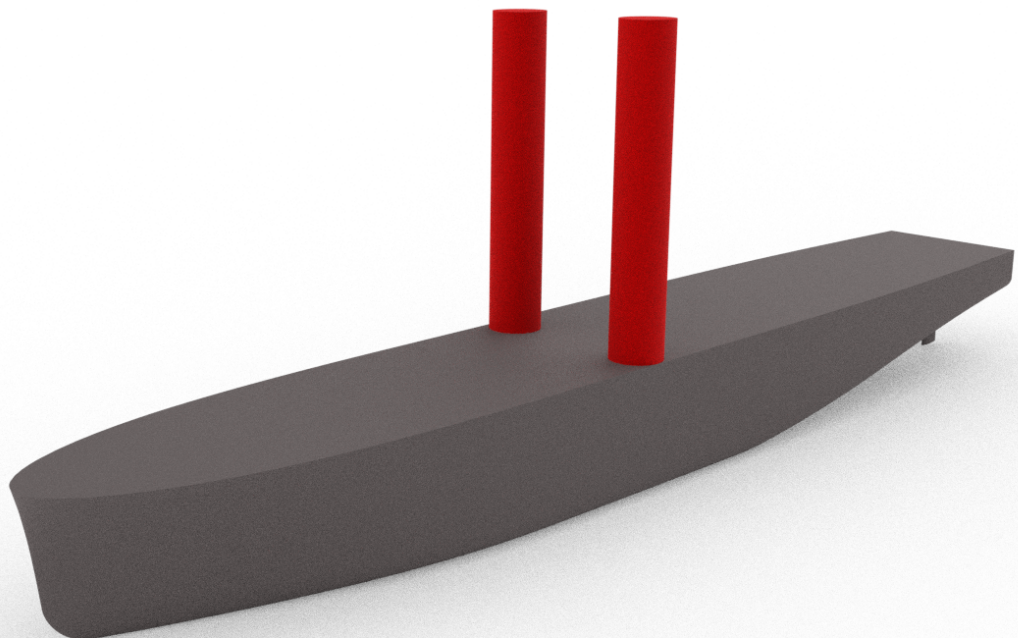


Thesis

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Multi-fidelity Bayesian optimization of wind assisted vessel hull for resistance



Thesis for the degree of MSc in Marine Technology in the specialization of Ship Design

Multi-fidelity Bayesian optimization of wind assisted vessel hull for resistance

by

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During the writing of this work, the author made use of Writefull to improve writing style and check grammar and spelling. The author takes full responsibility for the content.

Abstract

Wind assisted vessel hull optimization is more expensive than traditional vessels. This thesis tests if multi fidelity modeling may be a solution to reduce the computational cost of optimizing wind assisted vessel hulls.

A Bayesian optimization framework was coded that can use both single fidelity and multi fidelity data. A surrogate test problem of a 100 meter long wind assisted vessel was created based on CFD data and an empirical model. The first experiment compared the performance of the single and multi fidelity algorithms. The second experiment evaluated the impact of a better low fidelity by using weighted averages of the CFD and empirical as the low fidelity model. In the third experiment, the resulting vessels from optimizations with CFD and empirical models were compared to validate the necessity of including CFD in the optimization of wind assisted vessels.

The results of experiment one show that multi fidelity is only slightly faster, but has a larger spread meaning the slowest optimization takes longer.

Experiment two showed that a better low fidelity model drastically reduces the number of iterations needed to perform an optimization.

Experiment three showed that the vessels optimized using CFD differ significantly from those optimized with empirical methods.

Thus, multi fidelity modeling provided very limited improvements for the optimization of a wind assisted vessel when using empirical models and CFD. Significant improvements are possible with better low fidelity models. Lastly, empirical models used for wind assisted vessels are have limited usability for optimization.

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1

Introduction

The introduction of wind-assisted propulsion poses a new challenge to designers. The aerodynamic sideforce on a wind assisted vessel means the vessel heading and its direction of travel differ as can be seen in Figure 1.1. This results in a change in flow around the vessel and a difference in resistance (Plessas & Papanikolaou, 2024). Meaning that conventional empirical models, based on model tests, used to quickly evaluate the resistance of vessels are inaccurate and do not capture these complexities. This is a problem in the early stage design process, as quick methods, for example, empirical methods such as Holtrop and Mennen, 1982 are used to perform a viable optimization of the shape of the hull to reduce resistance as much as possible. With the inaccuracy this could lead to non optimum hulls

A solution to ensure the right optimum is found could be high-fidelity models. Examples of high-fidelity methods are CFD and model tests. These models are good at capturing accurate resistance regardless of the hull shape but are expensive and time consuming to perform. Therefore, they are not suitable for early stage design, as many evaluations are required in this design phase.

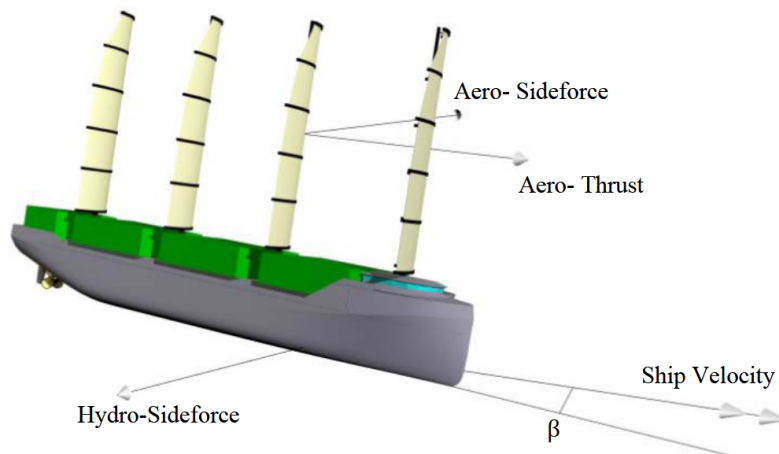


Figure 1.1: The difference between the heading and the direction of travel (van der Kolk, 2016)

Therefore, a method that combines accurate capture of resistance, even outside the empirical formula range, while still being fast enough to perform an optimization study within a reasonable time and cost is needed.

Multi fidelity modeling may be a solution to this problem (Huang et al., 2015). Multi fidelity modeling combines data from high-fidelity and low-fidelity models to reduce the computational load required (Toal, 2015).

While multi fidelity optimization has been tested on a multitude of optimization problems the applicability on the hull design wind assisted vessel is unknown. This gives the research question as given in the following section.

1.1. Research questions

The main research question of this thesis is: "To what extent can multi fidelity modeling aid the optimization of wind-assisted vessel hull?"

To break up this question, several sub-questions are asked. Firstly, some questions that are answered in the literature part of this thesis:

- Q1 What is the state of the art in the design of wind-assisted vessel hulls?
- Q2 What is the state of the art in modeling resistance for wind assisted vessels?
- Q3 How can multi fidelity modeling best be implemented for the proposed case?
- Q4 What implementation of multi fidelity optimization is best suited to the optimization of wind assisted vessel hull based on the results of the literature study?
- Q5 How can the multi fidelity framework be used to construct a multi fidelity model for resistance?
- Q6 What is the speed and accuracy of a multi fidelity model for predicting the resistance of a wind-assisted vessel?
- Q7 How suited is a multi fidelity model for an optimization study?

1.2. Outline

Chapter 2 will investigate the physical design and the design process of a wind-assisted hull to answer research question one. Chapter 3 will look at the different methods that can be used to calculate the resistance of a wind-assisted vessel. Chapter 4 will explore the use of multi fidelity modeling and surrogate-based optimization. Chapter 5 gives the methodology used for the first part of the research. Chapter 6 gives the verifications of the used methods. Chapter 7 gives the methodology and results for the comparison between CFD and the empirical method. Chapter 8 gives the results. Chapter 9 gives the conclusion to this thesis.

2

Wind-assisted hull design

This chapter discusses the physical design and the design process of a wind-assisted hulls in order to answer the research question: “What is the state-of-the-art in the design of wind-assisted vessel hulls?” In Section 2.1 the effects of adding wind assist to a ship are discussed. In Section 2.2 the goals of optimizing a wind-assisted hull are explained. In Section 2.3 the different relevant features for the design of a wind-assisted hull are presented. Section 2.3 is divided into three subsections; the first subsection 2.3.1 discusses the impact of global dimensions, the second subsection 2.3.2 discusses the impact of hull shaping, and the third subsection 2.3.3 discusses the effect of the appendages. The section 2.4 discusses the state-of-the-art of the design processes of wind-assisted vessels. Lastly, Section 2.5 concludes the chapter by summarizing the important features and design processes.

2.1. Effects of wind assist

Adding wind propulsion to a ship changes its sailing characteristics (Haripriyono et al., 2021; Jensen, 2022; van der Kolk, 2020). The main effect is the thrust that it provides, lowering the power required from the engine and therefore reducing the fuel usage. It has an additional effect; more degrees of freedom need to be taken into account when designing the vessel. First, the force acting on the sail induces a heel angle. Secondly, to counteract the side force generated by the sails, a counterforce needs to be generated. This force is generated by sailing with a drift angle relative to the direction of travel. This also results in a yaw moment because the center of lateral resistance (CLR) does not act at the same point as the side force created by the wind propulsion. The CLR tends to be in front of the center of effort of the wind propulsion (van der Kolk, 2020) due to the Munk yawing moment (Munk, 1923), which is a moment induced due to the low pressure region located on the stem and stern of the vessel that sails with a leeway angle as can be seen in Figure 2.1. This moment needs to be counteracted with a rudder deflection. The added leeway angle and deflection of the rudder add resistance. To sail with a constant heading and speed, all these forces and moments need to balance.

The change in thrust produced by the wind propulsion device means that the propeller works at different working points depending on the required thrust and the inflow speed. The inflow direction also changes, which affects the performance of the propeller. And because of the leeway angle, the thrust of the propeller is not in the direction of travel; therefore, a reduction of the leeway angle aligns the propeller thrust with the direction of travel.

This results in a more complicated design problem than in a normal vessel because the side force and the yawing moment need to be taken into account when minimizing the hull resistance.

2.2. Design goals for wind assisted hulls

To design a “good” wind-assisted hull, three important factors have been identified in the literature by searching for sources that explore the design of wind-assisted vessels. Firstly, the stability should be

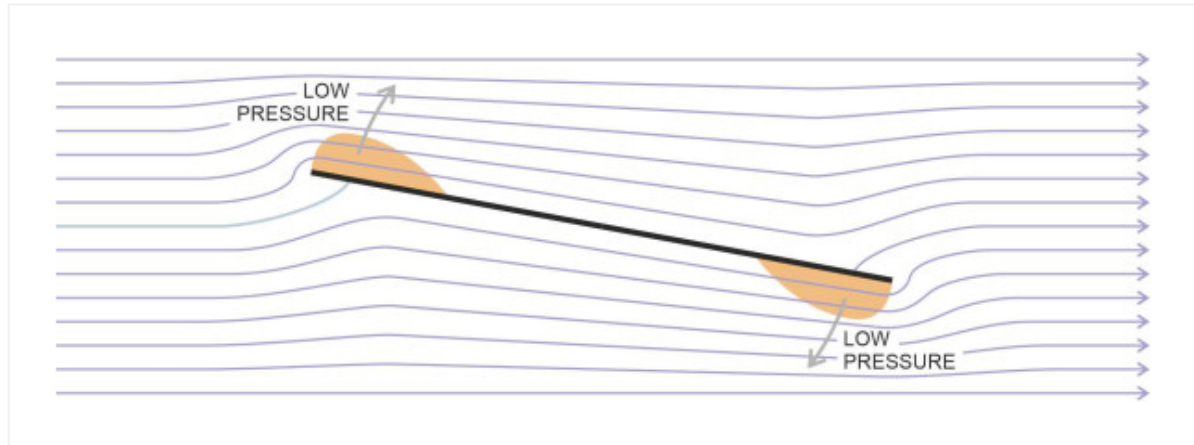


Figure 2.1: Munk moment caused by a low pressure regions at the windward stem and the leeward stern due to flow around a object with a leeway angle "The Contact Patch F.1816", 2021

high enough to ensure that the heel limits are not exceeded. Otherwise, the force of wind propulsion would need to be reduced (Lange, 2024; Tillig & Ringsberg, 2020). This means that the righting moment should be high enough to counteract the heeling moment generated by the wind assist device under normal wind conditions (Haripriyono et al., 2021). If this is not the case, the moment created by the wind propulsion would need to be reduced by reducing the propulsive power, thereby reducing energy savings. In addition, when operating in extreme weather without using its wind propulsion, the stability should be high enough to keep the vessel within safe limits.

Secondly, the yawing moment should be reduced to keep the ship maneuverable, by bringing the center of lateral resistance (CLR) and the center of effort of the drift force closer. This reduces the maximum deflection of the rudder needed to keep the ship on course and is a key design constraint according to (van der Kolk, 2020). According to Jensen, 2022:

“Based on the results, in general, the ship shows the behavior to turn quickly into the wind and slowly while turning against the wind. The effect this has on the maneuvers is that the Turning Circle is generally tighter when the initial turn is turning toward the wind, and larger when the ship is initially turning away from the wind” (Jensen, 2022).

The yawing moment should be limited to ensure that the rudder can generate sufficient moment to maneuver the vessel when wind propulsion is used.

Third, resistance must be reduced as much as possible. This is made up of several components. According to Larsson et al., 2010, the resistance can be broken down into the following components.

- Wave breaking
- Wave pattern
- Form effect on pressure
- Form effect on friction
- Roughness
- Flat plate friction

However, due to the required side force, a lift-induced resistance is also present (Larsson et al., 2010). This induced resistance is related to the lift efficiency of the hull and appendages. According to van der Kolk, 2020 “ ..., this induced drag may be significant for commercial ships, meaning that the thrust delivered by a wind propulsion might well be overwhelmed by this increase in resistance.”(van der Kolk, 2020).

Due to the relatively high aspect ratio of a rudder compared to the hull, it is a more efficient lifting surface than the hull. Therefore, for minimum resistance, having a high yawing moment may be beneficial, as this allows the rudder to generate lift instead of the hull. In the case of a wind-assisted vessel without high aspect ratio fins, the rudder is the highest efficiency lifting surface; therefore, it may be beneficial for the rudder to produce a higher proportion of lift compared to the hull.

2.3. Wind assisted hull features

By looking at literature on ship resistance, hull design, wind-assisted ship design, and vessel maneuvering, several aspects of a ship design have been investigated as features that may be important for the performance of a wind-assisted hull. These aspects will be discussed in this section.

2.3.1. Global dimensions

The breadth-to-draft ratio is an important aspect in improving the efficiency of side force production (Beukelman & Journée, 2001; Lange, 2024; van der Kolk, 2020, 2016). A vessel sailing at a leeway angle can be considered a very low-aspect wing (Beukelman & Journée, 2001). Therefore, the impact of breadth and draft is logical when thinking of the hull as a low-aspect wing. A decreased breadth over draft ratio means a higher aspect ratio wing. This was also observed in van der Kolk, 2020 where a decrease in B/T gave higher transverse loads. The same trend was observed by Lange, 2024. The slender hulls showed better lift-to-drag ratios, although this is mainly attributed to the reduced resistance at zero drift. The slender hulls did indicate a higher lift due to vortex generation, but due to the non-linear nature of this lift, this only scales at high drift angles, which according to this source were unlikely to occur in wind-assisted vessels (Lange, 2024). The observations in these sources are consistent with the theory presented by Beukelman and Journée, 2001. A slender vessel has a lower stability; this means that a slender vessel is more limited by the heeling moment. As can be seen in Figures 2.2 from Lange, 2024, having a small B/T reduces the advantage of wind assistance due to heel angle constraints. So, there is a clear trade-off when varying the slenderness between sailing performance and stability.

An additional aspect here is that the resistance and the side force increase with the heel according

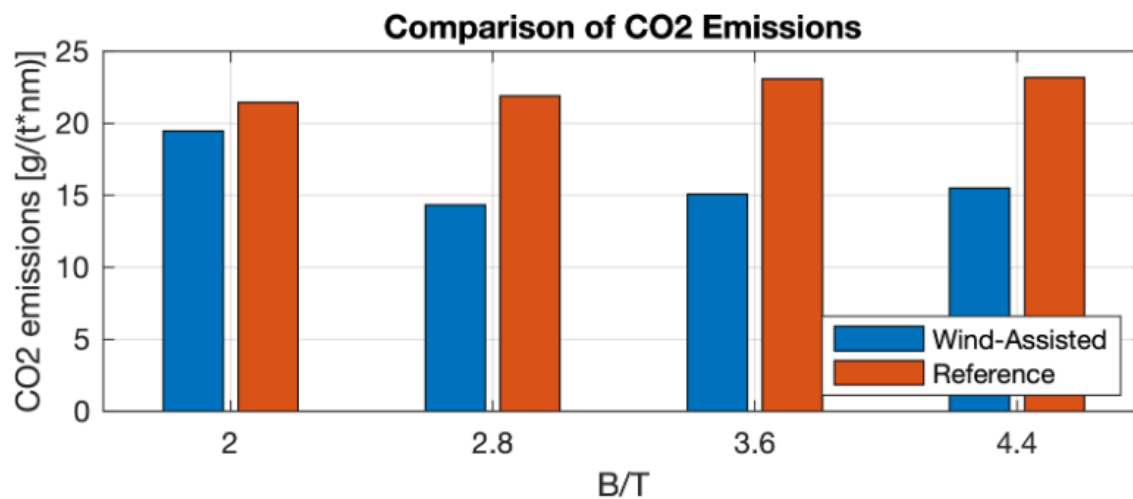


Figure 2.2: Emissions for ships with different B/T ratios from Lange, 2024

to van der Kolk, 2020. Although Lange, 2024 also mentioned that the sensitivity to small heel angles is small. Only small angles were observed in the design study conducted by Lange, 2024, but this is also due to the constraint on the heel of a maximum of 5 degrees. The design study performed by van der Kolk, 2020 predicted heel angles of up to 10 degrees. The relevance of heel is therefore very dependent on the vessel type and amount of wind assist that is examined.

2.3.2. Hull shape

From van der Kolk, 2020 and Hooft, 1994 and from the theory in Hoerner, 1965 it can be concluded that the transverse design of the hull has a significant impact on the lift performance exhibited by a hull. This is attributed in the literature to crossflow drag (Beukelman & Journée, 2001; Hoerner, 1965; Hooft, 1994; van der Kolk, 2020). That is, the lift due to the transverse flow and the vortex shedding along the hull due to sailing at a leeway angle. This part of the lift is influenced by the detailed features of the transverse profile, as the separation of the flow is highly dependent on local features.

Block and Prismatic coefficient

The midship coefficient has an impact according to van der Kolk, 2020. As the tests presented in this source indicate, higher midship coefficients have a higher efficiency of lift generation. This may be caused by a lower bilge radius, which leads to better flow separation. Parallels can be drawn again to the low aspect ratio wings (Beukelman & Journée, 2001). As presented in Gudmundsson, 2014 and Hoerner, 1965 the shape of a wingtip can influence the effective aspect ratio, as can be seen in 2.3. Where wingtips with a rectangular profile have a higher effective aspect ratio than rounded wingtips. This phenomenon was also observed by Beukelman and Journée, 2001 which used ship-like wing models with square and faired bilges. Higher transverse forces were observed with the square bilges. This gives experimental validation of the theory.

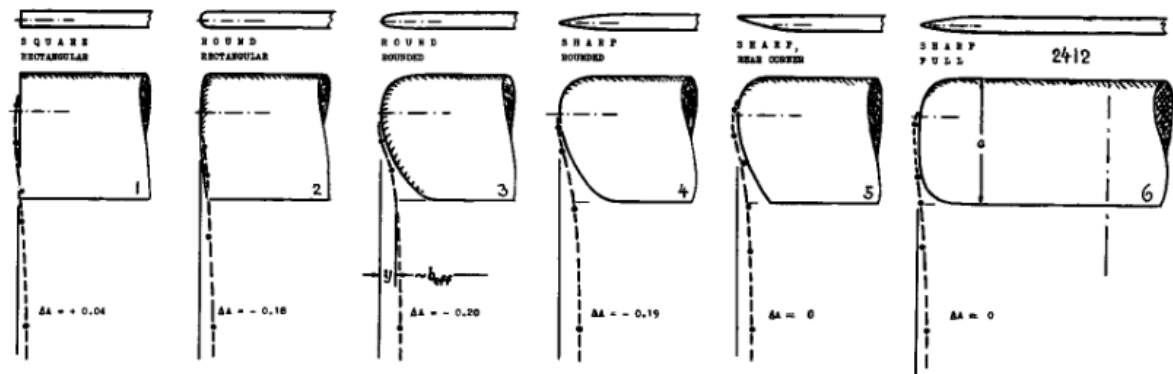


Figure 2.3: Wingtip configuration with Δ aspect ratio Hoerner, 1965

It should be noted that higher midship coefficients did have higher absolute resistance at the same leeway angles in the tests presented by van der Kolk, 2020. This means that a higher midship coefficient gives higher lift but also increases resistance, meaning an optimum has to be found that balances the induced drift resulting from higher drift angles and added resistance due to lower bilge radii. However, according to van der Kolk, 2020, the sailing efficiency was better for vessels with a higher midship coefficient. Meaning the induced drag in relation to lift is lower. The prismatic coefficient does not seem to have a large impact on the side force production. According to the regression analysis performed by Struijk, 2015, the prismatic coefficient has a small inverse relation to the creation of transverse forces. So an increase in the prismatic coefficient slightly decreases the produced side force. The prismatic coefficient does contribute greatly to the induced resistance according to Struijk, 2015. This would indicate that a high prismatic coefficient is bad for sailing efficiency. But according to Inoue, Hirano, and Kijima, 1981, the block coefficient, which tends to be highly correlated with the prismatic coefficient, has a positive correlation to the side force. In this study, it is not shown whether the block coefficient has been altered by altering the prismatic coefficient or the midship coefficient, or a combination of both. Therefore, the effect of the prismatic and block coefficients is unclear.

Deadrise

According to the same study by van der Kolk, 2020, increased deadrise, as seen in Figure 2.4, has a small negative effect on side force. Again, this is consistent with what the wingtip design theory would indicate. A deadrise reduces resistance to the cross-flow. This also means that the resistance is lower.

As seen in van der Kolk et al., 2021, the sail efficiency of the bare hull with deadrise was higher than that of an equivalent hull without deadrise. Another advantage that was observed in (van der Kolk, 2020; van der Kolk et al., 2021) for the model with deadrise was the decrease in the yawing moment. Lange, 2024 observed an increase in the lift coefficient for a vessel with deadrise. This was partially attributed to an increase in the draft that was necessary to maintain the same displacement. A reduction in resistance was also observed. Although the reduction in resistance was attributed to the better performance of the transom in the simulation, it was concluded that this was unlikely to transfer to the real world.



Figure 2.4: As presented by van der Kolk, 2020

Longitudinal center of buoyancy (LCB)

The data in Gerritsma et al., 1981 suggest that moving the LCB back reduces resistance and shifts the CLR forward. But this is a study of small sailing yachts, so it is unclear how relevant these data are. In addition, Struijk, 2015 also suggests that moving the LCB forward shifts the CLR backward. It should be noted that this observation was done on a vessel with a skeg, so shifting the LCB forward increased the skeg area. So, this conclusion may not be applicable to vessels without a skeg.

Bow shape

The effect of the bow shape on resistance, side force, and yaw moment appears very small based on the study by Zhang et al., 2022. However, these findings are only based on the study of three bows at one speed. So, only limited conclusions can be drawn from this. Struijk, 2015 identified in the literature some aspects of the bow that have an impact. Increasing the bow radius lowers the resistance and side force and shifts the CLR aft. Increasing the waterline entry angle has the same effect.

2.3.3. Appendages

According to Struijk, 2015 :“..., the focus should be on the influence of appendages, as its contribution is expected to be significant”(Struijk, 2015). Therefore, this section investigates several appendages that have been discussed in literature on wind-assisted vessel and maneuvering as potentially having effects on the resistance side force and CLR of vessels at leeway angles.

Bilge keel

Bilge keels, as seen in Figure 2.5a, were extensively studied by van der Kolk et al., 2021. In this research, it was concluded that the inclusion of bilge keels had a large impact on all relevant aspects of wind-assisted hull design. The side force increased when the bilge keels were included. Notably “Whereas the sailing efficiency for a hull fitted with bilge keels increased by at least 50% over the bare hull value, and this value appears to increase for the longest bilge keel, ...” (van der Kolk et al., 2021). So, increasing the length of the bilge keel increased the effect (van der Kolk et al., 2021). A linear relationship was observed between the height of the keel and the coefficient of side force and sailing

efficiency. The position of the bilge keel in the longitudinal direction did not show any effect on the side force or sailing efficiency in this study. However, it did show that the position has a large influence on the CLR. The addition of bilge keels resulted in an increase in resistance (van der Kolk et al., 2021). Yasukawa et al., 2018 also observed an increase in the generation of side forces. When a roll angle was introduced, the effect increased. Vinje Kramer and Steen, 2022 observed an increase in lift coefficient and a backward shift in the CLR when bilge keels were used. In this study, a reduction in rudder deflection was also observed. However, in Vinje Kramer and Steen, 2022 the inclusion of bilge keels did not improve fuel savings over the bare hull case in a simulated trip in the North Atlantic because the decrease in induced resistance was off-set by the increase in friction resistance. Based on the results of these studies, it can be concluded that the bilge keels improve the sailing efficiency and sideforce generation and therefore reduce the induced resistance, but their inclusion increases the frictional resistance. So, the effectiveness depends on the specifics of the vessel and the operational profile.

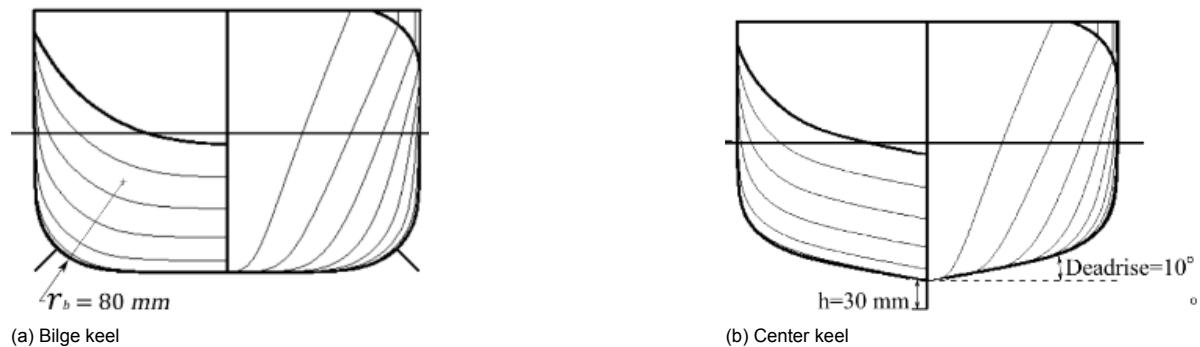


Figure 2.5: van der Kolk, 2020

Center keel

Research on low aspect ratio centerkeels, as seen in Figure 2.5b, is very limited, and only one accessible source discussed this was found. In van der Kolk et al., 2021 it is said: “..., the centerline keel does not appear to improve the sailing efficiency of the hull.” (van der Kolk et al., 2021) However, it did increase the side force, but also had a significant impact on resistance, as can be seen in the results in van der Kolk, 2020.

High aspect fin and dynamic fin

Vinje Kramer and Steen, 2022 proposes the use of a fixed or dynamic high-aspect fin to improve the generation of side forces and sailing efficiency, as well as to reduce the required deflection of the rudder. The high-aspect fixed fin was found to give results similar to those of bilge keels in terms of the reduction of the induced resistance. The dynamic fin did reduce the induced resistance by 33% in this study and decreased fuel usage by 4.5% over the case of a bare hull for the scenario with the highest fuel savings. This was in part because it was modeled as a retractable fin so it could be retracted in the case with low side forces to reduce frictional resistance. The results of this study show good performance, but the effectiveness will depend on the configuration of the vessel and the fin, as well as the operational profile. Lange, 2024 also investigated a similar device, as seen in Figure 2.6 and concluded that both a passive and an active fin give benefits. The fins showed improved performance over a bare hull for most of the operational envelope investigated in this case and showed the highest performance increase when there were high side forces. Parmo, 2024 showed that a fin can account for a large percentage of the side force produced and that a fin is most productive at small leeway angles.

Skeg

According to the literature examined in Struijk, 2015, the skeg has a significant impact on the CLR. Unfortunately, accessing the study that found this was not possible. The skeg was also responsible for

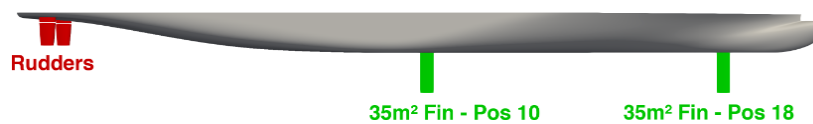


Figure 2.6: Proposed fins in Lange, 2024

an increase in side force, but also an increase in resistance. A skeg that was faired into the hull had, to a lesser extent, the same impact. The same trends can be found in the data presented in van der Kolk, 2020 where the side force increases but also the resistance. The effect on resistance is particularly high at high leeway angles. The reduction in the yaw moment can also be observed very clearly in the data. Lange, 2024 showed that the skegs, as shown in Figure 2.7 did improve the generation of side forces but that the increased resistance offset the reduction in induced resistance for most side forces in the operational profile investigated. The skeg only showed improvement over the bare hull at high side forces.

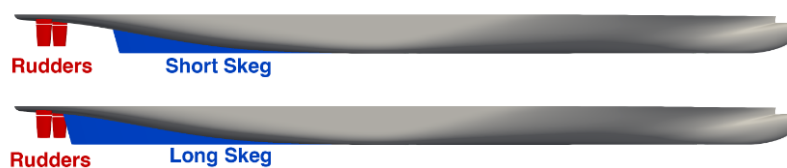


Figure 2.7: Proposed skegs in Lange, 2024

Rudder

The rudder is an important appendage in wind-assisted ship design. As a large Munk yawing moment is applied, as explained in Section 2.1, to wind-assisted vessels (van der Kolk, 2020). This needs to be counteracted to keep a steady course. The needed counterforce created by the rudder does give an extra induced resistance. According to Vinje Kramer and Steen, 2022 in 3 of the 4 cases they examined the rudder was the main source of induced resistance. The reason for this was that the rudder operated at very high lift coefficients. Therefore, having an efficient rudder can help reduce induced resistance. In J. Liu and Hekkenberg, 2016 it is said that a thinner section tends to be more efficient. However, this must be balanced with the structural element. As the rudder is subjected to relatively high loads, the section may need to be thicker. Lange, 2024 investigated the effect of flow on the rudders when sailing at a leeway angle. It was noted that the force on the rudder is linear with the angle of attack because of the high aspect ratio. In addition, it is noted that the performance of the rudders is highly dependent on the hull dimensions and shape. Inclusion of a skeg reduces rudder performance due to the inflow direction, as can be seen in Figure 2.8. However, as discussed in Section 2.3.3, the inclusion of a skeg moves the CLR aft, thus reducing the yawing moment that must be compensated for with the rudder.

Propeller

The propeller has a large impact on the flow around a vessel and its rudder. The flow around the vessel has a great impact on the efficiency of the propeller. Therefore, including the effects of the propeller may be important to gain complete insight into the optimized vessel as recommended by Lange, 2024. As shown in He et al., 2019, the hull optimized solely for resistance looks different than a hull optimized for self-propulsion. Furthermore, Meyer et al., 2022 shows that the drift angle affects the inflow of the propeller due to the vortices generated along the hull. Meyer et al., 2022 also shows a change in the flow field around the stern due to the addition of a propeller. Therefore, the addition of a propeller can change the resistance and side force. In order to create a vessel with the least amount of energy usage, the efficiency of the propeller as a result of inflow cannot be ignored. The reduction in hull resistance for wind-assisted operations may be offset by the loss in propeller efficiency.

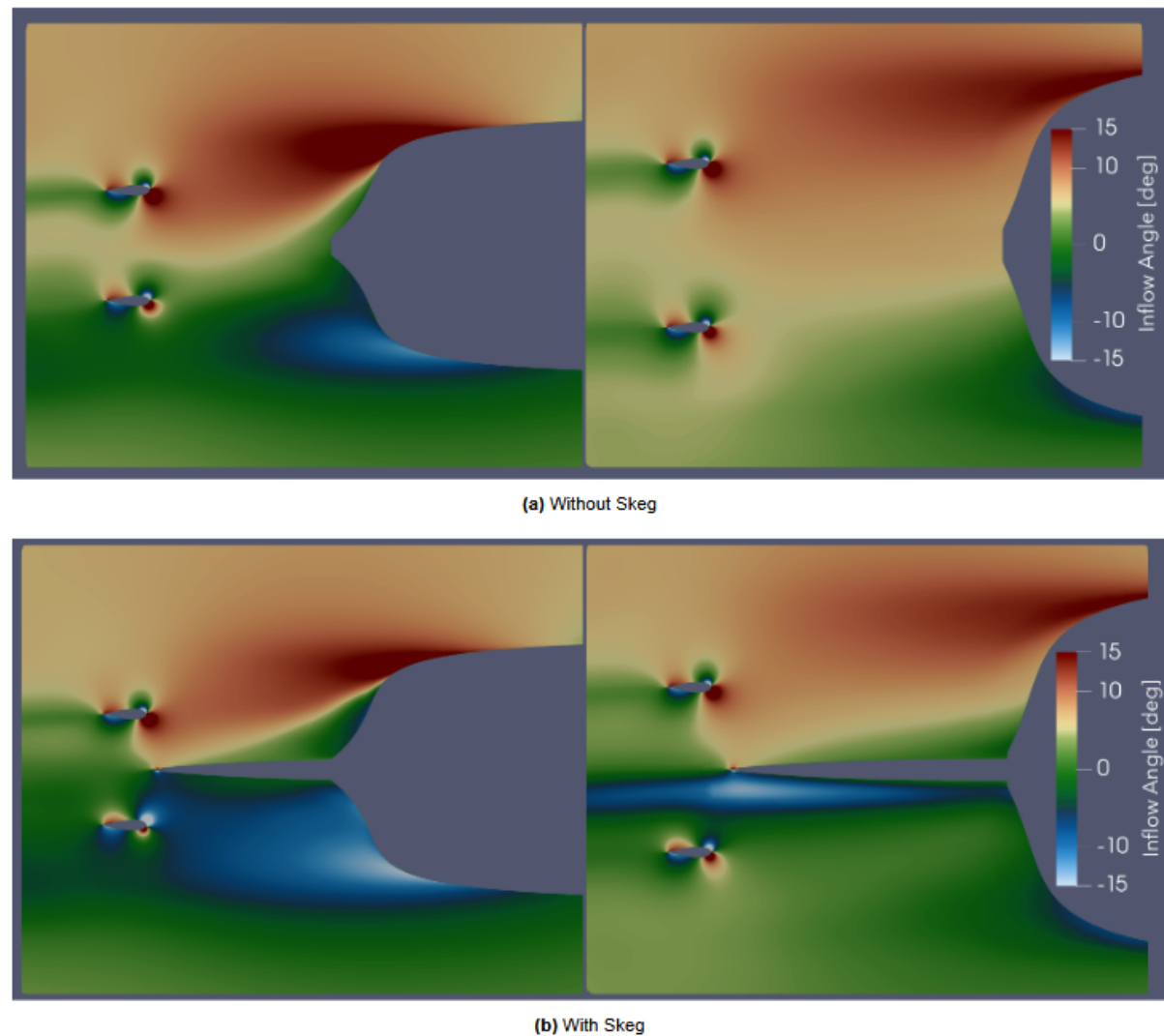


Figure 2.8: Inflow direction of rudders with and without skeg at different B/T ratios from Lange, 2024

2.4. Optimization of wind assisted ship hulls

In this section, the sources are presented that are related to optimizing and designing a hull of a wind-assisted vessel for resistance. These were the only papers that were found that did a design or optimization of a hull of a wind-assisted vessel that focused on resistance.

Plessas and Papanikolaou, 2024 looked at optimizing a very large crude carrier (VLCC) crossing the Atlantic for minimal fuel usage. This was done using a model that incorporated resistance, sail force, engine efficiency, and propeller efficiency. For the resistance model calibrated Holtrop & Mennen was used. So, the effect of the side force was ignored, as according to Tillig and Ringsberg, 2019 the difference would be between 2% and 7%. The optimized parameters are the engine, propeller pitch, propeller expanded area ratio, and five hull parameters; Which are length, breadth, depth, draft, and block coefficient. The optimization was performed using a combination of a genetic algorithm and a sequential quadratic programming (SQP) algorithm. A large initial sample is made using the SOBOL sequence of 5000 designs. The 50 best designs from the SOBOL sequence are the initial population for the genetic algorithm. The best design from the genetic algorithm after 500 generations is used as the initial value for the SQP algorithm. The resulting optimized vessel was a slender vessel. With the breadth at the minimum constraint and the depth at the maximum constraint.

In Lindstad et al., 2022 a 229 meter long dry-bulk carrier with wind assist is designed based on a 200

meter long dry-bulk carrier. This was done by scaling the vessel in the length direction and manually adjusting the local hull features around the bow and stern to create a realistic hull shape. This was evaluated using an empirical formulation for resistance. Here, the calm water resistance was calculated with the Holtrop-Mennen method and the added wave resistance using the method presented by Henk J.J. van den Boom and Thijs W.F. Hasselaar, 2014. The wind assisted vessel showed reduced power requirements compared to both the original 200 meter vessel and the lengthened vessel without wind assist.

2.5. Conclusion

The goal of this chapter was to identify important features and constraints for the optimization of a wind assisted vessel. This was done by looking at the literature on the design and optimization of wind assisted vessels.

For global dimensions, the B/T of the vessel is important, as it relates both to the aspect ratio and the stability. Lower B/T values reduce the induced resistance, but also reduce stability. This means that heel will increase and wind-assisted propulsion needs to be reduced to prevent exceeding the heel limit.

In terms of hull shape, the transverse design is important because of the component of the lift caused by the cross-flow and the effective aspect ratio. Lowering the bilge radius and increasing the deadrise both increase the efficiency of lift production. So lower induced drag at the same lift. The LCB and the bow shape both showed limited impact on the side force production.

For the appendages, the bilge keels and high-aspect fins were the most efficient in the production of side force. Skegs were also effective in producing side force and reducing the yawing moment. The center keels did increase side force production but not sailing efficiency, so the trade-off between lift and induced resistance stayed the same. The inclusion of these appendages increases the wetted area, and therefore increases frictional resistance. In return for this, inclusion of these appendages reduces the induced resistance. Therefore, the effectiveness of these design features is highly dependent on the amount of side force that needs to be created.

The rudder is the most important appendage as it compensates for the yawing moment. To do this, it operates at high lift coefficients. Therefore, the efficiency of the rudder is important. The propeller changes the flow around the rudder and stern, and the flow around the vessel has a large impact on the efficiency of the propeller.

Design and optimization studies focused on improving the resistance of wind-assisted vessels are mainly focused on global dimensions, and they use low-fidelity models to calculate resistance. In the next chapter, the different methods of predicting resistance are discussed and their applicability to this thesis is evaluated.

3

Resistance prediction

This chapter aims to answer the research question “What is the state of the art in predicting resistance for wind assisted ship hulls?” These resistance modeling methods will be assessed according to a set of requirements and measures. This includes the ability to model the side force and the yaw moment; this will be discussed in Section 3.1. In Section 3.2 the different methods are discussed. Starting with numerical models in subsection 3.2.2 and then empirical models are discussed in subsection 3.2.3. In Section 3.3 the conclusion can be found.

3.1. Requirements for resistance prediction models

In this section, the requirements and criteria for evaluating the different methods of predicting resistance, side force, and yawing moment are given. These are criteria to be able to assess the suitability of the methods for this study.

Outputs

The goal of the design process is to obtain a hull design with minimum resistance. Therefore, resistance is an important output of the model. But it is not the only result that is needed as a complete balance of forces and moments is required. The side force and yawing moment are therefore important outputs to get a vessel and configuration that balances all forces. In the case that a model does not output all the metrics, it is less suitable for this project. However, if it can be combined with an other limited model to get to a complete set of satisfactory outputs, this problem can be negated.

Inputs

The values and files that are the input for the methods should reflect the vessel as well as possible, and should align with the optimization variables. So, an effect of changing the variables can be observed. When in a method, the parameters have no response, as they are not an input value or are not related to an input value, the usability of this method is reduced.

Capture of physics

The model should capture as much of the physics as possible. If certain physical phenomena are ignored, this will reduce the accuracy of the results.

Speed

The less time the model needs, the better the model performs in this measure. This is a representation of both real-world and computer time (often expressed in core hours).

Precision and accuracy

The model should be as precise and accurate as possible. Less uncertainty is better. This mostly applies to numerical models as they are prone to numerical errors.

Verification and validation

When a model can be verified and/or validated, it gives a better insight into the accuracy of the model. Therefore, increasing confidence in the outcome of the optimization.

Access

An important aspect of models is whether they are available and usable. If models are difficult to obtain, they are unlikely to be useful in this study. The same is true for ease of use. A model should be relatively easy to get accurate results. If this is not the case, a lot of time will be required to set it up, which may not be available.

3.2. Available resistance prediction methods

According to Larsson et al., 2010 the resistance prediction methods can be divided into three categories. Model test, numerical methods, and empirical methods. These categories can be further subdivided into different specific methods.

3.2.1. Model tests

Model tests use a scaled-down version of the vessel to test the behavior of flow and resistance. This is then scaled up to make a prediction of the resistance of the ship at full scale. To capture all the physics, a towing tank or a flume tank can be used. Towing tank tests can be performed in several ways according to ITTC conventions ("ITTC Recommended Procedures and Guidelines 0.0", n.d.; "ITTC Recommended Procedures and Guidelines 75-02-02-01", n.d.; "ITTC Recommended Procedures and Guidelines 75-02-03-011", n.d.; "ITTC Recommended Procedures and Guidelines 75-02-03-014", n.d.; "ITTC Recommended Procedures and Guidelines 75-02-06-01", n.d.; "ITTC Recommended Procedures and Guidelines 75-02-06-02", n.d.) . In these conventions, it is recommended that for resistance, "ITTC Recommended Procedures and Guidelines 75-02-02-01", n.d. is used. In which the model is towed with the attachment in line with the shaft line. The model is allowed to sink and trim freely. An other way that was used in van der Kolk, 2020 is the captive method as described in "ITTC Recommended Procedures and Guidelines 75-02-02-01", n.d., in which the model is not allowed to move relative to the carriage. According to "ITTC Recommended Procedures and Guidelines 75-02-06-02", n.d., this is mostly meant to generate data for the validation of numerical methods or to generate data for the determination of hydrodynamic coefficients. The model can also be partially self-propelled as described in "ITTC Recommended Procedures and Guidelines 75-02-03-011", n.d. or fully self-propelled as in "ITTC Recommended Procedures and Guidelines 75-02-03-014", n.d. In these tests a propulsion unit is added to see the effect they have and to analyze the delivered power. The towing test can also be performed under free running conditions. This is done primarily to predict the maneuvering characteristics of a full-size vessel according to "ITTC Recommended Procedures and Guidelines 75-02-06-01", n.d. Therefore, it is not very relevant to the application needed in this thesis.

Measures

Model tests generate values for all required output variables if necessary measurement equipment is installed. Because the hull is used as generated, it takes into account all hull features. Features that are not part of the hull, such as appendages, can be included. Model tests capture all physics as the test takes place in the real world but some effects may be over- or underestimated due to different scaling of physical effects. This method can generate data of a single model, at different speeds at a relatively quickly as the only wait is for the time it takes for the facility to return to pre-test conditions. However, when the configuration needs to be changed, this can take more time, in particular, if the model needs to be changed. The preparation time is also high, certainly if multiple different models need to be created. In addition, making a new iteration based on the earlier acquired data, as is common in optimization algorithms, will take a long time due to the need to manufacture a new model.

The inaccuracy depends on the setup used and the number of runs performed at each measuring point. Measurements can be easily verified because all measuring equipment can be checked. Because the measurement takes place in real life, it is certain that no physical phenomena are ignored. The scaling of resistance to real-life conditions is well understood and is covered by "ITTC Recommended Procedures and Guidelines 75-02-03-014", n.d.

Access to a towing test and the models is very limited due to the limited number of available facilities and the high cost. Building enough models to cover the design space of a vessel with a large number of design variables will also be expensive. Therefore, access to this method is very limited. Although previously performed runs can be useful if the hull shape is similar and the model hull can be parametrized to fit within the new design space definition.

The limited accessibility and the need to change the model for all runs mean that using a model test is not well suited to this thesis.

3.2.2. Numerical methods

Larsson et al., 2010 mentions five numerical methods: Potential flow using the panel method, RANS (Reynold-average Navier-Stokes), LES (large eddy simulation), DES (detached eddy simulation) and DNS (direct numerical simulation). According to Larsson et al., 2010, LES and DNS would require too much computational power. According to "ITTC Recommended Procedures and Guidelines 75-03-02-03", n.d., DNS is not yet achievable and LES should only be used when the transient nature of the turbulence needs to be resolved on a very small scale. DES is a hybrid model between RANS and LES and "...the computational effort is too large for routine applications." (Larsson et al., 2010). More recent sources show that DNS is still very expensive to perform (Capuano et al., 2023). As shown in Liefvendahl and Johansson, 2021, LES is beginning to be applied to ships, but it is still too expensive to perform many evaluations. Therefore, the literature review will only include the potential flow panel method and the RANS method. Within these models, the settings and the resolution can be varied.

RANS

In this section, the RANS (Reynold-average Navier-Stokes) method will be explored. In the RANS method, the Navier-Stokes equations are time-averaged over a time larger than the largest turbulence scale to remove all turbulent fluctuations. This introduces unknowns, called Reynold stresses. Separate equations, called the turbulence model, are added to calculate the Reynold stresses. The RANS equations are solved discretely on a grid. In the following section, three options for simplification of reality in the model are discussed.

- Free surface
- Propeller modeling
- Euler equations

Free surface

There are four options to model the free surface. Firstly, the free surface can be ignored by modeling it as a flat surface with a slip condition on the waterline. This means that the velocity in the normal direction of the water plane is zero, but the speeds in the other directions are not restricted. In that case, the effect of wave-making resistance is completely ignored. Only the effects of viscous resistance and induced resistance are calculated. The advantage is that this is faster than resolving the free surface.

The second option is to use a hybrid method in which the wave elevation is calculated with an inviscid method, such as a panel method or the Euler equations. The water surface from this is then used with a slip condition. In this flow domain, a single phase RANS solution is calculated. Because the errors in the wave profile due to the viscous effects are larger at the stern of the vessel, the error in the aft flow of the vessel is the largest. However, this method has been shown to give good results in Huan and Huang, 2007. The advantage of this method is that because the free surface does not have to be resolved with the viscous method, it is faster than the next two methods.

The third option is to use an interface tracking. In this method, the flow domain is limited to the water flow. To calculate the free surface, a pressure boundary condition is set on the free surface. The flow is solved and the free surface is moved according to the volume flux through the free surface on each surface cell. This is repeated until the solution converges.

In the fourth method, called interface tracking, the flow domain contains both the water and air and the interface is tracked into the flow domain. Larsson et al., 2010 identifies two common methods for accomplishing this. Volume of fluid (VOF) and set of levels. In the VOF method an extra transport equation is solved for the water fraction. In the level set method, a function is initialized at $t = 0$ and thereafter the transport at $t > 0$ is defined by:

$$\frac{\partial \phi}{\partial t} + u_i \frac{\partial \phi}{\partial x_i} = 0$$

The particles that are on the surface stay on the surface because there is no flow through the surface. This means that the value of ϕ that is on the surface initially stays on the surface (Larsson et al., 2010). According to Larsson et al., 2010, the distance to the free surface is a frequently used function for ϕ . So, the surface can be found at $\phi = 0$.

Measures

Due to the results that come from the integration of pressure over the hull surface, it can output resistance, sideforce, and center of lateral resistance.

The input is a CAD representation of the vessel. Therefore, all inputs should see a response. Unless for computational reasons, certain features are not included. This could be a choice to reduce the computational cost for a lower fidelity.

Using the full capabilities of RANS, only time dependent and subgrid sized turbulence are ignored. Choices can be made to ignore more physics to speed up the simulation. Like discussed in Section 3.2.2, the free surface can be ignored or modeled in a simplified way. This means either the effect of waves is totally negated or the viscous effect on the waves is ignored.

RANS is computationally heavy compared to the panel method (Werner et al., 2007). The settings and simplifications as well as the required accuracy have a large impact on the computational cost. The hardware on which the simulation is run has a large impact on the time required.

The accuracy of RANS when all the physics is captured is quite good. Larsson et al., 2010 observed a standard deviation for the benchmark cases of 4% to 7% for the total resistance on scale in 2005. Full-scale resistance predictions were not yet helpful for power prediction. More recently Niklas and Pruszko, 2019 showed that full-scale CFD could acquire accuracies similar to towing tests compared to sea trials. Because of the numerical nature of RANS, it deals with the same uncertainties as described in the section about the panel method.

A verification of the results can be performed by looking at the resulting flow field to see if it is smooth or shows artifacts resulting from the grid. Furthermore, the wave pattern can be checked to see if it conforms to the kelvin wake angle. The grid error can be estimated using a grid convergence study. Such as the grid convergence index presented by Roache, 1994 based on Richardson extrapolation or with the method presented by Eça and Hoekstra, 2014 based on the least square error estimation method. Access to four RANS programs is available: OpenFOAM, Ansys (Fluent, CFX), and STAR CCM+.

Panel method

There have been many iterations of panel methods; in this section, only the state of the art of these methods is discussed. The state of the art of these methods is referred to as non-linear free surface panel methods. Most of the state-of-the-art programs are now more than two decades old (Larsson et al., 2010). But because of the advancement in computing power, they can run very fast. The panel method uses potential flow theory, in which water is approximated as an irrotational inviscid fluid.

In general, the free surface is well modeled. But because of the viscous effects are ignored it is not entirely accurate. The pattern is mostly accurate, but the difference can be seen mainly in the wave amplitude (Pacuraru, 2019).

Measures

The panel method outputs a value for resistance, lift, and moment Rotteveel and Quadvlieg, 2013. Due to the use of CAD design as an input, the results will respond to any changes in the design. However, it may not or show limited responsiveness to features that generate forces purely or mostly through viscous effects. For example bilge keels, their working principle is the triggering of separation of the flow at the bilge and the generation of a vortex. This effect is not captured directly in the method. Manual changes to wake surfaces may help alleviate these issues, but this is only speculation. Dry transoms are also not well modeled by the panel method due to the same problem (Larsson et al., 2010). Higher aspect appendages such as high aspect fins and rudders can be included, but do require a wake surface. The inclusion of a rudder may also interfere with the wake surface at the trailing edge of the vessel. Therefore, it may be necessary to include the effect of these appendages later on the basis of separate numerical or empirical calculations. Furthermore, the inclusion of a propeller is not possible. So, this method is not well suited if the effect of the propeller needs to be modeled.

This method is based on potential flow. Therefore, the viscous resistance components are ignored. These can form the majority of the resistance for some types of vessels (Larsson et al., 2010). This can be partially compensated for by adding flat plate resistance, but this ignores the form effect. Some panel methods add a boundary layer equation and integrate this over the streamlines, derived from the velocity field, to calculate the skin friction more accurately. Because wave resistance, which is well captured by the panel method, accounts for a larger percentage of the drag at higher Froude numbers, the panel method is better suited for high-speed ships.

The speed of the panel method depends on the settings used, with the number of panels being the most important variable. Generally, the panel method is fast compared to other fully viscous numerical models. In Werner et al., 2007 a panel method took 20 minutes compared to 80 hours for a fully viscous RANS simulation. It should be noted here that this is not for a vessel with a free surface. In 2010, Larsson et al., 2010 estimated that a typical non-linear case with 80.000-12000 panels took between 2 and 5 minutes.

Depending on the chosen program, the code may or may not be verified. Although the underlying idea is very similar according to Larsson et al., 2010, the approximate method can be verified. In addition, the discretization error can be verified by performing a grid refinement study. The program can be validated by experimental or RANS examples as in Rotteveel and Quadvlieg, 2013; Werner et al., 2007. A validation step can also be performed by looking at the results to verify that they perform according to known physical expectation, for example the Kelvin wake angle. The presence of artifacts in the results could also indicate errors.

The DelKelv panel method code is available. However, the code is at this moment not ready to model this exact problem as the creation and calculation of wake surfaces are currently not implemented. The integration of this code into the optimization loop will be difficult as there is no easy way to couple the Delkelv code to Python, which will be used for the optimization loop.

Conclusion

The numerical methods for calculating resistance, side force, and moment are well suited to the proposed research. Firstly, it allows for easy variation of design parameters. Secondly, it is responsive to all design inputs because the calculation is based on CAD models. It outputs all required output parameters. Third, RANS captures all the physics and has been shown to give an accurate prediction of resistance but is fairly slow. The panel method simplifies some physics, but is significantly faster. Fourth, these methods are available as well as support to help set up these simulations.

3.2.3. Empirical methods

Empirical methods use data from a number of tests, often model tests, to construct a model. According to Larsson et al., 2010, there are two variants: The systematic series and the statistical method. In the systematic series a parent hull is systematically varied by changing the dimensions and form parameters (Larsson et al., 2010). To make it scalable, the friction is removed from the test results. This means that the resistance can be scaled with the Froude number and the frictional resistance can be added based on other empirical formulas. This means that the resistance can be calculated on any scale. The construction of these methods is expensive, as many models need to be built and tested (Larsson et al., 2010).

In the statistical method, data from an unsystematic variation of ships are evaluated to find empirical relations between resistance and form parameters (Larsson et al., 2010). A famous example of this is the Holtrop and Mennen method, which used formulas based on physical evidence with empirical deterrent coefficients (Holtrop & Mennen, 1982; Larsson et al., 2010).

There are many available empirical models for resistance, but for this research, not only resistance in a straight line is needed. The side force moment and induced resistance are also needed. This limits the usable empirical models. Only one empirical model was found based on wind-assisted vessels. Looking at papers exploring the design of wind-assisted vessels, several alternative empirical methods were found.

Struijk, 2015 presents a regression of the Delft systematic wind-assisted series (DSWAS) at a Froude number of 0.168. So, this is only valid at one speed. However, it gives side force, moment, and residuary resistance, so total resistance minus friction resistance. It showed quite accurate yaw moment predictions (Struijk, 2015). Unfortunately, it showed poor results in predicting the side force (Struijk, 2015).

Articles exploring the design of wind-assisted vessels with the use of empirical models often used empirical models meant for estimation of maneuvering behavior. Either alone as in Viola et al., 2015, or in combination with separate resistance, as in Berendschot, 2019 and Tillig and Ringsberg, 2020. Reche-Vilanova et al., 2021 used a separate resistance model in combination with a model for induced resistance and side force for sailing merchant vessels. Plessas and Papanikolaou, 2024 did not include side force or induced resistance in their model. These models and their applications will be further explored in the next sections.

In the paper by Viola et al., 2015, the empirical maneuvering model created by Kijima, Katsuno, et al., 1990 was used. This was based on the captive towing test of 13 ships (Kijima, Katsuno, et al., 1990). This gives values for resistance, side force, and yawing moment.

Berendschot, 2019 split the resistance into several components. Consisting of calm water resistance, added resistance in waves, induced hull resistance, and induced rudder resistance. Here, the resistance to calm water is calculated using the Holtrop and Mennen, 1982 method. The added resistance in waves is calculated with an empirical formula. For the induced drag, the model by Kang and Hasegawa, 2007 was used which gives the induced resistance, the side force, and the yawing moment. For the induced resistance, the side force, and the moment of the rudder, a combination of analytical formulation with empirical coefficients was used with the addition of formulas in Kijima, Nakiri, and Furukawa, 1990; Kijima, Katsuno, et al., 1990 to account for the influence of the hull and propeller on the rudder.

Tillig and Ringsberg, 2019 used a similar setup. For lift and induced resistance they came to the conclusion that wing theory as presented in Hoerner, 1965 and Hooft, 1994 is more accurate than the empirical methods. This theory is implemented using a combination of coefficients derived from towing tests and formulas presented by Inoue, Hirano, Kijima, and Takashina, 1981. For the center of effort (COE), needed for the yawing moment, the model by Inoue, Hirano, Kijima, and Takashina, 1981 was deemed sufficiently accurate to be used.

Reche-Vilanova et al., 2021 uses Holtrop and Mennen, 1982 as a calm water resistance and side force

and induced drag with the method of Schenzle, 1985. For the forces produced by the rudder, the method is based on the systematic analysis by Whicker and Fehlner, 1958.

In the article by Plessas and Papanikolaou, 2024 a one degree-of-freedom model (1DOF) is used, meaning that the heel, trim, and leeway angle are not included. This means that the resistance was only made up of a calm water resistance calculated with Holtrop and Mennen, 1982 and the added resistance calculated with the semi-empirical SNNM method (S. Liu & Papanikolaou, 2016). The use of a 1DOF model means that the induced resistance is not taken into account, and therefore, the resistance is under predicted. "These savings may appear too optimistic, because of the limited accuracy of the employed 1DOF hydrodynamic modeling."(Plessas & Papanikolaou, 2024)

Measures

The output of empirical models depends on the used model; some models only output resistance, while others can output all relevant results. For example, Holtrop and Mennen, 1982 can only output calm water resistance in straight ahead conditions, while the model by Struijk, 2015 outputs the resistance, side force, and yaw moment. The selection of the empirical model will therefore be highly dependent on this metric.

The inputs on which the results are based also vary between different empirical models. This is therefore again an important aspect for selecting which models are best suited for this research.

The empirical model should capture all the physics if it is based on data that capture all the physics. Although some phenomenon may be simplified when fitting the data.

The speed of empirical models is very high because it is one- or multiple-evaluations of an analytical function. This can be done very quickly with a computer. Plessas and Papanikolaou, 2024 were able to evaluate the journey of a vessel, taking into account the interaction between the hull, propeller, engine and sail in a 1DOF model in approximately 1 second using semi-empirical formulas (Plessas & Papanikolaou, 2024). The simulation performed by Tillig and Ringsberg, 2019 took 320 seconds for 30 way points and 9 speeds. So, a time of about 1.2 seconds per evaluation.

For systematic series, the accuracy of is very dependent on whether the vessel is similar to the hull the series is based on. This was shown by Petersson, 2020, where a model based on the KVLCC2 hull under predicted the coefficient of resistance by 40% but the coefficient of drag FSD-5 hull was approximated lower than 4% when interpolating with data from the same series. Salim Kamil et al., 2022 compared the wave-making resistance of several methods with experimental data. This study showed high errors for the method by Holtrop and Mennen, 1982. For the Wigley hull, errors were observed that ranged from -25% to +40%, and for an OPV hull, the errors ranged between -20% and +15%. In the article by Sutulo and Guedes Soares, 2019 the use of empirical models for maneuvering was tested. This included pure methods, rudder and hull forces from the same method, and hybridized methods, where hull and rudder models were taken from different methods. This showed "The obtained numerical results have demonstrated that very few methods or combinations give reasonably accurate results for this vessel and some simulated responses even look unacceptable."(Sutulo & Guedes Soares, 2019). Further more "The performed comparison of the rudder outputs according to various models showed that while most models provide relatively close estimates of the forces in a straight run, this is much less so when the sway and yaw are present"(Sutulo & Guedes Soares, 2019). Therefore, Sutulo and Guedes Soares, 2019 says that most methods need some tuning before they can be used.

The combination of empirical models, as done by most of the papers examined, could add another source of inaccuracy. These models take a calm water resistance and add an induced resistance to account for the leeway angle. This assumes that the calm-water models are still valid at leeway angles. This assumes that the form resistance and wave making resistance are not influenced by leeway angles.

The results of empirical models can be validated with the use of CFD or model tests, as done in Tillig

and Ringsberg, 2020. Verification steps can be performed using known physical relations.

Because empirical models often come in the form of formulas or data that can be interpolated, this can be implemented in code quite easily. Because these are often included in articles, access to these empirical models will not be an issue.

Conclusion

In conclusion, empirical models have been shown to be a popular method in parameter optimization due to their ability to evaluate many designs in a short time and their capture of all physics that is included in the underlying data. However, from validation tests, it has been shown that empirical models are only applicable to vessels, speeds, and conditions for which they were intended, as outside of this range errors have been shown to be large. Furthermore, empirical models are based on a number of coefficients that may not fully capture the hull. This means that the empirical model should be chosen that is responsive to all variables in the optimization study. The output variables are also an important measure; there are few models that give a result for resistance, side force, and yaw moment. This problem is often solved by combining multiple empirical models. The most seen combination divides the resistance into a calm-water component, an induced component, and an added component. The Holtrop and Mennen, 1982 method is often used for the calm water component. Although several different models intended for capture maneuvering behavior are popular for calculating induced resistance.

Due to the high speed of empirical models, they may be useful in the optimization of wind-assisted vessels. Although the accuracy is limited because the model captures all physics that is in the underlying data, they are expected to represent global trends accurately. Therefore, they could be used as a low-fidelity model in a multi fidelity model.

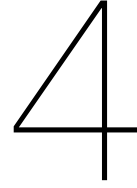
Empirical models also show potential for supplementing lower fidelity numerical models by adding missing components or physics. This reduces errors and increases the correlation with a higher fidelity model.

3.3. Conclusion

What is the state of the art in modeling resistance for wind assisted vessels? Numerical models and empirical models can be applied to this problem, while model tests are infeasible because of lack of access and long lead times for creating new geometries. Numerical models can get high accuracy when taking in to account all physics with a sufficient resolution, but this results in a computationally heavy calculation which takes a long time. Numerical models can also operate with simplifications to make it faster, such as with the panel method, non-viscous CFD or with a coarser grid, but this reduces the accuracy. Empirical methods are even faster, but are also more inaccurate, certainly if the model is applied outside the intended range. Therefore, the viable options for modeling the resistance, side force, and yawing moment are the following.

- Full RANS, using a free surface. The propeller may be added in this simulation depending on the added computational cost and the applied case.
- Euler equation, depending on the use, an empirical estimation for the frictional resistance can be added.
- The panel method, depending on the use, an empirical estimate for the frictional resistance can be added. Furthermore, because of the likely difficulties with modeling, the rudders may be added with empirical models.
- Empirical method using the Holtrop and Mennen, 1982 method combined with an extra model to calculate the induced lift and the yawing moment. Based on the required input, one of the methods presented in the following articles can be used (Berendschot, 2019; Reche-Vilanova et al., 2021; Tillig & Ringsberg, 2019).

The next chapter will discuss how these methods can be integrated into a multi-fidelity optimization framework.



Multi fidelity modeling and optimization

In this chapter the state-of-the-art of multi fidelity modeling (MFM) for the use in surrogate based optimization will be explored to answer the research question “How can multi fidelity modeling best be implemented?” In Section 4.1 the background of multi fidelity modeling and surrogate modeling is given. In Section 4.2 the theory of the Gaussian processes is explained. In Section 4.3 the theory behind Bayesian optimization is explained. Lastly, section 4.4 concludes how this theory can best be implemented.

4.1. Background

In this section, an explanation of what multi-fidelity modeling(MFM) is and what goes into constructing it is given. In the first subsection, the general explanation of MFM is given with an explanation of the different methods of MFM. In the second subsection, the concept of fidelities will be explained. In the third subsection, the concept of surrogate modeling will be briefly explained.

4.1.1. What is multi fidelity modeling

According to Fernández-Godino, 2023:

“Multi-fidelity models provide a framework for integrating computational models of varying complexity, allowing for accurate predictions while optimizing computational resources. These models are especially beneficial when acquiring high-accuracy data is costly or computationally intensive.”(Fernández-Godino, 2023).

This is therefore well suited when using expensive numerical simulations such as RANS.

Fernández-Godino, 2023 splits Multi-fidelity modeling into two categories Multi-Fidelity Surrogate Models (MFSM) and Multi-Fidelity Hierarchical Model (MFHM). MFSM creates a surrogate model that predicts the results of the high-fidelity model based on information from the low- and high-fidelity models. MFHM does not create a new model, but uses criteria and algorithms to choose which fidelity should be used. Peherstorfer et al., 2018 subdivides MFSM further into adaptation and fusion. In adaptation, a function for the difference between low- and high-fidelity data is created so that the approximate value of the high-fidelity model can be found based on a new low-fidelity data point. Fusion refers to the use of low- and high-fidelity data to create a new model using statistical tools. Because the goal is to use the multi fidelity model for surrogate-based optimization, as will be explained in Section 4.3, a surrogate based approach is better suited. This approach was also used by Charisi et al., 2024 in a similar optimization problem.

4.1.2. Fidelities

In a MFM distinctions need to be made between higher and lower fidelities. Higher fidelities are more accurate and precise. According to Fernández-Godino, 2023, there are three relations between high and low fidelities. The first is referred to as the “model”. This is explained as: “Change in the mathematical model that represents reality”(Fernández-Godino, 2023). So, this is the result of reducing the

	Advantages
Polynomial regression	Gives insight into the structure of the data, computationally simple
RBF	Gives exact results in already sampled points
NN	Able to fit complex non-linear and high dimensional systems
SVR	Good at handling non linear problems
GP	Includes the uncertainty of the prediction
	Disadvantages
Polynomial regression	Often don't capture higher order effects
RBF	Interpolation so results outside sample are not accurate
NN	Requires a lot of data
SVR	Parameter selection is crucial for a good fit
GP	Computationally heavy for large data sets

Table 4.1: Advantages and Disadvantages of different regression methods

captured physics. For example, a CFD that is fully viscous is changed to a potential flow CFD thereby ignoring the viscous effects on resistance. The second relation is a change in “accuracy”. Described in Fernández-Godino, 2023 as: “Difference in discretization, dimensionality, convergence” (Fernández-Godino, 2023). The difference in discretization refers to reducing the numerical fidelity, such as increasing the element size or increasing the time step. The dimension references the increase or decrease in the dimensions. For example, going from a 3D to a 2D simulation. The convergence refers to the residual error allowed before ending the simulation. The third difference is the “source”. This is if the result is from an experiment, a simulation, or real-world data. Experiments and real-world data are generally regarded as more accurate. In the case of a combination of these factors, the decision on which fidelity is the higher fidelity should be based on context(Fernández-Godino, 2023).

4.1.3. Surrogate modeling

An optimization algorithm generally performs many evaluations of its constraints and objective functions. These functions can be impractical to evaluate often, due to high computational costs (Koziel et al., 2011). To mitigate this cost interpolation and extrapolation of known data is possible. To do this, a function can be fitted through the known data points. This function is known as a surrogate model which can be used for optimization as described by Koziel et al., 2011 as “the optimization of the original objective is replaced by iterative re-optimization and updating of the analytically tractable and computationally cheap surrogate.”(Koziel et al., 2011).

There are several methods of building a surrogate model. According to Koziel et al., 2011, the most popular models are: Polynomial regression, radial basis function (RBF), neural networks (NN), support vector regression (SVR), and Gaussian process regression (GP). Based on Koziel et al., 2011, Samadian et al., 2024, Cheng et al., 2020 and McBride and Sundmacher, 2019 advantages and disadvantages of these systems are given in table 4.1.

Of these methods, Gaussian process regression will be used. This offers the advantage of having a built-in uncertainty quantification. This improves the efficiency of surrogate-based optimization as this helps to determine the useful points to sample, as will be discussed in Section 4.3. Furthermore, it has been shown to work for a multi-fidelity engineering optimization problem in Charisi et al., 2024.

4.2. Gaussian process

In this section, the concept of Gaussian process regression is explained. Then, the mathematical basis is given. Lastly, the proposed method for using Gaussian process regression in a multi fidelity model will be explained.

4.2.1. Concept

The idea of a Gaussian process relies on the assumption that points are correlated. The correlation between two points is described with the covariance. If this is one then the points are perfectly corre-

lated, meaning that if one of these two points is known, the other one is also known. If the covariance is zero, knowing one point says nothing about where the second point is. If it is somewhere in between, knowing one point gives some information about where the second point lies. For example, in Figure 4.1 the points have a covariance of 0.7 so knowing y_1 reduces the uncertainty of what y_2 is and changes the expected value.

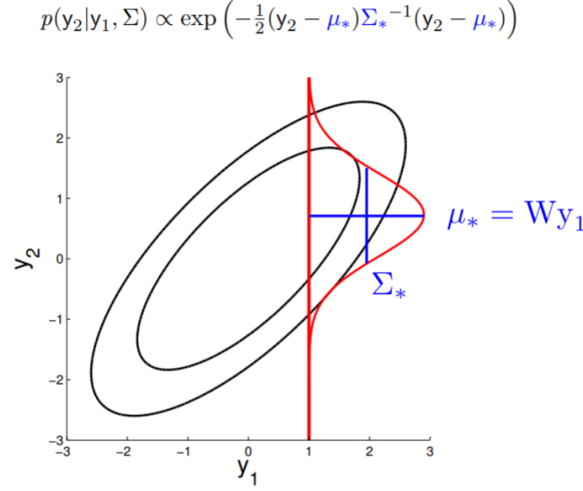


Figure 4.1: Correlation between two points with a covariance of 0.7 (Shi, 2019)

The covariance between points is described by the kernel function. This is often a function of the distance between points.

So, if one or more points are known, the probability distribution of all other points can be calculated based on the covariance that is based on the kernel function. This is often displayed as in Figure 4.2. Where the red points are the known points, the blue line is the mean of the distribution at each point, and the shaded area is the region that lies in between the mean plus and minus one standard deviation.

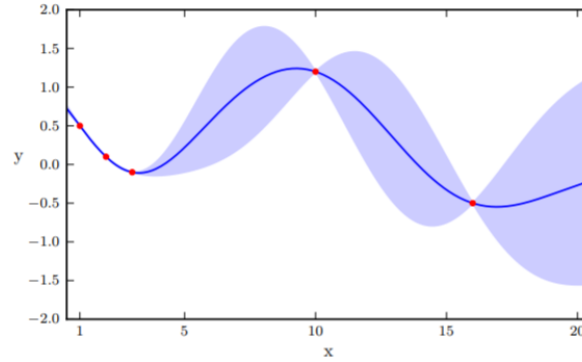


Figure 4.2: Gaussian regression plot (Shi, 2019)

4.2.2. Mathematical basis

A Gaussian process can be described as a combination of all possible fits expressed as a function that describes the output for each set of variables as a Gaussian distribution with a mean and a variance. To do this, the covariance between the point we want to sample and the data we have can be used. This is described by the following formulation for noise-free observations 4.1 (Rasmussen & Williams, 2008):

$$\begin{pmatrix} f \\ f_* \end{pmatrix} \sim \mathcal{N}\left(0, \begin{pmatrix} K & K_* \\ K_*^T & K_{**} \end{pmatrix}\right) \quad (4.1)$$

In this formula f is the vector containing the known data and f_* is the point that needs to be sampled. The $\mathcal{N}$ signifies a Gaussian distribution, and the K , K_* , K_*^T and K_{**} are the covariance matrices. According to Rasmussen and Williams, 2008, this formula can be solved for f_* for some given variables X_* that must be sampled with the following formulation 4.2.

$$f_* | X_*, X, f \sim \mathcal{N} \left(K(X_*, X)K(X, X)^{-1}f, K(X_*, X_*) - K(X_*, X)K(X, X)^{-1}K(X, X_*) \right). \quad (4.2)$$

This means that the value of f_* given some variables X_* with the known data with variables X and the results f is normally distributed with a mean of $K(X_*, X)K(X, X)^{-1}f$ and a variance $K(X_*, X_*) - K(X_*, X)K(X, X)^{-1}K(X, X_*)$. So, to solve this, only the K matrices are needed. This K matrix is made up of covariances. The K_* are determined by a covariance function. This covariance function is often referred to as the kernel. The squared-exponential (SE) covariance function in one dimension will be used to explain the basic concept. This SE kernel, also known as the radial basis function (RBF) kernel, has the following formulation 4.3:

$$k(x, x_*) = \sigma_f^2 \exp \left(-\frac{(x - x_*)^2}{2\ell^2} \right) \quad (4.3)$$

As can be seen, the covariance is a function of the squared distance between the point we want to sample and the data point. This distance term returns in many basic kernels (Duvenaud, 2014). The kernel therefore has the form seen in Figure 4.3

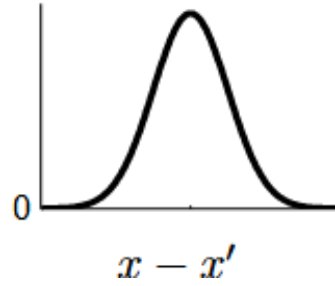


Figure 4.3: covariance as a function of distance in a SE Kernel as presented in Duvenaud, 2014

The formula 4.3 also has two more parameters: σ_f , and ℓ . These are referred to as hyperparameters and have to be set before fitting the data. As can be seen in Figure 4.4, the effect of changing the hyperparameter can have a large impact on the look of the fitted model (Duvenaud, 2014; Rasmussen & Williams, 2008).

Therefore, choosing these values correctly is very important to get a good fit. These values can also be optimized by maximizing the marginal log-likelihood (MLL) (Rasmussen & Williams, 2008). The expression for the MLL is seen in the formula 4.4

$$\log p(f | X, \theta) = -\frac{1}{2}f^T K_f^{-1}f - \frac{1}{2} \log |K_f| - \frac{n}{2} \log 2\pi \quad (4.4)$$

Here f are the observed data X are the variables on which the data are observed, θ is a vector containing the hyperparameters K_f is the covariance matrix for the data f and n is the amount of observed data.

Fortunately, the partial derivative with respect to the hyperparameters can be computed without significant extra calculation time because the most expensive calculation is the inversion of K which already needs to be performed to obtain the MLL (Rasmussen & Williams, 2008). This means that gradient-based optimizers can be used. The formula for the partial derivative with respect to the hyperparameters is given in Formula 4.5.

$$\frac{\partial}{\partial \theta_j} \log p(f | X, \theta) = \frac{1}{2}f^T K^{-1} \frac{\partial K}{\partial \theta_j} K^{-1}f - \frac{1}{2} \text{tr} \left(K^{-1} \frac{\partial K}{\partial \theta_j} \right) = \frac{1}{2} \text{tr} \left((\alpha \alpha^T - K^{-1}) \frac{\partial K}{\partial \theta_j} \right) \quad \text{where } \alpha = K^{-1}f \quad (4.5)$$

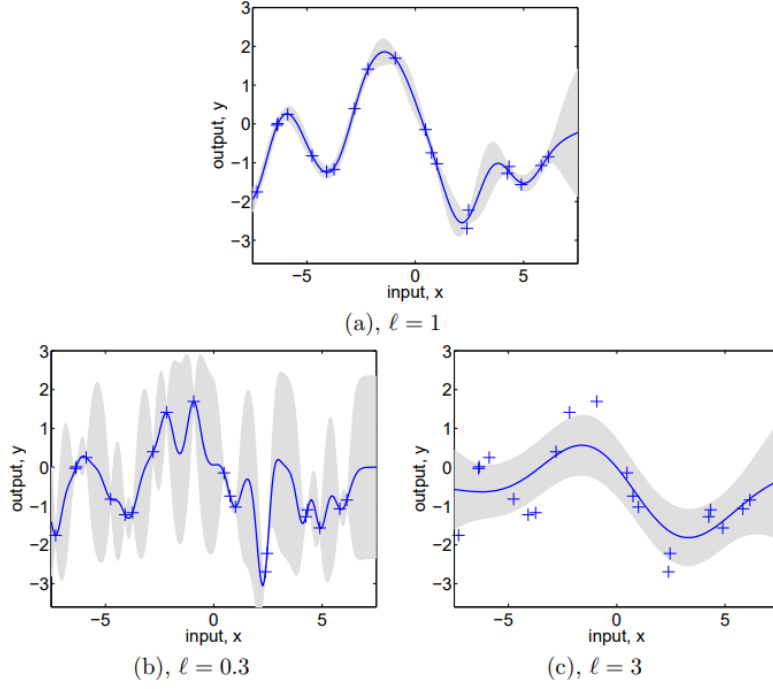


Figure 4.4: The effect of changing the length scale hyper parameter in a SE kernel as presented in Rasmussen and Williams, 2008

So, by choosing the right kernel, inputting sufficient data and optimizing the hyperparameters, a good fitting can be made that takes into account the prediction and the uncertainty of that prediction. However, as said by Duvenaud, 2014: “Choosing a useful kernel is equivalent to learning a useful representation of the input.” (Duvenaud, 2014). So, the choice of kernel is an important input that determines the performance of the Gaussian process regression.

4.2.3. Multi-fidelity Gaussian processing

There are multiple ways in which multi fidelity can be implemented in a Gaussian process (Fernández-Godino, 2023). In this thesis, the AR1 scheme will be used on the recommendation of N. Charisi, who used it in Charisi and Kana, 2023 and Charisi et al., 2024. According to Brevault et al., 2020, AR1 performs better than non-linear methods when training data is limited. AR1 works by determining the predictive distribution of the higher fidelity given multi fidelity results (Gratiet, 2013). The AR1 method assumes the Markov property 4.6 introduced by Kennedy and O’Hagan, 2000:

$$\text{Cov}(Z_t(x), Z_{t-1}(\tilde{x}) \mid Z_{t-1}(x)) = 0 \quad \forall x \neq \tilde{x} \quad (4.6)$$

This can be summarized as: “if $Z_{t-1}(x)$ is known, then nothing more can be learned about $Z_t(x)$ from any other run of the cheaper code $Z_{t-1}(x)$ for $x \neq x$ ” (Gratiet, 2013). Here, Z_t denotes the high fidelity model and Z_{t-1} refers to the low fidelity model. From this the equation for the high-fidelity model 4.7 is derived.

$$F_t(x) = \rho_{t-1}(x)F_{t-1}(x) + \delta_t(x) \quad (4.7)$$

F_t is the higher fidelity function F_{t-1} is the lower fidelity function $\rho_{t-1}(x)$ is the linear scaling function. $\delta_t(x)$ is the additive component, which is a Gaussian process independent of F_{t-1} (Charisi et al., 2024). According to Gratiet, 2013, the scaling factor ρ_{t-1} represents the degree of correlation and the scaling factor.

For a more in-depth look at the mathematics, readers are directed to the paper by Kennedy and O’Hagan, 2000 and Chapter 3 of the PHD dissertation by Gratiet, 2013.

4.3. Optimization

In this section, the optimization strategy will be discussed. First, a background on surrogate based optimization will be presented. Secondly, Bayesian optimization will be explained. Third, the acquisition function will be explained. And finally, the Bayesian optimization with a multi-fidelity model will be explained.

When optimizing expensive-to-evaluate problems, evaluating many designs becomes very expensive. So, only very efficient optimization algorithms are viable. Unfortunately, for these problems, the derivative is often not available and numerically determining the derivatives is expensive. Certainly, when the design space has many dimensions. A solution is to use surrogate-based optimization. By using previously collected data, a cheap surrogate model can be created. Using this, possible points of interest can be determined that can be sampled next.

Surrogate-based optimization follows the framework as shown in Figure 4.5. The first step is to decide which variables to optimize. Then an initial sampling plan needs to be made. These sampling points are then observed in the objective function. From these data a surrogate model is constructed. In this surrogate model, a search infill criterion is evaluated, this is also often called the acquisition function, which will be discussed in more detail in 4.3.3. This is a measure to assess which point or points should be evaluated next. The point or points with the maximum acquisition function value are then evaluated. With the addition of these new data, a new surrogate model can be fit and the process is repeated until a stopping criterion is reached.

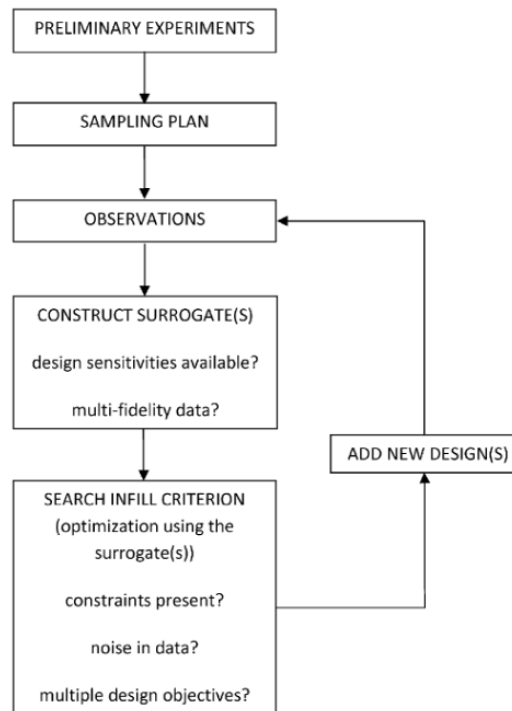


Figure 4.5: Surrogate-based optimization framework as presented in Forrester and Keane, 2009

4.3.1. Initial sampling

So, an initial sampling plan is implemented to give insight into the global design landscape. To do this, a design of experiments is made to gain maximum insight into the data with the given budget (Forrester & Keane, 2009). There are multiple methods recommended in Bhosekar and Ierapetritou, 2018 and Forrester and Keane, 2009:

- Space filling maximin (Pronzato, 2017)

- Latin hypercube sampling(LHS) (Shields & Zhang, 2016)
- Sampling techniques of Morris and Mitchell (Morris MD & Mitchell TJ., 1992)
- Orthogonal sampling
- Full and half factorial design
- Box-Behnken design
- Sobol and Halton sampling

This is not an exhaustive list of sampling strategies, and these sampling strategies also have different variants.

4.3.2. Bayesian optimization

According to Garnett, 2023, Bayesian optimization does not refer to a single algorithm, but to the philosophy that the decisions made by the algorithm are based on probability and Bayesian inference. “This critically includes the objective function itself, which is treated as a random variable to be inferred in light of our prior expectations and any available data.”Garnett, 2023.

In practice, this means that the model has uncertainty components and that the acquisition function is based on this uncertainty. That is why this form of optimization is compatible with the Gaussian process surrogate model, as uncertainty is automatically included.

4.3.3. Acquisition function

To determine what point to sample some policy for where the most improvement can be expected is required. Garnett, 2023 says: “In the Bayesian approach to optimization, policies are designed with reference to a probabilistic belief about the objective function, with this belief guiding the policy in making decisions likely to yield beneficial outcomes”(Garnett, 2023). So, it takes a probabilistic approach to choosing the next point to sample. In this choice a balance between exploitation, the search of points close to the current optimum, and exploration, the search in regions with high uncertainty away from the current maximum, is important. Here, the goal is not to waste resources on non-optimal regions while also not missing the global optimum.

There are many expressions to evaluate the benefit from points; these are known as acquisition functions. The three most commonly used acquisition functions in the literature (Hoffman & Shahriari, 2014) (Gan et al., 2021) are: probability of improvement (PI), expected improvement (EI), and upper or lower confidence bound (UCB) (LCB). Garnett, 2023 mentions several more acquisition functions, but due to the limited available time, these less commonly examined acquisition functions will not be discussed.

Probability of improvement works by calculating the probability that the objective exceeds the current found optimum plus a margin, in case of a maximization problem, and minus the margin, in case of a minimization problem. Using this, the point with the highest probability of improvement can be found. This is the point that should be sampled next. So, the acquisition function is 4.8:

$$\alpha_{pi}(x; \mathcal{D}, \tau) = \Pr(\phi > \tau \mid x, \mathcal{D}) \quad (4.8)$$

Where α_{pi} is the acquisition function, x is the point to sample, $\mathcal{D}$ is the given data, τ is the maximum found currently plus a margin and ϕ is the objective. The margin is an important parameter as a higher margin favors more exploratory behavior, as can be seen in figure 4.6.

Expected improvement uses the following formulation for the acquisition function 4.9:

$$\alpha_{EI}(x; D) = \int \max(\phi - \phi^*, 0) p(\phi \mid x, D) d\phi \quad (4.9)$$

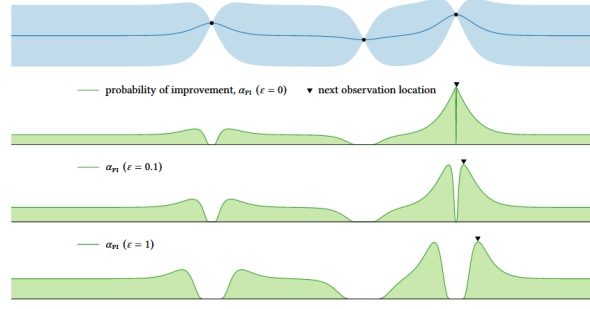


Figure 4.6: probability of improvement Acquisition function with different margins (ϵ) as presented in Garnett, 2023

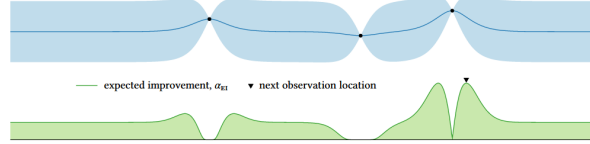


Figure 4.7: Expected improvement acquisition function as presented in Garnett, 2023

So, the integral of the improvement, compared to the current maximum, is weighted by the chance that it occurs. An example can be seen in Figure 4.7.

Upper confidence bound uses the value for which the result lies below it with a confidence π . Where a higher value of π leads to a more exploration-oriented behavior, as can be seen in Figure 4.8.

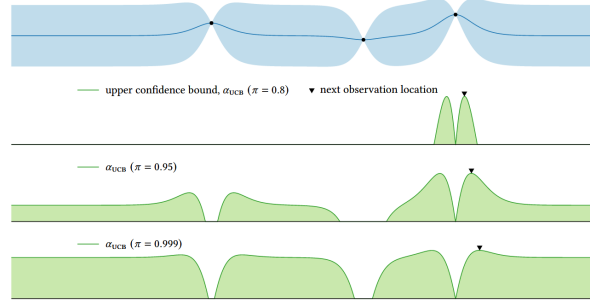


Figure 4.8: Upper confidence bound with different confidence intervals π shifted to the current maximum as presented in Garnett, 2023

The upper confidence bound and lower confidence bound are similar, where the lower confidence bound uses the chance that the value is above instead of below, and it is used for minimization problems instead of maximization problems.

Gan et al., 2021 tested these three methods and concluded that for most cases the expected improvement performed the best.

This is only for sequential sampling; because of parallel computing and the low cost of low-fidelity methods compared to the cost of performing a Gaussian process regression, it may be more efficient to sample multiple points at a time. This is called parallel or batch Bayesian optimization; more information on this can be found in Wang et al., 2023

4.3.4. MF Bayesian optimization

When applying Bayesian optimization in combination with a multi-fidelity Gaussian process, a choice needs to be made on which fidelity to sample. An option is to only sample the target fidelity as in Charisi et al., 2024. This is only viable if the low-fidelity is cheap enough so that it can be sampled in the initial sampling at a sufficient density for the whole design space.

An other option is to have an acquisition function that is able to weigh the gains against cost of the fidelities and select a optimum point and fidelity to sample as described in Section 3.7.2 of Wang et al., 2023 and in Section 11.5 of Garnett, 2023. An example of this can be seen in Figure 4.9 where a cost-adjusted expected improvement of a bi fidelity is presented. In this method, the expected improvement of the high and low fidelity are calculated. The expected improvement for low fidelity is scaled by the relative cost difference between low- and high fidelity. Then the fidelity for which the scaled expected improvement is higher is used.

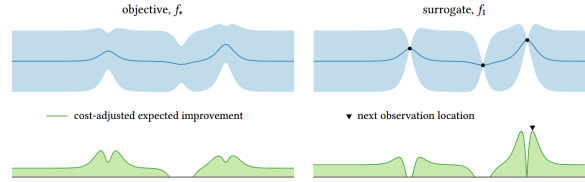


Figure 4.9: Bi-fidelity cost weighted expected improvement as presented in Garnett, 2023

Instead of a cost-weighted acquisition function, Zhou et al., 2017 uses the predicted improvement of a single high-fidelity evaluation and a batch of low-fidelity evaluations with an equal cost to decide the next sample.

Sequential sampling assumes that high- and low-fidelity models compete for the same resources. This may not be the case as it is possible that the high-fidelity model runs on a computer cluster while the low-fidelity model can run on the local computer, or due to diminishing returns in speed with increasing computational resources, it may be more efficient to run two evaluations parallel compared to one with double the resources. Therefore, asynchronous Bayesian optimization can be used as described in Khatamsaz et al., 2024 and Folch et al., 2023. The idea is that these calculations can run in parallel and points can be sampled sequentially in each fidelity. However, the same point should not be evaluated by both fidelities to avoid wasting resources. Folch et al., 2023 proposes three methods: Thompson sampling, fantasies, and local penalization.

Thompson sampling is an acquisition function that takes a random realization from the posterior, which represents one of infinite potential objective functions. Then the maximum of this function is sampled. Because of the random element, it is unlikely that this results in sampling the same point simultaneously, while it is still informed by previous data through the posterior. This acquisition function is also often used to create batches, as the process of creating batches is independent and therefore scales well. A visual representation can be found in figure 4.10.

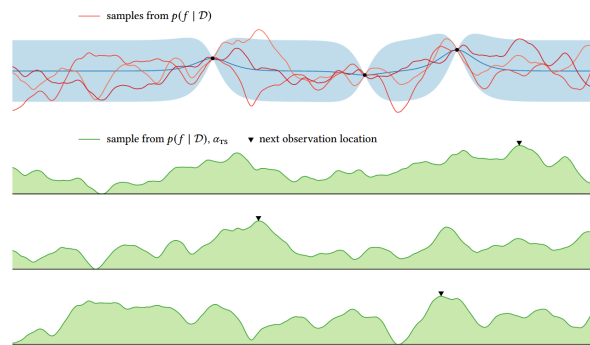


Figure 4.10: Thompson sampling as presented in Garnett, 2023

The fantasies method works by creating fantasy results to account for the simulations that are being performed. An intuitive way to do this is used in Khatamsaz et al., 2024 and discussed in Folch et al., 2023. By creating a result at the point that is currently being calculated with the result being the expected value, Folch et al., 2023 proposes the predictive mean, while Khatamsaz et al., 2024 uses the

predictive mean plus the expected improvement. So, the variance around that point is reduced; therefore, it will not be a good point to sample according to the acquisition function. When the calculation of the objective function is done, this fantasy sample is replaced by the actual sample.

The local penalty method applies a penalty to the acquisition function around the point that is being calculated. So, the acquisition function takes the form 4.10:

$$\tilde{\alpha}(x; D_t, \mathbb{Q}) = g(\alpha(x; D_t)) \prod_{x_{t,q} \in \mathbb{Q}} \psi(x_{t,q}) \quad (4.10)$$

where ψ are the penalty function and g is a transformation to ensure the acquisition function is positive. An example of how an acquisition function looks after the penalty can be found in Figure 4.11

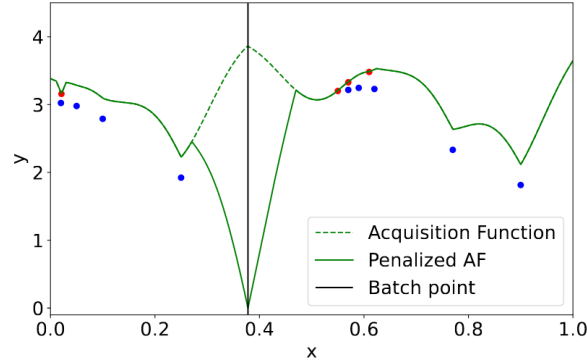


Figure 4.11: Acquisition function with a local penalty function as presented in Folch et al., 2023

4.4. Conclusion

This chapter discussed multi-fidelity Gaussian processes and Bayesian optimization. The conclusion is drawn on how to get the minimum viable algorithm.

To get a working multi fidelity Bayesian optimization algorithm, the minimum viable algorithm based on the information in this chapter is a linear bi fidelity Gaussian process using a squared exponential kernel. For Bayesian optimization, a sequential sampling cost weighted expected improvement acquisition function is deemed to be the best minimum viable option in the case both fidelities are sampled, while a sequential sampling upper confidence bound acquisition function for the target fidelity is the best minimum viable option if the low-fidelity is not sampled. The choice between this is based on the ratio between the cost of the low fidelity and the cost of performing a Bayesian optimization iteration. The initial samples can be collected with the Latin hypercube method.

5

Methodology

This chapter outlines the methodology for assessing if multi fidelity can aid the optimization of a wind-assisted vessel.

Section 5.1 explains the design of experiment. Section 5.2 covers the wind assisted vessel case used to evaluate optimization algorithms. Section 5.3 presents the optimization problem, detailing the objective function, parameters, and constraints. Section 5.3.4 discusses assumptions and simplifications. Section 5.4 focuses on the function and implementation of optimization algorithms. Section 5.5 evaluates objective and constraint functions, including parametric models, computational fluid dynamics, and the empirical methods. Section 5.6 identifies key performance indicators for evaluating the optimization algorithms.

5.1. Experiment setup

This section presents how the data will be gathered and which tests will be presented. Starting with the setup of the benchmark case that is used to assess the performance of the algorithm. Then the approach for the comparison between single fidelity and multi fidelity is presented. Lastly, the approach is presented to determine the impact of better low fidelity models on the performance of the multi fidelity optimization.

5.1.1. Benchmark case setup

Because of the non-deterministic nature of the optimization algorithms multiple optimization runs are needed to accurately assess the performance of the optimization algorithm. Performing the optimization using the actual case, with CFD, is time consuming, thus performing enough optimizations to draw a conclusion about the performance is too expensive. Therefore, a benchmark case is setup that is made using a Gaussian processes interpolation of the data from the actual case. This data originates from an optimization of the actual case and a Latin hypercube sample of the design space. 100 CFD data points are used to create the resistance, side force, and moment function. 200 points are used to create the function for underwater volume and maneuvering constraint.

5.1.2. Experiment 1: Comparison between single and multi fidelity optimization

The first test performed is the comparison between single fidelity optimization and multi fidelity optimization. The results of experiment 1 can be found in Section 8.2 To do this, the approach as seen in Figure 5.1 has been used.

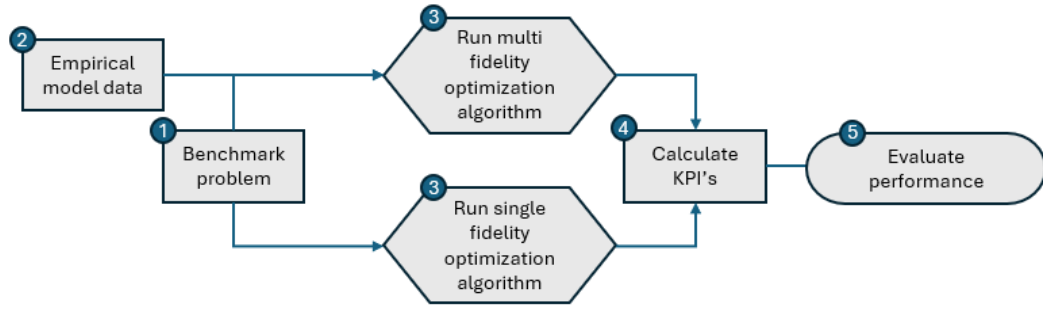


Figure 5.1: Approach of comparison between single and multi fidelity optimization

1. The benchmark problem as described in Section 5.1.1 is used to test the performance of the algorithms.
2. The empirical model is used to create data points to use in the multi fidelity optimization.
3. Running the optimizations. Both the single- and multi fidelity optimization algorithms are used to optimize the benchmark case. This optimization case is performed 10 times with each algorithm to make sure that the results are representative of the average performance. The algorithms are discussed in Section 5.4
4. For each optimization performed the key performance indicators (KPI's) are calculated. The KPI's that were used can be found in Section 5.6
5. Performance is evaluated using the KPI's

5.1.3. Experiment 2: Improved low fidelity models

The second test that was run was to see to what extent the performance of the multi fidelity is limited by accuracy of the low fidelity. To do this, low fidelities that were better correlated with the high fidelities were created by taking a weighted average between the empirical results and the test problem to see to what extent the performance improves. This is done using the approach as seen in Figure 5.2.

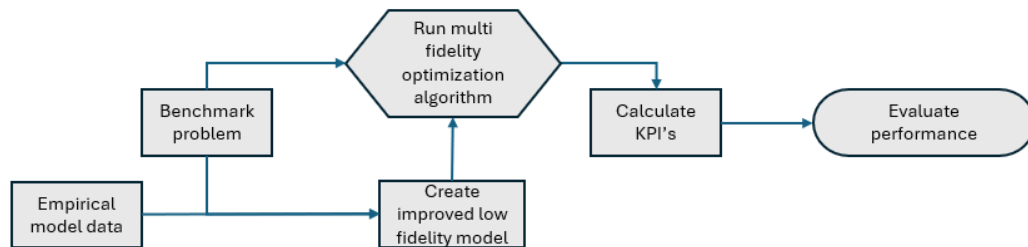


Figure 5.2: Approach of investigation into the influence of better low fidelity models

The approach is similar to the first test presented in Subsection 5.1.2. Instead of using the data from the empirical method directly as the low fidelity, a weighted average between the surrogate of the CFD and the empirical data is used. The formula used to calculate the weighted average is given in Equation 5.1.

$$\text{New low fidelity} = (1 - x) * \text{Old low fidelity} + x * \text{Surrogate of CFD result} \quad (5.1)$$

In this equation x represents the fraction of high fidelity information in the new low fidelity. So, a higher x leads to data closer to the surrogate of the CFD. The values used for x are 0.25, 0.5, and 0.75.

5.2. Wind assisted case study

This section presents the case study which is a representative optimization problem. So, the results on performance of the optimization algorithm are applicable to real world wind-assisted vessel optimization.

To achieve this objective, a case study was conducted on a 100 meter long general cargo vessel. The other principal dimensions were determined by examining existing wind-assisted vessels currently in operation. This was done by looking at all currently in service wind assisted vessels between 85 and 115 meters. This results in a list of 8 vessels. These vessels have a length-to-width ratio between 7.2 and 5.8 and a length-to-draft ratio between 20.7 and 13.7. The vessel that was chosen to base the main dimensions on is the Odda Marie, which is a multi purpose cargo vessel of 100.15 meters long 15.3 meters wide and a draft of 5.47 meters. During the creation of the hull shape, the dimensions were slightly altered. Increasing the width to 16 meters and reducing the draft to 5.3 meters. The Odda Marie has a given design speed of 15 knots which is about 7.7 m/s, which has been taken as the design speed for this case. The dimensions can be found in Table 5.1.

	unit	value
Length	<i>m</i>	100
Width	<i>m</i>	16
Draft	<i>m</i>	5.3
Block coefficient	—	0.666
Displacement	<i>m</i> ³	5650
Speed	<i>m/s</i>	7.7

Table 5.1: Main parameters for the wind assisted case study

This case considers a wind speed of 7 *m/s*, the most commonly encountered by vessels according to IMO, 2021. Due to the speed of the vessel and apparent wind speed, apparent wind angles greater than 66 degrees from the bow are not possible. Low apparent wind angles from the bow will result in low thrust and extra resistance, so Flettner rotors would not be activated in such a scenario. If the apparent wind angle approaches 66 degrees, the apparent wind speeds become very low. Therefore, an apparent wind angle between these scenarios is the best for the case study. A case with a 45-degree apparent wind angle from the bow was considered. This results in an apparent wind speed of 9.8 *m/s*. The choice was made to include two 24-meter high Flettner rotors with a diameter of 4 meters as offered by Norsepower, n.d. as shown in Figure 5.3. This is more wind assistance than what is currently installed in comparative wind assisted vessels. However, of the eight comparative vessels, only three have the wind assist device installed at the start.

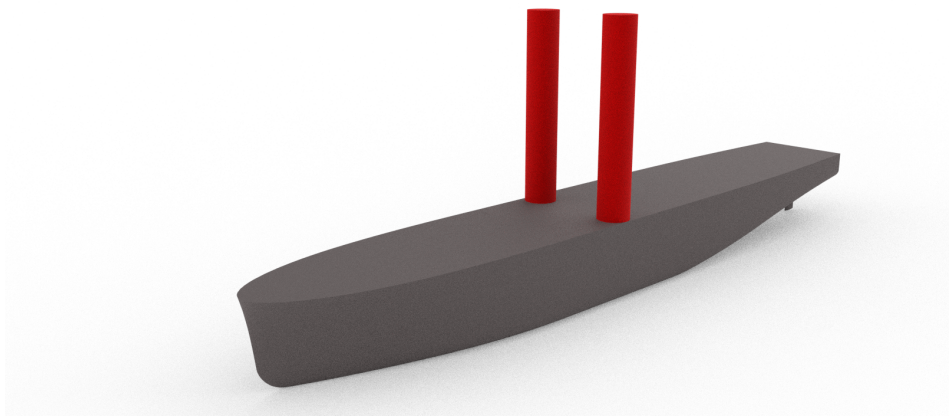


Figure 5.3: Vessel with Flettner rotors

The side force can be calculated with a lift coefficient of 10 and a drag coefficient of 3 as given in

Berendschot, 2019, which gives a calculated side force of 101.5 kN and a thrust of 54.7 kN. The side force is rounded to 100 kN for this case study. Propulsion is excluded in this optimization, making thrust irrelevant for the study.

5.3. Problem formulation

This section formulates the optimization problem, covering the objective function in Subsection 5.3.1, parameters in Subsection 5.3.2, constraints in subsection 5.3.3, and assumptions and simplifications in subsection 5.3.4. Lastly, in Subsection 5.3.5 the complete optimization formulation is given.

5.3.1. Objective function

The objective is to minimize the resistance F_X of the wind assisted vessel hull at service speed.

$$\text{minimize } F_X(x_0, x_1, x_2, x_3, x_4, x_5, x_6) \quad (5.2)$$

5.3.2. Design parameters

The design parameters and their range are:

- x_0 - Bilge radius $0.5 < x < 1.5$ meters
- x_1 - Parallel midship length $1 < x < 25$ meters
- x_2 - Parallel midship position $-10 < x < 5$ meters
- x_3 - Rudder length $1 < x < 4$ meters
- x_4 - Flettner rotor position from center $-50 < x < 50$ meter
- x_5 - Rudder angle $0 < x < 20$ degrees
- x_6 - Leeway angle $0 < x < 10$ degrees

A visual representation of the parameters can be found in Figures 5.4 and 5.5.

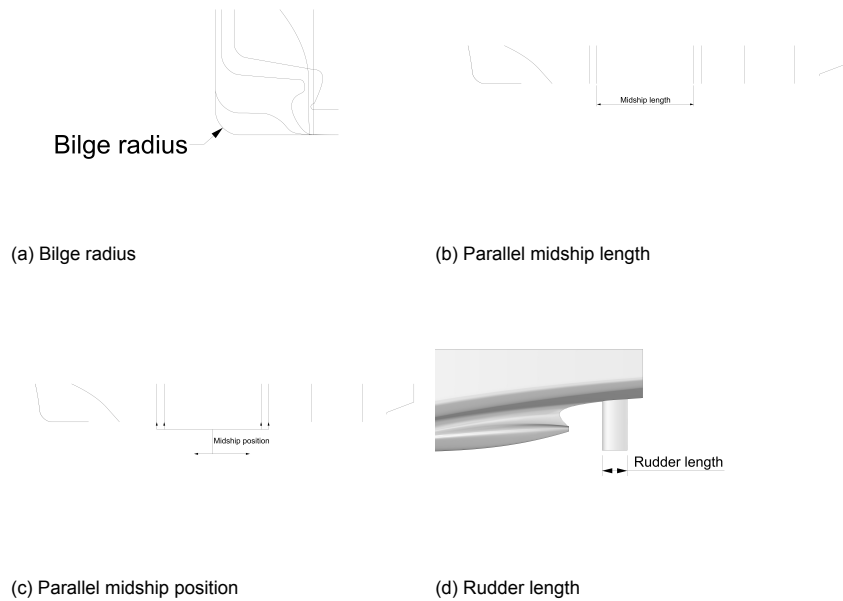


Figure 5.4: Parameters

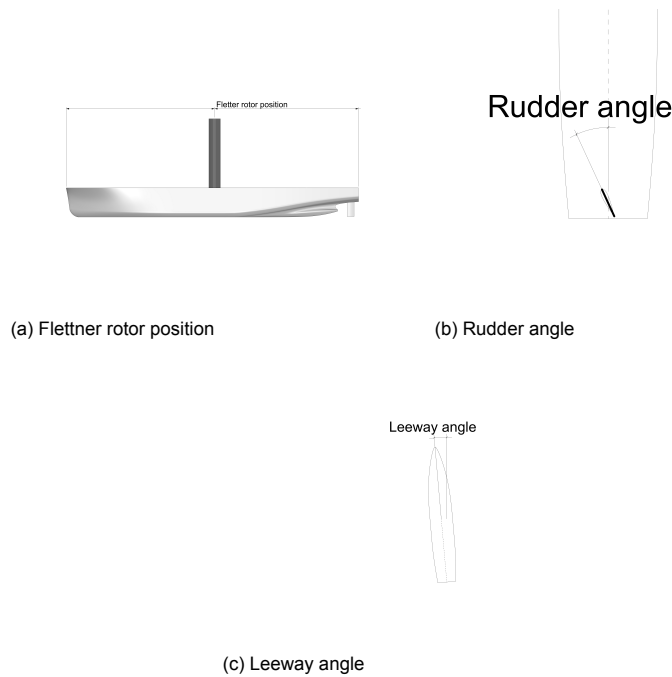


Figure 5.5: Parameters

The bilge ratio has a large impact on the side force as discussed in Chapter 2. It also has a large impact on the underwater volume. The length of the midship also has a large impact on the underwater volume. The position of the midship is expected to change the center of lift of the hull and thereby the moment. The length of the rudder has a large impact on the moment and the side force. In addition, a longer rudder increases friction resistance and reduces the lift efficiency of the rudder, due to the reduced aspect ratio. The position of the wind assist device has a large impact on the moment. The leeway angle and the rudder angle are vital parameters to be able to achieve a force and moment balance.

The variables are all normalized with equation 5.3, so their range is 0 to 1 so the parameters can be defined displayed in equation 5.4

$$x_{norm} = (x - \text{lower bound}) / (\text{upper bound} - \text{lower bound}) \quad (5.3)$$

$$0 \leq (x_0, x_1, x_2, x_3, x_4, x_5, x_6) \leq 1 \quad (5.4)$$

5.3.3. Constraints

This optimization considers four constraints.

- Underwater volume $\nabla = 5650m^3$
- Maneuvering constraint $> 5000 \text{ kNm}$
- Side force hull = side force Flettner rotor = 100 kN
- Moment = 0 kNm

The displacement is derived directly from the parametric model as described in Section 5.5.1. The maneuvering constraint is the excess moment that can be created to turn, computed using the empirical model as detailed in Subsection 5.5.3. The side force and moment are computed using CFD. For the multi fidelity algorithm side force and moment from the empirical model are also used.

As constraints are predicted using the surrogate model before evaluation, some errors are expected. To avoid the numerous evaluations needed to get the prediction error to zero, an error margin is added

in which the results are deemed acceptable.

$$\begin{aligned} \nabla &= 5650m^3 \pm 1m^3 \\ \text{Side force hull} &= 100kN \pm 1kN \\ \text{Moment} &= \pm 100kNm \text{ measured in relation to the center of the vessel} \end{aligned} \quad (5.5)$$

5.3.4. Assumptions and simplifications

To complete the optimization, some assumptions and simplifications have been made which are:

- The vessel has no roll or pitch angle
- The force of the wind acts only on the Flettner rotor
- No propeller is considered in this optimization

5.3.5. Full optimization description

Combining all parts give the total optimization problem in Equation 5.6.

$$\begin{aligned} &\text{minimize } Fx(x_0, x_1, x_2, x_3, x_4, x_5, x_6) \\ &\text{subject to:} \\ &0 \leq (x_0, x_1, x_2, x_3, x_4, x_5, x_6) \leq 1, \\ &Fy(x_0, \dots, x_6) - 100kN = 0, \\ &Nz(x_0, \dots, x_6) = 0, \\ &\nabla(x_0, x_1, x_2) - 5650 = 0, \\ &MCon(x_0, \dots, x_6) > 0. \end{aligned} \quad (5.6)$$

5.4. Optimization algorithm

This section introduces the optimization algorithm, starting with a flow chart 5.6, according to which the optimization process was setup, followed by a detailed explanation of each part.

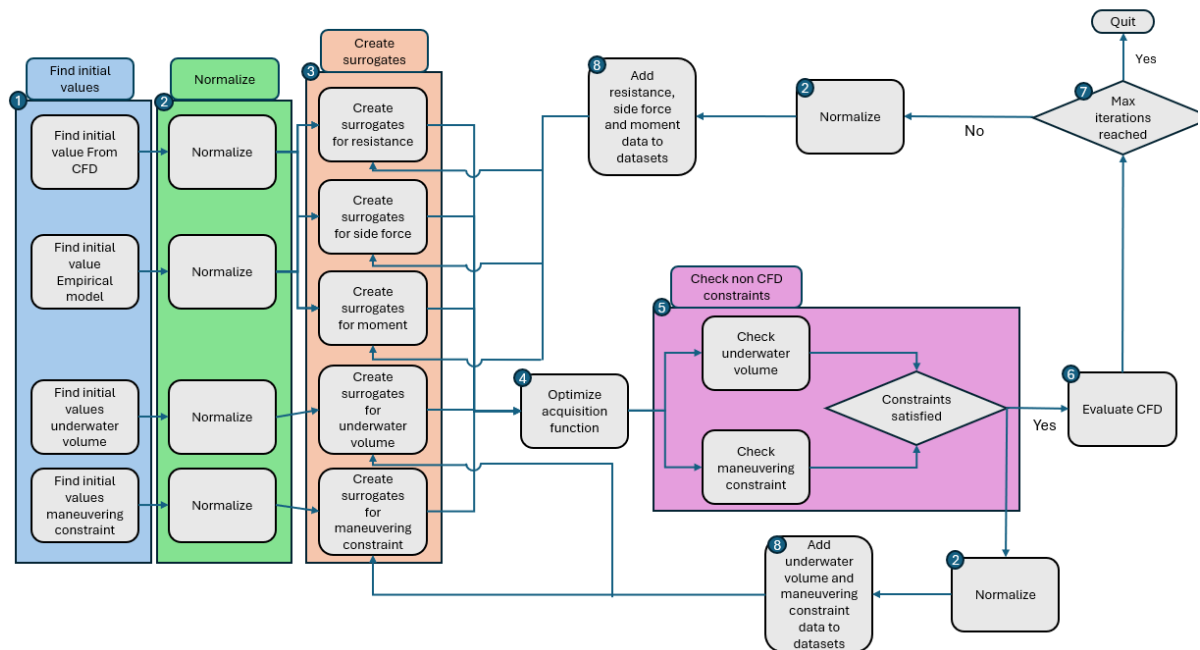


Figure 5.6: Optimization strategy

1. Find initial values

Initial values are required to create the first surrogates. This data can be split into two categories. The first category is the relatively inexpensive data, which is calculated with the parametric model and the empirical model as described in Subsection 5.5.1 and Subsection 5.5.3. These are the displacement, the maneuvering constraint, and the low fidelity resistance, side force, and moment. These take on the order of tens of seconds to calculate. The second category is the relatively expensive data, which is computed with CFD. These are the high fidelity resistance, side force, and moment. In this case this takes about 45 minutes on a cluster with 120 cores.

For the inexpensive data the choice was made to generate a large portion of the points early on for three reasons:

- Batching calculations saves time by avoiding repeated startup and shutdown of the CAD program Rhino between calculations. Therefore, generating large samples at once is more efficient than sampling individual points.
- Optimizing the acquisition function to find the best sampling position is time-consuming compared to sampling inexpensive data. If the chosen position is not viable due to an inaccuracy in the surrogate model, this effort is wasted. Therefore, adding more initial points can save time in the overall process.
- Evaluating the constraints takes too long for direct use in acquisition function optimization.

Therefore, 200 data points for these relatively inexpensive were sampled using the Latin hypercube method described in Shields and Zhang, 2016. Increasing the number of points would slow down the generation of the surrogate model, making the creation time significant compared to the evaluation time of the function. To perform Latin hypercube sampling, the Latin hypercube module from Emukit Paleyes et al., 2023 has been used.

For the expensive data one initial point is sampled of two reasons:

- Sampling without constraints places costly data in infeasible regions, offering little added value in finding the optimum.
- Comparing single and multi-fidelity optimization approaches requires examining behavior with limited high-fidelity data.

2. Normalization

All values are normalized. The goal is to get the objective and inequality constraints between 0 and 1 and the equality constraint between -1 and 1. To do this Equation 5.7 is used.

$$X_{norm} = (X - \text{expected value}) / \text{expected range} \quad (5.7)$$

For the objective function the expected value and range are estimated by looking at a sample of the empirical results. For the equality constraints the expected value is the constraint value. For maneuvering inequality constraint is the lower limit was used. For the side force and moment constraints the range is also estimated using the empirical model. For the maneuvering underwater volume constraints initial values have been used to estimate the range. This gives the following normalizations:

- Resistance normalized = $(F_x - 200kN) / 50kN$
- Underwater volume ∇ normalized = $(\nabla - 5650) / 200$
- Maneuvering constraint normalized = $(\text{Maneuvering constraint} - 5000kNm) / 2000kNm$
- Side force hull normalized = $(\text{Side force hull} - 100kN) / 1000kN$
- Moment normalized = $\text{Moment} / 50000kNm$

3. Create surrogate

Using the available data, from the initial sample and any subsequent iterations, the surrogate models are constructed. In total 5 surrogates are constructed:

- Objective function, representing the resistance
- Side force
- Moment
- Displacement
- Maneuvering constraint

In the multi fidelity implementation, the objective function, side force, and moment use multi fidelity surrogates, whereas displacement and maneuvering constraints use single fidelity surrogates due to lack of multi fidelity data.

Gaussian process regression, implemented using the GPy, 2012 Python package, is used to construct surrogate models. For the single-fidelity surrogates, the squared exponential kernel is used. Kernels are optimized in every iteration when creating surrogate models. The kernel length factor is optimized, but the variance is held constant to prevent altering the surrogate's variance. As this would complicate setting up the acquisition function by making it difficult to balance exploitation and exploration.

For the multi-fidelity surrogates the linear auto regressive scheme was used as described in Section 4.2.3. This was done using the linear multi-fidelity module from the Emukit (Paley et al., 2023) Python package. For both the low fidelity and high fidelity part the squared exponential kernels were used. In the first iteration, both the low-fidelity and high-fidelity length scales are optimized, but in subsequent iterations, only the high-fidelity kernel is optimized since the low-fidelity data remains unchanged.

4. Optimize acquisition function

The acquisition function quantifies the sampling utility of a point. This can be used to determine what point should be sampled next. As discussed in section 4.3.3 there are multiple acquisition functions. The lower confidence bound method was used. This takes the mean value minus a number, referred to as Beta, of standard deviations as explained in 4.3.3. Where more standard deviations leads to more exploratory behavior. In this case a beta of 3 was used, as this gave a good balance between exploration and exploitation.

The lower confidence bound method was preferred over the expected improvement and probability of improvement methods, because these methods compare new points with the best point previously found. If there are no viable points yet, such comparisons result in inaccurate acquisition function results. As this case starts outside the viable region, the first iterations are not expected to be viable.

To determine the next sampling point, the lowest lower confidence bound value must be identified, which is a minimization problem with the same parameter space and constraints as the full optimization. These constraints are represented by the created surrogates. The evaluation of the objective and constraints is inexpensive, and gradient data is available, enabling gradient-based optimization algorithms. For this purpose the trust region constraint local optimizer “SciPy documentation — SciPy v1.15.3 Manual”, n.d. was chosen. As it is expected that there will be local minima, multiple starting points are used. These starting points are chosen with the Latin hypercube sampling.

5. Check constraints

This step is skipped in the testing of the algorithm, because a surrogate of the constraints is used that relies on the same values as the initial values. This means the surrogate used for the optimization of the acquisition function is the same as the one the value would be tested against. As this part does not differ between the single and multi fidelity implementations this will have no impact on the results.

When considering an actual optimization problem this simplification can not be used. Therefore, before evaluating the costly CFD model, displacement and maneuvering constraints are checked to make sure the surrogate used to estimate these constraints were accurate. The new data is normalized and added too the dataset. If it is found that the point is not feasible the loop is set back to the creation of surrogates with the updated data sets. If both constraints are satisfied the CFD model is evaluated.

6. *Evaluate CFD model*

The CFD model is evaluated to find out what the resistance, side force and moment are. How this is done is described in 5.5.2. However in the testing the value is obtained for the surrogate of the CFD.

7. *Stopping*

If the maximum number of iterations has has been reached the optimization process is terminated. The maximum number of iterations will be determined by running one multi and one single fidelity optimization until the optimum is found. With this the required iterations can be estimated. A margin of 5 iterations is added to this. All further evaluations will be run to that number of iterations.

8. *Add data to datasets*

The acquired data is added to the datasets. If either the maneuvering or displacement constraint failed only these two values are added to the data sets. This means that only these surrogates have to be updated. If the CFD or surrogate of the CFD is evaluated the resistance, side force, moment, underwater volume, and maneuvering constraint values are added to the data sets.

5.5. Model evaluation

This section describes the method for evaluating objectives and constraints. Subsection 5.5.1 introduces the parametric model, which generates the geometry and values for the other models and gives the displacement constraint. Subsection 5.5.2 covers the computational fluid dynamics (CFD) setup, addressing high-fidelity objectives and constraints on side force and moment. Subsection 5.5.3 explains the empirical model for low-fidelity objectives, constraints on side force and moment, and the maneuvering constraint.

5.5.1. Parametric model

There are three requirements for the parametric hull:

- The model provides inputs for the different evaluation models. The CFD needs CAD geometry, while the empirical model requires hydrostatic coefficients and data, so these data types must be extracted.
- The model must represent a realistic cargo vessel, so low-fidelity models are applicable to give a realistic optimization problem.
- The model must be robust, capable of running unsupervised without crashing. It should provide outputs for all combinations of input parameters.

The choice was made to make the parametric hull in the Rhino CAD program using loft curves and to modify it by using Rhino scriptsyntax in Python. This combination of programs was chosen because there was an existing framework that used these programs. Using this combination, the existing framework could be adapted instead of having to start from scratch. This ensures that the method is robust, as it has been extensively tested by previous users. The existing framework included parametric hull transformation, limited hydrostatic data collection, and export, so the geometry can be used in CFD. New features include a rudder, incorporation of leeway angle, conversion from a half-ship to a full-ship model, and collection of additional data for the empirical model. In addition, a base geometry that can be transformed is needed, the transformations need to be specified as well as the relation between the parameters and the transformations need to be specified.

The parametric model uses hull lines as the basis for the geometry, requiring a number of curves to be specified and lofted to form the ship's hull. These curves are defined by a set of points; by moving

these points, the shape and position of the curve can be changed. There are three parameters that are incorporated in this way.

- Bilge radius
- Length of the parallel midship
- Lengthwise position of the parallel midship

Three transformations are needed to set these parameters. The absolute movement of the front of the parallel midship, the absolute movement of the back of the parallel midship, and the scaling of the bilge radius.

To add the rudder, the coordinates that define a NACA 0015 profile, as recommended in J. Liu and Hekkenberg, 2016, are scaled and translated to the right place. The z position of the bottom point is the margin that is needed under the rudder in relation to the bottom of the vessel, the top is placed just below the deck height. A closed third degree curve is made through the points. And a loft surface is made between the curves and closed. This rudder is rotated around one third of the length of the cord from the front. Then the rudder is cut off from the hull surface and attached to the hull. This is not realistic, as the rudder conforms perfectly to the hull. In reality, a gap will occur between the rudder and the hull. However, the choice was made to keep it like this as a small gap may introduce instability in the CFD due to meshing.

5.5.2. Computational fluid dynamics

The CFD, which acts as high fidelity in this case, has a few requirements. Firstly, it should include all relevant physics that are present in the real world case, so the case is representative of an engineering optimization problem. Secondly, the required time should be limited as much as possible to be able to collect as many data points as possible. The goal of this thesis is to find out what the added value of multi fidelity modeling is for the optimization of a wind assisted vessel. For this, having a small error with the real world in the resistance calculation is not a priority, while a faster CFD allows for more evaluations, which is more useful for answering the research question.

Implementation

For this case, the STAR CCM+ program was used. In this section the implementation of CFD is explained. Firstly, the new hull geometry needs to be imported. To achieve this, the macro that controls the simulation replaces the default hull object with the hull created with the parametric model. This macro will then start the meshing process, submit the simulation to the cluster, and write the results to a file that can then be read by the optimization code. For the mesh a Cartesian grid has been used. With 200 cells along the length of the vessel, meaning a size of 0.5 meters. The maximum cell size is 8 meters. Five refinement regions have been added to add more detail in the important regions. Three have been added to refine the Kelvin wake as can be seen in figure 5.7. The larger ones are scaled versions of the base and are scaled 15% and 30% in the x and y direction. The other two refinement regions are applied to the free surface to capture the waves. In the free surface refinement regions the z -direction of the cells is reduced as can be seen in figure 5.8.

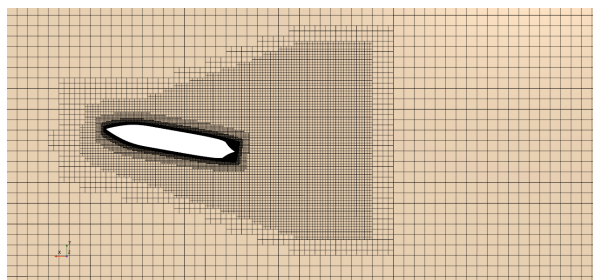


Figure 5.7: Horizontal mesh slice

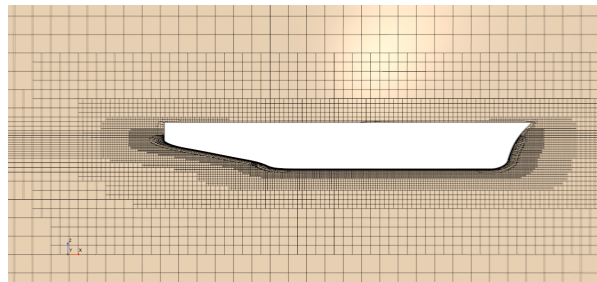


Figure 5.8: Vertical mesh slice

For the boundary layer, the desired y^+ value was 200, which is the upper end of the usable range of y^+ values. This reduces the number of cells to decrease the calculation time. To achieve this, the height of the first layer of the first prism layer was set at 0.0001 meters, with a total height of the prism layer of 0.9 meters which is made up of 18 layers as can be seen in figure 5.9. This means that the number of cells in the boundary layer is limited. This reduces the accuracy of the frictional resistance but speeds up the calculation. As frictional resistance is not expected to vary much between designs, this compromise between speed and accuracy is deemed acceptable.

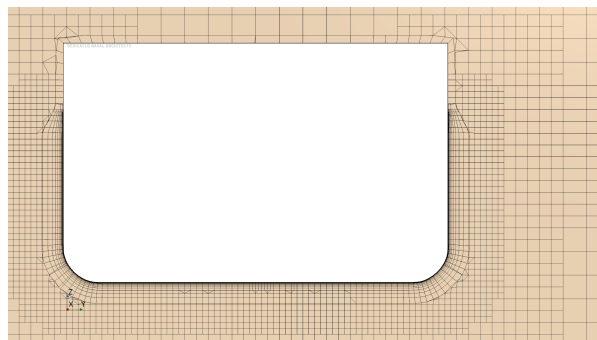


Figure 5.9: Vertical mesh slice

An unsteady solver was used with a total simulated time of 140 seconds. Of which the first 30 seconds is the ramp up time in which the speed increases from zero to the set value. Output values are averaged over the last 30 seconds to average out fluctuations. A time step of 0.05 seconds was used. With a minimum cell size of 0.5 meters and a speed of 7.7 m/s gives a CFL number of 0.77. For modeling the two-phase flow, the volume of fluid (VOF) method has been used.

5.5.3. Empirical method

The requirements for the empirical model are that it should be able to make distinction between designs, get quick results compared to CFD, and give the same outputs as the CFD so they can be used in the multi-fidelity optimization model. In this case, that means resistance, side force, and moment.

The empirical mode has been derived from Berendschot, 2019. From this, the implementation of Holtrop and Mennen, 1982 for calm water resistance has been used. Furthermore, the implementation of Kang and Hasegawa, 2007 for the prediction of the forces on the hull due to the leeway angle. Lastly, the code for the rudder forces based on Molland, 2011 and Kijima, Nakiri, and Furukawa, 1990 has been adopted. These implementations have been slightly altered by changing the inputs. This means that the input can be derived directly from the CAD model instead of using empirical estimations. This is done because this will increase the responsiveness to changes in the hull shape and therefore is expected to increase correlation with CFD. This means that the CAD geometry needs to be generated for each evaluation. This significantly slows down the model. The CAD derived values per sub model are included in table 5.2.

Variable	Holtrop and Mennen	Kang and Hasagawa	Rudder
∇	x		
Block coefficient	x	x	x
LCB	x	x	x
Prismatic coefficient	x	x	x
Wetted area hull	x		
Midship coefficient	x	x	x
Water plane coefficient	x		
Wetted area transom	x		
Wetted area rudder	x		
Block coefficient aft		x	x
Prismatic coefficient aft		x	x
Water plane coefficient aft		x	x
Rudder height			x

Table 5.2: CAD derived variables in the empirical models

Maneuvering constraint

The maneuvering constraint is based on the low fidelity model. This was done because this reduces the evaluation cost. This reduces the number of CFD evaluations that need to be performed. This will result in a less accurate measure of maneuverability. However, as the primary goal of this thesis is the evaluation of multi fidelity modeling in an optimization algorithm, the choice was made to use the empirical method to save time.

To calculate the maneuvering constraint, the following steps are executed.

1. The generation of the hull in CAD and the collection of the data for the low fidelity model as described in Section 5.5.3.
2. Set the straight ahead configuration to ensure that the moment and the side force are equal to zero. This is done with the use of a local optimizer. Although these are also equality constraints in the optimization, it can not be assumed that the configuration provided satisfies these constraints in the empirical method due to differences between the cfd and empirical method.
3. Find the rudder deflection with the maximum lift. As a stall angle is not implemented in the empirical method, the stall angle of the NACA 0015 profile was used. This is the stall angle for a 2D section. The effects of a finite wing and the wake of the hull are negated. For the NACA 0015 airfoil section the stall angle is 20 degrees. A deflection of the rudder must be found with an inflow angle of 20 degrees. This is done using a local optimizer.
4. The generated moment is calculated with the found deflection of the rudder. It is assumed that the Flettner rotors keep producing maximum lift for this case. The calculated moment is the maximum moment that can be generated to turn away from the wind.

The limit was determined by calculating the moment generated by a possible emergency turn in straight line sailing with a 10 degree rudder deflection with a 2 meter long rudder. This generates $5180kNm$ according to the empirical method. This was rounded to $5000kNm$ as the minimum.

5.6. Key performance indicators

This section presents performance indicators, explains their calculation, and discusses their relevance. To compare performance of the optimization algorithms for experiment one and two indicators are required. These are:

1. Number of iterations until the optimum is reached. This is the most important metric, as it decides how many iterations should be set to complete the optimization. This directly influences the time required and the amount of CFD evaluation. To calculate this metric, the minimum found at the

end of the optimization tests is taken and a small margin of 0.05% is added to compensate for small deviations in the solution. The number of iterations until the objective function reaches this threshold is the metric. So, a lower value is better.

2. Logarithmic plot of the simple regret of the objective function as given in Garnett, 2023. This can be calculated by subtracting the minimum found up until that iteration that satisfies all constraints, as can be seen in the equation 5.8.

$$r_t^{sim} = \min_{i=0}^t f(\mathbf{x}_i) - f(\mathbf{x}^*) \quad (5.8)$$

where $f(\mathbf{x})$ is the objective function t is the iteration and $\mathbf{x}^*$ is the global optimum. This is then plotted on a logarithmic scale, so that the convergence can be seen in all stages of optimization. This can be used to see how quickly the optimization converges.

3. A logarithmic plot of the absolute deviation from the side force and moment constraints. Because the constraints are normalized, so the equality constraint is at 0 the absolute value of the normalized constraint can be used. By plotting this on a logarithmic scale, the prediction error of the constraint models can be seen. As the side force and moment are approximated with either a single or a multi fidelity model the difference in performance can be observed.
4. A logarithmic plot of the absolute prediction error of the resistance. This is calculated by taking the absolute difference between the predicted resistance and the observed resistance. This gives the predictive accuracy of the surrogate model for resistance. This can be used to compare the predictive accuracy of the single- and multi fidelity surrogate models.

In Chapter 6 the methods described in this chapter are verified. In Chapter 7 the low and high fidelity evaluation methods are compared to check if the low fidelity can be used on its own. In Chapter 8 the results of the KPIs discussed above are presented. Lastly, in Chapter 9 the discussion and conclusion is presented.

6

Verification

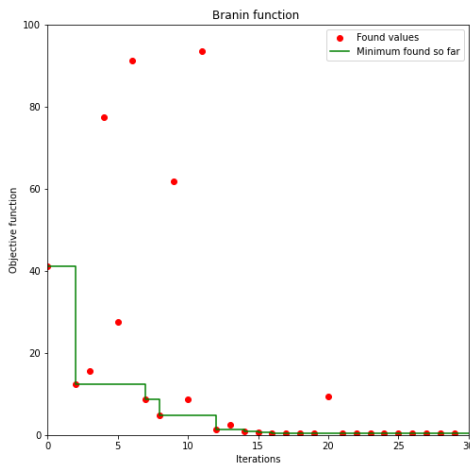
In this chapter the verification steps are explained starting with the optimization algorithm in Section 6.1. Then the parametric model is discussed in Section 6.2. In Section 6.3 the CFD is verified. Lastly, the empirical method is verified in Section 6.4.

6.1. Optimization algorithm

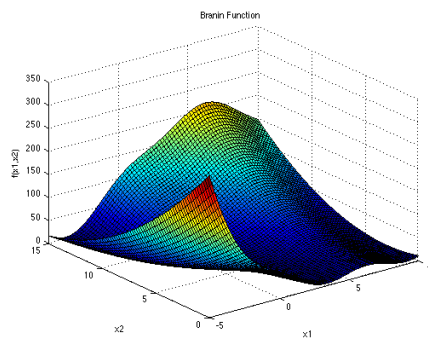
To verify that the optimization algorithm works as intended, a simple test function is used with a known optimum. This should confirm that an optimum can be found. To confirm the effectiveness of the optimization algorithm in finding the minimum of a function, it was tested on the Branin-Hoo function, which can be found in equation 6.1 (“Branin Function”, n.d.).

$$f(\mathbf{x}) = a(x_2 - bx_1^2 + cx_1 - r)^2 + s(1 - t) \cos(x_1) + s \quad (6.1)$$

This is a 2 dimensional test function with three minima at 0.397887 as can be seen in Figure 6.1b. The single fidelity has been tested on this to make sure it functions correctly. By verifying the single fidelity the multi fidelity can also be verified as the results of the single fidelity can be compared with the results of the multi fidelity to verify the same minima were found. The minimum found in 30 iterations by the single fidelity optimization algorithm is 0.39791 as can be seen in Figure 6.1a. This is deemed close enough to the actual optimum to verify that it can find the minimum.



(a) Found values during the optimization of the Branin function



(b) Branin function “Branin Function”, n.d.

6.2. Parametric model

To verify that the parametric model functions correctly, two things need to be verified:

1. For all combinations of parameters, a viable hull should be created.
2. The underwater volume calculation is correct.

To verify that the parametric hull is robust and can create hulls for all combinations of parameters, the hulls at the extremes of the bounds are generated. These have been chosen because on the bounds the chance of failure is the highest as these represent the point where the lines that define the hull come closest, which increases the chance of failure. These hulls are visually inspected to ensure that they look as expected. A random sample of the resulting hulls is shown in Figure 6.2

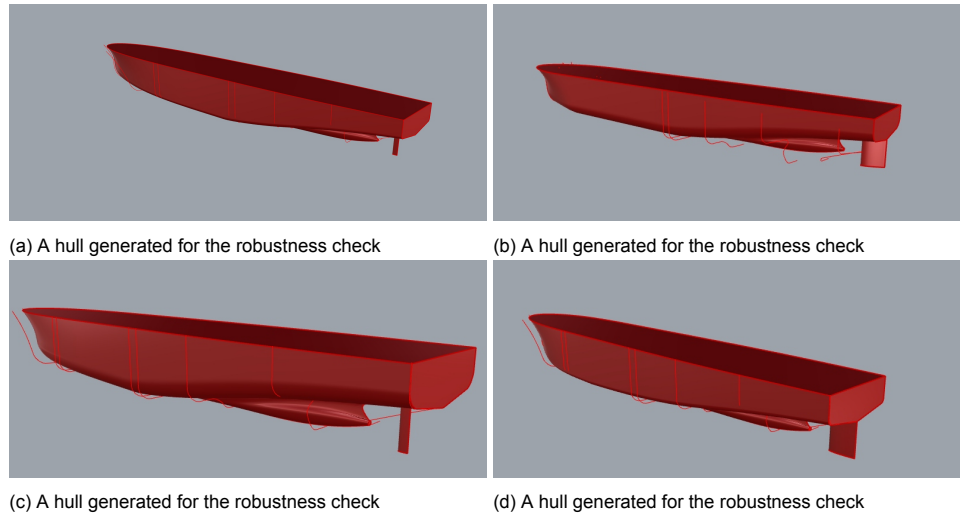


Figure 6.2: A selection of vessel that was generated to verify the robustness of the parametric model

To verify the calculation of the underwater volume two steps are taken. First, it is verified that the range is correct by calculating the block coefficient (C_b) with equation 6.2 to verify that the range is correct. The expected range for a general cargo vessel is between 0.55 and 0.75 (van Dokkum, 2016). The given underwater volume found by the parametric model is $5650m^3$. So, the block coefficient is 0.666 as calculated in equation 6.3, so the range is correct.

$$C_b = \nabla / (Length * Width * Draft) \quad (6.2)$$

$$5650 / (100 * 16 * 5.3) = 0.666 \quad (6.3)$$

Secondly, the change in displacement as a result of the bilge radius and midship length are evaluated to verify that the change in underwater volume follows the expected trend. The underwater value has been calculated at the minimum and maximum values for the bilge radius and midship length while keeping all other parameters constant. The results are presented in Table 6.1

Parameter	Expected effect	∇ at minimum [m^3]	∇ at maximum [m^3]	Verified
Bilge radius	Larger bilge radius leads to lower ∇	5675.2	5382.5	Yes
Midship length	Larger midship length leads to higher ∇	5374.2	5736.7	Yes

Table 6.1: Verification of the underwater volume in the parametric model

6.3. Computational fluid dynamics

To ensure that the CFD functions correctly a three step verification approach is used.

1. The first step is to verify that the STAR CCM+ software can correctly predict vessel resistance. This is done by looking at the validation cases of STAR CCM + presented in literature. Sarker and Tarafder, 2024 performed CFD calculations on three different hulls to validate the accuracy and concluded that STAR CCM+ can be used for for early stage design and hull form optimization.

2. The second step is to perform a grid convergence study of the used grid. This was done with the Eça and Hoekstra, 2014 method. For this, three geometrically similar grids were created with different numbers of cells with a mesh scaling factor between the grids of $\sqrt{2}$. A CFD calculation was run with each of these grids. The results in terms of resistance, side force, and moment were used to estimate the uncertainty of the roughest grid. This was done with the code by Marin ("Verification Tools", 2024). The resulting plots with the discretization uncertainty are shown in Figure 6.3

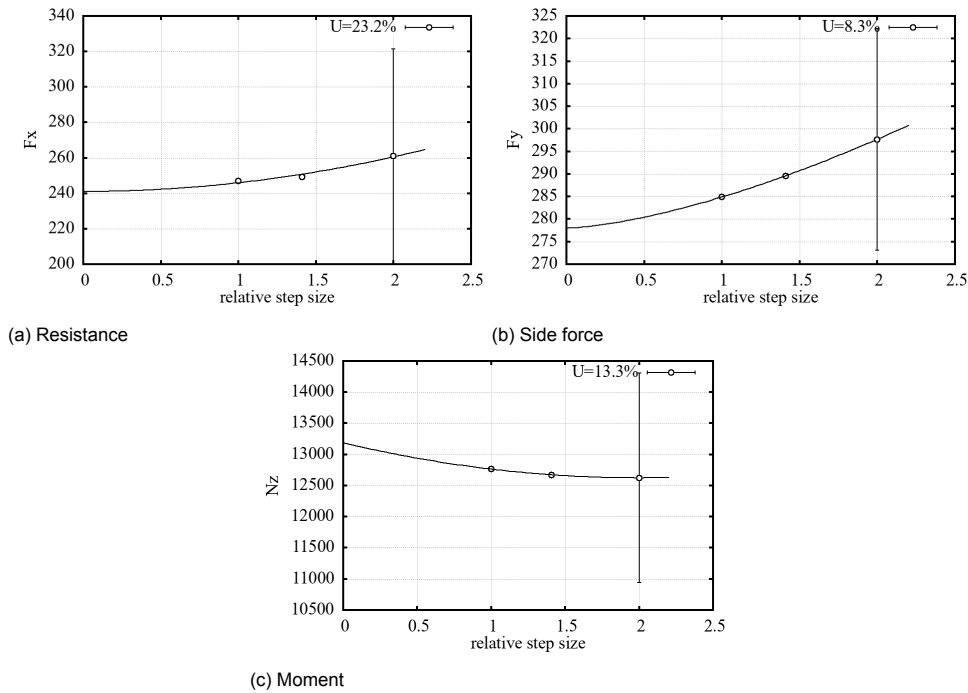


Figure 6.3: Uncertainty due to the discretization error for CFD according to the Eça and Hoekstra, 2014 method

As can be seen the uncertainty of the course grid is high. This means that the grid introduces an error, meaning the result changes if the grid is refined. This means that the results are not an accurate representation of the actual resistance of a vessel. However the choice was made to use this grid because of the lower calculation time while still providing a representative objective and constraint space. The reduced calculation time also means that more data points can be collected. This allows a better fit when creating the surrogate model that will be used to test the optimization algorithms. Which is deemed be more important than a very accurate resistance calculation in the creation of the optimization test problem.

3. The third step is to look at the results to ensure that the results behave physically and that used settings are correct.

- The first verification of the result is to look at the wave pattern.

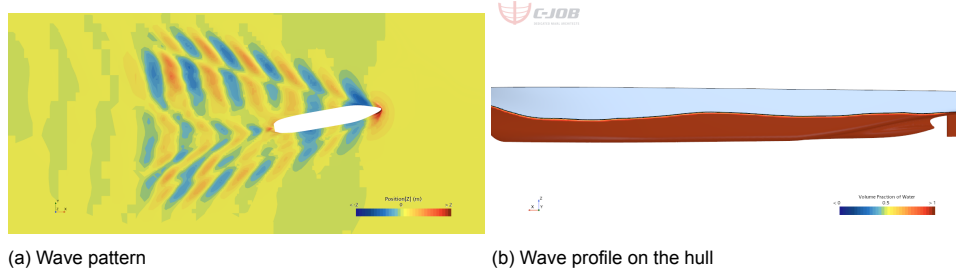


Figure 6.4: Waves patterns

The wave pattern lines up with the expected patterns. Measuring the wake angle it lines up with the expected kelvin wake angle of about 19 degrees on each side (Lord Kelvin, 1905). Further more the wave pattern shows no anomalies.

- The second step is to look at is the CFL number. The CFL (Courant–Friedrichs–Lewy) number relates to the CFL condition which is a condition for the convergence for solving partial differential equations Moura and Kubrusly, 2012. Generally this number should be kept below 1.

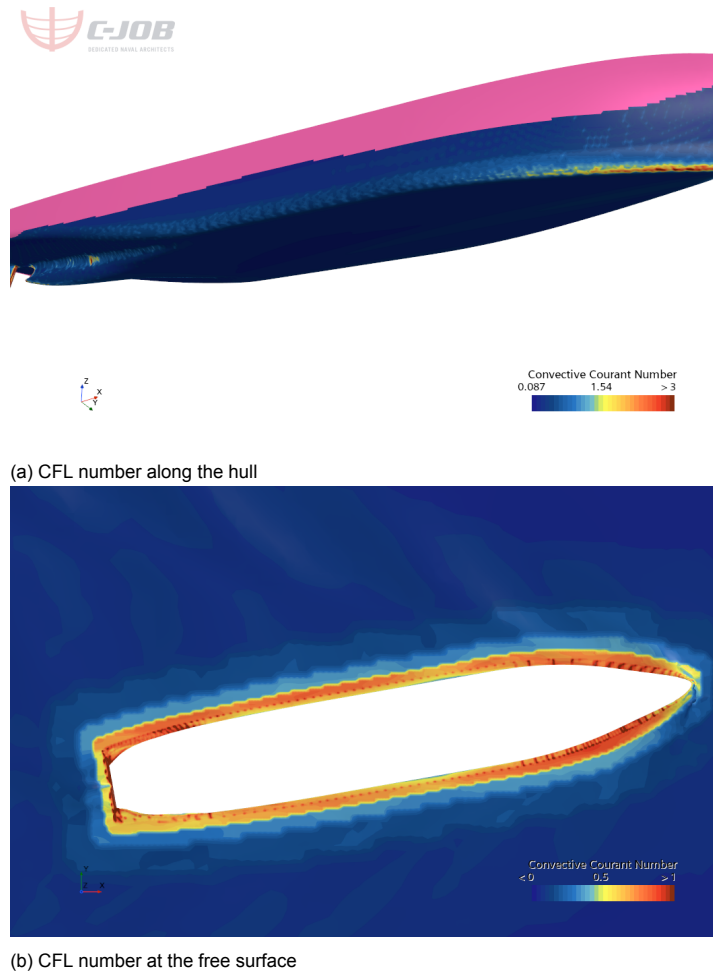


Figure 6.5: CFL numbers

The CFL number along the hull is generally under 1. A region with a high CFL number can be seen on the bow of the vessel in Figure 6.5a. This can be explained by the small cells along the hull combined with the high flow around the leading edge which results in a high CFL number. The same can be seen in Figure 6.5b where the CFL number is high at the boundary layer mesh.

- Lastly the Y^+ value is examined.

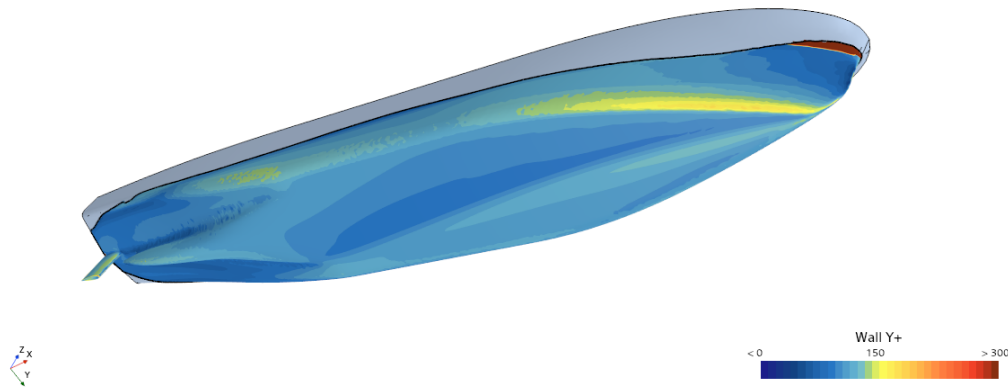


Figure 6.6: Y+ along the hull

As can be seen in figure 6.6 along the most of the hull the y+ value is below 200 as intended. At the bow wave the Y+ value is exceeded. However as it is only a small part of the hull the influence on the viscous resistance is expected to be small.

6.4. Empirical method

To verify that the empirical method works as intended, the expected relations between inputs and outputs are tested to verify that the model functions according to expectations. The tests and their results are presented in Table 6.2.

Input	Expected output	Actual output	Verified
A case with no leeway angle or rudder angle and the wind assist device in the center	moment and side force are 0	moment and side force are 0	Yes
Increase leeway angle from 0 to 10 degrees	increase in side force, moment and resistance	The side force becomes 650 kN, moment becomes 31589 kNm, resistance increases from 219 kN to 242 kN	Yes
Increase the rudder angle from 0 to 20	an increase in side force and resistance and a decrease in moment	The side force becomes 168 kN, moment becomes -11705 kNm, resistance increases from 219 kN to 231 kN	Yes
The wind assist device moves from the center to the bow	Moment decreases	The moment becomes -5000 kNm	Yes
rudder goes from 1 meter to 4 meters long	side force and resistance increase, moment decreases	side force increases from 19 kN to 44 kN and resistance increases from 218 kN to 222 kN, moment decreases from -1296 kNm to -3037 kNm	Yes

Table 6.2: Verification of the empirical model

Comparison between empirical and CFD results

This chapter aims to compare the empirical method with the CFD method to validate that the use of higher fidelity models is necessary in the optimization of wind assisted vessels and to see what how similar the models are. This is done in three steps. First, the correlation between the outputs is presented in Section 7.1. Then the correlation per parameter is presented in Section 7.2. Lastly, an optimization is performed on both the empirical model and CFD to see if the found optimums are similar to determine if the empirical method alone is suited for optimization. This is presented in Section 7.3.

7.1. CFD and empirical method correlation

In this section the data collected from the CFD and the same points from the empirical method are compared to determine the correlation between the two methods. First, the results of the CFD and empirical model are plotted against each other in Figure 7.1 and the correlation factor is calculated. The same process will be followed to determine the correlation between the surrogate of the high fidelity, which is used in the optimization tests, and the low fidelity. This to see if this correlation is similar.

In table 7.1 the Pearson correlation coefficients are shown. As can be seen, the correlations for the side force and the moment are very high. This means that the results from CFD and the empirical method are very similar. However, the correlation with respect to resistance is not as good.

	Resistance	Sideforce	Moment
CFD and empirical	0.738	0.984	0.940
Surrogate of CFD and empirical	0.744	0.958	0.899

Table 7.1: Correlation coefficients

It can also be seen in table 7.1 that the surrogate has a similar correlation as the direct CFD data. However, it should be noted that the data have been sampled slightly differently. The CFD data partially originate from two optimizations, with the rest of the data being sampled using the Latin hypercube method. Therefore, the data are more clustered compared to the correlation data set of the surrogate model, as can be seen in the figures 7.1. The data from the surrogate empirical is completely sampled with the Latin hypercube method. This means a higher variety of designs, as these samples are not subject to the constraints the optimization data set is subject to.

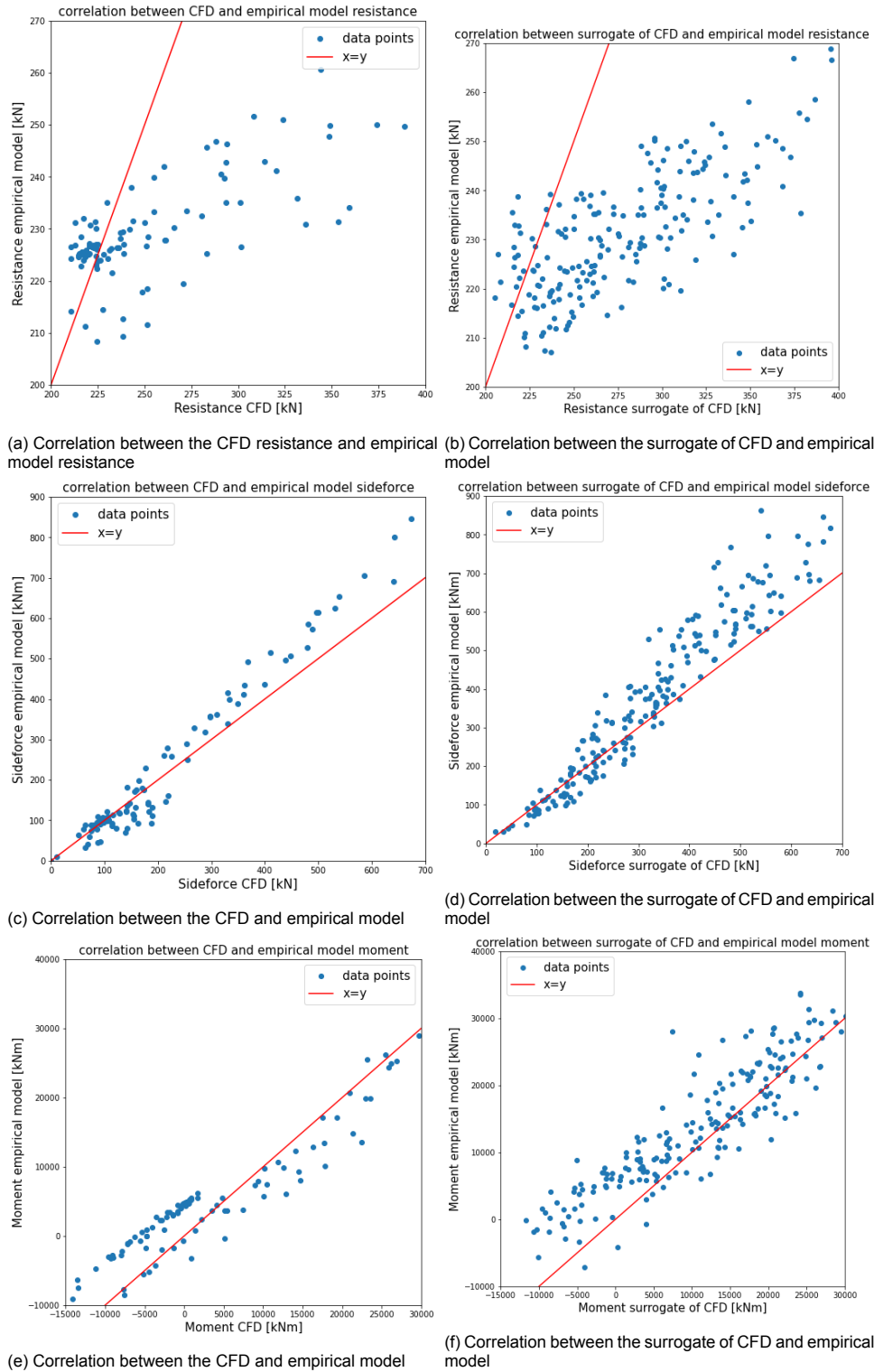


Figure 7.1: Correlation between CFD and the empirical method and surrogate of CFD and empirical model

7.2. Correlation per parameter

Not every parameters is captured with the same accuracy in the empirical model. In this section the experiment to see how well the influence of each parameter is captured by the empirical model is presented.

To test the correlation between the empirical method and CFD the surrogate of the CFD data as presented in Section 7.1 is used. This was done to reduce the number CFD calculations that need to be performed. For each parameter 11 samples are taken, spaced 0.1 apart while all other parameters are set at 0.5. for each sample the resistance, side force and moment is calculated with the empirical method and the CFD result is approximated with the surrogate model. This can be used to create a plot that gives a correlation between the empirical method and CFD with changes over one parameter. Two examples of these plots are given in figure 7.2. All plots can be found in Appendix A.

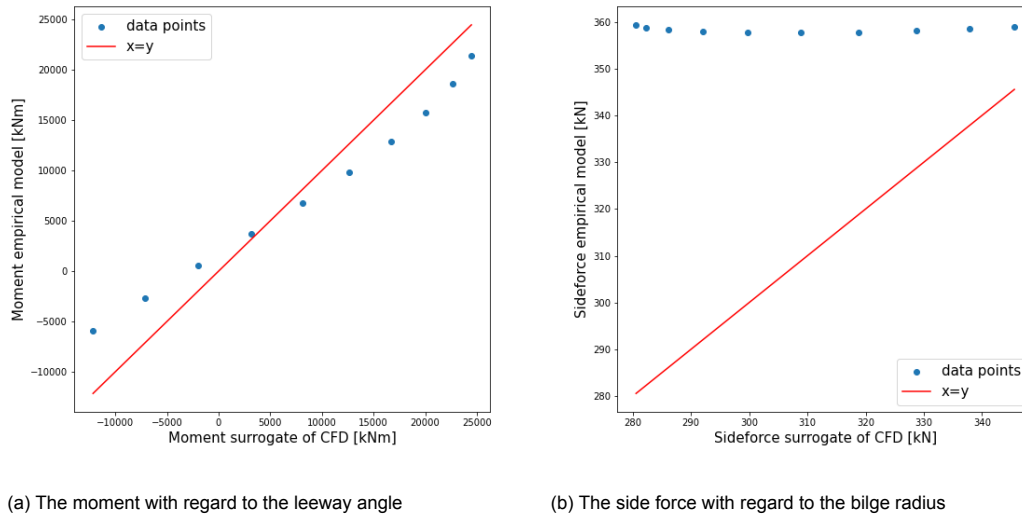


Figure 7.2: correlation between results of CFD and empirical model over one parameter

The results show that the influence of some parameters is captured well. For example the prediction of the empirical model for the moment resulting from the leeway angle is very good as can be seen in figure 7.2a. But for some the prediction of the empirical model has no correlation with results found with CFD as seen in figure 7.2b. This means that the side force predicted by the empirical model give no useful prediction for the results from CFD. So, the empirical model captures trends for some of the parameters well. But for other parameters the prediction from the empirical model gives little to no information about the behavior of the CFD.

7.3. Low and high fidelity optimization

The goal of this section is to investigate if the empirical model can be used for optimization. To validate the assumption that the empirical model only will result in a sub optimal vessel. To test this an optimization has been performed with the empirical model and the CFD. The resulting optimums are compared.

Due to a limited amount of time, the optimization using CFD could not be run till completion. This means that no vessel was found that satisfies all constraints. However, enough information is available to determine a region in which the optimum lies. Both optimizations were performed using the single-fidelity optimization as described in Chapter 5

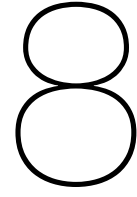
Of all vessels that were created in the optimization, four were selected to perform the comparison. The four vessels chosen have a combination of low constraint values and low resistance. These are presented together with the optimum found using the empirical model in Table 7.2.

Designs	1	2	3	4	Emp
Bilge radius (m)	0.99	1.07	1.14	1.18	0.58
Parallel midship length (m)	21.3	24	25.5	26.7	11.5
Parallel midship position from base (m)	-5.44	-4.15	-3.55	-3.61	-10
Rudder length (m)	2	1	3.37	3.25	1.42
Wind assist device location from center	50	50	29	-49	50
Rudder angle (degrees)	1.9	0	2.7	4.5	1.5
Leeway angle (degrees)	2	2.4	1.6	0	1.7
Moment deviation(kN)	1150	3885	-495	1122.5	-
Sideforce deviation (kN)	2.166	-14.100	34.100	-13.750	-
Resistance (kN)	209.8	208.1	212.0	212.1	-

Table 7.2: Vessel parameters of the best designs

Comparing the results from CFD and the empirical method the following observations are made.

- The optimal bilge radius and parallel midship length for CFD optimization and empirical methods are on opposite ends of the design space. Using the empirical method the optimum was found at close to the minimums of the both parameters. Using the CFD the optimum is found close to the maximum midship length. The bilge radius is likely constraint by the underwater volume constraint and is therefore close to the maximum that can be reached.
- The parallel midship positions found using CFD are in the middle of the design space while the optimum found using the empirical method is at the boundary of the design space. This may be caused by the larger parallel midship length and lack of inclusion of how smooth the vessel is in the empirical calculations.
- For the rest of the parameters the results of the empirical calculations are in the same range as those found using CFD. This is likely due to the fact that these values are well correlated as seen in Appendix A or, in the case of the location of the wind assist device, use the same calculation.



Results

In this chapter, the performance of optimization algorithms is analyzed. The first step is to determine the number of iterations for which the optimization algorithm must run. This is done in Section 8.1. The results of experiment 1 are presented in Section 8.2 where single- and multi fidelity algorithms are compared. In Section 8.3 the results of experiment 2 are presented. Here, the influence of better low fidelity models is analyzed.

8.1. Number of iterations

The first step is to determine how many iterations should be run. To find this limit, a single- and multi fidelity optimization is performed with 60 iterations. For the multi fidelity all low fidelity data is gathered at the start of the optimization. The convergence can be seen in figure 8.1. As can be seen, the single fidelity finds the minimum after 49 iterations and the multi fidelity finds the minimum after 41 iterations. Due to the expected variation, all subsequent runs are also run up to 60 iterations.

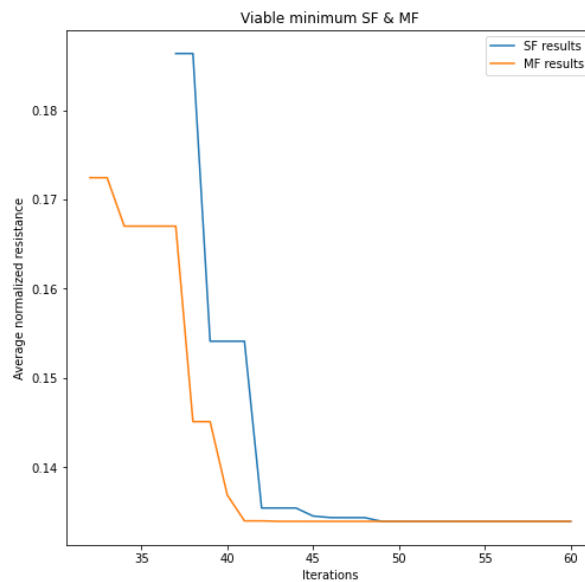


Figure 8.1: Objective function from 0 to 60 iterations

8.2. Comparison between single- and multi fidelity

In this section the results of experiment 1: 'the comparison between single- and multi fidelity' are presented. This is done with the KPI's as presented in Section 5.6.

1. Iteration in which the optimum is found:

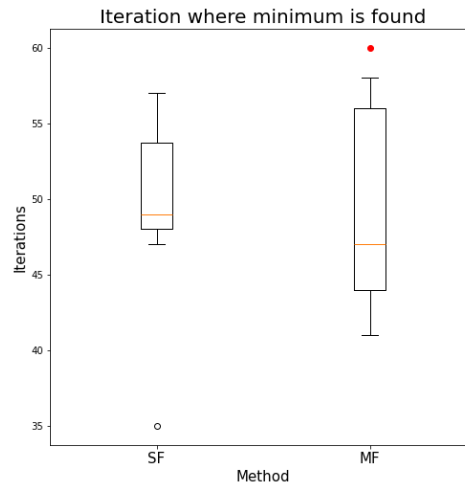


Figure 8.2: The iteration in which the minimum is found

Figure 8.2 shows that the median iteration in which the optimum is found is lower for multi fidelity. This indicates a better performance however the spread of the multi fidelity is also higher than the single fidelity. This means that the worst performing multi fidelity performs worse than the worst performing single fidelity. In this experiment one multi fidelity optimization run failed to converge on the global minimum instead it converged on a local minimum.

2. Simple regret:

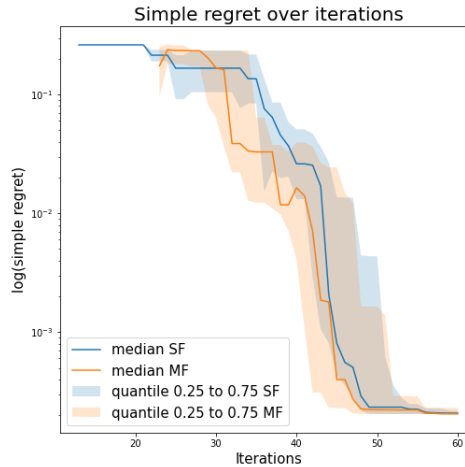


Figure 8.3: Simple regret

Figure 8.3 shows the simple regret mean and the interval from the 0.25 to the 0.75 quantile of the simple regret as explained in Section 5.6. It shows that the mean simple regret for the multi fidelity is lower than for the mean simple regret of the single fidelity algorithm. There is an overlap between the 0.25 to the 0.75 quantile interval from the single and multi fidelity. This means that a part of the single fidelity runs converge faster than the slower multi fidelity optimization runs. Overall the median simple regret of the multi fidelity is lower than the simple regret of the single fidelity. The difference decreases with the iterations.

3. Absolute error of side force and moment:

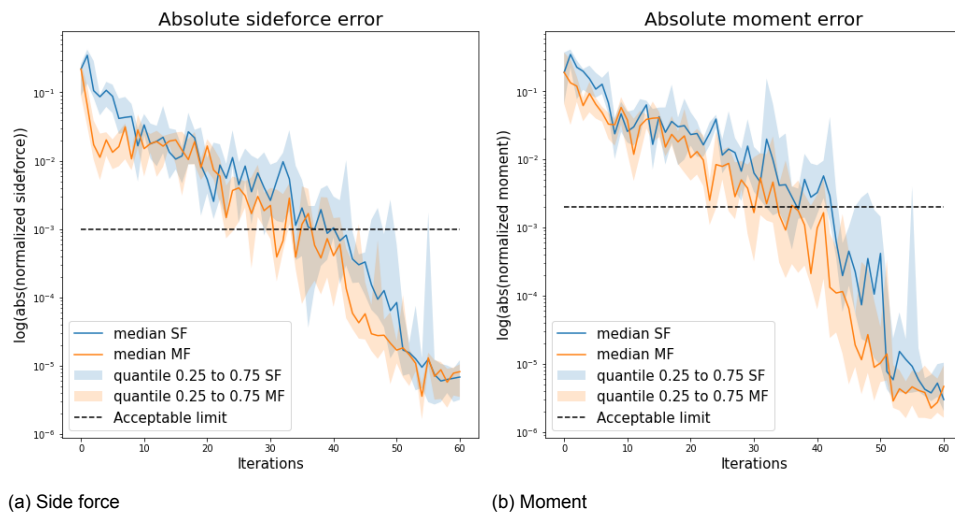


Figure 8.4: Absolute deviation from constraints

Figure 8.4 shows the error between the prediction and the observed value of the constraint. The medium error of the multi fidelity algorithm is lower for both the sideforce and the moment. Thus crossing the acceptable error limit a few iterations earlier. As the optimum has not been found yet this has little influence on the performance of the algorithm in this case.

4. Absolute prediction of resistance error:

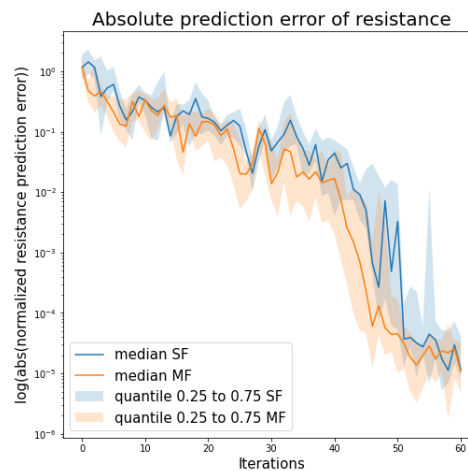


Figure 8.5: Prediction error of resistance

Figure 8.5 shows that the prediction error of the resistance when using multi fidelity the multi fidelity is lower then when single fidelity is used. The error differ only very slightly in the first 40 iterations after which the difference increases for 10 iterations. This could indicate that the multi fidelity algorithm enters the exploitation phase earlier leading to a earlier drop in prediction error.

The four KPIs of experiment 1 have shown that the multi fidelity generally performs better. The first KPI shows that the median multi fidelity optimization concludes quicker than the median single fidelity optimization. However, the spread for the multi fidelity is larger. Thus, the slowest multi fidelity optimization take longer then the slowest single fidelity. The second KPI shows that the simple regret, a measure for how far the run is converged, of the multi fidelity tends to be lower. KPIs 3 and 4 show that the error in the prediction of the side force, moment, and resistance is lower for multi fidelity algorithm.

8.3. Improved low fidelity

In this subsection the results of experiment 2 are discussed. This investigates the effect of having better low fidelity models. This is to check to what extent the algorithm is limited by the low fidelity model.

1. Iteration in which the optimum is found:

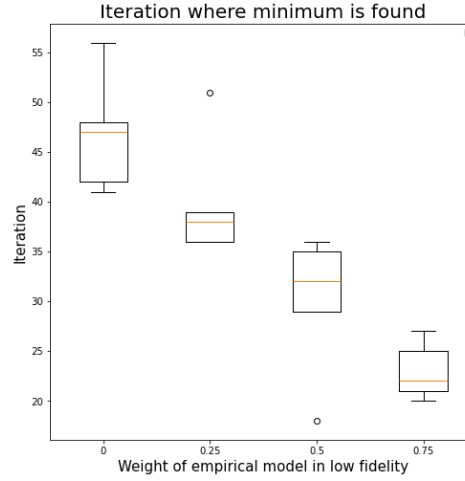


Figure 8.6: The iteration in which the minimum is found

Figure 8.6 shows the number of iterations needed till the optimization is converged for different level of correlation. It shows that an improvement in the low fidelity has a large impact on the performance of the optimization algorithm. With the 75% high fidelity reducing the required number of iterations by half in relation to the base case. The spread of does not show a significant difference between correlation level.

2. Simple regret:

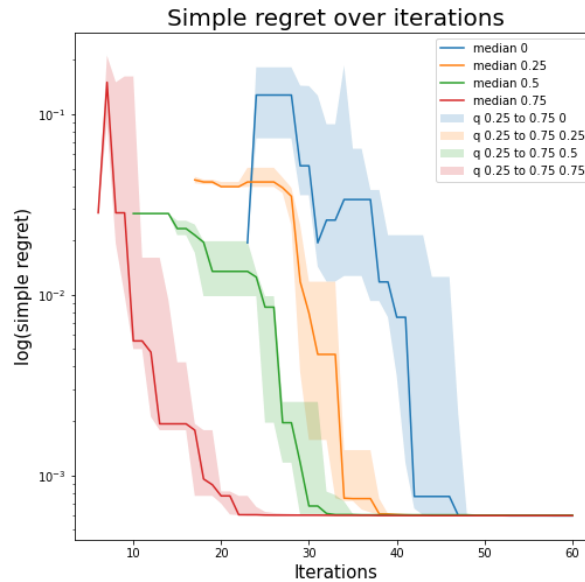


Figure 8.7: Simple regret

Figure 8.7 shows the simple regret for the four levels of correlation. Here the quicker convergence towards the optimum when the fidelities are more similar. The progression follows the same shape

but they are shifted. Showing that the first viable iterations are also occur earlier with better low fidelity models.

3. Absolute error of side force and moment:

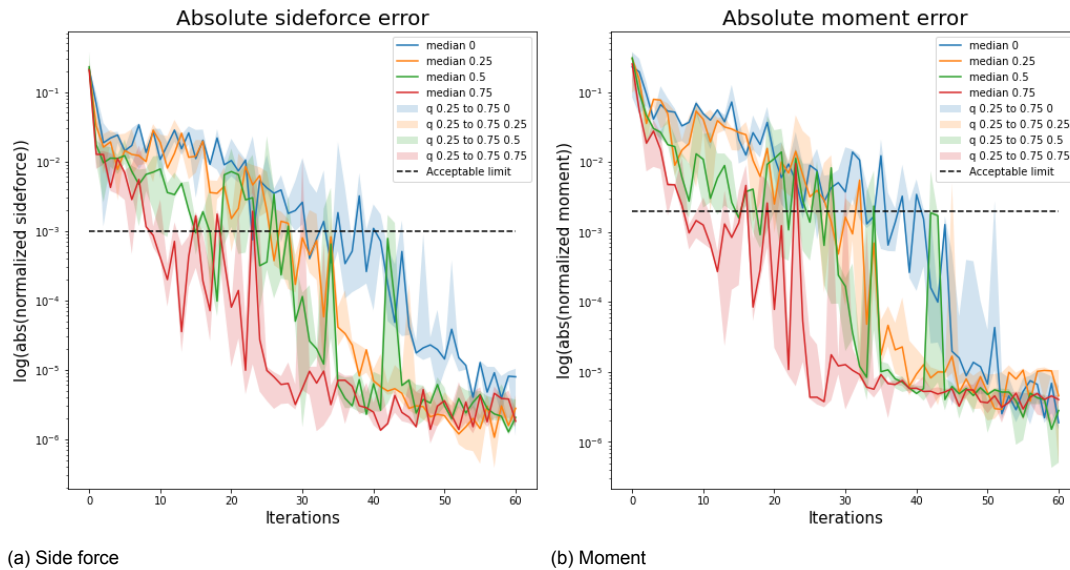


Figure 8.8: Absolute deviation from constraints

Figure 8.8 shows a quicker reduction of the deviation for the side force and moment when the low and high fidelity models are better correlated. A minimum error is reached for all levels of correlation between 10^{-5} and 10^{-6} . Both constraints are satisfied for the 0.75 high fidelity around 10 iteration. there is little difference between the 0.5 and 0.25 high fidelity weighted averages. Both consistently satisfying both constraints after about 30 iterations. This is still 10 iterations quicker than the base case which satisfies the constraints after 40 iterations.

4. Absolute prediction of resistance error:

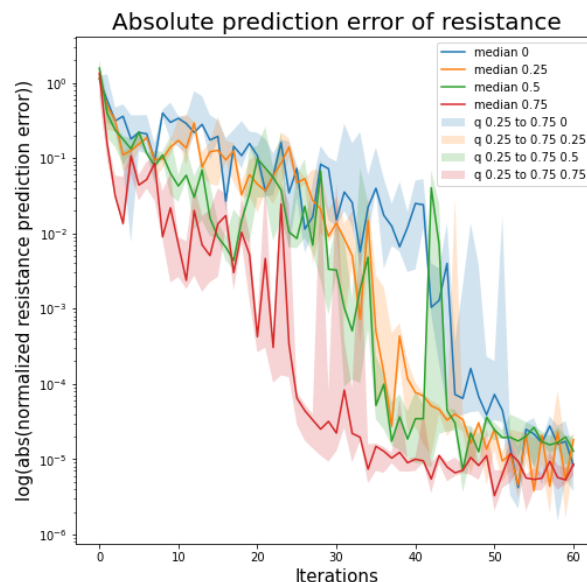


Figure 8.9: Prediction error of resistance

Figure 8.9 shows the error between the model predicted value and the observation. This shows

a similar trend as in KPI 3. With the 2.25 and 0.5 high fidelity weighted average performing similarly, with both a significant improvement over the best case. The 0.75 high fidelity shows a large improvement again.

The results from the KPIs show that an improved low fidelity model has a significant impact on the performance of the optimization algorithm. The differences in convergence between the improved low fidelity models are almost equally spaced. Looking at the prediction errors in KPIs 3 and 4 it can be observed that there is only a small difference between the errors from the 0.25 and 0.5 high fidelity weighted average.

9

Conclusion

In this chapter the discussion 9.1, conclusion 9.2, contribution 9.3 and future work 9.4 are presented.

9.1. Discussion

This discussion will be split into two parts; the first section 9.1.1 will discuss the optimization algorithm and the second section 9.1.2 will discuss the comparison between the empirical method and computational fluid dynamics(CFD).

9.1.1. Algorithm

In this section the results of the algorithm will be discussed.

The results of the comparison between single- and multi fidelity optimization show that multi fidelity performs similarly to single fidelity. The median number of iterations the multi fidelity optimization algorithm takes to find the optimum are less than the median number required by the single fidelity method. However, the distribution of the iteration in which the optimum is found is wider for the multi fidelity implementation. This means that to ensure the optimum is found when only using maximum number of iterations as a stopping criterion, the number of iterations set for multi fidelity optimization would need to be higher than for single fidelity. In the other KPIs, multi fidelity performs marginally better.

The results from experiment 2 show that with better low fidelity models multi fidelity optimization can reduce the iterations required to find the minimum. This means that with better low fidelity methods the inclusion of the multi fidelity method can provide significant speeds ups in the optimization of wind assisted vessels.

When using the optimization algorithm in a practical engineering application, the time spent setting up the optimization problem tends to be more expensive than the time spent running the optimization algorithm. This is a negative for the multi fidelity method as this requires the setting up of a second model. So, to be useful, the multi fidelity method would need to outperform the single fidelity method to be practical in real world situations.

This study investigated the performance of single- and multi fidelity optimization using a surrogate of the high fidelity model. This means that the objective landscape may have changed. Therefore, it may not be totally representative of the actual problem. The problem of having noise in the data due to the use of unsteady CFD is not reflected in the surrogate. This thesis considered a simplified case that does not include heel, pitch, or the inclusion of a propeller. This means that the results found are only applicable for a problem with the same limitations. Furthermore, this was a study of one method of incorporating multi fidelity in an optimization problem using one set of resistance prediction methods. This means that other methods of incorporating multi fidelity data in an optimization problem, or using a different set of resistance prediction methods, may have different results. Lastly, the maneuvering constraint is limited in its applicability. It only captures the instance at which the vessel starts maneuvering, which

does not say much about the actual maneuvering behavior of the design. Therefore, this cannot be relied on to determine if the ship is still maneuverable.

9.1.2. Comparison between empirical and CFD

In Chapter 7 the difference between the empirical method and CFD was investigated. Firstly it was shown that for some parameters the trends are well predicted while for other parameters there is little to no correlation. Secondly, the results from optimization using the empirical model and CFD are compared. This showed that the trends from the bilge radius and midship length are reversed in the empirical optimization results compared to the CFD results. However, the optimal values for the position of the wind assist device, the rudder size, the angle of the rudder, and the leeway angle are similar in the two methods. This shows that this empirical model has limited usability in the optimization of wind assisted vessel hulls. Because the hull optimized with the empirical model differs significantly from the hull optimized with high fidelity methods as shown in Chapter 7.

9.2. Conclusion

The objective of this thesis was to find out if and how multi fidelity can aid the optimization of the hull of a wind-assisted vessel. Firstly, a literature study was performed to identify a suitable method for incorporating multi fidelity modeling into an optimization study and relevant parameters of a wind assisted vessel for an optimization study. It was found that performing a surrogate based optimization with a linear multi fidelity model was the best suited method. The high fidelity CFD was chosen because it captures all the physics and can give accurate results. However, it is expensive to calculate. For the low fidelity, an empirical model was chosen. The empirical models chosen are Holtrop and Mennen, 1982 for straight ahead resistance combined with the implementation of Kang and Hasegawa, 2007 for predicting the forces on the hull due to the leeway angle. Lastly, the method for the rudder forces was based on Molland, 2011 and Kijima, Nakiri, and Furukawa, 1990. With the implementation of this code deriving from Berendschot, 2019. This method is very quick to calculate, but as wind assisted vessel resistance calculation is not the intended propose of these methods, the accuracy is expected to be low.

The first experiment compared the single fidelity and multi fidelity optimization. This showed that multi fidelity is slightly faster. However, because of the higher spread in how many iterations it takes to find the optimum, the number of iterations that are needed to ensure that the optimum is found is higher. In addition, it showed that multi fidelity converges quicker in the early parts of optimization but the difference reduces as the optimum is approached. The error prediction for multi fidelity optimization is slightly lower than single fidelity optimization.

The second experiment looked at what happens if the low fidelity is better correlated with the high fidelity. This showed that a better correlated low fidelity model can significantly improve the performance of the multi fidelity optimization algorithm. With a large improvement in all observed KPIs. In the prediction error, a large improvement was observed from the base case to the 25% high fidelity weighted average low fidelity model and from the 50% to the 75% high fidelity weighted average low fidelity model. Only a small difference could be seen between the 25% and 50% high fidelity weighted average low fidelity model.

In Chapter 7 the CFD method and the empirical method were compared. This showed that some over some parameters the predictive value of the empirical model was very good while other parameters were not represented well in the empirical model. The case was optimized using both methods; It was found that the found optimums differ significantly. Therefore, these empirical models are not suitable on their own to perform hull form optimization.

Based on these results, multi fidelity does not significantly aid the optimization of a wind assisted vessel when using this combination of low and high fidelity. It has also been shown that with better low fidelity methods multi fidelity can offer a significant improvement in performance. Lastly, the empirical models used alone are not suitable for hull form optimization.

9.3. Contribution

This thesis makes several contributions:

- Bench marked comparable single and multi fidelity optimization algorithms on a case of a minimization of the resistance of a wind assisted vessel hull, showing that multi fidelity offers a slight improvement over single fidelity, on average finding optimum solutions faster, although practical time savings are limited.
- Bench marked the impact of correlation between low and high fidelity for a multi fidelity optimization. Showing that better low fidelity models may offer significant speed ups in optimization.
- Highlighted the limitations of using selected empirical models for hull form optimization as the optimization results differ significantly between CFD and the used empirical models.

9.4. Future work

This section outlines the research needed to improve this research and address its limitations, focusing on optimization, force prediction, and the case.

Optimization

Multi fidelity, only one method of creating a multi fidelity model, the AR1 method, has been tried. This method is not good at adjusting the minima in the function. Therefore, using different, non-linear methods of constructing the multi fidelity may have different results. Furthermore, adding more fidelities may also add performance to the multi fidelity model.

Surrogate, a basic method of constructing the surrogate has been used. Only the radial basis kernel has been used; therefore, the ability of the surrogate to extrapolate is limited. Using different techniques of generating the surrogate such as compositional kernel may improve the usefulness of multi-fidelity.

Sampling, the use of multi fidelity sampling can help generate low fidelity data where the uncertainty is high. Thereby improving the efficiency of the multi fidelity optimization algorithm.

Resistance predictors

In this thesis, only one set of force prediction methods was used. Therefore, investigating different methods would give more insight into the applicability of multi fidelity for this case.

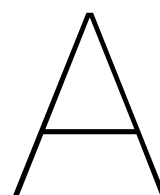
Most interestingly are the resistance predictors that are better correlated. This means that low fidelities are likely to become more expensive to evaluate. This would necessitate the use of multi fidelity sampling. Generating a large low fidelity data set would not be practical in a real world case. Another interesting improvement is finding a more accurate empirical method for predicting the resistance of a wind assisted vessel. The resistance correlation between the CFD and the empirical method used was shown to be not very good.

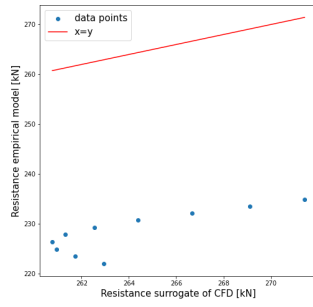
Case

As discussed in the discussion, the case that was used was simplified, as some aspects were ignored or simplified. Therefore, to better understand the design of wind assisted vessels, the impact of these aspects should be taken into account. Most importantly, the inclusion of a propeller. Other aspects are the inclusion of heel, pitch, and more accurate modeling of the wind assist device.

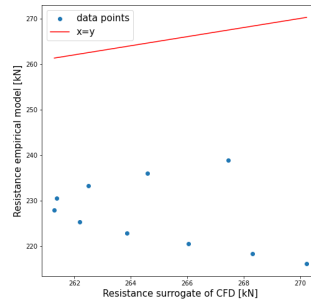
Furthermore, only one case was considered. To expand the understanding of the impact of the parameters featured in this thesis, more cases should be considered. This could be the inclusion of different types of hull, different levels of side force, and different speeds. The inclusion of an operational profile would also expand the understanding of a vessel that performs optimally in total instead of only in one situation.

The size of the design space has also not been varied. An analysis of the impact of the dimension of the design space may say more about the type of problem multi fidelity could be applied to. The impact of the type of landscape of the objective function should also be considered in different cases. As different types may benefit more from multi fidelity than others.

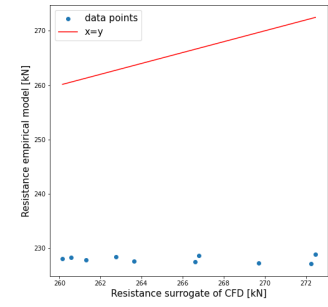




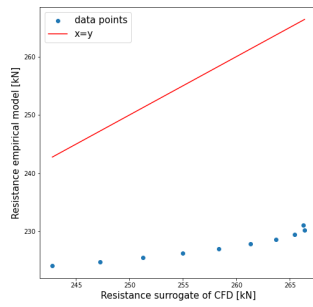
(a) Bilge radius



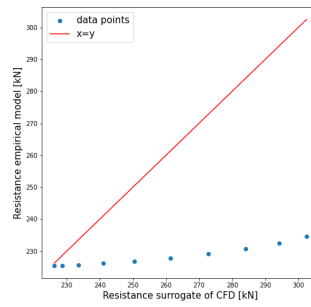
(b) Parallel midship length



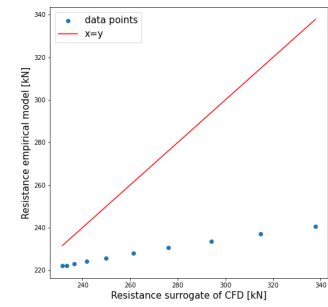
(c) Parallel midship position



(d) Rudder length

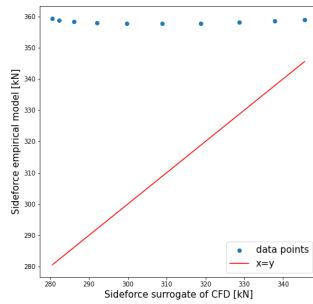


(e) Rudder angle

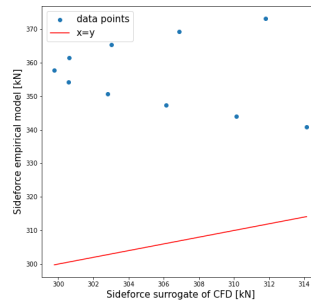


(f) Leeway angle

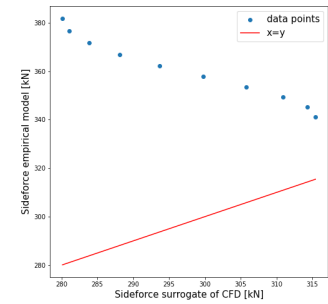
Figure A.1: Correlation between empirical and and CFD model resistance



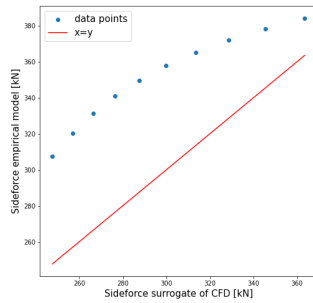
(a) Bilge radius



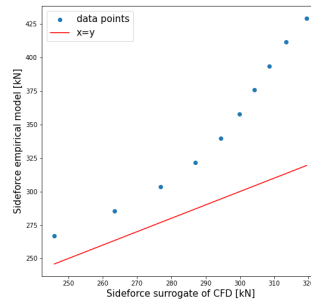
(b) Parallel midship length



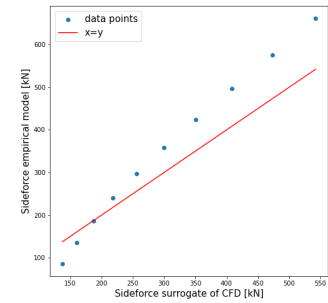
(c) Parallel midship position



(d) Rudder length

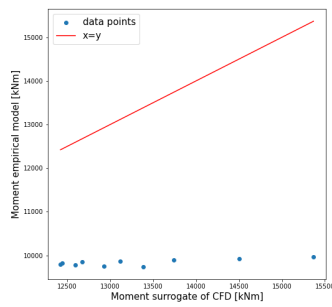


(e) Rudder angle

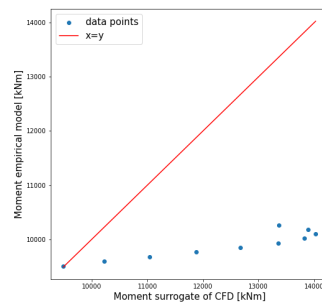


(f) Leeway angle

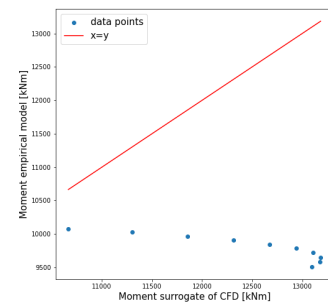
Figure A.2: Correlation between empirical and and CFD model side force



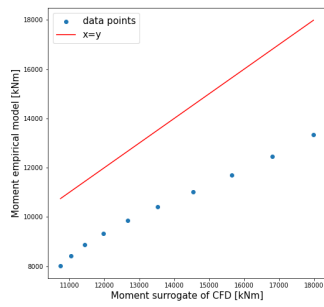
(a) Bilge radius



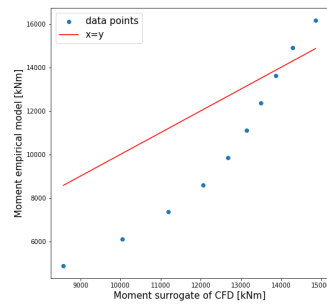
(b) Parallel midship length



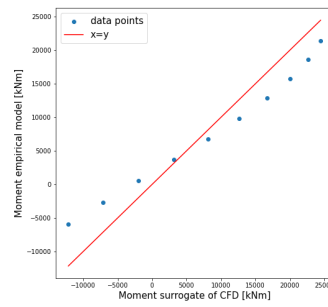
(c) Parallel midship position



(d) Rudder length



(e) Rudder angle



(f) Leeway angle

Figure A.3: Correlation between empirical and and CFD model moment

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