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Multi-criteria analysis for dredger dispatching under uncertainty

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Dredger dispatching is a complex decision making process in which multiple requirements and uncertain site conditions have to be taken into consideration simultaneously, for a specific dredging task. In evaluating the suitability of dredgers, besides quantitative assessments, qualitative assessments are often required to deal with uncertainty, subjectiveness and imprecision, which are best represented with fuzzy data. This paper formulates dredger dispatching as a fuzzy multi-criteria analysis model, and presents an effective algorithm for handling both crisp and fuzzy data in a straightforward manner. As a result, effective decisions can be made based on consistent evaluation results. An empirical study of a real case in China is conducted to demonstrate the applicability of the model. With its simplicity in both concept and computation, the model can be implemented as an effective decision aid in selecting dredgers for specific dredging tasks.

Keywords: fuzzy sets; multi-criteria decision analysis; dredger dispatching

Introduction

Inexpensive waterborne traffic is an important worldwide means of transport. To maintain its efficiency and effectiveness, dredgers must be dispatched regularly to remove the sediment from the bottom of channels which may block normal waterborne traffic. The dispatching process generally requires simultaneous consideration of task requirements and site conditions.[1,2] The task requirements, reflecting the dispatcher's major concern of the dredging task, are determined by such factors as the permitted dredging time, site importance, quality expectation, etc. The site conditions, directly affecting the dredger performance, are usually characterised by such factors as the soil condition, wave heights, and wind strength, etc.

The decision making process of dredger dispatching always involves uncertainty and imprecision. Site conditions are uncertain and unpredictable, and hard to assess accurately. The dispatcher's expression of the task requirements is often subjective and imprecise. This inexactness, subjectiveness and imprecision make the dispatching process complex and challenging.[3,4]

To assign the most suitable dredger to a specific dredging task, an evaluation of the overall performance of dredgers is required. The evaluation criteria are multiple and often structured in multi-level hierarchies, with quantitative and qualitative assessments being coexistent. It is evident that a multi-criteria analysis (MA) model with the capability of handling both quantitative and qualitative data is desirable for making the evaluation effective and consistent.

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In this paper, we present a fuzzy MA approach to deal with the dredger dispatching problem, with a case study on typical dredger dispatching situations in Shanghai, China. The approach can effectively evaluate the relative performance of each dredger for a specific dredging task, thus assisting the dispatcher in making decisions.

In the following discussion, we first describe the dredger dispatching problem in Shanghai, China, followed by a review of the existing fuzzy MA methodology. We then present a fuzzy MA model for solving the dispatching problem. Finally, we conduct an empirical study to demonstrate how the model can be used to support dispatching decisions under various dredging situations.

Dredger dispatching in Shanghai

Shanghai, situated in the lower reaches of the Yangtze river, is a major industrial city and the most important port of China. Waterborne transport, the lifeline of the city, plays a key role in promoting the city's prosperity in the booming Chinese economy by shipping cargo in and out, both nationally and internationally. Large quantities of soil from the upper reaches of the Yangtze river pour downstream and settle in the waterway between the river and the east China sea all year around, obstructing the normal waterborne traffic. As a consequence, keeping waterborne traffic running smoothly becomes a major task for the state-authorised dredging company, which has twelve trailing suction hopper dredgers.

As the most important decision made regularly by the company, dredger dispatchintg is often carried out in an *ad hoc* manner with unreliable interpretations. Dispatchers make decisions with their experience and intuition based on the information available. Task requirements and site conditions are so imprecise and uncertain that the dispatchers usually find it hard to express their assessments and judgements consistently.

Depending on the task requirements and the site conditions, various criteria have to be considered for evaluating the overall performance of dredgers with regard to a specific dredging task. A comprehensive investigation of the criteria affecting dredger performance has been carried out by consulting the experienced dispatchers in Shanghai. As a result, the hierarchical structure for the dredger performance evaluation problem in Shanghai is depicted as in Figure 1. We briefly discuss the criteria and their associated sub-criteria below.

The operating efficiency (C_1) of a dredger is signified by the actual daily dredging volume (V_a) (cubic meters of soil) that the dredger can complete during a day's work for a given site condition. V_a of a dredger 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

$$V_a = f_d \times f_s \times f_a \times V_d \tag{1}$$

where f_d, f_s and f_a ($0 < f_d, f_s, f_a \leqslant 1$) are the efficiency factors in relation to the draghead type, stability, and depth adaptability respectively, for a given soil condition and wave height.

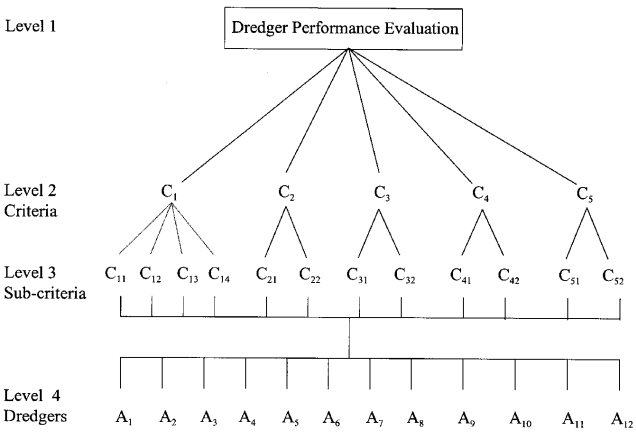
The operating cost (C_2) mainly consists of the oil consumption, crew's salary, and the maintenance cost. These costs are usually estimated by the financial department of the company based on the relevant historical data. Due to the nature of the dredging process, the oil consumption cost is generally separated from the total operating cost. Therefore, the oil consumption cost and other costs are the two sub-criteria for the operating cost, these are measured quantitatively.

Dredging quality (C_3) is concerned with the degree of satisfaction that the dispatcher has on the completed task, which is mainly affected by the dredging depth, the side slope, and the bed smoothness. From the dispatcher's perspective, the crew's experience and operating skills are the two most important sub-criteria, and they are assessed subjectively.

Dredger Safety (C_4) relates to the complexity of the site conditions and the skills of the crew assigned to a dredger. In general, crew safety awareness and crew safety training are the two main sub-criteria to be considered. They are assessed subjectively.

Dredger reliability (C_5) is of great concern in maintaining the dredging schedule and completing the task satisfactorily. The average maintenance rate and the operating life rate are the two main sub-criteria to be considered quantitatively. The former is determined by the ratio of the dredger maintenance frequency to its annual operating time, and the latter is calculated by the ratio of the dredger's depreciation lifetime to its total operating time.

The overall performance of the twelve dredgers (alternatives) ($A_1, A_2 \ldots, A_{12}$) for a given dredging task can be obtained by (a) assigning weights to the 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.



Legend:

C_1: Efficiency, C_2: Cost, C_3: Quality, C_4: Safety, C_5: Reliability.

C_{11}: Designed Daily Capacity, C_{12}: Draghead Type,
C_{13}: Dredger Stability, C_{14}: Dredger Depth Adaptability,
C_{21}: Oil Consumption Cost, C_{22}: Other Costs,
C_{31}: Crew Experience, C_{32}: Crew Operating Skills,
C_{41}: Crew Safety Awareness, C_{42}: Crew Safety Training,
C_{51}: Average Dredger Maintenance Rate, C_{52}: Dredger Operating Life Rate.

A_1: Dredger 1, A_2: Dredger 2, A_3: Dredger 3, A_4: Dredger 4,
A_5: Dredger 5, A_6: Dredger 6, A_7: Dredger 7, A_8: Dredger 8,
A_9: Dredger 9, A_{10}: Dredger 10, A_{11}: Dredger 11, A_{12}: Dredger 12.

Figure 1 Hierarchical structure of the dredger performance evaluation problem.

Multi-criteria analysis under uncertainty

Multi-criteria analysis (MA) is used to assist the decision maker (DM) in prioritising or selecting one or more alternatives from a finite set of available ones with respect to multiple, usually conflicting criteria.[5–9] With the characteristics of the dredger dispatching problem, MA is well suited for evaluating the overall performance of dredgers for a specific dredging task.

Uncertainty is often associated with human decision making.[10–13] Methods for handling uncertainty are developed basically along the lines of probability theory or fuzzy set theory. The former focuses on the stochastic nature of the decision making process, while the latter is concerned with the subjectiveness and imprecision of human judgements.[7,14] It is well recognised that stochastic methods such as statistical analysis cannot handle the subjectiveness and imprecision involved in the decision making process adequately.[7,12,13,15]

The application of fuzzy set theory[16] to MA provides an effective means of formulating decision problems in a fuzzy environment, where the information available is subjective and imprecise. The subjective assessments of the decision problem can be well handled by fuzzy data.[10–12,17–19]

Outranking theory and utility theory are the two main streams of development in fuzzy MA methodology. Successful applications of existing fuzzy MA approaches to decision making problems have been reported.[7,20–24] However, no single approach is exempt from criticism about its overall performance and practical use in tackling real problems. The approaches based on the outranking concept may be complex and hard to use.[7,25] For the approaches developed in the context of multi-attribute utility theory, the ranking of the fuzzy utility remains a challenging issue, as it is not straightforward and reliable.[7,26,27]

To effectively solve the dredger dispatching problem by fuzzy MA methodology, we propose an algorithm for handling both crisp and fuzzy data in a straightforward manner. To aggregate the DM's crisp and fuzzy assessments with respect to dredger performance and criteria importance, we take advantage of multi-attribute utility theory. The crisp data is normalised to make it comparable with the fuzzy data. To avoid the troublesome, unreliable process of fuzzy number ranking, we introduce the concept of the degree of optimality for each dredger with respect to each criterion, in order to transform a fuzzy performance matrix into a fuzzy singleton matrix. We then obtain an overall performance index for each dredger using the concept of the ideal solution.[28–30]

The fuzzy multi-criteria analysis model

The dredger dispatching problem usually consists of (1) a fleet of available dredgers, denoted as A_i $(i = 1, 2, \ldots, n)$ (2) a set of criteria C_j $(j = 1, 2, \ldots, m)$ and their associated subcriteria C_{jk} $(k = 1, 2, \ldots, p_j)$ if existent, about which the dredger performance is measured quantitatively or qualitatively, (3) a performance assessment of a dredger with respect to each criterion C_j or its associated sub-criteria C_{jk} if existent, resulting in the determination of the decision matrix for the criteria or their associated sub-criteria, and (4) a set of weighting vectors representing the relative importance of the criterion and its associated sub-criteria.

Linguistic values or terms have been found intuitively easy to use in expressing the subjectiveness and vagueness of the DM's assessments.[31–33] To facilitate the making of qualitative assessments in the dredger dispatching process, two linguistic variables, importance and capability, are used.

Using these two linguistic variables allows the dispatcher (the DM) to vaguely specify the importance of criteria and their associated sub-criteria, and to effectively assess the capability of each dredger in satisfying these criteria and sub-criteria. This setting greatly reduces the DM's cognitive burden in the evaluation process. For example, dreder A_1 has a 'high' capability to achieve criterion C_3, which has a 'medium' importance. The former term 'high' is a linguistic value of the capability variable, and the latter term 'medium' is a linguistic value of the Important variable. To simplify the computational process, triangular fuzzy numbers are used to represent the approximate distribution of these linguistic values, denoted as (a_1, a_2, a_3), where $0 \leqslant a_1 \leqslant a_2 \leqslant a_3 \leqslant 1$. a_2 is the most possible assessment value, and a_1 and a_3 are the lower and upper bounds respectively for reflecting the fuzziness of the assessment. Table 1 gives the states and their corresponding linguistic values of these two linguistic variables.[7,32]

To maintain the effectiveness of data needed, crisp numbers are used to represent the DM's crisp assessments with respect to quantitative criteria. This makes the evaluation process effective by not forcing the originally crisp captured data into a fuzzy format.

Expressed by either the linguistic values of the Capability variable defined in Table 1, or by crisp numbers, the decision matrix for criteria is given as

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{2}$$

where x_{ij} represents the DM's assessment of the performance rating of dredger $A_i (i = 1, 2, \ldots, n)$ with respect to

Table 1 Linguistic values of the 'Capability' of dredgers and the 'Importance' of criteria

Capability			*Importance*		
Assessment		*Membership function*	*Assessment*		*Membership function*
Very Low	(VL)	(0.0, 0.0, 0.3)	Very Unimportant	(VU)	(0.0, 0.0, 0.3)
Low	(L)	(0.1, 0.3, 0.5)	Unimportant	(U)	(0.1, 0.3, 0.5)
Medium	(M)	(0.3, 0.5, 0.7)	Medium	(M)	(0.3, 0.5, 0.7)
High	(H)	(0.5, 0.7, 0.9)	Important	(I)	(0.5, 0.7, 0.9)
Very High	(VH)	(0.7, 1.0, 1.0)	Very Important	(VI)	(0.7, 1.0, 1.0)

criterion C_j ($j = 1, 2, \ldots, m$). This is to be given by the DM or aggregated from the lower-level decision matrix for its associated sub-criteria.

If sub-criteria $C_{jk}(k = 1, 2, \ldots, p_j)$ are used for criterion C_j, a lower-level decision matrix is to be given, as in (3), where y_{ik} is the DM's assessments of the performance rating of dredger A_i with respect to sub-criteria C_{jk} of the criterion C_j, expressed in either linguistic or crisp value, dependent on the sub-criteria used.

$$Y_{C_j} = \begin{bmatrix} y_{11} & y_{21} & \cdots & y_{n1} \\ y_{12} & y_{22} & \cdots & y_{n2} \\ \cdots & \cdots & \cdots & \cdots \\ y_{1p_j} & y_{2p_j} & \cdots & y_{np_j} \end{bmatrix} \quad (3)$$

The weighting vectors for the evaluation criteria or sub-criteria can be directly given by the DM, or obtained by using the pairwise comparison of the analytic hierarchy process.[7,34] Expressed by the linguistic values of the Importance variable defined in Table 1, the weighting vectors W and W_j ($j = 1, 2, \ldots, m$) for the criteria and associated sub-criteria are represented by (4) and (5), where w_j and w_{jk} are the fuzzy weights of criterion C_j ($j = 1, 2, \ldots, m$) and its sub-criteria C_{jk} ($k = 1, 2, \ldots, p_j$) respectively.

$$W = (w_1, w_2, \ldots, w_j) \quad (4)$$

$$W_j = (w_{j1}, w_{j2}, \ldots, w_{jk}) \quad (5)$$

For the decision matrix given as in (2) or (3), a normalisation process using (6) is applied to the crisp data to make it compatible across criteria or sub-criteria. For simplicity of representation, we assume that the decision matrices in (2) and (3) are normalised.

$$z'_{is} = \frac{z_{is}}{\sqrt{\sum_{i=1}^{n}(z_{is})^2}}, \quad \begin{array}{ll} i = 1, 2, \ldots, n, & s = j \text{ or } k, \\ j = 1, 2, \ldots, m, & k = 1, 2, \ldots, p_j. \end{array} \quad (6)$$

If criterion C_j consists of sub-criteria C_{jk}, the decision vector $(x_{1j}, x_{2j}, \ldots, x_{nj})$ across the dredgers with respect to criteria C_j in (2) is first determined by

$$(x_{1j}, x_{2j}, \ldots, x_{nj}) = \frac{W_j C_{C_j}}{\sum_{k=1}^{p_j} w_{jk}} \quad (7)$$

This is an aggregation utility function for criterion C_j with a multi-level hierarchy. The utility function is the multiplication of the weighting vector W_j for its lower-level sub-criteria C_{jk} and the corresponding decision matrix Y_{Cj}. With the use of triangular fuzzy numbers, the arithmetic operations on fuzzy numbers are based on interval arithmetic.[35,36]

Clearly, although a two-level hierarchy is exemplified for the case studied in this paper, the use of the utility function for aggregating assessments from lower-level sub-criteria can be applied to the problem with multi-level hierarchies of the evaluation criteria.

A fuzzy performance matrix is then obtained by multiplying the weighting vector in (4) by the decision matrix in (2). Each fuzzy vector $(w_j x_{1j}, w_j x_{2j}, \ldots, w_j x_{nj})$ of the fuzzy performance matrix represents the fuzzy performance of all dredgers A_i ($i = 1, 2, \ldots, n$) with respect to criterion C_j ($j \in \{1, 2, \ldots, m\}$). To determine the relative performance of dredger A_i for each criterion C_j, their corresponding fuzzy performance $(w_j x_{ij})$ is compared with a fuzzy maximum $(M^j_{\max})$ and a fuzzy minimum $(M^j_{\min})$ respectively by

$$u_{h_j}(i) = \sup(w_j x_{ij} \cap M^j_{\max})$$

and (8)

$$u_{l_j}(i) = 1 - \sup(w_j x_{ij} \cap M^j_{\min})$$

The fuzzy maximum $(M^j_{\max})$ and the fuzzy minimum $(M^j_{\min})$ are defined as[37]

$$u_{M^j_{\max}}(x) = \frac{x - x^j_{\min}}{x^j_{\max} - x^j_{\min}}, \qquad u_{M^j_{\min}(x)} = \frac{x^j_{\max} - x}{x^j_{\max} - x^j_{\min}}, \quad (9)$$

where

$$x^j_{\max} = \sup \bigcup_{i=1}^{n} (w_j x_{ij}), \qquad x^j_{\min} = \inf \bigcup_{i=1}^{n} (w_j x_{ij}). \quad (10)$$

For each criterion C_j, $u_{h_j}(j)$ and $u_{l_j}(i)$ in (8) represent respectively the highest degree of approximation of dredger A_i's performance to the fuzzy maximum and the lowest degree of approximation of dredger A_i's performance to the fuzzy minimum.[10,38] This setting is in accord with the optimal decision of Bellman and Zadeh,[10] who state that 'in a fuzzy environment, objectives and constraints formally have the same nature and their confluence can be represented by the intersection of fuzzy sets'. As such, $u_{h_j}(i)$ and $u_{l_j}(i)$ can be regarded as the degree to which dredger A_i is the best dredger and not the worst dredger with respect to criterion C_j respectively.

The degree of optimality (or preferability) of dredger A_i over all other dredgers with respect to criterion C_j is thus determined by

$$r_{ij} = \frac{u_{h_j}(i) + u_{l_j}(i)}{2}, \qquad i = 1, 2, \ldots, n; \qquad j = 1, 2, \ldots, m. \quad (11)$$

A fuzzy singleton[39] performance matrix can be obtained by (11), given as

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \quad (12)$$

To obtain a crisp overall performance value for each dredger, the concept of the ideal solution[28–30] is used. This concept is capable of depicting the pursuit of the best performance with regard to each criterion in a simple mathematical form. The positive ideal solution r^+ and the negative ideal solution r^-, representing the best possible and the worst possible results of the dredgers respectively, are then determined by

$$r^+ = (r_1^+, r_2^+, \ldots, r_m^+), \qquad r^- = (r_1^-, r_2^-, \ldots, r_m^-), \quad (13)$$

where

$$r_j^+ = \sup(r_{1j}, r_{2j}, \ldots, r_{nj}), \qquad r_j^- = \inf(r_{1j}, r_{2j}, \ldots, r_{nj}), \quad j = 1, 2, \ldots, m. \quad (14)$$

From (12)–(14), the Hamming distance between dredger A_i and the positive ideal solution and the negative ideal solution can be calculated respectively by

$$s_i^+ = \sum_{j=1}^{m}(r_j^+ - r_{ij}); \quad s_i^- = \sum_{j=1}^{m}(r_{ij} - r_j^-) \quad i = 1, 2, \ldots, n. \quad (15)$$

Based on the concept that a preferred dredger is to be as close to the positive ideal solution as possible, and as far from the negative ideal solution as possible,[28–30,40] an overall performance index for dredger A_i across all criteria is determined by (16). The larger the performance index, the more preferred the dredger

$$P_i = \frac{s_i^-}{s_i^+ + s_i^-}, \qquad i = 1, 2, \ldots, n. \quad (16)$$

The algorithm for the fuzzy MA model presented above is summarised below:

1. Obtain the decision matrix for the sub-criteria, as expressed in (3).
2. Normalise the decision matrix by (6) for the sub-criteria obtained at Step 1 if quantitatively assessed data exists.
3. Determine the weighting vectors for the sub-criteria, as expressed in (5).
4. Obtain the decision vector for the criteria with sub-criteria by (7).
5. Determine the decision matrix for the criteria, as expressed in (2), by Step 4 or by the DM's assessment of the performance ratings of dredgers.
6. Normalise the decision matrix obtained at Step 5 by (6) for criteria with quantitative data.
7. Determine the weighting vector for the criteria, as expressed in (4).
8. Obtain the fuzzy performance matrix by multiplying the decision matrix obtained at Step 6 by the weighting vector determined at Step 7.
9. Determine the degree of optimality of each dredger regarding each criterion by (8)–(11), resulting in a fuzzy singleton matrix, as shown in (12).
10. Determine the positive ideal solution and the negative ideal solution by (13) and (14).
11. Calculate the Hamming distance between each dredger and the positive ideal solution and the negative ideal solution obtained at Step 10 respectively by (15).
12. Compute the overall performance index for each dredger by (16).
13. Rank the dredgers in descending order of their overall performance index value.

The empirical study

In this section, we present an empirical study of real situations that the dredging company in Shanghai have often confronted. The complexity and uncertainty of the dispatching process is illustrated, and the effect of the task requirements and site conditions on the selection of the most suitable dredger is exemplified.

We first consider the situation of three dredging tasks (I, II and III) represented by different task requirements for the same site condition. The criteria weights reflecting the different task requirements set out for the three tasks are given in Table 2. The weighting vectors for the associated sub-criteria are the same for the three tasks, given in Table 3. The performance ratings of the twelve dredgers with regard to the criteria and their associated sub-criteria are the same, because the site condition considered for the three tasks is the same.

Table 4 gives the designed daily dredging volume (V_d) of each dredger and the three efficiency factors (f_d, f_s and f_a) for the site condition considered. With the data in Table 4, the dredger performance with respect to the efficiency

Table 3 Weighting vectors for the associated sub-criteria

Weighting vector (W_j)	*Fuzzy weights for the associated sub-criteria* (w_{j1}, w_{j2})
W_2	((0.7, 1.0, 1.0), (0.1, 0.3, 0.5))
W_3	((0.5, 0.7, 0.9), (0.3, 0.5, 0.7))
W_4	((0.7, 1.0, 1.0), (0.3, 0.5, 0.7))
W_5	((0.3, 0.5, 0.7), (0.7, 1.0, 1.0))

Table 2 Weighting vectors for the criteria under three different tasks

Task	*Fuzzy weights for criteria (W)*
I	((0.5, 0.7, 0.9), (0.1, 0.3, 0.5), (0.5, 0.7, 0.9), (0, 0, 0.3), (0.5, 0.7, 0.9))
II	((0.3, 0.5, 0.7), (0.7, 1.0, 1.0), (0.5, 0.7, 0.9), (0, 0, 0.3), (0.5, 0.7, 0.9))
III	((0.5, 0.7, 0.9), (0.5, 0.7, 0.9), (0.5, 0.7, 0.9), (0.7, 1, 1), (0.5, 0.7, 0.9))

criterion is measured quantitatively by (1). Table 5 shows the result.

Quantitative and qualitative performance assessments about other criteria and their associated sub-criteria are given by crisp numbers and linguistic values respectively. Table 6 shows the results. The assessments for the oil consumption costs (C_{21}) and other costs (C_{22}) are adjusted by taking the reversal of the original data multiplied by 10 000 to make the comparison across all criteria consistent.

Table 7 shows the overall performance index value for each dredger and its corresponding ranking order. Clearly, dredger A_{12}, A_1, and A_8 are the preferred choice for the three tasks respectively.

The results shown in Table 7 indicate that different task requirements may result in a different dredger being selected for the same site condition. This demonstrates the complexity of dredger dispatching, and reflects the needs for a structural approach.

Table 4 Data for measuring 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}
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

Table 5 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

Table 6 Assessments for other criteria and associated 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

Table 7 Performance index of dredgers and their corresponding ranking order

	Task I		*Task II*		*Task III*	
Dredger	*Index value*	*Ranking*	*Index value*	*Ranking*	*Index value*	*Ranking*
A_1	0.4506	4	0.5051	1	0.5503	2
A_2	0.3902	8	0.4457	4	0.4273	5
A_3	0.2710	12	0.2995	12	0.2739	12
A_4	0.3622	10	0.3865	10	0.4068	7
A_5	0.3848	9	0.4067	6	0.3264	10
A_6	0.4280	5	0.4367	5	0.4088	6
A_7	0.3945	7	0.4049	7	0.4276	5
A_8	0.4791	2	0.4747	2	0.5573	1
A_9	0.3977	6	0.3897	9	0.3759	9
A_{10}	0.3368	11	0.3190	11	0.3089	11
A_{11}	0.4554	3	0.4032	8	0.3920	8
A_{12}	0.5207	1	0.4628	3	0.5214	3

To explore the robustness of the fuzzy MA model against various site conditions under the same task requirements, numerous tests were carried out. The performance assessments for the twelve dredgers were adjusted according to various soil conditions and wave heights. Figure 2 shows the overall performance rankings of dredgers under varying site conditions.

Dredger A_1 is the clear choice for soft clay and fine sand. When the soil condition is sand, the preferred dredger is A_8. As the wave height gradually increases at the work site for the task, A_7 replaces A_8 as the dominant dredger. Obviously, a performance-dominant dredger for one site may not be dominant for another. This demonstrates that the selection of the most suitable dredger is affected not only by the task requirements, but also by the site conditions. A simultaneous consideration of the task requirements and site conditions in dredger dispatching is thus necessary.

Further experiments were carried out to reflect various combinations of task requirements and site conditions. The weighting vectors of the five criteria and the performance assessments of the twelve dredgers were changed simultaneously. The experimental results showed that the multiplicity of the evaluation criteria, the subjectivity of the task requirements, and the uncertainty of the site conditions all influence the selection of the most suitable dredger. The

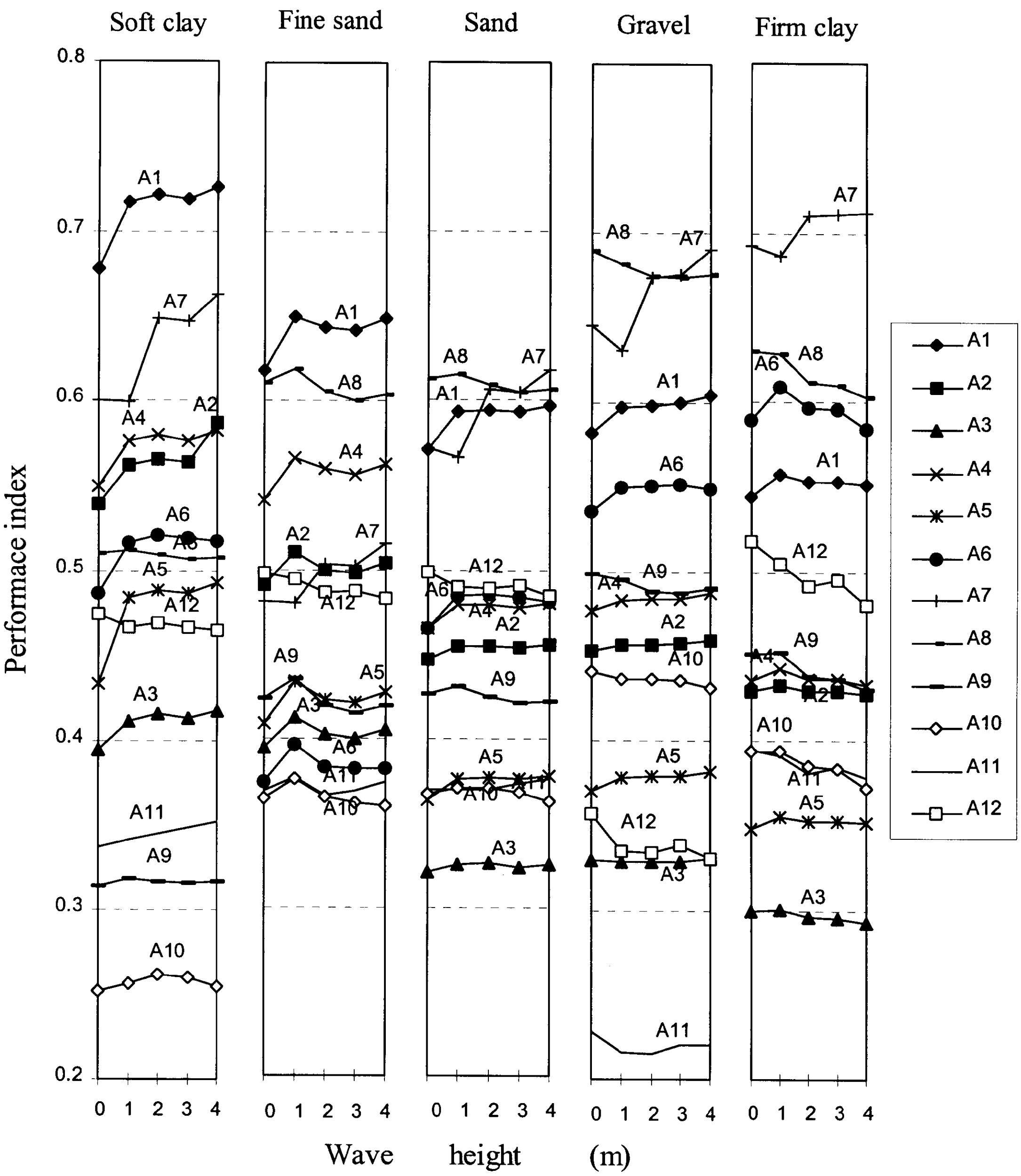


Figure 2 Dredger performance ranking under various soil conditions and wave heights.

expert dispatchers in the dredging company confirmed that no conflicting or unacceptable outcome was produced. In fact, for typical situations encountered by the company, the outcome of the fuzzy MA model was consistent with the decision made by the expert dispatchers.

In its implementation to the dredger dispatching problem in Shanghai, the model has been found easy to use. For a given dredging task, the dispatchers or the relevant authorities need to assess the importance of the criteria in linguistic terms to reflect their concerns about the requirements of the task. Factors considered in the assessment include: (a) the daily dredging volume required; (b) the allowable average daily operating cost; (c) the quality expectation on the dredging depth, width and side slope; (d) the danger level of the dredging site; and (e) the grade of the dredging site. In most situations, performance ratings of the available dredgers require being re-assessed only for the efficiency criterion to correspond to the site conditions of the task. This is because the performance ratings for other criteria are rarely changed with the site conditions.

After specifying the importance of the criteria using fuzzy data and performance ratings of the available dredgers using crisp or fuzzy data, the evaluation result can be generated within seconds of the computer time. The computational efficiency of the model would allow extensive what-if analysis of criteria weighting and performance assessment to take place within the available decision time frame. This would help the human dispatchers focus on the most promising dredgers for the dredging task, with a better understanding of their relative performance rankings for all situations concerned. With the development of user interfaces for specifying criteria weights and performance assessments, the model can be used by the human dispatchers as an effective decision aid in selecting dredgers for specific dredging tasks.

Conclusions

Uncertainty is often associated with the performance evaluation process of dredger dispatching. Traditional *ad hoc* approaches used by experienced dispatchers based on their knowledge and intuition may not always be consistent and reliable. In this paper, we have formulated the dredger dispatching problem as a fuzzy MA model to help the human dispatchers make effective and consistent decisions for various dredging tasks. We have also presented an algorithm to effectively handle both crisp and fuzzy data. This allows the data required by the model to be quantitatively measured or vaguely assessed by linguistic terms, thus facilitating the evaluation process. An empirical study of a real case in China has been conducted to examine the applicability of the model. The study shows that consistent evaluation results can be obtained for given task requirements and site conditions. The model is computationally simple and its underlying concept is comprehensible, thus making it of practical use in solving the general MA decision problem.

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