A METHODOLOGY FOR ASSESSING RISKS IN THE CONSTRUCTION PROCESS

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Construction projects are fraught with uncertainties and risks in their nature. The involvement of subjectivity and the absence of complete and precise information have seriously undermined the applicability of traditional modelling techniques, such as statistical and probabilistic method, which form the basis of many risk analysis approaches currently employed in the UK. On the other hand, fuzzy set theory was developed to enable ill-defined and complex problems to be modelled mathematically. However, previous studies to the use of fuzzy logic within the construction industry have proved to be either too simplistic or too specific in their applications. This paper investigates the core issues and current development of risk modelling and assessment in the construction process. A new risk assessment model based on fuzzy set theory is presented in order to tackle construction risks more effectively and efficiently. An illustrative example is included to demonstrate the proposed methodology.

Keywords: construction process, fuzzy set theory, risk assessment.

INTRODUCTION

Risk can be defined as the probability of a detrimental event occurring to the project (Baloi and Price 2003). Nowadays, risk management is regarded as a critical part of construction project management and many organizations have established a professional team or department for managing risks. Winch (2002) asserts that risk management is the core of project management regarding that a project is a procedure of diminishing uncertainty over time.

A recent survey finds that most of the risk analysis packages currently used in the UK employed probabilistic method to quantify uncertainty (Tah and Carr 2001). Those risk assessment tools and techniques have been widely used in the construction industry, for example, event tree analysis (ETA), Monte Carlo analysis, scenario planning, sensitivity analysis, failure mode and effects analysis (FMEA), programme evaluation and review technique (PERT), require high quality data obtained from a number of projects so that the sophisticated quantitative methods can be applied (Winch 2002). Regrettably, such data are hardly ever available.

Risk analysis is a complex subject fraught with uncertainty and vagueness. Two issues arise when one tries to quantify risks (Tah and Carr 2001):

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- How to integrate the uncertainty about initial predictions into the risk model, and
- How to accommodate the inherent vagueness and subjectivity that are associated with the predictions.

The industry tends to use probability distributions to interpret uncertainty. However, this method usually fails to address adequate liability to a satisfactory level. Furthermore, the identification and assessment of risks highly depend on experience and subjectivity. These assessments can be influenced by a number of factors, for example, economic related factors and political related factors, which are not well defined and hard to be quantified. Consequently, it is more difficult to deal with the second issue: handling of the vague and subjective information. Fuzzy sets and fuzzy logic have been claimed to be powerful in solving the problems associated with imprecise and incomplete information and subjectivity. However, they have not been sufficiently developed and widely applied in the construction industry (Carr and Tah 2001).

This paper presents a new risk assessment model based on fuzzy set theory. An illustrative example is used to demonstrate the proposed methodology.

THE RISK ASSESSMENT MODEL

A risk management system can be divided into five phases: risk classification, risk identification, risk assessment, risk response and risk monitor and review (Zhi 1995, Winch 2002).

Traditional risk assessment approaches and methodologies often do not capture the nature of the construction issues particularly when they involve inherent subjectivity and uncertainty. The uniqueness of projects has limited the applicability of statistical and probabilistic methods. Fuzzy set theory can effectively reduce the complexity of ill-defined problems and handling of imprecise information, improve the cognitive of expert systems and the control of uncertainty, and provide an efficient tool for decision making in a conflicting environment (Cox 1999). It is clear that more reliable results can be obtained by combining the fuzzy set theory into the process of risk assessment to facilitate the handling of uncertainty and vague information.

Fuzzy decision function and fuzzy inference are two dynamic techniques widely proposed for decision making and modelling. Fuzzy decision function is a tool combining decision objectives and constraints in identifying the decision maker’s preferences (Sousa and Kaymak 2002). Fuzzy inference introduces interpretations and transparency by approximating linguistic rules. This desirable facility generates a mapping between inputs and outputs described in the fuzzy rule-based system. A risk assessment model based on the above two fuzzy techniques is shown in Figure 1.

The stepwise descriptions of the new risk assessment model are given as follows:

Step 1: Survey and review risk-related data and information produced in the risk classification and risk identification phases.

Step 2: Determine and measure risk criteria for assessing risk magnitude (*RM*).

Step 3: Input the values of defined criteria into the fuzzy decision function. Fuzzy decision function consists of two main actions: fuzzification and aggregation.

Step 4: Input the aggregated criteria into the proposed fuzzy inference system.

Step 5: Defuzzification. Convert the fuzzy result of risk magnitude (RM^*) into a matching crisp value of RM.

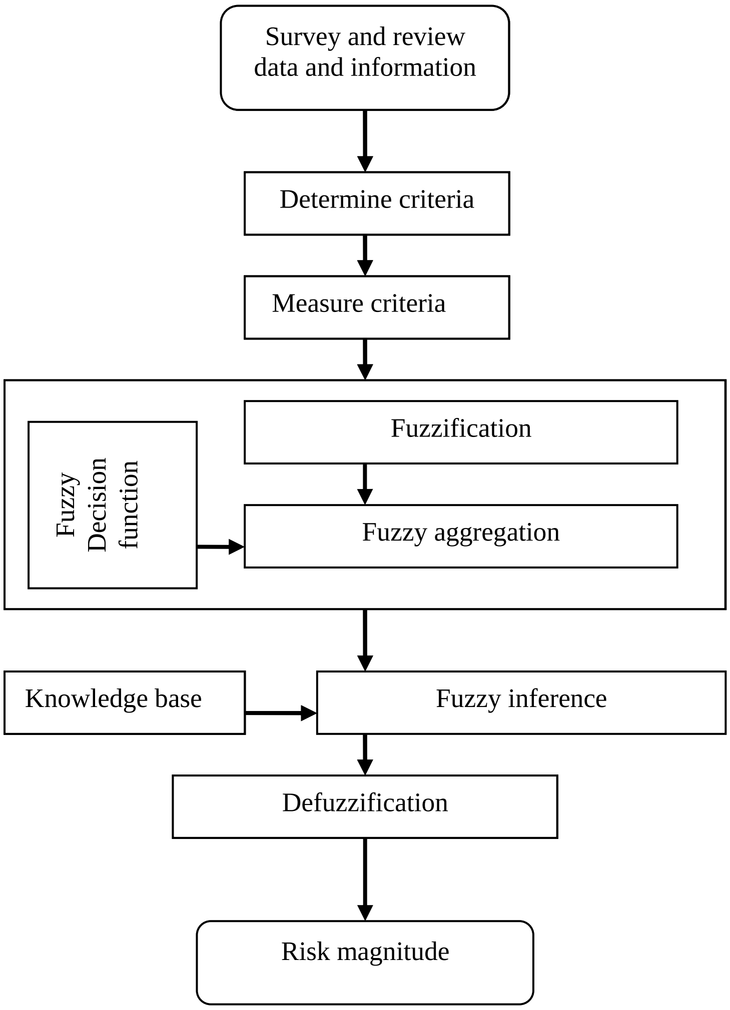

Figure 1: Risk assessment model

1. Survey and review risk-related data and information

Risk analysts are required to survey and review risk-related data and information produced in the risk classification and risk identification phases. In practice, risk assessment should involve a range of people with necessary skills, experience and expertise from different disciplines. Risk analysts, who are nominated by the top management or the risk management project team to undertake risk assessment tasks, should have:

- A deep understanding of the risk assessment method, including its scope and limitations;
- The appropriate ability and experience, including the ability to promote fruitful communication and teamwork, thorough knowledge of the subject under consideration and practical experience in risk assessment;
- The authority and the resources to carry out risk assessment tasks.

Since decisions made in the earlier stage apparently have greater impact on the final quality, cost and durations, risk assessment should start early at the project proposal stage and be developed continuously throughout the entire life cycle of the project (Thompson and Perry 1992).

2. Determine and measure risk criteria for assessing risk magnitude (*RM*)
Several risk criteria are used widely in judging risk magnitude, such as risk likelihood, risk severity, risk timing and risk impact. Risk likelihood and risk severity are frequently used as two fundamental criteria for risk assessment. A risk management project team assigned to a specific topic is required to provide their evaluation to each criterion corresponding to the defined risk. The results of these evaluations are crisp real numbers based on the domain designed for each criterion.

3. Input the values of defined criteria into the fuzzy decision function
Fuzzy decision function allows for linear and nonlinear inputs and can translate and scale these inputs to reach a decision value (Sousa and Kaymak 2002). The fuzzy decision function consists of two main actions: fuzzification and aggregation.

(1) Fuzzification
A fuzzifier is used to convert the measured crisp values into membership functions in the qualified variable sets. Lines, S-curves and bell shapes are the popular fuzzy shapes often used in fuzzy models. It is noted that constructing fuzzy sets should take into account the underlying semantic concept and the meaning of a fuzzy set should be interpreted in the context of the model.

(2) Aggregation
The chosen type of fuzzy aggregation depends on the purpose of the risk analysts and the boundary conditions imposed on the solution (Sousa and Kaymak 2002). Many aggregation methods are proposed in literature, such as minimum operator, maximum operator and ordered weighted averaging (OWA) operator. Different aggregation achieves different function. For example, if a risk analyst wants the output satisfying all the criteria simultaneously, a minimum operator is ideal. On the other hand, a maximum operator is used while a risk analyst wants to obtain the optimistic result. However, risk analysts often find that using a mixture of conjunction and disjunction in the decision is more realistic. In this case, averaging operator and compensatory operators are recommended. Sometimes, weight factors may be applied while considering the dissimilarity of contribution of assessors or criteria.

Through aggregation, the various inputted membership functions of each criterion are combined into a single membership value assigned to that criterion for fuzzy inference. This can be denoted as:

$$\mu_i = Agg(\mu_{i1}, \mu_{i2}, ..., \mu_{in}) \tag{1}$$

Where μ_i is the aggregated value of membership function of criterion *i*; $\mu_{i1}, \mu_{i2}, ..., \mu_{in}$ are the inputted membership values of criterion *i* measured by experts E_1, E_2,…, E_n, respectively.

The process of fuzzy decision function can be treated as a fuzzy optimization of multiple experts decision making. The crisp inputs have been fuzzified and aggregated into fuzzy outputs with each criterion having a distinct membership value which best represents the evaluation of all participated experts.

4. Input the aggregated criteria into the proposed fuzzy inference system
A fuzzy inference system generates a mapping between its inputs and outputs. It is normally supported by a rule base which comes from the acquired knowledge of risk analysts. A rule base formed by if-then rules is used for fuzzy inference.

Assume that the inference system has *n* risk criteria inputs $x_1, x_2, \ldots, x_n$ and one output *RM**. *RM** denotes the equivalent fuzzy set of *RM*. The if-then rules are written as:

R^k: If x_1 is A_1^k and x_2 is A_2^k and …and x_n is A_n^k then RM^* is B^k (2)

Where $A_1^k, A_2^k, \ldots, A_n^k, B^k$ denote membership functions of risk criteria $x_1, x_2, \ldots, x_n$, and risk magnitude *RM**, respectively; R^k , k=1,…,K is the *k*th rule in the rule base.

The if-then rules are based on the available repository of knowledge, including historical data, risk studies, experts' experience and their cognition to the project. They consist of part of the knowledge base and should be developed continuously throughout the project life cycle. The mechanism of the fuzzy inference system combines the input of risk criteria $x_1, x_2, \ldots, x_n$, with the rules developed by the risk management team, to calculate the output of risk magnitude *RM**. The main components of the inference system include fuzzy rule base and inference.

(1) Fuzzy rule base

Each fuzzy rule establishes a relation between two fuzzy regions: one is the antecedent - risk criteria $x_1, x_2, \ldots, x_n$, and the other one is the consequent - risk magnitude *RM**. Membership functions act as representations of linguistic variables in defining these fuzzy rules. Relation between antecedent and consequent is often treated as an implication operation. Under Mamdani's minimum operator, a fuzzy rule for risk inference can be represented by the membership function as follows:

$$\mu_{R^k}(x, RM^*) = \mu_1^k(x_1) \wedge \mu_2^k(x_2) \wedge \ldots \wedge \mu_n^k(x_n) \wedge \mu_{RM^k}(RM^*), k = 1, \ldots, K \quad (3)$$

Where $x \in X_1 \times X_2 \times \ldots \times X_n$ and $RM^* \in U$. *U* denotes the universe of *RM**. The total fuzzy relation R can be found by aggregating each fuzzy relation. However, the aggregation operator one chooses is up to the previous operator used in constructing individual rules. For example, since a Mamdani's minimum operator is used in Eq. (3) for interpreting R^k, now the maximum operator taking the union of individual rules can be used to obtain the total relation given by the membership function as follows:

$$\mu R(x, RM^*) = \bigvee_{k=1}^{K} R^k(x, RM^*) \quad (4)$$

(2) Inference
The inference mechanism determines which rules relate to the current situation are on and calculates the fuzzy output of *RM** according to the fuzzy inputs of risk criteria. The compositional rules of inference are used for this purpose. There are two principal methods of inference in fuzzy systems: the min-max method and the fuzzy additive method (Cox 1999). The fuzzy output *RM** is found by composing the fuzzy inputs with the total relation that is described by the fuzzy rules. Given fuzzy input *A**, the fuzzy output *RM** is

$$RM^* = A^* \circ R(x, RM) \quad (5)$$

Where symbol "$\circ$" denotes the compositional operation in fuzzy sets.

5. Defuzzification

Since the output of *RM** is a fuzzy set, defuzzification is required to translate the fuzzy results into a crisp result that can best represent *RM*. The most common defuzzification techniques include: centre of gravity (COG), centre-average, mean of maximum and centre of area (COA).

Because there are many methods in conducting fuzzification, fuzzy aggregation and defuzzification, it is important that risk analysts choose an appropriate type of operator according to the decision behaviour.

AN EXAMPLE

A risk management project team is formed to manage risks arising in the construction of a highway bridge. Foundation failure due to unexpected site conditions is identified as a risk. A risk assessment group consisting of six experts with high qualification regarding this subject is nominated by the risk management project team to undertake risk assessment by using the proposed risk assessment model.

Risk likelihood (*RL*) and risk severity (*RS*) are chosen as two criteria for assessing the corresponding output of risk magnitude (*RM*). Six experts agree that five levels of linguistic variables are used for the expression of *RL*, *RS* and *RM*: *very low* (*VL*), *low* (*L*), *medium* (*M*), *high* (*H*) and *very high* (*VH*). Triangular membership functions for the above expressions are employed and defined as shown in Figure 2 (adapted from Carr and Tah 2001).

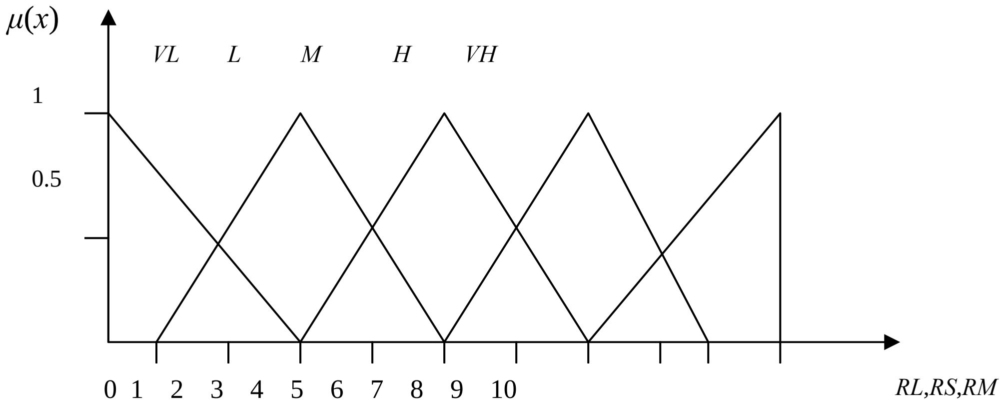

Figure 2: Fuzzy definition of *RL, RS* and *RM*

Risk likelihood highly depends on personal experience and historical data obtained from company documentation and industrial records. The linguistic terms of *RL* can be described as shown in Table 1.

Table 1: Risk Likelihood (*RL*)

Triangular fuzzy number	Description	General interpretation	Occurrence rate
(0,0, 3)	Very low	Occurrence is unlikely	Below 10^{-9}
(1,3,5)	Low	Likely to happen once during the life circle of the project	$10^{-7}$to 10^{-9}
(3,5,7)	Medium	Occasionally happen	10^{-5} to 10^{-7}
(5,7,9)	High	Frequently happen	10^{-3} to 10^{-5}
(7,10,10)	Vary high	Occurrence is almost inevitable	10^{-0} to 10^{-3}

However, the contexts of the above descriptions may vary from the nature of the risk and the risk management project team is required to define them before the evaluation taking place.

Risk severity is the degree of seriousness and the scale of the impact if the risk turns into reality. It may be evaluated under the consideration of its impact on time, cost, quality, environment, healthy and safety. Table 2 shows a description of *RS* for the risk of foundation failure due to unexpected site conditions.

Table 2: Risk Severity (*RS*)

Triangular fuzzy number	Description	General interpretation
(0,0, 3)	Very low	No delay or damage to the structure.
(1,3,5)	Low	Slight delay and minor damage to the structure.
(3,5,7)	Medium	Some delays. Intermediate damage to the structure.
(5,7,9)	High	Considerable delay and major damage to the structure.
(7,10,10)	Vary high	The foundation totally fails.

Risk magnitude is the output of the proposed risk assessment model. A general interpretation of its linguistic terms is shown in Table 3.

Table 3: Risk Magnitude (*RM*)

Triangular fuzzy number	Description	General interpretation
(0,0, 3)	Very low	Negligible
(1,3,5)	Low	Tolerable
(3,5,7)	Medium	Medium level. Require risk management
(5,7,9)	High	Substantial and intolerable
(7,10,10)	Vary high	Priory risk

If-then rules are the basis for fuzzy inference. Risk assessment group produces 25 rules in the rule base and presents them as shown in Table 4, where *VL*, *L*, *M*, *H* and *VH* represent *very low*, *low*, *medium*, *high* and *very high*, respectively. These rules are interpreted as, for example,

Rule 1: If *RL* is *very low* and *RS* is *very low*, then *RM* is *very low*.

Rule 2: If *RL* is *very low* and *RS* is *low*, then *RM* is *very low*.

Table 4: Table of if-then rules

Risk criteria		Risk likelihood (*RL*)				
		VL	*L*	*M*	*H*	*VH*
Risk severity (*RS*)	*VL*	*VL*	*VL*	*L*	*L*	L
	L	*VL*	*L*	*L*	*M*	*M*
	M	*L*	*L*	*M*	*H*	*H*
	H	*L*	*M*	*H*	*H*	*H*
	VH	*L*	*M*	*H*	*H*	*VH*

Six experts in the risk assessment group are now requested to give their evaluations to RL and RS in the defined score system, i.e. from 0 to 10, inclusive. Table 5 shows the evaluations of foundation failure due to unexpected site conditions measured by six experts in terms of RL and RS.

Table 5: Evaluation by six experts

Experts	Evaluation	
	RL	*RS*
E_1	3	7
E_2	3	7
E_3	2.5	7.5
E_4	2	8
E_5	2.5	7.5
E_6	3	6.5

1. Fuzzification

According to the fuzzy definition of *RL* and *RS* shown in Figure 2, fuzzification of the measured values is shown in Table 6.

Table 6: Fuzzification

Experts	Evaluation			
	RL		*RS*	
	Crisp	Fuzzy set	Crisp	Fuzzy set
E_1	3	{*L*, 1}	7	{H, *1*}
E_2	3	{*L*, 1}	7	{*H*, 1}
E_3	2.5	{*VL*, 0.17} {*L*, 0.75}	7.5	{*H*, 0.75} {*VH*, 0.17}
E_4	2	{V*L*, 0.33} {*L*, 0.5}	8	{*H*, 0.5} {*VH*, 0.33}
E_5	2.5	{*VL*, 0.17} {*L*, 0.75}	7.5	{*H*, 0.75} {*VH*, 0.17}
E_6	3	{*L*, 1}	6.5	{*M*, 0.25} {*H*, 0.75}

2. Fuzzy aggregation

In this case, it is assumed that all the experts have equal importance. Furthermore, the arithmetic mean is chosen as the aggregation operator. The aggregation procedure is shown in Table 7.

Table 7: Fuzzy aggregation

Criteria	Fuzzy aggregation
RL	*VL*: μ = (0.17+0.33+0.17) / 3 = 0.22 *L*: μ = (1+1+0.75+0.5+0.75+1) / 6 = 0.83
RS	*M*: μ = 0.25 / 1 = 0.25 *H*: μ = (1+1+0.75+0.5+0.75+0.75) / 6 = 0.79 *VH*: μ = (0.17+0.17+0.33) / 3 = 0.22

From Table 7 the outputs of the fuzzy decision function are two fuzzy sets:

RL^* = {(*VL*, 0.22), (*L*, 0.83)}, RS^* = {(*M*, 0.25), (*H*, 0.79), (*VH*, 0.22)}.

3. Fuzzy inference

The min-max rule of implication is used in this example. The principle of this method is using minimum operator in the rule consequent region while taking the maximum operator to calculate these minimized fuzzy sets in the output region. The fuzzy inference can be broken down into four steps (Bojadziev and Bojacziev 1997).

Step 1: Determining which rules are on in the rule base

From the mapping of inputs: $RL^* \times RS^*$, we can find the following 6 rules in Table 4 are fired:

If *RL* is *very low* and *RS* is *medium*, then *RM* is *low*;

If *RL* is *very low* and *RS* is *high*, then *RM* is *low*;

If *RL* is *very low* and *RS* is *very high*, then *RM* is *low*;

If *RL* is *low* and *RS* is *medium*, then *RM* is *low*;

If *RL* is *low* and *RS* is *high*, then *RM* is *medium*;

If *RL* is *low* and *RS* is *very high*, then *RM* is *medium*;

Step 2: Taking the minimum operator to calculate the strength of the 6 rules:

R 1: $\alpha_1 = \mu\, VL\,(RL^*) \wedge \mu\, M\,(RS^*) = min\ (0.22, 0.25) = 0.22$

R 2: $\alpha_2 = \mu\, VL\,(RL^*) \wedge \mu\, H\,(RS^*) = min\ (0.22, 0.79) = 0.22$

R 3: $\alpha_3 = \mu\, VL\,(RL^*) \wedge \mu\, VH\,(RS^*) = min\ (0.22, 0.22) = 0.22$

R 4: $\alpha_4 = \mu\, L\,(RL^*) \wedge \mu\, M\,(RS^*) = min\ (0.83, 0.25) = 0.25$

R 5: $\alpha_5 = \mu\, L\,(RL^*) \wedge \mu\, H\,(RS^*) = min\ (0.83, 0.79) = 0.79$

R 6: $\alpha_6 = \mu\, L\,(RL^*) \wedge \mu\, VH\,(RS^*) = min\ (0.83, 0.22) = 0.22$

Step 3: Determine the control outputs of these rules:

R 1: $\alpha_1 \wedge \mu\, L\,(RM^*) = \min\ (0.22, \mu\, L\,(RM^*))$

R 2: $\alpha_2 \wedge \mu\, L\,(RM^*) = \min\ (0.22, \mu\, L\,(RM^*))$

R 3: $\alpha_3 \wedge \mu\, L\,(RM^*) = \min\ (0.22, \mu\, L\,(RM^*))$

R 4: $\alpha_4 \wedge \mu\, L\,(RM^*) = \min\ (0.25, \mu\, L\,(RM^*))$

R 5: $\alpha_5 \wedge \mu\, M\,(RM^*) = \min\ (0.79, \mu\, M\,(RM^*))$

R 6: $\alpha_6 \wedge \mu\, M\,(RM^*) = \min\ (0.22, \mu\, M\,(RM^*))$

It is noticed that Rule 1, Rule 2, Rule 3 are included into Rule 4; Rule 6 is included into Rule 5.

Step 4: Taking the maximum operator to calculate the fuzzy decision outputs. Further to Step 3, the fuzzy decision output is given by the following aggregation

$$\mu_{agg}(RM^*) = \max\{\min(0.25, \mu L(RM^*)), \min(0.79, \mu M(RM^*))\}$$

This is a union of the three triangular fuzzy numbers *L* and *M* in the fuzzy set of *RM**.

4. Defuzzification

The final step of the proposed risk assessment model is to convert the fuzzy outputs into a crisp value to represent risk magnitude. By using the centre-average defuzzification operator, *RM* is given as follows:

$$RM = \frac{(3\times 0.25)+(5\times 0.79)}{0.25+0.79} = 4.5$$

Therefore, the overall risk of foundation failure due to unexpected site conditions is 4.5 on the *RM* expression scale, i.e. the risk is between *low* and *medium* with a belief of 75% for *medium* and 25% for *low*. This result provides the risk management project team with valuable information for risk response decision making.

CONCLUSIONS

This paper has presented a prototype risk assessment model based on fuzzy set theory. An illustrative example was studied and provided useful data for risk management.

The methodology utilizes two important fuzzy techniques: fuzzy decision function and fuzzy inference. It provides better handling of the subjective and ill-defined information arising in the construction process. Therefore, it is particularly useful when the precise and complete information are not available or are hard to obtain.

REFERENCES

Baloi, D and Price, A.D.F. (2003) Modelling global risk factors affecting construction cost performance. *International Journal of Project Management*, **21**, 261-269.

Bojadziev, G and Bojacziev, M (1997) *Fuzzy logic for business, finance, and management*. Singapore: World Scientific.

Carr, V. and Tah J. H. M. (2001) A fuzzy approach to construction project risk assessment and analysis: construction project risk management system. *Advances in Engineering Software*, **32** (10-11), 847-857.

Cox, E (1999) *The fuzzy systems handbook*. 2ed. New York: AP Professional.

Sousa, J.M.C. and Kaymak, U. (2002) *Fuzzy decision making in modeling and control*. Singapore: World Science.

Thompson, P. and Perry, J. (1992) (eds.) *Engineering construction risks: A guide to proect risk analysis and risk management*. London: Thomas Telford.

Tah, J. H. M. and Carr, V. (2001) Towards a framework for project risk knowledge management in the construction supply chain. *Advances in Engineering Software*, **32** (10-11), 835-846.

Winch, G.M. (2002) *Managing Construction Projects: An Information Processing Approach*. Oxford: Blackwell Science.

Zhi, H. (1995) Risk management for overseas construction. *International Journal of Project Management*, **13** (4), 231-237.