INCLUSION OF NON-FINANCIAL FACTORS IN LIFE-CYCLE DECISION-MAKING: A FUZZY APPROACH

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An effective algorithm has been developed to include non-monetary benefits of competing design alternatives in life cycle costing studies. The algorithm handles a number of competing alternatives with multiple aspects of needs desired by the client, analyses them systematically, and ranks them automatically. The unique feature of the algorithm, amongst others, is that it proceeds through logical steps that can be followed and assessed by decision-makers. Details of the computer implementation of the algorithm are presented. The solution of a selected example problem is also included to illustrate the theory of the algorithm. The development of this algorithm is in line with a series of innovative algorithms developed by the authors in recent years. These algorithms follow a novel theoretical framework that utilizes the inherent capabilities of fuzzy set theory, probability theory, statistics, and decision analysis. These algorithms will be integrated in a user-friendly life-cycle decision support tool.

Keywords: fuzzy set theory, life cycle costing, intangibles, public sector.

INTRODUCTION

The difficulties facing the implementation of life cycle costing (LCC) in the construction industry can be broadly classified into two main categories. The first category relates to the basic nature of the technique itself. There is a need to forecast a long way ahead in time, many factors such as life cycles, future operating and maintenance costs, and discount and inflation rates (Flanagan *et al.*, 1989). Thus, uncertainty is endemic to LCC, because it deals with the future and the future is unknown. Even more, there is a lack of appropriate, relevant and reliable historical information and data (Bull, 1993).

The second category relates to the way decisions are made within the construction industry. The design or component selection decisions can often be taken based on factors other than cost criteria. Most of these factors can not be assessed in a strict LCC framework. This is mainly because either they are in conflict with the main LCC objective or because they are mostly ‘non-financial’. Some of these factors are even intangible such as aesthetics. In many cases, these intangibles are also in conflict with results of LCC analyses (Wilkinson, 1996).

When financial factors is the only aspect of need to be considered, the problem is relatively straightforward. A number of algorithms have been developed by the authors to cover this issue in an LCC context (e.g. Kishk and Al-Hajj, 2000a, 2000b, 2001a, 2001b). These algorithms are based on a novel theoretical framework that utilizes the inherent capabilities of the fuzzy set theory (FST), probability theory and statistics to handle various facets of uncertainty in LCC modelling (Kishk and Al-Hajj, 1999).

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The objective of this paper is to outline an effective methodology to include non-financial attributes in the life-cycle decision making process. In the development of this methodology, all arguments are discussed in the context of building projects. It should be noted, however, that almost all these arguments apply to other types of projects as well. The rest of the paper is organized as follows. In the next section, the importance of including non-financial attributes in the decision-making process is highlighted. This is followed by a critical review of existing inclusion techniques. Then, the algorithm is briefly outlined and explained in the context of an example application. For the convenience of the reader, principal symbols used in the paper are given in an appendix.

IMPORTANCE OF INCLUSION

Ideally, successful designs should address all clients' aspects of need. To achieve an optimum design, professionals, therefore, need to assess the performance of their ideas with respect to their clients' aspects of need. Some of these measures, may be reduced to a monetary scale, i.e. monetary benefits, and thus can easily be incorporated into LCC calculations in the usual way, i.e. by considering it as negative costs. For example, an earlier availability of the building for its intended use by selecting a particular alternative may be considered as a monetary benefit because of the resulting additional rental income and reduced inspections, and administrative costs (Lopes and Flavell, 1998).

However, some aspects are basically non-financial and can only be assessed qualitatively, such as spatial arrangement, and aesthetic appeal. The need to include these non-financial attributes when appraising projects in the private sector is self-evident. Kirk and Dell'Isola (1995) pointed out two other situations where non-financial attributes have a decisive role to play even for the public sector. First, when life cycle costs of two alternatives are found to be essentially equal. In this case, these alternatives are assumed to be tied, and some means of breaking the tie is needed. Secondly, when the effect of uncertainties in the estimated life cycle costs of various options are so significant that no alternative clearly represents the least cost course of action. In these situations, a unique solution can not be achieved with an acceptable confidence level because the uncertainty of information produces a considerable decision uncertainty region (Kishk and Al-Hajj, 2000b, 2001b). Again one way of breaking such an uncertainty tie is by considering non-financial attributes.

EXISTING INCLUSION TECHNIQUES

Various techniques have been proposed to extend the LCC framework to account for multiple non-financial attributes. These techniques are derived from cost-benefit analysis, value and decision theories. Cost effectiveness (Fabrycky and Blanchard, 1991) is an approach that was derived from cost-benefit analysis. In this approach, various criteria are determined, and the performance of each alternative in relation to each of them is quantified. Although the method is systematic, it has three limitations. First, it forces the user to specify a precise quantitative measure for all criteria even for 'intangibles'. Secondly, it does not take into consideration the relative importance of various criteria to the client. Thirdly and more importantly, there is no definitive method for making the decision especially when both costs and effectiveness measures differ considerably.

Recognizing that subjective decision-making may destroy a complex and intricate LCC analysis, Dale (1993) recommends to base decision making on a broader front than a simple economic analysis by utilizing various methods of value engineering, where values are attributed to both objective and subjective arguments and decisions taken. The most illuminating perspective comes from multi-criteria decision-making (MCDM) theory in which intangibles can be treated in a non-monetary context while retaining costs within its natural monetary context. For example, the weighted evaluation (WE) method has been used in LCC studies by Kirk and Dell'Isola (1995). This method consists of two processes. First, criteria are identified and the weights of their relative importance are established. In doing so, each pair of criteria is compared, and the stronger of the two is scored according to the 'how important 1 to 5' scale (Figure 1). The final weights are determined such that the maximum weight is assigned a value of 10. The second process of the procedure is a rating and ordering process. A score is found for each alternative-criterion pair by multiplying the alternative rating, s_{ij}, by the criterion weight, W_j. The alternative with the highest total score is the recommended alternative, A^*, i.e.

$$A^* = A_i \left| S_i = \bigvee_{i=1,n} \sum_{j=1}^{m} W_j \cdot s_{ij} \right. \qquad (1)$$

Although the WE method introduces some objectivity into the decision-making process, it still has two limitations. First, decision-makers are forced to fix input parameters at single-value levels. This restricts any vagueness the decision-maker may have regarding the levels of those input variables (Lavelle *et al.*, 1997). Other researchers (e.g. Lopes and Flavell, 1998) even described such rigid scale as mechanistic and unsatisfactory. A similar note can be said about the use of a crisp scoring scale in the rating process. Secondly, the calculation of the final weights such that the maximum value is 10 seems arbitrary. The resulting set of weights is not normalized which is contrary to the usual practice and may have an effect on the final rating (Bass and Kwakernaak, 1977).

DESIGN OF THE ALGORITHM

All the situations that require the consideration of non-monetary factors fit in the scope of application of MCDM methods as stated by Ekel *et al.* (1999). Thus, other MCDM methods proposed in the literature were reviewed to identify effective solutions for the limitations of existing techniques. Other steps in the design of the algorithm included employing a suitable ranking procedure and computer implementation of the algorithm.

Other MCDM techniques

Two approaches may be identified in the area of MCDM under uncertainty. These are: probabilistic and fuzzy MCDM approaches. Some researchers (e.g. Kahne, 1975; Lavelle *et al.*, 1997; Kelly and Thorne, 2001) approached the MCDM problem probabilistically using simulation techniques where all weights and ratings are taken to be random variables and final ratings also become random. The major limitation of this approach is that it can only account for random uncertainties in input variables (Baas and Kwakernaak, 1977). Moreover, simulation techniques have been criticized for their complexity and their expense in terms of computation time and expertise required to extract the knowledge (Byrne, 1997).

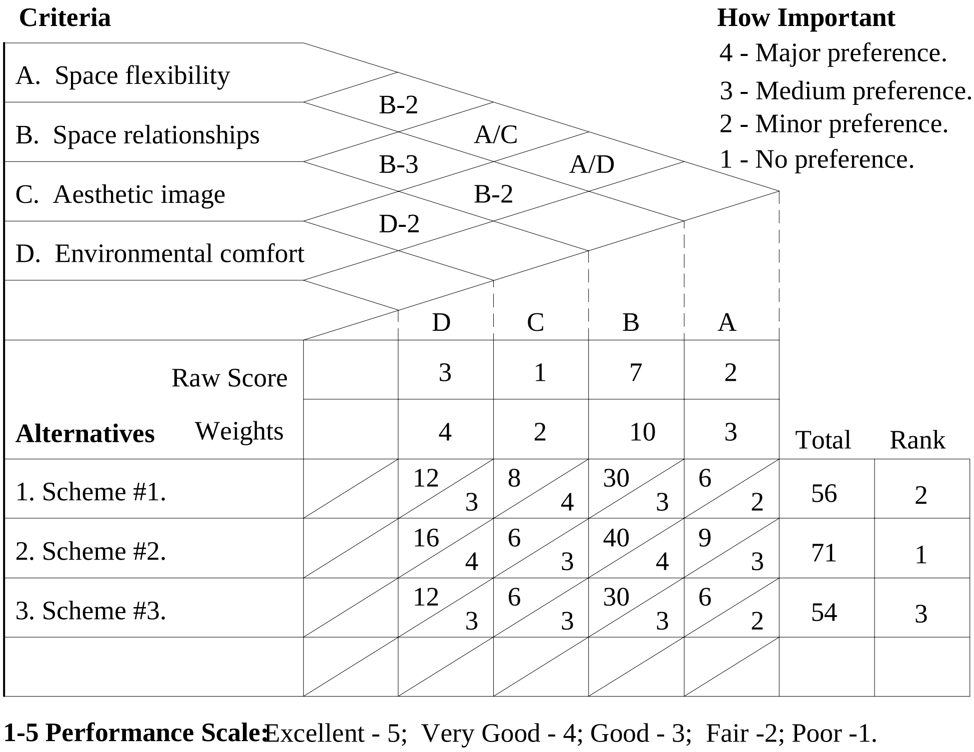

Figure 1: An example application of the weighted evaluation technique (Kirk and Dell'Isola, 1995).

On the other hand, the literature is rich in the area of the fuzzy MCDM techniques. In general, these methods are extensions of various deterministic MCDM methods such as the weighted evaluation and the analytical hierarchy process (AHP) (Saaty, 1980). Some of these methods are reviewed by Ribeiro (1996) and Ekel *et al.* (1999). Bass and Kwakernaak (1977) were the first to extend the classical weighted average formula to fuzzy numbers. Their contention was that the sort of uncertainty that comes into play here is better represented by the notion of fuzziness than that of chance. The most unique feature of their algorithm is that they employed the following normalized formula

$$\tilde{S}_i = \sum_{j=1}^{m} \tilde{W}_j \tilde{s}_{ij} \Big/ \sum_{j=1}^{m} \tilde{W}_j \qquad (2)$$

This formula has the desirable property that if the scores all are equal; the final weighted score is independent of the weights and equals the common value of the score. However, their methodology employed a non-linear programming algorithm that is too difficult to implement in practice. To tackle this difficulty Givens and Tahani (1987) and Dong and Shah (1987) proposed procedures, known as the modified DSW and vertex algorithms, respectively. In these procedures, a fuzzy set is approximated with series of intervals so that standard binary operations of interval analysis can be utilized. Other researchers (e.g. Yeh and Deng, 1997; Cheng *et al.* 1999) proposed a simplification to the problem by defuzzifying fuzzy numbers at some stage during calculations. However, this early defuzzification cancels out the main advantage of using the FST in dealing with imprecise and uncertain information. Another drawback of all the above techniques is that they do not address the issue of eliciting of weights (Ribeiro, 1996).

Many researchers (e.g. Weck *et al.* 1997; Cheng *et al.*, 1999) have developed fuzzy versions of Saaty's AHP method. In these versions of AHP, fuzzy numbers are usually used with pair-wise comparisons to compute the weights of importance of the decision criteria. The idea is to transform the pair-wise ratings, given by the decision-maker, into values such as 'about three' instead of 3. However, some researchers, e.g. Ribeiro (1996), criticized this approach in that it did not add much to the original AHP method. Besides, it has the disadvantage of 'early defuzzification' discussed above.

Ranking procedure

The second step was to choose an effective ranking procedure. The method proposed by Kaufmann and Gupta (1988) was employed. It is based on introducing a function known as the removal, R, which maps fuzzy sets to the real line and to use natural ordering. To add to the quality of the decision, two measures, CI_1 and CI_2, were employed to evaluate the rank order. These measures may be interpreted as measures of the confidence in the two statements: 'A is better than B' and 'A is at least as better as B', respectively, where A and B are two competing alternatives (Kishk and Al-Hajj, 2001a).

Computer implementation

To ensure the robustness and computational efficiency of the algorithm, two more issues were considered in the implementation of the algorithm. First, the α-cut method (Kaufmann and Gupta, 1988), was employed in the computer representation of all fuzzy sets. This representation method is robust and computationally effective than other methods. Furthermore, it allows the treatment of uncertainty to be built in the model itself. The second issue was to optimize fuzzy calculations by identifying the most appropriate method for carrying out the extended fuzzy operations. More details on these issues are discussed in Kishk and Al-Hajj (2000a).

The algorithm

Based on the above arguments, the following algorithm may be proposed.

1. Identify non-financial decision attributes.
2. Construct suitable fuzzy importance and performance scales, e.g. to use the fuzzy numbers $\tilde{1}$ to $\tilde{5}$ instead of the traditional 1 to 5 scale in the WE method (Fig. 2).
3. Initialize weights for attributes to zero.

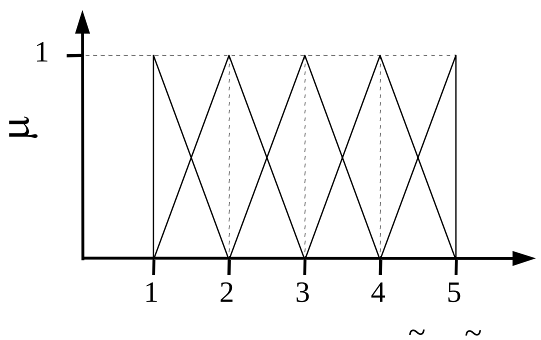

Figure 2: Triangular fuzzy subsets $\tilde{1}$ to $\tilde{5}$

4. For each pair of attributes, add the fuzzy subset of importance, $\tilde{I}_s$, to the weight of the more important attribute using the modified DSW algorithm.

5. Repeat steps 3 and 4 for all possible pair-wise comparisons. This procedure results in the weight sets, $\tilde{W}_j$.
6. Rate alternative i on the degree to which it performs with respect to criterion j . Then, assign the fuzzy subset associated with the identified degree of performance to the fuzzy alternative-criterion score, $\tilde{s}_{ij}$.
7. Repeat step 6 for all criteria.
8. Calculate the total fuzzy score for alternative i , $\tilde{S}_i$ (Eq. 2), using the vertex method.
9. Repeat steps 6 to 8 for all alternatives.
10. Alternatives are ranked according to the removals, R_i , and confidence measures in this ranking are calculated.

A flow chart of the proposed algorithm is shown in figure (3).

EXAMPLE APPLICATION

A selected example problem is included in this section to illustrate the efficacy and applicability of the proposed algorithm. In this example, a clinic facility layout is to be selected from three competing schemes. These schemes are to be evaluated in relation to four attributes: space flexibility, space relationships, aesthetic image, and environmental comfort. The solution to this example using the weighted evaluation technique is given in Kirk and Dell'Isola (1995) and is summarized in figure (1). The proposed algorithm was also used to solve this example. The triangular fuzzy subsets in figure (2) were employed to represent various preference and performance levels. It should be noted, however, that the algorithm is not restricted to these subsets and any normal convex subset can be used.

For example, an interval [0, 5] may be used to model the rating of the performance of an alternative regarding a certain criterion as 'not clear'.

Figure (4) shows the total normalized scores, of the three competing schemes. The algorithm yielded the same ranking as the WE method (Fig. 1). The removals for schemes 2, 1 and 3 are 4.52, 3.59 and 3.49, respectively. The measures of confidence in this ranking were also calculated and are summarized in Table (1).

Table 1: Measures of confidence

Rank	Alternatives	Scheme #2		Scheme #1		Scheme #3	
		CI_1	CI_2	CI_1	CI_2	CI_1	CI_2
1	Scheme #2	---	---	0.208	0.604	0.232	0.616
2	Scheme #1	0.000	0.396	---	---	0.026	0.513
3	Scheme #3	0.000	0.384	0.000	0.487	---	---

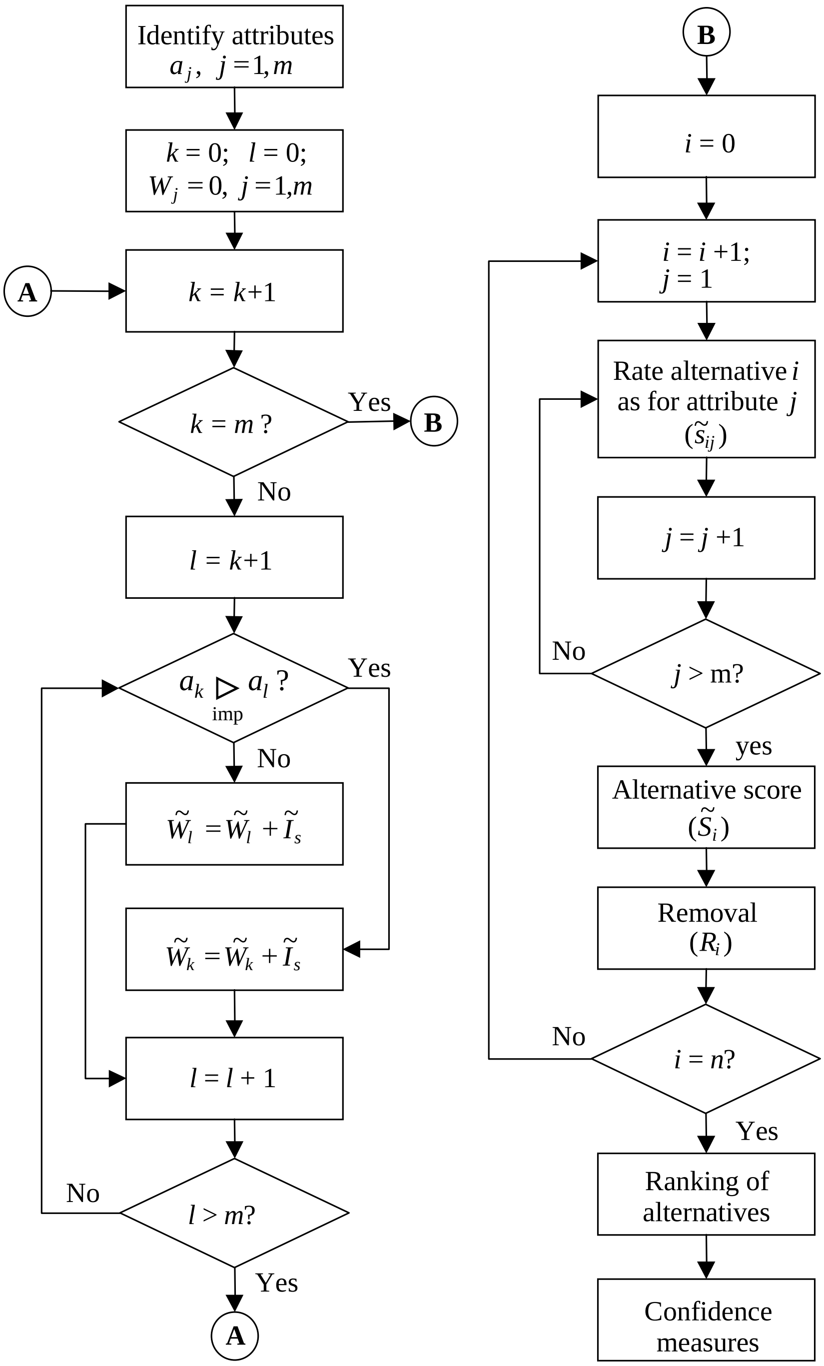

Figure 3: Flow chart of the proposed algorithm

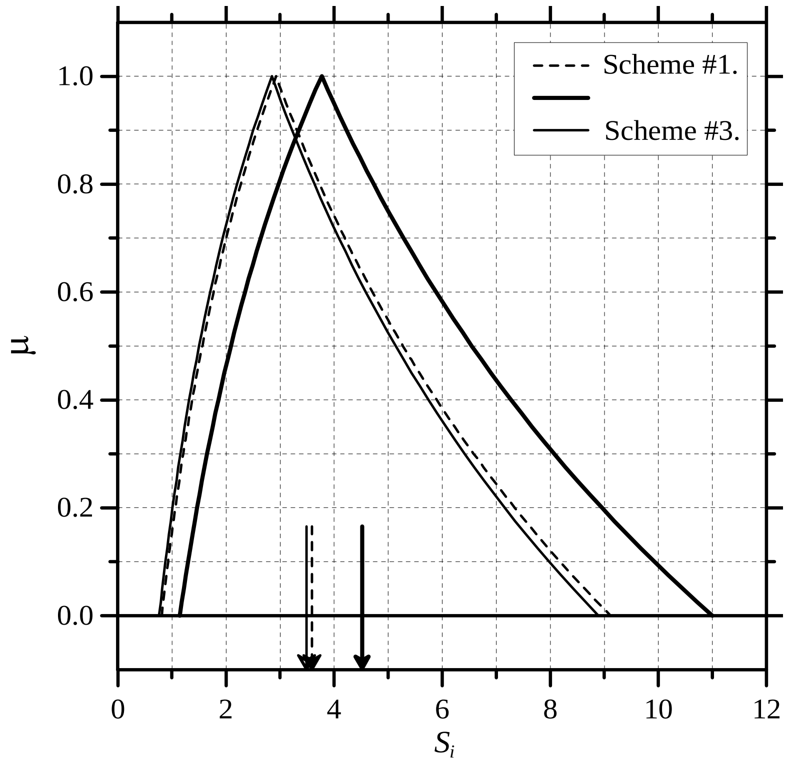

Figure 4: Membership functions of the total score of the three schemes

CONCLUSIONS

The importance of including non-financial attributes of projects in the decision-making process was discussed and existing inclusion techniques were critically reviewed. Then, an effective MCDM algorithm has been developed. The underlying concepts of the algorithm are simple and comprehensible. It has been designed around the deterministic, weighted evaluation technique. Besides, the fuzzy set theory is employed to handle the inherent uncertainty and imprecision of the human decision making process.

The proposed algorithm has three unique merits. First, it proceeds through the same logical steps as the weighted evaluation procedure. These steps can be followed and assessed by decision-makers. Secondly, the elicitation of importance weights is done through pair-wise comparisons without transforming imprecise information to crisp values early in the process. In addition, the final scores are calculated using a normalized formula instead of the arbitrary method of adjustment of weights in the traditional WE method. Thirdly, and more importantly, the algorithm ranks alternatives automatically and provide confidence measures in this ranking. These unique features of the algorithm provide the decision-maker with the flexibility and robustness required for making informed decisions.

This algorithm is the fifth in a series of innovative algorithms developed in recent years, to be integrated in a user-friendly life-cycle decision support tool. Details of this integration process and the solution of more life-cycle decision-making examples will be reported in a future paper.

REFERENCES

Baas, S., and Kwakernaak, H. (1977) Rating And Ranking Of Multiple Aspect Alternatives Using Fuzzy Sets. *Automatica*. 13(1): 47-58.

Bull, J. W. (1993) The Way Ahead for Life Cycle Costing in the Construction Industry. *Life Cycle Costing for Construction (ed. Bull, J. W.)*. Glasgow, UK: Blackie Academic and Professional.

Byrne, P. (1997) Fuzzy DCF: a Contradiction in Terms, or a Way to Better Investment Appraisal? *Proceedings of Cutting Edge,* RICS.

Cheng, C-H., Yang, K-L., and Hwang, C-L. (1999) Evaluating attack helicopters by AHP based on linguistic variable weight. *European journal of Operational research*. **116**: 423-435.

Dale, S.J. (1993) Introduction to Life Cycle Costing. *Life Cycle Costing for Construction (ed. Bull, J. W.).* Glasgow, UK: Blackie Academic and Professional.

Dong, W., and Shah, H. (1987) Vertex Method for Computing Functions of Fuzzy Variables. *Fuzzy Sets and Systems*. **24:** 65-78.

Ekel, P., Pedrycz, W., and Schinzinger, R. (1999) Methods Of Multicriteria Decision Making in Fuzzy Environment and Their Applications. *Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS,* (10-12 June), New York, 625-629.

Fabrycky, W. J., and Blanchard, B. S. (1991) *Life-Cycle Cost and Economic Analysis.* NJ, USA: Printice-Hall, Inc.

Flanagan, R., Norman, G., Meadows, J., and Robinson, G. (1989) *Life Cycle Costing - Theory and Practice.* BSP Professional Books.

Givens, J. and Tahani, H. (1987) An Improved Method of Performing Fuzzy Arithmetic for Computer Vision. *Proceddings of North American Information Processing Society (NAFIPS),* Purdue University, West Lafayette, USA, 275-280.

Kahne, S. (1975) A Procedure for Optimizing Development Decisions. *Automatica*. **11**: 261-269.

Kaufmann, A. and Gupta, M. M. (1988) *Fuzzy Mathematical Models in Engineering and Management Science.* The Netherlands: Elsevier Science Publishers B. V.

Kelly, M. and Thorne, M. C. (2001) An Approach to Multi-Attribute Utility Analysis Under Parametric Uncertainty. *Annals of Nuclear Energy*. **28**(9): 875-893.

Kirk, S., J., and Dell'Isola, A. J. (1995) *Life Cycle Costing for Design Professionals.* New York: McGrew-Hill Book Company.

Kishk, M., and Al-Hajj, A. (1999) An Integrated Framework for Life Cycle Costing in Buildings. *Proceedings of COBRA 1999 - The Challenge of Change: Construction and Building for the New Millennium*, University of Salford, (1-2 Sept), **2**: 92-101.

Kishk, M., and Al-Hajj, A. (2000a) A Fuzzy Model and Algorithm to Handle Subjectivity In Life Cycle Costing Based Decision-Making. *Journal of Financial Management of property and Construction*. **5**(1-2): 93-104.

Kishk, M., and Al-Hajj, A. (2000b) Handling Linguistic Assessments In Life Cycle Costing - A Fuzzy Approach. *Proceedings of the Construction and Building Research Conference Of The RICS Research Foundation (COBRA2000)*, The University of Greenwich, (30 Aug - 1 Sept), 228-243.

Kishk M., and Al-Hajj, A. (2001a) Integrating Subjective and Stochastic Data in Life Cycle Costing Calculations. *Proceedings of the First International Postgraduate Research Conference in the Built and Human Environment*, University of Salford, 15-16 March, 2001, 329-345.

Kishk, M., and Al-Hajj, A. (2001b) An innovative approach to integrating the analysis of uncertainty into life cycle costing. *Accepted for Publication in the First International Conference of Innovation in Architecture, Engineering and Construction*. Loughborough University, (19-20 July).

Lavelle, J., Wilson, J., Gold, H., and Canada, J. (1997) A Method for the Incorporation of Parametric Uncertainty in the Weighted Evaluation Multi-Attribute Decision Analysis Model. *Computers and Industrial Engineering*. **32**(4): 769-786.

Lopes, M.D.S., and Flavell, R. (1998) Project Appraisal – A Framework to Assess Non-Financial Aspects of Projects During the Project Life Cycle. *International Journal of Project Management*. **16**(4): 223-233.

Ribeiro, R. A. (1996) Fuzzy Multiple Attribute Decision Making: A Review and New Preference Elicitation Techniques. *Fuzzy Sets and Systems*. **78**: 155-181.

Saaty, T.L. (1980) *The Analytic Hierarchy Process*. New York: McGraw-Hill Book Company.

Weck, M., Klocke, F., Schell, H., and Ruenauver, E. (1997) Evaluating Alternative Production Cycles Using the Extended Fuzzy AHP Method. *European Journal of Operational Research*. **100**: 351-366.

Wilkinson, S. (1996) Barriers to LCC Use in the New Zealand Construction Industry. *Proceedings of the 7th International Symposium on Economic Management of Innovation, Productivity and Quality in Construction*, Zagreb, 447-456.

Yeh, C. H., and Deng, H. (1997) Algorithm for Fuzzy Multi-Criteria Decision-Making. *Proceedings of the IEEE International Conference on Intelligent Processing Systems (ICIPS)*, (28-31 Oct), **2**, 1564-1568.

APPENDIX: LIST OF SYMBOLS

$\tilde{A}$	A Symbol marked with a tilde represents a fuzzy quantity.
a_j	Non-financial attributes, $j = 1, m$.
CI_1, CI_2	Measures of confidence where $0 \le CI_1 \le 1$ and $0.5 \le CI_2 \le 1$.
$\tilde{I}_s$	The level of preference of an attribute in relation to another attribute.
n, m	Number of alternatives and non-financial attributes, respectively.
R_i	The ranking function (removal).
$\tilde{s}_{ij}$	The performance of alternative i, in relation to attribute j.
$\tilde{S}_i$	The total score of alternative i.
$\tilde{W}_j$	The weight of importance of attribute j.
$\vee$	The maximum of a set of values.
$\underset{imp}{\triangleright}$	More important than.
$\mid \text{condition}$	such that the condition is valid.