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Intelligent decision support for effectively evaluating and selecting ships under uncertainty in marine transportation

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ABSTRACT

This paper presents an intelligent decision support system for evaluating and selecting specific ships under uncertainty. A task-oriented procedure is developed for determining the relative importance of the evaluation and selection criteria with respect to a specific shipping task. A fuzzy multicriteria analysis algorithm is developed for determining the overall performance of each ship across all the selection criteria and their associated sub-criteria. An intelligent decision support system capable of integrating the developments above is proposed for facilitating the ship evaluation and selection process. An example is presented to demonstrate the effectiveness of the proposed intelligent decision support system.

1. Introduction

With the increasing globalization and the rapid growth in international trade exemplified by the growth of almost 70% from 1990 to 2004 (United Nations Conference on Trade, 2006), cargo shipping in marine transportation becomes increasingly important to all the stakeholders in international trade. This is especially the case in Australia due to its geographic location and its status as a major supplier of mineral materials in the world (Ang, Cao, & Ye, 2007). As a result, evaluating and selecting the most suitable ship from many available ships for a giving shipping task becomes a critical decision to be made in marine transportation.

Evaluating the suitability of individual ships for a specific task in marine transportation is complex and challenging. The complexity of the evaluation and selection process is due to: (a) the multidimensional nature of the problem (Deng & Wibowo, 2008), (b) the presence of multiple, often conflicting evaluation criteria and their associated sub-criteria (Balmat, Lafont, Maifret, & Pessel, 2009; Eleye-Datubo, Wall, & Wang, 2008), and (c) the existence of subjectiveness and uncertainty in the human decision making process (Wibowo & Deng, 2009; Zimmermann, 2000). The challenge of the evaluation and selection process comes from the need for making transparent and consistent decisions in a timely manner based on a comprehensive evaluation of the suitability of individual ships with respect to a specific shipping task (Ang et al., 2007; Meyrick and Associates, 2007).

Many approaches are developed for solving the ship evaluation and selection problem from different perspectives (Ang et al., 2007; Celik, Deha Er, & Fahri Ozok, 2009; Kandakoglu, Celik, & Akgun, 2009). Ang et al. (2007), for example, propose an integer programming approach for solving the ship evaluation and selection problem. Their approach focuses on maximizing the profit in evaluating and selecting individual ships while simultaneously considering the uncertainty on the shipping capacity in the decision making process. A weighting factor is introduced in assessing the overall suitability of individual ships for accommodating the fact that various objectives in a given situation are of different priorities. This approach is proved to be effective for addressing the ship evaluation and selection problem with limited resources (Gabriel, Kumara, Ordoneza, & Nasseriana, 2005). The approach, however, requires considerable computational effort due to the use of integer programming in the ship evaluation and selection process.

Celik et al. (2009) apply the analytical hierarchy process (AHP) (Saaty, 2007) for solving the ship evaluation and selection problem under uncertainty. With the use of this approach, multiple evaluation and selection criteria are simultaneously considered. To reduce the cognitive burden on the decision maker in the decision making process, pairwise comparison is used for assessing the performance of individual ships and the relative importance of the selection criteria. The approach is shown to be effective for solving the ship evaluation and selection problem. It, however, becomes cumbersome, and may lead to inconsistent decisions being made when the number of alternatives and criteria increases (Yeh, Deng, & Chang, 2000).

Kandakoglu et al. (2009) develop a hybrid approach by integrating business analysis, AHP (Saaty, 2007), and the technique on ordered preference by similarity to the ideal solution (TOPSIS) (Deng, Yeh, & Willis, 2000) for solving the ship evaluation and selection problem. Business analysis is used for adequately

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determining the evaluation and selection criteria through a comprehensive consideration of the interest of various stakeholders in the decision making process. AHP is used for assessing the relative importance of these evaluation and selection criteria. TOPSIS is adopted for determining the overall performance of individual ships across all the evaluation and selection criteria. The approach is found to be intuitively easy to understand and implement. This approach, however, is questioned on its modeling of the uncertainty and subjectiveness of the human decision making process.

This paper presents an intelligent decision support system (DSS) for effectively evaluating and selecting ships under uncertainty in marine transportation. To effectively handle the multi-dimensional nature of the problem, the methodology of multi-criteria is used. To adequately determine the relative importance of the evaluation and selection criteria with respect to a specific shipping task in the weighting process, a task-oriented procedure is proposed. To determine the overall performance of each ship across all the selection criteria and their associated sub-criteria on which the selection decision is made, a fuzzy multicriteria analysis algorithm is developed based on the concept of ideal solution and the degree of dominance. To demonstrate the applicability of the proposed intelligent DSS for solving the ship evaluation and selection problem under uncertainty, an example is presented.

In what follows, we first present the ship evaluation and selection problem in the context of multicriteria analysis, followed by a task-oriented procedure for determining the weightings of the selection criteria. We then develop a fuzzy multicriteria analysis algorithm for solving the ship evaluation and selection problem on which an intelligent DSS is proposed. Finally we present an example for demonstrating the applicability of the proposed intelligent DSS for solving the ship evaluation and selection problem under uncertainty.

2. Formulating the ship evaluation and selection problem

RightShip is formed as a joint venture company by two biggest producers of mineral resources in Australia including BHP Billiton and Rio Tinto. The objective of the company is to improve the decision making process of evaluating and selecting available ships with respect to a specific shipping task in the two companies respectively, and at the same time to offer its ship evaluation and selection services to their global customers involved in marine transportation. Since being formed in 2001, RightShip has grown substantially to serve a global client base far beyond its parent companies.

The challenge that RightShip faces in evaluating and selecting ships is to make timely and consistent recommendations to its customers on the selection of specific ships by adequately considering the interest of various stakeholders in the ship evaluation and selection process (Guneri, Cengiz, & Seker, 2009; Kandakoglu et al., 2009). To assign the most suitable ship to a specific task, the decision maker needs to evaluate the overall performance of each available ship with respect to the specific conditions of individual ships and the requirements of a given task (Deng & Wibowo, 2008; Vis, 2006). With the multi-dimensional nature of the ship evaluation and selection problem, multicriteria analysis provides a systematic framework for effectively solving the ship evaluation and selection problem (Yeh, Deng, Wibowo, & Xu, 2010).

A typical ship evaluation and selection problem is usually characterized by the availability of various ships and the presence of multiple, usually conflicting evaluation and selection criteria and their associated sub-criteria if existent. The ship evaluation and selection process consists of: (a) identification of the requirements for a specific shipping task, (b) assessment of the task requirements, (c) evaluation of the overall performance of all the available ships, and (d) selection of the most suitable ship.

Identifying the requirements of a shipping task for solving the ship evaluation and selection problem involves in determining the interest of various stakeholders in a given situation. These stakeholders may include the ship owner, the ship manager, the financial institution, and the insurance company (Barnhart & Laporte, 2007; Guneri et al., 2009). They often have different interests on the selection of a specific ship for a given task, reflected by the specific requirements on the selection of individual ships. For example, ship owners concern more about the overall efficiency of the ship (Balmat et al., 2009). Ship managers care more about the shipping cost and compliance with international regulations (Ang et al., 2007). Financial institutions are more interested in the return on their investment (Barnhart & Laporte, 2007). Insurance companies are concerned with the safety of each ship.

Task requirements as a reflection of the expectations of the stakeholders on a given task are usually assessed subjectively by the decision maker. This often leads to different weightings being given to various evaluation and selection criteria in the multicriteria decision making process. For example, a ship manager who concerns about the cost of the ship will give a higher weighting on the operating efficiency criterion. On the other hand, the insurance company who is more concerned about the safety of each ship will allocate a higher weighting to the ship risk potential criterion (Balmat et al., 2009; Kandakoglu et al., 2009).

The performance rating of individual ships with respect to each criterion or its associated sub-criterion is usually determined by the decision maker subjectively. With the determination of the performance of individual ships and the weightings of the evaluation and selection criteria, the overall performance of each ship across all the criteria and their associated sub-criteria can then be calculated on which the most suitable ship can then be selected.

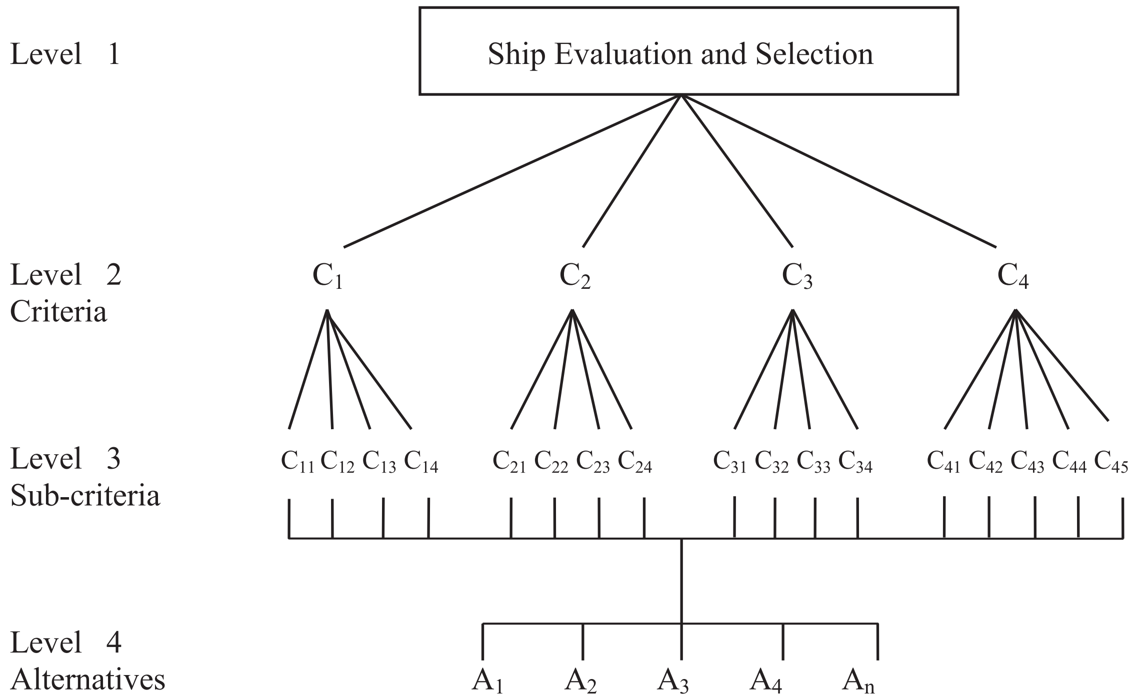
A typical ship evaluation and selection problem usually involves in the evaluation and selection of one or more ships (alternatives) from a set of n available ships (alternatives) A_i ($i = 1,2,\ldots,n$). These alternatives are to be assessed based on m evaluation and selection criteria C_j ($j = 1,2,\ldots,m$). Each criterion C_j may be broken down into p_j sub-criteria C_{jk} ($k = 1,2,\ldots,p_j$). Fig. 1 shows the hierarchical formulation of the ship evaluation and selection problem in the context of multicriteria analysis, in which the evaluation and selection criteria and their associated sub-criteria are discussed in the following.

The operating efficiency (C_1) is used for reflecting the subjective assessment of the decision maker on the financial feasibility of the ship with respect to the budget situation of an organization (Xie et al., 2008). It is measured by the fuel efficiency (C_{11}), the maintenance efficiency (C_{12}), the insurance cost (C_{13}), and the ship crew cost (C_{14}).

The ship capacity (C_2) reflects on the subjective perception of the decision maker on the features and specifications of each available ship (Xie et al., 2008). It is assessed by the size of the ship (C_{21}), the gross tonnage of the ship (C_{22}), the net tonnage of the ship (C_{23}), and the speed of the ship (C_{24}) (Balmat et al., 2009).

The level of risk (C_3) that each ship has reflects the decision maker's subjective assessment on the potential of failure of the ship during its journey (Barnhart & Laporte, 2007; Sambracos, Paravantis, Tarantilis, & Kiranoudis, 2004). This is measured by the weather condition and traffic density (C_{31}), the route near shallow waters (C_{32}), navigator failure (C_{33}), and machinery failure (C_{34}).

There are a large variety of cargoes including manufactured consumer goods, unprocessed fruits and vegetables, processed food, livestock, industrial equipments, processed materials, and raw materials in marine transportation (Barnhart & Laporte, 2007). The nature of the cargo therefore has a direct impact on the selection of a specific ship. As a result, the characteristics (C_4)



Legend:

C_1: Operating Efficiency, C_2: Ship Capacity, C_3: Risk Potential, C_4: Cargo Characteristics.

C_{11}: Fuel efficiency C_{12}: Maintenance efficiency
C_{13}: Insurance cost C_{14}: Ship crew cost

C_{21}: Size of the ship C_{22}: Gross tonnage of the ship
C_{23}: Net tonnage of the ship C_{24}: Speed of the ship

C_{31}: Weather condition and traffic density C_{32}: Route near shallow waters
C_{33}: Navigator failure C_{34}: Machinery failure

C_{41}: Level of corrosiveness C_{42}: Level of explosiveness, C_{43}: Level of toxicity
C_{44}: Level of radioactivity C_{45}: Level of flammability

A_i: Available ships, $i = 1, 2, .., n$.

Fig. 1. The hierarchical structure for ship evaluation and selection.

of cargo are used for reflecting the decision maker's concern on the type of cargo to be transported by the ship. This is measured by the level of corrosiveness (C_{41}), the level of explosiveness (C_{42}), the level of toxicity (C_{43}), the level of radioactivity (C_{44}), and the level of flammability of the cargo (C_{45}).

To evaluate the overall suitability of individual ships for a given task across all the evaluation and selection criteria and their associated sub-criteria, it is desirable to have a structured approach capable of: (a) adequately determining the weightings of the evaluation and selection criteria and their associated sub-criteria with respect to a specific task, (b) effectively aggregating the weightings of the criteria and the performance ratings of individual ships for determining the overall suitability of each ship across all the selection criteria and their associated sub-criteria, and (c) appropriately providing an interactive mechanism that allows the decision maker to interact with the system for exploring the implications of various decision making behaviors on the selection decision being made. As how to determine the criteria weightings consistently with respect to various task requirements in a timely and transparent manner is critical for making effective selection decision, the next section presents a task oriented procedure for determining the criteria weightings in the ship evaluation and selection process.

3. A weighting procedure

Criteria weighting is a preference elicitation process for determining the relative importance of the criteria with respect to the specific requirement of the task in multicriteria analysis (Yeh, Willis, Deng, & Pan, 1999). This process is usually used for reflecting the interest of the stakeholders in the decision making process with respect to the overall objective of the problem. Due to the multi-dimensional and often conflicting nature of the evaluation and selection criteria, consistently criteria weighting is critical for effectively solving the multicriteria evaluation and selection problem (Yeh et al., 2000).

There are many approaches developed for criteria weighting in multicriteria analysis. Saaty (1980), for example, develops the AHP for criteria weighting. A reciprocal pairwise comparison matrix is constructed along a subjective scale of 1–9. The criteria weightings are obtained by synthesizing various assessments in a systematic manner. This approach, however, may become cumbersome when the number of alternatives and criteria increases.

Tabucanon (1988) proposes a direct ranking and rating approach for criteria weighting. The decision maker is required to first rank all criteria according to their importance, then to rate them by giving each of them an estimated number such as 10 to indicate their relative degrees of importance. Criteria weightings are obtained by normalizing these raw estimations. The approach, however, obviously suffers from several limitations including the inadequacy in modeling the subjectiveness and imprecision of the human decision making process and the cognitive demanding on the decision maker in the subjective decision making process.

Wang and Luo (2010) propose a mathematical programming approach for criteria weighting based on the standard deviation of each criterion and their corresponding correlation with the overall assessment of the alternative. The approach is capable of incorporating the decision maker's subjective preference in determining the criteria weights. The weighting process, however, may become tedious and difficult to manage as the number of criteria increases.

In solving the ship evaluation and selection problem for accomplishing a specific task, the decision maker is usually required to consider all task requirements simultaneously in assessing the criteria weightings. This often places a heavy cognitive burden on the decision maker to assess precisely how and to what extent these task requirements influence the criteria weights due to the limitations on the amount of information that humans can effectively handle (Deng, 2005; Yeh et al., 2000). The presence of imprecision and subjectiveness in describing the task requirements further complicates the criteria weighting process. To effectively deal with this issue, a task oriented weighting procedure capable of producing consistent and reliable criteria weightings is proposed in the following.

A shipping task is usually characterized by four requirements including daily cost (T_1), ship condition (T_2), safety condition (T_3) and cargo type (T_4). The daily cost reflects on the allowable average cost for operating the ship. The ship condition is a measure of how efficient the ship is in handling the specific task (Balmat et al., 2009). The safety condition concern reflects on the possible failure of the ship during its operation. The cargo type is a measure on the type of the cargo being transported. For example, the concern of the decision maker on the daily cost (T_1) makes the decision maker give a higher weighting to the operating efficiency criterion (C_1). The concern about the safety condition of the ship (T_3) leads to a higher weighting being given to the risk potential criterion (C_3).

In the ship evaluation and selection process, experienced experts usually use their intuition and knowledge for making the decision in an ad hoc manner. This rule-of-thumb approach,

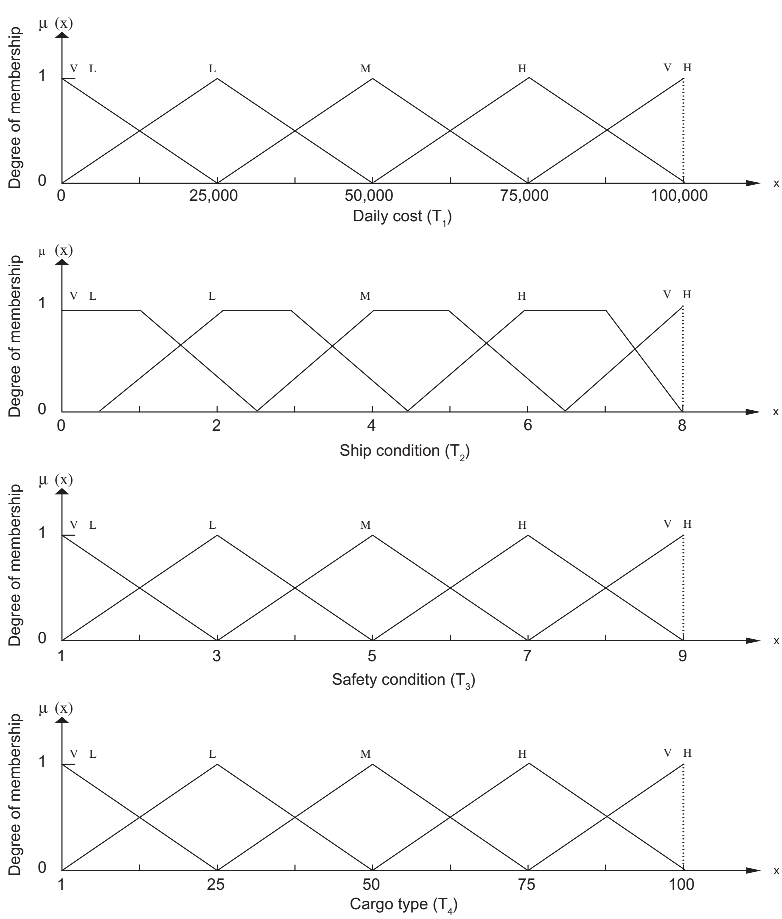


Fig. 2. Membership functions for describing the task requirements.

however, is not always reliable and consistent, due to the imprecise nature of human decision making and the information available (Hong, Lin, & Wang, 2003; Kandakoglu et al., 2009). To facilitate the weighting process, a production rule based approach is adopted.

To adequately model the uncertainty and imprecision of the weighting process, linguistic terms approximated by fuzzy numbers are used in knowledge representation and reasoning. To effectively reduce the cognitive demanding on the decision maker, individual production rules are developed for explicitly reflecting the effect of individual task requirements on the relative importance of the criteria.

A reasoning process is then followed in a given situation for determining the criteria weightings. Due to the presence of uncertainty, subjectiveness and imprecision in the evaluation process, fuzzy production rules are used (Guo, Zhu, Gao, Li, & Zhou, 2009; Zimmermann, 2000). A fuzzy rule is a conditional statement: IF (fuzzy proposition) THEN (fuzzy proposition) (Chen & Li, 2011; Hong et al., 2003). It is expressed by the decision maker in terms of linguistic statements according to the importance of the factors involved. These IF-THEN rules explicitly reflect the effect of the task requirement on the relative importance of the criteria in handling the multicriteria evaluation and selection problem. Each rule takes the form of: IF ⟨*requirement*⟩ THEN ⟨*outcome*⟩ where *requirement* describes the requirement of the task and *outcome* represents the impact of this requirement on the relative of individual criteria. This leads to the development of the fuzzy knowledge for determining the relative importance of the selection criteria with respect to a specific task.

For computational efficiency and ease of data acquisition, triangular fuzzy numbers are used for approximating the linguistic terms used (Chen & Hwang, 1992). These linguistic terms are used: (a) to describe the states of the corresponding task requirement, and (b) to represent the weightings of the corresponding criterion. Fig. 2 shows the membership function of the term set {Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)} based on extensive consultations with the industry experts.

The membership functions of the term set {Very Unimportant (VU), Unimportant (U), Medium (M), Important (I), Very Important (VI)} are used for representing the criteria weightings as shown in Fig. 3. In this study, the basic relative weights for criteria C_1, C_2, C_3, and C_4 are given as 0.4, 0.3, 0.2, and 0.15, respectively through consultations with the experts 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 four criteria.

Extensive consultations and interviews with the industry experts are conducted for developing the fuzzy knowledge base in criteria weighting. A set of 23 fuzzy rules is therefore constructed as shown in Table 1.

With the use of Table 1, the weightings of individual criteria can be determined based on assessing the specific situation of the task requirements. For example, Rule 1 states that IF task requirements T_1 is VL AND T_2 is VH AND T_3 is VH AND T_4 is VH THEN C_1 is U AND C_2 is VI AND C_3 is VI AND C_4 is VI. Rule 15 shows that IF task requirements T_1 is L AND T_2 is M AND T_3 is VH AND T_4 is L THEN C_1 is U AND C_2 is M AND C_3 is VI AND C_4 is M. These fuzzy rules are easily understood and can be readily modified by the decision

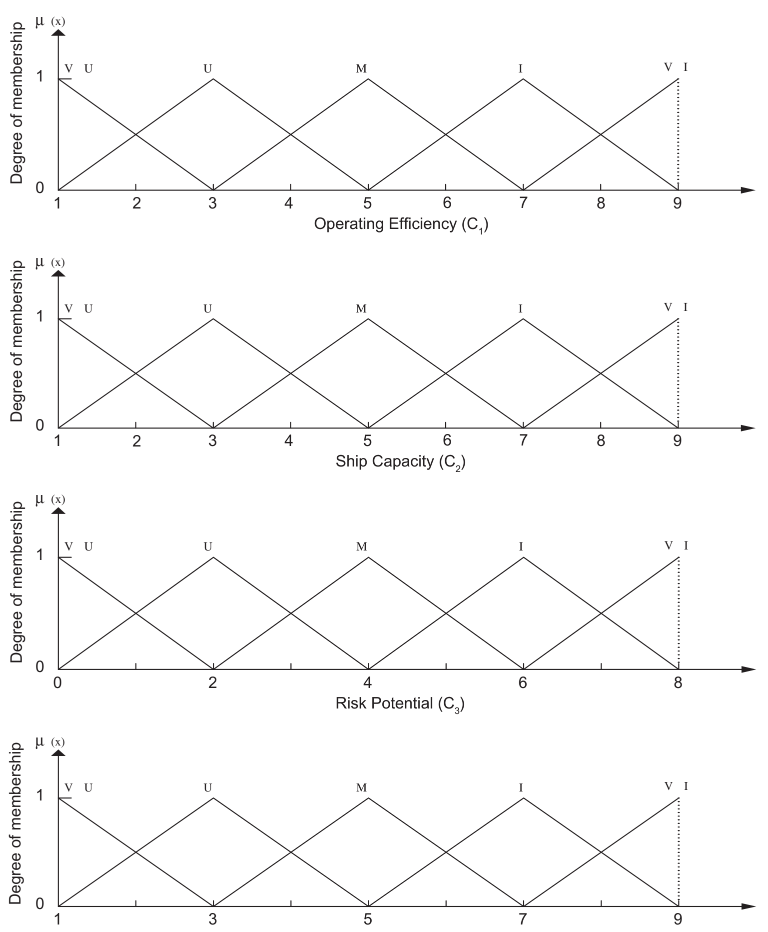


Fig. 3. Membership functions for representing criteria weightings.

Table 1
A summary of the fuzzy rules for criteria weighting.

Rule	IF				THEN			
	Daily cost (T_1)	Ship condition (T_2)	Safety condition (T_3)	Cargo type (T_4)	C_1	C_2	C_3	C_4
1	VL	VH	VH	VH	U	VI	VI	VI
2	VH	VL	VH	VH	VI	U	VI	VI
3	VH	VH	VL	VH	VI	VI	U	VI
4	VH	VH	VH	VL	VI	VI	VI	I
5	VH	VH	VH	VH	VI	VI	VI	VI
6	H	H	H	H	I	VI	I	I
7	M	M	M	M	M	M	M	M
8	VL	VL	VL	VL	VU	VU	U	U
9	VL	L	M	H	VU	U	I	I
10	L	VL	VH	M	U	VU	VI	M
11	M	H	VL	VH	M	I	U	VI
12	VH	L	H	VL	VI	I	I	U
13	H	VH	L	L	I	VI	U	M
14	H	VH	L	M	I	VI	U	M
15	L	M	VH	L	U	M	VI	M
16	M	L	L	VH	I	U	M	VI
17	VH	H	M	H	VI	I	M	I
18	L	M	H	L	U	M	I	M
19	L	H	L	VH	U	I	U	VI
20	H	L	VH	L	I	U	VI	M
21	L	L	H	L	U	U	VI	I
22	L	H	L	L	U	I	U	M
23	L	L	L	L	U	VU	U	U

maker, if necessary, to reflect a specific problem situation. To illustrate the effectiveness of the fuzzy rules for criteria weighting in relation to a specific task, an example is presented in Section 5.

4. A fuzzy multicriteria analysis algorithm

To effectively aggregate the criteria weightings and the subjective performance ratings, this section develops a fuzzy multicriteria analysis algorithm for evaluating the overall suitability of each ship against multiple criteria with multi-level hierarchies as shown in Fig. 1. The proposed algorithm integrates three important concepts in multicriteria analysis, including: (a) the multi-attribute utility theory (Keeney & Raiffa, 1993), (b) the degree of dominance (Deng, 1999), and (c) the degree of optimality (Yeh et al., 2000).

To model the subjectiveness and imprecision present in the multicriteria decision making problem, linguistic terms represented by triangular fuzzy numbers are used to facilitate the subjective assessment to be made by the decision maker. For a linguistic term represented as (a_1,a_2,a_3), a_2 is the most possible value of the term, and a_1 and a_3 are the lower and upper bounds respectively used to reflect the fuzziness of the term. In practical applications, triangular fuzzy numbers are commonly used to characterize linguistic information (Deng, 1999; Yeh et al., 2000). The popular use of triangular fuzzy numbers is mainly attributed to their simplicity in both concept and computation.

The fuzzy multicriteria analysis algorithm calculates an overall performance index for each ship across all the evaluation criteria and their associated sub-criteria if existent. The proposed algorithm starts with the determination of the performance rating of each ship A_i $(i = 1,2,\ldots,n)$ with respect to each criterion C_j $(j = 1,2,\ldots,m)$. As a result, a decision matrix for all the alternative ships can be obtained as follows:

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

where X_{ij} represent the linguistic assessments of the performance rating of ship A_i $(i = 1,2,\ldots,n)$ with respect to criterion C_j $(j = 1,2,\ldots,m)$.

The weighting vectors W and W_j $(j = 1,2,\ldots,m)$ for the criteria and their associated sub-criteria respectively can be represented based on the weight procedure discussed above as:

$$W = (w_1, w_2, \ldots, w_j, \ldots, w_m), \tag{2}$$

$$W_j = \left(w_{j1}, w_{j2}, \ldots, w_{jk}, \ldots, w_{jp_j}\right), \tag{3}$$

where w_j and w_{jk} are the fuzzy weights of criteria C_j and sub-criteria C_{jk}.

If sub-criteria C_{jk} $(k = 1,2,\ldots,p_j)$ are existent for criterion C_j, a lower-level decision matrix can be determined for all the ships, given as in (4) where y_{ik} are the decision maker's linguistic assessments of the performance rating of ship A_i with respect to sub-criteria C_{jk} of criterion C_j:

$$Y_{C_j} = \begin{bmatrix} y_{11} & y_{21} & \cdots & y_{n1} \\ y_{12} & y_{22} & \cdots & y_{n2} \\ \cdots & \cdots & \cdots & \cdots \\ y_{1p_j} & y_{2p_j} & \cdots & y_{np_j} \end{bmatrix}. \tag{4}$$

The weighted fuzzy performance matrix that represents the overall performance of each ship on each criterion can be determined by multiplying the fuzzy criteria weights (w_j) by the ships' fuzzy performance ratings (x_{ij}). If criterion C_j consists of sub-criteria C_{jk}, the decision vector $(x_{1j}, x_{2j}, \ldots, x_{nj})$ across all the ships with respect to criteria C_j can be determined by

$$(x_{1j}, x_{2j}, \ldots, x_{nj}) = \frac{W_j Y_{C_j}}{\sum_{k=1}^{p_j} w_{jk}} \tag{5}$$

Given the fuzzy vector $(w_j x_{1j}, w_j x_{2j}, \ldots, w_j x_{nj})$ of the performance matrix for criterion C_j, a fuzzy maximum ($M^j_{\max}$) and a fuzzy minimum ($M^j_{\min}$) can be determined as in (6) which represent respectively the best and the worst fuzzy performance ratings among all the ships with respect to criterion C_j:

$$\mu_{M^j_{\max}}(x) = \frac{x - x^j_{\min}}{x^j_{\max} - x^j_{\min}}, \quad \mu_{M^j_{\min}}(x) = \frac{x^j_{\max} - x}{x^j_{\max} - x^j_{\min}}, \tag{6}$$

where

$$x^j_{\max} = \sup \bigcup_{i=1}^{n} (w_j x_{ij}), \quad x^j_{\min} = \inf \bigcup_{i=1}^{n} (w_j x_{ij}). \tag{7}$$

The degree to which the fuzzy maximum ($M^j_{\max}$) dominates the weighted fuzzy performance ($w_j x_{ij}$) of ship A_i with respect to criterion C_j can be calculated as:

$$d^+_{ij} = d\left(M^j_{\max} - w_j x_{ij}\right) = \int D_{\left(M^j_{\max} - w_j x_{ij}\right)}(\alpha) d\alpha, \tag{8}$$

where

$$D_{M^j_{\max} - w_j x_{ij}}(\alpha) = \begin{cases} \frac{d^{L\alpha}_{\left(M^j_{\max} - w_j x_{ij}\right)} + d^{R\alpha}_{\left(M^j_{\max} - w_j x_{ij}\right)}}{2}, & 0 \leqslant \alpha \leqslant 1, \\ 0, & \text{otherwise}. \end{cases} \tag{9}$$

Similarly, the degree of dominance of the weighted fuzzy performance ($w_j x_{ij}$) of ship A_i over the fuzzy minimum ($M^j_{\min}$) with respect to criterion C_j is given as:

$$d^-_{ij} = d\left(w_j x_{ij} - M^j_{\min}\right) = \int D_{\left(w_j x_{ij} - M^j_{\min}\right)}(\alpha) d\alpha, \tag{10}$$

where

$$D_{\left(w_j x_{ij} - M^j_{\min}\right)}(\alpha) = \begin{cases} \frac{d^{L\alpha}_{\left(w_j x_{ij} - M^j_{\min}\right)} + d^{R\alpha}_{\left(w_j x_{ij} - M^j_{\min}\right)}}{2}, & 0 \leq \alpha \leq 1, \\ 0, & \text{otherwise}. \end{cases} \tag{11}$$

in which $d^{L\alpha}_{(w_j x_{ij} - M^j_{\min})}$ and $d^{R\alpha}_{(w_j x_{ij} - M^j_{\min})}$ are the lower bound and upper bound of the interval respectively, resulting from the cut on the difference set $(w_j x_{ij} - M^j_{\min})$.

Zeleny (1982) first introduces the concept of the ideal solution in decision analysis as the best or desired decision outcome for a given decision situation. Hwang and Yoon (1981) further extend this concept to include the negative ideal solution in order to avoid the worst decision outcome in the decision making process. This concept has since been widely used in developing various methodologies for solving practical decision problems (Deng et al., 2000; Zeleny, 1982). This is due to: (a) its simplicity and comprehensibility in concept, (b) its computation efficiency, and (c) its ability to measure the relative performance of the decision alternatives in a simple mathematical form.

In line with the above concept, the positive fuzzy ideal solution consisting of the fuzzy maximum with respect to each criterion across all ships and the negative fuzzy ideal solution consisting of the fuzzy minimum in regard to each criterion across all ships can be determined as follows:

$$A_{\max} = \left(M^1_{\max}, M^2_{\max}, \ldots, M^m_{\max}\right), \quad A_{\min} = \left(M^1_{\min}, M^2_{\min}, \ldots, M^m_{\min}\right). \tag{12}$$

Using the fuzzy ideal solutions as the common base for comparison, the degree of dominance that the positive ideal solution is on ship A_i ($i = 1, 2, \ldots, n$) can be calculated as follows:

$$d^+_i = \sum_{j=1}^{m} d^+_{ij}. \tag{13}$$

Similarly, the degree of dominance that each ship A_i ($i = 1, 2, \ldots, n$) has on the negative ideal solution can be determined as:

$$d^-_i = \sum_{j=1}^{m} d^-_{ij}. \tag{14}$$

A ship is preferred if it is dominated by the positive fuzzy ideal solution by a smaller degree, and at the same time dominates the negative fuzzy ideal solution by a larger degree (i.e. farther away from the negative fuzzy ideal solution; Deng et al., 2000; Yeh et al., 2000). Following this principle, an overall performance index for each ship A_i ($i = 1, 2, \ldots, n$) across all the criteria can be calculated by

$$P_i = \frac{(d^-_i)^2}{(d^+_i)^2 + (d^-_i)^2}. \tag{15}$$

The larger the performance index P_i, the more preferred the ship A_i.

5. An intelligent DSS framework

A DSS is a computer based information systems used to support decision making in situations where it is not possible or not desirable to have an automated system for performing the entire decision making process (Turban, Aronson, Liang, & Sharda, 2007). A DSS uses computers to: (a) assist decision makers for solving semi-structured problems; (b) support, rather than replace, managerial judgments; and (c) improve the effectiveness of decision making (Deng & Wibowo, 2008; Turban et al., 2007).

There are numerous applications of DSS for solving various problems in different industries due to their capacities in: (a) effectively addressing the needs of multiple decision makers (Yeh et al., 2010), (b) adequately modeling the subjectiveness and imprecision of the human decision making process (Zimmermann, 2000), and (c) greatly reducing cognitive demand on the decision makers in the decision making process (Wibowo & Deng, 2009). With the flexible and interactive characteristics of the DSS, the system helps the decision maker adopt a problem-oriented approach for solving the ship selection problem effectively and efficiently. This is achieved by allowing the decision maker: (a) to express their preferences linguistically and (b) to examine the relationships among the evaluation criteria, the available alternatives and the selection outcome.

This section presents an intelligent DSS framework for solving the ship evaluation and selection problem. The DSS is designed to help the decision maker choose the most suitable ship in a user-friendly manner by allowing the decision maker to express their requirements linguistically, and to fully explore the relationship between the criteria and the ships available in the selection process. Through an interactive exchange of information between the decision maker and the DSS, the decision maker can adopt a problem-oriented approach in the problem solving process (Deng & Wibowo, 2008). This problem-oriented approach is vital for effectively and efficiently solving the ship evaluation and selection problem.

The proposed DSS consists of six sub-systems, namely: (a) knowledge base, (b) working memory, (c) inference engine, (d) user interface, (e) knowledge acquisition, and (f) explanation. The knowledge base sub-system comprises of a database and a rule base. The database contains the membership function for approximating the linguistic terms commonly used, such as “the level of toxicity is low” or “the weather condition is very high”. The rule base contains a set of linguistic statements with antecedents and consequents respectively, connected by AND/OR operator. The knowledge base stores the domain knowledge acquired from experts. These knowledge and experience are represented in the form of IF–THEN rules. Together with an inference engine, intelligent guidance can be provided to: (a) interpret and evaluate the performance of available ships and (b) determine the course of action in the iterative planning process (Deng & Wibowo, 2008).

The working memory sub-system stores the input data and the information generated in the decision making process. The inference engine performs the function of reasoning, which is usually called fuzzy reasoning. This fuzzy reasoning is used for deriving conclusions from a set of fuzzy IF–THEN rules and from one or more given conditions (Zadeh, 1996).

The user interface sub-system serves to integrate various sub-systems for facilitating user friendly communications between the DSS and the decision maker. This sub-system provides the means for the decision maker to interface with the DSS including: (a) accessing the database and knowledge base; (b) inputting information such as the task requirements and the available ships; (c) displaying and evaluating alternative decisions; and (d) viewing the decision outcome. To provide the decision maker with the flexibility for customizing the system, the interface is designed in such a way that the decision maker can create, modify or eliminate task requirements, criteria, and available ships (Wibowo & Deng, 2009).

In the knowledge acquisition sub-system, a human expert interacts with the system for creating a knowledge base of what he/she knows in a particular subject area. The knowledge acquisition facility provides the decision maker with appropriate tools useful in knowledge acquisition. The explanation sub-system allows the system to present its reasoning outcomes.

The explanation sub-system is to enable the system display the motivation for all its actions and conclusions. The purpose of this sub-system is to: (a) explain to the decision maker that the system's conclusions are reasonable and (b) show how it reached those conclusions.

The application of the DSS consists of four phases, including: (a) identifying the decision maker's requirements including task requirements, criteria, ships available, and defining the membership functions; (b) constructing fuzzy rules; (c) determining the performance ratings of ships with respect to each criterion; and (d) selecting the most suitable ship. Fig. 4 shows the overall DSS framework for solving the ship evaluation and selection problem.

The first phase starts with identifying the task requirements, criteria, and ships available based on in-depth interviews with industry experts and analysis of the historical data and the concurrent environment. For ease of data acquisition and computational efficiency, triangular fuzzy numbers are used for representing linguistic terms.

The next phase focuses on developing the fuzzy rules. The DSS makes recommendations based on knowledge provided by the expert in the form of IF–THEN rules. The number of input variables

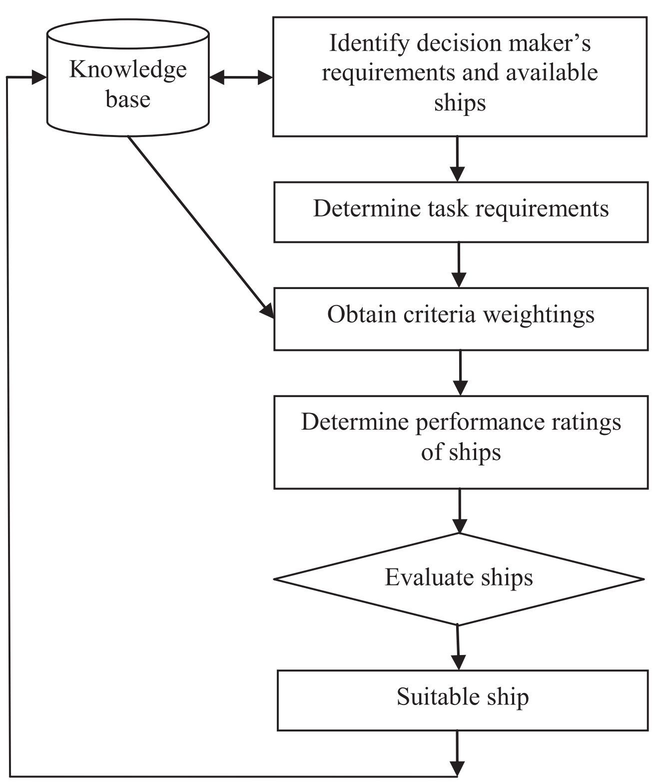


Fig. 4. A DSS framework for ship evaluation and selection.

and their associated membership functions determine the number of rules. Based on these rules, the DSS can process the task requirement and determine the relative importance of the selection criteria in relation to a specific task.

The performance rating of each ship with respect to each criterion is then subjectively assessed. In practical applications, both crisp and fuzzy data are often present in multicriteria analysis (Deng, 2005). As a result, the performance rating assessment can be represented by a crisp number or a linguistic term. In case the decision maker is not sure which linguistic values to choose, a defaulted linguistic value scale is presented. If the terms used in the scale are different from the terms the decision maker wants for criteria weighting, the proposed DSS tries to match the scale the decision maker wants with the existing scale in the knowledge base according to the number of terms used.

The next phase in the proposed DSS is designed to assess the overall suitability of each ship with respect to specific evaluation criteria and their associated sub-criteria for a given task. The overall performance of each ship is determined by aggregating the criteria weightings and ship performance ratings using the fuzzy multicriteria analysis algorithm discussed above. The most suitable ship in a specific situation will then be recommended to the decision maker. This leads to effective decisions being made (Deng & Wibowo, 2008).

6. An example

To demonstrate the applicability of the proposed intelligent DSS for solving the ship evaluation and selection problem, an example of the ship evaluation and selection problem is presented. Four evaluation criteria with respect to the four task requirements discussed above are identified, including operating efficiency (C_1), ship capacity (C_2), risk potential (C_3), and cargo characteristics (C_4) as shown in Fig. 1.

The ship evaluation and selection process starts with the DSS requesting the decision maker to choose either: (a) running a series of what-if scenarios or (b) solving the ship selection problem. If the decision maker chooses to run what-if scenarios, he/she is provided with a list of possible what-if scenarios and related options. If the decision maker selects to solve the ship selection problem, he/she will go through a series of dialog boxes which raises questions such as the sub-criteria weights, the performance assessments of available ships, and additional information to be included for processing. This leads to the use of the fuzzy multicriteria analysis algorithm for solving the problem.

In this case, the decision maker decides to perform a what-if scenario and test the impact of daily cost (T_1) on the criteria weights. Based on the option selected by the decision maker, the system requests the decision maker to enter the task requirements and criteria. The decision maker enters four task requirements (T_1, T_2, T_3, and T_4) and four criteria (C_1, C_2, C_3, and C_4) for the simulation. To facilitate the making of subjective assessments, the term set {Very Low (VL), Low (L), Medium (M)), High (H)), Very High (VH)} is used whose membership functions are given in Fig. 2.

The DSS carried out a simulation by adjusting one task requirement at a time while keeping the other task requirements unchanged. The state of the daily cost (T_1) is changed from the lowest to the highest and from the highest to the lowest respectively. In case of condition changes from the lowest to the highest, the daily cost is increased from 0 (VL) to 100,000 (VH). Based on the state and condition changes obtained in the simulation process, the system applies fuzzy rules stored in the knowledge base for determining the weightings of individual criteria with respect to the daily cost (T_1). Fig. 5 shows the impact of changing daily cost (T_1) on the criteria weightings after the simulation.

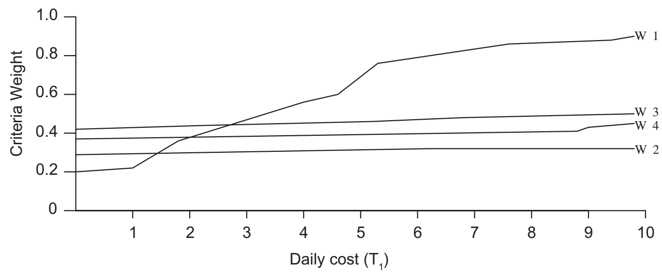


Fig. 5. Effect of daily cost (T_1) on criteria weights.

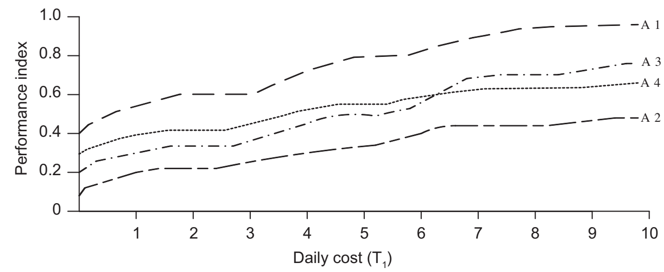


Fig. 7. Performance indexes under various daily cost requirements.

Table 2
Performance assessments of available ships.

Criteria and sub-criteria	Alternatives				
	A_1	A_2	A_3	A_4	A_5
Fuel efficiency (C_{11})	M	L	VH	M	H
Maintenance efficiency (C_{12})	M	VL	M	VH	M
Insurance cost (C_{13})	L	VL	VH	M	VH
Ship crew cost (C_{14})	M	M	M	VH	M
Size of the ship (C_{21})	L	VL	VH	M	VH
Gross tonnage of the ship (C_{22})	VH	M	VL	M	VL
Net tonnage of the ship (C_{23})	M	L	VH	M	H
Speed of the ship (C_{24})	M	VL	M	VH	M
Weather condition and traffic density (C_{31})	L	VL	VH	M	VH
Route near shallow waters (C_{32})	VH	M	VL	M	VL
Navigator failure (C_{33})	M	L	VH	M	H
Machinery failure (C_{34})	M	VL	M	VH	M
Level of corrosiveness (C_{41})	VH	H	H	VL	VH
Level of explosiveness (C_{42})	VH	M	H	VL	L
Level of toxicity (C_{43})	M	M	M	VH	M
Level of radioactivity (C_{44})	H	H	VL	M	H
Level of flammability (C_{45})	VL	VL	H	H	VH

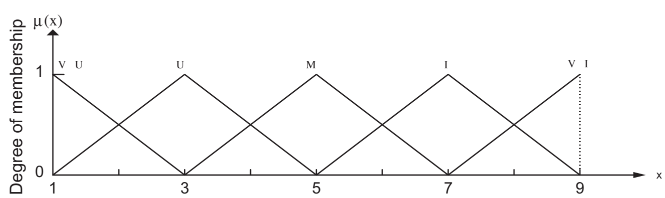


Fig. 6. Membership functions for representing sub-criteria weights.

Table 3
Weighting vectors for sub-criteria.

Weighting vector (W_j)	Fuzzy weights for sub-criteria (W_{jk})
W_1	(M, VI, VI, M)
W_2	(I, M, VI, VI)
W_3	(VI, M, U, VI)
W_4	(M, I, VI, VI, U)

The system provides three options for the decision maker to choose, on whether the decision maker would like to: (a) perform another what-if scenario, (b) continue and determine the performance of each ship, or (c) end the consultation process. In this case, the decision maker decides to use the criteria weightings obtained as in Fig. 5 to determine the overall performance of each ship under various daily cost requirements. This process begins with the decision maker choosing the second option from the DSS. Once the option is selected, the system instructs the decision maker to enter the performance assessments of available ships. Table 2 shows the result for the performance assessments of available ships.

The system would ask the decision maker for additional information. In this case, the sub-criteria weightings, which are not affected by task requirements, are included by the decision maker using the term set {Very Unimportant (VU), Unimportant (U), Medium (M), Important (I), Very Important (VI)} with membership functions defined in Fig. 6. Table 3 shows the weighting vectors for sub-criteria.

The system then retrieves the fuzzy multicriteria analysis algorithm from the knowledge base for determining the overall suitability of each ship under various daily cost requirements. Using the fuzzy multicriteria analysis algorithm illustrated as in (1)-(15), the overall performance of each ship is determined by the DSS in a computational efficient manner. Fig. 7 shows how the performance indexes are affected under various daily cost requirements. It also shows that changes in task requirements may affect the relative criteria weightings, resulting in a different ships being selected.

Sensitivity analysis can be conducted through changing the subjective assessments of the decision maker with respect to the decision variables when no clear-cut decisions are present. With the simplicity in concept underlying the DSS, the decision maker can interactively explore the problem in different manners so that a better understanding of the problem and the relationships between the decision and its parameters can be obtained. This would further improve the confidence of the decision maker in the selection process.

It is evident that the intelligent DSS is capable of assisting the decision maker in determining the criteria weightings and the overall performance of each ship in an effective and systematic manner. In particular, the use of the DSS for solving the ship evaluation and selection problem greatly reduce the decision maker's cognitive burden and further improve the consistence of the decisions being made.

7. Conclusion

This paper addresses the ship evaluation and selection problem under uncertainty. A task-oriented procedure is developed for determining the relative importance of the evaluation and selection criteria with respect to a specific task. A fuzzy multicriteria analysis algorithm is developed for calculating an overall performance index for each ship across all the selection criteria and their associated sub-criteria on which the selection decision is made. An intelligent DSS capable of integrating the developments above is proposed to facilitate the ship evaluation and selection process.

An example is presented for demonstrating the applicability of the proposed intelligent DSS for facilitating the evaluation and selection of available ships. It shows that the proposed DSS has a number of advantages for solving the ship evaluation and selection problem including the ability to help the decision maker better understand the problem and the implications of their decision behaviors, the flexibility to respond quickly to the decision maker's questions, and the capability to accommodate various task requirements in a given situation.

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