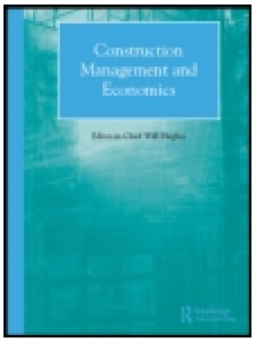

Routledge
Taylor & Francis Group

Construction Management and Economics

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

Risk analysis in construction: a paradigm shift from a hard to soft approach

Stephen W. Mack

To cite this article: Stephen W. Mack (1995) Risk analysis in construction: a paradigm shift from a hard to soft approach, Construction Management and Economics, 13:5, 385-392, DOI: 10.1080/01446199500000043

To link to this article: https://doi.org/10.1080/01446199500000043

Published online: 28 Jul 2006.

Construction Management and Economics (1995) **13**, 385–392

Risk analysis in construction: a paradigm shift from a hard to soft approach

STEPHEN W. MAK

Department of Building and Real Estate, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Risk analysis in construction is becoming more popular as competition, project size and complexity increase. Traditional risk analysis relies on rules of thumb. While this approach can work, it is neither robust nor reliable. The development of information technology has made the use of probabilistic estimating and simulation a practicable alternative. These techniques are, however, precise but not necessarily accurate as simplification and many assumptions are used. Further information technology development in expert systems and the paradigm shift in systems engineering from a hard to soft approach has promoted an alternative approach to risk analysis utilizing the theory of fuzzy sets which translates linguistic expressions (such as highly likely) into numerical membership functions. This paper introduces risk analysis in construction against characteristics of the industry. It is argued that normative theories in probability are not as applicable in the construction industry as first perceived. The concept of fuzzy sets is described and the difference in approach in modelling risk between probabilistic and fuzzy methods will be presented. Initial empirical study reveals the applicability of fuzzy sets theory in risk analysis. This is important in that a model of risk analysis can be developed requiring the user to express risk attitude linguistically. Moreover, the results are also in linguistic terms and can, therefore, be understood and interpreted correctly by the user.

Keywords: Risk, probability, fuzzy sets theory, expert systems, information technology.

Introduction

The purpose of risk analysis in estimating is to take into account the inherent uncertainty of the costs (or durations) of individual activities or elements within a project when assessing the anticipated final cost of a particular scheme. This enables the project director to evaluate the likelihood of meeting budget or time limits. Risk analysis has been synonymous with probabilistic analysis in that Bayesian type statistical inference is used (Raftery, 1985; Flanagan and Stevens, 1990). It is argued that the construction industry features a humanistic system in which this kind of probabilistic analysis is not necessarily appropriate. On the one hand, the harsh assumptions behind Bayesian statistics cannot easily be met. On the other hand, heuristics are still commonly employed. Subjective judgements dominate the whole risk analysis process. It is therefore necessary to explore new directions for risk analysis in construction. Fuzzy sets theory is introduced as an alternative approach. The feasibility of using fuzzy sets theory to building an expert system for risk analysis is explored and concluded by implications for empirical studies.

Information technology developments in decision support

The traditional approach to decision and control system design is shown in Fig. 1 (Gaines, 1987). This positivist paradigm underlies the methodologies of the physical sciences and technologies upon which they are based. The application of a *linear model with quadratic performance criteria* to natural systems is often attempted but, in general, it does not work. The reason for that is not because the tool was considered appropriate, but because it was the only tool available.

Figure 2 shows the four shifts in perspective that have taken place in the past two decades in fuzzy sets theory and expert systems. The first perspective is the rcognition of the fundamental inadequacy of conventional mathematics for coping with the analysis of biological systems by Zadeh in 1962. The second perspective is that which led to fuzzy sets theory. Optimal control theory was regarded as the peak achievement of system theory in the 1950s and 1960s. However, it proved limited in application because it demanded precision in system modelling that was impossible in practice. The third perspective is that which led to the success of linguistic fuzzy controllers and later expert systems. Modelling the way the expert performs the task rather than modelling the task itself is the primary characteristic of an expert system. The fourth perspective is an important one for both expert systems and fuzzy sets theory. The former are knowledge-based systems because they make provision for explaining the decisions reached in terms of the data and inferences used. Logics of uncertainty that aggregate evidence, such as probabilistic logics, do not provide a simple mechanism for explanation. Explicable logics have to be truth functional and non-aggregative. Fuzzy logic satisfies these requirements (Gaines, 1987). The ability to give explanations is seen by some philosophers of science as a key difference between models that make accurate predictions and scientific theories which can also provide causal explanations (Salmon, 1984).

Expert systems are knowledge-based systems in that they rely not only on data as an input, but also on (expert) knowledge. Typical features of an expert system include the following (Zimmermann, 1987).

1. The intended area of application is restricted in scope, ill-structured and uncertain. Therefore, no well-defined algorithms are available nor are there any that are efficient enough to solve the problem.
2. The system is, at least in part, based on expert knowledge which is either embodied in the system or can be obtained from an expert and be analysed, stored and used by the system.
3. The system has some inference capability and can use the knowledge in whatever way it is stored to draw conclusions.
4. The interfaces to the user on one side and the expert on the other side should be such that the expert system can be used directly and that no knowledge engineer is needed between the system and the expert.
5. Since heuristic elements are contained in an expert system, no guarantee of optimality or correctness is provided. Therefore, and in order to increase user acceptance, it is considered to be at least desirable that the system contains a *justification* or *explaining module.*

Step 1	Thoroughly instrument the system to be controlled or about which decisions are to be made.
Step 2	Use the instrumentation to gather data about the system behaviour under a wide variety of circumstances.
Step 3	From these data build a model of the system that accounts for this behaviour.
Step 4	From this model derive algorithms for decision or control that are optimal in terms of prescribed performance parameters.

Figure 1 The hard system approach

Characteristics of the construction industry

Humanistic system

A humanistic system is a non-mechanistic system in which human behaviour plays a major role. A single individual and his/her thought processes may also be viewed as a humanistic system (Zadeh, 1976). The high standards of precision which prevail in mathematics, physics, chemistry, engineering and other '*hard*' sciences stand in sharp contrast to the imprecision which pervades much of sociology, psychology, political science, history, philosophy, linguistics, art and related fields. This marked difference in the standards of precision is because the *hard* sciences are concerned in the main with the relatively simple mechanistic systems whose behavi-

PROBLEM 1: The models available are inadequate to capture the system.

Old Approach: Procrustean Design
Change to world to fit the model – normative technology.

Paradigm Shift: Model Realism
Use system methodologies and information technology that enable the natural world to be modelled without distortion and destruction.

PROBLEM 2: Optimal control is over-sensitive to system uncertainties.

Old Approach: Sub-Optimality
Use a sub-optimal controller that is robust.

Paradigm Shift: Model Uncertainty
Model the uncertainty as part of the system

PROBLEM 3: Data is unavailable or inadequate for modelling

Old Approach: Manage
Do not automate – leave to human decision/control

Paradigm Shift: Expert Systems
Model the person as a decision-maker or controller

PROBLEM 4: Neither a human nor an automatic system alone is adequate

Old Approach: *Ad hoc* System Design
Use a mixture of automatic and human decision/control

Paradigm Shift: Accountable Integration
Integrate automatic and human activity – make automation accountable ("why?" in ES)

Figure 2 Paradigm shifts in systems engineering from the hard to the soft systems approach our can be described in quantitative terms, whereas the *soft* sciences deal primarily with the much more complex non-mechanistic system in which human judgement, perception and emotions play the dominant role.

A humanistic system is therefore a system which mostly depends on human actions. In the tendering stage, the contractor needs to gauge a price for a project not yet built, for which he may not have seen the detailed drawings, on a site of which he may have no knowledge and with a work-force not yet organized (Hillebrandt and Cannon, 1990).

Project-based management

Projects form the basis of business transactions in the construction industry; therefore project management plays an important part in the design and construction activities, although this is not a unique feature of the industry. A project by itself has the character of a new and unique venture (Seiler, 1990). Experiences gained from finished projects cannot be fully transferred to new ones. The information at hand is often conflicting, inconsistent and incomplete. There are routine processes in projects with a high degree of novelty which are handled with a known and mastered technique, but in general the automation of generating, surveying and controlling working procedures could be more difficult than with conventional management tasks (without project characteristics).

Moreover, a construction project is an engagement over different points in time of several organizations such as consultants, contractors, subcontractors and suppliers, with a client system that it itself organizationally complex. The management of a construction project from inception to completion can be perceived as a function of a temporary multiorganization (TMO) comprising relevant parts of these component organizations (Cherns and Bryants, 1984). The TMO is indeed a device for handling uncertainty, the structure and mode of functioning of which will depend on the nature of the uncertainties and will change over time as the focus of uncertainty shifts during the course of the project. The actual performance of the TMO is, however, determined more by the managerial capabilities of its component organizations and their coordination than by the form of the contract being adopted.

Bidding environment and bidding uncertainties

The first decision facing a contractor is the decision to bid. Whether or not the bid is the response to an invitation by a prospective client is important. Recent research shows that decisions on what projects to bid for are generally taken at the operating unit level (Hillebrandt and Cannon, 1990). It is also shown that the reasons firms do not bid for a project include lack of skills, unsatisfactory payment arrangements, especially for work abroad, too many competitors, inadequate capacity in the estimating department and unsatisfactory experience in a particular area. For reasons such as unsatisfactory past experience with the client or the designer in personality or payment, high costs or inadequate information, firms will usually increase the bid price rather than refuse to bid.

In reality, contractors not only estimate the monetary cost of a project, but also the opportunity cost of undertaking it as well as the chances of obtaining it. There is rarely nothing worse than obtaining work too cheaply. The contractor's estimator produces a direct cost estimate, a site overheads estimate, a head office overheads estimate and a contract conditions estimate.

Whalen (1987) has set out three conditions in order for an estimator to appreciate what to do successfully in terms of bidding. First, they must comprehend all of the alternative courses of action from which they can choose. Second, all the consequences of each alternative course of action must be known. Third, the preference for a particular set of consequences among any other achievable set must be explored. However, the first condition can be limited in three ways.

1. Limited perception or imagination such that appropriate courses of action are not considered.
2. Immensity of choice because of the existence of too many courses of action.
3. Imprecision of specification, especially when a large number of alternative courses of action is due to a combinatorial explosion rather than a continuum.

These limitations invariably hinder the second and third conditions. In contract bidding, similar situations are faced by bidders. Skitmore (1989) has identified four bidding uncertainties.

1. Uncertainties caused by the variability in outcomes that occur generally irrespective of any bidding actions, for example, government legislation, economic prosperity and management efficiency, especially at site level.
2. Uncertainties caused by the inaccuracy in estimating outcomes due to imprecision in the estimating methods used, inability of the estimating personnel, inadequacy in information acquisition and insufficient acquisition and use of feedback from previous estimating activities.
3. Uncertainties caused by differences between the bidding models and the real or perceived bidding situation. This, to an extent, explains why statistical bidding models are generally not used.

4. Uncertainties concerning the acquisition of contracts.

Risk management for construction: The probabilistic approach reconsidered

Inappropriateness of Bayesian statistics

In order to utilize the rigorous treatment of statistical theory applied to uncertainties, as found in a mechanistic system, a precise description of probabilities is necessary. However, without the support of reliable historical data, subjective judgements are made on the probabilities of events. This entails the use of such parameters as means and standard deviations. By far, the use of these parameters is too complicated for the average practitioner in the construction industry. Worse still, complicated parameters may introduce more human errors based on misunderstanding or misinterpretation.

Bayesian statistics have been regarded as the normative theory in calculating probabilities. However, the Bayesian approach is a mechanistic one and necessitates demanding assumptions. It requires that the events to be combined in a Bayesian function be mutually exclusive, exhaustive and conditionally independent. In fact, Szolovits and Pauker (1978) suggest that the conditional independence assumption almost never holds in their domain of medical diagnosis. In construction, in evaluating the probability of delaying a project, there are so many causes that they cannot be exhaustively listed, not to mention their mutual dependence and correlation. For example, in a simple three-activity project, if the evaluated probability of delay of each activity is 0.2 then the probability of completing on time is 0.8. Using the Bayesian approach, the probability of delaying the project is $1 - 0.8^3 = 0.488$. This is based on the assumption that the three activities are mutually exclusive and independent. In reality, however, if the time required for activity 1 is lengthened, it can probably lengthen the time for activities 2 and 3. This will then make the probability of delaying the project much higher. On the other hand, having activity 1 delayed, the site management can then increase resources for activities 2 and 3 to recover time (at a higher cost, of course) and thereby reduce the probability of delay. This kind of judgement cannot be reflected in Bayesian calculations. The application of Bayesian theory is because it is normative and can produce a precise answer. The user always yields to the underlying assumptions unconsciously. The more complex the situation, the more difficult to apply the Bayesian approach successfully.

Research by cognitive psychologists shows that subjective judgements are flawed and erroneous (Kahneman and Tversky, 1972). They base their arguments on normative Bayesian theory. Dispute has, however, arisen on the validity of their arguments. It has been contested by some philosophers (see, for example, Cohen, 1989) and some artificial intelligence (AI) researchers (see, for example, Cohen, 1985). Both have queried the usefulness of the Bayesian approach in the area of expert systems. Shortcomings of the Bayesian approach are summarized as follows.

1. The assumptions involved in deriving a Bayesian combining function, that is, mutual exclusivity, exhaustive hypotheses and conditional independence of evidence in a hypothesis, do not always hold. Some authors suggest that the conditional independence assumption almost never holds in some domains (Cohen, 1985). An example in a construction project is that a delay in a critical activity will not only affect the duration of the project but also the total cost, but a delay in non-critical activity may only affect the cost of that activity (or it may have no effect at all).
2. The Bayesian view of probability does not allow one to distinguish uncertainty from ignorance, that is, one cannot tell whether a degree of belief was directly calculated from evidence or indirectly inferred from an absence of evidence (Cohen, 1985). By applying Bayes' formula, one has taken a tool which is meant to apply to situations in which uncertainty is based on randomness and applied it to a situation in which uncertainty comes from ignorance (Borden, 1987).
3. The single degree of belief is represented by a point estimate so it is difficult to verify its accuracy, however precise it may be (Cohen, 1985).

The use of heuristics

Heuristics is a word derived from the Greek word *heuriskein* meaning to discover (Daellenbach *et al.*, 1983). Heuristic problem solving is not a solution method in the sense that the simplex method of linear programming is, but rather it is a philosophy of or strategy for seeking out a method or methods that might produce a solution to a particular problem. Heuristic problem solving involves inventing a set of rules that will aid in the discovery of one or more satisfactory solutions to a specific problem. The emphasis is on sufficing, that is, being good enough. Optimality is, thus, never guaranteed. Heuristic methods are based on inductive inferences related to human characteristics of problem solving, such as creativity, insight, intuition and learning. A particular heuristic is followed because it promises, intuitively or from experience, to help in the search for an acceptable solution and if, in the process, a better rule is discovered, then the old one is discarded. So, while heuristic problem solving involves the use of currently accepted rules, it may also involve a search for even better rules to replace them.

The Baconian approach to assessing likelihoods is different (Cohen, 1970). Baconian functions grade probability by the extent to which all relevant facts are specified in the evidence, therefore they judge from provability to non-provability, as found in an incomplete system. This is directly opposite to the Pascalian approach which judges from provability to disprovability (Cohen, 1977) – see above reference to discarding an old rule.

The Baconian approach does not have the properties of complement and negation as found in the Pascalian approach. For example, if A is quite irrelevant to B then it is quite normal that both p_I $(B|A)$ and p_I (not-$(B|A)$) have zero-grade inductive reliability (as opposed to $p_I(B|A) = 1 - p_I$ (not-$B|A$)). For example, an increase in the price of crude oil may have a significant effect on the inflation rate in the UK, but it may have little effect on the building cost index because the price of crude oil and the building cost index are more remotely linked than the general inflation rate. So p (building cost will increase | crude oil price increased) $= 0$ and p (building cost will *not* increase | Crude oil price increased) $= 0$ can co-exist.

Professional development towards shallow, wide and domain-dependent knowledge

The essence and power of human reasoning is in its ability to grasp and use inexact concepts directly. Zadeh (1965, in Zadeh, 1980, p. 421) argues that attempts to model or emulate human reasoning by formal systems of increasing precision will lead to decreasing validity and relevance because most human reasoning is essentially shallow in nature. Brandon (1987) considers that in professional development there is a shift from textbook knowledge and general theories towards knowledge gained from experience, the former being deep, narrow and domain independent, while the latter is shallow, wide and domain dependent.

The distinction between domain independence and domain dependence is best illustrated by the difference between the Bayesian and Baconian approach in statistical inference. For example, the description in a tender document for an industrial building for a supermarket provides a high Pascalian probability for its simplicity and short project duration (because of the available statistics about this type of project), but it provides only a medium to low Baconian probability in this sense since the weight of evidence is rather light, as the site may be located in a traffic black-spot or may have been a rubbish tip and so on. It is this latter information that is usually possessed by a professional person and he or she often needs only rules of thumb to make judgements with regard to the cost and time, on top of a Pascalian evaluation.

Application of fuzzy sets theory within risk analysis

Modelling imprecise situations

Fuzzy sets theory was introduced by Zadeh (1965) with the intention of generalizing the classical notion of a set and to accommodate uncertainty in the non-stochastic sense.

> One of the aims of the theory of fuzzy sets is the development of a methodology for the formulation and solution of problems which are too complex or ill-defined to be susceptible to analysis by conventional techniques (Zadeh, 1980, p. 421).

Risk analysis is a task without a clearly discernible measure of success; it involves '*best guesses*', intuition and '*straw man*' estimates (Schmucker, 1984). The theory of fuzzy sets offers a natural model for a situation when a purely numerically based rating system demands a degree of precision on the part of the system rater which is both difficult to attain and difficult to interpret with confidence. Therefore, fuzzy sets theory is an attempt to remove linguistic barriers between humans, who think in fuzzy terms and machines that accept ony precise instructions (Gupta, 1977).

In ordinary set theory, an element either belongs or does not belong to the set A, where A has sharp boundaries. However, if the membership function is allowed to take values in the interval $[0, 1]$, A is called a fuzzy set. A does not, therefore, have sharp boundaries and the membership of x to A is fuzzy.

If the elements in a set A have the following properties:

a is present with degree of membership 0.3
b is present with degree of membership 0.6
c is present with degree of membership 0.8
d is present with degree of membership 1.0
e is present with degree of membership 0.5
f is present with degree of membership 0.0

A can be rewritten as, in fuzzy set format,

$$A = \{a|0.3, b|0.6, c|0.8, d|1.0, e|0.5\}$$

(f is neglected since its degree of membership is 0).

It is this expression of a fuzzy set that can be utilized to represent subjective judgement or linguistic variables. It is these linguistic variables which add to the uncertainty in the final outcome of any decision process.

Linguistic approach to expressing uncertainties

Complexity and precision bear an inverse relation to one another in the sense that, as the complexity of a problem increases, the possibility of analysing it in precise terms diminishes (Zadeh, 1972). As the complexity of the system increases, the ability to make precise and yet significant statements about its behaviour decreases. This trade-off between precision and significance continues until a threshold is reached beyond which complexity, precision and significance can no longer co-exist.

If the probability of an event is not known with precision, that is, with such descriptive parameters as mean and standard deviation, then it may be characterized linguistically as, say, quite likely, not very likely, highly unlikely and so on. It is quite natural and has indeed always been used by professionals not only in construction, but also in medicine, political science and law, etc. The essence of this linguistic approach is that it sacrifices precision to gain significance, thereby making it possible to analyse in an approximate manner those humanistic as well as mechanistic systems which are too complex for the application of classical techniques.

One inherent characteristic of linguistic description is imprecision because it depends upon human interpretation. Furthermore, linguistic expression often causes problems. Firstly, ambiguity, that is, the association with a given object of a number of meanings. An example is 'the design is expensive' which can mean 'the design fee is high' or 'the materials specified in the design is expensive' or 'the shape of the design is such that it is difficult to build and therefore expensive'. Secondly, generality, that is, the application of the symbol's meaning to a multiplicity of objects. Finally, vagueness, that is, a lack of clear-cut boundaries of the set of objects to which the symbol is applied. An example is 'the building is tall' in which *tall* can mean a different height to different people or in different places, for example a ten storey building is regarded as tall in the UK whereas buildings with less than 40 storeys may not be described as tall in Hong Kong.

Building blocks of fuzzy expressions

The very core of fuzzy sets theory models an imprecise situation such as the estimation of risk by allowing one to estimate the plausibility or the possibility of an element being a member of a set. The use of linguistic variables allows a precise modelling of imprecise statements such as high, low, fairly high, etc. Therefore, the notions of linguistic variables and of fuzzy sets are akin to the notions of goal and tools, respectively.

The set of natural language expressions in which the linguistic variable takes its values is not an unrestricted set of English phrases. Rather, it is a rich finite set and is usually specified by rule, instead of by an exhaustive list. The most natural form of the rule is that of a phrase-structure grammar.

As shown in Fig. 3, the terms in the building blocks <Hedge>, <Primary> and <Fuzzifier> are used to construct the elements of the set. Of these, the primary terms and the hedges are the most important. The primary terms are the fundamental notions from which all the other elements of the set are built and the hedges allow for the fine tuning of these primary terms. For example, if the evaluation of the risk in one work package or sub-system of a construction project is LOW (but there may be some features of the package that could undermine this), the hedge MORE OR LESS is attached to LOW. This is a modification of the basic feeling that the subsystem risk is low.

A fuzzy risk model

A contractor attempting risk analysis in tendering is encountering so many uncertainties that the use of traditional algorithmic reasoning cannot be applied effectively. On the one hand, it is difficult to describe something uncertain in precise terms. For example, there is no one single rule to evaluate the competency of a subcontractor. On the other hand, it is also impossible to infer a result from one statement. For example, the statement 'if the subcontractor is competent, then there will not be any delay' is too naïve to be accepted because many other factors contribute to delays. In addition, much of the information necessary to produce probabilities must be provided by individuals who are specialists

<Number> ::= ONE|TWO|THREE| . . . |EIGHT|NINE. . .

&

<Fuzzifier> :: = REASONABLY|BARELY|ABOUT

to build

<Fuzzy Number> :: = <Fuzzifier><Number>

e.g. *About four*

<Primary> :: = LOW|HIGH|MEDIUM

&

<Hedge> :: = NOT|VERY|FAIRLY|SLIGHTLY|MORE OR LESS

to build

<Hedged Primary> :: = <Hedged><Primary>|<Primary>

e.g. *Fairly low, high*

<Range Phrase> :: = <Hedged Primary> TO <Hedged Primary>

e.g. *More or less low TO medium*

Figure 3 A notation for a simple set of natural language expressions in the risk area under assessment. This information may involve interpretation and adjustment of objective data such as interest rates or judgements based on experience with no directly relevant data such as competitiveness. The information is therefore highly subjective.

An experienced estimator may know, subjectively, the time and cost required to complete a task in building up an estimate for an item. A project manager may also possess knowledge which is useful in assessing the keenness of competition in a particular project. For example, they may know that one competitor is desperate to win a project at that time – this may not be revealed by readily available information such as statistical data or the presence of a buoyant market. However, these are difficult to quantify by the traditional methods of probability or mathematics.

Risk analysis in cost estimating has been tackled by the Monte Carlo technique (Raftery, 1985; Al Bahar, 1988). The estimator is asked to suggest the probable, pessimistic and optimistic values for a part of the estimate and computer simulation is then applied to generate a number of times (for example, 500) to give a series of likely figures for the estimate. Monte Carlo simulation is in essence a form of sensitivity analysis.

The calculations give a picture of the range of possible results in the form of density and cumulative curves or histograms. A comparison is then made to show how realistic the basic estimate is with regard to the simulation, that is, the probability of the basic estimate being exceeded in the simulation.

As suggested above, uncertainties are basically qualitative rather than quantitative in nature, due to imprecision. Instead of giving an optimistic and pessimistic value in relation to a probable estimate, it may be more appropriate for the estimator to comment on his perception of the estimate linguistically. For example, 'it is highly likely that actual cost will exceed the estimate' or 'there is a low probability of exceeding this figure'. A very detailed analysis can be done, if necessary, according to the arrangement of a typical bill of quantities, as shown in Fig. 4. This system not only allows the estimator to put a subjective, fuzzy judgement on the cost estimate for each item, but also allows them to put a different fuzzy weighting for each item/section/bill to reflect its effect on the total cost of the project.

A fuzzy decision support system to help management make mark-up decisions may be postulated. This is presented diagrammatically in Fig. 5. The factors to be considered here can be more general in nature, for example, the effect of the whole project on the portfolio of the firm and external matters such as competitiveness and client appraisal. Of course, the fuzzy result obtained from the cost estimate is also one of the inputs. The management's expert judgement on each of these factors is communicated to the model using a series of natural

TOTAL COST ESTIMATE			estimated TOTAL cost resultant judgement reliability
BQ1	**BQ2**	**BQ9**	estimated BQ cost effect on total reliability
Section 1 Section 2 ... Section M	Section 1 Section 2 ... Section M	Section 1 Section 2 ... Section M	estimated section cost effect on bill reliability
Item 1 Item 2 ... Item N	Item 1 Item 2 ... Item N	Item 1 Item 2 ... Item N	estimated item cost effect on section reliability

Figure 4 Fuzzy risk analyser for cost estimate based on a bill of quantities

language expressions which have highly structured and unique definitions. Similarly, personal judgement, weighting and reliability factors for each item are fed into the system in order that a fuzzy result can be calculated.

Consistency and consensus of subjective judgements

The greatest difficulty in using fuzzy linguistic terms to express subjective judgements in risk analysis is the consistency and consensus between the one who makes and the one who interprets the judgements. Unless this is resolved, people will not make extensive use of judgements in risk analysis. Although little research has been done in this area, Mak (1992) attempted to test this consensus with 80 construction professionals and found that there was general agreement among the subjects with regard to the meanings of the expressions usually used to express uncertainties. He concluded that the

TOTAL EFFECT				Likelihood Reliability
Company	**Industry**	**Economy**	**Project**	Likelihood Weight Reliability
Ad hoc management team	Resources	Government legislation	Risk	Likelihood Weight Reliability
Cash flow	Client appraisal	Inflation		
Portfolio	Workload	Interest rates		
	Competitiveness			

Figure 5 Fuzzy decision aid to tendering

method of soliciting the definitions of these expressions by the ranking method was superior over the numerical method and that the approach or method employed to obtain a sensible input to the model is more important if risk management techniques are to be widely accepted by all parties in the construction industry.

Conclusions

Risk exists in every construction project. The traditional approach to tackling risk has been reactionary. The modern approach tends to be proactive and scientific. This is partly induced by the proliferation of information technology, whereby cheaper and more powerful hardware and software have become more readily accessible. Risk analysis has generally been carried out in a fairly rigid and mechanistic way, which is accurate but not precise. The humanistic and project-based nature of the construction industry exerts barriers to the successful application of normative theories of Bayesian probability and statistics. The advent of fuzzy sets theory and the paradigm shift in systems engineering have called for a soft approach to tackling problems. What is important is that expert judgements can be input as well as stored in the system, so that when information is not sufficient for an ordinary person to make a decision the system is able to help. Fuzzy sets theory is capable of representing linguistic expressions of uncertainty. Initial research shows that consistency and consensus exist in those linguistic expressions in a specific domain. Further research is required to build up a dictionary of terms of uncertainty to be stored in an expert system utilizing fuzzy sets.

References

Al Bahar, J.F. (1988) Risk management in construction projects: A systematic analytical approach for contractors, PhD dissertation, University of California, Berkeley.

Borden, A. (1987) Computer, know thine enemy, *AI Expert*, 2(7), 48–54.

Brandon, P.S. (1987) Expert systems – modelling professional expertise?, In Lansley, P.R. and Harlow, P.A. (eds) *Managing Construction Worldwide, Vol. 1: Systems for Managing Construction*, London, E. & F.N. Spon, pp. 580–90.

Cherns, A.B. and Bryant, D.T. (1984) Studying the client's role in construction management, *Construction Management and Economics*, **2**, 177–84.

Cohen, L.J. (1970) *The Implications of Induction*. London, Methuen.

Cohen, L.J. (1977) *The Probable and the Provable*. Oxford, Clarendon Press.

Cohen, L.J. (1989) *An Introduction to the Philosophy of Induction and Probability*. Oxford, Oxford University Press.

Cohen, P.R. (1985) *Heuristic Reasoning About Uncertainty: An Artificial Intelligence Approach*. London, Pitman.

Daellenbach, H.G., George, J.A. and McNickle, D.C. (1983) *Introduction to Operations Research Techniques*. Boston, Allyn and Bacon.

Flanagan, R. and Stevens, S. (1990) Risk analysis, In Brandon, P.S. (ed.) *Quantity Surveying Techniques: New Directions*, Oxford, BSP Professional Books, pp. 121–138.

Gaines, B.R. (1987) New paradigms in systems engineering from 'hard' to 'soft' approaches, In Kacprzyk, J. and Orlovski, S.A. (eds) *Optimization Models Using Fuzzy Sets and Possibility Theory*, Dordrecht, D. Reidel, pp. 3–12.

Gupta, M.M. (1977) Fuzzy-ism: the first decade, In Gupta, M.M., Saridis, G.N., and Gaines, B.R. (eds) *Fuzzy Automata and Decision Processes*, New York, Elsevier North-Holland, pp. 5–10.

Hillebrandt, P.M. and Cannon, J. (eds) (1990) *The Modern Construction Firm*. London, Macmillan.

Kahneman, D. and Tversky, A. (1972) Subjective probability: a judgment of representativeness, *Cognitive Psychology*, **3**, 430–54.

Mak, S.W.K. (1992) Risk analysis in construction: a study of subjective judgments, PhD thesis, University of London.

Raftery, J.J. (1985) *Risk Analysis in Construction Tendering: A Guide for Building Contractors*. Espoo, Technical Research Centre of Finland, Laboratory of Building Economics.

Salmon, W. (1984) *Scientific Explanation and the Causal Structure of the World*. Princeton, NJ, Princeton University Press.

Schmucker, K.J. (1984) *Fuzzy Sets, Natural Language Computations and Risk Analysis*. Rochland, Computer Science Press.

Seiler, R.K. (1990) Reasoning about uncertainty in certain expert systems: implications for project management applications, *Project Management*, **8**(1), 51–9.

Skitmore, R.M. (1989) *Contract Bidding in Construction*. London, Longman.

Szolovits, P. and Pauker, S.G. (1978) Categorical and probabilistic reasoning in medical diagnosis, *Artificial Intelligence*, **11**, 115–44.

Whalen, T. (1987) Introduction to decision making under various kinds of uncertainty. In Kacprzyk, J. and Orlovski, S.A. (eds) *Optimization Models Using Fuzzy Sets and Possibility Theory*, Dordrecht, D. Reidel, pp. 27–49.

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

Zadeh, L.A. (1972) Fuzzy languages and their relation to human intelligence, In *Man and Computer: the 2nd International Conference*, 11–16 Sept., Bordeaux, France, Basel, S. Karger.

Zadeh, L.A. (1976) A fuzzy-algorithmic approach to the definition of complex or imprecise concepts, *International Journal of Man–Machine Studies*, **8**, 249–91.

Zadeh, L.A. (1980) Fuzzy sets versus probability, *Proceedings of the IEEE*, **68**(3), 421.

Zimmermann, H.J. (1987) *Fuzzy Sets, Decision Making and Expert Systems*. Boston, Kluwer Academic Publishers.