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Theory and Methodology

Task oriented weighting in multi-criteria analysis

Chung-Hsing Yeh *, Robert J. Willis, Hepu Deng, Hongqi Pan

School of Business Systems, Monash University, Clayton, Vic., 3168, Australia

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Abstract

This paper presents a novel approach to criteria weighting, which often plays a crucial role in the selection of a finite set of alternatives involving multiple conflicting criteria for accomplishing a specific task. To ensure a consistent decision is always made in response to a given set of task requirements, a fuzzy knowledge base is constructed to formulate the imprecise weighting process taken by the decision maker (DM) under imprecision and vagueness. As a result, criteria weights are elicited by simply specifying the state of each individual task requirement. This task oriented weighting procedure is incorporated into a fuzzy multi-criteria analysis (MA) model, which is solved by an effective algorithm for evaluating the overall performance of the alternatives for a given task. An empirical study of a dredger dispatching problem in China is conducted to examine the effectiveness of the model. The concept of task oriented weighting and the algorithm presented have significance and general application in MA.

Keywords: Fuzzy sets; Multi-criteria analysis; Criteria weighting; Dredger dispatching

1. Introduction

Multi-criteria analysis (MA) is widely used in selecting the best alternative from a finite set of decision alternatives with respect to multiple, usually conflicting criteria (attributes). Each of the criteria is associated with a specific objective in the given decision context. MA methods that generate a cardinal preference of the alternatives require the decision maker (DM) to provide information in specific ways on (a) the relative importance (weights) of the criteria with respect to the objectives of the decision problem and (b) the performance ratings of the alternatives in relation to each criterion (Keeney and Raiffa, 1976; Hwang and Yoon, 1981; Zeleny, 1982; Colson and de Bruyn, 1989; Chen and Hwang, 1992; Vincke, 1992).

In many multi-criteria selection situations, the relative performance ratings of the alternatives are rarely changed in terms of the objectives of the task to be accomplished. In such situations, the requirements of the task, reflecting the objectives to be achieved, affect mainly the criteria weights. Effective decision making thus primarily lies in how the process of determining criteria weights

* Corresponding author. Tel.: +61 3 990 55808; fax: +61 3 990 55159; e-mail: chyeh@bs.monash.edu.au

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can be effectively and consistently linked with the task requirements.

Criteria weighting is a complex preference elicitation process in which multiple task requirements reflecting the DM's major concern about a specific decision problem have to be considered. These task requirements are usually expressed in linguistic and prescriptive forms, which are often uncertain, subjective and imprecise. In practice, the vague nature of the criteria makes it difficult for the DM to assess precisely how and to what extent these task requirements as a whole influence the criteria weights. As a result, inconsistent weights are often produced, which may lead to unreliable decision outcomes. It is evident that the development of a structured approach for assigning weights consistently with regard to various task requirements is desirable for solving practical MA problems. To this end, this paper presents a novel approach which can produce consistent criteria weights and decision outcomes for practical MA problems.

In subsequent sections, we first give an overview of criteria weighting in the context of multi-attribute value theory, and then present a dredger dispatching problem in Shanghai, China as a case study for the new MA model developed by this paper. A special feature of the model is the determination of criteria weights, which is based on a fuzzy knowledge base constructed for handling various task requirements. To handle both crisp and fuzzy data often existing in practical MA problems, an effective algorithm is developed to evaluate the overall performance of the alternatives. Finally, we conduct an empirical study to demonstrate how the model developed can be used to support the dredger dispatching process in Shanghai, China.

2. Criteria weighting

A number of methods for determining criteria weights in MA have been developed. A good comparison of some weight assessment techniques is given by Hobbs (1980), Hwang and Yoon (1981), Schoemaker and Waid (1982), and Barron and Barrett (1996). Here we review only the relevant methods developed for MA models using multi-attribute value theory. Approaches to criteria weighting for MA models based on outranking methods (Roy, 1996) are well discussed by Voogd (1983), Vansnick (1986), and Solymosi and Dombi (1986).

Keeney and Raiffa (1976) first present a value trade off approach. This approach requires the DM to compare pairs of the alternatives with respect to each pair of the criteria, with the assumption that both alternatives have identical values on the remaining criteria. The high value of one alternative is traded off for the low value of the other through a series of adjustments until an indifference value is achieved. The criteria weights are determined after numerous value tradeoff processes.

Saaty (1980) develops a pairwise comparison approach based on the hierarchical structure of the problem. A reciprocal pairwise comparison matrix is constructed based on a subjective scale of 1–9. Criteria weights are obtained by synthesising various assessments in a systematic manner. This approach is generalised by Takeda et al. (1987) to reflect the DM's uncertainty about the estimates in the reciprocal matrix. Barzilai (1997) analyses properties of acceptable solutions of this approach. Laarhoven and Pedrycz (1983), Buckley (1985) and Juang and Lee (1991) further extend this approach to accommodate the subjectiveness and imprecision inherent in the pairwise comparison process using fuzzy set theory (Zadeh, 1965). However, in certain situations this approach may cause the rank reversal phenomenon (Perez, 1995).

Von Winterfeldt and Edwards (1986) and Tabucanon (1988) propose a direct ranking and rating approach. The DM is required to first rank all criteria according to their importance, and then give each criterion an estimated numerical value to indicate its relative degree of importance. Criteria weights are obtained by normalising these estimated values.

Mareschal (1988) uses a mathematical programming model with sensitivity analysis to determine the intervals of criteria weights, within which the same ranking result is produced. The range sensitivity of criteria weights using different weight assessment methods is examined by Fischer

(1995). The sensitivity analysis approach is also used by Bana e Costa (1988) to deal with the uncertainty associated with the criteria weights in a municipal management decision environment. Sensitivity analysis gives DMs flexibility in judging criteria weights and helps DMs understand how criteria weights affect the decision outcome, thus reducing their cognitive burden in determining precise weights. However, this process may become tedious and difficult to manage as the number of criteria increases.

By recognising the fact that criteria weights are context-dependent, Ribeiro (1996) reviews and proposes preference elicitation techniques for use by the DM at run time to determine weights. In actual applications, the same DM may elicit different weights using different approaches, and no single approach can guarantee a more accurate result (Barron and Barrett, 1996). This may be mainly due to the fact that the DM cannot always provide consistent value judgements under different quantifying procedures. Different DMs using the same approach may give different weights due to their subjective judgements (Diakoulaki et al., 1995). As a result, inconsistent ranking outcomes may be produced, leading to ineffective decisions being made.

In addition, to solve the MA selection problem for accomplishing a specific task, existing approaches virtually require the DM to consider all task requirements simultaneously for assessing criteria weights. This often places a heavy cognitive burden on the DM due to the limitations on the amount of information that humans can effectively handle (Miller, 1956; Morse, 1977). The presence of imprecision and subjectiveness in describing the task requirements further complicates the criteria weighting process.

In the management of uncertainty with imprecision and vagueness, expert systems provide a framework in which human knowledge for making decisions is formulated in a flexible and user-adaptive manner (Zimmermann, 1987; Graham and Jones, 1988). The expert system approach is well suited to formulate the criteria weighting process, as it is in essence a human solution in terms of the selection of a preferred alternative for accomplishing a specific task. In this regard, the uncertainty of criteria weighting is of a fuzzy nature as the importance of the task requirements with respect to the selection criteria is usually expressed by the vague description of their semantic meaning in a nature language (Zimmermann, 1996). To facilitate the representation of the DM's imprecise judgement of criteria weighs, we construct a fuzzy knowledge base with fuzzy IF–THEN rules by explicitly considering the effect of individual task requirement on the importance of each criterion. This allows the DM to interact with the uncertain environment under which a decision has to be made. With the fuzzy knowledge base, the influence of various task requirements on the relative importance of criteria is aggregated. This results in consistent criteria weights for a given set of task requirements. To illustrate how the fuzzy knowledge base for criteria weighting can be constructed, we consider a dredger dispatching problem in China.

3. The dredger dispatching problem

The dredger dispatching problem is frequently confronted by a state-authorised dredging company in Shanghai, China. In order to maintain the efficiency and effectiveness of the waterborne traffic which is the lifeline of the city's economy, the dredging company has to regularly dispatch dredgers from its established fleet of 12 trailing suction hopper dredgers to excavate the sediments from the bottom of channels which may block normal waterborne transport.

To assign the most suitable dredger to a given maintenance dredging task, the dispatcher needs to evaluate the overall performance of all available dredgers based on site conditions and task requirements (Bray, 1979; Yell and Riddell, 1995). The current practice in Shanghai is that experienced dispatchers use their intuition and knowledge to select a dredger by a rule of thumb. However, this ad hoc approach is not always reliable and consistent, due to the imprecise nature of human knowledge and the information available for making assessments and judgements. To make effective decisions, all the factors (evaluation criteria) to be considered should be analysed simultaneously. In this regard, MA provides a systematic framework for managing decision problems of this kind. To formulate dredger dispatching as an MA problem, an investigation was conducted by consulting the expert dispatchers in Shanghai. Fig. 1 shows the hierarchical structure of the problem. The overall performance of 12 dredgers (alternatives) $(A_1, A_2, \ldots, A_{12})$ for a given dredging task can be obtained by (a) assigning weights to five criteria $(C_1, C_2, \ldots, C_5)$ and their associated p_j sub-criteria $(C_{jk},\ j = 1, \ldots, 5;\ k = 1, 2, \ldots, p_j)$, and (b) assessing the performance ratings of each dredger with respect to each criterion and its associated sub-criteria.

A dredging task is characterised by such requirements as daily volume (T_1), daily cost (T_2), quality expectation (T_3), relative danger level (T_4), and site importance (T_5). Daily volume is an indication of how many cubic metres of material a dredger is expected to handle. The daily cost is the allowable average daily operating cost, reflecting the dispatcher's concern about the dredging cost against the dedicated funds. The quality expectation is a reflection of the requirements of the relevant authorities on the dredging depth, width and side slope. The site danger level is used to reflect the dispatcher's concerns on the dredging safety. The site importance is determined by the grade of the dredging site, which reflects the overall social impact of the channel. These task requirements reflect the dispatcher's concerns in evaluating the performance of dredgers for a given task. They are usually determined qualitatively or quantitatively by the dispatchers or the relevant authorities.

In evaluating the suitability of dredgers for a given task, the problem of how various task requirements affect criteria weights has to be addressed. For example, more concern on the daily dredging volume (T_1) makes the dispatcher give a higher weight to the efficiency criterion (C_1). Less concern on the daily cost (T_2) leads to a lower weight for the cost criterion (C_2). It is therefore desirable to assign criteria weights consistently under a given set of task requirements for making reliable and effective decisions. In this paper, we propose a fuzzy knowledge-based approach to directly link various task requirements with criteria weights.

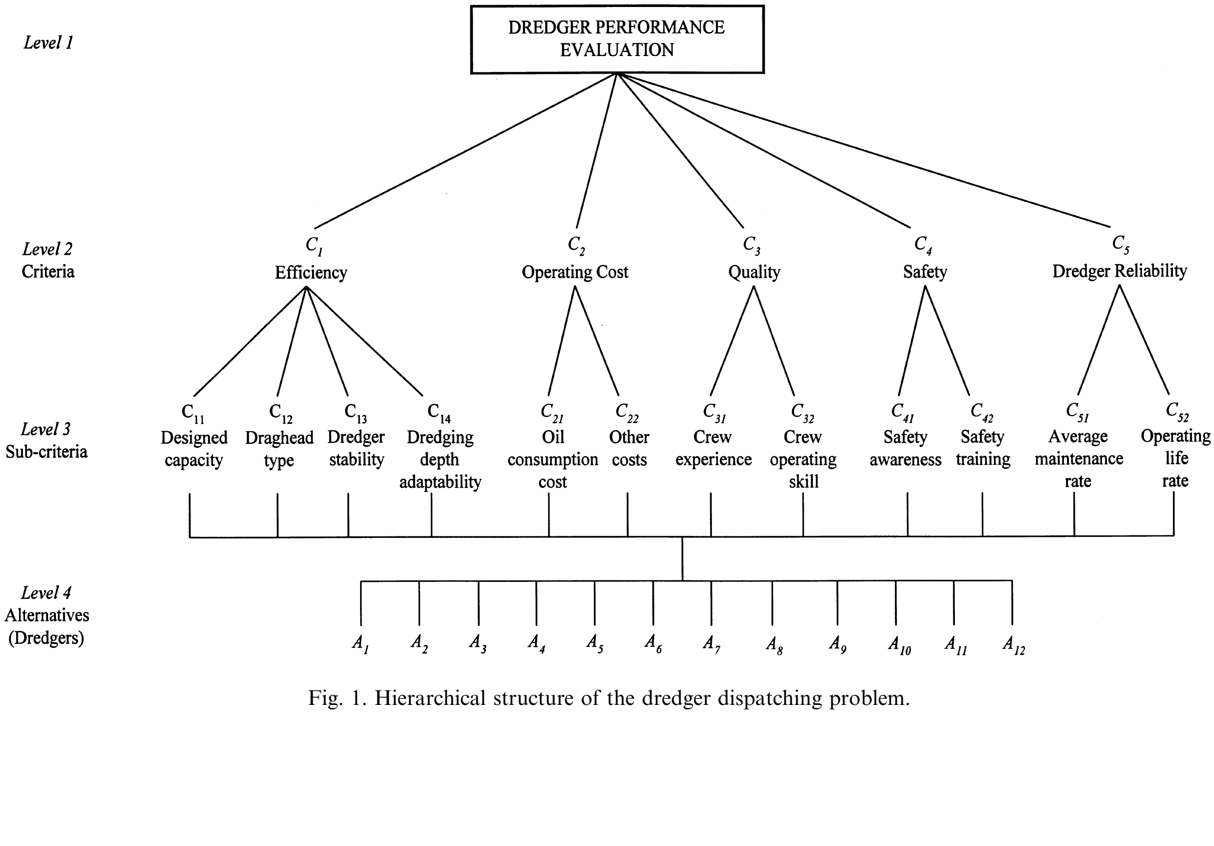


Fig. 1. Hierarchical structure of the dredger dispatching problem.

4. The fuzzy knowledge base for task oriented criteria weighting

As mentioned previously, the inherent imprecision and vagueness of the criteria weighting process can be best modelled by fuzzy set theory. Teodorovic (1994) and Marchalleck and Kandel (1995) give a good review of fuzzy set theory applications in transportation systems. Lotan and Koutsopoulos (1993), Vukadinovic and Teodorovic (1994), Milosavljevic et al. (1996), and Chang et al. (1998) show how fuzzy rules can be used to support dispatching and assignment decisions in transportation systems. In these applications, linguistic variables, represented by fuzzy numbers, have been found intuitively easy to use in expressing the uncertainty, subjectiveness and imprecision of human assessments (Zadeh, 1975).

Based on the current practice of dredger dispatching in Shanghai, knowledge of expert dispatchers for assessing the influence of each task requirement on criteria weights under various situations can be represented as a set of fuzzy IF–THEN rules. In these fuzzy rules, linguistic variables are used to represent the task requirements $(T_1, T_2, \ldots, T_5)$ and evaluation criteria $(C_1, C_2, \ldots, C_5)$. In the criteria weighting process, the dispatcher can easily use the linguistic terms defined for these linguistic variables to vaguely assess the importance of individual criteria with respect to a given set of task requirements. For ease of data acquisition and computational efficiency, trapezoidal or triangular fuzzy numbers are used to represent linguistic terms.

The construction of the fuzzy knowledge base starts with the definition of a set of linguistic terms (the term set) for each linguistic variable used (1) to describe the states of the corresponding task requirement or (2) to represent the weights of the corresponding criterion. Fig. 2 shows the membership functions of the term set {Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)} used to describe the states of task requirements, which were obtained through extensive consultations with the expert dispatchers in Shanghai.

To define the membership functions of the term set {Very Unimportant (VU), Unimportant (U), Medium (M), Important (I), Very Important (VI)} for representing weights of the corresponding criteria, we need to first determine the basic relative weights of the five criteria regardless of task requirements. This can be given by the DM or obtained by using existing criteria weighting methods reviewed previously, such as the analytic hierarchical process (Saaty, 1980; Juang and Lee, 1991). In this study, the basic relative weights for criteria C_1, C_2, C_3, C_4 and C_5 are given as 0.3, 0.2, 0.2, 0.15 and 0.15, respectively through consultations with the expert dispatchers when no specific task requirements are specified. This is the ratio of criteria weights to be obtained when the same linguistic term or value is assessed for all five criteria.

Fig. 3 shows the membership functions of linguistic terms used to elicit criteria weights. They are represented by triangular fuzzy numbers which are equally spread over the corresponding ranges, whose values are scaled to correspond to the ratio of the basic criteria weights. As such, the ratio of relative criteria weights is the same for situations where all five criteria have the same linguistic value.

With the linguistic terms and their membership functions defined in Figs. 2 and 3, a set of 52 fuzzy rules was constructed from the knowledge of expert dispatchers through interviews. Table 1 summarises these fuzzy rules for determining criteria weights under various task requirements. In Table 1, the number indicates the rule number and the minus sign denotes the negative operator "NOT". For example, Rule 10 is "IF T_1 *is H* AND T_2 *is VL* THEN C_1 *is VI*". Rule 31 states that "IF T_1 *is NOT VL* AND T_2 *is VL* AND T_3 *is H* THEN C_3 *is VI*". These fuzzy rules are easily understood and can be readily modified by the human dispatchers if necessary, to reflect a specific dispatching environment.

As to be presented in Section 6, extensive simulation tests have been conducted to verify the effectiveness of the fuzzy knowledge base in Table 2. After inputting the state of the five task requirements for characterising a specific dredging task, five crisp criteria weights are generated. This is achieved by an approximate reasoning process (Zadeh, 1979) with the centroid method

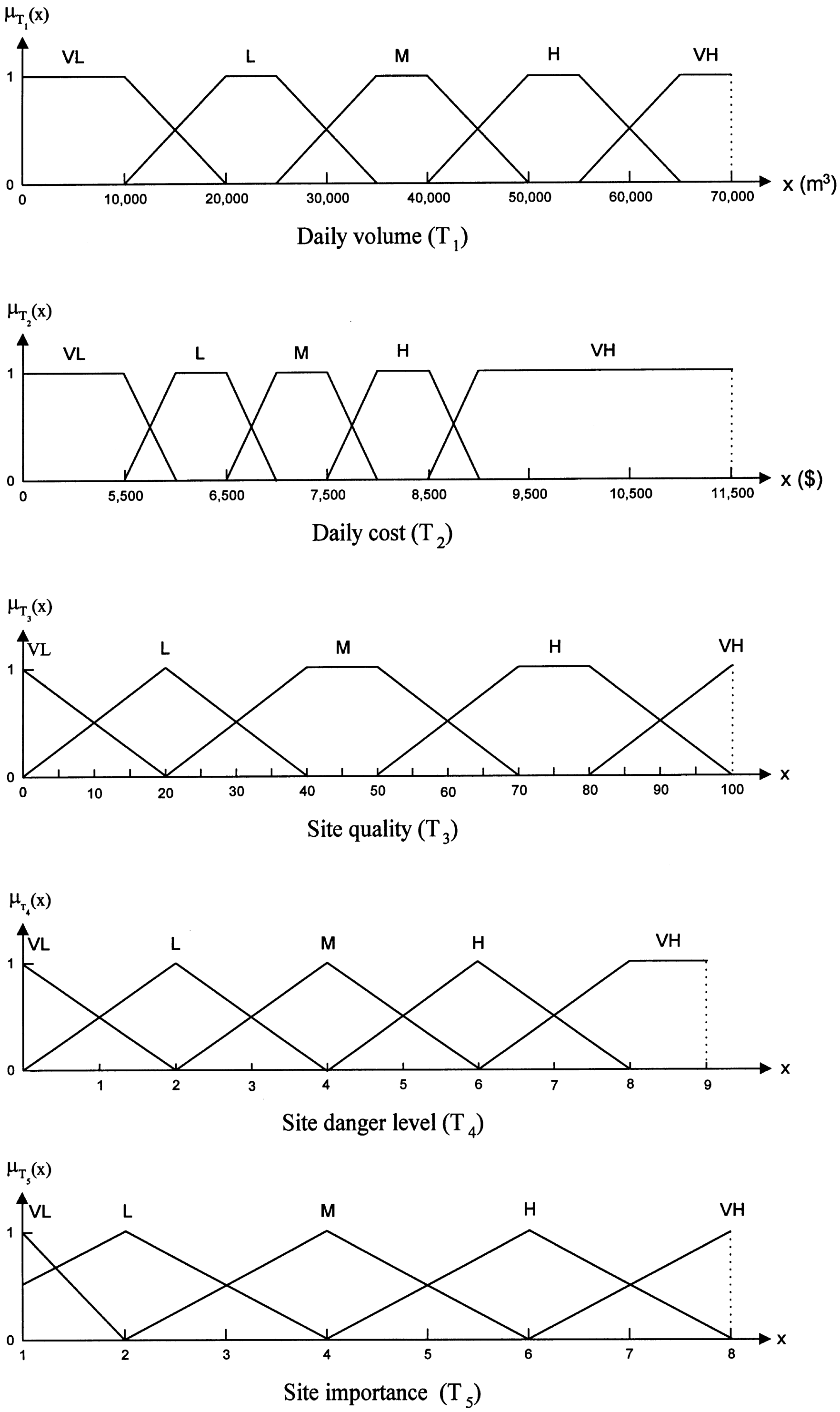


Fig. 2. Membership functions of linguistic terms used for describing task requirements.

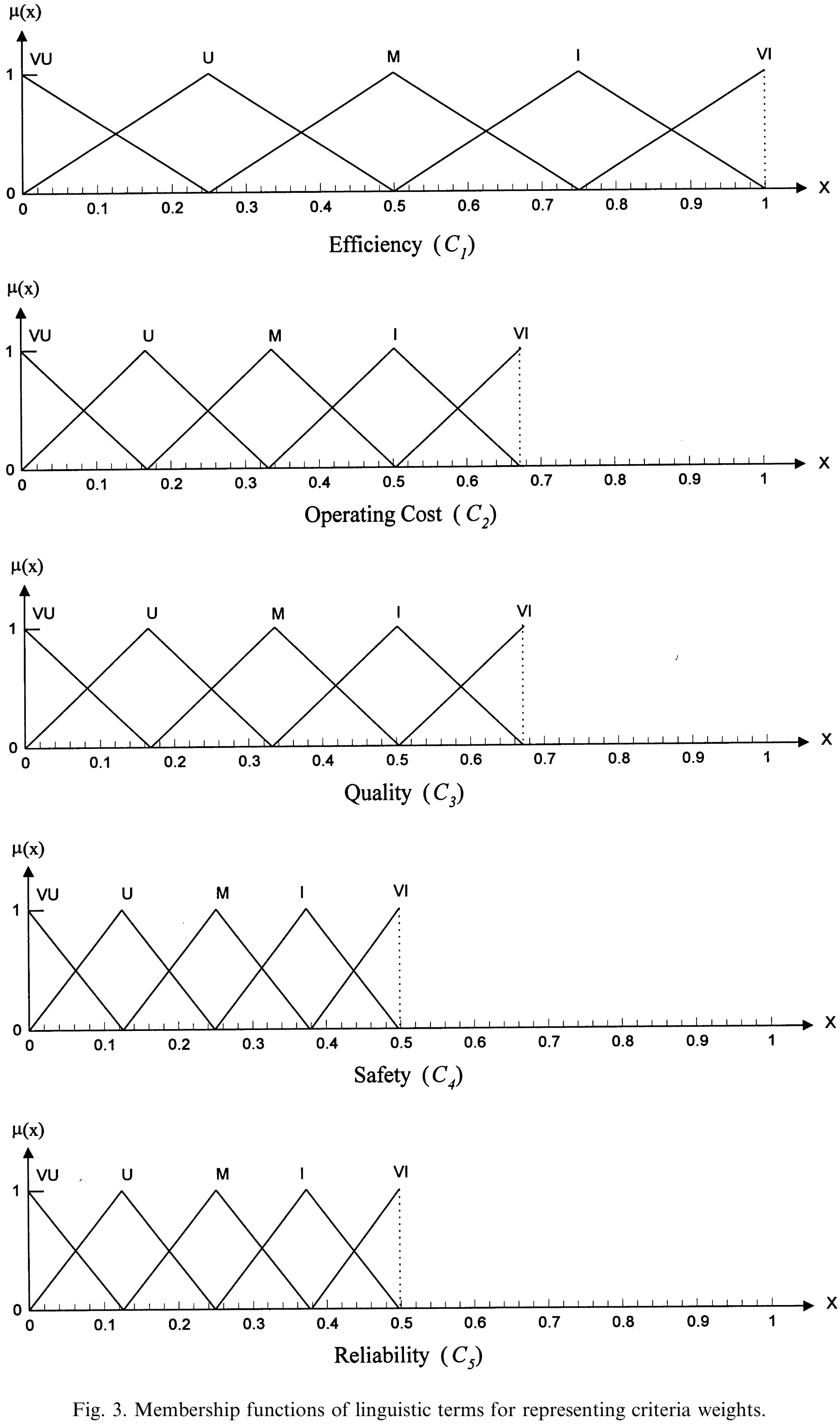


Fig. 3. Membership functions of linguistic terms for representing criteria weights.

Table 1
Fuzzy rules for determining criteria weights

THEN		C_1					C_2					C_3					C_4					C_5				
IF		VI	I	M	U	VU	VI	I	M	U	VU	VI	I	M	U	VU	VI	I	M	U	VU	VI	I	M	U	VU
T_1	VH	1					18						32				39	38				47,49				
	H	6,10,11	2																			48,50				
	M		7,9	3																						
	L			8	4							−30														
	VL					5						−25,−31	23,−26	24												
T_2	VH										12															
	H									13																
	M							17,21	14																	
	L						18,19,20,22	15														49,50				
	VL	10	9				16					30,31	32				39	38				47,48				
T_3	VH	11					19	17				25	23													
	H						20					30,31	26	24												
	M												32	27												
	L														28											
	VL															29										
T_4	VH						22	21									33					51	52			
	H																39,40	34								
	M																	38,41	35							
	L																			36						
	VL																				37					
T_5	VH	6	7	8													40	41				42				
	H																	38				47,48,49,50,51	43			
	M																						52	44		
	L																								45	
	VL																									46

Table 2
Data for measuring the operating efficiency of dredgers

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
V_d	45,000	42,000	48,000	49,000	43,000	51,000	52,000	53,000	52,500	53,900	70,000	72,000
f_d	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.9	1	1
f_s	0.95	0.95	0.95	0.95	0.95	0.95	0.9	0.9	0.95	0.9	0.95	0.95
f_a	1	1	0.97	0.97	0.98	0.987	0.97	1	1	1	0.95	0.95

as the defuzzification method. These crisp criteria weights are then used in the fuzzy MA model to be presented in the next section to generate a preference index for each dredger, on which the dispatching decision can be based. This task oriented weighting approach reduces the uncertainty of criteria weighting greatly, as (1) the task requirements can be specified by crisp or fuzzy data, and (2) no tedious, unreliable process is required.

5. The fuzzy MA model

In a fuzzy MA problem of evaluating n alternatives A_i $(i = 1, 2, \ldots, n)$, assessments are to be given to determine (1) the weighting vectors

$$W = (w_1, w_2, \ldots, w_m)$$

and

$$W_j = (w_{j1}, w_{j2}, \ldots, w_{jk}, \ldots, w_{jp_j})$$

$$(j = 1, 2, \ldots, m; k = 1, 2, \ldots, p_j),$$

and (2) the decision matrices

$$X = \{x_{ij}, i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m\}$$

and

$$Y_{c_j} = \{y_{ki}, k = 1, 2, \ldots, p_j;\ i = 1, 2, \ldots, n\}.$$

W and W_j represent the weighting vectors of m criteria C_j $(j = 1, 2, \ldots, m)$ and p_j sub-criteria C_{jk} $(k = 1, 2, \ldots, p_j)$ for the problem, respectively. x_{ij} and y_{ki} represent the performance ratings of alternative A_i with respect to criterion C_j and sub-criterion C_{jk}, respectively. Criteria weights and performance ratings can be given using crisp or fuzzy data.

With the problem structure defined above, mainstream fuzzy MA models in the context of multi-attribute additive value theory are developed along the line of the evaluation approach involving two phases (Zimmermann, 1987; Chen and Hwang, 1992): (1) the aggregation of the fuzzy assessments with respect to all criteria for each alternative, and (2) the ranking of the alternatives based on their aggregated overall assessments (fuzzy utilities). The main problem with this approach lies in the fact that the fuzzy utilities ranking procedure is not always straightforward and reliable.

To avoid the unreliable process of fuzzy utilities ranking, we develop an algorithm for generating a crisp preference index for each alternative. The algorithm effectively incorporates the crisp weights generated from the task oriented weighting approach presented in the previous section, and efficiently handles both fuzzy (qualitative) and crisp (quantitative) data obtained from the performance assessment process usually conducted by the DM. The algorithm is based on the additive value theory (Hwang and Yoon, 1981) which is simple and comprehensible.

The algorithm is given as follows:

Step 1: Normalise crisp data in the decision matrices for the criteria or sub-criteria to make them compatible across the criteria or sub-criteria by

$$x'_{ij} = \frac{x}{\sqrt{\sum_{i=1}^{n} (x_{ij})^2}} \quad \text{or}$$

$$y'_{ki} = \frac{y_{ki}}{\sqrt{\sum_{i=1}^{n} (y_{ki})^2}},$$

$$i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m;\ k; = 1, 2, \ldots, p_j.$$

For simplicity of representation, we assume that the decision matrices presented below are normalised.

Step 2: Aggregate the assessments from lower-level sub-criteria for each criterion C_j using fuzzy arithmetic (Kaufmann and Gupta, 1985) by

$$(x_{1j}, x_{2j}, \ldots, x_{nj}) = \frac{W_j Y_{c_j}}{\sum_{k=1}^{p_j} w_{jk}}.$$

This constitutes the decision matrix

$$X = \{x_{ij}, i = 1, 2, \ldots, n; j = 1, 2, \ldots, m\}$$

for the problem.

Step 3: For fuzzy data in the decision matrix X, calculate the relative performance of each alternative by comparing it with the best and worst performances of all alternatives with respect to each criterion, using Chen's fuzzy maximum and fuzzy minimum (Chen, 1985). This results in a fuzzy singleton (Zadeh, 1973) matrix as

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1m} \\ S_{21} & S_{22} & \cdots & S_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ S_{n1} & S_{n2} & \cdots & S_{nm} \end{bmatrix},$$

where

$$S_{ij} = \frac{1}{2}(u_{\mathrm{L}_j}(i) + u_{\mathrm{R}_j}(i)),$$
$$i = 1, 2, \ldots, n; j = 1, 2, \ldots, m.$$

$$u_{\mathrm{L}}(i) = 1 - \sup_x (x_{ij} \cap M^j_{\min}),$$
$$u_{\mathrm{R}_j}(i) = \sup_x (x_{ij} \cap M^j_{\max}),$$

where $M^j_{\max}$ and $M^j_{\min}$ are the fuzzy maximum and fuzzy minimum of the alternative performance with respect to criterion C_j, respectively, whose membership functions are defined as

$$\mu_{M^j_{\max}}(x) = \begin{cases} \frac{x - x^j_{\min}}{x^j_{\max} - x^j_{\min}}, & x^j_{\min} \leqslant x \leqslant x^j_{\max}, \\ 0, & \text{otherwise}. \end{cases}$$

$$\mu_{M^j_{\min}}(x) = \begin{cases} \frac{x^j_{\max} - x}{x^j_{\max} - x^j_{\min}}, & x^j_{\min} \leqslant x \leqslant x^j_{\max}, \\ 0, & \text{otherwise}. \end{cases}$$

$$x^j_{\max} = \sup \bigcup_{i=1}^{n} \{x, 0 < \mu_{x_{ij}}(x) < 1\},$$

$$x^j_{\min} = \inf \bigcup_{i=1}^{n} \{x, 0 < \mu_{x_{ij}}(x) < 1\}.$$

s_{ij} indicates the relative performance of alternative A_i over all other alternatives with respect to criterion C_j.

Step 4: Obtain the overall preference index for each alternative A_i by

$$p_j = \sum_{j=1}^{m} w_j s_{ij}, \quad i = 1, 2, \ldots, n.$$

The larger the index value, the more preferred the alternative.

6. The empirical study

An empirical study of the dredger dispatching problem in Shanghai, China is conducted to illustrate how the dispatching process can be effectively supported by the fuzzy MA model developed. The effect of the task requirements on criteria weights and its subsequent influence on the selection of the preferred dredger are examined.

In the dredger dispatching problem depicted in Fig. 1, the performance assessments of dredgers are given qualitatively or quantitatively by the dispatcher and kept unchanged in this study, since they are not affected by task requirements.

The operating efficiency of a dredger is signified by the actual daily dredging volume (V_{a}) that the dredger can complete during a day's work. It is determined by the designed capacity of daily dredging volume (V_{d}), draghead type, dredger stability, and dredger depth adaptability. It is measured quantitatively by

$$V_{\mathrm{a}} = f_{\mathrm{d}} \times f_{\mathrm{s}} \times f_{\mathrm{a}} \times V_{\mathrm{d}}, \tag{1}$$

where f_{d}, f_{s} and f_{a} $(0 < f_{\mathrm{d}}, f_{\mathrm{s}}, f_{\mathrm{d}} \leqslant 1)$ are the efficiency factors in relation to the draghead type, stability, and depth adaptability, respectively for a given dredging task. Table 2 shows the data used, and Table 3 shows the performance assessments of 12 dredgers for the efficiency criterion.

Quantitative and qualitative assessments on other criteria and their associated sub-criteria are given by crisp values and fuzzy values,

Table 3
Performance assessments for the efficiency criterion

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
C_1	34,200	31,920	35,386	36,123	32,026	38,256	36,317	42,930	44,888	43,659	63,175	64,980

respectively. To maintain the effectiveness of data, crisp numbers are used to represent the DM's quantitative assessments. The term set {Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)} is used to denote the fuzzy values, whose membership functions are given in Fig. 4. Table 4 shows the assessment result. The assessments for the oil consumption cost (C_{21}) and other costs (C_{22}) are adjusted by taking the reversal of the original data multiplied by 10,000 to make a consistent comparison across all criteria.

Sub-criteria weights, which are not affected by task requirements, are given directly by using the term set {Very Unimportant (VU), Unimportant (U), Medium (M), Important (I), Very Important (VI)} with membership functions defined in Fig. 5. Table 5 shows the result.

To help better illustrate how the task requirements affect the dispatching decisions via criteria weights, a simulation study has been carried out by adjusting one task requirement at a time while keeping others unchanged. The simulation result shows that a rather consistent ranking of dredgers is generated for changes in one task requirement only. This is due to the fact that the difference between the relative performance assessments of dredges is more significant than the slight change in the relative weights of criteria. As an example, Fig. 6 shows how the criteria weights and the corresponding preference indexes are affected under various daily volume requirements, while the other four requirements are kept unchanged.

In this simulation study, except for situations where the weight of the efficiency criterion (C_1) is relatively low, dredger A_{12} is almost always dominant due to the fact that its performance assessments are much superior to others. For example, dredger A_{12} is no longer the preferred one when

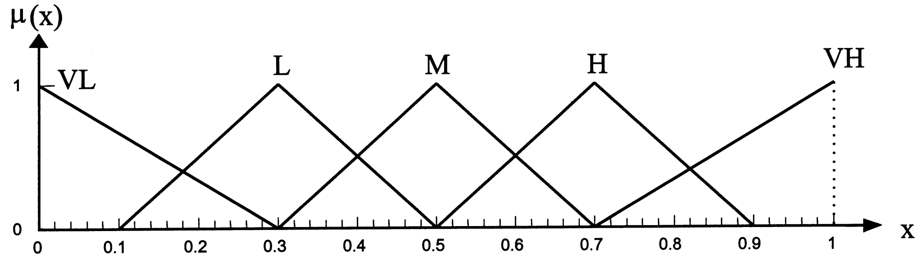


Fig. 4. Membership functions of linguistic terms used for qualitative assessments.

Table 4
Performance ratings for criteria and sub-criteria

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
C_{21}	400	384.62	270.27	263.16	222.22	212.77	208.33	185.19	188.68	196.08	133.33	125
C_{22}	2.5	2.381	2.222	2.128	2.083	2	1.887	2.083	1.818	1.667	1.429	1.389
C_{31}	H	M	L	H	VH	VL	M	H	VH	M	M	H
C_{32}	M	H	H	M	H	L	H	VH	VH	M	H	M
C_{41}	VH	M	L	H	VL	L	H	VH	M	VL	L	H
C_{42}	VH	H	L	M	L	M	M	H	VL	H	VL	M
C_{51}	0.65	0.88	0.41	0.71	0.60	0.83	0.84	0.93	0.43	0.82	0.55	0.42
C_{52}	2.5	1.667	2	1.423	5	10	3.333	2.6	1.111	1.25	1.667	2

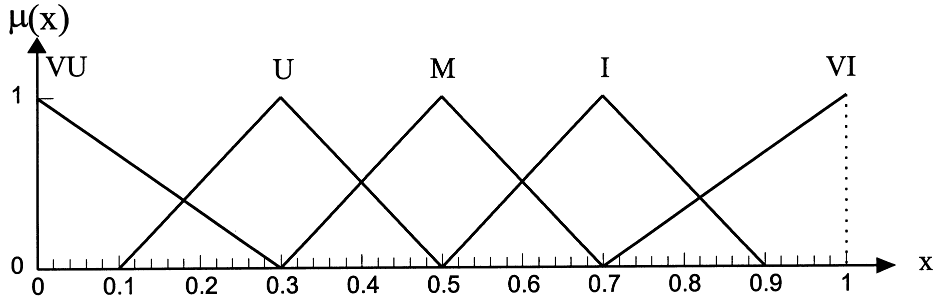


Fig. 5. Membership functions of linguistic terms used for representing sub-criteria weights.

Table 5
Weighting vectors for sub-criteria

Weighting vector (W_j)	Fuzzy weights for sub-criteria ((w_{j1}, w_{j2}))
W_2	(VI, U)
W_3	(I, M)
W_4	(VI, M)
W_5	(M, VI)

the daily volume requirement is below 27,000 m^3, as shown in Fig. 6. This indicates that the major difference in performance assessments between dredgers lies in the efficiency criterion. In addition, this seems to suggest that it is not necessary to assign the most efficient dredger to a task for which efficiency is not a major concern.

To examine the effect of various task requirements on the preference ranking of dredgers, further simulation study has been conducted. It is designed to cover all possible situations of task requirements and to verify the effectiveness of the fuzzy rules in Table 2. The states of the five task requirements are changed from the lowest to the highest and from the highest to the lowest respectively, resulting in the testing of 32 scenarios. In each scenario, the state of each task requirement is equally divided into 100 scales. As a result, 3200 different conditions of task requirements are examined altogether. For simplicity, we present only four representative scenarios here as an example to demonstrate the effectiveness of the model developed. Table 6 shows how the state of the five task requirements is changed in the four scenarios (A, B, C, and D). Figs. 7 and 8 show their corresponding preference rankings.

Figs. 7 and 8 reveal that changes in task requirements may affect the relative criteria weights, resulting in a different dredger being selected. Fig. 7(a) shows that the relative preference rankings of dredgers are almost unchanged when the task requirements are all changed simultaneously from the lowest condition to the highest condition. This is because similar linguistic values are used for the five task requirements, resulting in similar ratios of criteria weights. However, the difference between the relative preference rankings is increased as the state of the task requirements is changed in different directions, as shown in Fig. 7(b) and 8. This indicates that the relative preference ranking of dredgers coincides with the relative state of the task requirements. In this

Table 6
Changes of the states of five task requirements

	Task requirement				
Scenario	T_1	T_2	T_3	T_4	T_5
A	Low → High	High → Low	Low → High	Low → High	Low → High
B	Low → High	High → Low	High → Low	Low → High	Low → High
C	Low → High	Low → High	Low → High	Low → High	High → Low
D	Low → High	High → Low	High → Low	Low → High	High → Low

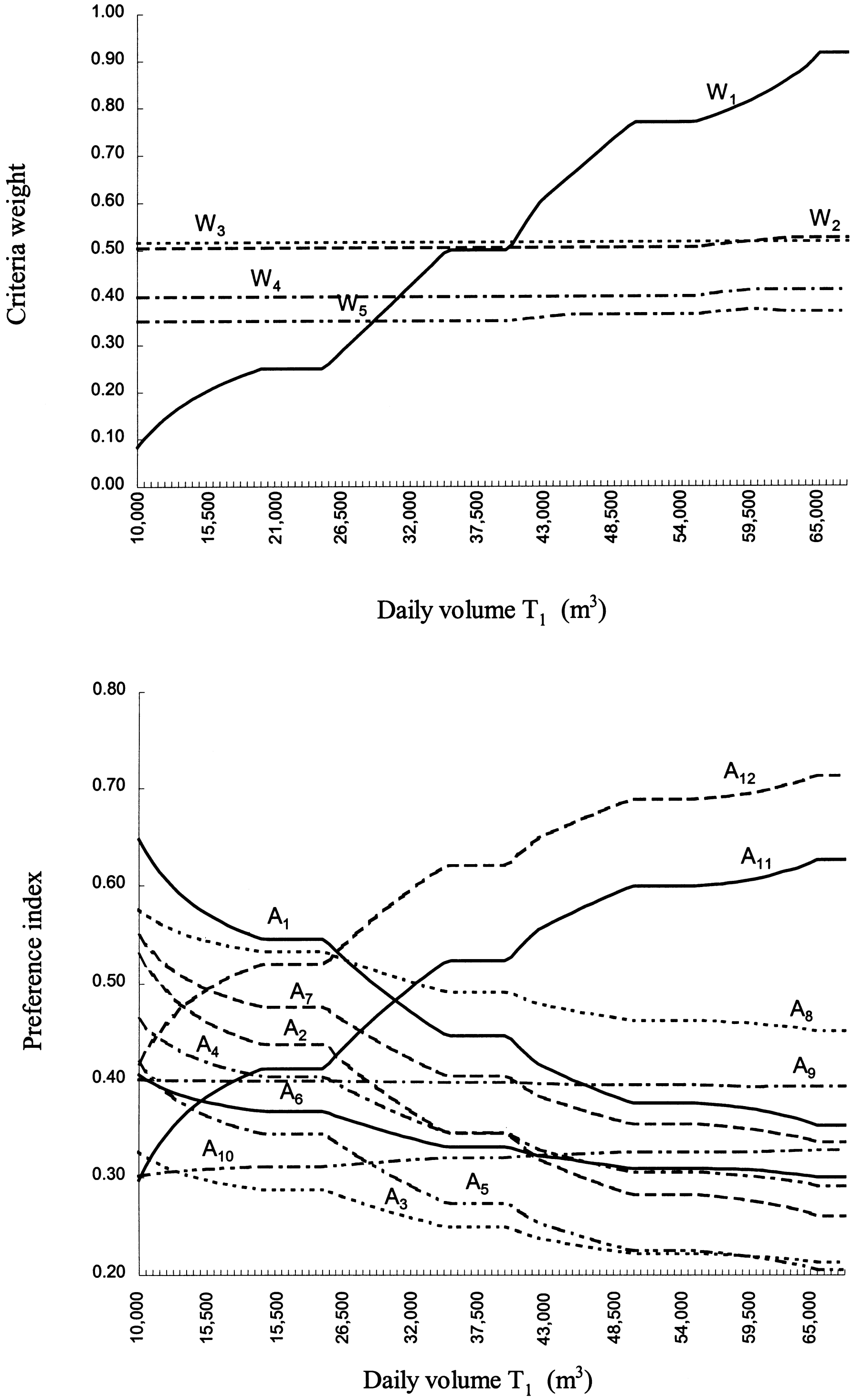
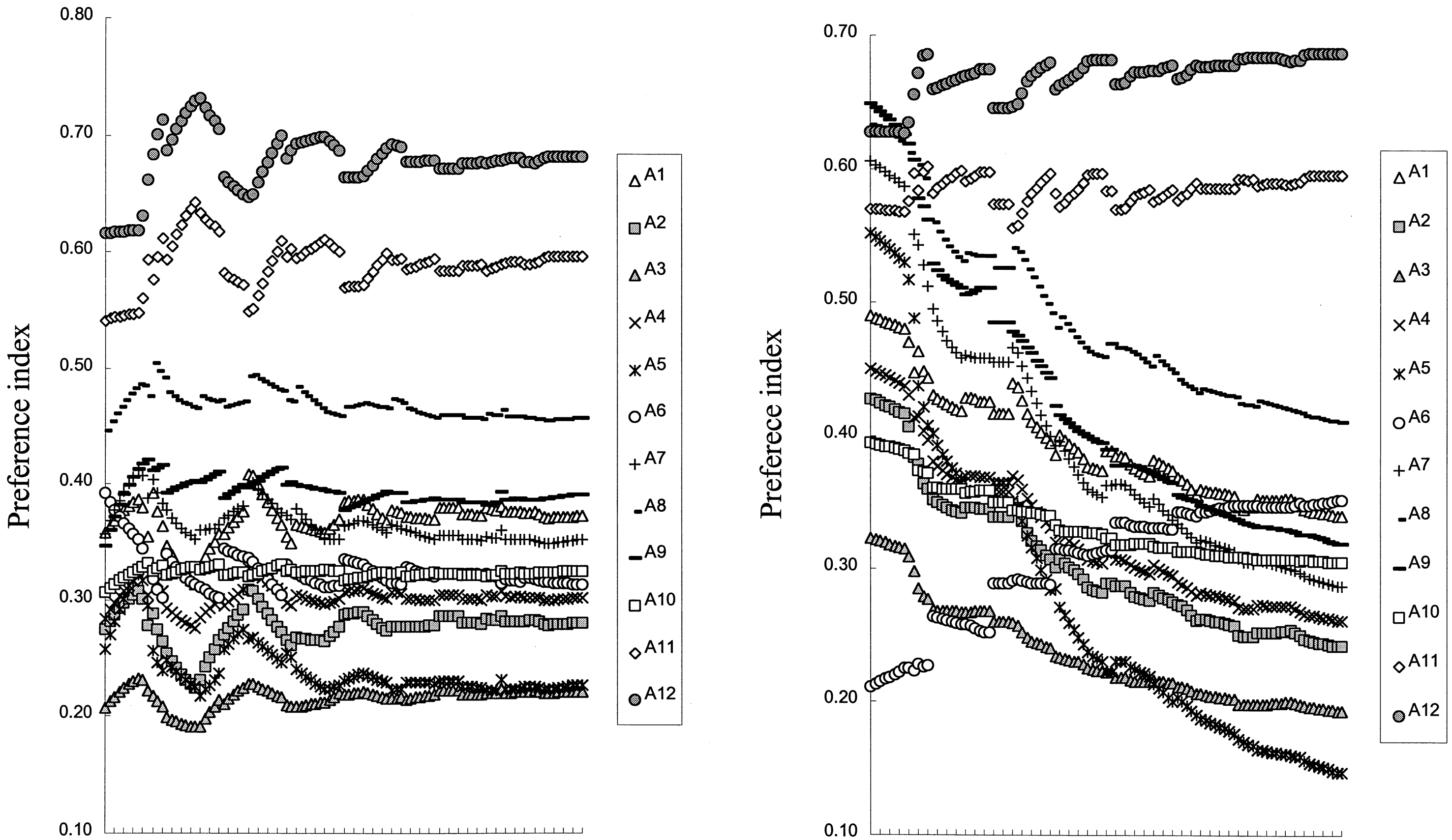


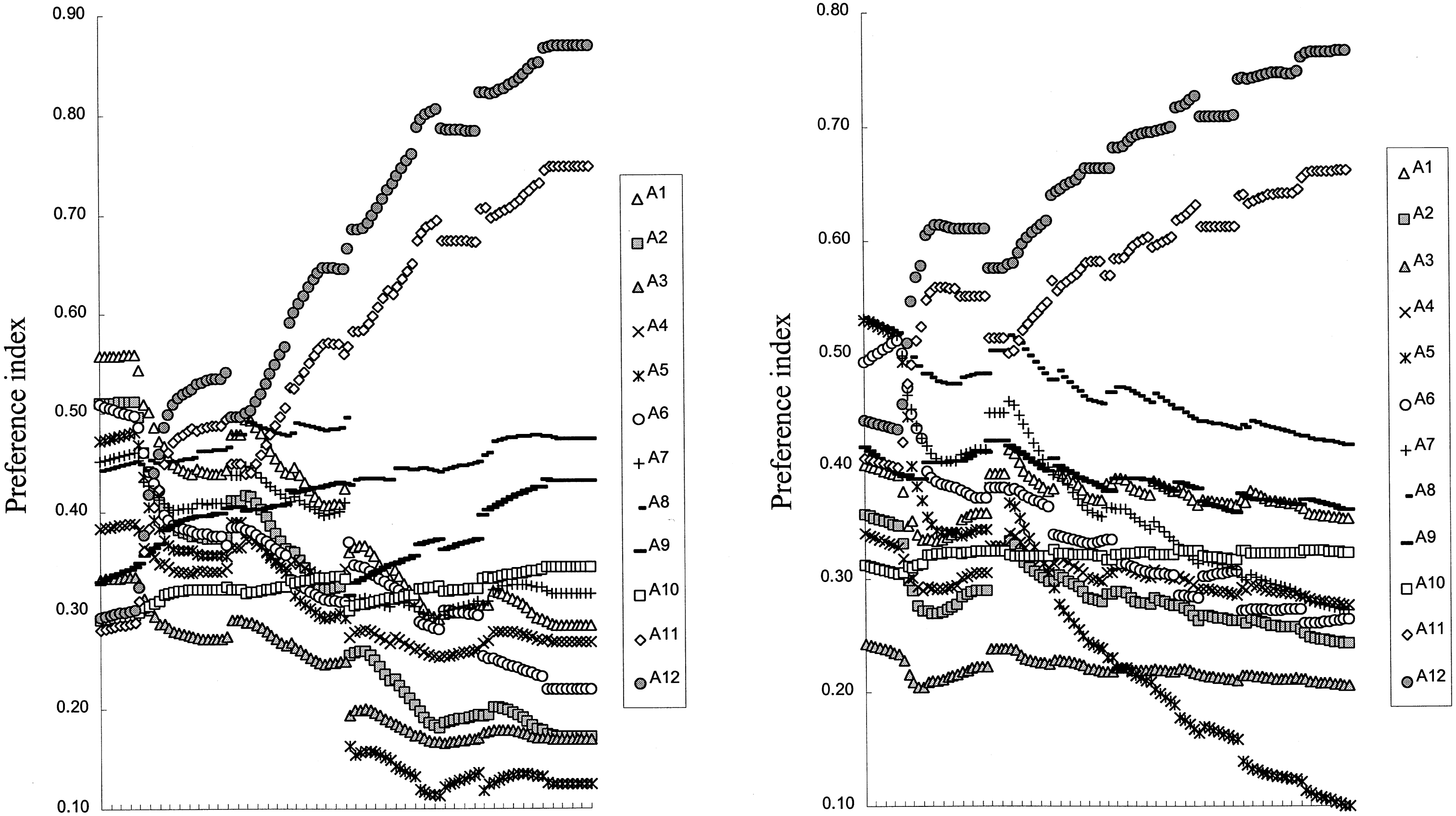
Fig. 6. Criteria weights and corresponding preference indexes under various daily volume requirements.



(a) 100 conditions of scenario A

(b) 100 conditions of scenario B

Fig. 7. Preference ranking for simulated conditions of scenarios A and B.



(a) 100 conditions of scenario C

(b) 100 conditions of scenario D

Fig. 8. Preference ranking for simulated conditions of scenarios C and D.

regard, the dispatcher should pay special attention in situations where the state of each task requirement is assessed quite differently from each other in terms of linguistic terms used in Fig. 2. In particular, when dredgers with relatively high performance ratings (such as A_{12}, A_{11}, and A_8) are not available, difficult decisions are to be made under uncertain task requirements. This result is consistent with the actual dispatching situations that the dispatchers have experienced.

The result of the extensive simulation study demonstrates the importance of determining criteria weights in accord with task requirements in dredger dispatching. This suggests a need for a consistent approach to criteria weighting in the dredger dispatching process under uncertainty. As a decision aid, the fuzzy MA model developed can generate the relative preference ranking for all dredgers available within seconds of the computer time, after simply specifying the state of each task requirement using crisp or fuzzy data. This would reduce the human dispatchers' burden in precise data gathering and complex manipulation, and enable them to focus on a small number of suitable dredgers with necessary information to make an effective decision for a specific dredging task.

7. Conclusion

Uncertainty is a major problem that the DM has to face when selecting the most suitable alternative for a specific task. Very often the task to be accomplished cannot be described precisely due to the time constraints, the immeasurable physical conditions, and particularly the uniqueness of the task requirements.

In this paper, we have presented a new fuzzy MA model to handle the multi-criteria selection problem with imprecise judgements. A particular feature of the model is that criteria weights are determined by fuzzy rules with the specification of the task requirements. It reduces the uncertainty associated with the criteria weighting process. In addition, an algorithm has been developed to produce an effective ranking of alternatives.

An empirical study of a dredger dispatching problem in China has been conducted with extensive simulation tests. The study has demonstrated the effectiveness of the model for solving the problem. The model has significance in the development of MA methodology for dealing with practical problems. With its simplicity in logic and efficiency in computation, the model has general applicability to actual MA problems.

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