A NEUROFUZZY DECISION-SUPPORT MODEL FOR MARK-UP ESTIMATION

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Uncertainty about the future lies at the heart of many decision problems including mark-up estimation. Numerous mark-up models have been proposed for possible use by contractors over a period of some fifty years. However, such models have not been popular amongst practitioners. Hence an innovative and practical neurofuzzy model is presented for possible use by Syrian contactors in making their bidding decisions. The rule base of this model was extracted from ninety-six real life bidding situations using the neurofuzzy technique. The model was tested on another fifteen projects, not used in the modelling process, and proved to be 91.7% accurate in simulating the mark-ups set in real life.

Keywords: Bidding, Mark-up, Neuro fuzzy, Fuzzy logic, Syria.

INTRODUCTION

Selection of an appropriate mark up for a new construction project is a very complex decision-making process. This complexity is due to many reasons including competition, uncertainty in the estimated cost and unpredictability of potential construction difficulties. The importance of making successful bidding decisions is indicated by the voluminous bidding strategies' literature. Bidding strategies have received considerable attention from academic researchers but not from practitioners. The practical application of these strategies has been limited by their mathematical complexity, the necessity for historic data, and a reliance on over-simplistic assumptions. Thus, in an attempt to develop a simple and practical mark-up model for possible use by Syrian construction contractors, key factors influencing the mark-up size in Syria were identified through a questionnaire survey. Subsequently, data on one hundred and eleven successful real-life bidding situations was collected from contractors operating in Syria. For the first time, the neurofuzzy modelling technique was used to extract the intuitive and heuristic rules underpinning the process of making the mark-up decisions from ninety-six of these projects. The remaining fifteen projects were selected randomly and held-back for use in validation and testing. This model proved to be robust and highly accurate in simulating the actual mark-ups of the validation sample. Although the proposed model was developed in a Syrian context, the methodology and the findings have a much broader applicability.

PREVIOUS MODELS

Numerous theoretical probabilistic bidding models based on the expected monetary value, i.e. expected profit, are reported in the bidding literature. Models based on the

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probability theory try to mathematically express the assumed relationship between the mark up and the probability of winning the contract, with the prime objective being the maximisation of the expected monetary value. Competitors' previous bids on all contracts for which the contractor prepared a cost estimate are used to calculate the probability of winning. The basic theory of this approach was first developed by Friedman (1956). The main disadvantage of Friedman's model is the necessity of historical data about competitors' bids. It also assumes that there is no significant difference between the bidders' cost estimates and that the competitors' bids are statistically independent.

Friedman's assumption of independence has created a great deal of controversy and debate among researchers (Ioannuo, 1988; Binjamin, 1969; Dixie, 1974).

Various authors, including: Fayek, (1996), Gates (1970a, 1970b, 1976), Dixie (1974), and King and Mercer (1985, 1987a, 1987b, 1988, 1990), have debated the validity and practicality of the probabilistic expected monetary value models. The most important points of their debates are the models' assumptions and the necessity of historical data about the competitors.

Benjamin (1969) proposed the first bidding model that provides for the uncertainty associated with the cost estimate and therefore with the expected profit for a given bid price. This model is composed of three main parts; a probability distribution function to express the uncertainty of the cost estimate; a non-linear utility function to present the contractor's preference for different amount of money; and a probability assessment of beating the lowest bidder.

Willenbrock (1973) outlined a procedure to determine the utility function of a contractor, so that the contractor's risk preferences could be incorporated into a tendering strategy. Ahmad and Minkarha (1987a, 1987b) developed a multi-dimensional utility mark-up model. They defined three utility functions for the contractor's preference structure, attitude towards loss, and the general overhead. The main advantage of this model is its ability to consider the contractor's preference structure and to handle multi-criteria decision-making problems. However, the necessity for historical data, which is usually difficult to obtain, undermines the applicability of this model. Also, the ill-defined utility function makes such models impractical because of the mathematical complexity (Fayek, 1996).

Other researchers modelled the mark up size decision as a simulation game including Harris and McCaffer (1989). Gates and Scarpa (1983) used the Delphi method as an attempt to develop a non-mathematical bidding model called the "Expert Subjective Pragmatic Estimate". Broemser (1968) proposed two bidding models that consider the effect of other factors besides maximising the expected profit. These factors include project size and risk of the job, amount of the job to be subcontracted, and the number of competitors. A linear regression was performed on past data to produce the effect of each of these factors on the mark up. The results of the regression analysis revealed that the probability of winning is not a function of the number of competitors as assumed by the previous models. More recently, Skitmore and Patchell (1990) have also suggested that the use of regression techniques might assist in modelling the bidding process.

In the last fifteen years, researchers have investigated the use of artificial intelligence techniques to model the decision-making process in competitive tendering. Moselhi et al (1993) argued that the application of Expert Systems (ESs) is very limited in the construction industry and favoured the use of Artificial Neural Networks (ANN).

Unlike ESs, ANNs are not based on if-then rules, the construction of which is extremely hard for unstructured and highly intuitive decisions such as the mark up size. They gain their analogy-based problem-solving capabilities by learning from examples. Moselhi et al (1993) proposed a neural network decision support system for mark up estimation called (DBID). They considered the bidding factors identified by Ahamd and Minkarah (1988) as the model inputs. Through a formal questionnaire survey, records of sixty-five real projects were collected from contractors in Canada and the United States for training the proposed system. Another seven case studies were used to test its generalisation ability (the mean absolute error was 15.11%). Li (1996a) developed a neural networks mark up model with five input factors (number of bidders, need for work, company size, construction cost, and inflation rate) and one output (mark up recommendation). Data about one hundred and fifty-five bidding cases collected for a bidding game curried out in an undergraduate construction project course. This data was used to train the developed model and other five cases were used to test it (mean absolute error was 10%). Neural networks offer many advantages including: the ability to learn from real life examples; incomplete and inconsistent data can be used in training and the ability to consider multiple criteria (Moselhi and Hegazy, 1991; Hagazy, 1994; Li, 1996a, 1996b; Li and Love, 1998; Li et al., 1999). On the other hand, the neural networks have some disadvantages such as: the data required for training is usually confidential; designing a neural network model is largely based on trial and error and amending the structure of a neural network is not possible by users to suit specific strategies (Dawood, 1995; Fayek, 1996; Li et al., 1999). However, despite these disadvantages, it is evident that ANN is one of the most useful tools for modelling the mark-up process. Paek, et al. (1993) reported a new approach using fuzzy set theory in the pricing of constriction risks. Tam et al. (1994) presented a fuzzy logic-based model for the estimation of an optimum mark up percentage. This model is based on a set of rules derived from mark up factors considered in Hong Kong. However, building the rule base is a very difficult task. Also, modelling a complex decision such as the mark up decision in as few as thirty if-then rules can be questionable. Fayek (1996, 1998) proposed a mark-up system that also utilises fuzzy logic. This system provides more than ninety factors that may affect the mark up size. This model, although it has many advantages over previous models, is mathematically complex and the number of inputs is very large. For example, if a user considers only ten factors from the list provided by the model, some fifty five pieces of input data would be required. However, it demonstrates that fuzzy logic enables more general relationships to be established between data items that affect the mark up size decision. Using such a technique is more likely to yield a system that is more representative of the mark-up estimation process and, hence, more widely applicable in the construction industry. Fuzzy logic allows assessments to be made in qualitative and approximate terms. Therefore, it can be argued that ANN and fuzzy logic techniques are among the most suitable techniques for modelling the competitive tendering process.

WHY USE NEUROFUZZY TECHNIQUES?

Fuzzy set theory is a generalisation of the conventional set theory. The concept of this theory was first introduced by Zadeh (1965). It is characterised by its membership function, which represents numerically the degree to which an element belongs to a set. Unlike conventional crisp set theory where elements are either in or out of a set, fuzzy set theory allows objects to have partial membership in a set. A membership value ranges between one (full membership) and zero (no membership). Fuzzy logic is a technology that translates natural language of decision policies into an algorithm. The main components of a fuzzy logic system are input linguistic variables, a rule base consisting of sets of "if-then" rules, and output linguistic variables. Each fuzzy rule has a weight called degree of support (DoS) representing its relative importance. Neurofuzzy techniques are a combination of ANN and fuzzy logic techniques. It provides a solution for the main drawbacks of both of these approaches. “Combining ANN systems with qualitative causal models can provide a good solution for the ANN problem of opacity” (Zadeh, 1994). Combining neural network systems with fuzzy models helps to explain their behaviour and to validate their performance. Neurofuzzy techniques are thus, a combination of the explicit knowledge representation of fuzzy logic with the learning power of neural networks. Neurofuzzy methods are purposely developed to automatically identify fuzzy rules and tune both the shapes of the membership functions and degrees of the validity of the identified rules. Neurofuzzy modelling involves the extraction of rules from a typical data set and the training of these rules to identify the strength of any pattern within the data set. Many alternative methods of integrating neural networks and fuzzy logic have been proposed in the literature (Yager, 1992). Amongst these is the Fuzzy Associate Memories (FAM) method, which is the most common approach. This method is based on a mathematical function that maps FAMs to neurones in the neural network.

Identification of Input Factors

The bidding literature shows that contractors in different countries consider different bidding factors. Although there are some common factors, they do not have the same importance in all countries. For example, the "project size" is ranked as the most important mark up factor in the Saudi Arabia (Abdul-Hadi, 1989; Shash and Abdul-Hadi, 1992-1993), as the third factor in the USA (Ahmed and Minkarah, 1988), as the ninth in the UK (Shash, 1995; Shash and Abdul-Hadi, 1993), and not referred to at all in Australia (Fayek, 1996). The results of these surveys differ due to different aims of the surveys, different bidding conditions, and different factors considered in each country (Odusote and Fellows, 1992). Therefore, a new survey was required to determine the tendering factors considered in the Syrian construction industry.

The survey was broadly based on the factors identified by Ahmad and Minkarah (1988). Contractors were prompted to score the importance of each factor by selecting the appropriate number on a scale from 0 to 6 (where: 0 means no importance; and 6 means extreme importance). Responses to the questionnaire helped to establish the relative importance of thirty-five mark-up factors, as explained in more detail in Wanous, *et al* (1998).

Only nineteen factors, which have an importance index (I) equal to or greater than 50% were considered to develop a simple questionnaire to collect data on real life bidding situations. Respondents were requested to provide the actual mark up (as a percentage of the total estimated cost) and their subjective assessments of current or recent bidding situations in terms of these nineteen factors. One hundred and eleven real life bidding cases were provided. Fifteen cases were randomly selected from this sample and reserved for validation purposes.

The remaining ninety-six bidding situations were used first to study the correlation between the contractors’ assessments of the mark up factors and the actual mark-ups. Eight factors that have marginal correlation with the mark up, i.e. $| r |< 0.5$, were omitted.

Table 1 shows the remaining eleven factors ranked according to their relationship with the actual mark up size as expressed by the absolute correlation coefficient | r |.

Table 1: Selection of the most influential mark-up factors

	The most influential mark-up factors	**r**	**| r |**
1	**Risks expected**	+0.71	0.71 *
2	**Availability of equipment owned by the contractor**	-0.64	0.64 *
3	Confidence in the cost estimate	-0.63	0.63 *
4	Availability of materials required	-0.62	0.62
5	Competence of the expected competitors	-0.61	0.61 *
6	Degree of buildability	-0.60	0.60
7	**Expected degree of competition (number of competitors)**	-0.58	0.58
8	Way of construction (mechanically/ manually)	-0.54	0.54 *
9	Rigidity of specifications	+0.53	0.53 *
10	Site clearance of obstructions	-0.53	0.53
11	Site accessibility	-0.51	0.51 *

r: correlation coefficient between the mark-up and the mark-up factors

To avoid double counting of certain factors, the interrelationship between these factors was analysed. If the correlation between any two factors was greater than 0.50 the one, which has less influence on mark up, was omitted. The remaining seven factors, indicated by an asterisk in Table 1, were chosen as input variables for the developed model.

Modelling

This is a series of interactive processes as illustrated in Figure 1. The initial design process involved the development of an empty fuzzy logic system, the input variables of which are the seven factors identified in the previous section.

The model has one output variable, which is the expected mark up percentage. At this stage the linguistic variables for the considered inputs and output were set starting with three terms (Low, Medium and High) for all input variables and five terms (Very Low to Very High) for the output variable (Altrock 1997). For all input variables, the cubic interpolative S-shaped membership function (MBF) was used because it has proved to be a highly accurate representation of human concepts

when dealing with complex decisions. For the output variable, the Λ-type, i.e. linear (L), was used. It is the most commonly adopted shape for output variables (Altrock 1997).

At this stage, the initial inference rules were developed from real projects using the fuzzyTECH 5.10b development software. It works as an intelligent assistant to generate and optimise membership functions and if-then rules from sample data. The rule base was arranged in four rule blocks and the degrees of support (DoS) of the generated rules were set to zero. DoSs will be modified during the training phase. The "MinMax" premise aggregation and the "Max" result aggregation operators were adopted. These will be optimised later in the modification phase. Finally, the center of maximum (CoM) output inference method was used. For information about fuzzy aggregation operators and inference methods, see Altrock (1997). The structure of this preliminary model identifies the fuzzy logic inference flow from the input space to the output space. This model does not have any knowledge at this stage because the degrees of support and weights of all its rules are set to zero.

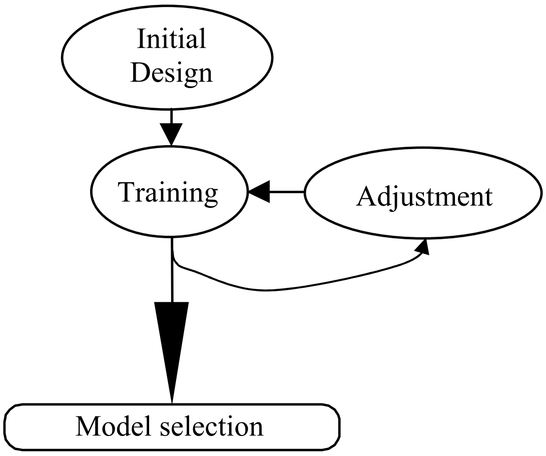

Figure 1. Framework of the development process

The fuzzyTECH development software was used to extract possible heuristic rules underpinning the process of making the mark-up decisions from the ninety-six cases used during the training phase. When training a fuzzy logic model, the degrees of support for important rules will be automatically increase while rules of low importance may remain close to zero. These latter rules might be omitted without significantly affecting the model's performance.

The average deviation between the actual and the predicted mark ups of the training examples is automatically produced by fuzzyTECH. It is a measurement of the training performance. The first model was able to map the input space of the training samples to the actual mark ups with an average error of 18% after five iterations. During the adjustment phase, eighteen other models were experimented with while recording the average deviation after training for the same number of iterations to enable a fair comparison between different development parameters. The model with the least average deviation (6%) was trained for more iterations to improve the model's performance in predicting the actual mark up values. The final average deviation was only 4.9%, which shows a high level of "expertise" learnt from the modelling sample. The structure of the final model is shown in Figure 2.

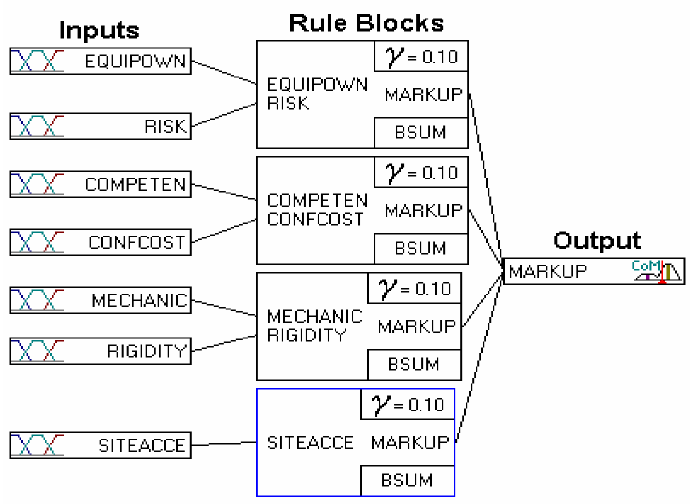

Figure 2: Structure of the final model

VALIDATION

The developed neurofuzzy mark up model proved to be very consistent as it produced the same output for the same cases. The accuracy of this model was examined using fifteen real-life bidding situations reserved for this purpose. The contractor's assessments of these situations were presented to the neurofuzzy mark up model as inputs to produce a mark up percentage for each situation. Table 2 shows the predicted/actual mark up values, absolute error, and percentage error for each one of the test cases. The root mean square error was only 0.013, indicating a high reliability of the developed model.

Table 2: Actual and predicted mark ups for unseen bidding situations

Project Number	Actual Mark up	Neurofzzy mark up ion	Error Absolute	(%)
1	0.12	0.133	0.013	10.4
2	0.14	0.140	0.000	0.0
3	0.15	0.127	0.023	15.3
4	0.13	0.132	0.002	1.9
5	0.18	0.169	0.011	6.1
6	0.15	0.127	0.016	10.7
7	0.18	0.188	0.008	4.3
8	0.16	0.146	0.014	8.6
9	0.12	0.107	0.013	10.8
10	0.11	0.121	0.011	10.0
11	0.10	0.111	0.011	11.0
12	0.09	0.103	0.013	14.5
13	0.13	0.125	0.005	3.8
14	0.15	0.149	0.001	0.7
15	0.11	0.123	0.013	11.8
Average			0.011	8.3
Root Mean Square error (RMS)			0.013	

The mean percentage absolute error is 8.3% as shown in Table 2. Therefore, it can be concluded that the developed model is (91.7%) accurate in simulating the actual mark ups of the validation sample.

CONCLUSION

Neurofuzzy is a powerful tool for developing fuzzy and neural network hybrid decision support systems. The application of this technology has enabled the development of an innovative mark up model. A systematic procedure was adopted to examine numerous models before the selection of the best model, which was then tested on unseen real-life bidding situations producing high accuracy results. This leads to the conclusion that the neurofuzzy technique is a valuable tool for modelling the mark up process in the construction industry. This model has a high potential of practical application, as users, unlike previous models, do not have to provide historical data on past projects and possible competitors or to perform complex mathematical computations.

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