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A novel method for the Holistic, Simulation Driven Ship Design Optimization under Uncertainty in the Big Data era

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Abstract

The changing fuel costs, tough and volatile market conditions, the constant societal pressure for a «green» environmental footprint combined with ever demanding international safety regulations setup a completely new framework for commercial ship design. Ballast Water Treatment Systems, the ambitious IMO agenda for de-carbonization of shipping by 2050, the Goal Based Standards and most importantly the revision of the IMO MARPOL Annex VI, constitute a framework with strict and often contradicting requirements. On the other hand, the global economic uncertainty, rapid fleet growth and unsteady demand of commodities create a volatile economic operating environment for shipping companies.

Ship design needs to adapt to this new reality. Holistic approaches, with lifecycle considerations, aiming at robust designs are deemed necessary. Such a methodology is presented herein. It is built within the software CAESES and is consisted by a geometrical model core with several integrated modules that cover stability, strength, powering and propulsion, safety, economics, as well as an operation simulation module, enabling the user to

simulate the response in variations of the geometrical, design variables of the vessel under uncertainty. The latter is captured in several levels including Economic, Environmental, Operational uncertainty as well as the inaccuracy of the methods themselves.

Keywords: Holistic Ship Design Optimization under Uncertainty, Simulation Driven Design, Surrogate Models, Design for Efficiency, Big Data, Digital Twin.

1 INTRODUCTION

The first decade of the 21st century and the dominating economic recession combined with a fall in freight rates (due to tonnage overcapacity) has threatened the financial sustainability of numerous shipping companies. At the meantime, following the Kyoto protocol and the societal pressure for greener shipping gave birth to a number of international environmental regulations legislated by the UN International Maritime Organization (IMO) and classification societies that set the scheme for future as well as existing ship designs. Among others, future vessels' carbon emissions are controlled both by technical and operational measurements while ballast treatment facilities must also be incorporated in order to mitigate the risk of reduced biodiversity due to the involuntary carriage of evasive species inside water ballast tanks.

When focusing in the dry bulk cargo transportation, the carriage of major bulk commodities, i.e. iron ore, coal and grain the iron ore and coal dominate this market. According to the United Nations UNCTAD Report [2], in 2017 a record 1,364 million tons of iron ore and 1,142 million tons of coals have been transported by sea. The total dry bulk seaborne trade in 2017 totaled at 4,827 million tons making iron ore and coal the dominant commodities with 28.3% and 23.7% of the total trade.

The bilateral trade for the two major commodities is in fact very specific. From one hand, the Chinese economy poses a constant demand for iron (for construction) and coal (for energy).

On the other hand the major iron ore exporters are located in South America (primarily Brazil) and Australia, while coal production in order of mil tons is concentrated in Indonesia, Australia and Russia with 383, 301, and 314 mil tons respectively. The present paper focuses on vessels intended for this trade which can be grouped in the Capesize / Very Large Ore Carrier (VLOC) segment of the shipping market. The design of such (and all) bulk carriers in general for the past decade (2008-2018) focused on the increase of efficiency by two means: increase of cargo carrying capacity and decrease of energy demands. In most cases the optimization, if any, is based on a single design point in terms of both speed and loading condition (draft and thus displacement) by the alternation of the local geometrical characteristics only. This paper in turn proposes the herein developed and proposed holistic methodology intended for the optimization of the basic design of large bulk carriers based on their actual simulated operational profile, for their entire lifecycle and under conditions of uncertainty. The speed and trading profile is simulated for the entire economic life of the vessel and the optimization focuses on the minimization of all operating costs, maximization of income, minimization of internal rate of return (IRR) summarized by the Required Freight Rate (RFR) from one hand and from the other the minimization of the energy footprint of the vessel expressed by the Energy Efficiency Design Index (EEDI) , simulated Energy Efficiency Operating Index (EEOI), lifecycle emissions as well as the minimization of the required water ballast amount for stability in order to minimize (or even eliminate) the energy and costs for the treatment of water ballast onboard.

2 OVERVIEW OF THE HOLISTIC METHODOLOGY

Holism, originating from the Greek word ὅλος (meaning all, entire, total), is the philosophical notion that all the properties of a given system (biological, chemical, social, economic, mental, linguistic, etc.) cannot be determined or explained by the sum of its component parts alone.

Instead, the system as a "whole" determines an important way how the parts behave. Aristotle in Metaphysics (H-6, 1045a8–10) (Aristotle, Ross [35]) examines the problem of the unity of definition and offers a new solution based on the concepts of potentiality and actuality. Although the concept of holism was pervasive, the term holism, as an academic terminology, was introduced by the South African statesman Jan Smuts in his 1926 book, Holism and Evolution (Smuts [50]) which defined holism as "The tendency in nature to form wholes that are greater than the sum of the parts through creative evolution".

2.1 Holistic Ship Design

The term Holistic Ship Design which is the core and basic notion and principle of the herein presented research work was first introduced by (Papanikolaou, [43]), where the generic ship design optimization problem is defined and presented in its holistic nature. The typical process flow of computational methodologies for performing all the necessary computations included in the different design aspects is also defined. Within the same context of Holistic Ship Design theory, the publication of (Papanikolaou, et al., [46]) , a product of a series of research projects, aimed at the systematic, Risk Based Optimization of AFRAMAX tankers (Papanikolaou, et al., [45]), focusing on the cargo carrying capacity, steel weight and accidental oil outflow. The same design concept and computational methodology has been further refined and evolved in the publications of (Sames, et al. [48]), (Papanikolaou, et al [44]) as well as (Nikolopoulos [9]). Applications of holistic ship design optimization principles applied for container vessels by using a fully parametric hull surface modeled in CAESES ® coupled with NAPA for compartmentation can be found in the studies of (Priftis, et al., [47]) as well as the previous studies of (Soultanias, [51]), (Koutroukis, et al., [41]) and (Nikolopoulos, et al., [42]). Subject model was originally developed for the parametric design and optimization of a novel containership with ellipsoidal mid-ship section in (Koutroukis, [13]) and is based on the same principle of parametric design and optimization as the tanker optimization studies previously presented.

Using the above work and their previous work and development of such design methodologies within the Ship Design Laboratory of the National Technical University of Athens, Authors herein present an evolved and further enhanced method fully incorporated in the CAESES ® CAD/CAE environment.

The methodology is holistic, in the sense that all of the critical aspects of the design are addressed under a common framework that takes into account the lifecycle performance of the ship in terms of safety efficiency and economic performance, the internal system interactions as well as the parameter correlations, design trade-offs and sensitivities. The workflow of the methodology has the same tasks as the traditional design spiral with the difference that the approach is not sequential but concurrent.

2.2 Simulation Driven Design

The embedding of a vessel's operation simulation within the early design process has not been adequately studied in the literature with only a handful of relevant examples available. Within the direction of simulation in early ship design, (Tillig, et al. [52]) propose a generic ship energy systems model that can predict the ship's energy consumption during different operational conditions, without however taking into account variation of the vessel's RPM, heavy running and potential limitations from the engine's torque (fuel) limit. In (Alwan et al [34]), an event-based simulation model is utilized in order to reduce the simulation cost using an event based operational profile instead of time-domain simulation of vessel operation, using discrete event simulation for analyzing system performance. A quasi-static discrete-event simulation model to replicate and assess the voyage of a general cargo vessel is proposed by (Sandvik, et al. [49]) using a prescribed route based on real time (15 minute) data and a constant speed assumption and could be potentially integrated in a design environment.

The primary novelty of the herein presented methodology is that it is simulation driven in the sense that the assessment of the key design attributes for each variant is derived after the simulation of the vessel's operation under different voyage profiles for its entire lifecycle instead of using a prescribed loading condition and operating speed (Nikolopoulos, Boulougouris [17]). The operation simulation takes into account the two predominant trade routes large bulk carriers are employed in using actual, real-time operating data from a fleet of large bulk carriers (Capesize and Newcastlemax). By employing such a technique, the actual operating conditions and environment with all uncertainties and volatilities connected to the latter is used to assess the merits of each variant of the optimization ensuring that the design will remain robust and attain its good performance over a range of different environments and for its entire lifecycle. The dimensioning of the principal components, e.g. the main engine and propeller is based on the margin allowed from a limit state condition assumed in the analysis.

2.3 Design under Uncertainty

The effects of uncertainty during all stages of Ship Design as well as its implications in Optimization studies is a well-studied topic in the literature with notable examples the works of (Hannapel, [39]) , (Hannapel & Vlahopoulos, [40]), examining two methods of Uncertainty modeling for ship design optimization, that of robust optimization and reliability-based optimization. An example of reliability-based design use of uncertainties in a Ship Design Multi-Disciplinary Optimization model is that of (Good, [38]). A two-stage stochastic programming for robust ship design optimization under uncertainty has been developed by (Diez & Peri, [36]), (Diez, et al., [37]).

For the present work, a comprehensive approach with regards to the uncertainty and the statistical modelling of the latter is followed as at the following distinctive levels/elements:

a. Weather and Environmental Uncertainties

b. Shipping Market Uncertainties

c. Methodology Uncertainty and Error Modeling

Missing values are a common issue in large data analysis. Missing data leads both to bias as well as loss of information. There are various ways of treating them. There is the “complete case” (Nguyen, Carlin, and Lee 2017) approach which discards individual observations containing missing data to provide only a dataset with completed observed data. Another method used is the data imputation (Little and Rubin 2019). Imputation is fundamentally a further layer of modelling whereby missing values are estimated from other predictor variables in the dataset. We have applied both as a systematic filtering of real-time data, and as generation of Probability Distribution Functions for the Speed, Wind, Waves and other voyage parameters that in turn are used as input in the simulation module.

2.4 Design and Simulation Environment

The environment in which the methodology is programmed and is responsible for the generation of the fully parametric hull surfaces is the CAESES CAE which is a CAD-CFD integration platform developed for the simulation driven design of functional surfaces like ship hulls, propeller and appendages, but also for other applications like turbine blades and pump casings. It supplies a wide range of functionalities or simulation driven design like parametric modeling, integration of simulation codes, algorithms for systematic variation and formal optimization. The holistic methodology proposed has the workflow depicted in Figure [1].

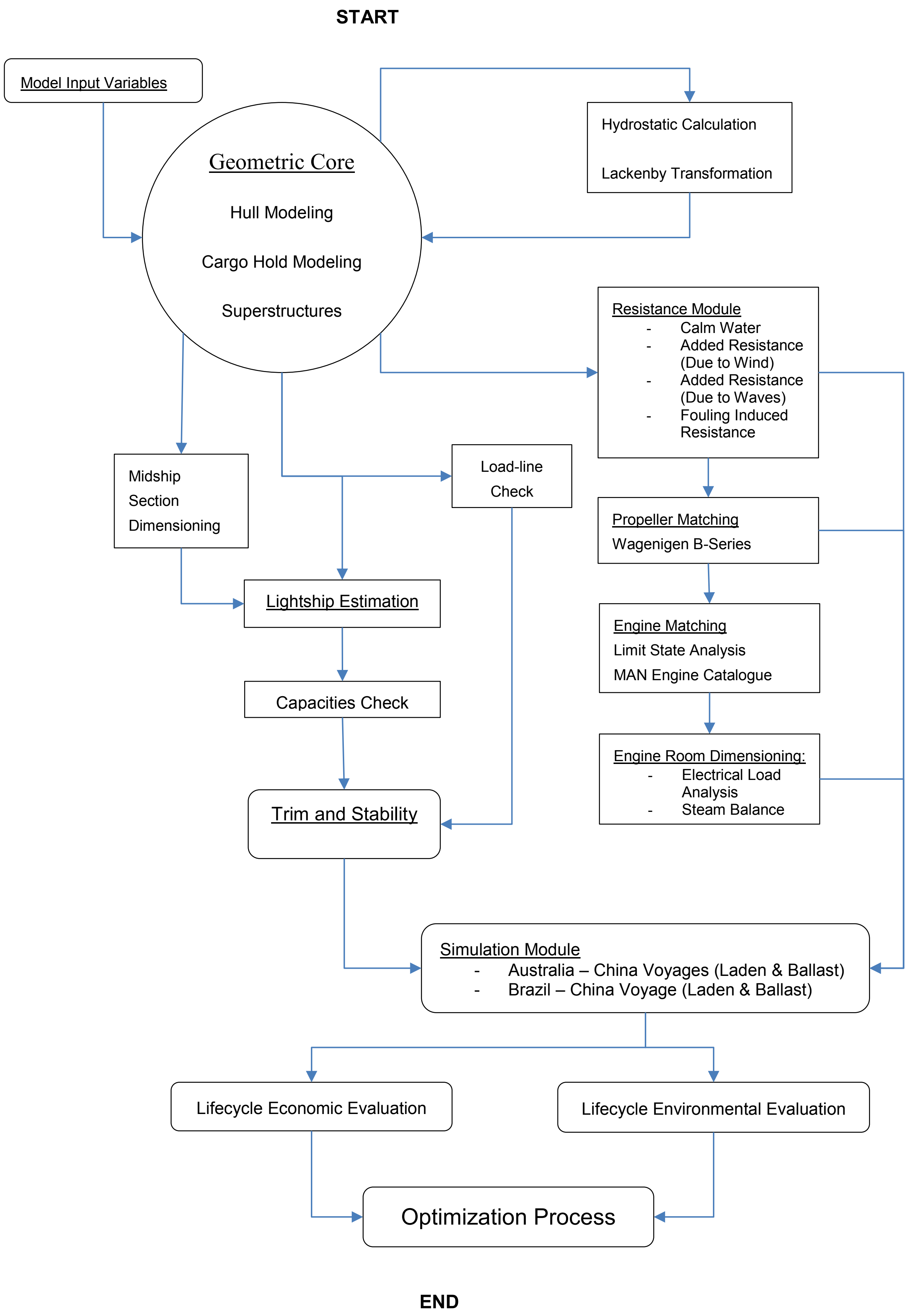

START
Model Input Variables
Geometric Core
Hull Modeling
Cargo Hold Modeling
Superstructures
Hydrostatic Calculation
Lackenby Transformation
Resistance Module
- Calm Water
- Added Resistance (Due to Wind)
- Added Resistance (Due to Waves)
- Fouling Induced Resistance
Midship Section Dimensioning
Load-line Check
Propeller Matching
Wagenigen B-Series
Lightship Estimation
Engine Matching
Limit State Analysis
MAN Engine Catalogue
Capacities Check
Engine Room Dimensioning:
- Electrical Load Analysis
- Steam Balance
Trim and Stability
Simulation Module
- Australia – China Voyages (Laden & Ballast)
- Brazil – China Voyage (Laden & Ballast)
Lifecycle Economic Evaluation
Lifecycle Environmental Evaluation
Optimization Process
END

Figure 1: Workflow of the Proposed Methodology

2.5 Geometric Core

The core of this methodology and any similar developed in a CAD/CAE system is the geometrical model (geometrical core). The original surface is produced as group of parametric sub-surfaces modeled in the CAESES.

2.6 Initial Hydrostatic Properties

The hydrostatic calculation aims on checking the displacement volume, block coefficient and center of buoyancy of the design. It is performed by an internal computation of CAESES and for its execution a dense set of offsets (sections) is required as well as a plane and a mirror plane.

2.7 Lackenby Variation

In order to be able to control the desired geometrical properties of the lines, and more specifically the block coefficient (Cb) and the longitudinal centre of buoyancy (LCB), the Lackenby variation [32] is applied. This variation is a shift transformation that is able to shift sections aft and fore accordingly. Instead of applying quadratic polynomials as shift functions, fairness optimized B-Splines are used allowing the selection of the region of influence and the smooth transition as well. The required input for the transformation is the extent of the transformation which in this case is from the propeller position to the fore peak and the difference of the existing and desired Cb and LCB as well[9].

Picture 1: Hull form surfaces following Lackenby variation with corresponding SAC curves

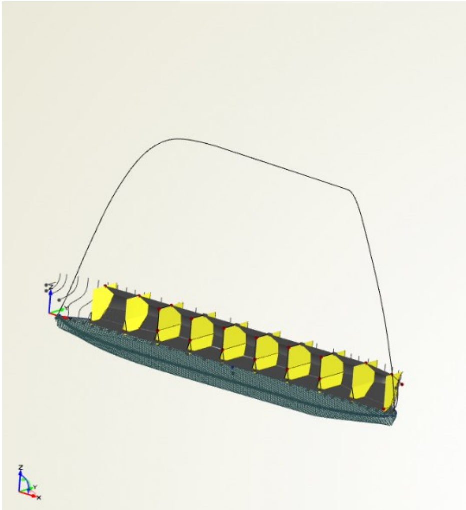
2.8 Cargo Hold Modeling

Using the output surface from the Lackenby variation, the cargo hold arrangement is generated with a feature of the CAESES and its capacity is calculated.

The cargo hold surfaces and their respective parametric entity were realized within CAESES. Furthermore, the hydrostatic calculations of CAESES were used to calculate the capacity of the cargo holds, which is necessary for most of the computations. The parameters/variables that are used for the Cargo Hold arrangement generation are the positions of the bulkheads, the position of the Engine Room bulkhead, the frame spacing as well as some local variables such as the hopper width and angle, the topside tank dimensions (width and height), the lower stool height and length and double bottom height.

The capacity of each tank is calculated by creating offsets for each one of the tank surfaces and joining them together. Afterwards, a hydrostatic calculation of the tanks takes place and the total capacity can be estimated and cargo density checked. Furthermore, a calibration factor derived from the parent hull is introduced in order to take into account the volume of the structural frames inside the cargo holds as well as a factor in order to derive with the Bale and Grain capacities.

The result of the parametric tank modeling can be also seen at the CAESES snapshot (picture [2])



Picture 2: Parametric Cargo Hold surfaces

2.9 Resistance Prediction

2.9.1 Calm Water Resistance

The resistance prediction of this model uses a hybrid method and two different approaches, depending on the optimization stage.

Initially, during the design of experiment and the global optimization phase, where a great number of variants is created there is a need for high processing speed and subsequently computational power. For this particular reason the Approximate Powering Method of Holtrop [6] is used that derives from experimental data and is a very fast method. Especially in bulk carriers it is very accurate too, since the wave making resistance as well as the viscous pressure resistance are very small fractions of the total resistance with the frictional resistance (direct function of the wetted surface) dominating all resistance components due to the dimensions and very small Froude number. The only inaccuracy of this method can be identified in the local viscous resistance effects and is common to all prediction methods.

However, in order to improve the prediction accuracy, especially for of design conditions such as the ballast condition, the coefficients for each component of the resistance used in Holtrop and Mennen methodology were recalibrated against the parent vessel model tests while the coefficients used for the powering prediction were calibrated both from model tests and analytical CFD calculations on the parent vessel (Nikolopoulos and Boulougouris [18]). In subject publication the constants and parameters from Holtrop and Mennen approximate power method were systematically varied with use of genetic algorithms with the goal of calibrating the method for minimum error against the statistical database used. The calibration database is consisted by the model tests (in both design, scantling and ballast loading conditions) of 7 different vessels with very similar geometric characteristics (full hull forms) and Froude number of the parent and target vessels. In total 111 points of power vs. speed for the Laden conditions and 61 points of power vs. speed for the Ballast conditions were assessed.

The calibration was performed by a systematic optimization approach. The optimization variables were the statistic coefficients as well as power values used in Holtrop methodology with a relatively big margin of variance as well as the introduction of some additional terms in existing equations. Then the methodology would be applied for each speed /power point of the model tests and the difference in powering would derive. The minimization of this difference is the optimization target of this particular sub problem. The applied algorithm for the optimization was the NSGA II [Deb, 33] with roughly 4,000 variants being produced in two steps for each condition. The first step was the calibration of the equations for the calculation of the bare hull resistance and power (EHP-Effective Horse Power) while the second calibrated the equations for applying the self-propulsion problem and thus calculating the delivered horse power (DHP). The result was an average difference of -4.3% and -0.20% of the EHP and DHP respectively, for the Ballast Condition and -1.94% and -6.5% of the EHP and DHP respectively for the Laden Conditions with the Holtrop results being more conservative (over estimation) than the model tests. The standard deviation, variances as well as a full statistical analysis was produced and the prediction error of the methodology was modelled in the IBM SPSS with a non-linear regression method as a function of the vessels dimensions, block coefficient and wetted surface and subsequently programed in the methodology.

The entire Holtrop method is programmed within the Framework and is also generated as a feature for later use. Actual data from the geometric model is also used, such as the entrance angle, prismatic coefficients etc., making the process more precise and representing of the specific design.

2.9.2 Added Resistance due to Wind

The vessel's added resistance due to wind is calculated for two separate occasions in subject methodology. The first being for the assessment for sizing the main engine at a prescribed condition for the latter and second, within the simulation of the vessel's operation for each leg and stage of the simulated voyage route. The tool used for the resistance is the formula of Fujiwara et al [24] which is also used in the ISO15016-2015 [20] when doing corrections in the measurements obtained in sea trials. Subject method is considered as reliable, robust and accurate as the formula contains sensitivities and correlations with the hull and deckhouses geometry (via the use of projected surfaces).

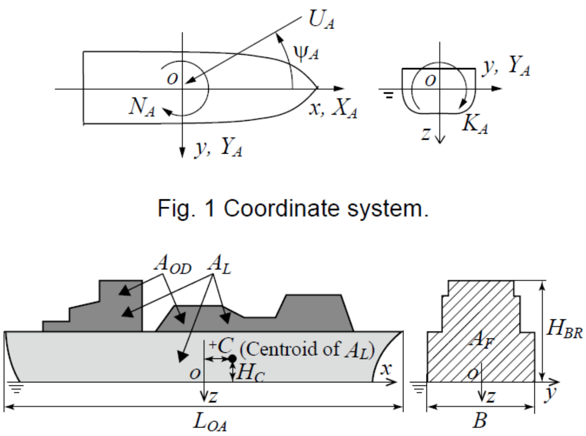


Figure 2: Coordinate system and input used in Fujiwara empirical formula for the estimation of added resistance due to wind [24].

2.9.3 Added Resistance due to Waves

The added resistance due to waves is similarly used in the two modules mentioned previously, namely main engine sizing and operational simulation. The tool used for the added resistance estimation is different depending on the stage of the optimization. For the initial stage, empirical formulae based on the Maruo far field are utilized while in a second stage, integrated panel codes using potential theory to solve the seakeeping motions problem and then through added mass calculate the added resistance. For the first stage, after assessing the method of Kwon et al [14, 15] as well as STAWAVE2 (as presented in ISO15016-2015 [20]) the new method of Liu et al. [25] for the estimation of added resistance in head waves is chosen instead. The method of Liu and Papanikolaou offers a fast and efficient calculation alternative to running a panel code, strip theory code or using RANS codes. The formula is based on best fitting of available experimental data for different types of hull forms. The formula, has been simplified to the extent of using only the main ship particulars and fundamental wave characteristics for the estimation of ship's added resistance.

The formula takes the below form:

$$R_{AW} = R_{AWR} + R_{AWM} \tag{1}$$

$$R_{AWR} = \frac{2.25}{2} \rho g B \zeta_a^2 a_d \sin^2 E \left(1 + 5\sqrt{\frac{L_{pp}}{\lambda}} Fn \right) \left(\frac{0.87}{C_B} \right)^{1+4\sqrt{Fn}} \tag{2}$$

$$R_{AWM} = 4 \rho g \zeta_a^2 B^2 / L_{pp} \bar{\omega}^{b_1} \exp\left[\frac{b_1}{d_1} \left(1 - \bar{\omega}^{d_1} \right) \right] a_1 a_2 \tag{3}$$

2.9.4 Fouling Related Resistance

The last environmental related added resistance factor taken herein into account both in the design modules (propulsion prediction and main engine selection) as well as input in the operational simulation module is that of marine biological fouling. More specifically, as the hull of the ship ages the average roughness value increases due to hull biological fouling. The effect of the hull roughness for the vessel's resistance can be calculated from the below formula (International [21]):

$$\frac{\Delta R}{R} = \frac{\Delta C_F}{C_T} = 0.044 * \left[(k_2/L)^{1/3} - (k_1/L)^{1/3}\right] \tag{4}$$

With k_2 and k_1 being the current and previous hull roughness respectively. The hull roughness increase on an annual basis is also estimated from [International [22]] which starts from an average and continues on an exponential rate. Furthermore, in order to further enhance the lifecycle considerations, the dry docking recoating is taken into account in the 5, 10, 15, 20 and 25 year interval with a reduction of the roughness to a level 10% higher than the previous coating system (e.g. roughness in 5 years is 10% higher than the newbuilding value, roughness in 10 years is 10% than the 5 year value etc.). The starting roughness value at the delivery stage of the vessel is assumed to be an average value of 97.5 microns (average of minimum reading of 75μ and maximum reading of 120μ).

The power increase corresponding to the above resistance increase is approximated by the following formula (International [19]):

$$1 + \frac{\Delta P}{P} = \frac{1+\Delta R/R}{1+\Delta\eta/\eta} \tag{5}$$

With the increase on the propeller open water efficiency being:

$$\frac{1}{1+\Delta\eta/\eta} = 0.30 * \left(1 + \frac{\Delta R}{R}\right) + 0.70 \tag{6}$$

2.10 Propeller Model

While the vessel's Propeller is not modelled geometrically at this current stage, it is assumed to be a part of the Wageningen B-Series of propellers. All the Wageningen polynomials are modeled within the methodology (Bernitsas [19]) so the open water diagrams of a propeller with a selected pitch, diameters, blade number and expanded area ratio can be derived. Following this, the self-propulsion equilibrium is conducted in the design speed in an iterative manner in order to derive the final propulsion coefficients, shaft horse power, torque, thrust and propeller revolutions (RPM). This is in turn used for the propeller-engine matching and the propulsion plant dimensioning.

The optimal selection of the propeller parameters (diameter, pitch, blades) is also part of the global/preliminary design stage

2.11 Main Engine and Engine Room dimensioning

2.11.1 Main Engine

After the propeller is dimensioned, the Main engine should be matched to that hull and propeller. In order to avoid the well-known (and rather recent) risk of underpowered vessels, instead of employing a weather and fouling margin (typically 15%), a dimensioning condition was in turn used as determined by users. This condition is such that the vessel should maintain the full speed and corresponding engine load, power and RPM at head and beam waves corresponding to sea state 5, with adverse (head) current of 1.5 knots, roughness due to fouling corresponding to 4 years without cleaning and the corresponding head wind of sea state 5. In addition to the power requirements of the above an RPM of 10% (in accordance with MAN B&W requirements [7]) is imposed as well as an additional margin of 5% which is considered for derating the main engine and ensuring smaller Specific Fuel Oil Consumption (SFOC).

For the final requirements the main engine is matched with the existing “G-Type”, “ultra-long stroke”, engines available from MAN [7]. Firstly an “engine library” with alternative configurations is created, which is utilized in the selection module in combination with an internal iterative procedure ensures that the engine will have sufficient light running margin and that the layout point on the diagram is close to the L2L4 line corresponding to bigger torque/MEP margins and smaller SFOC values. A Final SFOC curve from 10% to 100% is produced and corrected for the actual engine layout.

All engines within the engine selection library are Tier III compliant in accordance with the MARPOL Annex VI, Regulation 13 as amended by the IMO MEPC 66 requirement [26] for ships built after the 1st of January of 2016.

In addition to SFOC curves, curves of steam production from 20% to 100% are produced. These are used in turn as steam production curves in the operation simulation, in order to assess the potential load (if required) of the composite boiler to match the steam consumption requirements.

2.11.2 Diesel Generators

The electrical balance analysis of the parent vessel is normalized with the derived SMCR for each consumer and each condition respectively and the ratios are used within the methodology to determine the load of each consumer for the generated variants and thus the electrical load for each condition. The required alternator output is calculated based on this (after including a safety factor), while the prime movers (diesel generators) of the alternators are sized by assuming an 85% electrical efficiency.

2.11.3 Exhaust Gas Boilers

Similarly to the case of the electrical balance, the steam balance of the vessel is also non-dimensionalized. For applications of fuel tank heating (whether bunker or settling/service tanks) the steam consumption (in kg/h) is non-dimensionalized by the fuel tank capacity (calculated in intact stability module).

2.12 Lightship Weight Prediction

The lightship calculation follows the traditional categorization in three weight groups, the machinery weight, the outfitting weight and the steel weight.

2.12.1 Machinery Weight

The machinery weight calculation is based on the average of two methods: the Watson-Gilfillan formula and the calculation based on the Main Engines weight respectively.

The machinery weight estimation is based on a empirical formula due to Watson-Gilfillan[5]:

$$Wm = Cmd * Pb^{0.89} \qquad (7)$$

The average is used to balance out any extreme differences, and the coefficients of the Watson-Gilfillan formula are calibrated for low speed, two stroke engines based on statistic data available for a fleet of bulkers.

2.12.2 Outfitting Weight

The outfitting weight is also based on the average of two independent calculations. The Schneekluth method is one and the use of empirical coefficients for sub-groups of that particular weight group is the other one.

2.12.3 Steel Weight

During the initial design stages, and the selection of optimal main dimensions, it is necessary to identify the effect of the change of the principal dimensions of a reference ship on the structural steel weight. Thus, at first, an accurate calculation of the steel weight of the reference ship is conducted. Following this, the "Schneekluth Lightship Weight Method" was applied [Papanikolaou, 7]. Given that the steel weight for the parent vessel was available as derived from summing the individual steel block weights (from the shipbuilding process) a TSearch algorithm was employed in order to vary the values of the statistical coefficients and constants of subject methodology with the objective of the minimization of the difference between the actual and calculated values for the steel weight. The result was an accuracy of 0.3% which is more than acceptable within the scope of basic/preliminary design. The error was modeled also in the IBM SPSS as a function of the principal particulars and block coefficient.

2.13 Deadweight Analysis

The deadweight of the vessel is composed of subgroups such as the consumables, the crew weight and the deadweight constant. The Deadweight analysis is the prediction of the payload of the vessel based on the calculation of the consumables.

As mentioned before, the consumables for the machinery is calculated, namely the Heavy Fuel Oil for the main engines, and diesel generators, the Lubricating Oils of the engines and generators.

Furthermore, based on the number of the crew members (30), the fresh water onboard is calculated as well as the supplies and the stores of the vessel.

2.14 Stability and Load-line Check

The initial intact stability is assessed by means of the metacentric height of the vessel (GM). The center of gravity of the cargo is determined from the capacity calculation within the framework while the center of gravity for the lightship and consumables is determined from non-dimensioned coefficients (functions of the deck height) that derive from the information found in the trim and stability booklet of the parent vessel. All the above are calculated with the requirements of the IMO Intact Stability Code for 2008 [IMO, 5].

2.15 Operational Profile Simulation

This module is an integrated code within the methodology that simulates the actual operating conditions of the vessel for its entire lifecycle. Two trade routes are considered, the Brazil to China roundtrip and the Australia to China roundtrip. Each voyage is split into legs depending on distinctive sea areas.

For the Australia to China roundtrip the following legs are considered:

- Leg A: Sea Passage from W. Australia loading ports to Philippines being subdivided into 4 sub-legs.
- Leg B: Sea Passage from Philippines to Discharging port being subdivided into 4 sub-legs.
- Leg C: Only for the ballast leg to Australia a stop in Singapore for bunkering is considered.

For the Brazil to China roundtrip the following legs are considered:

- Leg A: Sea Passage from the Brazilian Loading port to the Cape of Good Hope in South Africa. This leg is subdivided into 4 equal sub-legs.

- Leg B: From the Cape of Good Hope in S. Africa to Indonesia and is subdivided into 4 equal sub-legs.
- Leg C: Sea Passage through the Malacca straight and Singapore including a port stay in Singapore for bunkering operations.
- Leg D: Sea Passage from Singapore through the Taiwanese straight into the discharging port of China. This leg is subdivided into to 2 sub-legs.

2.15.1 Input Data

For each one of the legs (given distance in nautical miles) the average speed and added resistance curves are input as well as the loading of the generators, the maneuvering time. If the leg includes a discharging, loading or bunkering port the port stay in hours is also used. Based on this profile the voyage associated costs together with the fuel costs are calculated on a much more accurate and realistic basis.

The input variables of the operation simulation model for each model can be seen in the below table [1].

Operational Simulation Input Parameters	
General	
ISO corrected SFOC Curve	Speed Power Curve - Calm Water
Auxiliary Engines Power (kW)	SFOC curve for auxiliary Engines
Auxiliary Engine Load during Cargo Hold Cleaning (%)	Time for Cargo Hold Cleaning (hours)
Main Engine SMCR (kW)	Main Engine Load in Manoeuvring (%)
Cylinder Oil Feed Rate (normalized average) (gr/kWh)	Electrical Power Required during Normal Sea Going (kW)
Blowers Electrical Power (kW)	Required Electrical Power during Manoeuvring (kW)
Main Engine SFOC during Manoeuvring (gr/kWh)	Sulphur Content in Fuel (%)
Main Dimensions	
Length Overall (m)	Length Between Perpendiculars (m)
Breadth (m)	Voyage Draft (m)
Wind Profile	
Total Lateral Projected Area (m^2)	Total Transverse Projected Area (m^2)
Lateral Projected Area of Superstructures above deck (m^2)	Fujiwara Hc (m)
Height of Superstructures (m)	
Added Resistance	
Wave Length Probability Distribution Function Curve	Entrance Angle Length (m)
Roughness Increase due to fouling (microns/year)	
Propulsion	
Thrust Deduction Curve	Wake Fraction Curve
Propeller Diameter (m)	Expanded Area Ratio (m^2)
Number of Blades	Pitch over Diameter Ratio
Propeller Shaft Mechanical Efficiency	Relative Rotative Efficiency
Speed – RPM Curve	
Electrical Loads during Loading (kW)	Time in Loading/Discharging Port (hours)
Time for maneuvering (hours)	
Sea Passage Leg	
Distance (nautical miles)	Average Transit Speed (knots)
Probability of Head Current	Probability of Astern Current
Low Current Velocity (knots)	Mid Current Velocity (knots)
High Current Velocity (knots)	
Sea Passage Leg – Singapore (additional)	
Manoeuvring Time (hours)	Electrical Load in Port (kW)
Port Stay for Bunkering (hours)	

Table 1: Operational Simulation Input Parameters

The process flow of the simulation code is also depicted in figure [3].

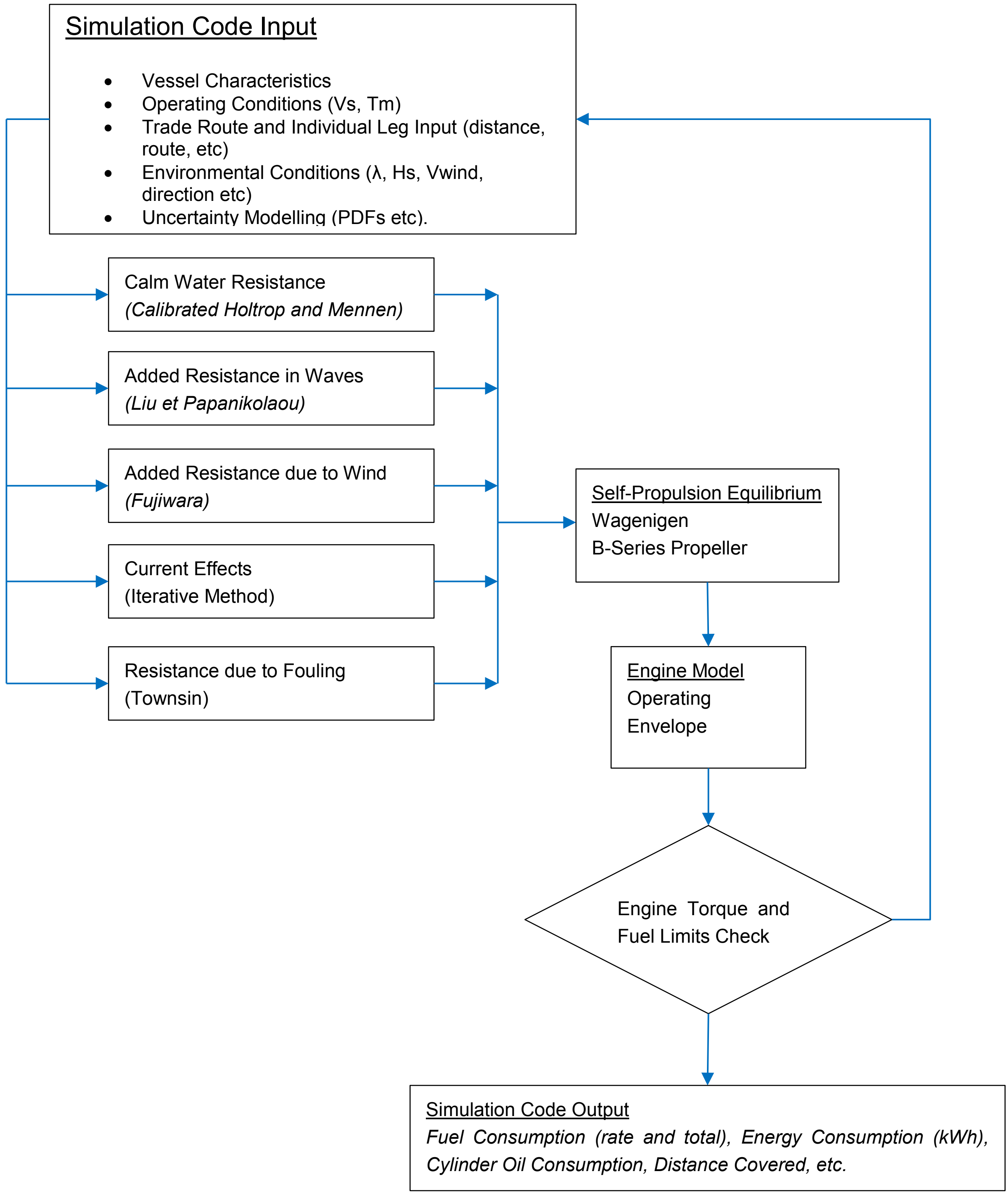


Figure [3]: Process flow of the vessel operation simulation code.

2.15.2 Added Resistance

For each leg, stage and corresponding time step the added resistance module is called from within the operational simulation module in order to calculate the added resistance. The final estimation is a probabilistic one, which means that the added resistance for different wave directions, wave heights and wave lengths is estimated and then a probabilistic figure is derived based on the probability distribution functions modeled from the onboard measurement data.

2.15.3 Environmental Parameters Modeling

The operating speed for which the added resistance (and thus added propulsion power) is calculated is also probabilistic.

Initially the uncertainty of the average operating speed per leg is applied. The probabilities of having a ±15% deviation from the estimated average of each leg are calculated from the probability density function derived from onboard data analysis. A probabilistic steaming speed is then produced from the weighted average of the higher and lower speeds.

2.15.4 Currents

The second source of uncertainty with regards to the operating speed is environmental and is related to the local currents. For each leg/sea area a statistical analysis from onboard collected data, reveals both the average as probability distribution of the current speed and current direction. In the simulation module these calculated probability distribution functions are used in order to estimate the probability of encountering a high, medium and low current (their amplitude is determined from the minimum, maximum and average speed from the onboard data). The correction to the operating speed is positive for the cases of astern current and negative for ahead current. The ahead and astern currents are considered for an "operating envelope" of ±45 degrees both in the ahead and astern term, as the side currents will only yield deviation rather than speed loss.

From the above mentioned two corrections the probabilistic ship speed is derived based on which both the calm water required delivered power is calculated as well as the added resistance and power calculations takes place.

2.15.5 Fouling

The fouling margin, is also calculated depending on the age of the vessel in the respective simulation stage by calling the fouling resistance calculation module described previously.

2.16 Economic Model

In total the code calculates the Operational Expenditure (OPEX), the Capital Expenditure (CAPEX), the Required Freight Rate (RFR), the Internal Rate of Return (IRR) as well as the IMO Energy Efficiency Operational Index (EEOI).

The Economic model also follows the principle of simulation driven design and design under uncertainty. The uncertainties in the economic model can be identified both in terms of the shipping market as well as the fuel prices which directly affect the fuel costs (burden to owners that operate in the tramp/spot markets).

The market uncertainty is predominately expressed by the uncertainty of the vessel's Earnings. Through the Clarkson's Shipping intelligence database (Clarkson's [23]), a probability distribution function for the Capesize earnings was produced based on the data from 1990 to 2015 which cover a typical vessel's economic (and engineering) lifetime. Based on the earnings the probability of high (150,000 USD/day TCE), mid (35,000 USD/day TCE) and low (5,000 USD/day TCE) were calculated and thus a probabilistic value for the vessel's annual as well as lifecycle (by applying the interest rates) profitability was derived. Apart from this earnings directly affect the other shipping markets, namely the acquisition market (both the S&P and Newbuilding market; for the case herein presented the second as well as the scrap market. For this particular reason and in order to further enhance the correlation to the vessel's design the newbuilding prices and scrap prices were expressed (after suitable adjustment) per ton of lightship and were correlated from the Clarkson's Shipping Intelligence database to the Earnings of the vessel with the following formulas:

$$\text{NBprice} = 157.335 * \text{Earnings}^{0.269} \quad (8)$$

$$\text{Scrap\_price} = 25.648 * \text{Earnings}^{0.244} \quad (9)$$

For both equations the value returned is USD/ton of lightship and serve as magnification factors for the acquisition and residual values of the vessel. Furthermore, the two last which are used for the CAPEX calculation, are also probabilistic by applying the same probabilities that are used for High, Mid and Low Earnings with the respective amounts introduced in the above presented formulas. By this way, it is able to accurately depict the volatility of the market and the response of each design variant as well as the effect of its dimensions to its lifecycle economic performance.

This is further enhanced by the calculation of the Fuel Price cost which is outside the usual time charter provisions of bulker Charter Party agreements. The Fuel prices cost is also probabilistic with the probabilities for High (1500 USD/ton), Mid (450 USD/ton) and Low (150 USD/ton) prices being derived from the probability distribution function that was calculated from the Clarkson's Shipping Intelligence Database.

This is a key point of this methodology, namely to optimize the vessel's design under uncertainty as the produced designs correspond to a more realistic scenario and the dominant variants of the optimization have a more robust behavior over a variety of exogenous governing market factors.

The derived probabilistic values of RFR and the deterministic value of the EEOI are the functions/targets used in the optimization sequence later.

2.17 Energy Efficiency Design Index Calculation

The Energy Efficiency Design Index (EEDI) is calculated according to the formula proposed in the IMO resolution MEPC.212(63), using the values of 70 % deadweight and 75% of the MCR of the engines and the corresponding reference speed:

$$EEDI = \frac{\left(\prod_{j=1}^{M} f_j\right)\left(\sum_{i=1}^{nME} P_{ME(i)} * CF_{ME(i)} * SFC_{ME(i)}\right) + \left(P_{AE} * CF_{AE} * SFC_{AE}\right)}{f_i * Capacity * V_{ref} * f_w} + \frac{\left\{\left(\prod_{j=1}^{M} f_j * \sum_{i=1}^{nPTI} P_{PTI(i)} - \sum_{i=1}^{neff} f_{eff(i)} * P_{AEeff(i)}\right) * CF_{AE} * SFC_{AE}\right\} - \left(\sum_{i=1}^{neff} f_{eff(i)} * P_{eff(i)} * CF_{ME} * SFC_{ME}\right)}{f_i * Capacity * V_{ref} * f_w} \tag{10}$$

The minimization of this index is one of the primary targets of the conducted optimization. The engine power is directly related to the resistance of the hullform, while the deadweight is also related to both the hullform in terms of displacement and to ship's lightship weight.

2.18 Modeling Uncertainties from Big Data Analysis

One of the novel aspects of this methodology has been the use of big data and the statistical analysis of the latter with the IBM SPSS toolkits for the creation of linear and non-linear regression formulas as well as probability distribution functions and descriptive statistical studies. The big data taken into account and analyzed (as already described in the various subcomponents of the methodology) are in two categories:

a. Onboard data (write about their origin) and production of PDF for environmental criteria.

The Onboard data were collected from the installed Vessel Performance Monitoring (VPM) System of a fleet of Capesize and Newcastlemax bulkers that operate both in the Brazil and Australia trade routes. This VPM system collects real time data (30sec logging and averaging into 5 minute intervals) of the vessel's Alarm and Monitoring System (AMS) and the vessel's navigational data from the Voyage Data Recorder (VDR) into an onboard server as per process flow in Figure [4]. This gathering, together with the use of signals from torque meters and flow meters provides an extensive database that is used for the statistical analysis with the IBM SPSS toolkit of the following parameters:

1. Operating Speed: Normal PDF with a Mean and Standard Deviation depending on the leg of the passage.
2. Wind Speed: Normal PDF with a Mean and Standard Deviation depending on the leg of the passage.
3. Wind Direction: Normal PDF with a Mean and Standard Deviation depending on the leg of the passage.
4. Current Velocity: Exponential with a scale of around 1 to 1.5 depending on the leg of the passage.
5. Current Direction: Normal PDF with a Mean and Standard Deviation depending on the leg of the passage.

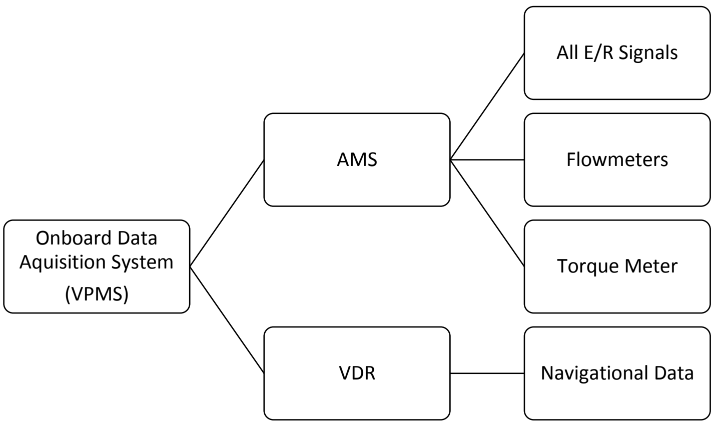


Figure 4: Process flow of the data acquisition system

b. Clarkson's Ship Intelligence Database for the modelling of market conditions.

The Clarkson's Shipping Intelligence Database (Clarkson's [23]) has been used extensively for the market modeling and studying of the correlations for the following parameters:

1. Capesize Earnings (1990 to 2015)

Lognormal PDF with Scale=23194.925 and Shape=0.830

2. Fuel Price - IFO380 (1990 to 2015)

Lognormal PDF with Scale=246.930 and Shape=0.711

3. Fuel Price – MGO (1990 to 2015)

Triangular PDF with min=101.25, max=1268.13 and mode=120.65.

3 DESIGN CONCEPT

3.1 Large Bulk Carrier Market

The focus of the present study lies within the large bulk carrier segment. The market for subject vessel size is positioned on the seaborne transportation of primary bulk commodities for industrial activities (iron ore, nickel ore and other major minerals) as well as for energy in the form of coal. As already mentioned, the trade routes for the above mentioned markets are between Latin America and the Far East (China primarily and then Korea and Japan) as well as between Australia and again the Far East. The optimal vessel for the maintenance of an efficient supply chain in these two routes is the primary objective of this study.

3.2 Baseline Vessel – 208k Newcastlemax

A parent, baseline vessel is herein used as a primary source of reference as well as calibration for the methodology and all the formulas/computations applied in the latter. The vessel chosen for this study belongs to the relevant recent segment of Newcastlemax Bulkers and is a newly delivered vessel (2015). The baseline parametric geometry has been adapted to fit the hull form lines available. As previously mentioned (chapter 2.9.1), the model test results of subject vessel were used to calibrate and better adapt Holtrop statistical methodology for the prediction of powering along the entire speed-power curve. The principal particulars of the vessel can be found in the below table [2]:

Baseline Vessel Principal Particulars	
Length over all	299.98
Lengthbetween perpendiculars	294
Beam	50
Scantling Draft	18.5
Deck Height	25
Cb	0.8521
Main Engine Specified MCR (kW)	17494 @ 78.7 RPM / MAN B&W 6G70ME-C9.2
Deadweight (tons)	Abt 208,000
Lightship Weight (tons)	26,120
Cargo Hold Capacity (m^3)	224,712.1

Table 2: Baseline Vessel Principal Particulars

3.3 Proposed Design Concept Characteristics

A small Froude number (slow speed) and full hull form is herein proposed as the base hull for the global optimization. The absence of a bulbous bow is evident as it is a recent trend in bulk carrier design as such absence assists in the reduction of the vessel frictional resistance (primary resistance component) while the wave making resistance is not increased. The effect of the bulbous bow on the above as well as the added resistance are investigated in depth in separate study. In addition, the use only of an electronically controlled Main Engine is considered and no Energy Saving Devices (wake equalizing duct, pre-swirl fin, bulbous rudder etc.) are considered since there is no such device installed on the parent vessel and further to the above such devices and their effect is to be considered in a post analysis study.

3.3.1 Simulation driven design, choice of hullform parameters

The assessment of the design is derived from the simulation of the operational, economic and trading profile (as per methodology in chapter In other words instead of using only one design point (in terms of draft and speed) multiple points are used derived from actual operating data of a shipping company.

3.4 Optimization Target/Goals

The target of any optimization procedure is always to achieve the most desiring values/properties for the set optimization objectives. The alteration of the designs and assessed entries is performed through the systematic variation of their distinctive parameters, while each one of the designs must comply with the set constraints, e.g. stability criteria/maximum dimensions or deadweight.

The generic targets or objectives in almost any ship design optimization problem are:

a. Competitiveness

The market and economic competitiveness of a an individual vessel variant is the core of any optimization as a vessel will always be an asset (of high capital value) and can be expressed by the following indices:

1. Required Freight Rate

The required freight rate is the hypothetical freight which will ensure a break even for the hypothetical shipowner between the operating costs, capital costs and its income based on the annual voyages as well as collective cargo capacity and is such expressed in USD per ton of cargo.

$$RFR = \frac{OPEX + CAPEX + Fuel\ Costs}{Annual\ Cargo\ Volume}$$

2. Operating Expenditure (OPEX)

The operating expenditure expressed on a daily cost includes the cost for crewing, insurance, spares, stores, lubricants, administration etc. It can indicate apart from the operator’s ability to work in a cost effective structure, how the vessel’s design characteristics can affect. The lubricant cost is based on actual feed rates used for subject engines as per the relevant service letter SL2014-537 of MAN [14].

3. Capital Expenditure (CAPEX)

The CAPEX is a clear indication of the cost of capital for investing and acquisition of each individual design variant. The acquisition cost is calculated from a function derived from actual market values and the lightship weight for vessels built in Asian shipyards, and more specifically in China.

4. Efficiency

The merit of efficiency is herein expressed by the IMO EEOI index. Although on the design basis in practice the IMO Energy Efficiency Design Index is used as a KPI and measure of the merit of efficiency in new design concepts as well as for any newbuild vessel, in this study the calculated Energy Efficiency Operating Index is used instead. The reason for this change is the use of the Operational Profile simulation module based on actual voyage input data for a fleet of vessels (statistically edited) per each stage of each voyage leg (refer to par. 2.10) thus given the cargo capacity calculation (par. 2.4) the EEOI can be derived, which can depict more accurately and realistically the efficiency of the design given the fact that it takes into account the actual operating profile. The actual transport efficiency of each variant is expressed by a simple ration of tons of CO_2 emitted to the tons of cargo multiplied by the actual distance covered. In addition to the above, operational practices such as slow steaming are considered together with their respective implications (e.g the use of two diesel generators in the normal sea going condition instead of one in order to cover the blower’s electrical load). Furthermore, the minimization of the required ballast water amount for the ballast conditions is set as optimization target.

3.5 Design Variables

From the below table [3], one can identify the selected design variables of the subject optimization problem. The latter are in three categories; principal dimensions, hull form characteristics (Cb, LCB and Parallel Midbody) and cargo hold arrangement parameters. The more detailed design variables of the hull form arrangement for the detailed shape of the bulbous bow (if any), flair and stem shape as well as stern shape are going to be assessed in a separate optimization study with the use of integrated CFD codes.

Design Variable	Lower Boundary	Upper Boundary
Length between Perpendiculars	275	320
Length Overall	280	325
Beam	42	55
Draft	16.5	19.5
Deck height	24	27
Hopper Height	7	10
Hopper Breadth (m)	2.5	4
Topside Height (m)	5	9
Topside Breadth (m)	8	12
Inner Bottom Height (m)	2	3
Block Coefficient Cb	0.84	0.87
LCB (%Lbp)	0.49	0.55
Bilge Height (m)	2.4	8
Bilge Width (m)	2.4	8
Propeller Diameter (m)	8	10
Propeller Expanded Area Ratio	0.35	0.55
Propeller Pitch over Diameter	0.75	1.2

Table 3: List and range of design variables of the optimization problem.

3.6 Optimization Procedure

The optimization procedure applied for this study follows the rational of any optimization loop in engineering as it is evident from Figure [5].

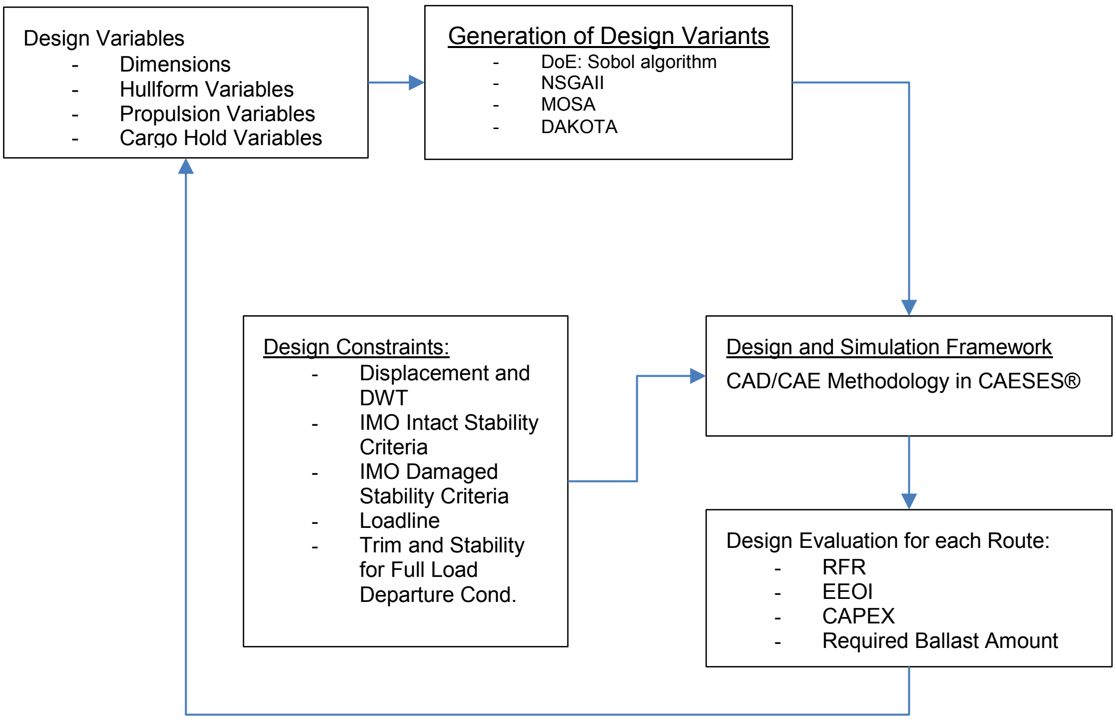


Figure 5: The optimization Loop applied.

For each iteration of the same loop the design variables receive their input values from the «design engine» applied in the CAESES. The design engine can either be a random number generator or an optimization algorithm depending on the optimization stage. The applied values then trigger the generation of a new variant from the holistic, parametric model that utilizes the developed methodology for that matter.

After the variant generation, the Design Objectives, which are selected as the measures of merit of each variant are logged and assessed accordingly while at the meantime the Design Constraints imposed are checked for compliance. The Design constraints chosen for this application were the calculated values for Deadweight, Cargo Specific Gravity and the Stability Criteria of the 2008 Intact Stability Code. The size restrictions (in terms of vessel's dimensions) were not used in constraints given the fact they were taken into account in the applied range of the Design Variables.

The optimization procedure described in this paper can be described as a stepped (multi stage) one. At first, it is necessary to explore and fully understand both the design space (potential for improvement with given constraints) as well as the sensitivity of the methodology by a Design of Experiments procedure, using a system available random number generator that follows the Sobol sequence procedure [30]. The sensitivity analysis is a very important, preparatory step in which it is ensured that no major, unreasonable manipulations occur. In addition to that it is important to see that the results are realistic both on a quantitative and qualitative basis, with the latter in need of particular attention since the design ranking and selection is the essence of optimization (the value of a favored design is not important than the relationship with all the other produced designs).

The following formal optimization runs utilize genetic algorithm techniques (NSGA II algorithm [28]). The formal optimization runs involve the determination of the number of generations and the definition of population of each generation to be explored. Then the generated designs are ranked according to a number of scenarios regarding the mentality of the decision maker. One favored design is picked to be the baseline design of the next optimization run, where the same procedure is followed. When it is evident that there little more potential for improvement the best designs are picked using the same ranking principles with utility functions, and are exported for analysis.

Both the SOBOL and NSGA II algorithms as well as a plethora of other variant generation and optimization algorithms are fully integrated and available within the CAESES.

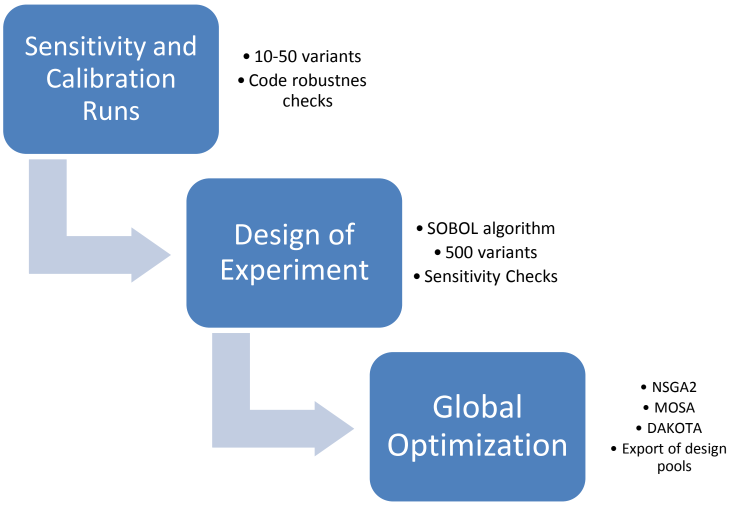


Figure 6: The different Optimization Stages.

3.7 Design of Experiment (DoE)

The Design of Experiment has the primary purpose of the calibration, test and sensitivity check of the methodology DoE serving as an exploitation step. The computational power required is small and a fast first impression of the design space is given. From the first indications, as anticipated, there is a strong scale effect which one can say that dominates this particular optimization problem. This effect is very common in ship design were the largest vessels usually dominate the smaller since the increase of cargo capacity does not trigger an equivalent increase in the powering requirements or the vessel's weight. In addition to the scaling effect it was observed as in the formal optimization algorithm that there was a strong linear correlation between the Required Freight Rate (RFR) and the EEOI, which was also anticipated since both functions use cargo capacity. The feasibility index was in a very high level (above 90%). In total 250 designs were created.

3.8 Global Optimization Studies

In this stage of the formal, global design optimization the NSGA II algorithm is utilized. The latter is a genetic, evolutionary algorithm that is based on the principles of biological evolution (Darwin [10]). As in the biological evolution each design variant is an individual member of a population of a generation. Each individual of the population is assessed in terms of the

Optimization Objectives, as well as its relation to the desired merits. For the application in ship design optimization it is usual to apply a large population for each generation with an adequate number of generations. The large population combined with a high mutation probability ensures that the design space is properly covered, while the number of generations ensures that there is a push towards the Pareto frontier for each case of objective combination. For this particular application a combination of 17 generations with 100 variants population each was selected. The mutation probability was increased from the default value by CAESES of 0.01 to 0.05 in order to increase mutation events that trigger the variation of the design variables and thus have a wider design space.

In Figure [6], the scatter plot of the generated design population is depicted, with the RFR of each design on the x-axis and the respective EEOI on y-axis. A distinctive linear correlation between the EEOI and RFR is evident. This has been observed regardless of the use of uncertainty functions and is attributed to the direct linear correlation of the fuel consumed and CO2 emissions (through the carbon conversion factors). We can see that the both the baseline as well as dominant variants are close to the middle of the straight cloud line comprised by the generated designs. It should be noted that the vessels with lower RFR has significantly increased OPEX and Required Ballast Water amount values making them thus less favored in the decision making process.

In Figure [7], the scatter plot of the RFR vs CAPEX is found. A clear Pareto frontier is formulated on which the decrease of CAPEX triggers in turn an increase in the RFR. This pattern can be attributed to the fact that these two objectives are contradicting. The RFR can be decreased by the increase of cargo carying capacity (and thus income) but this in turn will increase the vessel size and thus building cost. The CAPEX comprises the acquisition (new building) cost and dry-docking costs both of which have been formulated as a non-lnear function of the vessel's lightship. Rather interestingly, the baseline design is far from the pareto frontier to an increased CAPEX compared to the dominant variants, which have the smallest CAPEX values. The scatter plot of the RFR vs the OPEX (Figure [8]), shows the same pattern as the previous plot of CAPEX. Again here, the relationship of RFR to OPEX is antagonistic as the larger vessels with lower RFR values will have larger installed engines which will have significantly higher maintenance costs (non-linear function of vessel's SMCR) and require higher crewing and insurance costs (non-linear function of the vessel's GT). Like in the case of CAPEX the baseline design has a distance from the frontier, but in this case this is smaller due to the small OPEX of this vessel. Lastly, an interesting and clear Pareto frontier is observed in the scatter plot between the Required Ballast Water Amount and the vessel's OPEX. Here, the increase of Required Ballast will also correspond to an increase of the OPEX, which is rather sharp. The front is therefore localized at the bottom left corner of the graph. The underlying mechanism between this relationship is that the Ballast Water amount required, determines the ballast pumps capacity and in turn the Ballast Water Treatment System (BWTS) capacity and both of them Auxiliary Engines rating. The running cost of the BWTS is a significant component of the OPEX, both due to the higher maintenance costs of the electric generating plant but due to the cost of chemicals both for treatment and neutralization. The same will also apply for the relationship of Required Ballast Amount with CAPEX since the cost of the installation of the BWTS system is significant and an exponential function of the Ballast Pumps Capacity which is calculated basis on the Required ballast amount and ballasting and de-ballasting time (constant).

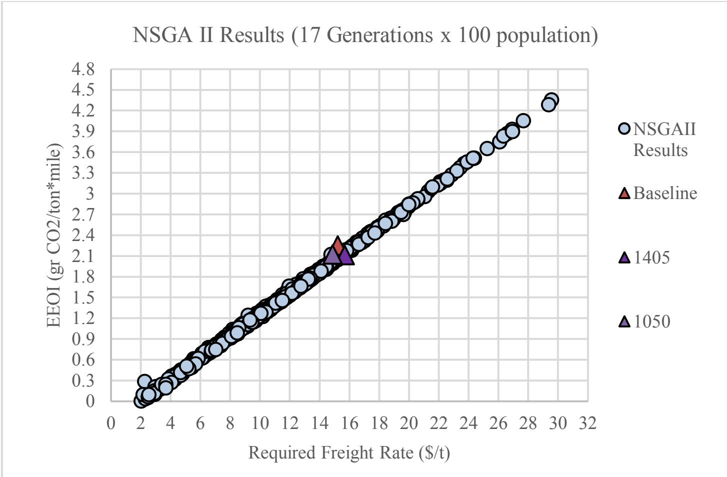


Figure 7: Scatter plot of the Optimization Results: RFR vs EEOI

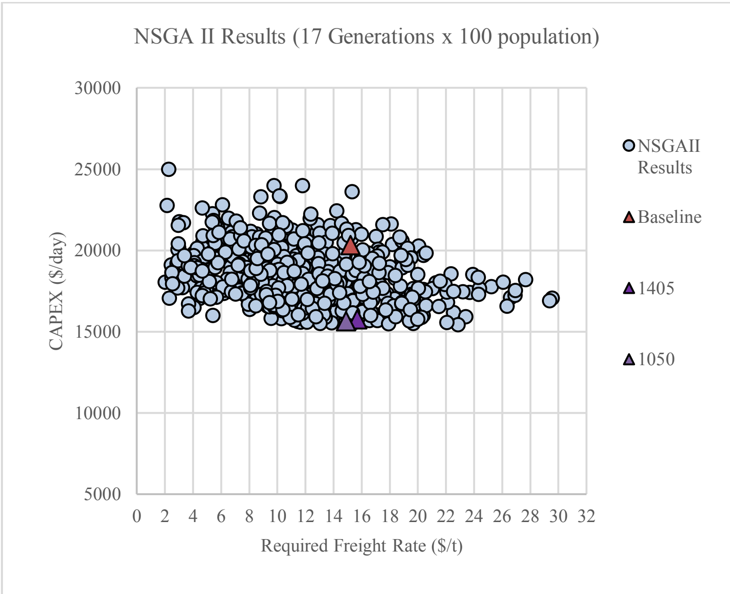


Figure 8: Scatter plot of the Optimization Results: RFR vs CAPEX

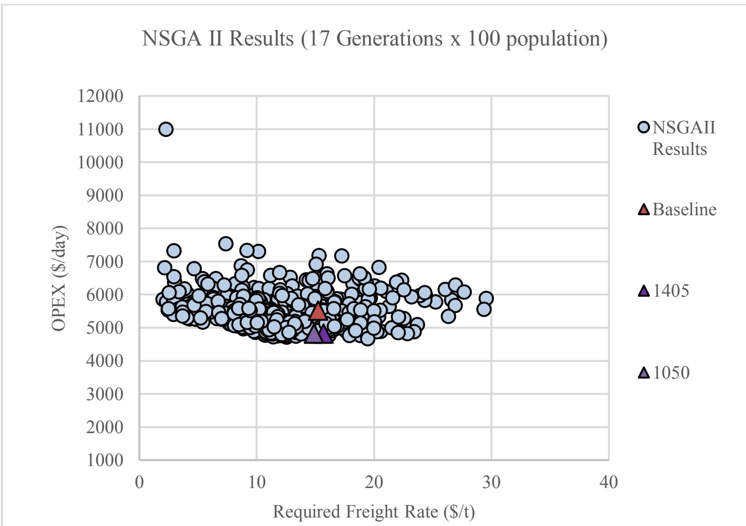


Figure 9: Scatter plot of the Optimization Results: RFR vs OPEX

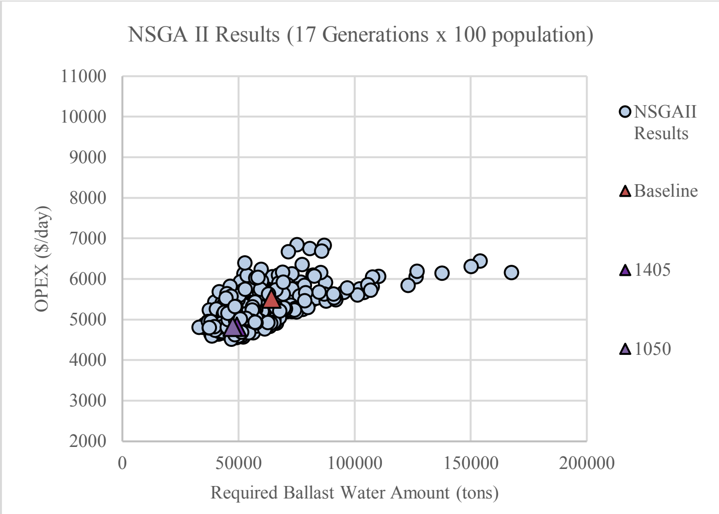


Figure 10: Scatter plot of the Optimization Results: Required Ballast Water Amount vs OPEX

3.9 Dominant Variant Ranking

One of the most critical steps during optimization of any system is the selection and the sorting of the dominant variants. For this particular reason it is necessary to follow a rational, rather than an intuitive, approach in order to consider in an unbiased way all trade-offs that exist. One such method is utility functions technique.

The optimum solution in our case would dispose the minimum EEOI, RFR, OPEX and CAPEX values. Instead of using fixed weights for the set criteria in the evaluation of the variants, we rather assume a utility function as following

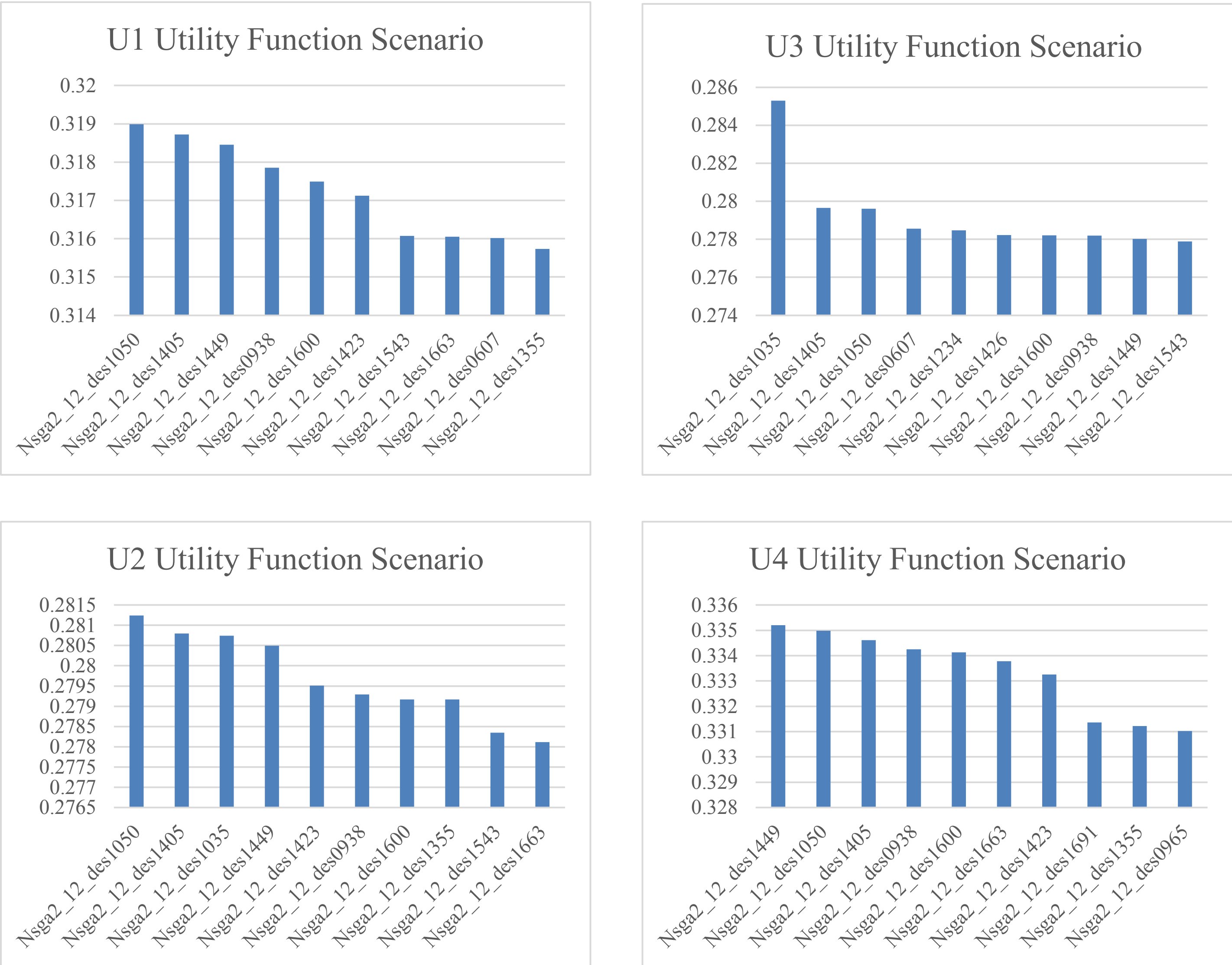
$$U = w_{EEOI} * u(EEOI) + w_{RFR} * u(RFR) + w_{CAPEX} * u(CAPEX) + w_{OPEX} * u(OPEX) \quad \textbf{(11)}$$

The utility of each design variant with regards to the optimization targets is normalized by the best attained KPI valuation of each design population. The weights assigned for each respective KPI of each variant are a linear function of the distance of the attained utility value to the maximum utility value (under the normalization has a value of 1) of the design population. The design population is in turned ranked in a descending order from the maximum to minimum attained utility as per equation (20). The top 10 most favourable designs are selected for each maximum weight scenario (Table [4]) as dominant variants resulting in the identification and sorting of 40 designs with best performance according to each utility scenario.

Maximum Objective Weight	U1	U2	U3	U4
RFR	0.2	0.3	0.2	0.1
EEOI	0.2	0.1	0.1	0.3
OPEX	0.2	0.1	0.3	0.1
CAPEX	0.2	0.2	0.1	0.3
Required Ballast Water Amount	0.2	0.3	0.3	0.2

Table 4: Weights used for the utility functions

Figure 11: Ranking of Dominant Variants with U1-U4 Scenario



Particulars	Baseline	ID1405	ID1050	ID1035
Lbp (m)	294	275	276.1	277.8
Beam (m)	50	42.15	42.353	42.718
Deck Height (m)	25	25	25.26	26.53
Cb	0.8538	0.8599	0.8555	0.844
LCB	0.51986054	0.52	0.499	0.5480
LOA (m)	299.98	279	278	278.7
Draft (m)	18.5	16.59	17.02	16.93

Topside Breadth (m)	12	8.27	11.33	9.468
Topside Height (m)	9	5.15	7.71	5.024
Hopper Height (m)	10	9.98	9.046	8.529
Hopper Breadth (m)	4	3.25	3.42	3.412
Double Bottom Height (m)	2.5	2	2.85	2.14
Propeller Diameter (m)	9	9.27	8.87	8.05
Propeller P/D	0.9	0.942731	0.763	0.804
Propeller Expanded Area Ratio	0.55	0.516	0.4544	0.459
Bilge Height (m)	2.4	5.19	2.16	6.901
Bilge Width (m)	2.4	6.06	2.58	2.512

Table 5: Principal Particulars of baseline and dominant variants

From the above ranking (Figures [10 to [13]) it is very interesting to observe that there is a certain repetition in the top three dominant variants from the ranking procedure. Furthermore, for scenario U3 where there is an equal weight for all objectives, the three top dominant variants are the ones from scenario's U1 and U2. All the above illustrate that the peak on the observed pareto front is strong and apart from that, the dominant variants that can be selected (e.g. #1405, #1050, #1035) perform better in a robust way under different assumptions and weights from the decision maker point of view. The characteristics of these three variants can be found in the table [5].

4 DISCUSSION OF THE RESULTS- FUTURE RESEARCH

From the table [6] below, we can observe that for design #1405 an increase of the RFR of 3% was observed with a decrease however of the EEOI by 6%, of the OPEX by 12% and CAPEX and Required Ballast Water amount by 23%. Design #1050 seems to be more promising as the improvements in EEOI, OPEX, CAPEX and Required Ballast Amount are marginally higher than these of the #1405, however the RFR is 2.23% lower than that of the baseline. The marginal reduction of the RFR can be justified by the reduction of generally vessel size primarily in terms of beam and length (beam given the fact that these vessels are not stability limited) and thus the reduction of the initial capital cost, while in the meantime the cargo capacity has inevitably decreased, reducing thus the profitability of the vessel.

Particulars	Baseline	1405	Difference %	1050	Difference %
RFR	15.22	15.69	3.09	14.88	-2.23
EEOI	2.25	2.11	-6.22	2.12	-5.78
OPEX	5520	4827	-12.55	4823	-12.63
CAPEX	20322	15771	-22.39	15648	-23.0
Required Ballast Water Amount	64244	49298	-23.26	47616	-25.88

Table 6: Design Objectives of the Baseline vs the Dominant Variants

From the above discussion we can conclude that the novel methodology herein proposed for the simulation driven design with lifecycle, supply chain and the actual operating in service parameters can successfully trigger a reduction in the RFR and EEOI via systematic variation and advanced optimization techniques. However, this is a preliminary work restricted only into illustrating the applicability and potential of this method.

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REFERENCES

[1] Stopford M. , "Maritime Economics 3rd Edition", Routledge, ISBN 978-0-415-27558-3

[2] United Nations Conference on Trade and Development, "Review of Maritime Transport 2017", UNCTAD secretariat calculations, based on data from Clarksons Research, 2017.

[3] Papanikolaou A., Holistic ship design optimization. Computer-Aided Design, doi:10.1016/j.cad.2009.07.002, 2009

[4] IMO, 2008 Intact Stability Code, Res. MSC.267(85), December 2008.

[5] Holtrop J., Mennen G.G.J., An approximate power prediction method, International Shipbuilding Progress 1982

[6] Papanikolaou A., "Ship Design - Volume A: Preliminary Design Methodology", Publ. SYMEON, 1988/1989, 2nd edition: 1999 (Greece).

[7] MAN B&W, Marine Engine Program 2015

[8] Nikolopoulos L. "A Holistic Methodology for the Optimization of Tanker Design and Operation and its applications", Diploma Thesis NTUA, July 2012.

[9] Darwin C., "On the origin of species by means of natural selection, or the preservation of favored races in the struggle for life", London: John Murray. [1st ed.], 1859.

[10] Abt C., Harries S., "Hull Variation and Improvement using the Generalised Lackenby Method of the FRIENDSHIP-Framework", The Naval Architect, RINA © September 2007.

[11] Koutroukis G., "Parametric Design and Multi-objective Optimization-Study of an Ellipsoidal Containership", Diploma Thesis NTUA, January 2012.

[12] Kwon, Y.J. (2008). "Speed Loss Due To Added Resistance in Wind and Waves", the Naval Architect, Vol. 3, pp.14-16

[13] Lu R., Turan O., Boulougouris E., Banks C., Incecik A., "A semi-empirical ship operational performance prediction model for voyage optimization towards energy efficient shipping", Ocean Engineering, 110, p 18-28, 2015.

[14] MAN Diesel and Turbo, Service Letter SL2014-587 «Guidelines of Cylinder Lubrication», Copenhagen 2014.

[15] Nikolopoulos L., Boulougouris E., 'Applications of Holistic Ship Theory in the Optimization of Bulk Carrier Design and Operation', EUROGEN 2015 Conference, September 2015 Glasgow.

[16] Nikolopoulos L., Boulougouris E., "A Study on the Statistical Calibration of the Holtrop and Mennen Approximate Power Prediction Method for Full Hull Form Vessels, Low Froude Number Vessels", SNAME Journal of Ship Production and Design, Vol., Month January 2018, pp 1-28.

[17] Bernitsas M.M., Ray D., Kiley P., "K_T, K_Q and Efficiency Curves for the Wageningen B-Series Propellers", University of Michigan, Report No.237, May 1981.

[18] [MEPC 68] – Publication of ISO15016:2015, Ships and marine technology – Guidelines for the assessment of speed and power performance by analysis of speed trial data, IMO, February 2015.

[19] International Marine Coatings, Propeller No.15, January 2003.

[20] International Marine Coatings, Propeller No.16, August 2003.

[21] Clarksons Shipping Intelligence database (https://sin.clarksons.net/)

[22] Fujiwara, T., Ueno, M. and Ikeda, Y. (2005), "A New Estimation Method of Wind Forces and Moments acting on Ships on the basis of Physical Component Models", J. of The Japan Society of Naval Architects and Ocean Engineers, 2, 243-255.

[23] Liu S., Shang B., Papanikolaou A., Bolbot V., "An Improved Formula for Estimating the Added Resistance of Ships in Engineering Applications", J. Marine. Sci. Appl. (2016) 15: 442.

[24] Marine Environment Protection Committee (MEPC), 66th session, 31 March to 4 April 2014.

[25] Cichowicz J., Theotokatos G., Vassalos D., (2015), “Dynamic Energy Modelling for ship life-cycle performance assessment”, Journal of Ocean Engineering 110 (2015).

[26] Deb K., Pratap A., Agarwaj S., Meyarivan T. (2002), “A fast and elitist multiobjective genetic algorithm: NSGA-II”, IEEE Transaction on Evolutionary Computation, Volume 6, Issue 2, April 2002.

[27] Ulungu E.L, Teghem J., Fortemps P.H, Tuyttends D. (1999), “MOSA method: a tool for solving multiobjective combinatorial optimization problems” Journal of Multi-Criteria Decision Analysis, Volume 8, Issue 4, July 1999.

[28] Sobol, I. M. (1976) "Uniformly distributed sequences with an additional uniform property". Zh. Vych. Mat. Mat. Fiz. 16: 1332–1337 (in Russian); U.S.S.R. Comput. Maths. Math. Phys.16: 236–242 (in English).

[29] LACKENBY, H (1950), “On the Systematic Geometrical Variation of Ship Forms”, Trans. INA, Vol. 92, pp. 289-315.

[30] Alwan, S., n.d. Simulation-based ship design and system engineering, RINA, Energy Efficient Ships 2016, November 2016, pp.9.

[31] Aristotle & Ross, W. D., 1981. Aristotle's Metaphysics. Oxford [England], Clarendon Press.

[32] Diez, M. & Peri, D., 2010. Two-stage Stochastic Programming Framework for Ship Design Optimization under Uncertainty. s.l., s.n.

[33] Diez, M., Peri, D., Fasan, G. & Campana, E., 2010. Multi-Disciplinary Robust Optimization for Ship Design. Pasadena, California, s.n.

[34] Good, N., 2006. Multi-Objective Design Optimization considering Uncertainty in a Multi-Disciplinary Ship Synthesis Model. Master Thesis, Virginia Tech, Blacksburg , Virginia.

[35] Hannapel, S., 2012. Development of Multidisciplinary Design Optimization Algorithms for Ship Design under Uncertainty. PhD Thesis, University of Michigan.

[36] Hannapel, S. & Vlahopoulos, N., 2010. Robust and Reliable Multidiscipline Ship Design. AIAA/SSMO Multidisciplinary Analysis Optimization Conference, Fort Worth, Texas, American Institute of Aeronautics and Astronautics.

[37] Koutroukis, G. et al., 2013. Multi-Objective optimization of a containership design. Mediterranean Marine Science.

[38] Nikolopoulos, L. et al., 2014. Holistic Approaches in Containership Design. London, UK, Royal Institution of Naval Architects.

[39] Papanikolaou, A., 2010. Holistic ship design optimization. Computer-Aided Design, Issue 42, pp. 1028-1044.

[40] Papanikolaou, A., Harries, S., Wilken, M. & Zaraphonitis, G., 2011. Integrated Ship Design and Multiobjective Optimization Approach to Ship Design, 15th Int. Conference on Computer Application in Shipbuilding, ICCAS, Trieste, Italy.

[41] Papanikolaou, A., Tuzcu, C., Tsichlis, P. & Eliopoulou, E., 2007. Risk-Based Optimization of Tanker Design. 3rd Int. Maritime Conference on Design for Safety, September 2007.

[42] Papanikolaou, A. et al., 2010. Optimization of an AFRAMAX Oil Tanker Design. Journal of Marine Science and Technology, 15(4).

[43] Priftis, A., Turan, O. & Boulougouris, E., 2018. Parametric design and holistic optimization of post-panamax containerships. International Marine Design Conference (IMDC) 2018, Helsinki, Finland, Taylor and Francis Group.

[44] Sames, P. et al., 2011. BEST Plus – Better Economics with Safer Tankers. Houston Texas, Society of Naval Architects and Marine Engineers (SNAME).

[45] Sandvik, E., Asbjornlett, B., Steen, S. & Johnsen, T., 2018. Estimation of fuel consumption using discrete-event simulation – a validation study. International Marine Design Conference (IMDC) 2018, Helsinki, Finland, Taylor and Francis Group.

[46] Smuts, H. J., 1927. Holism and Evolution. 1st ed. London: Macmillan and Company Limited.

[47] Soultanias, I., 2014. Parametric Ship Design and Holistic Design Optimization of a 9000 TEU Container Carrier. Athens, Greece: National Technical University of Athens.

[48] Tillig, F., Ringsberg, J., Mao, W. & Ramme, B., A generic energy systems model for efficient ship design and operation, Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, Vol 231, Issue 2, 2017, pg. 649–667.

[49] Little, Roderick J A, and Donald B Rubin. 2019. Statistical Analysis with Missing Data. 3rd ed. Vol. 793. John Wiley & Sons.

[50] Nguyen, Cattram D., John B. Carlin, and Katherine J. Lee. 2017. “Model Checking in Multiple Imputation: An Overview and Case Study.” Emerging Themes in Epidemiology 14 (1): 1–12. https://doi.org/10.1186/s12982-017-0062-6.