

A ROBUST HOLISTIC OPTIMIZATION SHIP DESIGN APPROACH WITH VOYAGE SIMULATION PRINCIPLES AND ITS APPLICATIONS

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L Nikolopoulos*, University of Strathclyde, UK and **E Boulougouris**, University of Strathclyde, UK

*Corresponding author. L Nikolopoulos (Email): lambrosnikolo@yahoo.gr

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SUMMARY

The challenges commercial shipping faces in terms of the IMO decarbonisation agenda in combination with volatile freight and capital markets call for the drastic rethinking of the way ships are designed and operated in the next decades. This paper presents a novel approach that allows the creation of a robust, market-informed, simulation-supported framework, able to systematically explore at an early stage the multi-variable, multi-objective design space for large oceangoing commercial vessels (bulk carriers, tankers, container ships etc.). It results in a rigorous exploitation of the available solutions improving the decision-making process. The Robust Holistic Optimisation Ship Design Approach (RHODA) combines voyage simulation with multiple layers of uncertainty: voyage, environmental, market and method. A case study on its impact on the design optimisation path for a conventional bulk carrier and its sensitivity and comparison to “deterministic” approaches is presented.

1. INTRODUCTION

Although the maritime decarbonization initiatives are predated, April 2018 marked the official pledge of the International Maritime Organization (IMO) to decarbonize shipping value chains by adopting an ambitious roadmap (later updated in MEPC 80 of June 2023), aiming at reducing the greenhouse gases generated by shipping by 50% by the Year 2050 and complemented by additional longer-term reductions. (International Maritime Organization (IMO), 2023). This target, that can only be met with the use of capital-intensive CO₂e abatement technologies (alternative fuels, carbon capturing, wind-assistance technologies), coupled with volatile capital and freight market environment impose the necessity of re-evaluating not only the vessels’ operational management but also the current design philosophy for major commercial vessels both on the preliminary and basic ship design stages of the ship design spiral (Lamb, 2009). The present paper presents the research work of the University of Strathclyde Maritime Safety Research Centre (MSRC) in developing, validating and applying in the preliminary stage of the ship design spiral a novel Robust Holistic Optimisation Design Approach (RHODA). Chapter 2 presents the key novelties of the Robust, Holistic Optimisation Design Approach (RHODA) along with its validation based on high-frequency voyage data. Chapter 3 examines the application of RHODA to the global optimisation problem of bulk carriers (VLOC and capsizes)

and its key differences with deterministic approaches run in parallel. Lastly, Chapters 4 and 5 focus on the discussion of key results and future work recommendations.

2. A ROBUST HOLISTIC SHIP DESIGN APPROACH

Robust optimization is a mathematical theory in optimization problems where a certain measure of resilience is sought against uncertainty in the value of problem parameters, inputs, variables and/or solutions (Bernitsas, et al., 2011). A good example of the general theory of Robust Optimisation (RO) and its use in adaptable models for multi-stage decision-making problems has been examined by (Bernitsas, et al., 2011) where both linear and discrete applications are considered while Robustness as a criterion for strategic decisions has been also examined. To this extent, robust and reliable ship design optimisation problems have been examined by (Wei, et al., 2020), (Hannapel & Vlahopoulos, 2010) and (Li, et al., 2016) but without considerations of freight/shipping market uncertainty or voyage simulation aspects. The use of holistic approaches in Ship Design can be identified firstly in the works of (Papanikolaou, 2010) which has been updated backed by further research work in (Papanikolaou, 2019) and (Papanikolaou, 2022), where the ship design optimisation general workflows are defined in a holistic context and applied in various cases. Application examples in holistic, risk-based tanker vessel design

optimisation can be found in (Papanikolaou, et al., 2010), (Papanikolaou, et al., 2011), (Sames, et al., 2011) and (Nikolopoulos, 2012). The method evolved significantly to a platform for holistic ship design under uncertainty in (Priftis, et al., 2018). The modelling of uncertainty in ship design together with its sensitivity of optimisation studies, is a topic studied extensively with notable example the work of (Hannapel, 2012), examining two methods of uncertainty modelling for ship design optimisation. A two-stage stochastic programming for robust ship design optimisation under uncertainty has been developed by (Diez & Peri, 2010), (Diez & Peri, 2010). The term simulation-driven design in the literature is commonly associated with hydrodynamic simulation around the vessel's hull with the use computational methods (e.g (Bertram, et al., 2023), (Bertram, et al., 2017), (Harries, 2008). However, for the present studies, the term refers to the simulation of the vessel's operation in actual voyage conditions. Use of such simulation tools in the early ship design is still limited in the literature. A good example of such is in (Tillig, et al., 2017), (Tillig & Ringsberg, 2018) where a generic ship energy systems model predicting ship's energy consumption during different operational conditions is used without however any consideration on vessel's propeller-to-engine matching (propeller curve in relation to engine torque limit). (Alwan, 2016) adopts an event-based simulation model using discrete event simulation for analysing system performance that can be integrated in ship design studies (not done yet) and (Sandvik, et al., 2018) follows a similar approach.

The authors' research activity in the MSRC expands the existing state-of-the-art by developing a Robust Holistic Optimisation Design Approach (RHODA). RHODA uses dynamic voyage simulation from the early design stage treating multiple layers of uncertainty (market, environmental, method, etc.) with enhanced machine-learning-based models based on "big-data" harvested from actual operating conditions. Unlike static and deterministic methods considering fixed loading conditions and singular design speeds, this method assesses and evaluates the key design attributes of each variant by simulating the vessel's operation over "wide" operating envelopes and voyage profiles on a lifecycle assessment (LCA). Furthermore, the method has evolved to integrate:

- Comprehensive weather model based on long-term probability distribution functions be specific to each worldwide geographic region, leg and sub-leg trade routes selected by the users.
- New models for added resistance in waves that are applicable for arbitrary directions and spectra of actual seaways.
- Utility functions that incorporate new logarithmic nominal weight distributions for enhanced Pareto frontier exploration and selection of "best trade-off" variants.

Furthermore, a "deterministic based" equivalent of the method is hosted in the same environment to benchmark and assess the simulation effect in the optimization flow and robustness of the resulting designs.

2.1 RHODA DESIGN ENVIRONMENT

The software environment that hosts all processes, modelling and engineering flows is the CAESSES[®] Computer Aided Engineering (CAE) platform which is a CAD-CFD integration platform ((Harries & Abt, 2019), (Harries & Nowacki, 1999), (Harries, 1998)) with the RHODA workflow illustrated in Figure 1.

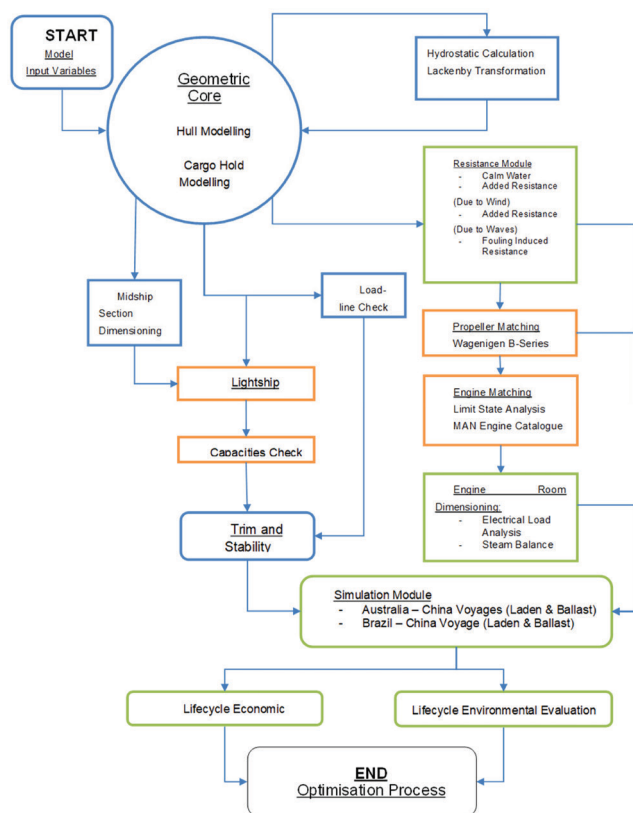


Figure 1. RHODA Process overview

In Figure 1, process boxes in blue and orange represent standardized RHODA modules for hull modelling, hydrostatics, powering and lightship estimation. The geometric core of the RHODA method has been developed in the CAD/CAE system CAESSES using a group of fully parametric sub-surfaces that are joined together to form an original fully parametric hull surface, which is then transformed with the Lackenby transformation to achieve the target hydrostatic properties (Block Coefficient and LCB) (Lackenby, 1950). The cargo holds surface generation and complete compartmentation of each design variant is also performed in CAESSES[®] based on the final surface produced. The RHODA architecture has been developed

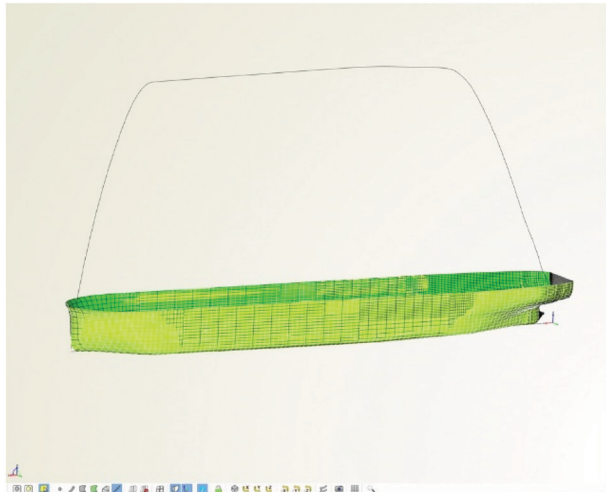


Figure 2. Hullform parametric surface modelling of RHODA in CAESES®

to flexibly accommodate any calm water resistance model available to the user since the simulation input is a speed-resistance curve. Such a modular approach allows the use of either hybrid methods, direct numerical results from RANS solvers as well as surrogate models (Forrester, et al., 2008). Furthermore, for design studies where a wider design space exploration is necessary, Machine Learning techniques coupled with empirical methods are used instead (Holtrop & Mennen, 1982), (Holtrop, 1984), (Nikolopoulos & Boulougouris, 2019).

2.2 KEY RHODA NOVELTIES

Key novel modules of RHODA represented in orange process boxes in Figure 1 are described in this chapter.

2.2 (a) Engine – Propeller – Hull Matching with Limit State Analysis

A novel aspect of RHODA is the use of a limit state approach instead of sea margins for propulsion power estimation (engine capacity). The limit state condition is defined as the set of environmental, loading, fouling and other conditions affecting propulsion power for which the in-service vessel, should be able under constant power have no involuntary loss of the maximum design speed. The delivered horsepower (DHP) necessary to adhere to this limit state condition is in turned then assumed each designs's main engine Specified Maximum Continuous Rating (SMCR). An example of such can be the following:

- Laden Condition
- Sea State 5 at head seas (45o angle) along with corresponding wind conditions.
- Adverse (head) current of 1.5 knots.
- Hull roughness increase arising from fouling equivalent to 4 years from docking/cleaning.

The results of this limit-state analysis are matched with the existing 2-stroke engines available from the marine engine program of MAN (MAN, 2017). The developed “engine digital twin library” with all different layouts of models (based on bore/stroke) and number of cylinders and programmed within CAESES® (Nikolopoulos & Boulougouris, 2018). An iterative procedure is followed for engine matching in the engine module code as shown in Figure 3, targeting the minimization of design point specific fuel oil consumption (SFOC) for each selection. The output of the module is the resulting engine SFOC curve of the engine produced for the entire load range (10–100%) along with auxiliaries sizing (exhaust gas flow, heat and electrical balance etc.)

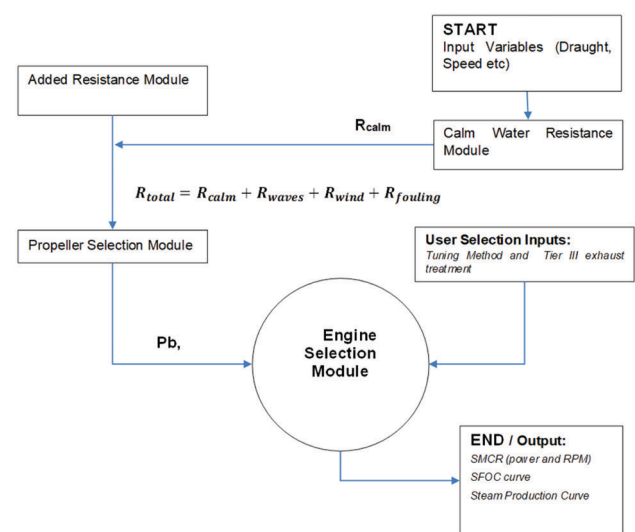


Figure 3. Engine Selection with Limit State Approach

2.2 (b) Dynamic Voyage Simulation Capability

The key aspect of the novelty of the RHODA method is the dynamic voyage-simulation module where the “Digital Twin” of each different design optimisation variant (that is a variant of the parent, baseline vessel) is assessed in actual seaways Figure 4. This uses a “Big Data” based model subject to a systematic statistical analysis with the IBM SPSS® toolkit. The “Big Data” dataset used are key onboard measurements acquired from an automatic, real-time data acquisition system, “Vessel Performance Monitoring System (VPMS)” (Figure 5). VPMS monitors and logs 30 second interval data available from onboard sensors of all vessel key systems and automatically averaged into 5-minute bundles. The total pool of data created from VPM has a total size of 1.37GB and 1.5 million recordings (Nikolopoulos & Boulougouris, 2020) and come from 5 sistership bulk carriers with approximately 320,000 lines of readings per vessel for a period of 4 years in operation (2015–2019). These data are used for modelling the following in RHODA voyage-simulation module:

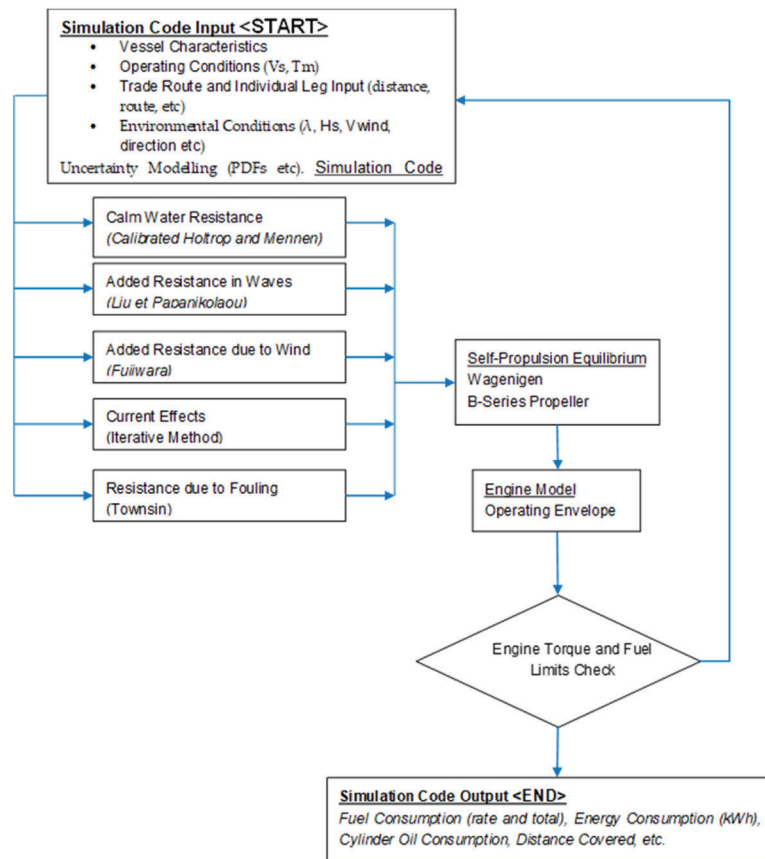


Figure 4. Voyage Simulation process flow in RHODA

- Voyage profile/history and main waypoints;
- Probability Distribution Functions (PDF) for modelling environmental conditions (i.e Wind, Wind Direction, Wave, Wave Direction, Current and Current Direction);
- PDFs for Operating Speed per Voyage Profile Leg.
- Calibration of Holtrop and Mennen methodology for full hull forms operating at lower Froude Numbers (Nikolopoulos & Boulougouris, 2019)).

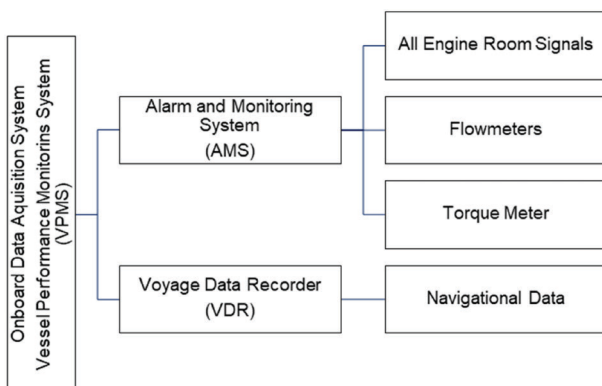


Figure 5. Onboard Data Acquisition System (VMPS)

For each one of the voyage legs, the average transit speed and added resistance curves are used as input as well as the loading of the generators, and the time in voyage

when the ship is manoeuvring and/or transiting through canals. If discharging, loading or a stoppage for bunkering are included in a voyage leg, then the corresponding port stay-in hours are also used. The RHODA method has also evolved to incorporate multiple detailed and complimentary to each other weather models. Such include probability distribution functions (PDFs) derived from coordinate and timestamp-matched satellite hindcast data that, depending on their availability, can be also blended with Long Term Statistical models for specific sea regions, with distribution shape parameters taken from the DNV-RP-C205 recommended practice on environmental conditions and environmental loads (DNV, October 2010). Further details on the environmental model employed can be found in Table 1 for the case of waves, in Table 2 for wind and in Table 3 for sea currents. Current corrections are made using the iterative method of ISO15016-2015 which is the prevailing standard in the industry for correcting sea trial data during newbuilding construction. As such the method does not segregate hull and propeller but considers the self-propelled ship directly with the effect being quantified directly on the speed level.

In the design environment, non-dimensional loads of electrical consumers onboard from the parent vessel along with additional loads applicable (e.g. in case of dual fuel designs the Fuel Gas Supply System), are modelled in a detailed Electrical Load Analysis following the same

Table 1. Environmental Models used for waves

Waves – Matched Satellite Weather Data (wind waves and swell)	
Data:	Satellite weather hindcast data matched to timestamp and coordinates.
$H_{\text{wave LADEN}}$	Weibull Distribution α : 1.528 β : 1.209 γ : 0.000
$H_{\text{wave BALLAST}}$	Weibull Distribution α : 1.974 β : 1.005 γ : 0.000
Φ_{WAVE}	Assumed to be the same as the prevailing wind generating the waves
Zero Crossing	Assumed same as in Long Term Wave Statistics
Waves – Long Term Wave Statistics (CMA Joint Environmental Model)	
Data:	DNV Global Weather Statistics (DNV October 2010)
H_{wave}	Weibull Distribution $f_H(h) = \frac{\beta_{HS}}{\alpha_{HS}} \left(\frac{h - \gamma_{HS}}{\alpha_{HS}} \right)^{\beta_{HS}-1} \exp \left\{ - \left(\frac{h - \gamma_{HS}}{\alpha_{HS}} \right)^{\beta_{HS}} \right\}$ $\mu = E[\ln Tz] = \alpha_0 + \alpha_1 h^{a_2}$ $\sigma = \text{std}[\ln Tz] = b_0 + b_1 e^{b_2 h}$
Φ_{WAVE}	Assumed same with satellite model,
Zero Crossing	$f_{TZ/HS}(t h) = \frac{1}{\sigma t \sqrt{2\pi}} \exp \left\{ - \frac{(\ln(t - \mu))^2}{2\sigma^2} \right\}$

template and method as in standard shipbuilding practice. Following, that the alternator and then generator engine are dimensioned. The dimensioned engine fuel consumption map is derived from the digitized data of makers in RHODA. In the simulation environment, the specific fuel consumption (or gas with pilot in DF applications) is input along with the alternator load. For each time step depending on the weather and load conditions an ELA is repeated and the auxiliary engines load determined with which the SFOC curve is interpolated and the auxiliary engine consumption derived. The same depending is done for the steam balance and depending on ambient conditions the boiler consumption (if any) is derived.

2.2 (c) Validation with Actual Operating Data

The voyage simulation module has been systematically validated using an onboard data pool matched with completed voyages. The validity of the simulation code is assessed with regards to the agreement of the predicted delivered power (Pb), and speed with the equivalent data measured onboard. In all timeseries presented, blue

Table 2. Environmental Models used for wind

Wind – Onboard Data	
Data:	Vessel anemometer
Parameter	Fitted Distribution
V_{WIND}	Gamma Distribution Shape: 4.277 Scale: 0.289
Φ_{WIND}	Normal Distribution Mean: 170.461 Standard Deviation: 77.537
Wind – Satellite Data	
Data:	Satellite weather hindcast data matched to timestamp and coordinates.
Parameter	Fitted Distribution
$V_{\text{WIND LADEN}}$	Weibull Distribution α : 5.037 β : 2.152 γ : 0.000
$V_{\text{WIND BALLAST}}$	Lognormal Distribution a: 4.697 b: 0.471
$\Phi_{\text{WIND LADEN}}$	Exponential Distribution Scale Parameter: 0.023
$\Phi_{\text{WIND BALLAST}}$	Exponential Distribution Scale Parameter: 0.023

Table 3. Environmental models used for sea currents

Current – Onboard Data	
Data:	Crew Noon Reports
Parameter	Fitted Distribution
$V_{\text{current LADEN BRAZIL}}$	Exponential Distribution Scale: 1.484
$V_{\text{current LADEN AUSTRALIA}}$	Normal Distribution Mean: 0.674 Standard Deviation: 0.465
$V_{\text{current BALLAST BRAZIL}}$	Exponential Distribution Scale: 1.532
$V_{\text{current BALLAST AUSTRALIA}}$	Exponential Distribution Scale: 1.113
Φ_{CURRENT}	Uniform Distribution Minimum: 0 Maximum 337.50
Current – Matched Satellite Weather Data	
Data:	Satellite weather hindcast data matched to timestamp and coordinates.
Parameter	Fitted Distribution
$V_{\text{current LADEN AUSTRALIA}}$	Exponential Distribution, Scale: 2.268
$V_{\text{current BALLAST AUSTRALIA}}$	Lognormal Distribution a: 0.402 b: 0.819
$\Phi_{\text{CURRENT LADEN}}$	Normal Distribution Mean: 183.461 StDev: 95.815
$\Phi_{\text{CURRENT BALLAST}}$	Normal Distribution Mean: 195.128 Standard Deviation: 96.570

timelines indicate real data acquired and orange RHODA model predictions.

Delivered Power Prediction

Figure 6 represents a typical Laden voyage simulation timeseries of the Delivered Power in kW in Laden condition.

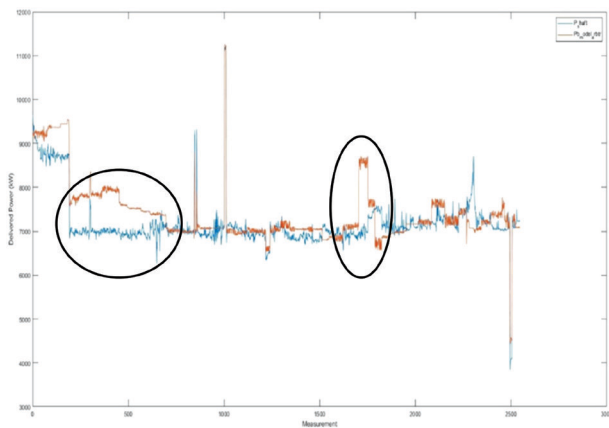


Figure 6. Delivered Power Prediction (Laden)

Predicted power (orange timeline) values appear to agree very well with actual recorded values (blue timeline) since most propulsion power fluctuations are adequately followed in both magnitude and trend illustrating a good dynamic response of the RHODA code. For the most of the timeseries, predictions have an accuracy between 5 and 10%. The Ballast condition timeseries, shown in Figure 7, indicate an even stronger agreement with all predicted values nearly coinciding to the corresponding actual recorded ones throughout all peaks, fluctuations and steady state conditions and in no case being out of a band of $\pm 5\%$ deviation from actual.

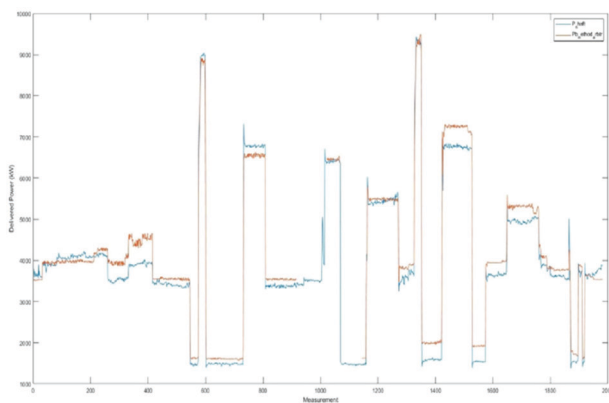


Figure 7. Delivered Power Prediction (Ballast)

Deviations observed between the predicted and measured Delivered Power (P_b) for specific cases occur due to one of the following reasons:

- Main Engine RPM fluctuation and engine acceleration phenomena are not filtered out in the data cleansing stage.
- Vessel stoppages (short e.g for engine inspections) cannot be filtered out in the data cleansing stage.
- Asynchronous data logging of the measuring instrument/sensor (in this case M/E torquemeters) with the data acquisition device onboard. This can happen due to different data harvesting frequencies between the sensor and the alarm monitoring system (AMS) of the vessel as well as between the AMS and the data acquisition device. In general, for this study, 30sec data have been used. As the data frequency is higher such asynchronous data logging events will be more frequent.
- Accuracy of measuring sensors. Torque meters in general are accurate measuring devices that require annual calibration to retain their measuring fidelity. The issue with power meter readings has been also addressed in the ISO 15016 standard for sea trials where two measurement instruments are used (International Organization for Standardization, 2015).

When looking at the distribution of the percentage of deviation of shaft power prediction from onboard measured data (), it can be seen that it follows a normal distribution shape with the majority of recordings being placed in the -5% to $+5\%$ distribution band.

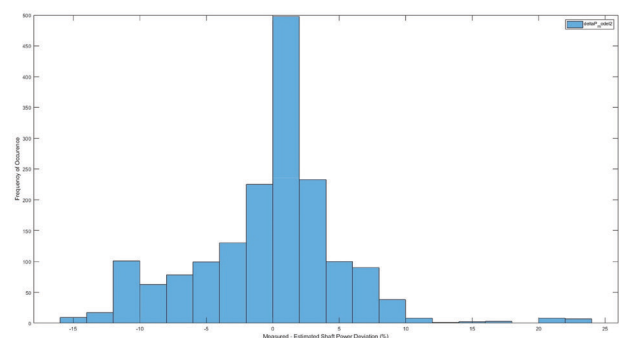


Figure 8. Frequency Distribution (Histogram) of Shaft Power Deviation

Speed Over Ground Prediction

The prediction accuracy of the speed over ground (SoG) in the Laden condition depicted in Figure 8 with the blue timeseries being the onboard measurement (from vessel's DGPS), and the orange timeline, the equivalent simulation code estimated values for a typical laden condition at a 5-minute time step. Although the agreement is in general acceptable, there are speed over ground (SoG) drops in

the 700th measurement that haven't been captured by the simulation code. Furthermore, at the last measurements, the agreement between prediction and measured data is limited.

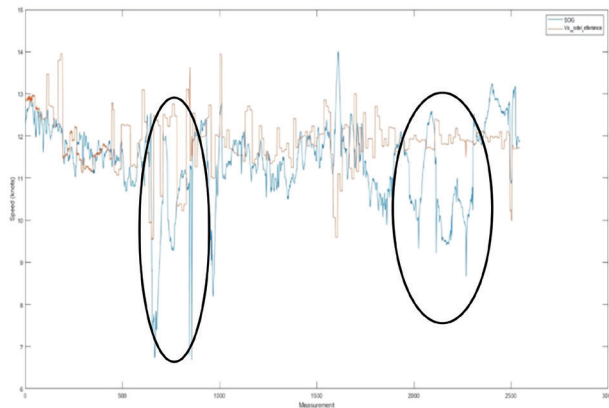


Figure 9. SoG Prediction (Laden)

The Ballast condition speed over ground (SoG) simulation timeline is shown in Figure 9. The blue timeline shows actual onboard measurements (from vessel's DGPS), and the orange timeline, the equivalent simulation code estimated. Although for the first 200 loggings the simulation prediction is not in agreement with the onboard data for speed over ground with predicted figures doing an overestimation of more than 30%, the rest of the timeseries calculated predictions agree well with onboard measurements having an accuracy of the $\pm 10\%$ error band.

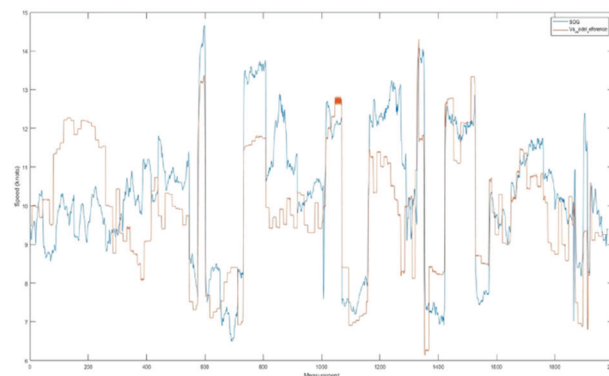


Figure 10. SoG Prediction (Ballast)

Issues with speed over ground and speed through water prediction are more common, however when examined as an error distribution histogram they remain at satisfactory level of $\pm 10\%$ deviation of prediction from onboard measurement. The reasons for such include the following:

- Low accuracy of onboard speed log especially in the case of air entrapment on the vessel's flat bottom region or fouling formation around the sensor.

- Asynchronous data logging of the DGPS speed value with the data acquisition device onboard.
- Incorrect matching of the historic data from weather provider for sea currents. Currents have an inherent dynamic variation of both direction and velocity, in the direct vicinity of the ship's precise coordinates for a given timestamp. From practical, onboard, experience a current of 1 knot affecting the vessel can be -1 knot or 2 knots within 100meters at the Port or Starboard side of the vessel. Existing capabilities for capturing and modelling the uncertainty of sea currents for this case is limited.

Considering that all power and speed trends are fairly predicted by the RHODA simulation model compared to onboard measurements it can be concluded that the discrepancies identified are such that they will not change neither the magnitude of calculations and estimations made in the design stage, nor change the ranking between the generated variants in the optimization stage. As the main focus of this research is on ship design optimization, the agreement of the simulation model to actual (not experimental) data is considered sufficient for using it in such studies.

2.2 (d) Shipping Freight Market & Lifecycle Economic Analysis

The lifecycle economic analysis and evaluation of each variant is comprised by the assessment of the Operational Expenditure (OPEX), the Capital Expenditure (CAPEX) leading to the assessment of the Required Freight Rate (RFR) based on a discounted monetary inlet and outlet flows model (Nikolopoulos & Boulougouris, 2018) and (Nikolopoulos & Boulougouris, 2020). The model is built on two main layers of uncertainty: on one hand the uncertainty of the freight rate of the specific shipping market and the fuel price uncertainty on the other using "big data" from actual freight markets between 1990 and 2015 (Clarksons Shipping Intelligence, 2015) and produces equations for predicting the acquisition and disposal prices of the ship as a function of the lightship weight and of the freight market earnings. Additionally, the dry docking maintenance costs of a fleet of 75 large bulk carriers from 2005 to 2020 have been mapped, filtered, analysed with descriptive statistics and fitted with non-linear regression formulae for major cost categories as a function of the crew number, DWT, MCR and vessel's age. Similarly OPEX non-linear regression formulae have been generated as functions of the vessel's age, crew number and MCR. The main component of OPEX, namely the fuel cost, is also calculated on a probabilistic basis on high/mid/low scenarios, with the occurrence probability being calculated by the probability distribution functions shown in Table 4 which are fitted to actual data of bunker pricing between 1990 and 2020. The Required Freight Rate is derived from the above calculation, represents

the breakeven of the vessel for the potential shipowner investment and is expressed from equation (1)

$$RFR = \frac{\text{Total Costs Discounted}}{\text{Round Trips} * \text{Annual Cargo} * \text{Years}} \quad (1)$$

Where discounted total cost is the net present value of all CAPEX, OPEX and fuel costs mentioned above. The above is realized and mathematically programmed in the form of monetary flows and timeseries with positive flows being income and negative flows being expenses similar to Figure 10. As the vessel's lifetime is a significant time (assumed 25 years for this instance), each monetary flow is referenced to year "0" which marks the vessel's delivery by use of the Net Present Value (NPV) formulation. All costs are modelled on an annual rate, in order to be able to have a common denominator with the annual costs and thus produce the RFR value. This metric is considered as the best representation of a vessel's economic performance in Ship Design Studies (Papanikolaou, 2010), (Papanikolaou, 2014), (Nikolopoulos, 2012) and is a centrepiece in all optimization studies being a core optimization target. In an effort to further push for innovative ship designs, a carbon taxation figure was added to the RFR formula as well. The Carbon Tax is calculated from the annual CO₂ emissions (derived from voyage simulation tools) multiplied by a CO₂ tax on USD/ton CO₂e that is given in three cases: low (50 USD/t), medium (100 USD/ton) and high (200 USD/ton). Given that Emission Trading Schemes (ETS) are not yet in place, an even weight distribution among the three values is assigned.

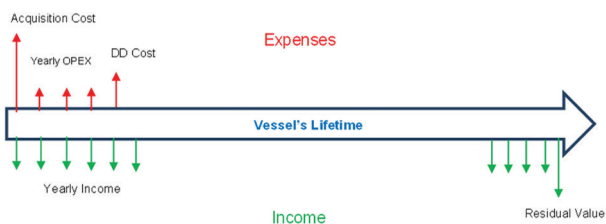


Figure 11. Monetary Flows over time modelled for RFR calculation

3. APPLICATION TO LARGE BULK CARRIER OPTIMISATION

3.1 BASELINE & DESIGN CONCEPT

A common ship type is used as a basis for optimization case studies, that of large bulk carriers (above Capesize dimensions), commonly referred to as Very Large Ore Carriers. For all optimisation runs, two sub-segments have been considered: Newcastlemax Bulk Carriers (size limitations to fit Newcastle port of Australia); and WOZMAX Bulk Carriers (West Australia Max vessel that

can fit all Western and Northern Australia ports excluding Newcastle). Two trade routes corresponding to most of the the large bulk carrier trading activities have been fully modelled with a leg subdivision approach (Figure 10, Figure 11):

- Route A (4,797 nautical miles): West Australia to Northern China roundtrip (Port Hedland to Qingdao via Singapore straight in ballast let)
- Route B (11,358 nautical miles): Brazil to Northern China roundtrip (Tubarao to Qingdao via Singapore Straight).

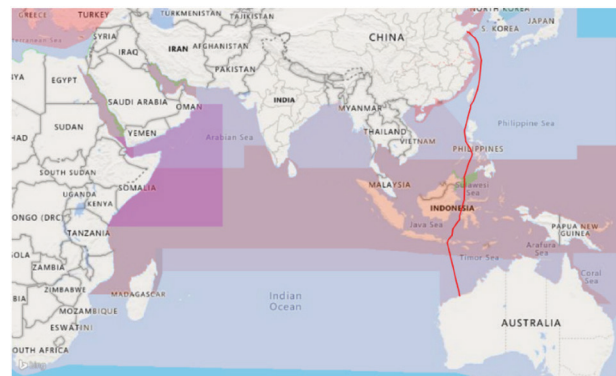


Figure 12. Route A Voyages simulated

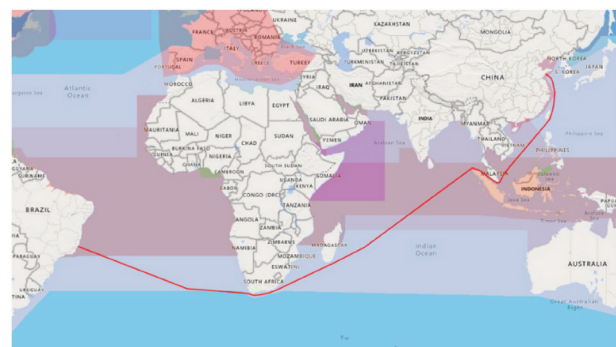


Figure 13. Route B Voyages Simulated

3.2 OPTIMISATION PROCEDURE & STRATEGY

The optimisation procedure follows the rationale of any optimisation loop in engineering as shown in Figure 19. For each new sequence of this optimisation loop, a new ship variant is generated with the appropriate geometric detail and designed in line with the RHODA process flow depicted in Figure 12 that is activated upon loop initiation.

3.2 (a) Optimisation Variables Goals and Constraints

The variables considered from the optimization studies along with the objectives and constraints are indicated in Table 1.

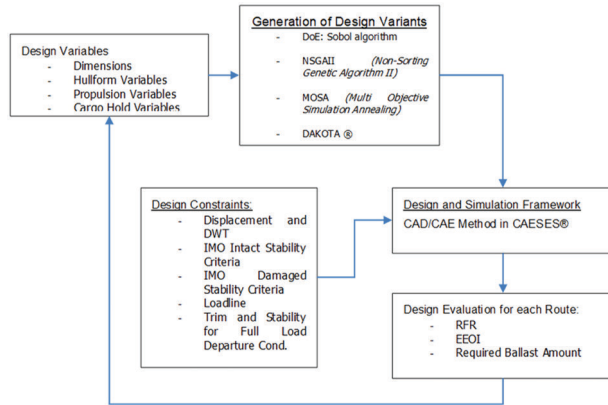


Figure 14. Generic Optimisation Sequence

Table 4. Summary of RHODA optimisation runs examined

Vessel Case Study	Optimisation Run ID	Number of Variants	Success Rate
Newcastlemax	NMAX-Sim_02	1500	54%
WOZMAX	WOZMAX-Sim_01	1500	53%
WOZMAX	WOZMAX-Sim_01	3000	56%

3.2 (b) Sorting and Ranking Dominant Variants

The sorting, ranking and selection of dominant designs from pareto frontiers are done using utility functions. Utility functions create ratios of the values of optimization objectives of each variant to the local optimization objectives multiplied by weights which are attributed by the designer/decision maker. Instead of applying fixed weights for the variants evaluation in terms of optimization targets (*EEOI*, *RFR*, Ballast Water Amount), a utility function (*U*) is used as per below equation (2) with weight values adjusted in accordance to how close each design is to each objective minimum value:

$$U_i = w_{EEOI} * u(EEOI)_i + w_{RFR} * u(RFR)_i + w_{Ballast} * u(Ballast)_i \quad (2)$$

Where:

- i design variant
- U_i , total design variant utility;
- $u(EEOI)_i = \left(1 - \frac{EEOI_i}{EEOI_{max}}\right)$, nominal utility of design i for *EEOI* objective;

(3)

$$w_{EEOI}(i) = \begin{cases} w_{EEOI}max * u(EEOI)_i, \\ w_{EEOI}max * (0.2182 \ln(u(EEOI)_i) + 0.9818) \end{cases}$$

nominal weight of design for *EEOI* objective in cases of linear (upper) or logarithmic weight distribution depending on utility relation to optimal utility value; (4)

- $w_{EEOI}max$, maximum weight for *EEOI* objective for variant with best (i.e. lowest) *EEOI* value (applicable for all other optimization objectives) as per Table 5.

Table 5. Weights of different utility functions

Maximum Objective Weight	U1	U2	U3	U4	U5 Logarithmic
$w_{RFR}max$	1/3	0.3	0.2	0.5	1/3
$w_{EEOI}max$	1/3	0.3	0.2	0	1/3
$w_{BW}max$	1/3	0.4	0.6	0.5	1/3

The best 10 ranked designs per weight scenario in accordance with the above equations are then selected for post-processing. A unique contribution of the RHODA method is that for the first time in ship design optimisation studies a logarithmic distribution of utility weight instead of linear is used with a distribution as in Figure 13 and equation (4).

The weights of the utility functions do not directly affect the optimization results themselves but the instead decision maker's pick from the pareto front. The use of a logarithmic utility weight distribution considerably accelerates the selection of "best trade-off" designs assists especially in cases where Pareto fronts generated are highly polarized (Nikolopoulos & Boulougouris, 2020).

3.3 GLOBAL OPTIMISATION STUDIES RESULTS

The RHODA method application in global ship design optimisation studies is comprised by:

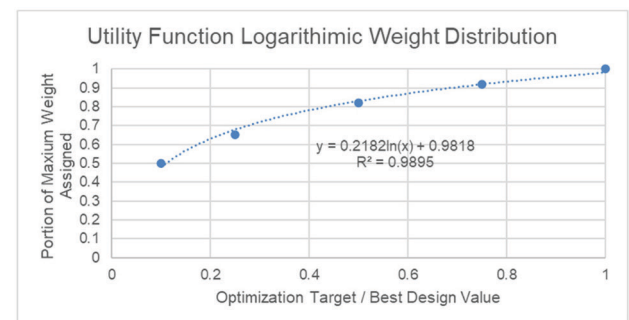


Figure 15. New logarithmic weight distribution for utility function

Table 6. Range of Design Variables in Optimisation studies

Design Variable	Lower Boundary	Upper Boundary
Length Between Perpendiculars (L_{bp}) – m	275	340
Breadth (B) – m	45	65
Scantling Draft ($T_{scantling}$) – m	17	22
Deck Height (D) – m	24	30
Cargo Hold Hopper Height – m	6	12
Cargo Hold Hopper Breadth – m	3	6
Cargo Hold Topside Height – m	4	12
Cargo Hold Topside Breadth – m	6	15
Block Coefficient (C_b)	0.7	0.87
LCB – % L_{bp}	0.505	0.525
Bilge Height – m	2.4	7
Bilge Width – m	2.4	7
Propeller Diameter (D_{prop}) – m	8	10
Propeller Expanded Area Ratio (A_E/A_o)	0.4	1
Pitch Over Diameter Ratio (P/D)	0.7	1.2
Number of Propeller Blades (Z)	4	5

- Baseline Deterministic runs with equivalent optimization setup (variables, targets, constraints).
- Sensitivity analysis on key results of simulation-based optimization runs and Design of Experiment (DoE)
- Global ship design optimization runs with RHODA (voyage simulation-based).

Parallel to RHODA global runs, equivalent deterministic optimisation runs (same parameters and targets) have been conducted for benchmarking the voyage simulation effect on the optimization process (against existing methods).

The key presentation of results is done with the use of two-dimensional scatter diagrams of the optimisation targets. Each marker in light blue represents a fully dimensioned, realized and successful variant produced from the optimization while dominant variants selected from the utility functions are represented in colour. The optimisation run IDs are the prefix of each design depicted in the results figures shown and a summary of the optimisation runs are given in Table 5. The success rate indicated is the percentage of feasible designs (designs that have all constraints fulfilled) against the total number of designs generated by the algorithm. The number of design variants for each run is derived from the product of the number of generations of designs (15) and the population of each generation (100). The selection of generations and population of each is made such in order to allow

for sufficient design space per generation and enough generation to converge to optimal designs with limitations from computational power requirements. For reader's reference it should be indicated that the 1500-variant run requires approximately 125 hours to be completed. The change from 1500 to 2000 variants was made in a second run (starting from the same baseline) in order to quantify and assess the effect of higher number of generations (20 instead of 15) which indeed showed a more dense pareto front (Figure 19).

3.3 (a) Key Results from Deterministic Optimisation Runs

The economies of scale generally anticipated in ship design are generally observed in the results of the deterministic optimisation runs where larger vessel variants clearly dominate and outperform the design space both in terms of RFR and EEDI. Additionally, we have observed a strong conflict between the optimization goals (RFR/EEDI and Required Ballast amount). Designs that prioritize minimum RFR and/or EEDI do not perform optimally in terms of Required Ballast Water due to the significant correlation between RFR and EEDI.

An exploration of different optimization engines available in CAESSES® was done at this stage with the focus on design space characteristics, algorithms and convergence to pick the most appropriate engine for the simulation-based runs. The algorithms examined where the NSGAI, (Deb, et al., 2002)), MOSA (Ulungu, et al., July 1999)) and DAKOTA which has an NSGAI-based computational core. From this exercise the following observations have been made:

- *Best in Design Success Rate: MOSA*

The MOSA algorithm had for either of the design concepts (NMAX and WOZMAX) a higher variant success rate (95.8% and 94.0%) compared to the other design engines (DAKOTA 80.3% and 85.6% respectively and NSGAI 75.9%, and 78.0%).

- *Best in Convergence: MOSA*

The MOSA design engine converged to optimal, Pareto front designs considerably faster compared to other two engines (NSGAI and DAKOTA).

- *Best in Optimization Effect: NSGAI*

The best optimisation target results were given by the NSGAI algorithms, with a design cloud similar to the other design engines (MOSA and DAKOTA) but has been “translated” and “pushed” to pareto optimal regions of the scatter diagrams having on average 5% better results on optimization objectives. Additionally, the NSGAI design pool illustrated the highest improvement percentage for all optimisation targets (19.0%)

- *Best in Design Cloud Density, Coherence and pareto shape: DAKOTA and NSGAI*

These two design engines generally create design spaces with denser scatter diagrams from one hand and from the other, allow for easier picking optimal designs.

After evaluating all the above findings from deterministic runs, it was decided that for simulation-based runs, NSGAI would be the sole Design Optimization algorithm.

3.3 (b) Sensitivity Analysis of Simulation-Based Runs

The RHODA method sensitivity analysis has the target of assessing the effect of simulation on the optimisation path. This is succeeded by having concurrent calculations of the equivalent deterministic figures of the optimization targets (single speed, no voyage simulation) against lifecycle voyage simulation-based optimization results for each design variant of the design space. By the comparison and superimposition of the optimisation objectives of each module, the effect of simulation can be clearly identified. Two such comparisons are made, one for the EEDI (deterministic-based objective) versus *EEOI* (simulation-based objective) of each design variant and one for the RFR (deterministic-based objective) versus RFR (simulation-based objective). Figure 14 is the scatter diagram of the nominal, deterministic-based RFR (x-axis) versus the simulation-based RFR (y-axis), with each light blue marker representing a fully realized and dimensioned design variant produced from the RHODA optimisation method and coloured markers representing dominant

Freight Rate calculated from the output of the voyage simulation module for actual operating speed profiles, and in real seaways accounting for hull fouling and vessel aging (LC consideration) as well.

A first observation is that RFR has an uncertainty range between 20% and 35%. More specifically, for a constant value of deterministic-based RFR of 7.0 USD/ton, the equivalent RFR derived from simulation has values starting from 7.4 and ranging up to 9.0 USD/ton, corresponding to a variance of 40% in magnitude. Another observation is that as regions of minimum RFR are examined (RFR-optimal regions of the Pareto fronts), such variance between values of the simulation-based RFR values is reduced significantly. (left-hand side peak in Figure 14). The conclusion from the above is that the RFR calculated on a deterministic basis for a single design point (i.e. laden and ballast nominal conditions at nominal continuous rating load speed) will not properly project the actual commercial performance of the vessel under realistic market conditions, real voyages and operations.

Figure 15 is the scatter diagrams of the deterministic-based EEDI against the simulation-based *EEOI*. The key observation for this graph is that for a constant EEDI, the voyage simulation generated Energy Efficiency Operating Index (*EEOI*) corresponding values have a variation magnitude of up to 52%. This means that for design candidates with the same nominal EEDI rating and under the same simulated voyage input and assumptions, their actual voyage operating performance (expressed by *EEOI*) varies significantly. For example, in Figure 15, for a level of EEDI of 2 tonCO₂e/ton*mile, the *EEOI* derived from voyage simulation for each different design have values starting at 4.3 and ranging up to 5.4 tonCO₂e/ton*mile. This difference in actual performance efficiency wouldn't be identified if only EEDI was used for the assessment. If the EEDI constant value is increased to 2.2 tonCO₂/ton*mile, the range of *EEOI* from voyage simulation is higher (4.3 to 6.5 tonCO₂/ton*mile). For the WOZMAX designs (Figure 16), the variance is also higher (up to 70%) due to the bigger range of design variables for such runs which create a larger design space, magnifying existing model uncertainties of EEDI.

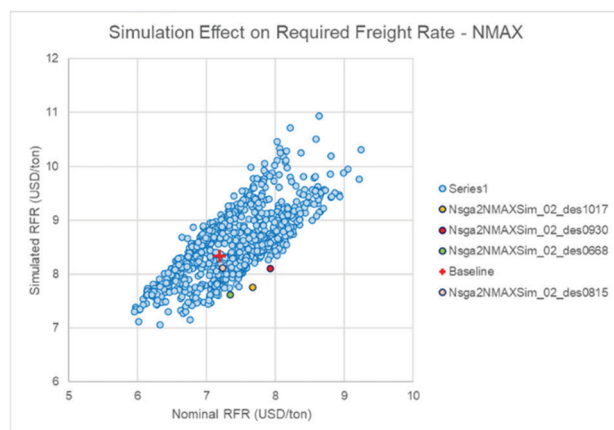


Figure 16. Sensitivity and effect of simulation on the Required Freight Rate

variants picked from utility functions. Axis x represents the Nominal Required Freight Rate that would be applicable for each design candidate if no voyage simulation was conducted and its calculation based on a single speed with no added resistance considerations and vessel performance in actual seaways. Axis y on the other hand is the Required

EEOI data from sisterships range significantly depending on the fouling state of the vessel and the prevailing market conditions dictating operating speeds or charter party requirements so such a comparison could complicate the reader, however it is very valuable to be done for a separate analysis if not already in available in the literature (e.g. publications from SHOPERA R&D project). Regarding the well commented difference of EEDI and *EEOI* this is a key takeaway of this research work. Namely the suitability of EEDI is more that of a design constraint rather than an optimization objective. The reason for the variance is that EEDI observes only the performance at the design (maximum) speed without considering added

resistance due to waves, wind or following whereas *EEOI* calculates the actual CO₂ emission from actual operation in actual seaways. That is why we also mention that for the purpose of this work this is simulated *EEOI*. So indeed, designs with the same *EEDI* rating at the same design speed (predetermined value for all design variants generated) can have big variations in *EEOI* under the same operating profile due to different design characteristics triggering differences in calm water resistance and propulsion in lower speeds (operating speeds are typically between 10.5–11.5 knots against 14.5 knots design speed) and most importantly due to different ass resistance in waves. The latter is greatly influenced by differences in dimensions and block coefficients as also highlighted in the original publications of the SNMM methods by Liu and Papanikolaou.

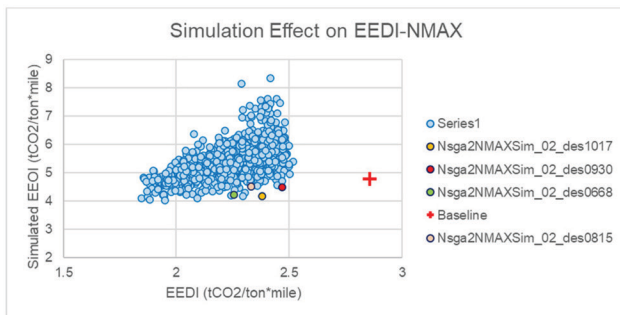


Figure 17. Sensitivity and effect of Simulation on EEDI

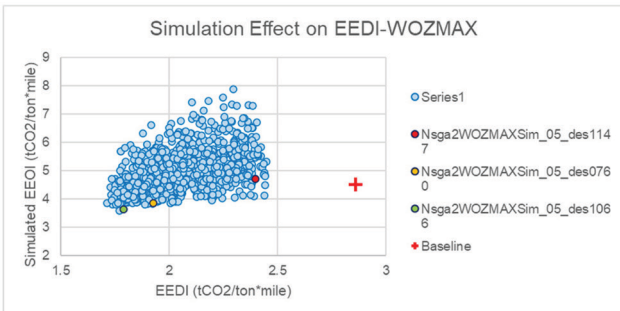


Figure 18. Sensitivity Analysis and Scatter between EEDI and Simulated EEOI – WOZMAX Case Studies

3.3 (c) Key Results from Simulation-Based Optimisation Runs

The global design optimisation run results for Newcastlemax and WOZMAX design concepts are examined in this section. The design cloud diagram of the voyage simulation generated *EEOI* against simulated RFR for the Newcastlemax case study can be seen in Figure 17, where the entire design population is depicted in light blue markers and coloured markers identify the

dominant variants picked by the utility function. These two optimisation targets have a strong linear correlation and a narrow band design cloud when compared to deterministic results due to the synchronous calculation of these two objectives in the RHODA simulation module.

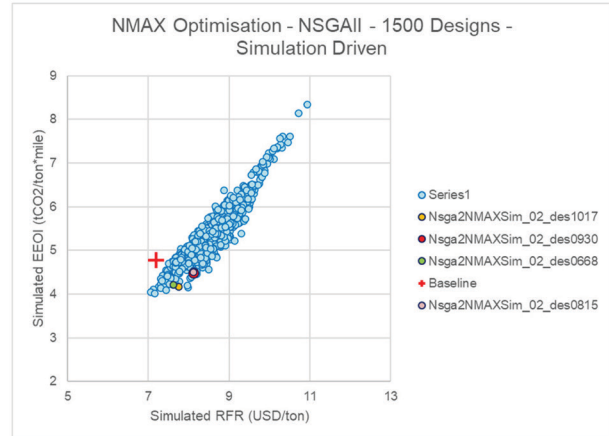


Figure 19. Scatter Diagram between simulated EEOI and RFR – NMAX Case Studies

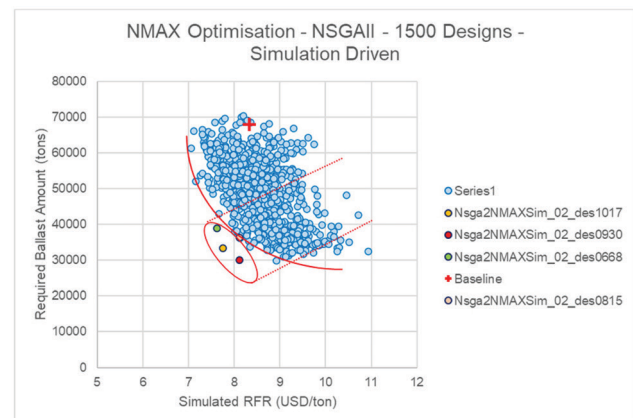


Figure 20. Scatter Diagram between simulated RFR and Required Ballast Amount– NMAX Case Studies

The simulation-based RFR versus the Required Ballast Water amount scatter diagram for the NMAX case stage is found in Figure 18. Designs located on the characteristic arc-shaped Pareto frontier, dominate the rest of the scatter diagram nearby regions (red lines on graph). The centre of the Pareto arc of Figure 18 with a marked red circle includes the designs featuring the “best compromise” between RFR and/or *EEOI* performance and the minimisation of Ballast Water (Designs 0815 & 1017 in Table 6). If Design 0815 is taken as an example, a ballast water amount reduction of Pareto is combined with a 11.5% better *EEOI* than the baseline vessel *EEOI*.

The shape of the design cloud scatter diagram of Required Ballast Water versus the voyage simulation generated RFR are almost identical for the case of Required Ballast

Water and simulation-based *EEOI* for both Newcastlemax and WOZMAX designs. For the case of WOZMAX case studies, two optimisation runs have been set, one with 1500 variants and one with 2000 variants. The second run had the same population for each generation (100 designs) but had 20 generations instead of 15 in order to illustrate the effect of the number of generations on the density of the pareto frontier. Figure 19 shows the design cloud diagram between the simulated RFR and the minimum Required Ballast Water for the WOZMAX case study for both runs, with light blue markers representing design variants from the first run (1500 population) and pink markers designs from the second (2000 population). From this superimposition, it is observed that design cloud, albeit of the similar form to previous, is translated horizontally towards the left areas (Pareto optimal regions) and the pareto frontier regions of previously thin design density (1500 variant runs), are now filled with design variants in the 2000 variant run. Interestingly, during design ranking, the top ranked IDs have an order of variant generation after the 1000th design.

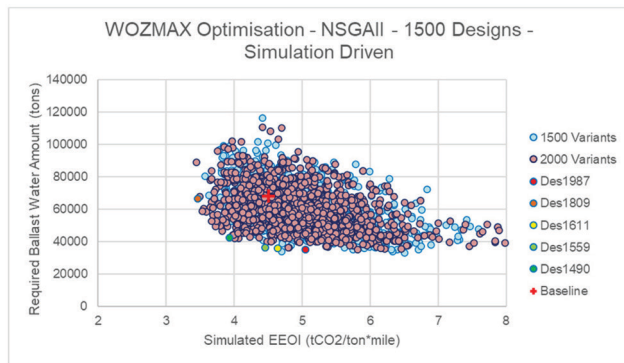


Figure 21. Scatter Diagram of Optimisation Variants between Required Ballast Amount and simulated *EEOI* – WOZMAX Case Studies (1500 and 2000 designs)

4. RESULTS DISCUSSION AND ANALYSIS

In Table 6, the selected dominant variants of each respective optimisation run are presented in terms of the optimisation target improvement (%) when compared to the baseline vessel.

From the Newcastlemax runs, Design ID668 has a simulation-derived RFR reduced by 9% combined with a 12% lower voyage-simulated *EEOI* and a 43% lower Required Ballast amount. When looking at the deterministic objectives (RFR, *EEDI*) of this particular design *EEDI* is reduced by 21% while the prescriptive-based RFR is 2% higher than the baseline. This is a typical example of how the RHODA method optimisation principle creates an additional dimension of the design space as in deterministic-based optimisation runs with a single prescriptive-based calculation, such a design would have been discarded during variant selection due to the seeming underperformance in RFR.

Another notable example is Design ID1490 (WOZMAX case study) that has a 10.5% improvement in simulation-based RFR, 12.7% reduction in *EEOI* and 37.5% reduction in Required Ballast. Again, such a design wouldn't have been neither generated nor selected in a deterministic optimisation study with no voyage simulation aspects since the equivalent prescriptive-based RFR of this design is 6.8% higher than the baseline. In Table 5 and Table 4, the principal particulars of the NMAX and WOZMAX dominant variants can be summarized respectively. Interesting observations on the resulting designs are the following:

- For NMAX case studies, designs with RFR and *EEOI* optimal values have a length between on the upper boundary (300m) of variable range.
- For WOZMAX case studies designs with the best RFR and *EEOI* values have the largest lengths, while the

Table 7. Optimisation objectives result for dominant variants

Design I. D	RFR improvement *Simulation Based	RFR improvement *Prescriptive	EEOI Improvement	EEDI Improvement	Ballast Amount Improvement
Baseline	–%	–%	–%	–%	–%
ID1017	–7%	+7%	–12%	–17%	–51%
ID668	–9%	+2%	–12%	–21%	–43%
ID930	–3%	+10%	–6%	–14%	–56%
ID1147	1.6%	0.0%	4.3%	–16.1%	–50.5%
ID760	–12.2%	–5.2%	–14.6%	–32.6%	–27.6%
ID1066	–15.9%	–17.9%	–19.4%	–37.4%	+0.8%
ID1987	+3.7%	+10.7%	+12.0%	–20.9%	–48.7%
ID1809	–19.0%	–9.5%	–23.1%	–35.9%	–2.6%
ID1559	–2.6%	+1.0%	–1.0%	–19.4%	–46.7%
ID1490	–10.5%	+6.8%	–12.7%	–22.6%	–37.5%

shorter vessels are ships with the minimised Ballast Water amounts. Furthermore, designs having best trade-offs between RFR, *EEOI* and Required Ballast Water have lengths on the intermediate range but with wider beam.

- For WOZMAX case studies, designs with bigger beam generally have better RFR and *EEOI* values.
- For both case studies, all dominant variants have draught values on the largest part of the parameter range with scantling draughts between 21.5 and 21.9 meters. The dynamic voyage simulation at actual operating speeds triggers a smaller power increase for increased draught than single design point assumptions. At the same time, the increase in displacement from design draught (and thus deadweight and cargo capacity) offsets its corresponding loss from smaller block coefficient (C_b) values.
- The block coefficients of all variants dominating the Pareto fronts created from the RHODA method, are at the minimum boundary of the range of this parameter, ranging between 0.72 and 0.75. The reduction in C_b , reduces directly calm water resistance and thus installed power, but at the same time also reduces the added resistance due to waves in actual seaways at the frequent operating speeds of the trade routes assumed (also identified by (Liu, et al., 2020)). The cargo loss of slender hulls is offset and compensated by overall larger dimensions. This observation comes also to agreement with the ship design optimisation results for slender, low Froude number bulk carriers in the publications of (Lindstad, et al., 2022) and (Linstad, et al., 2022).

Table 8. Principal particulars of dominant NMAX variants

Particular	ID1017	ID668	ID930
L_{bp} (m)	298.38	293.09	291.93
Beam (m)	47.94	45.04	45.04
Draught (m)	21.15	21.94	21.86
Deck height (m)	27.65	28.97	28.99
Hopper Height (m)	10.00	6.89	6.84
Hopper Breadth (m)	3.48	4.43	3.17
Topside Height (m)	4.45	11.01	10.71
Topside Breadth (m)	12.19	14.84	11.69
Block Coefficient C_b	0.725	0.780	0.722
LCB (% L_{bp})	0.51	0.51	0.51
Bilge Height (m)	5.19	3.51	3.51
Bilge Width (m)	4.71	4.98	5.56
Propeller Diameter (m)	8.02	8.01	8.04
Propeller Expanded Area Ratio	0.634	0.428	0.428

(Continued)

Table 8. (Continued)

Particular	ID1017	ID668	ID930
Propeller Pitch over Diameter ratio	0.931	1.048	1.048
Propeller Number of Blades	5	5	5
Required Freight Rate (RFR) (USD/ton)	8.11	7.61	8.10
<i>EEOI</i> ($CO_2/ton \cdot mile$)	4.50	4.21	4.48
Required Ballast Water Amount (tons)	36236	38987	30033
SMCR (kW)	17277	18325	18243
EEDI Constraint ($CO_2/ton \cdot mile$)	2.33	2.25	2.47

Table 9. Principal particulars of dominant WOZMAX variants

Particular	ID1987	ID1809	ID1559	ID1490
L_{bp} (m)	287.27	320.78	309.15	294.74
Beam (m)	52.26	51.95	47.31	51.94
Draught (m)	21.83	21.08	21.72	20.97
Deck height (m)	29.80	29.39	28.63	28.64
Hopper Height (m)	7.44	11.88	11.35	8.29
Hopper Breadth (m)	4.24	3.40	4.52	3.36
Topside Height (m)	11.29	11.29	4.92	8.75
Topside Breadth (m)	6.28	11.00	7.19	8.41
Block Coefficient C_b	0.720	0.823	0.726	0.746
LCB (% L_{bp})	0.51	0.51	0.51	0.51
Bilge Height (m)	6.00	3.79	2.59	4.89
Bilge Width (m)	6.88	5.56	6.86	5.82
Propeller Diameter (m)	8.08	8.19	8.08	8.02
Propeller Expanded Area Ratio	0.43	0.41	0.622	0.478
Propeller Pitch over Diameter ratio	1.068	1.036	1.069	0.949
Propeller Number of Blades	5	5	4	5
Required Freight Rate (RFR) (USD/tonc)	19.38	15.14	18.21	16.72
<i>EEOI</i> ($CO_2/ton \cdot mile$)	5.04	3.46	4.46	3.936
Required Ballast Water Amount (tons)	34873	66193	36208	42470
SMCR (kW)	19966	19452	18867	18273
EEDI Constraint ($CO_2/ton \cdot mile$)	2.26	1.83	2.30	2.21

- Dominant variants of both NMAX and WOZMAX studies have moulded deck heights at the range of 28 to 29 metres which is at the upper bound of the range of this variable. This increase triggered by the generation process allows for higher scantling draughts while complying with minimum freeboard and load line constraints (International Maritime Organization (IMO), 1966).
- In the RHODA method voyage simulation module, instead of examining a single propeller operating point (e.g at normal continuous rating), the propeller operation is considered over the entire speed range, under dynamic loads and in real seaway conditions. As a result, the required propeller diameter and expanded blade area ratio are reduced for dominant variants combined with an increase in propeller pitch and number of blades increase.

5. CONCLUSIONS

A Robust, Holistic Optimisation Design Approach (RHODA) that embeds Digital Twin and hybrid methods with dynamic voyage simulation in the preliminary ship design stage has been developed, validated and subsequently deployed in the systematic optimisation of two different case studies of conventional, large bulk carriers. Results indicate a significant optimisation potential for all optimisation targets and indicate a high degree of robustness when compared to deterministic, “single design point” equivalent results of the same optimisation engines. The use of actual operating data allows for the implementation of a realistic voyage simulation module from the preliminary ship design stage and creates robust designs assessed over different operating speeds. Such a simulation-based optimisation, not previously examined in the ship design state-of-the-art before has a considerable potential for supporting ship designers, shipbuilders and shipowners in robust ship designs that will comply and respond to current need for decarbonizing shipping in a financially sustainable manner.

The RHODA method has also been developed to optimise the design of novel Zero Emission vessels that use ammonia (NH₃) as a fuel (Nikolopoulos & Boulougouris, 2023). Additionally, its modular architecture can embed any kind of surrogate models created from numerical calculations or directly integrate computational codes. Lastly, an area of future development of the presented RHODA method is intended to include the integration of addressing Wind Assisted Propulsion (WASP) and Carbon Capture and Storage (CCS) simulation models and their comparative, synchronous and synergy assessment to Zero Emission fuels.

6. ACKNOWLEDGMENTS

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