prequalification
Current Role Vs. **Experience In Contractor Prequalification**		

	Current role	Experience in Project Evaluation
Current Role Vs. **Experience In Project Evaluation**		

Part B:

Defining Worth Function for Surety Expert Experience Measures

In this section we will identify the Upper limit, Lower limit and three intermediate values to construct a function for each experience measure as in the Figure below. The proposed function will represent the relationship between the attribute value and the corresponding worth value.

The LOWER LIMIT (or less) will have 0% (NO) worth value AND UPPER LIMIT (or more) will have 100% (FULL) worth value for each of the surety expert experience measures identified. Please provide the numerical or linguistic limits for each measure. The evaluation is limited to surety underwriters and brokers who working in surety bonding in construction industry.

1. Experience in Surety for Construction (ESC)

Quantification Method (**Numerical**, e.g., 10 years)

	Lower Limit (L_L)	Intermediate Values			Upper Limit (U_L)
Years of Experience					
Worth Value/Percentage	**0%**				**100%**

Appendix E – Sample for the Information about the CDPM's Inputs and Outputs

Input Number	Evaluation Criteria	Description	Linguistic Descriptors	Quantification	Min Value	Max Value	Critical If	Favourable If
1.00000	Project Aspects Evaluation	Evaluation of two categories; Project Team and Project Specifics/Scope	Unacceptable - Acceptable - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.10000	Project Team Evaluation	Evaluation of project stakeholders (Owner, Subcontractors, Architect / Engineer (Design Consultant), and Contractor)	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11000	Owner Evaluation		Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11100	Owner Type	The "Owner type" factor can be either "PUBLIC" or "PRIVATE Known" " Private Unknown.	PrivateUnknown - PrivateKnown - Public	(Categorical) Crisp Values (Pubic, PrivateKnown, PrivateUnknown)	1	4	Private Unknown	Public
1.11200	Owner Funding	Owner Funding Ability 1. The existence of financial responsibility clause on bid document. 2. Confirmation of project financing. 3. Overall surety underwriter/broker satisfaction regarding the owner ability to fund the project	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11300	Owner/O.Agent Experience	The owner or owner agent experience in construction industry.	Low - Medium - High	Real Numbers (# years)	0	15	< 5	Higher
2.11300	Owner/O.Agent Reputation	The owner or owner agent reputation in construction industry.	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.12120	Subcontractors Evaluation		Unqualified - Qualified - Very Qualified	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.12122	Subcontractors Bonds Value	Provided bonding value (Total bonds that will be obtained from subcontractors) total bonds value to the total subcontracting value	Low - Medium - High	Real Numbers (% Percent)	0	100	<25	Higher
1.12125	Subcontractors Experience	The average years of experience that the assigned subcontracts have in construction industry.	Low - Medium - High	Real Numbers (# years)	0	15	<2	Higher
1.12126	Overall Subcontractors Qualification	1. The policy around prequalifying of subcontractors (formal or realistic informal process). 2. Relationship with the general contractor. 3. Subcontractor's availability of resources.	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.12127	Subcontracts Scope Gaps	Indicates if the general contractor ensured that there are no scope gaps on the assigned subcontracts. 1. Is the scope for each subcontractor is well defined? 2. Has the contractor developed a good procedure to ensure that there are no scope gaps? 3. Holding of sufficient meetings between subcontractors 4. Overall review for all subcontractors` roles	Many Gaps - Some Gaps - No Gaps	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11000	Architect / Engineer (Design Consultant) Evaluation		Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11100	A/E Experience	What is their experience?	Low - Medium - High	Real Numbers (# years)	0	15	< 5	Higher
1.11200	A/E Reputation	What is their Character? Have you worked with them previously?	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher
1.11300	A/E Liability Insurance	What level of Errors and Omissions do they carry? What is their claims history?	Poor - Average - Good	Predetermined Rating Scale of 1-5	1	5	< 3	Higher

Appendix F – Sample of the Input's Relative Importance Weights Questionnaire for the CDPM

General Contractors Surety Prequalification: Criteria Weighting-2

*1. Specify the influence of the following input variables on the Owner Evaluation:

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Owner Type (Private Unknown - Private Known - Public)	○	○	○	○	○	○
Owner funding ability	○	○	○	○	○	○
Owner or owner agent experience	○	○	○	○	○	○
Owner or owner agent reputation	○	○	○	○	○	○

Comment:

*2. Specify the influence of the following input variables on the Subcontractors Evaluation:

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Obtaining bonds from subcontractors and total value of Bonds obtained	○	○	○	○	○	○
Subcontractors Experience	○	○	○	○	○	○
Overall Subcontractors Qualification	○	○	○	○	○	○
Scope Gaps between subcontractors	○	○	○	○	○	○

Comment:

*3. Specify the influence of the following input variables on the Architect/Engineer (Design Consultant)Evaluation:

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Architect/Engineer Experience	○	○	○	○	○	○
Architect/Engineer Reputation	○	○	○	○	○	○
Architect/Engineer Liability Insurance	○	○	○	○	○	○

Comment:

General Contractors Surety Prequalification: Criteria Weighting-2

***7. Specify the influence of the following input variables on the Contractor Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Contractor Last Financial Evaluation	◯	◯	◯	◯	◯	◯
Contractor Current Evaluation	◯	◯	◯	◯	◯	◯

Comment:

***8. Specify the influence of the following input variables on the Project Team Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Owner Evaluation	◯	◯	◯	◯	◯	◯
Subcontractors Evaluation	◯	◯	◯	◯	◯	◯
Architect/Engineer (Design Consultant) Evaluation	◯	◯	◯	◯	◯	◯
Contractor Evaluation	◯	◯	◯	◯	◯	◯

Comment:

***9. Specify the influence of the following input variables on the Project Type/Complexity Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Past Similar (Type/Complexity) Projects	◯	◯	◯	◯	◯	◯
Key Employee Type/Complexity Experience	◯	◯	◯	◯	◯	◯
Project Manager Type/Complexity Experience	◯	◯	◯	◯	◯	◯

Comment:

***10. Specify the influence of the following input variables on the Project Size Evaluation:**

	No Influence	1 "Minor Influence"	2	3	4	5 "Significant Influence"
Past Projects Experience in size	◯	◯	◯	◯	◯	◯
Ratio to largest project	◯	◯	◯	◯	◯	◯
Project Manager Size Experience	◯	◯	◯	◯	◯	◯

Comment:

Appendix G – Sample of the Hypothetical Cases for the CDPM

Case #	Owner Evaluation								Subcontractors Evaluation							
	Owner Type	Owner Funding	Owner/O.Agent Experience	Owner/O.Agent Reputation	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score	Subcontractors Bonds Value	Subcontractors Experience	Overall Subcontractors Qualification	Subcontracts Scope Gaps	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score
G1					0.9616	0.6840	0.4714						0.9616	0.6840	0.4714	
1	Public	1	1	1	2.5	1.5	1.0	1.84	0	1	1	1	1.0	1.0	1.0	1.00
2	Public	3	0	3	4.0	2.5	3.0	3.29	5	7	1	4	3.0	2.0	2.0	2.45
3	Public	5	0	5	4.5	3.5	4.0	4.07	20	13	1	5	3.5	2.5	3.0	3.07
4	PrivateKnown	1	6	2	1.5	2.0	1.5	1.66	55	1	4	1	3.5	3.0	2.0	3.00
5	PrivateKnown	3	6	3	2.5	3.5	3.0	2.93	50	8	4	4	4.0	3.5	2.5	3.50
6	PrivateKnown	5	5	5	4.3	4.6	4.0	4.33	55	13	4	5	4.0	4.0	4.5	4.11
7	PrivateUnknown	1	9	1	1.0	2.5	1.5	1.60	80	1	5	1	3.0	3.5	2.5	3.05
8	PrivateUnknown	3	11	3	2.5	3.0	4.0	3.00	90	7	5	4	5.0	4.0	4.5	4.57
9	PrivateUnknown	5	15	5	4.5	4.0	4.6	4.36	80	13	5	5	4.5	5.0	4.5	4.66
10	Public	1	5	5	3.6	2.0	3.0	2.95	83	3	3	1	3.5	3.0	3.0	3.23

Case #	Architect / Engineer (Design Consultant) Evaluation							Last Financial Evaluation										
	A/E Experience	A/E Reputation	A/E Liability Insurance	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score	Working Capital Trend	Tangible Net Worth Trend	Gross Profit Margin Trend	Net Profit Margin Trend	Debt to Equity Ratio	Gross Profit Margin	Net Profit Margin	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score
G1				0.9616	0.6840	0.4714									0.9616	0.6840	0.4714	
1	0	1	1	1.5	2.0	2.0	1.77	-30	-15	-50	-35	0.8	0	0	1.5	1.0	2.5	1.56
2	7	1	4	3.3	3.0	4.0	3.36	-16	-30	-4	3	0.6	10	6	4.3	3.5	5.0	4.19
3	13	1	5	4.0	4.5	4.5	4.27	-20	-25	40	30	0.9	24	15	4.3	4.0	5.0	4.35
4	8	2	1	3.0	3.0	3.5	3.09	10	6	-35	-30	1.9	3	1	3.0	3.0	4.0	3.20
5	5	2	2	2.5	3.0	3.0	2.76	6	10	-9	-4	2.4	10	6	3.0	3.0	4.0	3.21
6	5	4	5	4.3	4.0	4.0	4.13	10	10	31	48	2.2	23	15	4.3	4.0	5.0	4.35
7	10	4	1	3.0	3.0	3.5	3.09	30	28	5	-47	3.2	3	2	3.0	3.0	4.0	3.20
8	13	2	2	3.4	3.0	3.5	3.27	27	30	1	1	2.9	10	6	4.3	4.0	5.0	4.35
9	8	3	5	4.3	4.5	4.0	4.29	30	25	50	40	3	22	11	4.3	4.0	5.0	4.35
10	11	1	2	3.0	3.0	3.5	3.09	-28	30	0	35	2.9	4	5	3.2	3.0	4.0	3.32

Case #	Current Evaluation									Project Type/Complexity Experience Evaluation						
	Work on Hand to Aggregation Limit	Overbilled	Underbilled	Contractor`s Cash Flow	Contractor`s Operating Line	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score	Past Similar (Type/Complexity) Projects	Key Employee Type/Complexity Experience	Project Manager Type/Complexity Experience	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score
G1						0.9616	0.6840	0.4714					0.9616	0.6840	0.4714	
1	5	0	0	1	1	1.5	1.5	2.0	1.61	0	1	1	1.5	2.0	1.5	1.66
2	40	1	11	3	2	2.5	2.0	3.0	2.45	6	2	6	3.0	3.5	4.0	3.36
3	80	1	25	5	1	1.5	1.5	2.0	1.61	9	2	9	4.0	4.0	4.5	4.11
4	68	12	3	1	4	3.0	2.5	3.0	2.84	5	3	5	3.0	3.5	3.0	3.16
5	26	15	11	2	5	3.0	3.0	3.5	3.09	2	0	10	3.0	2.5	4.0	3.04
6	26	12	11	4	1	2.5	3.0	2.0	2.56	7	3	3	3.0	3.0	4.0	3.22
7	34	15	23	5	5	4.3	3.5	4.0	3.97	7	4	3	3.0	3.0	3.0	3.00
8	44	5	9	3	3	2.7	3.0	3.0	2.89	9	5	9	4.3	4.0	5.0	4.35
9	47	21	19	2	1	1.5	1.5	2.0	1.61	0	4	0	1.5	2.0	2.0	1.77
10	53	25	0	1	5	4.0	4.5	5.0	4.40	10	3	5	3.0	3.0	4.0	3.22

Case #	Project Size Experience Evaluation							Project Location Experience Evaluation						
	Past Projects Experience in size	Ratio to largest project	Project Manager Size Experience	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score	Contractor Past Projects Experience in Location	Average Staff Location Experience	Project Manager Location Experience	OUTPUT Expert 1	OUTPUT Expert 2	OUTPUT Expert 3	Aggregated Score
G1				0.9616	0.6840	0.4714					0.9616	0.6840	0.4714	
1	0	5	1	1.6	1.0	2.0	1.50	0	0	0	1.5	1.0	1.0	1.23
2	5	25	5	2.8	3.5	3.0	3.06	7	1	7	2.5	2.0	3.5	2.56
3	10	20	9	4.3	3.5	4.0	3.97	9	2	9	4.0	3.0	4.5	3.78
4	10	46	1	3.0	4.0	3.0	3.30	3	2	8	2.5	2.0	2.5	2.35
5	10	25	7	3.2	3.0	3.0	3.07	4	0	10	2.5	2.0	3.0	2.45
6	5	19	6	3.0	3.0	3.0	2.98	5	7	9	4.0	3.0	3.5	3.58
7	6	89	3	3.2	3.5	3.0	3.23	7	3	5	4.0	4.0	3.0	3.79
8	6	96	0	3.0	2.5	3.0	2.82	0	9	6	4.0	5.0	3.5	4.22
9	9	40	6	3.3	3.0	3.0	3.13	9	7	0	4.0	4.0	3.0	3.77
10	0	40	3	2.2	2.0	3.0	2.30	1	8	7	4.0	3.0	4.0	3.69

Appendix H – Sample of the MBF Estimation

Questionnaire for the CDPM

General Contractors Surety Prequalification: CRITERIA QUANTIFICATION

1. PARTICIPANT INFORMATION

Dear respondent,

The University of Alberta, Hole School of Construction Engineering would like to ask for your help in creating a decision-making model to assist surety underwriters and brokers in the construction industry. The model will account for many of the factors that surety underwriters and brokers use when evaluating a contractor. It will help to assess a contractor's risk rating for bonding. It will also provide recommendations of conditions to be met by a contractor prior to bonding being given, and will be useful as a quality improvement tool for the contractor. The model will take into account both qualitative (subjective) and quantitative (objective) factors. As you know, many of them are based on expert opinion and judgment or have a range of acceptable values. To compound this problem, relationships between the factors are non-linear and difficult to anticipate. One advantage to the model will be its ability to formalize a very complex decision while being able to follow its logic. This model will not replace the experience and judgment of surety underwriters and brokers, it will only help to verify decisions and investigate the impact of slight changes to contractor qualification data.

Intent of The Survey:
The following questionnaire will help us to determine the measurement of each criterion. You will be asked to quantify certain linguistic terms that are used to describe the each criterion. For each linguistic term (eg. poor, average, good) please select more than one answer for each question unless you feel that only one answer is applicable. When answering these questions keep in mind that you are referring to a GENERAL CONTRACTOR.

CLARIFICATION:
The presented evaluation criteria **are not** limited to what you are currently using for the purpose of general contractor prequalification process. The study includes **more in-depth** evaluation criteria for prequalification process enhancement.

The approximate time to complete the questionnaire is 40 minutes.

Note that:
The data is confidential and your identity will not be shared with other respondents.

Thank you very much for your time and cooperation. It is greatly appreciated.

If you have any questions please feel free to contact:

Adel Awad
Email: alawad@ualberta.ca

2. OWNER FUNDING ABILITY

"Owner funding" indicates the owner funding ability evaluation.
There are several points related to this issue, such as;
1. Existence of financial responsibility clause on bid document.
2. Confirmation of project financing.
3. Type of confirmation provided.
4. The surety underwriter/broker satisfaction regarding the owner ability to fund the project.

1. What would you consider is a POOR Owner Funding situation? Please check all applicable boxes.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and HIGH surety underwriter/broker satisfaction regarding the owner ability to fund the project.

2. What would you consider is a AVERAGE Owner Funding situation? Please check all applicable boxes.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and HIGH surety underwriter/broker satisfaction regarding the owner ability to fund the project.

3. What would you consider is a GOOD Owner Funding situation? Please check all applicable boxes.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and LOW surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ No financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, No Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and AVERAGE surety underwriter/broker satisfaction regarding the owner ability to fund the project.

☐ Financial responsibility clause on bid document, Confirmation of project financing, and HIGH surety underwriter/broker satisfaction regarding the owner ability to fund the project.

General Contractors Surety Prequalification: CRITERIA QUANTIFICATION

5. SUBCONTRACTORS BONDS VALUE

Provided bonding value (Total bonds that will be obtained from subcontractors)
The percentage of the total bonds value to the total contract value

1. What would you consider a LOW Bonds to be? Please check all applicable boxes.

☐ 0% ☐ 5% ☐ 10% ☐ 15% ☐ 20% ☐ 25% ☐ 30% ☐ 35% ☐ 40% ☐ 45% ☐ 50% ☐

2. What would you consider a AVERAGE Bonds to be? Please check all applicable boxes.

☐ 0% ☐ 5% ☐ 10% ☐ 15% ☐ 20% ☐ 25% ☐ 30% ☐ 35% ☐ 40% ☐ 45% ☐ 50% ☐

3. What would you consider a HIGH Bonds to be? Please check all applicable boxes.

☐ 0% ☐ 5% ☐ 10% ☐ 15% ☐ 20% ☐ 25% ☐ 30% ☐ 35% ☐ 40% ☐ 45% ☐ 50% ☐

6. SUBCONTRACTORS EXPERIENCE

The average years of experience that the assigned subcontracts have in construction industry.

1. How many YEARS of experience would classify Subcontractors Experience as having POOR Construction Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10 ☐ 11 ☐ 12 ☐ 13

2. How many YEARS of experience would classify Subcontractors Experience as having AVERAGE Construction Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10 ☐ 11 ☐ 12 ☐ 13

3. How many YEARS of experience would classify Subcontractors Experience as having GOOD Construction Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10 ☐ 11 ☐ 12 ☐ 13

22. CONTRACTOR CASH FLOW

“Cash flow” can be expressed as a measure of a contractor company's financial health. Equals cash receipts minus cash payments over a given period of time.
Contractor should provide cash flow for the proposed project and all projects on hand.
There are several points can be used for rating the Cash Flow factor, such as;
1. Quality of the provided cash flow.
2. Readability of the cash flow.
3. Ability to handle the anticipated volume of work.
4. Any anticipated shortage of cash.
5. Actions to face shortage of cash.
6. The impact on the balance sheet in terms of liquidity and debt.

1. What would you consider is a POOR Cash Flow?
Please check all applicable boxes.

☐ POOR established cash flow, NOT readable cash flow, POOR Ability to handle the anticipated volume of work, HIGH anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept

☐ AVERAGE established cash flow, AVERAGE readable cash flow, POOR Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept

☐ AVERAGE established cash flow, AVERAGE readable cash flow, AVERAGE Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept

☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept

☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, NO anticipated shortage of cash, , and No negative impact on the balance sheet in terms of liquidity and dept

2. What would you consider is a AVERAGE Cash Flow?
Please check all applicable boxes.

☐ POOR established cash flow, NOT readable cash flow, POOR Ability to handle the anticipated volume of work, HIGH anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept

☐ AVERAGE established cash flow, AVERAGE readable cash flow, POOR Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept

☐ AVERAGE established cash flow, AVERAGE readable cash flow, AVERAGE Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept

☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept

☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, NO anticipated shortage of cash, , and No negative impact on the balance sheet in terms of liquidity and dept

3. What would you consider is a GOOD Cash Flow?
Please check all applicable boxes.

- ☐ POOR established cash flow, NOT readable cash flow, POOR Ability to handle the anticipated volume of work, HIGH anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept
- ☐ AVERAGE established cash flow, AVERAGE readable cash flow, POOR Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, NO Actions to face shortage of cash, and POOR impact on the balance sheet in terms of liquidity and dept
- ☐ AVERAGE established cash flow, AVERAGE readable cash flow, AVERAGE Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept
- ☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, AVERAGE anticipated shortage of cash, SOMEWHAT REASONABLE Actions to face shortage of cash, and AVERAGE impact on the balance sheet in terms of liquidity and dept
- ☐ GOOD established cash flow, GOOD readable cash flow, GOOD Ability to handle the anticipated volume of work, NO anticipated shortage of cash, , and No negative impact on the balance sheet in terms of liquidity and dept

27. PAST PROJECTS EXPERIENCE IN SIZE

The number of projects done in the past within the same size

1. How many PROJECTS would classify a general contractor as having LOW Past Projects in Size Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

2. How many PROJECTS would classify a general contractor as having AVERAGE Past Projects in Size Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

3. How many PROJECTS would classify a general contractor as having HIGH Past Projects in Size Experience?
Please check all applicable boxes.

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

Appendix I – Sample of the MBF Interpolation Results for the CDPM

	Solution No.			1	2	3	4	5	6	7	8	9	10	11	12
Owner Evaluation	Owner Funding Ability	Poor	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	1.75	1.00	1.75	1.75	1.00	1.00	1.75	1.75	1.00	1.00	1.75	1.00
			d	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
		Average	a	1.00	1.75	1.00	1.75	1.00	1.75	1.00	1.75	1.00	1.75	1.75	1.00
			b	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			c	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			d	5.00	4.63	4.63	5.00	4.63	5.00	4.63	5.00	4.63	5.00	4.63	5.00
		Good	a	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			b	4.63	5.00	4.63	4.63	4.63	4.63	5.00	5.00	5.00	5.00	4.63	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
	Owner/O.Agent Experience	Low	a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			c	2.00	0.00	2.00	2.00	2.00	0.00	0.00	2.00	2.00	2.00	0.00	2.00
			d	6.00	6.00	5.00	6.00	6.00	6.00	6.00	5.00	5.00	5.00	6.00	6.00
		Medium	a	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			b	4.50	4.50	6.00	5.00	5.00	5.00	5.00	5.00	5.00	4.50	4.50	6.00
			c	7.25	6.00	7.25	6.00	7.25	6.00	7.25	6.00	7.25	7.25	6.00	7.25
			d	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
		High	a	6.00	7.50	6.75	6.00	6.00	7.50	7.50	6.75	6.75	6.75	7.50	6.00
			b	10.00	9.35	10.00	10.00	10.00	9.35	9.35	10.00	10.00	10.00	9.35	10.00
			c	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
			d	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
	Owner/O.Agent Reputation	Poor	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
			d	4.00	3.22	3.50	4.00	4.00	3.22	3.22	3.50	3.50	4.00	3.22	3.50
		Average	a	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
			b	3.10	3.10	3.10	3.10	3.10	3.10	3.10	3.10	3.10	3.10	3.10	3.10
			c	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
		Good	a	3.00	3.80	3.50	3.80	3.50	3.00	3.50	3.00	3.80	3.00	3.80	3.50
			b	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

	Solution No.			1	2	3	4	5	6	7	8	9	10	11	12
Subcontractors Evaluation	Subcontractors Bonds Value	Low	a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			c	25.00	25.00	26.00	25.00	25.00	25.00	25.00	26.00	26.00	25.00	25.00	26.00
			d	45.00	37.50	41.00	45.00	45.00	37.50	37.50	41.00	41.00	45.00	37.50	41.00
		Medium	a	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00
			b	37.50	45.00	37.50	37.50	37.50	45.00	45.00	37.50	37.50	45.00	37.50	45.00
			c	71.50	71.50	65.00	71.50	71.50	71.50	71.50	65.00	65.00	71.50	65.00	71.50
			d	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00
		High	a	65.00	71.50	68.20	71.50	68.20	65.00	68.20	65.00	71.50	65.00	71.50	68.20
			b	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00	80.00
			c	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
			d	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	Subcontractors Experience	Low	a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			c	4.00	4.00	5.60	4.00	4.00	4.00	5.60	4.00	4.00	4.00	5.60	4.00
			d	7.00	9.75	7.00	6.30	7.00	9.75	7.00	6.30	7.00	9.75	7.00	6.30
		Medium	a	4.00	5.50	5.50	4.75	4.75	4.75	4.75	5.50	4.75	4.00	5.50	5.50
			b	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00
			c	9.30	9.30	9.00	9.30	9.00	9.00	9.30	9.00	9.30	9.30	9.30	9.00
			d	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
		High	a	9.00	9.30	9.00	9.30	9.00	9.30	9.00	9.30	9.00	9.30	9.00	9.30
			b	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
			c	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
			d	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
	Overall Subcontractors Qualification	Poor	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	1.85	1.35	1.90	1.85	1.35	1.90	1.85	1.35	1.90	1.85	1.35	1.90
			d	4.00	4.00	3.75	4.00	4.00	3.75	4.00	4.00	3.75	4.00	4.00	3.75
		Average	a	1.00	1.00	1.75	1.85	1.85	1.85	1.85	1.85	1.85	1.00	1.75	1.00
			b	3.70	4.00	4.00	3.35	3.35	3.35	3.35	3.35	3.35	4.00	4.00	3.70
			c	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
		Good	a	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			b	5.00	3.70	5.00	5.00	5.00	5.00	3.70	3.70	3.70	5.00	3.70	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
	Subcontracts Scope Gaps	Many Gaps	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	1.00	1.35	1.50	1.00	1.00	1.35	1.35	1.50	1.50	1.00	1.35	1.50
			d	4.00	4.00	3.65	4.00	4.00	4.00	4.00	3.65	3.65	4.00	4.00	3.65
		Some Gaps	a	1.00	1.50	1.25	1.50	1.25	1.00	1.25	1.00	1.50	1.00	1.50	1.25
			b	3.20	3.10	3.10	3.10	3.10	3.20	3.10	3.20	3.10	3.20	3.10	3.10
			c	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
		No Gaps	a	3.00	3.70	3.75	3.00	3.00	3.70	3.70	3.75	3.75	3.70	3.75	3.00
			b	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

	Solution No.			1	2	3	4	5	6	7	8	9	10	11	12
Architect / Engineer (Design Consultant) Evaluation	A/E Experience	Low	a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
			c	4.00	4.50	5.25	4.00	4.00	4.00	4.50	4.50	4.50	5.25	5.25	5.25
			d	7.00	8.00	6.00	7.00	7.00	7.00	8.00	8.00	8.00	6.00	6.00	6.00
		Medium	a	4.00	5.20	4.00	5.20	4.00	5.20	5.20	4.00	5.20	5.20	4.00	5.20
			b	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00
			c	7.00	7.00	9.00	9.00	8.00	8.00	9.00	8.00	8.00	9.00	8.00	8.00
			d	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
		High	a	7.00	9.00	8.00	7.00	7.00	7.00	9.00	9.00	9.00	8.00	8.00	8.00
			b	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
			c	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
			d	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
	A/E Reputation	Poor	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	1.80	1.00	1.40	1.40	1.80	1.00	1.80	1.00	1.40	1.80	1.00	1.40
			d	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
		Average	a	1.80	1.00	1.40	1.40	1.80	1.00	1.00	1.80	1.40	1.80	1.00	1.40
			b	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			c	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
		Good	a	3.00	3.25	3.00	3.25	3.25	3.00	3.00	3.25	3.25	3.00	3.25	3.25
			b	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
	A/E Liability Insurance	Poor	a	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			b	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
			c	1.85	1.00	1.78	2.00	2.00	2.00	1.85	1.85	1.00	1.00	1.78	1.78
			d	3.20	3.35	4.00	3.50	3.50	3.50	3.20	3.20	3.35	3.35	4.00	4.00
		Average	a	1.00	1.85	1.40	1.00	1.85	1.40	1.00	1.00	1.85	1.85	1.40	1.40
			b	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
			c	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
		Good	a	3.00	3.85	3.42	3.00	3.85	3.42	3.42	3.85	3.00	3.42	3.00	3.85
			b	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			c	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
			d	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

Appendix J – Sample of CDPM Developed Rule Base

Rule Block "AE_RB"

IF			THEN	
AE_Experience_	AE_Reputation	AE_Liability_Ins	DoS	AE_Evaluation
NA	NA	NA	1.00	NA
NA	NA	Poor	1.00	Poor
NA	NA	Average	1.00	Average
NA	NA	Good	1.00	Good
NA	Poor	NA	1.00	Poor
NA	Poor	Poor	1.00	Poor
NA	Poor	Average	1.00	Poor
NA	Poor	Good	1.00	Average
NA	Average	NA	1.00	Average
NA	Average	Poor	1.00	Poor
NA	Average	Average	1.00	Poor
NA	Average	Good	1.00	Average
NA	Good	NA	1.00	Good
NA	Good	Poor	1.00	Poor
NA	Good	Average	1.00	Poor
NA	Good	Good	1.00	Average
Low	NA	NA	1.00	Poor
Low	NA	Poor	1.00	Poor
Low	NA	Average	1.00	Poor
Low	NA	Good	1.00	Average
Low	Poor	NA	1.00	Poor
Low	Poor	Poor	1.00	Poor
Low	Poor	Average	1.00	Poor
Low	Poor	Good	1.00	Average
Low	Average	NA	1.00	Poor
Low	Average	Poor	1.00	Poor
Low	Average	Average	1.00	Average
Low	Average	Good	1.00	Average
Low	Good	NA	1.00	Average
Low	Good	Poor	1.00	Average
Low	Good	Average	1.00	Average
Low	Good	Good	1.00	Average
Medium	NA	NA	1.00	Average
Medium	NA	Poor	1.00	Poor
Medium	NA	Average	1.00	Average
Medium	NA	Good	1.00	Average
Medium	Poor	NA	1.00	Poor
Medium	Poor	Poor	1.00	Poor
Medium	Poor	Average	1.00	Average
Medium	Poor	Good	1.00	Average
Medium	Average	NA	1.00	Average
Medium	Average	Poor	1.00	Average

IF			THEN	
Medium	Average	Average	1.00	Average
Medium	Average	Good	1.00	Good
Medium	Good	NA	1.00	Average
Medium	Good	Poor	1.00	Average
Medium	Good	Average	1.00	Average
Medium	Good	Good	1.00	Good
High	NA	NA	1.00	Good
High	NA	Poor	1.00	Average
High	NA	Average	1.00	Good
High	NA	Good	1.00	Good
High	Poor	NA	1.00	Average
High	Poor	Poor	1.00	Average
High	Poor	Average	1.00	Average
High	Poor	Good	1.00	Good
High	Average	NA	1.00	Average
High	Average	Poor	1.00	Average
High	Average	Average	1.00	Good
High	Average	Good	1.00	Good
High	Good	NA	1.00	Good
High	Good	Poor	1.00	Average
High	Good	Average	1.00	Good
High	Good	Good	1.00	Good

Rule Block "Aspects_RB"

IF		THEN	
Team_Evaluation	Project_Specific	DoS	Project_Aspects
NA	NA	1.00	NA
NA	Poor	1.00	Unacceptable
NA	Average	1.00	Acceptable
NA	Good	1.00	Good
Unqualified	NA	1.00	Unacceptable
Unqualified	Poor	1.00	Unacceptable
Unqualified	Average	1.00	Unacceptable
Unqualified	Good	1.00	Acceptable
Qualified	NA	1.00	Acceptable
Qualified	Poor	1.00	Unacceptable
Qualified	Average	1.00	Acceptable
Qualified	Good	1.00	Good
Very_Qualified	NA	1.00	Good
Very_Qualified	Poor	1.00	Acceptable
Very_Qualified	Average	1.00	Good
Very_Qualified	Good	1.00	Good

Rule Block "Contractor_RB"

IF		THEN	
Last_Financ_Eval	Current_Evaluati	DoS	Contractor_Evalu
NA	NA	1.00	NA
NA	Poor	1.00	Unqualified
NA	Average	1.00	Qualified
NA	Good	1.00	Very_Qualified
Poor	NA	1.00	Unqualified
Poor	Poor	1.00	Unqualified
Poor	Average	1.00	Unqualified
Poor	Good	1.00	Qualified
Average	NA	1.00	Qualified
Average	Poor	1.00	Unqualified
Average	Average	1.00	Qualified
Average	Good	1.00	Very_Qualified
Good	NA	1.00	Very_Qualified
Good	Poor	1.00	Qualified
Good	Average	1.00	Very_Qualified
Good	Good	1.00	Very_Qualified

Appendix K – Sample of the Final Trained MBFs, Rule Bases, and FESs Descriptions

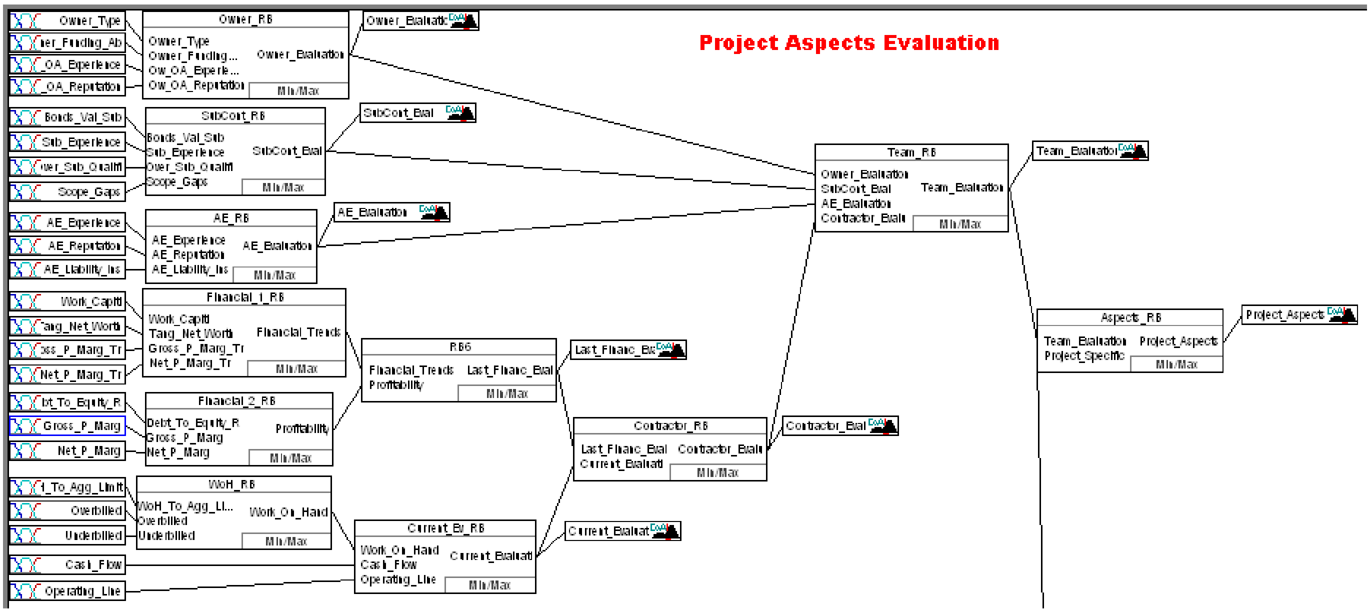
Project Aspects Evaluation

Description

Input Variables	40
Output Variables	14
Intermediate Variables	7
Rule Blocks	21
Rules	1760
Membership Functions	244

Project Aspects Evaluation Statistics

Part of the System Structure



Structure of the Fuzzy Logic System (Project Aspects Evaluation)

Sample of the Project Aspects Evaluation Variables

Inputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	AE_Experience		Number_of_ Years	-1	15	-1	NA Low Medium High
3	AE_Reputation		Rating	0	5	0	NA Poor Average Good
4	Bonds_Val_Sub		Percent	-1	100	-1	NA Low Medium High

Fuzzification Methods

Compute MBF

Categorical Variable

Fuzzy Input

Look up MBF

Display

Outputs

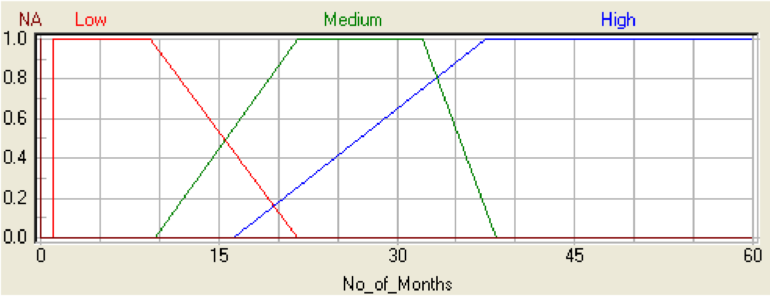
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
41	AE_Evaluation		Rating	0	5	0	NA Poor Average Good
42	Contractor_Evalu		Rating	0	5	0	NA Unqualified Qualified Very_Qualified

Intermediates

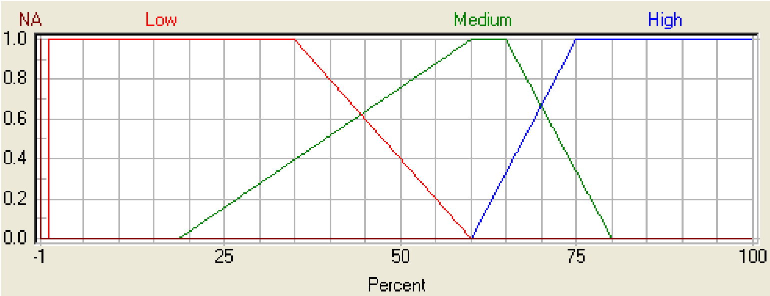
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
55	Cost_1		-	-	-	-	NA low medium high
56	Cost_2		-	-	-	-	NA low medium high

Sample of the Trained Project Aspects Evaluation MBFs

Input Variable "Project_Duration"



Input Variable "Ratio_To_larg_Pr"



Sample of the Trained Project Aspects Evaluation Rules

Rule Block "AE_RB"

IF			THEN	
AE_Experience	AE_Reputation	AE_Liability_Ins	DoS	AE_Evaluation
NA	NA	NA	0.90	NA
NA	NA	Poor	1.00	Poor
NA	NA	Average	1.00	Average
NA	NA	Good	1.00	Good
NA	Poor	NA	1.00	Poor
NA	Poor	Poor	1.00	Poor
NA	Poor	Average	0.80	Poor
NA	Poor	Good	1.00	Average
NA	Average	NA	1.00	Average
NA	Average	Poor	1.00	Poor
NA	Average	Average	1.00	Poor
NA	Average	Good	1.00	Average
NA	Good	NA	1.00	Good
NA	Good	Poor	0.70	Poor
NA	Good	Average	1.00	Poor
NA	Good	Good	1.00	Average
Low	NA	NA	1.00	Poor
Low	NA	Poor	1.00	Poor

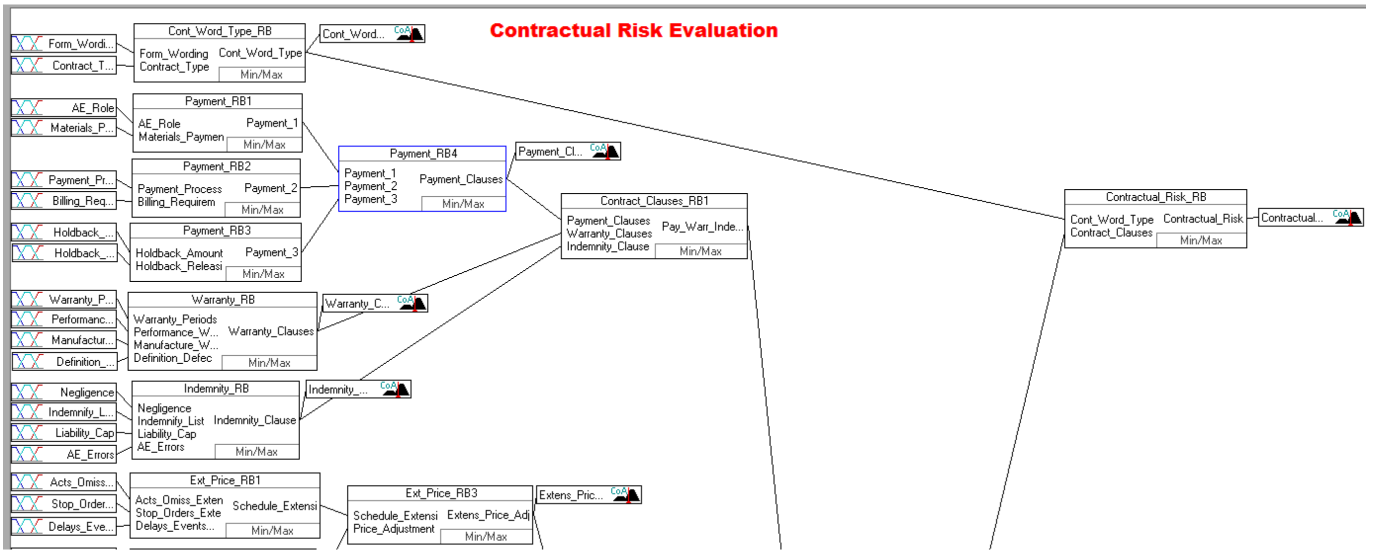
<u>**Contractual Risk Evaluation**</u>

Description

Input Variables	43
Output Variables	12
Intermediate Variables	11
Rule Blocks	23
Rules	1097
Membership Functions	237

Contractual Risk Evaluation Statistics

Part of the System Structure



Structure of the Fuzzy Logic System (Contractual Risk Evaluation)

<u>Sample of the Contractual Risk Evaluation Variables</u>

Inputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	Acts_Omiss_Exten		Crisp_Values	1	3	1	NA No Yes
2	Acts_Omiss_Price		Crisp_Values	1	3	1	NA No Yes
3	AE_Errors		Crisp_Values	1	3	1	NA Yes No

Variables of Group "Inputs"

Outputs

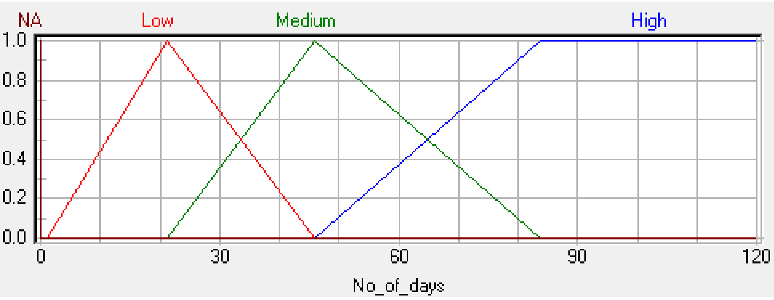
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
44	Bonding_Security	CoA	Rating	0	5	0	NA Poor Average Good
46	Contract_Clauses	CoA	Rating	0	5	0	NA Poor Average Good

Intermediates

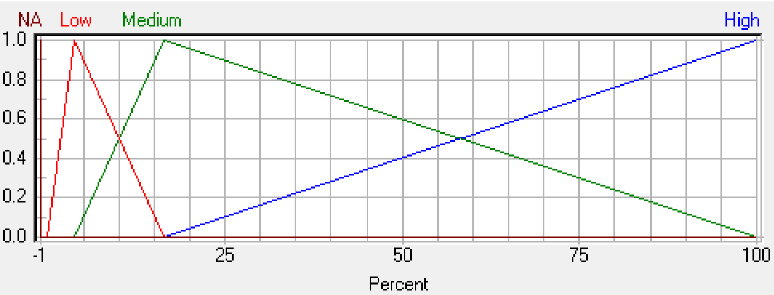
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
56	Bid_Bond		-	-	-	-	NA low medium high
57	Consent_of_Suret		-	-	-	-	NA low medium high

<u>Sample of the Trained Contractual Risk Evaluation MBFs</u>

Input Variable "Bid_Bond_Period"



Input Variable "Bid_Bond_Value"



Sample of the Trained Contractual Risk Evaluation Rule Blocks

Rule Block "Bonding_Security_RB1"

IF			THEN	
Bid_Bond_Type	Bid_Bond_Value	Bid_Bond_Period	DoS	Bid_Bond
Owner_Wording	NA	NA	1.00	low
Owner_Wording	NA	Low	1.00	medium
Owner_Wording	NA	Medium	1.00	medium
Owner_Wording	NA	High	1.00	low
Owner_Wording	Low	NA	1.00	medium
Owner_Wording	Low	Low	0.80	high
Owner_Wording	Low	Medium	0.90	medium
Owner_Wording	Low	High	0.80	medium
Owner_Wording	Medium	NA	1.00	medium
Owner_Wording	Medium	Low	1.00	medium
Owner_Wording	Medium	Medium	0.20	medium
Owner_Wording	Medium	High	0.10	low
Owner_Wording	High	NA	1.00	low
Owner_Wording	High	Low	1.00	medium
Owner_Wording	High	Medium	0.40	low

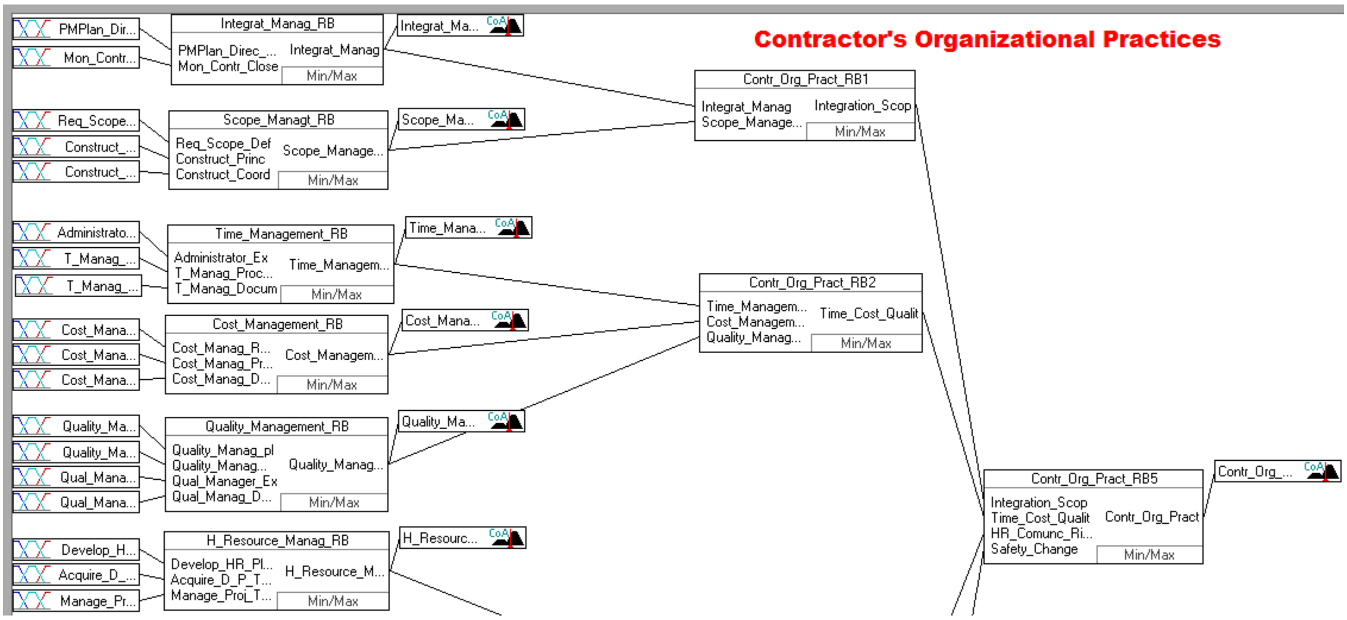
<u>Contractor’s Organizational Practices</u>

Description

Input Variables	37
Output Variables	12
Intermediate Variables	4
Rule Blocks	16
Rules	1827
Membership Functions	202

Contractor’s Organizational Practices Statistics

Part of the System Structure



Structure of the Fuzzy Logic System (Contractor’s Organizational Practices)

<u>Sample of the Contractor’s Organizational Practices Variables</u>

Inputs

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	Acquire_D_P_Team		Rating	0	5	0	NA Poor Average Good
2	Administrator_Ex		Number_of_Years	-1	20	-1	NA Low Medium

#	Variable Name	Type	Unit	Min	Max	Default	Term Names
							High
3	Change_Manag_ Doc		Rating	0	5	0	NA Poor Average Good

Outputs

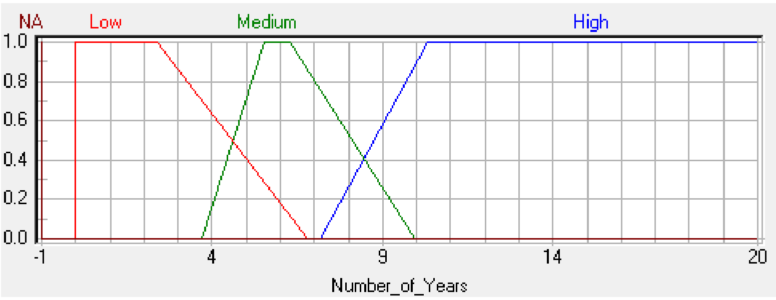
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
38	Change_Manage men		Rating	0	5	0	NA Poor Average Good
39	Communications_ M		Rating	0	5	0	NA Poor Average Good
40	Contr_Org_Pract		Rating	0	5	0	NA Unacceptable Acceptable Good

Intermediates

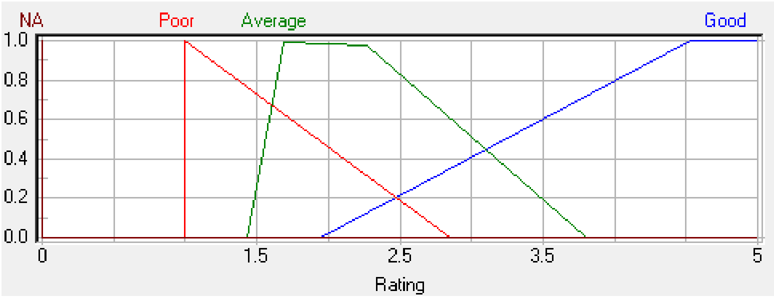
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
50	HR_Comunc_Ris k_P		-	-	-	-	NA low medium high
51	Integration_Scop		-	-	-	-	NA low medium high

<u>Sample of the Trained Contractor's Organizational Practices MBFs</u>

Input Variable "Administrator_Ex"



Input Variable "Cost_Manag_Proce"



Sample of the Trained Contractor's Organizational Practices Rule Blocks

Rule Block "Communications_M_RB"

IF			THEN	
Communic_Mang_Pr	Communication_Ro	Communica_Mng_Do	DoS	Communications_M
NA	NA	NA	0.90	NA
NA	NA	Poor	1.00	Poor
NA	No	Poor	0.60	Poor
NA	No	Average	1.00	Average
NA	Yes	Average	1.00	Average
NA	Yes	Good	1.00	Good
Poor	NA	NA	0.90	Poor
Poor	NA	Poor	1.00	Poor
Poor	Yes	NA	1.00	Average
Poor	Yes	Poor	1.00	Poor
Poor	Yes	Average	0.90	Poor
Poor	Yes	Good	1.00	Average
Average	NA	NA	0.90	Average
Average	NA	Poor	1.00	Average
Average	No	Poor	1.00	Poor
Average	No	Average	1.00	Average
Average	No	Good	0.80	Average
Average	Yes	NA	1.00	Good
Average	Yes	Poor	1.00	Average

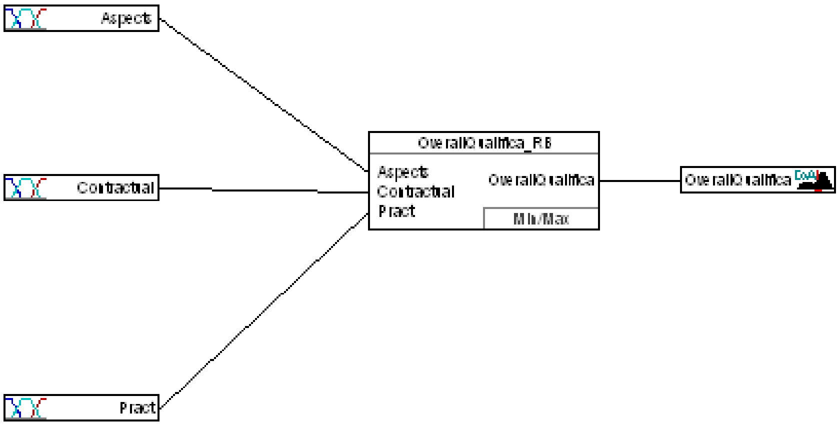
Overall Contractor Default prediction FES

Description

Input Variables	3
Output Variables	1
Intermediate Variables	0
Rule Blocks	1
Rules	64
Membership Functions	18

Overall Contractor Default prediction FES Statistics

System Structure



Structure of the Fuzzy Logic System (Overall Contractor Default prediction)

<u>Sample of the Overall Contractor Default prediction Variables</u>

Inputs

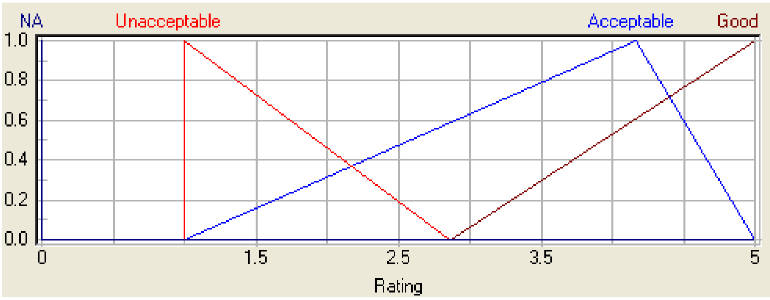
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
1	Aspects		Rating	0	5	0	NA Unacceptable Acceptable Good

Output

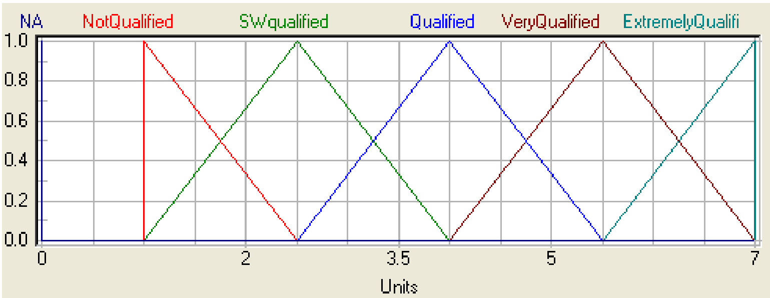
#	Variable Name	Type	Unit	Min	Max	Default	Term Names
4	OverallQualifica	CoA	Units	0	7	0	NA NotQualified SWqualified Qualified VeryQualified ExtremelyQualifi

Sample of the Trained Overall Contractor Default prediction MBFs

Input Variable "Contractual"



Output Variable "OverallQualifica"



Sample of the Trained Overall Contractor Default prediction Rules

IF			THEN	
Project_Aspects	Contractual_Risk	Contr_Org_Pract	DoS	OverallQualifica
NA	NA	NA	0.90	NA
NA	NA	Unacceptable	1.00	NotQualified
NA	NA	Acceptable	1.00	Qualified
NA	NA	Good	1.00	VeryQualified
NA	Unacceptable	NA	1.00	NotQualified
NA	Unacceptable	Unacceptable	1.00	NotQualified
NA	Unacceptable	Acceptable	0.20	SWqualified
NA	Unacceptable	Good	1.00	SWqualified
NA	Acceptable	NA	1.00	VeryQualified
NA	Acceptable	Unacceptable	1.00	SWqualified
NA	Acceptable	Acceptable	1.00	VeryQualified
NA	Acceptable	Good	0.30	VeryQualified
NA	Good	NA	1.00	Qualified
Acceptable	Unacceptable	Acceptable	0.70	Qualified
Acceptable	Unacceptable	Good	1.00	Qualified
Acceptable	Acceptable	NA	1.00	ExtremelyQualifi
Acceptable	Acceptable	Unacceptable	1.00	Qualified