Effect of uncertainty on techno-economic trade-off studies: ship power and propulsion concepts

Arthur Vrijdag, Erik-Jan Boonen & Markus Lehne

Published online: 10 Aug 2018.

Submit your article to this journal ⬈

View Crossmark data ⬈

Taylor & Francis
Taylor & Francis Group

Effect of uncertainty on techno-economic trade-off studies: ship power and propulsion concepts

Arthur Vrijdag[a], Erik-Jan Boonen[b] and Markus Lehne[c]

[a]Department of Maritime and Transport Technology, Delft University of Technology, Delft, Netherlands; [b]Research and Development Department, Damen Shipyards, Gorinchem, Netherlands; [c]BALance Technology Consulting, Bremen, Germany

ABSTRACT
Results of trade-off studies aiming to compare different ship power and propulsion configurations inherently contain uncertainty. This is true for both the technical part and for the financial part of the trade-off study. The technical part typically includes the system characteristics of the vessel as inputs, resulting in predicted fuel consumption and emissions at various ship speeds. Fuel consumption numbers subsequently feed into the financial part of the analysis which typically includes prices of equipment, fuel prices or fuel price scenarios, the discount factor and other aspects such as the operational profile which plays an important role in the trade-off study. Finally, financial KPI's such as Net Present Value and payback period can be compared between different power and propulsion concepts, thereby supporting decision makers in the selection of a specific configuration or retrofit. In this paper, the effect of uncertain input parameters on both the intermediate technical output and on the financial KPI's is demonstrated by means of a case study. The study shows that the uncertainty associated with relevant KPI's is sufficiently large to warrant further investigation beyond accepting model predictions as completely accurate, particularly when conducting techno-economic trade-off analysis of ship power and propulsion configurations. In the broader context, consideration of uncertainty is a must for statutory and regulatory authorities in the formulation of policy.

Abbreviations: ASD-tug: azimuthing stern drive tug; DE: diesel engine; DF: discount factor; DG: diesel generator set; G: generator set; GB: gearbox; H: hotel load; KPI: key performance indicator; M: electric motor; MCS: monte carlo simulation; NPV: net present value; PTO: power-take-off; PP: payback period; SFC: specific fuel consumption; SUA: system uncertainty analysis; VFD: variable frequency drive;

Nomenclature

Notation

m	mass kg
R	cashflow euro
x	input
y	linking variable
z	output
ε	model error
η	efficiency -
μ	mean value
σ	standard deviation

Subscripts

DE	diesel engine
DG	diesel generator set
f	fuel
gb	gearbox
h	hybrid

i,j,k	indices
s	shared
t	time
vfd + m	variable frequency drive plus electric motor

Introduction

One of the most important steps in the design of a ship is the selection of a ship power and propulsion concept. A large part of the costs of the ship is attributable to this system, particularly in conventional vessels. Therefore, this choice is usually supported by calculations and/or simulations regarding the technical and financial comparison between various concept options. Traditionally, concept selection is purely based on financial grounds, although nowadays the importance of a green image associated with certain power and propulsion options can help a ship-owner to choose a system based on emission-related parameters as well.

Both the technical and the financial performance predictions are based on uncertain input parameters such as for instance specific fuel consumption of the engines and the development of fuel price over time. As a result of this input uncertainty, the outputs of both the technical and the financial part of trade-off studies are uncertain as well: the results should not be seen as the absolute truth, but more as an estimated mean value with a bounded uncertain range describing the probability of the outcome. Having an idea of the size of this uncertain range is crucial in appreciating the value of a prediction based on a simulation model. In case the uncertainty is found to be unacceptably large, the model prediction can be dismissed, or additional efforts can be made to decrease the uncertainty, and thereby improve the quality of the prediction.

Quantification of output uncertainty is not new and various methods are available to quantify the uncertainty in the predicted outputs, which have been applied in ship power and propulsion system studies. Uncertainty analysis has been used to quantify the validity of a simulation model based on a comparison between uncertain model predictions and uncertain full-scale measurements (Vrijdag, Schulten, Stapersma, and van Terwisga, 2007; Vrijdag, Stapersma, and van Terwisga, 2009). Furthermore, uncertainty analysis has been used to quantify the uncertainty in ship performance predictions, mainly aiming to understand risk in contractual ship performance values from a shipyard perspective (Vrijdag, 2014; Vrijdag, de Jong, and van Nuland, 2013; Vrijdag and de Vos, 2012).

Although not directly related to ship performance predictions and trade-off studies by means of simulation models, there are other maritime-oriented publications that demonstrate the importance of a good understanding of the effect of uncertainty. In the field of model scale testing of ships a detailed example of measurement uncertainty is for instance given by Longo and Stern (2005). The importance of full-scale measurement uncertainty feeding into ship performance monitoring software is demonstrated by Aldous, Smith, Bucknall, and Thompson (2015).

The effect of uncertainty on techno-economic comparison has been taken into account in different fields such as carbon capture techniques (van der Spek et al., 2017) and car drivetrain concepts (van Vliet, Kruithof, Turkenburg, and Faaij, 2010). Although there exist a significant number of publications on trade-off studies regarding different power and propulsion concepts of ships (Benvenuto, Campora, and Trucco, 2014; McIntyre and Gemmel, 2012; Partridge, Arén, Lindqvist, and Johansson, 2012; Sofras and Prousalidis, 2014), as far as known to the authors the effect of uncertainty on both the technical and financial comparison between various concepts has not been demonstrated in literature. This is surprising, especially since the importance of a good understanding of uncertainties is likely to grow with increasing complexity of ship systems and associated simulation tools required to enable both technical and financial analysis of complex ship energy grid systems.

In this paper, a trade-off study regarding two potential power and propulsion concepts for a harbour tug is carried out, including the effect of uncertainty propagation. Following a review of uncertainty propagation theory and an introduction of the two concepts, the hourly fuel consumption of both systems at different ship speeds is predicted including its uncertainty. Subsequently, the uncertainty in financial KPI's such as payback period (PP) and Net Present Value (NPV) is investigated, including the relative importance of technical and financial uncertainty on the financial KPI's. The case study reveals how quantification of uncertainty in the KPI's can support rational decision making and ensure decision makers do not rely on predictive models without an understanding of the tolerances applicable to the estimates presented by them. Note that the paper does not intend to select one of the two system concepts or to demonstrate a possible new concept, but rather aims to make transparent what role uncertainty plays in the comparison of multiple possible ship power and propulsion concepts. Further note that the approach as given here considers the ship level. Whilst not examined in detail in this paper, the approach described is scalable in terms of factors to be compared and traded-off against, where an expression of inherent uncertainty allows a more balanced decision to be made. A possible extension for the future would, for instance, be to look at the fleet-level uncertainties.

Prior to commencing the uncertainty analysis, it is important to understand the different types of uncertainty under consideration. Subsequently, a description of the System Uncertainty Analysis (SUA) method (Du and Chen, 2002) is given.

Types of uncertainty

There are various ways to categorise types of uncertainty. In this paper the categorisation as introduced by Schulten and Stapersma (2007), based on (Isukapalli, 1999), is used:

Theory uncertainty is the uncertainty in the underlying physical principles of the model. Examples of underlying physical principles are the laws of Newton, which are not uncertain at all if the model deals with classical mechanics. Models regarding quantum mechanics can, however, be assumed to have some degree of uncertainty in the underlying physical principles.

Model uncertainty is a direct result of the fact that a model is a simplified representation of reality. Estimation of model uncertainty is in theory possible by comparing outcomes of models of various levels of structure, detail and resolution. Since a model often consists out of many different sub models and underlying assumptions, this soon becomes a difficult task, especially for complex models.

Parameter uncertainty indicates the uncertainty which is introduced due to uncertainty in the input parameters of the model under consideration. Typical examples are the specific fuel consumption of an engine, the gearbox efficiency and so on.

Measurement uncertainty is the uncertainty introduced in the measurement and post-processing phase.

In this paper, the estimation of the output uncertainty is based on model input parameter uncertainty, while other types of uncertainty are not considered. The following section summarises how, by making use of the SUA approach, the uncertainty of the outputs of the involved (technical and financial) sub models is related to the uncertainty in inputs, correctly taking into account the effect of uncertain inputs that are shared among sub models.

General description of a multidisciplinary system with uncertainties

In this section, a general description of the SUA approach is given, based on (Du and Chen, 2002) and (Vrijdag et al., 2007). Further on in this paper, this method is applied to a ship power and propulsion trade-off study. Figure 1 shows a total system built up out of n interconnected sub systems. Common inputs to multiple sub systems are
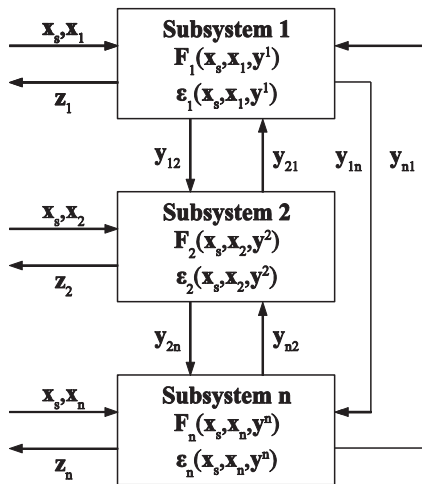

Figure 1. Coupled multidisciplinary sub systems (Du and Chen, 2002).

called *shared parameters* and denoted $\mathbf{x}_s$. Inputs particular to a certain sub system are denoted by $\mathbf{x}_i$, where $i = 1, n$ denotes the sub system under consideration. Linking variables are denoted $\mathbf{y}_{ij}, i \neq j$, and are interconnecting the various sub systems, where the signal goes from sub system i to sub system j.

For ease of notation Du and Chen introduce $\mathbf{y}_i = \{\mathbf{y}_{ij}|j = 1, n, i \neq j\}$, as the set of linking variables coming from sub system i, as input to all other sub systems. Outputs coming from all sub systems except sub system i, used as input to sub system i are abbreviated as $\mathbf{y}^i = \{\mathbf{y}_1, \ldots, \mathbf{y}_{i-1}, \mathbf{y}_{i+1}, \ldots \mathbf{y}_n\}$.

Introducing the notation $\mathbf{F}_{yi}$ for the sub system model, and $\boldsymbol{\varepsilon}_{yi}$ for the corresponding model error, the linking variables are described by

$$\mathbf{y}_i = \mathbf{F}_{yi}(\mathbf{x}_s, \mathbf{x}_i, \mathbf{y}^i) + \boldsymbol{\varepsilon}_{yi}(\mathbf{x}_s, \mathbf{x}_i, \mathbf{y}^i) \tag{1}$$

As an equivalent for the outputs $\mathbf{z}_i$ of the sub system i we find

$$\mathbf{z}_i = \mathbf{F}_{zi}(\mathbf{x}_s, \mathbf{x}_i, \mathbf{y}^i) + \boldsymbol{\varepsilon}_{zi}(\mathbf{x}_s, \mathbf{x}_i, \mathbf{y}^i) \tag{2}$$

Summarising, the goal of uncertainty analysis is to find the mean values $\boldsymbol{\mu}_{yi}$ and $\boldsymbol{\mu}_{zi}$ and accompanying variances $\boldsymbol{\sigma}_{yi}$ and $\boldsymbol{\sigma}_{zi}$ of linking and output variables $\mathbf{y}_i$ and $\mathbf{z}_i$, given the mean values and variances of input variables and model errors $\boldsymbol{\mu}_{xs}, \boldsymbol{\mu}_{xi}, \boldsymbol{\sigma}_{xs}, \boldsymbol{\sigma}_{xi}, \boldsymbol{\mu}_{\varepsilon yi}, \boldsymbol{\mu}_{\varepsilon zi}, \boldsymbol{\sigma}_{\varepsilon yi}$ and $\boldsymbol{\sigma}_{\varepsilon zi}$. For the reader interested in the mathematical background of how to get from input uncertainty to output uncertainty, the mathematical approach is given here. For those more interested in the relevance of uncertainty analysis in trade-off studies, it is possible to pick up the story just after Equation (13).

Before the total model can be split up into the several sub models, the mean values of the linking variables $\mathbf{y}_i$ and outputs $\mathbf{z}_i$ have to be known in the working point under consideration. Using the same notation as Du and Chen

$$y_{yi} = \mathbf{F}_{yi}(\boldsymbol{\mu}_{xs}, \boldsymbol{\mu}_{xi}, \boldsymbol{\mu}_y^i) + \boldsymbol{\mu}_{\varepsilon yi} \tag{3}$$

$$\boldsymbol{\mu}_{zi} = \mathbf{F}_{zi}(\boldsymbol{\mu}_{xs}, \boldsymbol{\mu}_{xi}, \boldsymbol{\mu}_y^i) + \boldsymbol{\mu}_{\varepsilon zi} \tag{4}$$

Deriving system variance

This section presents a summary of the SUA method by Du and Chen:

> To obtain the variances of system outputs, first linking variables $\mathbf{y}_i, i = 1, n$, are linearised by the first order Taylor approximations expanded at the mean values identified in Eq.(3) through system level evaluations. Multiple linking variables are derived simultaneously based on a set of linear equations. Second, we approximate a system output by the first-order Taylor expansion with respect to input variables $\mathbf{x}_s, \mathbf{x}_i$ and linking variables $\mathbf{y}_i$ in

each sub-system. After substituting $\mathbf{y}_i$ with the approximation derived earlier, we have the approximation of a system output as the function of input variables $\mathbf{x}_s$ and $\mathbf{x}_i$ only. Finally, based on the approximated system output, its variance is evaluated. The detailed procedure is as follows. From Eq.(1), the linking variables $\mathbf{y}_i$ are approximated using Taylor's expansion as:

$$\Delta \mathbf{y}_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{\partial \mathbf{F}_{yi}}{\partial \mathbf{y}_j} \Delta \mathbf{y}_j + \frac{\partial \mathbf{F}_{yi}}{\partial \mathbf{x}_s} \Delta \mathbf{x}_s + \frac{\partial \mathbf{F}_{yi}}{\partial \mathbf{x}_i} \Delta \mathbf{x}_i$$
$$+ \Delta \boldsymbol{\varepsilon}_{yi} (i = 1, n) \tag{5}$$

which can be written in a matrix form:

$$A \Delta \mathbf{y} = B \Delta \mathbf{x}_s + C \Delta \mathbf{x} + D \tag{6}$$

where:

$$A = \begin{bmatrix} \mathbf{I}_1 & -\frac{\partial \mathbf{F}_{y1}}{\partial \mathbf{y}_2} & \cdots & -\frac{\partial \mathbf{F}_{y1}}{\partial \mathbf{y}_n} \\ -\frac{\partial \mathbf{F}_{y2}}{\partial \mathbf{y}_1} & \mathbf{I}_2 & \cdots & -\frac{\partial \mathbf{F}_{y2}}{\partial \mathbf{y}_n} \\ \cdots & \cdots & \cdots & \cdots \\ -\frac{\partial \mathbf{F}_{yn}}{\partial \mathbf{y}_1} & -\frac{\partial \mathbf{F}_{yn}}{\partial \mathbf{y}_2} & \cdots & \mathbf{I}_n \end{bmatrix}, B = \begin{bmatrix} \frac{\partial \mathbf{F}_{y1}}{\partial \mathbf{x}_s} \\ \frac{\partial \mathbf{F}_{y2}}{\partial \mathbf{x}_s} \\ \cdots \\ \frac{\partial \mathbf{F}_{yn}}{\partial \mathbf{x}_s} \end{bmatrix},$$

$$C = \begin{bmatrix} \frac{\partial \mathbf{F}_{y1}}{\partial \mathbf{x}_1} & 0 & \cdots & 0 \\ 0 & \frac{\partial \mathbf{F}_{y2}}{\partial \mathbf{x}_2} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \frac{\partial \mathbf{F}_{yn}}{\partial \mathbf{x}_n} \end{bmatrix} D = \begin{bmatrix} \boldsymbol{\varepsilon}_{y1} - \boldsymbol{\mu}_{\varepsilon y1} \\ \boldsymbol{\varepsilon}_{y2} - \boldsymbol{\mu}_{\varepsilon y2} \\ \cdots \\ \boldsymbol{\varepsilon}_{yn} - \boldsymbol{\mu}_{\varepsilon yn} \end{bmatrix},$$

$$\Delta \mathbf{x}_s = \mathbf{x}_s - \boldsymbol{\mu}_{xs}, \Delta \mathbf{x} = \begin{bmatrix} \mathbf{x}_1 - \boldsymbol{\mu}_{x1} \\ \mathbf{x}_2 - \boldsymbol{\mu}_{x2} \\ \cdots \\ \mathbf{x}_n - \boldsymbol{\mu}_{xn} \end{bmatrix},$$

$$\Delta \mathbf{y} = \begin{bmatrix} \mathbf{y}_1 - \boldsymbol{\mu}_{y1} \\ \mathbf{y}_2 - \boldsymbol{\mu}_{y2} \\ \cdots \\ \mathbf{y}_n - \boldsymbol{\mu}_{yn} \end{bmatrix}$$

in which $\mathbf{I}_i, i = 1, n$, are the identity matrices. (Cited from Du and Chen)

Since the variances in linking variables $\mathbf{y}_i$ are required, Equation (6) can now be written as

$$\Delta \mathbf{y} = A^{-1} B \Delta \mathbf{x}_s + A^{-1} C \Delta \mathbf{x} + A^{-1} D \tag{7}$$

Using a similar procedure the error in outputs $\mathbf{z}_i$ is derived. As follows from Equation (2)

$$\Delta \mathbf{z}_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{\partial \mathbf{F}_{zi}}{\partial \mathbf{y}_j} \Delta \mathbf{y}_j + \frac{\partial \mathbf{F}_{zi}}{\partial \mathbf{x}_s} \Delta \mathbf{x}_s + \frac{\partial \mathbf{F}_{zi}}{\partial \mathbf{x}_i} \Delta \mathbf{x}_i$$
$$+ \Delta \boldsymbol{\varepsilon}_{zi} (i = 1, n) \tag{8}$$

This is written in matrix form as

$$\Delta \mathbf{z} = E \Delta \mathbf{y} + F \Delta \mathbf{x}_s + G \Delta \mathbf{x} + H \tag{9}$$

Substitution of Equation (7) into Equation (9) delivers

$$\Delta \mathbf{z} = E[A^{-1} B \Delta \mathbf{x}_s + A^{-1} C \Delta \mathbf{x} + A^{-1} D]$$
$$+ F \Delta \mathbf{x}_s + G \Delta \mathbf{x} + H \tag{10}$$

Regrouping per uncertainty source results in

$$\Delta \mathbf{z} = [E(A^{-1} B) + F] \Delta \mathbf{x}_s + [E(A^{-1} C) + G] \Delta \mathbf{x}$$
$$+ (EA^{-1}) D + H \tag{11}$$

where
$$E = \begin{bmatrix} 0 & \frac{\partial \mathbf{F}_{z1}}{\partial \mathbf{y}_2} & \cdots & \frac{\partial \mathbf{F}_{z1}}{\partial \mathbf{y}_n} \\ \frac{\partial \mathbf{F}_{z2}}{\partial \mathbf{y}_1} & 0 & \cdots & \frac{\partial \mathbf{F}_{z2}}{\partial \mathbf{y}_n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial \mathbf{F}_{zn}}{\partial \mathbf{y}_1} & \frac{\partial \mathbf{F}_{zn}}{\partial \mathbf{y}_2} & \cdots & 0 \end{bmatrix},$$

$$F = \begin{bmatrix} \frac{\partial \mathbf{F}_{z1}}{\partial \mathbf{x}_s} \\ \frac{\partial \mathbf{F}_{z2}}{\partial \mathbf{x}_s} \\ \cdots \\ \frac{\partial \mathbf{F}_{zn}}{\partial \mathbf{x}_s} \end{bmatrix},$$

$$G = \begin{bmatrix} \frac{\partial \mathbf{F}_{z1}}{\partial \mathbf{x}_1} & 0 & \cdots & 0 \\ 0 & \frac{\partial \mathbf{F}_{z2}}{\partial \mathbf{x}_2} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \frac{\partial \mathbf{F}_{zn}}{\partial \mathbf{x}_n} \end{bmatrix}, \Delta \mathbf{z} = \begin{bmatrix} \mathbf{z}_1 - \boldsymbol{\mu}_{z1} \\ \mathbf{z}_2 - \boldsymbol{\mu}_{z2} \\ \cdots \\ \mathbf{z}_n - \boldsymbol{\mu}_{zn} \end{bmatrix},$$

$$H = \begin{bmatrix} \boldsymbol{\varepsilon}_{z1} - \boldsymbol{\mu}_{\varepsilon z1} \\ \boldsymbol{\varepsilon}_{z2} - \boldsymbol{\mu}_{\varepsilon z2} \\ \cdots \\ \boldsymbol{\varepsilon}_{zn} - \boldsymbol{\mu}_{\varepsilon zn} \end{bmatrix}.$$

From standard error propagation theory, it is known that the variance of the sum p_3 of two stochastic distributed parameters p_1 and p_2 is generally given by

$$\sigma_{p_3}^2 = \left(\frac{\partial p_3}{\partial p_1} \right)^2 \sigma_{p_1}^2 + \left(\frac{\partial p_3}{\partial p_2} \right)^2 \sigma_{p_2}^2$$
$$+ 2\sigma_{p_1 p_2} \left(\frac{\partial p_3}{\partial p_1} \right) \left(\frac{\partial p_3}{\partial p_2} \right) \tag{12}$$

Application of Equation (12) to the summation carried out in Equation (11) is simplified when the four sources of uncertainty $\mathbf{x}_s$, $\mathbf{x}$, D and H are (assumed) mutually independent. In that case the covariance-term $\sigma_{p_1 p_2}$ in Equation (12) equals zero such that the variance of the

system outputs can be written as a straightforward summation of individual uncertainty contributions

$$\mathbf{D}_z = \mathbf{ID}_{xs} + \mathbf{JD}_x + \mathbf{KD}_{y\varepsilon} + \mathbf{D}_{z\varepsilon} \qquad (13)$$

in which $\mathbf{I} = \{i_{ij}\}, \mathbf{J} = \{j_{ij}\}, \mathbf{K} = \{k_{ij}\}$, and $i_{ij} = \{\mathbf{E}(\mathbf{A}^{-1}\mathbf{B}) + \mathbf{F}\}^2_{ij}$, $j_{ij} = \{\mathbf{E}(\mathbf{A}^{-1}\mathbf{C}) + \mathbf{G}\}^2_{ij}$, $k_{ij} = \{\mathbf{EA}^{-1}\}^2_{ij}$ and $\mathbf{D}_z =$

$$\begin{bmatrix} \sigma^2_{z1} \\ \sigma^2_{z2} \\ \dots \\ \sigma^2_{zn} \end{bmatrix}, \quad \mathbf{D}_x = \sigma^2_x, \quad \mathbf{D}_{xs} = \begin{bmatrix} \sigma^2_{x1} \\ \sigma^2_{x2} \\ \dots \\ \sigma^2_{xn} \end{bmatrix}, \quad \mathbf{D}_{y\varepsilon} = \begin{bmatrix} \sigma^2_{y\varepsilon 1} \\ \sigma^2_{y\varepsilon 2} \\ \dots \\ \sigma^2_{y\varepsilon n} \end{bmatrix},$$

$$\mathbf{D}_{z\varepsilon} = \begin{bmatrix} \sigma^2_{z\varepsilon 1} \\ \sigma^2_{z\varepsilon 2} \\ \dots \\ \sigma^2_{z\varepsilon n} \end{bmatrix}.$$

Vectors $\mathbf{D}_z$, $\mathbf{D}_{xs}$, $\mathbf{D}_x$, $\mathbf{D}_{y\varepsilon}$ and $\mathbf{D}_{z\varepsilon}$ describe the variances of the various variables. Matrices $\mathbf{I}$, $\mathbf{J}$ and $\mathbf{K}$ are the squared global sensitivity matrices. The global sensitivities include the propagation of uncertainties over the sub system boundaries via the matrix $\mathbf{A}$.

Key characteristic of the SUA method is that the *global sensitivities* are derived from *local sensitivities*. The end result of the SUA method is the uncertainty (variance) of the output variables as expressed in the vector $\mathbf{D}_z$.

In the following section, the two power and propulsion concepts are described, including a brief description of the underlying technical and financial models including their parameters, linking variables and relevant outputs. Once these are defined, the SUA method is applied and results that demonstrate the importance of uncertainty in model predictions are presented and discussed.

Power and propulsion concept description

The two power and propulsion concepts of an azimuthing stern drive (ASD) harbour tug that are compared in this paper are shown in Figures 2 and 3. The first concept is a traditional mechanical system of an ASD tug, loosely based on (Damen, 2017), with two azimuthing thrusters,
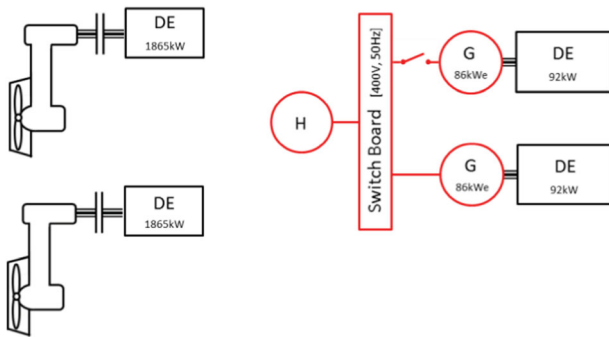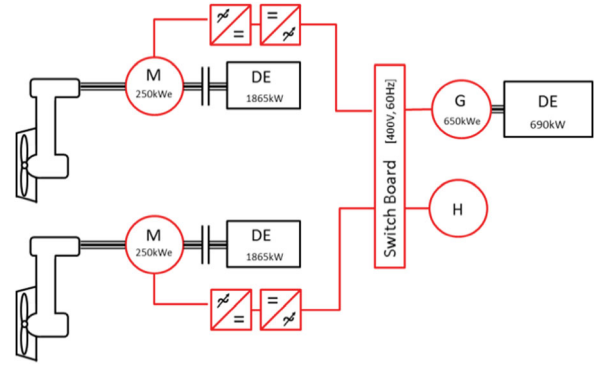

Figure 3. An alternative hybrid concept for an ASD.

two fixed pitch propellers in nozzles driven by two high-speed diesel engines (DE's). Completely separated from the propulsion system, the electric power required to supply the hotel load (indicated by an H) can be generated by two small diesel generator sets (DE + G's), of which normally only one is running and online.

The alternative concept as shown in Figure 3 is a hybrid system in which a choice can be made between driving the thrusters with the diesel engines or with the shaft mounted electric motors (indicated by an M). These motors are fed by variable frequency drives (VFD's), which, in turn, are fed by a single generator. Driving the thrusters by the diesel engines and the electric motors simultaneously is not possible in this particular concept but it is possible to use the electric motor as a power-take-off (PTO) and via this route supply the hotel load with the diesel engines. In that case, the generator is switched off completely.

At all four ship speeds relevant for this study the mechanical system runs in the same operating mode: both diesel engines are running and only one generator is supplying the hotel load while the other is switched off. The hybrid concept uses different operating modes for different ship speeds at 0.5, 4 and 8 kts the generator supplies all the electric power to feed the hotel load and the electric propulsion motors. At 12 kts the main diesel engines are used for propulsion and the electric motors are used as generators to supply the hotel load. In the moored condition it is assumed that for both vessels the hotel load is supplied by an on-board diesel generator.

Technical model

Both technical concepts have been modelled in a simulation model, resulting in predictions of fuel consumption per hour at four different ship speeds and in the moored condition. Since this paper is not about ship energy grid modelling, the technical model is not discussed in detail. On a high abstraction level, the technical
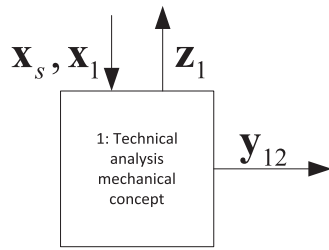

Figure 2. A traditional ASD tug power and propulsion concept.

Figure 4. Technical model.

model of the conventional ASD is however shown in Figure 4, making use of the notation as introduced earlier. The inputs of the technical model are given in Tables A1 and A2. Careful inspection of those tables shows that only four technical input parameters are considered to be uncertain, although in reality, many other technical parameters are uncertain as well such as for instance ship resistance and propeller efficiency. Because this paper focusses on demonstrating the importance of uncertainty propagation, and less on the absolute values of the output uncertainty, this is deemed acceptable.

The selected uncertain parameters are: 'specific fuel consumption of the diesel engine' SFC_{DE}, 'gearbox efficiency' η_{GB}, 'combined efficiency of variable frequency drive and motor' η_{vfd+m} and 'diesel generator efficiency' η_{DG}. Note from the tables that uncertainty of the four selected parameters is defined for each considered ship speed separately. The size of the input uncertainty is based on expert opinion, with a general trend of increasing uncertainty when operating further away from the nominal point.

Financial model

The financial model that is used in this paper is highly simplified but does contain sufficient detail to demonstrate the key concepts and importance of uncertainty propagation. At a high abstraction level, the model is given in Figure 5, but a more detailed description is given here in words. All financial input parameters (and shared input parameters) including their estimated uncertainty are listed in Tables A1, A2 and A3.
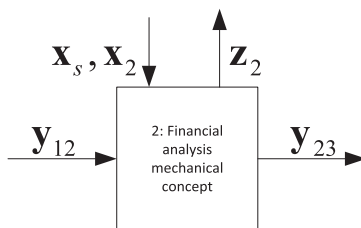

Figure 5. Financial model.

The model contains capital cost, running cost, operational cost and revenue. The capital cost contains the purchase cost of the vessel and the second-hand value at which the ship is sold. For simplicity, it is assumed that the purchase is made without loan such that no interest and redemption have to be taken into account. Furthermore, it is assumed that the ship is sold on the second-hand market after 10 years. Per concept, the most important two parameters of the capital cost model are the initial purchase cost of the ship and the estimated second-hand value.

The running cost contains the annual personnel cost and the maintenance cost. Both are assumed equal for both ships (although one could argue that this depends on the balance between the reduced maintenance cost of the hybrid ship due to less running hours of the main engines and the increased cost due to the increase in electrical components). The four uncertain model parameters are the assumed annual cost of personnel and maintenance plus their associated annual escalation rates.

The operational cost consists of fuel cost. Other costs could be included but for reasons of simplicity, they are omitted now. Uncertain inputs are the hourly fuel consumption of each ship at the four speeds plus the moored condition (delivered by the technical analysis), the number of hours spent at each ship speed, the fuel price and the assumed linear annual fuel price increase.

The annual revenue is defined by the assumed average hourly revenue when sailing (not when moored) multiplied by the number of sailing hours. The average hourly revenue is assumed to increase exponentially over time. This simplified revenue model can be improved, but the important effect of more revenue when sailing more hours is included.

The assumed operational profile of the tug only includes free sailing plus the moored condition and does not include towing. This is a highly simplified profile but is considered acceptable in the light of the goal of this study. Further note that the number of hours spent at each ship speed is considered uncertain, and the number of moored hours is determined by subtracting the number of annual sailing hours at each ship speed from the total amount of hours available in one year. In this way, despite the uncertain annual sailing hours at each speed, the total hours including the moored condition always add up to a full year.

The outputs of the financial model are the annual fuel consumption and the financial KPI's. The financial KPI's that are considered in this paper are the PP and the NPV. The PP is defined as the period of time (in years) required to recoup the funds expended in an investment. The main drawback of this KPI, especially when the PP is longer

than a few years, is that it does not account for the time value of money, risk, financing, or other important considerations such as the opportunity cost. Nevertheless, it is often used because it is easy to apply and understand. With $R_{t,in}$ and $R_{t,out}$ representing the non-discounted annual cash inflow and outflow as a function of time, the payback period is defined as the time (in years) for which

$$\sum_{t=0}^{N} R_t = 0$$

$$R_t = R_{t,in} - R_{t,out}$$

(14)

Once expressions for cash inflow and outflow as a function of time are known, the equation can be solved for the payback period.

The NPV is the sum of net cash flows R_t, corrected for discount factor DF, over a period of t years. In this case, exponential discounting is applied

$$
\begin{aligned}
NPV(DF, t) &= \sum_{t=0}^{N} \frac{R_t}{(1+DF)^t} \\
&= \underbrace{\sum_{t=0}^{N} \frac{R_{t,in}}{(1+DF)^t}}_{\text{cumulative discounted income}} \\
&\quad - \underbrace{\sum_{t=0}^{N} \frac{R_{t,out}}{(1+DF)^t}}_{\text{cumulative discounted costs}}
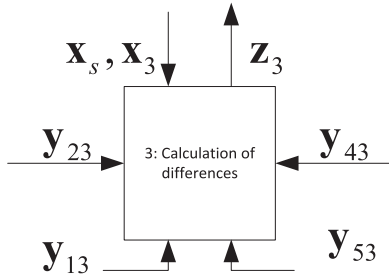\end{aligned}
$$

(15)

Figure 6. ΔKPI model.

The discount factor that is chosen is dependent on the industry sector and is normally chosen higher for longer term investments due to the increased risk.

ΔKPI's

Besides the technical and financial sub models an additional sub model is created to calculate the ΔKPI's between the two concepts. An abstract representation of this model is given in Figure 6. The ΔKPI's are defined by

$$\Delta PP = PP_h - PP$$

$$\Delta NPV_t = NPV_{t,h} - NPV_t$$

$$\Delta m_{f,annual} = m_{f,annual,h} - m_{f,annual},$$

where the subscript h stands for 'hybrid'. These ΔKPI's are straightforward outputs once the individual KPI's of the ships are known, but as will be shown, the effect of uncertain inputs $\mathbf{x}_i$ and uncertain shared inputs $\mathbf{x}_s$ on individual KPI's and on ΔKPI's can be quite different.

Application of SUA on a power and propulsion concept trade-off study

In Figure 7, a power and propulsion concept trade-off analysis is put in an SUA framework similar to Figure 1. It shows the technical and financial analysis of one concept on the left-hand side with results feeding into the centre sub model. The same is done for the alternative concept on the right-hand side. The outputs of sub models 1, 2, 4 and 5 are the uncertain results of the individual concepts.

The centre sub model calculates the differences in performances and KPI's between the two concepts. Note that although only two concepts are compared in this case study, it is possible to include more concepts in the analysis.

As shown, each sub model has its own dedicated inputs $\mathbf{x}_i$ and outputs $\mathbf{z}_i$. Furthermore, the relevant linking variables $\mathbf{y}_i$ are shown as well as the inputs $\mathbf{x}_s$ that are shared between multiple (but not necessarily all) sub models.
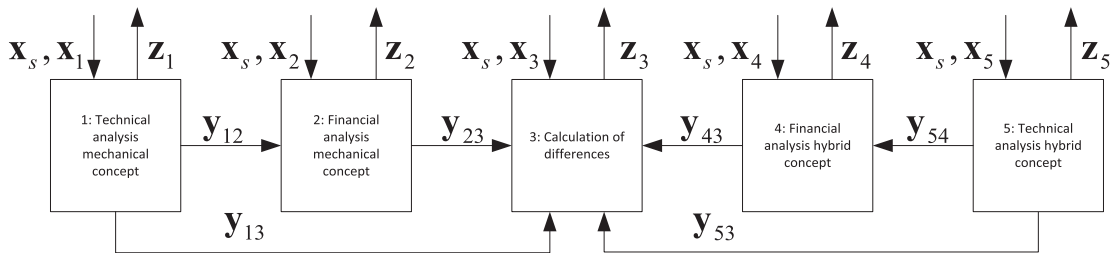

Figure 7. Interconnected sub models of a power and propulsion trade-off study.

The uncertain input parameter vectors x_1, x_2, x_4, x_5 and x_s were given in Tables A1, A2 and A3, where the parameter names, their mean values and their assumed uncertainty are listed. Vector x_3 is not given because it is an empty vector. Vectors D, H, $D_{y\varepsilon}$ and $D_{z\varepsilon}$ are all assumed zero, meaning that bias and model uncertainty are not taken into account.

After defining the input parameter values and uncertainties, the local sensitivities (required for the $A, B, C, E, F,$ and G-matrices) are derived numerically by implementing small input perturbations into the isolated technical and financial sub models and observing the resulting effect on the outputs and linking variables. Based on the assumed input uncertainties and the local sensitivities the squared global sensitivity matrices I, J, K and subsequently the output variances D_z are determined following the SUA approach.

To illustrate the application of the SUA method, some intermediate results related to the output *fuel consumption at 8 knots* $\dot{m}_{f,8kts,h}$ (which is an output of sub model 5) of the hybrid concept are given here

The value and uncertainty of the parameters in x_5 were given in Table A2. The sensitivities of $\dot{m}_{f,8kts,h}$ to the relevant parameters in x_5 are visualised in Figure 8. Note that the normalised sensitivity $\frac{\partial z}{\partial x} \cdot \frac{x_0}{z_0}$ is shown on the y-axis, where subscript 0 indicates the unperturbed input and output value. A normalised sensitivity of 1 indicates that a 1% change in input parameter results in a 1% change in output.

As expected the fuel consumption of the hybrid system at a speed of 8 kts is not dependent on the SFC of the main diesel engine because it is not running at that speed. Secondly, the fuel consumption is equally sensitive to the efficiencies $\eta_{GB,8kts,h}$ and $\eta_{vfd+m,8kts,h}$, which again is to be expected. Finally, the sensitivity to diesel generator efficiency $\eta_{DG,8kts,h}$ is -1 which also is in line with
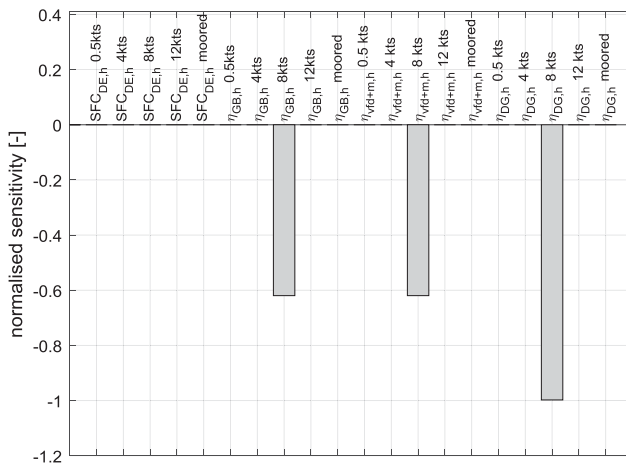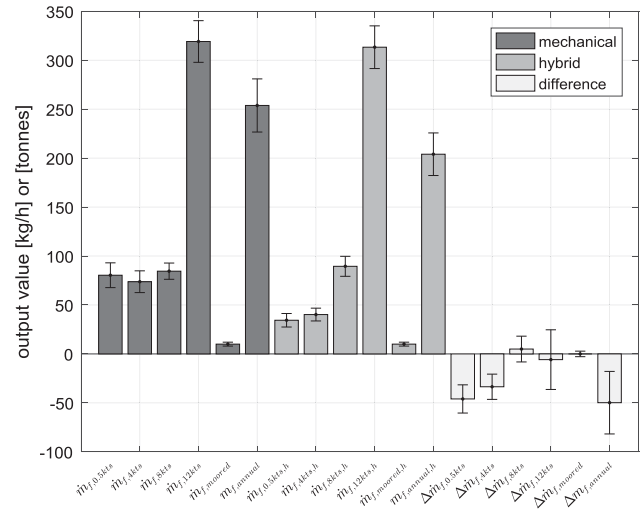
Figure 9. Fuel consumption related outputs with 95% confidence intervals.

the expectation. The sensitivity of $\dot{m}_{f,8kts,h}$ to all shared parameters x_s is 0 and is therefore not shown.

By making use of Equation (13) the uncertainty in $\dot{m}_{f,8ks,h}$ is determined as shown in the 9th bar in Figure 9. The figure shows that the 95% confidence interval of fuel consumption of the hybrid system at 8 kts is 89.5 ± 10.2 kg/h. The 95% confidence intervals of other fuel related outputs are shown as well, including the annual fuel consumption of both systems in tonnes. As shown, the difference in fuel consumption mainly lies at the lower speeds, which is explained by the possibility of the hybrid system to run at low propeller rpm, while the mechanical system cannot run at such low propeller rpm and therefore has to rotate the azimuthing thrusters sideways to create low forward thrust and thus low speed.

The annual fuel consumption of the traditional system $m_{f,annual}$ is predicted as 254 ± 20 tonnes, while the annual fuel consumption of the hybrid system $m_{f,annual,h}$ is predicted to be 204 ± 17 tonnes. The difference in annual fuel consumption $\Delta m_{f,annual}$ is predicted to be -50 ± 32 tonnes. This large interval of $\Delta m_{f,annual}$ clearly demonstrates the great importance of understanding the uncertainties when using model predictions to support decision making. The authors, therefore, suggest that fuel-saving claims related to retrofits or alternative concepts should always be considered in the light of the associated uncertainty.

Without giving all the intermediate results, further propagation and introduction of uncertainty, as modelled by the SUA approach, leads to the prediction of uncertain financial KPI's as shown in Figure 10, where the total output uncertainty is represented by the left most uncertainty interval on each vertical bar. The figure shows that the payback period for both systems lies around 6.3
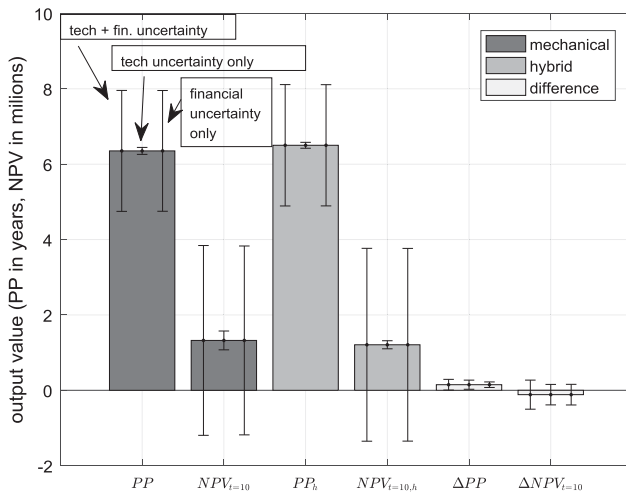
Figure 8. Sensitivity of $\dot{m}_{f,8kts,h}$ to a number of input parameters.

Figure 10. Financial KPI's with 95% confidence intervals. PP in years and NPV in millions of Euro's.

years with a slight preference for the mechanical system. However, this slight preference is nullified by the large uncertainty which is comparable for both systems.

The $NPV_{t=10}$ predictions (in millions of Euro's) are comparable as well, with a slightly higher value for the mechanical concept. The uncertainty of both NPV values is large, even to the extent that it is larger than the predicted NPV value itself. As a result, the uncertainty in $\Delta NPV_{t=10}$ is significant compared to the mean predicted value, indicating that the chances of one concept outperforming the other (from the NPV point of view) are close to 50%. Note that the shown uncertainty interval is not a straightforward summation of the uncertain NPV of the two concepts but, by making use of the SUA approach, correctly takes into account the subtle difference between the effect of uncertain parameters and uncertain shared parameters. More importantly, these results show that there is no certain outcome of the comparison in terms of $\Delta NPV_{t=10}$, which opens up the door to make an investment decision based on other KPI's, such as for instance the annual difference in CO_2 production $\Delta m_{annual,CO_2}$ or other harmful emission related KPI's. Although such KPI's are not presented in this paper, based on the rightmost bar in Figure 9, in combination with the direct relation between fuel consumption and emission of CO_2, it is clear that even when taking into account uncertainty, the hybrid system will produce less CO_2.

The authors believe that, in the context of ship power and propulsion trade-off studies, quantification of the uncertainty associated with technical and financial performance predictions (as for instance shown in Figures 9 and 10) does support rational decision making. Policymakers should also be aware of the importance of uncertainty in predictions because a good policy should

be robust with respect to an uncertain environment, especially given the relatively long lifetime of ships and their systems.

The authors do acknowledge that in a commercial environment the time required to perform an uncertainty analysis is not always available. It is therefore recommended to, as far as this is feasible, implement uncertainty analysis features in commercially oriented concept trade-off tools. One example where uncertainty analysis is supported is known to the authors: the ship Life Cycle Performance Assessment (LCPA) tool (Lehne, Norden, Wurst, and Nagel, 2015), implemented in the EU JOULES project (JOULES, 2017) supports uncertainty calculations, provided the user has modelled the cases to compare in this particular tool. The extra effort is between one day and one week depending on the complexity and the level of detail chosen (LCPA-tool, 2017).

Relative importance of technical and financial uncertainty

The large output uncertainties as represented by the left most error bars in Figure 10 can raise the question whether they mainly stem from either technical or financial input uncertainty (or from both). This is investigated using a two-step process. Step 1 assumes that all uncertainty is technical, and all financial parameters are correct. Step 2 assumes the reverse case, where all uncertainty is financial, and technical parameters are assumed to be certain. On the basis of the analysis depicted in Figure 10, the contribution of financial uncertainty is the most dominant consideration for the individual KPI's PP and NPV of both the mechanical and the hybrid concept. This indicates that the predicted financial performance of an individual tug mostly depends on financial factors and is only slightly dependent on the technical parameters that govern fuel consumption. On the other hand, the uncertainty in outputs ΔPP and $\Delta NPV_{t=10}$ is almost equally affected by the uncertainty in financial parameters and technical parameters. This is explained by the fact that almost all implemented financial parameters are so-called shared parameters, which affect both concepts similarly, thereby having less effect on ΔPP and $\Delta NPV_{t=10}$. Because of that, the relative importance of uncertainty in fuel consumption (driven by uncertain technical parameters) becomes higher.

Conclusions

The performed analysis is highly simplified, with only a limited number of uncertain model parameters. Furthermore, the authors do not claim that the complex relations

between operating profile, revenue and operating cost are modelled in detail including all existing (indirect) interactions. However, it was shown how uncertainty propagation through the linked technical and financial domain can be modelled, giving insight into the sensitivities and output uncertainties that play a role in trade-off studies.

From the results as presented in Figure 10, it is concluded that uncertainty plays a very important role and should be taken into consideration to support rational decision making and to ensure that decision-makers do not rely on predictive models without an understanding of the tolerances applicable to the estimates presented by them. Although not explicitly shown here, this becomes especially relevant in case new (less well understood) technologies are introduced. Quantifying the effect of uncertainty can in such cases help to reduce publication bias by making transparent that although new concepts or new fuels might look promising, their characteristics can be very uncertain.

A remaining difficulty related to any parameter uncertainty analysis method lies in the estimation of the input uncertainty. Although some manufacturers provide data on the uncertainty in nominal performance, data on part load operating points remains scarce. Estimation of uncertainty in financial parameters is perhaps even more difficult, especially with increasing prediction horizons.

Recommendations

In order to ensure that the effect of uncertainty on techno-economic trade-off studies of ship power and propulsion concepts are properly understood by decision-makers, the following is recommended:

(1) Conduct uncertainty analysis and communicate its importance when reporting the results of power and propulsion (trade-off) studies.
(2) Differentiate between the effect of shared and independent uncertain input parameters, so that decision-makers can focus on the factors with significant relevance for system selection only.
(3) Include uncertainty analysis features in concept trade-off tools, as far as this is feasible.
(4) Accept that uncertainty analysis can be affected by the non-linear behaviour of the techno-economic system under consideration. To quantify the importance of the non-linearities in the system, uncertainty analysis results obtained by the SUA approach should be compared with other methods such as Monte-Carlo Simulation.
(5) Ensure that decision-makers understand that whilst uncertainty analysis enables more informed decisions to be made, it does not provide a 'correct' answer.

Disclosure statement

Funding

References

Aldous L, Smith T, Bucknall R, Thompson P. 2015. Uncertainty analysis in ship performance monitoring. Ocean Eng. 110:29–38.

Benvenuto G, Campora U, Trucco A. 2014. Comparison of ship plant layouts for power and propulsion systems with energy recovery. J Mar Eng Technol. 13(3):3–15.

Damen. 2017. ASD tug 2810. [accessed 2017 Aug 09]. http://products.damen.com/en/ranges/asd-tug/asd-tug-2810.

Du X, Chen W. 2002. Efficient uncertainty analysis methods for multidisciplinary robust design. AIAA J. 40(3):545–552.

Isukapalli SS. 1999. Uncertainty analysis of transport-transformation models [PhD]. Rutgers: The State University of New Jersey.

JOULES. 2017. JOULES project FP7/2007-2013 grant agreement no 605190. [accessed 2017 Nov 25]. http://www.joules-project.eu.

LCPA-tool. 2017. BAL.LCPA Life Cycle Performance Assessment tool. [accessed 2017 Nov 25]. http://lcpa.bal.eu.

Lehne M, Norden C, Wurst S, Nagel R. 2015. *Life cycle performance assessment - method and tool for decision makers*. Paper presented at the international conference on computer applications in shipbuilding; Bremen.

Longo J, Stern F. 2005. Uncertainty assessment for towing tank tests with example for surface combatant DTMB model 5415. J Ship Res. 49(1):55–68.

McIntyre B, Gemmel G. 2012. *Selecting the Type 26 GCS power and propulsion design*. Paper presented at the 11th international naval engineering conference (INEC); Edinburgh, UK.

Partridge RJ, Arén P, Lindqvist P, Johansson LD. 2012. *Optimisation of power and propulsion for underway replenishment vessels*. Paper presented at the international naval engineering conference (INEC); Edinburgh, UK.

Schulten P, Stapersma D. 2007. A study of the validity of a complex simulation model. J Mar Eng Technol. (A10). 6(2):67–77.

Sofras E, Prousalidis J. 2014. Developing a new methodology for evaluating diesel – electric propulsion. J Mar Eng Technol. 13(3):63–92.

van der Spek M, Fernandez ES, Eldrup NH, Skagestad R, Ramirez A, Faaij A. 2017. Unravelling uncertainty and variability in early stage techno-economic assessments of carbon capture technologies. Int J Greenh Gas Control. 56: 221–236.

van Vliet OPR, Kruithof T, Turkenburg WC, Faaij APC. 2010. Techno-economic comparison of series hybrid, plug-in hybrid, fuel cell and regular cars. J Power Sources. 195(19):6570–6585.

Vrijdag A. 2014. Estimation of uncertainty in ship performance predictions. J Mar Eng Technol. 13(3):45–55.

Vrijdag A, de Jong J, van Nuland H. 2013. *Uncertainty in bollard pull predictions*. Paper presented at the third international symposium on marine propulsors (SMP); Launceston, Tasmania, Australia. www.marinepropulsors.com/proceedings/2013/9B.4.pdf.

Vrijdag A, de Vos P. 2012. *Uncertainties and margins in the ship propulsion design process*. Paper presented at the 11th international naval engineering conference (INEC); Edinburg, UK.

Vrijdag A, Schulten P, Stapersma D, van Terwisga T. 2007. Efficient uncertainty analysis of a complex multidisciplinary simulation model. J Mar Eng Technol. 6(2):79–88.

Vrijdag A, Stapersma D, van Terwisga T. 2009. Systematic modelling, verification, calibration and validation of a ship propulsion simulation model. J Mar Eng Technol. 8(3):3–20.

Appendix

Table A1. Input parameters to sub model 1 and 2.

Parameter name	μ_x		$\sigma_x/\mu_x \cdot 100\%$
Technical parameters x_1			
$SFC_{DE,0.5kts}$	248	[g/kWh]	7.5
$SFC_{DE,4kts}$	253	[g/kWh]	7.5
$SFC_{DE,8kts}$	251	[g/kWh]	5
$SFC_{DE,12kts}$	221	[g/kWh]	3
$\eta_{GB,0.5kts}$	0.87	[-]	7
$\eta_{GB,4kts}$	0.85	[-]	7
$\eta_{GB,8kts}$	0.84	[-]	4
$\eta_{GB,12kts}$	0.93	[-]	2
Financial parameters x_2			
Initial cost ship	7,700,000	[euro]	0.0
Second hand value	2,566,667	[euro]	10.0

Table A2. Input parameters to sub model 2 and 4.

Parameter name	μ_x		$\sigma_x/\mu_x \cdot 100\%$
Technical parameters x_5			
$SFC_{DE,12kts,h}$	213	[g/kWh]	3
$\eta_{GB,0.5kts,h}$	0.23	[-]	25
$\eta_{GB,4kts,h}$	0.64	[-]	10
$\eta_{GB,8kts,h}$	0.84	[-]	4
$\eta_{GB,12kts,h}$	0.90	[-]	2
$\eta_{vfd+m,0.5kts,h}$	0.33	[-]	15
$\eta_{vfd+m,4kts,h}$	0.76	[-]	5
$\eta_{vfd+m,8kts,h}$	0.90	[-]	2
$\eta_{DG,0.5kts,h}$	0.24	[-]	10
$\eta_{DG,4kts,h}$	0.29	[-]	8
$\eta_{DG,8kts,h}$	0.37	[-]	5
$\eta_{DG,moored,h}$	0.24	[-]	10
Financial parameters x_4			
Initial cost hybrid ship	8,200,000	[euro]	0
Second hand value hybrid ship	2,733,333	[euro]	10

Table A3. Shared parameters.

Parameter name	μ_{xs}		$\sigma_{xs}/\mu_{xs} \cdot 100\%$
Technical parameters x_s			
N.A.			
Financial parameters x_s			
Fuelprice	840	[euro]	0
Annual fuelprice increase	30	[euro/y]	20
Discount factor	0.09	[-]	10
Average revenue per sailing hour	900	[euro]	5
Annual revenue escalation	1.02	[-]	1
Annual personnel cost	400,000	[euro]	2
Annual personnel cost escalation	1.02	[-]	1
Annual maintenance cost	50,000	[euro]	3
Annual maintenance cost escalation	1.02	[-]	1
Market uncertainty factor in 10 years	1	[-]	10
Annual operating hours at 0.5 kts	1000	[h]	10
Annual operating hours at 4 kts	200	[h]	10
Annual operating hours at 8 kts	700	[h]	10
Annual operating hours at 12 kts	100	[h]	10

Table A4. Nominal outputs and uncertainties.

output name	μ_z		Tech. + fin. uncertainty σ_z/μ_z [%]	Tech. uncertainty only σ_z/μ_z [%]	Fin. uncertainty only σ_z/μ_z [%]
PP	6.35	[year]	13%	1%	13%
$NPV_{t=10}$	1,323,666	[euro]	95%	9%	95%
$m_{f,annual}$	253828	[kg]	5.3%	3.9%	3.7%
PP_h	6.50	[year]	12%	1%	12%
$NPV_{t=10,h}$	1,208,639	[euro]	106%	4%	106%
$m_{f,annual,h}$	204011	[kg]	5%	4%	3%
$\Delta\dot{m}_{f,0.5kts}$	−46.00	[kg/h]	16%	16%	0%
$\Delta\dot{m}_{f,4kts}$	−33.55	[kg/h]	19%	19%	0%
$\Delta\dot{m}_{f,8kts}$	4.97	[kg/h]	132%	132%	0%
$\Delta\dot{m}_{f,12kts}$	−5.83	[kg/h]	261%	261%	0%
$\Delta\dot{m}_{f,moored}$	0.00	[kg/h]	NA	NA	NA
ΔPP	0.15	[year]	48%	41%	25%
$\Delta NPV_{t=10}$	−115,028	[euro]	168%	118%	119%
$\Delta m_{f,annual}$	−49817	[kg]	32%	26%	19%