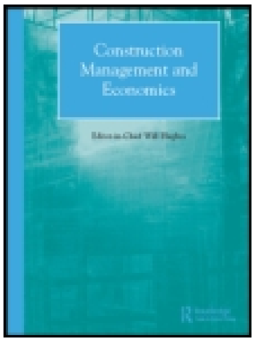

Construction Management and Economics

ISSN: 0144-6193 (Print) 1466-433X (Online) Journal homepage: www.tandfonline.com/journals/rcme20

Decision models for analysis and evaluation of construction contractors

Jeffrey S. Russell

To cite this article: Jeffrey S. Russell (1992) Decision models for analysis and evaluation of construction contractors, Construction Management and Economics, 10:3, 185-202, DOI: 10.1080/01446199200000018

To link to this article: https://doi.org/10.1080/01446199200000018

Published online: 28 Jul 2006.

Construction Management and Economics, 1992, **10**, 185–202

Decision models for analysis and evaluation of construction contractors

JEFFREY S. RUSSELL

Department of Civil and Environmental Engineering, University of Wisconsin, Madison, WI 53706, USA

The concept of a hybrid computerized decision support system for the evaluation of construction contractors' suitability to perform the work associated with a project is presented. Previously developed decision tools are summarized and justification for the creation of such a system is proposed. The system configuration is described along with the modelling techniques available for each aspect of prequalification decision-making.

Keywords: Computer application, decision-making, construction contracts, contractor prequalification.

Introduction

Several decision tools for modelling engineering management problems exist. Such tools range from qualitative to quantitative in their treatment of available data relevant in decision-making. The adoption of any tool to a given engineering management decision domain has both advantages and disadvantages or tradeoffs in obtaining an optimum or 'best' possible solution to the problem.

One decision domain involves prequalification of construction contractors prior to allowing them to participate in the bidding process. Prequalification involves the screening of contractors by an owner according to a given set of criteria, in order to determine their competence to execute the work associated with a given project.

Prequalification decision-making typically involves criteria for which data are qualitative, subjective, and imprecise. The process is often performed without the aid of a computer tool to manipulate these types of data presented in prequalification decisions. Moreover, only a single decision methodology has been applied in previous research to model the domain problem.

This paper introduces a framework for a computerized hybrid decision support tool that analyses construction contractors' characteristics and capabilities in light of their suitability to perform the project requirements. Such a tool should integrate existing computer software packages and decision modelling techniques to allow for maximum utilization of available contractor data in decision-making.

The limitations of currently implemented prequalification systems justifies the development of the hybrid decision tool presented in this paper. These systems lack the simultaneous integration of both qualitative and quantitative data involved in prequalification decisions to their full extent or potential.

Furthermore, the amount of contractor prequalification expertise varies from organization to organization. The existence of such a tool will benefit industry professionals lacking prequalification experience. Thus, enhanced performance of the prequalification task should be achieved by these organizations.

Decision scheme methodology

A hierarchical process for developing decision support systems for construction management related problems can be introduced. A possible hierarchy for contractor evaluation and analysis is shown in Fig. 1. As shown, it contains eight levels:

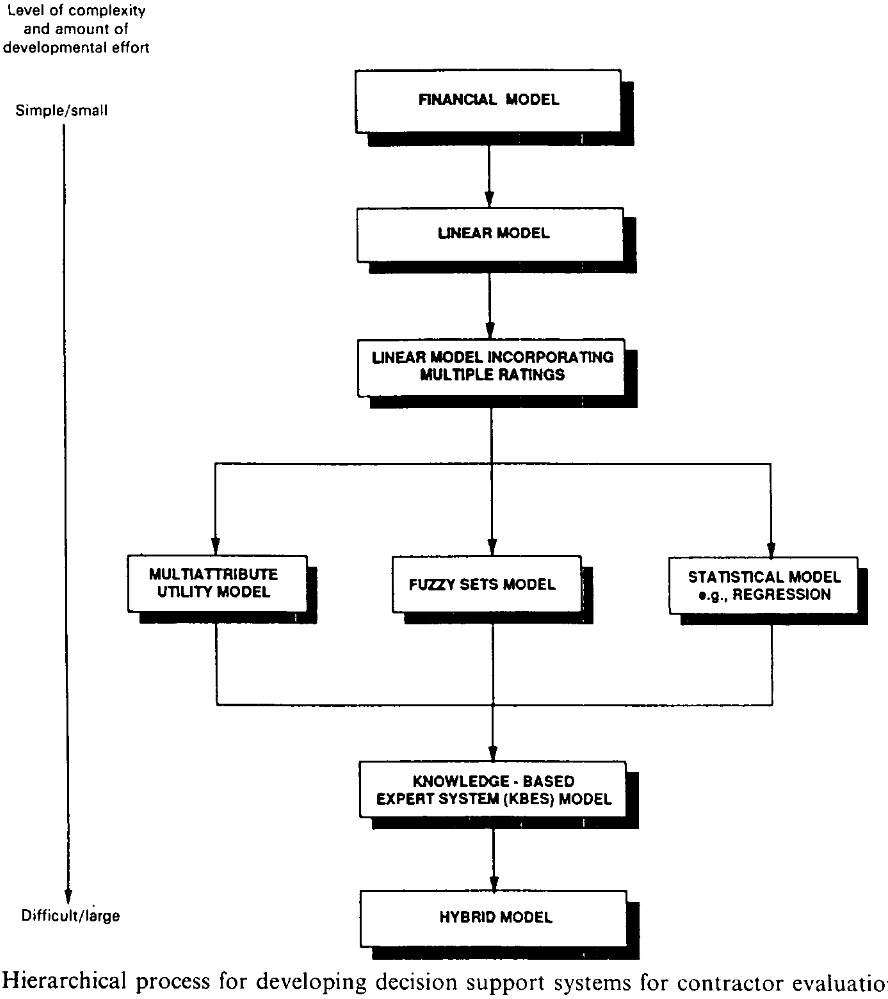

Fig. 1. Hierarchical process for developing decision support systems for contractor evaluation and analysis.

1. *Financial model* – formulae that incorporate financial parameters to arrive at the maximum amount of uncompleted work a contractor can have under contract at any one time.
2. *Linear model* – a method to combine decision criteria that are subjectively weighted and rated by a decision maker, and combined into a single measure.

3. *Linear model incorporating multiple ratings* – a method to combine decision criteria that are subjectively rated where multiple ratings and their corresponding probabilities are possible for a given criterion, and are combined into a single measure that account for the imprecision and uncertainty associated with the process.
4. *Multiattribute utility model* – a method to combine qualitative and quantitative decision criteria that are aggregated to arrive at an expected utility where risk, uncertainty, and the decision maker's preferences are modelled and considered.
5. *Fuzzy set model* – a method to model qualitative criteria by determining the degree of membership to a set via membership functions that are elicited from a decision maker and combined into an aggregate measure.
6. *Statistical model* – a method to quantitatively evaluate criteria relevant in decision-making techniques such as least squares regression of logistic regression where a dependent variable and independent variable exist: discriminate and factor analysis are other techniques relevant to decision modelling.
7. *Knowledge-based expert system (KBES) model* – a methodology to combine qualitative and quantitative criteria in the form of heuristics or 'rules of thumb' to aid in decision-making.
8. *Hybrid model* – a method which integrates all the above described decision modelling techniques.

Also shown in the figure are the levels of complexity and the amount of development effort required in the creation of a decision support system for a given modelling method. The level of complexity ranges from simple to difficult while the amount of development effort spans from small to large.

This hierarchy can be applied to contractor prequalification as well as other engineering management problems such as evaluation of new technology and project site selection. Two methods not presented in the figure but which may be pertinent to modelling these types of domain problems includes mathematical programming (i.e. linear programming) and deterministic or stochastic simulation. Example applications of mathematical programming and simulation can be found in Stark and Mayer (1983) and Halpin and Woodhead (1976), respectively.

Decision support systems for contractor prequalification

A generic logic in regard to the decision-making process for contractor prequalification has been identified (Russell and Skibniewski, 1988). A flow diagram representing this process is presented in Fig. 2. As shown, the decision is binary: 1. qualify the contractor or 2. disqualify the contractor. Several decision analysis techniques exist for modelling prequalification decision-making. Previously developed decision support systems are described below.

Financial model

Mathematical formulae for prequalification purposes are utilized by many state departments of transportation (DOTs) to determine the maximum financial capabilities of a contractor (Netherton, 1978). This calculated value establishes the maximum amount of uncompleted work a contractor may have on hand at any one time. These formulae have been developed

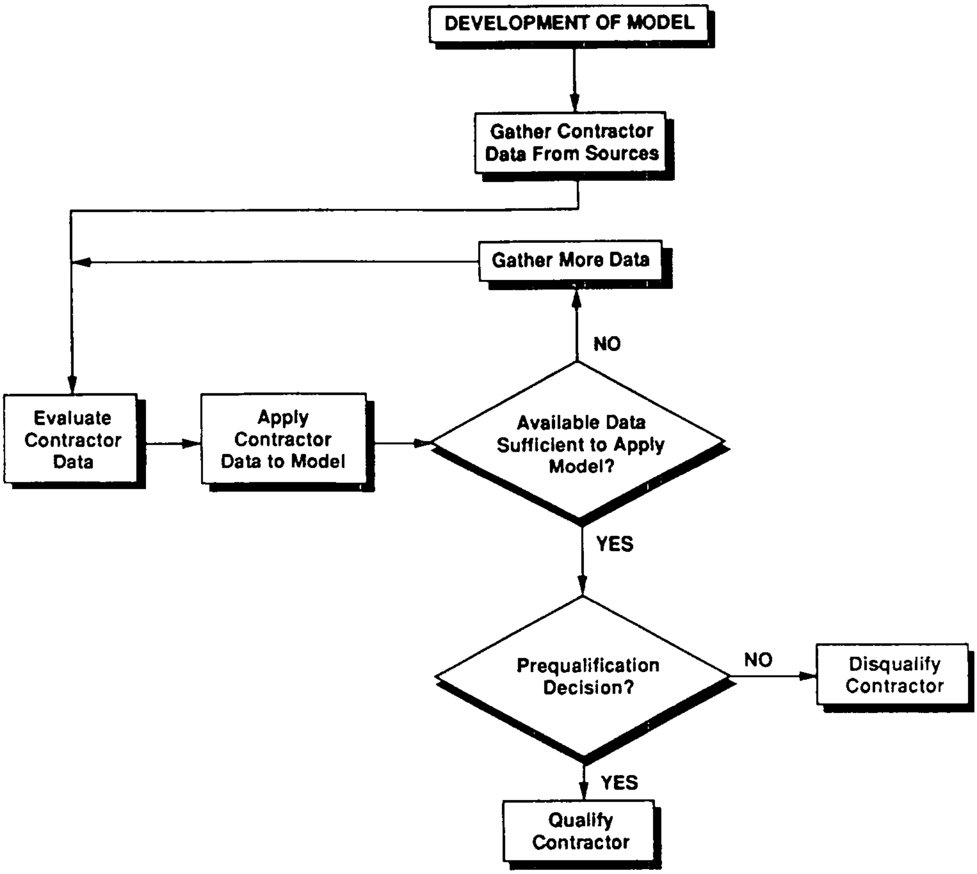

Fig. 2. Flow diagram of contractor prequalification process.

based on *ad hoc* procedures to model the problem and the evaluation process is typically performed on an annual basis.

The formula typically utilizes parameters from a financial statement (balance sheet) to arrive at a contractor's maximum aggregate amount of uncompleted work-on-hand. A judgemental reduction of this calculated value to reflect items such as contractor safety, past performance, and co-operation is usually applied. Some example formulae are presented below.

$$\mathrm{MFC} = (\mathrm{NCA} \times C)M \qquad (1)$$

in which MFC is the 'maximum financial capabilities'; NCA is the applicant's net current assets; C is a multiplying coefficient (e.g. 10); and M is a subjective modifying coefficient on a scale of 0.0 to 1.0

$$\mathrm{MFC} = [(\mathrm{CA} - \mathrm{CL})C)]M \qquad (2)$$

in which CA is the applicant's net current assets; CL is the applicant's net current liabilities; and C and M are the same as defined previously.

$$\text{MFC} = (\text{NW} \times C)M \tag{3}$$

in which NW is the applicant's net worth. These formulae do not make the maximum utilization of available contractor data. Their ability to adequately ascertain a contractor's performance capabilities and capacity were found to be inaccurate (see Nittany Engineers and Management Consultants, 1985).

Linear model

A formalized systematic process exists to develop linear models for evaluating alternatives in construction management. This process is described in Russell *et al.*, (1989). A linear model is frequently used in the prequalification process and is shown in Equation 4:

$$\text{AR}_j = \sum_{i=1}^{n} (W_i)(R_{ij}) \tag{4}$$

in which AR_j is the aggregate weighted rating of candidate j; n is the total number of decision criteria in the model; W_i is the weight of the decision criterion i (where the summation of $W_i = 1.00$ for $i = 1, 2, 3, 4 \ldots n$); and R_{ij} is the rating of decision criterion i of candidate j on a specified scale (e.g. 1.0 into 10.0). An example application of this model can be found in (Russell and Skibniewski, 1988).

To aid in the performance of contractor prequalification, a computerized algorithm, QUALIFIER–1, has been developed by the author (see Russell and Skibniewski, 1990). The model's structure, decision parameters, and corresponding weights embedded within the program are based on statistically analysed questionnaire data. Details regarding the questionnaire survey are presented in (Russell, 1988).

The linear prequalification model is formalized by Equation 5:

$$\text{AR}_k = \sum_{i=1}^{n} W_i \sum_{j=1}^{m_i} (W_{ij})(R_{ijk}) \tag{5}$$

in which AR_k is the aggregate weighted rating of candidate contractor k; n is the number of CDFs (from Factor Analysis results); W_i is the weight of the CDF i described on a scale from 0.0 to 1.0 (0 is 'unimportant' and 1 is 'important'), the summation of $W_i = 1.0$ for $i = 1, 2, 3, 4, \ldots n$; m_i is the number of DFs describing the CDF i on a scale from 0.0 to 1.0 where the summation of $W_{ij} = 1.0$ for $j = 1, 2, 3, \ldots m_i$ and $i = 1, 2, \ldots n$; R_{ijk} is the rating of the DF j describing the CDF i on a scale from 1.0 to 10.0 (1 is 'unsatisfactory' and 10 is 'excellent') for candidate contractor k.

This program calculates an aggregate weighted rating for candidate contractors based on subjective input data for each decision factor. The ratings are then rank-ordered and relevant statistics are provided for each decision factor and aggregate weighted rating based on the sample of contractors. These calculated values provide a guide for rational prequalification decision-making. Several options exist for specifying the decision parameters structure and weighting. Details of QUALIFIER-1 along with an example application are provided in (Russell and Skibniewski, 1990).

Numerous sources for data are available to arrive at a decision regarding the condition of a decision parameter. One of the drawbacks of this program is that it requires a user to be knowledgeable on what and how the evaluation is to be performed. A deterministic rating is given by a decision maker after a subjective analysis and synthesis of the available contractor data is completed. Various items can impact the obtained results, which are human-dependent, including information overload, incompetent personnel, personal biases, and lack of experience and knowledge within the domain.

The assumption of additivity of the model's decision parameters has been made. Furthermore, the model does not account for imprecision and/or uncertainty associated with data submitted by the contractor or judgement applied in evaluating these data by the owner.

Linear model incorporating multiple ratings

This section presents two variations of a linear model which permits multiple ratings as previously discussed.

This decision model is similar to the linear model described in the previous section. The difference lies in the subjective ratings input into the model. In the previous case, one subjective deterministic rating for a criterion is required. For this model, mulitiple ratings for a criterion are possible. In the first variation each rating has an associated probability of occurrence that is assumed to be normally distributed. This model is formalized by Equation 6:

$$\mathrm{EAV}_k = \sum_{j=1}^{m} (W_j)(\mathrm{EAR}_{jk}) \tag{6}$$

in which EAV_k is the earned aggregate value for candidate k; m is the total number of criteria in the model; W_j is the weight of decision criterion j; EAR_{jk} is the earned aggregate rating for criterion j of candidate k. The earned aggregate rating is calculated by Equation 7:

$$\mathrm{EAR}_{jk} = \sum_{i=1}^{n} (P_i)(R_{ijk}) \tag{7}$$

in which EAR_{jk} is the earned aggregate rating for criterion j of candidate k; n is the total number of ratings used for a criterion; P_i is the subjective probability assigned by the decision maker to each individual ratings where the summation of P_i is equal to 1.00 for $i = 1, 2, 3, 4, \ldots n$; R_{ijk} is the individual rating i for criterion j of candidate k.

An example application can include criteria of management capabilities ($W_1 = 0.30$) and financial stability ($W_2 = 0.70$). Contractor X was rated by the decision maker as follows: 7 (probability 0.40), 8 (0.50), and 9 (0.10) for management capabilities; and 7 (0.60), 7.5 (0.30), and 8 (0.10) for financial stability. The earned aggregate ratings were 7.70 and 7.25, respectively. Using the weights listed above, the earned aggregate value for Contractor X is 7.39 [(7.70) (0.30) + (7.25) (0.70)]. Upon the calculation of the earned aggregate value for each contractor, the values are rank-ordered. These values provide a means by which rational decision-making can be made.

The second variation of this model includes permitting a decision maker to use three ratings: optimistic, most likely, and pessimistic similar to the PERT (Project Evaluation Review Technique) scheduling technique.

The formulae used in the PERT calculations process are introduced by Equation 8:

$$t_e = \frac{a+4m+b}{6} \tag{8}$$

in which t_e is the expected time; a is the optimistic duration; m is the most likely duration (or mode); and b is the pessimistic duration. The standard deviation can be found from the formula in Equation 9:

$$\sigma = \frac{b-a}{6} \tag{9}$$

in which b and a are the same as defined in Equation 8. The variance can be found by squaring the standard deviation.

In the context of contractor prequalification analysis, the PERT approach can be applied to the linear model previously outlined (Equation 4). However, the linear model must be restated as in Equation 10:

$$\mathrm{AR}_j = \sum_{i=1}^{n} (W_i)(t_{eij}) \tag{10}$$

in which AR_j is the aggregate weighted rating for candidate j; n is the number of decision criteria in the model; W_i is the weight of criterion i; and t_{eij} is the expected rating or criterion i for candidate j. By substituting R_{eij} for t_{eij}, the equation can be restated as:

$$\mathrm{AR}_j = \sum_{i=1}^{n} (W_i)(R_{eij}) \tag{11}$$

in which R_{eij} is the expected rating.

To illustrate this approach the same criteria as in the previous example are used: management capabilities ($W_1 = 0.30$) and financial stability ($W_2 = 0.70$). Contractor X was rated by a decision maker as follows: 8 optimistic, 5 most likely, and 3 pessimistic for management capabilities and 7, 6, and 4, respectively for financial stability. The R_{eij} is 5.17 and 5.83 and the standard deviation is 0.83 (variance -0.69) and 0.50 (0.25) for management capabilities and financial stability, respectively. As a result, AR_j is 5.63 [(5.17)(0.30)+(5.83)(0.70)] with a variance of 0.94 (0.69+0.25).

The probability that Contractors X's aggregate rating is less than or equal to the calculated aggregate rating of 5.63 can be determined. For example, the probability that Contractor X's aggregate rating is less than or equal to the value of 5.63 is 0.50 (50% chance). For the value of 7.00 it is 0.9207 (92.07% chance). The probability that Contractor X's aggregate rating will fall within the range of 5.0 to 7.0 is 0.6629 (66.29% chance). Similar calculation can be applied to the individual criteria (i.e. management capabilities of financial stability).

In addition to the probability calculations, more analysis can be performed using the aggregate ratings and the variance. A tradeoff between the level of variation and the magnitude of the overall aggregate rating can be made. For a description of this analysis process as well as the advantages, disadvantages and assumptions of these described models see Russell and Ahmad (1989).

These models provide an improvement over their predecessor in that they permit the decision maker to apply multiple ratings for a given contractor, thus accounting for imprecision and/or uncertainty associated with the data submitted by the contractor and the owner's subjective evaluation of these data. Consequently, a better estimate (i.e. weighted average) of the aggregate value is made. However, these models are still dependent upon subjective inputs by a decision maker.

Multiattribute utility model (Diekmann, 1981)

The evaluation process of contractors requires multiple objectives and criteria. Diekmann (1981) applied multiattribute utility theory to a case study in the evaluation and selection of contractors for a cost-plus type contract.

In multi-objective decision-making such as that of contractor evaluation and selection a multidimensional utility function is used. One formulation of such a function is shown in Equation 12:

$$U(x)=\pi_1 u(x_1)+\pi_2 u(x_2)+\ldots\pi_n u(x_n) \tag{12}$$

in which $u(x_i)$ is the single attribute utility function of x_i; and π_i is a scaling coefficient for attribute x_i. Such a model has assumed additivity among its attributes. This is a significant assumption in that the coefficients of interaction terms among the model attributes have been assumed to be equal to zero. Thus, the joint interaction of the attributes contained in the model is assumed negligible. Relevant literature describing the impact of this assumption is given by Raiffa (1969), Keeney (1973), and Keeney and Raiffa (1976).

This model permits a decision maker to quantitatively represent his preferences via utility functions, evaluate qualitative data typically submitted by contractors, and account for risk and uncertainty in a contractors' performance. Models previously described rely on a decision maker's subjective and, in some cases, unstructured evaluation of qualitative data present in the evaluation process.

In conjunction with utility theory, value hierarchies were employed by Diekmann (1981). A value hierarchy is a means by which the objectives of the owner are subdivided and classified into lower level objectives and measurable criteria. Therefore, the objectives and evaluation criteria are established subjectively by the decision maker. The higher level objectives used in Diekmann's example included cost exposure, company stability, quality of product, and management capabilities.

Inputs necessary from a decision maker to apply multiattribute utility theory includes:

1. Value hierarchies – to describe in a hierarchical fashion the objectives of the owner.
2. Scaling coefficients π_i – to establish the amount of importance of each criteria given the prevailing circumstances surrounding the problem.
3. Utility functions $u(x_i)$ – to permit the decision maker to formalize his preferences over varying levels of values for a decision criteria.

4. Probability density functions $f(x_i)$ – to assess the risk and uncertainty associated with the criteria evaluated.

The expected utility of each contractor's expected performance is calculated by Equation 13:

$$\mathrm{EU}(C_k) = \sum_{i=1}^{i=n} \int_{\infty}^{\infty} \pi_i u(x_i) f(x_i)_k \, \mathrm{d}x \tag{13}$$

in which $\mathrm{EU}(C_k)$ *is the expected utility of contractor* k; π_i is the scaling function for objective (criteria) i; $u(x_i)$ is the utility function for objective (criteria) i; and $f(x_i)_k$ is the probability density function of contractor k performance regarding objective i.

As a result of the developed value hierarchies and utility theory, the expected utility for each contractor is calculated and rank-ordered for each objective as well as the aggregate expected utility. These values assist the decision maker in formalizing and documenting their evaluation process and making subsequent decisions. An example application of this decision methodology is presented by Diekmann (1981).

Fuzzy sets model (Nguyen, 1985)

Another approach to modelling the contractor prequalification decision-making process is fuzzy sets. Nguyen (1985) applied this methodology to the evaluation and selection of bidders based on cost, presentation of bid information, and past experience. In this evaluation, decision makers are typically faced with qualitative variables such as contractor experience. Varying degrees of contractor experience exist. These varying degrees can be expressed as linguistic variables such as 'poor', 'good', and 'very experienced'. The measurement of such degrees of experience can be made using fuzzy sets. In classical set theory the contractor is either experienced or not (i.e. a crisp decision which can be represented by a binary number 0 or 1).

Fuzzy sets were first discussed by Zadeh (1965). A description of their potential application to civil engineering is given by Brown and Yao (1983). They permit information to be treated based on varying degrees of confidence. These varying degrees of membership are measured on a continuum from 0 to 1. A fuzzy set can be represented by Equation 14:

$$A = \{[x, \mu_A(x)]\} \tag{14}$$

where $x \in A$ and $A \in U$, and in which A is a fuzzy set within a space of objectives U; x is a continuous linguistic variable where each value corresponds to a degree of support or belief of $\mu(x)$; $\mu_A(x)$ is a grade of membership of x in A measured on a continuum from 0 to 1 where $\mu_A(x) = 0.0$ represents non-membership of x in A and $\mu_A(x) = 1.0$ represents full membership of x in A.

An example fuzzy set can include very competent classification expressed by: very competent = {0.1/0.0, 0.4/0.2, 0.6/0.6, 0.8/0.7, 1/0/0.6}. In this example the values assumed by the variable very, x is given as {0.1, 0.4, 0.6, 0.8, 1.0}. The corresponding membership function or the amount of belief that these values are true includes {0.0, 0.2, 0.6, 0.7, 0.6}. The membership functions are elicited from a decision maker.

Several mathematical operations of fuzzy set theory exist (Nguyen, 1985).

1. Assume U and V are two fuzzy sets, a fuzzy relation R in $U \times V$ is a fuzzy subset of $U \times V$, each element having a dual grade of membership $\mu_R(x, y)$ with $x \in U$ and $y \in V$.
2. If A and B are both fuzzy subsets of U, then the operation (or requirement) of A 'AND' B is a fuzzy subset $A \cap B$ with grade of membership:

$$\mu_{A \cap B}(x) = \mathrm{Min}[\mu_A(x), \mu_B(x)] \tag{15}$$

3. Likewise, A 'OR' B is a fuzzy subset with

$$\mu_{A \cup B}(x) = \mathrm{Max}[\mu_A(x), \mu_B(x)] \tag{16}$$

4. 'NOT A' (or complement of A) has grades of membership of:

$$\mu_A(x) = 1 - \mu_A(x) \qquad x \in A \tag{17}$$

5. Assume A is a fuzzy subset of U, and B is a fuzzy subset of V, then the operation A 'AND' B is a binary relation.

$$\mu_R(x, y) = \mathrm{Min}[\mu_A(x), \mu_B(y)] \tag{18}$$

The projection of R on U is a fuzzy subset of

$$\text{Proj. } R(x) = Max[\mu_R(x, y)] \text{ for all } x \in U,\ y \in V \tag{19}$$

Example illustrations using these relationships can be found in Brown and Yao (1983).

An illustration which includes the aggregation of the three criteria to contractor selection previously mentioned using fuzzy sets is presented by Nguyen (1985).

Statistical model (Jaselskis, 1988)

Several statistical techniques exist which can result in the development of decision models. The primary techniques include Factor Analysis, Discriminant Analysis, and Regression Analysis.

Models developed by Jaselskis and Ashley (1991) which can be potentially applied to contractor prequalification use a logistic regression technique to aid in predicting the probability of success for a construction project. Inputs to the models include the project manager, project team, and expected planning and control efforts.

Binomial discrete choice models were developed that relate to: 1. achieving 'outstanding' construction project performance, 2. achieving 'better than expected' schedule performance, and 3. achieving 'better than expected budget performance'. The results obtained from these models includes the probability for achieving one of these measures of project success as well as confidence interval estimates for these assessments.

The most common nonlinear model used in modelling discrete choice problems is the 'Logit model'. Its mathematical function is expressed in Equation 20:

$$F(Z) = e^z/1 + e^z \tag{20}$$

in which $F(Z)$ is equal to the probability of success and Z equals the discriminate function that discriminates against outstanding *vs* average projects.

In order to develop a logit model which incorporates all aspects of contractor prequalification, factor identification is necessary. This had been accomplished in a questionnaire where respondents rated prequalification decision factors on a scale from 0 to 4, 0 = low impact and 4 = high impact. Using the questionnaire items, which were subjectively highly rated, additional objective data collected by interviews or questionnaires, are necessary for the model building process.

The samples will need to be split into two discrete categories: 1. average contractors and 2. failed contractors. A statistical test will be applied to the collected criteria data to determine if there is a significant difference among the two populations. This will aid in defining the decision criteria to be implemented within the final model. Based on the number of samples obtained, confidence in the number of variables included in the model, variance in the estimated probability of success, and confidence intervals for the estimated probabilities can be determined.

Knowledge-based expert system model

QUALIFIER-2, a prototype knowledge-based expert system has been previously developed (Russell *et al.*, 1990). The system represents a large amount of effort in the knowledge acquisition and compilation areas. As a result of the use of this system, a more structured approach to the process can be achieved. Thus, consistent, rational, and timely decisions can be made regarding the admission and participation of contractors in the bidding process.

The decision model presents a procedure to be followed by a prequalification official as a means to formalize the contractor analysis process. This is achieved by representing the prequalification problem by a hierarchy of decision parameters. A decision tree of each parameter contained in the hierarchy is employed. QUALIFIER-2 is implemented within a commercially available expert system shell, Knowledge Engineering System (KES®) (KES, 1986). The current working system is operational on a Gould PN9080 mainframe computer and on IBM PC and compatible microcomputers.

The current working system uses a 'backward chaining' inference mechanism. The evaluation of a particular level contained in the model is represented as a rule-based production system of lower level parameters. Pertinent domain knowledge is represented by 'if . . . then' production rules. Numerous facilities (e.g. help, explanation, and recommendation) are also provided to aid in a consultation.

The developed decision model separates the contractor prequalification problem into a number of subproblems. These subproblems consist of five distinct linear levels within the model hierarchy. Each level can be characterized by numerous other lower-level decision parameters pertinent to evaluating a given level. At each level, inferences are based on a set of 'if . . . then' production rules.

The model is comprised of the following levels (or modules):

1. References/reputation/past performance – preliminary screening criterion.
2. Financial stability – to evaluate the financial condition and longevity of each candidate contractor.
3. Status of current work programme – to evaluate contractor's current workload and determine any severe difficulties with ongoing projects.

4. Technical expertise – to evaluate technical characteristics of contractor.
5. Project-specific criteria – to evaluate if candidate contractor can provide unusual expertise or specialized facilities required by the project.

For a more complete description of the decision model and its components (see Russell, 1988).

In its present state, QUALIFIER-2 is a prototype system which has embedded two levels, 'references/reputation/past performance' and 'financial stability'. For efficient processing of data and subsequent decision-making, the 'reference/reputation/past performance' level has each been broken down into two parts, the 'initial prequalification decision' and the 'second prequalification decision'. All three levels represent a decision point in the systems analysis process. The system has four possible decision responses which can be rendered at each decision point:

1. Qualify (continue to next level).
2. Disqualify (terminate the analysis).
3. Unsure (prior to making the decision, the judgement of the user must be exercised; e.g. more data collection and analysis may be required).
4. Unknown (based on the variable responses input, the system's knowledge base does not contain rules(s) which incorporate these variable responses to draw a conclusion).

Since the initial system development, two additional levels of the model (status of current work programme and technical expertise) have been coded. A more complete description of the system can be found in Russell *et al.* (1990) with an example application in Russell (1988).

Hybrid model configuration

A conceptual flow diagram for the contractor prequalification analysis process is shown in Fig. 3. To begin the process, a contractor will be given a previously formatted diskette where the data necessary for the evaluation will be outlined and inputted using a computer keyboard. A possible structure containing these data can be found in Russell (1988). It is envisioned that as automated real-time data collection technology advances and becomes more cost effective, all relevant project-specific data for prequalification will be collected in this manner. This will permit more timely, accurate, and comprehensive data to be collected and replace current data collection practices.

Contractor data will be stored on the diskette and be sent back to the evaluation entity to facilitate easy access. This will reduce the amount of effort required by contractors to supply data requested. Traditionally these data are typed on complicated, cumbersome, and poorly designed questionnaire forms. A contractor must duplicate the completed form in order to have a record of the submitted material. If the form is lost and another copy is requested, the information must be retyped on to a new form. Furthermore, previously completed forms are not in a format to permit efficient retrieval for comparison purposes and data analysis.

The diskette is sent back to the evaluation entity where these data will be stored in the contractor's database. It is expected that an expert system to test the validity of submitted data will be developed to protect the evaluation entity against fraudulent or incorrect input of contractor data. Next, these data will be ported to the hybrid decision model for

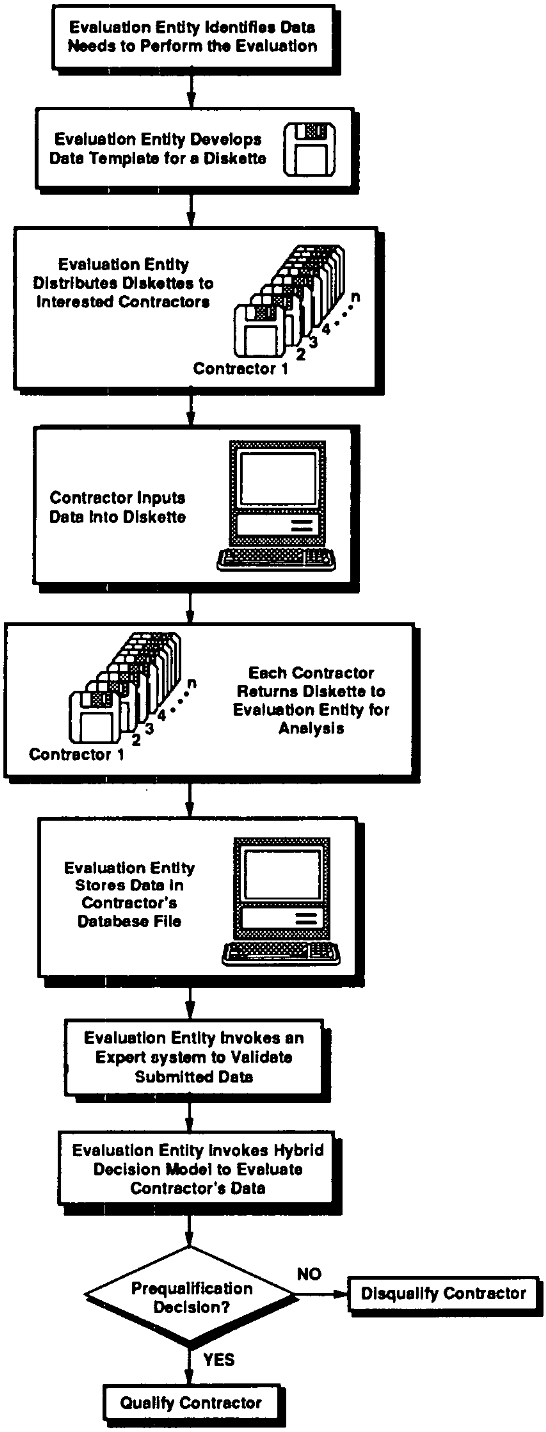

Fig. 3. Conceptual flow diagram for contractor prequalification analysis process.

processing where a prequalification decision will be determined. The user will have the option to override the system decision. Based on the user's decision, a letter to notify the candidate contractor of the prequalification decision will be generated. If the contractor is disqualified, the letter will state the reason(s) for such a conclusion. The final analysis will be stored in the contractor's database file for documentation purposes.

The hybrid decision model will consist of the five levels or modules contained in the previously described and implemented knowledge-based expert system model. However, the modelling procedures used in each module will not exclusively be a production rule-based system. Each module and its proposed modelling technique is shown in Table 1. The modules have been assigned based on the characteristics of module and modelling techniques.

Table 1. Hybrid contractor prequalification decision model configuration

Module index and name (1)	Modelling technique applicable (2)
1. References/reputation/past performance	knowledge-based expert systems binomial discrete choice logit simulation multiattribute utility theory
2. Financial stability[a]	knowledge-based expert systems cash flow algorithm ratio analysis trend analysis simulation
3. Status of current work program[a]	knowledge-based expert systems critical path method (CPM) algorithm cost analysis algorithm variance analysis
4. Technical expertise	fuzzy sets
5. Project-specific criteria	knowledge-based expert systems

[a] Collection of project data in real-time will significantly enhance the evaluation performed in these modules.

Knowledge-based expert systems, binomial discrete choice logit models, simulation, and utility theory can be applied to model module 1. A contractor's past performance can be accurately evaluated using logit models.

The financial stability module can be modelled by knowledge-based expert systems, ratio analysis, trend analysis, and a cash flow algorithm. The developed system should have graphic capabilities to represent trends of selected financial parameters over time. Knowledge embedded within the program can evaluate these graphical data and make recommendations regarding their status.

Prior work completed at Massachusetts Institute of Technology (MIT) on a case flow management system could be used to augment the financial stability module (Reinschmidt and Frank, 1976).

Ratio and trend analysis are also possible. Given that financial data are contained in a database, relationships among various parameters can be monitored. For example, the relationship between working capital levels and backlog of completed work-on-hand over time may be of interest. Knowledge embedded in the expert system could evaluate these relationships.

Simulation can be used to project the contractor's financial profile given various scenarios. In order to accomplish this task, data from module 3 would be necessary to determine the level of profit attainable by a contractor.

The Status of Current Work Program module will integrate knowledge-based expert systems with existing tools such as critical path scheduling (CPM) and cost analysis techniques. However, the Status of Current Work Program module contained in the knowledge base will have provisions to accept data collected in real-time on current construction projects and compare them to the estimated values. Such data include: crew configurations, wage rates, quality of material installed, person–hours expended, percentage of task completed, and cost and schedule performance. Thus, the status of the contractor's current projects can be assessed at a given point in time during the project life and also the estimates are provided on expected performance given his current state and suggestions of possible solutions to correct poor performance are permitted. This will also permit the contractor's financial stability to be monitored in real-time and, as performance is monitored, the overall project profitability can be determined. This will allow the financial stability of the contractor to be determined.

It is envisioned that project drawings and specifications will universally be developed using computer aided design and drafting (CADD) system and word processor, respectively. This information will be used to automatically generate the estimated material quantities and construction costs, schedule the project, and recommend resource configurations to perform the given tasks (see Fig. 4). Once real-time data collection technology is implemented on to construction jobsites, the monitoring tasks will be fully automated. This will permit an interface between the financial stability and status of current work program module to be established.

Technical expertise can be best modelled by fuzzy sets as a result of its subjective qualitative nature. Project-specific criteria could be modelled by knowledge-based expert systems as a result of the knowledge relevant to characterize a given project type (e.g. general building, highway) is amendable to 'if . . . then' production rules.

Justification for hybrid decision support system

Each of the previously described individual modelling techniques does not maximize the usage of data available for prequalification decision-making. Varying types of data are presented; quantitative, qualitative but artificially quantified and qualitative. In part, this is a result of the restricted capabilities and flexibility that each modelling technique has adequately to model each aspect of the problem domain. A systematic integration of these methodologies into a hybrid decision support system would be beneficial. Such a system would enhance the ability to arrive at solutions as well as use available data to its full potential.

It is estimated that the cost of development and implementation of the described system will be approximately $150 000. Once the system has been implemented, the development costs can be spread over multiple applications in the form of a user fee. Users of the system are envisioned to be project owners (both private and public), contractors for subcontractor

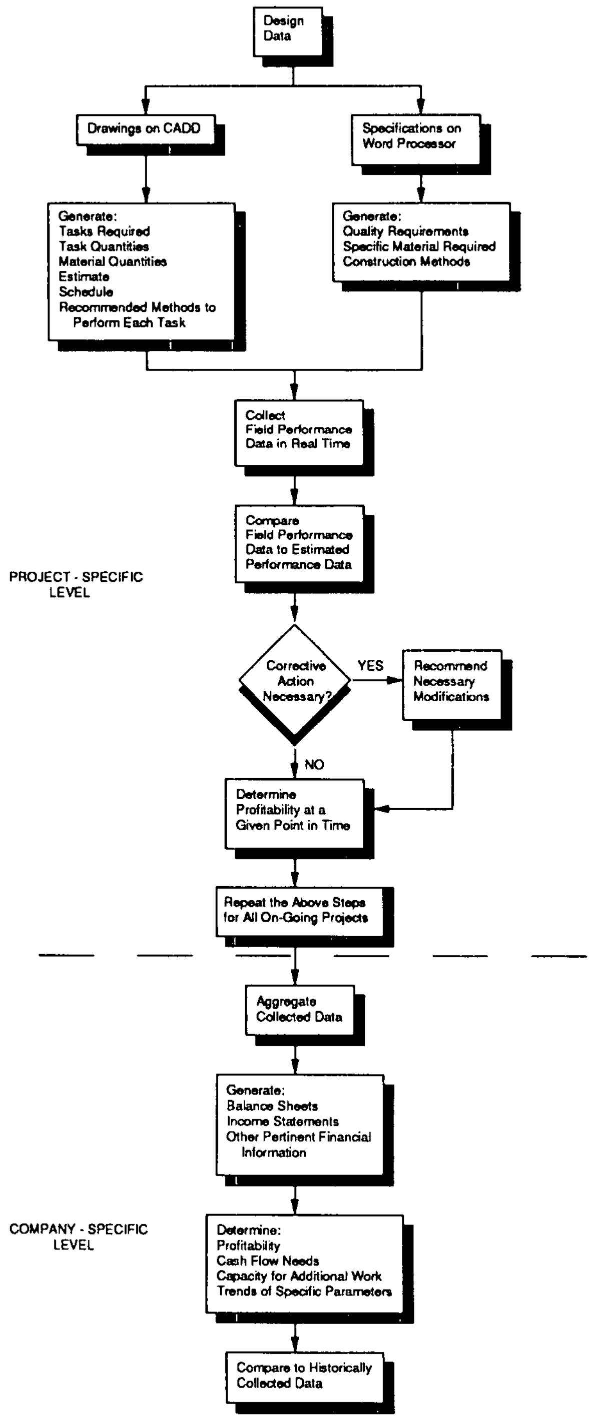

Fig. 4. Automation of data collection and analysis at the project and company levels.

evaluation and analysis, construction managers, and surety companies. Assuring contractors in a pro-active manner of fair treatment and evaluation is expected to be required. The legal ramifications of the system from a public owner's perspective will also need to be assessed.

Conclusions

A hybrid decision support system is expected to be a feasible tool to aid in decision-making regarding contractor prequalification. As outlined in this paper, there is currently no decision aids which use available data to its full extent. Consequently, each aid has limitations in arriving at a solution. At the same time, a hybrid design approach permits the domain to be subdivided into parts and the application of the best decision modelling techniques to be applied. This system, when fully developed and implemented, can be used to aid individuals in evaluating contractors and to determine their suitability to perform the requirements associated with a specific project.

The generic hybrid system framework outlined in this paper is suitable for all possible types of construction. However, some modifications to tailor the system and address industry-specific needs and characteristics will be required. It is anticipated that the system will become quite large, given the number of data collected and contractor's input. Thus, a modular approach to the system's development and implementation within the personal computer environment has been recommended.

Implementing a hybrid system for evaluating construction contractors can contribute significantly to reducing contractor failures and increasing the efficiency of the construction industry. This, in turn, can result in reduced construction costs and enhance our competitiveness in both domestic and international markets. Also, this hybrid approach to decision support development can be extended to other relevant domains within the construction industry in lieu of the typically used single-modelling approach.

Acknowledgements

The author wishes to express his thanks to the Wisconsin Alumni Research Foundation, University of Wisconsin, Madison, Wisconsin, Project Number 133–N–762 for financial support to initiate this research.

References

Brown, C.B. and Yao, J.T.P. (1983). Fuzzy sets and structural engineering, *Journal of Structural Engineering, ASCE*, **109**, 1211–25.

Diekmann, J.E. (1981). Cost-plus contractor selection, *Journal of the Technical Councils, ASCE*, **107**, 13–25.

Halpin, D.W. and Woodhead, R.W. (1976). *Design of Construction and Process Operations*, John Wiley & Sons, Inc., New York, NY.

Jaselskis, E.J. (1988). Achieving construction project success through predictive discrete choice models. Unpublished PhD thesis, University of Texas at Austin.

Jaselskis, E.J. and Ashley, D.B. (1991). Optimal allocation of project management resources for achieving construction project success, *Journal of Construction Engineering and Management, ASCE*, **117**(2), 321–40.

Keeney, R.L. (1973). Concepts of independence in multi-attributed utility theory. In *Multi-Criterion Decision Making*, (edited by J.L. Cochrane and M. Zeleny), University of South Carolina Press, Columbia, SC.

Keeney, R.L. and Raiffa, H. (1976). *Decision with Multiple Objectives Preferences and Value Trade-Offs*, John Wiley & Sons, Inc., New York, NY.

Knowledge Engineering Systems (KES®) (1986). *Knowledge Base Author's Manual*, Production Systems (PS), Software Architects and Engineering Inc., Arlington, VA, USA.

Netherton, R. (1978). Licensing and qualification of bidders. In *Selected Studies in Highway Law*, (edited by John C. Vance), Vol. 3, Chapter 6, pp. 1043–122.

Nguyen, V.U. (1985). Tender evaluation by fuzzy sets, *Journal of Construction Engineering and Management, ASCE*, **111**, 231–43.

Nittany Engineers and Management Consultants, Inc. (1985). A synthesis of the prequalification procedures of six state departments of transportation. A report for the Federal Highway Administration.

Raiffa, H. (1969). Preferences for multi-attributed alternatives, RM-5869-DOT, The Rand Corporation, Santa Monica, CA.

Reinschmidt, K.F. and Frank, W.E. (1976). Construction cash flow management system, *Journal of Construction Engineering and Management, ASCE*, **104**, 615–27.

Russell, J.S. (1988). A knowledge-based system approach to the contractor prequalification process. Unpublished PhD thesis, Purdue University, West Lafayette, IN.

Russell, J.S. and Ahmad, I. (1989). A PERT approach to contractor prequalification analysis. Thirty Fourth Annual Association of Cost Engineers, Boston, MA, D1.1–D1.6.

Russell, J.S. and Skibniewski, M.J. (1988). Decision criteria in contractor prequalification, *Journal of Management in Engineering, ASCE*, **4**, 148–64.

Russell, J.S. and Skibniewski, M.J. (1990). QUALIFIER-1: contractor prequalification model, *Journal of Computing in Civil Engineering, ASCE*, **4**(1), 77–90.

Russell, J.S., Skibniewski, M.J. and Cozier, D.R. (1990). QUALIFIER-2: knowledge-based system for contractor prequalification, *Journal of Construction Engineering and Management, ASCE*, **116**(1), 155–69.

Russell, J.S., Skibniewski, M.J., Killen, T.S. and Robinson, J.H. (1989). Evaluating alternatives in construction management. Presented at the Construction Congress I, American Society of Civil Engineers, 1989 San Francisco, CA, pp. 340–48.

Stark, R.M. and Mayer, R.H. (1983). *Quantitative Construction Management Uses of Linear Optimization*, John Wiley & Sons, Inc., New York, NY.

Zadeh, L.A. (1965). Fuzzy sets, *Information and Control*, **8**, 338–53.