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Evaluating alternative energy carriers in ferry transportation using a stochastic multi-criteria decision analysis approach

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ABSTRACT

As part of ship acquisition decision making, owners and key stakeholders need to evaluate ship design and technology solutions across economic and environmental criteria in addition to safety and other regulatory requirements. Changes in technology, market, fiscal and other regulatory conditions may furthermore significantly influence value retention over the investment period. Multi-criteria decision making (MCDM) provides structure and clarity in otherwise complex decision problems, allowing decision makers to identify promising courses of action in a holistic manner. Combined with stochastic evaluation techniques, MCDM may facilitate problem exploration and learning in situations where outcomes are uncertain. In this article, we combine two variants of "Stochastic Multicriteria Acceptability Analysis" (SMAA) with "Technique for Ordering of Preference by Similarity to Ideal Solution" (TOPSIS) to evaluate the use of biofuels, natural gas and electricity on Norwegian ferry crossings. We analyze uncertain criteria values for environmental impacts, costs, fuel access and public acceptance across seven ferry combinations for a crossing. Criteria weighting is performed deterministically and stochastically to extract and interpret the conditions under which alternatives perform well or poorly. The case study shows that all-electric propulsion is preferable, while plug-in hybrid solutions with natural gas also give a robust performance. The approach is beneficial in handling multiple, uncertain performance metrics and provides a transparent and holistic foundation for evaluating marine emission reduction technology options in ship acquisition decision contexts.

1. Introduction

Shipboard emissions of greenhouse gases (GHGs), sulfur oxides (SO_x), nitrogen oxides (NO_x) and particulate matter (PM) poses global environmental threats and is harmful to human health (Bengtsson et al., 2014; Bengtsson et al., 2012; Bengtsson et al., 2011; Brynolf et al., 2014; Brynolf et al., 2014; Andersson et al., 2016). International regulations currently encompass mandatory requirements for engine standards, fuel quality requirements and emission reduction measures for maritime transportation (International Maritime Organization; Regulation (EU), 2015; Directive, 2012). This has led to an increase in research and applications of alternative energy carriers, power systems and abatement technologies. While several studies show that such technologies may significantly reduce both upstream and operational air emissions from marine fuels (Brynolf et al., 2014; Bengtsson et al., 2014; Bengtsson et al., 2012; Bengtsson et al., 2011), operators must also be mindful of financial, technical, social and other performance

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metrics when making decisions during ship acquisition or retrofitting. Multi-criteria decision analysis (MCDM) enables operators and other decision makers to combine performance information across multiple criteria with their subjective priorities to form an overall evaluation of alternatives. Such approaches have been explored in (Deniz and Zincir, 2016; Ren and Liang, 2017; Ren and Lützen, 2015; Ren and Lützen, 2017; Corbett and Chapman, 2006) where several performance metrics and uncertainties are taken into account when a discrete set of emission reduction options are defined. These approaches allow analyzing costs and benefits, extending pure monetary performance metrics.

An intrinsic part of technology investment evaluations in ship acquisition are short- and long-term uncertainties originating from fluctuating external conditions. In evaluating alternative fuels, power systems and abatement technologies in shipbuilding or retrofitting, the ability to encompass these fluctuations is of special importance to the value of the analysis. Rapid developments in fuel supply infrastructure, variation in energy costs, as well as technology maturity and development of future policies may all substantially affect the outcome of various technology options (Gaspar et al., 2015; Niese and Singer, 2013). Such disruptions may render certain choices suboptimal or obsolete over time with a resulting value loss for operators over the investment period.

In this article, we propose a stochastic multi-criteria decision analysis approach to evaluate alternative energy carriers in ferry transportation, taking uncertainties into account. The approach attempts to accommodate situations where courses of action are subject to stochastic uncertainties, cardinal and ordinal criteria are necessary to evaluate performance of alternatives and input data needs to be defined in a crisp manner. In Section 2, we explore previous studies handling uncertainties in ship acquisition decision problems before introducing the proposed SMAA-TOPSIS approach in Section 3.1. Section 3.2 further details a case study used to exemplify the approach before results from the application are described in Section 3.2.4. In Section 4, we discuss the properties of the approach as well as the practical and policy implications of our results. Finally, Section 5 summarizes the conclusions of our study.

2. Handling uncertainties in MCDM

In MCDM, problem modeling and analysis implies defining relations between alternatives in performance and criteria with regard to importance. Uncertainty may be defined as lack of information to deterministically define these relations and may originate due to intrinsic variability in the system under study (aleatoric), lack of knowledge (epistemic) or competing interpretations (ambiguity) (Warmink et al., 2010). Inadequate handling of uncertainties in the overall valuation may result in the recommendation of suboptimal solutions or solutions that are insufficiently robust.

Former MCDM approaches for evaluating ship design and subsystem selection has largely resorted to fuzzy modeling in dealing with uncertainties. An early example of this is found in (Ölçer and Odabaşi, 2005) where a fuzzy multi-criteria group decision making procedure was applied to a selection of propulsion/maneuvering systems for a double-ended passenger ferry. In this study, criteria such as maneuverability and reliability were modeled as trapezoidal fuzzy numbers using expert judgement. A similar approach was applied in (Ölçer et al., 2004) where six ship design alternatives were compared using fuzzy modeling and expert opinions. Both these studies used TOPSIS to aggregate the crisp (defuzzified) ratings of alternative courses of action. A fuzzy multi-criteria group decision analysis using TOPSIS was also employed in (Ren and Liang, 2017) to comparatively assess marine fuels across 11 sustainability criteria. A refined version of fuzzy TOPSIS, coined Approximate TOPSIS, was applied to an oil tanker selection problem in (Yang et al., 2011).

Another popular method combined with fuzzy modeling in ship design and system evaluations is Analytical Hierarchy Process (AHP). In (Ren and Lützen, 2015) fuzzy AHP was used to define weights and criteria scores for marine emission reduction technologies and fuels across nine sustainability criteria. In (Bulut et al., 2015) fuzzy AHP was extended by using a rotational priority investigation (RPI) and applied to a marine engine selection problem. In (Yang et al., 2009), fuzzy modeling was combined with Evidential Reasoning (ER) to an oil tanker selection problem to deal with both imprecision and incompleteness. Here, belief degrees were defined on linguistic terms for scoring alternatives across criteria. Fuzzy ER was also applied to a marine fuel selection problem in (Ren and Lützen, 2017), where 15 criteria were used to assess LNG, wind and nuclear power for ship propulsion. In this study, weights and criteria scores were defined using fuzzy modeling, before ER was used to establish degrees of preference among pairs of alternatives and ultimately a final ranking.

Although there are several examples of MCDM combined with fuzzy modeling techniques to address uncertainties in ship design and acquisition decision problems, little is currently done to tackle problems featured by aleatoric and epistemic uncertainties. This could be the case when criteria uncertainties need to be crisply defined, for example when data is derived from literature or based on analytical forecasting models. In situations where decision makers wish to include such data or scenario information, stochastic modeling techniques might be useful as they allow preserving the crisp interpretation of data throughout the analysis.

To handle these decision contexts, we apply a stochastic multi-criteria approach to evaluate alternative marine fuels and power systems. By combining “Stochastic Multicriteria Acceptability Analysis” (SMAA) and “Technique for Ordering of Preference by Similarity to Ideal Solution” (TOPSIS) descriptive measures are extracted to evaluate various energy carriers in the face of uncertainties. SMAA is in this case advantageous to fuzzy variants of MCDM by permitting the direct use of available information on both short and long-term performance uncertainties. The approach also reduces the cognitive burden on decision makers and experts by inverse weight space exploration. This may furthermore increase the learning outcome in the intervention without extensive data requirements. As SMAA techniques provide an extension of MCDM to accommodate uncertainties, they may be combined with any method to offer decision support in problems with uncertain outcomes. The selection of TOPSIS in our case is due to its low complexity and modeling requirements, as elaborated in (Aspen et al., 2015).

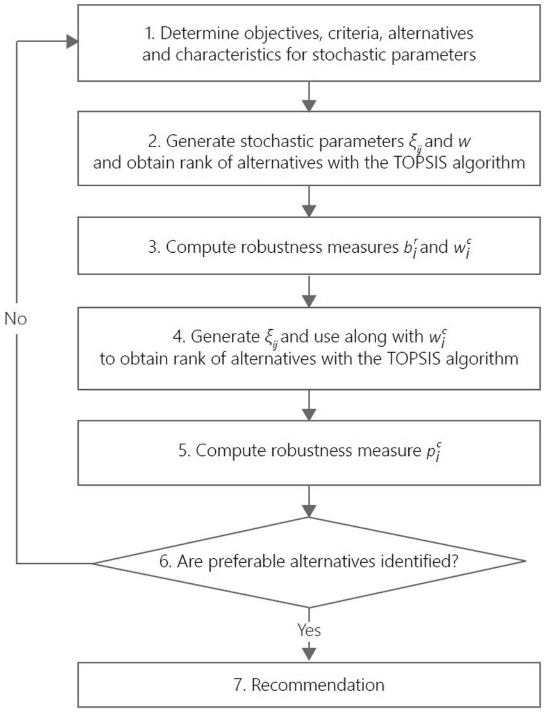


Fig. 1. Steps in the application of SMAA-TOPSIS.

3. Material and methods

3.1. Computational framework

This study combines two variants of “Stochastic Multicriteria Acceptability Analysis”, SMAA-2 and SMAA-O, with “Technique for Order Preference by Similarity to Ideal Solution” (TOPSIS), hereafter named the SMAA-TOPSIS approach. We select this particular combination of techniques as it helps to explore the decision problem with imperfect data and is well suited to using forecasts and other information to determine model parameters in the decision problem. Previous literature has described approaches that combine TOPSIS and SMAA-2 for cardinal criteria (Okul et al., 2014; Zhu et al., 2018). The SMAA-TOPSIS approach used in this study advances this technique by handling also ordinal criteria information in the sampling and mapping procedure via the SMAA-O variant. A similar approach for interval ranking of ordinal criteria may be found in (Ana et al., 2009). Fig. 1 shows all the steps in the combined approach.

3.1.1. SMAA-2

“Stochastic Multicriteria Acceptability Analysis” (SMAA) was developed by Lahdelma and Salminen (Lahdelma and Salminen, 2001) to take into account uncertain criteria values and preference information. In this method, uncertainties are modeled using stochastic parameters and measures of robustness derived to evaluate alternative courses of action. The weight space is furthermore analyzed to obtain preferences that correspond to various ranks for each alternative. This is beneficial when decision maker (DM) preferences are difficult to determine, for instance due to time constraints, reluctance or an inability to express them.

We implement SMAA-2 using a stochastic simulation model where uncertain criteria values are represented using stochastic variables, ξ_{ij}, with assumed probability distributions. We also define stochastic weights using a uniform distribution. A utility function, in our case the TOPSIS algorithm further described in later sections, is used to map these stochastic parameters on to utility distributions, $u(\xi_i, \mathrm{w})$. In SMAA-2, these utility distributions are used to compute descriptive measures. In this article, we will focus on three such measures: *rank acceptability indices, central weight vectors* and *confidence factors*.

The *rank acceptability index* b_i^r measures the set size of valuations giving alternative x_i rank r. The indices are in the interval 0 to 1 where a low value indicates that the alternative is unlikely to obtain the rank r, while a high value indicates a high probability of attaining the rank with the given stochastic parameters. The rank acceptability index for the first (i.e. best) rank position is denoted a_i. When implemented using a stochastic simulation model, the index is computed as the proportion of iterations for which an alternative hits rank r (Tervonen and Lahdelma, 2007). The measure is useful to distinguish robust alternatives that attain high rank acceptability for high ranks. It is also useful in identifying promising solutions that frequently attain other good ranks as well as solutions that attain mainly low ranks.

The second measure extracted from the acceptability analysis is *central weight vectors,* w_i^c,which is the expected center of gravity of the set of favorable rank weights. The metric represents the best weight distribution that favors an alternative with the given stochastic parameters and selected utility function, and may be interpreted as a representation of the preferences of a typical decision maker that favors an alternative x_i.

The final measure explored in this study is the *confidence factor* p_i^c, which measures the probability of an alternative to obtain the first rank position with its central weight vector and stochastic criteria values. This helps evaluate whether criteria measurements are accurate enough to distinguish efficient alternatives. When derived using a stochastic simulation model, the confidence factor is computed as the proportion of iterations where alternative i hits the first rank position using its central weight vector.

3.1.2. SMAA-O

For ordinal criteria, mappings to cardinal values is necessary to implement a compounding utility function. The approach is implemented as described in (Lahdelma et al., 2003). Ordinal ranking of criteria is conducted by assigning a rank level number for each alternative $r_q = 1, \cdots, q^{max}$ where 1 is the best and q^{max} is the worst rank level number. Although the distances between points on an ordinal scale are not known, we may presume that some unknown cardinal measures correspond to the known ordinal measures. As ordinal scales are insensitive to monotone increasing transformations, we may model ordinal criteria by simulating permissible mappings from ordinal to cardinal values (Lahdelma et al., 2003).

To account for uncertainty, we permit rank intervals for ordinal criteria. The rank of alternatives across ordinal criteria is sampled from its respective interval to form a weak order before the abovementioned cardinal mapping procedure. A similar approach using rank intervals to account for uncertainty in ordinal criteria performance is demonstrated in (Ana et al., 2009).

3.1.3. TOPSIS

Various aggregation functions may be used with SMAA-methods to rank alternatives. In this study, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Hwang and Yoon (Hwang and Yoon, 1981) is selected as it is a simple and intuitive model. TOPSIS has been applied to multiple ship designs and system evaluations as seen in (Ren and Liang, 2017; Yang et al., 2011; Alarcin et al., 2014; Yang, 2012; Ölçer and Ballini, 2015). In this method, alternatives are ranked according to their distance to the ideal point and negative ideal point. TOPSIS requires that each criterion has monotonically increasing or decreasing utility. The method is implemented as described in (Hwang and Yoon, 1981). A normalized decision matrix is constructed using vector transformation with the elements

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} i = 1, \cdots, m; j = 1, \cdots, n \tag{1}$$

where x_{ij} is the value of the i-th alternative along the j-th criterion. A weighted normalized decision matrix is then constructed with elements

$$z_{ij} = y_{ij} w_j i = 1, \cdots, m; j = 1, \cdots, n \tag{2}$$

where w_j is the weight of the j-th criterion.

The positive ideal solution a^* and the negative ideal solution a^- are defined as follows:

$$a^* = \{(\underset{i}{max} z_{ij} | j \in J), (\underset{i}{min} z_{ij} | j \in \hat{J}) | \ i = 1, \cdots., m\} = \{z_1^*, z_2^*, \cdots, z_n^*\} \tag{3}$$

$$a^- = \{(\underset{i}{min} z_{ij} | j \in J), (\underset{i}{max} z_{ij} | j \in \hat{J}) | \ i = 1, \cdots., m\} = \{z_1^-, z_2^-, \cdots, z_n^-\} \tag{4}$$

where J is the index set of benefit criteria and $\hat{J}$ is the index set of cost criteria. The distance of an alternative to the positive and negative ideal solutions are then computed as follows:

$$S_i^* = \sqrt{\sum_{j=1}^{k} (z_{ij} - z_j^*)^2} i = 1, \cdots. m \tag{5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{k} (z_{ij} - z_j^-)^2} i = 1, \cdots. m \tag{6}$$

where S_i^* is the positive ideal point and S_i^- is the negative ideal point. Finally, the relative closeness of each alternative to the ideal solution is obtained from

$$C_i^* = \frac{S_i^-}{(S_i^- + S_i^+)} \quad 0 \leq C_i^* \leq 1, \quad i = 1, \cdots, m \tag{7}$$

Alternatives are ranked based on their closeness to the ideal solution

$$if C_i^* > C_{i'}^* \quad then \quad a_i P a_{i'} \tag{8}$$

$$if C_i^* = C_{i'}^* \quad then \quad a_i I a_{i'} \tag{9}$$

3.1.4. The integrated SMAA-TOPSIS approach

Fig. 1 shows the 7 steps of the SMAA-TOPSIS approach, where SMAA-2, SMAA-O and TOPSIS are integrated to support energy carrier selection in ferry acquisitions.

In *step 1*, the problem is structured through defining overall objectives, criteria and alternatives to be analyzed and furthermore defining stochastic distributions of criteria values and/or preferences. Total lack of preference information may be represented by a uniform weight distribution.

In *step 2*, stochastic parameters ξ_{ij} and weights are generated to analyze the problem using the TOPSIS algorithm. This implies randomly generating a decision matrix and weight vector using the representative distributions defined in *step 1*. For ordinal criteria, ordinal criteria values are first randomly generated before mapped to a cardinal value using SMAA-O.

In *step 3*, descriptive measures b_i^r and w_i^c are computed using results from all iterations.

In *step 4*, stochastic parameters ξ_{ij} are generated and used along with the central weight vector $w_i^c$to evaluate alternatives using the TOPSIS algorithm.

In *step 5*, results from *step 4* are used to obtain the confidence factor p_i^c.

In *step 6*, descriptive measures and central weight vectors are evaluated to identify preferable alternatives. This entails identifying alternatives that have a high rank acceptability and confidence factor. If preferable alternatives are identified, recommendations may be made to decision makers in *step 7*. If no alternatives are considered preferable, it is necessary to loop back to *step 1* to identify new alternatives, criteria or preference information necessary to achieve problem resolution.

The accuracy of SMAA calculations rely on the number of iterations performed in the analysis. To achieve error limits of 0.01 with 95% confidence for descriptive measures b_i^r and p_i^c, 9604 Monte Carlo iterations are necessary (Tervonen and Lahdelma, 2007). In our case study 10 000 iterations were performed. An elaborate account of accuracy of results from Monte Carlo simulations may be found in (Milton and Arnold, 1995).

3.2. Description of the transportation case

The case explores a recent tender for a Norwegian ferry crossing with technology-specific requirements. In 2017, the Norwegian Public Roads Administration issued a contract for the period 2021–2029 on the Molde-Vestnes connection, specifying permissible energy carriers for the ferries. To reproduce the case, double-ended monohull passenger ferries are used as baseline concepts to evaluate admissible energy carriers. Connection and ferry characteristics are specified in Table 1.

3.2.1. Alternatives

The tender specifies that two ferries should be all-electric (AE) while two should be plug-in-hybrid (PIH) ferries in combination with biodiesel (BD), liquefied biogas (LBG) or liquefied natural gas (LNG). This generates three options (A1-A3). We also include four alternatives (A4-A7) where all four ferries are either AE or PIH using each of the permissible energy carriers. This gives a total of seven alternatives, as listed in Table 2.

3.2.2. Criteria and uncertainties

Five criteria are used to evaluate the performance of alternative technologies for alternative marine fuels and powering options, as described in Table 3. The criteria cover various dimensions of sustainability and are selected based on a problem structure developed for the case study decision context (Aspen et al., 2018), as well as the criteria used by the concession authorities, the Norwegian Public Roads Administration (NPRA), to evaluate bids.

GHG emissions: The carbon footprint from fuels consumed on an annual basis is used to account for GHG emissions. This builds on data obtained from life cycle assessments, where an inventory of upstream processes as well as combustion is used to build an emission profile. The system boundaries for data included in this case study are well-to-propeller (WTP). In our case, only LNG is assigned operational GHG emissions. Although CO_2-emissions from the combustion of biofuels are typically equivalent to that of fossil fuels based on energy content, these emissions are by convention not attributed operational emissions as this is short-cycled CO_2 (Florentinus et al., 2012). Upstream emissions from biofuels may occur due to energy intensive production of feedstock as well as

Table 1
Specification of the transportation case.

Connection and ferry characteristics	
Distance connection (km)	11.5
Contract period (years)	8
Crossing time / time at quay (min)	33 / 10
Number of daily trips	104 (4 × 26)
Length over all (m)	104
Beam moulded (m)	17,5
Draft (m)	3,2
Car capacity	125
Passenger capacity	415
Car deck arrangement	Tween deck
Hull material	Steel

Table 2
Combination of powering options for the four ferries explored in the case study.

Alternatives	AE	LBG_PIH	LNG_PIH	BD_PIH
A1	2	2		
A2	2		2	
A3	2			2
A4	4			
A5		4		
A6			4	
A7				4

Table 3
Criteria for the ferry transportation case.

	Criteria	**Measurement**	**Description**	**Objective**
y_1	GHG emissions	Annual t CO_2-equivalents	Annual t emissions of greenhouse gases from fuel production and combustion	Minimize
y_2	NO$_x$-emissions	Annual t NO$_x$ emissions	Annual t emissions of NO$_x$ from fuel combustion	Minimize
y_3	Acquisition cost	M$	Investment costs of ferries	Minimize
y_4	Fuel access	Ordinal rank	Expected access to selected energy carrier(s). Ordinal rank in the interval 1–7 where 1 is the best rank	Minimize
y_5	Public acceptance	Ordinal rank	General acceptance for technology solution. Ordinal rank in the interval 1–7 where 1 is the best rank	Minimize

distribution (Bengtsson et al., 2012; Zaimes et al., 2013). Emissions from electricity production depends on which electricity mix is assumed in the analysis (Maritime, 2015). Annual fluctuations in the market as well as meteorological conditions may also influence the mix emission profile. In a long-term perspective, the degree of conformance to international legislation on emission reductions also adds to the uncertainty of greenhouse gas emissions from electricity production (Bringedal, 2016).

NO$_x$-emissions: Operational NO$_x$-emissions come from combustion of biofuels and LNG. For biodiesel, emission levels depend on the make, age and combustion characteristics of the engine as well as the operational profile of the vessel, but is usually close to that of conventional fuels. NO$_x$-emissions from biogas are significantly reduced compared to fossil fuels, (see Bengtsson et al., 2012; Brynolf et al., 2014; Florentinus et al., 2012; Bringedal, 2016). Naturally, fully battery powered vessels have zero operational NO$_x$-emissions as no fuel is combusted during operation.

Fuel access: As there might be uncertainty as to whether various energy carriers are expected to be available in the contract period, we also include fuel access as a criterion. This might impact energy costs as well as access to new contracts and the secondhand price of ferries. Uncertainty in access to fuel over time is linked to technological and market conditions (Aspen et al., 2018)

Public acceptance: Public acceptance relates to expectations concerning the general attractiveness for the alternatives in society over the contract period. This criterion also links to expected regulatory development (Aspen et al., 2018).

To evaluate uncertainties in the GHG emission criteria (y_1), we use forecast data and uncertainties provided in the literature. For NO$_x$-emissions, we assume a ± 20 percent uncertainty for values in the literature, while for acquisition costs (y_3), we assume a ± 10 percent uncertainty from values provided in a ferry evaluation tool (Bringedal, 2016). Fuel access and public acceptance are ranked using expert judgement. We assume that all uncertainties may be represented using uniform distributions. Criteria values for all options are shown in Fig. 2.

3.2.3. Preferences

For *stochastic weights*, values are sampled uniformly in the interval between 0 and 1 and further normalized as described in (Tervonen and Lahdelma, 2007). In each iteration, sampled weight vectors are inserted in the TOPSIS model to compute utilities and ranks of all alternatives.

For comparative and interpretive purposes when analyzing results, we also define *deterministic weights* that represent three different priority regimes for a decision maker. These follow three regimes where *economic priority* reflects a preference orientation that emphasize acquisition cost and fuel access. *Environmental priority* assign weights to air emissions, while *social priority* emphasizes the criteria NO$_x$-emissions and public acceptance. Table 4 shows weight vectors used in simulations to represent these priorities.

3.2.4. Results

For each priority regime as well as the stochastic weight case, the decision problem is analyzed using the SMAA-TOPSIS stochastic simulation model with 10,000 iterations. Fig. 3 shows rank acceptabilities, b_i^r,for all seven alternatives with criteria ranges as defined in Fig. 2 and priority regimes as specified in Table 3. As is shown in Fig. 3, option A4 in which all four ferries are all-electric, performs consistently well both for the stochastic weight case, as well as the environmental and social priority regimes. This option has the highest rank acceptability for the first rank position in these instances. The opposite may be said for A6 and A7, the hybrid LNG and biodiesel options respectively, which perform well in the economic priority regime, and attain mainly low ranks in all other priority regimes. Options A1-A3 in which all-electric and plug-in hybrid variants are mixed on the crossing, have a consistent mid-range

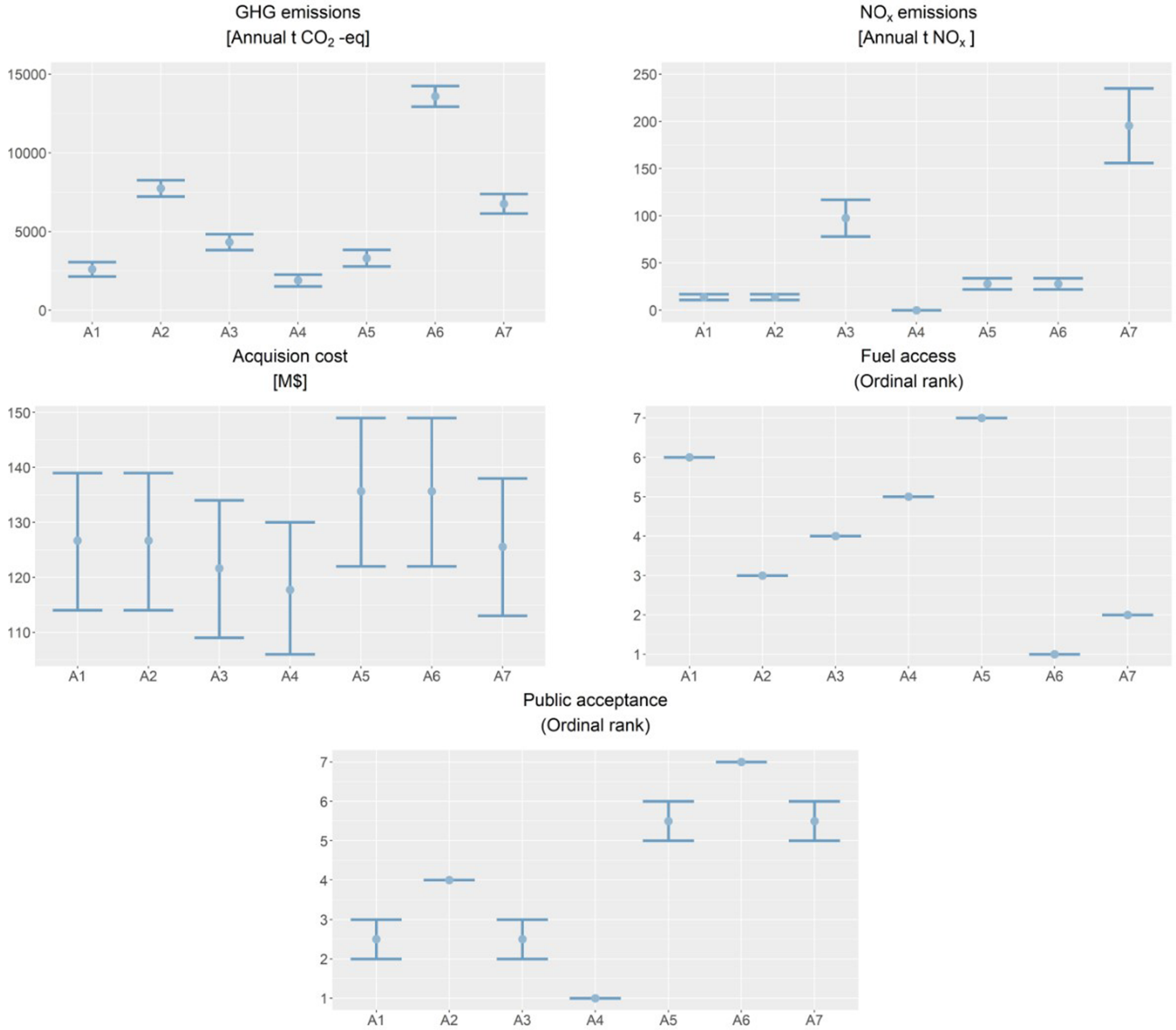


Fig. 2. Ranges for seven powering options across four criteria.

Table 4
Deterministic weight vectors.

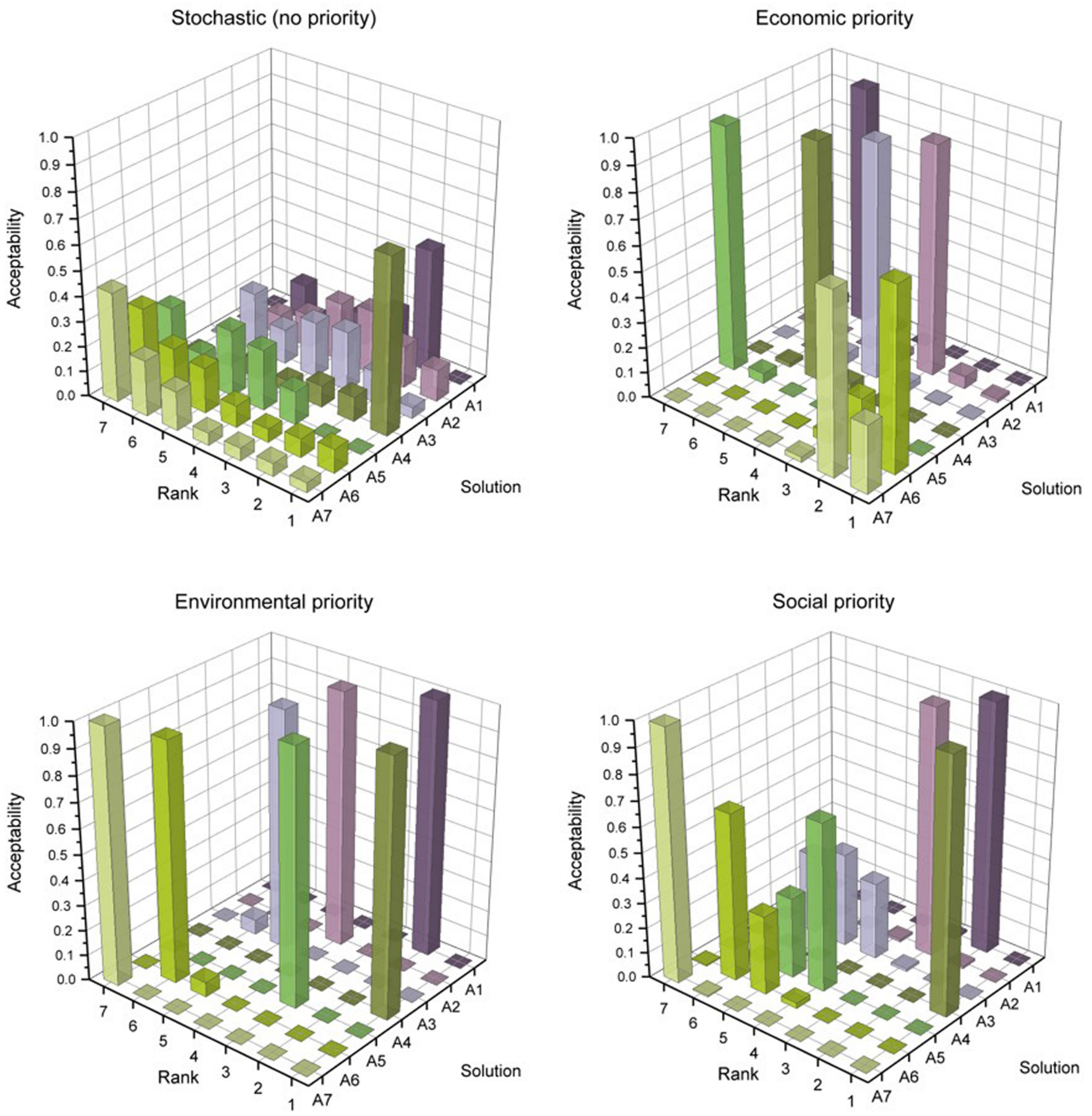
Priority regime	GHG emissions (annual t CO_2-eq)	NO_x emissions (annual t NO_x)	Acquisition cost (M$)	Fuel access (Ordinal rank)	Public acceptance (Ordinal rank)
Economic priority	0	0	0.5	0.5	0
Environmental priority	0.5	0.5	0	0	0
Social priority	0	0.5	0	0	0.5

performance across all regimes. These options are neither the best, nor the worst, in any of the regimes.

Since the stochastic weight case simulates all possible weight distributions the values may be used to evaluate the robustness of the observed results. To elaborate on this, we analyze parameters derived from weight space exploration as given in Table 5. All values are rounded and expressed as percentages. Recalling that central weight vectors w_i^c are computed as the mean of all weight vectors that favor an alternative i, these may be used to interpret preference conditions under which an alternative performs well.

Firstly, using only all-electric ferries (A4) has the highest rank acceptability at 70 percent. As the set size of favorable rank weights is high for this option, we also see that the central weight vector, w_c, distributes weights relatively evenly across most criteria. This shows that the alternative is robust with the given uncertainties on preferences and criteria values.

Next, options including LNG, A2 and A6, also attain first rank positions in 13 and nine percent of iterations respectively. The central weight vector for these two options emphasizes NO_x-emissions, acquisition cost and fuel access. Options including biodiesel, A3 and A7 also attain some first rank positions when analyzed with stochastic weights. These central weight vectors assign the lowest


Stochastic (no priority)

Economic priority

Environmental priority

Social priority

Fig. 3. Rank acceptabilities for alternatives with stochastic weights (no priority) and three deterministic priority regimes.

Table 5

Acceptability indices, confidence factors and central weight vectors for the seven alternatives (percentages, rounded values).

Alt	a_i	p_i^c	W_c				
			GHG emissions (annual t CO_2-eq)	NO_x emissions (annual t NO_x)	Acquisition cost (M$)	Fuel access (Ordinal rank)	Public acceptance (Ordinal rank)
A1	0*	3	14	11	62	4	10
A2	13	68	11	26	20	31	13
A3	4	34	20	6	21	30	23
A4	70	100	24	21	20	12	23
A5	0	–	–	–	–	–	–
A6	9	78	8	16	20	47	9
A7	4	63	20	4	19	46	10

* A1 obtain first rank position in few iterations. Acceptability index becomes zero due to rounded numbers.

weight to NO_x-emissions. In very few iterations, A1, which includes two hybrid biogas ferries, also attains first rank position. The alternative of using only hybrid biogas ferries on the crossing never attains the first rank position in the stochastic weight case.

To further evaluate robustness in attaining the highest rank across stochastic criteria values we resort to confidence factors p_i^c, which show the percentage of all iterations an alternative attained the best rank using its central weight vector. High values indicate a high robustness with the given central weight vector and vice versa.

It is clear that A4, with four all-electric ferries, is a very robust alternative with a confidence factor of 100 percent. This means that a stakeholder with preferences aligned to the central weight vector for this option could be confident in the evaluation with the given uncertain criteria values.

Furthermore, options A2, A6 and A7 also show relatively high consistency in attaining the first rank position when analyzed with their respective central weight vectors. The most robust among these is alternative A6, the hybrid LNG option, with a confidence factor of 78 percent. At the other end, option A1, the all-electric and hybrid biogas combination, has a low confidence factor with only three percent of first rank positions. This means that even if a decision makers has preferences akin to the central weight vector for this option, there are other options that are more preferable. In this particular case, this is option A4, which has an acceptability index of 97 percent when analyzed with the central weight vector for option A1.

In summary, the overall most promising solution with the given criteria, uncertainties and aggregation method are four all-electric ferries (A4). Among the permissible options for the case study explored (A1-A3), option A2, two all-electric and two hybrid LNG ferries, is the most promising.

4. Discussion

4.1. Properties of the integrated SMAA-TOPSIS approach

The proposed SMAA-TOPSIS approach has several practical and technical properties that are beneficial when dealing with problems of a multi-dimensional and uncertain nature. Firstly, the approach integrates *multiple perspectives* in the comparative assessment of alternative technology options. The TOPSIS algorithm combines incommensurate and potentially conflicting criteria into a single quantity for assessing overall performance. The approach also permits information on mixed scale levels through the combination of SMAA-O and SMAA-2 techniques. This is convenient in situations where both quantitative and qualitative performance metrics form part of the decision frame. In our case study, cardinal criteria for emissions and cost are mixed with ordinal criteria for fuel access and public acceptance.

Secondly, the approach specifically address *criteria uncertainties*, which is an important feature of technology investment problems. For alternative marine fuels and power systems, factors such as feedstock, conversion and distribution technologies along with regulatory conditions may vary significantly over the investment period, ensuing in a great bandwidth of potential outcomes. Stochastic modeling enables the use of short and long-term projections, while at the same time alleviating decision makers or domain experts from the burden of providing judgements on highly uncertain parameters. Although a uniform distribution was assumed for criteria in this case study, the decision problem may be modeled using any distribution. The rank acceptability index derived from the analysis helps evaluate performance of alternatives and further classify them in terms of robustness. This is clearly seen in the case study, where the option of four all-electric ferries exhibited robust performance, even with the given criteria uncertainties. The index is useful when decision makers need to distill from an initial set of alternatives a subset of acceptable solutions for further examination.

Thirdly, missing or uncertain *preference information* is also conveniently handled in the approach. In contrast to tedious elicitation procedures necessary in deterministic approaches, stochastic modeling allows dealing with situations where no or only partial preference information is accessed. The inverse weight space exploration in SMAA is based on the extraction of central weight vectors, which helps identify underlying preferences consistent with favoring various alternatives. Confidence factors further add to this interpretation by indicating the robustness of alternatives when analyzed with their respective weight vectors, again increasing the learning outcome and reducing the cognitive strain on decision makers. As was seen in our case study for the four LNG ferry options, an alternative with a low acceptability index may still attain a high confidence factor. This means that decision makers with preferences aligned to the central weight vector for this option may evaluate it as promising, even if it has a low acceptability index. Furthermore, a decision maker whose priorities are more evenly distributed among criteria may view the option of four all-electric ferries as robust, since it has both a high acceptability index and confidence factor.

Decision makers and analysts must however be mindful of the properties of the approach and its implications for results. TOPSIS is a value-function method, fully compensatory with regard to criteria tradeoffs in computing its utility measure, i.e. the ideal solution distance (Sen and Yang, 1998). With compensatory methods, poor performance along a majority of criteria may be offset with exceptionally good performance in those remaining. This may be of concern when criteria are selected to operationalize sustainability dimensions (Polatidis et al., 2006). As the aggregation procedure does not penalize imbalance in criteria performance, alternatives considered unsustainable may still attain high ranks. In the SMAA-TOPSIS approach, the rank acceptability index may theoretically favor imbalanced alternatives. However, central weight vectors and confidence factors will partially help detect and evaluate this phenomenon in cases where weights are not deterministic. Regardless, it is important to ensure that decision makers consider all alternatives acceptable and furthermore consent to full compensation prior to applying the SMAA-TOPSIS approach. If decision makers are reluctant to accept full compensation, non– or only partially compensatory methods could be used. Outranking methods are often less compensatory in nature and could easily replace TOPSIS in the suggested approach. Examples of SMAA with outranking methods may be seen in (Ana et al., 2009; Corrente et al., 2014; Tervonen et al., 2009).

Another important feature of TOPSIS is that it is a value function method where weights represents criteria tradeoffs or scaling constants (Belton and Stewart, 2002). The evaluation of central weight vectors using SMAA-TOPSIS should therefore fully explain criteria scales to facilitate interpretation among decision makers. Specifying tradeoffs between pairs of criteria following from central weight vectors could for instance help clarify their implications. In situations where multiple criteria may be used to represent the same dimension, the problem could furthermore be revisited with different criteria sets to see how central weight vectors and other performance measures vary.

While different aggregation procedures may produce different results for the same decision problem, it is important to carefully select an MCDM method that exhibits the technical and practical properties compliant to the characteristics of the decision problem at hand (Aspen et al., 2015). If sufficient information and resources are available in the decision context, additional MCDM methods may be used along with SMAA to validate results or identify potential conflicts. Since TOPSIS is a value theory method, it could be useful to compare results to an application of SMAA with an outranking method, such as for instance SMAA-PROMETHEE (Corrente et al., 2014) , or SMAA-TRI (Tervonen et al., 2007,) , if relevant. Although such an endeavor would require additional input parameters to be modeled, it could also create a greater learning outcome for decision makers.

While the SMAA-TOPSIS approach comprehensively deals with problem uncertainties, some shortcomings are observed. As descriptive measures primarily build on the inverse weight space exploration, a deeper understanding of criteria variability is still missing. This is relevant for long-term investments as decision makers may wish to spend resources reducing uncertainties or discerning critical criteria.

4.2. Practical and policy implications

The case study demonstrates the workability of the approach when evaluating emission reduction technology solutions. The approach may be useful to owners, operators, naval architects, suppliers and other critical decision makers during the planning phase of ship acquisition. At this stage, the performance expectations and requirements of the ship are defined to further evaluate the overall business concept (Vassalos, 2009; Cushing, 2011). When evaluating a tender, industry decision makers may use the approach to conduct an initial appraisal of alternative technology solutions using uncertain parameters. As the design description matures throughout the acquisition process and more information is accessible, the approach may be reapplied to reconsider and validate technology and design choices. Other decision problems concerning emission reduction technology in ship acquisition involves the development, appraisal and selection of competitive tenders and long-term technology strategies (Aspen et al., 2018). While the first concerns both technology ambition, contract pricing and other bid characteristics in a specific tender process, the second concerns target technologies on which to build organizational competence and capabilities over a longer time period (Aspen et al., 2018). Both may benefit from the demonstrated approach as they concern the selection of emission reduction technology in both near and long-term perspectives.

The proposed approach may also be useful to concession authorities during the tendering process to explore and shape requirements and eventually select bids. Using multi-criteria approaches in public procurement is already commonplace and the Norwegian Public Roads Administration already adopt a scoring model for evaluating bids at state ferry crossings [see e.g. Norwegian Public Roads Administration, 2015]. The SMAA-TOPSIS approach could be used to analyze performance uncertainties and explore economic and environmental risks. The inverse weight space analysis also brings subjective opinion into explicit account, which could be useful in instances where multiple actors and opinions needs to be handled.

5. Conclusions

In this article, we have demonstrated a stochastic multi-criteria decision analytical approach to a marine emission reduction technology selection problem using a case study of energy carrier selection on a Norwegian ferry crossing. The approach combines “Technique for Ordering of Preference by Similarity to Ideal Solution” (TOPSIS) with “Stochastic Multicriteria Acceptability Analysis” (SMAA) techniques to reduce problem dimensionality and handle aleatoric and epistemic uncertainties.

We find that the practical and technical properties of the approach is helpful when handling multi-criteria problems of an uncertain nature. The TOPSIS algorithm helps reduce multiple criteria into a single dimension to compare alternatives across performance metrics that are initially incommensurate. SMAA techniques furthermore facilitate the combination of both quantitative and qualitative information in this procedure, and simplify preference modeling by employing inverse weight space exploration. More importantly, criteria uncertainties are possible to model using forecast data and other critical expert information often issued on novel and partly unproven technologies. Several descriptive measures are then extracted to evaluate alternatives and conditions under which they exhibit good and poor performance. In sum, this reduces the resource requirements and strain put on decision makers during the formal problem modeling and provides critical information when appraising alternatives with uncertain outcomes.

This approach has potential as a useful tool for operators and concession authorities alike in comparatively evaluating multiple options for long-term contracts involving uncertainties. Although these decision frames vary, uncertainties related to emission reduction technologies persist. The proposed SMAA-TOPSIS approach may be used to convey this uncertainty and facilitate problem learning. In contrast to current practices, where deterministic performance is assumed in the tender decision making process, descriptive measures may be included in the overall evaluation of ferry alternatives. From the operator perspective, this could help determine which options should form the bid. For concession authorities that currently apply a predefined deterministic weight regime when bids are evaluated, this approach may assist in exploring the robustness of bids with respect to preferences.

Several drawbacks of the suggested approach originate from that of the TOPSIS aggregation method, e.g. cardinal weight assignment and full compensation. However, SMAA could be combined with several MCDM methods and the general stochastic approach and evaluation measures could be applied in these types of decision contexts.

The case explored in this paper consisted of crisp criteria with epistemic or aleatoric uncertainty. In instances where some criteria are of a fuzzy nature, it may be necessary to apply fuzzy techniques to handle this imprecise feature of the problem at hand. Further integration would allow addressing problems with several forms of uncertainty.

The proposed approach could be extended with additional techniques to further elaborate on criteria uncertainties. SMAA descriptive measures focus on variability in criteria weights to evaluate alternatives. For technology investment problems, it is also useful to identify how uncertain criteria parameters impact on overall results and further target criteria for which more information should be collected. Integrating additional sensitivity analysis techniques and value of information analysis could cater to this need.

Another useful extension of this approach is to use the approach in methods where multiple stakeholder groups are explicitly addressed regarding criteria and preferences. Although SMAA techniques are tailored for situations where preferences are uncertain, its usefulness in situations where multiple actors with diverging concerns and performance metrics is yet to be demonstrated.

CRediT authorship contribution statement

Dina Margrethe Aspen: Conceptualization, Methodology, Software, Data curation, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Project administration. **Margnus Sparrevik:** Supervision, Writing - review & editing.

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