TOWARDS EFFECTIVE CONSIDERATION OF NON-FINANCIAL FACTORS IN THE DESIGN AND MANAGEMENT OF CONSTRUCTION ASSETS

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- The decisive role of non-financial factors in the design and management of construction assets is highlighted and existing techniques used to include these factors in the decision-making process are critically reviewed.
- An effective algorithm has been developed to include non-monetary benefits of competing design alternatives in whole-life costing studies.
- 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.

Keywords: Intangibles, Life Cycle Cost(ing), MCDM, Whole life cost(ing).

INTRODUCTION

A major barrier to the implementation of whole-life costing (WLC) is the way decisions are made within the construction industry. The design or component selection decisions can often be taken based on multiple factors in addition to cost criteria, e.g. aesthetics, strength of materials, fire-protection, safeguarding of use, durability and utilisation (Bogenstatter, 2000). Ferry and Flanagan (1991) highlighted the role of non-financial attributes in the screening of technically acceptable options before conducting a WLC exercise. Kirk and Dell'Isola (1995) pointed out two other situations where non-financial attributes have a decisive role to play. First, when whole-life 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. One way of breaking the tie in both cases is by considering non-financial attributes.

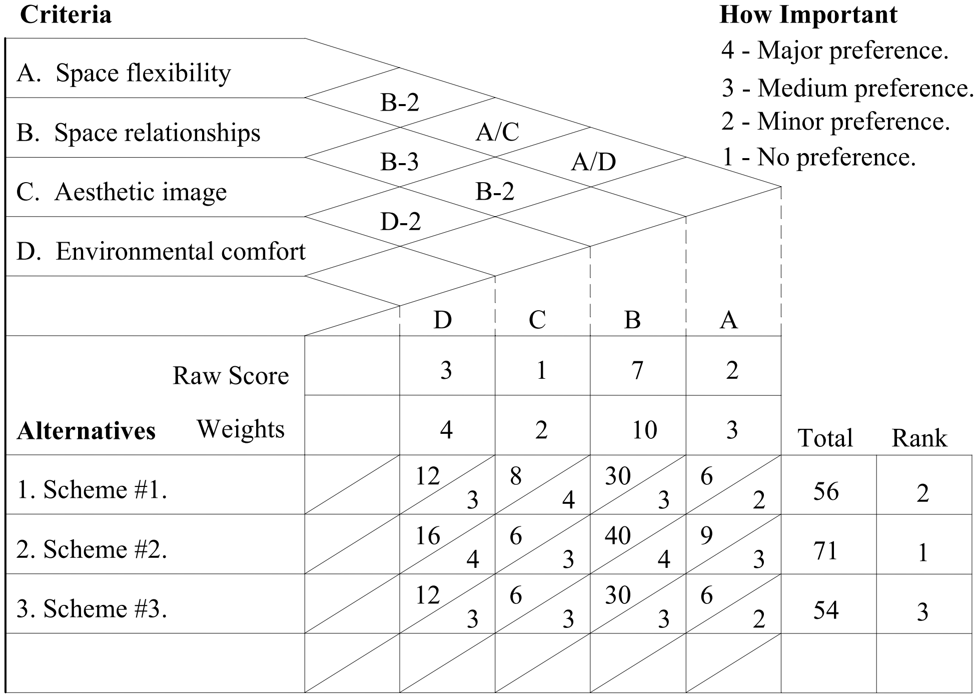
To achieve an optimum design, professionals, therefore, need to assess the performance of their ideas with respect to multiple criteria reflecting their clients' aspects of need. Some of these factors may be reduced to a monetary scale, i.e. monetary benefits, and thus can easily be incorporated into WLC 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). Other aspects, however, are basically non-financial and can only be assessed qualitatively, such as spatial arrangement, and aesthetic appeal.

There exist a number of methods that can be used to extend the WLC framework to consider non-financial factors. 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 and compared to minimum system requirements (or thresholds) and decision taken. 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. Thirdly, there is no definitive method for making the decision especially when both costs and effectiveness measures differ considerably.

Another illuminating perspective comes from multi-criteria decision 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 WLC studies by many researchers including Flanagan *et al.* (1989), Ferry and Flanagan, 1991, Kirk and Dell'Isola (1995), among others. The weighted evaluation 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 (Fig. 1). The final weights are determined such that the maximum weight is assigned a value of 10. The second process is a rating and ordering process. A criterion score is found for each alternative-criterion pair by multiplying the alternative rating, s_{ij}, by the criterion weight, W_j. The total score of each alternative is the sum of its individual criteria scores. The recommended alternative, A^*, is the one with the highest total score, i.e.

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

where S_i is total score of alternative i and n and m are the number of competing alternatives and decision criteria, respectively.



1-5 Performance Scale: Excellent - 5; Very Good - 4; Good - 3; Fair -2; Poor -1.

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

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 normalised which is contrary to the usual practice and may have an effect on the final rating (Baas and Kwakernaak, 1977).

In this paper, an effective methodology to include non-financial attributes in the whole life costing decision-making process is outlined. 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. In the next section, various MCDM techniques are critically reviewed with emphasis on their suitability to be employed in WLC-based decision-making. Then, the algorithm is briefly outlined and explained in the context of an example application.

MCDM METHODS

According to Ekel *et al.* (1999), the application of MCDM techniques is associated with the need to solve problems in which solution consequences cannot be estimated with a single criterion or problems which can be solved on the basis of a single criterion, however their unique solutions are not achieved because the uncertainty of information produces decision uncertainty regions. It is interesting to note that all the situations that require the consideration of non-monetary factors in WLC studies fit in the scope of application of MCDM methods. Thus, other published MCDM methods have been reviewed to identify solutions for the limitations identified in the previous section. These approaches can be broadly categorized into classic, probabilistic and fuzzy methods.

Classical MCDM Techniques

Classical MCDM methods require the determination of alternative ratings and criteria weights by eliciting the decision-maker (DM)'s judgements/preferences. In doing so, crisp values are commonly used to represent these ratings and weights, which are implicitly or explicitly aggregated by a utility function. The overall utility of an alternative represents how well the alternative satisfies the DM's objectives. The simplest and most employed function is the weighted average formula (equation 1).

The weighted evaluation (WE) technique is an example of classical MCDM methods. In general, classical MCDM methods suffer from the same main disadvantage of the WE method, i.e. all input parameters are restricted to point estimates. However, alternative ratings and criteria weights cannot always be assessed and subjectivity and vagueness are often involved (Zadeh, 1975a, 1975b). These may come from various sources such as un-quantifiable information and incomplete information (e.g. by describing the performance of an alternative regarding an attribute as 'not clear' (Baas and Kwakernaak, 1977).

Probabilistic Techniques

Some researchers (e.g. Kahne, 1975a, 1975b; Kelly and Thorne, 2001) approached the MCDM problem probabilistically using simulation techniques. In two consecutive papers (Kahne, 1975a; 1975b), Kahne proposed a method based on the Monte Carlo simulation to represent uncertainties by allowing each variable (rating or weight) to be a random variable, usually but not necessarily uniformly distributed. In this probabilistic framework, the final ratings also become random variables. In the last phase of evaluation, various alternatives are ranked in order of descending magnitude and the best alternative is selected such that it has the highest probability of being first. Baas and Kwakernaak (1977) criticised Kahne's method because it used non-normalised weighted final rating, where the weights do not necessarily add up to unity, contrary to the usual practice. The method proposed by Kelly and Thorne (2001) is basically similar to Kahne's approach with two slight exceptions. First, it employs normalised weights. Secondly, the final output of their procedure is distributions of rankings for various alternatives. These distributions are used directly to aid decision-making, or indirectly, by considering additional measures derived from them.

One limitation of the above methods is that they followed a simulation approach. Simulation techniques have been criticised for their complexity and their expense in terms of computation time and expertise required to extract the knowledge (Byrne, 1997). Other researchers who approached the MCDM problem probabilistically did not utilise simulation techniques. For example, Lavelle *et al.* (1997) developed a probabilistic version of the WE model. In this approach, weights and ratings are represented by independent uniform, triangular or beta random variables; and an iterative multivariate integration scheme is used to approximate probabilistic weighted evaluations of various alternatives. Obviously, this method tackles the main drawback of simulation techniques. However, it still has the main disadvantage of the probabilistic approach, i.e. it can only model random uncertainties.

Fuzzy Techniques

Bellman and Zadeh (1970) proposed to incorporate fuzziness in human decision-making. Since then, an immense literature has been developed in the area of fuzzy MCDM techniques. In general, these techniques are extensions of various deterministic methods such as the WE and the analytical hierarchy process (AHP) (Saaty, 1980). In the following, some of these methods are discussed in the context of three desirable features reflecting how weights of importance are elicited and handled and how extended fuzzy operations are implemented. Obviously, these desirable features have been chosen to identify appropriate methods for overcoming various limitations of methods currently used within the WLC framework.

Eliciting of Weights

Although establishing weights of importance of decision criteria is a crucial issue, most MCDM techniques do not address it. In almost all methods of establishing attribute weights, the decision-maker is asked to specify a rating for each alternative from ‘most’ to ‘least’ important. In doing so, a direct scoring approach or a pair-wise approach is utilised. In the first approach, weights are directly assigned to various criteria using a normalised fuzzy linguistic scale defined by a number of subsets representing various grades of importance.

In the pair-wise approach, however, each attribute is compared individually against all other attributes. Generally, methods of pair-wise comparisons may be divided into two classes (Takeda and Yu, 1995). In the first class, $m-1$ comparisons are required to identify weights for m criteria. The second class requires all $m(m-1)/2$ possible comparisons. Saaty’s analytical hierarchy process (AHP) (Saaty, 1980) is an example of methods within this class. The use of pair-wise comparisons is more objective because it allows a fairer and less biased comparison (Ross, 1995). Because the favourable feature of pair-wise comparisons, many researchers (e.g. Boender *et al.*, 1989; McCahon and Lee, 1990; Mon *et al.*, 1994; Cheng and Mon, 1994; Carnahan *et al.*, 1994; Weck *et al.* 1997; Cheng, 1999; Deng, 1999) have developed fuzzy versions of the AHP method where fuzzy numbers (FNs) are used with pair-wise comparisons to compute the weights of importance. 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), criticised the fuzzy AHP approach in that it does not seem to add much to the original AHP approach as Saaty proposed to use the intermediate weights 2, 4, 6 and 8 as compromise values.

In addition to the fuzzy AHP, Triantaphyllou and Lin (1996) developed fuzzy versions of four more classical MCDM methods. They tested the five methods and their analysis revealed that approaches that employ pair-wise comparisons are more capable of capturing a human’s appraisal of ambiguity in complex decision-making situations. They attributed this to the flexibility and realism of pair-wise comparisons in accommodating real-life data.

However, almost all the methods that utilise pair-wise comparisons suffer from the disadvantage of employing an approximate method of performing extended fuzzy operations (Kishk, 2001). In addition, fuzzy numbers representing pair-wise comparisons need to be defuzzified at an early stage of the process. In the fuzzy AHP method, this defuzzification process has to be done very early so that the eigenvalues and eigenvectors of the reciprocal matrices can be calculated. This early defuzzification cancels out the main advantage of using the FST in dealing with imprecise and uncertain information. Besides, a lot of information is lost in the defuzzification process. For example, all FNs with the same centroid are treated as identical regardless of their shape if the centroid defuzzification method is employed. It is interesting to note that although the WE method utilises pair-wise comparisons, no attempt to develop a fuzzy version of this method has been found in the literature.

Normalisation of Weights

Baas 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 normalised formula

$$S_i = \sum_{j=1}^{m} W_j s_{ij} \Big/ \sum_{j=1}^{m} W_j \tag{2}$$

This formula has the desirable property that if the scores are equal, the final weighted score is independent of the weights and equals the common score value. However, their methodology employed a non-linear programming algorithm that is too difficult to implement in practice.

Handling Fuzzy Numbers

The use of fuzzy numbers to represent weights and ratings in fuzzy MCDM methods entails two requirements. First, the need to implement the extension principle (Zadeh, 1975) to derive the overall ratings. Secondly, the necessity of ranking the resulting fuzzy numbers representing overall ratings. Baas and Kwakernaak (1977) and Kwakernaak (1979) developed two algorithms to implement the extension principle. These algorithms are accurate but are too difficult to apply in practice. Later, various algorithms that utilise the α-cut concept, e.g. the modified DSW (Givens and Tahani, 1987) and vertex algorithms (Dong and Shah, 1987) have been developed to be used in MCDM problems. Other researchers (e.g. Yeh and Deng, 1997; Cheng *et al.* 1999; Hsu and Jiang, 1999) proposed a simplification to the problem by defuzzifying fuzzy numbers at some stage during calculations. This approach is favoured by some researchers, e.g. Ribeiro (1996), because it simplifies the ranking process. However, the problem of 'early defuzzification' discussed above arise.

On the other hand, there exist a number of effective fuzzy ranking methods. Two effective ranking techniques have been outlined by Kishk and Al-Hajj (2000) and have been successfully used in Fuzzy WLC modelling. These methods can be employed in the MCDM extension of the WLC framework with only one exception: the best alternative, A^*, is determined as the one with highest final fuzzy score. Besides, the confidence measures defined in Kishk and Al-Hajj (2000) need to be redefined accordingly.

HANDLING FINANCIAL ATTRIBUTES

Another issue had to be addressed: how to handle financial attributes, e.g. whole life costs. As previously discussed, a non-financial attribute is a benefit for which it is desired to have maximum value. For a cost criterion, however, it is desired to have a minimum value. To include a cost criterion in the decision making process, a cost analysis is first conducted and alternatives are ranked accordingly. Then, they are rated such that the lowest cost alternative is assigned 'excellent' on the performance scale. The final ranking is attained following the usual MCDM methodology. The best alternative, A^*, is determined as

$$A^* = A_i \left| S_i^C = \bigvee_{i=1,n} \left(\sum_{k=1}^{m_c} W_k \cdot s_{ik} + \sum_{j=1}^{m} W_j \cdot s_{ij} \right) \right. \tag{3}$$

where S_i^C is the total combined score of alternative i considering both benefit and cost attributes, m_c is the number of cost criteria and W_k and s_{ik} are the weighing coefficients and ratings of cost criteria. For the special case of one cost criterion, e.g. *WLC*, equation (3) becomes

$$A^* = A_i \left| S_i^C = \bigvee_{i=1,n} \left(W^{WLC} \cdot s_i^{WLC} + \sum_{j=1}^{m} W_j \cdot s_{ij} \right) \right. \tag{4}$$

In the framework of the construction industry, this approach was followed by Norton (1992).

Another approach has been proposed by Kirk and Dell'Isola (1995) where the final ranking of alternatives is based on benefit to cost (BTC) ratios. A BTC ratio of an alternative i is calculated as

$$BTC_i = \frac{S_i}{WLC_i} \tag{5}$$

where WLC_i is the WLC measure of alternative i which can be a net present value (NPV) or the equivalent annual cost (EAC) as appropriate (Kishk, 2001). Because a BTC ratio is a cost effectiveness measure, the best alternative, A^*, should have the maximum BTC ratio, i.e.

$$A^* = A_i \left| BTC_i = \underset{i=1,n}{\vee} \frac{S_i}{WLC_i} \right. \tag{6}$$

Kishk (2001) has shown that the use of BTC ratio is recommended in the case of uncertainty-tied alternatives. However, it can only be used if there is a single cost criterion to be considered. Besides, it does not reflect the relative importance of financial and non-financial attributes. Furthermore, the treatment of non-financial benefits is different from what is usually done in WLC regarding monetary benefits, i.e. by considering them as negative costs. The use of the total combined score is also crucial when no detailed cost results are available or when the relative importance of cost and non-financial criteria should be considered.

DESIGN OF THE ALGORITHM

In this section, a novel algorithm is proposed. First, a MCDM approach is selected. Then, all necessary equations are defined and implemented in the form of a computational algorithm.

The Approach

The above discussion reveals that a fuzzy MCDM approach based on pair-wise comparisons and the normalised weighted average formula (equation 2) is most desirable. Because of the limitations of the fuzzy AHP approach, a fuzzy version of the WE technique would be more desirable. It employs pair-wise comparisons and derives weights of importance through a simple summation process. This would enable the α-cut concept to be used and thus the 'early defuzzification' limitation can be avoided. Another merit of the WE is that it is not restricted to the use of fuzzy numbers 1 to 9 to represent pair-wise comparisons. Furthermore, the WE method is the most commonly used method within the WLC framework. These additional simplicity and intuitiveness properties of the WE technique are two properties that are seen as extremely important for the fuzzy MCDM algorithm to be realised by practitioners.

The Fuzzy WE Formula

Because of its advantages, the normalised formula proposed by Baas and Kwakernaak (equation 2) is employed. For Fuzzy input, this formula becomes

$$\widetilde{S}_i = \sum_{j=1}^{m} \widetilde{W}_j \cdot \widetilde{s}_{ij} \Bigg/ \sum_{j=1}^{m} \widetilde{W}_j \tag{7}$$

Similarly, the total combined score (equation 4) and the BTC (equation 5) can be normalised as follows

$$\widetilde{S}_i^C = \frac{\widetilde{W}^{WLC} \cdot \widetilde{s}_i^{WLC} + \sum_{j=1}^{m} \widetilde{W}_j \cdot \widetilde{s}_{ij}}{\widetilde{W}^{WLC} + \sum_{j=1}^{m} \widetilde{W}_j} \tag{8}$$

$$B\widetilde{T}C_i = \frac{\widetilde{S}_i}{W\widetilde{L}C_i} \tag{9}$$

The Algorithm

Based on the above arguments, the following algorithm may be proposed (Fig. 2).

1. Identify non-financial decision attributes.
2. Construct suitable fuzzy importance and performance scales, e.g. to use the fuzzy numbers $\widetilde{1}$ to $\widetilde{5}$ instead of the traditional 1 to 5 scale in the WE method (Fig. 3). It should be noted, however, that the algorithm is not restricted to these subsets and any normal convex subset can be used. For example, these subsets can be used to define performance ratings such as 'fair to good', 'very good to excellent' (Fig. 4), 'poor to fair' and 'good to very good' (Fig. 5). In the limit, the interval [1, 5] may be used to model the rating of the performance of an alternative regarding a certain criterion as 'not clear' (Fig. 6).
3. Initialize weights for attributes to zero.
4. For each pair of attributes, add the fuzzy subset of importance, $\widetilde{I}_s$, to the weight of the more important attribute using the restricted DSW algorithm.
5. Repeat steps 3 and 4 for all possible pair-wise comparisons to obtain the weight sets, $\widetilde{W}_j$.
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, $\widetilde{s}_{ij}$.
7. Repeat step 6 for all non-financial criteria.
8. Calculate the total score $\widetilde{S}_i$ (equation 7) using the vertex method.

9. The appropriate WLC algorithm is identified to manipulate various costs and values.
10. Calculate a WLC measure for alternative i. This measure could be in the form of an NPV measure or an EAC measure depending on the case at hand.
11. Calculate the BTC ratio from equation (9) using the restricted DSW algorithm.
12. Rate the performance of alternative i such that the lowest cost one is rated ‘excellent’.

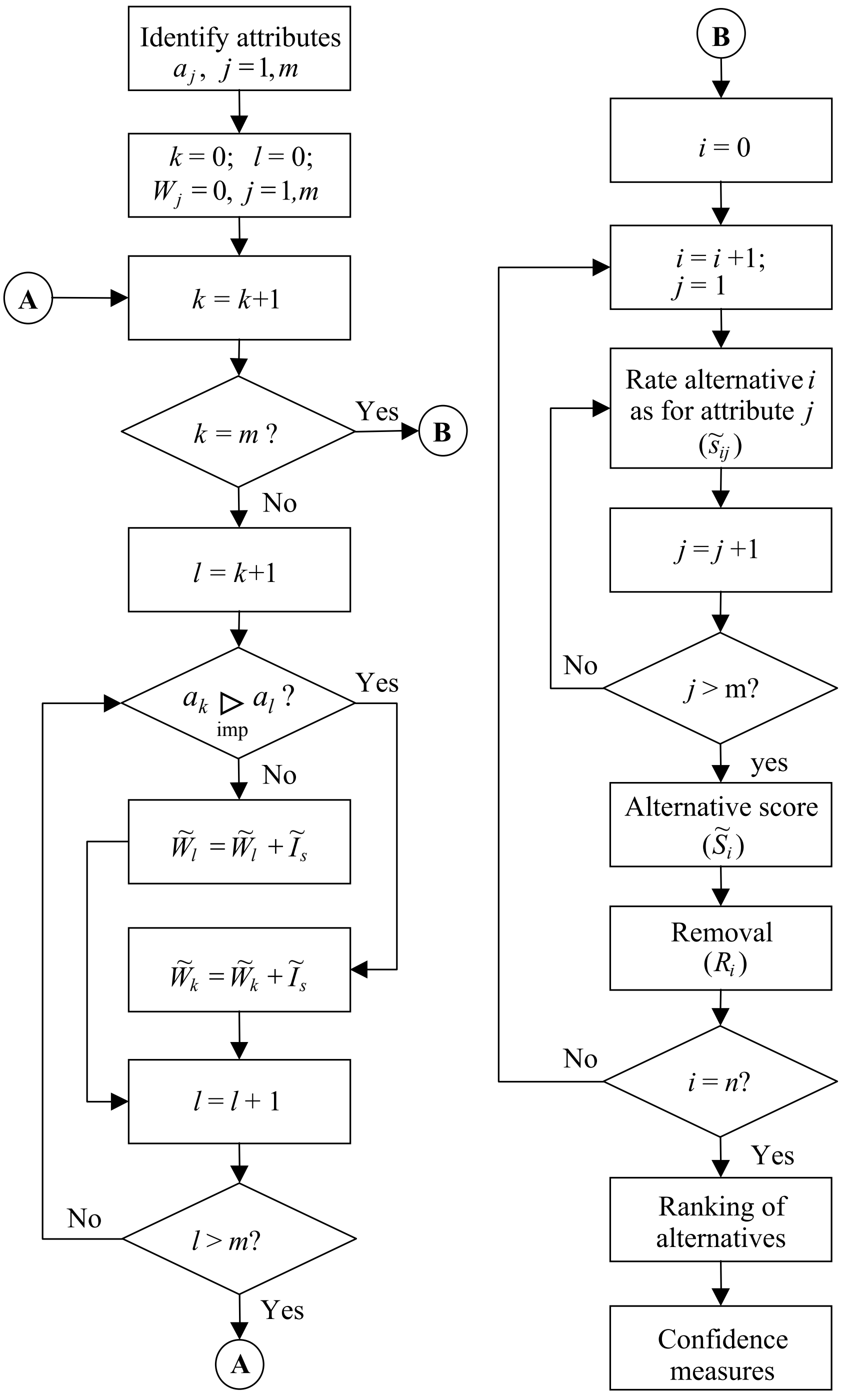


Figure (2): Flow chart of the fuzzy WE algorithm.

13. Calculate the total combined score, $\widetilde{S}_i^C$ (equation 8) using the vertex method.

14. Repeat steps 6 to 13 for all alternatives.

15. Alternatives are ranked according to the removals of the total combined scores or BTC ratios, and confidence measures in this ranking are calculated.

The proposed algorithm has been implemented into a computer routine using the MATLAB® programming environment (The MathWorks, 2000)

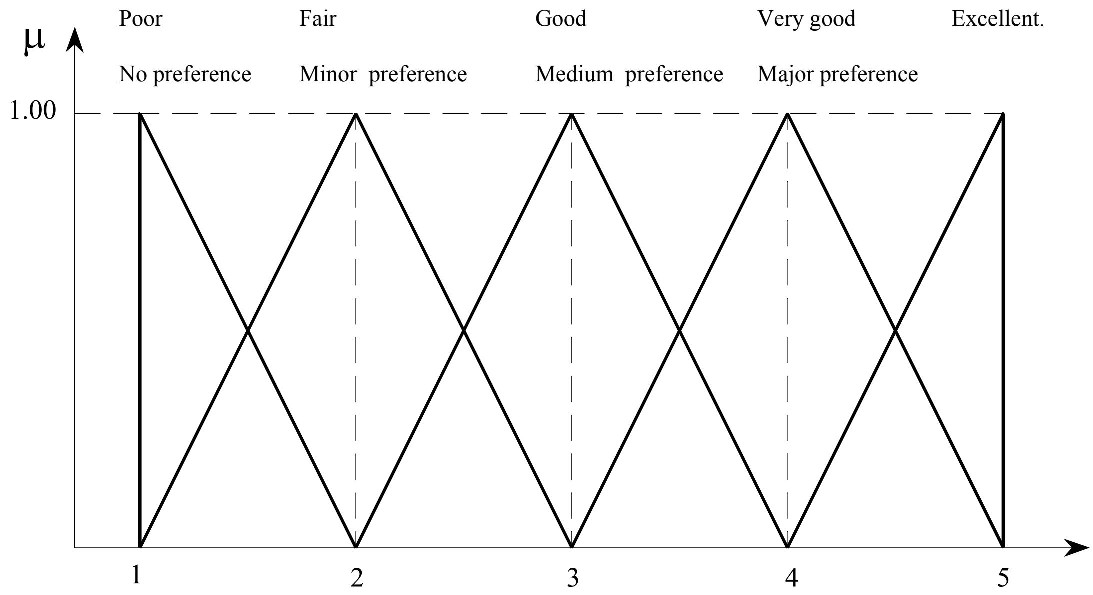


Figure (3): Triangular fuzzy subsets $\tilde{1}$ to $\tilde{5}$.

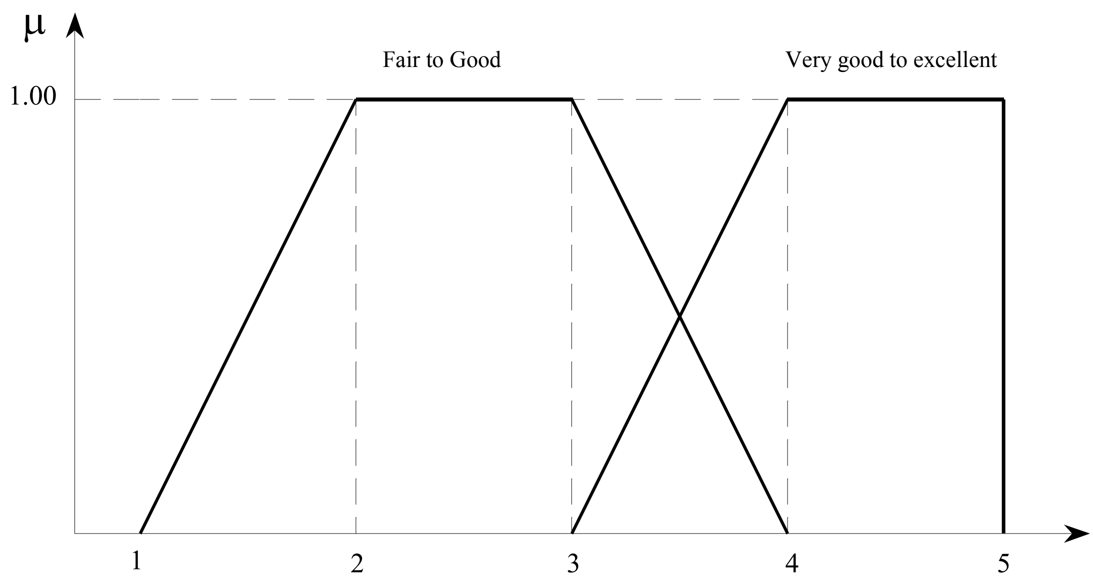


Figure (4): Fuzzy numbers ‘fair to good’ and ‘very good to excellent’.

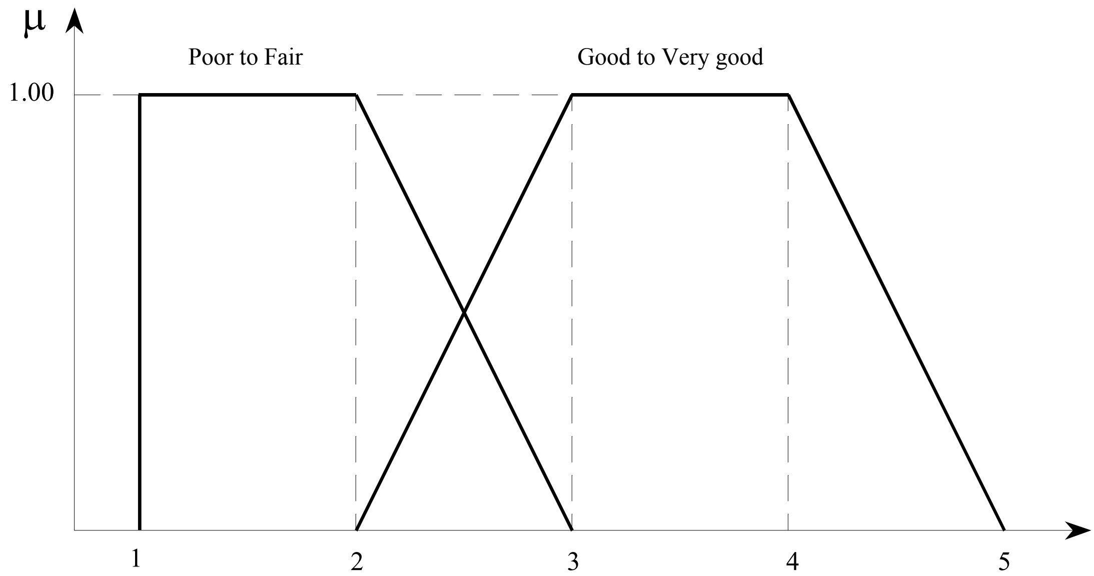


Figure (5): Fuzzy numbers 'poor to fair' and 'good to very good'.

Figure (6): Fuzzy number 'not clear'.

AN EXAMPLE APPLICATION

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 summarised in Fig. (1).

The proposed algorithm has been also used to solve this example. The triangular fuzzy subsets in Fig. (3) were employed to represent various preference and performance levels. Because only non-financial attributes are involved, the three schemes were ranked according to their total normalised scores, S_i (equation 7) which are depicted in Fig. (7). The recommended ranking is schemes 2, 1 and 3, with corresponding removals of the total score, S_i, of 4.52, 3.59 and 3.49, respectively. This ranking is the same as that obtained by the WE method (Fig. 1). The measures of confidence in this ranking were also calculated and are summarised in Table (1).

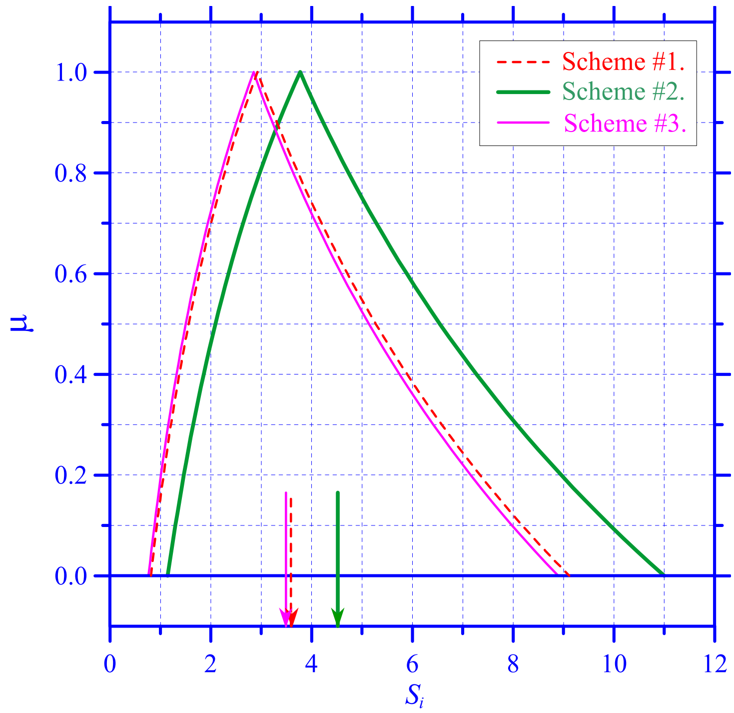


Figure (7): Total scores of various design schemes.

Table (1): Measures of confidence in ranking.

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	---	---

To illustrate the efficacy of the algorithm, the same example is considered but assuming that the designer used a conservative rating for the space relationships of scheme 2, e.g. 'good to very good' (Fig. 5) instead of 'very good'. Figure (8) shows the resulting normalised scores. Although scheme 2 remains the recommended option, the MF of its total score has wider intervals as a result of the conservative rating. In addition, the removal of its score becomes 4.35 instead of 4.52 for the more specific case. Furthermore, the measures of confidence in ranking decreased as shown in Table (2).

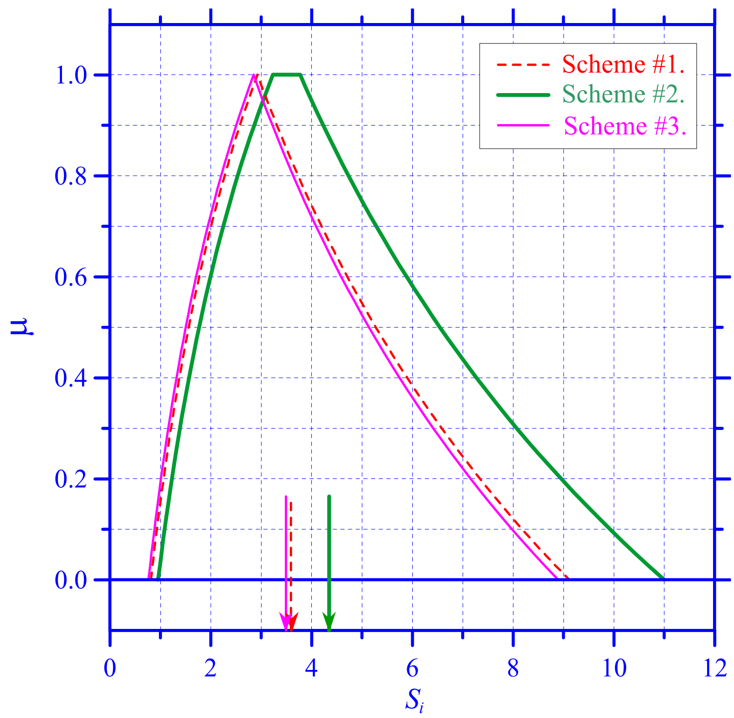


Figure (8): Total scores of various schemes for the 'conservative' case.

Table (2): Measures of confidence in ranking for the 'conservative' case.

Rank	Alternatives	Scheme #2		Scheme #1		Scheme #3	
		CI_1	CI_2	CI_1	CI_2	CI_1	CI_2
1	Scheme #2	---	---	0.171	0.585	0.194	0.597
2	Scheme #1	0.000	0.415	---	---	0.026	0.513
3	Scheme #3	0.000	0.403	0.000	0.487	---	---

The example is solved once more assuming a 'not clear' (Fig. 6) rating for the space relationships of scheme 2. Figure (9) shows the resulting total normalised scores. Again, scheme 2 remains the recommended option but the removal of its score becomes 4.25. As expected, the corresponding measures of confidence in ranking are more conservative than the previous two cases summarised in Table (3). As expected, the new measures of confidence in ranking are more conservative than the previous two cases.

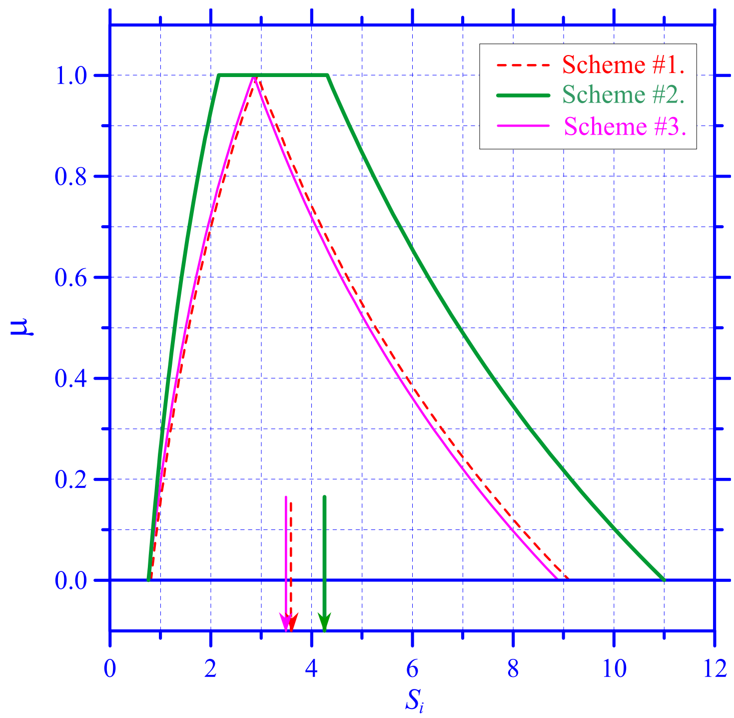


Figure (9): Total scores of various schemes for the 'not clear' case.

Table (3): Measures of confidence in ranking for the 'not clear' case.

Rank	Alternatives	Scheme #2		Scheme #1		Scheme #3	
		CI_1	CI_2	CI_1	CI_2	CI_1	CI_2
1	Scheme #2	---	---	0.170	0.569	0.187	0.580
2	Scheme #1	0.033	0.431	---	---	0.026	0.513
3	Scheme #3	0.008	0.420	0.000	0.487	---	---

For a clearer comparison, the membership functions for the total score of scheme 2 for the three cases are depicted in Fig. (10). These results show the efficacy of the algorithm in modelling various degrees of fuzziness.

CONCLUSIONS

Non-financial attributes of projects have a decisive role to play in many situations. Most of these factors, however, cannot be assessed in a strict WLC framework because they are mostly 'non-financial' or even intangible such as aesthetics. Existing methods used to extend the WLC framework to consider non-financial factors fall short from considering inherent uncertainties of the processes of eliciting weights of importance and ratings of alternatives.

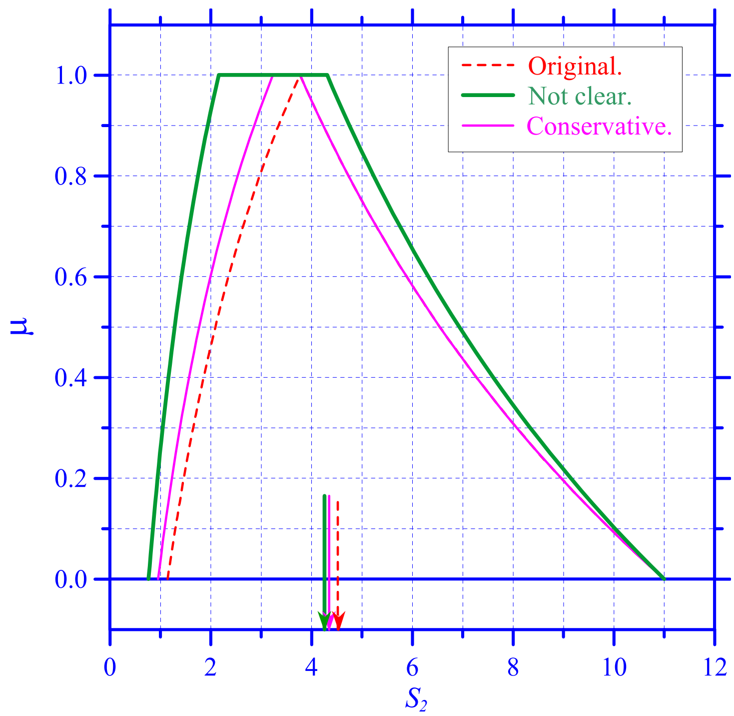


Figure (10): The total score of scheme #2 for various cases.

Other published methods for MCDM under uncertainty including probabilistic and techniques have been reviewed to identify solutions to the limitations of existing methods. Based on this review, a fuzzy version of the WE method has been developed and implemented into a computational algorithm.

The proposed algorithm has three unique merits. First, the elicitation of importance weights is done through pair-wise comparisons without transforming imprecise information to crisp values early in the process. Secondly, 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, alternatives are automatically ranked and confidence measures in this ranking are provided. These unique features provide the decision-maker with the flexibility and robustness required for making informed decisions.

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