Robust Design Optimization for Operational Profile

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Abstract

The work deals with the actual necessity of creating optimal ship designs under uncertainty, also referred as Robust Design Optimization (RDO). The consideration of uncertainties in the optimization process is the future trend of ship design as a more realistic scenario is taken into account leading to the development of more efficient vessels and thus more environmental friendly.

Several optimization methods were tested for a hull form improvement concerning the total resistance of the vessel at forward speed in calm water condition. The operational profile has been taken into account as a single-objective problem in which several operating conditions are suitably weighted, as a single-objective problem in which one operating point is dominant while others are considered as constraints and as a multi-objective optimization task in which the best design is selected from the Pareto-set. Furthermore, a hybrid method via Gauss-Markov estimation was also tested. The robustness was considered via sensitivity check on slight variation of uncertain operational characteristics. All the processes are compared among them and, in addition, with a single objective optimization process for one specific operational condition. Each approach merits and drawbacks are pointed out in an investigation of which approach is particularly suited for hull form development. The criteria to judge pros and cons are quality of the achieved results (e.g. energy efficiency), computational effort (e.g. number of Computer Fluid Dynamics (CFD) runs needed) and sensitivity to changes (e.g. influence of slight changes on the operational conditions). The study case is an existing vessel that had a change in the operation leading to higher fuel consumption. In addition, the optimization is focus on changes of the forebody form of the vessel (e.g. bulbous bow).

Finally, the analysis is suitable to assist ship designers regarding the necessity of performing a robust optimization or a typical optimization process plus sensitivity analysis and thus create in short time optimal ship designs even under uncertainties.

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Hélio Bailly Guimarães – Rostock, January 2014

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Declaration of Authorship

I declare that this thesis and the work presented in it are my own and have been generated by me as the result of my own original research.

Where I have consulted the published work of others, this is always clearly attributed.

Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.

I have acknowledged all main sources of help.

Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma.

Rostock 15th of January 2014

Hélio Bailly Guimarães

CHAPTER I

1. INTRODUCTION

This thesis deals with the actual necessity of creating optimal ship designs under uncertainty, also referred as Robust Design Optimization (RDO). The optimization process of ship hull forms is suffering an increasingly necessity to undertaken several operational conditions and slight variations on the navigation and construction definitions. Thus, to achieve high-quality results, which kind of optimization process is more suitable? What about computer effort? I.e. which approach is particularly suited for hull form development? These are the main questions that are investigated in this thesis work.

The study was carried out based on the FRIENDSHIP-Framework (FFW) software thanks to a close cooperation between the EMSHIP European Program in Advanced Ship Design with Prof. Dr.-Ing. R. Bronsart from the University of Rostock and the German company FRIENDSHP SYSTEMS.

1.1. Motivation

Lots of effort are been put into the development of more environmental friendly devices for the transport of goods and people. This thesis deals with this actual task, yet in a different approach than usually. The optimization applied on ship design process represents a potential benefit for environment and great payoffs. A vessel that is optimized, consumes less fuel, therefore it is better for the whole chain of the transportation system including the environment itself. However, for a good performance uncertainties must be taken in account in the design phase. In the other hand, the approach to make it possible, Robust Design Optimization (RDO), is very complex and time consuming and finally not yet consider in most of the design projects. This work is motivated by the challenge to understand and clarify which approach is particularly suited for the development of a robust hull form design and thus create in short time optimal ship designs even under uncertainties.

1.2. Objective

The objective of this investigation is to study the possibility of performing a roust design optimization of a vessel including the operational profiles and yet focus in variations of the hull form. In addition, Computational Fluid Dynamic (CFD) is to be used to analyze the efficiency and sensitivity of the model. Furthermore, is of the interest to compare several optimization approaches and its pros and cons that can be defined by the quality of the achieved results (e.g. energy efficiency), computational effort (e.g. number of CFD runs needed) and sensitivity to small changes (e.g. influence of operational conditions). Finally, the results could orient ship designer about the necessity/possibility of performing a robust optimization or a typical optimization process, sensitivity analysis etc.

1.3.Methods and Procedures

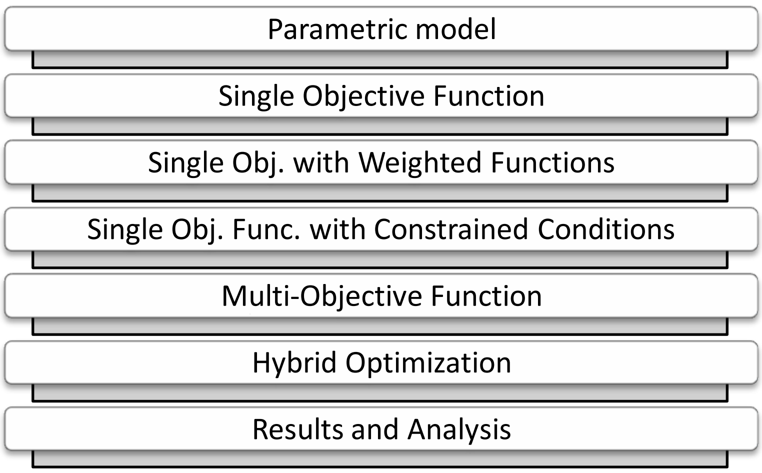
A model of an existing vessel is created and evaluated under several different optimization approaches with the goal to understand how to deal with optimal ship designs under uncertainties and several operational conditions.

The study output a series of data that possibility the analysis and comparison of every different optimization process applied to a same problem basis (model, conditions etc.).

To proceed with the study regarding different operational conditions, two main operating characteristics are taken into account. And, the optimizations focus on local variations of the hull form (e.g. bulbous bow, shoulder) and analyzed via CFD regarding the total resistance of the vessel. Finally, the robustness of the model is considered by means of sensitivity analysis.

1.4.Research Overview

The numerous optimization design process that were performed was done in the order presented in the following scheme.



The scheme summarizes in topics the optimization processes that were used in the study. Single-objective problem for each operation condition; single-objective problem in which several operating conditions are suitably weighted; single-objective problem in which one operating point is dominant while others are considered as constraints; multi-objective optimization task in which the best design is selected from the Pareto-set and Hybrid method (via Gauss-Markov estimation)

CHAPTER II

2. LITERATURE REVIEW

In the recent years it was possible to see some progress in optimization for ship design (Ray el al, 1995 [1], Pinto et al 2004 [2], Papanikolaou 2009 [3]). However, these methods are not generally accepted or widely used in practical ship design. The explanation for this is not simple. It is definitely true that there are some analytical and computational obstacles that still have to be overcome in order to make the optimization process a practice on ship design. But, furthermore, robust and automated procedures has shown to be a serious challenge as well as the necessity of undertaken several operating conditions (Diez and Peri 2010 [4], Nowacki 2009 [5], Zang et al 2004 [6], Diez et al 2010 [7], [8]).

The optimization applied on ship design process represents a potential benefit and great payoffs. However, actual products, such as vessels, must have a good performance under uncertain or variable operational conditions. Regarding this aspect Marczyk 2000 [9] states that, in a deterministic engineering context optimization is associated to specialization and consequently, it is the opposite of robustness. Robust design optimization objective is to overcome such drawback, Diez and Peri 2010 [4], Diez et al 2010 [7], to have an optimal solution able to keep the good performance characteristics in a wide range of uncertain parameters involved in the design process.

In this literature review some aspects of design optimization and robust optimization is presented for the better understanding of the problem and highlight critical aspects that must be taken into account.

2.1. Design Optimization

Design optimization, namely the selection of the best solution out of many feasible ones is intrinsically coupled with the design process, Papanikolaou 2009 [3]. A ship design may take into account several complex functions (cargo storage, propulsion, navigability) and the complex integration of those various systems. The optimization of a ship corresponds to the interest of the designer, which can lead to conflicting requirements resulting from the design constrains and optimization criteria (optimization for cost efficiency, for satisfactory safety of the cargo, for the environmental requirements). The way to overcome this difficulties and to outcome a compromise is with intensive discussions between highly experiences decision makers, ship designer, ship builders and end-users. Once defined the main objectives and proposes of the vessels the design optimization can take place.

Why optimize? As seen the optimization process can be very complex involving many aspects of engineering, computer sources , robust analysis and conflicting interests of clients, safety etc. However, an optimized design can diminish the risk associated with new builds and moreover because it provides higher profits. In a competitive market a better design represents a lot, regarding robust designs, for instance, in the early and mid 80's Motorola applied the Six Sigma Quality strategy, +-σ standard deviations between the mean and the nearest specific limit, and documented more than $16 billion in savings, Zang et al 2004 [6]. In addition, the time-to-market is constantly decreasing and to push the knowledge gained during the early design stages helps in all parties involved (shipyards, consultants, model basin, etc) and all team who contribute to the success of the design (managers, naval architects etc) to develop a better design, Harries 2007 [10]. The better knowledge in early stage acts directly in the complex problem described by Papanikolaou 2009 [3], pointed out herein.

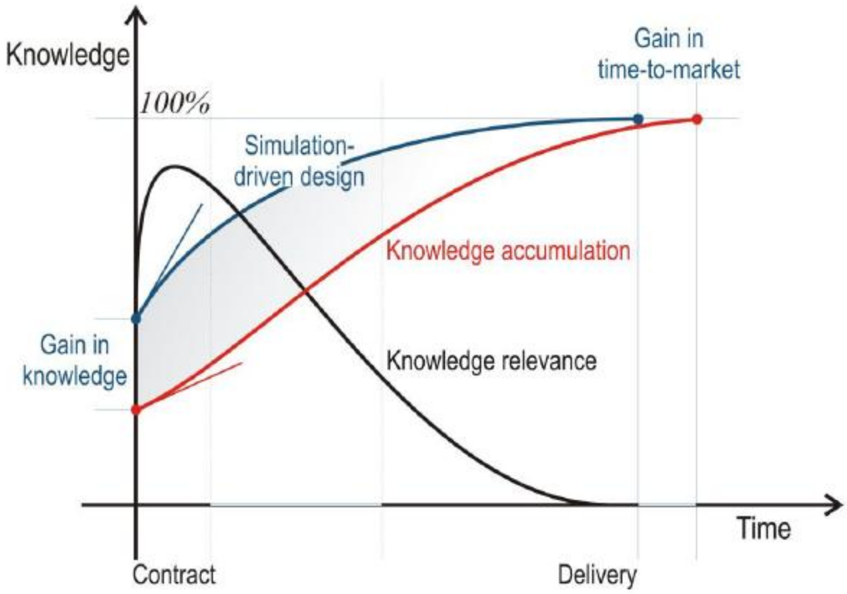


Figure 1 – Knowledge accumulation and relevance for decision-making Harries 2007 [10], Harries 2013 [11].

The consequence, in cost, due to the early stage knowledge is well explained in the Figure 2. The cost reduction is a direct effect of the knowledge gain thanks to the integration of ship-design modeling, simulation, and optimization.

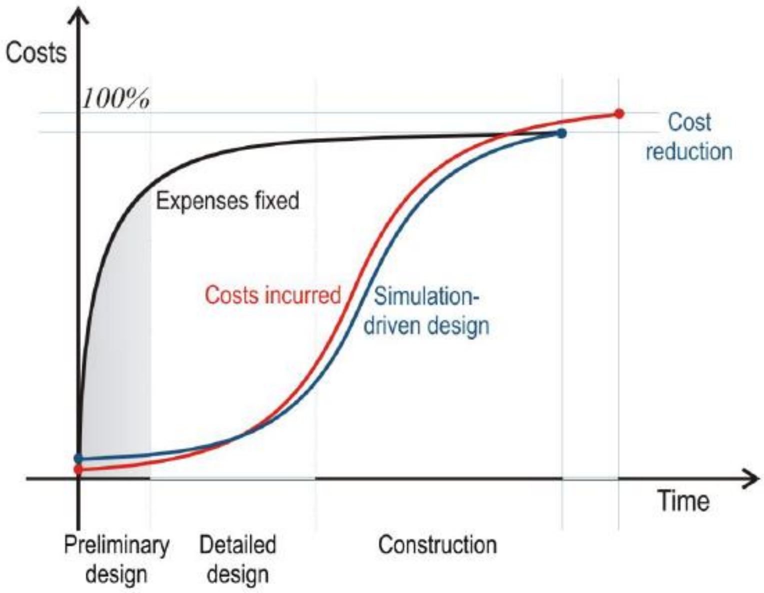


Figure 2 – Cost in design Harries 2013 [11]

Finally, the importance of performing an optimization process was cited, as to have a better product and increase the profits. Also, was briefly described some intricacies of the process, Marczyk 2000 [9], Diez and Peri 2010 [4], Nowacki 2009 [5], concerning computer aide and robust design challenges. In addition, some intrinsic complexities of the problem presented on Papanikolaou 2009 [3] work, regarding the conflicts of interests and regulations of all parts involved in the project. Nevertheless, many works is been done to solve these problems in a certain way to make the design optimization process possible to be widely used in practical ship design, Harries 2007 [10], Duffy et al [12], Harries 2007 [13], Marinmec 2008 [14], Kim 2008 [15], Jacquim 2007 [16]. However, robust ship design optimization still is a big challenge.

2.2. Generic Ship Design Optimization Problem

Due to the holistic ship design characteristic it is necessary to undertake multi-objective and multi-constrained optimization procedures. The generic ship design optimization problem and the basic elements are defined by Papanikolaou 2009 [3] as:

- ***Optimization criteria*** (merit functions, goals): This refers to performance/efficiency indicators that may be eventually reduced to an economic criterion. The ship design optimization criteria are in general complex nonlinear functions of the design parameters (vector of design variables) and are in general defined by algorithmic routines in a computer-aided design procedure.

- ***Constraints*****:** This refers to a list of mathematically defined criteria resulting from safety, market conditions, cost of materials or other case-specific constrains.
- ***Design parameters***: This refers to a list of parameters as ship's main dimensions
- ***Input data***: This includes traditional owner's specifications/requirements, initial form etc
- ***Output***: This includes the entire set of design parameters for which the specified optimization criteria/merit functions obtain mathematically extreme values (minima or maxima); for multi-criteria optimization problems optimal design solutions are on the so-called Pareto front and may be selected on the basis of tradeoffs by the decision maker/designer.

Figure 3 resumes schematically the aforementioned optimization problem.

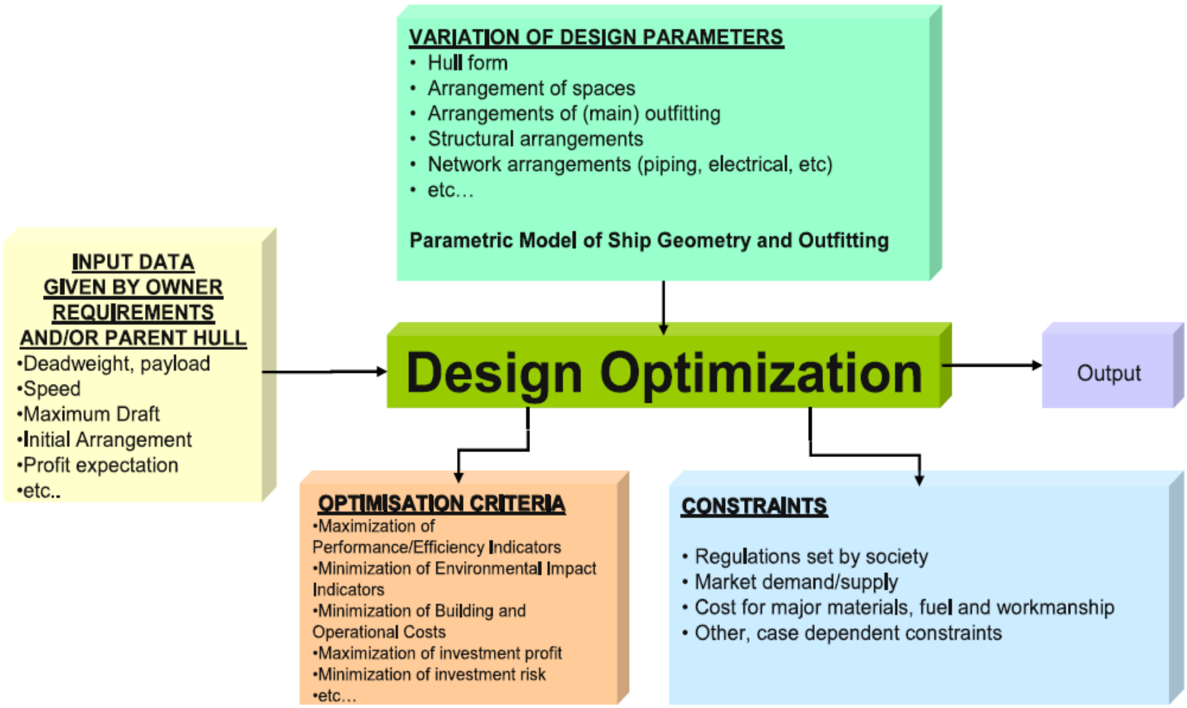


Figure 3 – Generic ship design optimization problem defined by Papanikolaou 2009 [3]

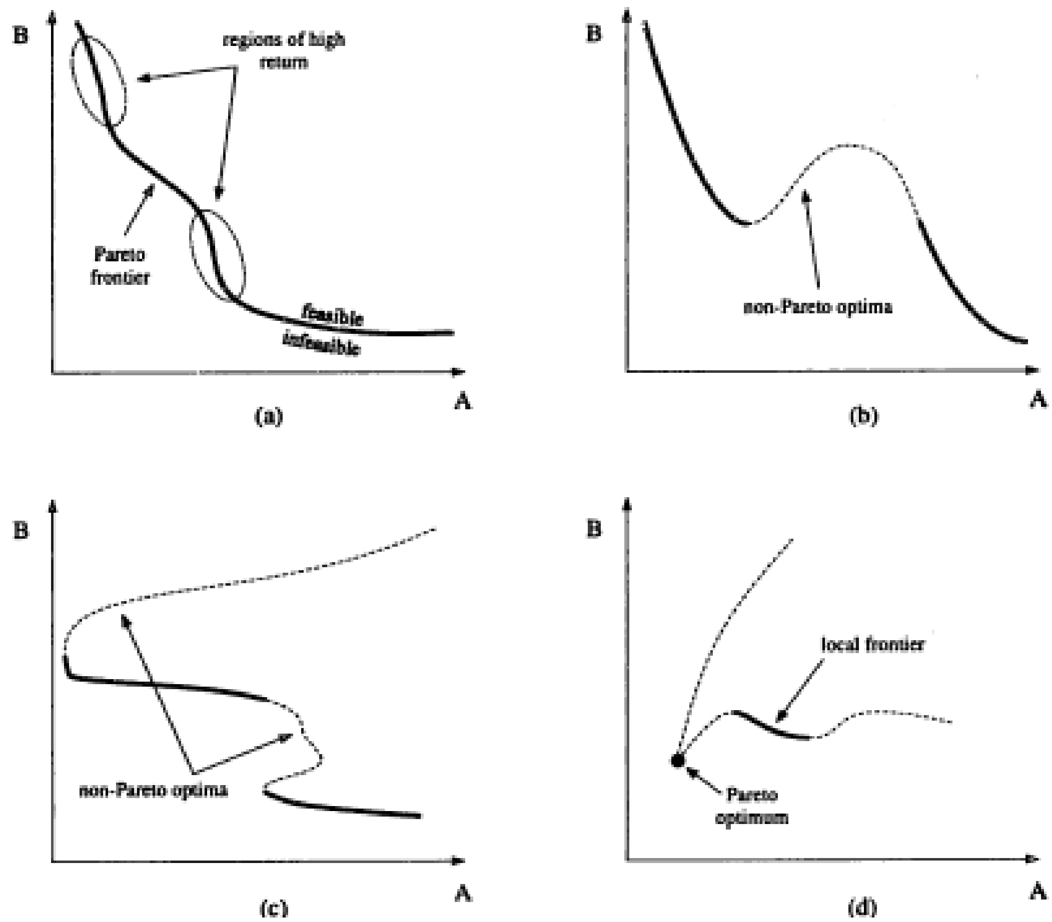


Figure 4 – Notional Pareto frontier in two-objective space, with objectives A and B to be minimized. (a) Continuous frontier, showing regions where objective B can improve significantly with little tradeoff of objective A. (b) Discontinuous frontier, with non-Pareto optima at the concave. (c) Discontinuous frontier with two non-Pareto, feasibility-limited regions. (d) Non-conflicting objectives, showing local optima. Taken from Thomas 1998 [18].

For the exploration and final selection of Pareto design solutions a variety of strategies and techniques may be employed as those presented in Harries et al 2003 [17] and Thomas 1998 [18].

2.3. Robust Optimization

The classical optimization design process do not consider uncertainties and as consequence the performance of the final design may significantly drop in off-design conditions, when the deterministic assumptions used no longer hold, Diez et al 2010 [7]. The probability that the product fail is very high, 50% in accordance with optiSLang [19], due to the fact that in many cases the optimal case lies close to a constrain.

In the last twenty years, various non-deterministic methods have been developed in the attempt to consider uncertainties on product design. Zang et al 2004 [6] classified these approaches into two classes: reliability-based methods and robust design based method. The reliability methods estimate the probability distribution of the system's response based on the probability distribution of the parameters. However, the variation is not minimized in this approach, which is mainly used for risk assessment. In the other hand, robust design improves the quality of a product by minimizing the effect of uncertainties without eliminating the causes.

A design is considered robust when it is insensitive to the effects of variability, as operational variations, construction uncertainties etc. In Robust design the uncertain parameters are taken into account by the usage of probabilistic distributions which is somehow included in the definition of the optimal criteria (objective function). The foundations of robust design was developed by Taguchi in the 1950's and has been successfully applied to various industrial fields (Zang et al 2004 [6], Beyer et al 2007 [20]).

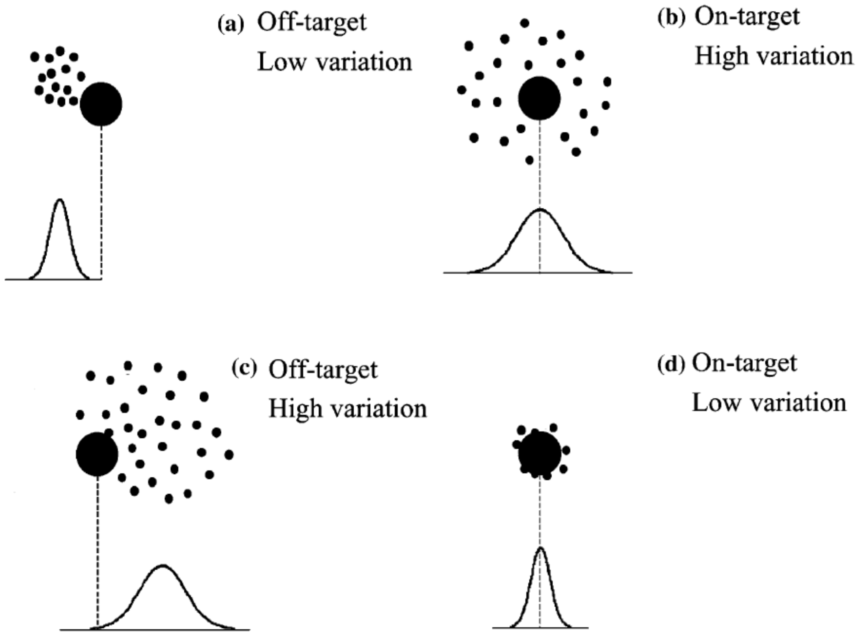


Figure 5 – Different types of performance variations. Zang et al 2004 [6].

The Figure 5 presents different types of performance variations, where the big dot denote the target and the small points represents the response distribution and the associated distribution density function. The item (d) on the figure represents the aim of robust design, which is to make the system response as close as possible to the target with low variations without eliminating the noise factors. (Zang et al 2004 [6], Phadke 1989 [21]).

The typical optimization process aims to minimize the objective functions, differently the robust design optimization objective is to minimize both the deviation in the mean value and the performance function, subject to constrains. (Jurecka 2006 [22]).

In order to clarify the concept the application performed by Zang et al 2004 [6] in a dynamic system is briefly presented on Figure 6 . Where RD's are solutions obtained with different weight on the objective function, which considers the mean value and the standard deviation. RD1 represents the optimization performed to minimize the elevation in a given frequency; TD is a reference solution also optimized for a given frequency but with a higher value of the damping coefficient, these results represent the traditional optimization process. For RD11 the optimization is performed with the objective to minimize the standard deviation. In the results the trade-off between the mean value and standard deviation can clearly be observed as the bigger the importance of the standard deviation on the objective function the flatter is the response (insensitive to variations on the frequency). Finally, a robust design would be RD6, for example, which compromise the good (lower) response for the given frequency, but also presents lower response for others frequency as it as an uncertainty.

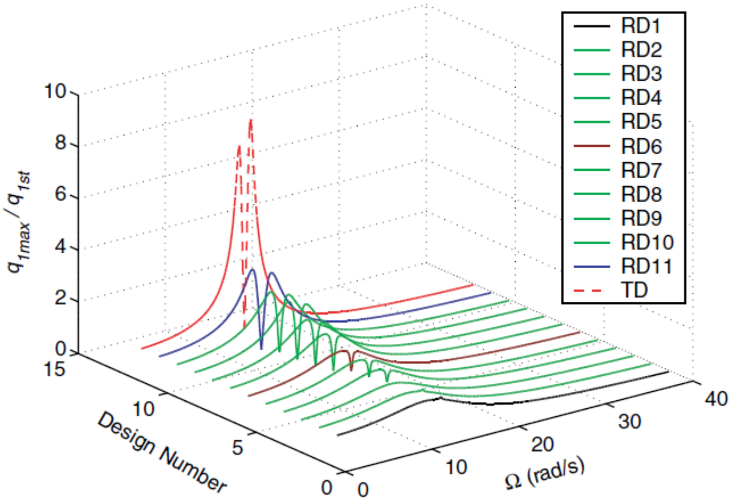


Figure 6 – Robust design results of a mass-spring system compared with traditional solution. Zang et al 204 [6]

Figure 7 illustrate schematically an optimization process that include uncertainties of the design variables, objective function and constrains.

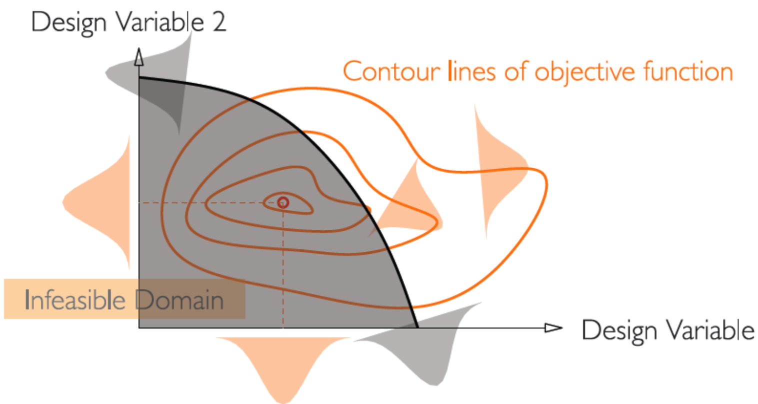


Figure 7 – “Sources of uncertainty in design optimization” optiSLang [19]

The quantities of mean and standard deviation may be calculated, if the PDF (Probability Density Function) is known. However, for the ship design application these PDF's are usually unknown and so often it is assumed that the variables have independent normal distributions as in Diez and Peri 2010 [4] and Diez et al 2010 [8].

In robust design the management of uncertainties became very important. The source of uncertainty might be classified into two main types, external and internal (Diez and Peri 2010 [4], Du and Chen 2000 [23]). External ones are related to design variables as operating conditions. Internal uncertainties are related to the accuracy in computing.

In accordance to Diez and Peri 2010 [4], the operational profile and environmental condition may be considered as intrinsic stochastic functions, which mean values and standard deviations are not influenced by the designer. The typical optimization process uses the deterministic approach to manage different operating profiles in the design optimization as a linear combination of the ship performance regarding different operating conditions. However, on robust design the optimization is focus on the uncertain variation of the operational profile, undertake on a stochastic point of view. The aim is to minimize the effect of the unknown involved, without suppressing it.

Moreover, in accordance to optiSLang [19] there are two possibilities to solve a RDO (Robust Design Optimization) problem, an iterative way or by the usage of response surfaces. In the iterative way, the problem is solved by the usage of deterministic methods, and then a robustness evaluation at the deterministic optimum is performed. After that, another optimization process is performed within different scenarios and the related robustness is also achieved. This process is repeated until the wanted robustness value is achieved. This approach is similar to the "multi-point optimization" described by Diez and Peri 2010 [4], in his work the authors highlighted a drawback of this process, which is that it depends on designer experience and sensitivity. Furthermore, no information about the performance variation is available to the optimizer.

Finally, one of the major barriers in the robust optimization application is the computational expense of the uncertainty analysis, Jiangtao et al 2010 [24]. Additionally, the author propose the surrogate model as a possible solution to overcome this difficulty, the same solution is used by Jing et al 2013 [25], both with application on aeronautics.

CHAPTER III

3. CASE OF STUDY

3.1. The Vessel

The study relies on an existing RoPax (cargo and passenger ferry) of the shipping company Acciona Trasmediterranea. The operational condition of the designed vessel had changed and consequently a gap for improvement and fuel saving is expected. On this scope hull form optimization specialists engineers of FRIENDSHIP SYSTEMS performed a retrofit study of the vessel. A small area of the hull (bulbous bow) was selected to be optimized in hydrodynamic terms of total resistance of the vessel and concerning the actual operational condition of the ship.

The robust optimization process, topic of the herein research; should guarantee good performance even under uncertainties in operational profile. Thus, the RoPax vessels became a natural candidate to demonstrate advantages and disadvantages of the implementation of robust optimization method in the ship hull form design versus a typical optimization process. Furthermore, it possibility to demonstrate the advantages of an early design optimization, even when maintaining the hull form main characteristics.

Figure 8 – Case of Study. RoPax ferry [26]

Table 1 – Main dimension of the vessel

Main Dimensions	
LOA =	172 m
Lpp =	157 m
Beam =	26 m
Draft =	6.2 m
GT =	26 916 t

3.2. Operational Profile

The robustness of the hull form is checked regarding the operational profile, more precisely the observed variation on draft and speed of the ship during her operation. Sea states are also a typical operational variation that can classify a vessel as robust or not, but it is not in the scope of this work.

The average velocity and draft of the vessel during the operations are to be used as the main condition for optimization. The RoPax vessel has higher probability of navigation with speed above the average than slower. In other words it has to be able to keep schedule even on a port delay scene. Consequently, the second velocity condition considered is slightly higher than the mean speed.

- V_1: Average velocity. Condition used for typical single objective optimization process.
  - Fn_1= 0.259. V_1= 19.77 Knots.
- V_2: Above average velocity. Together with condition 1 (V_1) is used for multi-objective optimization process
  - Fn_2= 0.288. V_2= 22.00 Knots

Finally, the draft of the vessel varies quasi randomly, thus a small plus, minus variation of it is used for the robustness check.

- T: Average draft. Condition used for typical single and multi-objective optimization task.
  - T= 6.20 m
- $\mathrm{T} \pm \Delta t$: plus, minus variation of draft for robustness check.

4. PARAMETRIC MODEL

4.1.Parametric Approach

Parametric models permits geometry variation defined by a few parameters. For example, a design of a cube with 6 sides. 8 vextex points are needed to define the cube, each point has 3 (X, Y and Z) coordinate information, wich leads to a big amount of data to define and vary the cubic geometry. In the other hand, a parametric model of a cube will be the case wich the form is defined by a few parameters as, length, width and depth.

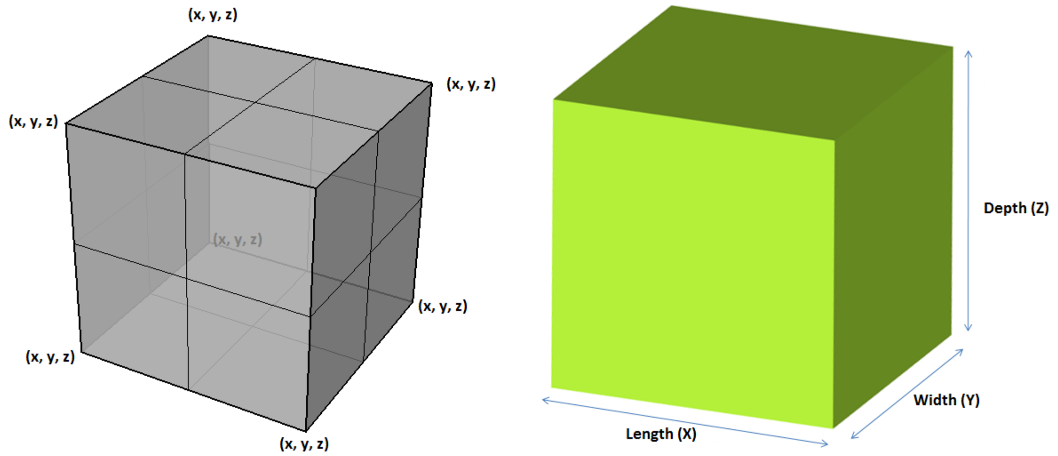


Figure 9 – Left Geometric model of a cube defined by its vertexes. Right: Parametric model of a cube defined by its main dimensions.

Finally, a parametric model possibility the automatic form variation, without any manual vertex manipulation, by a few parameters keeping the geometry as a cube, or a hull form. For further information on parametric design please refer to (Harries 1998) [27]

The parametrical model of the case of study was created usign FRIENDSHIP-Framework via advanced features of the software as meta surfaces which allows the user to design parametric surfaces based on arbitrarily complex curve descriptions.

The model agrees with the vessel geometry based on the lines plane of the real vessel and provided dimentions.

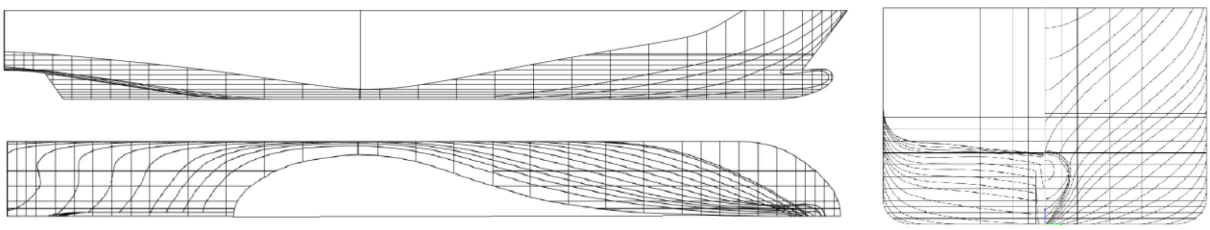


Figure 10 – Lines plan of the RO-PAX Ferry

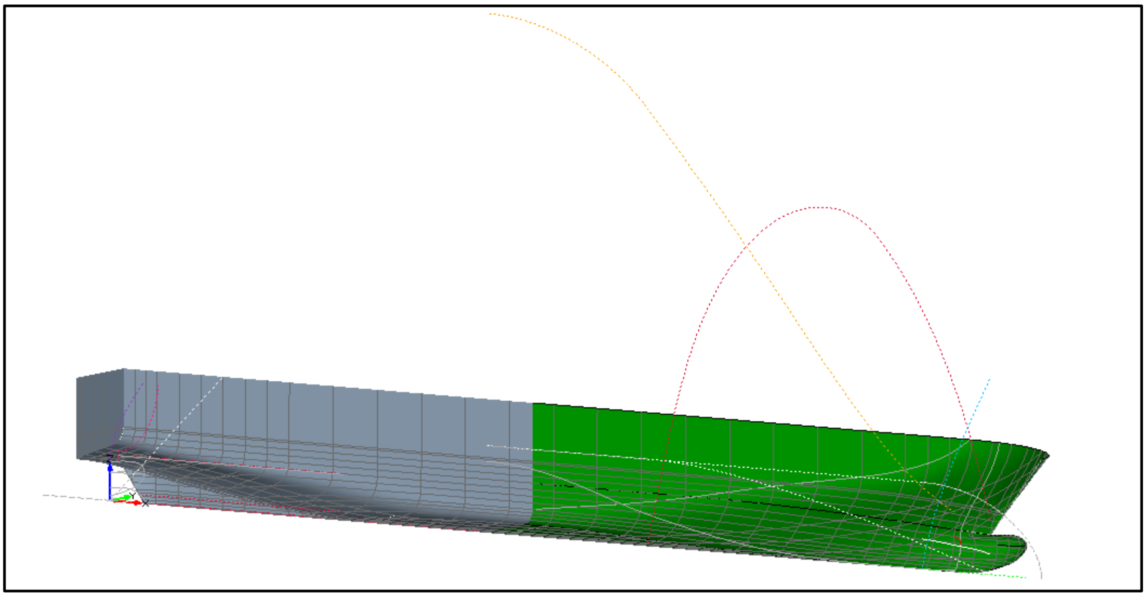


Figure 11 – Parametric model and its control curves

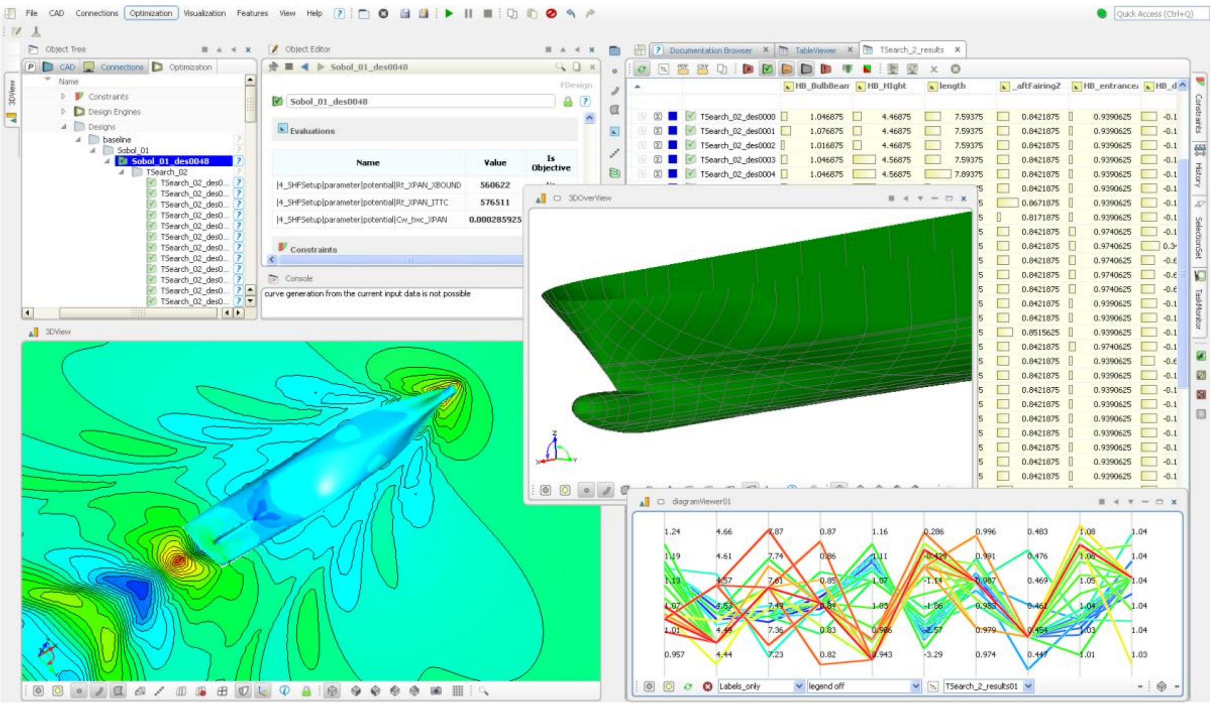


Figure 12 – FRIENDSHIP Framework overview

4.2. Parameters

The definition of a fully parametric model of an entire hull form is based on a large number of parameters. These parameters are the input that defines the geometry and its variation can imply on large changes (e.g. the Beam and length of the vessel) or small details (e.g. the fullness of the upper part of the bulbous bow).

In order to optimize the vessel a few parameters has to be defined as the critical ones. In the case of this study only the forebody of the ship is to be optimized thus, some parameters are selected to control the changes on the selected area of the geometry. The parameters selection was based on an extended study of the influence of each variable regarding it optimization improvement i.e. the “capability” of each parameter on reducing the total resistance of the vessel. The study was divided in three parts; Study_1, 2 and 3

- Study_1
  12 Design Variables [5 Bulb, 3 water line, 4 section curve and shoulder]
- Study_2
  7 Design Variables [3 Bulb, 1 water line, 3 section curve and shoulder]
- Study_3
  10 Design Variables [4 Bulb, 2 water line, 4 section curve and shoulder]

It is known from experience that the number of parameters should be kept as minimum as possible for an efficient optimization process. Study_1 corroborates this concept showing that twelve design variables is a large number leading to a big number of designs to cover all possible combination of parameters. Furthermore, the design of experiments (DoE) study provides information enough to classify the design variables in order of influence to the resistance reduction. It is necessary to mention that this is a tentative classification due to the fact that the range (which defines de percentage of parameter variation) is defined by the designers and so in the classification. Anyhow, this classification helps on the design variable selection.

Table 2 – Example of design variables influence on the total resistance

Variation to 0.1% reduction of R_t	
Design Variable	**Deviation [%]**
Shoulder Position	7 %
DWL Fullness	10 %
Bulb Beam	11 %
Length	27 %
Entrance Angle	38 %
…	…

The second study, with a small number of parameters, proved that 7 design variables is not enough to reach all important form variation that possibility the optimization to derives to a geometry with real improvement of the total resistance.

Table 3 – Comparison between Studies 1, 2 and 3 regarding number of design variables and optimization efficiency

	Design Var.	Feasible Designs	CFD runs	Performance
Study_1	12	64%	116	2.03%
Study_2	7	83%	111	1.57%
Study_3	10	78%	141	1.87%

Finally, the model with ten parameters (Study_3) was chosen for further studies as it presents a good behavior during the optimization process, not limiting much the variety of forms (low number of design variables), neither leaving it too free which leads to a large number of unfeasible designs (due to the high number of design variables)

In Figure 13 the optimization results for the three cases is presented. In the abscissa is the number of designs and in the ordinate axis the total resistance of the vessel in terms of percentage related to the resistance of the base model (base model= 0%). The "dots" represents the quasi random search (SOBOL method) and the connected points are the optimization process (TSearch).

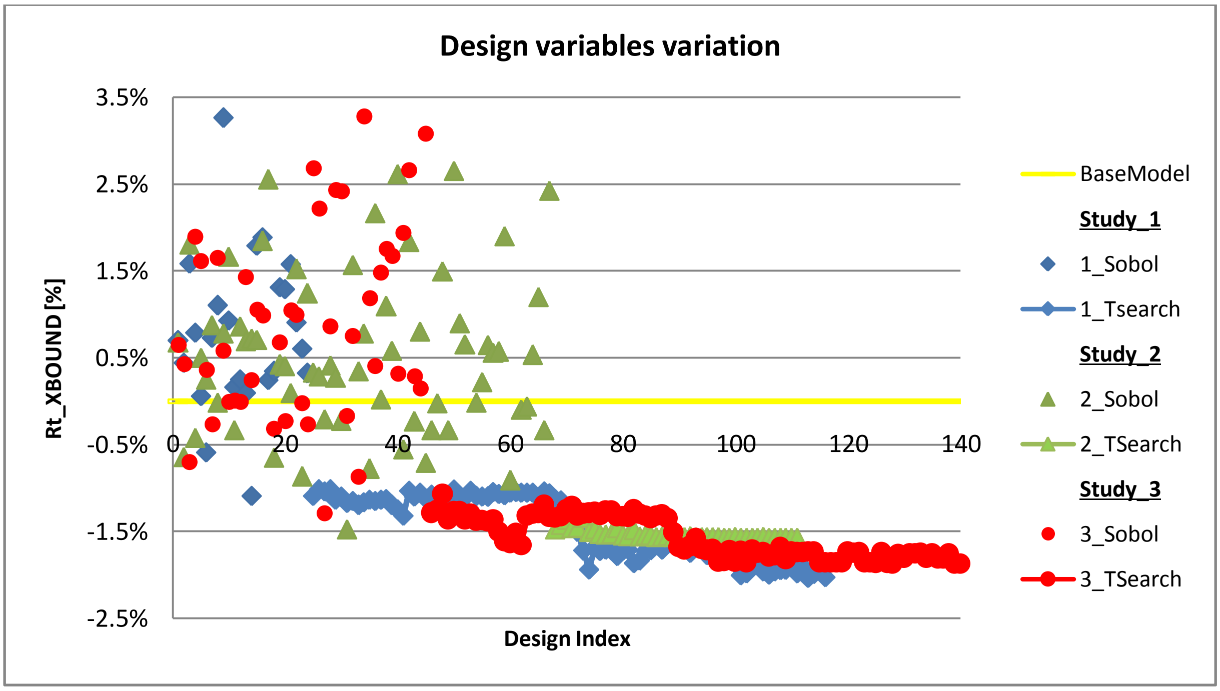


Figure 13 – Sobol + TSearch for the three cases of Study.

4.3. The Model

The parametric model was created using FFW with a big number of parameter that defines and control the shape of the hull. Default values of the parameters generate geometry with identical characteristics of the base model vessel. For the optimization process only the forebody is changed and this variation is made via 10 parameters that are described in the following.

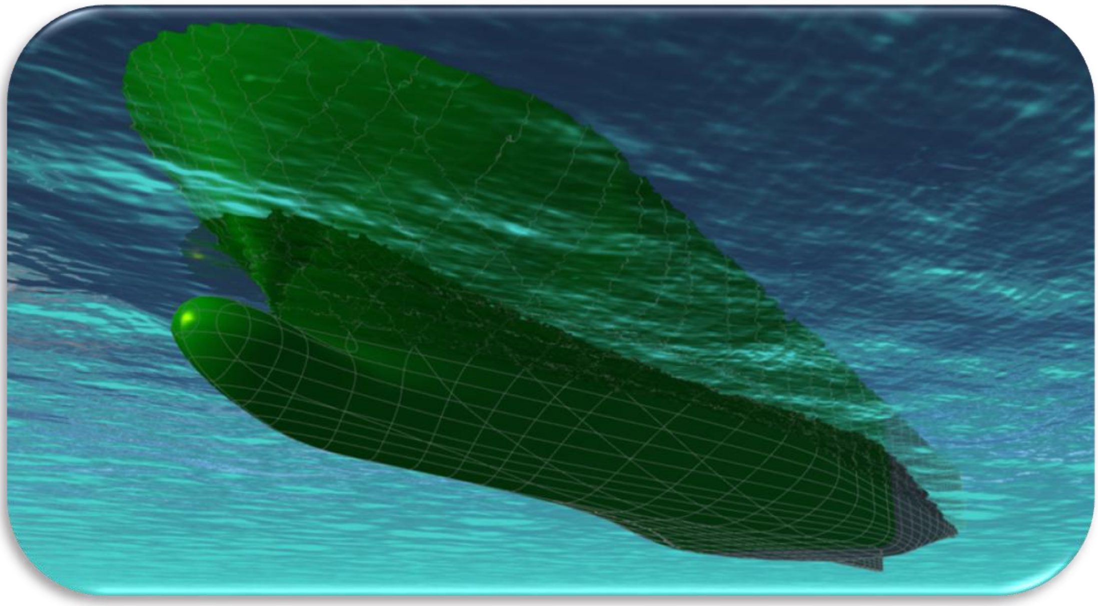


Figure 14 – Parametric model. Diver view created at FFW.

Bulb variation

- Bulb beam: Controls the width of the bulb
- Bulb length: Defines the length (X position) of the forward tip of the bulb
- Bulb height: Defines the high (Z position) of the forward tip of the bulb
- Bulb after fairing: Defines the inclination of the after part of the bulb that connects it to the hull.

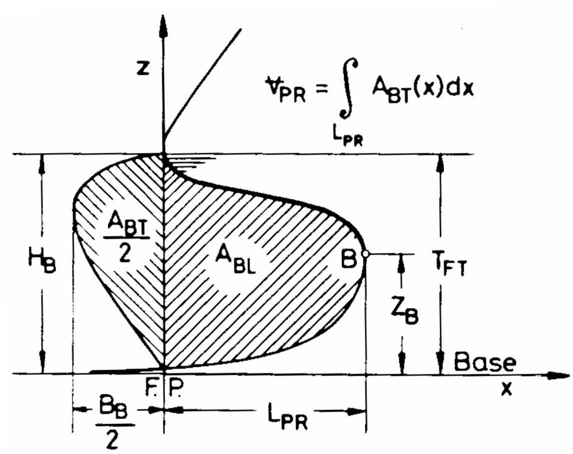


Figure 15 – Bulb quantities given by Kracht 1978 [28]. Bulb Beam = $B_B/2$. Bulb Length=L_{PR}. Bulb Height= Z_B

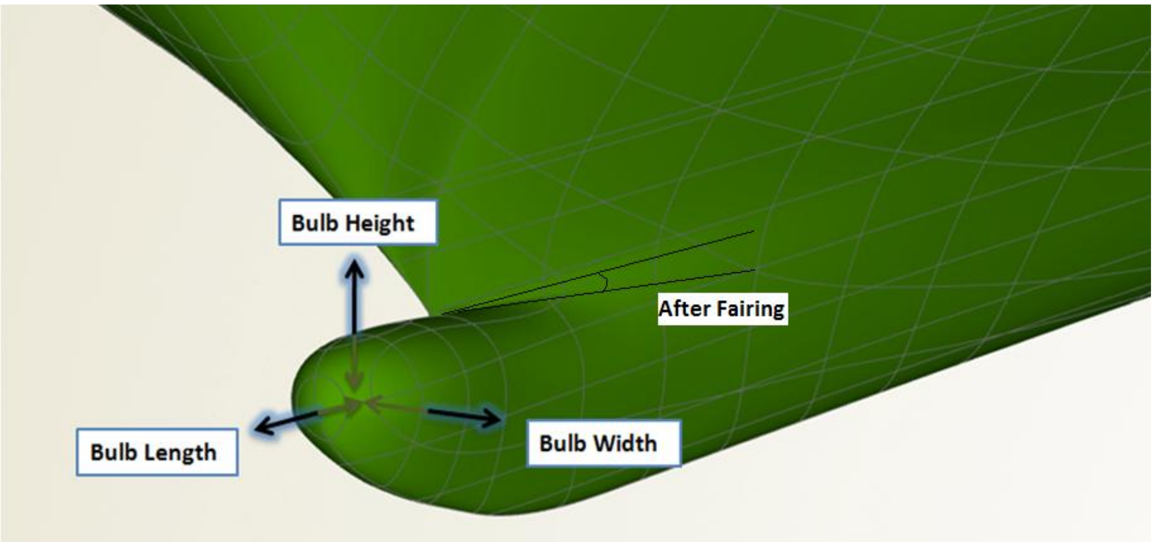


Figure 16 – Bulb form variation on FFW.

Water line variation

- Entrance angle: Controls the entrance angle of the waterline at the bow regarding the X-Y plane.
- Waterline fullness: Controls the area of the waterline (X-Y plane) keeping the same angles at both ends.

Others forebody variations:

- Flare at DWL: defines the inclination of the section curve at water line position.
- Section area: varies the forebody volume.
- Section area longitudinal distribution: distribution of volume along x-axis.
- Shoulder position: Defines the variation of the shoulder X position.

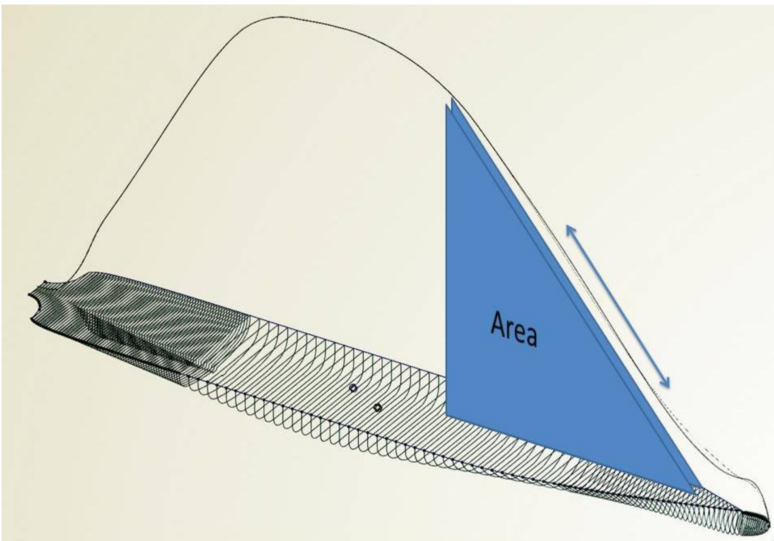


Figure 17 – Illustration of the section area variation (triangle shows the affected area, arrow point the variation on the area distribution).

4.4. Constraints

In order to generate, by automatic parameters variation, only desirable and smooth surfaces some constraints are used. The design variables range is setup in a way to cover all possible variation of each parameter (e.g. from a thin to a wide bulb). However, some combination of parameters are not appreciated as a design of a wide bulb combined with a narrow slim body just after it could induce some undesirable vortices illustrated in Figure 18

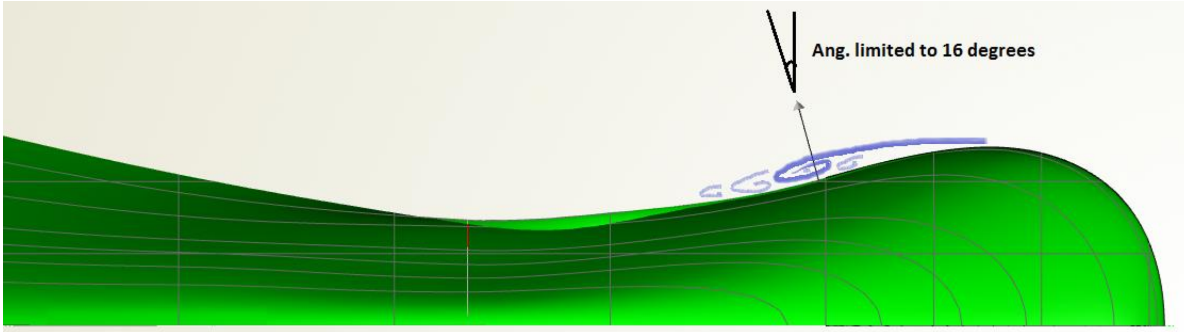


Figure 18 – Top view of the cut bulb at Max Bulb Beam. Illustration of possible fluid separation.

The “pin head” bulb geometry happens due to the combination of some parameters. This shape could be avoided by limiting the range of the related parameters, but then many interesting possible designs would be lost. A second solution for this problem could be to co-relate some of these parameters, in a way that both regions vary in the same “direction” e.g. thinner the bulb, slender body. However, by this method the angle highlighted at the Figure 18, for example, would be fixed, discarding the possibility of optimization of such angle. Finally, some constraints are used to avoid unwished designs. For the bulb angle a limit of 16 degrees is defined, the number is a common sense and don’t rely in any scientific research. That constraint and some others are described in the following.

- Bulb angle: Avoid the “pin head” geometry of the bulb by analyzing the normal of the surface at the aft bulb region.

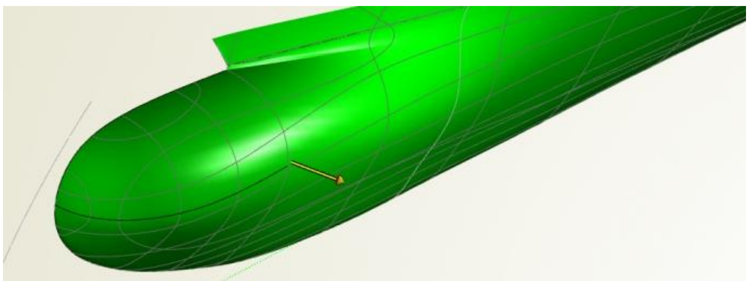


Figure 19 – Normal arrow at specific point on bulb surface to control and avoid “pin head” geometries.

- Concave bulb: Avoid concave geometries on the top of the bulb.

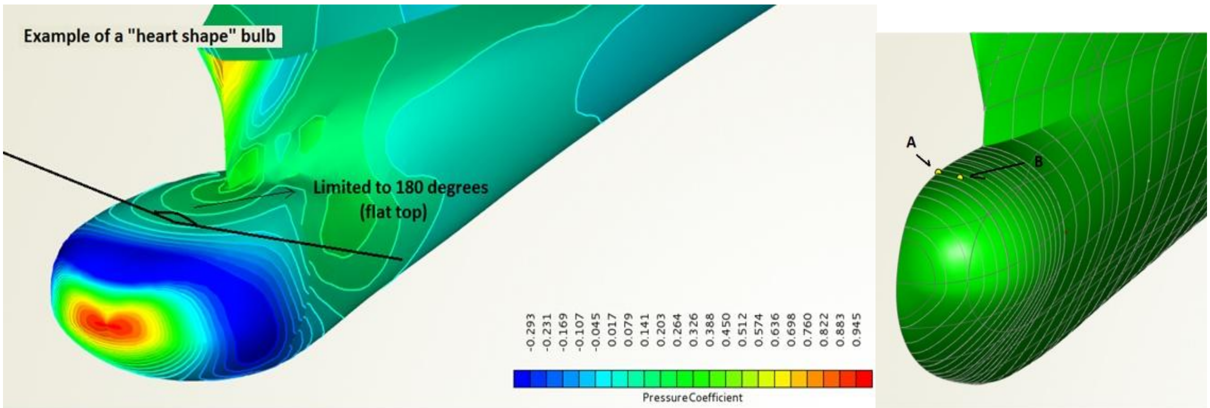


Figure 20 – Leftt: Pressure coefficient at a “heart shape” bulb. Right: Points “A” and “B” used to shape control

- Aft bulb fairing high: Avoid the aft fairing of the bulb to be higher than the draft, to guarantee smooth offsets.

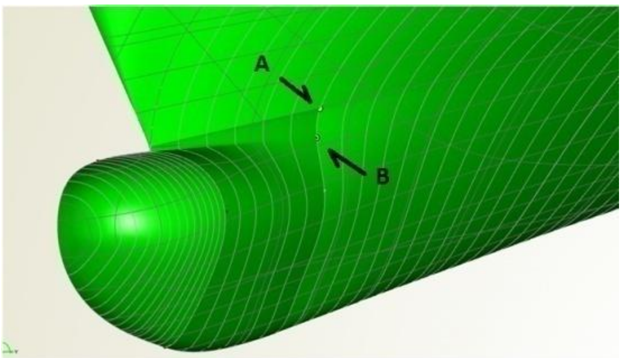


Figure 21 – Illustrate the controls points “A” and “B” used to avoid unwished designs due to the cross of the aft fairing of the bulb and the hull form at dwl.

5. CFD METHOD

In order to perform an optimization of a hull-form regarding the resistance, seakeeping etc the corresponding value must be somehow estimated, for that CFD is a suitable tool. There are several of kinds of solvers and which one has their own pros and cons for each specific application regarding accuracy and computational costs. As shown on Figure 22 very accurate and detailed methods are very costly, thus it is very important to well select the tool to be used in each case in order to achieve results that represents well the phenomena necessary for the study within the minimum cost possible.

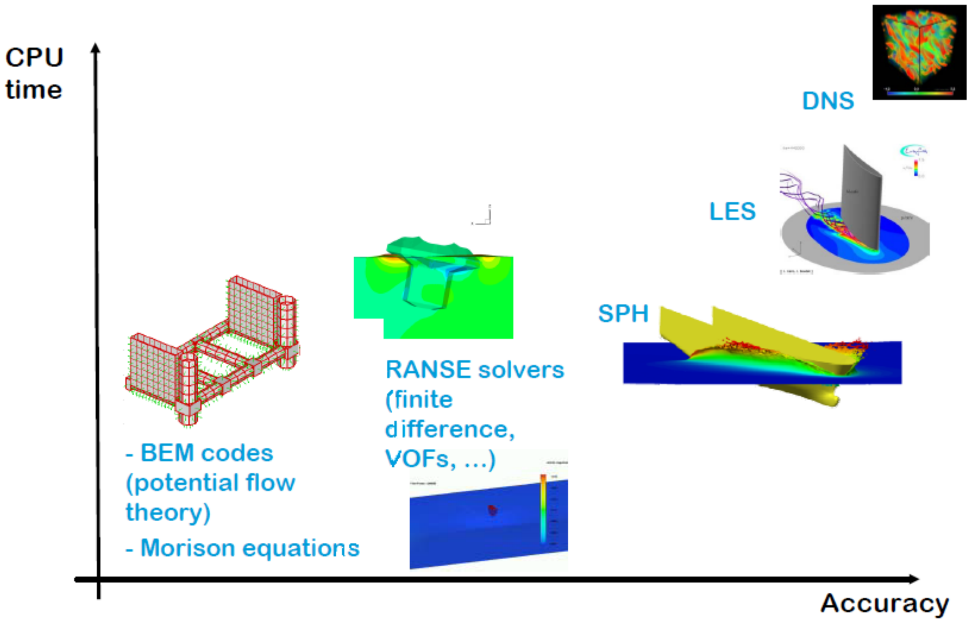


Figure 22 – CFD methods, CPU time x Accuracy, Ferrant [29]

Potential flow codes are more commonly used for optimization regarding the wave resistance by evaluating the variance of fore and midi body of the hull forms. For the stern region, where viscous effects are dominant, the study should be done by the usage of RANS solvers. The extended time need to perform a resistance prediction considering the viscous effects together to the big amount of designs that must be evaluated in order to perform the proposed study, robust optimization, led the authors to concentrate the optimization on the forebody region. Thus, potential calculation is suitable for the resistance prediction of the vessel and widely used.

The total resistance of the vessel is estimated by the wave pattern resistance that is computed by SHIPFLOW CFD software, SHIPFLOW CFD is jointly developed in Flowtech International AB and Chalmers University of Technology.

To compute the resistance, two techniques are used: pressure integration and transverse wave cut obtained by the non-linear panel method (potential-flow). In accordance to Koh et al

2005 [30] the transverse wave cut technique is the most robust one. The pressure integration method is sensitive to local irregularities of the panels that describe the hull surface; in addition the wave pattern is less sensitive to these irregularities, which could explain that the wave cut technique is superior to pressure integration. The wave profile plan must be located at some distance from the model in order to avoid the non-linear effects and there is no requirement for any analytical extension in the transverse wave cut technique, Koh et al 2005 [30]. In SHIPFLOW, the multiple TWC method (MTWC) is used to predict the wave pattern resistance, this technique uses several, non-equidistant transverse wave cut behind the ship. Furthermore, TWC's can be truncated at any length outside Kelvin wedge leading to a lower dimensions requirement of the free-surface grid and thus reducing the computational time.

Further details of the CFD configuration used for total resistance prediction are given in the following pages.

5.1.Mesh

A fine mesh is auto generated on SHIPFLOW, by XMESH, for both hull and free-surface based on the offsets of the parametric model, with a number of panels of 10 thousands approximately.

The XMESH module is also executed during the potential flow computation as the sinkage, trim and non-linear iterations are performed and the panelization is updated for each iteration. Furthermore, XMESH generates the panels used for a sink-disk representation of a propeller in the potential flow. The sink-disk agrees with the geometry of the real vessel propeller.

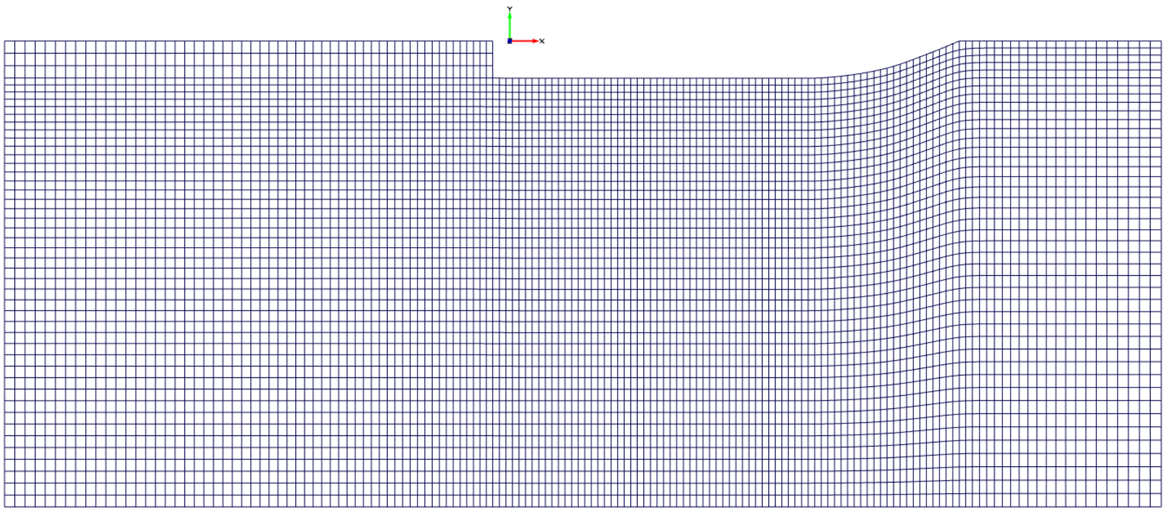


Figure 23 – Detail of mesh of free surface auto generated on SHIPFLOW

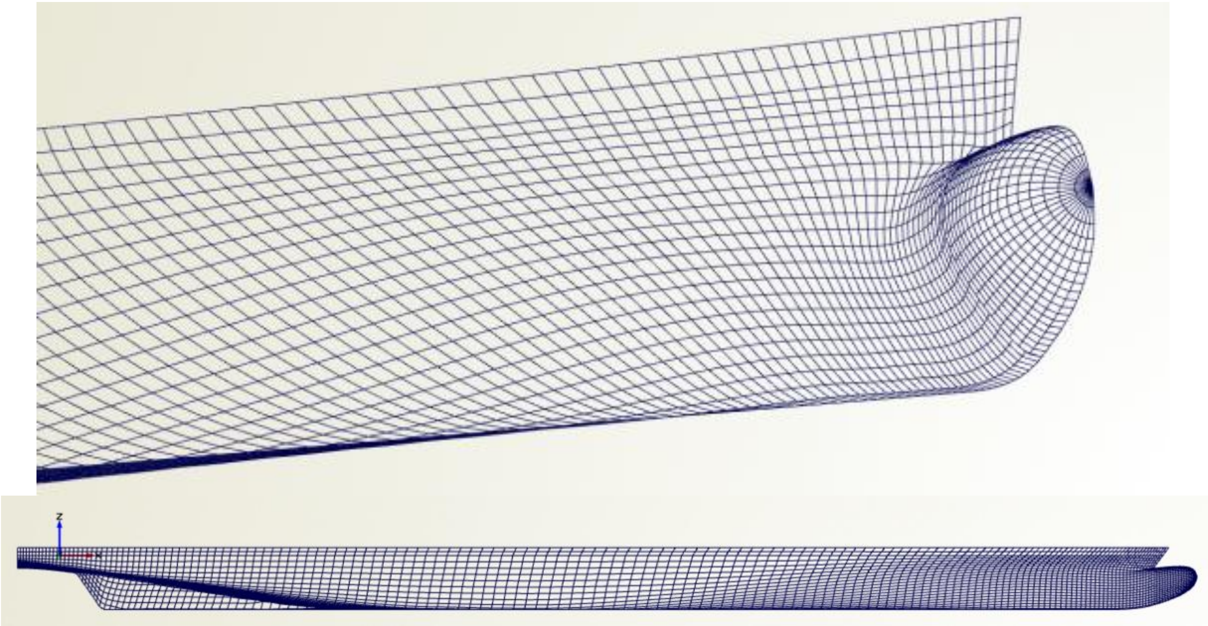


Figure 24 – Detail of mesh on body surface auto generated by SHIPFLOW

5.2.XPAN

The potential flow solver used on the SHIPFLOW is the XPAN, which is based on a surface singularity panel method. Some of the considerations are listed below:

- Transom stern is considered
- Free sinkage and trim condition
- Non-linear free surface boundary condition
- Single-model solution as base flow

5.3.XBOUND

The viscous resistance is estimated by two different methods, ITTC-57 equation and XBOUND which computes a thin boundary layer on the hull (Momentum integral equations along streamlines traced from a potential flow computation).

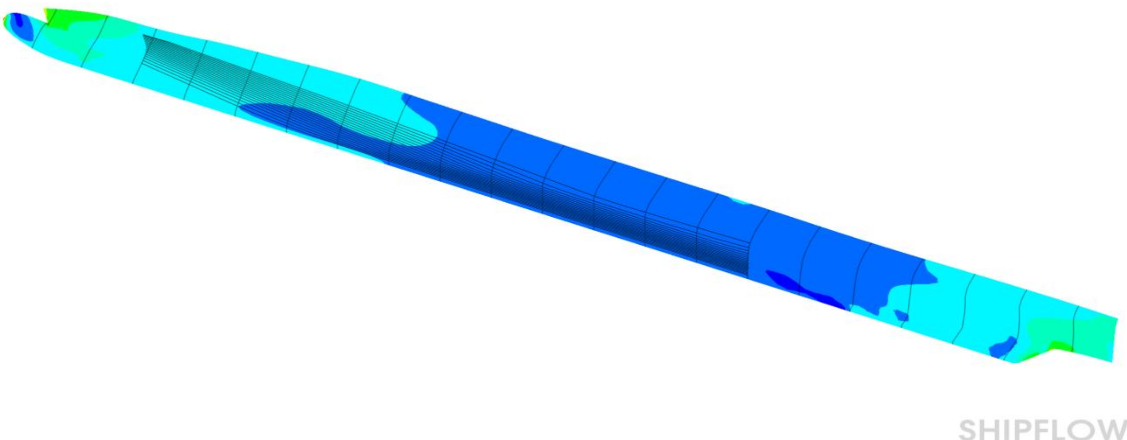


Figure 25 – XBOUND, streamlines traced from the potential flow computation.

The method given by ITTC 57 is the Equation 1:

$$C_f = \frac{0.075}{(LogR_n - 2)^2} \qquad \text{(Equation 1)}$$

The second approximation, XBOUND, has a higher computational cost, but it is considered to be more accurate. The difference between both calculations is computed for some designs as following.

$$Difference\ (\%) = \frac{Rt_{ITTC} - Rt_{XBound}}{Rt_{XBound}} \qquad \text{(Equation 2)}$$

Finally, considering all randomly selected designs the average and standard deviation of this difference is in Table 4.

Table 4 – Design of Experiments random selected designs, table presents the statistics of the difference between total resistance computed via ITTC and XBOUND methods

DoE ITTC x XBOUND		
Min	1.60 %	Stand. Deviation
Mean	2.10 %	0.39 %
Max	3.19 %	

Considering that the best design obtained in the presented DoE presented an improvement of only 1.1% relative to the total resistance of the base model and that the difference between the calculation using ITTC formula and XBOUND method is around 2.1% with standard deviation of 0.39% it is decided to perform the XBOUND calculation for all design on the optimization process. Furthermore, the total resistance calculation by XBOUND is used as objective function on the optimization process.

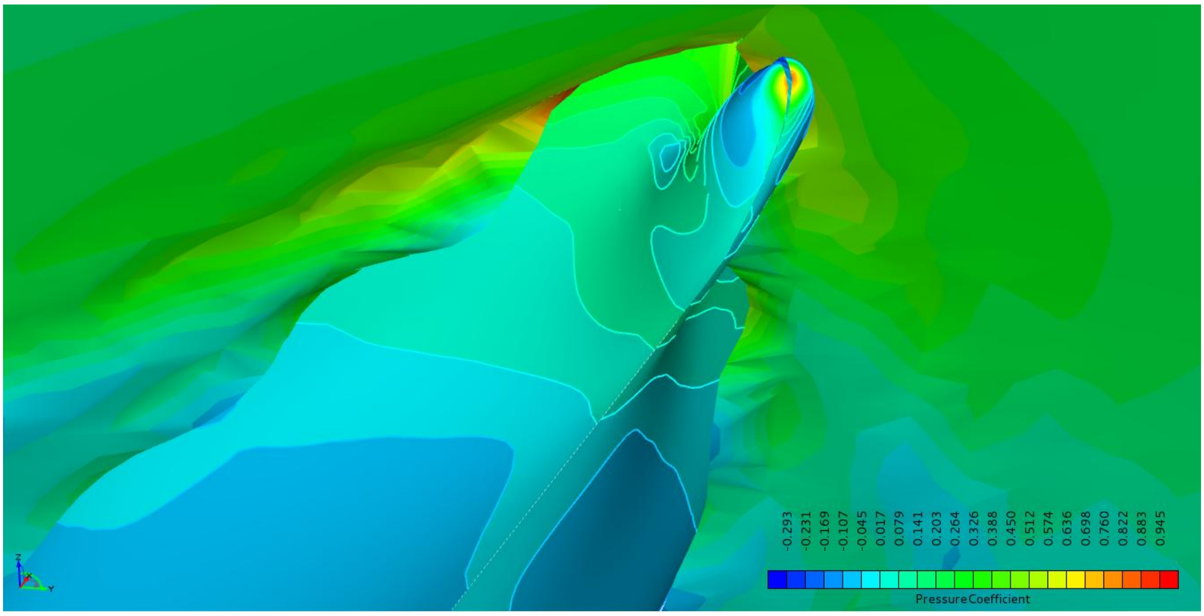


Figure 26 – Result example. Pressure on the body surface and free surface elevation for two different models displayed simultaneously, one half design at starboard and other design on the port board.

6. SINGLE OBJECTIVE OPTIMIZATION

6.1. Design of Experiments

The optimization processes applied on this project consist, as first step, to perform a study of the design space. Usually the Design of Experiments (DoE) is driven by a random or quasi-random process and it has a big importance as well to drives the optimization process towards the global optimum and not to local minimum when performing deterministic optimization process for instance. See Figure 27 for illustration

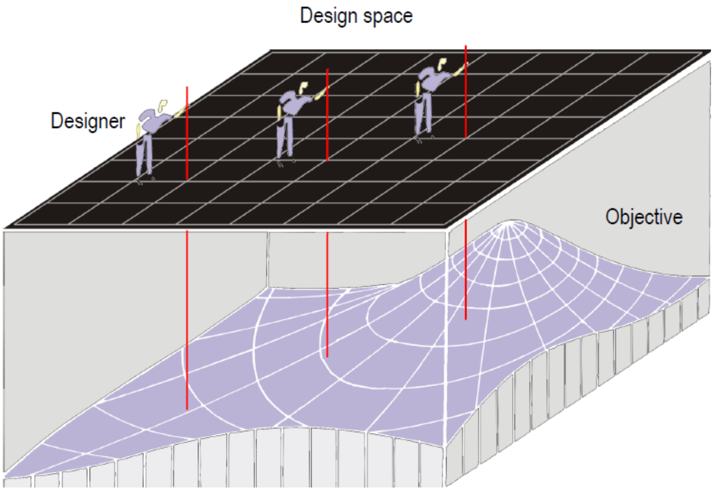


Figure 27 – Exploration of design space, Harries [11]

Design of Experiments techniques enables designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results of the design. This technique was also applied to select the design variable used on the optimization in this project as seem in section 4.2 Parameters.

For this project the DoE is performed using the SOBOL method. SOBOL or also known as quasi-random or low discrepancy sequence is a deterministic algorithm that imitates the behavior of a random sequence with the aim of performing a uniform sampling of the design space.

The Figure 28 represents the sampling of the design space obtained via SOBOL where each column, defined by “dots”, are one design variable and the “dots” represent one single design and in the ordinate it is represented in percentage the relation of the design variable in the defined range (bounds) obtained by the following:

$$if\ D_{esign\ \ Var} > M_{ean\ \ Value} : Y = \frac{D_{esign\ \ Var} - M_{ean\ \ Val}}{B_{Upper\ \ Bound} - M_{ean\ \ value}} \qquad \text{(Equation 3)}$$

$$if\ D_{esign\ \ Var} < M_{ean\ \ Value} : Y = \frac{M_{ean\ \ Val} - D_{esign\ \ Var}}{B_{Lower\ \ Bound} - M_{ean\ \ value}} \qquad \text{(Equation 4)}$$

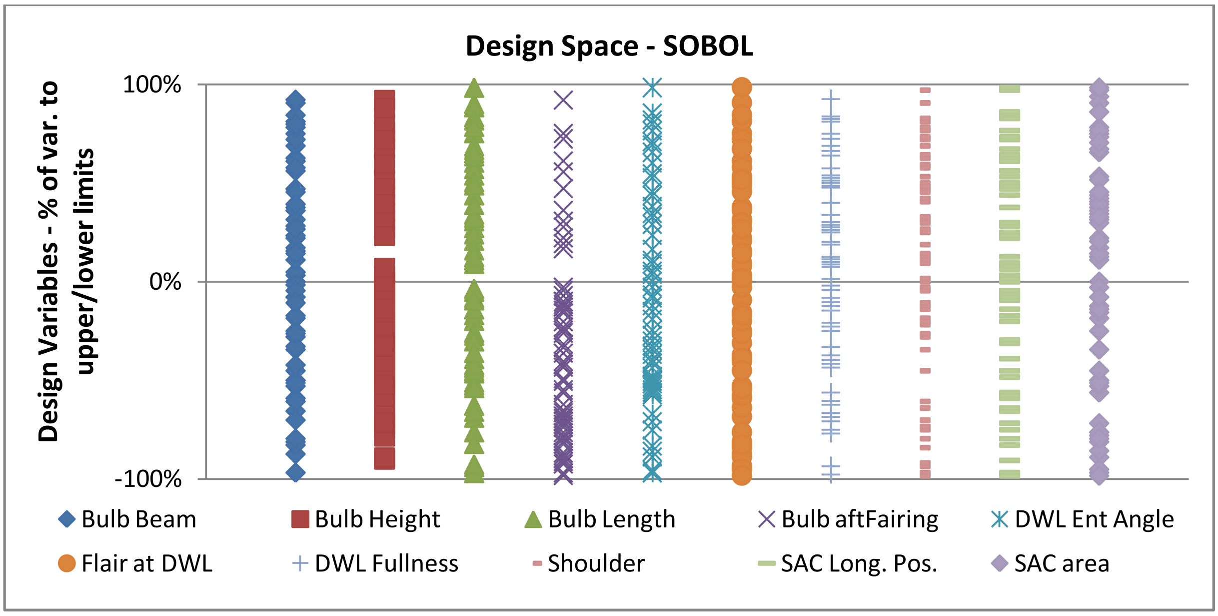


Figure 28 - Design space sampling performed using SOBOL

Finally, the DoE study within 55 feasible designs presented a good result, as it is shown to well cover the design space, all range for every design variable. With these results in hands, the best design can be selected and on it the optimization technique performed.

6.2. Optimization Process

For the optimization itself the TSearch method was chosen. It consists of exploratory moves starting from the initial point, selected after performing an exploration on the design space, and followed by global moves in the descent search in successful exploratory moves. The solver is reliable for small scaled, single-objective optimizations problems with inequality constraints. It detects a descent search direction in the solution space, and keeps the search in the feasible domain. More information can be found in Hilleary 1966 [31].

In the first case:

- Objective Function is Total Resistance Rt_XBOUND

With the conditions of speed/draft:

  - V_1=19.77 Knots
  - Draft of T=6.2m

The Figure 29 presents the results for the optimization process together with the designs obtained on the DoE study, displayed by their indexes (order of creation) and in the ordinate is the total resistance in percentage relative to the base model.

$$Rel.Resistance = \frac{D_{esign\ R_t} - BM_{R_t}}{BM_{R_t}} \qquad \text{(Equation 5)}$$

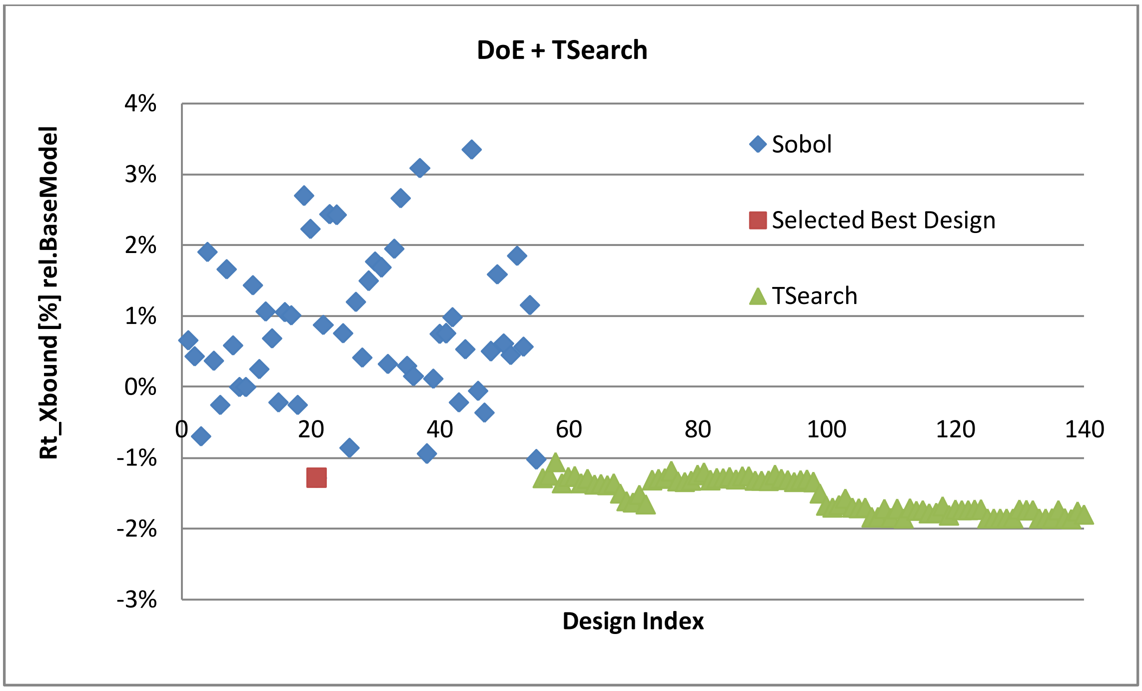


Figure 29 – Single objective optimization process via TSearch

The optimized model has a wave resistance reduction of 12.65%, an expressive result. However, regarding the total resistance, where the viscous effects are estimated using XBOUND (Momentum integral equations along streamlines), the reduction is of 1.87% related to the base model.

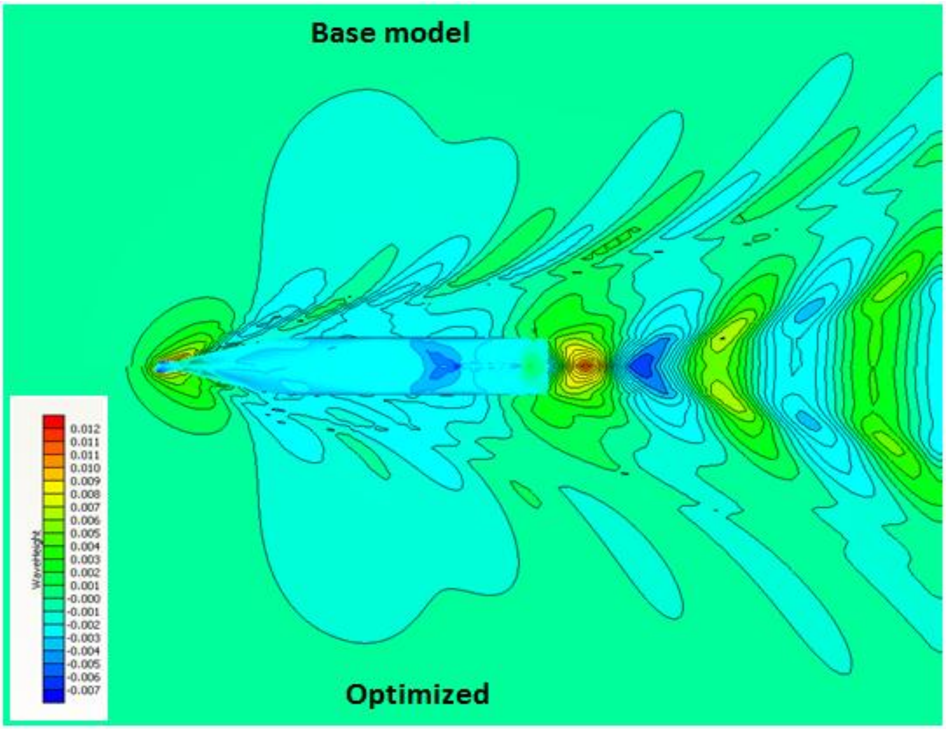


Figure 30 – Wave height comparison between Base model and Optimized model.

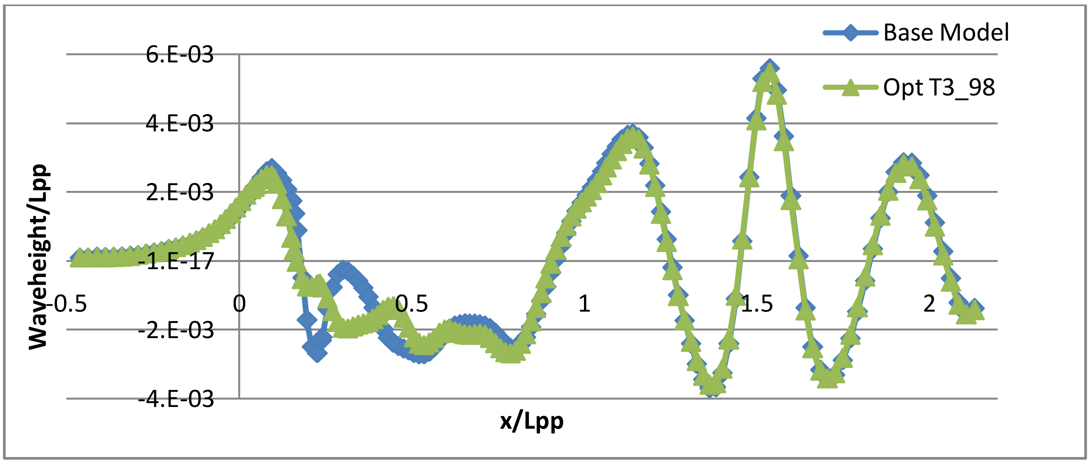


Figure 31 – Wave cut comparison between base and optimized model.

The optimized geometry has a longer and wider bulb as can be observed in Figure 32. Furthermore, the shoulder was shifted forward, the volume of the front part of the SAC increased and the entrance angle a bit wider than the base model.

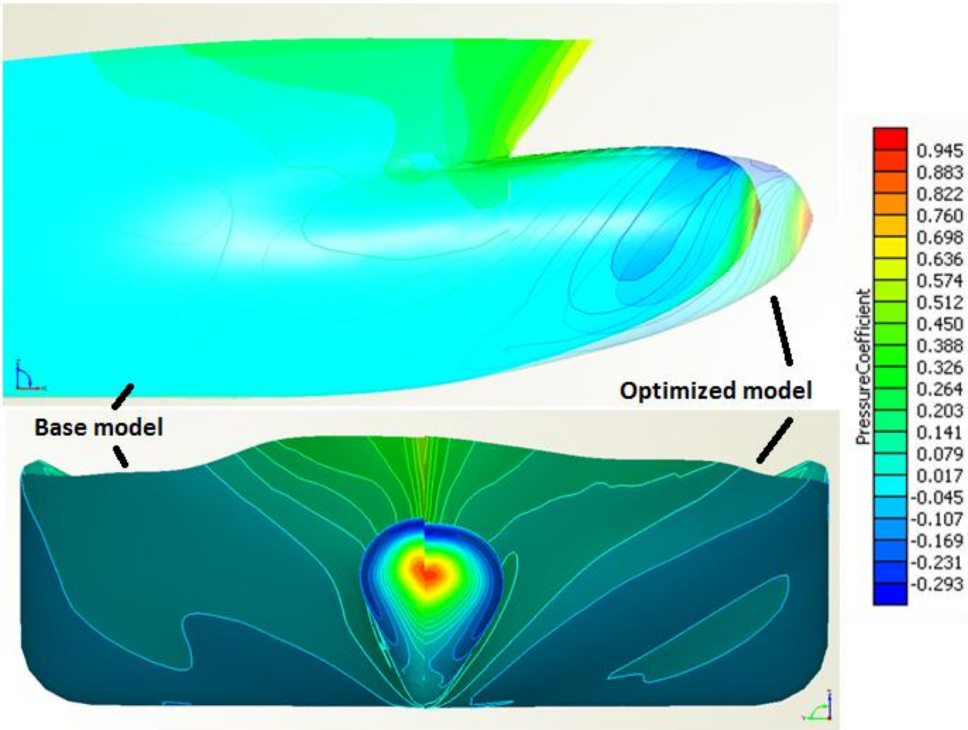


Figure 32 – Base model and optimized model (shadow/right) comparison.

Finally, the same process, TSearch optimization, is done for a second operational condition in which the objective function is the resistance at speed V_2:

In the second case:

- Objective Function is Total Resistance Rt_XBOUND

With the conditions of speed/draft:

  - V_2=22.00 Knots
  - Draft of T=6.2m

The model optimized for condition 2 (Min: Rt_{V2}) presents a reduction of the wave resistance of 4.89%, and for total resistance 1.98% of reduction relative to the base model in the condition of velocity equals to 22knots. Furthermore, when comparing both models, optimized for V_1 and V_2, in both conditions the tradeoff can be observed in a seesaw behavior of the vessel when changing condition, Figure 33.

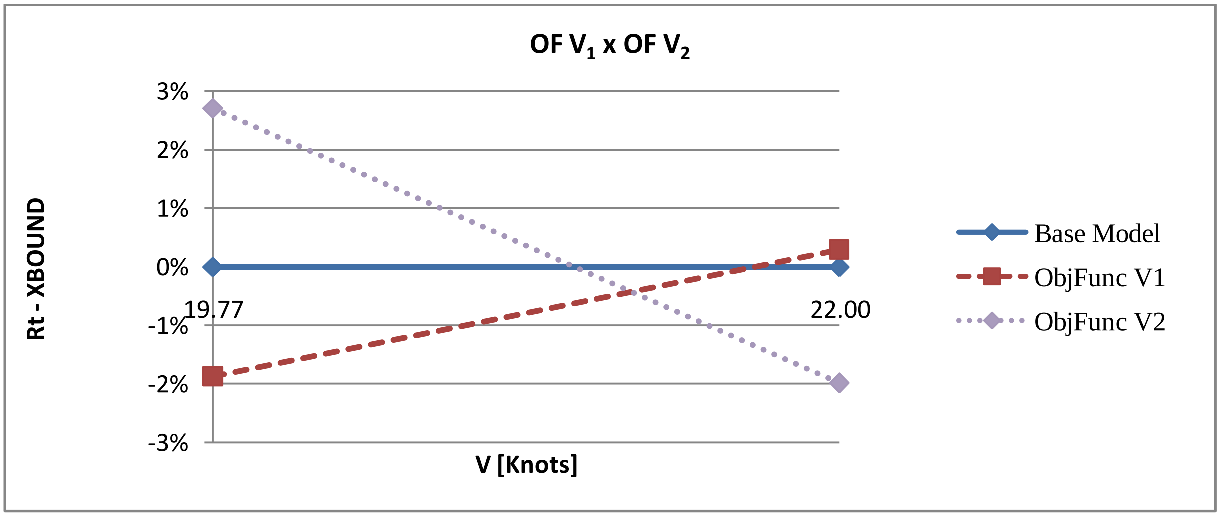


Figure 33 – Single objective optimization for V_1 and V_2

The model optimized for Rt_{V2} in the contrary of the optimized for Rt_{V1} has a shorter, slight higher and wider than the base model. The shoulder was slightly shifted forward, the volume of the front part of the SAC reduced and the entrance angle a bit wider than the base model. Some of the variations and the pressure coefficient can be observed in Figure 34.

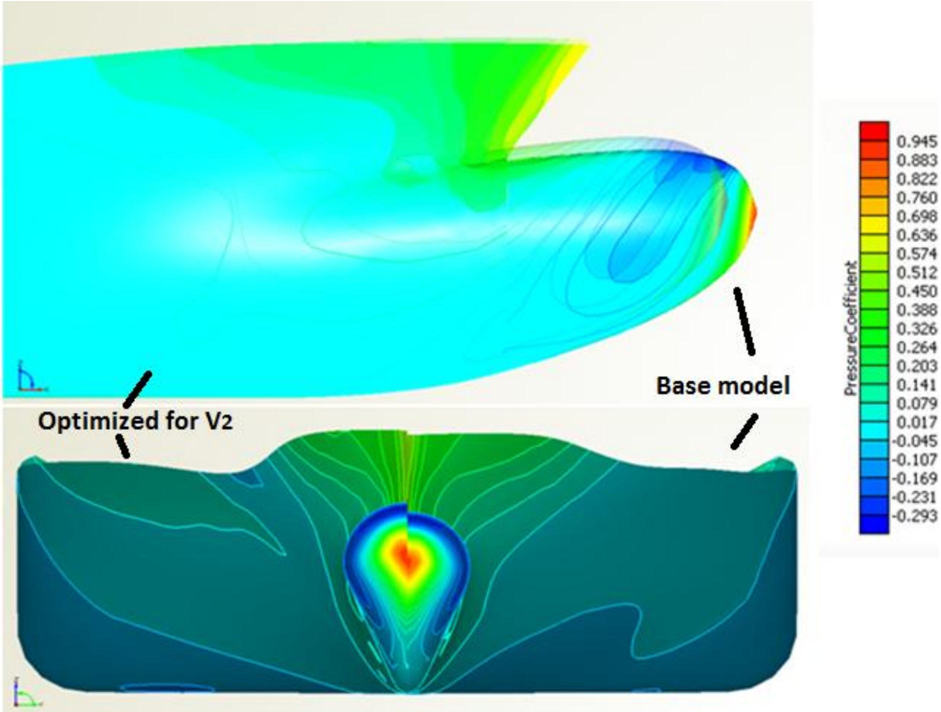


Figure 34 – Comparison of base model and optimized (shadow/left) for Rt_{V2} at V_1

7. SINGLE OBJECTIVE OPTIMIZATION (WEIGHTED FUNCTION)

A method to perform a multi-objective optimization is the weighting method, where the objective function is defined as a weighting function as the barycenter of all the functions used as criteria Guillerm and Le Touzé 2013 [32]

$$f_{weighting}(x) = \sum_{i=1}^{m} \alpha_i f_i(x), \ \sum_{i=1}^{m} \alpha_i = 1 \qquad \text{(Equation 6)}$$

7.1. Design of Experiments

The design space was studied by the usage of SOBOL algorithms where both operational conditions were considered on the calculation. The designs analyzed were the same as seem in 6.1 and so the design space coverage is guaranteed as seem in 6.1. The difference is that the analysis of each model, via SHIPFLOW, is now done for all conditions and the relative resistance to the base model can be seem in Figure 35.

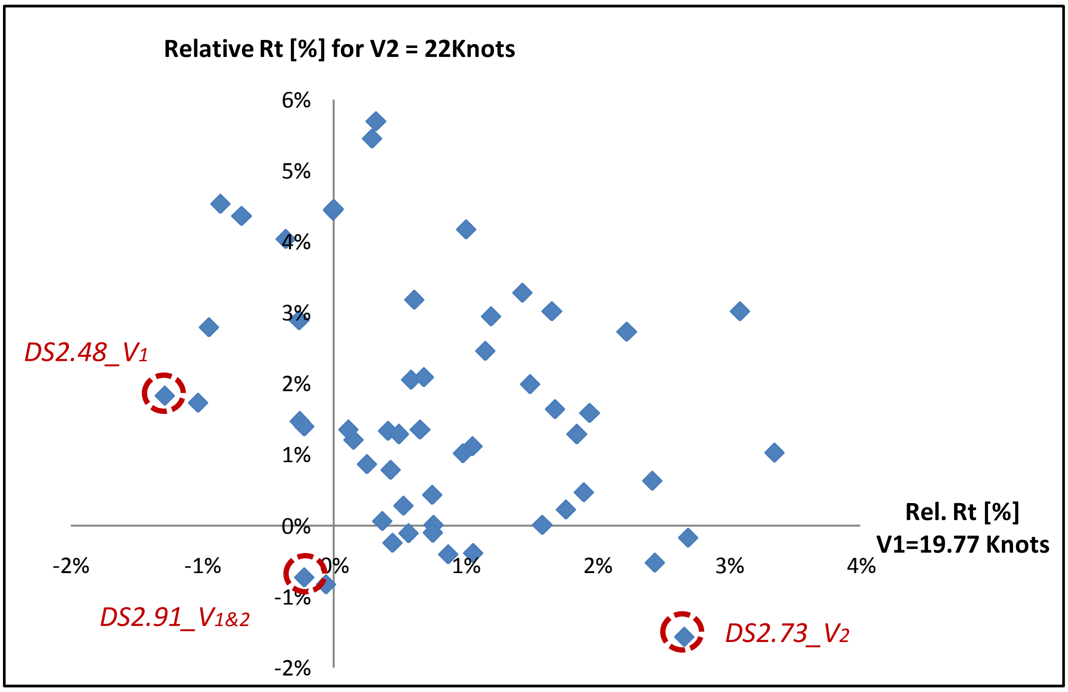


Figure 35 – DoE [SOBOL] 55designs analyzed for 2 different operational conditions

Finally, the best design concerning the improvement in both operational conditions is chosen having as criteria as the model that is better for both equally:

$$Criteria: Min\,(R_{tm}) \qquad R_{tm} = 0.5 * R_{tV1} + 0.5 * R_{tV2} \qquad \text{(Equation 7)}$$

The design selecting for the DoE can be visualized in Figure 35 as the Design "DS2.91_$V_{1\&2}$". For reference the designs selected for the single objective optimization in 6.2 that were selected by the criteria of minimum resistance regarding to only one velocity are also highlighted on the Figure 35 as "DS2.48_V_1" for optimization for regarding the Rt_{V1} and "DS2.73_V_2" for Rt_{V2}.

7.2. Optimization Process

For the consideration of two different operational conditions as objective function on the optimization process several techniques were used where the conditions are defined by the variation of the velocity (V_1= 19.77 and V_2= 22.00 Knots). A single objective optimization method is performed, in this case TSearch was once again used, and the objective function (OF) is defined as following:

$$OF = \alpha * R_{tV_1} + (1-\alpha) * R_{tV_2} \qquad \text{(Equation 8)}$$

Where α is the weight coefficient

$$0 < \alpha < 1$$

If $\alpha = 0$or $\alpha = 1$ it is a single objective problem where only one condition is considered and the results would be similar to those observed previously (6.2 Optimization Process)

The optimization was done by the usage of TSearch tool based on the gradient method. Three different values for the weight were considered:

i. $\alpha = 0.25$
ii. $\alpha = 0.50$
iii. $\alpha = 0.75$

7.2.1. α = 0.25

The weight of 0.25 means that 25% for the objective function is due to the resistance of the vessel at velocity V_1 and 75% related to the Rt_{V2}.

In the Figure 36 it can be observed a major reduction of the resistance for the velocity 2 of 22 Knots, as expected from the objective function defined. It can also be observed that in both operational conditions the total resistance is reduced by the weighted method where both are considered in the optimization process. Finally, it can also be observed that some designs during the process present a worse resistance than the base model (some designs present a positive relative resistance for V_1) as it is not treated as a constraint, but further on the designs is once again improved and the final results presents a reduction of resistance for both speed conditions.

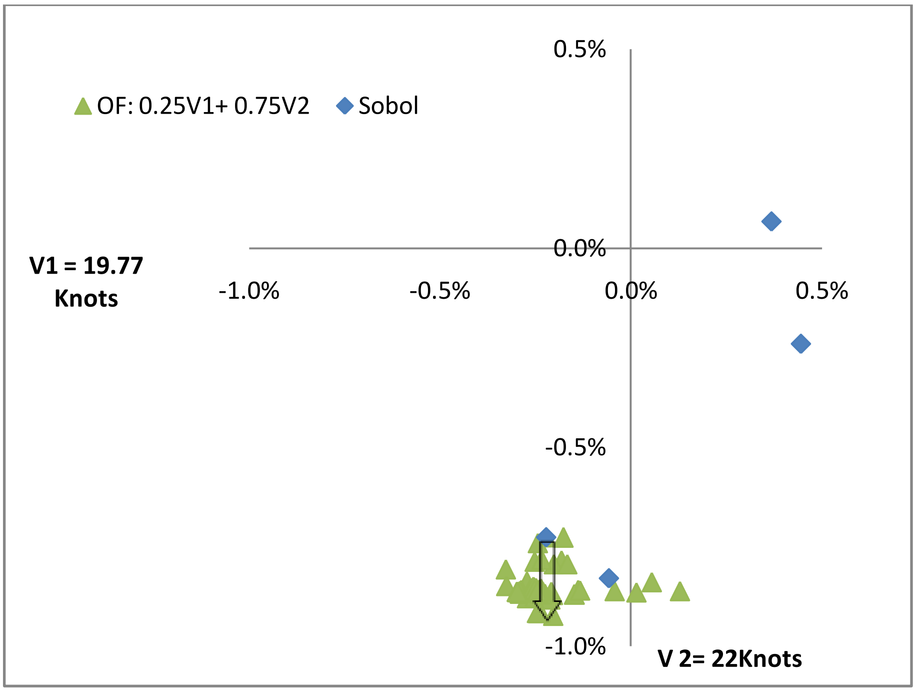


Figure 36 – Weighted function α = 0.25. Values in % rel. to Rt Base Model at respective condition.

7.2.2. α = 0.50

The weight of 0.50 means that each 50% for the objective function is driven by one of each resistance analysis of the vessel Rt_{V1} and Rt_{V2}.

As expected the optimization process for α=0.5 has an improvement a bit more equivalent for both condition when compare with the others weights. The improvement tendency is represented by the arrow on Figure 37

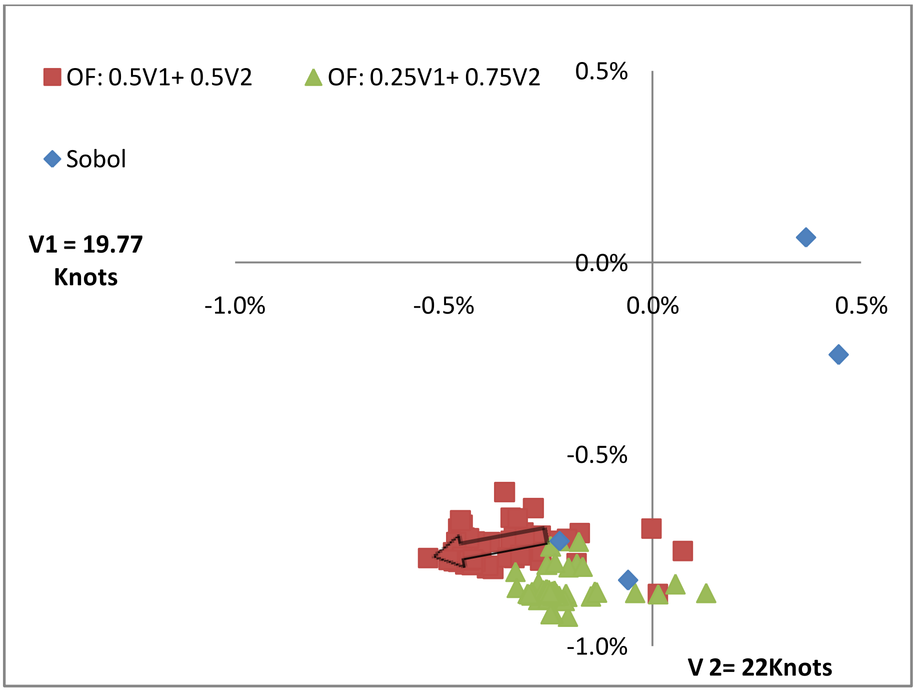


Figure 37 – Weighted function α = 0.5. Values in % rel. to Rt Base Model at respective condition.

7.2.3. α = 0.75

When weight is 0.75, 75% of the objective function is related to the resistance of the vessel at velocity V_1 and only 25% relative to the Rt_{V2}.

The arrow on Figure 38 shows the tendency of the optimization process for a larger reduction for Rt_{V1} (abscissa) when compared to the Rt_{V2} (ordinate).

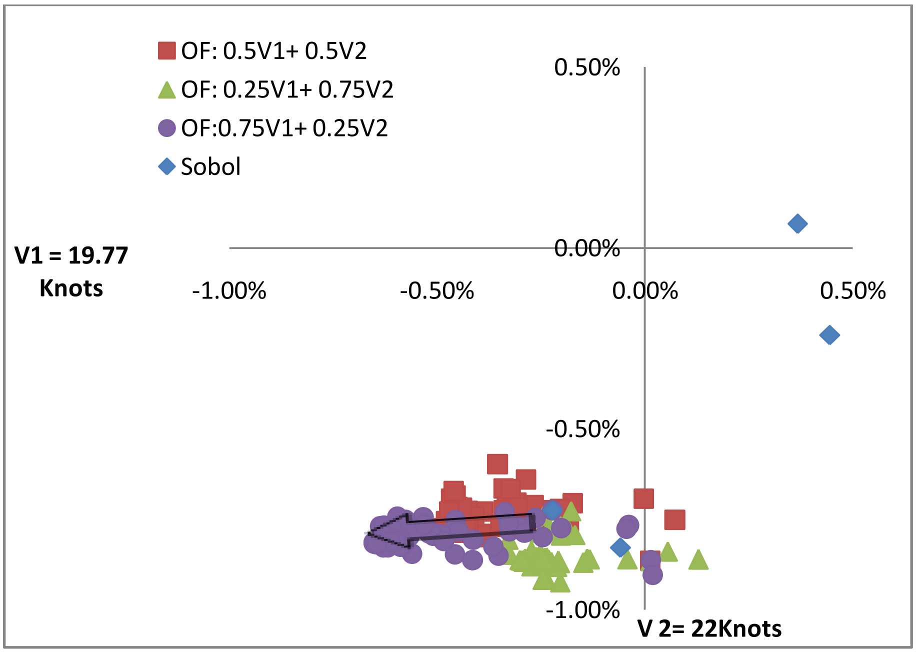


Figure 38 – Weighted function α = 0.75. Values in % rel. to Rt Base Model at respective condition.

It can also be observed on Figure 38 the comparison between the three optimization process with different weights and that the case of α=0.75 has a higher improvement from the initial design. It can be justified as the initial selected model has already a lower resistance for V2 (-0.22% for Rt_{V1} and -0.73% for Rt_{V2}) which gives more possibility for improvement when performing an optimization process.

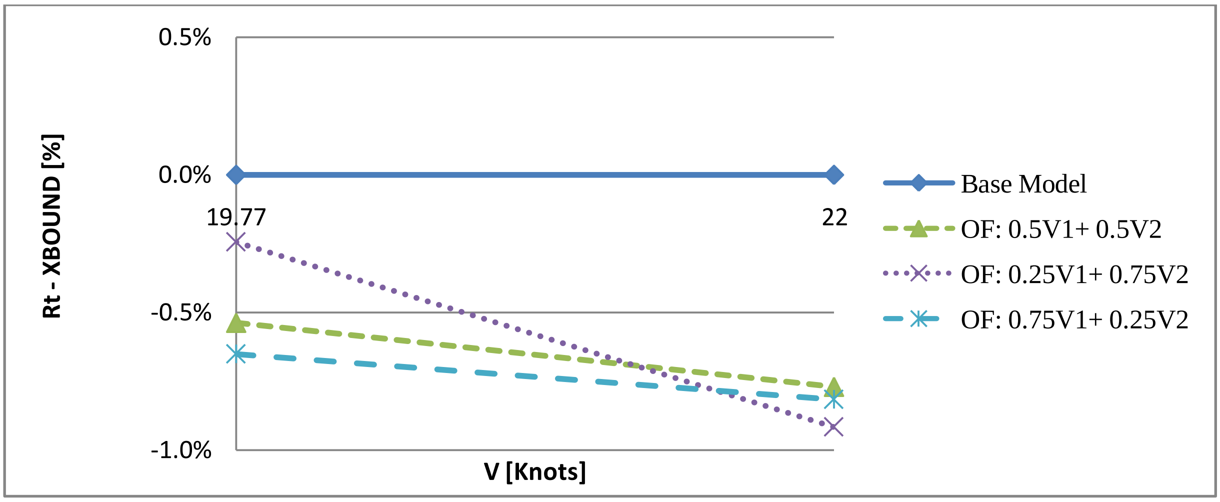


Figure 39 – Weighted function. Comparison of all optimum designs regarding the Rt for both speed conditions.

Finally, as it can be observed on Figure 39 that the tradeoff characteristic is presented, as expected, when varying the weight, once for higher the weight better is the improvement regarding R_{tV1}. In addition the weighted method possibility the optimization of the vessel for multiple objectives (Min R_{tV1} and R_{tV2}), as the vessels is optimized for both V_1 and V_2 conditions, and yet using the single objective gradient method TSearch. However, the improvement is quite reduced when comparing with the previous method, single objective optimization.

8. SINGLE OBJECTIVE OPTIMIZATION (CONSTRAINED)

The second approach used to perform a design optimization considering different operational conditions and yet single-objective functions, is via constraints. In this case one operating point is dominant while others are considered as constraints.

$$Min{:}\, Rt_{Operatio\ nPointj}$$

$$for{:}\, Rt_{OPi} \leq\ Rt_{BaseModelOPi} \qquad \text{(Equation 9)}$$

Where: i ≠ j.

8.1. Optimization initial design

For the selection of the initial model to perform the optimization process, it is a common practice to perform a DoE to avoid local minimums as explained and applied in 6.1 and 7.1. The design of experiments performed using the SOBOL method and the selection of the best design, for the optimization via single objective process with constraints, is the same as the design selected on 7.1 as it represents the best design for both operational conditions herein considered (Rt_{V1} and Rt_{V2}).

However, in addition to the optimization process applied to the selected design "DS2.91_$V_{1\&2}$" it was performed a second study for the TSearch taking as initial design the base model.

8.2. Optimization process

The optimization method is once again the gradient based (TSearch) and was performed for the cases:

$$Min{:}\, R_{tV_a} \qquad for{:}\, R_{tV_b} \leq\ R_{tBMV_b} \qquad \text{(Equation 10)}$$

Where: a = [1,2] and b= [2,1]

Finally, the optimizations of the following cases are presented:

I. Start point: Base Model:
   a. $OF{:}\, R_{tV_1} \quad C{:}\, R_{tV_2} \leq R_{t\ BM\ V_2}$
   b. $OF{:}\, R_{tV_2} \quad C{:}\, R_{tV_1} \leq R_{t\ BM\ V_1}$

II. Start Point: Best SOBOL Design
   a. $OF{:}\, R_{tV_1} \quad C{:}\, R_{tV_2} \leq R_{t\ BM\ V_2}$
   b. $OF{:}\, R_{tV_2} \quad C{:}\, R_{tV_1} \leq R_{t\ BM\ V_1}$

8.2.1. From Base Model

Figure 40 presents the results of the optimization process using a gradient based method starting from the base model (initial design) for both Rt_{V1} as objective and Rt_{V2} for the constraint and vice versa. The results are expressed in terms of the relative resistance to the base model in percentage. A greater improvement of the model is observed when using this method achieving reductions of the total resistance of the vessel greater than 2.5%.

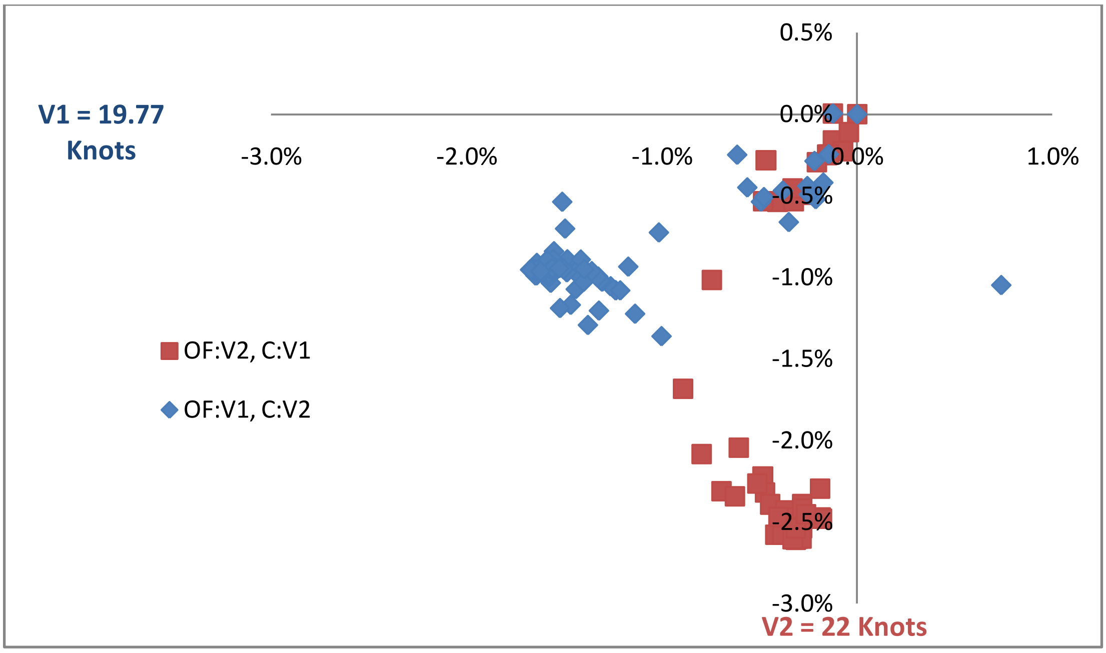


Figure 40 – Single Objective + Constraints. Optimization for condition 1 & 2 beginning from the Base Model. Values in % rel. to Rt Base Model at respective condition.

When comparing the improvement of the model regarding both conditions a slight similar behavior of a seesaw can be observed when varying the objective from one condition to another, Figure 41.

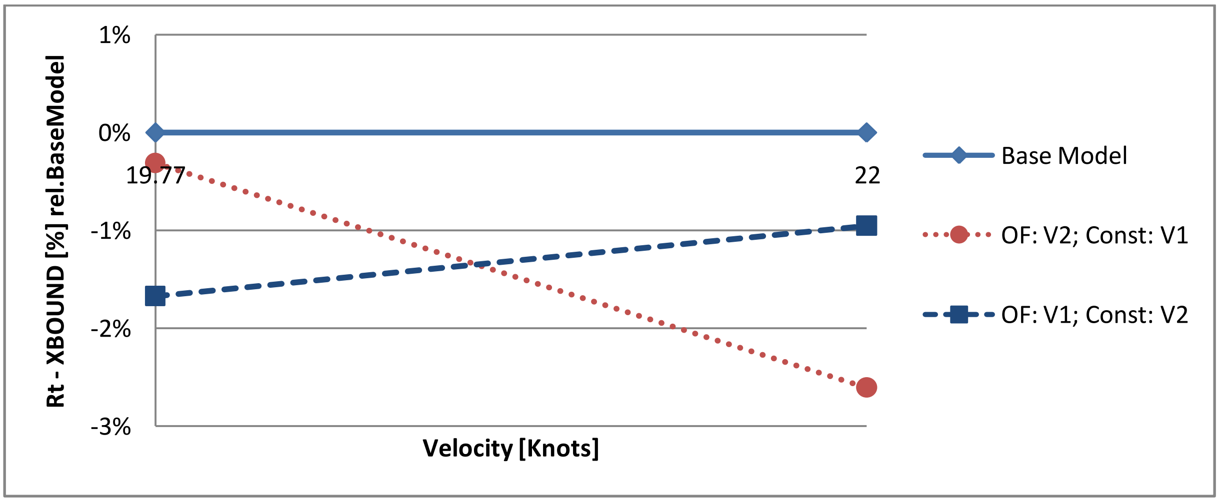


Figure 41 – Single obj. with constraints and base model as initial design. Comparison of optimum designs regarding the Rt for both speed conditions.

Furthermore, a larger percentage of resistance reduction is observed when optimizing with constraints than the equivalent optimization with weighted function, it might be justified as in this case there is no competition among the objectives. Finally, it is nice to observe that even with the good improvement, the resistance for the non-objective condition is still lower than for the base model, as it is a constraint.

The behavior of the optimization for a dominant operating point with others considered as constraints is double-check by the variation of the start point, as by the usage of the gradient based method a large influence of the initial point can be expected.

8.2.2. From DoE Best Design

The performance of the selected DoE best design "DS2.91_$V_{1\&2}$" can be observed in the Figure 35. The same model is represented by the red dot in the Figure 42 together of the results of the TSearch optimization process.

In Figure 42 a large improvement for the Rt_{V1} can be observed. However, the result for optimization taken Rt_{V2} as OF is not as good as. The second case presents very little resistance reduction.

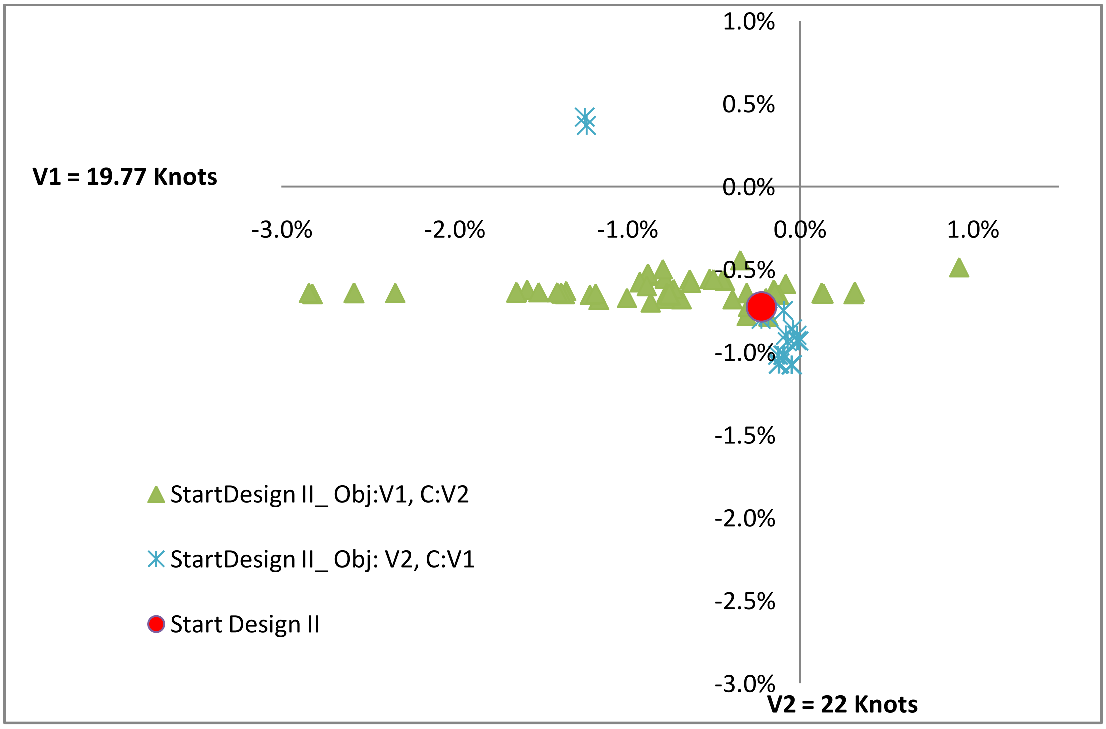


Figure 42 – Single objective optimization with constraints start from DoE best design. Values in % rel. to Rt Base Model at respective condition.

Figure 43 presents a comparison of the optimization process for case of single objective function with constrains for two different initial designs for the start of the optimization process. For the case where the Rt_{V1} is the objective and Rt_{V2} the constraint the improvement when the start is already a better design, obtained by the DoE study, presents a higher reduction of the resistance when compared with the optimization starting from the base model design. In other words the objective of performing a DoE beforehand is accomplish, it accelerate the process and could avoid local minimums. However, in the other hand the case of optimization for Rt_{V2} with Rt_{V1} as constraint the expected results, of a better improvement when starting from the best DoE design did not happened. It could be justified as the optimization process got trapped in a local minimum in that region when optimizing for the Rt_{V2}. As can be observed in Figure 40 and Figure 43 the process when starting from the base model made a “belly shape” over passing the possible local minimum in which the second process could have got trapped. It’s important to mention that the design variables are the values to be optimize and then could be stuck in a local minimum of the result analysis and not the other way around.

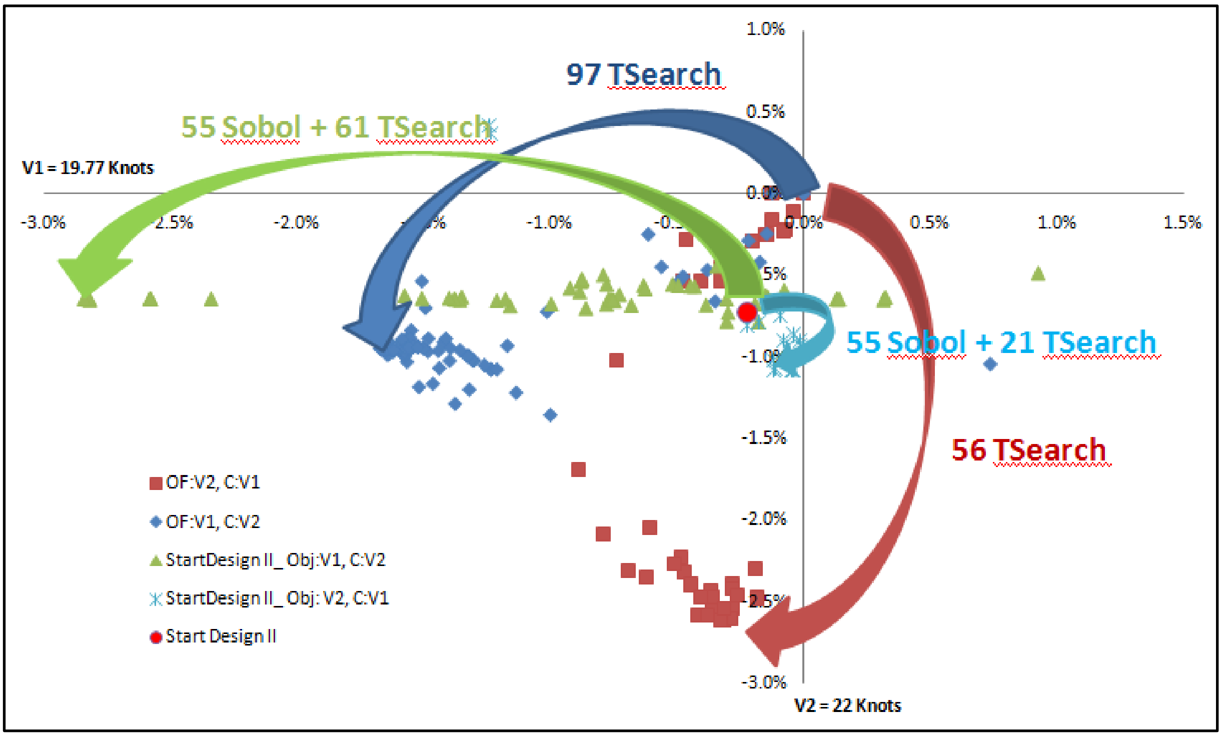


Figure 43 – Comparison of results regarding number of design needed and resistance improvement for different starting point of the optimization process. Values in % rel. to Rt Base Model at respective condition.

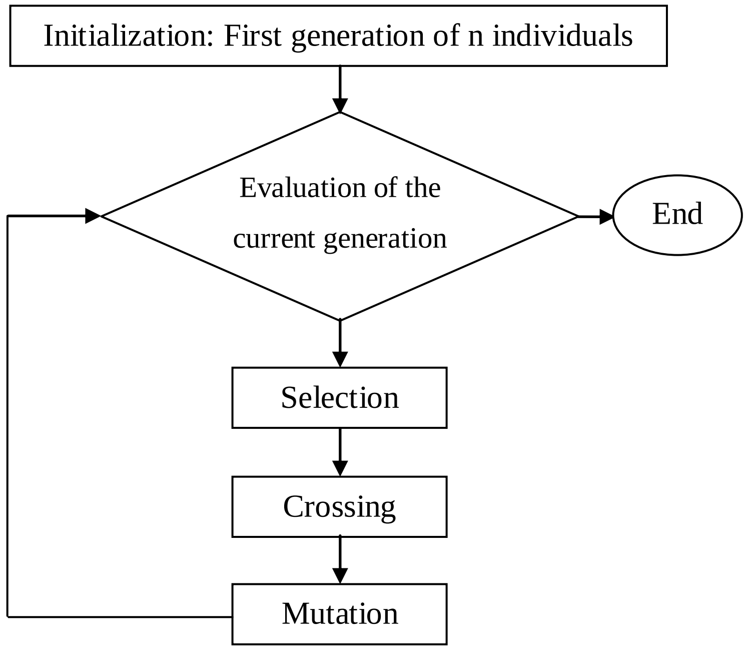
9. MULTI-OBJECTIVE OPTIMIZATION

The multi-objective optimization seeks for the optimization of:

$$f(x) = (f_1(x), \dots, f_i(x)) \qquad \text{(Equation 11)}$$

In general there is no design in which all the functions are minimal as there is no unique optimum design to a multi-objective optimization problem. However, there is a set of points that represents the best compromise between the various objectives called Pareto Frontier.

Genetic algorithms are used to perform multi-objective optimization. Coming from the evolution theory the general principle of a genetic algorithm can be represented by: modeFRONTIER [33]



9.1. Optimization Process

The algorithm chosen for the multi-objective optimization process is the non-dominated sorting based multi-objective evolutionary algorithm NSGA-II.

The results presented a low percentage of designs in which both results Rt for V_1 and V_2 were achieved. A big number of numerical errors were identified compromising the optimization process. Several tests were performed in order to determine the origin of those numerical errors. However, besides small details in the calculation set up that were slight modified to a better response, no reason for the big number of unfeasible designs were identified.

Three optimization processes were performed, all using the well known algorithm NSGAII.

i. Case I
- Generations: 30
- Population size: 24

ii. Case II [Start point]
- Generations: 12
- Population size:20

Both with the mutation and crossover probability of 0.9 and 0.01 respectively, these values are in accordance to the recommendation of the specialist and developers of the FRIENDSHIP-Framework for this study.

9.1.1. Case I

In the first case 720 unique designs were created and evaluated; the process took 18 days and 12 hours approximately running in a local machine with 8 cores, 2.67 Ghz. However, only 96 designs, 13.3%, are feasible designs with the results of the total resistance for both V_1 and V_2, 32 designs, 4%, are unfeasible due to the geometry constraints and all the others 592 designs, 82%, has a numerical error of some sort for the resistance estimation of one speed or both.

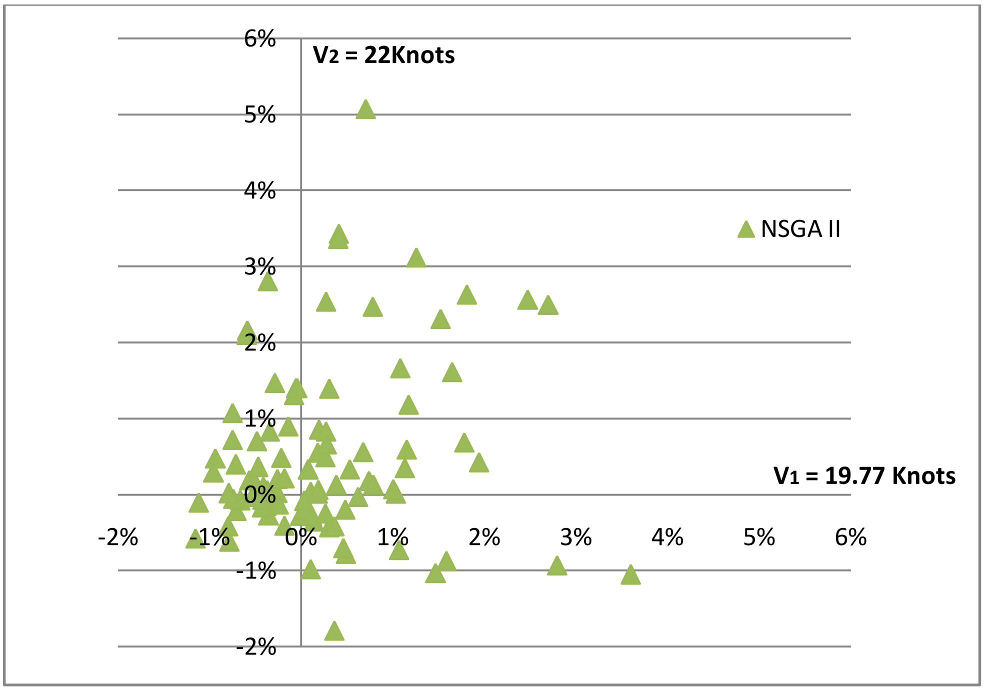


Figure 44 – Multi-Objective. Case I large number of Designs

In Figure 44 each of the 96 feasible designs are represented by a dot distributed by the relative resistance to the base model for V_1 in the abscissa and V_2 in the ordinate axis. It can be observed that most of the designs had a higher resistance when compared to the base model (positive values), unfortunately. Small improvements, around 1%, were observed leading to the conclusion that the algorithm didn't worked as expected.

9.1.2. Case II

Genetic algorithms as NSGA II are optimization process that should not depend on the initial design; the mutation property should cover every possibility of the space design when the enough number of designs (generations and populations) is created. However, an optimization with a different initial design was performed, not to avoid local minimum, but attempting to move the "cloud" of design resistance a bit more towards the wanted area of better performance designs. The case II is a multi-objective optimization by the usage of the same genetic algorithm as in case I, NSGA II. Nonetheless, using as initial design the best DoE design, "DS2.91_$V_{1\&2}$", which was selected for the consideration of both conditions at once, refer to section 7.1 for details.

Finally, 240 unique designs were generated and evaluated; the process took 5 days and 16 hours approximately. Nevertheless, once again, only 82 designs, 34%, are feasible designs with resistance estimation for both V_1 and V_2 conditions.

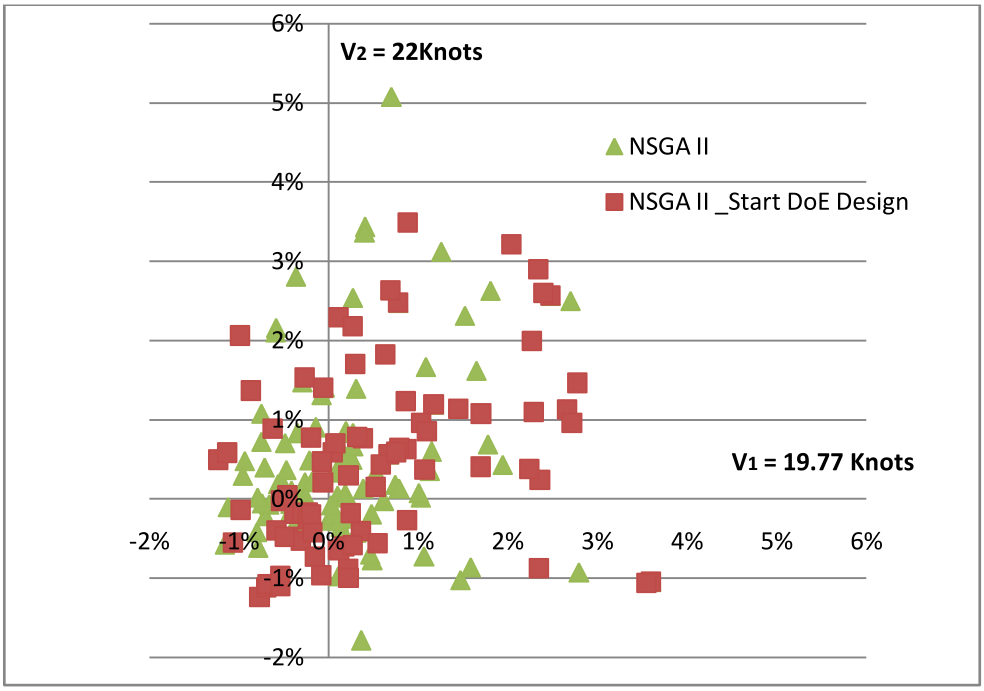


Figure 45 – Multi-Objective. Case II initial design from DoE.

In Figure 45 the comparison of case I and II is displayed, where both cases are presented in the graphic with the relative Rt_{V1} in the abscissa and the Rt_{V2} in the ordinate.

Regardless, the difference in number of designs the improvement of the design is very similar for both cases.

In Figure 46 the same results are presented, however with a zoom in the area of interest, designs that have reduced resistance when compared to the base model (negative values in the graphic). In this image is possible to observe that the optimization starting from the best model on the DoE (red squared dots) achieved better results with designs with more than 1% of resistance reduction, although the difference is too small and could be insignificant when the noise of the CFD results are considered.

Figure 46 – Multi-Objective. Case II initial design from DoE, zoom in the designs of interest.

Finally, the results presented demonstrate a behavior, for a multi-objective optimization by means of genetic algorithms, which differ to the common expectations. The process seams not to converge to the global minimum even with a huge amount of designs. The selection of an initial design proves to influence the results, given better designs, again not as expected. However, these conclusions are based on results of an optimization process in which several designs have no response from the CFD calculation. The lack of results could lead to a malfunction in the algorithm and the optimization of the model an impossible task.

10.SENSITIVITY ANALYSIS

In accordance to optiSLang [19] one of the possibilities to solve a RDO problem is the iterative way, in which the problem is solved by the usage of deterministic methods and then a robustness evaluation at the deterministic optimum is performed. Some deterministic and stochastic optimization process was performed and already presented. Optimum designs via different methods were defined which allow an analysis of the most suitable one.

The robustness of the design is evaluated regarding the sensitivity to uncertainties variations on the draft of the vessel.

For the sensitivity analysis the best achieved designs of some of the optimization processes were selected and the Rt_{V1} and Rt_{V2} for several draft values studied. All the four optimum selected designs are highlighted in Figure 47 in which all the main designs are also displayed for comparison.

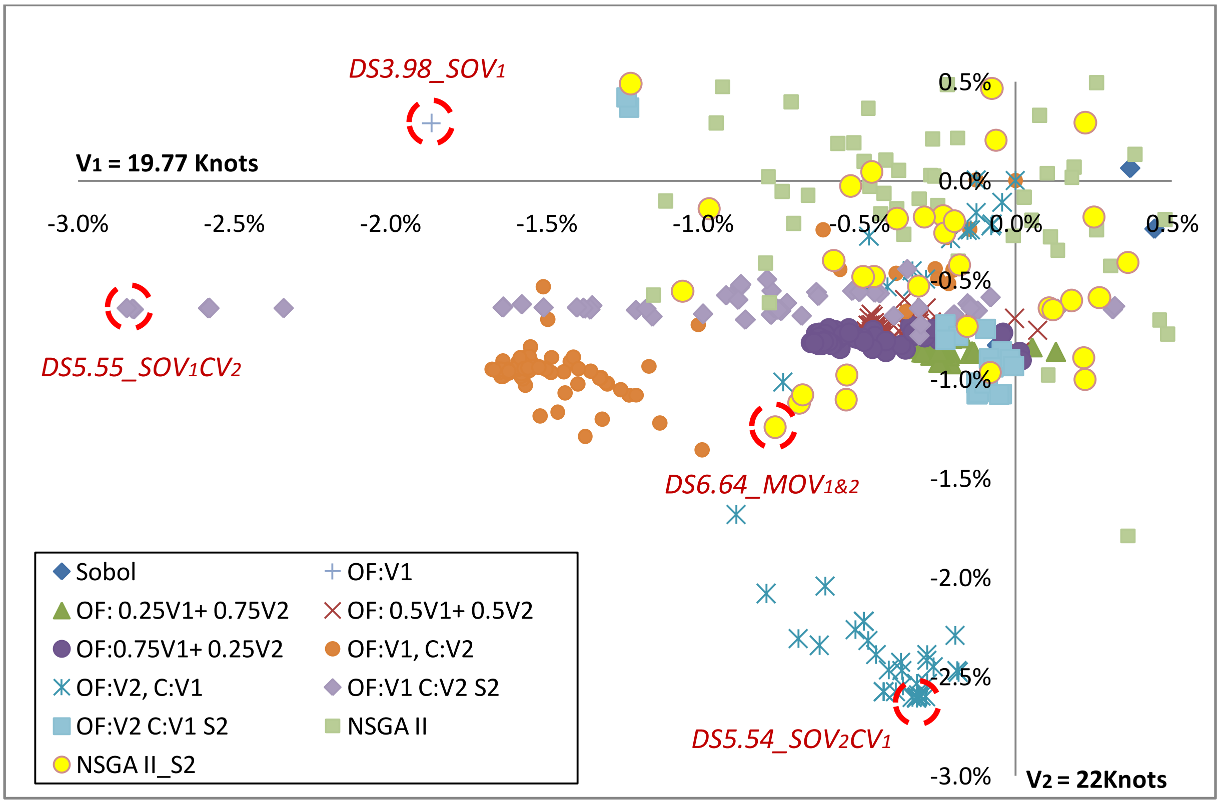


Figure 47 – Main designs obtained by all optimization process. Relative Rt_{V1} to the base model in the abscissa and relative Rt_{V2} in the ordinate axis in percentage. Selected best designs highlighted.

The selected designs are:

- DS3.98_SOV$_1$: The best design obtained via Single Objective Optimization, OF: Rt_{V1}
- Ds5.55_SOV$_1$CV$_2$: Best design obtained via Single Objective Optimization with Constraints. OF: Rt_{V1} and C: $Rt_{V2} \leq Rt_{V2\ \mathrm{Base\ Model}}$
- DS5.54_SOV$_2$CV$_1$: Best design obtained via Single Objective Optimization with Constraints. OF: Rt_{V2} and C: $Rt_{V1} \leq Rt_{V1\ \mathrm{Base\ Model}}$
- DS6.64_MOV$_{1\&2}$: Selected design obtained via Multi-objective Optimization.

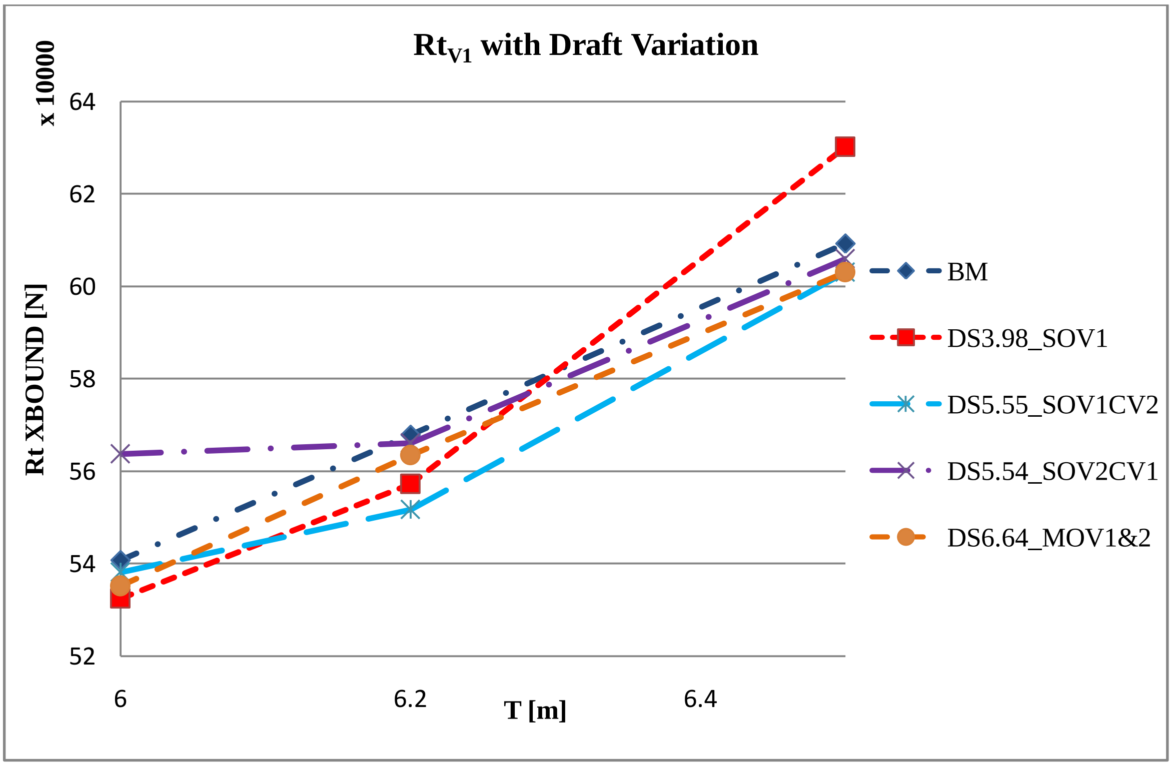


Figure 48 – Sensitivity analysis of draft variation for selected designs under velocity one condition.

In Figure 48 the variation of the resistance due to changes in the draft is presented for the condition of velocity equal to 19.77Knots (V_1), for the selected designs. The draft variation from 6.0m to 6.5m is shown in the abscissa and in the ordinate is the Total Resistance. It can be observed that the model has an almost linear response to the variation on the draft. Moreover, the optimized models for the condition of T=6.2m demonstrate an improvement not only for this draft, but also for the others tested (T=6.0 and 6.5) in most of the cases, even that the resistance reduction is slightly less for the conditions outside of the optimized one. The results leads to the conclusion that the optimization process did not compromised the sensitivity of the model regarding variations on the draft as the designs presented a better performance than the base model in the design conditions but also for different draft conditions.

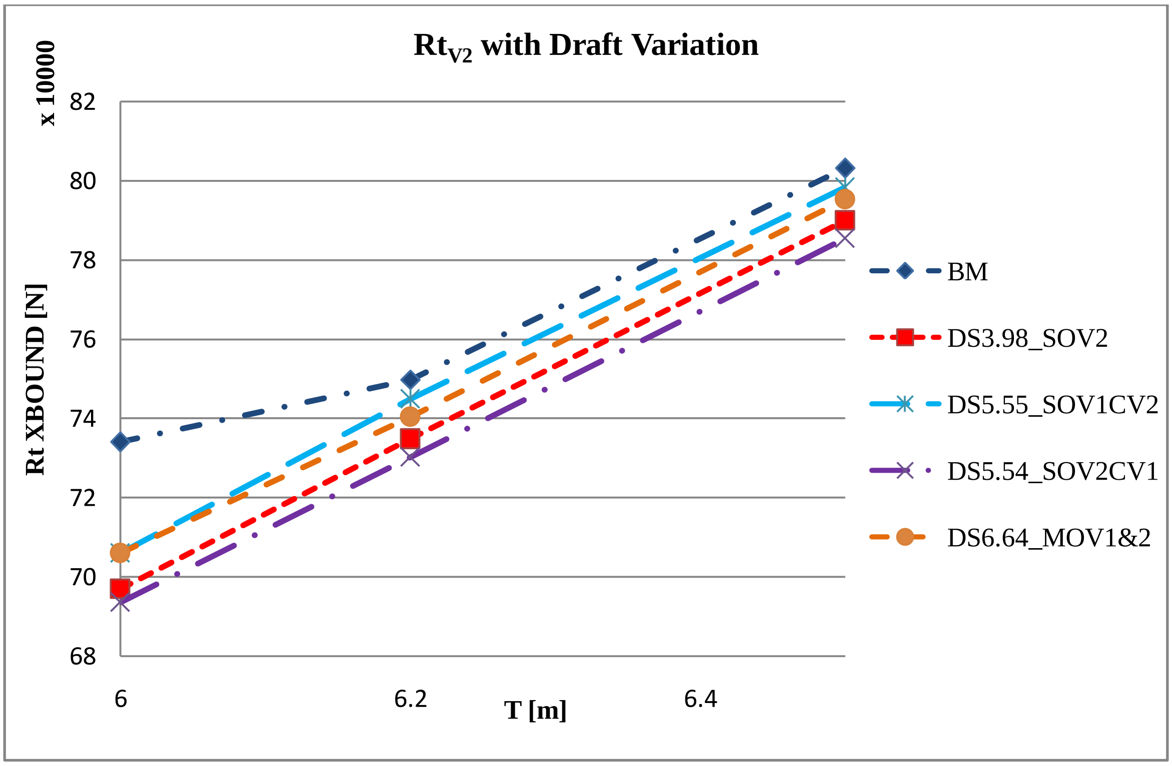


Figure 49 – Sensitivity analysis of draft variation for selected designs under velocity 2 condition

In addition, the sensitivity to the draft variation for velocity equals 22knots (V_2), it can be observed that the improvement is mainly the same for the design draft and for the conditions of T=6.0m and 6.5m, it can be observed by the parallel regression lines in Figure 49.

From the presented results it can be concluded that the optimization of the vessel for determined conditions didn't lead to any additional sensitivity of total resistance due to draft variation. The conclusion is not exactly what was expected for an optimization process. This could be justified by the fact that the initial model, base model, was already good at the tested conditions and consequently the improvement after the optimization process is very small and finally the expected consequence of robustness reduction could not be well appreciated.

11.HYBRID MODEL

One of the major barriers in the robust optimization application is the computational expense to analysis the huge amount of data necessary to undertake uncertainties. This difficulty can be easily appreciated on the previous sections where the various optimizations process was described. Jiangtao et al 2010 [24] propose the surrogate model as a possible solution to overcome this difficulty. Moreover, in accordance to optiSLang [19] the usage of response surfaces could be a possibility to solve a RDO problem. In order to test this kind of approach a linear prediction is performed by means of Gauss-Markov estimation or Gaussian process regression also known as Kriging as a technique named after the South African engineer D. G. Krige, Teukolsky et al 2007 [34]

To perform a linear prediction a base of data is necessary. In order to analyze the influence of the necessary input, several tests were done as presented in the following.

Furthermore, the smoothness of the regression between points can also be controlled. The smoothness coefficient was optimized for each case of study, as to give a better response using the input data set, as reference for this process the resistance prediction of the base model was used. In others words, several designs are used in the input data for the prediction of the resistance of the base model and the smoothness coefficient varies until the one that better approximate the estimated value to the real resistance of the base model for each condition. It is valuable to note that the coefficient is not varying for each input set in the input influence study.

11.1. Input dependency

The input of data, which is used by Kriging method to estimate the resistance of a new design, has a big influence in the results due to the nature of the problem. Thus input sets with 25, 40 and 50 designs were tested. In the following some analysis considering the quality and quantity of input designs are presented.

In Figure 50 the quality of the inputs with 25 and 40 designs are shown in terms of the coverage on the variation of the design variables. Each column in the figure, defined by “dots”, is one design variable and the “dots” represents one single design. In the ordinate it is represented in percentage the relation of the design variable in the defined range (bounds). It can be observed that for 25 designs the complete range of variation of each design variable is not as well covered as for the case with 40 designs.

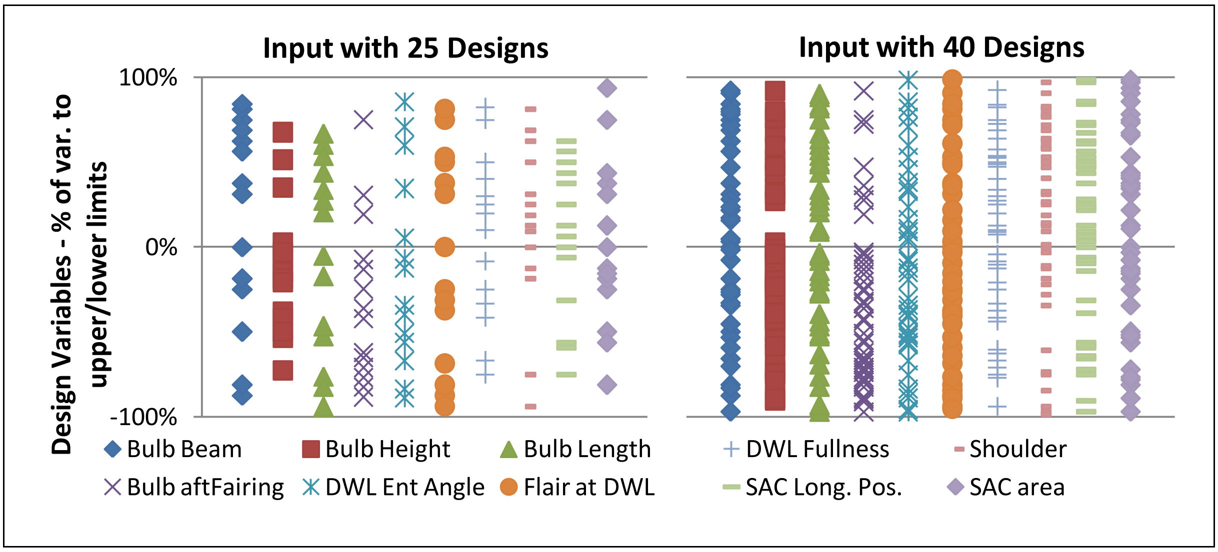


Figure 50 – Design space coverage of input for Kriging. Left 25 Designs. Right 40 Designs.

The resistance of five different designs, randomly chose, were tested using the Kriging and further on those models were analyzed using CFD for comparison, see Figure 51.

The 30 designs (25 input plus 5 test cases) for one case and the 45 designs for the second case are displayed in Figure 51 in he left and right respectively. The designs are shown in crescent order of resistance (Rt_{V1}) for better visualization, in the abscissa a design index is used to present the results and in the ordinate is the total resistance of each model. Furthermore, the error between the CFD and Kriging estimation is presented for the 5 test cases. It is valid to observe that, besides one design, the kriging estimation of the design resistance that exists in the input have an error of practically zero. However, when the model is not in the input an error from 0.02% to 2.48% for the case with 25 inputs and 0.23% to 1.37% for the case with 40 designs in the input is observed.

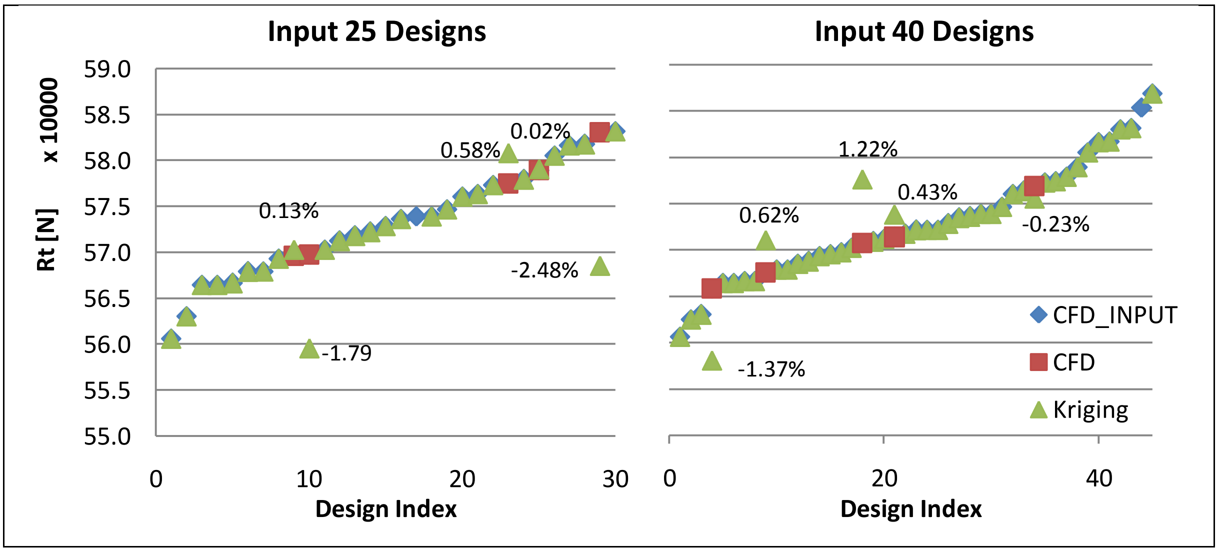


Figure 51 – Interpolation versus CFD resistance estimation. Left 25 input Designs. Right 40 input Designs.

Considering the reduced number of designs and furthermore, the reduced quality of designs it is expected some notable difference between the results using each input set. Nevertheless, as can be observed in Figure 51 the relative error of the prediction of the resistance via Kriging and CFD are in the same range for both input cases.

A further study with 50 designs for the input is done. The input designs cover the totality of the range of variation for all design variables, as can be observed in Figure 52

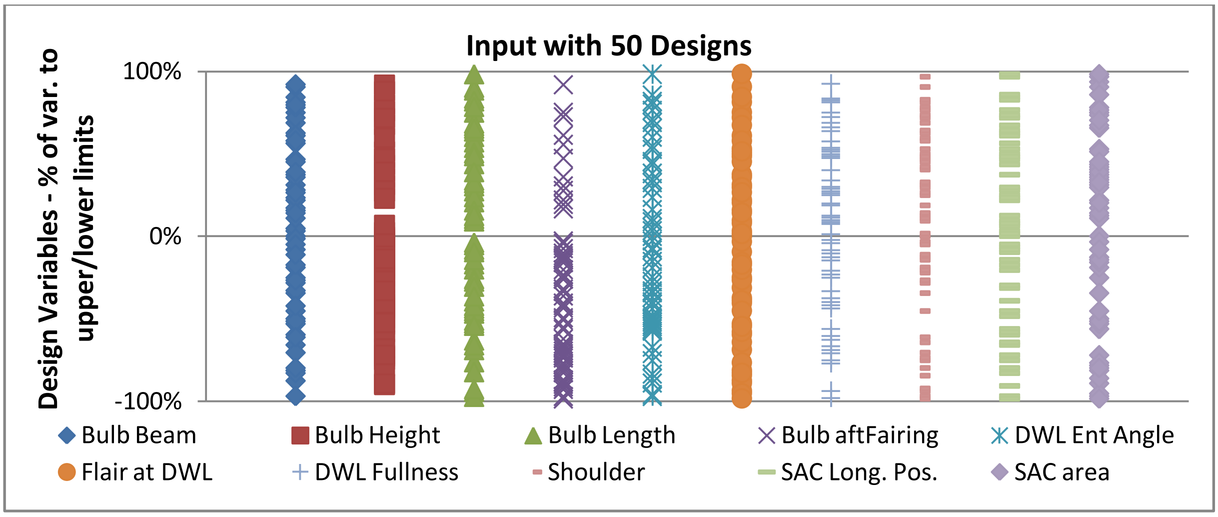


Figure 52 – Design space coverage for 50 designs input for Kriging.

Once again the resistance of five different designs was estimated using the Kriging and CFD for comparison. The 55 designs (50 input plus 5 test cases) are displayed in Figure 53 The error between the CFD and Kriging estimation is presented in the figure for the 5 test case, once again besides one model when the kriging is used in the estimation of the resistance that exists in the input, the error is zero. However, when the model is not in the input an error from 0.10% to 3.01% is observed, which is also in the same range of error for the cases with 25 and 40 designs in the input.

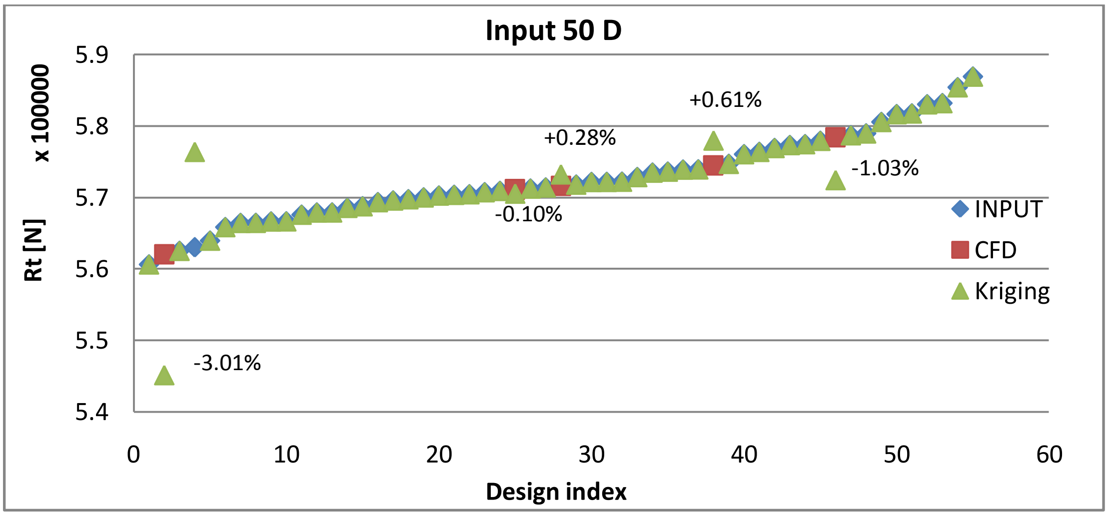


Figure 53 – Kriging input set 50D. Interpolation versus CFD resistance estimation.

In order to double check the importance of the quality of the input data, besides the quantity, a second set of input, keeping the same amount of data, is tested as can be viewed in Figure 54. It can be observed that the behavior of the estimation for the second set is very similar to the first one, thus the input selecting make a different in the response, but yet quite small.

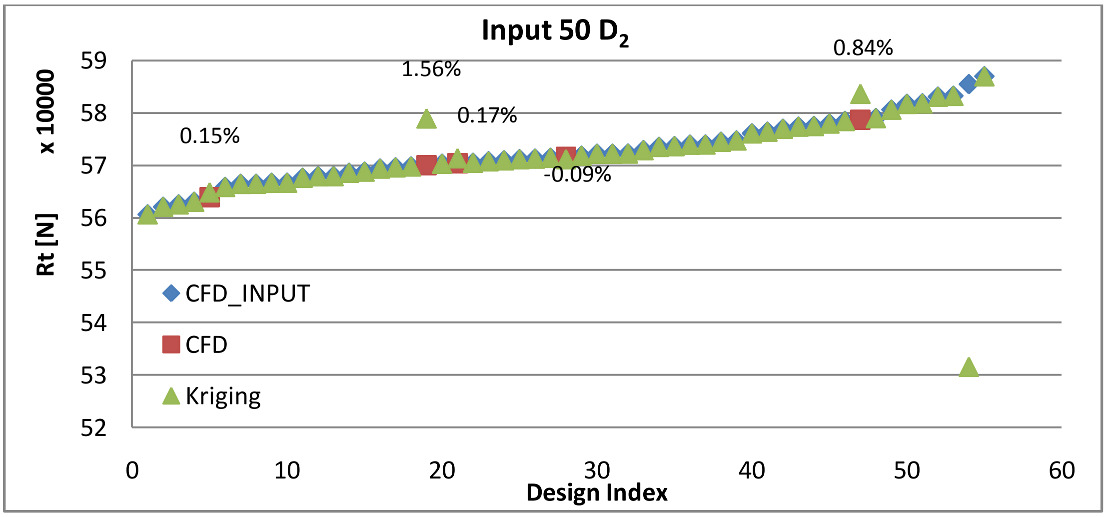


Figure 54 – Kriging input set 50D_2. Interpolation versus CFD resistance estimation.

Finally, it can be concluded that the quality of the input data has some influence on the results. The most important conclusion is that the error depends on the characteristics of the estimated design itself. In other words, besides the number of inputs, an important aspect of the input data set is the relationship, characteristics defined by the design variables, between the designs in the input and the objective design. These results are somehow in accordance to the recommendations of optSLang [19] that mention: "*Experiences show, that solving on one global response surface doesn't give good results. Otherwise adaptive approaches work well for most problem formulations*".

11.2. Optimization tests

Based on the input with 55 designs some optimization process were performed and compared with the same process performed using only CFDs. The optimization method is a typical DoE plus TSearch with the difference that the resistance analysis is not done by CFD calculation, but by linear prediction using the kriging method.

In Figure 55 the complete process of optimization by CFD and Kriging are displayed. The ordinate of the graphic is the relative resistance to the base model and in the abscissa a design index is shown. The index is not related to the number of designs created, but assigned to each design in order to facility the understanding and interpretation of the results. The dots presented from design index 0 to 45 represent the DoE study by the usage of the SOBOL method, for both CFD and Kriging resistance prediction. The best design obtained in the DoE is selected and the TSearch performed and presented by the connected dots in Figure 55. The selection of the "best design" obtained from the Kriging prediction is not as direct as for the CFD analysis, where the design with minimum resistance was chosen. In the linear prediction case some "bad designs" with design variables with values equal to the bounds and very low or very high resistance response are obtained and should be manually eliminated by the designer.

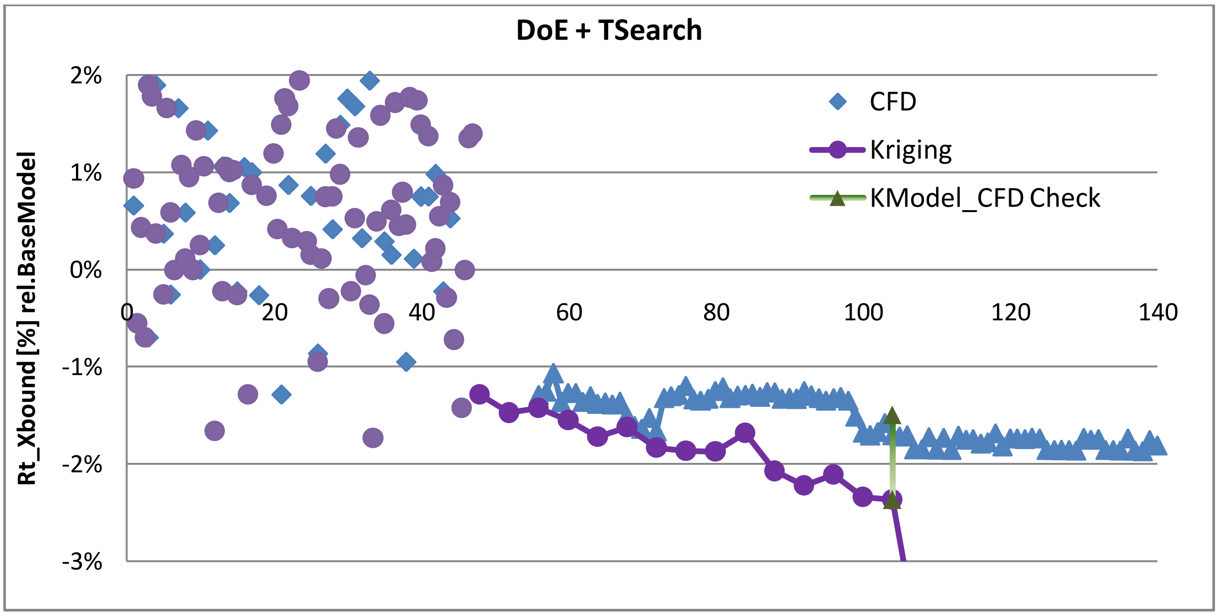


Figure 55 – Optimization via Kriging. DoE + TSearch using CFD versus Kriging plus a CFD check of the best model achieved.

Furthermore, the CFD analysis of the optimum design obtained by the usage of Kriging is shown in Figure 55. The linear prediction shows to have underestimated the resistance, in 0.88% as show in Table 5, when compared to the CFD estimation. However, the optimum design show to have yet a good performance and using a reduced number of CFD runs, 55 were used for the input. The reduction of CFD runs leads to a reduction of almost 1/3 of the necessary time to perform the whole optimization process.

Table 5 – Comparison between optimization with CFD and Kriging resistance analysis.

Optimization using:	CFD Runs	Predicted R_t reduction	CFD R_t reduction	Difference
CFD	151	-1.87 %	-1.87 %	zero
Kriging	55	-2.37 %	-1.49 %	-0.88 %

In addition, the performance of the optimum design obtained applying the Kriging technique and the analysis by CFD are compared regarding the performance in both velocities

1 and 2 in Figure 56. The relative resistance of the Kriging design is shown by both linear prediction and by the after CFD analysis.

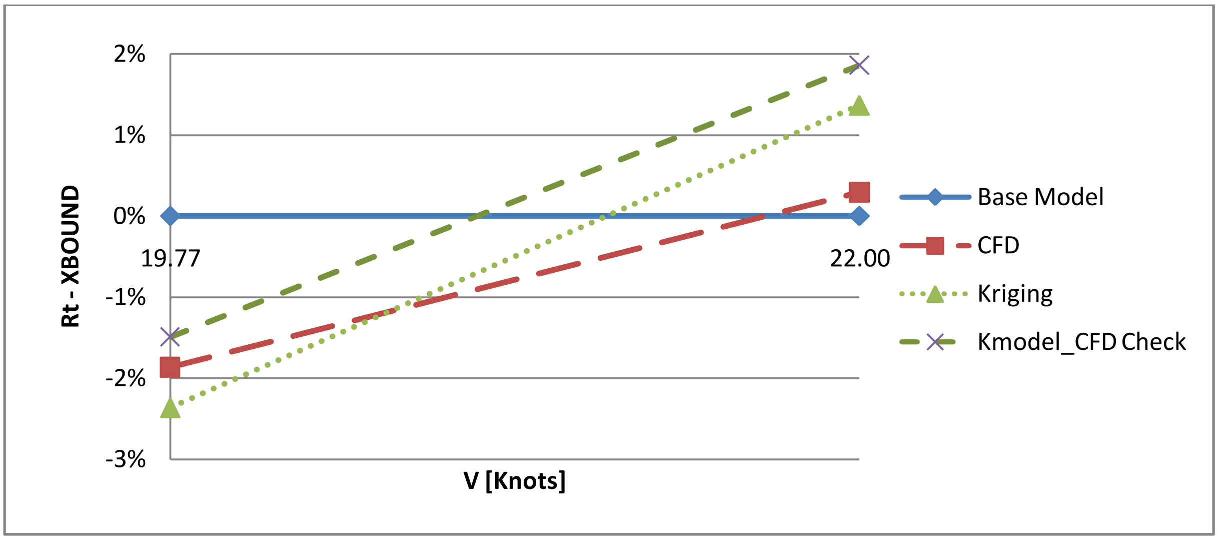


Figure 56 – Comparison of the optimum design obtained using CFD and Kriging plus the CFD check of the best design obtained via Kriging.

Several others tests and processes were done using the kriging prediction which shows an average error of 2% in the resistance estimation for improved designs, not existing in the input set. The results show a big potential on this method that could lead the designers to an optimum combination of design variables, betters models, within a reduced time of calculation. However, a good knowledge of the response surface, inputs and outputs, is necessary to handle the input data and most important to interpreted the output and perform a smart selection and further evaluations on the designs. In addition, the method present yet space for improvement as adaptively response surface.

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CHAPTER IV

12.RESULTS and ANALYSIS

12.1. State of the Art in Optimization

In Table 6 the number of CFD runs necessary to perform the optimization for each method is presented side by side with final performance obtained relative to the base model. It is important to notice that the number of CFD runs in the table represent only the feasible results (error-free), for the Multi-Objective case the number of CFD runs is low due to the high number of designs with numerical errors in the CFD analysis as mentioned in 9.1.1.

Table 6 – Number of CFD runs and rel. resistance to base model (Vel 1= rel. Rt_{V1}) for each optimization method.

			CFD runs		Performance	
			DoE+Opt	**DoE**	**Vel 1**	**Vel 2**
Single Condition	**DoE + TSearch**	OF: **V1** + Zero*V2	151	55	-1.87%	0.29%
		OF: Zero*V1 + **V2**	123	55	2.71%	-1.98%
Multiple conditions	**Single Obj. Weighted Function**	OF: **0.25*V1 + 0.75*V2**	131	55	-0.24%	-0.92%
		OF: **0.5*V1 + 0.5*V2**	129	55	-0.54%	-0.77%
		OF: **0.75*V1 + 0.25*V2**	131	55	-0.65%	-0.82%
	Single Obj. + Constraints	OF: **V1** + Zero*V2; **C: V2**	97	none	-1.67%	-0.95%
		OF: Zero*V1 + **V2; C: V1**	56	none	-0.32%	-2.61%
		OF: **V1** + Zero*V2; **C: V2**	116	55	-2.84%	-0.64%
		OF: Zero*V1 + **V2; C: V1**	76	55	-0.05%	-1.08%
	Multi-Objective	OF: **V1** and **V2**	96	none	-1.16%	-0.58%
		OF: **V1** and **V2**	137	55	-0.77%	-1.24%

The resistance regarding the condition one, Rt_{V1}, represented in the table by the column *Vel 1* presented the lowest value for the optimization case where the single objective with constraints were applied (OF: V1 + zero*V2; C:V2). A reduction of 2.84% in the total resistance for condition one and reduction of 0.64% for condition two can be observed. The second best improvement was achieved by the application of the single objective method (DoE + TSearch for OF: V1 + zero*V2) a reduction of 1.87% is observed for condition one. However, an increase in the total resistance of 0.29% is given for the second condition. Moreover, for the optimization process using constraints 61 designs were necessary, besides the 55 DoEs, which is a lower number of CFD runs when compared to the 96 designs created in the single objective optimization process. This result proves that the optimization as a single-objective problem in which one operating point is dominant while others are considered as constraints presents the best behavior for the example tested. The good results could be justified by the fact that this method combined the high level of reduction of the resistance observed for the single-objective case with the multi-objective characteristic introduced by the constraints.

The single-objective with weighted function presented a low level of reduction, from 0.24% to 0.92%. The low level of improvement could be a consequence of a conflict between the two objectives misleading the optimization algorithm to the optimal solution.

Finally, the multi-objective optimization process, also, presented low level of reduction. It can be justified by the high number of designs that have some numerical error on its CFD analysis. From the 720 unique designs that were created and evaluated only 96 designs, 13.3%, are feasible designs with the results of the total resistance for both V_1 and V_2. 592 designs, 82%, have a numerical error of some sort for the resistance estimation of one speed or both.

The sensitivity of the models regarding variations on the draft is very low and can be neglect as presented in 10.SENSITIVITY ANALYSIS.

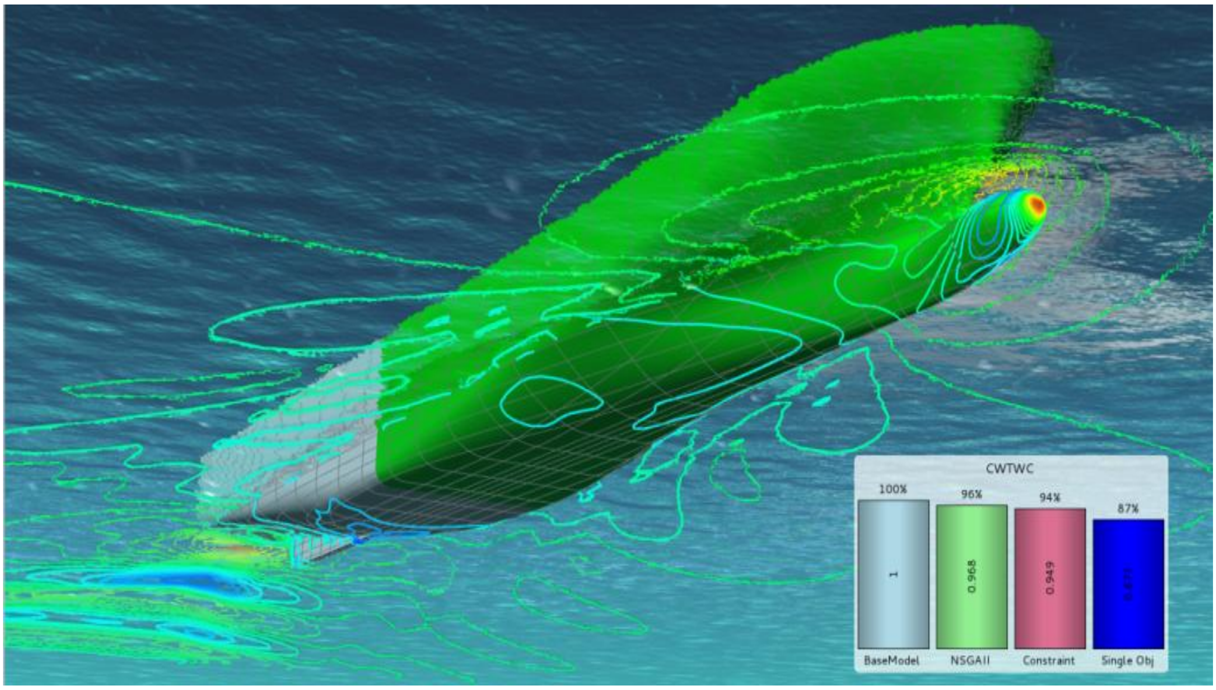

Figure 57 – Isolines on the body and free surface. SHIPFLOW/ FRIENDSHIP-Framework. Bar chart compares the wave resistance by different optimization methods

12.1.1. Geometry Trends

When comparing the optimum designs obtained by the several optimization processes some trends of the form characteristics are observed.

Table 7 – Geometry trend of the optimized bulbous bow.

		Bulbous bow							
		Beam		Length		Height		Aft Fairing	
DoE + TSearch	OF: **V1** + Zero*V2	55%	**Wider**	45%	**Longer**	-6%	**Lower**	-10%	**Rounded**
	OF: Zero*V1 + **V2**	3%	**Wider**	-22%	**Shorter**	80%	**Higher**	57%	**Flat**
Single Obj. Weighted Function	OF: **0.25*V1 + 0.75*V2**	71%	**Wider**	79%	**Longer**	-10%	**Lower**	26%	**Flat**
	OF: **0.5*V1 + 0.5*V2**	71%	**Wider**	79%	**Longer**	-16%	**Lower**	26%	**Flat**
	OF: **0.75*V1 + 0.25*V2**	66%	**Wider**	69%	**Longer**	-16%	**Lower**	33%	**Flat**
Single Obj. + Constraints	OF: **V1** + Zero*V2; **C: V2**	29%	**Wider**	23%	**Longer**	58%	**Higher**	-58%	**Rounded**
	OF: Zero*V1 + **V2; C: V1**	18%	**Wider**	30%	**Longer**	100%	**Higher**	75%	**Flat**
	OF: **V1** + Zero*V2; **C: V2**	52%	**Wider**	58%	**Longer**	-17%	**Lower**	37%	**Flat**
	OF: Zero*V1 + **V2; C: V1**	71%	**Wider**	68%	**Longer**	-10%	**Lower**	48%	**Flat**

In Table 7 it is shown for each optimization process the tendency of the geometry characteristic. The analysis if performed by the relative value of the design variable that defines the geometry. For example, the bulbous bow for the first case presents a value 55% wider which means that the parameter that controls the width of the bulb is in between the mean value (base model) and the upper bound, in 55% of that range.

The optimized bulbous bow for every case is wider than the bulb of the base model and mainly longer bulbs are observed. The height of the bulb is in general a little bit less than the base model. A few cases present a higher bulb, this second case mainly when the model is optimized for the second speed condition (20 knots). The after fairing of the bulbous bow is in general flat (horizontal) with the exception for the two cases when the model is optimized regarding the velocity condition one. For the case of single-objective function Rt_{V1} with constraint for Rt_{V2} the combination of a higher bulb with a low percentage of “flatness” on the after fairing leads to the conclusion that besides the flat characteristic of the after fairing in these cases the flow at this region is oriented downward as shown in Figure 58.

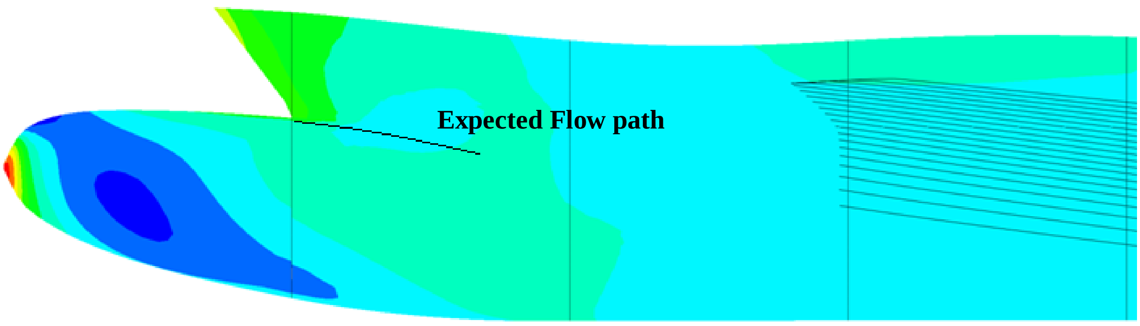

Figure 58 – Side view of optimized model by OF: V1 + zero*V2; C:V2.

Regarding the water line fullness all the optimized models presented a reduction in the water line area, Table 8. The shoulder, also in all the cases, is moved forward. Finally, the section area of the sections in the forebody presented a reduction in most of the cases leading to a reduction of the volume at this region.

Table 8 – Geometry trend of the optimized forebody. DWL fullness, should position and section area.

		DWL Fullness		Shoulder		Section Area	
DoE + TSearch	OF: **V1** + Zero*V2	-21%	Less area	91%	Forward	78%	More volume
	OF: Zero*V1 + **V2**	-64%	Less area	7%	Forward	-91%	Less volume
Single Obj. Weighted Function	OF: **0.25*V1 + 0.75*V2**	-2%	Less area	45%	Forward	-45%	Less volume
	OF: **0.5*V1 + 0.5*V2**	-2%	Less area	46%	Forward	-45%	Less volume
	OF: **0.75*V1 + 0.25*V2**	-15%	Less area	47%	Forward	-45%	Less volume
Single Obj. + Constraints	OF: **V1** + Zero*V2; **C: V2**	-18%	Less area	43%	Forward	43%	More volume
	OF: Zero*V1 + **V2**; **C: V1**	-100%	Less area	69%	Forward	0%	Less volume
	OF: **V1** + Zero*V2; **C: V2**	-2%	Less area	47%	Forward	-42%	Less volume
	OF: Zero*V1 + **V2**; **C: V1**	-15%	Less area	55%	Forward	-45%	Less volume

12.2. Hybrid Method

For the Hybrid model several tests were performed with a fixed input set of 55 designs obtained from a DoE analysis.

Table 9 – Number of CFD runs, meta-models, predicted performance and CFD analysis of the optimal models obtained using the Hybrid method with Kriging.

			CFD runs		Meta Models		Performance [Predicted]	
			DoE	Verification	DoE	Optimization	Vel 1	Vel 2
Single Condition	DoE + TSearch	OF: **V1** + Zero*V2	55	1	93	19	-2.37%	1.37%
		OF: Zero*V1 + **V2**	55	1	93	41	2.91%	-2.46%
Multiple conditions	Single Obj. Weighted Function	OF: **0.25*V1 + 0.75*V2**	55	1	93	42	-1.06%	-0.86%
		OF: **0.5*V1 + 0.5*V2**	55	1	93	19	-3.65%	-0.64%
		OF: **0.75*V1 + 0.25*V2**	55	1	93	16	-3.65%	-0.64%
	Multi-Objective	OF: **V1** and **V2**	55	1	93	240	-3.28%	-1.43%

			Performance [CFD Check]			
			Vel 1	rel error	Vel 2	rel error
Single Condition	DoE + TSearch	OF: **V1** + Zero*V2	-1.49%	-0.88%	1.86%	-0.48%
		OF: Zero*V1 + **V2**	3.34%	-0.42%	-0.29%	-2.17%
Multiple conditions	Single Obj. Weighted Function	OF: **0.25*V1 + 0.75*V2**	-0.20%	-0.88%	1.86%	-2.65%
		OF: **0.5*V1 + 0.5*V2**	-1.01%	-2.67%	2.33%	-2.91%
		OF: **0.75*V1 + 0.25*V2**	-1.01%	-2.67%	2.33%	-2.91%
	Multi-Objective	OF: **V1** and **V2**	0.73%	-3.99%	2.43%	-3.77%

It is important to observe two main results presented in Table 9. Firstly the reduced number of necessary CFD runs to perform the optimization when compared with the classical method in Table 6. Secondly is the relative error of the results presented in the lower part of Table 9 that indicates that the Gauss-Markov estimation underestimate the resistance of the design from 0.42% to 3.99%. This results show a high potential of this method to solve RDO-problems in the design of ships due to the reduction of necessary analysis. However, it is also necessary to improve the method; a few recommendations are given as the implementation of an adaptive surface response for a better interpolation towards the desire results.

12.3. Optimum model

Considering the good performance of the design obtained with the optimization by single-objective with constraints some further analysis is performed in this model. The design has an improvement of the wave resistance of 8.31% for speed condition one and 6.84% for speed two. When the viscous effects are introduced by momentum integration (XBOUND) the total resistance reduction is of 2.84% and 0.64% for V1 and V2 respectively, highlighting the importance to consider the viscous effects in the optimization process. In Figure 59 the wave pattern of the base model, in top, and of the optimum design, bottom, are presented for the velocity condition one (V_1 = 19.77Knots). It can be easily observed the reduction of the wave height generated by the vessel advancing in calm water.

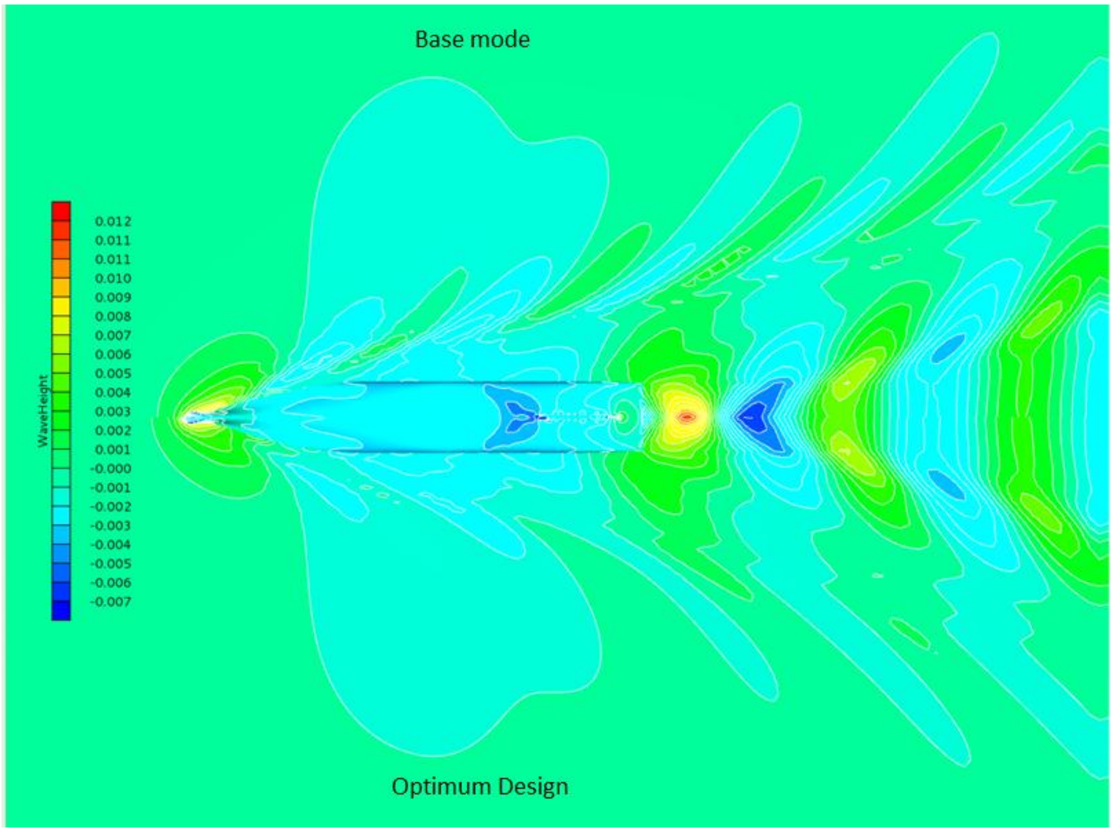

Figure 59 – Wave pattern of the optimize and base hull form

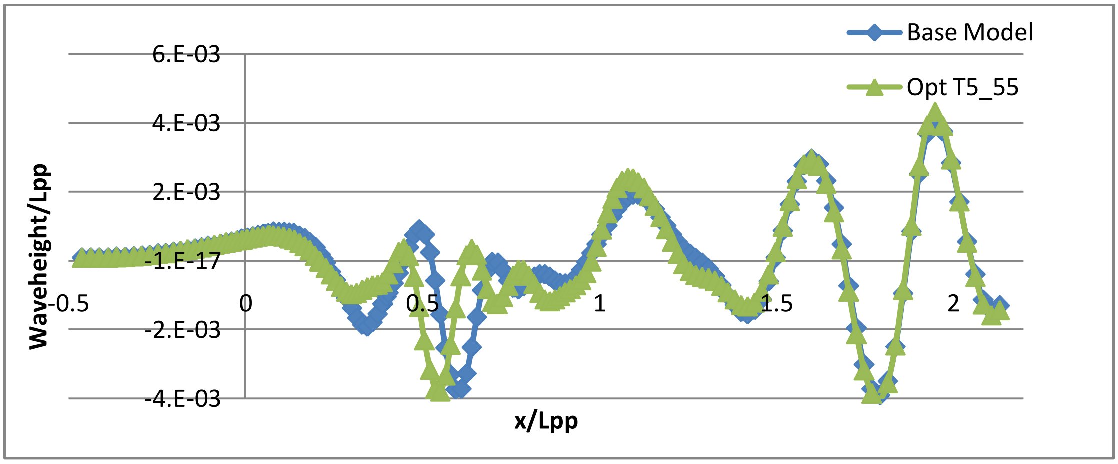

Figure 60 – Wave cut. Base and Optimum model.

The variation of the wave generated by the vessel can also be observed by the wave cut far from the body presented in the Figure 60. The differences in the wave pattern and wave cut are due to variations on the hull form as presented in Figure 61. In the body plan present in Figure 61 the optimum design, in red, is compared with the station lines of the base model, in gray. It can be observed that only the forebody of the vessels present some differences. The bulbous bow is a bit wider and it can also be observed that the flare in the water line is more vertical than the base model. The Figure 61 is obtained by the offset that are used for the CFD calculation; it is nice to observe the smoothness of the hull form which guarantees a good mesh and finally reliable results.

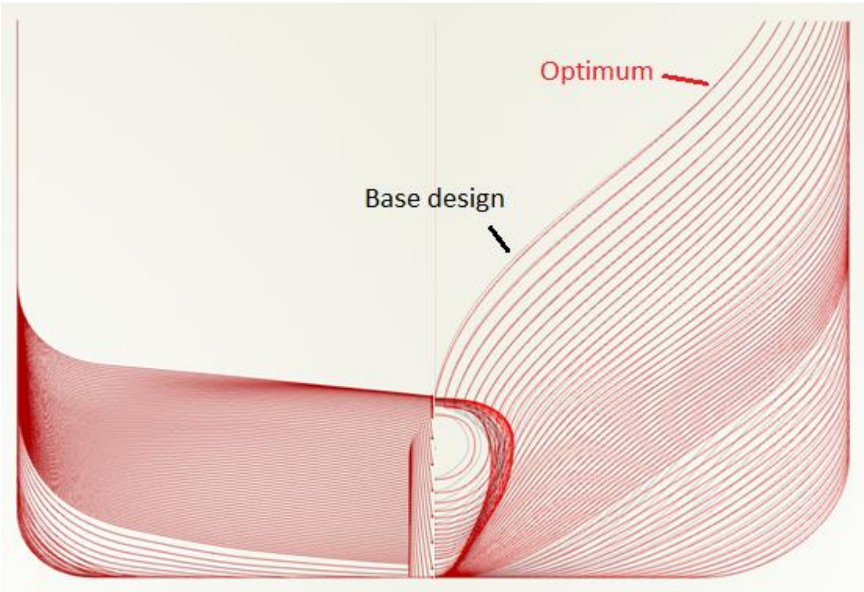

Figure 61 – Body plan of the optimum model versus base design.

The optimized geometry when compared with the base model has the shoulder moved forward, and less volume in the forebody and a longer bulb, characteristics that can be observed in Figure 62. The optimized model is presented in the top part of the figure in shadow for the side view and in the bottom part in the right hand side. The colors in the hull form represent the pressure coefficient.

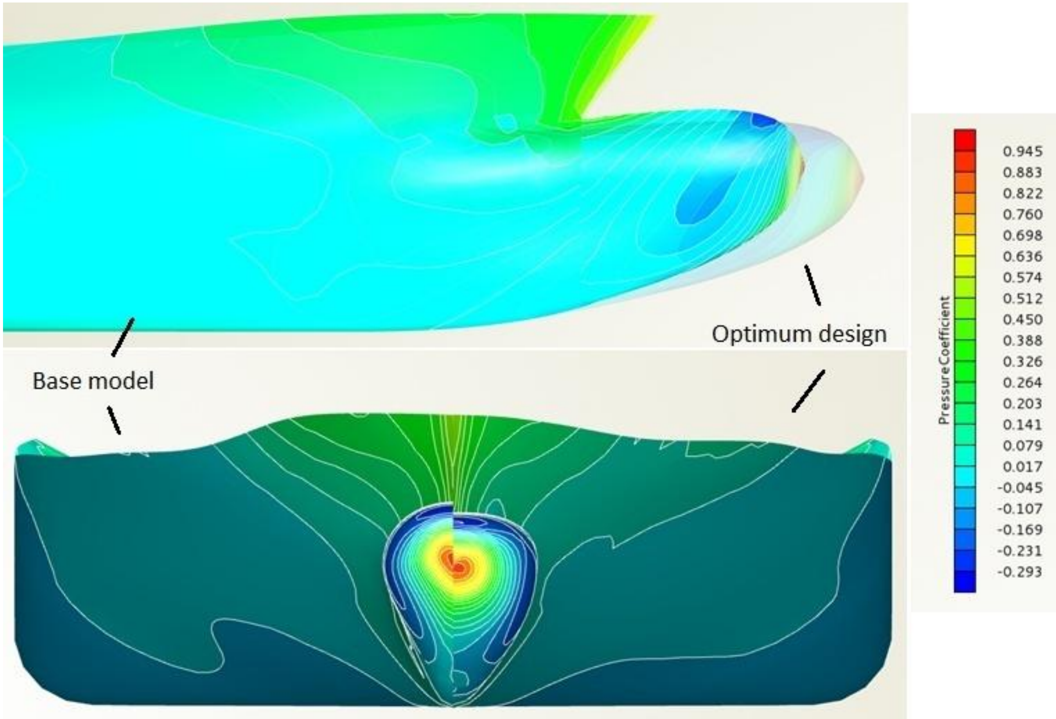

Figure 62 – Base model and optimum design (shadow/right) forebody with isolines and pressure coefficient.

In Figure 63 the total resistance of the vessel is presented for three different drafts at velocity one, in the left hand side, and for velocity two, in the right side. The optimization process was performed for a fixed draft of 6.2m, however the optimum vessel present a good performance not only at this draft but also for different drafts conditions. Leading to the conclusion that the optimized model have a level of sensitivity, regarding uncertainties on the draft value, similar to the base model.

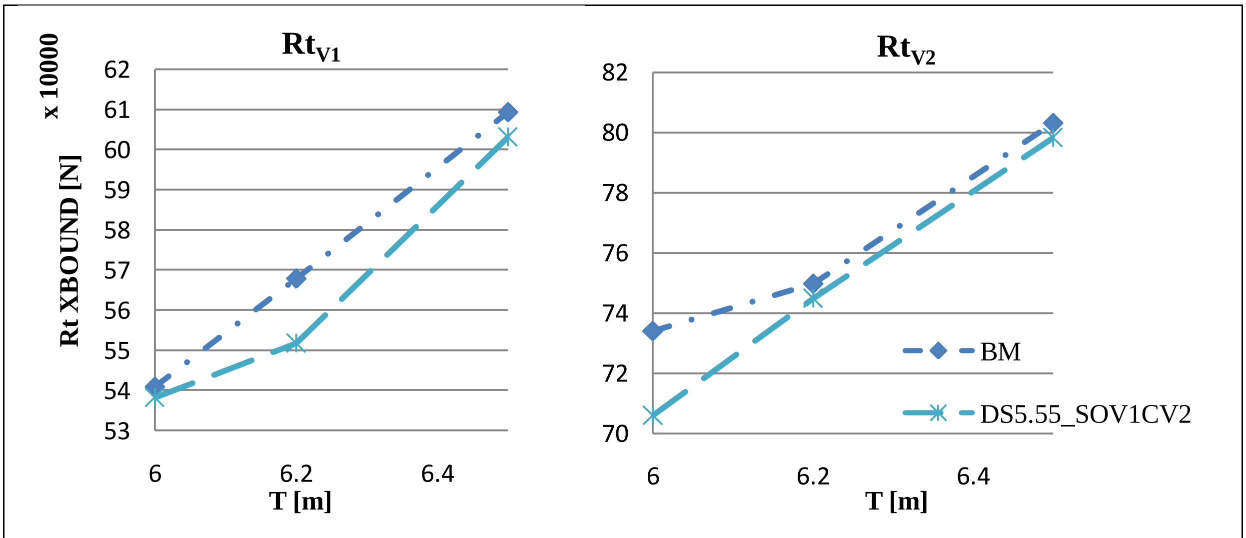

Figure 63 – Sensitivity for variations of the draft.

The behavior of the selected optimum design for the whole operational range of speed is presented in Figure 64. It can be observed that the improvement of 2.84% at the velocity one (19.77knots) is rapidly lost for a higher resistance, around 1%, when navigating at speed of 20knots. However, the resistance of the vessel for others velocities around 20 knots also present a light reduction, finally the small variation of 1% on the resistance could be related to numerical oscillations on the analysis.

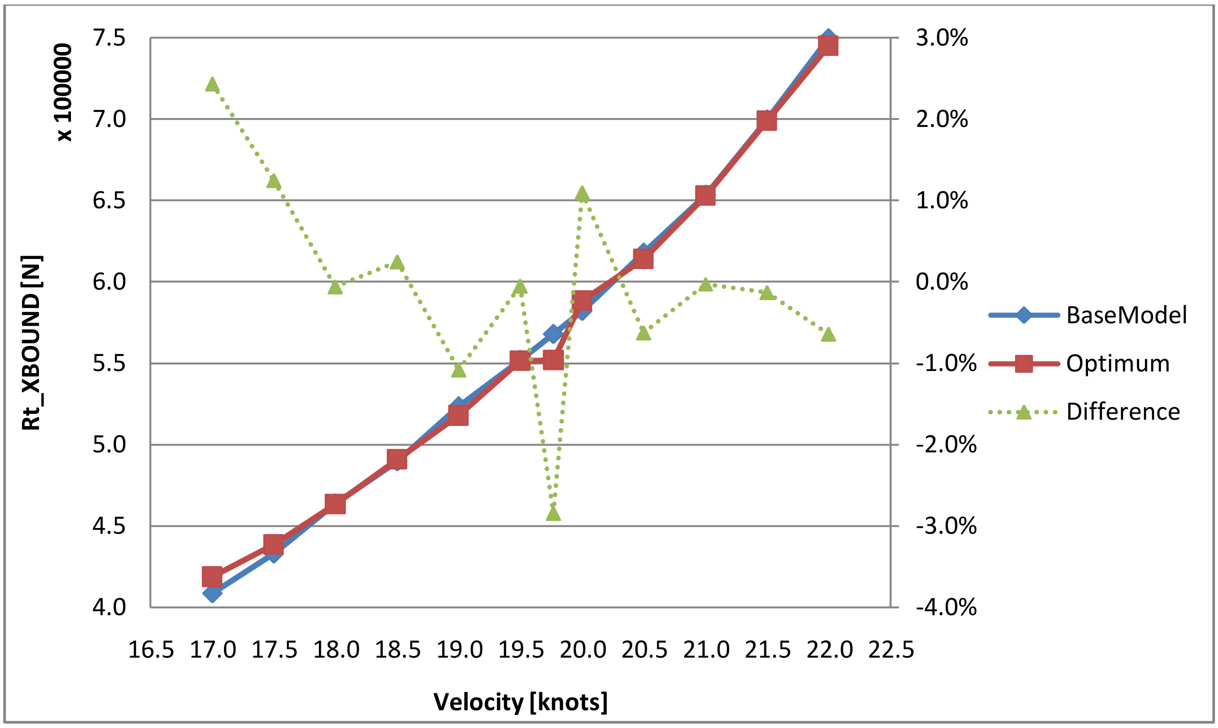

Figure 64 – Total resistance of base model and optimum model at whole range of operational speed. In the secondary axis the relative difference in percentage is presented.

In conclusion, the selected design from the optimization presents a good behavior at variations on the draft, and also a small improvement in the total resistance for the main operational velocities. Furthermore, the improvement observed is yet too light and could be affected by oscillation in the CFD calculation, so further analysis should be performed as RANS calculations of the model. It is important to conclude that the initial design is already very good and not much can be squeezed from this model to improve its performance by changing the forebody.

CHAPTER V

13. SUMMARY

The robust optimization process using Monte Carlo methods requires a vast number of solver runs making the task using computational fluid dynamic (CFD) impracticable. However, to analyze small variations of the form some precise methods are necessary, usually CFD tools can be essential to possibility the analysis and comparison between models regarding characteristic of interest. In a tentative to solve robust design optimization (RDO) problems and yet using CFDs some techniques were tested in this work. Two kinds of approaches for solving RDO-problems with a moderate effort were performed.

An iterative approach was tested, first solving the deterministic problem and secondly performing a sensitivity check at the deterministic optimum. An extended study with all main optimization processes was applied in this project using deterministic and genetic methods followed by sensitivity analysis of the optimum designs created. The advantages and drawbacks of various kinds of optimization methods were presented based on the quality of the achieved results (e.g. energy efficiency), computational effort (e.g. number of CFD runs needed) and the robustness by the sensitivity to changes (e.g. influence of slight changes on the draft).

The second applied approach to solve RDO-problems was to use response surfaces. This method was studied by the application of Gauss Markov estimations (Kriging). A simple method that can save a lot of time, however, yet needs numerous improvements for accurate results.

Finally, the results were presented and compared. The numerous of optimization process tested and analyzed in this project represent a step towards the robust design optimization for operational profile applied to the ship design. This approach should be the future in the ship design offices that are working to make better products, for high profits and more environmental friendly.

14. CONCLUSION

The state of the art in optimization was performed on a typical hull form. Furthermore, an uncommon method, using meta-models, was tested for the optimization of ship design. The study leads to several conclusions regarding robust optimization techniques applied to variations of hull forms and it analysis using CFD as the following.

The single objective method leads to a very good improvement for the condition set as objective. However, for conditions that are not in the objective suffers a strong degrade, an expected conclusion due to the consequently specialization of the product mentioned by Marczyk 2000 [9].

The optimization with different objective conditions included in the objective function by a weight presented a very low degree of improvement. The resistance reduction on a level lower than expected could be justified by a conflict between the two conditions misleading the gradient method, TSearch, of the global minimum. In addition, it can also be concluded that, as expected, the weight is an efficient way to move the objective from one condition to another in a smooth way.

The optimization as a single-objective problem, in which one operating point is dominant while others are considered as constraints, presented very good results. This method combines the benefits of a single objective optimization, but yet improving the vessels for others characteristic, considered as constraints.

The multi-objective optimization by means of genetic algorithm, NSGAII, didn’t present a good improvement. Considering the high number of necessary designs it leads to a very expensive method with high cost/benefits.

Furthermore, the optimization using CFD, have a complication factor due to numerical errors of some designs. In other words, some designs that are created and used during the optimization process have some errors in their resistance estimation (e.g. non-convergence). How the algorithm deals with these erroneous designs could be a key factor that leads to good results or not. In addition, when operational conditions are added to the objective of the problem the necessary number of CFD runs for each design increases proportionally. The higher number of designs could lead to more problematic designs which can compromise the optimization process.

In conclusion, the proper selection of the optimization method for each case of study proves to be a key factor in order to achieve good results. For the studied case the single objective with constraints prove to be the best method, avoiding objective conflicts and achieving good results with the gradient method with a reasonable number of designs. This conclusion could be different for another model or form variation as it depends on the problem and a brief study of the most suitable method should be performed.

The usage of the above mentioned methods plus a sensitivity check prove to be an efficient way of performing a robust design. Nonetheless, this can be affirmed for the case that the model has low levels of sensitivity or yet for the cases which the initial model is already very good and the optimization leads to a small improvement, as in the studied case. The necessity of repeating the process to achieve the requested robustness could lead to a very long process. To avoid long and unrealistic design time the hybrid method could be a solution.

The hybrid method using Gauss-Markov estimation shows an average error of 2% in the resistance estimation for improved designs, not existing in the input set. The results show a big potential for this method that could lead designers to an optimum combination of design variables, betters models, within a reduced time of calculation. Nevertheless, a good knowledge of the response surface, inputs and outputs, is necessary to handle the input data and most important to interpreted the output and perform a smart selection and further evaluations on the designs. In addition, the method needs several improvements for a good and feasible behavior as the auto selection of inputs or adaptively response surface.

Finally, before applying robust optimization techniques the model most be studied and the necessity of performing such kind of study proved, e.g. analysis of sensitivity. In the case that the robust optimization is necessary meta-models should be used for the process as a solution to perform the calculation in a feasible time.

15.RECOMMENDATIONS

An adequate optimization method should be selected for each case of study; tests with simplified analyses should be performed for the selection.

For the optimization processes it is important to have a good initial design that can be obtained via DoE (e.g. SOBOL method).

The necessity of performing robust optimization design should be verified by means of potential to improve and sensitivity check.

Response surfaces method should have not only a global response surface but an adaptive approach should work better.

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