

**EVALUATION OF THE VIABILITY OF OPTIMISED
HULL FORMS FOR BULK CARRIERS**

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of the requirements for the award of the degree of Master of Science in Maritime
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DECLARATION

I certify that all the material in this dissertation that is not my own work has been identified, and that no material is included for which a degree has previously been conferred on me.

The contents of this dissertation reflect my own personal views, and are not necessarily endorsed by the University.

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ABSTRACT

In line with the Paris Agreement (2015), and IMO GHG Strategy 2023, the global maritime industry faces immense pressure and urgency to reduce CO₂ emissions. The decarbonisation of the global bulk carrier fleet presents a critical opportunity to reduce CO₂ emissions through energy efficiency improvement, considering that they account for 25% of the global shipping emissions. This study investigates the viability of optimised hull forms as a decarbonisation pathway for bulk carriers, by focusing on the Japan Bulk Carrier (JBC).

The research developed a workflow for hull form optimisation using open-source tools, including FreeCAD for parametric modelling, OpenFOAM for Computational Fluid Dynamics (CFD), and Dakota Toolkit for Multi-Objective Genetic Algorithm (MOGA) optimisation. The optimisation objectives were to maximise the reduction in resistance, and to minimise the loss in displacement, by altering parameters bulb depth (Z_b), and speed (U_m). The White Box Model was used to estimate fuel consumption, from which the economic and environmental impact was quantified.

The optimised hull form demonstrated a maximum of 4.2% reduction in resistance, which translated into an average annual fuel cost consumption saving of 2.264%, translating into \$372,907.09. Furthermore, a 3.094% average annual reduction in CO₂ emissions was estimated. And, optimised hull forms for the global bulk carrier fleet projected a 0.439% or 163 million tonnes reduction in total CO₂ emissions by 2050, with an estimated total fuel cost savings of \$4.8 billion by 2050.

This research explored the applicability of open-source platforms to enhance the accessibility to hull form optimisation, especially in Least Developing Countries (LDCs) and Small Island Developing States (SIDS). This study advocates for the broader integration of improved ship energy efficiency into national maritime policies, to accelerate global decarbonisation efforts.

Keywords: hull form optimisation, Energy efficiency, Japan Bulk Carrier, decarbonisation

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LIST OF ABBREVIATIONS

3D	Three-Dimension
CAD	Computer-Aided Design
CII	Carbon Intensity Indicator
CFD	Computational Fluid Dynamics
CO₂	Carbon dioxide
EEDI	Energy Efficiency Design Index
EU	European Union
FFD	Free Form Deformation
GHG	Greenhouse Gases
IMO	International Maritime Organisation
ITTC1975	International Towing Tank Convention 1975
LDCs	Least Developed Countries
MARPOL	International Convention for the Prevention of Pollution from Ships
MEPC	Marine Environment Protection Committee
OpenFOAM	Open Field Operation and Manipulation
RANS	Reynolds-Averaged Navier-Stokes Equations
SDG	Sustainable Development Goals
SEEMP	Ship Energy Efficiency Management Plan
SIDS	Small Island Developing States
STL	Stereolithography file
USD	United States Dollars

1. INTRODUCTION

1.1. BACKGROUND

Shipping is one of the most energy-efficient modes of transport, facilitating 80% of international trade in metric tonnes (UNCTAD, 2025). According to EEA (2020), shipping ranks among the lowest in energy consumption at approximately one megajoule per ton-km. By 2021, shipping exhibited the lowest transportation cost per ton-mile globally, at \$0.29 per ton-mile, mainly due to economies of scale, which have lowered operating costs and enhanced shipping's suitability for bulk transportation (Rodrigue, 2024). Shipping's high reliance on fossil fuels leads to high CO₂ emissions, which contribute to climate change.

In 2018, the global shipping industry contributed 2.9% of global anthropogenic CO₂ emissions (EU, 2024). According to IMO (2020), there was a 9.6% increase in CO₂ emissions from the global shipping industry between 2012 and 2018. Without intervention, the global shipping industry's CO₂ emissions are expected to grow (IMO, 2020). In line with the Paris Agreement (2015) and United Nations (UN) Sustainable Development Goal (SDG) 13, the International Maritime Organisation (IMO) adopted the IMO GHG strategy to boost energy efficiency and to ensure the reduction of CO₂ emissions from global shipping to net zero by 2050 (IMO, 2018; IMO, 2023b). To boost implementation of the IMO GHG strategy, amendments to MARPOL Annex VI were adopted, introducing the Energy Efficiency Design Index (EEDI), Ship Energy Efficiency Management Plan (SEEMP), and the Carbon Intensity Indicator (CII) (IMO, 2011; IMO, 2021).

Additionally, the IMO also recommended several technical methods to improve the fleet's energy efficiency, including operational optimisation, hull form and propeller optimisation, renewable and alternative fuel solutions, and waste heat recovery systems (IMO, n.d.-a). Hull form optimisation is a well-established method for enhancing a ship's hydrodynamic performance by reducing the hull's total resistance (DNV-GL, 2025a). Hull form optimisation using numerical methods has evolved since the 1980s (Papanikolaou, 2010), and it utilises innovative methods such as Computer-Aided Design (CAD) and Computational Fluid Dynamics (CFD) to provide high precision and accurate predictions (Li et al., 2013). However, hull form optimisation tools are usually very expensive and require high computational resources, which prohibit implementation in low-income economies. To manage financial cost, open-source tools can be applied to hull form optimisation, but often information on their

integrated use and accuracy is inadequate. This research will study the applicability of open-source tools for hull form optimisation of the Japan Bulk Carrier (JBC), evaluate the viability of optimised hull forms, and explore their impact on global shipping CO₂ emissions.

1.2. PROBLEM STATEMENT

The global shipping fleet contains 122,039 vessels, where 14,459 are bulk carriers, and 2,047 are capesize bulk carriers (Clarksons, 2025). Although bulk carriers account for 12% of the global shipping fleet, they are responsible for 25% of the global shipping CO₂ emissions (Clarksons, 2025; OECD, 2025). This highlights the high sensitivity of global shipping CO₂ emissions to the operational bulk carrier fleet. With the estimated growth of 9.6% in the bulk carrier fleet by 2030 (Clarksons, 2025), CO₂ emissions from bulk carriers are projected to rise, thus the need for immediate and effective decarbonisation strategies. This makes bulk carriers a critical focus group for energy efficiency improvement and zero or low-carbon innovations.

One of the well-established methods to deliver energy efficiency improvement is hull form optimisation, which can deliver energy efficiency improvement between 1% to 10% (H. Wang & Lutsey, 2013). Since hull design directly impacts hydrodynamic resistance and fuel consumption, hull form optimisation presents a promising pathway for emissions reduction in bulk carriers (Zhu et al., 2024). The main advantage of hull form optimisation is the ability to deliver long-term energy efficiency improvement with a minimal need for further hull adjustment, except for routine hull maintenance such as hull cleaning (Tadros et al., 2023).

Hull form optimisation is a computationally intensive approach, requiring significant time, financial investment, and computing resources. To counter these prohibitive costs, there is a need to study the applicability of open-source tools and to optimise the process workflow for better accuracy while balancing computing requirements for various stages of the ship design. Additionally, further research is required to evaluate the suitability of optimised hull forms for a specific category of ships, for example, bulk carriers. This will ensure that the energy efficiency gains are consistent with industry requirements.

Computational Fluid Dynamics (CFD) is one of the methods for hull form optimisation with reduced financial cost and time while maintaining accuracy, as compared to towing tank tests and empirical methods. This research explored the applicability of the open-source CFD approach for hull optimisation using the Japan Bulk Carrier ship model. The research also

assessed the environmental and economic impact of optimised hull forms on the global bulk carrier fleet.

1.3. AIM AND OBJECTIVES

1.3.1. AIM

The goal of this research is to evaluate the viability of the optimised hull forms for the global bulk carrier fleet by investigating the economic and environmental impacts due to hull form optimisation.

1.3.2. OBJECTIVES

The objectives of this research are:

- a) To develop an initial parametric model of a bulk carrier ship. This is the initial hull form to be studied for performance improvement.
- b) To produce an optimised hull form design for the JBC bulk carrier.
- c) To evaluate the environmental and economic impact of the optimised hull form on the global bulk carrier fleet.

1.4. RESEARCH QUESTIONS

The “meta-question” of this research is “How viable are optimised hull forms for the global bulk carrier fleet?”. The underlying questions of this research include the following:

- a) How can cost-effective and globally accessible methods be applied to achieve hull form optimisation?
- b) To what extent does hull form optimisation improve the energy efficiency of the Japan Bulk Carrier?
- c) What are the economic and environmental impacts of the implementation of optimised hull forms for bulk carriers?

1.5. SCOPE, ASSUMPTIONS, AND LIMITATIONS

This research provided insights into the economic and environmental impact of hull form optimisation for bulk carriers, with a specific focus on the Japan Bulk Carrier (JBC) model. The research workflow utilised open-source tools, including FreeCAD for parametric modelling, OpenFOAM for Computational Fluid Dynamics (CFD), and Dakota Toolkit for

optimisation. This study aligned with the IMO GHG Strategy and contributed insights into the key role of hull form optimisation in maritime decarbonisation. To enable the modelling, the following simplifications and assumptions were made:

- a) Simplification of available shipping datasets, research results, and operational data for bulk carriers.
- b) The design and operational information on the JBC ship closely represent the wider capesize bulk carrier fleet.
- c) Simplification in the modelling of the physical conditions for the computational domain was necessary for the derivation of meaningful results and conclusions.
- d) The White Box Model employed for the estimation of fuel consumption and power computes near realistic estimates of ship operation behaviours.

Despite efforts to simplify complex physical phenomena with assumptions, several limitations were faced. These include the following:

- a) Limited computing resources restricted the level of complexity of Computational Fluid Dynamics (CFD) simulations. A twelve-core computer with eight Gigabytes of Random Access Memory (RAM) was utilised to undertake this research.
- b) Limitations in modelling of overly complex and constantly varying real-world conditions like sea roughness, weather conditions, and hull roughness. These change rapidly over a given operational period and hence were not fully incorporated.
- c) Limited access to ship specific operational datasets for capesize bulk carriers, therefore necessitating the reliance on publicly available datasets.
- d) The specific fuel consumption of the engine was assumed to be constant, which limited the analysis to varying engine loads and operational conditions.

2. LITERATURE REVIEW

2.1. MARPOL ANNEX VI & SHIP ENERGY EFFICIENCY

The International Maritime Organisation's MARPOL convention aims to protect the marine environment from pollution by shipping operations and accidents. MARPOL Annex VI specifies the mandatory technical and operational energy efficiency requirements, including the Energy Efficiency Design Index (EEDI), Ship Energy Efficiency Management plan (SEEMP), and Carbon Intensity Indicator (CII), aimed at improving ship designs and operational efficiency, and tracking emissions from ships (IMO, n.d.-b). The EEDI focuses on promoting efficient ship designs by setting standards on allowable CO₂ emissions per tonne-mile, hence energy-efficient hull design, equipment, and machinery (IMO, 2011), and it influences the choice of hull form, fuels, engines, and propulsion systems. To attain EEDI requirements, design optimisation is undertaken especially for the hull and propeller to improve hydrodynamic performance (Kristensen & Lützen, 2012b).

2.2.SHIP RESISTANCE

2.2.1. RESISTANCE COMPONENTS

Total resistance, R_T , is the force required to tow a bare hull at a given speed from a position of rest (Birk, 2019, Kristensen & Lützen, 2012a) and is composed of viscous or frictional resistance (R_V), wave-making resistance (R_W) and air drag (R_{AA}), and is represented as shown in Equation (1) (USNA, 2020; Prabowo et al., 2022). Viscous resistance is due to the action of the viscous fluid on the hull's surface over the Wetted Surface Area (WSA) as the ship moves through water (USNA, 2020; Prabowo et al., 2022). It is dependent on the fluid density (ρ), WSA, speed (V), and coefficient of drag (C_v) as shown in ITTC1975's definition in Equation (2) (Kristensen & Lützen, 2012a; Prabowo et al., 2022), where the C_v is derived as shown in Equation (3). The coefficient of drag is dependent on the Reynolds number (R_n), a dimensionless number that defines the condition of the fluid as laminar or turbulent, by determining the ratio of between the force of inertia and viscosity, and defined in terms of speed (V), length at waterline (l) and the kinematic viscosity (ν) as shown in Equation (4). According to Edward (1988), viscous resistance accounts for 80-85% of the total resistance in slow-speed ships and approximately 50% in high-speed ships. Viscous resistance is minimized by reducing the WSA, and length and beam balancing (Prabowo et al., 2022). Length and beam balancing

affect the carriage capacity; therefore, an optimum compromise between displacement and WSA should be made to reduce resistance while catering to the shipowner's requirements.

$$R_T = R_V + R_W + R_{AA} \quad (1)$$

$$R_V = (\rho * C_V * WSA * V^2) / 2 \quad (2)$$

$$C_V = 0.075 / (\text{Log } R_n - 2)^2 \quad (3)$$

$$R_n = V * l / \nu \quad (4)$$

Wave-making resistance is the resistance component attributed to the involuntary energy loss due to the generation of transverse and divergent waves along the WSA (Edward, 1988 ;Birk, 2019; USNA, 2020). Wave-making resistance is dependent on the Froude number, F_n , a dimensionless number that relates the ship's speed and the speed of waves in the water and is defined in terms of ship speed (V), acceleration due to gravity (g), and length of the vessel (L) as shown in Equation (5). Wave-making resistance is highly dependent on the hull form adopted during the design stage (Kristensen & Lützen, 2012a). Wave-making resistance is usually minimized by bulbous bow addition and increasing the ship's length (USNA, 2020). The Wave-making resistance is estimated in terms of displacement (Δ), fluid density (ρ), acceleration due to gravity (g), and F_n as shown in Equation (6) (Holtrop & Mennen, 1982).

$$F_n = V / \sqrt{g * L} \quad (5)$$

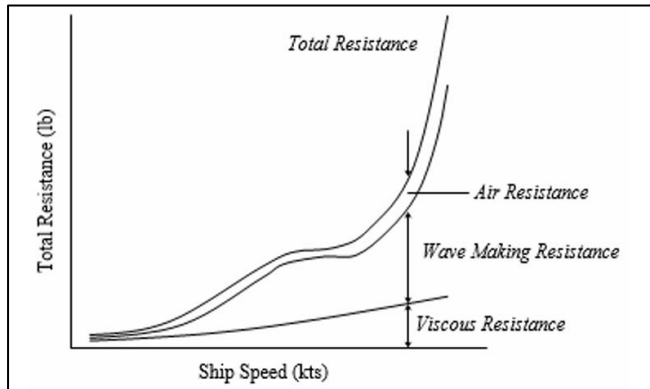
$$R_w = c_1 * c_2 * c_5 * \Delta * \rho * g * (e^{-m_1 * F_n^d}) * \cos(\lambda * F_n^{-2}) \quad (6)$$

Where λ is the wavelength, c_1 , c_2 , and c_3 are empirical coefficients related to hull form, and m_1 and d are empirical constants related to ship speed.

The total resistance is dominated by viscous resistance over wave-making resistance at slow speeds, while at high speeds, the wave-making resistance dominates over viscous resistance, as shown in Figure 1 (USNA, 2020). At high speeds, wave-making resistance increases due to interference between waves, creating superimposed crests and troughs. However, air resistance and viscous resistance also increase significantly, which becomes a limiting force for further increment in vessel speed (USNA, 2020).

Figure 1

Components of total resistance at various vessel speeds.



Source: USNA (2020).

Air resistance can be defined as the resistance of a ship's hull due to movement through air in the absence of wind (Kristensen & Lützen, 2012a; USNA, 2020). Air resistance increases with an increase in the air draught, and affects the extruding superstructure more than the hull (Kristensen & Lützen, 2012a). Air resistance generally accounts for approximately 1% to 8% of the total resistance, depending on the ship type, and is prevalent for high-speed ships, ships with high superstructure, and large sailing areas (USNA, 2020). Air resistance is reduced by optimising the hull and superstructure; however, a cost-benefit analysis should be considered to ensure operational cost savings outweigh related construction costs (USNA, 2020). Bulk carriers are slow-speed ships with low Froude numbers, dominated by viscous resistance, with minimal wave-making and air resistance.

A study by Grlj et al. (2025) of the Japan Bulk Carrier (JBC) ship model showed that the total resistance was made up of 98% of viscous resistance and 2% of wave-making resistance at speeds between 11 knots and 13 knots, while at speeds between 14 and 16 knots, viscous resistance made up 97% and wave-making resistance accounted for 3%. The ratios of resistance components were consistent with the predictions of USNA (2020) that wave-making resistance is minimal at slow speeds and increases with the increase in speed. The study by Grlj et al. (2025) showed the possibility of tackling both wavemaking resistance and viscous resistance in the JBC model for total resistance since both had considerably impactful values; however, the speed of the vessel must also be optimised since it dictates the prevalence of wave-making resistance.

2.2.2. HOLTROP AND MENNEN RESISTANCE

The Holtrop and Mennen method is based on regression analysis and is utilised in early design stages for the estimation of calm water resistance and power for displacement ships (Molland et al., 2017; Holtrop & Mennen, 1982). It is widely considered as one of the most accurate methods for prediction of resistance (Alaaeldeen Mohamed Elhadad et al., 2023; Elin & Felicia, 2020), and is used alongside Computational Fluid Dynamics (CFD) simulations as a low-cost alternative for validation of resistance estimates. The Holtrop and Mennen method is applicable to Froude Numbers less than 0.45, Prismatic Coefficients from 0.55 to 0.85, and length to beam (L/B) ratio between 3.9 and 9.5 (Elin & Felicia, 2020; Holtrop & Mennen, 1982; Nikolopoulos & Boulougouris, 2019). In comparison, the Japan Bulk Carrier model has Froude numbers between 0.1 and 0.2, a prismatic coefficient of 0.86, and a L/B ratio of 6.4. Although having a prismatic coefficient at the edge of the prescribed range of 0.55 to 0.85, the Holtrop and Mennen method can be adopted.

The Holtrop and Mennen method defines total resistance (R_T) using six major resistance components including viscous resistance (R_v) dependent on form factor ($1+k_1$), wavemaking resistance (R_w), appendage resistance (R_{APP}), additional bulbous bow induced pressure (R_B), immersed transom pressure resistance (R_{TR}), model ship correlation resistance (R_{corr}) and air resistance (R_A), as shown in Equation (7) (Holtrop & Mennen, 1982). The form factor depends on the prismatic coefficient (C_p), length at waterline (l), longitudinal centre of buoyancy (LCB), beam (B), length of run (L_R), and moulded draught (T), as shown in Equation (8). L_R is estimated as shown in Equation (9). The coefficient C_{12} is estimated as shown in Equations (10), (11), and (12), C_{13} as shown in Equation (13), and C_{stern} is approximated by values in Figure 2.

$$R_T = R_v (1 + k_1) + R_{APP} + R_w + R_B + R_{TR} + R_{corr} + R_A \quad (7)$$

$$(1+k_1) = c_{13} \{0.93 + c_{12}(B/L_R)^{0.92497}(0.95 - C_p)^{-0.521448}(1 - C_p + 0.0225LCB)^{0.6906}\} \quad (8)$$

$$L_R/L = 1 - C_p + 0.06C_p + 0.06C_p * LCB / (4C_p - 1) \quad (9)$$

$$C_{12} = (T/L)^{0.2228446} \quad \text{when } T/L > 0.05 \quad (10)$$

$$C_{12} = 48.20 (T/L - 0.02)^{2.078} + 0.479948 \quad \text{when } 0.02 < T/L < 0.05 \quad (11)$$

$$C_{12} = 0.479948 \quad \text{when } T/L < 0.02 \quad (12)$$

$$C_{13} = 1 + 0.003C_{stern} \quad (13)$$

Figure 2*Values of C_{stern}*

Afterbody form	C_{stern}
V-shaped sections	− 10
Normal section shape	0
U-shaped sections with Hogner stern	+ 10

Source: Holtrop & Mennen (1982).

For ship propulsion or powering requirements, the model estimates the thrust deduction factor, wake fraction, and propeller characteristics, based on the Wageningen B-Series propeller profiles. The estimated effective power (P_E) can be expressed as a product of total resistance (R_T) and reference speed (V), as shown in Equation (14). The shaft power (P_S) required to overcome the resistance is expressed as a product of the effective power and transmission efficiency (η), as shown in Equation (15) (Elhadad et al., 2023).

$$P_E = R_T * V \quad (14)$$

$$P_S = P_E * \eta \quad (15)$$

The Holtrop and Mennen method was used by Elhadad et al. (2023) to validate the total resistance results of CFD analysis of a surface combatant ship, DTMB 5415, using ANSYS software with flow solver STAR-CCM+. It was concluded that resistance estimates from CFD were in proximity to those predicted by the Holtrop and Mennen method; however, the results improved with an increase in the fineness of the meshes. This study strongly indicates that the Holtrop and Mennen method is a highly accurate tool that can be used to validate data from CFD simulations. While a study by Emre et al. (2016) used the Holtrop Method to validate resistance results of CFD simulations for a Trawler hull form using Numeca FINE/Marine and Star-CCM+ software, and observed that the results from both Holtrop and Mennen resistance and CFD simulations were close estimates and followed identical curves. The fact that both results followed the same curve illustrated the capacity to support error modelling between the results from both methods, for improved accuracy. In agreement with Elhadad et al. (2023), it was also observed that the quality of the results obtained depended on the fineness of the mesh.

A study by Islam et al. (2022) compared scaled ship resistance and power prediction estimates from two CFD software, NavCAD and OpenFOAM, for three ship hull models, including two containers (KTC and DTC) and a tanker (KVLCC2), to results from three empirical methods,

including the series 60, Holtrop and Mennen, and Andersen. The results from empirical methods were very close to the results from CFD, with the maximum deviation being 3.7%; this highlights the capacity of empirical methods to validate high accuracy models like CFD. A comparison between the estimates of the three empirical methods concluded that the Holtrop and Mennen method provides better estimates for both resistance and propulsion. Based on the results of Elhadad et al. (2023), Emre et al. (2016), and Islam et al. (2022), it can be concluded that the results from the Holtrop and Mennen method are of high accuracy and can validate the results from CFD simulations; therefore, it was adopted for this research for validation.

2.3. HULL FORM OPTIMISATION

Optimisation is a quantitative numerical method of finding the best estimate to a set of linear and non-linear functions under stipulated conditions, constraints, and variable ranges that specify the feasible set of solutions (University of Washington, 2025). Hull form optimisation is design-based and it employs a combination of Computer-Aided Design (CAD), Computational Fluid Dynamics (CFD) solvers, and optimisation algorithms to develop, evaluate, and rank the fitness of design solutions to specified design objectives (Ang et al., 2015). The three main processes in hull form optimisation include parametric modelling, hydrodynamic performance evaluation, and objective fitness evaluation (Li et al., 2013).

2.3.1. PARAMETRIC MODELLING

Parametric modelling is the definition of the 3D hull model in terms of the ship's cardinal dimensions and parameters, with clear geometric relationships controlling the topology within the model and specific constraints controlling the allowable degree of freedom for deformation within the model (Zhou et al., 2022). Parametric modelling utilises the principal particulars of the ship as shown in Figure 3 to develop a constrained model that conserves the ship's most fundamental performance and operational requirements; however, parametric modelling can be either partial or fully parametric (Guha & Falzarano, 2015; Yang & Huang, 2016; Reis, 2022). Partial parametric modelling approaches are mainly used to achieve local deformation by using parameters to define specific components of the hull, which can be altered to develop optimum design solutions, while keeping other components constant (Reis, 2022). While fully parametric modelling is utilised to achieve global deformation by utilising parameters to define all hull components in terms of the principal parameters and integral properties such as volume and area (Reis, 2022).

Figure 3*Fundamental parameters for parametric modelling.*

Si #	Parameters	Sample values	Si #	Parameters	Sample values
1	Length	242	14	BulbLowerAngle	0.0
2	Beam	32.2	15	BulbUpperAngle	47
3	Draft	10.8	16	BulbUpperLength	7.0
4	PropellerClearance	11	17	SternI	0
5	BilgeRadius	3.0	18	SternII	4.0
6	Height	17	19	ParallelMidshipI	32.6
7	DeadRiseAngle	3	20	ParallelMidshipII	51
8	FlatOfSideAngle1	52	21	ParallelMidshipIII	55.2
9	FlatOfSideAngle2	60	22	FlatOfSideI	63.4
10	BulbWidth	4	23	FlatOfSideII	78.6
11	BulbLength	12	24	FwdShoulder	101.1
12	BulbHeight	8	25	BowContour	111
13	BowOverHangAngle	47			

Source: Guha & Falzaranoa (2015).

Effective parametric modelling should enable the flexibility of global and local deformation of hull forms, while conserving the constraints required of the final design, and also catering to the requirements of the ship owners to maintain its applicability for industry (Han et al., 2012). For the representation of curved surfaces, data sets representing segmented sections of the curve and defining the complete mathematical model underlying the curve are used, for example, using the B-splines and Non-Uniform B-Splines (NURBS) (Han et al., 2012). NURBS are considered the de facto standard for parametric modelling due to the high flexibility and ability to represent very complex shapes like hull forms. Its high precision allows for the exact representation of complex shapes without over-simplification, while high control delivered by nodes, weights, and vectors allows for precise control during deformation (J. H. Ang et al., 2015). A NURBS curve is defined in terms of the B-spline basis functions ($N_{i,p}$), control points (P_i), and weights of control points (w_i) as shown in Equation (16), while the representation of a NURBS surface of degree (p, q) can be defined in terms of B-Spline basis functions $N_{i,p}$ and $N_{j,q}$, control points ($P_{i,j}$), and weights of control points ($w_{i,j}$) as shown in Equation (17). Usually, the parametric model is structured as a collection of manifold faces described by vertices, edges, and faces for solid model representation (WOLFRAM, 2025a; WOLFRAM, 2025b).

$$C(u) = (\sum_{i=0}^n N_{i,p}(t) w_i P_i) / (\sum_{i=0}^n N_{i,p}(t) w_i) \quad (16)$$

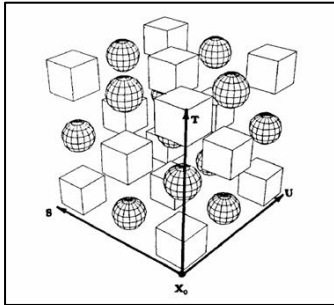
$$S(u) = (\sum_{i=0}^n \sum_{j=0}^m N_{i,p}(u) N_{j,q}(v) w_{i,j} P_{i,j}) / (\sum_{i=0}^n \sum_{j=0}^m N_{i,p}(u) N_{j,q}(v) w_{i,j}) \quad (17)$$

2.3.2. FREE FORM DEFORMATION (FFD)

Free Form Deformation (FFD) is a technique for the manipulation of solids in parametric modelling for local or global modification of surfaces based on underlying constraints and degrees of freedom (PyGEM, 2021; Sederberg & Parry, 1986). Local FFD utilises one or a group of control points to alter the position of the curve or surface, which disturbs the positions of the immediate neighbourhood, causing a prediction of a new best-fit curve or surface (PyGEM, 2021). In contrast, global FFD utilises the total set of control points within the design to alter the positions of various points on the curve or surface, based on a specified position of relocation of a chosen control point, thus causing a prediction of a new curve or surface as the best-fit for the whole range of data (Sederberg & Parry, 1986). To illustrate FFD, consider the local coordinate system shown in Figure 4 with axes S, T, U, and origin X_0 . Any point, X, within this 3D space can be referenced with coordinates (s, t, u), defined as shown in Equations (18) and (19) (Prochazkova, 2017; Sederberg & Parry, 1986).

Figure 4

An illustration of a local coordinate system with axes S, T, and U.



Source: Sederberg & Parry (1986).

$$X = X_0 + sS + tT + uU \quad (18)$$

$$s = \frac{T*U(X-X_0)}{T*U.S}, t = \frac{S*U(X-X_0)}{T*U.T}, u = \frac{S*T(X-X_0)}{S*T.U} \quad (19)$$

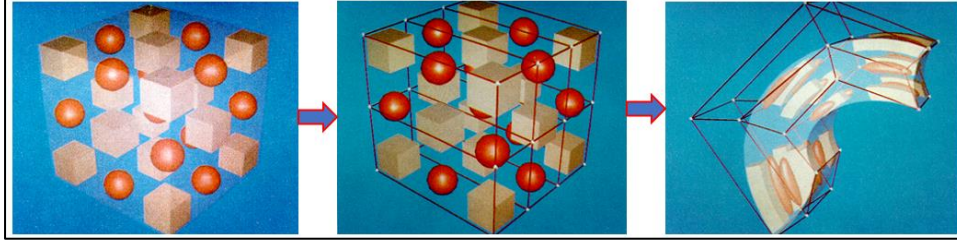
A grid of control points P_{ijk} defined by Equation (20) can be imposed as a lattice, to form $t+1$ planes in the S direction, $m+1$ planes in the T direction, and $n+1$ planes in the U direction. FFD can therefore be undertaken by moving point P_{ijk} from its position on the lattice to a new position X_{ffd} defined by Equation (21), within the 3D space. This is done by fitting a deformation function based on the trivariate tensor product Bernstein polynomial to predict the new positions of control points. Consequently, the surface within the lattice is stretched to fit the derived curve, as shown in Figure 5.

$$P_{ijk} = X_0 + \frac{i}{l}S + \frac{j}{m}T + \frac{k}{n}U \quad (20)$$

$$X_{ffd} = \sum_{i=0}^l \binom{l}{i} (1-s)^{l-i} s^i \left[\sum_{j=0}^m \binom{m}{j} (1-t)^{m-j} t^j \left(\sum_{k=0}^n \binom{n}{k} (1-u)^{n-k} u^k P_{ijk} \right) \right] \quad (21)$$

Figure 5

An illustration of the deformation process.



Source: Sederberg & Parry (1986).

There are three general ways to implement shape alteration using parametric approaches, including the basis shape approach, the discrete approach, and the polynomial and spline approach (Koshakji et al., 2013). The basis shape approach uses a set of parameters defining the geometry and topology of the 3D solid to modify the shape and surface of that entity (Koshakji et al., 2013). Linear and non-linear relationships between model elements, for example, vertices, splines, polylines, and nodes, are defined, and they set the allowable degree of freedom. The basis shape approach has the advantage of being able to strongly maintain geometric relationships, with the ease of production of smooth shapes, and high support for multi-objective optimisation (Samareh, 1999). Additionally, it requires significantly fewer computing resources as compared to the discrete, and the polynomial and spline approach; however, it may be challenging to describe non-linear geometric relationships.

The discrete approach uses boundary points forming a lattice of structured offset points, engulfing the shape of interest, to guide positional alteration and prediction of the optimal surface (Koshakji et al., 2013). The discrete approach is easy to implement, but it requires high computational resources. It requires a large set of design variables to maintain a smooth surface, due to the high degree of freedom within the control lattice. The difficulty in maintaining a smooth surface and the large number of design variables required reduce the feasibility of adaptation to real-world optimisation problems without over-simplification (Koshakji et al., 2013; Mohammadi & Pironneau, 2001).

The polynomial and splines approach leverages control points along splines and polynomials to predict positions of the modified surface, thus greatly reducing the total number of design

variables required to maintain a smooth surface as compared to the discrete approach (Koshakji et al., 2013). This approach is widely used, as it has less computational cost as compared to the discrete approach, and samples a wider design space as compared to the basis shape approach. However, for complex designs or surfaces, it can be difficult to fit polynomials or splines without discontinuities that may affect the smoothness or consistency in the modified shapes (Berkenstock et al., 2024).

For this research, the basis shape approach was employed to modify the initial hull. Its low computing requirements in comparison to other approaches gave the flexibility to implement deformation with limited resources, while exploring the design space within prescribed parameter limits. Additionally, the basis shape approach's ability to conserve geometric relationships ensured that desired design properties are conserved, which reduced variables in the optimisation problem, therefore making the process simpler.

2.3.3. OPENFOAM

OpenFOAM is an open-source Computational Fluid Dynamics (CFD) software designed to solve complex fluid flows through performing simulations to evaluate fluid behaviours under set conditions (Haddadi, 2025; Shahzad, 2017). It is a collection of engineering libraries that predict flow behaviours for laminar and turbulent flows of compressible and incompressible fluids with transient and steady-state conditions (Shahzad, 2017). OpenFOAM incompressible solvers compute Reynolds Average Navier-Stokes Equations (RANS) to solve pressure-velocity computations in transient or steady-state conditions (Haddadi, 2025).

OpenFOAM transient solvers are time-variant and utilise the Pressure Implicit with Splitting of Operators (PISO) algorithm to solve the continuity equation shown in Equation (22), and the momentum equation shown in Equation (23) related to kinematic pressure (p) and velocity (u) (OpenCFDLtd, 2024). While steady state solvers maintain the same conditions throughout simulation and use the Semi-Implicit Method for Pressure Linked Equations (SIMPLE) to solve the continuity equation shown in Equation (22) and momentum equation shown in Equation (24) related to kinematic pressure (p), velocity (u), stress tensor (R) and momentum source (S_u) (OpenCFDLtd, 2024).

$$\nabla \cdot u = 0 \tag{22}$$

$$\frac{\partial}{\partial t}(u) + \nabla \cdot (u \cdot u) - \nabla \cdot (\nu \nabla u) = -\nabla p \tag{23}$$

$$\nabla \cdot (u \cdot u) - \nabla \cdot R = -\nabla p + S_u \quad (24)$$

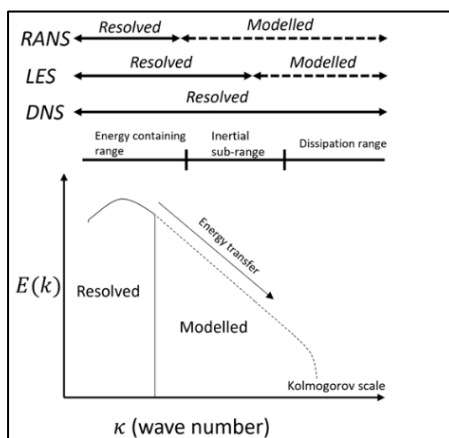
The OpenFOAM software was used by Cordier et al. (2017) to perform flow simulation around the hull of a low-speed hull form (dredger) and a high-speed hull form (cruise vessel) at varying speeds. The results were compared to those from a commercial CFD software, SHIPFLOW, and towing tank tests to assess their accuracy. The deviation between the results of OpenFOAM and the towing tank test was between 1% and 3%, while for SHIPFLOW, it was between 1% and 4%. This highlights that OpenFOAM can produce very high accuracy results to support marine flow studies with computational models that closely represent the actual conditions.

2.3.4. TURBULENCE MODELING

Turbulence modelling is the prediction of chaotic and unsteady fluid flow, which is characterised by a wide range of interacting vortical structures using numerical simulation (IdealSimulations, 2022). It tracks how energy cascades from eddies to small-scale dissipation by converting kinetic energy into thermal energy through viscous effects. Fluid flows over a solid boundary create a boundary layer with turbulent properties; therefore, turbulence modelling is essential for accurate prediction of total resistance (IdealSimulations, 2022). There are three main turbulence models used within Computational Fluid Dynamics (CFD), including the Direct Numerical Simulations (DNS), the Large Eddy Simulation (LES), and the Reynolds Averaged Navier-Stokes (RANS), as shown in Figure 6.

Figure 6

An illustration of the resolution and modelling ranges for DNS, LES, and RANS.



Source: Fidelis (2024).

The DNS method solves for turbulence without modelling, by direct application of the Navier-Stokes Equations (IdealSimulations, 2022). The DNS method provides the most accurate CFD solutions (Fidelis, 2024). However, the DNS requires a very fine spatial and temporal

resolution, and high computational resources; therefore, it is not feasible for complex industrial applications. The LES method resolves large eddies and models small eddies, thus reducing computation cost as compared to the DNS (Fidelis, 2024). The LES method is more accurate than the RANS method; however, it requires very high computational resources and time as compared to RANS (Fidelis, 2024; IdealSimulations, 2022). The RANS method models turbulence as the averaged result of the Navier-Stokes Equations, which reduces the computational cost compared to DNS and LES (Fidelis, 2024; IdealSimulations, 2022); however, there is a reduction in accuracy in comparison to DNS and LES (Fidelis, 2024). The RANS method is the most widely used due to its moderate requirement for computing resources and high accuracy.

The RANS method can be implemented with both the K-Omega standard model ($k-\omega$) and the K-Omega Shear Stress Transport ($k-\omega$ SST) model for improved accuracy. The $k-\omega$ turbulence model depends on the turbulent kinetic energy (k) and specific dissipation rate (ω) to predict turbulence within the boundary layer (Wilcox, 1988). While the $k-\omega$ SST depends on the turbulent kinetic energy and dissipation rate, with extensions to capture flow separation close to the wall, and to overcome the dependency on the free stream values of k and ω (OpenCFDLtd, 2024b). The $k-\omega$ SST model is more accurate than the $k-\omega$ model (Shahzad, 2017); however, it requires more computational modelling. The RANS method with the $k-\omega$ SST model was chosen for this research due to its moderate requirement of computing resources as compared to DNS and LES, and high accuracy adequate for design operations (IdealSimulations, 2022).

2.3.5. GENETIC OPTIMISATION ALGORITHM

Optimisation is the determination of the minimum or maximum fitness solution to a given problem (Carr, 2014). The three main traditional types of optimisation methods are calculus-based, exhaustive search, and random search (Carr, 2014; Goldberg, 1989). Calculus-based methods are gradient-based, and they determine the local minima and maxima solutions by following changes in the gradient, directly or indirectly (Carr, 2014; Goldberg, 1989). Gradients describe how small changes in the input affect the objective function, and point to the direction of the steepest ascent or descent (Antoniadis, 2024). Calculus-based methods have the advantage of being well established, and are quick at finding local optimum solutions; however, they search for local optima instead of global solutions, and can be insufficient for

cases where the global neighbourhood is unknown or where multiple optima occur nearby (Carr, 2014).

Exhaustive search algorithms determine global optima by undertaking an exhaustive search of all values within the design space for a given objective function (Carr, 2014). These rely on the definition of a finite or infinite discretised search space, defining all possible values for each parameter, on which the fitness evaluation is undertaken (Goldberg, 1989). Exhaustive algorithms have the advantage that they determine a very accurate global representation of the design space since they exhaust all possible alternatives. However, they are the least efficient, and they require too much time and computing resources, since in most cases, the design spaces are vast with multiple parameters (Carr, 2014; Goldberg, 1989).

In contrast, random search optimisation methods are derivative-free methods that determine optimum solutions by iteratively sampling values within the design space, and convergence depends on the probability that samples are close to the optima (Carr, 2014; Zabinsky, 2009). These undertake a broad exploration of random samples within the design space, after which, exploitation by refinement of the best-fit solutions is undertaken to determine optima (Carr, 2014; Zabinsky, 2009). Random search methods can employ random search techniques to sample solutions randomly across the design space, and adaptive search techniques to adjust the search strategy based on previous evaluations to determine where the high probability areas occur for future sampling (Zabinsky, 2009).

Random sampling methods have the advantage of being simple, more practical, and being able to determine optima much quicker than exhaustive search optimisation at comparable accuracy, and at reduced time and computing resources (Zabinsky, 2009); however, the drawback is that the optimum solutions depend on the probability that samples are close to the optima. Additionally, they are easier to implement for complex problems, since they depend on objective function evaluation rather than gradients and Hessian matrices (Zabinsky, 2009). A Hessian matrix is a square matrix of second-order partial derivatives of a scalar-valued function, describing how a gradient varies with respect to changes in parameter values (Chugh, 2025). Examples of random search optimisation methods include pure random search, simulated annealing, genetic algorithms, particle swarm optimisation, ant colony optimisation, and cross-entropy method.

Genetic algorithms are based on the evolutionary principle, where a population evolves iteratively by retaining members that meet required fitness criteria for a given objective

function (Carr, 2014; Guha & Falzaranoa, 2015). The objective functions, also referred to as fitness functions, are the criteria against which each design alternative is iteratively evaluated to determine optima (Carr, 2014; Guha & Falzaranoa, 2015). Genetic algorithms mimic the biological evolution process based on an initial randomly sampled population from the design space. Through crossover to swap over parameter values, and mutation to randomly change parameter values, a new population is created for further evaluation (Carr, 2014).

Genetic algorithms can be single or multi-objective, requiring the minimization or maximization of objective functions, subject to specific constraints that describe the degrees of freedom within the design space (Guha & Falzaranoa, 2015). For multi-objective optimisation, design solutions are represented using a Pareto front, showing a set of solutions where one objective cannot be improved without making the others worse, called the Pareto optimal solutions (Coello et al., 2007). This research explores the application of multi-objective genetic algorithms for hull form optimisation of the Japan Bulk Carrier.

2.4. PROPULSION AND GHG EMISSIONS

2.4.1. POWER REQUIREMENTS

Propulsive power, also described as the effective power (P_E), is the power required to tow the ship at a given speed in calm water conditions (Molland et al., 2017). Propulsive power estimates are the basis for the estimation of a ship's fuel and operating costs (Molland et al., 2017). Propulsive power estimates depend on the characteristics of the chosen propulsion system, and can be determined through model experiments, the use of standard series data, theoretical methods, and data from similar existing systems (Molland et al., 2017). Theoretically, propulsive power requirements are computed by the evaluation of the power delivered, propulsive efficiency, and the brake power. The power delivered, (P_D) can be derived from the effective power (P_E) and propulsive efficiency (η_D) as shown in Equation (25), while propulsive efficiency (η_D) can be defined as the product of the open water efficiency (η_o), the hull efficiency (η_H) and the relative rotative efficiency (η_R) as shown in Equation (26).

$$P_D = P_E / \eta_D \quad (25)$$

$$\eta_D = \eta_o * \eta_H * \eta_R \quad (26)$$

The Hull efficiency (η_H) can be derived from the thrust deduction factor (t) and wake fraction (W_T) as shown in Equation (27). And, for single screw ships, using the block coefficient (C_B),

the thrust reduction factor (t) is estimated as shown in Equation (28), and the wake fraction (W_T) is estimated using Harvald's approximation as shown in Equation (29).

$$\eta_H = \frac{(1-t)}{(1-W_T)} \quad (27)$$

$$t = 0.5 * C_B - 0.1 \quad (28)$$

$$W_T = 0.7 * C_B - 0.1 \quad (29)$$

Since computations in the design phase mostly utilise scaled models, the model's power delivered (P_{Dm}) is scaled to derive the corrected ship power delivered (P_{Ds}) as shown in Equation (30), using the scale correction factor (scf). Using the ship power delivered (P_{Ds}) and transmission efficiency (η_T), the brake power (P_B) requirement can be estimated as shown in Equation (31). Finally, the fuel consumption (FC) can be estimated from brake power (P_B) and specific fuel consumption (SFC) as shown in Equation (32). However, for realistic fuel consumption estimates, three main corrections due to changing draughts, weather conditions, and speed fluctuations at different maritime zones have to be considered (Bialystocki & Konovessis, 2016).

$$P_{Ds} = P_{Dm} * scf \quad (30)$$

$$P_B = P_{Ds} * (1/\eta_T) \quad (31)$$

$$FC = P_B * SFC \quad (32)$$

2.4.2. FUEL CONSUMPTION MODELS

According to Stopford (2008), fuel consumption accounts for up to 50% of all operating expenses for any given voyage. This indicates that operational costs are highly sensitive to a ship's fuel consumption behaviour, where even small changes significantly affect profitability. Additionally, the choice of bunker fuel is directly linked to the quantity of CO₂ emissions from the ship, as it depends on the fuel's carbon factor and quantity consumed (IMO, 2023a). Therefore, a reduction in fuel consumption directly reduces operating costs and CO₂ emissions for any given ship. The main factors influencing a ship's fuel consumption include voyage distance, weather conditions, hull roughness, propeller condition, draught, and speed (Bialystocki & Konovessis, 2016).

The three ship fuel consumption models include the White Box Model (WBM), Black Box Model (BBM), and Grey Box Model (GBM) (Fan et al., 2022; K. Wang et al., 2022). The WBM

is based on the mechanical analysis of the floating state and hydrodynamics for a given ship. Fuel consumption estimates are based on the properties of the engine, transmission efficiency, and the total resistance of the ship's hull (Yan et al., 2021). The complete analysis of factors affecting fuel consumption during a voyage can be complex, and often simplified for easier handling of the WBM, hence making it more implementable (Yan et al., 2021); however, for extreme voyage conditions, the prediction accuracy can be low (Wei et al., 2021; Yan et al., 2021). For accuracy improvement, ship resistance can be evaluated in differing weather and sea conditions applied depending on the percentage of the voyage taking up specified conditions (Fan et al., 2022; K. Wang et al., 2022).

The BBM relies on data analysis through a combination of statistical and machine learning models (Xie et al., 2023). Statistical models based on regression with probabilistic approaches are used to determine the relationship between fuel consumption and variables, while approximation functions are used by machine learning models to estimate fuel consumption with a level of ambiguity (Xie et al., 2023). Both statistical and machine learning models are complex to implement and require a large volume of data as compared to the WBM, and the relationships between various factors affecting fuel consumption are derived from the data (Xie et al., 2023). The BBM has a higher accuracy due to the capacity to represent complex relationships between fuel consumption and factors such as wind, weather, and waves at sea that require high-dimensional models (Xie et al., 2023). The two major disadvantages of the BBM are the inability to explain the internal workings of the machine learning models and the need for large volumes of data (Xie et al., 2023).

The GBM applies both mechanical modelling and data analysis, relying on hydrodynamics, and parameters adjusted with actual operational data to improve the accuracy (Ma et al., 2023). It uses a mix of the WBM and BBM, introducing the BBM to explain relationships that cannot be modelled with WBM (Coraddu et al., 2017). The GBM is more accurate than both the WBM and BBM, while being faster than the BBM (Ma et al., 2023), and it limits the ambiguity within computations while reducing the amount of data required by the BBM (Coraddu et al., 2017); however, it requires significantly more computing resources than the WBM (Ma et al., 2023).

This research utilised the WBM, relying on resistance and power estimates from CFD and statistical analysis of external factors, including distance, fuel price, and ocean zones, to predict fuel consumption. The WBM was chosen because it requires less data in comparison to GBM and BBM, while still delivering high accuracy of estimates.

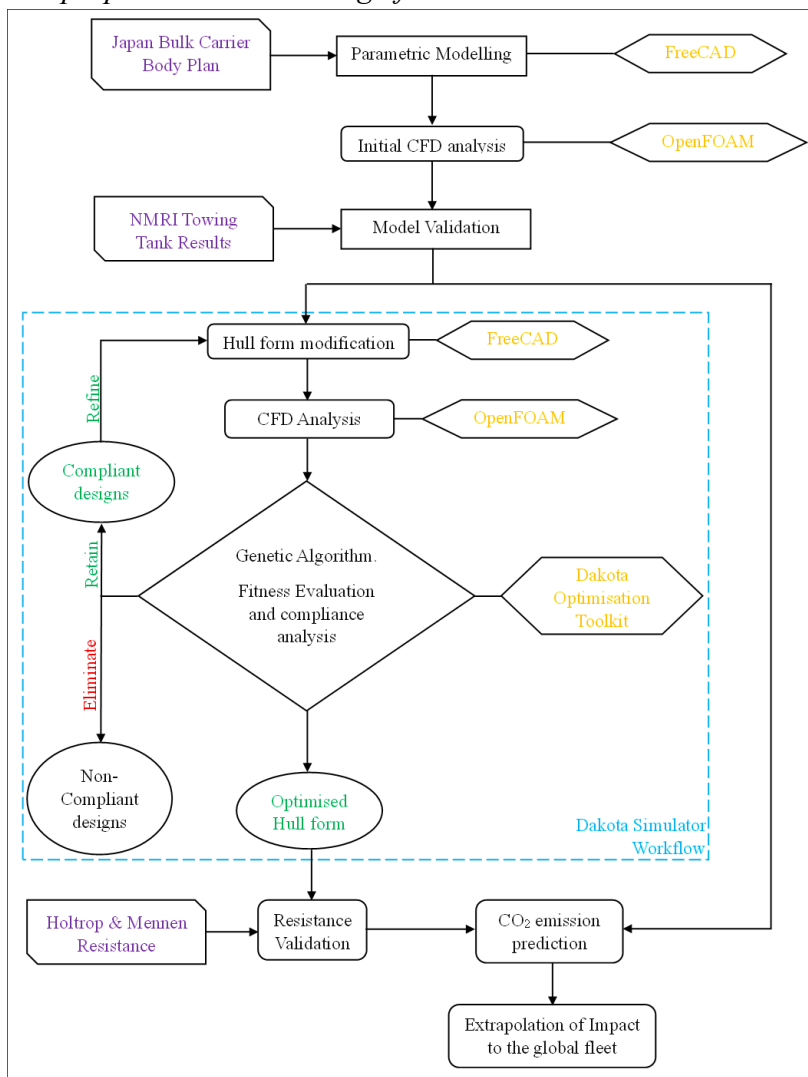
3. METHODOLOGY

3.1. RESEARCH METHODS

This research utilised quantitative methods, including hull form optimisation, hydrodynamic performance analysis, and impact evaluation to predict optimised hull designs and fuel consumption, and to assess CO₂ emissions. The study employed integrated numerical, graphical, and statistical techniques using tools such as Computer-Aided Design (CAD), Computational Fluid Dynamics (CFD), and Multi-Objective Genetic Algorithms to model and interpret hydrodynamic performance, economic, and CO₂ emissions patterns. The methodology's workflow sequence detailing the data, tools, and analytical steps used is shown in Figure 7.

Figure 7

The proposed research design flow chart.



Source: Author.

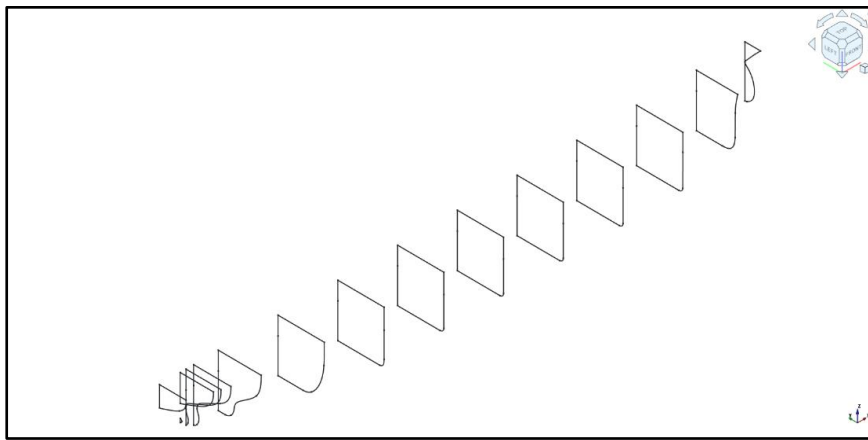
3.2. METHODOLOGY

3.2.1. HULL MODELLING AND MESHING

The parametric modelling of half of the hull of the JBC ship model (Nobuyuki, 2015) was undertaken in FreeCAD software, at the scale of 1:40, to reduce the computational requirements at later stages. Fourteen main sections were created along the ship's centre line, and section curves were digitized along the hull surface of the JBC ship, as shown in Figure 8. Additional sections at the bulbous bow were recreated, as described in the later section 3.3.4.3.

Figure 8

Sections representing half of the JBC hull.

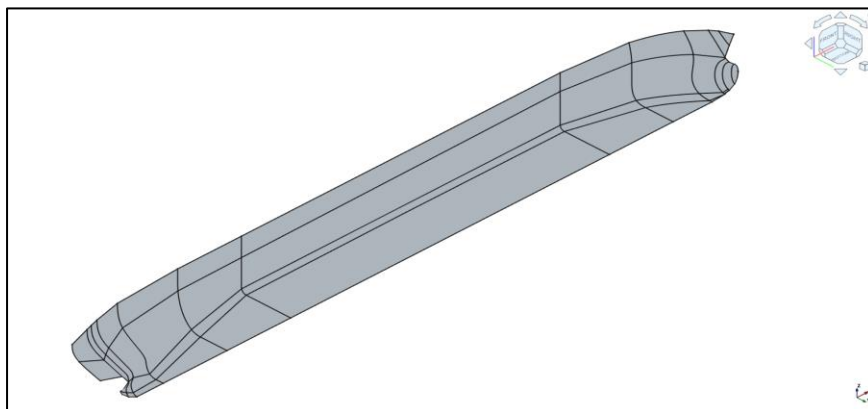


Source: Author.

Constraints for each section curve were defined to describe the geometric, and dimensions were linked to the principal parameters of the JBC ship. The sections were then lofted to generate the surface of the watertight 3D model of half of the JBC ship, as shown in Figure 9. The surface of the parametric model was then refined for smoothness.

Figure 9

Parametric 3D model of half of the hull.

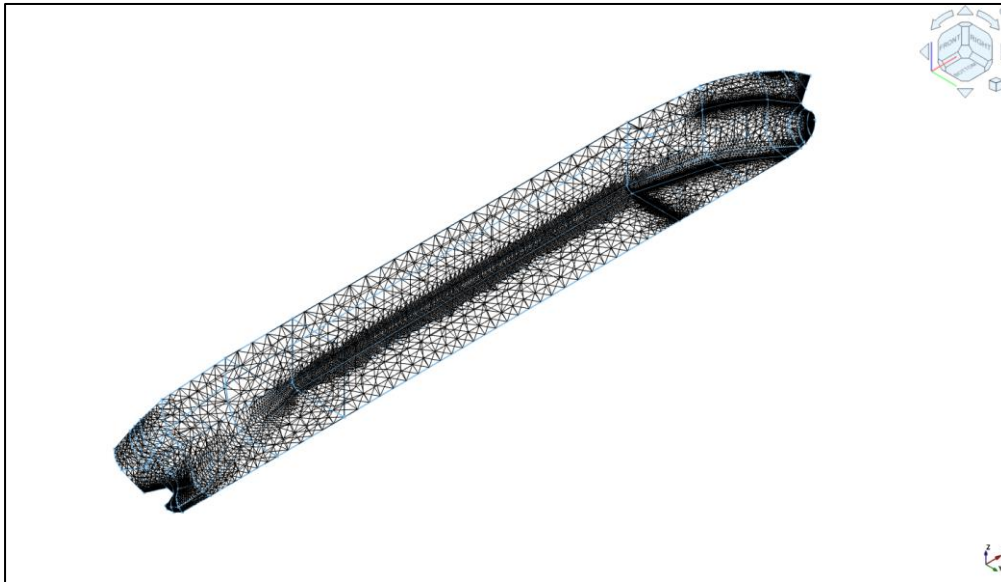


Source: Author.

A geometry check was undertaken to verify that no errors were compiled within the developed model. The parametric model's surface was then meshed by tessellation to a very fine level, as shown in Figure 10. The meshed parametric model was then exported as a Stereolithography (STL) file to enable validation of the model and for initial hydrodynamic performance analysis.

Figure 10

Tessellated 3D mesh of the parametric JBC model.



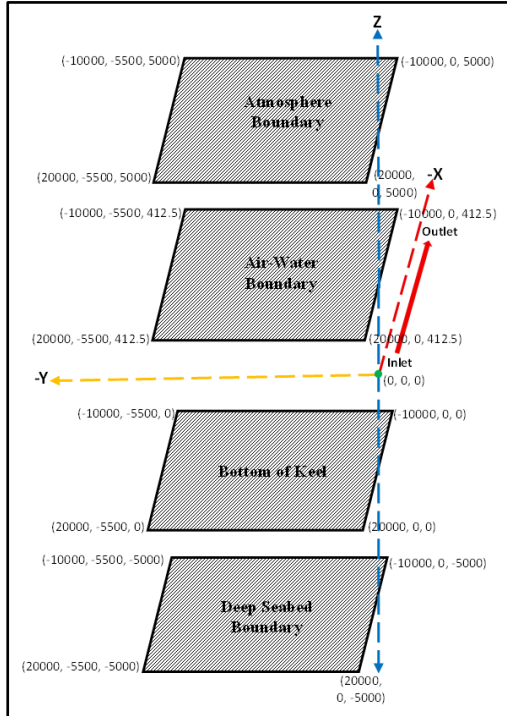
Source: Author.

3.2.2. CFD COMPUTATIONAL DOMAIN

The computational domain simulated multi-phase fluid flow of an air-water system representing the open sea. The bounding box with minimum $(-10, -5.5, -5)$, and maximum $(20, 0, 5)$, was considered after a mesh independence study with varying domain sizes to ensure the simulation results were independent of the size of the computational domain. The inlet face was stationed adjacent to the bow, while the outlet face was adjacent to the stern. The orientation within 3D space, boundary planes, and coordinates of the edges of the computational domain are illustrated in Figure 11. To ensure adequate capture of water-air interaction, the divisions within zones hosting the air-water boundary were increased, and further refinement using OpenFOAM's snappyHexMesh utility was used to refine regions around the sharp edges of the hull surface. The mesh divisions used for the x, y, and z axes were 100, 60, and 60, respectively; while the grading for the three zones was $(1, 1, 0.2)$, $(1, 1, 0.5)$, and $(1, 1, 1)$, respectively.

Figure 11

Planes representing the boundaries of the CFD computational domain.



Source: Author.

3.2.3. INITIAL CFD ANALYSIS AND BASELINES

3.2.3.1. SIMULATION CONSTANTS

The reference height for the water-air free surface was set at 0.4125m. The surface tension for the water-air free surface was set to 0.072N/m. The following assumptions were made to define the conditions at sea for water and air:

- The water and air phases are Newtonian fluids, with constant viscosity.
- The density of seawater is 1025.068 kg/m³.
- The density of air at sea is 1.225 kg/m³.
- The average temperature is 15 °C.
- Acceleration due to gravity is 9.81m/s².
- Kinematic viscosity of air is 1.48*10⁻⁵m²/s.
- Kinematic viscosity of water is 1.1892×10⁻⁶m²/s.

3.2.3.2. SCALING VELOCITY, PRESSURE, AND TIME TO MODEL

Scaling velocity depends on preservation of Froude number and the appropriate application of physical principles governing the free-surface flow, to ensure similarity in wave and gravity driven effects. The Froude number is defined using velocity (U), acceleration due to gravity

(g), and the Length of the hull (L), as shown in Equation (33). According to the Froude model law, the Froude number of the model should be similar to the Froude number of the full ship, as shown in Equation (34). Therefore, the relationship between model and full ship is described as shown in Equation (35), and simplified to involve scale (full length of ship, L_{full} to model ship length L_{model}), as shown in Equation (36), to estimate model speed. Similarly, the time can be scaled by Equation (37). Additionally, the atmospheric pressure, which is the force per unit area exerted onto the water surface by the atmosphere, was scaled using Equation (38) from 101,325Pa at full scale to 2,533.125Pa at model scale.

$$Fr = U / \sqrt{gL} \quad (33)$$

$$\frac{L_{full}}{L_{model}} = 40 \quad (34)$$

$$U_{full} / \sqrt{g * L_{full}} = U_{model} / \sqrt{g * L_{model}} \quad (35)$$

$$U_{model} = U_{full} / \sqrt{\frac{L_{full}}{L_{model}}} \quad (36)$$

$$t_{model} = t_{full} \sqrt{\frac{L_{full}}{L_{model}}} \quad (37)$$

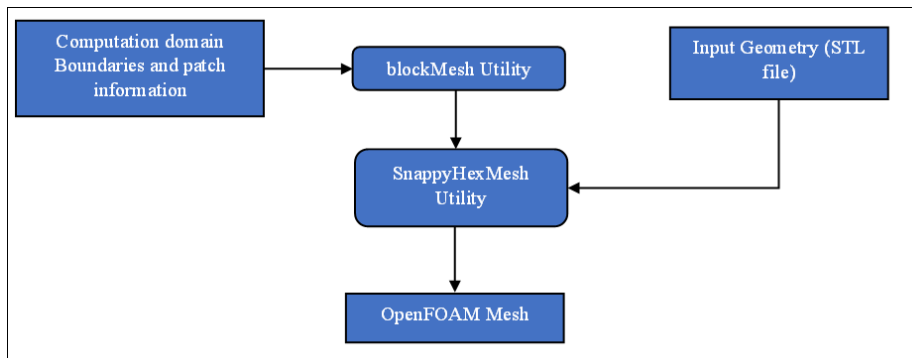
$$P_{model} = P_{full} / 40 \quad (38)$$

3.2.3.3. COMPUTATIONAL DOMAIN MESHING

The blockMesh and snappyHexMesh utility tools from OpenFOAM were used for meshing using the workflow shown in Figure 12.

Figure 12

Workflow for meshing with BlockMesh and snappyHexMesh.

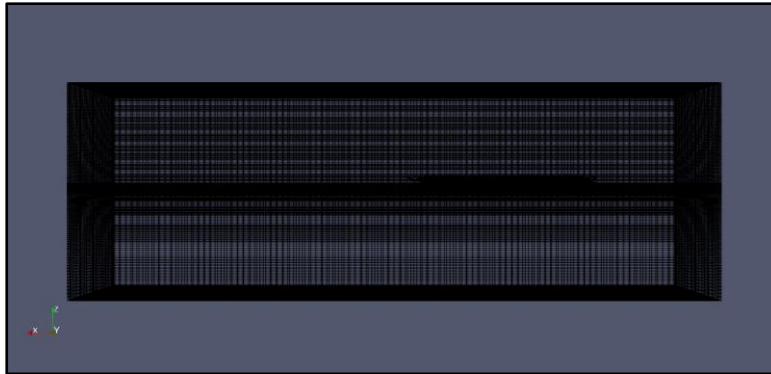


Source: Author.

The blockMesh utility was used to generate a rectangular mesh of the computational domain, as shown in Figure 13, with edges minimum $(-10, -5.5, -5)$, and maximum $(20, 0, 5)$, and the number of cells in each direction set as $n_x = 100$, $n_y = 60$, and $n_z = 60$. The grading factors used for mesh below draught line were $g_x = 1$, $g_y = 1$, and $g_z = 0.2$, to ensure that the cells are finer towards the water line, at the waterline, $g_x = 1$, $g_y = 1$, $g_z = 0.5$, for a finer mesh to capture air-water and hull-water interactions. Above the waterline, $g_x = 1$, $g_y = 1$, $g_z = 1$ to ensure that cell size is maintained from the top of the atmosphere towards the waterline to reduce computational resources needed. The blockMesh utility is controlled by the blockMeshDict file attached in Appendix 1.

Figure 13

The background mesh of the computational domain.

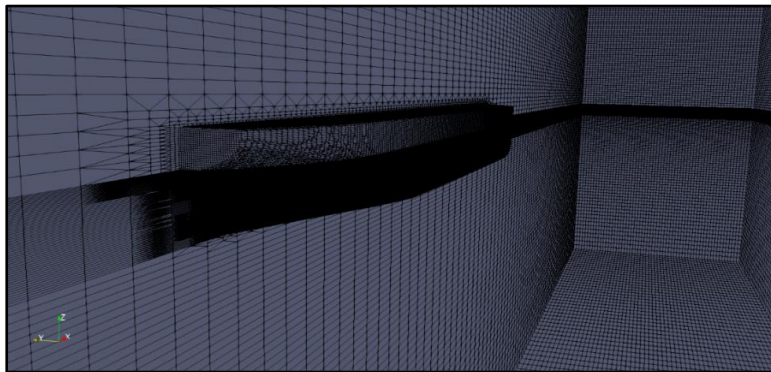


Source: Author.

The snappyHexMesh utility used the background mesh created by blockMesh and the input geometry, the Stereolithography (STL) file for the parametric model, to refine the mesh around sharp edges. The snappyHexMesh utility controls are contained within the snappyHexMeshDict file attached in Appendix 1. The result of the meshing process is shown in Figure 14.

Figure 14

Resultant fused mesh of hull and computational domain from meshing.



Source: Author.

3.2.3.4. CFD SOLVER

The OpenFOAM Volume of Fluid (VOF) incompressible solver interFoam was chosen for the two-phase air-water flow simulation. This solver is designed to handle multiphase flows of incompressible immiscible fluids, which applies to this case. The solver also has the ability to accurately model the interactions at the hull-water interface. The boundary conditions for pressure (P) and velocity (U) files were described as shown in Table 1. The P and U files forming the OpenFOAM setup are attached in Appendix I.

Table 1

Boundary conditions for pressure and velocity.

Patch no.	Boundary	Velocity	pressure
0	inlet	fixedValue	zeroGradient
1	outlet	inletOutlet	zeroGradient
2	atmosphere	pressureInletOutletVelocity	prghTotalPressure
3	bottom	slip	zeroGradient
4	Side	symmetryPlane	symmetryPlane
5	midPlane	symmetryPlane	symmetryPlane
6	hull	fixedValue	zeroGradient

Source: Author.

Turbulence modelling was undertaken to simulate the interactions of particles within the boundary layer. Turbulence modelling was simulated using the Reynolds Averaged Simulation (RAS) employing the k-omega Shear Stress Transport (komegaSST) model. The boundary conditions for the computational domain boundaries in the turbulent kinetic energy file (k), turbulent viscosity (ν_t) file, and specific dissipation rate (ω file) were as shown in Table 2.

Table 2

Boundary conditions for k , ν_t , and ω .

Patch no.	Boundary	K	ν_t	Omega
0	inlet	fixedValue	calculated	fixedValue
1	outlet	inletOutlet	calculated	inletOutlet
2	atmosphere	inletOutlet	calculated	fixedValue
3	bottom	fixedValue	calculated	fixedValue
4	Side	symmetryPlane	symmetryPlane	symmetryPlane
5	midPlane	symmetryPlane	symmetryPlane	symmetryPlane
6	hull	kqRWallFunction	nutkRoughWallFunction	omegaWallFunction

Source: Author.

3.2.3.5. POSTPROCESSING AND VALIDATION

The results from the OpenFOAM simulation were visualised in ParaView software to review the evolution of the interaction of the hull surface with water, and to monitor the changes in the water-air interface. The dynamic pressure, P_{rgh} , defined as the total pressure acting on a given surface (p) minus the hydrostatic component, was used as the main statistic for initial design evaluation. To compute the total resistance on the hull surface in the x-direction, a sum of viscous and pressure forces in the x-direction was computed, and validation was done by comparison to results from NMRI (2015b). The Initial results were then set as baseline values for further analysis.

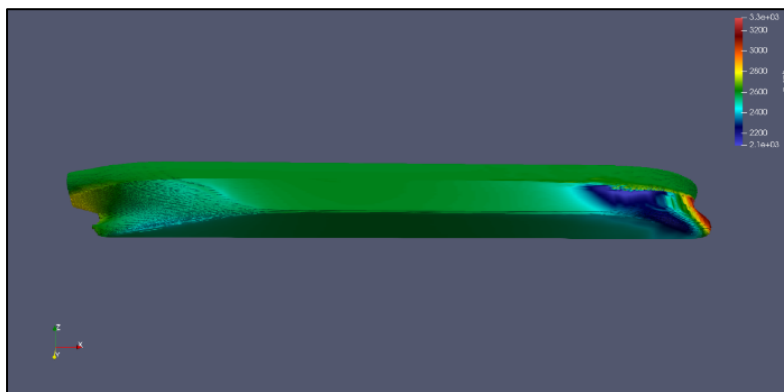
3.2.4. HULL ALTERATION AND OPTIMISATION

3.2.4.1. IDENTIFICATION OF IMPROVEMENT AREAS

The dynamic pressure (P_{rgh}) was analysed using the results of the initial hydrodynamic performance analysis, as shown in Figure 15. The analysis revealed that the bow section experiences the highest dynamic pressure, especially at low speeds. At the bulb area, particle streams were deflected towards the bottom of the ship; however, with an initial upward deflection to create a wave on the water surface. This created an enlarged region of high dynamic pressure at the bulb.

Figure 15

A visualisation of dynamic pressure changes over the JBC hull.



Source: Author.

The effects of the pressure force at the bulb can be explored by optimising the bulb depth (Z_b), which influences the bulb entry angle that directs the flow of particles on the hull surface. To address this possibility, the research focused on the adjustment and deformation of the bulb section by altering the location of the bulb depth (Z_b), to investigate if a reduction in the dynamic pressure and total resistance of the model can be achieved.

3.2.4.2. PROBLEM FORMULATION

The main objectives are to maximize the reduction in total resistance (R_T), and to minimize the loss in Displacement (D) for the Japan Bulk Carrier (JBC) by optimizing the bulb depth (Z_b) and vessel speed (U_m), while ensuring that there is minimal change in the position of the centre of gravity (CoG) to maintain stability properties. The changes in displacement were constrained to $\pm 1\%$ to conserve the cargo capacity, and the change in centre of gravity was constrained to $\pm 0.05\%$, while the range of the bulb depth was 0.19054m to 0.3m. The total resistance (R_{TM}) can be expressed in terms of bulb depth (Z_b), the height of the foremost point of the bulbous bow from the bottom of the ship, and vessel speed (U_m), as shown in Equation (39). The objective function (1) is defined as the fractional change in the total resistance of the modified hull form (R_{TM}) as compared to the initial hull form (R_{TI}), expressed as ΔR_T , as shown in Equation (40). While the objective function (2) can be expressed as the fractional change in the displacement of the modified hull form (D_M) as compared to the initial hull form (D_I), expressed as ΔD , as shown in Equation (41). The constraints on change of displacement and centre of gravity, and range of values for Z_b , and U_m are shown in Equations (42), (43), and (44). A sensitivity study was undertaken for parameters Z_b and U_m to determine the impact of a change of each parameter on the total resistance and displacement estimates.

$$R_{TM} = f(Z_b, U_m) \quad (39)$$

$$\text{Objective (1)} = (R_{TM} - R_{TI})/R_{TI} = \Delta R_T \quad (40)$$

$$\text{Objective (2)} = (D_M - D_I)/D_I = \Delta D \quad (41)$$

With constraints:

$$\Delta D = \pm 1\% \quad (42)$$

$$\Delta \text{CoG} = \pm 0.05\% \quad (43)$$

$$0.19054 \leq Z_b \leq 0.3, \text{ and } 0.98 \leq U_m \leq 1.27 \quad (44)$$

3.2.4.3. DESIGN SPACE

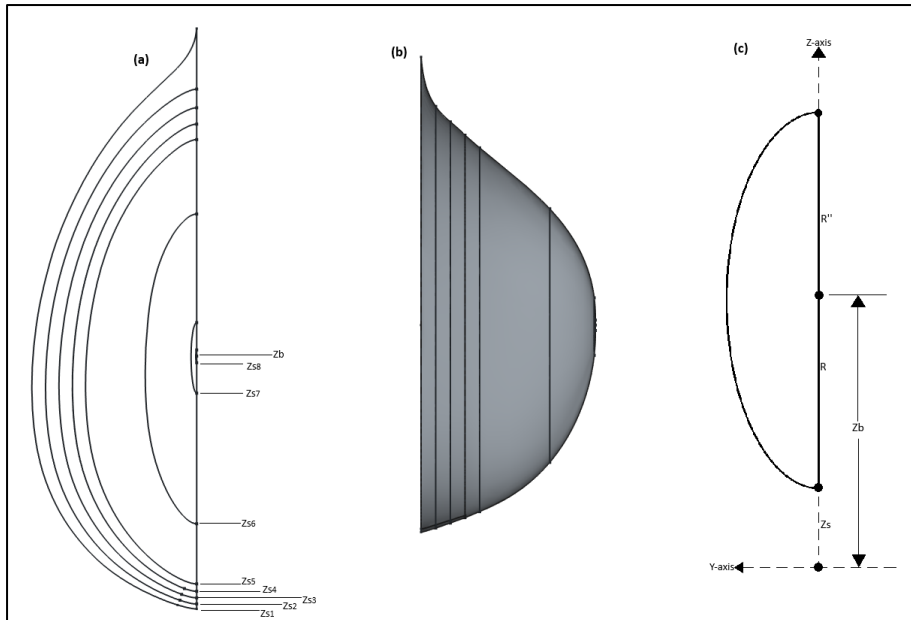
The potential hull forms were explored by altering values of the bulb depth (Z_b) for local deformation of the bulb using the parametric model. A lattice engulfing the local region for refinement with bounding box maximum (3.49984, 0, 0.42008), minimum (3.64898, -0.1156, 0.01333), was defined to limit deformation to the specified region. Eight sections were defined

to guide the deformation at various regions of the bulb and to maintain geometry and topology, as shown in Figure 16 (a) and (b).

Each section was defined as an ellipse with four major parameters including Z_s , the vertical distance between bottom of ship and bottom of section, Z_b , the vertical distance coinciding with the height of the foremost bulb point from the bottom of ship, R , the vertical distance from the bottom of a section to the position Z_b , and R'' , the difference between the vertical diameter, d , of section measured from bottom of a section to top of section, and the value of R as shown in Figure 16 (c). The Parameter d was used to define the sum of initial values of R and R'' .

Figure 16

Parametric sections of the bulb area.



Source: Author.

After each adjustment of Z_b to a new position Z_b' , the new position of Z_s , denoted Z_s' , was computed as the scaled position due to the change in Z_b , as shown in Equation (45), since the ratio of $Z_b:Z_b'$ was equal to the ratio $Z_s:Z_s'$. The value of R was computed as the difference between Z_b' and Z_s' as shown in Equation (46), and R'' was computed as the difference between d and R as shown in Equation (47). However, the position of Section 1 was kept static to enforce geometric consistency with the other body of the parametric model; therefore, the change in position Z_{s1}' at section 1 was compensated by partial distribution to sections 2, 3, and 4.

For the adjustment of sections 2-4, the normalised difference between initial values of Z_s at section 1 versus initial values at sections 2-4, P_c , was computed as shown in Equation (48).

The weights to guide the adjustment, C , at each section were then computed as the ratio between P_c at a given section to the sum of all values of P_c , as shown in Equation (49). Therefore, the adjustment, $adj1$, was defined by the initial bottom position at section 1 (Z_{S1}), and the projected position of the same bottom position due to a change in Z_b (Z_{S1}'), as shown in Equation (50).

$$Z_{S'} = (Z_s * Z_b') / Z_b \quad (45)$$

$$R = Z_b - (Z_s * Z_b') / Z_b \quad (46)$$

$$R'' = d - Z_b + (Z_s * Z_b') / Z_b \quad (47)$$

$$P_c = (Z_{S_i} - Z_{S1}) / Z_{S1} \quad (48)$$

$$C_i = P_{c_i} / \sum P_c \quad (49)$$

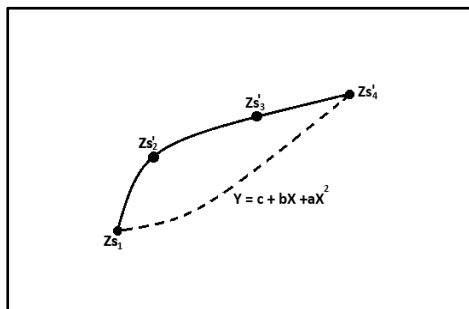
$$adj1 = -(C_i * Z_{S1}' - C_i * Z_{S1}) \quad (50)$$

An additional adjustment was made for sections 2 and 3 to ensure a smooth entry curve with respect to position Z_{S1}' . After $adj1$, the entry curve at position Z_{S1} , was as shown in Figure 17. A best-fit parabolic curve was fitted using the formula $Y = aX^2 + bX + c$, where Y was the distance from positions Z_{S_i}' to the estimated curve, and X was the position on the x-axis of the design space. The coefficients a , b , and c were -0.00154, 10.62032, and -18298.3, respectively. By scaling, the ratio of values of Y at highest change in bulb depth (Y_{0i}) to any other change, j , within the range of values of Z_b (Y_j), was equal to the ratio of the total range of the values of bulb depth proposed, 0.10946m, to any other possible change, k , within range of values of Z_b (ΔZ_b). Therefore, the adjustment, $adj2$, would be equal to $-Y_j$, which can be computed as shown in Equation (51).

$$adj2 = -Y_j = -(Y_{0i} * \Delta Z_b) / 109.64 \quad (51)$$

Figure 17

Bottom curve at sections 1-4 after adjustment 1.



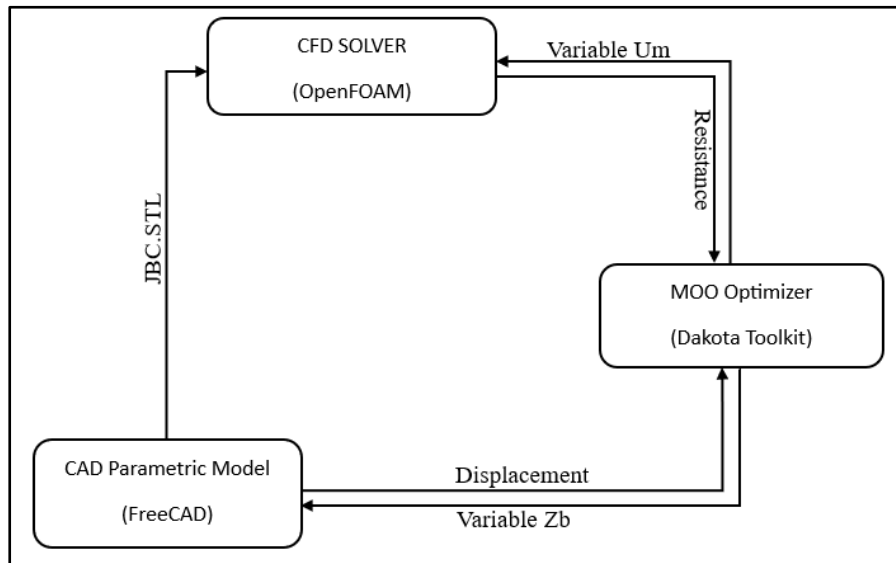
Source: Author.

3.2.4.4. DESIGN ALTERATION AND OPTIMISATION

The baseline values were computed as a basis for evaluation during hull optimisation. The Dakota optimisation toolkit was used to implement the optimisation process by facilitating interoperability between OpenFOAM and FreeCAD. The optimisation workflow is shown in Figure 18.

Figure 18

Optimisation workflow.

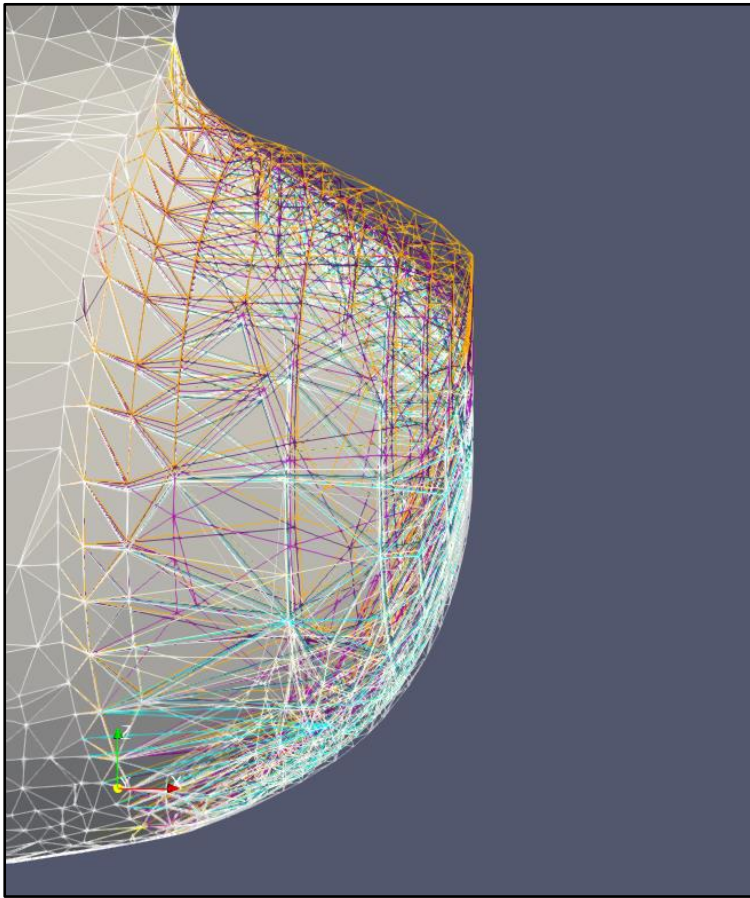


Source: Author.

Various combinations of bulb depth and speed were used to develop an initial population. Each design variant was analysed by Computational Fluid Dynamics (CFD) simulation to evaluate the effects of the hull form modification on total resistance. The fitness to the optimisation objective functions was evaluated for each model using the Multi-Objective Genetic Algorithm (MOGA), employing the non-dominated sorting algorithm (based on Pareto-ranking evolutionary strategy), to eliminate non-compliant models of the population. The surviving models were further refined and reevaluated for fitness to objective functions and compliance with constraints. The visualisation of the meshes for design alternatives is shown in Figure 19. Due to limitations in computing resources, the convergence criteria for the optimisation were set to either 50 iterations or 10 new generations. At convergence, the design with the best fitness score to the objective function was chosen as the optimised solution. The Dakota input file setting up methods and parameters for optimisation, the simulator script bash file performing batch execution of necessary files and tools, and Python files computing hull modification, objective (1) and (2), and change in centre of gravity are attached in Appendix II.

Figure 19

Design alternatives from the modification of the bulb depth parameter.



Source: Author.

3.2.5. EMISSIONS SIMULATION

Fuel Consumption was predicted using the White Box Model (WBM), where the mechanical characteristics of the propulsion system were used to estimate fuel consumption. The Wärtsilä RT-flex96C engine with the specific fuel consumption (SFC) of 171g/kWh (WÄRTSILÄ, 2023) was the basis for the estimation of fuel consumption. Using the results of the total resistance of the initial hull form (R_{TI}) and the optimised hull form (R_{TM}), the brake power of both models was estimated. The brake power was used to estimate the fuel consumption (FC) per hour. It was assumed that the bulk carrier ship operates in tramp shipping, where it will roam multiple routes in the world. It was also assumed that the velocity of the ship depends on the maritime zone of operation, with slow speeds close to the continental shelf, medium speeds within the mesopelagic zone, and optimal speed within the bathypelagic, abyssal plain, and hadal zones as described in Figure 20. This implies that the probability that a ship will spend time in any given zone on any voyage is directly proportional to the prevalence of the given zone, therefore forming a prediction criterion for the ship's velocity profile.

Figure 20

Maritime zones of the ocean, with their percentage coverage.

Depth	Zone	Percentage of Ocean Area	Cumulative Percentage	Depth resolution
0—200m	A. Continental Shelf	8.7	8.7	50m ^a
200—1000m	B. Continental Slope / Mesopelagic	5.8	14.5	100m
1000—4000m	C. Continental Slope / Bathypelagic	36.3	50.8	200m
4000—6000m	D. Abyssal Plain	48.6	99.4	200m
>6000m	E. Hadal Zone	0.6	100	1000m

Source: Webb et al. (2010).

The three vessel speeds considered included slow speed (U_s) of 12 knots, medium speed (U_m) of 13 knots, and peak speed (U_p) of 14.5 knots. The percentage of coverage for each ocean depth zone was then converted to weights to represent the probability that the ship will spend voyage time in a given zone, with weights for slow speed (W_s), medium speed (W_m), and peak speed (W_p) as shown in Equations (52). A synthetic normalised dataset of randomly predicted values for total operating days (ΣO_d) per year for 25 years was generated to form the basis of computations for total fuel consumption per year. Equation (53) was used to evaluate the predicted total fuel consumption per year for the initial hull (TFC_0) and optimised hull form (TFC_m). The total annual fuel savings (TFS) were computed as the difference between the annual TFC_0 and TFC_m as shown in Equation (54).

$$W_s = 8.7/100 = 0.087; W_m = 5.8/100 = 0.058; W_p = (36.3+48.6+0.6)/100 = 0.855 \quad (52)$$

$$TFC = (W_s * FC * 24 * \Sigma O_d) + (W_m * FC * 24 * \Sigma O_d) + (W_p * FC * 24 * \Sigma O_d) \quad (53)$$

$$TFS = TFC_0 - TFC_m \quad (54)$$

The environmental impact was calculated as the annual emissions savings (TeS), computed as the product of the total annual fuel savings (TFS) and the IMO's carbon conversion factor for HFO (C_f) (IMO, 2023a), as shown in Equation (55). To compute the economic impact in fuel savings, a dataset of the average global fuel prices (gfc) for the years 2000 to 2025 (EU, 2025) was used as the basis for computations. The total annual operational cost savings due to optimisation (TCS) was computed as the product of the total annual fuel savings (TFS) and the average global fuel price (gfc) per specific year, as shown in Equation (56).

$$TeS = TFS * C_f \quad (55)$$

$$TCS = TFS * gfc \quad (56)$$

Additionally, the total loss in carriage capacity (CC_L) of the vessel was computed as the difference in DWT of the initial model (DWT_0) and the optimised model (DWT_m) as shown in

Equation (57). The economic impact due to loss of cargo carriage capacity was computed using the average annual global capsize historical earnings (gcp) per day between 2000 and 2024, from the Clarkson's Shipping Intelligence Network (Clarksons, 2025), as shown in Figure 21. The annual revenue loss due to the reduction in cargo capacity (TRL) was computed using the total loss in carriage capacity (CC_L), average annual global charter prices per year (gcp), DWT of the initial model (DWT_0), and predicted total operating days per year (ΣO_d) as shown in Equation (58). The net fuel cost saving (NCS) due to hull form optimisation was then computed as the difference between the total annual operational cost savings (TCS) and the annual revenue loss due to the reduction in cargo capacity (TRL), as shown in Equation (59).

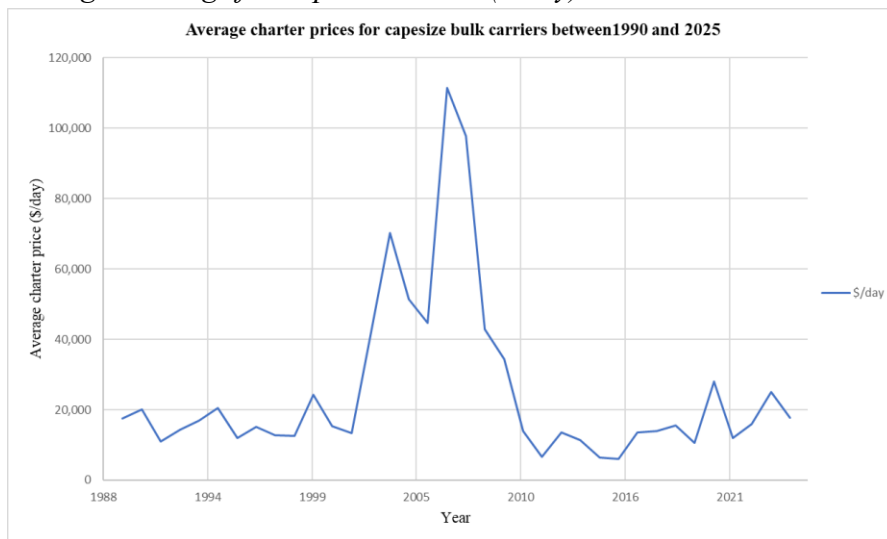
$$CC_L = DWT_0 - DWT_m \quad (57)$$

$$TRL = CC_L * (gcp/DWT_0) * \Sigma O_d \quad (58)$$

$$NCS = TCS - TRL \quad (59)$$

Figure 21

Average earnings for capsize bulkers (\$/day) between 1990 and 2025.



Source: Clarksons (2025).

4. CASE STUDY: THE JAPAN BULK CARRIER

4.1. THE JAPAN BULK CARRIER (JBC)

The Japan Bulk Carrier (JBC) model is a capesize single-crew hull design developed by the Japan National Maritime Research Institute (NMRI), the Yokohama National University, and the Shipbuilding Research Centre of Japan (SRC), with support from the Class NK. The geometry of the hull of the JBC ship is provided by NMRI (2015a), and the body plan by Nobuyuki (2015), as shown in Figure 22. The key design particulars of the JBC are shown in Table 3.

Table 3

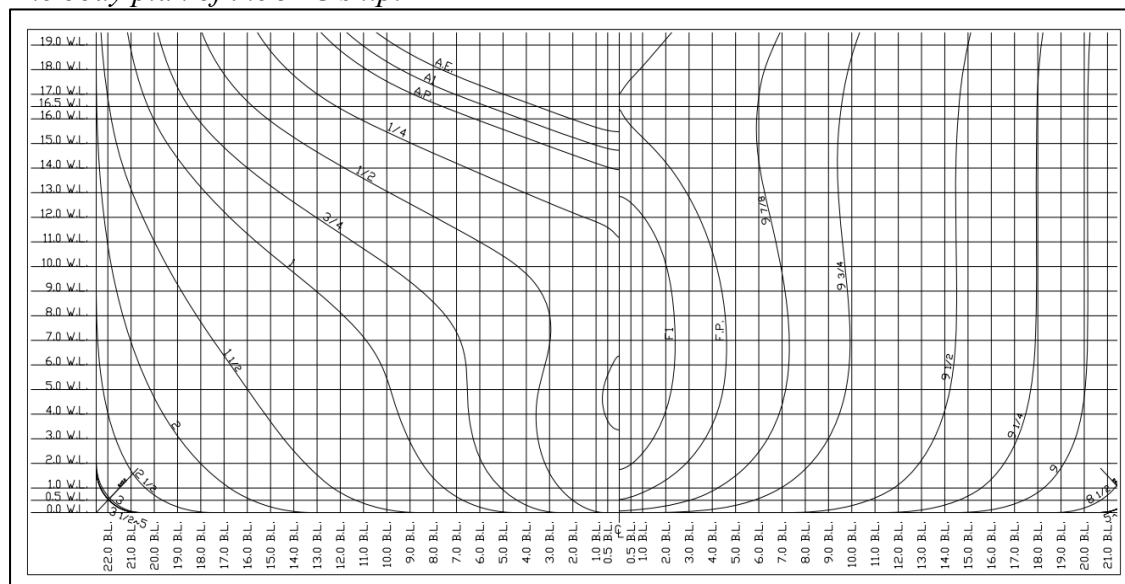
JBC hull data and geometry

No.	Main Particulars	Value	Units
1.	LOA	291	m
2.	Beam, B	45	m
3.	LPP	280	m
4.	LWL	285	m
5.	Draught	16.5	m
6.	Displacement	178370	m ³
7.	WSA	19556.1	m ²

Source: Nobuyuki (2015).

Figure 22

The body plan of the JBC ship.



Source: Nobuyuki (2015).

There are multiple studies focusing on the improvement of the JBC's hydrodynamic performance through hull modification, including the bow (Jeong & Jeong, 2020; X. Liu &

Wan, 2018), rudder (Bekhit et al., 2020), Energy Saving Devices (Furcas et al., 2020; Kormaz, 2015; Wu et al., 2022), propeller (Z. Liu et al., 2021), and stern (X. Liu et al., 2023). Additionally, towing tank tests including resistance and self-propulsion tests were undertaken using a scale model of the JBC ship (Nobuyuki, 2015), and a full-scale bare hull test using Computational Fluid Dynamics were studied (Jennie et al., 2015). However, no physical full-scale tests have been undertaken.

4.2. INITIAL DESIGN VALIDATION AND BASELINES

4.2.1. REYNOLDS NUMBER AND FROUDE NUMBER

The Reynolds numbers at various speeds were computed, as shown in Table 4, to determine the fluid flow characteristics around the ship's hull. The Reynolds numbers ranged between 5,780,356.542 at 0.98m/s, and 7,475,613.858 at 1.27m/s, which are high, symbolising a turbulent fluid flow. This is due to the long length of the vessel (280m), which supports turbulent boundary layer development. Therefore, the flow solver used to determine total resistance should be capable of resolving turbulence effects within the air-water fluid system. Additionally, the level of mesh cell divisions should be fine enough to support discretization at the air-water free surface, to adequately resolve wave and pressure force effects.

Table 4

Reynolds numbers at various model speeds.

No.	U_m (m/s)	Rn ($U_m L/\nu$)
1.	0.982	5,780,356.542
2.	1.137	6,692,734.612
3.	1.189	6,998,822.738
4.	1.27	7,475,613.858

Source: Author.

In comparison, the Froude numbers were low, as shown in Table 5. These ranged between 0.1183 and 0.1533, and indicated a displacement fluid flow regime around the ship's hull that is dominated by viscous resistance and low wave-making resistance. This is due to the low/moderate operational speed associated. The low Froude numbers indicate minimal interference within the boundary layer since wave-making is low. This reduces the turbulence within the computational domain, and therefore, implies that the total resistance can be estimated more reliably using Computational Fluid Dynamics (CFD) and empirical approaches like Holtrop and Mennen (Elin & Felicia, 2020; Holtrop & Mennen, 1982).

Table 5*Froude numbers at various model speeds.*

No.	U_m (m/s)	$F_n (U_m/\sqrt{gL})$
1.	0.982	0.1183
2.	1.137	0.1372
3.	1.189	0.1435
4.	1.27	0.1533

*Source: Author.***4.2.2. MESH INDEPENDENCE VALIDATION**

The background mesh independence study was undertaken by conducting simulations of the same hull mesh with varying background mesh sizes to determine the effect of mesh size on the accuracy of resistance estimates, as shown in Table 6. The accuracy of resistance estimates improved with the increase in mesh volume dimensions, because increasing the distance to computational domain boundaries reduced disturbances and pressure buildup within the system. Additionally, the accuracy of resistance estimates increased with the increase in mesh divisions, because the smaller cell divisions support finer feature refinement, improved discretization, and stability within the computational domain. The accuracy, as compared to the Japan National Maritime Research Institute (NMRI) towing tank test results, improved from a deviation of 76.6% to 38.14% at the highest background mesh resolution; however, the solver runtime increased from 0.86 hours to 2.17 hours.

Table 6*Resistance of the model ship at speed 0.98m/s using varying background mesh sizes.*

No.	volume dimensions (m*m*m)	Mesh divisions (nx, ny, nz)	Timestep (s)	Half-ship Resistance, (N)	Deviation from NMRI Results (%)	solver runtime (hrs)
1.	20 * 3.5 * 5.0	60, 50, 50	0.05	23.098	76.65	0.86
2.	25 * 4.5 * 7.5	80, 55, 55	0.05	20.313	55.36	1.27
3.	30 * 5.5 * 10	100, 60, 60	0.05	18.054	38.14	2.17
4.	30 * 5.5 * 10	100, 60, 60	0.005	11.320	13.58	5.12

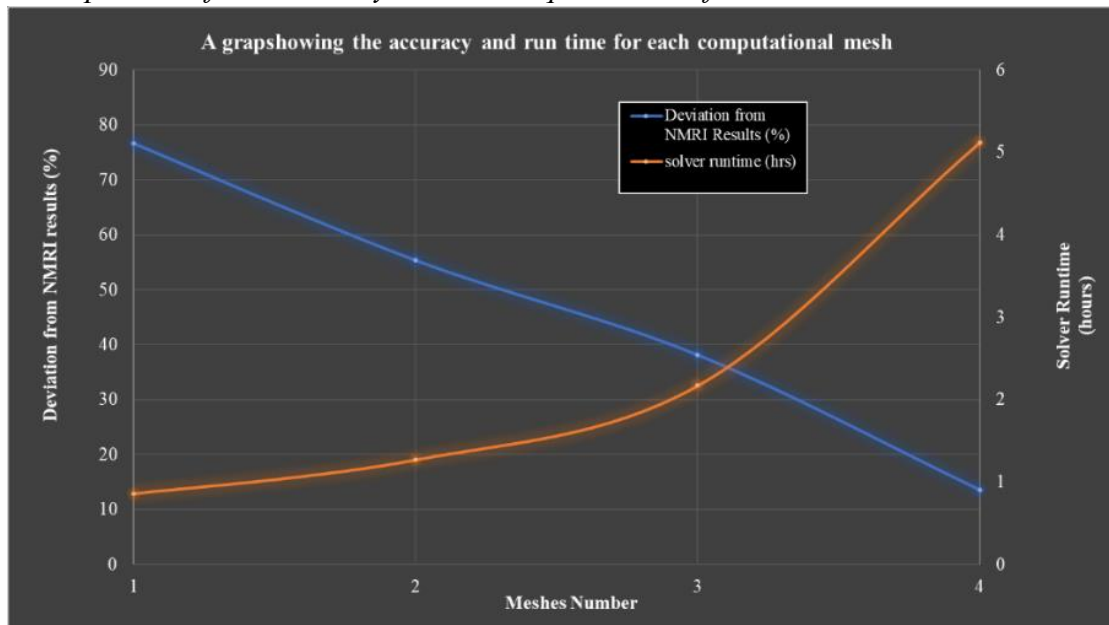
Source: Author.

At the mesh volume dimensions (30*5.5*10) and divisions (100, 60, 60), the reliability and precision of resistance estimates reduced with wildly varying results as compared to other mesh estimates. The CFD solver failed execution at mesh divisions above (100, 60, 60), due to solver

divergence. This indicated that the option of volume dimensions (30*5.5*10) and divisions (100, 60, 60) was the optimal background mesh to execute the CFD solver reliably with adequate accuracy and optimal runtime, as shown in Figure 23. However, the accuracy of the resistance estimates could be improved by lowering the time-step to below or equal to 0.005s, but with an increase in the computation time. At the timestep of 0.005s, the accuracy of resistance estimates improved to a deviation of 13.58%, with a runtime of 5.12 hours. To balance accuracy, solver efficiency, and solver runtime requirements, all other computations within this research requiring multiple iterations were undertaken using the timestep of 0.05s, at reduced time requirements. The timestep 0.005s was used for high accuracy resistance estimates, used for validation of the initial hull model against NMRI towing tank test results.

Figure 23

A comparison of the accuracy and time requirements of each mesh studied.



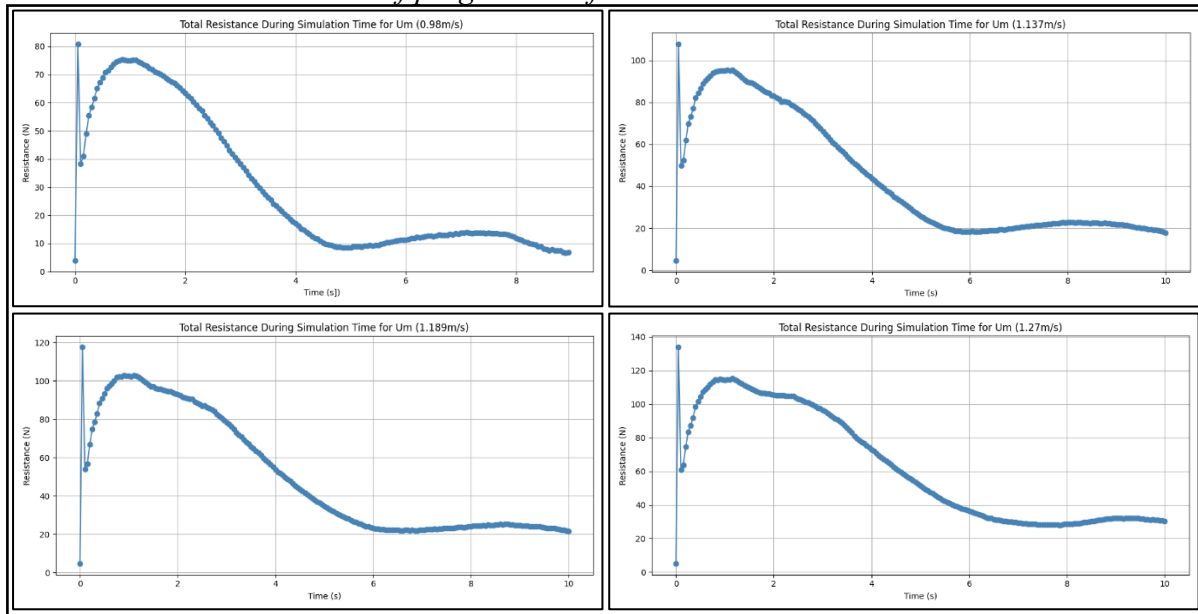
Source: Author.

4.2.3. FLOW STABILIZATION TIME FOR CFD SOLVER

The time taken for the flow to stabilise with minimal deviation in the values of total resistance was studied at speeds 0.98m/s, 1.137m/s, 1.189m/s, and 1.27m/s, as shown in Figure 24. The flow stabilised at approximately 5 seconds for 0.98m/s and 1.137m/s, and at approximately 6 seconds for 1.189m/s and 1.27m/s. The increase in time required for flow stabilisation was due to the increase in Reynolds and Froude numbers at high speeds, which increased the turbulence and the wave-affected area around the ship; this is consistent with predictions by Ovchinnikov (2019).

Figure 24

Total resistance at each time of progression of the simulation at 0.98m/s.



Source: Author.

4.2.4. RESISTANCE VALIDATION USING NMRI RESULTS

The average total resistance after flow stability was computed at speeds 0.98m/s and 1.189m/s, as shown in Table 7, where the total resistance at time, t , was computed as the sum of pressure and viscous forces in the x-direction. A comparison to the resistance results from NMRI (2015b) showed a percentage deviation of -14.3% and 23.2%. This indicates that the parametric model closely represents the body plan provided for the JBC ship, and can be used to study the resistance of the JBC.

Table 7

Total Resistance versus the results from the NMRI towing tank tests.

No.	U_m (m/s)	OpenFOAM $0.5R_T$ (N)	OpenFOAM R_T (N)	NMRI Test Results R_T (N)	Deviation (N)	% Deviation
1.	0.98	11.227	22.454	26.195	-3.736	14.3
2.	1.189	23.423	46.846	38.039	8.807	23.2

Source: Author.

4.2.5. VALIDATION OF DISPLACEMENT

The displacement of the initial hull model was compared to the displacement given by NMRI (2015b). The estimated total displacement, D , of the model was 2.7862m^3 as shown in Table 8. This had a percentage deviation of 0.000287% as compared to the displacement given by

NMRI (2015b). This reaffirmed that the parametric model closely replicated the shape of the JBC.

Table 8

Calculated displacement of the model ship versus the NMRI displacement results.

No.	$0.5D_m(m^3)$	$D_m(m^3)$	NMRI $D(m^3)$	Deviation (m^3)	% Deviation
1.	1.3931	2.7862	2.7870	-0.0008	$2.870e^{-4}$

Source: Author.

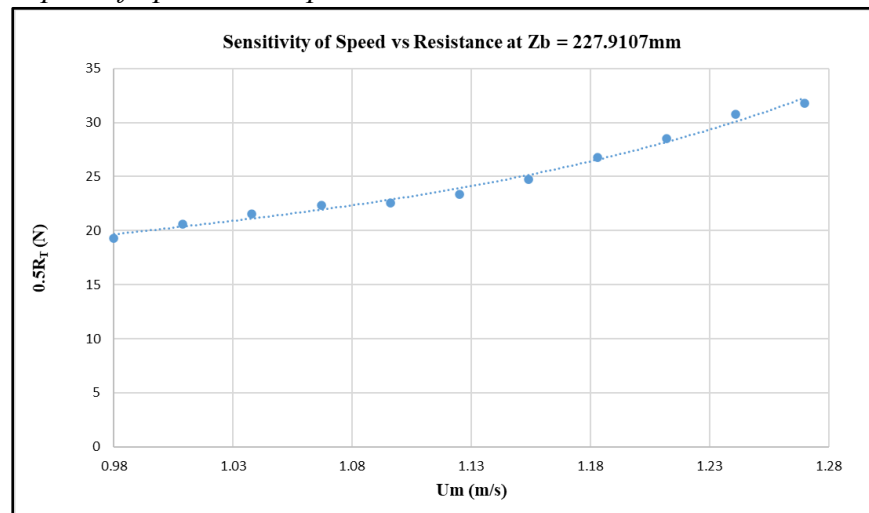
4.3. PARAMETER SENSITIVITY

4.3.1. SPEED (U_m) SENSITIVITY

To understand the sensitivity of total resistance to vessel speed, changes in speed were tracked over the desired speed range, as shown in Figure 25. The relationship between speed and resistance was non-linear, and the total resistance was directly proportional to the third-order polynomial of the operational speed. There was a gradual increase in resistance at low speeds between 0.98m/s and 1.1m/s, indicating low sensitivity, and a sharp increase in resistance between speeds 1.1m/s and 1.27m/s, indicating high sensitivity. This was consistent with the relationship described by USNA (2020). The low sensitivity at low speeds implies minimal turbulence and a near-laminar flow with minimal effect on resistance; however, at higher speeds, the high sensitivity indicates high turbulence, which significantly impacts resistance. This confirms that the resistance estimates can be determined more reliably at low speeds than at high speeds.

Figure 25

Impact of operational speed on total resistance at $Z_b=227.9107mm$.



Source: Author.

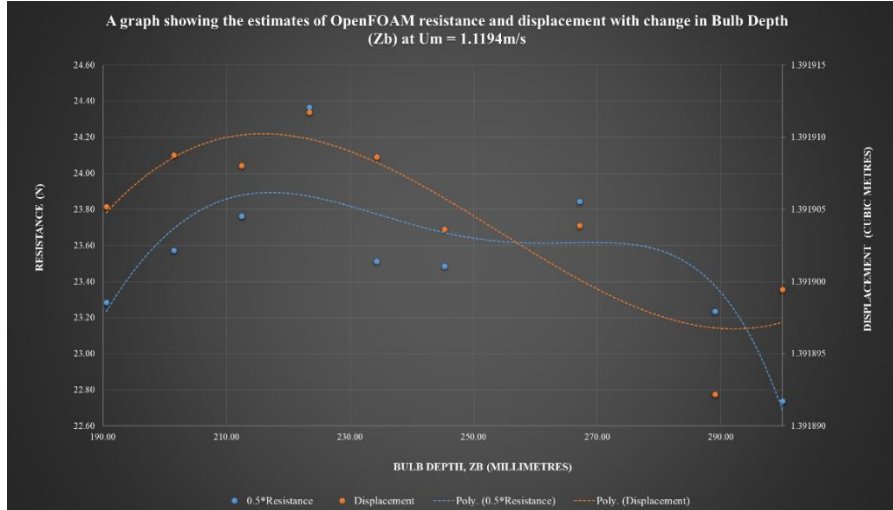
4.3.2. BULB DEPTH (Zb) SENSITIVITY

The sensitivity of resistance estimates and the displacement to bulb depth (Zb) was investigated at a constant speed of 1.1194m/s, over the range from 190.54mm to 300mm, as shown in Figure 26. For resistance, for Zb values from 0 mm to 222 mm, and 238mm to 265mm, there was an increase in resistance, while for values 222mm to 238mm, and 265mm to 300mm, there was a sharp decrease in resistance. These sharp changes in resistance indicate high sensitivity to changes in bulb depth.

For displacement, Zb values from 0 mm to 225 mm, the displacement values increased gradually, while for values between 225 mm and 300 mm, the displacement values reduced gradually; however, the difference between the maximum change in displacement was small. The gradual change indicated that displacement has low sensitivity to changes in bulb depth. The difference in the sensitivity of resistance and displacement to the bulb depth confirms that changes in bulb depth can significantly reduce or increase resistance while minimally affecting the displacement, which is beneficial for the maintenance of the cargo capacity.

Figure 26

Impact of change in bulb depth (Zb) on resistance and displacement.



Source: Author.

4.4. MULTI-OBJECTIVE GENETIC ALGORITHM OPTIMISATION

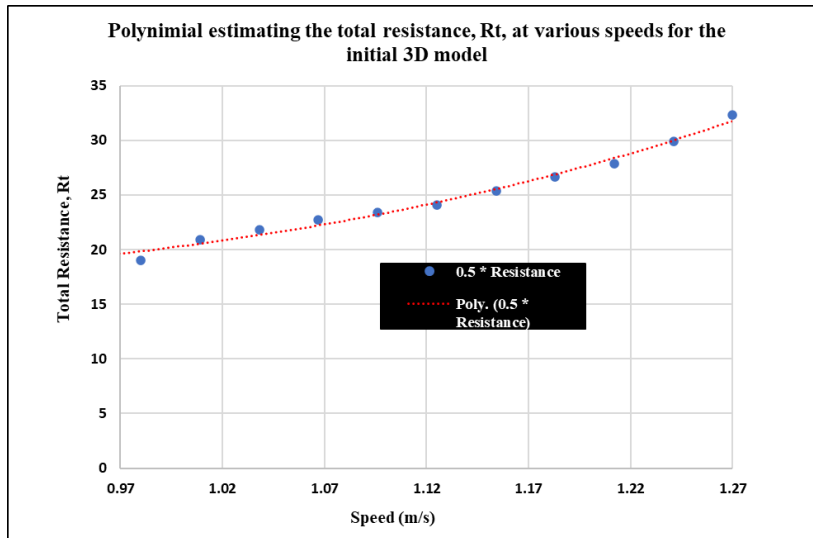
4.4.1. BASELINE RESISTANCE MODEL

The resistance of the initial hull form was evaluated for speeds between 0.98m/s and 1.27m/s using ten intervals, as shown in Figure 27. The underlying curve predicting the total resistance based on speed within the prescribed range was estimated as a third-degree polynomial with coefficients $a=750.99$, $b= -2467.2$, $c = 2729.3$, and $d= -992.92$, and the coefficient of

determination, R^2 , of 0.9983, indicating that the curve closely approximates estimates of the underlying model. The function of the curve predicting the total resistance of the initial hull form was used to estimate resistance baselines for comparison with estimates from the modified hull forms during objective function evaluation.

Figure 27

Estimation of the base model for total resistance.



Source: Author.

4.4.2. PARETO FRONT

The Multi-Objective Genetic Algorithm (MOGA) was initialised using 10 initial designs, with a uniform replacement mutation type of mutation rate 0.1, and random shuffle crossover type. Since the computing resources were limited (8 cores), no concurrent processing was implemented. The convergence or termination conditions were set to a maximum of 50 function evaluations or 10 generations. A total of 10 generations were evaluated, utilising 30 function evaluations, leading to two Pareto points as shown in Table 9.

Table 9

Pareto points representing best-fit function evaluation designs.

No.	Zb (mm)	Um (m/s)	ΔR_T	ΔD
1.	227.9107	1.1194	-0.04155616	-0.000864604
2.	222.8108	1.1298	-0.038898495	-0.000862208

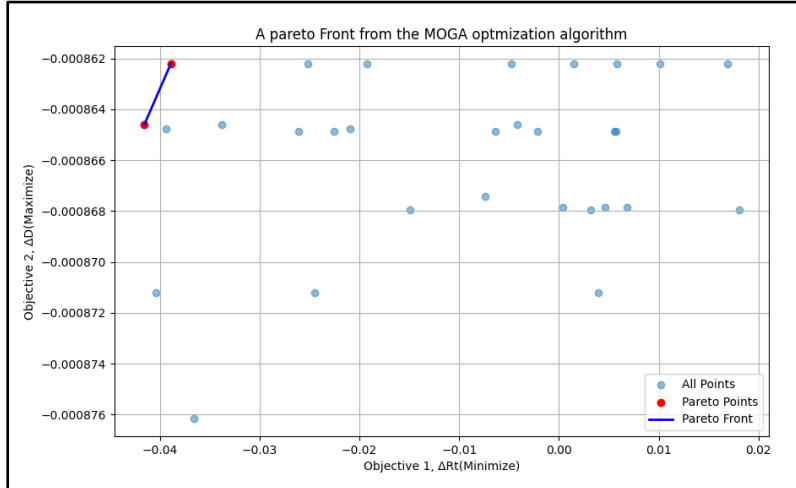
Source: Author.

Since the difference between the change in displacement (ΔD) for the two best designs was very small (0.0000024), the design with the best value for change in resistance, -0.041556, was chosen as the optimum design solution. A graph showing the evaluated objective 2 against

objective 1 for each design, the Pareto front, from the Multi-Objective Genetic Algorithm optimisation, is shown in Figure 28. The results showing the design variations, estimated resistance, and objective function evaluations from the optimisation process are attached in Appendix 2 Table 1.

Figure 28

Pareto front for the multi-objective optimisation of 30 alternative designs of the JBC ship.

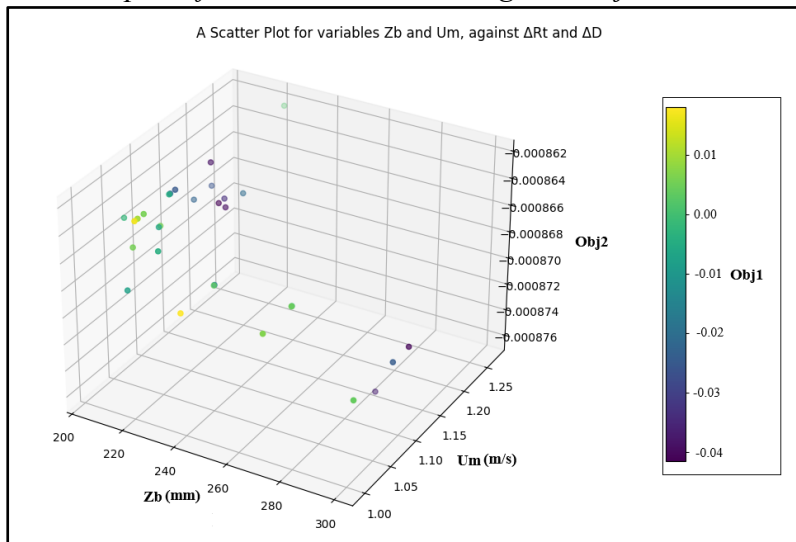


Source: Author.

Additionally, a four-dimensional scatter plot of variables bulb depth (Z_b) and speed (U_m) against optimisation objective (1) and objective (2) was plotted as shown in Figure 29. The best performing designs were between bulb depth (Z_b) values 200mm and 230mm, and speed (U_m) values between 1.10m/s and 1.20m/s. This indicated that a modification of the bulb depth is most beneficial at higher speeds.

Figure 29

A scatter plot of variables Z_b and U_m against objectives 1 and 2.



Source: Author.

4.4.3. RESISTANCE PROFILE AT THE OPTIMISED BULB DEPTH

The initial and optimised hull forms were reevaluated to determine the total resistance of each design at speeds 0.98m/s, 1.1194m/s, and 1.137m/s, as shown in Table 10. At 0.98m/s, the percentage reduction in total resistance was minimal at 0.6%, because the Froude number was low and the wavemaking resistance is very little. However, the 0.6% resistance reduction is attributed to a reduction in bulb-induced pressure resistance, and a reduction in viscous resistance since the wetted surface area was reduced.

Table 10

Re-evaluation of total resistance between optimised and initial hull form.

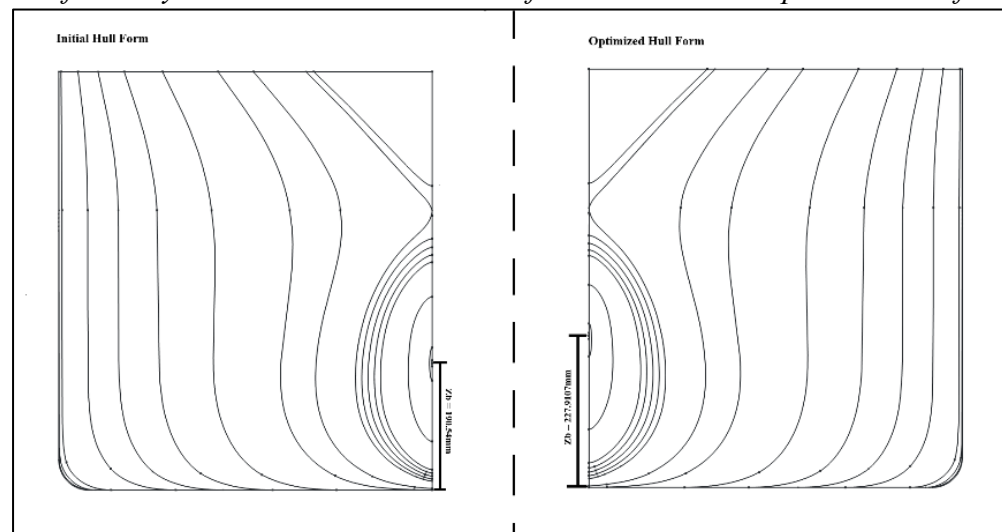
Speed (m/s)	R_{Ti} (N)	R_{TM} (N)	%reduction in R_T (N)
0.98	18.194	18.085	0.6
1.1194	26.181	25.058	4.2
1.137	28.008	27.074	3.3

Source: Author.

At 1.1194m/s, the percentage reduction in resistance was maximum at 4.2%, and 3.3% at 1.37m/s. This is because at increased speeds, there is an increase in Froude numbers and wave-making potential for a ship's hull, and consequently, the bulbous bow's creation of countering wave systems also increases. Therefore, there is a significant reduction in wave-making resistance. However, the resistance reduction decreases between 1.1194m/s and 1.137m/s, indicating that 1.1194m/s is the optimum speed for maximum resistance reduction. The forebody plan of the initial versus optimised hull forms is shown in Figures 30 and 31, with vertical changes at the bulb area.

Figure 30

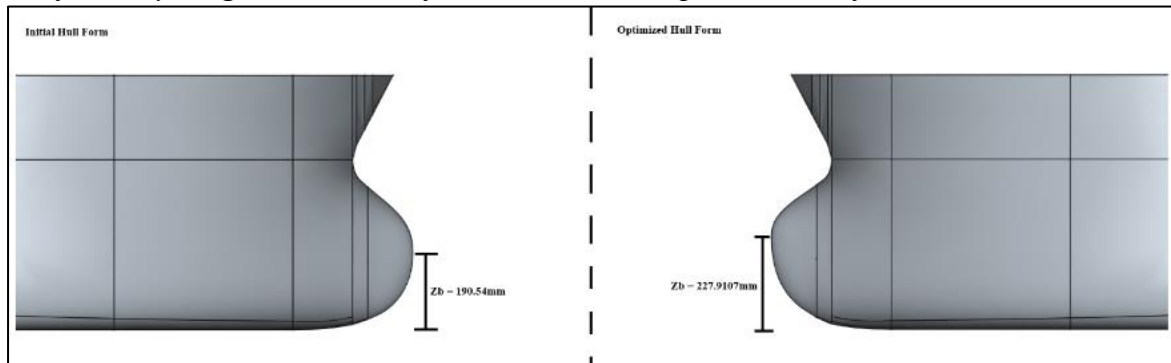
The forebody cross-sectional hull lines of the initial versus optimised hull forms.



Source: Author.

Figure 31

The forebody longitudinal view of the initial versus optimised hull forms.



Source: Author.

4.4.4. RESISTANCE VALIDATION BY HOLTROP AND MENNEN

The OpenFOAM resistance estimates for the optimised hull form at operational speeds between 0.98m/s and 1.137m/s were compared to estimates by the Holtrop and Mennen method, as shown in Table 11. The deviation of the estimates between OpenFOAM and Holtrop resistance was between 15.26% and 30.35%, and it increased with the increase in speed. This was because at higher speeds, the turbulence within the computational domain is increased, thus requiring higher discretization; however, since the resolution of the background mesh was maintained, the OpenFOAM solver estimated higher resistance.

Table 11

Comparison of OpenFOAM resistance estimates against Holtrop and Mennen resistance.

No.	U_m (m/s)	0.5R _T (N), OpenFOAM	R _T (N), OpenFOAM	R _T (N), Holtrop & Mennen	Deviation (N)	Deviation (%)
1.	0.98	18.085	36.17	31.38	4.74	15.26
2.	1.1194	25.058	50.116	40.38	9.736	24.11
3.	1.137	27.074	54.148	41.54	12.608	30.35

Source: Author.

4.5. POWER ESTIMATION

The brake power requirements were estimated for operational speeds between 0.98m/s and 1.137m/s, as shown in Table 12, to determine the changes in power requirements with respect to speed. The estimated brake power required for the initial hull form ranged between 16,227.96 kW and 30,185.93 kW, while for the optimised hull form, it ranged between 16,130 kW and 29179.30 kW. The percentage reduction in brake power required between the initial and optimised hull forms increased with the increase in speed, with the maximum reduction of 3.33% at 1.137 m/s.

Table 12

Brake power estimates for the initial hull form and optimised hull form.

Speed (m/s)	Brake power for the initial hull (kW)	Brake power for the optimised hull (kW)	Percentage reduction in brake power (%)
0.98	16,227.96	16,130.74	0.5991
1.1194	18,612.15	18,500.64	0.5991
1.137	30,185.93	29,179.30	3.3348

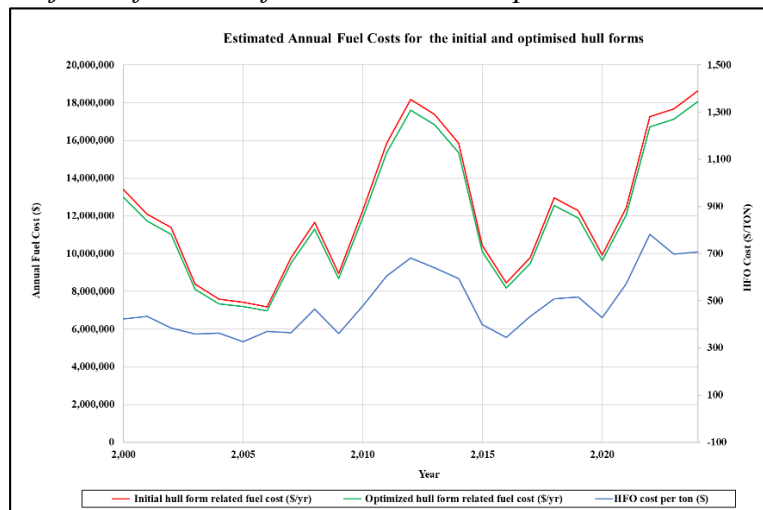
Source: Author.

4.6. ECONOMIC IMPACT

The average fuel consumption for the initial and optimised hulls was 25,030 and 24,256 tonnes of HFO, respectively. This showed a 3.092% reduction in fuel consumption and indicates that a reduction in resistance contributes to a significant cut in fuel consumption. The total fuel cost followed the same curve as the average HFO fuel cost, as shown in Figure 32, indicating the high sensitivity of operational costs on the fuel price. Figure 32 also indicates that optimised hulls are advantageous and give greater fuel cost savings at periods of high prices, indicating that optimisation creates a buffer against fuel price volatility. The average percentage reduction in annual fuel costs was 2.264%, which translates into an average annual gross fuel cost savings of \$372,907.09.

Figure 32

Projected fuel costs for the initial and optimised hulls.



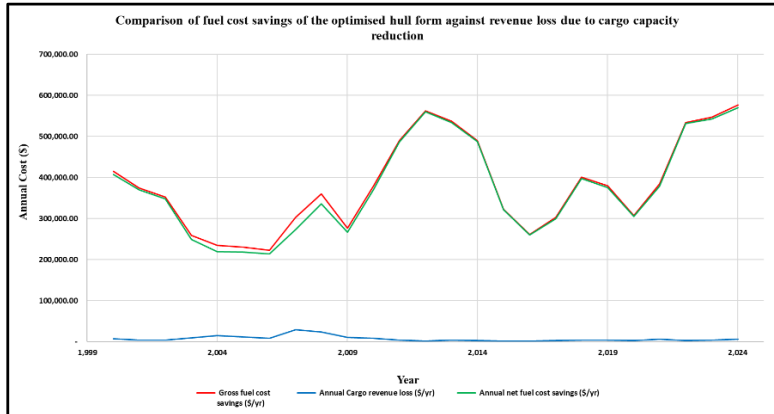
Source: Author.

The estimated average annual cargo revenue loss was \$7,222.51, a total of \$180,560 in 25 years, which is in comparison 1.9% of the estimated annual gross fuel cost savings. The estimated average annual net fuel cost savings were \$372,907.09, with a total of \$9.322 million in 25 years. This indicated that hull form optimisation has a significant benefit to the ship

owner, illustrating long-term savings that greatly outweigh the revenue loss. The estimated annual gross fuel cost savings and annual net fuel cost savings against the annual cargo revenue loss are shown in Figure 33. The table showing estimates of economic impact on vessel operations is attached as Appendix III Table 1.

Figure 33

Estimated net fuel savings for optimised hull versus the cargo revenue loss.



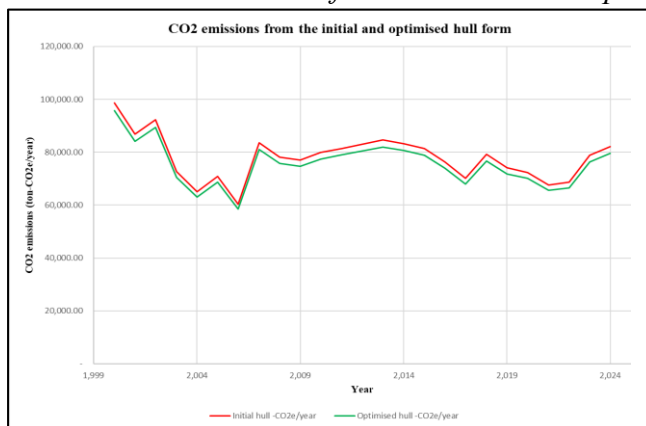
Source: Author.

4.7. ENVIRONMENTAL IMPACT

The annual estimated CO₂ emissions for the initial and optimised hull forms are shown in Figure 34. The average annual reduction in CO₂ emissions was 2412 tonnes, with a total of 60,289 tonnes in 25 years; this represents a 3.094% reduction, which was equal to the average annual reduction in fuel consumption. This indicates that the quantity of CO₂ emissions depends directly on the quantity of fuel consumed. This also showed that the optimised hull form can deliver long-term emissions reductions from optimisation. The table showing estimates of environmental impact on vessel operations is attached as Appendix III Table 1.

Figure 34

Estimated CO₂ emissions from the initial and optimised hull forms.



Source: Author.

5. ANALYSIS OF RESULTS

5.1. ACCURACY

For validation with NMRI results and Holtrop and Mennen results, high and moderate accuracy CFD estimates were required, respectively. This justifies the need for process optimisation before undertaking CFD simulations, since the accuracy and resources employed should depend on the design task requirements. Holtrop and Mennen's moderate accuracy estimates are typically for preliminary design, while towing tank test high accuracy estimates are usable for final design evaluation.

Correspondingly, CFD methods for the preliminary design stage require moderate solver fidelity, with reduced mesh resolution and moderate computing resources, for exploration of a wide design space. In contrast, for final design evaluation, high solver fidelity, with increased mesh resolution and higher computing resources, is required. However, since adaptive meshing and structured meshing were not fully implemented, the solver's ability to resolve flow separation and wave interference, especially at high speeds, was limited; this constrained the accuracy of measurements. Since this research was undertaken with moderate accuracy, the findings of this research are usable for the preliminary design. However, further studies into the uncertainty in the estimated CFD results should be conducted to guide further shape refinement.

5.2. IMPACT OF OPEN-SOURCE TOOLS

This research demonstrated the capability of open-source tools to deliver high accuracy and dependable results for hull form optimisation, while utilising limited computing resources. This can be beneficial for ship design industries, especially in Least Developed Countries (LDCs) and Small Island Developing States (SIDS). The availability of open-source CFD software can ably support skills development and energy efficiency improvement in the domestic shipping fleet. This would significantly contribute towards the IMO GHG Strategy by boosting the decarbonisation of the domestic maritime fleets.

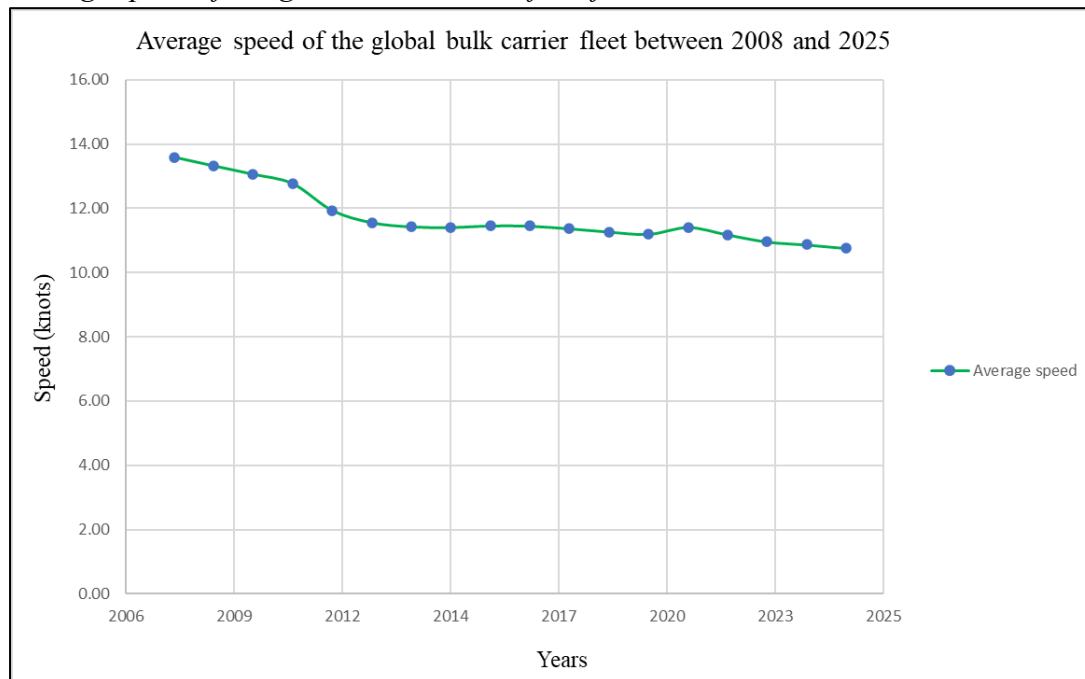
5.3. HULL FORM OPTIMISATION

The design speed of the initial hull was 14.5 knots, which is much higher than the current average speed of bulk carriers, 11.4 knots (Clarksons, 2025), as shown in Figure 35. From the optimisation process, the speed 13.76 knots ($U_m = 1.1194\text{m/s}$) was identified as the optimum speed, which is a 5.1% reduction from the design speed. This reduction in speed is essential

since it ensures that the design modifications are effective even at low speeds, and the optimised hull demonstrated a 0.6% resistance reduction at 12 knots ($U_m = 0.98\text{m/s}$), which can deliver significant fuel savings. Additionally, improvement in fluid flow over the ship's hull reduces the load on the propulsion and engine system, thus decreasing the wear of constituent components. This can positively impact the ship's maintenance and actively reduce maintenance costs.

Figure 35

Average speed of the global bulk carrier fleet from 2008 to 2025.

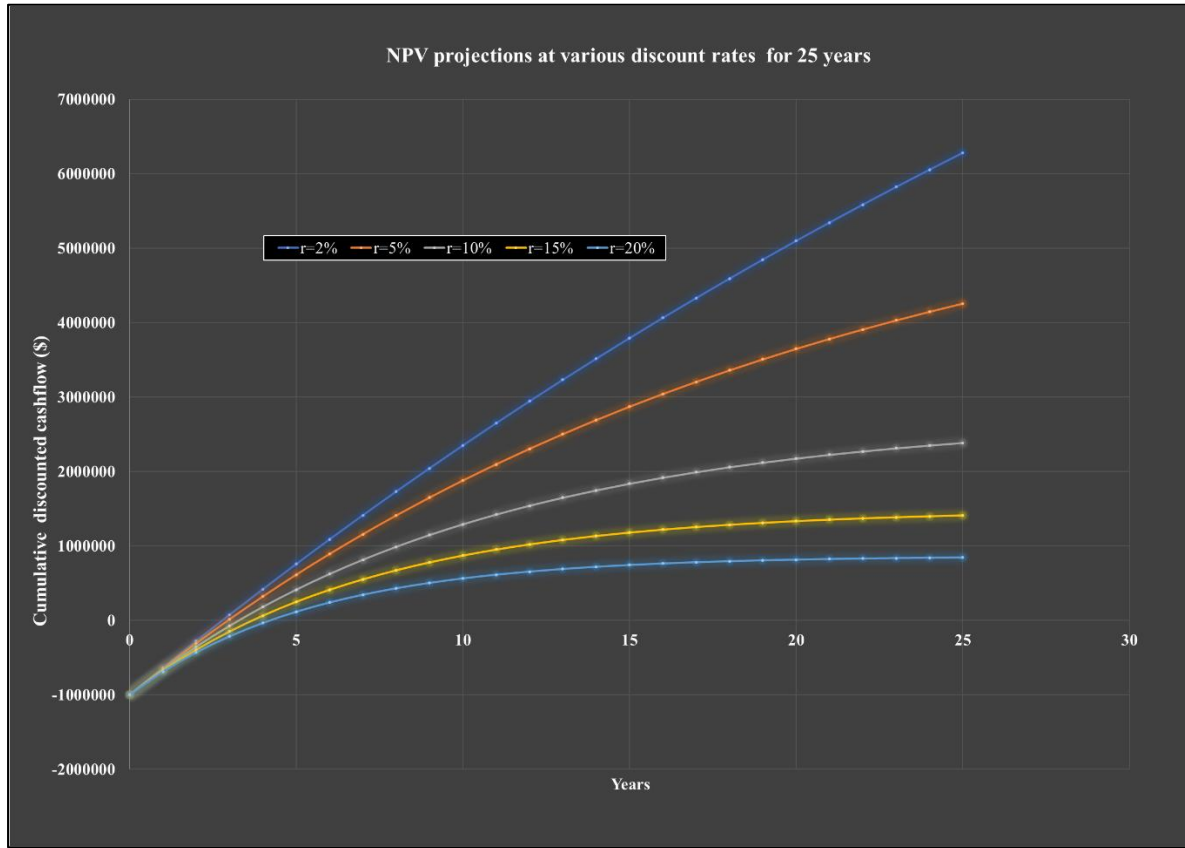


Source: Clarksons (2025).

The advantage of bulbous bow optimisation is that it can be retrofitted for an existing vessel with minimal impact to its structure and stability. Typically, modifications are made at the bow section only. This implies that the vessel's time within drydock for retrofit will be minimal, therefore reducing the revenue loss due to operational downtime. Based on the implementation costs for bulbous bow optimisation at \$1,000,000 (DNV-GL, 2025b), and the average net fuel cost savings \$372,907.09, the Net Present Value (NPV) over 25 years was estimated between \$6,280,435 and \$844,990 at discount rates between 2% and 20%, respectively, as shown in Figure 36. And, the payback time was estimated between 2.79 and 4.23 years. This indicates that hull form optimisation is highly profitable for shipping operations, even at high interest rates. The NPV and payback time computations are shown in Appendix III Table 3.

Figure 36

NPV projections at varying discount rates



Source: Author.

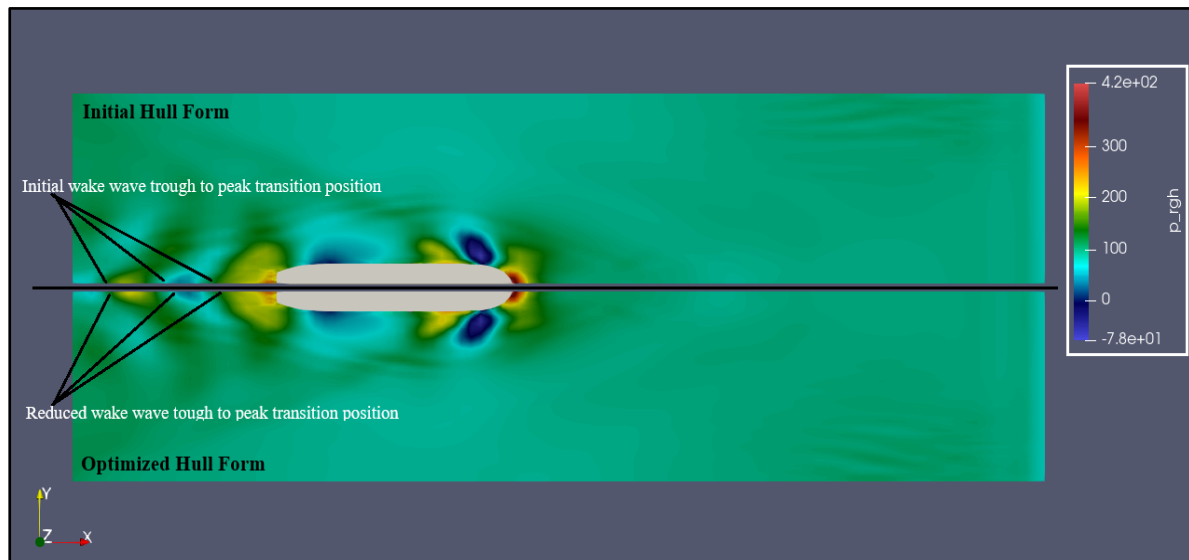
5.4. EFFECT ON RESISTANCE

The modification of the bulb depth affected the bulb entry angle, bulb shape, wetted surface area, and bulb induced pressure. The reduction in wetted surface area reduced the frictional resistance, the change in the bulb entry angle reduced the bulb induced pressure resistance, and the change in bulb shape reduced the amplitude of wave forms produced by the bulbous bow at various operational speeds, thus reducing the optimum speed for wave cancellation. This wide impact of the bulb shape, therefore, highlights its high significance in resistance reduction.

Additionally, the hull form optimisation resulted in a noticeable reduction in the amplitude of wave peaks and troughs produced by the optimised hull in comparison to the initial hull form at the same speed, as shown in Figure 37. The more efficient wave cancellation at the reduced optimum speed led to the alteration of the phase distribution in the wake wave system. While the optimisation process gained resistance reduction by bulb optimisation, more resistance reduction can be gained by exploration of other parameters like the vessel's beam, draught, length, and trim (Adam et al., 2024).

Figure 37

Visualised wave pattern of the initial and optimised hull forms at 1.1194m/s.



Source: Author.

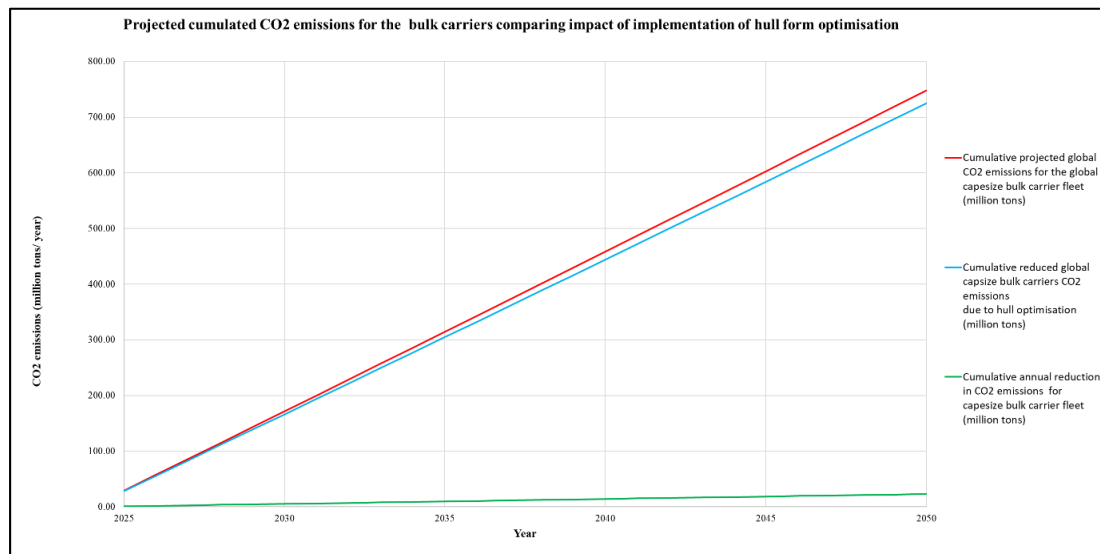
5.5. IMPACT ON THE GLOBAL SHIPPING FLEET

Based on the estimated annual fuel cost savings of \$372907.09, a single ship can save a total of \$9.322 million by 2050, and if the global bulk carrier fleet is considered, \$4.8 billion can be saved by 2050. This presents an advantage for ship operations' profitability, especially with the industry switching to alternative fuels that can be much costlier than Heavy Fuel Oil (HFO). Although the cargo revenue loss was minimal, the retrofitting or construction costs have to be integrated into the economic impact for a more realistic cost-benefit analysis. Additionally, vessels of various types and sizes require varying objectives for hull optimisation, and no one solution can be applied to all.

Using linear regression, the impact of hull optimisation on CO₂ emissions was extrapolated to the global fleet of capesize bulk carriers, which projected a 3% reduction of CO₂ emissions in 25 years, as shown in Figure 38. The projected CO₂ emissions reduction will further reduce the total CO₂ emissions from the global bulk carrier fleet by 0.439%, and the total Tank-to-wake emissions of the global shipping fleet by 0.101% in 25 years. If hull form optimisation is applied to the global bulk carrier fleet, with a general 3% reduction in CO₂ emissions for various bulk carrier sizes, a reduction of 163 million tonnes of CO₂ emissions can be achieved, which translates to a 0.712% reduction in global shipping fleet tank-to-wake CO₂ emissions by 2050. The table showing CO₂ emissions estimates for the impact of hull optimisation on the global shipping fleet is attached as Appendix III Table 2.

Figure 38

Projected impact on CO2 emissions of the global capesize bulk fleet by 2050.



Source: Author.

6. CONCLUSION

Hull form optimisation is a well-established method the hydrodynamic performance improvement of ships. This research demonstrated the critical role of hull form optimisation in improving energy efficiency and reducing CO₂ emissions across the global shipping fleet. By optimising the bow section of the Japan Bulk Carrier (JBC), the study achieved a reduction in resistance and assessed the viability of the implementation of optimised hull forms. The key findings were as follows:

- i. Computational Fluid Dynamics (CFD) accuracy. CFD methods can produce results with accuracies comparable to empirical approaches and towing tank tests. However, the accuracy of CFD results depends on the mesh resolution and computational resources, which make it both time and computationally intensive.
- ii. Accessibility to open-source tools. Open-source CFD tools can deliver precise and high accuracy results to support hull form optimisation. This boosts the accessibility to hull form optimisation for ship designers in Least Developed Countries (LDCs) and Small Island Developing States (SIDS), where proprietary design software may be unaffordable. This accessibility supports the decarbonisation of domestic shipping fleets.
- iii. Economic viability. Although bulk carriers operate at moderate speeds, they benefit from hull form optimisation. In this study, a 2.264% reduction in average annual fuel cost was estimated while lowering the optimised speed from 14.5 to 13.76 knots. The savings from hull optimisation significantly outweighed the loss in cargo carrying capacity, making it beneficial for both new builds and retrofits.
- iv. Impact on CO₂ emissions. Hull form optimisation could reduce the CO₂ emissions from the global bulk carrier fleet by up to 3%, and global shipping emissions by 0.712% by 2050. However, a greater impact can be attained by integration of hull optimisation with alternative/renewable fuel technologies and operational improvements.

Beyond the observed technical insights, this research revealed wider economic, environmental, and policy implications, underscoring its relevance to global maritime decarbonisation efforts. The broader implications include:

- i. Cost-effective innovative development. The demonstration of the use of open-source tools, including FreeCAD, OpenFOAM, and Dakota Toolkit, provides a scalable and

affordable pathway for ship designers in less privileged regions to adopt hull optimisation, therefore lowering the barrier to entry.

- ii. Strategic economic and environmental impact. Based on the estimated net annual fuel cost savings of \$372,907.09 per capesize ship, and assuming the fuel prices and fleet size remain stable, the global capesize bulk carrier fleet can realise over \$4.8 billion by 2050. The reduction in CO₂ emissions from the global shipping fleet directly supports the IMO's GHG Strategy and the United Nations SDG 13.
- iii. Maritime policy. As a baseline study, this research advocates for the inclusion of energy efficiency improvement into national maritime decarbonisation policies, particularly for LDCs and SIDS.

This research established a replicable open-source workflow that is a foundation for further research into the development of a robust multi-objective hull optimisation toolkit. Future research should focus on extending this methodology into an integrated open-source marine-oriented CFD optimisation platform freely accessible to all ship designers, especially in LDCs and SIDS. This research confirmed the viability of the implementation of optimised hull forms and demonstrated that hull optimisation can serve a greater transformative role towards IMO's decarbonisation targets. At this juncture, innovations towards decarbonisation must meet the required urgency and have universal applicability to support policy-making and ship designs that embrace energy efficiency improvement as standard practice, especially for domestic fleets.

LIST OF REFERENCES

- Adam, S., Gebremicheal, G. H., Swaminathan, R., Sabr, Mohammed. A., Habtom, S., Huruy, S., & Yassin, U. (2024). Design and optimisation of ship hull for better fuel efficiency. *International Journal of Science and Research Archive*, 13(1), 029–036. <https://doi.org/10.30574/ijrsra.2024.13.1.1526>
- Ang, J. H., Goh, C., & Li, Y. (2015). Key challenges and opportunities in hull form design optimisation for marine and offshore applications. *2015 21st International Conference on Automation and Computing (ICAC)*, 1–6. <https://doi.org/10.1109/IConAC.2015.7313953>
- Antoniadis, P. (2024, March 18). *Optimisation: Gradient-Based Algorithms*. <https://www.baeldung.com/cs/optimization-gradient-based-algorithms>.
- Bekhit, A. S., Pacuraru, F., & Pacuraru, S. (2020). *Hull-propeller-rudder interaction of the JBC ship model*. 420091. <https://doi.org/10.1063/5.0027325>
- Berkenstock, D., Lessard, L., & Alonso, J. (2024). Orthonormal polynomial bases for airfoil design. *IEEE Conference Proceedings*.
- Bialystocki, N., & Konovessis, D. (2016). On the estimation of ship's fuel consumption and speed curve: A statistical approach. *Journal of Ocean Engineering and Science*, 1(2), 157–166. <https://doi.org/10.1016/j.joes.2016.02.001>
- Birk, L. (2019). *Fundamentals of ship hydrodynamics: Fluid mechanics, ship resistance and propulsion: Vol. I* (I). John Wiley & Sons Ltd. <https://lccn.loc.gov/2018060347>
- Carr, J. (2014). *An introduction to Genetic Algorithms*.
- Chugh, V. (2025, June 16). *Hessian Matrix: A guide to second-order derivatives in optimisation and beyond*. <https://www.datacamp.com/tutorial/hessian-matrix>.
- Clarksons. (2025). *Shipping Intelligence Network*. <https://sin.clarksons.net/>.
- Coello, C. A. C., Lamont, G. B., & Veldhuizen, Da. Van. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (2nd ed.).
- Coraddu, A., Oneto, L., Baldi, F., & Anguita, D. (2017). Vessels fuel consumption forecast and trim optimisation: A data analytics perspective. *Ocean Engineering*, 130, 351–370. <https://doi.org/10.1016/j.oceaneng.2016.11.058>
- Cordier, S., Morand, L., Roux, J. M., & Cortey, E. (2017). *Application of OpenFOAM to hull form optimisation at STX France*. <https://www.cfd-numerics.com/wp-content/uploads/2017/02/etude-de-cas-stx-coque.pdf>
- DNV-GL. (2025a). *GreenVoyage2050. Hull form optimisation*. <https://greenvoyage2050.imo.org/technology/hull-form-optimization/>.
- DNV-GL. (2025b). *GreenVoyage2050. Hull retrofitting*. <https://greenvoyage2050.imo.org/technology/hull-retrofitting/>.

- Edward, V. L. (1988). *Principles of Naval Architecture: Volume II - Resistance, Propulsion and Vibration: Vol. Volume II* (V. L. Edward, Ed.). The Society of Naval Architects and Marine Engineers. <https://www.sname.org/principles-naval-architecture>
- EEA. (2020, November 23). *EEA. Are we moving in the right direction? Indicators on transport and environmental integration in the EU: TERM 2000.Energy efficiency.* <https://Www.Eea.Europa.Eu/Publications/ENVISSUENo12/Page027.Html>.
- Elhadad, A. M., El-Ela, A. M. A., & Hussien, M. M. (2023). Matlab Implementation using Holtrop and Mennen Method of Bare Hull Resistance Prediction for Surface Combatant Ship Coupled with CFD. *CFD Letters*, 15(10), 1–11. <https://doi.org/10.37934/cfdl.15.10.111>
- Emre, Ç., Bekir, Ş., & Burak, Y. (2016). *Determination of the resistance of a displacement type hull form by means of different CFD solvers.* https://www.researchgate.net/profile/Olgun-Konur/publication/325416423_EFFECT_OF_SEA_WATER_COOLING_SYSTEMS_TO_THE_ENERGY_EFFICIENCY_OF_SOLAR_PANELS_ON_MARINE_VESSELS/links/5b0d0e7ca6fdcc8c25368ca4/EFFECT-OF-SEA-WATER-COOLING-SYSTEMS-TO-THE-ENERGY-EFFICIENCY-OF-SOLAR-PANELS-ON-MARINE-VESSELS.pdf#page=183
- EU. (2025, August). *Energy: Weekly Oil Bulletin.* https://Energy.Ec.Europa.Eu/Data-and-Analysis/Weekly-Oil-Bulletin_en.
- Fan, A., Yang, J., Yang, L., Wu, D., & Vladimir, N. (2022). A review of ship fuel consumption models. *Ocean Engineering*, 264, 112405. <https://doi.org/10.1016/j.oceaneng.2022.112405>
- Fidelis. (2024). *Turbulence modelling techniques in CFD – DNS vs LES vs RANS.* <https://Www.Fidelisfea.Com/Post/Turbulence-Modeling-Techniques-in-Cfd-Dns-vs-Les-vs-Rans>.
- Furcas, F., Vernengo, G., Villa, D., & Gaggero, S. (2020). Design of Wake Equalizing Ducts using RANSE-based SBDO. *Applied Ocean Research*, 97, 102087. <https://doi.org/10.1016/j.apor.2020.102087>
- Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimisation, and Machine Learning.* Reading: Addison-Wesley.
- Grlj, C. G., Degiuli, N., & Martić, I. (2025). Assessment of the effect of speed and scale on the total resistance and its components for a bulk carrier. *Results in Engineering*, 26, 105095. <https://doi.org/10.1016/j.rineng.2025.105095>
- Guha, A., & Falzarano, J. (2015). Application of multi-objective genetic algorithm in ship hull optimisation. *Ocean Systems Engineering*, 5(2), 91–107. <https://doi.org/10.12989/ose.2015.5.2.091>
- Haddadi, B. (2025). *OpenFOAM Basic Training* (7th ed.).
- Han, S., Lee, Y.-S., & Choi, Y. B. (2012). Hydrodynamic hull form optimisation using parametric models. *Journal of Marine Science and Technology*, 17(1), 1–17. <https://doi.org/10.1007/s00773-011-0148-8>

- Holtrop, J., & Mennen, G. G. J. (1982a). An approximate power prediction method. *International Shipbuilding Progress*, 29(335), 166–170. <https://doi.org/10.3233/ISP-1982-2933501>
- Holtrop, J., & Mennen, G. G. J. (1982b). An approximate power prediction method. *International Shipbuilding Progress*, 29(335), 166–170. <https://doi.org/10.3233/ISP-1982-2933501>
- IdealSimulations. (2022). *Turbulence models in CFD*. <https://www.idealsimulations.com/resources/turbulence-models-in-cfd/>.
- IMO. (n.d.-a). *Improving the energy efficiency of ships*. <https://www.imo.org/en/Ourwork/Environment/Pages/Improving%20the%20energy%20efficiency%20of%20ships.aspx>.
- IMO. (n.d.-b). *Improving the energy efficiency of ships*. <https://www.imo.org/en/OurWork/Environment/Pages/Improving%20the%20energy%20efficiency%20of%20ships.aspx>.
- IMO. (2011). *Resolution MEPC.203(62). Amendments to the Annex of the Protocol of 1997 to amend The International Convention for the Prevention of Pollution from Ships, 1973, as modified by The Protocol of 1978 relating thereto*.
- IMO. (2018). *Resolution MEPC.304(72): Initial IMO strategy on reduction of GHG emissions from ships*.
- IMO. (2020). *Fourth IMO GHG Study 2020*. <https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/Fourth%20IMO%20GHG%20Study%202020%20-%20Full%20report%20and%20annexes.pdf>
- IMO. (2021). *Resolution MEPC.328(76). Amendments to the Annex of the Protocol of 1997 to amend The International Convention for the Prevention of Pollution from Ships, 1973, as modified by The Protocol of 1978 relating thereto*.
- IMO. (2023a). *Resolution MEPC.376(80). Guidelines on life cycle GHG intensity of marine fuels (LCA guidelines)*.
- IMO. (2023b). *Resolution MEPC.377(80): 2023 IMO strategy on reduction of GHG emissions from ships*.
- Islam, H., Ventura, M., Guedes Soares, C., Tadros, M., & Abdelwahab, H. S. (2022). Comparison between empirical and CFD based methods for ship resistance and power prediction. In *Trends in Maritime Technology and Engineering Volume 1* (pp. 347–357). CRC Press. <https://doi.org/10.1201/9781003320272-38>
- Jennie, A., Marko, H., Arash, E., & Rickard, B. (2015, September). CFD Simulations of the Japan Bulk Carrier Test Case. *Proceedings of the 18th Numerical Towing Tank Symposium*.
- Jeong, K.-L., & Jeong, S.-M. (2020). A Mesh deformation method for CFD-based hull form optimisation. *Journal of Marine Science and Engineering*, 8(6), 473. <https://doi.org/10.3390/jmse8060473>

- Kormaz, K. B. (2015). *CFD predictions of resistance and propulsion for the JAPAN Bulk Carrier (JBC) with and without an Energy Saving Device* [Masters, Chalmers University of Technology]. <https://publications.lib.chalmers.se/records/fulltext/219361/219361.pdf>
- Koshakji, A., Quarteroni, A., & Rozza, G. (2013). Free Form Deformation techniques applied to 3D shape optimisation problems. *Communications in Applied and Industrial Mathematics*.
- Kristensen, H. O., & Lützen, M. (2012a). *Prediction of resistance and propulsion power of ships*. https://www.mek.dtu.dk/english/-/media/institutter/mechanik/sektioner/fvm/english/software/ship_emissions/wp-2-report-4-resistance-and-propulsion-power-final.pdf
- Kristensen, H. O., & Lützen, M. (2012b, June 11). *Existing design trends for tankers and bulk carriers-design changes for improvement of the EEDI in the future. Paper presented at IMDC2012*. https://backend.orbit.dtu.dk/ws/portalfiles/portal/33437984/Kristensen_and_L_tzen_IMDC_06_Jan_2012.pdf
- Li, S., Zhao, F., & Ni, Q.-J. (2013). Multi-Objective optimisation for ship hull form design using SBD technique. *Tech Science Press. CMES*, 92(2), 123–149. <https://www.techscience.com/CMES/v92n2/26935/pdf>
- Lindbergh, E., & Ahlstrand, F. (2020). *Methods to predict hull resistance in the process of designing electric boats*. <https://www.diva-portal.org/smash/get/diva2:1465549/FULLTEXT01.pdf>
- Liu, X., & Wan, D. (2018, June 24). Hull form optimisation of JBC based on resistance and propulsion performances. *The 13th OpenFOAM Workshop (OFW13)*. <https://dcwan.sjtu.edu.cn/OpenFOAM2018/wp-content/uploads/2018/06/OFW13-15-146.pdf>
- Liu, X., Wan, D., & Lei, L. (2023). Multi-fidelity model and reduced-order method for comprehensive hydrodynamic performance optimisation and prediction of JBC ship. *Ocean Engineering*, 267, 113321. <https://doi.org/10.1016/j.oceaneng.2022.113321>
- Liu, Z., Liu, X., Wan, D., & Xu, Jing. (2021, June 20). Ship resistance and wake optimisation of JBC considering hull-propeller interaction based on CFD. *The 31st International Ocean and Polar Engineering Conference*.
- Ma, Y., Zhao, Y., Yu, J., Zhou, J., & Kuang, H. (2023). An interpretable Gray Box Model for ship fuel consumption prediction based on the SHAP Framework. *Journal of Marine Science and Engineering*, 11(5), 1059. <https://doi.org/10.3390/jmse11051059>
- Mohammadi, B., & Pironneau, O. (2001). *Applied shape optimisation for fluids*.
- Molland, A. F., Turnock, S. R., & Hudson, D. A. (2017a). *Ship Resistance and Propulsion*. Cambridge University Press. <https://doi.org/10.1017/9781316494196>
- Molland, A. F., Turnock, S. R., & Hudson, D. A. (2017b). *Ship resistance and propulsion: practical estimation of ship propulsive power*. Cambridge University Press. https://assets.cambridge.org/97811071/42060/excerpt/9781107142060_excerpt.pdf

- Nikolopoulos, L., & Boulougouris, E. (2019). A study on the statistical calibration of the Holtrop and Mennen approximate power prediction method for full hull form, low Froude number vessels. *Journal of Ship Production and Design*, 35(01), 41–68. <https://doi.org/10.5957/JSPD.170034>
- NMRI. (2015a). *Japan Bulk Carrier (JBC)*. https://T2015.Nmri.Go.Jp/Jbc_gc.Html.
- NMRI. (2015b). *National Maritime Research Institute. JBC (Japan Bulk Carrier) resistance and self-propulsion test results in designed full load and ballast conditions*. <https://Www.Nmri.Go.Jp/En/Study/Intellectual/Db/Jbc2/>.
- Nobuyuki, H. (2015). *JBC test data in NMRI*. <https://t2015.nmri.go.jp/Presentations/Day1-AM2-JBC-TestData1-Hirata.pdf>
- OECD. (2025). *Distribution of annual carbon dioxide (CO₂) emissions from shipping worldwide from 2019 to 2023, by type of ship*. <https://Www.Statista.Com/Statistics/772795/Global-Carbon-Dioxide-Emissions-from-Shipping-by-Class/>.
- OpenCFDLtd. (2024a, January 2). *OpenFOAM Users Guide*. <https://Doc.Openfoam.Com/2312/Quickstart/>.
- OpenCFDLtd. (2024b, January 2). *OpenFOAM Users Guide*. <https://Doc.Openfoam.Com/2312/Quickstart/>.
- Ovchinnikov, K. D. (2019). *Analysis of total resistance for different ship speeds*. <https://www.isprasopen.ru/2019/docs/Ovchinnikov.pdf>
- Papanikolaou, A. (2010). Holistic ship design optimisation. *Computer-Aided Design*, 42(11), 1028–1044. <https://doi.org/10.1016/j.cad.2009.07.002>
- Prabowo, A. R., Martono, E., Muttaqie, T., Tuswan, T., & Myung B., D. (2022). Effect of hull design variations on the resistance profile and wave pattern: A case study of the patrol boat vessel. *Journal of Engineering Science and Technology*, 17(1).
- Prochazkova, J. (2017). *Free form deformation methods - The theory and practice*. https://www.researchgate.net/profile/Jana-Prochazkova-4/publication/314261522_FREE_FORM_DEFORMATION_METHODS_-_THE_THEORY_AND_PRACTICE/links/58be96d14585150d8487050e/FREE-FORM-DEFORMATION-METHODS-THE-THEORY-AND-PRACTICE.pdf
- PyGEM. (2021, July 7). *Free-Form Deformation*. <https://Mathlab.Github.Io/PyGeM/Ffd.Html>.
- Reis, P. H. C. (2022). *Parametric modelling of hull forms for merchant ships*. <https://www.bing.com/ck/a?!&&p=f39261a26315c71b8b7f77b6dd2b739cde1d475f025670edb0ba8911e396c57fJmltdHM9MTczNzQxNzYwMA&ptn=3&ver=2&hsh=4&fclid=27982d46-10fb-6e75-31e2-394911796f22&psq=examples+of+hull+form+parametric+modelling+techniques&u=a1aHR0cHM6Ly9mZW5peC50ZWNUaWNvLnVsaXNib2EucHQvZG93bmxxvYWRGaWxlLzExMjYyOTUwNDM4NDAYMDMvRXh0ZW5kZWRYbnN0cmFjdF84NDU1NC5wZGY&ntb=1>

- Rodrigue, J.-P. (2024). *The geography of transport systems*. Routledge. <https://doi.org/10.4324/9781003343196>
- Samareh, J. A. (1999). A survey of shape parameterization techniques, in CEAS AIAA ICASENASA. *Langley International Forum on Aeroelasticity and Structural Dynamics*.
- Sederberg, T. W., & Parry, S. R. (1986). Free-Form Deformation of solid geometric models. *ACM SIGGRAPH Computer Graphics*, 20(4), 151–160. <https://doi.org/10.1145/15886.15903>
- Shahzad, M. T. (2017). *Ship resistance computations using OpenFOAM* [Erasmus Mundus Master Course in “Integrated Advanced Ship Design”]. West Pomeranian University of Technology.
- Stopford, M. (2008). *Maritime Economics* 3e. Routledge. <https://doi.org/10.4324/9780203891742>
- Tadros, M., Ventura, M., & Guedes Soares, C. (2023). Review of the Decision Support Methods Used in Optimizing Ship Hulls towards Improving Energy Efficiency. *Journal of Marine Science and Engineering*, 11(4), 835. <https://doi.org/10.3390/jmse11040835>
- UNCTAD. (2025, April 23). *Shipping data: UNCTAD releases new seaborne trade statistics*. <https://unctad.org/News/Shipping-Data-Unctad-Releases-New-Seaborne-Trade-Statistics>.
- University of Washington. (2025). *What is optimisation?* https://sites.math.washington.edu/~burke/Crs/515/Notes/Nt_1.pdf.
- USNA. (2020). *EN400: Principles of ship performance. Course notes*. United States Naval Academy.
- Wang, H., & Lutsey, N. (2013). *Long-term potential for increased shipping efficiency through the adoption of industry leading practices*. https://theicct.org/wp-content/uploads/2021/06/ICCT_ShipEfficiency_20130723.pdf
- Wang, K., Wang, J., Huang, L., Yuan, Y., Wu, G., Xing, H., Wang, Z., Wang, Z., & Jiang, X. (2022). A comprehensive review on the prediction of ship energy consumption and pollution gas emissions. *Ocean Engineering*, 266, 112826. <https://doi.org/10.1016/j.oceaneng.2022.112826>
- Webb, T. J., Vanden Berghe, E., & O’Dor, R. (2010). Biodiversity’s Big Wet Secret: The global distribution of marine biological records reveals chronic under-exploration of the deep Pelagic Ocean. *PLoS ONE*, 5(8), e10223. <https://doi.org/10.1371/journal.pone.0010223>
- Wei, N., Yin, L., Li, C., Li, C., Chan, C., & Zeng, F. (2021). Forecasting the daily natural gas consumption with an accurate white-box model. *Energy*, 232, 121036. <https://doi.org/10.1016/j.energy.2021.121036>
- Wilcox, D. (1988). Reassessment of the scale-determining equation for advanced turbulence models. *AIAA Journal*, 26(11), 1296–1360.
- WOLFRAM. (2025a). *NURBS Curve*. <https://mathworld.wolfram.com/NURBSCurve.html>.

- WOLFRAM. (2025b). *NURBS Surface*.
<https://Mathworld.Wolfram.Com/NURBSSurface.Html>.
- Wu, P.-C., Chang, C.-W., & Huang, Y.-C. (2022). Design of Energy-Saving Duct for JBC to reduce ship resistance by CFD method. *Energies*, 15(17), 6484. <https://doi.org/10.3390/en15176484>
- Xie, X., Sun, B., Li, X., Olsson, T., Maleki, N., & Ahlgren, F. (2023). Fuel consumption prediction models based on Machine Learning and mathematical methods. *Journal of Marine Science and Engineering*, 11(4), 738. <https://doi.org/10.3390/jmse11040738>
- Yan, R., Wang, S., & Psaraftis, H. N. (2021). Data analytics for fuel consumption management in maritime transportation: Status and perspectives. *Transportation Research Part E: Logistics and Transportation Review*, 155, 102489. <https://doi.org/10.1016/j.tre.2021.102489>
- Yang, C., & Huang, F. (2016). An overview of simulation-based hydrodynamic design of ship hull forms. *Journal of Hydrodynamics*, 28(6), 947–960. [https://doi.org/10.1016/S1001-6058\(16\)60696-0](https://doi.org/10.1016/S1001-6058(16)60696-0)
- Zabinsky, Z. B. (2009). *Random search algorithms*. Department of Industrial and Systems Engineering, University of Washington. <https://courses.washington.edu/inde510/516/AdapRandomSearch4.05.2009.pdf>
- Zhou, H., Feng, B., Liu, Z., Chang, H., & Cheng, X. (2022). NURBS-based parametric design for ship hull form. *Journal of Marine Science and Engineering*, 10(5), 686. <https://doi.org/10.3390/jmse10050686>
- Zhu, S., Lv, S., Chen, K., Fang, W., & Cao, L. (2024). *Research progress on intelligent optimisation techniques for energy-efficient design of ship hull forms*.

blockMeshDict File

63

snappyHexMeshDict File

```
----- C++ -----
// \ / F i e l d      | OpenFOAM: The Open Source CFD Toolbox
// \ / O p e r a t i o n | Website: https://openfoam.org
// \ / A n d             | Version: 12
// \ / M a n i p u l a t i o n |
-----*/

FoamFile
{
    format      ascii;
    class       dictionary;
    object      snappyHexMeshDict;
}

// ***** //

// Which of the steps to run
castellatedMesh true;
snap           true;
addLayers      true;

// Geometry. Definition of all surfaces. All surfaces are of class
// searchableSurface.
// Surfaces are used
// - to specify refinement for any mesh cell intersecting it
// - to specify refinement for any mesh cell inside/outside/near
// - to 'snap' the mesh boundary to the surface
geometry
{
    hull
    {
        type triSurfaceMesh;
        file "JBC.stl";

        patchInfo
        {
            type wall;
        }
    }
};

// Settings for the castellatedMesh generation.
castellatedMeshControls
{
    // Refinement parameters
    // -----

    // If local number of cells is >= maxLocalCells on any processor
    // switches from from refinement followed by balancing
    // (current method) to (weighted) balancing before refinement.
    maxLocalCells 1000000;

    // Overall cell limit (approximately). Refinement will stop immediately
    // upon reaching this number so a refinement level might not complete.
    // Note that this is the number of cells before removing the part which
    // is not 'visible' from the keepPoint. The final number of cells might
    // actually be a lot less.
    maxGlobalCells 4000000;

    // The surface refinement loop might spend lots of iterations refining just a
    // few cells. This setting will cause refinement to stop if <= minimumRefine
    // are selected for refinement. Note: it will at least do one iteration
    // (unless the number of cells to refine is 0)
    minRefinementCells 4;

    // Number of buffer layers between different levels.
    // 1 means normal 2:1 refinement restriction, larger means slower
    // refinement.
    nCellsBetweenLevels 3;

    // Explicit feature edge refinement
    // -----

    // Specifies a level for any cell intersected by its edges.
    // This is a featureEdgeMesh, read from constant/geometry for now.
    features
    {
        {
            file "JBC.eMesh";
            level 3;
        }
    };

    // Surface based refinement
    // -----

    // Specifies two levels for every surface. The first is the minimum level,
    // every cell intersecting a surface gets refined up to the minimum level.
    // The second level is the maximum level. Cells that 'see' multiple
    // intersections where the intersections make an
    // angle > resolveFeatureAngle get refined up to the maximum level.

    refinementSurfaces
    {
        hull
        {
            // Surface-wise min and max refinement level
            level (2 3);
        }
    }

    resolveFeatureAngle 45;

    // Mesh selection
    // -----

    // After refinement patches get added for all refinementSurfaces and
    // all cells intersecting the surfaces get put into these patches. The
    // section reachable from the insidePoint is kept.
    // NOTE: This point should never be on a face, always inside a cell, even
    // after refinement.
    insidePoint (0 -1 0.2);

    // Whether any faceZones (as specified in the refinementSurfaces)
    // are only on the boundary of corresponding cellZones or also allow
    // free-standing zone faces. Not used if there are no faceZones.
    allowFreeStandingZoneFaces true;
}
```

P File

```
/*-----*- C++ -*-----*\
=====
\\      / F ield      | OpenFOAM: The Open Source CFD Toolbox
\\      / O peration  | Website: https://openfoam.org
\\      / A nd        | Version: 12
\\      / M anipulation|
=====
\*-----*/
FoamFile
{
    format      ascii;
    class       volScalarField;
    location    "0";
    object      p_rgh;
}
// ***** //

dimensions      [1 -1 -2 0 0 0];

internalField   uniform 0;

boundaryField
{
    //- Set patchGroups for constraint patches
    #includeEtc "caseDicts/setConstraintTypes"

    inlet
    {
        type      zeroGradient;
    }

    outlet
    {
        type      zeroGradient;
    }
    inside
    {
        type      zeroGradient;
    }
    outSide
    {
        type      zeroGradient;
    }
    atmosphere
    {
        type      prghTotalPressure;
        p0        uniform 2533;
        value      uniform 0;
    }
    bottom
    {
        type      zeroGradient;
    }
    side
    {
        type      symmetryPlane;
    }
    midPlane
    {
        type      symmetryPlane;
    }
    hull
    {
        type      zeroGradient;
    }
}
// ***** //
```

U File

```
/*----- C++ -----*/
=====
\\      / F ield      | OpenFOAM: The Open Source CFD Toolbox
\\      / O peration  | Website: https://openfoam.org
\\      / A nd        | Version: 12
\\      / M anipulation|
=====
FoamFile
{
    format      ascii;
    class       volVectorField;
    location    "0";
    object      U;
}
// ***** //

dimensions      [0 1 -1 0 0 0 0];

internalField   uniform (-0.982 0 0);

boundaryField
{
    //- Set patchGroups for constraint patches
    #includeEtc "caseDicts/setConstraintTypes"

    inlet
    {
        type      fixedValue;
        value      uniform (-0.982 0 0);
    }

    outlet
    {
        type      inletOutlet;
        inletValue uniform (0 0 0);
        value      uniform (0 0 0);
    }
    inside
    {
        type      zeroGradient;
    }
    outside
    {
        type      zeroGradient;
    }
    atmosphere
    {
        type      pressureInletOutletVelocity;
        value      uniform (0 0 0);
    }
    bottom
    {
        type      slip;
    }
    side
    {
        type      symmetryPlane;
    }
    midPlane
    {
        type      symmetryPlane;
    }
    hull
    {
        type      noSlip;
    }
}
```

APPENDIX II: DAKOTA SUPPORTING FILES

DAKOTA INPUT FILE

```
# Usage:
# dakota -i dakota_case.in -o log.dakota_stdout -e log.dakota_stderr

environment
  #graphics
  tabular_data
  tabular_data_file = 'table_out.dat'

#####
method
  moga
  output verbose
  max_function_evaluations = 50
  seed = 23421
  population_size = 10
  print_each_pop
  final_solutions = 3
  initialization_type unique_random
  #####
  crossover_type shuffle_random
  #####
  mutation_type replace_uniform
  mutation_rate = 0.1

  #SET HERE PARAMETERS FOR MOGA
  fitness_type domination_count
  convergence_type metric_tracker
  num_generations = 10
  #####

model
  single

variables
  continuous_design = 2
  cdv_lower_bounds 190.54 -1.27
  cdv_upper_bounds 300.00 -0.98
  cdv_descriptors 'x1' 'x2'

interface
  fork
  asynchronous
  evaluation_concurrency = 1
  analysis_driver = 'simulator_script'
  parameters_file = 'params.in'
  results_file = 'results.out'
  work_directory directory_tag

  copy_files = 'templatedir/*'

# uncomment to leave params.in and results.out files in work_dir subdirectories
# named 'workdir' file_save directory_save

## when using conmin_frog (above) with analytic_gradients (below),
## need to turn off the active set vector as the interface does not parse it.
#deactivate active_set_vector

responses
  num_objective_functions = 2
  no_gradients
  no_hessians

  nonlinear_inequality_constraints = 1
  upper_bounds = 0.001
  lower_bounds = -0.001

  sense 'min' 'max'
```

DAKOTA SIMULATOR SCRIPT – BASH SCRIPT

```
#!/bin/bash
# Sample simulator to Dakota system call script
# See Advanced Simulation Code Interfaces chapter in Users Manual

# $1 is params.in FROM Dakota
# $2 is results.out returned to Dakota

# -----
# PRE-PROCESSING
# -----
# Determine evaluation ID from directory name
EVAL_ID=$(echo "$PWD" | grep -o '[0-9]*$')

# Assign cores based on parity
if (( EVAL_ID % 2 == 0 )); then
    CORES="4-7"
else
    CORES="0-3"
fi

# Incorporate the parameters from DAKOTA into the template, writing X.in
# Use the following line if SNL's APREPRO utility is used instead of DPrePro.
# ../aprepro -o '*' -q --nowarning X.template X.in

python3.11 /home/cfd/dakota/dakota-6.20.0/bin/dprepro $1 input.template input.txt
python3.11 /home/cfd/dakota/dakota-6.20.0/bin/dprepro $1 U.template U.in

# -----
# ANALYSIS
# -----

echo " "
echo "*****"
echo "Running in directory: "
pwd
echo "*****"
echo " "

mydir=$(basename $PWD)
#Move templates files from the right location
cp -r ../case/* .

cp -r 0.orig 0
cp U.in 0/U
rm -rf 0.orig

echo " "
echo "*****"
echo "Generating mesh in FreeCAD"
echo "*****"
echo " "

echo "generating and modifying JBC.STL"

python3.11 JBCSTL.py

cp JBC.STL constant/triSurface/JBC.STL
cp JBC.STL constant/geometry/JBC.STL

echo "blockMesh"
blockMesh > log.blockmesh

echo "surfaceFeatures"
surfaceFeatures > log.surfaceFeatures

echo "decomposePar"
decomposePar > log.decomposePar

echo "snappyHexMesh"
mpirun -np 8 snappyHexMesh -overwrite -parallel > log.snappyHexMesh

echo "reconstructParPar"
reconstructParPar > log.reconstructPar

rm -rf processor0
rm -rf processor1
rm -rf processor2
rm -rf processor3
rm -rf processor4
rm -rf processor5
rm -rf processor6
rm -rf processor7

echo "setFields"
setFields > log.setFields

echo "decomposePar"
decomposePar > log.decomposePar

echo "interFoam"
mpirun -np 8 interFoam -parallel > log.solver

echo "reconstructParPar"
reconstructParPar > log.reconstructPar

touch $mydir.foam

# -----
# POST-PROCESSING
# -----

#Analysing the displacement

echo "Computing displacement"
python3.11 Obj2.py
```

```

#Analysing the CoG
echo "Computing change in CoG"
python3.11 CoG.py

#Create results file

echo "Evaluating objective function"
python3.11 Obj1.py

echo "exporting objective functions to results.txt"
paste -d ' ' results.txt displacement.txt cons.txt> results.txt
paste -d ' ' results.txt displacement.txt cons.txt> results.out

cp results.txt $2
rm results.txt

#CHECK IS results.out is empty
if [ -s "results.out" ]
then
    echo " "
    echo "*****"
    echo "results.out OK (not empty)"
    pwd
    echo "Is the current directory: "
    echo "*****"
    echo " "
    # do something as file has data

else
    echo " "
    echo "*****"
    echo "results.out is empty"
    echo "Creating dummy file"
    echo "Check directory: "
    pwd
    echo "to track the problem "
    echo "*****"
    echo " "
    # do something as file is empty

    #cp ../casebase/dummy_value.out .
    mv dummy_valueMOO.out $2
fi

```

HULL MODIFICATION FILE – PYTHON FILE

```
import sys
sys.path.append("/mnt/x/squashfs-root/usr/lib")
sys.path.append("/mnt/x/squashfs-root/usr/Mod")

import FreeCAD
import shutil
import math
import os
import Part
import Mesh
import pymeshfix as mf
import numpy as np
import trimesh

# Function DEFINITIONS
def read_xl_from_params(file_path):
    with open(file_path, 'r') as f:
        for line in f:
            if 'xl' in line:
                return float(line.strip().split()[0])
    raise ValueError("xl not found in params.in")

def update_bulb(obj, ZB):
    spreadsheet = obj.getObject('Spreadsheet')
    if not spreadsheet:
        raise ValueError("Spreadsheet 'parameters' not found")
    spreadsheet.set('Zb', str(ZB))
    obj.recompute()

def convert_to_solid(doc):
    scale_obj = doc.getObject('Scale')
    if not scale_obj:
        raise ValueError("Object 'Scale' not found")

    # Create a solid from the shape
    solid_shape = Part.makeSolid(scale_obj.Shape)

    # Add it to the document as 'Solid'
    solid_obj = doc.addObject("Part::Feature", "Solid")
    solid_obj.Shape = solid_shape
    doc.recompute()
    return solid_obj

def export_stl(obj, filename):
    solid_model = obj.getObject('Solid')
    if not solid_model:
        raise ValueError("Object 'Solid' not found")
    #mesh = solid_model.Shape.tessellate(0.003)
    #Mesh.Mesh(mesh).write(filename, "STL")
    _obj = [solid_model]
    Mesh.export(_obj, path)
    del _obj_

# PARAMETERS
xl = read_xl_from_params('params.in')
ZB = float(xl)
print(f"Zb={ZB}")
path = "JBC1.STL"

# GEOMETRY SETUP
print("loading jbc_hull.FCStd")
doc = FreeCAD.openDocument('jbc_hull.FCStd')
print("recomputing bulb")
update_bulb(doc, ZB)
doc.recompute()
print ("successfully recomputed bulb")

# CONVERT TO SOLID
print("converting to solid")
solid_obj = convert_to_solid(doc)

# EXPORT TO STL
print("exporting to .stl")
export_stl(doc, path)

# REPAIR STL
print("repairing mesh")
mesh = trimesh.load_mesh("JBC1.stl") # Load your mesh from an STL file

vertices = np.array(mesh.vertices) # Convert to the format pymeshfix expects (vertices and faces)
faces = np.array(mesh.faces)
meshfix = mf.MeshFix(vertices, faces) # Create a MeshFix object
meshfix.repair(verbose=True) # Repair the mesh and make it watertight

print("mesh repair successful")
meshfix.save("JBC.stl") # Save the repaired mesh to a new STL file

print("Successfully exported STL.")
```

OBJECTIVE (1) EVALUATION – PYTHON FILE

```
import re
import math

def read_x2_from_params(file_path):
    with open(file_path, 'r') as f:
        for line in f:
            if 'x2' in line:
                return float(line.strip().split()[0])
    raise ValueError("x2 not found in params.in")

def extract_total_resistance_x(filename):
    total_resistances = []

    with open(filename, 'r') as file:
        for line in file:
            # Match the pressure and viscous forces in x-direction
            match = re.match(r"^\d+\s+\s+\s+([[-\d.e+]])", line)
            if match:
                pressure_x = float(match.group(1))

            # Match the viscous drag right after pressure
            drag_match = re.search(r"\s+([[-\d.e+]])\s+([[-\d.e+]])", line)
            if drag_match:
                drag_x = float(drag_match.group(1))

            # Sum of pressure and drag in x-direction
            total_resistance = pressure_x + drag_x
            total_resistances.append(total_resistance)

    last_50 = total_resistances[-50:]

    if last_50:
        avg_resistance = sum(last_50) / len(last_50)
        return avg_resistance
    else:
        return None

filename = 'postProcessing/forces/0/forces.dat'
ART = extract_total_resistance_x(filename)
Abs_ART = (-ART)
print(Abs_ART)

#read value of resistance from params.in
x2 = read_x2_from_params('params.in')
x = -float(x2)
print("x2="+f"{x}")

Rt0 = 0
Rt0 = (750.99*x**3)-(2467.2*(x**2))+(2729.3*x)-992.92 #Estimate initial resistance at given speed
print(Rt0)

Delta_R = (Abs_ART-Rt0)/Rt0 #compute the change in resistance
print(Delta_R)

#Write Delta_R to a text file
with open("results.txt", "w") as f:
    f.write(f"{Delta_R:.6f}\n")

with open('resistance.txt', 'w') as file:
    file.write(str(ART))
```

OBJECTIVE (2) EVALUATION – PYTHON FILE

```
import trimesh
import numpy as np
from shapely.geometry import Polygon
from shapely.ops import triangulate
from stl import mesh

def clip_and_cap_stl(input_stl_path, output_stl_path, draft_height):
    #Load mesh
    mesh = trimesh.load_mesh(input_stl_path)
    if not isinstance(mesh, trimesh.Trimesh):
        raise TypeError("Loaded mesh is not a Trimesh object")

    #Define planes
    plane_origin = np.array([0, 0, draft_height])
    plane_normal = np.array([0, 0, 1])

    #Slice mesh below draft
    sliced = mesh.slice_plane(plane_origin, -plane_normal)

    #Get intersection contour
    section = mesh.section(plane_origin=plane_origin, plane_normal=plane_normal)
    if section is None or len(section.entities) == 0:
        raise ValueError("No intersection found at the draft height")

    #Extract 2D coordinates from Path3D section
    contour_2D = []
    for entity in section.entities:
        points_3D = section.vertices[entity.points]
        #project onto XY-plane
        contour_2D.extend(points_3D[:, :2])

    #sort into polygon
    contour_2D = np.array(contour_2D)
    polygon = Polygon(contour_2D).convex_hull

    #Triangulate polygon
    triangles = triangulate(polygon)

    #Convert triangles to 3D
    cap_faces = []
    for tri in triangles:
        coords = np.array(tri.exterior.coords)[:-1] #Remove the duplicate last point
        coords_3D = np.column_stack((coords, np.full(len(coords), draft_height)))
        cap_faces.append(coords_3D)

    # define cap-mesh
    cap_vertices = np.vstack(cap_faces)
    cap_faces_idx = [[i, i+1, i+2] for i in range(0, len(cap_vertices), 3)]
    cap_mesh = trimesh.Trimesh(vertices=cap_vertices, faces=cap_faces_idx)

    #Combine mesh
    watertight = sliced + cap_mesh
    watertight.remove_unreferenced_vertices()

    #Export Stl
    watertight.export(output_stl_path)
    print(f"Watertight clipped STL saved to: {output_stl_path}")

def compute_volume(stl_path):
    #Load the new STL file
    your_mesh = mesh.Mesh.from_file(stl_path)
    volume = 0.0

    #compute volume
    for i in range(len(your_mesh.vectors)):
        # Get the vertices of the triangle
        v0, v1, v2 = your_mesh.vectors[i]

        # Compute the signed volume of the tetrahedron formed with the origin
        tetra_volume = np.dot(v0, np.cross(v1, v2)) / 6.0
        volume += tetra_volume

    return abs(volume) # Return absolute volume

clip_and_cap_stl("JBC.stl", "JBChelowDraft.stl", draft_height=0.4125)
stl_file = "JBChelowDraft.stl"
vol = compute_volume(stl_file)
#print(f"Volume of STL object: {vol:.6f} m3")

#Objective 2 evaluation
Disp0=1.393113
Dispm=vol

Delta_D=(Dispm-Disp0)/Disp0

with open('displacement.txt', 'a') as f:
    f.write(f"{Delta_D}\n")
```

CoG CONSTRAINT EVALUATION FILE – PYTHON FILE

```
import numpy as np
from stl import mesh
import math

def compute_center_of_mass(stl_file_path):
    model_mesh = mesh.Mesh.from_file(stl_file_path)

    total_volume = 0.0
    weighted_sum = np.zeros(3)

    for i in range(len(model_mesh.vectors)):
        v1, v2, v3 = model_mesh.vectors[i]
        origin = np.array([0.0, 0.0, 0.0]) #use origin to form tetrahedron

        #Compute volume of the tetrahedron
        tetra_volume = np.abs(np.dot(v1 - origin, np.cross(v2 - origin, v3 - origin))) / 6.0

        #Compute centroid of the tetrahedron
        tetra_centroid = (v1 + v2 + v3 + origin) / 4.0

        total_volume += tetra_volume
        weighted_sum += tetra_volume * tetra_centroid

    center_of_mass = weighted_sum / total_volume
    return center_of_mass

#function call
stl_path = 'constant/geometry/JBC.stl'
x, y, z = compute_center_of_mass(stl_path)

x0=0.08204111503468564
y0=-0.2650715434029383
z0=0.32503088500481303

cons=math.sqrt((x-x0)**2+(y-y0)**2+(z-z0)**2)

with open('cons.txt', 'w') as file:
    file.write(str(cons))
```

Table 1*Results from the Multi-Objective Genetic Algorithm optimisation*

Eval_id	Zb (mm)	Um (m/s)	ΔD , Obj 2	ΔCoG	Rt0 (N)	Rt (N)	Rt-Rt0 (N)	ΔRT , Obj 1
1	218.2532916	1.119390159	-0.00086486	0.0015934	24.10960	23.56558	-0.54401	-0.022564
2	219.1766075	0.997295229	-0.00086743	0.0015988	20.03894	19.89046	-0.14848	-0.007410
3	222.8108182	1.057834102	-0.00086221	0.0015877	22.36724	21.93762	-0.42962	-0.019208
4	227.9107688	1.012377121	-0.00086460	0.0015928	20.73110	20.64364	-0.08746	-0.004219
5	230.5227357	1.151769751	-0.00086478	0.0015931	25.12600	24.59952	-0.52647	-0.020953
6	239.2656455	1.055881781	-0.00086794	0.0015998	22.30712	22.37764	0.07052	0.003161
8	268.2169663	1.057045641	-0.00086786	0.0015996	22.34304	22.44607	0.10303	0.004611
9	284.6143708	1.136035066	-0.00087616	0.0016170	24.60810	23.70789	-0.90021	-0.036582
10	299.7703647	1.087699592	-0.00087119	0.0016062	23.22705	22.65877	-0.56827	-0.024466
11	239.2656455	0.997295229	-0.00086794	0.0015998	20.03894	20.40063	0.36169	0.018049
13	299.7703647	1.012377121	-0.00087119	0.0016062	20.73110	20.81339	0.08230	0.003970
14	218.2532916	1.057045641	-0.00086486	0.0015934	22.34304	22.19983	-0.14320	-0.006409
15	222.8108182	1.002058466	-0.00086221	0.0015877	20.26764	20.47234	0.20470	0.010100
16	239.2656455	1.057045641	-0.00086794	0.0015998	22.34304	22.00979	-0.33325	-0.014915
17	268.2169663	1.057834102	-0.00086786	0.0015996	22.36724	22.37543	0.00819	0.000366
18	222.8108182	1.012377121	-0.00086221	0.0015877	20.73110	20.85184	0.12074	0.005824
19	268.8203855	1.002058466	-0.00086786	0.0015996	20.26764	20.40541	0.13777	0.006797
20	218.2532916	1.151769751	-0.00086486	0.0015934	25.12600	24.47044	-0.65555	-0.026091
21	218.2532916	1.059840583	-0.00086486	0.0015934	22.42836	22.55638	0.12802	0.005708
22	218.2532916	1.012377121	-0.00086486	0.0015934	20.73110	20.84599	0.11489	0.005542
23	227.9107688	1.119390159	-0.00086460	0.0015928	24.10960	23.10769	-1.00190	-0.041556
24	230.5227357	1.119390159	-0.00086478	0.0015931	24.10960	23.15963	-0.94997	-0.039402
26	222.8108182	1.066533787	-0.00086221	0.0015877	22.62782	22.05898	-0.56884	-0.025139
27	222.8108182	1.129782572	-0.00086221	0.0015877	24.41597	23.46622	-0.94974	-0.038898
28	222.8108182	1.056026493	-0.00086221	0.0015877	22.31160	22.20439	-0.10721	-0.004805
29	227.9107688	1.129782572	-0.00086460	0.0015928	24.41597	23.59143	-0.82454	-0.033770
30	204.9929314	1.056026493	-0.00086486	0.0015933	22.31160	22.26372	-0.04788	-0.002146
31	222.8108182	1.268188038	-0.00086221	0.0015877	32.08584	32.13486	0.04902	0.001528
32	222.8108182	0.996794107	-0.00086221	0.0015877	20.01431	20.35161	0.33731	0.016853

APPENDIX III: FUEL SAVINGS AND CO₂ EMISSIONS ESTIMATES

Table 1

Estimation of fuel consumption and CO₂ emissions for both the initial and optimised JBC hull models

year	Operational days per year (days)	Original hull form fuel consumption per year (tons)	Optimized hull form fuel consumption	Fuels savings (tons)	Fuel cost per ton (\$)	Initial hull form CO ₂ emissions per year (tCO ₂ e)	Optimised hull form CO ₂ e per year (tCO ₂ e)	Annual CO ₂ emissions reduction (tCO ₂ e)	Cumulative CO ₂ emissions reduction (tCO ₂ e)	Initial hull form related fuel cost (\$/yr)	Optimized hull form related fuel cost (\$/yr)	Gross fuel cost savings (\$/yr)	Cumulative Fuel savings (\$)	Annual Cargo revenue loss (\$/yr)	Annual net fuel cost savings (\$/yr)	Cumulative net savings (\$)	Annual net fuel cost savings (%)
2,000	273.00	31,707.43	30,726.43	981.01	423.15	98,736.95	95,682.09	3,054.86	3,054.86	13,416,909.21	13,001,798.73	415,110.48	415,110.48	7,644.40	407,466.08	407,466.080	1.842
2,001	240.00	27,874.67	27,012.24	862.42	434.08	86,801.71	84,116.12	2,685.59	5,740.45	12,099,900.99	11,725,537.90	374,363.09	789,473.57	4,255.33	370,107.77	777,573.85	1.137
2,002	255.00	29,616.83	28,700.51	916.33	384.10	92,226.82	89,373.38	2,853.44	8,593.88	11,375,774.08	11,023,815.01	351,959.08	1,141,432.65	3,917.94	348,041.14	1,125,614.98	1.113
2,003	201.00	23,345.03	22,622.75	722.28	358.69	72,696.43	70,447.25	2,249.18	10,843.06	8,373,657.26	8,114,581.73	259,075.53	1,400,508.18	9,535.29	249,540.24	1,375,155.22	3.681
2,004	180.00	20,906.00	20,259.18	646.82	362.28	65,101.28	63,087.09	2,014.19	12,857.26	7,573,785.75	7,339,457.73	234,328.02	1,634,836.20	14,571.98	219,756.04	1,594,911.27	6.219
2,005	196.00	22,764.31	22,060.00	704.31	326.50	70,888.06	68,694.83	2,193.23	15,050.49	7,432,533.30	7,202,575.54	229,957.76	1,864,793.96	11,630.06	218,327.70	1,813,238.97	5.057
2,006	167.00	19,396.12	18,796.02	600.10	370.43	60,399.52	58,530.80	1,868.72	16,919.21	7,184,869.31	6,962,574.11	222,295.20	2,087,089.16	8,615.15	213,680.05	2,026,919.02	3.876
2,007	231.00	26,829.37	25,999.28	830.08	364.82	83,546.65	80,961.77	2,584.88	19,504.09	9,787,925.08	9,485,093.02	302,832.06	2,389,921.22	29,672.09	273,159.97	2,300,078.99	9.798
2,008	216.00	25,087.20	24,311.02	776.18	464.31	78,121.54	75,704.51	2,417.03	21,921.12	11,648,121.65	11,287,736.32	360,385.33	2,750,306.55	24,337.32	336,048.02	2,636,127.00	6.753
2,009	213.00	24,738.77	23,973.37	765.40	361.61	77,036.52	74,653.06	2,383.46	24,304.58	8,945,709.80	8,668,935.33	276,774.46	3,027,081.02	10,555.62	266,218.85	2,902,345.85	3.814
2,010	221.00	25,667.92	24,873.77	794.15	477.94	79,929.91	77,456.93	2,472.98	26,777.56	12,267,634.58	11,888,081.92	379,552.66	3,406,633.68	8,762.84	370,789.82	3,273,135.67	2.309
2,011	225.29	26,166.29	25,356.72	809.57	605.32	81,481.82	78,960.82	2,520.99	29,298.55	15,838,914.07	15,348,868.34	490,045.74	3,896,679.42	3,646.26	486,399.48	3,759,535.15	0.744
2,012	229.58	26,664.65	25,839.67	824.99	681.46	83,033.73	80,464.72	2,569.01	31,867.56	18,170,875.44	17,608,680.33	562,195.11	4,458,874.53	1,734.91	560,460.20	4,319,995.35	0.309
2,013	233.87	27,163.02	26,322.61	840.41	639.64	84,585.64	81,968.61	2,617.02	34,484.59	17,374,458.87	16,836,904.38	537,554.50	4,996,429.02	3,654.97	533,899.53	4,853,894.87	0.680
2,014	230.00	26,713.22	25,886.73	826.49	593.33	83,184.97	80,611.28	2,573.69	37,058.28	15,849,668.76	15,359,290.28	490,378.48	5,486,807.50	3,014.71	487,363.77	5,341,258.64	0.615
2,015	225.00	26,132.50	25,323.98	808.52	399.28	81,376.61	78,858.87	2,517.74	39,576.02	10,434,156.94	10,111,330.89	322,826.05	5,809,633.55	1,652.54	321,173.52	5,662,432.16	0.512
2,016	211.00	24,506.48	23,748.26	758.21	344.53	76,313.17	73,952.09	2,361.08	41,937.10	8,443,178.07	8,181,951.61	261,226.46	6,070,860.01	1,468.57	259,757.88	5,922,190.04	0.562
2,017	194.00	22,532.02	21,834.90	697.13	434.18	70,164.72	67,993.87	2,170.85	44,107.95	9,782,991.26	9,480,311.85	302,679.41	6,373,539.42	3,014.89	299,664.52	6,221,854.56	0.996
2,018	219.00	25,435.63	24,648.67	786.96	509.28	79,206.56	76,755.96	2,450.60	46,558.55	12,953,744.79	12,552,964.32	400,780.47	6,774,319.89	3,542.37	397,238.10	6,619,092.66	0.884
2,019	205.00	23,809.61	23,072.96	736.65	515.27	74,143.13	71,849.19	2,293.94	48,852.49	12,268,409.06	11,888,832.43	379,576.62	7,153,896.51	3,670.87	375,905.76	6,994,998.42	0.967
2,020	200.00	23,228.89	22,510.20	718.69	427.80	72,334.76	70,096.77	2,237.99	51,090.48	9,937,368.89	9,629,913.14	307,455.75	7,461,352.27	2,462.64	304,993.11	7,299,991.53	0.801
2,021	187.00	21,719.01	21,047.04	671.97	572.12	67,633.00	65,540.48	2,092.52	53,183.00	12,425,804.49	12,041,358.16	384,446.34	7,845,798.61	6,046.66	378,399.67	7,678,391.21	1.573
2,022	190.00	22,067.44	21,384.69	682.75	782.03	68,718.02	66,591.93	2,126.09	55,309.09	17,257,370.57	16,723,438.71	533,931.86	8,379,730.47	2,602.44	531,329.42	8,209,720.63	0.487
2,023	218.00	25,319.49	24,536.12	783.37	698.18	78,844.89	76,405.48	2,439.41	57,748.50	17,677,601.24	17,130,667.72	546,933.53	8,926,663.99	3,986.66	542,946.86	8,752,667.49	0.729
2,024	227.00	26,364.79	25,549.08	815.71	706.84	82,099.95	79,559.83	2,540.12	60,288.62	18,635,686.74	18,059,110.67	576,576.07	9,503,240.06	6,566.33	570,009.74	9,322,677.23	1.139
Total	5,387.75	625,756.70	606,396.20	19,360.51		1,948,606.37	1,888,317.75	60,288.62	60,288.62	307,157,050.22	297,653,810.16	9,503,240.06	9,503,240.06	180,562.83	9,322,677.23	9,322,677.23	2.264

Source: Author.

Table 2*Projection of impact of optimised hull on the global maritime GHG emissions*

Year	Global shipping fleet Tank-to-Wake CO2e/year (million tons)	Projected cumulative global CO2e over 25 years (million tons)	Projected global CO2e for the global bulk carrier fleet (million tons)	Projected global CO2e for the global capsize bulk carrier fleet (million tons)	Cumulative projected global CO2 emissions for the global capsize bulk carrier fleet (million tons)	reduced global capsize bulk carriers CO2e due to hull optimisation (million tons)	Cumulative reduced global capsize bulk carriers CO2 emissions due to hull optimisation (million tons)	Annual reduction in CO2 emissions for capsize bulk carrier fleet (million tons)	Cumulative annual reduction in CO2 emissions for capsize bulk carrier fleet (million tons)	Reduced Global shipping fleet Tank-to-Wake CO2e/year (million tons)	Cumulative reduced Global shipping fleet Tank-to-Wake CO2e/year (million tons)
2025	887.537	887.537	204.133	28.97	28.97	28.07	28.07	0.90	0.90	886.64	886.64
2026	875.931	1763.467	201.464	28.59	57.56	27.70	55.78	0.88	1.78	875.05	1,761.69
2027	870.889	2634.357	200.305	28.42	85.98	27.55	83.32	0.88	2.66	870.01	2,631.70
2028	871.793	3506.150	200.512	28.45	114.44	27.57	110.89	0.88	3.54	870.91	3,502.61
2029	872.697	4378.847	200.720	28.48	142.92	27.60	138.50	0.88	4.42	871.82	4,374.42
2030	873.600	5252.447	200.928	28.51	171.43	27.63	166.13	0.88	5.30	872.72	5,247.14
2031	874.504	6126.950	201.136	28.54	199.97	27.66	193.79	0.88	6.19	873.62	6,120.76
2032	875.407	7002.357	201.344	28.57	228.55	27.69	221.48	0.88	7.07	874.52	6,995.29
2033	876.311	7878.668	201.551	28.60	257.15	27.72	249.19	0.88	7.96	875.43	7,870.71
2034	877.214	8755.882	201.759	28.63	285.78	27.75	276.94	0.89	8.84	876.33	8,747.04
2035	878.118	9634.000	201.967	28.66	314.44	27.77	304.71	0.89	9.73	877.23	9,624.27
2036	879.021	10513.021	202.175	28.69	343.13	27.80	332.51	0.89	10.62	878.13	10,502.40
2037	879.925	11392.946	202.383	28.72	371.85	27.83	360.34	0.89	11.50	879.04	11,381.44
2038	880.828	12273.774	202.591	28.75	400.60	27.86	388.20	0.89	12.39	879.94	12,261.38
2039	881.732	13155.506	202.798	28.78	429.38	27.89	416.09	0.89	13.28	880.84	13,142.22
2040	882.635	14038.141	203.006	28.81	458.18	27.92	444.01	0.89	14.18	881.74	14,023.97
2041	883.539	14921.680	203.214	28.84	487.02	27.95	471.95	0.89	15.07	882.65	14,906.61
2042	884.442	15806.122	203.422	28.87	515.89	27.97	499.93	0.89	15.96	883.55	15,790.16
2043	885.346	16691.468	203.630	28.90	544.78	28.00	527.93	0.89	16.86	884.45	16,674.61
2044	886.249	17577.718	203.837	28.93	573.71	28.03	555.96	0.89	17.75	885.35	17,559.97
2045	887.153	18464.871	204.045	28.96	602.67	28.06	584.02	0.90	18.65	886.26	18,446.22
2046	888.056	19352.927	204.253	28.98	631.65	28.09	612.11	0.90	19.54	887.16	19,333.38
2047	888.960	20241.887	204.461	29.01	660.66	28.12	640.22	0.90	20.44	888.06	20,221.45
2048	889.864	21131.751	204.669	29.04	689.71	28.15	668.37	0.90	21.34	888.96	21,110.41
2049	890.767	22022.518	204.876	29.07	718.78	28.17	696.54	0.90	22.24	889.87	22,000.28
2050	891.671	22914.188	205.084	29.10	747.88	28.20	724.75	0.90	23.14	890.77	22,891.05
Total	22914.188	22914.1882	5270.263	747.88	747.88	724.75	724.75	23.14	23.14	22,891.05	22,891.05

Source: Author.

Table 3

NPV and payback period analysis for hull form optimisation at discount rates 2%, 5%, 10%, 15%, and 20%.

discount rate, r =			2%			5%			10%			15%			20%		
Year	CF_A	CCF_A	(1+r)^n	DCF	CDCF	(1+r)^n	DCF	CDCF	(1+r)^n	DCF	CDCF	(1+r)^n	DCF	CDCF	(1+r)^n	DCF	CDCF
0	-1000000	-1000000	1.0000	-1000000	-1000000	1.0000	-1000000	-1000000	1.0000	-1000000	-1000000	1.0000	-1000000	-1000000	1.0000	-1000000	-1000000
1	372907	-627093	1.0200	365595	-634405	1.0500	355149.6	-644850	1.1000	339006	-660994	1.1500	324267	-675733	1.2000	310756	-689244
2	372907	-254186	1.0404	358427	-275978	1.1025	338237.7	-306613	1.2100	308188	-352806	1.3225	281971	-393762	1.4400	258963	-430281
3	372907	118721	1.0612	351399	75421	1.1576	322131.2	15518	1.3310	280171	-72635	1.5209	245192	-148569	1.7280	215803	-214478
4	372907	491628	1.0824	344509	419929	1.2155	306791.6	322310	1.4641	254701	182065	1.7490	213211	64642	2.0736	179836	-34643
5	372907	864535	1.1041	337753	757682	1.2763	292182.5	614493	1.6105	231546	413611	2.0114	185401	250042	2.4883	149863	115220
6	372907	1237443	1.1262	331131	1088813	1.3401	278269	892762	1.7716	210496	624108	2.3131	161218	411260	2.9860	124886	240106
7	372907	1610350	1.1487	324638	1413451	1.4071	265018.1	1157780	1.9487	191360	815468	2.6600	140190	551450	3.5832	104072	344178
8	372907	1983257	1.1717	318273	1731724	1.4775	252398.2	1410178	2.1436	173964	989432	3.0590	121904	673354	4.2998	86726	430904
9	372907	2356164	1.1951	312032	2043756	1.5513	240379.2	1650557	2.3579	158149	1147581	3.5179	106003	779357	5.1598	72272	503176
10	372907	2729071	1.2190	305914	2349670	1.6289	228932.6	1879490	2.5937	143772	1291353	4.0456	92177	871534	6.1917	60227	563403
11	372907	3101978	1.2434	299915	2649585	1.7103	218031.1	2097521	2.8531	130702	1422054	4.6524	80154	951688	7.4301	50189	613591
12	372907	3474885	1.2682	294035	2943620	1.7959	207648.6	2305169	3.1384	118820	1540874	5.3503	69699	1021387	8.9161	41824	655415
13	372907	3847792	1.2936	288269	3231889	1.8856	197760.6	2502930	3.4523	108018	1648892	6.1528	60608	1081995	10.6993	34853	690269
14	372907	4220699	1.3195	282617	3514506	1.9799	188343.4	2691273	3.7975	98198	1747090	7.0757	52702	1134698	12.8392	29044	719313
15	372907	4593606	1.3459	277075	3791581	2.0789	179374.7	2870648	4.1772	89271	1836361	8.1371	45828	1180526	15.4070	24204	743517
16	372907	4966513	1.3728	271643	4063224	2.1829	170833	3041481	4.5950	81155	1917516	9.3576	39851	1220376	18.4884	20170	763687
17	372907	5339421	1.4002	266316	4329540	2.2920	162698.1	3204179	5.0545	73778	1991294	10.7613	34653	1255029	22.1861	16808	780495
18	372907	5712328	1.4282	261094	4590635	2.4066	154950.6	3359130	5.5599	67071	2058365	12.3755	30133	1285162	26.6233	14007	794502
19	372907	6085235	1.4568	255975	4846610	2.5270	147572	3506702	6.1159	60973	2119338	14.2318	26202	1311364	31.9480	11672	806174
20	372907	6458142	1.4859	250956	5097565	2.6533	140544.8	3647247	6.7275	55430	2174768	16.3665	22785	1334149	38.3376	9727	815901
21	372907	6831049	1.5157	246035	5343601	2.7860	133852.2	3781099	7.4002	50391	2225159	18.8215	19813	1353962	46.0051	8106	824007
22	372907	7203956	1.5460	241211	5584811	2.9253	127478.2	3908577	8.1403	45810	2270970	21.6447	17229	1371190	55.2061	6755	830761
23	372907	7576863	1.5769	236481	5821293	3.0715	121407.8	4029985	8.9543	41646	2312615	24.8915	14981	1386172	66.2474	5629	836390
24	372907	7949770	1.6084	231844	6053137	3.2251	115626.5	4145611	9.8497	37860	2350475	28.6252	13027	1399199	79.4968	4691	841081
25	372907	8322677	1.6406	227298	6280435	3.3864	110120.5	4255732	10.8347	34418	2384893	32.9190	11328	1410527	95.3962	3909	844990
NPV (\$)			6,280,435			4255732			2,384,893			1,410,527			844,990		
PBP (years)			2.79			2.95			3.29			3.70			4.23		

Source: Author