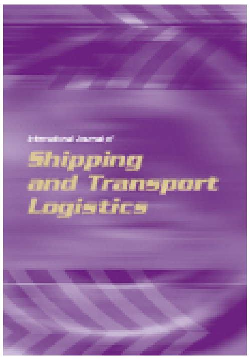

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Applying public information to make green shipping investment decisions

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Abstract: Confronted with a surfeit of green shipping information and a variety of alternative fuels and technologies, the investment decisions facing shipping companies have become increasingly complex. Applying the novel granular fuzzy pay-off method (FPOM), this paper aims to provide a conceptually meaningful, understandable and easily applicable methodology for investment in green shipping. Based on public information, this paper conducts a case study relating to four popular kinds of ship fuels (namely diesel, LNG, methanol and hydrogen) to show how to use this method in financing a green ship. The results show that this methodology performs well under such a scenario. It indicates that, for the case study presented, LNG is an excellent transitional green fuel for use in the near future, regarding both financial benefit and emissions reduction. In addition, compared to the price of carbon, in the short-term fuel costs are more influential in a shipping company's green shipping investment decision process.

Keywords: green shipping finance; alternative fuel; carbon price; granular fuzzy pay-off method; FPOM; possibilistic mean; probabilistic mean.

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1 Introduction

In common with other sectors, the shipping industry is expected to take responsibility for reducing its greenhouse (GHG) emissions. This inevitably involves shipping companies in making decisions on their green investments. However, owing to the considerable uncertainty over the technical viability, availability and price of alternative fuels, as well as over the potential future regulatory landscape (IEA, 2021; Cullinane and Yang, 2022). most of the shipping sector, but particularly smaller entities, are still holding back on required investments in order to 'wait and see' how things develop.

It should come as no surprise that the main players that are undertaking green shipping investment are the container and passenger sectors, where the market is dominated by a few very large carriers. In contrast, given the nature of the competition in the market (Stopford, 2009), the distribution of market shares in the dry bulk shipping sector is much more even. This means that the first-mover advantage of using green ships or technologies that the container and passenger sectors benefit from may not accrue to dry bulk shipping companies that transport low value goods (Yin et al., 2019). This is reflected in the orderbook for alternative fuel engine ships, most of which are container ships and with only a small number of dry bulk ships (DNV, 2024; Mærsk Mc-Kinney Møller Center, 2022).

Compared to diesel, LNG is regarded as a cheaper fuel alternative with lower emissions and higher efficiency, but it is still a fossil fuel which is not sustainable. Ammonia is harmful and will cause NOx emissions. Methanol has been tested in container shipping and is totally green on a 'well-to-wake' basis from production to use. However, uncertainty exists over potential production capacity and, therefore, its availability. Also, its price is much higher than other fuel alternatives. Another emissions-free fuel is hydrogen which, combined with the use of fuel cell technology, has been regarded as a viable fuel for green shipping. However, again, the current market price is a deterrent to investing in the technology required for utilising this fuel.

Making a choice between alternative fuels and committing to a given development plan for green shipping is a difficult process involving many uncertainties. Once shipping companies have taken their decisions to commit to and invest in one fuel, they may be faced with an unaffordable sunk cost if the future fuel of choice does not match their choice (Pomaska and Acciaro, 2022; Wang et al., 2022). From another point of view, other shipping industry stakeholders, such as ports, fuel providers, green technology providers, are similarly confused by the same situation. Because of the sheer number of alternative pathways available to shipping decision makers, the complex implications of each available pathway (for example, as implied by the interdependence between alternative fuels and green technology) and the vast array of public and private information of varying accuracy with which they are confronted, it is very important that shipping decision makers exercise due diligence in their research into the costs and benefits of investing in green shipping (Metzger, 2022; Metzger and Schinas, 2019; Pomaska and Acciaro, 2022; Schinas and Metzger, 2019; Schinas et al., 2018; Wang et al., 2022; Yin et al., 2019).

In an effort to ease the difficulties for shipping decision makers, this paper adopts the granular fuzzy pay-off method (FPOM) to develop pathways for investing in green shipping. The paper contributes to existing research in a number of ways:

1 In order to deal with the uncertainty in green shipping investment, this paper introduces the newly developed practical granular FPOM (Cabrerizo et al., 2020) into the analysis of green shipping finance. A detailed comparison between a series of FPOM calculations is carried out to help shape a good understanding of this methodology.

2 Four types of Panamax dry bulk ship newbuildings are compared based on accessible public information to provide an example of using the method. The real option values of the newbuilding LNG-fuelled ship, methanol-fuelled ship and hydrogen-fuelled ship are compared with that of conventional diesel-fuelled ships,

3 Giving consideration to possible future fuel and carbon prices, the results of this paper shed light on potential green shipping investment pathways for a forecast period to 2035.

4 The results of the analysis inform policy makers and shipping industry decision makers, respectively, as to how best to stimulate and instigate green shipping investments.

The work is structured as follows: a literature review on green shipping is provided in Section 2, including an element relating explicitly to the development of fuzzy theory and FPOM. Section 3 provides a mathematical exposition of FPOM, followed by its application to green shipping in Section 4. The results of this analysis are discussed in Section 5, while Section 6 concludes the paper.

2 Literature review

2.1 Green shipping

As concerns over the environmental footprint of shipping activities have increased, it is no surprise that that there has been a greater focus on research analysing green technology investment in the shipping industry (Shi et al., 2018). Although the term 'green shipping' has become very popular in recent years, academics have striven to find a conceptually meaningful and acceptable definition to describe it (Lai et al., 2011, 2013; Prokopenko and Miskiewicz, 2020; Wu et al., 2020b). Wu et al. (2020b) argued that, compared to 'sustainable shipping', 'green shipping' concentrates more on the health of nature rather than being anthropocentric. Specifically, shipping companies' green performance has been widely analysed (Yang, 2018; Yang et al., 2013), with a focus on activities that could improve the green performance of businesses (Lun et al., 2015) and, related to this, corporate image and reputation (Pang et al., 2021).

On the basis of forecasts of a continuous growth in world trade (IMO, 2020), a focus solely on operational measures will not prove sufficient to achieve, or even approach, a target of zero-emissions by 2050. Since the main source of shipping emissions is the fuel that is burned, albeit in transit or in port (Chen et al., 2022), there are heated discussions as to what is, or should be, the emerging future pathway for the shipping fuel mix (Lindstad et al., 2021). Within this debate, LNG represents a much more mature and understood technology, since it has been in use as a marine fuel for several decades in LNG carriers. LNG also has greater available supply, compared with other green fuels such as methanol and hydrogen, as well as obviously lower emissions compared with diesel (Tvedten and Bauer, 2022). At the time of writing, the ship newbuilding orderbook reveals that 85.3% of ships on order are being built to run on conventional fuel, while another 10.31% of ships on order will run on LNG (DNV, 2023). This suggests very strongly that LNG is regarded by the shipping industry as the fuel of choice in the short- to medium-term for transitioning from diesel fuel to fully emission-free fuel.

Electric ships are also a desirable choice, with a high possibility of achieving emission-free operations if green electricity is available. The possibility of electric propulsion has received significant attention from both short-sea and inland waterway shipping (Wang et al., 2022). However, the issues of charging and safety remain a challenge for implementing this form of propulsion in ocean shipping. By adopting an approach based on the rough set and TOPSIS methods and including LNG, LPG, methanol, HVO, pure battery, hydrogen fuel cell and ammonia fuel cell as potential alternative fuels, Xuan et al. (2022) confirmed that LNG outperformed other alternative fuels in running large coastal ro-ro passenger vessels, while pure battery power outperformed the alternatives in small inland river vessels.

2.2 Fuzzy pay-off method

It is clearly the case that players within the shipping industry are facing difficult decisions with respect to investing in alternative fuel technologies. Which fuel should they opt for and when should they make the required investment? These decisions are having to be made within the context of significant uncertainty; around not only the performance, future price and availability of the different options, but also the future regulatory regime for shipping emissions within which such decisions will have to be made. The significant nature of the uncertainties involved would seem to be an appropriate context for the application of fuzzy set theory.

The concept of the fuzzy set was first introduced by Zadeh (1965) in order to provide a framework for dealing with problems characterised by uncertainty, in which the source of imprecision is the absence of sharply defined criteria of class membership. A refined version of fuzzy set theory, introducing the type-2 fuzzy set (with the original version now regarded as a type-1 fuzzy set), was later presented in Zadeh (1975). However, as the general form of this extension involved 3-dimentional fuzzy numbers, empirical application proved difficult. For this reason, the interval type-2 fuzzy set was introduced to simplify applications based on this concept (Mendel et al., 2006) and became the basis of applications in granular fuzzy model analysis (Morente-Molinera et al., 2019).

The FPOM is a decision-making technique, originating from fuzzy set theory, that was introduced to better deal with the uncertainty or ambiguity in the values of potential investment outcomes arising from imprecision in available public or private information and the subjective interpretation of that information. The fundamental definition of FPOM is based on the calculation of the product of *the proportion of the area of the positive part in the whole fuzzy NPV distribution* and *the mean value of the positive side of the NPV* (Stoklasa et al., 2021). Within the FPOM literature, there has been significant discussion around the latter element of this product – mainly in terms of whether to use the possibilistic mean (Collan et al., 2009; Stoklasa et al., 2021) or the probabilistic mean (Borges et al., 2018).

The possibilistic mean (Carlsson and Fullér, 2001) is a method of combining fuzzy numbers, which are sets of possible values representing uncertainty. It considers the probability of each value in the set and calculates a weighted average based on these probabilities. On the other hand, the probabilistic mean (Dubois and Prade, 1987) is a method of combining values that are uncertain because they are the result of random processes. The probabilistic mean calculates the expected value of a random variable, which is the average of all the possible outcomes weighted by their respective probabilities. In summary, the possibilistic mean is used when the uncertainty in the inputs is represented as fuzzy numbers, while the probabilistic mean is used when the uncertainty is represented as the result of a random process.

Although the possibilistic mean was applied in the original exposition and applications of FPOM (Carlsson and Fullér, 2003; Collan et al., 2009), the model was found to occasionally violate the basic financial theory that the real option value should be no smaller than the related NPV (Borges et al., 2018). Thus, Borges et al. (2018) introduced the probabilistic mean to the FPOM, in the form of the centre of gravity FPOM (COG-FPOM). Since then, however, an updated variant of the original FPOM, utilising the possibilistic mean, has been developed in Stoklasa et al. (2021) which overcomes the shortcomings of the original possibilistic version.

2.3 The application of FPOM in green shipping investment

Metzger and Schinas (2019) introduced the original FPOM and the CoG-FPOM into the analysis of investment in green shipping technology, using a pay-as-you-save model previously expounded in Schinas and Metzger (2019) as the basis for the calculation of fuzzy real option values. Metzger (2022) further elaborated this body of work by incorporating market-based measures (MBMs) into their FPOM. Interestingly, the results indicated that carbon pricing had already begun to have an influence on the investment decisions of shipping companies, even though this regulatory measure had not yet been implemented.

Zhang and Yin (2021) extended their previous work on shipping investment decisions (Yin et al., 2019) using the fuzzy real option value (fuzzy ROV) combined with the binomial tree model and confirmed the effectiveness of fuzzy ROV theory for the analysis of shipping investments.

3 Methodology

The application of the FPOM can be roughly divided into two stages, the first of which relates to finding a representative number for the fuzzy set, which will be discussed in Section 3.1 and the other part, outlined in Section 3.2, is related to optimising the fuzzy number or the fuzzy set itself, through the application of the granular method.

3.1 FPOM and the choice between possibilistic mean and probabilistic mean

The first step in applying the FPOM is to transform crisp values, or NPVs in this paper, into fuzzy numbers in the form of sets of possible values, representing the degree of uncertainty. The triangular and trapezoidal distributions are the most popular membership functions to use when applying the FPOM, where three or four cash flow scenarios (respectively) are needed to create the membership functions. These are as follows:

- an optimistic estimation of the NPV (the highest possible), with a membership value equal to 0
- a basic estimation of the NPV (i.e. the most likely to happen) with a membership value equal to 0 (if a trapezoidal distribution is applied, then two basic expectations are needed)
- a pessimistic estimation of the NPV (the lowest possible), with a membership value equal to 0.

The membership value represents the degree of the estimated NPV belonging to the fuzzy set, meaning any estimated NPV higher than the optimistic scenario or lower than the pessimistic scenario does not belong to the fuzzy NPV, and vice versa. The NPV of each scenario is obtained by running the following calculation:

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1+r)^t} \tag{1}$$

where CF_t is the cash flow in year t, r is the risk-adjusted discount rate.

Next, since an option means the right to invest rather than the obligation, the FPOM attributes 0 to the pay-off distribution (the membership) of any estimated negative NPV. Thus, the fuzzy real option value (*ROV*) (Carlsson and Fullér, 2003; Collan et al., 2009) is calculated as:

$$ROV = \frac{\int_0^{\infty} \mu(x)dx}{\int_{-\infty}^{\infty} \mu(x)dx} * E(A_+) \tag{2}$$

$$\bar{M}(A) = \int_0^1 a * (\alpha_l(\alpha) + \alpha_u(\alpha)) d\alpha \tag{3}$$

$$COG(A) = \frac{\int_r^s x * \mu(x)dx}{\int_r^s \mu(x)dx} \tag{4}$$

where fuzzy NPV A is a fuzzy set of the real line $\mathbb{R}$, $\mu(x)$ is the membership function of A by using the x-cut notation and, in this scenario, $A \in \mathcal{F}_N([r, s])$. Also, A can be described by the membership function using α-cut notation, written as $\{[a_l(\alpha), \alpha_u(\alpha)]\}_{\alpha=0}^{l}$, where $a_l(\alpha)$ and $a_u(\alpha)$ are the lower and upper membership functions of A. $\int_0^{\infty} \mu(x)dx$ is the area of positive NPV, $\int_{-\infty}^{\infty} \mu(x)dx$ describes the whole NPV, and $E(A_+)$ should be the representative number of the positive side of the fuzzy set (Carlsson and Fullér, 2003). Collan (2009) adopted the possibilistic mean ($\bar{M}(A)$), while Borges et al. (2018) introduced the probabilistic variant FPOM, i.e., COG-FPOM, using the probabilistic mean ($COG(A)$) to avoid the problem of violating finance theory.

As it can be easily found, ROV comprises two parts, with the first following the definition of proportion and the second being the expectation of the fuzzy interval. Again, the definition of proportion relates to the definition of probability, where ROV is constructed by a probabilistic part multiplied by an expectation part. Thus, the expectation part is expected to be a probabilistic mean. Stoklasa et al. (2021) later transformed the ROV into a fully possibilistic form and provided evidence that the improved possibilistic FPOM could also avoid violating finance theory. This work further provided a means for the fast calculation for triangle membership distribution.

The possibilistic FPOM can be written as

$$ROV_{pos} = \frac{\int_0^{\infty} \mu(x)dx}{\int_{-\infty}^{\infty} \mu(x)dx} * \bar{M}(A_+) \tag{5}$$

And the COG-FPOM is

$$ROV_{COG} = \frac{\int_0^{\infty} \mu(x)dx}{\int_{-\infty}^{\infty} \mu(x)dx} * COG(A_+)$$

$$= \frac{\int_0^{\infty} \mu(x)dx}{\int_{-\infty}^{\infty} \mu(x)dx} * \frac{\int_0^{\infty} x * \mu(x)dx}{\int_0^{\infty} \mu(x)dx} = \frac{\int_0^{\infty} x * \mu(x)dx}{\int_{-\infty}^{\infty} \mu(x)dx} \tag{6}$$

To better understand the possibilistic mean, the expression could be written as:

$$\bar{M}(A) = \int_0^1 a * (\alpha_l(\alpha) + a_u(\alpha))\, d\alpha = \frac{\int_0^1 a * \frac{(\alpha_l(\alpha) + a_u(\alpha))}{2} d\alpha}{\int_0^1 \alpha d\alpha} \tag{7}$$

This shows the possibilistic mean is the level-weighted average of the arithmetic means of all α-level sets. In one more step, the possibilistic mean could be rewritten as:

$$\bar{M}(A) = \int_0^1 a * (\alpha_l(\alpha) + a_u(\alpha))\, d\alpha = \frac{1}{2} * \left(\frac{\int_0^1 a * \alpha_l(\alpha) d\alpha}{\int_0^1 \alpha d\alpha} + \frac{\int_0^1 a * \alpha_u(\alpha) d\alpha}{\int_0^1 \alpha d\alpha} \right) = \frac{\bar{M}(A_l) + \bar{M}(A_u)}{2} \tag{8}$$

where $\bar{M}(A_l)$ and $\bar{M}(A_u)$ are the lower possibilistic and upper possibilistic mean values of A respectively. That is, the (crisp) possibilistic mean of A can be calculated as an arithmetic mean. More details can be found in Carlsson (2001).

3.2 Granular FPOM

The FPOM discussed in Subsection 3.1 applies the optimistic-, basic-, and pessimistic-NPV that are estimated by one object (e.g., an expert or simply averaging a group of experts' scenario-based estimations). However, in reality, estimating the NPV or the decision-making process is always carried out among a group of people with different backgrounds. In other words, they may have different estimations on the NPVs, even when they are given the same information about the project. This interpersonal uncertainty leads to *n*-dimensional data. Obviously, the choice of simply averaging the *n*-dimensional data is not good enough to obtain *one*-dimensional data that could soundly represent the original data. More convincing measures are urgently needed.

Regarding such an issue, the granular FPOM was adopted. Again, the interval type-2 fuzzy number was applied in this variant FPOM for the purposes of easy understanding and costless calculation and of course, fitness of purpose.

The basic idea of the granular FPOM is to generate the next type's information granules by using the former type's information granules (type-0 → type-1 → type-2). After that, calculate the fuzzy ROV with the type-2 fuzzy NPV following the FPOM discussed in Subsection 3.1. The inputs of the whole process (see Figure 1) or the information granules of type-0 are the estimated NPVs (optimistic, basic, pessimistic) from a group of experts. The step-by-step algorithm for this process is described below.

3.2.1 Step 1: Constructing the intervals of type-1 fuzzy NPV

In Step 1, intervals for three scenarios (i.e., $s = \{opt, b, pess\}$) will be given as $[a^s_{opt}, b^s_{opt}]$. Each interval will be calculated in the same way using their related NPVs, written as $Z^s = \{z^s_i \mid z \in \mathbb{R}, i = 1, 2, ..., n\}$. Thus, to simplify the expression, the notation without scenario considerations are applied in the following calculations, that are a_{opt}, o_{bpt}, and z_i.

The criteria *specificity* (Marin et al., 2018; Yager, 1992) gets its mathematical expression as:

$$sp([w,b]) = 1 - \frac{|b-w|}{|z_{\max} - w|} \tag{9}$$

and the expression for criteria *coverage* (Esteve-Calvo and Lloret-Climent, 2006) is as follows:

$$\operatorname{cov}([w,b]) = \frac{card\{z_k \,|z_k \in [w,b]\}}{card\{z_k \,|z_k > w\}} \tag{10}$$

where w is the arithmetic mean of z_i, $z_{\max}$ is the maximum value among z_i, i.e., $w = \frac{1}{n}\sum_{i=1}^{n} z_i$ and $z_{\max}$ = $\operatorname{argmax}_{k=1,2,\ldots,n} z_k$. Taking a closer look at $sp([w, b])$ and $cov([w, b])$, it is easy to find that, $sp([w, b])$ decreases with the distance between b and w, while $cov([w, b])$ increases with the distance. That means these two criteria cannot reach their maximum values at the same time. Consequently, finding an optional b that maximise the production of $sp([w, b])$ and $cov([w, b])$ is a good way to find the representative upper bound of the interval of type-1, that is defined as:

$$b_{opt} = \arg\max_{b} \{sp[w,b] * \operatorname{cov}[w,b]\} \tag{11}$$

Similarly, the lower bound is given by:

$$a_{opt} = \arg\max_{a} \{sp[a,w] * \operatorname{cov}[a,w]\} \tag{12}$$

where

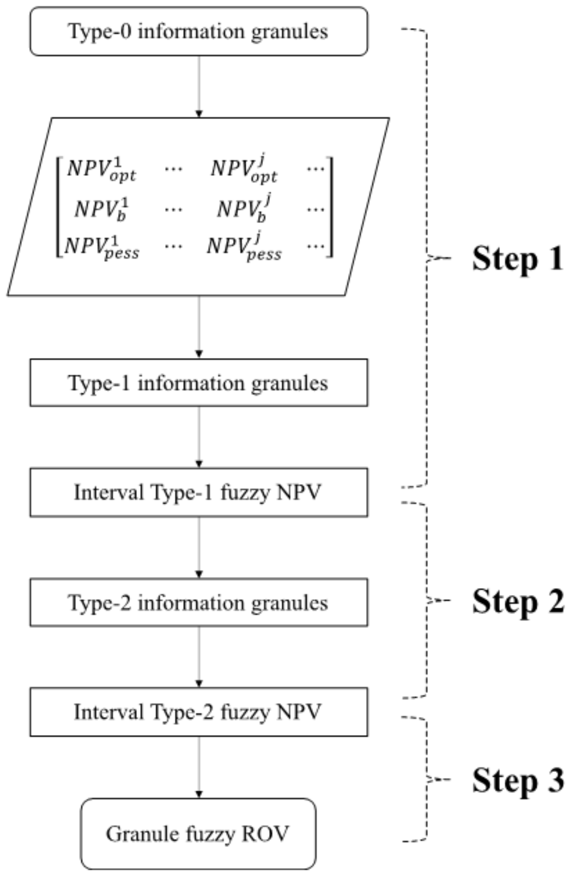
$$sp\left([a,w] = 1 - \frac{|w-a|}{|z_{\min} - w|}\right) \tag{13}$$

$$\operatorname{cov}\left([a,w] = \frac{card\{z_k \,|z_k \in [a,w]\}}{card\{z_k \,|z_k < w\}}\right) \tag{14}$$

and $z_{\min} = \text{argmin}_{k=1,2,\ldots,n} z_k$.

The intervals for three scenarios are then obtained, that are $[a_{opt}^{opt}, b_{opt}^{opt}]$, $[a_{opt}^{b}, b_{opt}^{b}]$, and $[a_{opt}^{pess}, b_{opt}^{pess}]$.

Figure 1 The process of granular FPOM



3.2.2 Step 2: Building the interval of type-2 fuzzy NPV

The interval type-2 fuzzy set $(\tilde{A} = (A^u, A^l))$, also named the first-order uncertainty fuzzy set, describes the uncertainly of the type-1 membership function and attracts more attention from researchers than the general type-2 fuzzy set $(\tilde{A})$ because of its simplicity. More specifically, a general type-2 fuzzy set is a 3-dimensional fuzzy set, and an interval type-2 fuzzy set is a special case whose 3rd dimensional values are constant at 1 (Wu et al., 2020a). Concepts such as upper membership function (*UMF*), lower membership function (*LMF*), and footprint of uncertainty (*FOU*) (Wu and Mendel, 2007; Wu et al., 2019) are some of the fundamental elements of the interval type-2 fuzzy set. Both *UMF* and *LMF* are type-1 fuzzy sets, constructed by the upper (and lower) bound of type-1 intervals. The maximum membership of *UMF* has to be 1, while *LMF* could be non-normal, meaning that its maximum membership is not necessarily equal to 1. *FOU* is built from the region between *UMF* and *LMF*. This paper applies a trapezoidal *UMF* and a triangular *LMF*.

The interval type-2 fuzzy set is written as

$$\tilde{A} = \left(A^u, A^l\right) = \left(\left[a_l^u, \underline{a}^u, \overline{a}^u, a_u^u\right], \left[a_l^l, a^l, a_u^l, h^l\right]\right)$$

where $h^u = 1$ implies the maximum membership of *UMF*, $h^l \in (0, 1]$ and determines the maximum membership of a non-normal *LMF*.

Relating to Step 1, in terms of the trapezoidal *UMF* $\mu_{A^u}(x)$,

$$a_l^u = a_{opt}^p$$
$$\underline{a}^u = a_{opt}^b$$
$$\overline{a}^u = b_{opt}^b$$
$$a_u^u = b_{opt}^o$$

Points $(a_l^u, 0), (\underline{a}^u, 1), (\overline{a}^u, 1)$ and $(a_u^u, 0)$ are the acmes of the related trapezoidal.

For elements of the triangular *LMF* $\mu_{A^l}(x)$,

$$a_l^l = b_{opt}^p$$
$$a_u^l = a_{opt}^o$$
$$a^l = \frac{a_u^l * \left(\overline{a}^u - a_l^l\right) + a_l^l * \left(a_u^l - \underline{a}^u\right)}{\left(\overline{a}^u - a_l^l\right) + \left(a_u^l - \underline{a}^u\right)}$$
$$h^l = \frac{a_u^l - a^l}{a_u^l - \underline{a}^u}$$

Similarly, the acmes of the related triangular *LMF* $\mu_{A^l}(x)$ are $(a_l^l, 0), (a^l, h^l), (a_u^l, 0)$. Furthermore, the mathematical expressions of $\mu_{A^u}(x)$ and $\mu_{A^l}(x)$ are easily written by using real numbers. Then, the FOU is

$$FOU\left(\tilde{A}\right) = \bigcup_{x \in X} \left[\mu_{A^u}(x), \mu_{A^l}(x)\right] \tag{15}$$

3.2.3 Step 3: Calculating the fuzzy ROV

Following the theory discussed in Subsection 3.1, the interval type-2 fuzzy real option value can be written as

$$\begin{aligned} ROV &= \frac{area_{FOU(\tilde{A})_+}}{area_{FOU(\tilde{A})}} * E\left(\tilde{A}_+\right) \\ &= \frac{\int_0^{\infty} \left[\mu_{A^u}(x) - \mu_{A^l}(x)\right]}{\int_{-\infty}^{\infty} \left[\mu_{A^u}(x) - \mu_{A^l}(x)\right]} * E\left(\tilde{A}_+\right) \end{aligned} \tag{16}$$

Meanwhile, the Nie-Tan method (Nie and Tan, 2008) has been applied for centroid computation for an interval type-2 fuzzy set, which has become regarded as an excellent way of simplifying the calculation of DE, fuzzifying the interval type-2 fuzzy set (Mendel and Liu, 2013). It is given by:

$$c_{NT}\left(\tilde{A}\right) = \frac{\int_a^b x*\left(\mu_{A^u}(x)+\mu_{A^l}(x)\right)dx}{\int_a^b \left(\mu_{A^u}(x)+\mu_{A^l}(x)\right)dx} \tag{17}$$

Finally, we rewrite the real option value as

$$\begin{aligned} ROV &= \frac{\int_0^\infty \left[\mu_{A^u}(x)-\mu_{A^l}(x)\right]}{\int_{-\infty}^\infty \left[\mu_{A^u}(x)-\mu_{A^l}(x)\right]} * c_{NT}\left(\tilde{A}_+\right) \\ &= \frac{\int_0^\infty \left[\mu_{A^u}(x)-\mu_{A^l}(x)\right]}{\int_{-\infty}^\infty \left[\mu_{A^u}(x)-\mu_{A^l}(x)\right]} * \frac{\int_0^\infty x*\left(\mu_{A^u}(x)+\mu_{A^l}(x)\right)dx}{\int_0^\infty \left(\mu_{A^u}(x)+\mu_{A^l}(x)\right)dx} \end{aligned} \tag{18}$$

4 Data and case study

The uncertainty about alternative fuels and the emissions limitations that will be imposed by regulatory organisations such as the IMO, to some extent constitute barriers to shipping industry decisions on green shipping investment. In addition, the imprecise nature of the available information on alternative fuels makes it difficult for shipping decision makers to arrive at logical, rational and objective investment decisions. Thus, a FPOM for real option valuation, with information available at the granular level, is adopted with the aim of providing some conceptually meaningful results and showing how to apply such an accessible approach to green ship investment.

In this section, the following research questions are posed as part of an illustrative case study.

- Is it a good choice to order a new low emission or totally emission free ship for the operating period 2025 to 2035?
- If it is, then which kind of fuel is the optimal choice for the vessel – LNG, methanol or hydrogen?

The object of the study is an 82,000dwt Panamax dry bulk ship.[1] The shipowner is assumed to pay the newbuilding price at the beginning of the period, as well as the fixed cost and the operating cost (e.g., fuel cost, emissions cost and so on) during its operation (10 years). Freight is regarded as the revenue. The ship has a residual value after its 10-year operation. Based upon equation (1), a generic function for each type of ship and each alternative fuel scenario can be written as:

$$NPV = -NB + \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} + \frac{RV}{(1+r)^n} \tag{19}$$

where NB is the newbuilding price, CF_t is the net cash flow of year t, r is the adjusted-discount rate, and RV is the residual value. More specifically, the cost of fuel and emissions is assumed to account for 80% of the operating cost (Stopford, 2009) and a 10% annual depreciation rate is applied. Thus, year t's cash flow and the residual value of a ship could be calculated as:

$$CF_t = FR * Q - AOC_t - AFC \tag{20}$$

$$AOC_t = \left(Fuel\ Cost_t + Emissions\ Cost_t\right)/0.8 \tag{21}$$

$$RV = NB * \left(1 - r_{Annu\ dep}\right)^n \tag{22}$$

…where the notation is as follows:

CF_T	year t's cash flow
FR	10-year average freight rate
AOC_t	year t's annual operating cost
AFC	annual fixed cost, assuming they are the same over the n years considered
Q	annual freight volumes
$r_{Annu\ dep}$	annual depreciation rate.

Expert estimations of the 10-year average freight rate and the carbon price are generated using reliable information and two mutually independent random numbers. Additionally, although the public's reactions to the same information usually follow a normal distribution, only 10 experts are assumed in this case study, so that a uniform distribution is applied. The results would be more meaningful if the real estimated data was available to us. Setting mutually independent random numbers for freight rate estimation and carbon price estimation is reasonable (see Table 1). Both random numbers are generated by Scipy, a scientific computing package for Python, following uniform distribution (loc = 0.5, scale = 1, random state = 123 (for freight rate)/456 (for carbon price)).

Table 1 Random numbers

Experts	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
					Random numbers					
Freight rate	1.20	0.79	0.73	1.05	1.22	0.92	1.48	1.18	0.98	0.89
Carbon price	0.75	0.66	1.28	1.31	1.13	1.10	1.39	1.26	0.68	0.65

Note: Rounded to 0.01 for presentational purposes.

For the freight rate scenario, firstly, the Baltic Panamax Index (BPI) over 12-yeara (from 2011 to 2022) is applied as the reference of each expert's estimation about the freight rate (see Figure 2). Year t's maximum-, median- and minimum- BPI indices are obtained from the original BPI index. Then we average the 12-year maximum-, median- and minimum- BPI indices. Next, the optimistic (pessimistic) freight rates are calculated as equal to the basic freight rate times the ratio of average maximum (minimum) BPI to the median, where the basic freight rate is 20$/t (Yin et al., 2019). Finally, experts' (j) estimations about the 10-year average freight rates are their random numbers for freight rate times the baseline (which can be regarded as the public information) of the optimistic-, basic- and pessimistic- freight rates. The generating process is shown in Figure 3.

Figure 2 Yearly average of BPI (2011–2022) (see online version for colours)

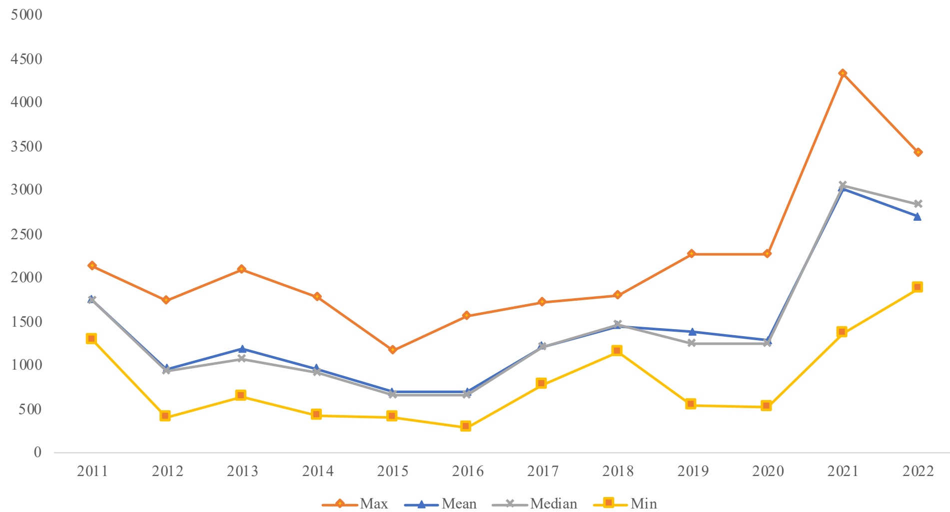
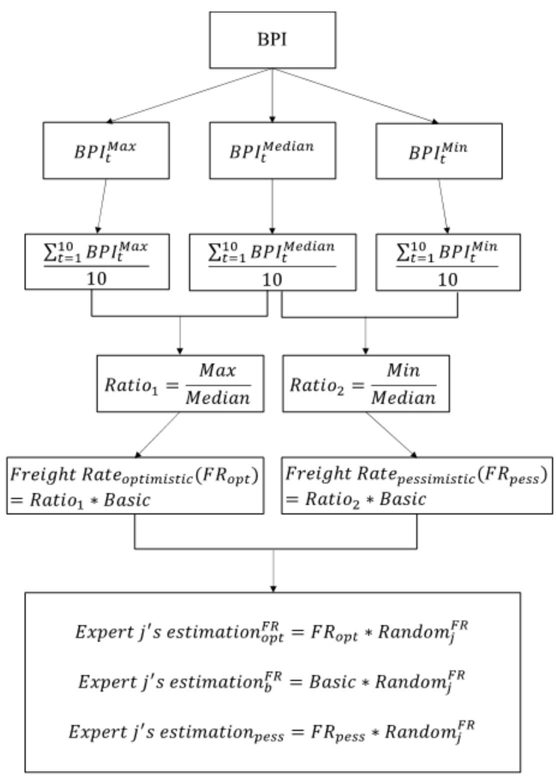


Figure 3 Estimation generating process (freight rate)



The estimations of the carbon price can be obtained in a similar way. The most commonly expected carbon price, within IMO's ambition, ranges from 22$/t$CO_2$ to 95$/t$CO_2$ during 2023~2030. From 2030, the carbon price may increase up to 135$/t$CO_2$ (DNV, 2024). Based on reliable public information, this paper sets the baseline carbon price as shown in Table 2. Moreover, as the optimistic, basic and pessimistic scenarios are related to the net present value, and the carbon price is regarded as part of the operating cost, the optimistic carbon price is the smallest (cheapest), while the pessimistic carbon price is the largest (most expensive).

Table 2 Carbon price

Unit: $t/CO₂				
Period	*Public information*	*Expectation scenarios*		
		Optimistic	*Basic*	*Pessimistic*
2023–2030	22 ~ 95	22	50	95
From 2030	up to 135	60	135	300

The newbuilding prices for an LNG-fueled, Methanol-fuelled and Hydrogen-fuelled ship are, respectively, about 1.3, 1.1 and 1.2 times that of a similar sized Diesel-fuelled ship.[2] The newbuilding price of a Panamax dry bulk ship (82,000 dwt) in this paper, is 30.14 million USD. Summary figures for this case study are shown in Table 3.

Table 4 shows the results of the net present values (type-0) for each kind of ship and each scenario. Following the discussion in Section 3, the granular fuzzy real option value for each kind of ship is obtained, where the fuzzy *ROV* of the diesel-fuelled ship, LNG-fuelled ship, methanol-fuelled ship, and hydrogen-fuelled ship are found to be 17.15 million dollars, 19.42 million dollars, 0, and 0, respectively. This suggests that it will not be a profitable choice to order an emission-free newbuilding anytime in the near future. Figure 4 provides more details about the interval type-2 fuzzy NPV $\tilde{A}$. The trapezoidal $UMF\ \mu_{A^u}(x)$, is represented by the blue line and the triangular $LMF\ \mu_{A^l}(x)$ is the yellow line. $FOU(\tilde{A})$ is described by the shaded region, with the positive part marked by both dark shadow and oblique line. Methanol can be seen to have a small positive part, but the hydrogen is totally in the negative region. This suggests that the *ROV* of the methanol-fuelled ship has a higher possibility to be larger than 0, making it a good investment choice if the original inputs are changed. Referring to what has been previously discussed, the real estimations from experts can provide more reliable results. Anyway, as this kind of method shows the direction of investment, we can still come to the conclusion that ordering a methanol-fuelled ship is a better choice than a hydrogen-fuelled ship in terms of economic benefit. The reason will be briefly discussed in the following section.

Table 3 Case data

Panamax, 82000dwt	*Unit*	*Diesel*	*LNG*	*Methanol*	*Hydrogen*
Panel A: Original data					
Newbuilding price	$mm	30.14	34.0582	33.4554	36.168
Annual Fixed Cost	$mm	2	2	2	2
Annual freight volumes (Q)	tmm	0.8	0.8	0.8	0.8
Risk-adjusted discount rate	/	8%	8%	8%	8%
Annual depreciation rate	/	10%	10%	10%	10%
Fuel consumption/day	t	30	/	/	/
Days at sea/year	days	310	310	310	310
Fuel unit cost_2025 [1]	$	663.5	0.8*Cost_Diesel/GJ	2.5*Cost_Diesel/GJ	6*Cost_Diesel/GJ
Fuel unit cost_2035	$	663.5	0.8*Cost_Diesel/GJ	2*Cost_Diesel/GJ	3*Cost_Diesel/GJ
GHG impact (WTW) [2]	tCO_2/t	3.828	3.6	0 (Bio)	0
Panel B: Data after simple calculation [3]					
Residual value (RV)	$mm	10.51	11.88	11.67	12.61
Fuel consumption/year	t	9300	/	/	/
Fuel cost_2025	$mm	6.17	4.94	15.43	37.02
Fuel cost_2035	$mm	6.17	4.94	12.34	18.51
CO_2 emissions/year	t	35,600.4	26,344.296	0	0

Notes: [1] (1) The price of diesel is the average price of the period 2017 to 2020 (Pomaska and Acciaro, 2022).
(2) Unit fuel costs of LNG, methanol and hydrogen are based on the cost of diesel for heating. For example, 2.5 means the unit fuel cost of methanol = 2.5*unit fuel cost of diesel/GJ (IEA, 2021; Lloyd's Register and UMAS, 2020).
[2] Well-to-Wake. Methanol is regarded as totally free from CO2 emissions by the IMO, taking the whole process from production to usage into consideration (IMO, 2018; Japan, 2020; Mærsk Mc-Kinney Møller Center, 2022).
[3] Rounded to 0.01 for presentational purposes.

Table 4 Numerical results of case study

	Net present value										w (Mean)	z_{max}	z_{min}	Type-1 Interval		FPOM
	1	2	3	4	5	6	7	8	9	10				b_{opt}	a_{opt}	
Panel A: Diesel																
Optimistic	98.70	32.80	16.69	69.24	98.52	50.50	138.34	91.49	64.32	50.19	71.08	138.34	16.69	98.70	50.19	17.15
Basic	20.68	–20.70	–41.57	–7.84	14.25	–16.59	35.77	7.45	–0.52	–9.19	–1.83	35.77	–41.57	14.25	–20.70	
Pessimistic	–53.08	–76.22	–107.66	–89.36	–70.24	–87.02	–67.31	–78.89	–62.72	–66.55	–75.90	–53.08	–107.66	–66.55	–89.36	
Panel B: LNG																
Optimistic	107.79	41.67	27.24	79.86	108.63	60.56	149.16	101.97	73.23	59.02	80.91	149.16	27.24	108.63	108.63	19.42
Basic	32.33	–9.57	–26.65	7.24	28.21	–2.76	51.31	22.22	10.71	1.86	11.49	51.31	–26.65	32.33	–2.76	
Pessimistic	–36.43	–59.98	–84.17	–65.55	–48.77	–65.82	–42.51	–55.71	–46.94	–51.16	–55.70	–36.43	–84.17	–46.94	–65.82	
Panel C: Methanol																
Optimistic	38.18	–28.61	–38.26	14.55	41.92	–6.32	84.45	36.28	3.09	–11.36	13.39	84.45	–38.26	41.92	41.92	0
Basic	–30.02	–73.42	–79.69	–45.37	–27.59	–58.93	0.05	–31.25	–52.82	–62.21	–46.13	0.05	–79.69	–27.59	–27.59	
Pessimistic	–84.56	–109.25	–112.82	–93.30	–83.18	–101.01	–67.45	–85.26	–97.53	–102.88	–93.72	–67.45	–112.82	–83.18	–83.18	
Panel D: Hydrogen																
Optimistic	–88.40	–155.18	–164.83	–112.02	–84.66	–132.89	–42.13	–90.29	–123.48	–137.94	–113.18	–42.13	–164.83	–84.66	–84.66	0
Basic	–156.60	–199.99	–206.26	–171.95	–154.16	–185.51	–126.53	–157.83	–179.39	–188.79	–172.70	–126.53	–206.26	–154.16	–154.16	
Pessimistic	–211.13	–235.83	–239.40	–219.87	–209.75	–227.59	–194.02	–211.83	–224.11	–229.45	–220.30	–194.02	–239.40	–209.75	–209.75	

Notes: Unit: $mm

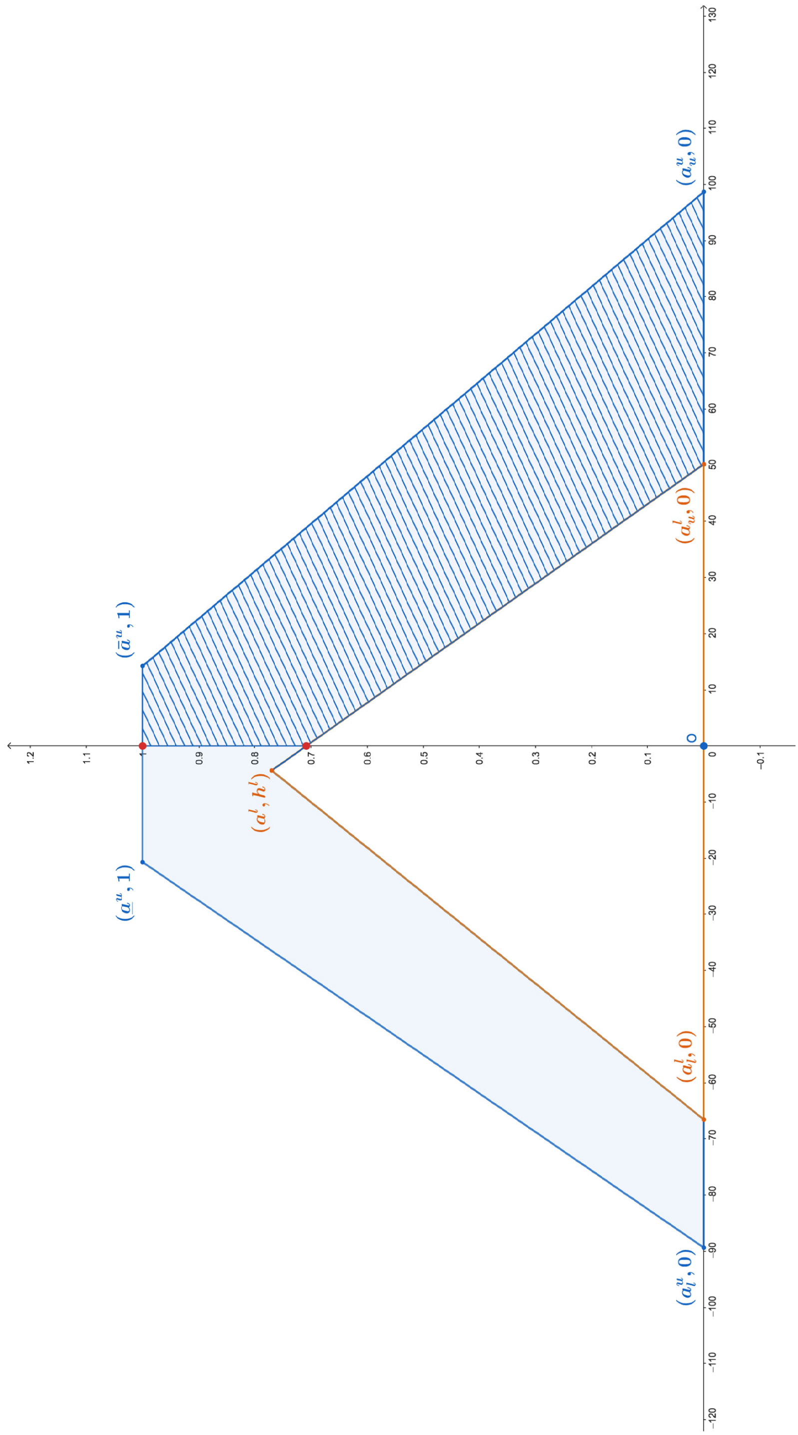
$a_u^u = b_{opt}^o, a_u^l = a_{opt}^o, \overline{a}^u = b_{opt}^b, \underline{a}^u = a_{opt}^b, a_l^l = b_{opt}^p, a_l^u = a_{opt}^p, a^l, h^l$

$A^u = \{(a_l^u, 0), (\underline{a}^u, 1), (\overline{a}^u, 1), (a_u^u, 0)\}$

$A^l = \{(a_l^l, 0), (a^l, h^l), (a_u^l, 0)\}$

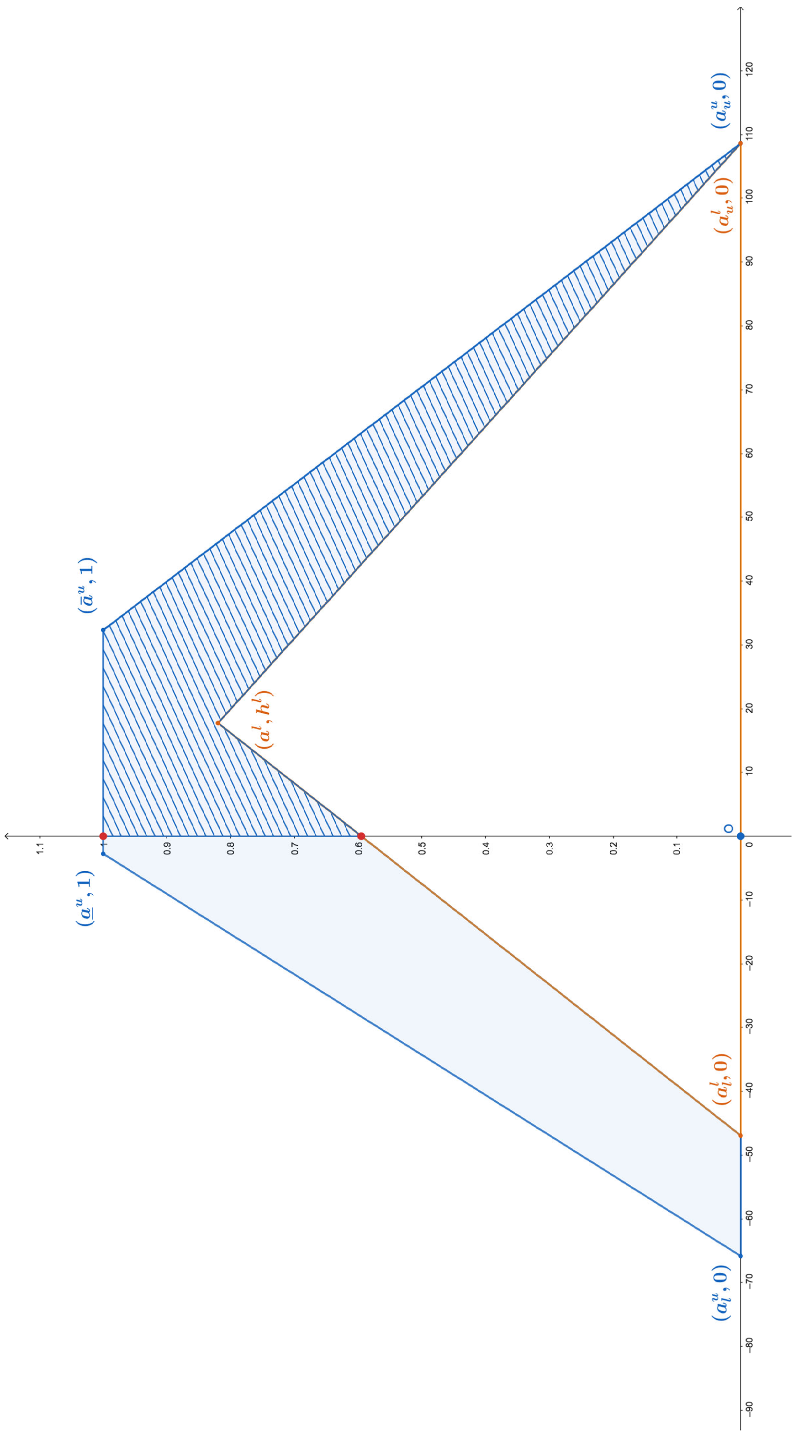
Accurate to 0.01 for exhibition purpose.

Figure 4 Interval type-2 fuzzy NPV $\tilde{A}$ associated with newbuilding ships, (a) diesel (b) LNG (c) methanol (d) hydrogen (see online version for colours)



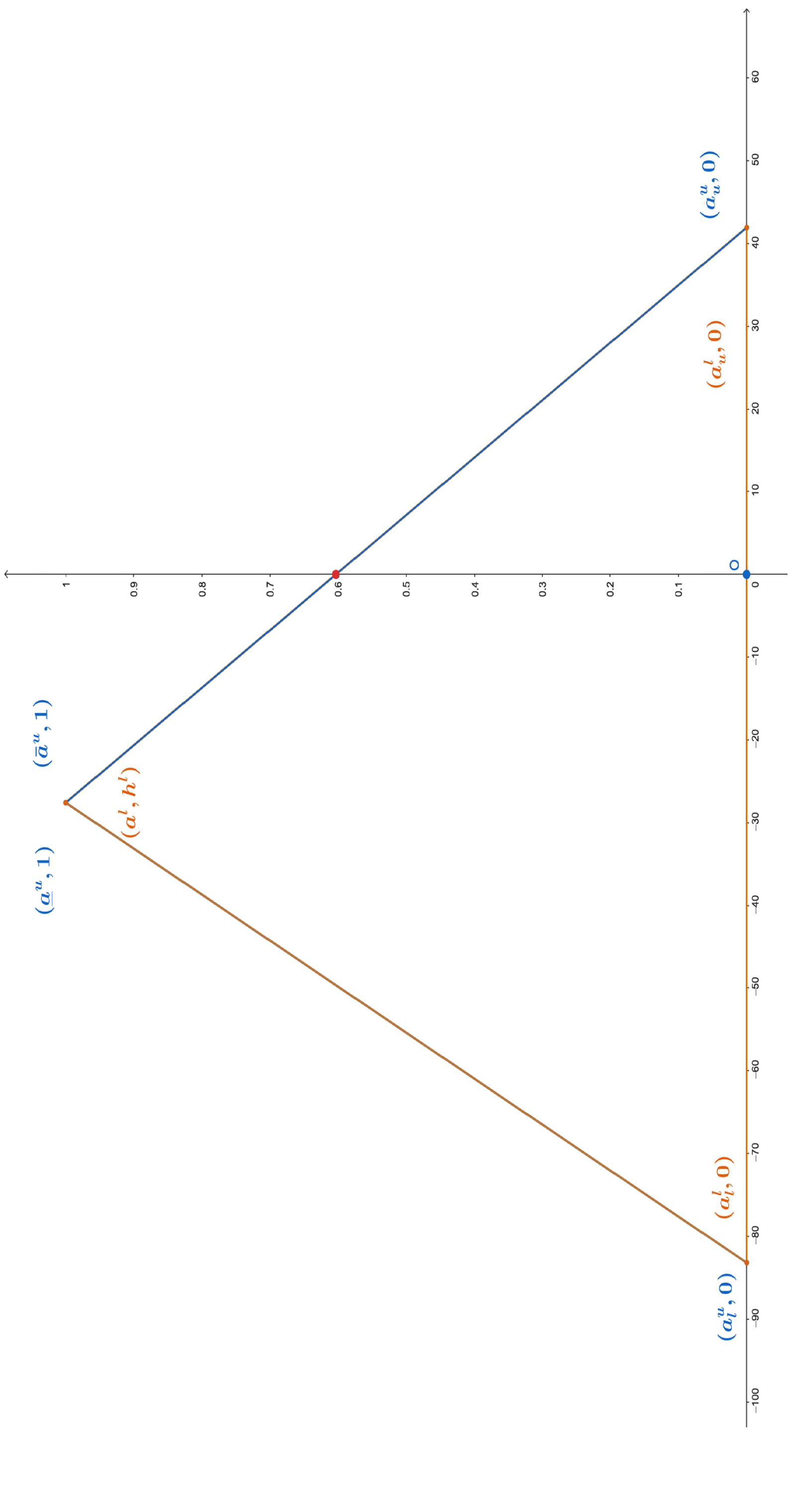
(a)

Figure 4 Interval type-2 fuzzy NPV $\tilde{A}$ associated with newbuilding ships, (a) diesel (b) LNG (c) methanol (d) hydrogen (continued) (see online version for colours)



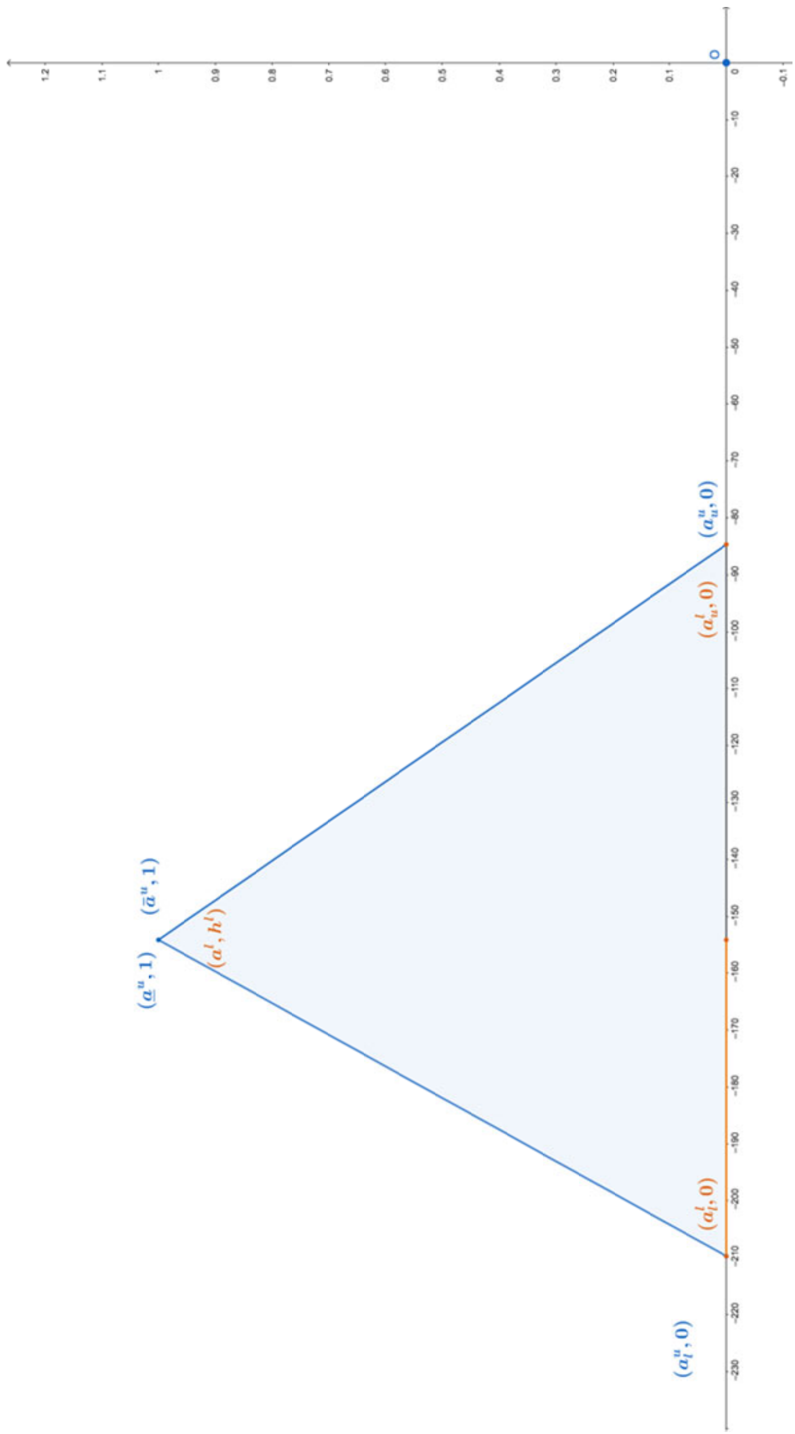
(b)

Figure 4 Interval type-2 fuzzy NPV $\tilde{A}$ associated with newbuilding ships, (a) diesel (b) LNG (c) methanol (d) hydrogen (continued) (see online version for colours)



(c)

Figure 4 Interval type-2 fuzzy NPV $\tilde{A}$ associated with newbuilding ships, (a) diesel (b) LNG (c) methanol (d) hydrogen (continued) (see online version for colours)



(d)

5 Discussion

The aim of a real option value is to find the right time to 'exercise the option' which would maximise investment value. It focuses more on a company's strategic decisions and enlarges the freedom of financial options available to a company (Carlsson and Fullér, 2003). The expression of a crisp *ROV* is

$$ROV_{t*} = \max_{t=0,1\ldots,T} ROV_t = NPVe^{-\delta t}N\left(d_1\right) - Xe^{-rt}N\left(d_2\right) \tag{23}$$

where $N(d)$ is the probability that a random number drawn from a standard normal distribution will be less than d, X is the fixed costs, δ represents the value lost over the duration, r can be regarded as the riskless return, d_1 and d_2 are functions of *NPV*, *X*, *r*, δ and *T*, which are positive with *NPV*. The fuzzy real option value is calculated by replacing crisp NPV and X with fuzzy numbers [more detail can be found in Carlsson and Fullér (2003) and Collan et al. (2009)].

No matter what variant of the FPOM is utilised, the *ROV* or fuzzy *ROV* are positively related to the current value of the expected cash flow, cash flow volatility, riskless returns, and time to maturity, but negatively related to the expected value of fixed cost and value lost during the option. Based on such an idea, we could rethink the results in Section 4 and take a look at the original input into the FPOM, namely the NPV. According to equations (19) to (22), the *NPV* can be written in a combined form as

$$NPV = -a * NB + \sum_{t=1}^{n} \frac{FR * Q \dfrac{Fuel\ Cost_t + Emission\ Cost_t}{0.8} - AFC}{(1+r)^t} \tag{24}$$

where $a \in (0, 1)$ is the cost of the newbuilding price that has been partly reduced by the ship's residual value. *NB*, *FR*, *Q*, *AFC*, *r* as well as *a* are the constant values in our case. In reality, shipping companies (especially dry bulk shipping companies) have little power to change these factors. In other words, they are mostly decided and influenced by the market.

Thus, we pay more attention to the fuel cost and emissions cost. Expert No. 6's data are shown, whose random number is 1.104, the closest to 1 in our sample. We believe this data is a good representative to illustrate the estimations of the emissions cost, as well as the annual operating cost (see Figure 5 and Table 5). To focus on the comparison of the four kinds of fuels, only the pessimistic scenarios of diesel and LNG are shown in Figure 5. The results of three scenarios can be found in Table 5. The black line and black dotted line show two fossil fuels, i.e., diesel and LNG, and the grey lines represent methanol and hydrogen, respectively. From 2025 to 2030, the annual cost of running a hydrogen-fuelled (methanol-fuelled) ship is almost 3–4 (1.5–2) times that of a diesel-fuelled ship and an LNG-fuelled ship. After 2030, when the development of non-fossil fuels is expected to decrease the cost of usage, the price for hydrogen remains largely higher than diesel and LNG (about 1.5–2 times). However, the annual cost of a methanol-fuelled ship is expected to fall below that of diesel and LNG from 2030. This suggests that a great possibility for the optimum timing of investing in a new methanol-fuelled dry bulk ship might be 2030. In addition, the hydrogen-fuelled ship seems to cost less than a diesel-fuelled ship after 2035, which also requires shipping companies to keep their eyes on the development of hydrogen as a marine fuel.

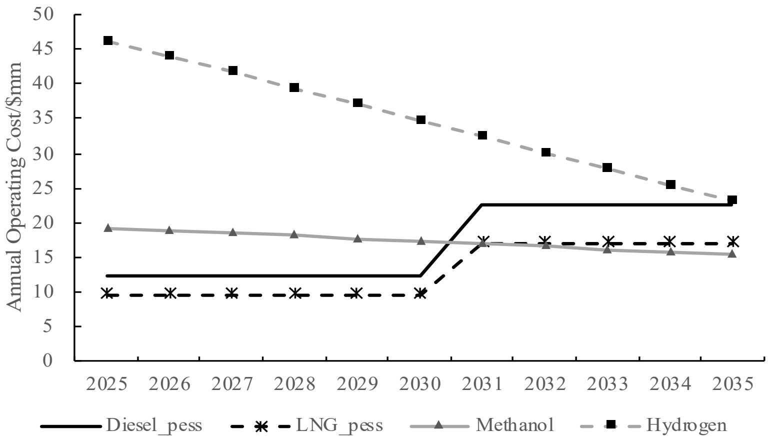
Table 5 Part of the annual operating cost

		2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Panel A: Fuel cost												
Diesel		6.17	6.17	6.17	6.17	6.17	6.17	6.17	6.17	6.17	6.17	6.17
LNG		4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94
Methanol		15.43	15.12	14.81	14.50	14.19	13.88	13.58	13.27	12.96	12.65	12.34
Hydrogen		37.02	35.17	33.32	31.47	29.62	27.77	25.92	24.07	22.21	20.36	18.51
Panel B: Estimated emission cost												
Diesel	Optimistic	0.86	0.86	0.86	0.86	0.86	0.86	2.36	2.36	2.36	2.36	2.36
	Basic	1.97	1.97	1.97	1.97	1.97	1.97	5.31	5.31	5.31	5.31	5.31
	Pessimistic	3.73	3.73	3.73	3.73	3.73	3.73	11.79	11.79	11.79	11.79	11.79
LNG	Optimistic	0.64	0.64	0.64	0.64	0.64	0.64	1.75	1.75	1.75	1.75	1.75
	Basic	1.45	1.45	1.45	1.45	1.45	1.45	3.93	3.93	3.93	3.93	3.93
	Pessimistic	2.76	2.76	2.76	2.76	2.76	2.76	8.73	8.73	8.73	8.73	8.73
Panel C: Annual operating cost												
Diesel	Optimistic	8.79	8.79	8.79	8.79	8.79	8.79	10.66	10.66	10.66	10.66	10.66
	Basic	10.17	10.17	10.17	10.17	10.17	10.17	14.35	14.35	14.35	14.35	14.35
	Pessimistic	12.38	12.38	12.38	12.38	12.38	12.38	22.45	22.45	22.45	22.45	22.45
LNG	Optimistic	6.97	6.97	6.97	6.97	6.97	6.97	8.35	8.35	8.35	8.35	8.35
	Basic	7.99	7.99	7.99	7.99	7.99	7.99	11.08	11.08	11.08	11.08	11.08
	Pessimistic	9.62	9.62	9.62	9.62	9.62	9.62	17.08	17.08	17.08	17.08	17.08
Methanol		19.28	18.90	18.51	18.13	17.74	17.35	16.97	16.58	16.20	15.81	15.43
Hydrogen		46.28	43.97	41.65	39.34	37.02	34.71	32.40	30.08	27.77	25.45	23.14

Notes: Unit: $mm
Rounded to 0.01 for presentational purposes.

From another point of view (see Table 5), it can be easily found that fuel cost (Panel A) is much higher than estimated emissions cost (Panel B), suggesting that the most influential factor in green shipping investment is fuel cost. It is only after 2030, when an increase in the price of carbon is expected, that the pessimistic (most expensive) estimations about emissions costs become higher than fuel cost. Consequently, for regulatory organisations and a society calling for the greening of shipping, the best way forward is to find a green and affordable fuel.

Figure 5 Annual operating cost



6 Concluding remarks

This paper introduces the novel granular FPOM to green shipping finance. Although the type-2 fuzzy numbers applied in this methodology cannot guarantee a better result than type-1 fuzzy numbers (because of the possibility that they become 'over-fuzzy'), the results obtained show the effectiveness of applying such a methodology to the shipping industry. The results obtained are in accord with shipping companies' strategic decisions and institutional analysis (DNV, 2024; Japan, 2020; Mærsk Mc-Kinney Møller Center, 2022). A detailed process is shown in this paper along with an easily understandable discussion about the method, which makes it possible for shipping companies to carry out their own investment analysis, through the use of a spreadsheet.

The case study analysed within the paper reveals that fuel cost is the dominant factor that can influence the decisions of shipping companies and that over the duration of the analysis from 2025-2035, it is not a good time to invest in either methanol-fuelled or hydrogen-fuelled dry bulk ships. However, LNG as a fuel is found to be a profitable potential replacement for diesel-fuelled ships.

Despite the fact that a quite specific case study has been utilised to illustrate the presented model, the concept and methodology expounded in this paper have great potential for wider application and generalisability. For example, the model can be applied for informing policy aimed at influencing the commercial adoption of alternative maritime fuels. Various hypothetical scenarios can be tested using the presented model to assess their likely aggregate effect on costs and environmental impact, as well as the likely timing of when these impacts will emerge. As such, the efficacy of alternative policy proposals can be evaluated, especially for particular market segments. For example, alternative policy proposals for the global, regional or national imposition of various fuel levies can be evaluated, as can the effects of different dynamics in carbon prices (Christodoulou and Cullinane, 2023). Such scenario testing of alternative policies in relation to the timing of adoption of alternative maritime fuels has been widely proposed (e.g. Acciaro, 2014; Foretich et al., 2021; Prussi et al., 2021; Xing et al., 2021; Christodoulou and Cullinane, 2022; Solakivi et al., 2022; Xiao and Lam, 2023). The outcomes from such an analysis could also be finessed to account for predictions on the emerging available supply to the market of the various alternative maritime fuels.

In addition to its potential influence on the policy arena, at a more microeconomic level, future research in this area could also aim to shed more light on combining the possibilistic mean and granular FPOM to provide a more effective and calculation-costless methodology for helping shipping companies to optimise the nature and timing of their investment decisions in diverse and novel ship designs and associated fuel technologies. As pointed out in Yang and Mekrangsiman (2023), such a contribution to a company's CSR strategy provides the possibility of not only environmental, but also financial gains.

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Notes

1 For succinctness, the exposition which follows presents only summary workings and results for the case study. For readers that are interested in the detail of the case study calculations, these are available in an excel spreadsheet file at: https://docs.google.com/spreadsheets/d/15vFV15pz8FsbrbMKcHQFpMtTAXZo2aIa/edit?gid=1318478586#gid=1318478586.

2 According to public news, the newbuilding prices of LNG- fuel ship and Methanol-fuelled ship are about 1.1%~1.15% that of a Diesel-fuelled ship, and together with the information that there are some newbuilding orders for Hydrogen-fuelled ships, we could come to the conclusion that the newbuilding price of the Hydrogen-fuelled ship is acceptable (although might be a little higher), if we assume it is 20% higher than a diesel-fuelled ship.