Examining the use and application of Multi-Criteria Decision Making Techniques in Safety Assessment

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Abstract

Maritime safety is a critical issue and attracts the interest of academics, professionals and policy-makers. There are many approaches and many references available in the literature; however, most of them do not use the Multi-Criteria Decision Making (MCDM) methodological and decision-making tools used and tested in other fields. The fundamental question is the quality of results one may extract out of existing data and measurements by using new MCDM techniques. A side-problem is the complexity involved when using these techniques as well as the applicability of the extracted results.

In the first section a literature investigation presents MCDM application in marine safety issues mainly. Then some methodological remarks set the framework of further application. An illustrative example of safety equipment selection is presented and discussed, as well as some points of concern or for further scrutiny. All MCDM techniques are well known, and widely applicable. The paper concludes with a discussion over the applicability of these techniques in the marine environment in relationship to established methods, such as the Formal Safety Assessment (FSA).

Key words

MCDM, ELECTRE, TOPSIS, AHP, Safety Assessment

1 Introduction – Problem Outline

In the literature very few marine safety related studies use Multi-Criteria-Decision-Making (MCDM) techniques. Although MCDM have been widely used in other fields for safety-related problems, this noted absence of such applications either in research, academic references or in real-life applications was the very first trigger for further research. In the marine literature, researchers use various models and follow many difficult methodologies in order to support decisions and choices; some only illustrative examples are only available for the MCDM group of tools.

Safety issues are really at the core of marine engineering generally; researchers and institutions have to extract and impose safety rules on design and operation of marine systems, and it is expected these rules to have a positive impact, i.e. to enhance safety by mitigating risks and increasing the reliability of a system. Moreover, day-to-day operations are viewed continuously (or at least should be) under the prism of safety. ‘Safety first’ panels and similar warning notes are found everywhere on board and all documents convey the message of the wider goal of ‘safe shipping’. Consequently, the marine industry is at its core a safety-driven industry. Yet safety is not the only drive; cost, competitiveness, security and marine environment protection are some of the major forces influencing decisions.

It is out of scope to examine all safety methodologies used currently in the literature, yet it is interesting to examine the use of MCDM techniques. In other industries, MCDM techniques are widely applied. Nevertheless, MCDM techniques are not the panacea for all decision problems and definitely there is a need for more academic work in order to bridge gaps. A critical issue for the application of various MCDM techniques is the justification of the outcome; an illustrative example is provided, based on actual business data (available also in the literature) for the selection of a system. Three different MCDM methods are used and three different outcomes are extracted (as expected). This inherent attribute might be well known and justified in the literature, yet it impedes further the use of such methods in daily business.

In the first section a short literature review is provided focused on ‘safety’ as a ‘notion’ and the use of MCDM techniques. Then, remarks on the general decision-making model as well as some points of concern are presented. This analysis is followed by an illustrative numerical example, highlighting some of the drawbacks. The analysis concludes with some remarks and comments on all the above.

2 Literature review

Safety attracts research and innovation as societal awareness increases and there is a natural tendency in reducing the external cost of various risk-bearing activities. Especially in the marine environment and business, safety was the driving force behind the formation of the industry, as classification societies, the International Maritime Organization (IMO) and other inter-governmental and independent bodies, can attribute their existence or focus specifically on safety aspects among others. Safety consists also a multidisciplinary field of research and various fields of engineering and science; therefore it is a rather complex task to provide a complete literature review on this subject. For the purposes of this paper, literature review is limited to recent marine-safety related papers as well as some publications in the MCDM field.

A search under the term ‘marine safety’ under the title of ‘Marine Technology’ Journal published by the Society of Naval Architects and Marine Engineers (SNAME) yields 16 titles of papers published in the last 8 years (1998-2006). It has to be noted that the above result is not the direct response of the query on ‘safety’ as term, but a refined outcome, focused on ‘safety’ as a ‘concept’ and not its specific applications (say life-rafts, stability, etc). Researchers have used various risk and engineering models but not any MCDM model, although a well renown method, the Analytic Hierarchy Process (AHP) has been used by the Specialist Committee on Safety of High Speed Marine Vehicles of the ITTC as early as 1999 (ITTC, 1999).

On the other hand, researchers have used MCDM models on safety problems in other fields. Fenton and Neil (2001) have used Bayesian Belief Nets (BBN) and MCDA (multi-criteria decision aid) in order to support a decision in a nuclear-engineering application. Interestingly enough the decision-pattern is similar to many in the marine engineering environment and business. BBNs can be very helpful for research and applications in the marine and maritime fields as they involve uncertainty and conditional probabilities. BBNs have been used in numerous safety-related problems, such as the DATUM, SHIP, DeVa and SERENE (ESPRIT) projects, in reliability projection applications as well as quality (defect-density) in safety (Fenton et al., 2001, p.308). To the best of author’s knowledge BBNs have not found application up to date in pure marine engineering application, although similar theoretical and practical issues have been thoroughly addressed. Furthermore, BBNs provide an interface with MCDM techniques, which usually lack memory and do not support any influential links of interrelated attributes.

MCDM techniques have been used in the past for safety problems; in related journals one can find many research-papers using MCDM techniques. Lately Merrick and Harrald (2007) published their work on safety on ports and waterways in INTERFACES, using AHP as a decision-support method.

Specific interest shall be given to the paper of Yang et al. (2001) as a debatable application of how AHP is used. Yang et al. use the cost – benefit model suggested by Saaty (also in 2001, p. 222), which has been heavily criticized by Bernhard (1990). In this paper a safety-equipment selection model is presented. Such problems are very frequent in practice and most importantly they highlight the trade-off between safety and cost, or generally the necessary trade-off between negative (say cost) attributes and positive ones (such as increased reliability). Generally the use of AHP for controversial goals, as in the case of a trade-off between negative and positive attributes has ignited many discussions, as Saaty’s proposition stumbles upon theoretical gaps. Nevertheless, it is a technique that rational (as expected in the von Neuman set of axioms) practitioners can easily understand and apply.

Last but not least; Triantaphyllou et al. (1997) present their work on the sensitivity of MCDM techniques on the basis of a similar safety problem. Triantaphyllou outlines the sensitivity problem dually: the goal is to find the most sensitive criterion as well as the most sensitive attribute. By the term ‘sensitive’ Triantaphyllou highlights, the smallest relative change leading to a rank reversal. Intuitively one may think that the most critical criterion is the one with the highest weight. This is misleading and numerically not always the case.

Given the above, one can relatively safely argue that MCDM techniques have already found applications in non-marine fields, but their use is up to day, limited. This is also one of the triggers for this research: to examine the applicability and the limitations of MCDM techniques in marine applications.

In the marine environment, Formal Safety Assessment (FSA), cost-benefit analysis (CBA) and other methods are widely applied. The book of Khristiansen (2005) provides a solid basis for reference and further research.

3 Comments on the General Model

Security-establishing, safety-prevention, planned maintenance scheduling applications are based on the assessment of an initial risk, i.e. on a set of probabilities. Furthermore it is required by the decision-maker to provide thorough input and evidence-supported probabilities. Decisions are commonly taken on the basis of potential alternatives evaluation with respect to multiple criteria. According the Hobbs and Meier (2000, p. 6), decision analysis has six basic functions:

1. To structure the process.
2. To display the trade-offs among criteria.
3. To help people reflect upon, articulate, and apply value judgments concerning acceptable trade-offs, resulting in recommendations concerning alternatives.
4. To help people make more consistent and rational evaluations of risk and uncertainty.

5. To facilitate negotiation.
6. To document how decisions are made.

Generally, multi-attribute decision problems are classified in the following way. The super class of decision models is found in the literature as Multi-Criteria Decision Making (MCDM), which is a branch of general class of operations research (OR) models dealing with decision problems under the presence of a number of decision criteria. This class is divided into Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM). MODM studies decision problems of continuous space, and the Kuhn-Tucker approach, known as *vector-maximum,* is most probably the very first attempt to solve such problems. In contrary MADM techniques concentrate on problems of discrete nature. From this point and on, the terms MCDM and MADM will be referred indiscreetly. All MADM methods have some aspects in common. These are the notions of alternatives, and attributes (or criteria, goals) as described next (Triantaphyllou, 1998):

- **Alternatives**: Alternatives represent the different choices of action or entities available to the decision maker. Usually, the set of alternatives is assumed to be finite, ranging from several to hundreds. They are supposed to be screened, prioritized and eventually ranked.
- **Multiple attributes**: Each MADM problem is associated with multiple attributes. Attributes are also referred to as "goals" or "decision criteria" and are commonly understood as parameters or characteristics. Attributes represent the different dimensions from which the alternatives can be viewed. In cases in which the number of attributes is large (e.g., more than a few dozens), attributes may be arranged in a hierarchical manner. That is, some attributes may be major attributes. Each major attribute may be associated with several sub-attributes. Similarly, each sub-attribute may be associated with several sub-sub-attributes and so on. Although some MADM methods may explicitly consider a hierarchical structure in the attributes of a problem, most of them assume a single level of attributes (e.g., no hierarchical structure).
- **Conflict among attributes**: Since different attributes represent different dimensions of the alternatives, they may conflict with each other. For instance cost may conflict with profit, etc.
- **Incommensurable units**: Different attributes may be associated with different units of measure. For instance, in the case of buying a used car, the attributes "cost" and "mileage" may be measured in terms of dollars and thousands of miles, respectively. It is this nature of having to consider different units which makes MADM to be intrinsically hard to solve.
- **Decision weights**: Most of the MADM methods require that the attributes be assigned weights of importance. Usually, these weights are normalized to add up to one.
- **Decision matrix**: An MADM problem can be easily expressed in matrix format. A decision matrix A is an (M × N) matrix in which element a_{ij} indicates the performance of alternative Ai when it is evaluated in terms of decision criterion C_j, (for i = 1,2,3,..., M, and j = 1,2,3,..., N). It is also assumed that the decision maker has determined the weights of relative performance of the decision criteria (denoted as w_j, for j = 1,2,3,..., N). This information is best summarized in Table 1.

Given the previous definitions, then the general MADM problem can be defined as follows (Zimmermann, 1991):

Definition 1-1: *Let A = {A_i, for i = 1,2,3,... ,M} be a (finite) set of decision alternatives and G = {g_i , for j = 1,2,3,..., N} a (finite) set of goals according to which the desirability of an action is judged. Determine the optimal alternative A* with the highest degree of desirability with respect to all relevant goals g_i.*

	Criteria							
		C_1	**C_2**	**C_3**	**…**	**C_j**	**…**	**C_n**
	weights	w_1	w_2	w_3		w_i		w_n
Alternatives	A_1	a_{11}	a_{12}	A_{13}	…	a_{1j}	…	a_{1n}
	A_2	a_{21}	a_{22}	A_{23}	…	a_{2j}	…	a_{2n}
	A_3	a_{32}	a_{32}	A_{33}	…	a_{3j}	…	a_{3n}
	⋮					⋮		
	A_i	a_{i2}	a_{i2}	a_{i3}	…	a_{ij}	…	a_{in}
	⋮					⋮		
	A_m	a_{m2}	a_{m2}	a_{m3}	…	a_{mj}	…	a_{mn}

Table 1: Decision Matrix for a Discrete Decision-Making Problem

This tabular format implies a single hierarchy and is known as *decision matrix.* In this formulation:

let C_1, C_2, C_3, …, C_n be the decision criteria

let A_1, A_2, A_3, …, A_m be the decision alternatives

let w_j (for j = 1, 2, 3, …, n) be the weight of criterion C_i

let a_{ij} be the performance of alternative A_i when it is examined in terms of criterion C_j

The concealed meaning of the above formulation is that an MCDM problem with a given decision matrix is in essence a problem for a set of known alternatives and for a set of known criteria. Other alternatives and analysis under other criteria is not the case in the MCDM formulation and the decision-maker has to determine both alternatives and criteria before proceeding to further steps. The problem formulation goes through a three-phase procedure:

1. determination of the pertinent data
2. process of the data
3. interpretation of the results and the feedback mechanism

In the first phase, the decision maker has to evaluate the quality and the availability of data. Given or calculated data may be taken into account indifferently of their nature: stochastic – deterministic, qualitative – quantitative, stable – dynamic, etc. The second phase deals with the selection of the proper technique and the execution of the necessary calculations. It is interesting to note that there is no single method considered as the most suitable or the most acknowledged for the general problem. Furthermore the results for a given set alternatives and attributes may significantly vary when comparing different methods. Popular MCDM methods, such as the weighted sum model (WSM), the weighted product model (WPM), the analytical hierarchy process (AHP) and its revisions or alterations, the family of techniques ELECTRE (Elimination Et Choix Traduisant la Réalité), UTADIS, TOPSIS, etc may lead to different conclusions. This has also been proven in the MCDM literature (Triantaphyllou and Mann, 1989). Of course there are some criteria ensuring the stability of the final solution as well as the validity of both the mere decisions and the whole procedure, but this is not the case in the text. Finally in the third phase the decision maker has to interpret the results and to find the most critical criterion. The outcome of this phase is most commonly the results of a sensitivity analysis under specific rules.

The MCDM methods are classified according to the available data as well; so deterministic, stochastic and even fuzzy MCDM methods can be applied to various problems. Another common way to classify MCDM problems is the number of the decision makers involved in the process. Hence if there is only one decision maker then the method is called <u>single</u> and if there are more decision makers then it is called as <u>group</u> MCMD method. Common deterministic, single MCDM methods are the Weighted Sum Method (WSM), the Weighted Product Method (WPM) AHP, Elimination and Choice Translating Reality (ELECTRE) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). There are other ways to classify MCDM problems as well as other categories the above-mentioned methods may fall into. For example AHP can easily incorporate fuzzy data as well as assist in group decision-making.

Considering the above model-structure, it is obvious that ranking and clustering of the alternatives extracted through any method, such as AHP, WSM, etc. does not contain any memory, in other words experiences, risks, biases expressed in previous stages of decision-making shall either be considered as criteria if possible or completely omitted. In practice, most safety problems involve uncertainty, and at least from an analytical point of view, a Bayesian approach is the only tool transferring 'experience' or 'probability' from stage to stage. In the model structure, there it is no link between stages, whatsoever.

In most safety applications, clients and users are interested in a single attribute, such as safety or reliability. Rules and regulations suggest a specific limit or threshold, in order to determine whether an element or a system is 'reliable', i.e. trustworthy. Nevertheless, these attributes are by nature based or defined on multiple criteria. An extreme example could be the following: a decision-maker faces with the dilemma whether to deploy or not a highly sophisticated safety system on board. The final decision could be justified on technical grounds, say level of reliability, yet the decision-maker should also take into account economical, environmental, political criteria, as well as the critical one of functionality.

Another point of concern is the discrete nature of the above modeling; in most cases a decision-maker faces problems of discrete mathematics, yet it is possible to face problems of continuous nature. Generally, it is easy to transform a continuous parameter, such as time to discrete ranges. For example, the decision-maker has to decide on the timing of his action and the range is between 0800 to 1200, so the continuous space is transformed to intervals such as [0800,0830], (0830,0900], … , (1130,1200]. Infinite and even continuous parameters are 'chopped' into discrete ranges, depriving the modeler from exploiting the wealth of continuous space information and from using advanced mathematical tools.

Last but not least, most safety problems deal with a 'positive' and a 'negative' notion, such as 'safety' and 'cost'. Most methods cannot adequately deal simultaneously with these conflicting attributes. A goal programming approach demands a proper mathematical form, not always possible in real-world applications, AHP has not convinced academics (xxx, xx) although some business cases are reported, and other methods are either to 'naïve' or cumbersome.

The above MCDA model has limitations, as shown above and especially for safety problems, where attributes may be conflicting or even interdependent. Therefore, most modelers work on the basis of three critical assumptions:

1. all relevant criteria are well-defined, i.e. it is possible to compute or estimate a_{ij}
2. all relevant criteria are certain, i.e. a_{ij} has a deterministic rather than a stochastic value
3. all relevant criteria are independent.

However, even a simplified example yields the limitation of this formulation; an owner has to select three vessels on the basis of the following criteria: age, engine, consumption, speed and price. Even if for all criteria the attribute a_{ij} is available, the criteria of consumption, speed and engine are interrelated and not independent.

Analyzing further the notion that criteria are always well defined, let's quote an example provided by Fenton and Neil (2000, p.9) in order to explore some real-life MCDA application. By defining safety as the probability of failure (pdf), it is rather difficult to calculate this probability properly for a system or an element, when the system is in most cases (practically all time long) in an idle mode, or decommissioned, simply because there is no demand. Criteria, such as safety, functionality, cost, security, are considered as 'abstract'. In the literature one can find ways to mitigate this problem and measure vague criteria. Besides, the problem is not modeling vagueness but to deal with synthetic criteria, i.e. criteria that can be decomposed. AHP and the hierarchical decomposition of the target offers potential to researchers and decision-makers to work with independent and well-defined criteria. One should always recall that decomposition is not sufficient to define a higher level, and some degree of vagueness or unexplained reasoning may be left out. Furthermore, decomposition shall not be confused with casual dependence. Concluding this issue, one should keep in mind that a current measurement, say an a_{ij} element will not always reflect the attribute per criterion and alternative, as it can be time-dependent. Such a time-dependency has been considered in literature (for example, Saaty, 1985) but it is rather difficult to apply in practice.

Methods requiring a utility function may not be of direct assistance in safety problems. Theoretically, a utility function may reveal the degree of risk-aversion of a decision-maker, yet it is difficult to extract an accurate function, or a function that can into account emotional and other subjective parameters that may come up upon decision-time and lacks scale. Methods not requiring a utility function may be user-friendlier, yet they lack mathematical consistency, at least by using von Neuman and Morgenstern axioms, namely:

1. Ordering of Alternatives
2. Dominance
3. Cancellation
4. Transitivity
5. Continuity
6. Invariance

Many researchers have used the Analytic Hierarchy Process (AHP) as a tool towards estimating safety-related optimum (or preferable) alternatives. For example, Rabanni et. al. (1996) have used AHP not only for the forward and backward planning in transportation problems, but specifically for road safety and accident prevention, as well as for a typical cost-benefit analysis.

In the literature AHP has been heavily criticized. The fundamental axioms of Saaty have been scrutinized many times in the literature (for example in Barzilai, 1999). Also the use of Saaty's scale is debatable, although AHP permits the use of practically any scale selected by the decision-maker. Last but not least, the eigenvector justification is considered as weak (Crawford et al., 1985).

Nevertheless, in real world application, the major drawbacks of any MCDM method are practically the following:

1. The issue of rank reversal
2. Sensitivity
3. What if a criterion or a new alternative is added?

Theoretically, Saaty has provided some interesting, rational explanations on rank reversal. The 'fallacy of rank preservation' is an idea that can be supported and Saaty directly hits the core of the theory of decision-making as an axiom of von Neuman and Morgenstern is violated. Sensitivity is not necessarily an issue; Triantaphyllou et al (1997) have provided some numerical tools for the extraction of the most sensitive attributes. Yet it is not only a numerical problem, but also a conceptual one, as in some techniques, this procedure may affect original biases of the decision-maker. Finally the addition of an alternative or of criterion practically creates a new problem, and it would be wrong to compare results (preference) given an old and a new set of attributes and alternatives.

However, the great theoretical gap is the lack of a methodology, even better a 'rule of thumb' for practitioners, in selecting the most suitable MCDM technique for a given problem. It is possible to combine techniques successfully (for example, Tsaur et al, 2002), yet the process strongly depends on the capabilities of the modeler. As it is well known and widely admitted there is no guidance or rule in selecting the most suitable MCDM method. The selection is based on the capabilities of the researcher, as well as some objective limitations; when a large data-set of alternatives is under consideration, AHP is not the most suitable method, for example. Consequently, researchers may have to test and examine many MCDM methods before considering the most appropriate one. On the other hand, an MCDM method may easily solve more problems than one simultaneously. Consequently the question set is what is the most suitable MCDM method for safety-related problems, what are the limitations and how can somebody mitigate these problems.

4 An Illustrative Example

The scope of this example is to show the limitations of widely applied MCDM techniques in routine situations. AHP, ELECTRE and TOPSIS are used given the same numerical input. A shipping company has to replace elements of safety-related software. Supposing the following criteria and characteristics, as the most important items to focus:

- Detailed information about the crewmembers and their behavior
- Availability of presenting data per ship and/or sector (deck/engine/other)
- Cost-control
- Comparison with industry- or literature-based data
- Planning, preview and scenarios of risk management

The above items are evaluated according to nine criteria, some of them related to the company and some to the software system. After a detailed research of suppliers of the system under consideration, the company has excelled three potential suppliers or partners. The weighting has been carried out by a point system and by the priorities of the company, for the needs of this example these points are defined as following:

Company	System
5 = very good	3 = surpasses the request of delivery
4 = good	2 = achieves the request of delivery
3 = satisfying	1 = achieves the request of delivery partly
2 = sufficient	0 = does not achieve the request of delivery
1 = insufficient	

After evaluating the three different alternatives according to the prescribed criteria the decision matrix is formulated:

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
	1	3	2	2	2	2	1	2	2
A1	4	4	3	5	5	4	5	4	5
A2	5	3	4	5	5	4	5	5	5
A3	3	5	4	5	3	5	5	3	2

4.1 TOPSIS

Given the decision matrix, the following numerical steps consist the algorithm of TOPSIS:

1. Construct the normalized decision matrix $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$, where x_{ij} the elements of the decision matrix above.

$$R = \begin{bmatrix} 0.566 & 0.566 & 0.469 & 0.577 & 0.651 & 0.530 & 0.577 & 0.566 & 0.680 \\ 0.707 & 0.424 & 0.625 & 0.577 & 0.651 & 0.530 & 0.577 & 0.707 & 0.680 \\ 0.424 & 0.707 & 0.625 & 0.577 & 0.391 & 0.662 & 0.577 & 0.424 & 0.272 \end{bmatrix}$$

2. Construct the weighted normalized decision matrix $V = \left[w_j r_{ij} \right]$

$$V = \begin{bmatrix} 0.566 & 1.697 & 0.937 & 1.155 & 1.302 & 1.060 & 0.577 & 1.131 & 1.361 \\ 0.707 & 1.273 & 1.249 & 1.155 & 1.302 & 1.060 & 0.577 & 1.414 & 1.361 \\ 0.424 & 2.121 & 1.249 & 1.155 & 0.781 & 1.325 & 0.577 & 0.849 & 0.544 \end{bmatrix}$$

3. Determine the ideal and negative-ideal solutions

$$A^* = \left\{ \left(\max v_{ij} / j \in J \right) \left(\min v_{ij} / j \in J' \right) i = 1,2,3,\dots,m \right\} = \left\{ v_{1*}, v_{2*}, \dots, v_{n*} \right\}$$

$$A^- = \left\{ \left(\min v_{ij} / j \in J \right) \left(\max v_{ij} / j \in J' \right) i = 1,2,3,\dots,m \right\} = \left\{ v_{1-}, v_{2-}, \dots, v_{n-} \right\}$$

where:

J={j=1,2,3,…,n and j is associated with benefit criteria} and

J'={j=1,2,3,…,n and j is associated with cost criteria}

So,

A^* = {0.707, 2.121, 1.249, 1.155, 1.302, 1.325, 0.577, 1.414, 1.361}

A^- ={0.424, 1.273, 0.937, 1.155, 0.781, 1.060, 0.577, 0.849, 0.544}

4. Calculate the separation measure, i.e. the distances of each alternative from the ideal and negative-ideal solution

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2}, i = 1,2,3,\dots,m$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2}, i = 1,2,3,\dots,m$$

that yields:

$$S^* = \begin{vmatrix} 0.669 \\ 0.889 \\ 1.157 \end{vmatrix}$$

$$S- = \begin{vmatrix} 1.104 \\ 1.198 \\ 0.942 \end{vmatrix}$$

5. Calculate the relative closeness to the ideal solution:

$$C_{i*} = \frac{S_{i-}}{S_{i*} + S_{i-}}$$, where $0<C_i<1$ and $i=1,2,3,\ldots,m$

Apparently an alternative Ai is closer to the ideal solution as C_{i*} approaches to 1. By performing the calculations, it yields:

$$C_i \quad \begin{vmatrix} 0.622535 \\ 0.574070 \\ 0.448911 \end{vmatrix}$$

6. Rank the preference order: given the above results $A_1 \succ A_2 \succ A_3$

The algorithm of TOPSIS offers many advantages to the decision-makers, especially for non-academics, who usually do not consider deeper methodological problems. The first advantage is that TOPSIS offers a Euclidean solution, i.e. it is easily conceivable. Secondly, TOPSIS does not use any specific preference scale. The decision-maker selected the scale used before. Any other scale could be easily numerically accommodated, but it is assumed that the decision-maker has an understanding over different scales, say log-linear, linear, etc. Thirdly, all calculations can easily be performed on normal PC-compatibles.

4.2 *ELECTRE*

Using the same input as before, the necessary calculations are performed following the steps of ELECTRE algorithm. ELECTRE is a rather cumbersome algorithm, yet it has been widely applied and is the point of origin many similar algorithms (ELECTRE-family).

Given the decision matrix and after its normalization, as per first step of the TOPSIS method, ELECTRE algorithm proceeds with the weighting of the normalized matrix, i.e. V=RW, where R the normalized matrix as in TOPSIS and W the diagonal matrix of the weights.

Then the concordance and discordance sets have to be determined. For each pair of alternatives k and l ($k,l = 1,2,3,\ldots, m$ and $k \neq l$) the set of decision criteria J is divided into two subsets. The concordance set of the two alternatives A_k and A_l, is explained as the set of all criteria for which A_k is preferred to A_l. That is: $C_{kl} = \{j, y_{kl} \geq y_{lj}\}$ for $j=1,2,3,\ldots,n$

On the other hand the complementary subset is the discordance set, which is $D_{kl} = \{j, y_{kl} < y_{lj}\}$ for $j=1,2,3,\ldots,n$

By following the above numerical steps, ELECTRE will yield the following arithmetic results,

$$C = \begin{bmatrix} & 12 & 10 \\ 14 & & 12 \\ 10 & 10 & \end{bmatrix}$$

$$D = \begin{bmatrix} & 0.7362 & 0.5196 \\ 1.000 & & 1.000 \\ 1.000 & 0.9623 & \end{bmatrix}$$

$$\underline{c} = \frac{\sum_{k=1}^{3}\sum_{l=1}^{3} c_{kl}}{m(m-1)} = \frac{68}{6} = 11.33$$

$$F = \begin{bmatrix} & 1 & 0 \\ 1 & & 1 \\ 0 & 0 & \end{bmatrix}$$

$$\underline{d} = \frac{\sum_{k=1}^{3}\sum_{l=1}^{3} d_{kl}}{m(m-1)} = \frac{5.218}{6} = 0.869$$

$$G = \begin{bmatrix} & 1 & 1 \\ 0 & & 0 \\ 0 & 0 & \end{bmatrix}$$

$$E = F \times G = \begin{bmatrix} & 1 & 0 \\ 0 & & \\ 0 & 0 & \end{bmatrix}$$

The last matrix E suggests that $A_1 \succ A_2$. No further information is given about the relationship of A_3 and the rest alternatives. Depending on the aim of the problem, one would also consider a further weighting of the criteria, and this procedure would alter the final outcome. Yet, this reveals also the inherent disadvantage of ELECTRE, where arbitrary interventions, as in the case of the thresholds $\underline{c}$ and $\underline{d}$ influence heavily the final outcome.

This deficiency of the method is known and well-discussed in the literature, therefore, ELECTRE is preferred in cases with a large set of alternatives and few criteria. However, in the real-world application as above, ELECTRE is heavily out-preferred by a simpler method such as TOPSIS.

4.3 *Analytic Hierarchy Process*

The AHP method is well discussed in the literature and its presentation is omitted here. Given the same decision matrix, the weighting of the criteria as in TOPSIS, and using direct relative comparisons of the alternatives, the result is easily calculated as $A_2 \succ A_1 \succ A_3$. One would directly argue that the scale used (see section 4.1 TOPSIS) is not the one used by Saaty or other researchers. Evidently the use of different comparison scales will yield a different outcome.

5 MCDM and Marine Applications

By using a simple safety-renewal example, it is demonstrated that every method yields a different outcome. This is expected from the theory but actually jeopardizes the efforts of a decision-maker to support a decision on rationality. The outcomes have not even gone through the numerical-hefty and complicated procedure of the sensitivity analysis, i.e. to find the most sensitive criterion and the most sensitive element, a slight change of them would result a rank reversal.

Considering the above, current MCDM techniques cannot fully reason out such simple safety decisions in a real world application. The issue of subjectivity rises not only for the evaluation of alternatives and the weighting of criteria but also in the selection of the method. However, a combination of these methods could yield some interesting results. Tsaur et al. (2002) combined successfully AHP, fuzzy sets and TOPSIS for the evaluation of the service quality of an airline; this is not the only example in the literature that combines MCDM techniques. A more objective perspective involving AHP and TOPSIS could include the following steps:

1. Use of a 'tested' scale, such as the one provided by Saaty or Lootsma, or other researchers, given also the scale and the magnitude of the problem.
2. Extract the relative weights of criteria by using AHP procedures; this will highlight subjectivity in the decision-making process, yet rationalizing input.
3. Use TOPSIS for the evaluation of the criteria; it is numerically and conceptually easier for the decision-maker to understand the deviation from an ideal and a negative-ideal target.

Such an approach would permit a better analysis and comparison of the criteria, as these have to form a hierarchy. The initial 9×9 matrix cannot be adequately handled, so a further breakdown into 'clusters' of criteria is necessary. For example three clusters of three criteria each would yield comparisons of four 3×3 matrices. The handling and the analysis of a 3×3 matrix is more convenient and more straightforward, therefore the approximation of criteria weights, can also be better justified.

The evaluation of alternatives by TOPSIS is as objective as possible. The decision depends heavily on data set, i.e. the number of criteria and the attributes of the alternatives. The same applies for all methods, as the addition or the omission of a criterion may lead to rank reversals.

Another point of concern is sensitivity analysis. Following the procedure described by Triantaphyllou (1997), both AHP, TOPSIS and any other method, such as the Weighted Sum Method (WSM) or the Weighted Product Method (WPM), can be further scrutinized, given that the comply with the basic model-structure. In conclusion, such a combination could easily justify the outcome yet methodologically the fundamental question which method is more appropriate has still not been answered. Nevertheless, it still necessary for scientists to produce a technique or methodology for the selection of the most suitable MCDM techniques for safety-related problems.

In view of the above remarks, it is easy to conclude that MCDM techniques can be a powerful tool in decision-making yet not the most appropriate for marine applications. Although specific MCDM modeling can be of interest or useful, one should into account the following two points, when dealing with applications in the marine environment.

The first point is the choice of an MCDM technique over a well-established method, such as the Formal Safety Assessment (FSA). FSA is a technique, primarily used by the International Maritime Organization (IMO) as a tool, specially designed, to assist maritime regulators in the process of improving and deriving new rules and regulations (Kristiansen, 2005, p. 282). FSA is not a pure MCDM technique, although there are many similarities. Group decision-making is possible; weight attribution is also possible, hierarchical structures are required, scenarios are evaluated, and interactions between factors are encountered, however there is a strong focus on risk assessment. One could argue that FSA is a 'construction' that fits many techniques and compromises many approached towards a specific goal. A point of interest is the 'generic ship' prescribed for evaluating measurements and deriving rules. Another is the analysis of stakeholders.

Obviously, any MCDM method can deal with the problem of stakeholders easier or consider better rule-making, yet it would demand highly-trained modelers for dealing with the marine problem. There is a trade-off between expertise in MCDM and the applicability of the method. It is a rather difficult task to evaluate decision-making methods; there is none procedure or pattern widely accepted by the scientific community. A recent attempt to evaluate methods in a port-marketing application, offers a good basis for further discussion, as the criteria were hierarchically set according to the needs of AHP (Schinas et al., 2006). Some of the criteria used are:

1) Usability
    a) Easiness of data collection
    b) Time and effort devoted towards a result
    c) Resources (people and level of expertise)
    d) Necessity to cooperate with other parties in order to get a result
2) Validity
    a) Data manipulation (towards a specific outcome)
    b) Sensitivity of the output
    c) Self-control loops
3) Ability to Support Decisions
    a) Reliability
    b) Endurance
    c) Strategic & tactical decisions

In view of the above criteria, a direct comparison of any MCDM method and a widely applied one, as FSA, is possible. Obviously, both the criteria-set and the comparison per criterion are subjective, but one could plainly argue, that FSA is relatively more attractive method over data collection, required expertise and effort as well as strategic and tactical decisions. An MCDM method can be considered as more attractive over reliability, endurance, sensitivity and self-control. Data-manipulation and co-operation with other parties are considered as very vague criteria, as they strongly depend on the intentions of the decision-maker, the structure of the criteria and the expertise. Nevertheless, the above analysis suggests, that an established method, such as FSA may not be as 'rational' and 'robust' as a MCDM method, but requires less expertise, time and effort, and it is focused on marine cases. An interesting question would be if any MCDM method could widely be applied in the future for marine cases. The answer would be negative, if structures (criteria-sets) are not uniform, i.e. 'one suits all' approach, and positive if the structure would be uniform.

The second point of concern is the making of rules and the promotion or safeguarding of safety in a holistic approach; as stated before FSA is a tool for rule-making. Obviously no rule is perfect, engulfs many compromises and synthesizes many goals, and there are cases where its application leads to undesirable results. However, a holistic approach in safety is necessary, and an MCDM technique, as many other techniques, such as FSA, cost-benefit analysis, etc. cannot deal with all problems and cases. Consequently, what would be more interesting is research and presentation of evidence that a specific method is more appropriate for specific group of problems. For example, AHP is widely applied method but there are both theoretical and practical problems when dealing with positive (benefit) and negative (cost) objectives.

In conclusion, currently widely applied in other fields MCDM techniques can only be of assistance in marine-cases for given and specific problems; it is not easy to replace specialized techniques, such as the FSA. On the other hand, MCDM techniques can provide a more rational and scientifically sounder basis for consideration of complex problems in marine safety. Nevertheless, the issue is not the 'competition' between methods but research on the appropriateness of a method to deal with a specific group of problems. Generally, it is difficult if not impossible to select on pure rational criteria a MCDM method, but given a specific target, setting limitations, some criteria and the comparison scales, it is possible to validate MCDM methods.

6 Literature

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