UNIVERSITY OF TURKU

# Ship hull shape optimisation to increase energy efficiency of ships

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Bachelor's thesis

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The optimisation of a ship hull shape plays an important role in increasing energy efficiency and reducing fuel consumption in maritime transport. This thesis examines three approaches to hull shape optimisation: design of experiments, the adjoint method and machine learning-based methods. The study begins by outlining the fundamental principles of computational fluid dynamics and hull parametrisation, forming the basis for evaluating hull performance and enabling shape modification. In addition, the advantages and limitations of each optimisation method are briefly discussed.

Design of experiments showed to be a useful tool for exploring different hull concepts and identifying important design parameters, making it a useful tool for early-stage hull design. The adjoint method, in contrast, demonstrated its applicability in optimising existing hull shapes by computing the gradient of an objective function. Machine learning-based methods showed significant potential in accelerating the hull design process by reducing reliance on computationally demanding simulations. Findings show that the complementary use of these methods enables an efficient workflow for optimising a ship’s hull shape.

**Key words**: ship hull optimisation, shape optimisation, computational optimisation

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# 1 Introduction

## 1.1 Introduction to the topic

Maritime shipping plays an important role in global trade but is simultaneously a major source of transportation emissions worldwide. In 2023, the maritime shipping industry was responsible for roughly 703 million metric tons of carbon dioxide emissions, accounting for roughly 10% of all transportation emissions worldwide (Tiseo, 2024). As environmental regulations keep tightening up, the maritime industry needs to adapt by implementing various solutions to reduce emissions and improve sustainability.

One of the most effective ways to reduce the environmental impact of ships is designing them to consume as little energy as possible. Since fuel expenses are responsible for up to 50% of maritime transportation costs (García et al., 2020), shipowners have not only environmental reasons but also financial motives to seek opportunities for lowered fuel consumption. By enhancing a vessel’s design to minimise fuel consumption, both environmental and economic benefits can be achieved.

One of the most important factors influencing a ship’s fuel efficiency is its resistance to motion, which is mostly caused by water’s viscous forces acting on the hull, which generate frictional resistance along the hull. Since hull resistance significantly affects a ship’s overall performance, optimising hull shape during the ship’s design phase is an effective way to reduce ship’s resistance to motion, leading to lower fuel consumption and, consequently, reduced emissions.

Ship hull’s hydrodynamic optimisation is a complex task. The optimisation process could be conducted in laboratory facilities utilising towing tank experiments, but it requires significant resources (Aksenov et al., 2015). Today, various computational methods can be utilised for hull optimisation, making the process more efficient.

## 1.2 Objectives and structure

This thesis focuses on the computational methods for ship hull optimisation, examining the working principles and workflows of each approach. In addition, case studies are presented to demonstrate the practical application of each method.

The thesis begins with an introduction to the methods used in hull design and optimisation, including computational fluid dynamics and hull parametrisation. This is followed by an examination of three hull shape optimisation techniques, including design of experiments, the adjoint method, and machine learning -based methods. Finally, the advantages and limitations of each approach are discussed.

In this thesis, artificial intelligence tools were used for language polishing.

# 2 Methods

The optimisation of a hull requires systematic approach that includes hydrodynamic analysis, appropriate computational representation of the hull and the application of optimisation techniques. In this chapter, computational fluid dynamics is examined as a tool for hydrodynamic analysis, followed by ship hull parametrisation as a method for representing the hull in a form suitable for optimisation.

## 2.1 Computational fluid dynamics

Computational fluid dynamics (CFD) is a method to simulate complex fluid behaviour numerically. This includes evaluating flow characteristics such as fluid velocity, pressure and turbulence. The fluid flow is described by a set of equations, and by analysing them, fluid behaviour can be understood.

In the field of engineering, CFD is used to evaluate fluid behaviour within new designs before they are manufactured. In the context of ship hull optimisation, CFD is used to evaluate ship hull's hydrodynamic performance, and it represents an industry norm in modern ship design (Aksenov et al., 2015).

In this chapter, a brief introduction to CFD is provided to establish an understanding of its principles and relevance to hull shape optimisation. The workflow of CFD is typically divided into three stages: pre-processing, solving and post-processing (Tu et al., 2018). Therefore, it is convenient to examine the CFD workflow in this sequence.

### 2.1.1 Pre-processing

In the beginning of a CFD analysis, some pre-processing must be done to prepare for the analysis. First, the flow properties must be determined. Determining Reynolds and Froude numbers is relevant, as they are important dimensionless parameters in describing fluid flow. Reynold's number represents the ratio of inertial forces to viscous forces, whereas Froude number represents the ratio of inertial forces to gravitational forces. In the context of shipbuilding, they are defined as:

$$Re = \frac{\rho U L_{pp}}{\mu} \tag{1}$$

$$Fr = \frac{u}{\sqrt{gL_{pp}}} \tag{2}$$

where ρ and μ are the density and dynamic viscosity of the fluid, u is the flow velocity relative to the hull, $L_{pp}$ is the distance between the ship perpendiculars, and g is gravitational acceleration (ITTC, 2014).

The geometry of the flow region, known as the computational domain, must be determined in the beginning as well (Tu et al., 2018). In the context of evaluating a ship hull, computational domain represents the fluid surrounding the ship hull. According to ITTC (2014), the computational domain should extend at least one ship length upstream, downstream, and laterally from the hull, preferably further if Froude number is small.

After creating the computational domain, a computational mesh is generated across the entire domain. The purpose of the mesh is to divide the domain into smaller subdomains, allowing the fluid to be represented as a series of discrete portions. This discretisation enables solving the fluid flow equations numerically. The amount of these subdomains, or cells, is directly proportional to the accuracy of the analysis output (Tu et al., 2018).

Boundary conditions are the following matter to be determined during the pre-processing. This consists of determining the flow inlet velocity at the upstream and determining wall boundary conditions for the ship hull. One approach for determining wall boundary conditions is the near-wall-resolving approach, in which the fluid flow equations are solved all the way down to the viscous sublayer located near the hull surface. The viscous sublayer is a region where viscous forces are dominant, where fluid velocity gradually decreases and approaches zero as it gets closer to the hull. (ITTC, 2014)

### 2.1.2 Solving

As the pre-processing has been done, the numerical solving of the fluid flow equations can be conducted. First, it is appropriate to introduce the fundamental equations governing fluid flow in ship hull optimisation context.

The first equation to be introduced is the continuity equation, also known as the conservation of mass. It states that the mass of fluid entering a control volume equals the mass of fluid flowing out of the control volume, plus any accumulation of fluid mass in the control volume (Ji et al., 2023). The continuity equation is described as:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho u) = 0 \tag{3}$$

where $\nabla = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}, \frac{\partial}{\partial z}\right)$ (Ji et al., 2023).

In the context of shipbuilding, the flow velocity is relatively low and density changes are negligible, allowing the fluid to be treated as incompressible. With this assumption, the continuity equation simplifies to:

$$\nabla \cdot u = 0 \tag{4}$$

The second set of equations governing fluid flow are the Navier-Stokes equations. They describe the conservation of momentum and mass in a viscous fluid and are among the most important equations used in CFD. The Navier-Stokes equation is described as:

$$\rho \left(\frac{\partial u}{\partial t} + u \cdot \nabla u\right) = -\nabla p + \mu \nabla^2 u + \rho g \tag{5}$$

where μ is dynamic viscosity (García et al., 2020).

The continuity equation and the Navier-Stokes equations provide a fundamental description of fluid flow. However, in most situations, Navier-Stokes equations cannot be solved analytically. Therefore, an alternative version of the Navier-Stokes equations, Reynolds-Averaged Navier-Stokes (RANS) equations has been developed. Using RANS equations is the most widely adopted approach in evaluating ship hydrodynamics at present (Aksenov et al. 2015).

The greatest benefit of using RANS equations instead of solving the Navier-Stokes equations directly is that the flow properties changing with time, such as velocity and pressure, can be described as a sum of the time-averaged mean component and the fluctuating component. This representation is called the Reynolds decomposition, and it offers a more computationally efficient representation of turbulent flows. For velocity, the decomposition can be described as:

$$u(t) = \overline{u} + u'(t) \tag{6}$$

where $\overline{u}$ is the mean component and u'(t) is the fluctuating component (Versteeg and Malalasekera, 2007)

As the time-dependent properties are decomposed in the formulation of the RANS equations, a set of additional unknowns, the Reynolds stresses, are introduced in RANS equations (Tu et al. 2018). These require separate turbulence modeling to describe the turbulent flow. In general, there are various options for modeling the turbulence, but for ship hulls, ITTC (2014) states that "The k-ω family of linear eddy-viscosity models seems to be by far the most widely used ones" (ITTC, 2014, p.7).

### 2.1.3 Post-processing

In the phase of post-processing, the numerical data provided by the fluid flow equations is transformed into valuable insights of ship hull's hydrodynamic performance. The results can be represented in multiple ways, either visually or quantitatively.

The visual representation of the results can be done by describing the fluid flow with streamlines or contour plots around the hull. Streamlines can effectively display the fluid behaviour near the hull, whereas contour plots can be used to describe e.g. hull surface pressure or hull skin-friction (ITTC, 2014).

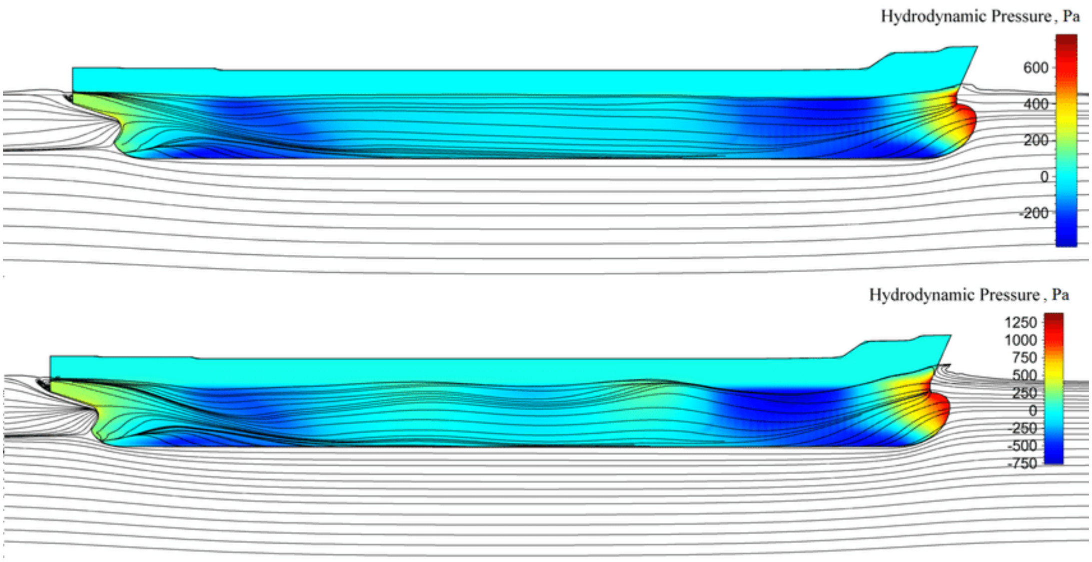


Figure 1. Visual representation of hydrodynamic pressure and streamlines on a hull with Fr = 0,160 (top) and Fr = 0,212 (bottom).

*Reprinted from Ocean Engineering, Vol. 130, J. Bašić, N. Degiuli, R. Dejhalla, 'Total resistance prediction of an intact and damaged tanker with flooded tanks in calm water', p. 13, Copyright (2017), with permission from Elsevier.*

In addition to visual representation, hull performance can be described using various parameters computed with CFD results. These parameters can be used as performance indicators, which allow the evaluation and comparison of different hull concepts conveniently. For example, a total resistance coefficient, denoted as $C_T$, can be calculated using:

$$C_T = \frac{R_T}{\frac{1}{2}\rho S U^2} \tag{7}$$

where $R_T$ is the total resistance derived from the CFD simulation results and S is the hydrostatic wetted surface area of the ship (ITTC, 2014).

In conclusion, CFD is an important tool in analysing a ship hull's hydrodynamic performance. From the results gained through CFD, hull concepts can be evaluated and compared to each other effectively, allowing for informed decision-making in the phase of hull design.

## 2.2 Hull parametrisation

Ship hull parametrisation is an important step in the process of optimising hull shape. While the hull shape can be represented as a three-dimensional model – such as a model created through computer aided design – optimising the hull shape requires a more flexible representation to modify the geometry in a convenient manner. A solution for this is to manipulate the hull shape with a set of design variables which are linked to certain characteristics of the hull shape. The aim of this is to enable a systematic way of optimising the hull shape.

Parametric modelling can be divided into fully parametric and partially parametric modelling. In fully parametric modelling, the entire hull shape is described in terms of parameters whereas in partially parametric modelling only the changes in the existing hull shape are described (Harries et al., 2019). In the following two subsections, the fully parametric approach and the free-form deformation approach, as a partially parametric method, are introduced.

### 2.2.1 Full parametric approach

In the full parametric approach (FPA) the ship hull is described completely in terms of mathematical parameters, typically points or curves. These curves, known as characteristic curves, define surfaces which furthermore represent the shape of the hull. By changing these parameters, the hull shape can be manipulated systematically during the optimisation process.

The parameters are defined according to the design requirements of the ship, considering e.g. total length and beam. With these requirements, the shape of the hull's longitudinal feature curves, boundary curves and cross-sectional curves are determined. The parameters can be divided into three categories, sorted by their significance. The first category includes principal particulars, including e.g. length between perpendiculars and moulded draft. The second category includes local feature parameters, which affect the generation of the characteristic curves locally, such as control points or fixed angles. The third category includes the feature parameters needed for defining cross-sectional curves and include e.g. slope and curvature. (Zhou et al., 2022)

A recent study by Kim et al. (2024) applies the FPA in defining the hull of a small ship. In the study, the hull was described by four characteristic curves: profile line, deck line, chine line and bottom line. These curves were represented using 19 control points, which were furthermore defined by 4 constants and 29 parameters. To generate cross-sectional curves, the hull was divided into six regions. The parameters defined in the study are illustrated in Fig. 2.

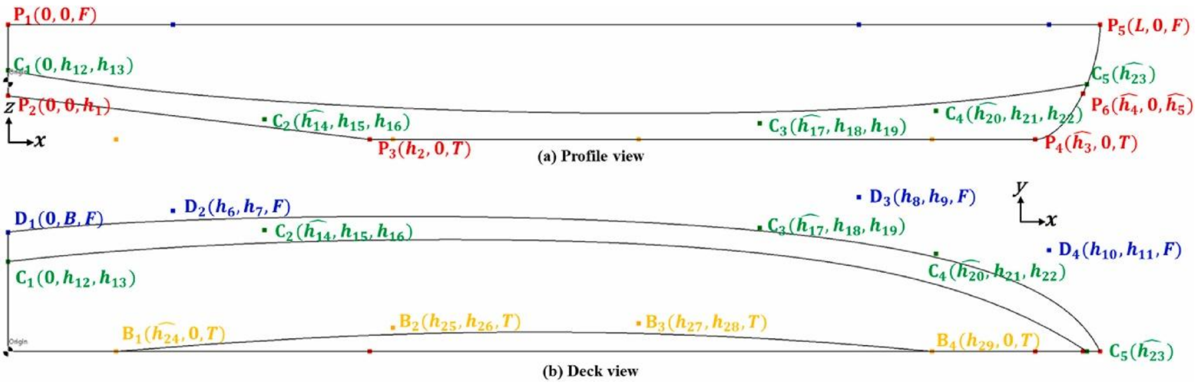


Figure 2: A representation of a small ship's hull with characteristic curves and control points.
*Reprinted from Kim et al. (2024), licensed under CC BY-NC-ND 4.0.*

### 2.2.2 Free form deformation approach

The free form deformation (FFD) approach is a method for achieving hull shape variations. FFD is based on the geometric relation established between an object of which shape is to be modified and a cubic lattice of points, also known as the FFD control volume, built around the object. The object, a hull shape in this case, does not have to be modelled parametrically, as variations in the FFD control volume function as the design variables in shape optimisation. (Coppedé et al., 2018)

A recent study by Liu et al. (2023) applies FFD in deforming a vessel's stern shape. With only three design variables in the FFD control volume, the stern shape could be modified. In Fig. 3, the green cubic area represents the FFD control volume, whereas the red dots represent the movable parameters $x_1$, $x_2$ and $x_3$.

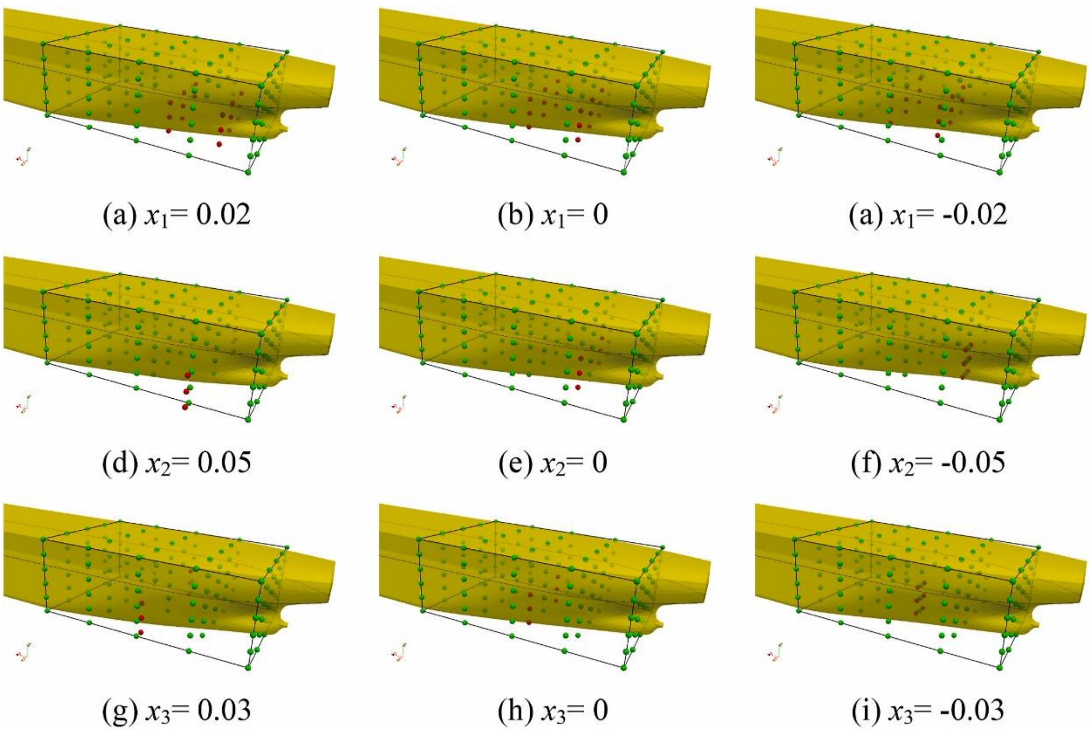


Figure 3. Stern shape modification with FFD. Reprinted from Liu et al. (2023)



Both methods are commonly used in shipbuilding, each with their own advantages and limitations. The benefit of using FFD over FPA is that it is capable to reduce the number of design variables to be controlled, which makes the method useful for shape optimisation or early-stage design (Coppedé et al., 2018). However, use of FPA has shown better results in creating more feasible and realistic hull shapes in optimisation compared to FFD (Brizzolara et al., 2015).

# 3 Optimisation techniques

The aim of optimising the shape of a ship hull is to reduce the hydrodynamic resistance of the hull by systematically modifying the geometry of the hull. Several optimisation techniques can be applied for ship hulls, each utilising a different approach to the problem. In this chapter, three different approaches – design of experiments, adjoint method and machine learning methods – will be examined in the context of hull shape optimisation.

## 3.1 Design of experiments

Design of experiments (DOE) is a systematic method for planning and conducting experiments to analyse the relationship between input factors and output responses of a system. In general, DOE can be used in various tasks in the field of engineering. For example, it can be used for optimising processes and designs, improving quality or reducing costs in any industry. In addition, DOE is useful for identifying significant input factors affecting the output responses. Moreover, it also helps to recognise the input factors which have little to no impact on output responses. (Abedin et al., 2024)

### 3.1.1 Workflow

The workflow of DOE described by Montgomery (2013) follows a structured approach consisting of several key stages. These include recognition of the problem, selection of the response variable, choice of factors, levels and range, choice of experimental design, performing the experiment, statistical analysis of the data, and conclusions and recommendations.

First, the purpose of conducting DOE should be addressed. Examining from the hull shape optimisation point of view, DOE can be applied in multiple ways. During the early design phase, DOE can be used for generating different hull concepts or identifying the most significant input factors affecting hull performance. Additionally, DOE can be used to obtain data for creating a surrogate model, which is a mathematical approximation of the evaluations (e.g. CFD simulations) conducted within DOE (Liu et al., 2017).

After addressing the purpose of DOE, the selection of the response variable must be chosen. For ship hulls, a response variable could be some hull performance metric, such as hydrodynamic resistance.

Next, the input factors, or design variables, along with their ranges, should be chosen. In the case of a ship hull, these variables may include some dimensions or parameters of the hull. For example, a study by Huang and Yang (2016) used DOE as a part of optimising a cargo ship's hull for reduced drag. They defined the design variables as bulbous bow length, width and height, along with entrance angle, fore-body variation, run angle and after-body variation. Each of these variables was expressed in terms of parameters, with predefined ranges that determined the extent to which they could be adjusted during the optimisation process.

The next step is selecting the experimental design technique, which determines how the possible design concepts, or samples, to be evaluated are chosen withing the design space. There are several options to choose from, which each having their own advantages and limitations.

The most straightforward approach for the design technique is the factorial design. In factorial design, a matrix of factors is used to simultaneously modify design parameters, allowing for the analysis of their impact on the design (Dangat et al., 2021). A so-called full factorial design is a method where all possible combinations of input factors and their levels are explored. With 2 input factors, the design space can be described explicitly by a coordinate plot, where each factor represents an axis. With two input factors ($x_1$ and $x_2$), each with a range of [0.2, 1.0] and 5 levels for each factor, the sample points in full factorial design would be distributed as shown in Fig. 4.

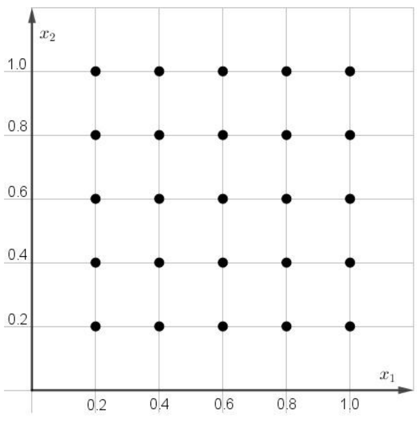


Figure 4. Full factorial design sample points on a coordinate plot.

As described in Fig. 4, a 2-factor, 5-level experiment would result a total of 25, or $5^2$ sample points. Based on this, the amount of sample points in a full factorial design can be generalised as $a^b$, where $a$ denotes the number of levels and $b$ denotes the number of input factors. However, as earlier mentioned, the amount of input factors in a hull optimisation setting may be significantly greater than two, leading to an impractical amount of sample points. As each sample point correspond to an individual hull concept, the evaluation of each concept with e.g. CFD simulations would require an immense amount of computational resources, taking into account that each hull concept might be evaluated with several flow velocities. In most cases, this makes full factorial design impractical in hull shape optimisation.

However, the amount of sample points can be reduced by using a different approach on experimental design. A method called latin hypercube sampling (LHS) provides a more effective way to generate and analyse sample points. In LHS, the design space is divided into levels (as in Fig. 4), with only one sample point generated per level (Bates et al., 2003). LHS is also a so-called space-filling design, which aims to distribute the sample points evenly across the design space (Montgomery, 2013). Thus, compared to full factorial design, LHS reduces significantly the number of sample points while maintaining broad exploration of varying input factor values. The distribution of sample points in a 2-factor, 5-level design space using LHS is shown in Fig. 5.

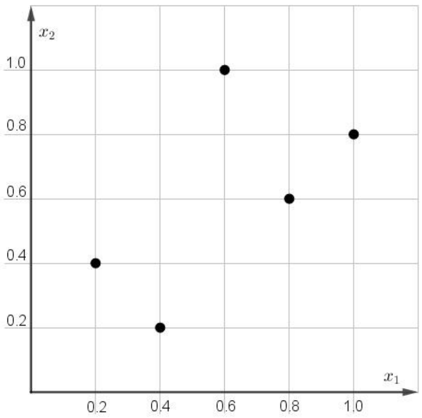


Figure 5. LHS sample points on a coordinate plot.

The LHS shown in Fig. 5 is a so-called random LHS, meaning that the sample points are distributed randomly across the design space. While the method aims to distribute the sample points evenly across the design space, random LHS may still result in uneven coverage of the design space. A solution to this problem is the optimal latin hypercube design (OLHS), which is a modified LHS in which the distribution of the sample points is optimised (Liu et al., 2017). Instead of randomly spreading the sample points across the design space, they are arranged in a way that maximises the spread across the design space. The distribution of the sample points is best illustrated using a 2-factor, 9-level design-space, as shown in Fig. 6.

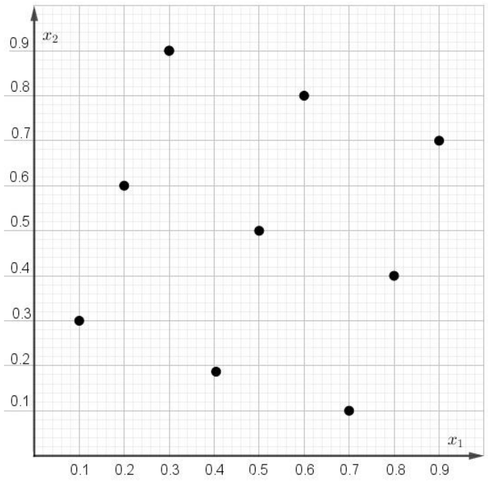


Figure 6. OLHS sample points on a coordinate plot.

Once the experimental design is chosen, the next step is to conduct the experiment, i.e. evaluate the concepts corresponding to the sample points in the design space. In the case of ship hulls, the evaluation of concepts is often done through CFD simulations, possibly with multiple flow velocities. It is important to use the same testing conditions in evaluating each concept to be able to compare the results. This includes maintaining computational domain settings, flow properties, mesh settings and other relevant parameters constant.

After conducting the tests, the output data is analysed. According to Montgomery (2013), statistical methods should be used to analyse the data in an objective manner. A technique used in optimisation problems, including hull shape optimisation, is the analysis of variance (ANOVA). ANOVA is a statistical analysis method that employs a variance model to examine the effects of different variables (Jeong and Kim, 2013). With ANOVA, the most significant variables affecting hull performance can be identified. As DOE can be utilised in creating concepts for further optimisation, this information allows the further optimisation to focus on the more significant variables, while being able to ignore the parameters that have little to no effect on hull performance.

### 3.1.2 Application in hull shape optimisation

DOE is a useful method in hull shape optimisation, as it can be used to systematically explore multiple design concepts with varying design variables. DOE is often paired with other optimisation methods. For example, a study by Lin et al. (2018) applied DOE as a part of the hull shape optimisation process of a twin-sked fishing vessel.

In their study, after defining the design variables and their ranges, DOE is conducted using the OLHS method in generating the sample points. After this, all the concepts corresponding to the sample points are evaluated with CFD simulations under four flow velocities. The data gained from these simulations is used to construct surrogate models. Following this, the influence of each design variable on the design is quantified using the ANOVA method. Finally, a multi-objective optimisation algorithm is applied, which leads to a 5,4 % average reduction in total resistance compared to the initial design.

Another study by Huang and Yang (2016) demonstrates the use of DOE as a part of optimising the hull shape of a cargo ship, with the goal of reducing drag. After defining the design variables and their ranges, DOE is conducted using the LHS method to generate a total of 70 sample points across the design space. The concepts corresponding to these sample points are evaluated with CFD simulations under three flow velocities. With the data obtained from these simulations, three surrogate models are constructed. After this, the surrogate models are further optimised using a multi-objective optimisation algorithm. A reduction in total resistance ranging from 6,42% to 13,10% is achieved compared to the initial hull shape, depending on the flow velocity.

These case studies show that DOE can be applied to enhance the process of optimising hull shape by exploring systematically design variations. However, while DOE is a great tool for exploring the global design space, it is often paired with another optimisation technique as it does not essentially provide accurate gradient information for a more precise optimisation. In the next chapter, the adjoint method is examined as an alternative approach.

## 3.2 Adjoint method

### 3.2.1 Method introduction

The adjoint method is a mathematical technique which can be utilised for shape optimisation. The adjoint method is based on calculating so-called parametric sensitivities, denoted as $\partial J/\, \partial x_n$. They describe how an objective function $J$ changes as the values of design parameters $x_n$ are changed. In other words, these sensitivities represent the gradient of the objective function with respect to the design parameters. In the context of hull shape optimisation, the objective function can describe e.g. drag, and these parametric sensitivities can be used to modify the geometry of the hull, which ultimately aims to increase the performance of the hull. (Brenner et al., 2015)

In hull shape optimisation, the adjoint analysis yields a so-called shape sensitivity, denoted as $\partial J/\partial n_k$, which is represented as a field over the hull's surface. It indicates the rate of change of the object function with respect to normal displacement of hull surface cells. The normal displacement, denoted as $n_k$, describes how much a hull surface cell, or an individual point on the hull surface, is displaced in the normal direction as the hull shape is altered. (Brenner et al., 2015)

To link the shape sensitivities to the design parameters, an additional term is required to formulate the parametric sensitivity. The parameter variation, also known as design velocity, denoted as $\partial n_k/\partial x_n$, describes the gradient of the surface displacement in normal direction with respect to the design parameters. In addition to this, a weighing factor, denoted as $A_k/A_{\text{avg}}$, describes the relative local cell size. This scales the sensitivity contributions appropriately by dividing the local cell size $A_k$ by the average cell size in the model $A_{\text{avg}}$. (Brenner et al., 2015)

By taking the product of these three terms and creating a sum over the hull surface, the parametric sensitivity can be calculated. It is mathematically expressed as:

$$\frac{\partial J}{\partial x_n} = \sum_k \frac{\partial J}{\partial n_k} \frac{\partial n_k}{\partial x_n} \frac{A_k}{A_{\text{avg}}} \tag{8}$$

where $\frac{\partial J}{\partial n_k}$ denotes adjoint shape sensitivity, $\frac{\partial n_k}{\partial x_n}$ denotes design velocity, and $\frac{A_k}{A_{avg}}$ denotes relative local cell size (Brenner et al., 2015)

### 3.2.2 Workflow

The workflow of the adjoint method described by Kelecy (2021) consists of four key stages, including a CFD run, adjoint calculation, sensitivity data and mesh update. The process begins with a CFD evaluation of the initial design to determine the objective function value. Next, parametric sensitivities are calculated, providing the necessary information for the subsequent mesh update, where the geometry is adjusted.

It is notable that the modifications done with one adjoint calculation leads to rather small changes in geometry. For this reason, the workflow described above is performed iteratively in practice. This approach allows for gradual improvements, leading to the optimal design through small incremental steps.

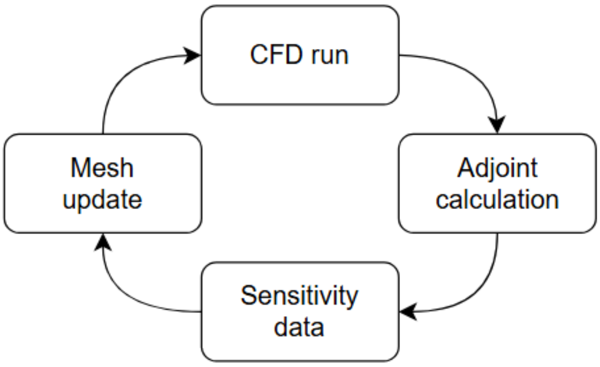


Figure 7. Iterative workflow of the adjoint method. *Adapted from Kelecy (2021).*

The adjoint method computes sensitivities to obtain the the full gradient of the objective function, with its computational cost remaining independent of the number of design parameters (Brenner et al., 2015). In contrast to more conventional methods like DOE, where computational cost increases with the number of parameters due to additional CFD simulations, the adjoint method requires only one CFD run per cycle, remaining unaffected by the number of parameters. Thus, the computational cost of the adjoint method is only dependent on the number of conducted cycles. This makes it particularly suitable for optimisation problems with a large number of parameters.

### 3.2.3 Application in hull shape optimisation

The adjoint method can be applied in various ways during hull shape optimisation. It can be used as a preliminary analysis tool to examine the significance of different design parameters before employing another optimisation technique. Alternatively, it can function as a standalone technique in the shape optimisation process. Next, these different approaches will be examined through two case studies.

A recent study by Nazemian and Ghadimi (2022a) applied the adjoint method as a part of optimising the hull shape of a trimaran ship. In their study, the optimisation was conducted using a hybrid sequential strategy, including a combination of an adjoint solver for clarifying significant regions of the hull geometry and a CAD-based multi-objective optimisation platform for the shape optimisation. The adjoint analysis was conducted at the initial stage of the process to gain insight into choosing useful and efficient design variables and parameter ranges for the optimisation process. Based on the adjoint-derived sensitivities, 11 design variables were chosen. The optimisation was conducted using the FFD method and a multi-objective optimisation algorithm. As a result, a 13,3 % resistance reduction compared to the initial hull was achieved.

A study by Nazemian and Ghadimi (2022b) demonstrates the use of the adjoint method in conjunction with CFD for optimising the hull shape of a trimaran ship. The aim of the study was to minimise total drag, which was accomplished by iteratively deforming the geometry using mesh morphing, based on adjoint sensitivity analysis and CFD simulations. This approach allowed for shape modifications without requiring CAD remeshing, which reduced computational cost significantly. With only five iterations, the resistance of the hull was reduced by 6,67 %. The incremental reduction of hull resistance during the optimisation process is illustrated in Fig. 8.

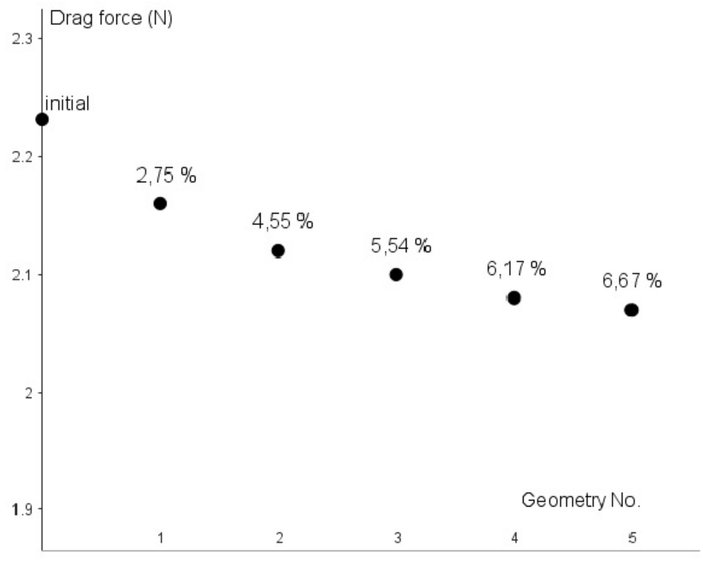


Figure 8. Incremental reduction of the drag. *Adapted from Nazemian and Ghadimi, (2022b).*

The adjoint method is a computationally efficient approach for hull shape optimisation, as its computational cost remains independent of the number of design variables. This makes it particularly a great technique for hull optimisation since describing a hull's geometry may require a large number of parameters.

## 3.3 Machine learning methods

Machine learning (ML) refers to a subfield of artificial intelligence that enables computers to learn from data and make predictions and decisions without direct programming (ISO, n.d.). In recent years, the application of ML methods in ship hull optimisation has been widely studied in an attempt to offer an alternative approach to conventional optimisation methods. ML methods can significantly reduce design cycle time compared to traditional methods (Bagazinski and Ahmed, 2023). This would be beneficial in shipbuilding, especially in hull optimisation, as the conventional design process including CFD simulations are time- and computationally demanding. By employing ML methods in hull optimisation, the design process of a ship can be accelerated.

ML can be applied in the process of hull design in several ways. One approach is employing ML for predicting object features, such as drag, to reduce the reliance of CFD simulations. ML can also be employed for direct hull optimisation, where ML algorithms directly modify the initial hull shape to reach better performance. (Trinh et al., 2024)

In the following subsections, the two approaches are examined in hull shape optimisation setting.

### 3.3.1 Machine learning for resistance prediction

The evaluation of the performance of a ship's hull through CFD simulations offers precise information about the flow behaviour around the hull, but it requires a considerable amount of computational resources and time. The phase of evaluating performance could be accelerated using data-driven, ML based methods that can evaluate the performance of a hull significantly faster than CFD simulations.

ML methods are based on a large amount of existing data, which is used to train an ML model for predicting hull performance. By learning patterns and relationships between hull parameters and corresponding resistance values, the resistance of a hull can be predicted without the use of CFD simulations. (Gemelli, et al., 2024)

The accuracy of ML-based hull resistance prediction depends on the choice of the learning algorithm. Various algorithms have been applied for ship hull resistance setting. Among these, a method called Gaussian process regression (GPR) is a widely used algorithm for hull resistance prediction due to its ability to provide accurate and generalisable predictions of ship resistance (Gemelli, et al., 2024). GPR models are widely used in ML in general, as they additionally enable the representation of uncertainty in the predictions (Wang, 2023).

GPR is a non-parametric regression method, which assumes that the data given for the model obeys a multivariate Gaussian distribution (Zhang et al., 2024). Based on training data – consisting of various hull resistance values with specific design parameters in hull resistance setting – GPR attempts to determine a distribution over functions that best fit the given data (Wang, 2023). This is achieved by conditioning the Gaussian process on the training data and computing a distribution over possible functions that describe the relationship between the design parameters and the corresponding hull resistance values. Figure 9 illustrates this distribution, where the red crosses denote known data points derived from the training data, and the coloured curves denote the possible functions that best fit these data points. The blue shaded area represents the uncertainty of the results.

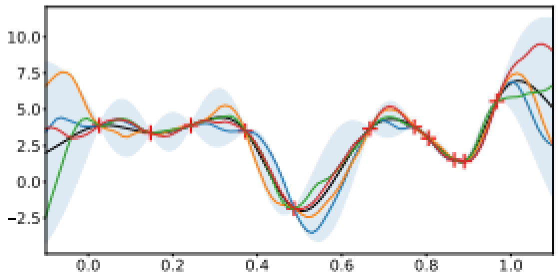


Figure 9. Possible functions plotted on function space based on training data points.

*Reprinted from "An Intuitive Tutorial to Gaussian Process Regression," J. Wang, Computing in Science & Engineering, Vol. 25, p.2, (2023). © 2023 IEEE.*

With GPR, the hull resistance can be predicted using existing data by establishing a relationship between design parameters and hull resistance values. Although training a GPR model requires access to a suitable dataset and sufficient time for model training, a trained model can predict hull resistance with given design parameters much faster than CFD simulations.

A recent study by Gemelli, et al. (2024) demonstrates the application of GPR in predicting hull resistance of a sailing yacht. Their research focuses on developing a ML-based model using GPR to estimate the resistance of a bare yacht hull. The study utilises a dataset including 50 sailing yacht hull shapes and corresponding resistance values, evaluated across Froude numbers ranging from 0.1 to 0.6. To train the model, 90 % of the dataset was used, while the rest 10 % was used to test the model. After training, the model achieved a root mean square error of approximately 430 N and an $R^2$ value of 0.99. These results show a great accuracy in the model's predictions.

The use of ML models in predicting hull resistance based on hull shape features offers a viable alternative to computationally demanding CFD simulations. While a pre-trained ML model gives predictions quickly and with reasonable accuracy, the training phase requires significant time and enough suitable data. Additionally, the testing phase of the ML model also requires time, as the model's accuracy must be evaluated well before it can be used to reliably reduce the dependence of CFD simulations. However, since resistance-predicting ML models are trained on existing hull performance data, their use in designing a new hull shape may result in only small changes to the geometry, which may limit the innovation of completely new hull shapes.

### 3.3.2 Machine learning for shape optimisation

In addition to predicting hull performance with ML methods, ML can be used to modify the hull shape directly, thus optimising the hull shape. From various ML methods, generative adversarial networks (GANs) have shown great promise in optimising hull shapes directly.

GANs are a type of neural network architecture, which are designed to generate data that resemble real data. A typical GAN consists of training data and two neural networks. The first neural network, a generator (G), creates synthetic data by mapping a latent space to the data distribution of interest. Another neural network, a discriminator (D), attempts to distinguish the training data from the data generated by G. These two neural networks are trained simultaneously in an adversarial process, where G improves its ability to create data similar to training data, whereas D improves its classification ability. This training is done until G and D reaches equilibrium in such way that G is able to generate high-quality synthetic data. (Khan et al., 2023)

GANs are used in various engineering tasks, including topology optimisation and design and optimisation of aircraft (Khan et al., 2023). GANs have been also applied in ship hull design and optimisation, enabling the generation of innovative hull shapes with optimised performance. A notable example is ShipHullGAN, a model proposed in a study by Khan et al. (2023), which applies GANs to create optimised hull geometries.

ShipHullGAN is a deep convolutional GAN-based parametric model designed to generate and optimise hull geometries. ShipHullGAN is trained on a dataset of 52 591 ship designs, covering various vessel types, including container ships, tankers and crew supply vessels. During training, a space-filling approach is used to capture the diversity in the training data. The model follows the typical generator-discriminator training approach, with an additional shape-signature tensor which aims to provide not only geometrically but also physically valid design alternatives. (Khan et al., 2023)

ShipHullGAN can be applied in various stages of hull design. In the early stages of design optimisation, the model can be used to explore various concepts with preliminary optimisation criteria, such as resistance, or with constraints, such as physical dimensions. The model can also be used to optimise existing hull shapes by creating design variants of a parent hull. (Khan et al., 2023)

ShipHullGAN demonstrates well that the application of GANs can accelerate the processes of hull concept generation and shape optimisation. However, GANs have their limitations. As previously mentioned in section 3.3.1, ML models require a large dataset for training, which may cause challenges in developing a suitable GAN-based model. In the case of ShipHullGAN, this was less of a concern, as a dataset of over 52 000 ship designs were used for training. Despite this, Khan et al., (2023) noted that some designs generated by the model appeared implausible from a practical point of view, indicating that the expert oversight is still necessary to identify potential inconsistencies in the generated hulls.

# 4 Discussion

This thesis examined various computational methods for ship hull shape optimisation, including the design of experiments approach, the adjoint method, and machine learning based techniques consisting of drag prediction and direct shape optimisation. Each of these methods have strengths in certain optimisation scenarios, but they also have limitations. In this chapter, the advantages and limitations of each optimisation method is discussed.

## 4.1 Design of experiments

DOE is a relatively straightforward optimisation method as it is based on generating a set of hull concepts using a specific technique – such as LHS – to distribute sample points across the design space, thus producing hull concepts with varying design parameters. This makes DOE particularly useful in earlier stages of hull design, where it is essential to gain an understanding of how different parameters influence hull performance. In addition to guiding hull design, DOE can be useful in training ML models, as it is desirable train the models with a broad range of data.

However, DOE has notable limitations in certain scenarios. Since it is based on manipulating a set of design variables, the amount of sample points increases as well. This leads to DOE-based optimisation becoming time consuming with a larger set of design parameters. Additionally, as the performance of the hull concepts corresponding to the sample points is often evaluated using CFD simulations, the time needed for the evaluation phase increases with the number of sample points as well. On the other hand, DOE could be applied in the initial phase of optimisation using a smaller set of parameters, or alternatively, the CFD simulations could be accelerated using a coarser computational mesh. This would lead to faster results with the expense of some accuracy.

## 4.2 Adjoint method

Adjoint method is a powerful optimisation method based on calculating the gradient of an objective function with respect to each parameter. This approach provides precise information about the influence of each design variable on hull performance. One of its main advantages compared to DOE is that the influence of each design variable, i.e. the gradients, can be calculated with only one CFD simulation per objective function. This makes it computationally efficient and therefore particularly suitable for optimisation problems with a large set of design variables.

Despite the method’s computational efficiency, the adjoint method has also its limitations. Most notably, it is primarily used for optimising existing hull shapes rather than generating completely new hull designs. This makes it less suitable for the initial phase of hull design, where exploring a broad range of different hull concepts may be more relevant. On the other hand, since DOE is a great tool for exploring hull concepts, it could be paired with the adjoint method by selecting an initial hull concept using DOE and then performing a more precise optimisation using the adjoint method.

## 4.3 Machine learning methods

ML-based methods have recently gained interest in the context of ship hull optimisation due to their potential to reduce the time required for both designing and optimising hull shapes. One approach examined in this thesis is ML-based drag prediction, specifically using GPR, which demonstrated the potential to reduce reliance on computationally expensive CFD simulations. Once trained, a ML-based drag prediction model can significantly accelerate the phase of evaluating different hull concepts, making the whole optimisation process much more efficient.

However, the accuracy and generalisability of ML-based drag prediction models remain highly dependent on the quality and diversity of the training data. If the training data does not represent a sufficiently large range of different hull geometries or flow conditions, the model may produce inaccurate results, especially for hull types that were underrepresented in the training data.

Another ML-based approach examined in this thesis is the direct hull optimisation using GANs. In ship hull design context, GANs have shown the ability to generate completely new hull shapes based on the training data and the adversarial training process. This approach holds significant potential for accelerating the overall process of designing and optimising hull shapes.

Despite their great potential, GAN-based hull optimisation has notable limitations, too. Like any ML model, the accuracy of GANs is highly dependent on the quality and diversity of the training data. If the training data is not broad enough or contains inconsistencies, the generated hull shapes may end up being physically unrealistic. As a result, the hull concepts produced by GANs cannot be fully trusted without further evaluation. However, if the method is further developed and its reliability improved, it holds a great potential to significantly change the way ship hulls are designed.

# 5 Conclusion

The maritime shipping industry is under increasing pressure to improve its environmental performance due to regulations and the need to reduce greenhouse gas emissions. Since hull resistance is responsible for a major part of ship's energy consumption, optimising hull geometry is an important part in the process of designing energy-efficient ships.

This thesis examined the computational methods for optimising the hull shape of a ship in aim to reduce hull resistance and thus increase energy efficiency. The three approaches examined – design of experiments, adjoint method and machine learning methods – showed capabilities in different phases of designing a ship hull.

Design of experiments showed to be a useful tool in the earlier stages of hull design, where it is essential to explore different hull concepts and to identify the most significant design variables affecting hull performance. In contrast, the adjoint method showed to be an effective method for optimising the geometry of an existing hull concept. Machine learning methods meanwhile demonstrated potential to accelerate the design process of ship hulls by reducing the reliance on computationally expensive CFD simulations.

While each method has their own limitations, their combined use can support an efficient workflow for ship hull optimisation. With these approaches, the design of ship hulls with an optimal hull shape for lowered hydrodynamic resistance can be enabled, contributing to more environmentally friendly maritime transport.

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