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Design methodology for holistic optimisation of offshore supply vessels using genetic algorithms

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Project in Marine Systems Design
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“Holistic design and optimisation process for hull dimensioning of offshore service vessels”

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Background

After the offshore downturn in 2014, the utilisation rate of offshore service vessels (OSVs) have fallen drastically from above 90% to almost 50%. The high complexity of the vessels has consistently raised the capital expenditure of these vessels as well as the operating costs due to multiple operational modes. As the utilisation rate begins to improve in Q3 2019, there is a need to improve the vessel design process to decrease the associated costs of engineering and construction.

However, a holistic approach when optimising the design is necessary, as sub-optimisation of each module of the vessel will not necessarily improve overall efficiency during operation. Therefore, a study should be completed regarding the parametric design and holistic optimisation of the OSV.

Overall aim and focus

The overall aim of the project is to evaluate and analyse current design models for the optimisation of hull geometry for offshore service vessels with the possibility of implementing a new model based on a holistic optimisation process. The methodology should include a parametric model of an OSVs external geometry in addition to the development of the tools required for the determination of the design constraints and efficiency indicators. The model(s) should be used to evaluate the parametrically generated design.

Scope and main activities

The candidate should presumably cover the following main points:

1. Provide an overview of the currently existing design models and evaluate their strength, weaknesses and possible area of improvement to be used in the new model
2. Develop an overview of the main challenges and constraints with the design of current offshore support vessels
3. Develop a framework of a modelling system that evaluates the key performance indicators of offshore support vessels in terms of life cycle costs for North Sea operations
4. Discuss and conclude the validity of the current models and the developed model

Modus operandi

At NTNU, Assistant Professor Svein Aanond Aanondsen will be the responsible advisor.
The work shall follow the guidelines given by NTNU for the MSc Project work.

Svein Aanond Aanondsen
Assistant Professor/Responsible advisor

Preface

This paper is a result of a course for students at the Department of Marine Technology at the Norwegian University of Science and Technology (NTNU). In the course, the student shall write a report within the chosen field of specialisation with the guide of one or more supervisors. The project is equivalent to 7.5 credits.

I would first like to thank my supervisor and thesis advisor, Assistant Professor Svein Aanond Aanondsen. He has been crucial in keeping me on the right path in both my research and my work in DelftShip. He has allowed me to decide both the theme and content of the thesis but has steered me in the right direction where he saw fit. I am very grateful for the weekly meetings and all his time, effort and supervision throughout the semester.

Furthermore, I would like to thank my peers in my office at NTNU for their input and academic discussion regarding the project thesis subject.

December 17, 2019

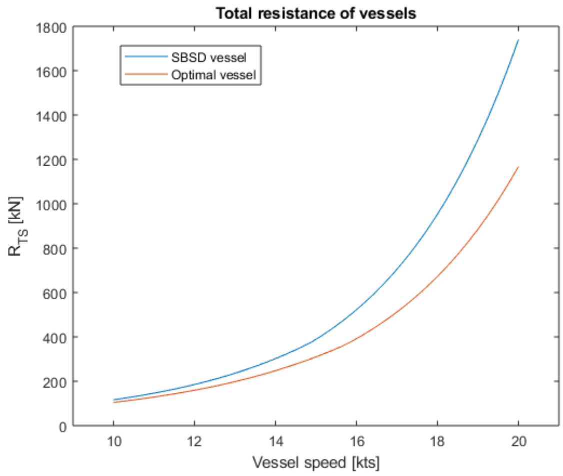
Summary

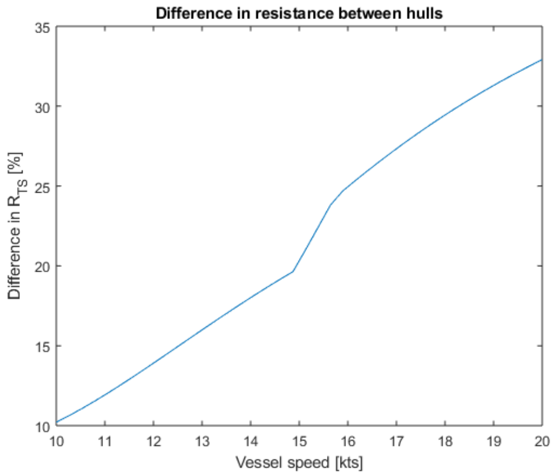
This thesis investigates how the hull geometry of an offshore support vessel can be optimised through the use of a ship design process and a multi-variable genetic algorithm. The report considers multiple design methodologies such as system based ship design, simulation-based design, design building block and bin packing problems. A thorough assessment of each process' benefits and limitations was undertaken to choose the methodology best suited for the overall objective of the project work. A qualitative evaluation was first completed, followed by an analytical hierarchy evaluation process to objectively choose the best design methodology. Based on its simplicity, applicability and ease of setting up, the system based design methodology was chosen as the foundation for the offshore support vessel design.

The scope of the project consists of mapping the various design methodologies used in today's ship design industry, but does not, however, include completing an entire design process evaluating all necessary system on board. Thus, a sample case was chosen that included the design specification of an anchor handling, tug and supply vessel with a gross tonnage of 6,800 and a length overall of 94.0 meters. This vessel was then chosen as the vessel to be optimised in the second part of the thesis. Since no geometry was given for the vessel, a hull model was created in DelftShip, with the exact main dimensions and hydrostatic data. With all the parameters of this vessel known, an objective function was created consisting of reducing the vessel's resistance.

Hollenbach's empirical resistance prediction model represents the objective function of the minimisation. This numerical method considers some vessel main dimensions and coefficients to estimate the total resistance. Hollenbach's method is based on almost 500 towing tests and is one of the most reliable numerical estimation methods in estimating resistance on displacement vessel. Therefore, six main dimensions were chosen as variables and a genetic algorithm was used for the optimisation. The problem formulation consisted of creating upper and lower bounds for each variable as well as linear and non-linear constraints. When determining the bounds and constraints of the optimisation, two main aspects had to be considered. Firstly, the constraints need to be strict enough to have a vessel that is sufficiently similar to the original vessel for a comparative study. Secondly, the objective function value would no be reduced if the constraints and bounds forced the main dimensions to be identical, and the constraints were subsequently relaxed to increase the solution space. Instead of focusing on creating a better hull through identical main dimensions, more focus was given in keeping the hydrostatic coefficients and dimension ratios nearly identical to the original vessel.

The genetic algorithm was able to successfully minimise the average resistance of the vessel in the range of ten to twenty knots by approximately 15%. The optimised hull form (in orange), has a lower resistance than the original hull for all velocities. Additionally, the difference between the two hulls' resistance increases with increasing vessel speed, thus confirming the optimality throughout the speed interval selected.





With a reduced objective function value, the algorithm has proven useful to achieve its goal. However, given that small changes in the hull geometry will significantly alter the vessel's seagoing performance, a sensitivity analysis was conducted. The analysis showed that while finding the global optimum, the model was highly sensitive to both the constraints and the parameters of the genetic algorithm itself. Small adjustments in the constraint that involved the ratio between the waterline length and length overall showed a significant change in the objective function value. Furthermore, various parameters, such as the population size and tolerance of the genetic algorithm, were altered to investigate the following changes. Since the optimisation tool is highly dependent on randomness in its search methods, no clear trend emerged when varying population size, tournament size or constraint tolerance. While an apparent convergence would be desirable to determine the optimal algorithm settings, it has not affected the solution and is thus accepted as it is.

The results indicate that the genetic algorithm has reduced the objective function value to a global minimum, but there are limitations in optimising a hull form in this manner. Due to the inter-connectivity of the main dimensions with the hydrostatic coefficients, a better optimisation platform would include direct geometric optimisation by considering the displaced volume and the sectional area distribution of the vessel. However, due to the limited access into the source code behind the hull modelling program, this process was not possible to achieve in with the given time and resources.

Acronyms

AHP	Analytical hierarchy process
AHTS	Anchor handling tug and supply vessel
bbl	Barrel (42 US gallons \sim 158 litres)
BPP	Bin packing problem
BPP-1	One-dimensional bin backing problem
CAD	Computer-aided design
CAE	Computer-aided engineering
CDF	Computational fluid dynamics
CR	Consistency ratio
DBB	Design Building Block
DES	Discrete event simulation
DNV	Det Norske Veritas (Norwegian classification authority)
DSE	Design Space Exploration
DWL	Draught at deadweight laden condition
DWT	Deadweight
FEA	Finite element analysis
GA	Genetic algorithm
GT	Gross tonnage
IMDC	Intermaitonal Maritime Design Conference
KPI	Key performance index
LCB	Longitudinal centre of buoyancy
LCC	Life cycle cost
MOGA	Multi objective Genetic Algorithm
OCV	Offshore construction vessel
OSV	Offshore support vessel
PSV	Platform supply vessel
RCPSP	Resoruce constrained project scheduling problem
SAC	Sectional area curve
SBD	Simulation-based design
SBSD	System based ship design
SEED	Simulation environment for engineering design
TA	Draught at aft perpendicular
TF	Draught at forward perpendicular
VCG	Vertical centre of gravity
VR	Virtual reality

Nomenclature

C_{FS}	Frictional resistance coefficient
$C_{R,FnKrit}$	Critical Froude number residual coefficient
$C_{R,Hollenbach}$	Hollenbach residual coefficient
$C_{R,Standard}$	Standard residual coefficient
C_B	Block coefficient
C_M	Midship area coefficient
C_P	Prismatic coefficient
C_R	Residual resistance coefficient
C_W	Waterplane area coefficient
D_P	Propeller diameter
$F_{N,Krit}$	Critical Froude number
F_N	Froude number
L_{OA}	Length overall
L_{OS}	Length of submerged hull
L_{PP}	Length between perpendiculars
L_{WL}	Length waterline
N_{Boss}	Number of bossings
N_{Brac}	Number of brackets
N_{Rud}	Number of rudders
N_{Thr}	Number of thrusters
p_m	Mutation rate
R_{NS}	Reynold's number
R_{TS}	Total resistance

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1 Introduction

1.1 Background

Since the first oilfields of Norway were discovered in the 'Ekofisk' field in 1969, the Norwegian shipbuilding industry has served the offshore oil and gas exploration industry well. The Norwegian fossil resources have created an enormous wealth not only for the country in general but the maritime industry as well. The dependency for offshore orders has been apparent for some yards when the oil price plummeted in 2014 and 2016, resulting in cancelled operations, empty order-books and low utilisation rate. The utilisation has fallen drastically from above 90% pre-2014 to almost 50% [1]. The empty order books may also be a result of the OSV's high outfitting complexity that has consistently raised the capital expenditure as well as increased operational costs for multiple operational modes [2].

In order for the local yards to survive, they must reduce the lead time from order to delivery and reduce the costs of design. By developing models that can provide decision support in the early phases of complex vessel design, working hours and their associated costs can be reduced. Traditional vessel design of ship types such as tankers and bulk vessels have for a long time been standardised with little change in the process since the start of modern shipping. As the offshore support vessel market matured, standards have been implemented, and measures are taken for standardising modules for the production of vessels with elaborate designs. However, not all of these designs are optimal in every condition, and sub-optimisation of individual systems and components does not necessarily create an optimised vessel [3].

This report will mainly focus on the most general OSVs that operate in the North Sea offshore market. Due to their extreme outfitting and 'one-job' specialisation, the vessels covered in this report will mostly consist of platform supply vessels (PSV) and anchor-handling, tug and supply vessels (AHTS). Offshore construction vessels (OCV) will not be evaluated due to their need for specialised deck equipment and the desire for a generalised model. Based on reports from the last decade, OSVs are the type of vessels that are most frequently ordered and represent the majority of offshore vessel types servicing the oil and gas industry in Norway [4]. By focusing on these types of vessels, the model will be able to cover the majority and thus make it as standardised as possible.

In today's shipbuilding industry, with particular focus on the Norwegian offshore yards, there are several design methods and processes applied. Different models such as system based ship design, building blocks or bin packing processes are applied across different yards, design offices and countries. These design processes act as a tool in the early phases of a new design with further optimisation tools used for refining the initial designs. Although there is a general understanding of how to design an offshore vessel, such as accepted breadth-width and depth-draught ratios, these may not always be the optimal dimensions for the vessel's specific purpose. It is therefore essential to assess, evaluate and verify these standards by developing a modelling tool to minimise uncertainty and increase the decision-support for the designers. However, in order to comprehend the demand and functional requirements of these vessels, one must also look at the market outlook to determine what sort of OSV is most desirable in the short-term future.

1.2 Offshore market outlook

In terms of offshore investments, multiple market factors show that the leading offshore indices continued upward in 2018 with oil prices remaining uncertain. The offshore drilling rig industry had an improvement in the last quarter of 2018 when the utilisation rate reached 70%, showing a 3% increase from the same time in 2017. Despite its apparent improvement, the term rates for offshore vessels have remained depressed. The global utilisation rate for OSVs has been around 60% throughout 2018 and has seen little change in the first half of 2019 [1] [5]. Table 1.1 shows the Norwegian and regional term and spot prices for OSV's.

North Sea OSV Market	**Spot [£/day]**	**Term [£/day]**
AHTS, 20k+ BHP	42,350	18,000
PSV, >900m^2	9,845	12,500
Regional OSV Market		**Term [$/day]**
W.Africa PSV, >900m^2	-	13,000
Brazil PSV, 900m^2	-	19,000

Table 1.1: Offshore market situation in August 2019 [1].

One of the most critical drivers in the market outlook is the upcoming enforcement of the IMO 2020 Sulphur Cap. Both carriers and charterers are competing for medium-term charters towards the end of 2019 to best mitigate the potential disruption stemming from the new regulatory charges [6]. It is therefore believed that the charter rate for both the North Sea and West Africa term rates will increase towards the end of the last quarter in 2019.

The market cycle of the offshore support industry closely follows the rise and fall of the oil price. In the second half of 2014, the oil price had been at over $100/bbl for over three years. Oil companies were overspending even at this price level but created an increased growth in supply in all oil sectors during the same time. After the price fall in 2015, the global OSV fleet was estimated to have grown at least 5.7% with PSVs growing 9%. However, the utilisation rate has been falling steadily since mid-2014. As owners are increasingly willing to lay up their vessels due to weak demand forecasts, over 80 PSVs have been laid up since the market bust. In 2015, it was estimated that the utilisation of the entire offshore fleet decreased by 26% with an average rate of 76% throughout the year. Large PSVs were able to keep the rate up at almost 85%, while medium-sized vessels were down to 65%. By December 2015, it was estimated that a third of all offshore vessels were in lay-up [5].

The steep fall in oil price and the more heightened capital discipline amongst charterers created little hope for the growth of demand for OSVs. Its demand is mostly driven by production and rig support, and to some extent, offshore and subsea construction support. The PSV's most important market driver is the amount of production support needed, while rig support mostly affects the AHTS segment. Luckily, the market cycle seems to have turned heading towards a new boom. The oil price has increased with more than 60% from the lowest in 2015 and more than 90% from the ten-year low in January in 2016[1]. Utilisation rates are also showing strong signs of improvement with the overall OSV utilisation rate increasing from barely 60% in the fourth quarter of 2018 to 67.5% in the third quarter of 2019. As of mid-December 2019, estimations show that the utilisation rate is at 85% for PSVs and 97% for AHTS [7].

1.3 Objectives

The research objective of this project report is to evaluate the currently available design processes and determine their strengths and weaknesses in order to develop an improved model that can optimise the hull dimensions for OSVs. One part of the project will be an evaluation of the models and the optimisation methods, while the other will be the development of an optimisation model. Hence two key questions arise during the preliminary investigation:

1. What current design process and which optimisation model will give the best results when designing in the early phase for OSVs?
2. What input parameters are necessary to introduce in the design model and what are the necessary output in order to reduce uncertainty and increase the decision support?

The methodology should include a parametric model of an OSVs external geometry in addition to the development of the tools required for the determination of the design con-

[1] Brent spot oil prices and utilisation rates extracted on November 9, 2019.

straints and efficiency indications. The model(s) should be used to evaluate the parametric generated design. The objectives of this report can, therefore, be broken down to several sub-objectives as listed below and are likely to be necessary steps for the forthcoming process evaluation and model development:

1. Evaluate the most common design processes and optimisation tools used in ship designs
2. Explore and identify key numbers from existing OSV fleet for constraint creation
3. Develop initial input model for initial dimensions creation
4. Create geometric hull in DelftShip based on optimised data
5. Analyse optimality of generated hull

1.4 Scope and Limitations

The main scope of this report is two-sided. The first part involves the evaluation and analysis of currently existing design processes/models that are used in today's ship designing industry. Key areas of focus are the processes' strengths and weaknesses, and to fully comprehend the possibilities each process brings and in which cases it is best suited. The first part will also be a similar evaluation of different optimisation tools/models that are available and used in the maritime industry. Their complexity and flexibility will determine which model is best suited for the coming hull optimisation in part two.

The scope for the second part of this report includes the creation of a design process with an integrated optimisation tool that is to be used for early-phase designs and the reduction of uncertainty. The model should aim at receiving specific input criteria, before determining volume and area requirements and then create an OSV hull that creates a feasible solution. The optimised model hull will then be evaluated according to its key performance indicators (KPI's) represented primarily by its wave resistance, and possibly installed power and life cycle cost (LCC).

When modelling the hull in the second part, the hull modelling software DelftShip will be used. However, the output data - consisting of the hull control points, hydrostatic values and stability parameters - is not easily manipulated from a third party software. Hence, any new optimised solution has to be manually integrated into DelftShip for evaluation. The process makes the optimisation and hull generation process slightly less automated, but from experience-based numeric hull form transformations, no more than fifteen iterations are likely necessary before reaching the desired solution. Also, the type of OSV will have to be pre-determined when creating the input data for the model. Thus, either a PSV or AHTS should be chosen to be modelled.

2 Literature review

2.1 Characteristics of the ship design process

In today's maritime industry and among ship designers, there is no single ship design process that is entirely generic. The different approaches to ship design and their corresponding processes change continuously; however, all processes have some key standard features. Commonly for all the design processes evaluated in this chapter, the designer must understand the shipowner's requirements while also refining the requirements per the customer's demands. Additionally, it is said that both art and science are reflected in the shipbuilding process, albeit the role of science is steadily growing at the expense of art, but creativity remains a cornerstone in the design process [8].

In more general terms, the objective of any design effort besides creating the information to build a vessel, is to satisfy the shipowner's requirements at minimum cost. Regardless of the design process, the designer should always inform the shipowner of design options that might increase the acquisition cost but generate considerable savings in the vessel's operational and maintenance costs throughout its life cycle. Essentially, any design process has to fulfil the criteria of creating safe, reliable and, as economical as possible, designs within the constraints imposed by the available technology and the shipowners budget [9] [10].

2.1.1 The design spiral

Ship design is a complex process and has proven too complicated to be described by a set of equations which can be solved directly. Therefore, most processes are iterative in its early stages. Each step of the design process is analysed and modified several times until all requirements are satisfied, and the design represents a feasible solution. In general terms, educated guesses are made as to hull size, displacement and main dimensions get the design process started. As more information becomes available, the initial guesses are modified. Figure 2.1 shows Gale's design spiral that has been used to characterise the general design process. In this particular representation, the ship designer moves through the design process in a sequential series of steps, each dealing with an analytical task. After the completion of all steps in one round, the solution is likely to be either unfeasible or unbalanced. A second cycle should then be completed in the same sequence. This process is then repeated until a viable solution is produced and all requirements are fulfilled [8] [11].

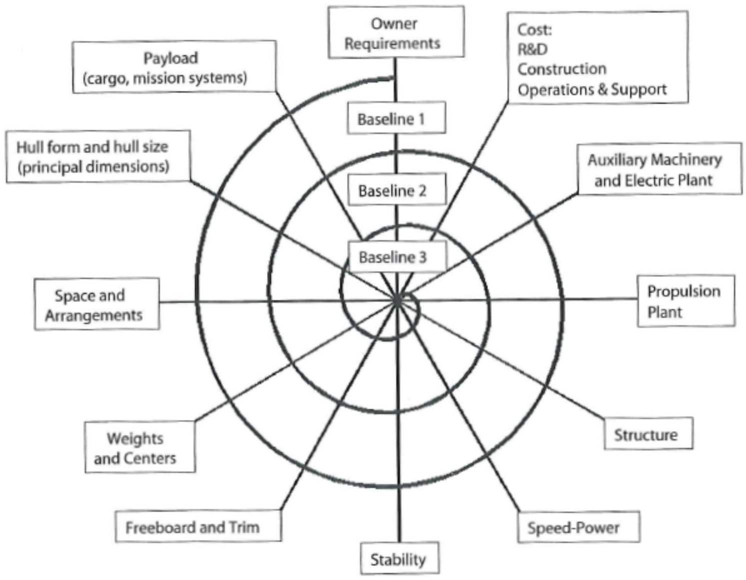

Figure 2.1: Design spiral presented by Gale[8].

2.1.2 Design phases

When creating a new ship design, the process is often subdivided into different phases. The different phases are sometimes divided based on the nature of the work to be done, the required design skills or the level of detail necessary to be delivered. The design phase is often concerning the documentation needed for a yard during a bid, having to present a brief specification before an outline specification and then a technical specification. It should, however, be noted, that this is not the case for all design processes or yards. In prosperous times were short lead time is critical; designers might develop designs without the input from customers basing their work on speculation [8].

The phases can be divided into two major groups; basic design and product engineering [6]. The basic design can further be divided into the following four phases:

1. Concept design
2. Preliminary design
3. Contract design
4. Functional design

whereas the product engineering is often divided into:

1. Transitional design
2. Workstation or fabrication design

During basic design, the ship design itself is completed on a system-by-system basis. During the product engineering, however, the ship design is translated into technical production drawings with additional production annotations for yard workers to understand how to manufacture the vessel.

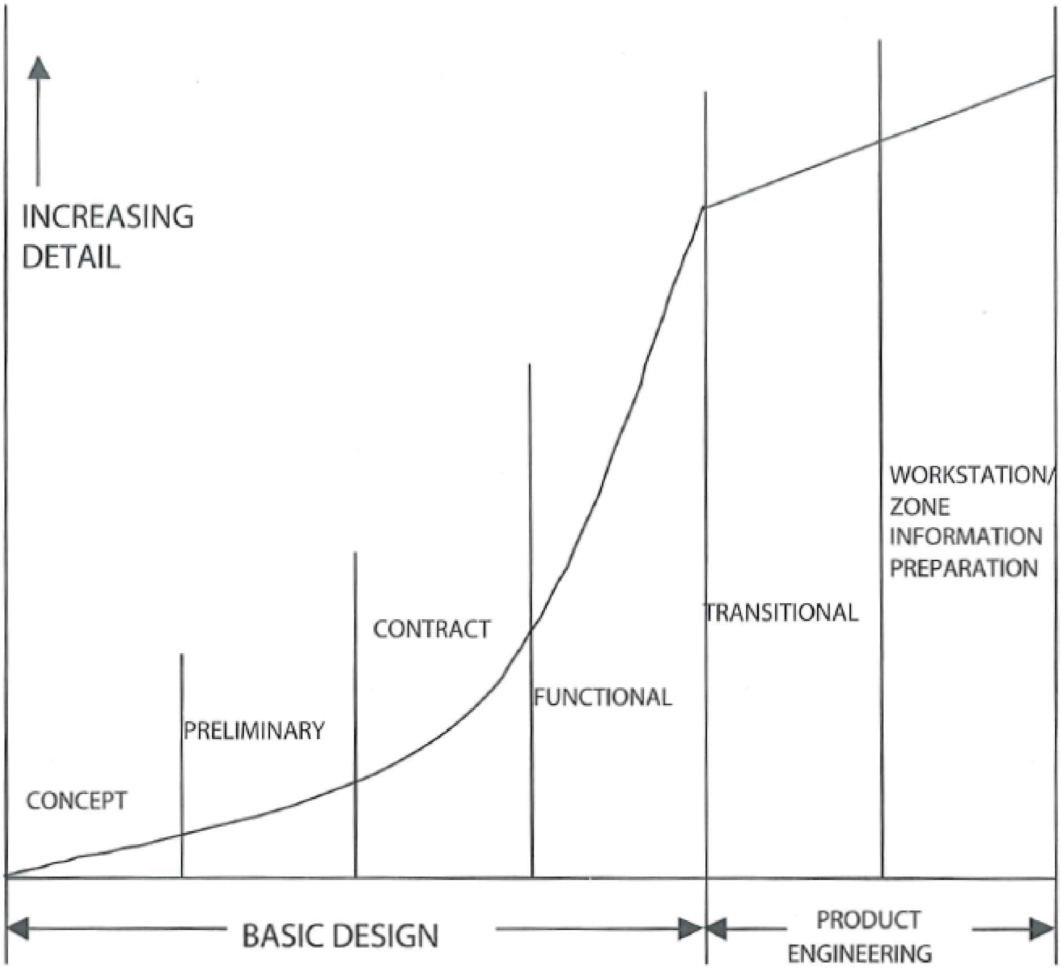

Figure 2.2: The different phases of the ship design process [8]

Figure 2.2 describes the design phases and the product engineering phases according to the increase in the level of detail. Most of the work that is done in this report will be based on the concept design phase as the model chosen in section 3.3 primarily develops a concept design that aims at reducing design uncertainty in early phase projects.

2.2 System Based Ship Design

2.2.1 Origin & overview

System based ship design (SBSD) was first introduced at the International Maritime Design Conference (IMDC) in Kobe, Japan, in 1991. Since its introduction, the design methodology has been successfully implemented on several different types of vessels. The process allows the design of a vessel to be developed with a high degree of detail without further commitment to specific dimensions, layouts or arrangements. As SBSD has been further adapted towards the offshore industry, additional breakdown structures have been developed to identify appropriate systems, weights, areas and volumes. Several efforts and designs have also been created based on experience, having evaluated traditional designs and their specific functions. As a result, the methodology has, in the last years, created the foundation for modular designs [12].

The essential aspect of the SBSD model is to limit the amount of re-work for the ship designer. Traditionally, the main dimensions and capacity were selected beforehand and then evaluated before a redesign would be necessary. SBSD, on the other hand, first evaluates the customer requirements, i.e. the vessel's mission statement before determining the functional requirements of the vessel to initially size the ship. Only after these steps begins the iterative process of parametric exploration, evaluation of performance and economic analysis. Mainly, this process decreases the number of steps that have to be iterated and redone during the ship design process. Figure 2.3 shows the straightened design spiral that does not have to be iterated multiple times.

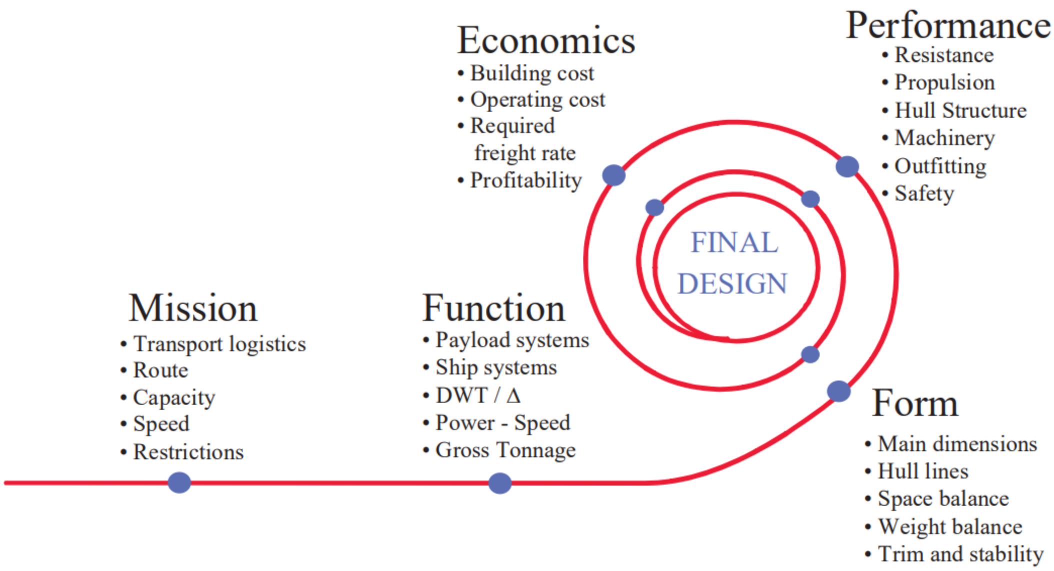

Figure 2.3: The System Based Design Process

2.2.2 System breakdown structure for OSV's

Furthermore, Figure 2.3 represents the general process of the system based ship design. Different from Gale's circular design spiral, not all steps have to be iterated multiple times. Avoiding changes is especially important for the mission statement, as this should not be changed alongside the overall function of the vessel. The following points of the SBSD spiral contain generally:

- **Customer requirements - Mission statement**
  The mission statement of the vessel defines the cargo and transportation capacity of the vessel in terms of cargo/slop tanks, endurance, i.e. fuel capacity and what operating conditions the vessel should be able to operate at
- **Functional requirements - initial sizing of the ship**
  The initial sizing of the vessel is determined by the volume requirements that are calculated based on the prior customer requirements and independent of the hull lines and the main dimensions. The size of the vessel will also give preliminary estimates on the weight of the vessel
- **Form - Parametric exploration**
  After the overall volume requirements are set, the more specific main dimensions of the hull can be decided with a corresponding layout
- **Engineering synthesis**
  The vessel's performance is analysed and evaluated in terms of speed, endurance and safety
- **Evaluation of the design**
  After the engineering is completed, the build cost and operating costs are calculated in order to get a life cycle cost (LCC). In some cases, environmental factors are also considered to determine the emissions over a lifetime.

Furthermore, the functions of the vessel are divided into payload systems and ship systems. The former category represents the 'revenue-generating' systems such as payload systems for cargo, deck handling equipment and storage capacity. Figure 2.4 shows the functional structure for OSV's, which is closely related to the Norwegian SFI system grouping. In addition to the SFI system not distinguishing between ship systems and task-related systems, the system breakdown for the SBSD process includes additional systems such as wood covering for the decks, helicopter platforms and equipment uniquely used for offshore vessels.

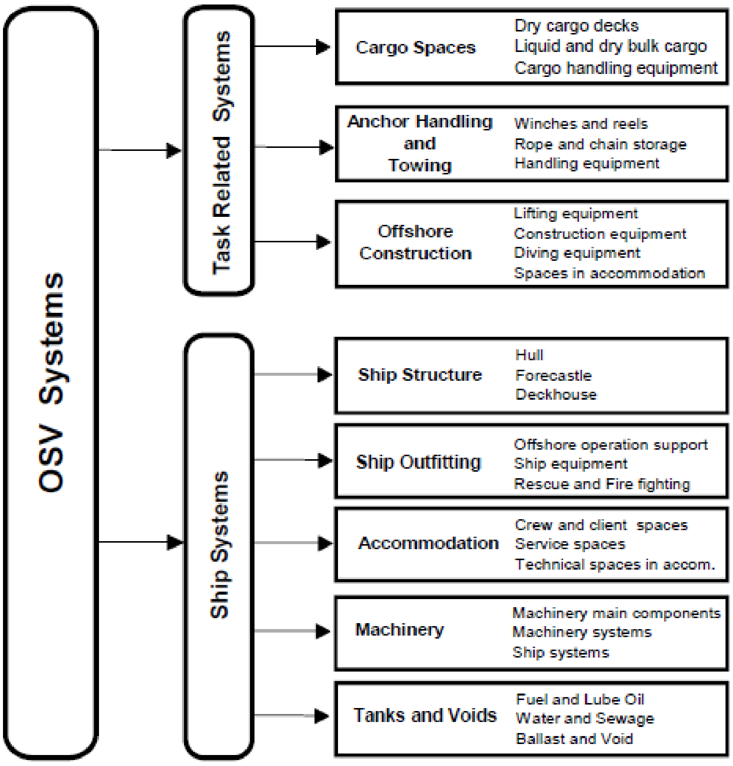

Figure 2.4: System breakdown structure for OSV's divided into task related systems and ship systems [11]

2.2.3 Experience-based data in system based ship design

When using the SBSD for creation of main particulars, data points from existing vessels is required to serve as a link between the individual system requirements and the required space and area for each system of the vessel. Levander and Erikstad gathered a collection of data from OSV, herein including PSV's, AHTS', and OCV's. The vessels data collected has been thoroughly analysed to verify discrepancies between listed gross tonnage and what is written in their DNV certification documents. Furthermore, a comprehensive analysis and evaluation of general arrangements are made in order to calculate the enclosed area and volume spaces on board. However, since offshore support vessels are outfitting intensive, precise measurements of the area occupied by equipment is a difficult task.

In hopes of getting a more updated vessel database with more data points to improve the regression accuracy, over 1,000 vessels have been evaluated based on data from the online vessel database Sea-web [13]. The main characteristics of the vessels have been compared to their gross tonnage through statistical regression analysis. Figure 2.5 shows the relationships between deadweight or installed power with the gross tonnage. In terms of service speed, the top two scatter plots relate to the vessels' Froude numbers and service speed. It is interesting to note for both this analysis and the original in Levander's article, the correlation between the block coefficient C_B and the Froude number F_N has a R^2-value as low as ∼0.03, indicating that the fullness of the hull (i.e. concerning the C_B) is not proportional to the vessel's operating speed. In essence, this means that the fullness of the hull is not necessarily determined by service speed of the vessel, but other factors such as the customer requirements for specialised equipment, thus determining the necessary area and volume of the vessel.

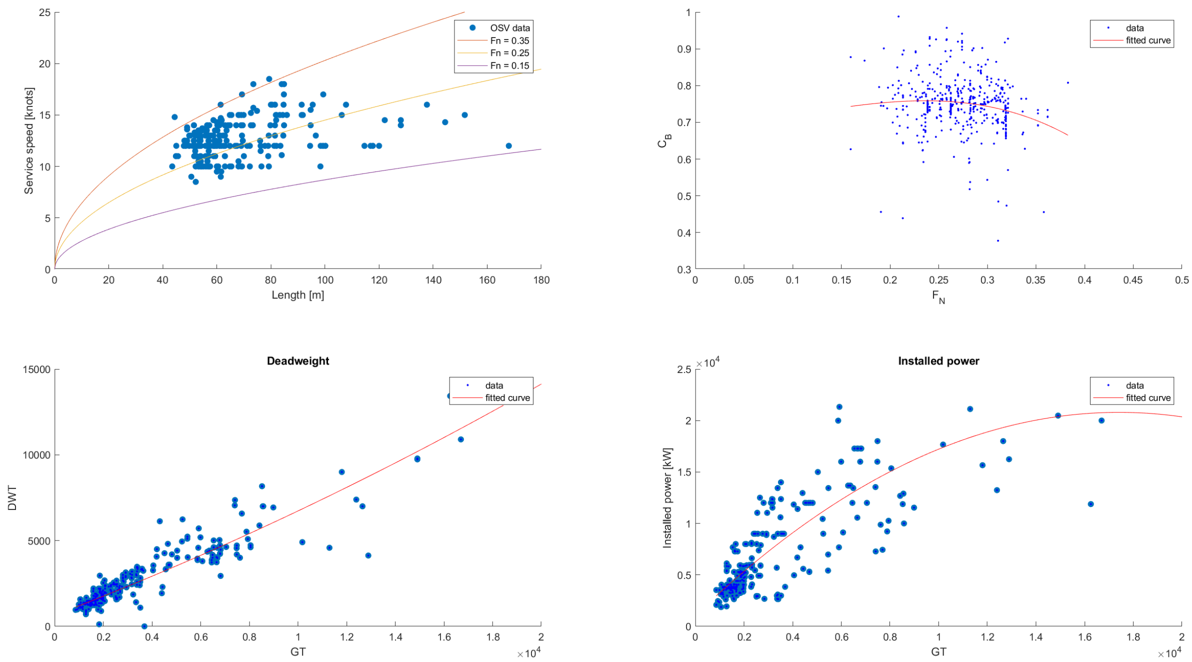

Figure 2.5: Data points for OSV's in relation to gross tonnage

Figure 2.5 does, however, show a much stronger correlation when evaluating the gross tonnage (GT) of the vessels. Relationships between deadweight (DWT) and installed power [kW] with GT have a R^2-value of 0.92 and 0.70 respectively[2]. The gross tonnage is a much more precise indicator statistically when using information from the data sets to determine dimension coefficients in the SBSD process. This is also the case regarding the main dimensions of the hull concerning the gross tonnage.

[2] Values are based on 2nd degree polynomial fitting curves with no robustness taken into account. With bi-square robustness, R^2-values increase to 0.98 and 0.94 respectively.

2.2.4 Summary of System Based Ship Design

The system based ship design model creates a useful breakdown structure for the OSV and thus provides a sound platform for the efficient development of conceptual design solutions for all types of OSVs. The breakdown structure that is used also provides a foundation for modular product architecture. While the process does not need a starting point from an existing ship, the model is dependent on data from previous ships that can be exploited indirectly to provide area and space requirements for the core vessel systems. Using this data makes for an efficient model, but does to some degree limit innovation as the designer wishes to stay within the bounds of the data points. However, the amount of re-work is limited, both because of the more straightforward area and volume calculation but also because of the straightened design spiral, having only to evaluate the functional requirements based on the mission statement of the vessel once. In essence, the process is a simpler and less formal approach to visualise the conceptual solution to a potential customer without committing to certain main particulars of the hull [12].

2.3 Simulation-based Ship Design

2.3.1 Overview and applications

Simulation-based design (SBD) in general, is a field of growing interest to engineers and researches in multiple disciplines. In simulation-based design, simulation is the primary means of design evaluation and verification. By validating the design process through simulation processes, a company may be able to design superior products in less time and at a lower cost [14]. The primary purpose of the simulation technology is to reduce the ship development time and capital investment, in addition to risk reduction, optimisation of the design and improved efficiency [15]. In today's engineering design process, simulation-based design tends to be used in two situations:

1. Where the analysis tools that are required to determine the design performance parameters are well qualified and operate directly on information from the computer-aided design (CAD) system
2. Where the costs associated with classic prototype testing and construction, and large scale testing may result in a costly and time consuming activity

In order for a simulation-based design process to be efficient and sufficiently precise, the user needs to provide the technology and associated software tools that can be applied in a wide variety of design situations. The performance and parameter evaluation of any software used in the simulation needs to include the same level of complexity to verify the results. In the case of prototype testing, a simulation software essentially needs to consider all the parameters that come in to play with the real-life model and be able to simulate its behaviour as it would during the testing.

Mainly, traditional ship design involving a sequential development process that starts with an owner's requirements and ending with the operation of the ship is changed with a more flexible design process. Figure 2.6 shows how simulation comes into play when using virtual design technology. The visualisation tools integrate the design of for example the hull, with the construction designs for building the vessel or may be used for visualising the vessel's behaviour during operation [15].

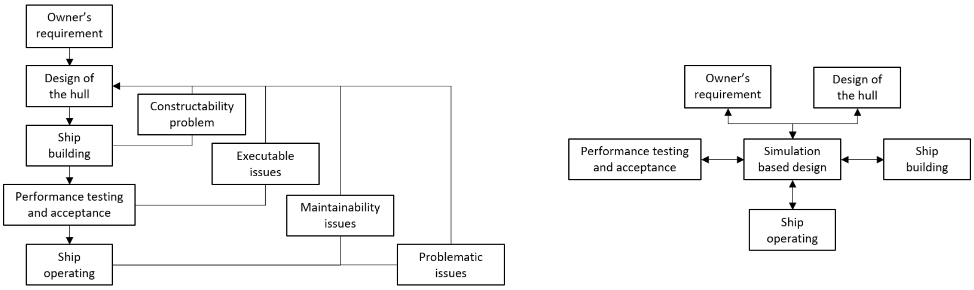

Figure 2.6: (From left to right:) Traditional ship design process and SBD process [15].

2.3.2 System components

The simulation-based design process has a set of functional components that need to interact. As seen in figure 2.7, the components consist of product data managers, CAD tools and computer-assisted engineering (CAE) tools that are frequently used in the industry. Additionally, some features represent the simulation environment for engineering design (SEED) that are depicted within the dashed lines. The interaction between the SEED components and the traditional CAD and CAE features are activated during an engineering simulation.

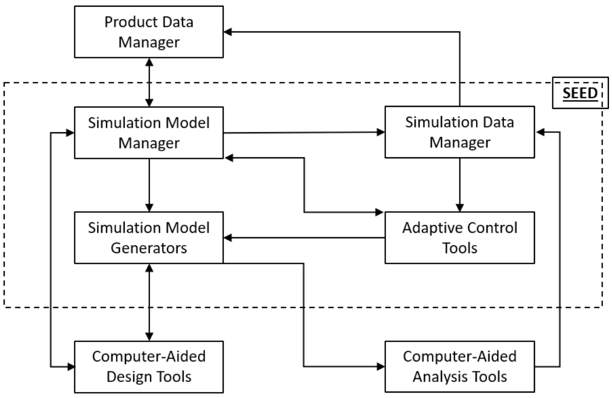

Figure 2.7: The functional components within simulation-based design [14].

The Product Data Manager initiates the process and considers which performance parameters are to be evaluated for a given design. The SEED components will then interpret the parameters and return them in a format that can be used in the simulation process. While the parameters to be changed are done in the product data manager, the CAD tools of the system handle the interactions with the model, such as the geometry and other visual design aspects. Furthermore, the CAE tools of the system will complete the engineering analysis. The tools may consist of one-dimensional engineering methods such as performance models or finite element analysis. It is important to note that the CAE tools operate according to a specific analysis method which is not necessarily maintained as part of the design representation.

Within the SEED functional components, the simulation model manager provides the simulation base with the information needed by other components, while the simulation data manager is responsible for storing the simulation result during the simulation process. The adaptive control tool is responsible for selecting and controlling the simulation model. The control ensures that the performance parameters evaluated in the simulation are as accurately as possible and within the requested accuracy. Lastly, the simulation model generator is responsible for constructing the model used by the CAE tools while considering information from the design [14].

2.3.3 Simulation process in ship design and ship building

The ship design process has changed over time, where the design process is predominantly based on first-principle simulation-based design and less of experience-based design. Consequently, conventional stand-alone analyses of a ship's performance parameters are increasingly interfaced and integrated with computational tools that employ advanced modelling and design techniques. Traditionally, ship designs entail a somewhat chaotic process of combining several analyses with tested or creative solutions. The analyses are sometimes completed in parallel before being evaluated and then possibly rejected or modified.
However, with new and improved simulation tools, optimisation processes can be integrated and thus creating new and more realistic applications. The simulation tools can also be used to simulate bottom-up approaches within shipbuilding and its structural design work. Hulls optimised for the minimisation of production costs without hydrodynamic sacrifice can be created through simulation of the production process while considering the vessel's performance parameters.

Furthermore, simulation has allowed the naval architect to perform stability analyses, both in intact and damaged conditions already in the early phases of the design process. Other 'classical' applications of computational simulations for ships involve computational fluid dynamics (CFD) and finite element analysis (FEA) in structural analyses. While CFD analyses have mostly been performed to analyse the hull and propeller, simulations have been extended to wind, fire (in ship rooms such as engine rooms) and ice-breaking. Aerodynamic analyses have additionally been performed to evaluate the superstructure and ventilated rooms onboard a vessel, and thus simulate the behaviour of a ship in strong winds. Fire simulations have also been used for the ship design process in regards to planning the general arrangement in case of passenger evacuation. This would typically involve discrete event simulation (DES) which has evolved rapidly and has proven to be a versatile tool in the ship design and planning process [16].

The use of simulation in the shipbuilding process can support and improve operational and strategic planning of the yard's operation, particularly in the assembly-line type of construction. This simulation would typically consist of event simulations where individual elements of the construction trigger the execution of other events, each with a given attribute. While the theory behind the simulation of the construction process is relatively simple, the simulation can give beneficial quantitative insight in determining bottlenecks or assembly time. Like all simulation processes, the essential aspect of the model is to correctly and accurately set up the model with all the necessary attributes that reflect the real-life process. When evaluating a ship design through simulation or simulating construction times, human behaviour is likely to have a negligible effect on production time and construction space. However, when using simulation to determine ship evacuation, one has to simulate and predict human behaviour during stressful situations. The common trend is to equip each simulated human with a certain degree of perception and reasoning capability, but simulating irrational behaviour is difficult [16]. Hence, simulation-driven ship design regarding deck layout and general arrangement should consider the human perception, but may have limited attributes regarding the human interaction with the design.

If the human perception and ergonomics of the vessels space is essential, simulation using virtual reality (VR) has also been employed in some cases. Such simulations can be performed both for performing tasks during the building of a ship or during human-vessel interactions. The latter can, for example, be illustrated by simulating VR mannequins that load a torpedo in confined spaces in a submarine or crew operations in a cramped engine room.

2.3.4 Summary of simulation-based ship design

This section illustrates how simulation-based design in the ship design process can be used to integrate several stand-alone analyses together, creating a cost-effective and more streamlined process. SBD can also be used to improve the efficiency and operability of a yard by simulating the construction and assembly process without compromising a vessel's hydrodynamic performance. Additionally, simulation has been used to simulate human behaviour and its interaction with the technology and space onboard, especially applicable to evacuations and personnel movement. While limited by the modelling of human behaviour, such simulations would benefit the naval architect in the general arrangement planning. However, whether the design process involves simulation of human behaviour or the vessel's performance, the simulation is only as good as the level of accurate, realistic modelling. While some attributes are more natural to simulate realistically and model, other problems such as CFD for waves, wind or fire may be more difficult and thus render incorrect or inaccurate descriptions.

2.4 Design Building Block

The Design Building Block (DBB) approach has been in used since its introduction in 1981 and incorporated into the PARAMARINE software produced by the Graphics Research Corporation, a company associated with the UK Ministry of Defence naval ship design agency and supported by the GODDESS ship design computer system. The design process has since been used on various design for combat vessels of the Royal Navy [17].

2.4.1 Development of the Design Building Block Approach

In 1981, Professor D.J. Andrews of University College London proposed a new way to approach ship design, intending to integrate the architectural issues in the early stages of the design phases. The proposal consisted of a more holistic approach to ship design with an integrated architecturally centred synthesis that included a spatial layout that could not be found in the conventional sequential ship design process. The new design method would take into consideration the issues of personnel movement, ease of outfitting and adaptability of the vessel at a much earlier stage, at the point where the design was not completely fixed and open for change. The newly proposed design process also consisted of a graphically-oriented computed aided design tool to be used for early-stage ship designs. To encourage innovation, the tool should provide flexibility in the definition of the design and have the possibility to reconfigure the spatial model to explore various solutions generated by the user [18].

Figure 2.8 represents the conventional sequential ship design process where the designer's influence has a significant effect on the design aspects. The process goes through a sequential series of steps, where each step may be iterated again before advancing to the next step. It is interesting to note that the sequential process with the possibility of reiteration for each step draws certain similarities to that of the design spiral later presented by Gale, depicted in figure 2.1.

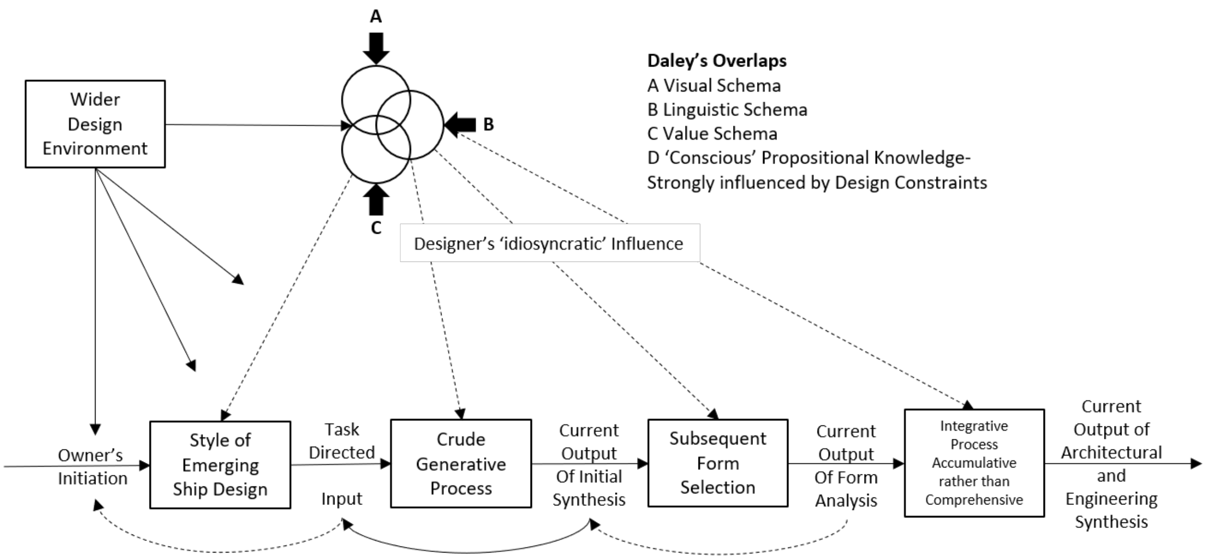

Figure 2.8: The sequential synthesis process in Ship Design [19].

The holistic model of the ship synthesis is depicted in figure 2.9, showing how the spatial and stylistic aspects of the design is taken into consideration creating a feedback process that accounts for a full parametric exploration.

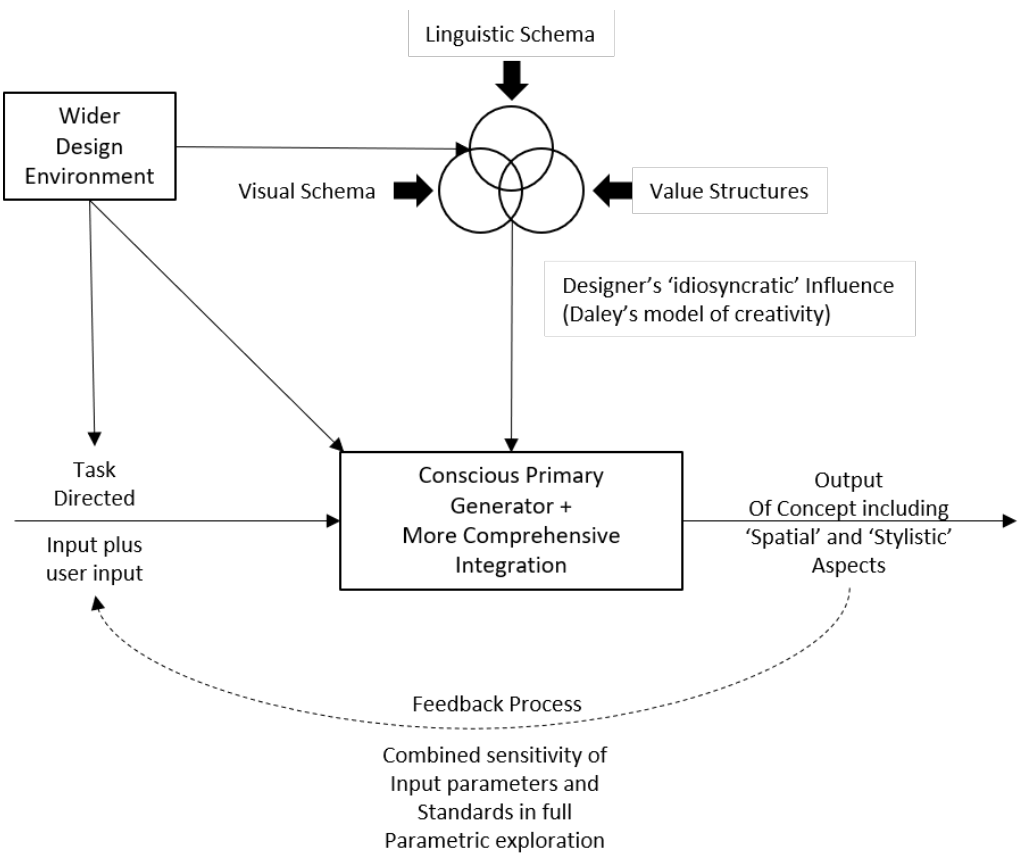

Figure 2.9: The fully integrated ship synthesis logic [19].

2.4.2 Breakdown of procedure for new designs

Since the Design Building Block Model has been mainly used for combatant vessels, the following example of the functional hierarchy breakdown represents the design structure for a frigate. However, the design methodology for DBB can be used for a range of different vessels [17], [18].

1. **Preparation stage**
   An identification of design generators and required function required on board is completed. Definition of necessary weapon systems and ship features to handle their performance. The user defines the preliminary hullform, margins and standards. The endurance and cargo capabilities are dined based on numerical algorithms. Lastly, the output objects of the process are chosen

2. **Major Feature Design Stage**
   Here the first definition of the new design is done by selecting Design Building Blocks for FIGHT group and smaller Building Blocks in areas of uncertainty. Based on the selected Building Blocks, and the pre-defined requirements of the FIGHT group, estimations of personnel space are estimated.

3. **Major Feature Design Stage - Initial sizing**
   Based on the chosen Building Blocks, the initial estimate of the overall vessels size and displacement is completed followed by the first generation of the hull form. Initial resistance estimations are completed based on the generated hullform.

4. **Major Feature Design Stage - Machinery Selection**
   Initial machinery sizing is completed based on the vessel style (MOVE Building Block) in addition to resistance estimate and endurance requirements.

5. **Major Feature Design Stage - Layout**
   The initial layout is generated in accordance to the pre-selected Building Blocks FIGHT, MOVE (machinery) and INFRASTRUCTURE (accommodation), similar to figure 2.10. Several layouts should be generated with alternative solutions, where some may be rejected or retained for parallel development before final choice.

6. **Super Building Block Design Stage**
   An increased level of detail of the general arrangement enables the placement of Super Building Blocks such as auxiliary machinery and fuel tanks. With more detailed layout now decided, structural weight estimates are completed using weight distribution and historical data. Stability assessment is then completed for intact

stability and some damage cases.

7. **Design Building Block Design Stage - Numerical Balance**
   An implementation of scaling algorithms for weight estimation are completed and VCG placement based on items on individual decks is calculated. Further iteration is conducted to create a numerical balance between the total Design Building Block weight and the vessel displacement in addition to the total volume demand and the enclosed volume. The ship design 'solution' at this stage is not balanced yet as the Design Building Blocks of supporting systems such as ship stores, weapons maintenance and workshops have not been placed.

8. **Design Building Block Design Stage - Development of design**
   Further detailing on weight placement is completed for the Design Building Blocks, considering both geometry and location. An iteration of parametric hullform design with variation of block coefficient C_P, midship coefficient C_M, LCB position, length, beam and draught is completed. When iteration is complete, additional performance assessments are carried out[3].

9. **Achievement of naval architecturally balanced design**
   A report is prepared, outlining the complete design and the systems defined by the requirements in step 1.

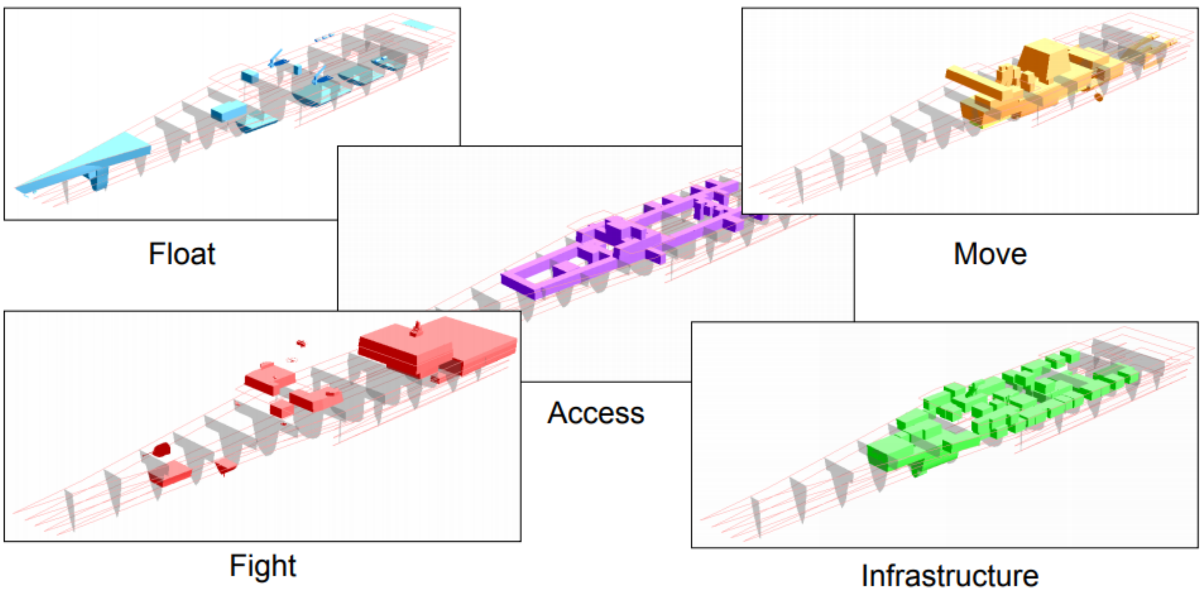

Figure 2.10: Example of Design Building Block functional groups [20]

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[3]Due to the nature of a combat vessel, these performance features include external shape of vessel and Radar Cross Section in relation to external detection and degree of stealth.

2.4.3 The architectural synthesis process

Figure 2.11 represents Andrews' synthesis model where an algorithm has been used of initial sizing but also featuring a configuration model. The process gives a clear representation of the process of iteration that takes place in the later stages of the design right through the final points for the creation of drawings. It is important to note that the first steps may be iterated, but after the concept design has been chosen, the whole process continues without re-iteration of the early stages. The procedure detailed in this section can be compared to the visual representation in the following figure.

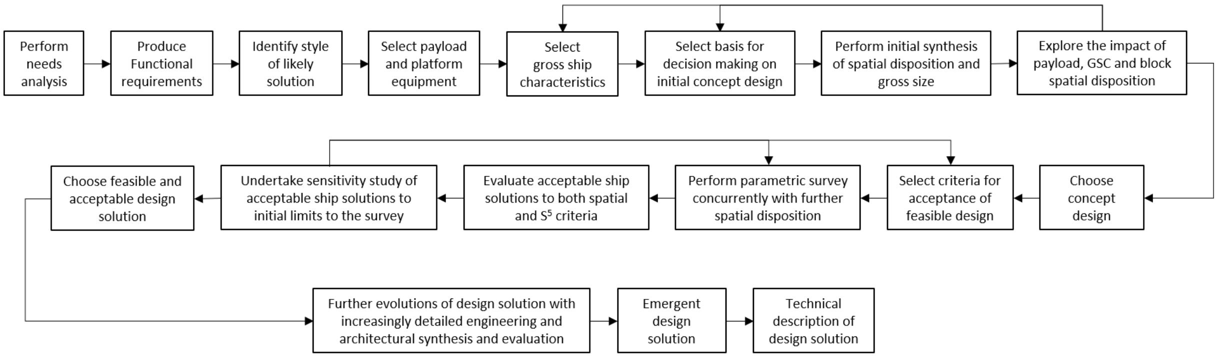


Figure 2.11: Representation of the ship design process incorporating architectural aspects in a fuller synthesis, as proposed by [21].

2.4.4 Summary of Design Building Block methodology

The Design Building Block methodology was created with the aim of not having to commit to the earliest designs by using pre-defined building blocks that could be amended and moved throughout the process. Since the initial sizing is done after the building blocks are selected, the methodology verifies that the hull form will have sufficient volume to support all the necessary systems. However, in contrast to the System Based Ship Building methodology, parameters such as the block coefficient and midship coefficient are defined at a much later stage, and thus not necessarily using data from similar vessels. This process, however, is helped by scaling algorithms that will help determine these parameters. The main dimensions are, therefore, finally iterated once the layout is decided upon and committed. One could, therefore, argue that this may create a very logical and well-placed layout within the vessel, but can limit the possibilities for the hull form and its optimality in terms of stability, seakeeping and resistance.

2.5 Bin Packing

2.5.1 Design scheduling tool

As seen with the previous models, space is a limited resource within the hull form and is also a key resource in a ship block design process. The iterative design process that is common in several design methodologies renders a complicated scheduling problem due to limited space and precedence constraints, e.g. what part of the vessel must be designed before the other. A resource-constrained project scheduling problem (RCPSP) is related to minimising the project makespan under the available resources and precedence constraints. For such a construction problem, the Bin Packing Problem process can be applied [22].

The bin packing problem (BPP) involves putting as many boxes in a limited bin size in order to minimise the height. This can be translated into a ship design problem, where the different areas or systems of a ship are represented by boxes that have to be fitted inside a constrained space. The design problem can be classified into two categories consisting of 2-dimensional and 3-dimensional problems. For the former, the bin packing problem is usually solved by heuristic methods such as Bottom-Left algorithm and Bottom-Left-Fill algorithm. Since the bin packing problem (BPP) belongs to an NP-hard problem, [23] have adopted a one-dimensional problem to solve the two-dimensional problems in an effort of simplifying the algorithm.

2.5.2 The one-dimensional bin packing problem

The one-dimensional bin packing problem (BPP-1) consists of packing a given set of items, having different sizes, into a minimum number of equal-sized bins. The BPP-1 problem is defined as a set $J = \{1, ..., n\}$ of n indivisible items, where each has a specific size or weight given by $w_j \, (j = 1, ..., n)$. In order to keep the generality of the problem, it is assumed that these weights are integral. Each item has to be packed into one bin m, having the capacity c. The total weight/space of items contained in any bin must also not exceed the total capacity. Hence, we have the condition of feasibility given by $w_j \leq c$ for all j [24]. Consequently, the mathematical formulation of the problem can be described by the following [25]:

$$\min z = \sum_{i=1}^{n} y_i \tag{2.1}$$

$$\text{subject to} \quad \sum_{j=1}^{n} w_j x_{ij} \leq c y_i \quad i \in \mathcal{N} = \{1, ..., n\} \tag{2.2}$$

$$\sum_{i=1}^{n} x_{ij} = 1 \quad j \in \mathcal{N} \tag{2.3}$$

$$y_i \in \{0, 1\} \quad i \in \mathcal{N} \tag{2.4}$$

$$x_{ij} in \{0, 1\} \quad (i, j) \in \mathcal{N}, \tag{2.5}$$

where

$$y_i = \begin{cases} 1, & \text{if bin } i \text{ is used;} \\ 0, & \text{otherwise} \end{cases} \tag{2.6}$$

and

$$x_{ij} = \begin{cases} 1, & \text{if item } j \text{ is assigned to bin } i; \\ 0, & \text{otherwise} \end{cases} \tag{2.7}$$

The optimisation problem outlined in equations 2.1 - 2.5 minimises the number of bins for a given capacity c. Contrarily, one can also solve the problem that minimises the capacity c for a given number of bins m.

A comparison can be drawn between the minimisation problems and the planning and equipment placement problem in ship design. The minimisation problem outlined above could involve minimising the amount of outfitting within each section of the vessel that has a given area and volume capacity. Consequently, the reciprocal minimisation problem can be interpreted as minimising the necessary area and volume for a given set of functional equipment (bins) that has to be included in the vessel.

2.5.3 Summary of Bin Packing process

While the bin packing method can be used for space optimisation within a hull and determine the optimal location of the vessel's functional areas, the bin packing method is also useful in the design process itself. As the ship block construction space is a bottleneck in this process, the production scheduling optimisation is essential to improve the efficiency of the shipbuilding process from design to construction.

2.6 Optimisation models

This section aims to evaluate several optimisation models and methods that are used in various ship design processes today. Although there are many more optimisation models that are not mentioned in the subsequent sections, the scope of the evaluation had to be limited and will thus focus on the methods that are most frequently applied.

2.6.1 Multi Objective Genetic Algorithm (MOGA)

A genetic algorithm used for multi-objective optimisation is a search heuristic inspired by Charles Darwin's theory of natural evolution. The algorithm reflects the process of natural selection where the best solutions are selected for reproduction in order to produce better solutions for the next iterations. The algorithm creates a population of individuals represented by chromosomes which are a series of character strings. These chromosomes are then tested in against the objective function repeatedly, so see what solutions are optimal. In multi-objective optimisation problems of M objectives and J constraints, the problem can be formulated as:

$$\min_{x \in \mathbf{X}} \{f_1(x), \ldots, f_M(x) | g_j(x) \geq 0, j \in [1, J]\}, \tag{2.8}$$

where we search for design alternatives x in the design space $\mathbf{X}$ confined within variable the bounds. The goal is to find such x that will minimise the objective $f(x)$ while satisfying all the constraints $g(x)$. If all the constraints are satisfied, the solution is feasible and belongs in the feasible set Ω, which is denoted by:

$$\Omega = \{x \in \mathbf{X} | g_j(x) \geq 0, j \in [1, J]\} \tag{2.9}$$

The solution to equation 2.8 is a Pareto optimal alternative, represented by x^*. This means that there is no better alternative than x^* in the objective space $\mathbf{Y}$ (whose feasible space is denoted with $\mathbf{Y}^{\Omega}$) [26]. This alternative represents the rational choice and belongs to a set of Pareto optima $\widehat{\Omega}$, which is also called Pareto frontiers and can be defined as:

$$\widehat{\Omega} = \left\{x \in \Omega | \nexists x^k, f(x^k) < f(x), \forall x^k \in \mathbf{X} \setminus \mathbf{x}\right\} \tag{2.10}$$

The process of natural selection starts with a selection of the fittest individuals from a population. These individuals will then produce offspring which inherit the characteristics of the parents and will be added to the next generation. If the parents have the best fit, their offspring will be better than their parents and therefore have a better chance of surviving. This process is repeated until a generation of the fittest individuals is found. This process is then applied for a search problem where we can consider a set of solutions for a problem and select the best ones. The following five phases are considered in the genetic algorithm:

1. Initial population
2. Fitness function
3. Selection
4. Crossover
5. Mutation

Each possible solution for the optimisation problem generated by the genetic algorithm is called a chromosome. In the mathematical formulation of the optimisation problem, each chromosome is made up of a series of decision variables that represent a possible solution of the optimisation problem at hand, e.g. multiple main dimensions for a vessel's hull. In a N-dimensional problem, a chromosome is an array of size $1 \times N$ and is defined as:

$$X = (x_1, x_2, \ldots, x_i, \ldots, x_N) \tag{2.11}$$

where X represents a feasible solution to the optimisation problem, x_i is the ith decision variable of the feasible solution X and N is the number of decision variables. The genetic algorithm must then generate the initial population with a random generation of chromosomes. The population size, i.e. the number of possible solutions is denoted as M. The possible solutions based on the population is represented by a matrix of chromosomes of size $M \times N$ [27].

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_j \\ \vdots \\ X_M \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,i} & \cdots x_{1,N} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,i} & \cdots x_{2,N} \\ & & & \vdots & \\ x_{j,1} & x_{j,2} & \cdots & x_{j,i} & \cdots x_{j,N} \\ & & & \vdots & \\ x_{M,1} & x_{M,2} & \cdots & x_{M,i} & \cdots x_{M,N} \end{bmatrix} \tag{2.12}$$

Here, X_j is the jth solution and where $x_{j,i}$ is the ith decision variable of the jth solution with a population size of M. Each variable represents a floating point number. Some of the initially generated possible solutions are selected as parents to produce a new generation. The selection in the genetic algorithm involves choosing some individuals from the population for reproduction. There are several methods for selecting the parent population, where the most common methods are proportionate selection and tournament selection.

In the tournament selection, a fitness function assigns a fitness to a set of solutions. The size of the set is used-defined and described as the tournament size. The fitness level is used to associate a probability of selection for each chromosome or solution. The best solution receives the best rank and the worst solution to the lowest rank. The solutions are then assigned a probability proportionate to its rank. A tournament selection with a size of 1 is equal to random selection. The genetic algorithm must now generate new solutions to progress towards the optimal solution. The parent solutions make children that make up the entire or part of the next generation. The next generation will, therefore, contain a combination of parent and children population. The crossover ratio between these two populations will be a user-defined parameter. Figure 2.12 shows an example of the procedure of producing a new generation based on the first generation.

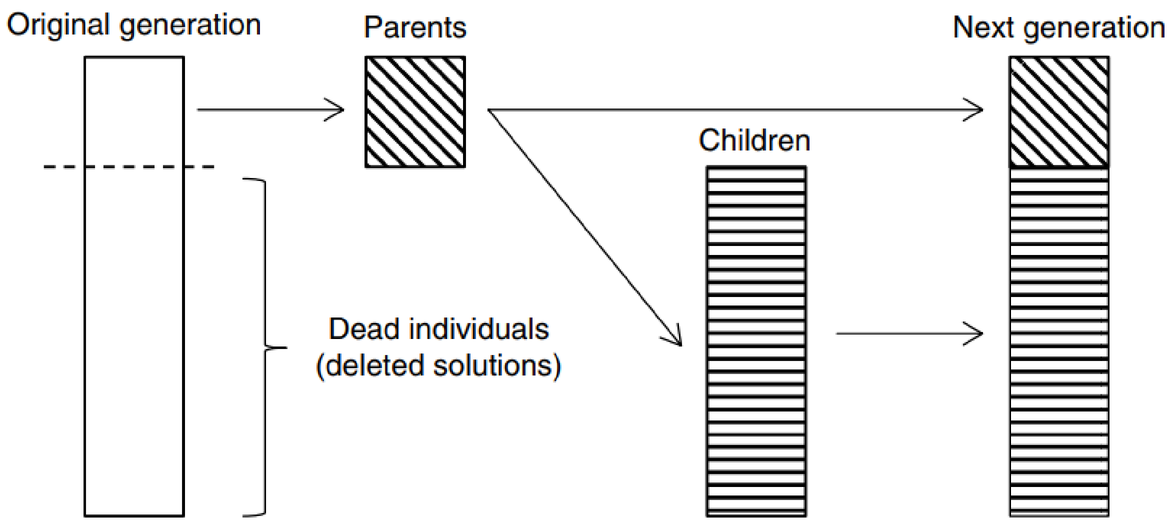


Figure 2.12: The process of creating a new generation from the previous generation [27].

Since the genetic algorithm can have a large number of decision variables in the initial $M \times N$ population matrix, several variables can be evaluated simultaneously without additional complexity. It is especially applicable when evaluating several main dimensions for a vessel hull, having to consider multiple objectives and constraints such as volume and stability requirements while minimising wave resistance and vessel motions.

The crossover phase in the genetic algorithm is one of the most critical phases. The crossover operator generates new offspring by exchanging genes between the parents. This process means that the new solution will receive some decision variables from one of the parents and the rest of the variables from the other parent solution. There are several types of crossover processes such as one-point, two-point and scattered crossover. Another way of generating children from the parent solutions is a mutation. This process introduces new genetic material to the population by replacing some of the genes of an offspring randomly. This process is mainly used in order to maintain diversity within the population and prevent premature convergence in the solution. The genetic algorithm is terminated when the population converges significantly, i.e. the offspring chromosomes are not significantly different from the previous generation.

2.6.2 Generalised Lackenby

The Generalised Lackenby came from the need of a more comprehensive system of form derivation. The method consists of a precise adjustment of the fullness of the hull to independently change the prismatic coefficient and the length of the middle body. The process also considers the relative fullness of the fore and aft body to further change the position of the longitudinal centre of buoyancy (LCB). By considering the curve of areas of the basis ship for the one-half body, the process employs a numeric approximation to change the fineness and thus changing the length of the parallel middle body. The change in fineness is brought about simply by adjusting the length of the parallel middle body and contracting or expanding the entrance or run as necessary [28].

When evaluating the hull resistance of a vessel, numerous hull and shape parameters are used in the calculation. This would typically include parameters such as length, breadth, draught, block coefficient (C_B), prismatic coefficient (C_P), the LCB and the midship coefficient (C_M). Since all of these parameters are closely interconnected, it is therefore difficult to perform sensitivity studies and evaluate changes in resistance based on one or more variables. This would be the case if the length is varied as C_P and the LCB would change as well. It is therefore desirable to be able to change some of these parameters while maintaining constant values for the other parameters. The Lackenby approach is such a process, where some parameters are maintained constant, using the sectional area curve. By varying C_P, LCB and parallel middle body, both forward (p_f) and aft (p_a), the Lackenby method changes the distribution of the hull's sectional area [28], [29].

The change in the forebody and after body prismatic coefficients, denoted by $\delta\phi_f$ and $\delta\phi_a$ respectively are given by:

$$\delta\phi_f = \frac{2\left[\delta\phi_t\left(B_a + \overline{z}\right) + \delta\overline{z}\left(\phi_t + \delta\phi_t\right)\right] + C_f \cdot \delta p_f - C_a \cdot \delta p_a}{B_f + B_a} \tag{2.13}$$

$$\delta\phi_a = \frac{2\left[\delta\phi_t\left(B_f - \overline{z}\right) - \delta\overline{z}\left(\phi_t + \delta\phi_t\right)\right] - C_f \cdot \delta p_f + C_a \cdot \delta p_a}{B_f + B_a} \tag{2.14}$$

There are, however, limits to the degree of variation for the change in C_P, thus limiting the range of $\delta\phi_f$ and $\delta\phi_a$. The following limit for the aft and body coefficients is intended to avoid very steep sectional area curves at the forward and aft and is given by:

$$\delta\phi = \frac{\delta p\left(1-\phi\right) \pm \frac{1}{2}A\left(1 - \frac{\delta_p}{1-p}\right)}{1-p} \tag{2.15}$$

A more detailed explanation is given in Appendix A further describing the reasoning behind equation (2.13) to (2.15).

While the Lackenby method is commonly used as an optimisation tool in several ship design software such as FriendShip Systems' CAESES and NAPA, the method is merely a tool for variation of hull shapes. It needs additional supporting optimisation algorithms to determine what prismatic coefficient is necessary. When the hull shape is changed, within the limits given by equation (2.15), another round of iteration is necessary to determine the change in the objective function, rendering this method unnecessary complex and inefficient during the early phase ship design process.

2.6.3 Design Space Exploration

A design space exploration (DSE) refers to an activity of exploring design alternatives before their implementation. The power to operate on the space of potential design candidates renders DSE useful for many engineering tasks, including rapid prototyping, optimisation and system integration. However, the main challenge of the DSE is its vast design space that can reach upwards of billions of possibilities, rendering the exploration futile. The key idea is that many of the design candidates may be considered equivalent as far as the user is concerned, and thus only a small subset of the space needs to be explored [30].

In the process of design, space exploration involves the discovery and evaluation of design alternatives during system development. When there are comparable values that can be used to evaluate two designs against each other, DSE can be used to perform optimisation by eliminating inferior designs and generate a set of final candidates that can be studied in more depth. While the main focus of the DSE in this paper is concerning its use within optimisation, it is also relevant to mention its use in developing prototypes to increase the user's understanding of the impact of the design decisions while also taking complex system dynamics into account [31].

During the early stages of ship design and the onboard system design, a number of combination problems arise and can be solved using a design space exploration. In the DSE, a large number of possible vessel configurations and system combinations can be evaluated in trade-off analyses. The purpose of the DSE in ship design is to provide the naval architect with insight throughout the process. The DSE can easily show the trade-off between the requirements, constraints, technical solutions and KPI's, thus creating decision support in the early phases of the design process. Although a DSE might be a useful tool in the early phases of the design process, naval architects tend to avoid a lengthy DSE and base their designs on experience and heuristics in pursuit of speeding up the design lead time [32].

The following list is some of the more frequent combinatorial problems encountered and where DSE techniques could be adopted. It is, however, important to note that as the Design Building Block approach, the subsequent combinatorial problems are related to the system design of surface combatants with primary focus on survivability during operation.

1. The numbers of possible ship configurations relating to the onboard systems' position in the vessel. The optimal solution will be dependent on the hull space and the given set of requirements that can either by fixed or negotiable.

2. The number of possible system topologies in different distribution systems containing n number of components is extremely large. The optimal solution will be dependent on the constraints and non-negotiable requirements such as technically feasible system solutions and design objectives such as fuel consumption, costs and system robustness.

3. The number of possible ways to route the connections of the vessel's distribution systems is extremely large. The optimal solution will be dependent on several constraints for each compartment and individual requirements based on the system's application.

4. The number of possibilities on dividing the total power demand on board the vessel on n different power supplying systems with m different types, within a certain energy effect is extremely large. The optimal solution will be dependent to on the energy storage capacity, efficiency and flexibility in arrangement and operation.

2.7 Closing remarks on Literature

Section 2 has considered the various design and optimisation processes to map the current methodologies applied in ship design and vessel performance optimisation. While some processes like system based ship design consist of designing a vessel with a high degree of detail, other processes like simulation-based design are more applicable and efficient in evaluating a pre-generated design. The differences are also applicable for the optimisation methods where the genetic algorithm can give an early indication of what the optimal main dimensions can be, while the Lackenby methodology is a tool for further processing of a generated hull form. Based on the descriptions of each process in the current report section, there are some overlaps in the methodologies and thus creating possible combinations to be adapted.

Consequently, this literature review gives insight into what process is most effective depending on the goal of the user, i.e. the naval architect. The ship design process has been improved from its somewhat chaotic, traditional process and has been formalised in numerous works by several naval architects and marine engineers. It is also important to note that the design methods have been developed for different purposes, thus also having to consider what type of vessel is being designed. This is particularly true regarding the system based ship design, initially developed for cruise vessels, while the design building block methodology was developed for the Royal Navy's surface combatants.

3 Design process evaluation

3.1 Evaluation of design processes

Section 2.2 to 2.5 has presented various design processes that are used in today's ship design industry, adopted for multiple vessel types and design application. While some of the methodologies assume different levels of 'preprocessing' of design, they can all be adapted to create a systematic and holistic approach to the complex problem of ship design.

The subsequent evaluation process aims to decide on the best approach of holistic ship design for an offshore support vessel. It is important to consider both the method's complexity, required knowledge of the vessel and preparations necessary before the process can be started. Additionally, each method has been developed for a specific vessel type that is not necessarily an offshore support vessel, and its applicability in the current design process should be considered. The design processes that will be considered in the evaluation are:

1. System Based Ship Design (SBSD)
2. Simulation-based (ship) Design (SBD)
3. Design Building Block (DBB)
4. Bin Packing Problem (BPP)

3.1.1 System Based Ship Design

The SBSD process was first introduced in 1991, initially intended for cruise vessels but has later been applied in the design process for multiple vessel types, among others, offshore supply vessels.

- **Possibilities and benefits**
  - Simple breakdown structure that identifies the functional requirements outlined in the project brief reflected in the customer's requirements
  - Simpler approach enabling an early concept visualisation without committing to main particulars in early design phases
  - Use of experience data and one-time mission statement creation limits the amount of re-work and necessary iteration during the concept design phase
- **Limitations and drawbacks**
  - Use of experience-based data coefficients may limit innovation in hull form and main dimensions

  - Extraordinary and uncommon functional requirements may narrow operational scope of the vessel, i.e. becoming too specialised (also possible in the opposite case, where multi-purpose OSV becomes 'multi-useless')
  - Optimisation of main particulars, areas and volume is based on an iterative process, and true optimum of main particulars has to be modelled separately

3.1.2 Simulation-based design

Simulation-based *ship* design is primarily used as a decision support tool for the verification process of ship design. Common uses within ship design involve CFD analyses and discrete event simulations involving human interactions with the vessel.

- **Possibilities and benefits**
  - Cheaper and faster to simulate discrete or continuous events than experimental analyses conducted with a scaled model(s)
  - Easy implementation of numeric or heuristic optimisation tools in the simulation process as the simulation data manager integrates both CAD and CAE elements simultaneously
  - Possibility of extending simulation scope beyond technical parameters through simulation of human interaction with the vessel and quasi-rational behaviour for evacuation simulation or construction
- **Limitations and drawbacks**
  - The simulation needs to consider a sufficient amount for variables to validate the design problem correctly - "the simulation is only as good as the model's accuracy."
  - Despite its interesting applicability, simulation of fluids, smoke and fire require large processing powers when considering 3D effects
  - Extremely difficult to correctly simulate human behaviour when simulating an assembly process involving human interaction or vessel evacuation procedures

3.1.3 Design Building Block

The Design Building Block process was developed in 1981 and applied primarily in the design and general arrangement of surface combat vessels for the Royal Navy. Special focus is given on personnel movement and functional components that is key to a warship.

- **Possibilities and benefits**
  - Definition of necessary internal components is decided at an early stage, thus assuring that the main dimensions selected in later stage fulfil the area and volume requirement previously defined

  - Involves a holistic approach with an integrated architecturally centred synthesis that considers the spatial requirements and limitations for the on-board personnel
  - Promotes innovative solutions through flexibility in the design definitions through a flexible reconfiguration of the spatial model, thus exploring various solutions simultaneously before a choice of concept design

- **Limitations and drawbacks**
  - Main dimensions are chosen at a very late stage in the design process and after the spatial layout has been chosen, thus limiting the possibility of optimised hull form and seakeeping ability
  - Building blocks that are to be placed inside the hull have to be pre-defined by the user and cannot easily be divided into smaller blocks, thus limiting the flexibility of the position in the vessel
  - Multiple void spaces may be generated after the spatial layout is decided and hull form is chosen due to the size and position of the pre-defined building blocks, i.e. over-dimensioning of the hull volume

3.1.4 Bin Packing Problem

The bin packing problem is closely related to a resource-constrained project scheduling problem and can be applied in the ship design process where different areas or functions of the vessel is represented by boxes that have to be packed together with an optimal manner. The BPP can also be used for scheduling within the ship design or construction process, where each bin represents a task to be completed.

- **Possibilities and benefits**
  - Possible to solve the Bin Packing problem through heuristics and problem complexity can be altered through using either a one-dimensional or two-dimensional approach
  - Possible to integrate the scheduling aspect of the BPP into the ship design enabling more efficient ship construction to avoid bottleneck operations
  - Considers all precedent constraints in both the scheduling and design problem definition, thus avoiding any iteration or changes in parameters that are previously decided
- **Limitations and drawbacks**
  - The BPP problem belongs to an NP-hard computational complexity that is not easily solved and is likely to need sophisticated algorithms
  - The process is only concerned with the scheduling and placement of bins in the vessel, and may not give an indication of hull form of main dimensions

3.2 Evaluation of optimisation process

Some of the design processes previously evaluated may contain some degree of design optimisation. However, this usually involves scheduling or spatial optimisation which does not consider the hull. Section 2.6 has therefore focused on optimisation methods that are used in today's ship design industry and applied in the case of optimal hull geometry and main dimensions. The optimisation methods that will be evaluated for hull optimisation consists of:

1. Multi Objective Genetic Algorithm (MOGA)
2. Generalised Lackenby
3. Design Space Exploration (DSE)

3.2.1 (Multi Objective) Genetic Algorithm

A genetic algorithm reflects the process of natural selection by rejecting weak solutions over other feasible solutions that represent a better fit. The genetic algorithm is used in hull optimisation by treating each main dimension parameter as a variable in the population matrix and evaluate their fitness in regards to the objective function represented by, i.e. the total resistance of the vessel.

- **Possibilities and benefits**
  - The genetic algorithm can simultaneously evaluate a large number of parameters without excessive computational time while minimising one or multiple objective functions
  - The use of selection, crossover and random mutation can guarantee a wide range of solutions, thus minimising the possibility of converging into a local minimum in the solution space
  - Modelling the genetic algorithm is relatively easy compared to other optimisation algorithms with the same objective, thus making the model flexible and applicable also for hull optimisation with relative ease
- **Limitations and drawbacks**
  - The algorithm is sensitive to the number of generations and population size defined by the user, thus generating incorrect results if these parameters are not adjusted accordingly
  - When modelling the heuristic that determines the selection or crossover, it can be difficult to get the algorithm to compute the exact intended action defined by the user
  - Although randomness in the mutation lowers the probability of early convergence in a local minimum, the algorithm may still not find the global optimum of the solution space

3.2.2 Generalised Lackenby

It is important to note that the Generalised Lackenby process is not necessarily an optimisation method, but rather a systematic numerical approximation to change the hull into a more desirable shape that *may* be more optimal. However, the target output of the process must be determined beforehand with a separate heuristic.

- **Possibilities and benefits**
  - The method offers a systematic variation that considers the fineness of the hull geometry while also considering hydrostatic parameters such as C_B, C_P and longitudinal centre of buoyancy
  - Little computational complexity for the calculation and thus short computation time for output generation
  - The method is widely used as the industry standard when integrated with another optimisation tool as the theory of the hull variation is suitable for hull modelling software that involves splines
- **Limitations and drawbacks**
  - There are limits to the degree of the variation and change in the block coefficient as there is a limited range in the change of $\delta\phi_f$ and $\delta\phi_a$
  - The method is only a tool for the variation of the hull shape and would need supporting optimisation algorithms to determine the geometric optima of the hull

3.2.3 Design Space Exploration (DSE)

DSE is used for exploring various design combinations and evaluate their feasibility and optimality through an internal trade-off study. The method has mainly been applied in the design of surface combatants.

- **Possibilities and benefits**
  - The method gives insight to the designer on how the different parameters and requirements of the vessel will affect the designs KPI's
  - Many design candidates can be studied simultaneously where the most feasible candidates will be part of a subset which will be studied more closely to decrease the computation time
- **Limitations and drawbacks**
  - The number of possible feasible design combinations may be huge (depending on the number of variables) and may result in a complex and lengthy optimisation process if the algorithm is not able to sort into optimal subsets

– Naval architects tend to avoid a lengthy DSE and rather base their designs on experience and heuristics, thus saving time in the sacrifice of an optimal solution

3.3 Choice of design methodology for further modelling

Having considered the benefits and drawbacks of each design methodology, one should carefully choose a methodology that is best suited for the subsequent modelling and optimisation. The choice of optimisation model will be based on the choice of design methodology, thus chosen accordingly after the final evaluation of the design process.

3.3.1 Analytical Hierarchy Process

In order to consistently evaluate fairly without bias, a measurement process known as Analytic Hierarchy Process (AHP) has been adopted in order to choose the design process. In the AHP, four different attributes describing the design methodologies are used for evaluation. The attributes are:

1. **Simplicity:** evaluates the degree of simplicity in setting up the design model, the numerical calculations (if any) and the computational time for generating output
2. **Applicability:** evaluates to what degree the design process is applicable to all vessel types, a limited number of types or just one
3. **Optimisation:** evaluates whether the design process has a 'built-in' optimisation module that generates some form of optimality of design layout
4. **Preliminary:** evaluates to what degree preliminary work has to be done before the core process of the model can take place and effectively generate results

Before the different design processes are compared against each other, it is important to make a pairwise comparison between the attributes by creating a weighted priority. This makes it clear to the user from the start what the focus of the hierarchy is and thereby determining the best feasible option. Table 3.1 shows the pairwise comparison of the listed attributes. Looking at the first row, the third column (from left to right), a value of 5 is given as it is considered 'much more important' that the model is less complex than the model containing a degree of optimisation. Consequently, optimisation is only a fifth of the importance of simplicity. Essentially this means that a simple model is rewarded more than a model that has the ability to optimise [33]. Cells denoted with 1 shows that the attributes have equal importance. The full description of all numerical values in table 3.1 can be found in table 3.2 in Appendix B.1.

Attribute	Simplicity	Applicability	Optimisation	Preliminary	Priority
Simplicity	1	1/3	5	3	0.27
Applicability	3	1	5	7	0.57
Optimisation	1/5	1/5	1	1	0.08
Preliminary	1/3	1/7	1	1	0.08

Table 3.1: Pairwise comparison of attributes, with consistency ratio, CR = 0.038.

3.3.2 Consistency of evaluation

However, to evaluate each model fairly, a further step has been taken to ensure consistency in choices and relationships both for the pairwise comparison of attributes in table 3.1 and in the tables of appendix B. As described, the CR of the pairwise comparison has a consistency ratio of 0.038 - thus only 3.8% inconsistent. A matrix A - like the attribute matrix above - is said to be consistent if $a_{ij}a_{jk} = a_{ik}$, $\forall i, j, k$. In the AHP, consistency is desired, but too much consistency is undesired as it deals with human judgement and rationale.

Furthermore, Saaty proved that for a consistent reciprocal matrix, the largest Eigen-value is equal to the size of the comparative matrix, or given by $\lambda_{MAX} = n$. Consequently, a Consistency Index (CI) was created to represent the degree of consistency using the following formula:

$$CI = \frac{\lambda_{MAX} - n}{n - 1} \tag{3.1}$$

The CI is then compared to a Random Consistency Index (RI). This is a randomly generated reciprocal matrix which uses the scale of $\frac{1}{9}, \frac{1}{8}, ..., 1, ..., 8, 9$ and then sees if the random consistency is about 10% or less, using 500 samples. The consistency ratio (CR) is therefore given by $CR = \frac{CI}{RI}$. If the CR exceeds 0.1, the values of the matrix are likely to need reexamination. Hence, with all CR values of the AHP matrices < 0.1, a consistent and fair evaluation process has been numerically guaranteed [33].

3.3.3 choice of design process

Having chosen the desired attributes for the AHP and evaluated the various design methodologies against one another, a total score can be generated based on the priority of the attributes and the individual scores. Table 3.1 shows that the applicability of the model has the highest priority followed by simplicity, the possibility of optimisation and the degree of preliminary work necessary, respectively. By multiplying the scores of each model given by the attribute matrices with the priority scope of each attribute, we get the total score of each model as illustrated in table 3.2.

Design process	Simplicity	Applicability	Optimality	Preliminary	Total Score
SBSD	0.59	0.43	0.06	0.57	0.44
SBD	0.25	0.38	0.19	0.21	0.32
DBB	0.09	0.13	0.52	0.11	0.16
BPP	0.06	0.07	0.24	0.11	0.09
Sum	1.00	1.00	1.00	1.00	1.00

Table 3.2: Priority vector of the resulting analytical hierarchy process for choosing design methodology.

Table 3.2 shows that the system based ship design has the highest score, followed by the simulation-based design process with the second-highest score. SBSD scores the highest in all categories but one, and most importantly in terms of simplicity, the attribute with the highest priority. However, since SBSD is only an iterative process with no adoption of optimisation, it scores the lowest in the attribute involving optimisation. As the focus of this report is introducing an optimisation module to geometric hull design, one could argue that DBB could be more suitable then what the AHP states. However, due to its vast amount of necessary preliminary work of defining the building blocks, the methodology is severely punished in the AHP.

In terms of the scores for applicability, one must bear in mind that the judgement given in the AHP was with designing an offshore support vessel. Despite the fact that SBSD was intended initially for cruise vessels, newer generations have made it possible to apply its design process for almost any vessel type. This is also applicable for simulation-based ship design as it is not limited by the vessel type, whereas DBB and BPP are both highly directed at the design of combat vessels. Their methodology and optimisation formulation may be possible to apply on other vessel types, although not frequently done.

With all consistency ratios below 10%, a consistent judgement has been made, rendering the system based ship design process most suitable for this report's objective of designing a hull for an OSV. This methodology will then be used as the foundation for the choice of main parameters, area and volume requirements and hydrostatic values. However, since the SBSD merely iterates its results, it is desirable to choose a separate optimisation process. While both DBB and BPP score much better on the optimisation attribute, their models are limited to the internal and spatial layout of the vessel and have little consideration regarding any hull optimality. Therefore, a separate hull optimisation method will be chosen that together with the SBSD will perform a holistically optimised hull form.

3.3.4 Choice of optimisation process

While the choice of a design process defines how a vessel is designed, there is somewhat less flexibility in the choice of hull optimisation methods. Section 2.6 evaluates the presented optimisation and hull variation methods that are used in today's industry. At the end of the iterated SBSD process, the main dimensions of the hull and hydrostatic parameters represent the output. While the overall objective is a geometric modelling of the hull, the output from the design process only gives parameters and not exact geometry. Consequently, it is desirable to evaluate these main dimensions and change their values according to an objective function. Thus, the chosen optimisation method must be able to evaluate multiple parameters simultaneously as a hull's main dimensions are all interconnected.

The generalised Lackenby hull variation method considers hydrostatic parameters such as C_B, C_P and LCB through numerical variation of the sectional area curve (SAC). However, the desired values of these parameters have to be determined heuristically. Although a heuristic variation using the Lackenby method might improve the value of the objective function, it does not strive for an optimal solution like a DSE process or through the use of a genetic algorithm.

The latter optimisation methods are in many ways intertwined in the fact that evolutionary algorithms, such as the GA, are the most common and widely used in DSE. Its evolutionary algorithms apply random changes of a starting set of configurations to iteratively improve their Pareto set of solutions when optimising multiple objectives. However, due to the ample design space, using a GA in the DSE process may result in long computational time. Hence, the algorithm is often combined with other exact methods such as multi-objective integer linear program problem and a pseudo-boolean solver to constrain the GA within the feasible search space [34]. Additionally, evolutionary algorithms in DSE are often used as multi-objective optimisation, which is not necessarily the right approach for the hull modelling. An essential consequence of having multiple objectives is that the optimal solutions may not all be unique. Since the problem does not necessarily have a single optimal solution, the solutions consist of several optima represented by the points that lie on the Pareto curve.

Since the scope of the OSV modelling is limited to the hull design, it may not be necessary to complete a multi-objective optimisation as costs and seakeeping KPI's are not evaluated in this report. Hence, performing a complete design space exploration involving an exhaustive search is likely to be impractical due to a large number of parameters in the design space and therefore, long computation time. Therefore, a single objective stand-alone genetic algorithm will be used as the optimisation tool for further modelling.

4 Hull model optimisation

4.1 Initial design

Section 3.3 shows that the most expedient design methodology for an OSV is the SBSD approach. Consequently, the following section aims to optimise a hull that is designed using SBSD. The hull form optimisation shall consider all the system based requirements according to the design methodology. However, a thorough design process where all systems are considered is a time-consuming process. A detailed analysis has to be completed for each onboard system in order to compute the volume and area requirements of the vessel. Iterating a vessel design through the design spiral is not within the scope of the report, and thus an example vessel that is modelled using SBSD is chosen.

The design concept that has been chosen for the subsequent hull optimisation is an AHTS that is to perform towing missions in the North Sea, based in Stavanger, Norway. The vessel includes accommodation space for 25 vessel crew and 10 client workers. Also, the vessel will have 750 m^2 of deck area in addition to liquid and dry bulk cargo tanks totalling 3,500 m^3. Based on the work done by Erikstad and Levander (2012), the design process has generated the main dimensions for the AHTS vessel, outlined in table 4.1 [12].

Main dimension	**Length [m]**	**Relationship**	**Ratio [-]**
L_{OA}	94.00		
L_{WL}	90.00		
L_{OS}	92.27	L_{OA}/B	4.27
B	22.00	B/T	3.55
T_{DWL}	6.20	C_B	0.661
T_{MAX}	7.50	C_W	0.870
D_M	9.50	C_M	0.988
Freeboard	3.30	C_P	0.669

Table 4.1: Main dimensions from SBSD geometric definition. The ratios of column 3 relates to the draught at deadweight loading condition, T_{DWL}.

Additionally, based on the coefficients that determine the necessary area and volume, the system summary estimates a gross tonnage (GT) of approximately 6,800 and a deadweight of 4,200 tonnes. The values in table 4.1 and the estimated gross tonnage are both within the expected parameters of earlier vessels that operate within the same segment.

Figure 4.1 and 4.2 show that the vessel is appropriately dimensioned according to the global OSV fleet that includes, in this case, PSV, AHTS and OCV. There is a trend for all vessel segments showing the relationship between the vessel's deadweight and the gross tonnage. The block coefficient's relationship with the vessel's Froude number, however, is more inconclusive by the fact that there is no consistent trend. However, given the example vessel's service speed of 11.9 knots - that converts to ∼0.21 F_N shows that it is within the extreme values of figure 4.2.

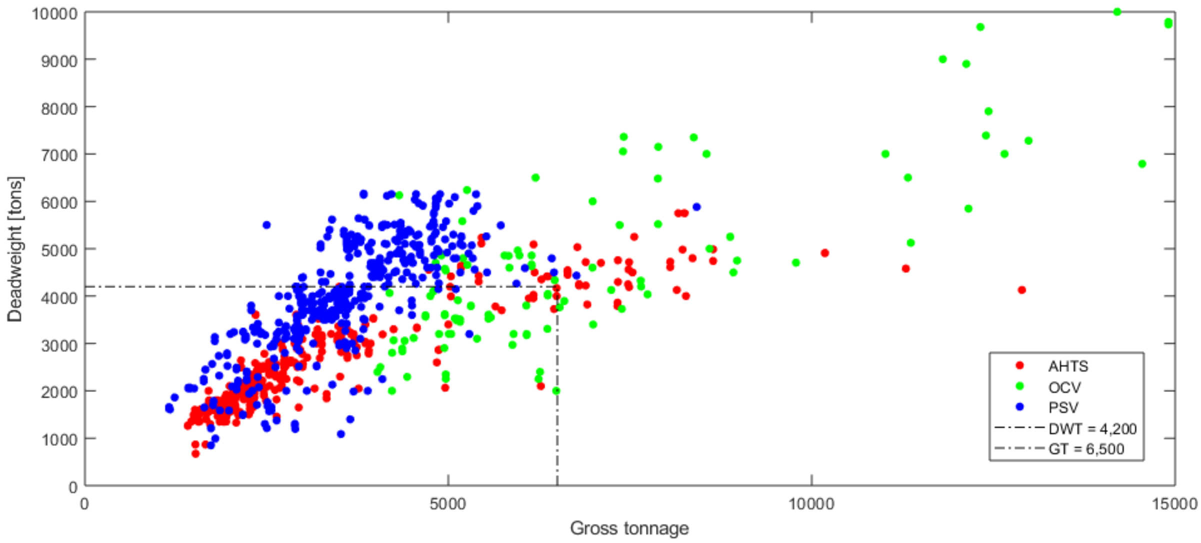


Figure 4.1: Deadweight versues gross tonnage represented by the global OSV fleet.

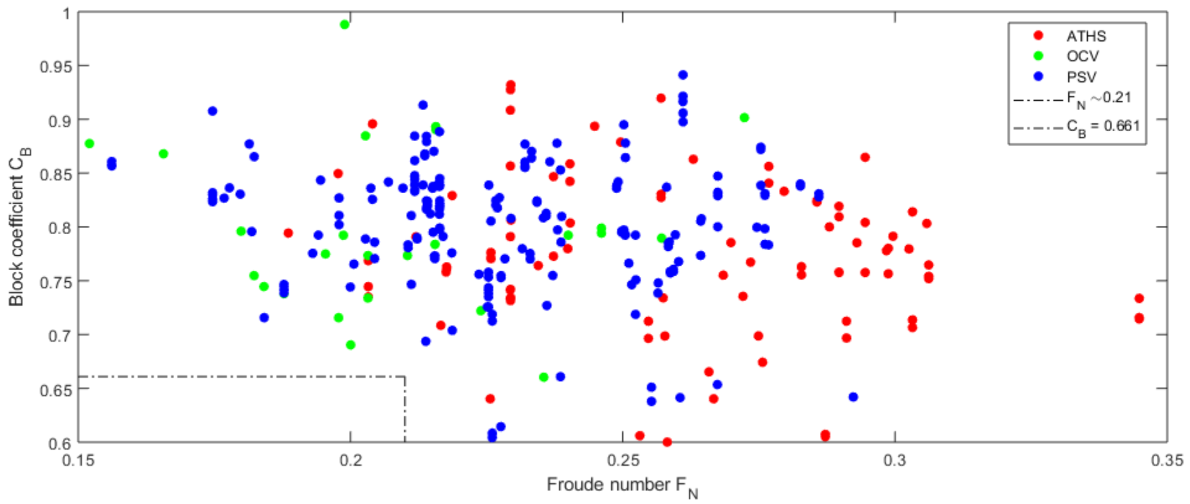


Figure 4.2: Froude number versus block coefficient of global OSV fleet.

4.2 Modelling the original hull

From the SBSD process, an example hull of an AHTS is chosen to be optimised. The output from the design process is represented in table 4.1. While it is important to optimise the main dimensions that will be used in the resistance estimation, it is also essential to generate a geometric model. The geometric model will be created in DelftShip and will directly represent the main dimensions and the coefficient of the example vessel. Two vessels that have identical main dimensions may have very different hull geometries, but if the hydrostatic coefficients are identical as well, then the geometry of the vessels is likely to be equal in shape. Figure 4.3 and 4.4 illustrates the original vessel as modelled with the main dimensions and hydrostatic data from the original AHTS. 4.1.

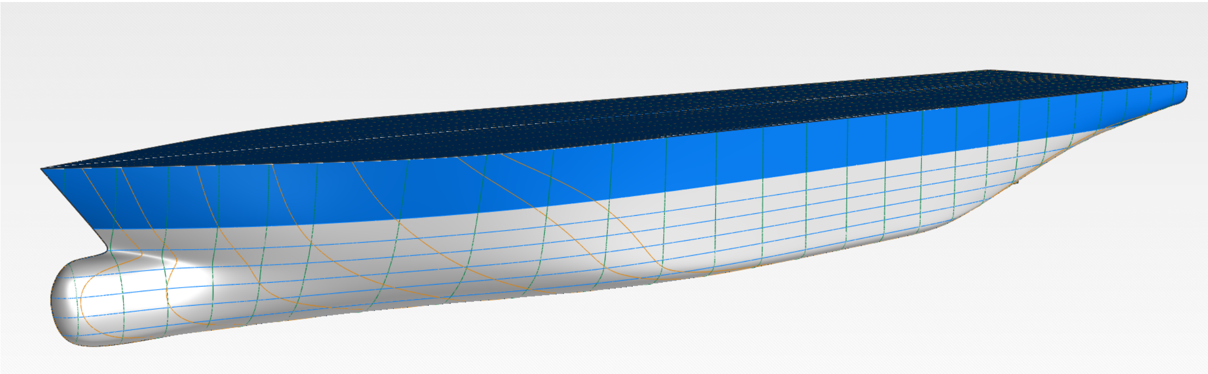


Figure 4.3: DelftShip model of original OSV hull seen from the bow.

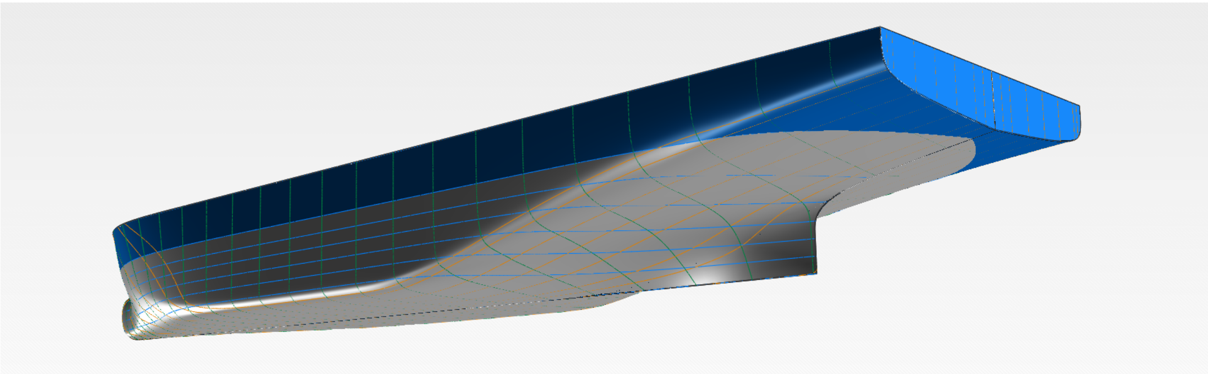


Figure 4.4: DelftShip model of original OSV hull seen from aft.

Since all of the coefficients and main dimensions are closely related and interconnected, a small change in one dimension or spline in the model is likely to change more than one parameter. Some of the parameters of the generated hull geometry are therefore identical to that of the AHTS while others have small deviations. However, a satisfactory level of accuracy is achieved in the hull geometry as none of the parameters deviates more than 1% from its expected value. Now that the hull form has been defined, the genetic algorithm may optimise the main dimensions to optimise the hull geometry further.

4.3 Optimisation algorithm

The process of the genetic algorithm to be used is described in figure 4.5. The parameters of the algorithm are carefully chosen to maximise the likelihood of converging towards the global optima. Hence, careful consideration is done when choosing selection, crossover and mutation methods in addition to population size and the number of generations.

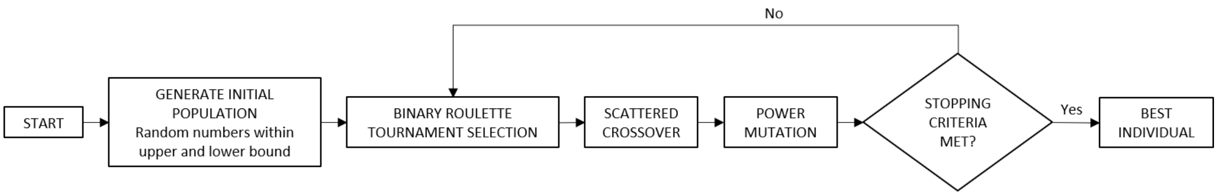
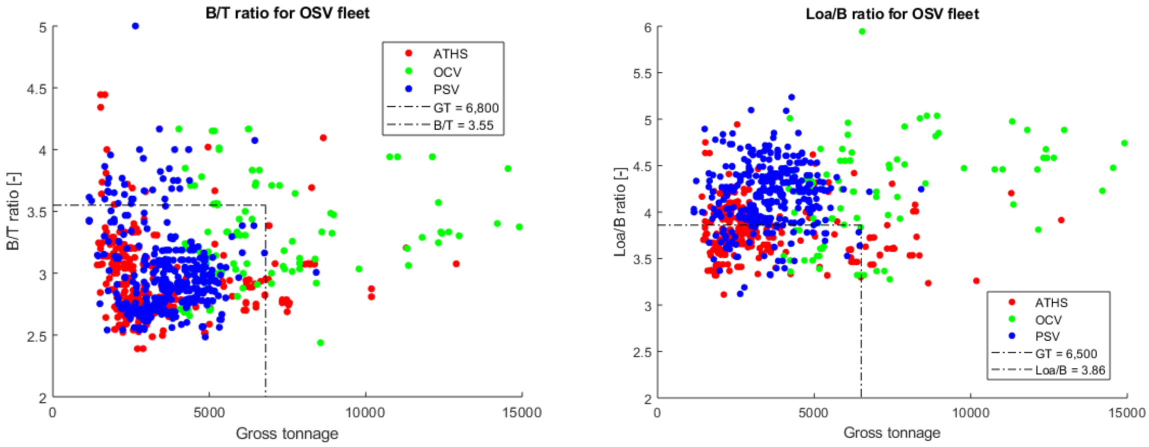


Figure 4.5: Process of the evolutionary model.

4.3.1 Constraints

To be able to compare the optimised hull with the original AHTS' hull, the optimisation should not deviate too much from the main dimensions. Hence, a set of constraints are applied to the optimisation model. One of the most important outputs of the SBSD is the area and volume requirements and the optimised hull should, therefore, have nearly identical hull volume to the original vessel. Additionally, it is desirable for this process that the hull ratios such as length-breadth and breadth-draught are kept close to the original dimensions. Figure 4.6 illustrate the two ratios of the global OSV fleet. The intersection of the dashed lines represents the point of the original vessel.



(a) Breadth-Draught ratios.

(b) Length-Breadth ratios.

Figure 4.6: Geometric ratios for decision support in deciding model constraints.

The scatter plot in figure 4.6a shows that most AHTS' have a B/T ratio between 2.5 and 4. Meanwhile, figure 4.6b show that the L_{OA}/B ratios for AHTS' lie around 3.0 to 4.5. By evaluating a cumulative density graph of the ratios for each vessel type, it shows that 90% of the values are within the intervals as mentioned earlier. Hence, these are the upper and lower bounds in the constraints, as illustrated in equation (4.4) and (4.5). By using the same C_B value for both vessels, the displaced volume can be calculated, as thus used as a constraint as shown in equation (4.2) below.

$$\min R_{TS} \tag{4.1}$$
$$\text{subject to } L_{OA} \times B \times T \times C_B \geq 8,500 \tag{4.2}$$
$$|TF - TA| \leq 0.1 \tag{4.3}$$
$$3.5 \leq \frac{L_{OA}}{B} \leq 4.5 \tag{4.4}$$
$$2.5 \leq \frac{B}{\left(\frac{TA+TF}{2}\right)} \leq 4.0 \tag{4.5}$$
$$0.94 \leq \frac{L_{WL}}{L_{OA}} \leq 0.98 \tag{4.6}$$
$$LOS \leq L_{OA} \tag{4.7}$$

Additionally, both L_{OS} and L_{WL} must be shorter than the length overall of the vessel. In order to avoid large volumes of the hull to be outside the water, the length of the waterline should be within 94-98% of the L_{OA}, denoted by equation (4.6). With the constraints thoroughly evaluated, the objective function consists of minimising the total resistance and will be further evaluated in en ensuing sections.

4.3.2 Upper and lower bounds

The upper and lower bounds for the six different variables are also important to investigate carefully. While wanting a similar ship to the original, larger intervals between the upper and lower bounds (UB and LB respectively) creates a larger feasible area for the genetic algorithm on which to operate. However, the constraints and bounds of the ratios have to be considered. Thus, the values of the UB and LB were evaluated to find the right balance and difference between them. By example, the bounds for the length and the breadth are determined from formula denoted in equations 4.8 and 4.9.

$$\frac{LB(L_{OA})}{\text{UB(B)}} \geq \text{LB}\left(\frac{L_{OA}}{\text{B}}\right) \tag{4.8}$$
$$\frac{UB(L_{OA})}{\text{LB(B)}} \leq \text{UB}\left(\frac{L_{OA}}{\text{B}}\right) \tag{4.9}$$

This approach is applied for all variables and thus creating the lower and upper bounds for the optimisation model. Note that while the draught at the forward and aft perpendicular may vary between five and seven meters, the constraint given in equation 4.3 decide the vessel is only allowed a 0.1 m trim at deadweight draught condition.

Dimension	**Lower bound (LB)**	**Upper bound (UB)**
Length over all, L_{OA}	85.0	105.0
Length waterline, L_{WL}	85.0	105.0
Length of submerged hull, L_{OS}	85.0	105.0
Breadth, B	20.0	24.0
Draught at FP, TF	5.0	7.0
Draught at AP, TA	5.0	7.0

Table 4.2: Upper and lower bounds of optimisation variables. All in metres.

Although not commonly used in modelling, the submerged hull length is an important parameter in Hollenbach's empirical resistance prediction. For the AHTS, it represents the length from the bulb to the end of the waterline aft.

4.3.3 Algorithm parameters

As presented in section 2.6, the genetic algorithm has five phases that consist of creating an initial population, evaluating the variables to the fitness function (in this case Hollenbach's empirical resistance calculation), selection, crossover and lastly mutation. The phases are repeated if no feasible solution is found. The initial population is chosen randomly with a uniform distribution, but each variable must be within the upper and lower bound. This means that for the chromosome with six variables, defined as $X = (x_1, x_2, ..., x_6)$, must have an initial population of:

$$X_0 = \left(rand\left(UB_1 - LB_1\right), \left(UB_2 - LB_2\right), ..., rand\left(UB_6 - LB_6\right)\right). \tag{4.10}$$

Before the selection of chromosomes can start, the initial values of the variables are evaluated against the objective function. In practice, it involves MATLAB calling on the function calculating the hull's resistance using the initial values as input. By changing the main dimensions, there will be some changes in the coefficients of the vessel. However, the waterplane area and block coefficient are kept constant, while the prismatic coefficient is the quotient of C_B and C_M and thus changed accordingly throughout the optimisation.

Selection

Selection is the third phase of the genetic algorithm process where chromosomes are chosen randomly from the population to be further evaluated. The tournament selection chooses each parent by choosing the tournament size players at random and then choosing the best out of that set to be a parent [35]. Determining the most beneficial tournament size can be difficult, as the smallest possible size of 2 will choose a random solution, while a tournament size equal to the population will choose all for all the following generations. Thus, as a rule of thumb, one can estimate that the tournament size should approximately 20% of the population size [36]. The tournament selection algorithm with k amount of players is described Algorithm 1.

Algorithm 1: Tournament selection with k players

for *chromosome i = 1 to population size* **do**
- Choose k individuals from the population at random;
- Calculate cumulative fitness, total fitness (P_i) and sum of proportional fitness;
- Choose the best individual from the tournament with probability P_1;
- Choose the second best individual with $P_2 = p \times (1 - p)$;
- Choose the third best individual with probability $P_3 = p \times (1 - p)^2$;
- Choose the kth best individual with probability $P_k = p \times (1 - p)^k$;

end

Crossover

The fourth phase of the genetic algorithm is the crossover, where two parents are combined to form children for the next generation. There are multiple possibilities in choosing a crossover algorithm, and for this optimisation, the scattered crossover is used. This type of crossover creates first a random binary vector. The genes from the first parent are chosen if the corresponding random number is one, while genes from the second parent are chosen if the value is zero. The process is applied for all the chromosome's numbers and combines the genes to form the first and second child. An example is shown in table 4.3 where a random vector decides which genes from which parent is chosen to form the children solutions.

Parent 1	x_1	x_2	x_3	x_4	x_5	x_6	x_N
Parent 2	y_1	y_2	y_3	y_4	y_5	y_6	y_M
Random vector	1	1	0	1	1	0	0
Child 1	x_1	x_2	y_3	x_4	x_5	y_6	y_N
Child 2	y_1	y_2	x_3	y_4	y_5	x_6	x_N

Table 4.3: Example of scattered crossover with random binary vector.

Mutation

The last phase of the genetic algorithm involves the mutation of chromosomes. The optimisation for the hull uses a feasible adaptive mutation that involves randomly generating directions that are adaptive concerning the last successful or unsuccessful generation. The probabilities of mutation are adapted depending on the fitness values of the individuals. The adaptation of the mutation rate p_m allows the individuals having fitness values that are above average to maintain their genetic material while forcing the individuals below-average fitness values to disrupt [37].

$$p_m = \frac{k_2 \left(f_{max} - f\right)}{f_{max} - f_{avg}}, \quad f \geq f_{avg} \tag{4.11}$$

The mutation rate adaptation rule is given in equation (4.11), where f represents the fitness value of the individual. The constant k_2 is chosen as 0.5 as described in the paper by Srinivas and Patnaik [38].

4.3.4 Objective function - Hollenbach's resistance estimation

Hollenbach's resistance estimation represents the objective function of the optimisation. The method is applicable for vessels with single or twin screw and was developed based on the test data of the Schiffbau Versuchsanstalt in Vienna, Austria. The method has a narrower range of applicability than Holtrop's method but seems to provide reliable results, especially for displacement vessels of single and double screws [39]. The estimated resistance is divided into five components that include frictional resistance, residual resistance, correlation allowance, appendage resistance and environmental resistance. For each of these components, a dimensionless coefficient is computed and is built up of various coefficients as illustrated in figure 4.7.

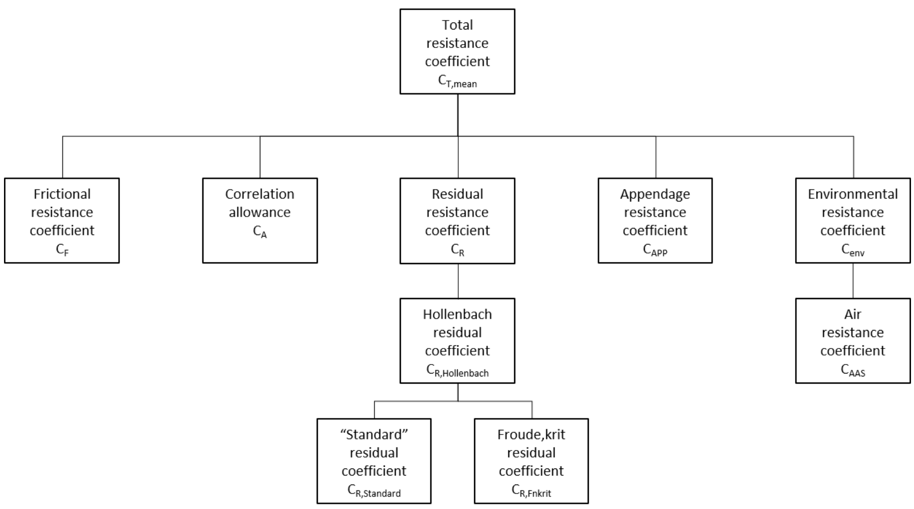


Figure 4.7: Build-up of various resistance coefficients in Hollenbach's resistance method.

Hence, the total resistance coefficient for the full-scale vessel can be calculated through the sum of the five different coefficients previously listed:

$$C_{T_{mean}} = C_F + C_{R_{mean}} + C_A + C_{APP} + C_{env} \tag{4.12}$$
$$C_{T_{min}} = C_F + C_{R_{min}} + C_A + C_{APP} + C_{env} \tag{4.13}$$
$$C_{T_{max}} = h_1 C_{T_{mean}}, \tag{4.14}$$

where h_1 is given as a coefficient factor of 1.194 for single-screw vessels and 1.206 for twin-screw vessels, both for design draught condition. The total calm water resistance is then computed using the total resistance coefficient from equation (4.12):

$$R_{TS_{mean}} = \frac{1}{2}\rho V_S^2 S C_{T_{mean}} \tag{4.15}$$

In essence, equation (4.15) becomes the main objective function for the optimisation. The formulae for the total resistance coefficients give the best-fit curve, i.e. the mean total resistance coefficient, but also the resistance curve describing the upper and lower envelope. These values represent the minimum a design may hope to achieve after extensive optimisation of the ship lines if the design is *not* subject to restrictions [40]. Since the limiting minimum and maximum values will not be exceeded with a probability of 95%, this can be interpreted as the 95% confidence interval of the resistance method. The resistance interval between the maximum and minimum possible resistance can be found in figure 5.4 in the results of the subsequent section.

While the main dimensions that are optimised in the genetic algorithm may not be part of the objective function outlined in equation (4.15), the variables *do* have a direct effect on the residual resistance coefficient that makes up the majority of $C_{T_{mean}}$. As seen in equation (4.16), the main dimensions are all included in this formula, but it is not clear as to what would happen to the residual resistance coefficient if the main dimensions were to change.

$$C_{R,Hollenbach} = C_{R,Standard} \cdot C_{R,Fnkrit} \cdot k_L \cdot \left(\frac{T}{B}\right)^{a1} \left(\frac{B}{L}\right)^{a2} \left(\frac{L_{OS}}{L_{WL}}\right)^{a3} \left(\frac{L_{WL}}{L}\right)^{a4} \left(\frac{D_P}{T_A}\right)^{a6} \left[1 + \frac{T_A - T_F}{L}\right]^{a5} (1 + N_{rud})^{a7} (1 + N_{Brac})^{a8} (1 + N_{Boss})^{a9} (1 + N_{Thr})^{a10} \tag{4.16}$$

5 Results

5.1 Results from optimisation

Through the use of the genetic algorithm, optimal hull dimensions are generated and have successfully improved the resistance. The resistance calculation evaluates the resistance for 40 velocities uniformly distributed between 10 and 20 knots, and the objective function is, therefore, the average resistance for all these velocities. The algorithm evaluated six different main dimensions of the vessel, as listed in table 5.1. For comparative purposes, the resistance calculation assumes equal hydrostatic coefficients. Thereupon, the resistance is minimised, and the resulting hull has an average resistance between 10 and 20 knots of 422.94 kN, 75.15 kN lower than the original hull.

Main dimensions	**Original vessel**	**Optimised vessel**
L_{OA}	94.000	99.064
L_{WL}	90.000	93.120
L_{OS}	92.270	99.064
B	22.000	22.015
TA	6.200	5.862
TF	6.200	5.862
Relationships and coefficients		
L_{OA}/B	4.27	4.50
B/T	3.55	3.76
C_B	0.661	0.661
C_W	0.870	0.870
C_M	0.988	0.988
C_P	0.669	0.669
Total resistance [kN]	**498.05**	**422.94**

Table 5.1: Original and optimised main dimensions and relationships.

This change corresponds to a 15% reduction when considering the average of all velocities. However, the difference in resistance from the original hull to the optimised hull is not uniform. Figure 5.1 shows that the difference in the hull resistances increases somewhat proportional to the vessel speed. The percentage difference in the resistance of the two hulls is presented in figure 5.2. It is interesting to note the sudden change in resistance difference that occurs between 15 and 16 knots.

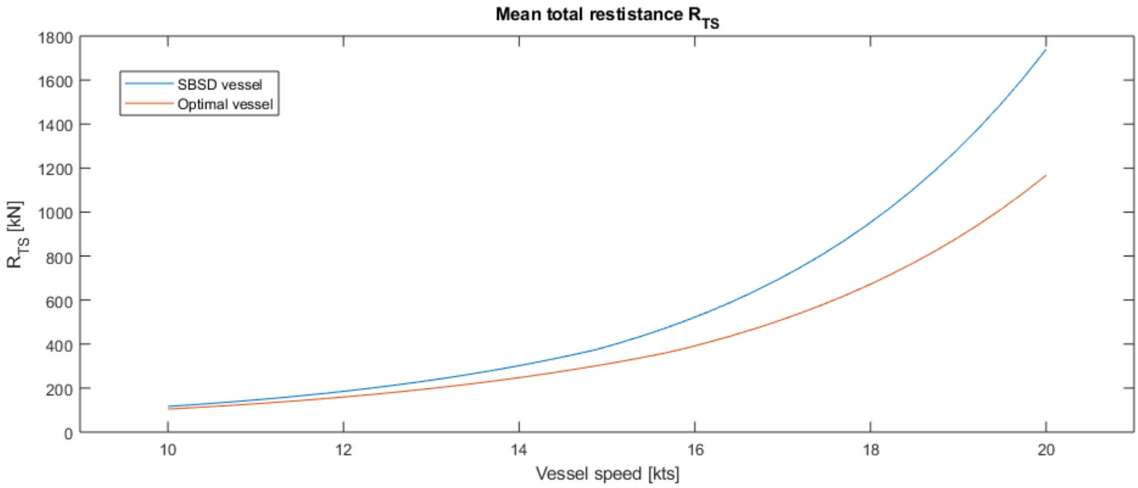


Figure 5.1: Mean total resistance for various vessel speeds.

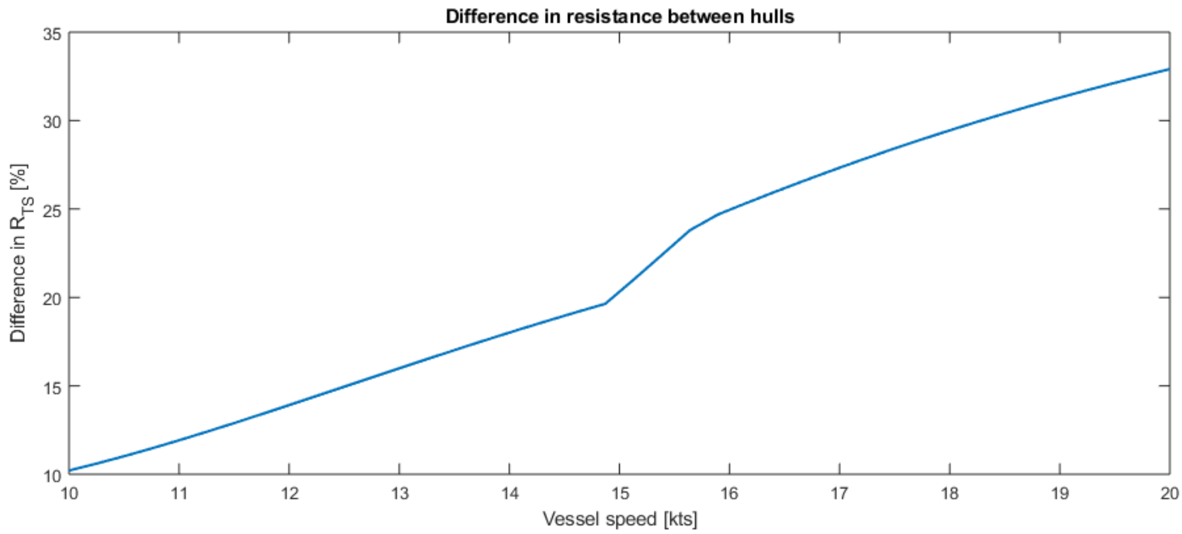


Figure 5.2: Difference in hull resistance between original hull and optimised hull.

The change in the difference of resistance is mainly due to the prediction methods of Hollenbach, in consideration of the vessels' critical Froude number ($F_{N,Krit}$). In the resistance estimation method, it is assumed that for a ship exceeding the critical Froude number, the wave resistance will grow faster than predicted. The critical Froude number is given by equation (5.1) while the added resistance coefficient due to the aforementioned effect is given by equation (5.2). The coefficients c and d are some of the coefficients for computation of the standard resistance coefficient in Hollenbach's method [39].

$$F_{N,krit} = d_1 + d_2 \cdot C_B + d_3 \cdot C_B^2 \tag{5.1}$$

$$C_{R,Fnkrit} = \max\left[1.0, \left(\frac{F_N}{F_{N,Krit}}\right)^{c1}\right] \tag{5.2}$$

The added resistance exerted on the vessel is applied when the vessel passes the critical Froude number. If the vessel operates at a lower speed, the added resistance coefficient $C_{R,FnKrit}$ will have a value of one as shown in equation (5.2). Since the total residual coefficient for Hollenbach $C_{R,Hollenbach}$ is a product of the standard residual resistance and the added residual resistance due to $F_{N,Krit}$, there will be no added resistance when $F_N < F_{N,Krit}$.

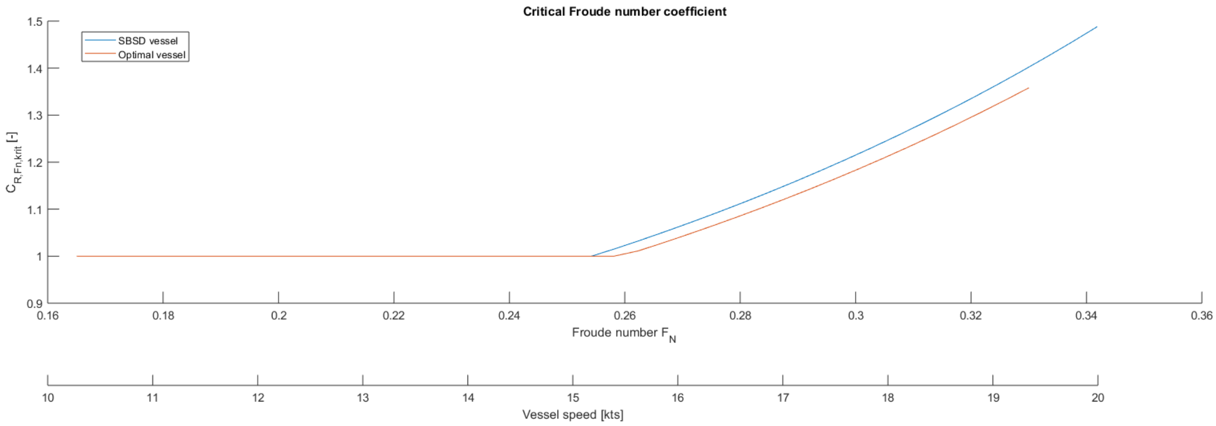


Figure 5.3: Added residual coefficient for critical Froude number.

Figure 5.3 shows clearly where the critical point is for each vessel. In Hollenbach's model, the length of the submerged hull (L_{OS}) is the length used to calculate both Froude numbers. For both vessels, $L_{OS}/L_{OA} < 1$ and thus the Froude length $L_{Fn} = L_{OS}$. However, the optimal hull is somewhat longer, and thus the critical Froude number is higher. From figure 5.3, the added resistance is applied at $F_N = 0.25$ for the original SBSD vessel and at $F_N = 0.26$ for the optimised hull. While the optimal vessel has a lower resistance for all speeds between 10 and 20 knots, it may save fuel by sailing below 15.6 knots. The resulting graphs from the resistance comparison can be found in appendix C.

Hollenbach's resistance method does, as mentioned earlier, consider the possible minimum and maximum values possible to achieve using hull lines optimisation. With that, the probability that this threshold is exceeded is only 5%. Thus, it is not likely that even the optimised vessel will be beneath the minimum resistance at a given speed. However, for verification, figure 5.4 plots the total resistance of both vessels, but with additional maximum and minimum points of the original vessel.

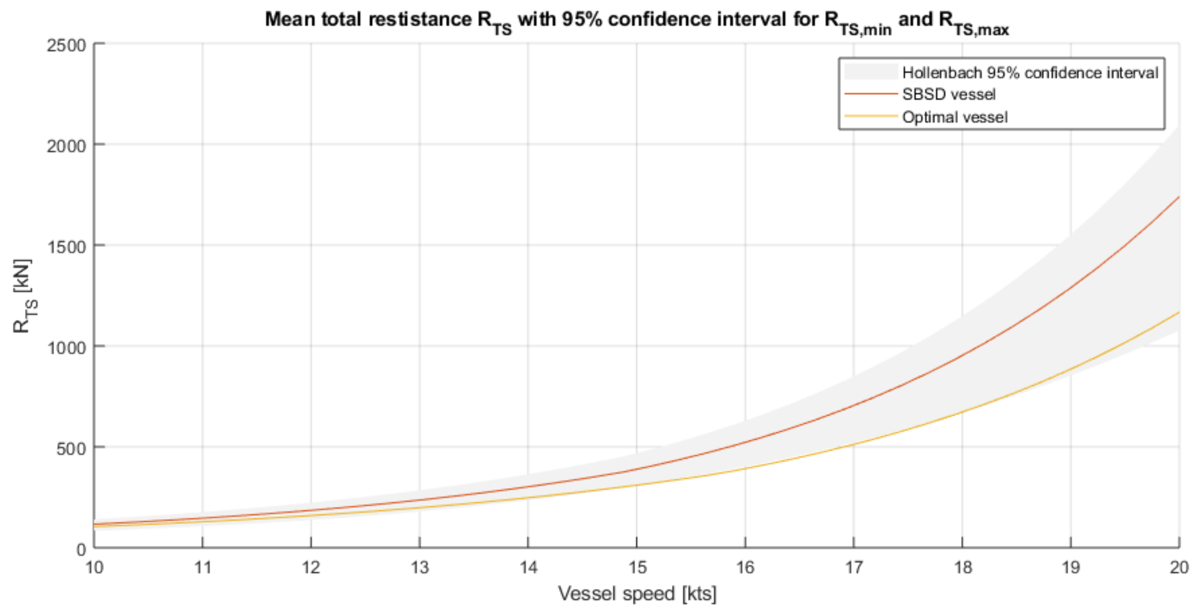


Figure 5.4: Mean total resistance for original and optimised vessel with 95% confidence interval.

From figure 5.2, it is known that the difference between the two vessels - when evaluating mean resistance - is approximately 33% at 20 knots. At the same speed, the maximum and minimum resistance values for the original vessel is 2,095 kN and 1,078 kN, respectively. Hence, the optimal vessel with a resistance of 1,167 kN at 20 knots is only 7.6% higher than the Hollenbach's theoretical absolute minimum. The theoretical minimum is based on an optimisation of not only the main dimensions but also the individual hull lines. While the theoretical minimum of original vessel's resistance is lower than that of the optimal vessel, the optimised hull resistance *does* veritably go below the theoretical minimum in the region of approximately 15 to 17 knots. However, this is likely a side-effect of the added residual coefficient due to the critical Froude number, as illustrated in figure 5.3.

5.2 Resulting hull geometry

Now that the optimisation has been completed, the new and optimal hull can be modelled in DelftShip, similar to the original hull. The main dimensions are a limited source of information when generating the geometric model, and thus the hydrostatic coefficients are important in determining the actual geometry of the hull. It is especially important with regards to the block coefficient and prismatic coefficient that are closely related. Looking at figure 5.5 and 5.6, the general hull form is quite similar to the original. However, with a L_{OA}/B ratio higher than the original vessel, the hull form is slimmer in its shape. Additionally, the length of the submerged hull, L_{OS} is longer than the original as well as the L_{OS}/L_{OA} ratio being higher. For the original vessel, this ratio was 0.98, whereas 1.0 for the optimised hull form.

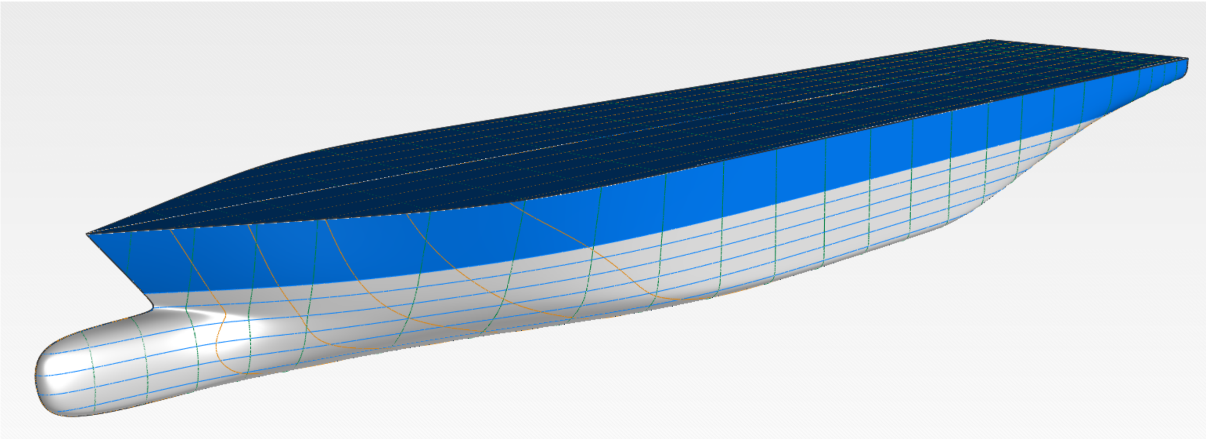


Figure 5.5: DelftShip model of optimised OSV hull seen from the bow.

In order to avoid considerable change in the aft area, L_{OS} was increased by increasing the length of the bulb in the bow. With an increased bulb volume, the volume displacement increases, and the change has to be taken into account by reducing the fullness of the hull. To systematically vary the displacement of the submerged hull, the control lines at the forward and aft shoulder are varied as to change the length of parallel middle body. This method is very similar to the generalised Lackenby method, but no numerical estimation was made in this instance, as trial and error proved sufficiently accurate with few iterations necessary.

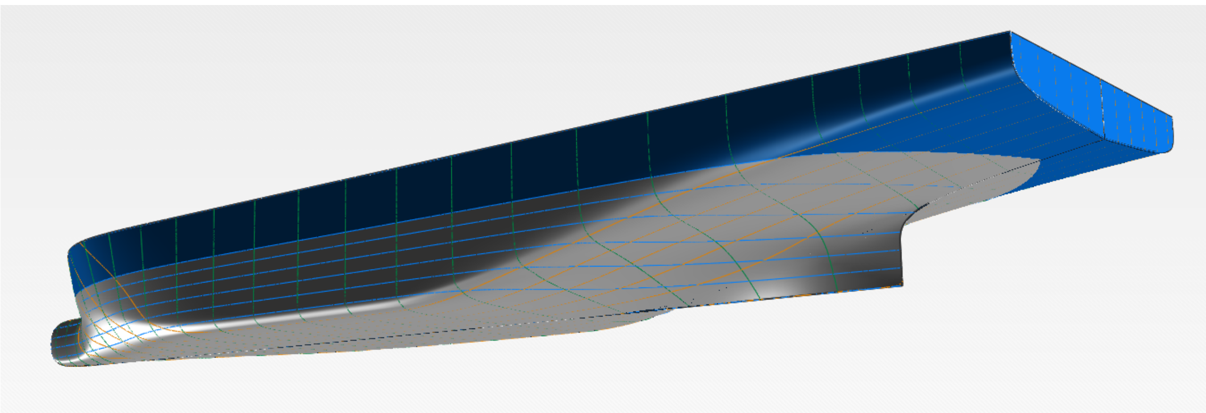


Figure 5.6: DelftShip model of optimised OSV hull seen from aft.

While the combination of the main dimensions and the hydrostatic represents a feasible and optimal solution, one might argue that not all the changes are necessarily optimal in terms of fluid flow around the bow or from a structural point of view. The possible quasi-optimality relates primarily to the bulb and bow area. A shorter bulb might be more advantageous from a structural point of view to avoid any singularities, and the shortened submerged length can be compensated with an elongation in the aft.

Despite the results from the algorithm and the generated hull form, one should also consider the stability criteria that represents part of the feasibility. From the SBSD process, it is already known that the intact stability is sufficiently high and that the vessel is stable in calm waters. However, it is also of interest to assess the resulting stability in normal loading conditions at different heel angles. Figure 5.7 illustrates the righting lever, i.e. the GZ length, versus the heeling angle.

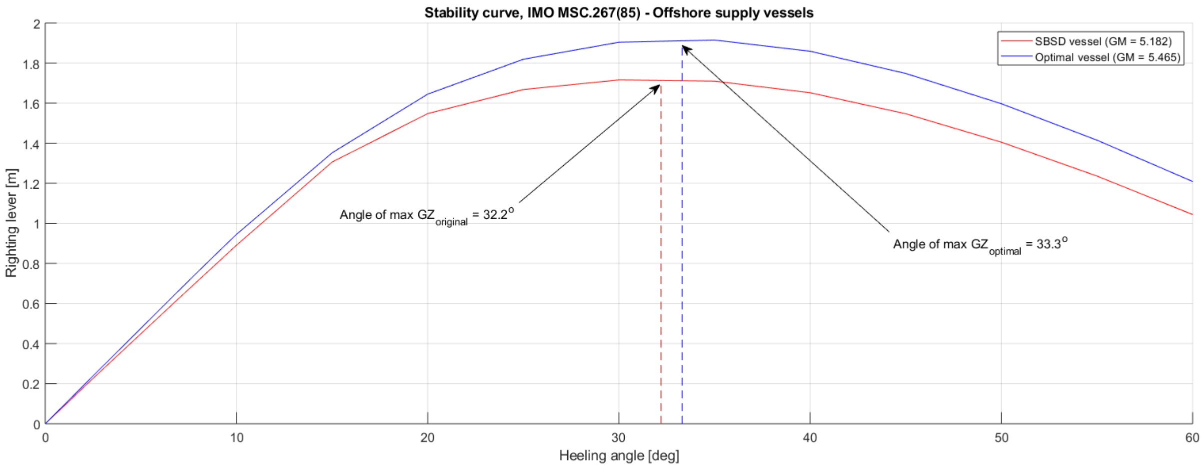


Figure 5.7: GZ curve for the original and optimal hull geometry.

For comparing the two vessels, both GZ-curves are plotted in the figure above. One of the stability criteria for OSV is max(GZ) $\geq$ GZ(30°), which is valid for both vessels. Calculation of the GZ curve is a complex process that involves the calculation of the moving centre of buoyancy as well as the submerged volume of the vessel at different heel angles. Consequently, the stability of the vessel was not part of the objective function, but rather a sub-constraint of the resulting hull geometry. As long as the vessel passed IMO's criteria for minimum stability for offshore vessels, IMO MSC.267(85), the hull geometry and the optimised main dimensions represent a feasible solution. Additionally, one can observe that the optimality has had a positive effect on the hull in terms of increasing the righting lever for all heeling angles resulting in a somewhat stiff vessel.

6 Analysis and discussion

Based on the optimised parameter values in table 5.1, the improved hull is somewhat slimmer in its shape as the L_{OA}/B ratio has increased 5.1%, from 4.27 to 4.50. Due to the strict volume requirements that were made for comparative reasons, the increased length and breadth has resulted in a shorter draught. Consequently, the B/T ratio has also increased, with approximately 5.6%. With the hydrostatic coefficients being held constant for both vessels, it is therefore of interest to evaluate the sensitivity of the vessels' relationship factors. Figure 6.1 illustrates the change in the objective function value with the changing relationship values.

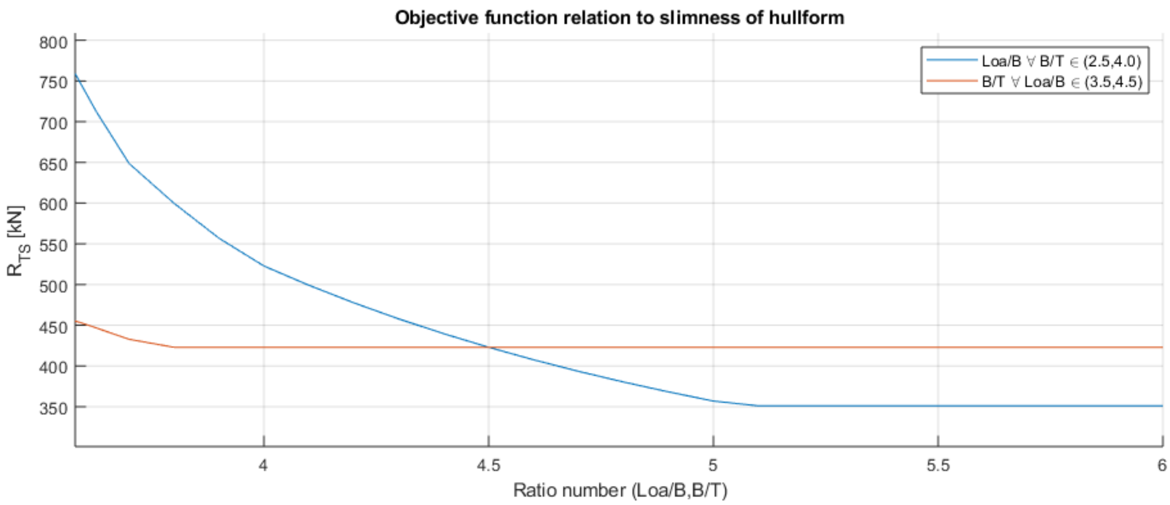


Figure 6.1: Objective function value in relation to main dimensions relationships.

The figure shows that a slimmer hull will give a reduced resistance, however, only up to the point where L_{OA}/B is 5.1. The variable L_{OA}/B-ratio represented by the blue line assumes that $2.5 \leq$ B/T ≤ 4.0 as given by the initial constraints of the optimisation algorithm. Accordingly, if the genetic algorithm were not constrained regarding the L_{OA}/B-ratio, the optimal value would be 5.1, with a mean resistance of approximately 351 kN. However, this change would deviate too much from the original vessel hull, and a comparative study would not be possible.

However, when considering the change in objective function concerning the change of B/T-ratio, figure 6.1 shows that the optimal B/T-ratio is well within the constraints of the optimisation at 3.76. The optimal values are given the constraint interval of $3.5 \leq L_{OA}/B \leq 4.5$. Noticeably, the optimality point of the optimisation is the point where the two lines of figure 6.1 intersect. When varying the ratios above, small variations in the hydrostatic coefficients may change, but with little effect on the objective function due to the strict volume and waterplane area constraints.

6.1 Sensitivity analysis

The genetic algorithm is known to compute reliable results with a high likelihood of reaching the global optimum. The phases of the method, such as the crossover and mutation considerably reduce the likelihood of converging into quasi-optimal solutions or terminating the optimisation prematurely. While only the genetic algorithm has been used for the hull optimisation, the results are tested with other algorithms in MATLAB to ensure that they all conclude with the same optimality. All the algorithms have reached an identical solution.

Furthermore, it is also of interest to evaluate the sensitivity and robustness of the optimisation. The previous section described some the sensitivity, but most importantly, visually showing that the solution is optimal given the designated constraints. An unconstrained optimisation would naturally give a lower objective value, but such a process would deviate too far from the reality of the task. There is, however, the possibility of changing the constraints to evaluate the possible results from said changes. With regards to the length constraints, the model assumes that $L_{WL} \leq L_{OA}$ and $0.94 \leq L_{WL}/L_{OA} \leq 0.98$. As described in previous sections, the different length dimensions have a great effect on the slimness of the hull, and therefore the resistance. One could, therefore, evaluate the sensitivity of the relationship between L_{WL} and L_{OA} to get a better picture of the model's sensitivity.

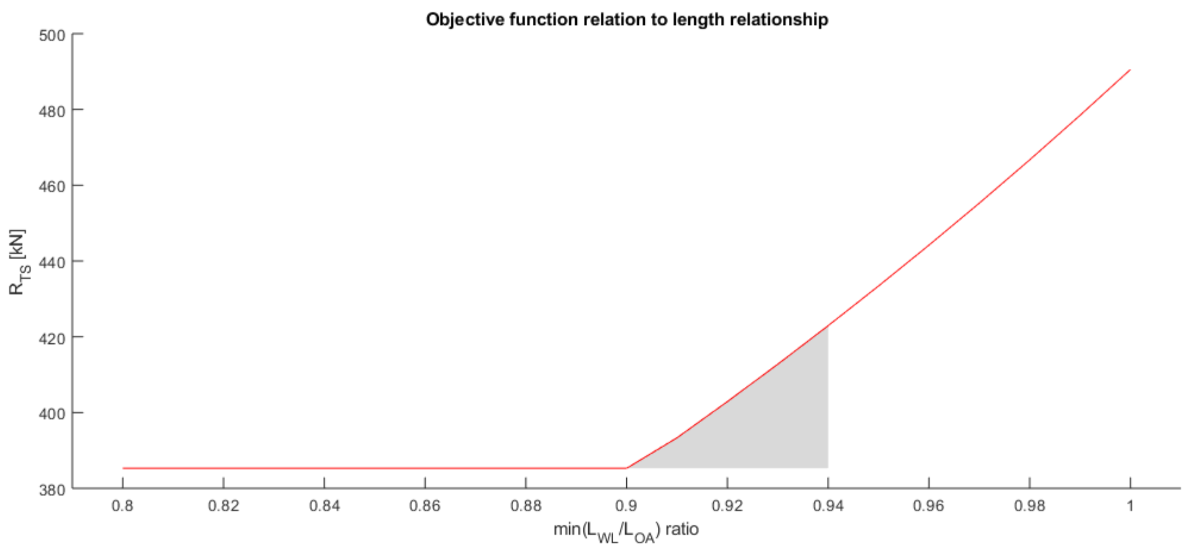


Figure 6.2: Variation of waterline length to length overall.

Figure 6.2 shows the varying ratio values for L_{WL}/L_{OA} from 0.8 to 1.0. The original vessel's ratio was equal to 0.96, while the optimal ratio is at the lower bound at 0.94. Based on the plot illustrated above, one can observe that the algorithm will always choose the lowest possible ratio but only down to 0.9. Any ratio chosen below this value will not yield a better objective function value. The constraint that sets 0.94 as the lower bound tries to keep the ratios fairly similar to the original vessel but does, in turn, increase the objective function. The added resistance resulting from $L_{WL}/L_{OA} \geq 0.94$ is equivalent to only 57.65 kN, represented by the shaded area in figure 6.2. However, if the ratio were to be allowed to be as low as 0.9, the bulb would likely become even longer, or the overhang aft would be elongated.

While the line between 0.9 to 1.0 is not entirely linear, a linear slope can be assumed between 0.94 and 0.95 and would result in ~11 kN increase of the objective function if L_{WL} is increased by one meter. This change shows that the model is quite sensitive to the upper and lower bound variables in addition to the non-linear constraints.

6.2 Analysis of algorithm settings

Another critical aspect of the optimisation robustness concerns the options of the genetic algorithm in MATLAB. The options entail tweaking the mutation and crossover settings as well as the population size and tolerance of the algorithm. The size of the population, i.e. the number of individual chromosomes that investigate the feasible area is vital in reaching the global optimum. A small population may result in convergence in local optima, while too large of a population will drastically increase the computation time without any significant improvement. Hence, the optimisation algorithm was run about 50 times with different population sizes to see the effect on the objective function. The resulting data is plotted in figure 6.3. While it would be desirable to see an apparent convergence of the objective function as the population size increases, there is no such trend. Due to the randomness of mutation and crossover, there are still large spikes in the objective function, even with a large population size.

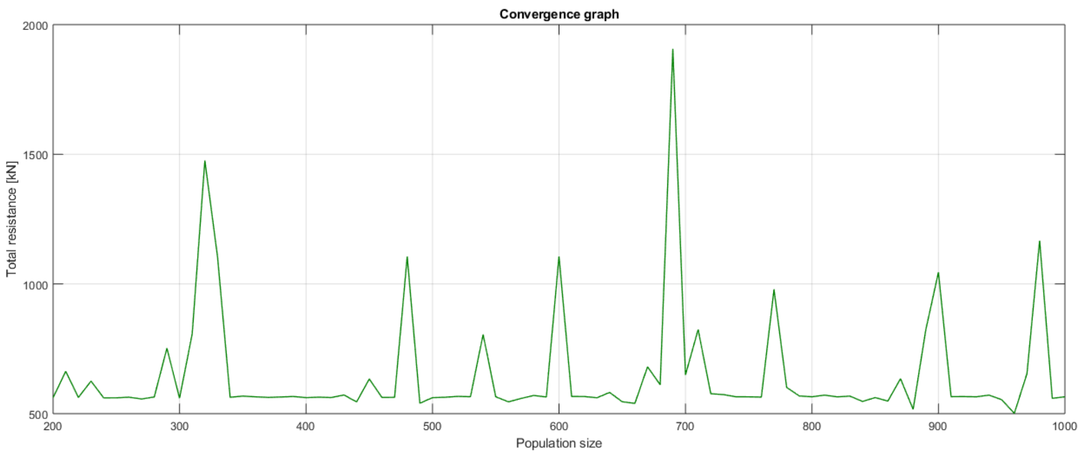


Figure 6.3: Variation of population size's effect on the objective function value.

The tolerance constraint and function constraint were both 10^{-6} for this convergence test, with a tournament size of $k = 0.2M$, where M is the population size. Since the objective function does not converge with a higher population, the most desirable population is the lowest possible, given a low objective function value. The convergence test of figure 6.3 was completed five times for verification of consistency. While the position of the most significant spikes varied for each run, the interval between 200 and 300 was always among the intervals with the lowest objective function value. Hence, for the optimisation, a population size of 250 was chosen with a tournament size of $k = 50$.

To further verify that the right options of the algorithm are chosen, a similar convergence test was completed for the tolerance constraint and function constraint. These values represent the allowed deviation from the constraint bounds and act as a termination criterion. If the solution's variables are similar enough to the constraints, i.e. below the accepted tolerance, the stopping criteria of the algorithm are met, and an optimal solution is presented. Figure 6.4 illustrates the objective function value with a varying tolerance.

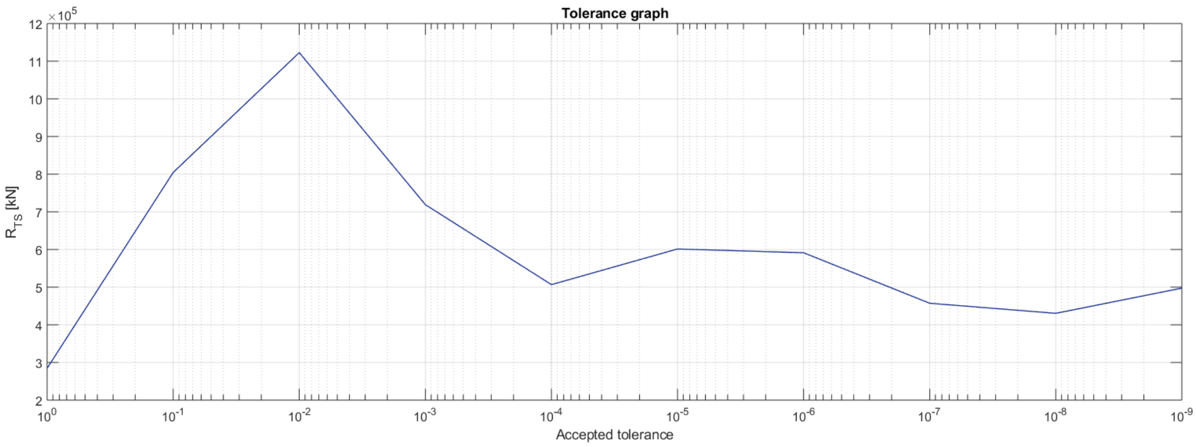


Figure 6.4: Variation of constraint tolerance and function tolerance, and the effect on the objective function value.

In this instance, the function tolerance and constraint tolerance were equal, with a population and tournament size equal to the decided values previously described. High tolerance is likely to give lower objective function values, but with a larger deviation from the fitness functions and the constraints. It is therefore desirable to choose the point where the objective function value stabilises, and not necessarily the global minimum. While there is not an apparent convergence of the objective value, figure 6.4 shows a somewhat stabilising objective function value when the constraint is greater than 10^{-4}. Henceforth, the function and constraint tolerance were set at this value as it represents a suitable balance between the solution accuracy and the computation time.

7 Conclusion

This report has evaluated multiple design and optimisation methods to determine their strengths and weaknesses and determine which is most suitable, given the aim of the project. A quantitative approach has also been undertaken to fairly evaluate the design process candidates. Considering its simplicity, level of detail and flexibility in vessel types, the system based ship design process was chosen. Due to the time and scope restriction of the thesis work, an entire SBSD process was not completed. The subsequent optimisation process, used, therefore, an OSV that was modelled precisely according to the SBSD methodology.

With the chosen design process, a limited number of optimisation methods were suitable. The genetic algorithm was chosen for its ability to evaluate multiple variables with little setup complexity thoroughly. As a result, six different main dimensions of the vessel were optimised to reduce the total resistance of the vessel in speeds from 10 to 20 knots. Consequently, the single-objective genetic algorithm managed to reduce the average resistance for the speed range with approximately 15%. The reduction in vessel resistance increases proportionately to the vessel speed, resulting in more than 30% savings when cruising at 20 knots.

The optimisation has proven reliable with excellent results that have been verified by testing with multiple solvers. Although no definite pattern has emerged when adjusting the population size or tolerance, the convergence tests have portrayed the sensitivity and robustness of the algorithm. Since the genetic algorithm relies heavily on randomness in the crossover, selection and mutation, one can conclude that the optimisation is unlikely to converge into local minima, albeit with high sensitivity concerning the population size. The sensitivity is also apparent regarding the constraints of the problem formulation, where small changes in variable's ratios had a significant impact on the objective function value. The strict constraints were necessary for the comparative analysis, and seemingly the high sensitivity derives from the problem formulation in the optimisation.

In conclusion, the resulting optimal hull features a feasible geometry. Most of the hull's aspects are reasonable with the possible exception of the elongated bulb. Although it is within the bounds of the optimisation model, it may not be optimal from a structural or hydrodynamic point of view. However, seeing as such analyses were outside the main scope of the project, one can conclude that the new OSV hull fulfils the system requirements outlined by the system based ship design process and the constraints and bounds of the genetic algorithm.

7.1 Further work

Software communication

The work presented in this report has successfully achieved to optimise the hull of the original AHTS with its genetic algorithm, but there are additional elements that could be added to improve the solution and the robustness of the model.

One of the greatest challenges in the optimisation is the strong relationship between the main dimensions and the hydrostatic coefficients, as they are often dependent on volume input for calculation. To fully develop a method that decides not only the main dimensions but also the geometry of the hull at various stations, the algorithm has to communicate with the hull modelling software. Potentially, this process could be completed by running DelftShip in batch mode through MATLAB, involving constant communication and feedback between the software.

However, such a batch file does not exist as the source code of DelftShip is not possible to automatically extract, and neither the hydrostatic data of the hull. It is likely that if possible, this process would further improve the objective function. Additionally, output data such as stability and damage stability could also be evaluated and considered in an improved and realistic objective function. However, programming and mending the source code of the software is beyond the scope of the work outlined in this report but may be possible in future projects.

Multi-objective optimisation

Section 2.6 evaluated multiple optimisation methods, among other the multi-objective genetic algorithm process. Having chosen the genetic algorithm as the tool for the optimisation has given improved and verifiable results. However, with only hull resistance as a measure of goodness, the optimisation is not a multi-objective, but a multi-variable optimisation. By adding one or more fitness functions such as fuel consumption, life cycle costs or emissions, a Pareto front could be generated from the algorithm. It is likely that such a process would better reflect the challenges a naval architect would face in the design of an offshore support vessel and thus create more realistic trade-off analyses. Despite the more realistic approach of multiple objectives, the added computational time has to be considered as there are several optima along the Pareto front. The added complexity of the calculation is also likely to have a snowball effect on the time spent analysing and evaluating the results.

Sea-keeping analysis and power requirements

An offshore support vessel operating in the North Sea is highly dependent on good sea-keeping abilities. The sea-keeping abilities determine how the vessel behaves in different waves and is essential when determining whether an operation is possible to complete with a given weather-window. Section 4.2 and 5.2 show that both vessels have an intact stability well above the criteria in addition to sufficient righting lever in roll motions. The intact stability and stability in its default loading condition does not, however, describe the vessel's sea-keeping abilities, and such a study should be undertaken in future works. As part of multi-objective optimisation, it would benefit the design solution if the sea-keeping parameters were considered in the objective function, by, e.g. minimising pitch and roll motions.

7.2 Master thesis developments

The work done in this report represents a project thesis that will act as a foundation for further work that is to be completed in the final master thesis. The scope of the master thesis is similar in its optimisation, but will most likely switch vessel type from OSVs to an FPSO. Additionally, the suggested work will be included in the optimisation of the vessel. It is most likely that a multi-objective optimisation process will be included, focusing on the sea-keeping abilities of the vessel, as well as CAPEX, operability and deck area.

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APPENDIX

A | Generalised Lackenby Method

The explanations and detailing outlined in this appendix represents a concise summary from the initial article outlining the Lackenby approach [28].

For the basis ship:
ϕ = the prismatic coefficient of the half-body
$\overline{x}$ = the fractional distance from midships of the centroid of the half-body
p = the factional parallel middle of the half-body
x = the factional distance of any transverse section from midships
y = the area of the transverse section at x expressed as a fraction of the maximum ordinate

For the derived forms:
$\delta\phi$ = the required change in the prismatic coefficient of the half-body
δp the consequent change in parallel middle body
δx the necessary longitudinal ship of the section at x to produce the required change in prismatic coefficient
h = the fractional distance from midships of the centroid of the added 'sliver' of the area represented by $\delta\phi$

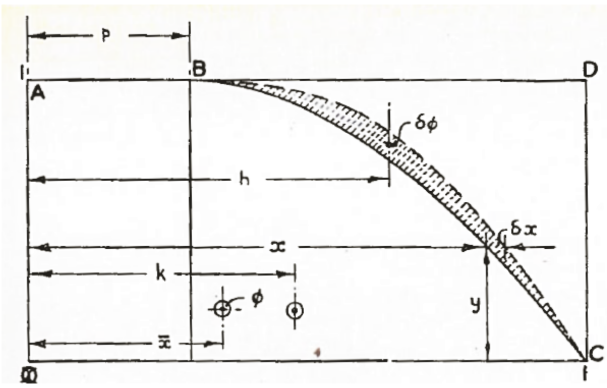


Figure A.1: The curve A B C represents the curve of the areas of the basis ship for one half of the body.

The necessary change in the station spacing is given by δx_f for stations in front of the midship and by δx_a aft:

$$\delta x_f = (1 - x_f) \left\{ \frac{\delta p_f}{1 - p_f} + \frac{(x_f - p_f)}{A_f} \left[\delta\phi_f - \delta p_f \frac{(1 - \phi_f)}{(1 - p_f)} \right] \right\} \tag{A.1}$$

$$\delta x_f = (1 - x_a) \left\{ \frac{\delta p_a}{1 - p_a} + \frac{(x_a - p_a)}{A_a} \left[\delta\phi_a - \delta p_a \frac{(1 - \phi_a)}{(1 - p_a)} \right] \right\} \tag{A.2}$$

The constants A, B and C are given by:

$$A = \phi\,(\phi 1 - 2\overline{x}) - p\,(1 - \phi) \tag{A.3}$$

$$B = \frac{\phi\,[2\overline{x} - 3k^2 - (1 - 2\overline{x})]}{A} \tag{A.4}$$

$$C = \frac{B\,(1 - \phi) - \phi\,(1 - 2\overline{x})}{1 - p} \tag{A.5}$$

While figure A.1 represented the sectional area half body, figure A.2 represents the complete sectional area curve, each half-body of which is one unit long and one unit maximum ordinate. The full line A B C represents the basis areas curve and the dotted line the derived curve.

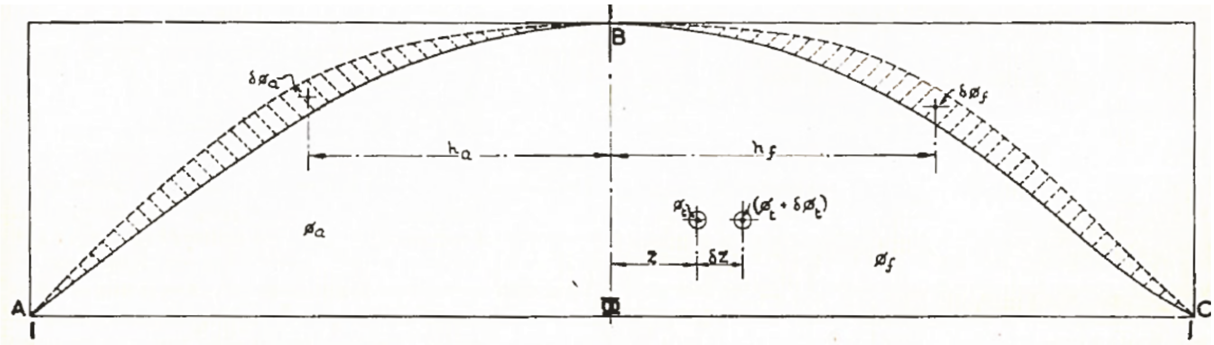


Figure A.2: Complete sectional area curve.

ϕ_t = the total prismatic coefficient of the basis ship
$\delta\phi_t$ = the required change in total prismatic coefficient
ϕ_f = the forebody prismatic coefficient of the basis ship
ϕ_a = the afterbody prismatic coefficient of the basis ship
$\delta\phi_f$ = the change in forebody prismatic coefficient
$\delta\phi_a$ = the change in afterbody prismatic coefficient
$\overline{z}$ the distance of the LCB in the basis ship from midships expressed as a fraction of the half-length (positive forward of midships, negative aft)
$\delta\overline{z}$ = the required fractional shift of the LCB in the derived form

$$\delta\phi_f = \frac{2\,[\delta\phi_t\,(B_a + \overline{z}) + \delta\overline{z}\,(\phi_t + \delta\phi_t)] + C_f \cdot \delta p_f - C_a \cdot \delta p_a}{B_f + B_a} \tag{A.6}$$

$$\delta\phi_f = \frac{2\,[\delta\phi_t\,(B_f - \overline{z}) - \delta\overline{z}\,(\phi_t + \delta\phi_t)] - C_f \cdot \delta p_f + C_a \cdot \delta p_a}{B_f + B_a}, \tag{A.7}$$

the necessary change in station spacing is given by δx_f for stations in front of the midship and δx_a for the aft.

B | Analytical hierarchy process

Initial matrix	S	A	O	P	n^{th} root	λ_V	A_V	λ
S	1.00	0.33	2.00	3.00	1.189	0.22	0.882	4.021
A	3.00	1.00	5.00	7.00	3.201	0.59	2.371	4.014
O	0.50	0.20	1.00	1.00	0.562	0.10	0.418	4.027
P	0.33	0.14	1.00	1.00	0.467	0.09	0.347	4.031
					5.420	**1.000**		
n	4							
λ_{MAX}	4.023							
CI	0.008							
CR	0.009							

Simplicity	SBSD	SBD	DBB	BPP	n^{th} root	λ_V	A_V	λ
SBSD	1.00	3.00	7.00	7.00	3.482	0.592	2.429	4.100
SBD	0.33	1.00	3.00	5.00	1.495	0.254	1.029	4.047
DBB	0.14	0.33	1.00	2.00	0.556	0.094	0.382	4.037
BPP	0.14	0.20	0.50	1.00	0.346	0.059	0.242	4.107
					5.879	**1.000**		
n	4							
λ_{MAX}	4.073							
CI	0.024							
CR	0.027							

Applicability	SBSD	SBD	DBB	BPP	n^{th} root	λ_V	A_V	λ
SBSD	1.00	1.00	5.00	5.00	2.236	0.429	1.774	4.135
SBD	1.00	1.00	3.00	5.00	1.968	0.378	1.517	4.019
DBB	0.20	0.33	1.00	3.00	0.669	0.128	0.536	4.174
BPP	0.20	0.20	0.33	1.00	0.340	0.065	0.269	4.130
					5.213	**1.000**		
n	4							
λ_{MAX}	4.115							
CI	0.038							
CR	0.042							

Optimisation	SBSD	SBD	DBB	BPP	n^{th} root	λ_V	A_V	λ
SBSD	1.00	0.50	0.11	0.14	0.298	0.057	0.243	4.276
SBD	2.00	1.00	0.50	1.00	1.000	0.191	0.798	4.188
DBB	9.00	2.00	1.00	3.00	2.711	0.517	2.117	4.097
BPP	7.00	1.00	0.33	1.00	1.236	0.236	0.997	4.231
					5.245	**1.000**		
n	4							
λ_{MAX}	4.198							
CI	0.066							
CR	0.073							

Preliminary	SBSD	SBD	DBB	BPP	n^{th} root	λ_V	A_V	λ
SBSD	1.00	3.00	5.00	5.00	2.943	0.572	2.293	4.006
SBD	0.33	1.00	2.00	2.00	1.075	0.209	0.837	4.006
DBB	0.20	0.50	1.00	1.00	0.562	0.109	0.438	4.002
BPP	0.20	0.50	1.00	1.00	0.562	0.109	0.438	4.002
					5.142	**1.000**		
n	4							
λ_{MAX}	4.004							
CI	0.001							
CR	0.002							

B.1 Result matrix and criteria

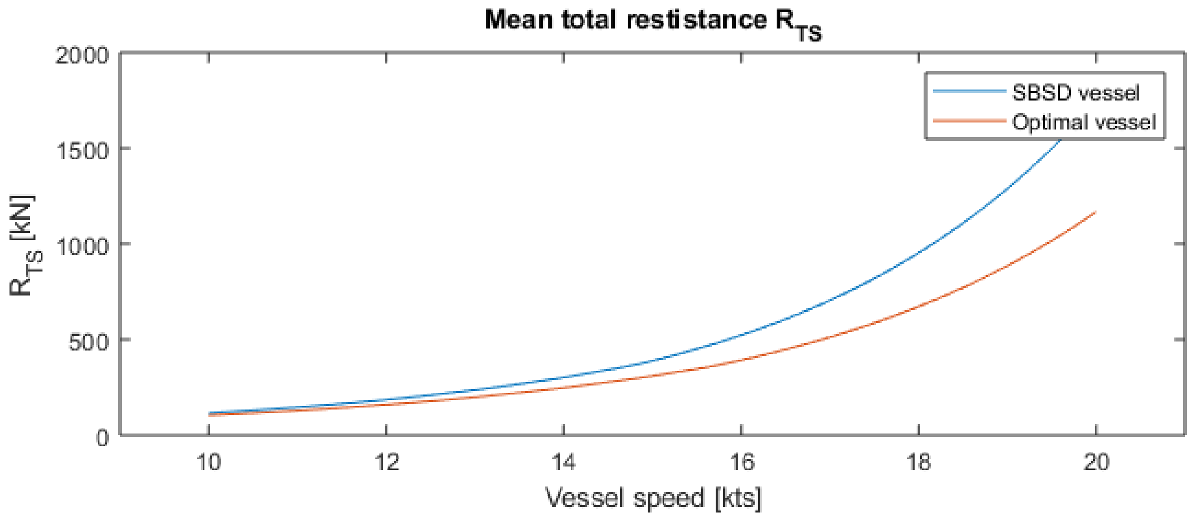
Intensity of importance	Definition	Explanation
1	Equal importance	Two factors contribute equally to the objective
3	Somewhat more important	Experience and judgement slighlt favour one over the other
5	Much more important	Experience and judgement strongly favour the one over the other
7	Very much more important	Experience and judgement very strongly fabour one over the other. Its important is demonstrated in practise.
9	Absolutely more important	The evidence favouring one over the other is of highest possible validity
2,4,6,8	Intermediate values	When compromise is needed

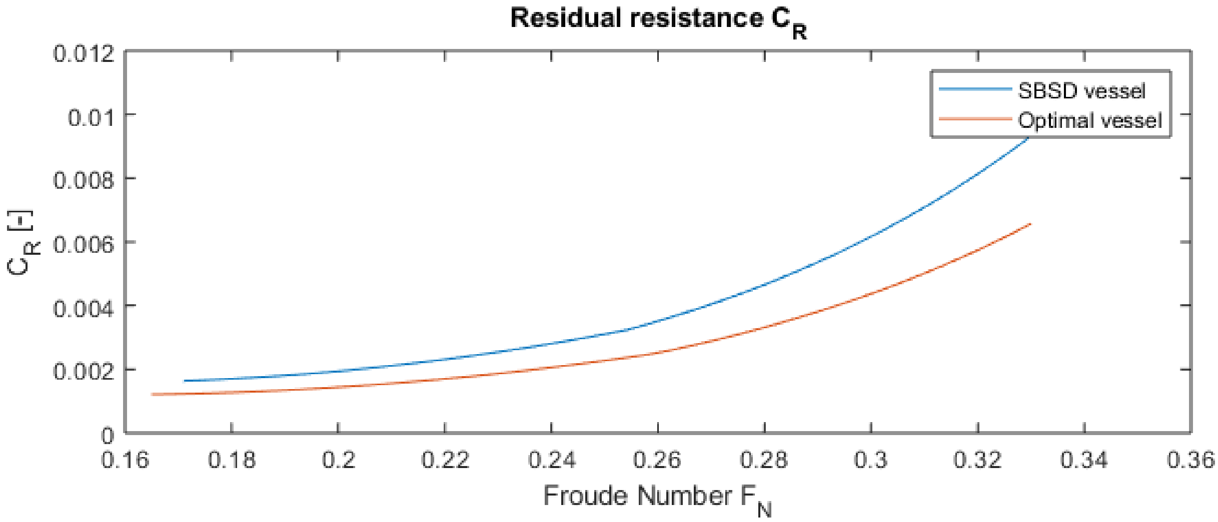
Figure B.1: Criteria for evaluating attributes.

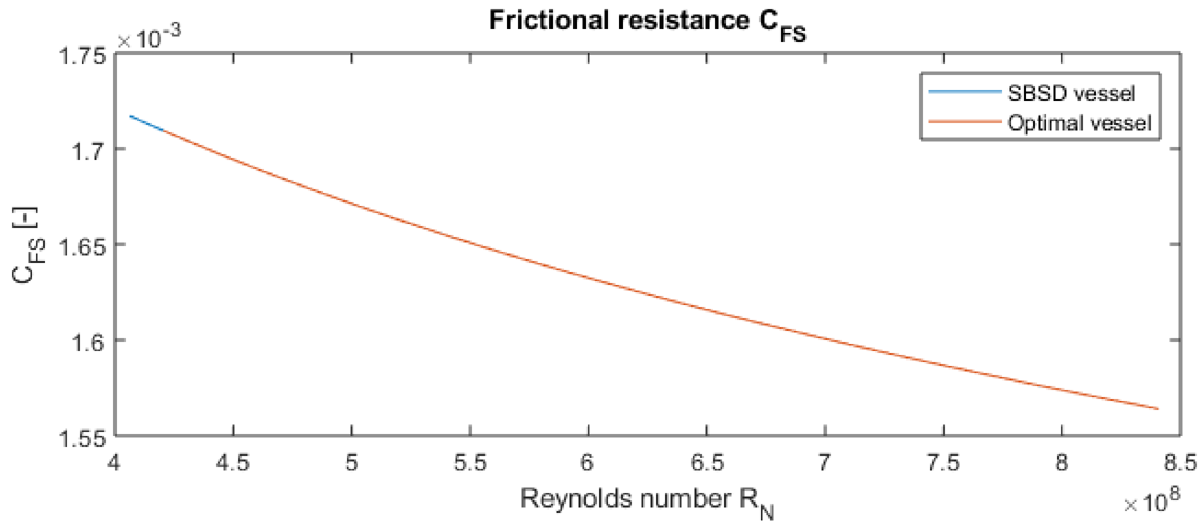
System	Simplicity	Applicability	Optimisation	Preliminary	Score
SBSD	0.59	0.43	0.06	0.57	0.44
SBD	0.25	0.38	0.19	0.21	0.32
DBB	0.09	0.13	0.52	0.11	0.16
BPP	0.06	0.07	0.24	0.11	0.09
Sum	1.00	1.00	1.00	1.00	1.00

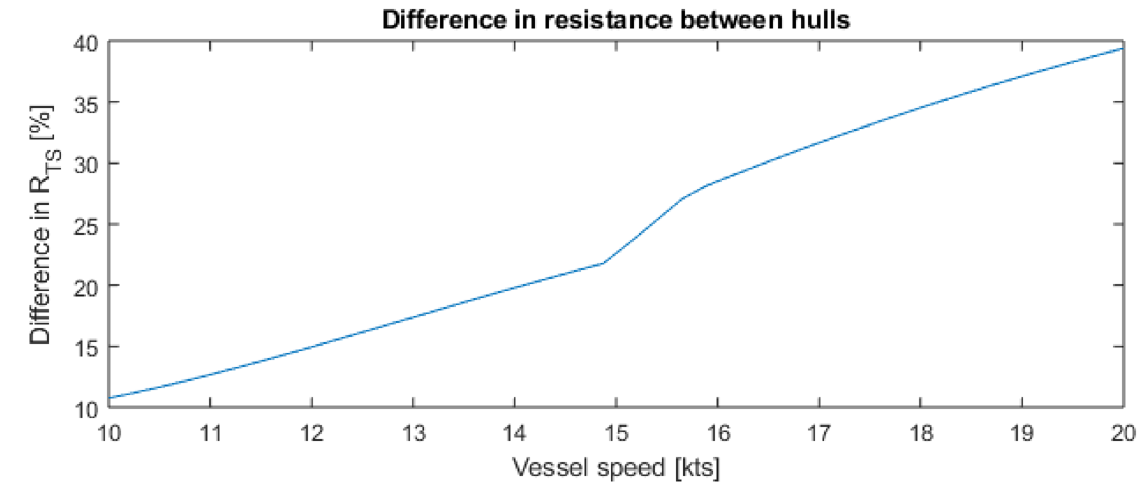
Figure B.2: Resulting vectors for each of the modelling processes.

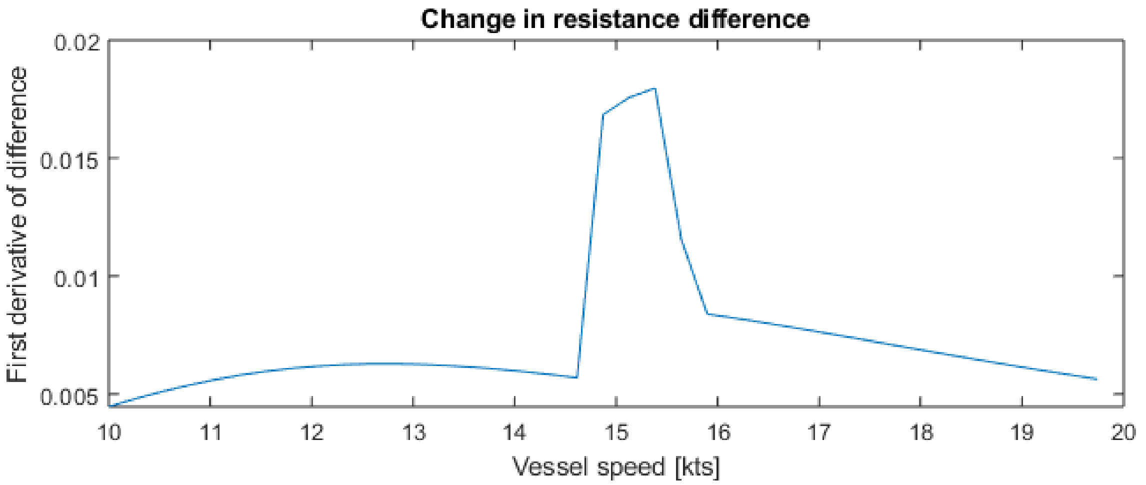
C Results diagrams

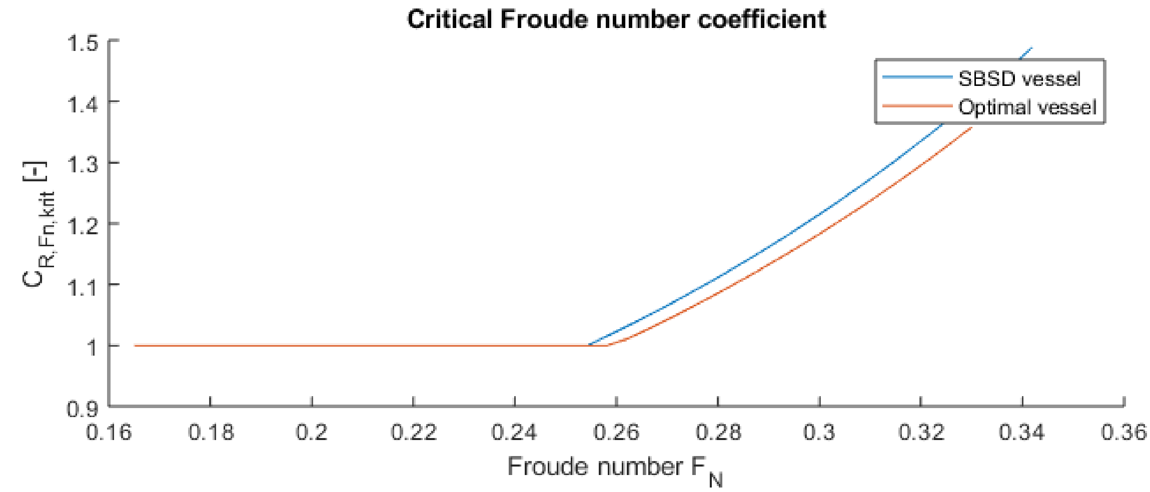


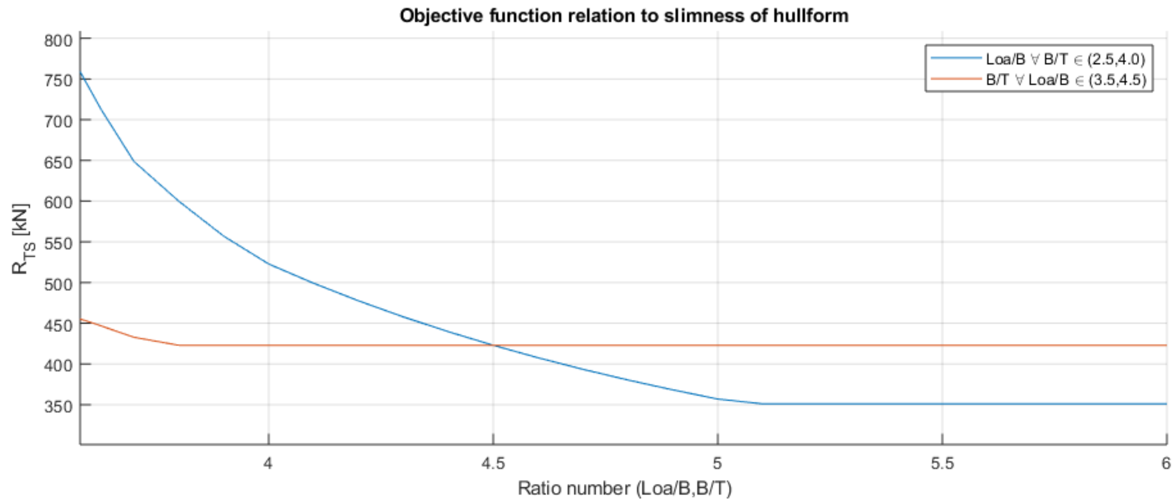


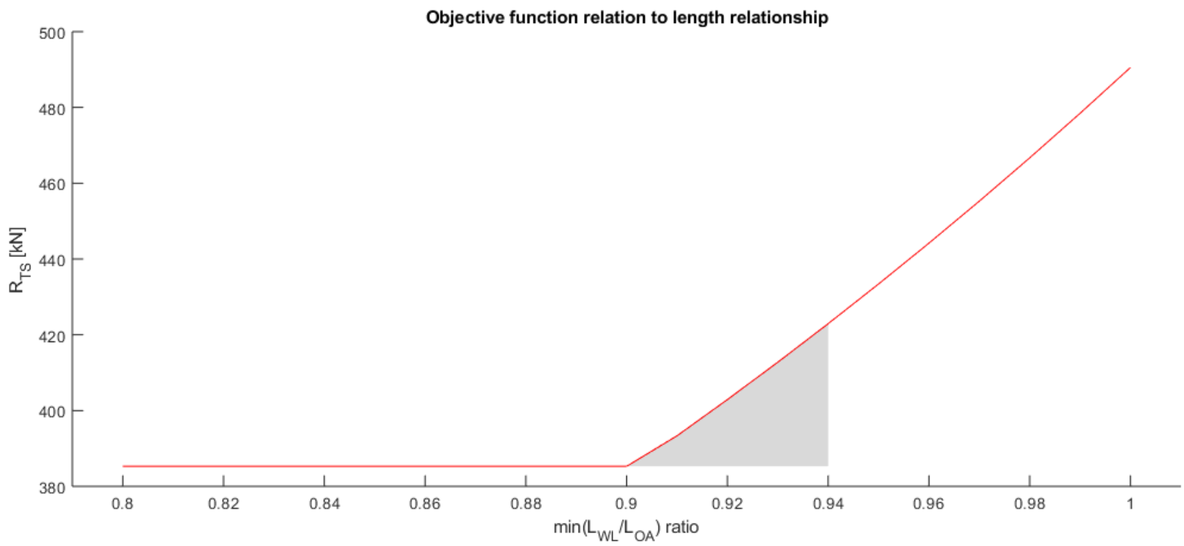


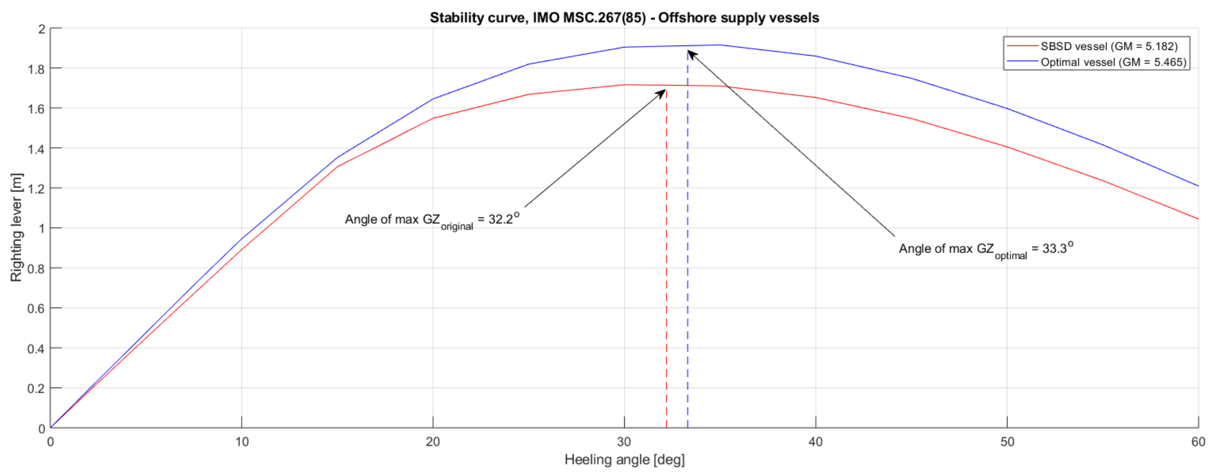

Difference in resistance between hulls
Difference in R_{TS} [%]
40
35
30
25
20
15
10
10 11 12 13 14 15 16 17 18 19 20
Vessel speed [kts]


Change in resistance difference
First derivative of difference
0.02
0.015
0.01
0.005
10 11 12 13 14 15 16 17 18 19 20
Vessel speed [kts]

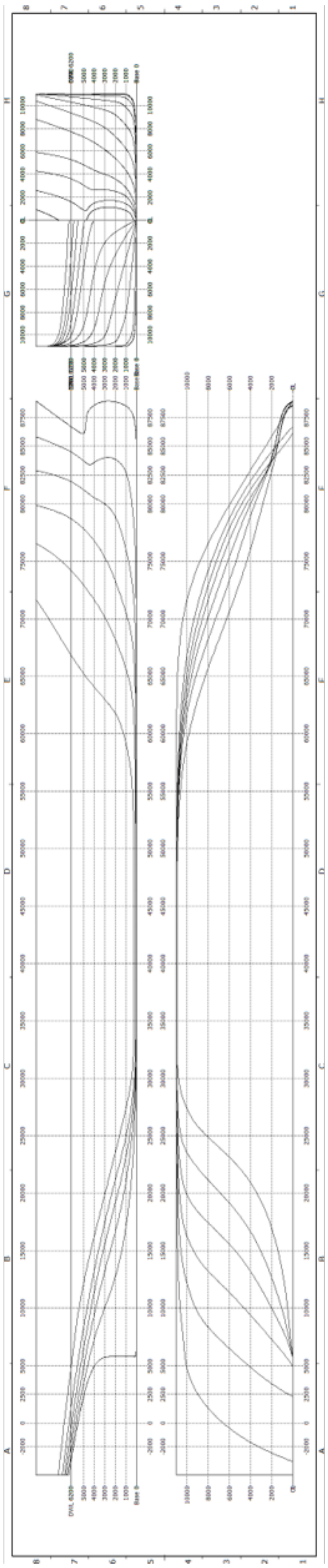

Critical Froude number coefficient
$C_{R,Fn,krit}$ [-]
1.5
1.4
1.3
1.2
1.1
1
0.9
0.16 0.18 0.2 0.22 0.24 0.26 0.28 0.3 0.32 0.34 0.36
Froude number F_N
SBSD vessel
Optimal vessel


Objective function relation to slimness of hullform
Loa/B ∀ B/T ∈ (2.5,4.0)
B/T ∀ Loa/B ∈ (3.5,4.5)
R_TS [kN]
800
750
700
650
600
550
500
450
400
350
4
4.5
5
5.5
6
Ratio number (Loa/B,B/T)


Objective function relation to length relationship
R_TS [kN]
500
480
460
440
420
400
380
0.8
0.82
0.84
0.86
0.88
0.9
0.92
0.94
0.96
0.98
1
min(L_WL/L_OA) ratio

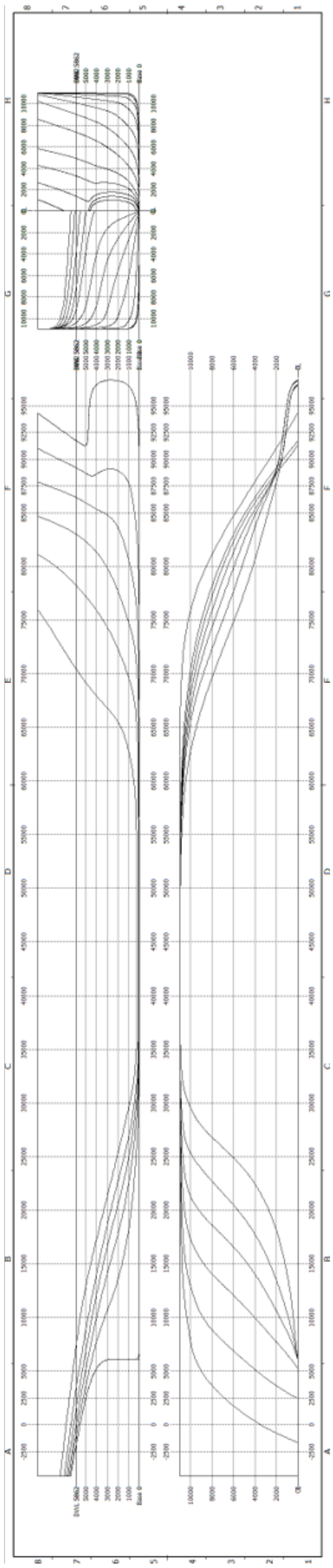

Stability curve, IMO MSC.267(85) - Offshore supply vessels
SBSD vessel (GM = 5.182)
Optimal vessel (GM = 5.465)
Angle of max GZ_original = 32.2°
Angle of max GZ_optimal = 33.3°
Righting lever [m]
Heeling angle [deg]

D | Lines plan



Original OSV – ATHS

LINES PLAN NOT TO SCALE



Optimal OSV – ATHS

E MATLAB-scripts

E.1 main.m

```
clear all
close all

% Non-linear constraints function input
nonclon = @nlcon;

% Upper and lower bounds
lb = [85 20 5 5 80 80];
ub = [105 24 7 7 105 105];

% Random number generation for initial values
for j = 1:6
    x0(j) = (ub(j)-lb(j)).*rand(1,1) + lb(j);
end


% linear constraints
A = [];
b = [];
Aeq = [];
beq = [];

% Call for the fitness function
FitFcn = @optimal_resistance;
nvars = 6;

% Choose solver
% Genetic algorithm = 1
% Minimum constrained nonlinear multivariable algorithm = 2
% Global search algorithm = 3

algorithm_choice = 1;

if algorithm_choice == 1

        % ----------- GENETIC ALGORITHM ----------------------%

        generations = 100;
        stall_limit = 100;
        pop_size = 400;
```

```
        tournament_size = 24;
        function_tolerance = 1e-6;
        constraint_tolerance = 1e-6;

        % GA options
        options_GA = optimoptions('ga','PlotFcn',{@gaplotrange,...
            @gaplotbestf,@gaplotdistance});
        options_GA = optimoptions(options_GA,'PopInitRange',[lb;ub]);
        options_GA = optimoptions(options_GA,'Generations',generations,...
            'StallGenLimit',stall_limit);
        options_GA = optimoptions(options_GA,'PopulationSize',pop_size);
        options_GA = optimoptions(options_GA,'SelectionFcn',...
            {@selectiontournament,tournament_size});
        options_GA = optimoptions(options_GA,'CrossoverFcn',...
            {@crossoverscattered});
        options_GA = optimoptions(options_GA,'MutationFcn',...
            {@mutationadaptfeasible});
        options_GA = optimoptions(options_GA,'Display','iter');
        options_GA.InitialPopulationMatrix = x0;
        options_GA.FunctionTolerance = function_tolerance;
        options_GA.ConstraintTolerance = constraint_tolerance;

        % Genetic algorithm
        [x,fval,exitflag,output,population,scores] = ga(FitFcn,nvars,...
            A,b,Aeq,beq,lb,ub,nonclon,options_GA);

        % Print best variable values
        fprintf('\nGenerations: %.0f \n',generations);
        fprintf('Stall generation limit: %.0f \n',stall_limit);
        fprintf('Population size: %.0f \n',pop_size);
        fprintf('Tournament size: %.0f \n',tournament_size);
        fprintf('Function tolerance: %d \n',function_tolerance);
        fprintf('Constraint tolerant: %d \n',constraint_tolerance);

elseif algorithm_choice == 2

        % ---------- FMINCON ALGORITHM ---------------------------------%
        options = optimoptions('fmincon','PlotFcn',@optimplotfval);
        options.Algorithm = 'interior-point';
        options.Display = 'iter';
        options.MaxFunEvals = 1E5;
        options.MaxIter = 5E3;

        % Minimum of constrainted onlinear multivariable function
        [x,fval,exitflag,output] = fmincon(FitFcn,x0,A,b,Aeq,beq,lb,ub,...
            nonclon,options);

```

```
        else
        % ---------- GLOBAL SEARCH ------------------------------------%

        gs = GlobalSearch;
        problem = createOptimProblem('fmincon','objective',FitFcn,'x0',...
            x0,'Aineq', A,'bineq',b,'Aeq', Aeq,'beq',beq, 'lb',lb,...
            'ub',ub,'nonlcon',nonclon);
        [x,fval] = run(gs,problem);

end % if

fprintf('\nMean total resistance: %.2f [kN]\n',fval/1000);

fprintf('\nLOA: %.3f [m]\n',x(1));
fprintf('Lwl: %.3f [m]\n',x(5));
fprintf('Los: %.3f [m]\n',x(6));
fprintf('B:   %.3f [m]\n',x(2));
fprintf('TF:  %.3f  [m]\n',x(3));
fprintf('TA:  %.3f  [m]\n',x(4));
```

E.2 nlcon.m

```

function [c,ceq] = nlcon(x)

% Equalities
ceq1 = (8450/0.661) - x(1)*x(2)*((x(3)+x(4))/2);     % Vessel volume
ceq2 = 0.8 - 1640/(x(5)*x(2));                       % Waterplane area
% ceq3 = (x(1)/x(2)) - 4.27;                         % LOA/B ratio = 4.27;
% ceq4 = 3.55 - (x(2)/((x(3)+x(4))/2));              % B/T ratio = 3.55;

% Inequalities
c1 = abs(x(3)-x(4)) - 0.00;                          % Longitudinal trim
c2 = 3.5 - x(1)/x(2);                                % LOA/B >= 3.5
c3 = x(1)/x(2) - 4.5 ;                               % LOA/B =< 4.5
c4 = 2.5 - x(2)/((x(3)+x(4))/2);                     % B/T >= 3.0
c5 = x(2)/((x(3)+x(4))/2)- 4.0;                      % B/T <= 4.0
c6 = x(6) - x(1);                                    % Los <= LOA
c7 = x(5) - x(1);                                    % Lwl <= LOA
c8 = 0.94 - x(5)/x(1);                               % Lwl/LOA >= 0.94
c9 = x(5)/x(1) - 0.98;                               % Lwl/LOA <= 0.98

c = [c1 c2 c3 c4 c5 c6 c7 c8 c9];
ceq = [ceq1 ceq2];

end
```

E.3 hollenbach_test.m

```
close all
clear all

% Imports vessel data from Excel file
[Vessel, LOA_data, Lwl_data, Los_data, B_data, TF_data, TA_data, Cb_data, ...
    Cp_data, Cw_data, Cm_data, Dp_data, Abt_data, NRud_data, NBrac_data, ...
    NBoss_data, NThr_data] = importfile('hydrostatics.csv');

datapoints = 40;     % Number of datapoints to be evaluated
vessels = 2;         % Number of vessels evaluated

results = zeros(datapoints,vessels);


for i = 1:vessels

    LOA = LOA_data(i);
    Lwl = Lwl_data(i);
    Los = Los_data(i);
    B = B_data(i);
    TF = TF_data(i);
    TA = TA_data(i);
    Cb = Cb_data(i);
    Cp = Cp_data(i);
    Cw = Cw_data(i);
    Cm = Cm_data(i);
    Dp = Dp_data(i);
    Abt = Abt_data(i);
    NRud = NRud_data(i);
    NBrac = NBrac_data(i);
    NBoss = NBoss_data(i);
    NThr = NThr_data(i);

    % Maximum and minimum speed range [kts]
    v_min = 10;
    v_max = 20;

    % Speeds to be investigates
    Vsvec1 = linspace(v_min,v_max,datapoints);
    Vsvec = Vsvec1*0.514444;

    % Estimation of wetted surface
    T = (TF+TA)/2;
```

```
    S = LOA*(2*T+B)*sqrt(Cm)*(0.453 + 0.4425*Cb - 0.2862*Cm - ...
        0.00346*B/T + 0.3696*Cw) + 2.38*Abt/Cb;

    % Form factor calculation
    phi = (Cb/LOA) * (  (B) * (TF+TA)  )^.5;
    k = .6 * phi + 145 * phi^3.5;

    rho = 1025;      % Seawater density
    gravk = 9.81;    % Gravity
    nu = 1.1395E-6; % Kinematic viscocity


    %Calculation of 'Froude length', Lfn:
    if Los/LOA < 1
       Lfn = Los;
    elseif (Los/LOA >= 1) && (Los/LOA < 1.1)
       Lfn = LOA+2/3*(Los-LOA);
    elseif Los/LOA >= 1.1
       Lfn = 1.0667*LOA;
    end

    % ------- Constants of Hollenbach method --------------%

    % Mean and minimum resistance coefficients design draught
    if NThr == 1
        a = [-0.3382 0.8086 -6.0258 -3.5632 9.4405 0.0146 0 0 0 0];
        b = [-0.57424 13.3893 90.5960; 4.6614 -39.721 -351.483; ...
            -1.14215 -12.3296 459.254];
        d = [0.854 -1.228 0.497];
        e = [2.1701 -0.1602];
        f = [0.17 0.20 0.60];
        g = [0.642 -0.635 0.150];

        a_min = [-0.3382 0.8086 -6.0258 -3.5632 0 0 0 0 0 0];
        b_min = [-0.91424 13.3893 90.5960; 4.6614 -39.721 -351.483; ...
            -1.14215 -12.3296 459.254];
        d_min = [0 0 0];
        e_min = [1 0];
        f_min = [0.17 0.2 0.6];
        g_min = [0.614 -0.717 0.261];

    elseif NThr == 2
        a = [-0.2748 0.5747 -6.7610 -4.3834 8.8158 -0.1418 -0.1258 ...
            -0.0481 0.1699 0.0728];
        b = [-5.24750 55.6532 -114.950; 19.2714 -192.388 388.333; ...
            -14.357 142.738 -254.762];
        d = [0.897 -1.457 0.767];
```

```
        e = [1.8319 -0.1237];
        f = [0.17 0.24 0.60];
        g = [0.50 0.66 0.50];

        a_min = [-0.2748 0.5747 -6.7610 -4.3834 0 0 0 0 0 0];
        b_min = [3.27279 -44.1138 171.692; -11.5012 166.559 -644.456; ...
            12.4626 -179.505 680.921];
        d_min = [0 0 0];
        e_min = [0 0];
        f_min = [0.14 0 0];
        g_min = [0.952 -1.406 0.643];

    end

    cc = 0;
    % Loop over velocities
    for Vs = Vsvec

        cc = cc + 1;

        % Calculation of Froude number and critical Froude number
        Fn = Vs/sqrt(gravk*Lfn);
        Fnkrit = d*[1 Cb Cb^2]';

        c1 = Fn/Fnkrit;          % c1 coefficient
        c1_min = Fn/Fnkrit;

        Rns = Vs*Lwl/nu;                  % Reynold's number for ship
        CFs = 0.075/(log10(Rns)-2)^2;     % ITTC-75 friction line for ship

        % Calculation of C_R for given ship
        % Mean value

        CRFnkrit = max(1.0,(Fn/Fnkrit)^c1);

        kL = e(1)*LOA^(e(2));

        % Calculation of residual resistance coefficient 'standard'

        CRstandard = [1 Cb Cb^2]*(b*[1 Fn Fn^2]')/10;

        CR_hollenbach = CRstandard*CRFnkrit*kL*prod([T/B B/LOA Los/Lwl...
            Lwl/LOA (1+(TA-TF)/LOA) ...
                Dp/TA (1+NRud) (1+NBrac) (1+NBoss) (1+NThr)].^a);

        CR = CR_hollenbach*B*T/S;           % Resistance coefficient
        C_Ts = CFs + CR;                    % Total resistance coeff. ship
```

```
        R_T_mean = C_Ts*rho/2*Vs^2*S;      % Total resistance to the ship


        % Minimum values

        CRstandard_min = [1 Cb Cb^2]*(b_min*[1 Fn Fn^2]')/10;

        CR_hollenbach_min = CRstandard_min*prod([T/B B/LOA Los/Lwl ...
            Lwl/LOA (1+(TA-TF)/LOA) Dp/TA (1+NRud) (1+NBrac) (1+NBoss) ...
            (1+NThr)].^a_min);

        CR_min = CR_hollenbach_min*B*T/S;

        % Total resistance coefficient of the ship
        C_Ts_min = CFs + CR_min;
        % Total resistance
        R_T_min = C_Ts_min*rho/2*Vs^2*S;

        C_Rvec(cc) = CR;
        R_T_meanvec(cc) = R_T_mean;
        Fnvec(cc) = Fn;
        CFsvec(cc) = CFs;
        Rnvec(cc) = Rns;
        Fnkritvec(cc) = CRFnkrit;

    end

    % Writes resistance data to results matrix
    results(:,1) = Vsvec1;          % Vessel speed [kts]
    results(:,i+1) = R_T_meanvec;   % Mean total resitance: 2,3

    results(:,i+3) = C_Rvec;        % Cr coefficient: 4,5
    results(:,i+5) = CFsvec;        % Cfs coefficient: 6,7
    results(:,i+7) = Fnkritvec;     % Cr,Fnkrit coeff: 8,9

    results(:,i+9) = Fnvec;         % Froude number: 10,11
    results(:,i+11) = Fnkritvec;    % Critial Froude numbers: 12,13
    results(:,i+13) = Rnvec;        % Reynolds numbers: 14,15

end

difference = (results(:,2)-results(:,3))./(results(:,2));
derivative = diff(difference);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%------------------------------- FIGURE 1 ------------------------------%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
figure

subplot(3,1,1)
plot(Vsvec1,results(:,2)/1000)
hold on
plot(Vsvec1,results(:,3)/1000)
hold off
xlabel('Vessel speed [kts]')
ylabel('R_{TS} [kN]')
legend('SBSD vessel','Optimal vessel')
title('Mean total restistance R_{TS}')
xlim([9 21])

subplot(3,1,2)
plot(results(:,10),results(:,4))
hold on
plot(results(:,11),results(:,5))
ylabel('C_R [-]')
xlabel('Froude Number F_N')
legend('SBSD vessel','Optimal vessel')
title('Residual resistance C_R')

subplot(3,1,3)
plot(results(:,14),results(:,6))
hold on
plot(results(:,15),results(:,7))
hold off
ylabel('C_{FS} [-]')
xlabel('Reynolds number R_N')
title('Frictional resistance C_{FS}')
legend('SBSD vessel','Optimal vessel')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%------------------------------- FIGURE 2 ------------------------------%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

figure

subplot(3,1,1)
plot(Vsvec1,difference*100)
xlabel('Vessel speed [kts]')
ylabel('Difference in R_{TS} [%]')
title('Difference in resistance between hulls')

subplot(3,1,2)
plot(Vsvec1(1:39),derivative)
```

```
xlabel('Vessel speed [kts]')
ylabel('First derivative of difference')
title('Change in resistance difference')

subplot(3,1,3)
hold on
plot(results(:,10),results(:,8))
plot(results(:,11),results(:,9))
xlabel('Froude number F_N')
ylabel('C_{R,Fn,krit} [-]')
title('Critical Froude number coefficient')
legend('SBSD vessel','Optimal vessel')
ylim([0.9 1.5])

figure
hold on
plot(results(:,10),results(:,8))
plot(results(:,11),results(:,9))
ylabel('C_{R,Fn,krit} [-]')
title('Critical Froude number coefficient')
legend('SBSD vessel','Optimal vessel')
ylim([0.9 1.5])

ax1 = gca;
axPos = ax1.Position;
ax1.Position = axPos + [0 0.3 0 -0.3];
ax2 = axes('position', (axPos .* [1 1 1 1e-3]) + [0 0.15 0 0],...
    'color', 'none');
ax2.XLim = [10 20];
ax1.XLabel.String = 'Froude number F_N';
ax2.XLabel.String = 'Vessel speed [kts]';
```

E.4 ga_convergence.m

```
clear all

% Non-linear constraints function input
nonclon = @nlcon;

% Upper and lower bounds
lb = [85 20 5 5 80 80];
ub = [110 24 7 7 105 105];

% Random number generation for initial values
for j = 1:6

x0(j) = (ub(j)-lb(j)).*randi(1,1) + lb(j);

end

% linear constraints
A = [];
b = [];
Aeq = [];
beq = [];

FitFcn = @optimal_resistance;
nvars = 6;

k_size = 4:2:30;

for i = 1:length(k_size)

        options_GA = optimoptions('ga');
        options_GA = optimoptions(options_GA,'PopInitRange',[lb;ub]);
        options_GA = optimoptions(options_GA,'Generations',100,...
            'StallGenLimit',20);
        options_GA = optimoptions(options_GA,'PopulationSize',400);
        options_GA = optimoptions(options_GA,'SelectionFcn',...
            {@selectiontournament,k_size(i)});
        options_GA = optimoptions(options_GA,'CrossoverFcn',...
            {@crossoverscattered});
        options_GA = optimoptions(options_GA,'MutationFcn',...
            {@mutationadaptfeasible});
        %options_GA = optimoptions(options_GA,'Display','iter');
        options_GA.InitialPopulationMatrix = x0;
        options_GA.FunctionTolerance = 1e-6;
```

```
        options_GA.ConstraintTolerance = 1e-6;

        % % Genetic algorithm
        [x,fval,exitflag,output,population,scores] = ga(FitFcn,nvars,A,...
            b,Aeq,beq,lb,ub,nonclon,options_GA);

        values(i) = fval;

        remaining_i = (i/length(k_size))*100;
        fprintf('\nComplete tolerance: %.2f \n',remaining_i)

end

figure
plot(k_size,values)
grid on
xlabel('Tournament size')
ylabel('Total resistance [kN]')
```

E.5 stability_righting_lever.m

```

% Heeling angle of test
heeling_angle = [0 2 5 10 15 20 30 40 50 60];

% Righting lever for orignal and optimal vessel
GZ_original = [0 0.181 0.449 0.891 1.306 1.548 1.716 1.652 1.405 1.044];
GZ_optimal = [0 0.191 0.476 0.945 1.352 1.645 1.904 1.859 1.597 1.209];


figure
grid on
hold on

% Arrow start and ending location
x1 = [0.45 0.545];
y1 = [0.56 0.8];

x2 = [0.7 0.56];
y2 = [0.50 0.88];

annotation('textarrow',x1,y1,'String',...
    'Angle of max GZ_{original} = 32.2^o ')
annotation('textarrow',x2,y2,'String',...
    'Angle of max GZ_{optimal} = 33.3^o ')

% Figure
plot(heeling_angle,GZ_original,'r')
plot(heeling_angle,GZ_optimal,'b')
plot([32.2 32.2],[0 1.7],'r--')
plot([33.3 33.3],[0 1.89],'b--')
xlabel('Heeling angle [deg]')
ylabel('Righting lever [m]')
title('Stability curve, IMO MSC.267(85) - Offshore supply vessels')
legend('SBSD vessel (GM = 5.182)','Optimal vessel (GM = 5.465)')
ylim([0 2])
```