Abstract

There is a growing need for developing new technologies to drive the global shipping into a carbon-neutral industry. This Master’s Thesis presents a generic route optimization model for cargo vessels with wind assisted propulsion systems. An early stage tool to predict environmental savings by finding optimal routes for cargo vessels equipped with any sailing device. Systematic studies are developed for the optimization parameters in order to observe their influence on the optimization performance. The route optimization model is used for a wind-assisted cargo vessel for route crossing the North Atlantic as an example application.
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Chapter 1

Introduction

There is an imperative need to reduce the greenhouse gas emissions from the global shipping industry. The 90% of global trade takes place in the ocean. Marine operations are one of the major contributors to the greenhouse gas emissions. Nitrogen and sulphur oxides, NOx and SOx respectively, are the two main pollutants of the ship’s emissions. Those emissions have disastrous effects on the ozone layer which influence the greenhouse effect and, therefore, the global warming. Between 3% and 5% of the global greenhouse gas emissions are generated by the shipping industry.

There is the necessity of developing new technologies in order to drive global shipping to an eventual carbon-neutral industry. However, this is a large term objective. IMO resolution 2030/2050 targets to reduce the greenhouse gas emissions in a 50% by 2050 [10]. This goal is not reachable at the time being with the existing technologies. It is crucial to drive the shipping industry into a transition process where new solutions are implemented.

It is a fact that wind is one of the primary sources of energy. New solutions such as wind assisted propulsion systems are implemented on existing vessels as well as on new constructions in order to reduce the fuel consumption and, thus, carbon emissions. Routing technologies for vessels with wind propulsion devices can play a major role in the fuel reduction by using the weather conditions in benefit of the sailing devices.

Wind may not be the definitive solution to drive global shipping into a carbon-neutral industry but can play a key role in the transition process to a greener future.
Chapter 2

Objectives

The object of this Master’s Thesis is to generate a generic route optimization model (ROM) in order to predict fuel savings of cargo vessels with Wind Assisted Propulsion Systems. The main scope is to increase the fuel savings and therefore, reduce the carbon emissions by taking maximum benefit of the environmental conditions. Route Optimization Model is an early design stage tool that predicts potential savings of the cargo vessels when implementing Wind Assisted Propulsion Systems as a retrofit on existing or new-construction cargo vessels.

The route is optimized with the main intention to reduce the fuel consumption, nonetheless, keeping track of the Estimated Arrival Time (ETA) which is a crucial factor in the shipping industry. The environmental conditions are exploited in maximum benefit of the sailing devices.

ROM aims to be a generic tool that can be used for any cargo vessel with Wind Assisted Propulsion Systems, regardless of the purpose of the vessel, its dimension or the wind devices it uses. Moreover, ROM is suitable for any global sea trade route.

2.1 Joint project

This Master’S Thesis is a joint project with Performance Prediction Program for Wind-Assisted Cargo Ships done by Martina Reche Vilanova.
Chapter 3

Wind Assisted Propulsion Systems

It is a fact that there is a growing need for finding new technologies in order to be able to reduce carbon emissions in the global shipping. Wind-propulsion technologies sound to be the obvious solution when dealing with the CO$_2$ emission reduction. However, pure wind sailing appears to be a complex solution since the ocean wind may not have constantly the ideal conditions to maintain the desired speed and heading of the sailing vessel. On top of the the dimensions that a single or a group of sailing devices need to entirely propel a merchant vessel.

With the scope of CO$_2$ emission reduction, Wind Assisted Propulsion Systems (WAPS) are an auspicious solution. It is a versatile solution since it can be installed as a retrofit on existing vessels or implemented on new constructions. WAPS use the thrust generated by the sailing devices in order to reduce the fuel consumption of the vessel.

There are different solutions to take advantage of the wind as a source of energy to generate thrust. It is a growing market where different technologies are being explored. The most common devices are flettner rotors, rigid sails, soft sails or kite sails. The following Figure shows the flettner rotor in the top-left, rigid sail in the top-right, soft sails in the bottom-left and kite sail in the bottom right.
The four images show completely different technologies but all of them pursuit the same aim, reduce the fuel consumption of the vessel by generating thrust by making use of its sailing devices. More than one sailing devices are usually installed in order to maximize the thrust generated.

Beside of those, the market for such technologies is expanding and new devices are appearing. Reefable rigid and soft sails are under development in order not to have difficulties in strong wind conditions as well as while loading or unloading the cargo they transport at the harbour.

Wind Assisted Propulsion Systems are on-going techniques under development. However, they are promising technologies with a clear aim of driving to a more sustainable shipping.
Performance Prediction Program

As mentioned in Chapter 2, this is a joint project with Performance Prediction Program for Cargo Wind Assisted Vessels. In order to know how the vessel performs depending on variables of the vessel itself, such as its speed, as well as external conditions as wind or waves, it is needed a Performance Prediction Program (PPP). The Performance Prediction Program calculates the power required by the engines depending on different parameters:

- Ship speed
- True Wind Speed
- True Wind Angle
- Significant wave height

Those have been considered the most relevant parameters to constitute the input for the Performance Prediction Program. In order to obtain the output desired, i.e. delivered power of the engines, the PPP uses a balance algorithm based on Newton’s Method to find the equilibrium between the hull and sail forces.

A Performance Prediction Program has been considered instead of Velocity Prediction Program because the main objective is to lower the \( \text{CO}_2 \) emissions while meeting the Estimated Arrival Time. The PPP calculates the delivered power for any combination of the different input parameters within a certain range. Oppositely, the Velocity Prediction Problem calculates the velocity that the vessel could perform by the combination of the mentioned parameters. A VPP is commonly used in sailing races or situations where the main objective is the speed.
4.1 Principles of the Optimization

Optimization is the improvement of an existing system. The root of the word optimization is optimal, which means best. The concept best varies depending on the objective the system has. Therefore, optimization can be understood as finding the best solution over all the feasible solutions with regards to a specific objective.

A regular optimization problem formulation process can be defined by the following bullet points:

- Necessity for optimization
- Objective function formulation
- Optimization variables election
- Constraints determination
- Variable bounds arrangement
- Optimization algorithm selection dependent on the characteristics of the optimization problem
- Optimal solution finding

After knowing the formulation process of an optimization problem, the problem itself can be defined. A general constrained optimization problem can be defined in general terms as follows:

\[
\begin{align*}
\min, \max & \quad f(x) \\
\text{subject to} & \quad g_i(x) = c_i \text{ for } i = 1,...,n \text{ for equality constraints} \\
& \quad h_j(x) \geq d_j \text{ for } j = 1,...,m \text{ for inequality constraints}
\end{align*}
\]  
(4.1.1)

Where \( f(x) \) defines the function that wants to be minimized or maximized and \( g(x) \) and \( h(x) \) define the equality and inequality constraints functions respectively. The
4.1. **OBJECTIVES**

In optimization an objective \( f(x) \) is the function that is desired to be minimized or maximized, depending on the optimization problem. Cost or energy functions are examples of objectives that are usually desired to be minimized. Contrarily, reward or utility functions are commonly demanded to be maximized.

4.1.2 **Free variables**

The free variables \( x_n \) are the parameters that are allowed to be tuned in order to find the optimal solution. These parameters have a valid range where they can be altered to find the most suitable value for each variable in any particular problem. As wider this range is, more computational effort is needed since there are more values to check. The same happens with the number of free variables of the optimization problem. A greater number of free variables will have a significant cost in terms of computational time.

4.1.3 **Constraints**

Constraints are the bounds in the optimization problem. The constraints represent utilitarian relation between the free variables and other design parameters that limit the design space due to physical phenomena or resource limitations. There exist two types of constraints:

- **Inequality constraints.** The utilitarian relations among the variables have to be larger than / smaller than or equal to a given value.

- **Equality constraints.** The utilitarian relations in this case have to be equal to a given value.

Hard constraints are required to be satisfied while soft constraints are preferred but not required to be satisfied. In the development of this thesis only hard constraints are considered.

To stay competitive in the shipping industry it is crucial to follow optimal routes at any time. There are many different optimization methods in order to approach the
problem under study. It is crucial to correctly formulate the objective and constraints of the optimization problem in order to succeed in the optimization process. Multi-objective approach is the method used in order to solve the route optimization problem for vessels with Wind Assisted Propulsion Systems since more than one competing objectives aim to be met at the time. See Ch.5.4.

### 4.2 Multi-objective approach

Multi-objective optimization is not only used in mathematical procedures. In most of the daily life conflicts is it necessary to find the best solution over multiple clashing objectives. The main particular of the multi-objective optimization consists of having multiple solutions. When talking about optimization it is common to think that it exists only one optimal solution with regards to the objectives and that fulfills the constraints but this is often not the case for real world optimization problems. The answer for a Multi-objective optimization is able to find of a set of solutions that define the best trade-off between the conflicting objectives. The Pareto-front delimits the feasible design region, where the solutions are located, and the unfeasible one.

![Pareto-front representation between confronting objectives. Adapted graph from www.mathworks.com](www.mathworks.com)

Figure 4.1: Pareto-front representation between confronting objectives. Adapted graph from www.mathworks.com

Multi-objective optimization problem differs from Single-objective one in multiple aspects, according to [13]:

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4.2. MULTI-OBJECTIVE APPROACH

• More than one targets for the optimization. These targets have conflict between each other.

• Pareto-optimal set as answer of the Multi-objective optimization problem.

According to the second bullet point, the Pareto-optimal front is a non-dominated set of optimal solutions. A non-dominated set is a group of solutions \( P' \) that are not dominated by any of the feasible solutions of the problem \( P \).

The non-dominated set of solution is the so-called Pareto-optimal front. This front varies depending if the objective functions are minimized or maximized. The following figure shows an example of the different Pareto-optimal fronts for a Multi-objective optimization with two objectives:

![Figure 4.2: Pareto-optimal front for different combinations of objective functions. [13]](image)

It can be clearly seen that the Optimal-front differs between the four cases depending on the objective functions \( (f_1 \text{ and } f_2) \). The non-dominated set \( P' \) (represented by the black continuous curve) is placed in a different place of the feasible solution region (represented by the solid grey). The top-left and bottom-right sketches represent the two objective functions minimized and maximized, respectively. The top-right and bottom-left in this case have one of the objective functions that needs to be minimized and, the other one, maximized. The top-right sketch has a discontinuity in the Pareto-optimal front which is given by the shape of the feasible design region.

There are a great number of solutions that build this Pareto-optimal set that represents the best trade-off between the competing objectives, but when optimizing it is com-
monly desired to find the only optimal solution.

A clever arrangement could be to collect the ideal objective vectors. This is, collecting the optimal solution with regards to each objective in order to build the ideal objective vector. However, the ideal objective vector is the so-called Utopian vector which represents a non-existing solution for the problem. In Figure 4.1 the Utopian plot is represented and it can be clearly seen that is located in the unfeasible region.

There are two different ways to find the optimal solution, according to [13].

- **Ideal Multi-objective optimization procedure.**
  This procedure consists of analyzing the Pareto-optimal solutions after they are computed with higher-level of information than the one used to get the set of solutions. This information can be usually not technical or qualitative in order to find the optimal solution among all the others.

- **Preference based Multi-objective optimization procedure.**
  The preference based method has as its foundation the construction of a single objective function. The new objective function is built as the sum of the original objective functions where the weight of them is proportional to its preference over the other objectives. With this procedure, the Multi-objective optimization problem becomes a Single-objective optimization problem. The solution for this new problem will become a single optimal result. However, this is a more subjective method than the ideal process due to the relative weighting of the objectives.

### 4.3 Optimization algorithms

An optimization algorithm is an iterative procedure which compares various solutions until the optimal is found. There are two main types of optimization algorithms:

- **Deterministic algorithms.**
  Deterministic algorithms are characterized by having explicit criteria to step from solution to solution within the population.

- **Stochastic algorithms.**
  Stochastic algorithms are a nature-inspired optimization algorithms with inherent randomness that have probabilistic transition rules while displacing among solutions.

Biological models follow stochastic processes. Stochastic algorithms are remarkably more complex than deterministic algorithms. However, they can also solve complex problems with several local optimal solutions and still be able to find the global optimal set of solutions. The route optimization is a sophisticated problem due to the numerous
Genetic Algorithms

A Genetic Algorithm is a stochastic population-based optimization method that works as an analogy to nature. Genetic algorithms follow biological evolutionary processes. The principle of these algorithms could be summarized in one sentence: the fittest individuals of each generation are the ones which survive. This is the so-called elitism that characterizes genetic algorithms. The new individuals are created by interchanging genetic material from the previous solutions (their parents). A solution or individual is represented as a chromosome, an array that contains information about each solution. In order to create the new generations, genetic operations such as crossover or mutation are used. Crossover is the action where one or more bits are interchanged between two arrays at random positions. In mutation, bits from the chromosome array are altered in random positions.

The structure of a regular Genetic algorithm can be summarized according to [15]. Firstly, the optimization problem is transformed so it can be understood by the algorithm, binary language it is commonly used. In order to follow, an initial random population is generated. Each point or chromosome is evaluated according to the objective functions. The fitness of each solution is determined by comparing it to the rest of chromosomes. After, with the fitter individuals a subset population is created, the less favoured individuals are eliminated. Pairs of the subset population are selected randomly in order to create a new generation by using mutation and crossover techniques. When the optimal solution is found this process can be stopped, otherwise more individuals need to be evaluated until the optimal one is encountered.

It has been decided to work with genetic algorithms due to their hard points:

- Robustness. Genetic algorithms consider a population of chromosomes. Every chromosome means a possible solution. A large population number avoids the possibility of finding a local optimal solution and confuse it with the global optimal solution before encountering it. The population size affects the possibility of finding the optimal solution, thus, it is important to allow a relatively large population number. The population size is required to be as large as it needs to find the optimal solution but not too broad because this will mean an unnecessary number of searches and thus, a massive computational effort.
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• **Simplicity.** Genetic algorithms are characterized for being quite generic algorithms that do not need a large knowledge of the search space. Pure mathematical methods are often too complex, which is not desired when approaching a practical optimization problem, what is the case in this thesis.

• **Efficiency for problems that involve a great number of variables.** In this optimization problem a relatively large number of free variables will be used. See Ch.5.4.

Genetic algorithms have the drawback of presenting high computational effort when solving problems with complex constraints. This drawback can be balanced with the easy implementation of the algorithm in parallel architecture that speeds up the optimization procedure.

The Genetic Algorithm used is the Non-dominated Sorting Genetic Algorithm due to the experience that DNV-GL has with this algorithm together with the broad sources of literature available.

4.4.1 Non-dominated Sorting Genetic Algorithm - NSGA-II

The main intention of a Multi-objective optimization algorithm is to find the maximum number of Pareto-optimal solutions in order to be able to find the optimal solution vector. Which is achieved by improving the adaptive fit of a population to find the Pareto-optimal set.

As a genetic algorithm, the descendant population ($Q_t$) is generated by interchanging genetic material from the parent population ($P_t$), with a population size of $N$ each. The genetic material is combined by using genetic operators such as crossover or mutation. After that, $P_t$ and $Q_t$ are mixed to find a new generation ($R_t$) which will have a size of $2N$.

NSGA-II is a non-dominated sorting algorithm which classifies the population into the different non-dominated fronts ($F_n$). Within that front, none of the solutions can be improved with regards to one objective without degrading the other objectives. This is done for the entire population $R_t$. The new parent population $P_{t+1}$ is populated first with points of the first non-dominated front ($F_1$) and continues with the second ($F_2$), third ($F_3$) and successively. The total size of the population $R_t$ is $2N$, therefore, it is possible that not all the fronts are placed in the $N$ vacancies. Since the number of fronts is limited, the fronts that can not be allocated are discarded. When reaching the last front that can be accommodated, the slots available in this front will be reserved for the points from that front which give the higher diversity of the entire set of points instead of an automatic discard of points [7][13]. The procedure of NSGA-II is schematized in the following figure.
NSGA-II is the evolution of the Non-Sorting Genetic Algorithm (NSGA) which was one of the earliest Evolutionary Algorithms. NSGA has been broadly used to solve Multi-objective optimization problems. However, with the emergence of new algorithms over the pass of the years, NSGA have been criticized due to lacks in the performance of the algorithm. The main problems with the original NSGA were, as explained in [3], the large computational complexity of the non-dominated sorting, the lack of elitism of the algorithm. These problems are the ones amended in the NSGA-II.

### 4.4.2 Design of Experiment

It is required to develop a Design of Experiment (DOE) table as starting point for an optimization process. A DOE is a statistical approach used to collect information regarding the design space of the optimization problem. The DOE studies the tendencies of the optimization variables in benefit of the objectives of the optimization. With this first sampling it is observed which are the optimal regions to run the optimization process. The DOE will be used by the main algorithm to start the optimization process in the most convenient region with the already known main tendencies of the optimization variables.

In order to obtain a DOE is a random quasi-random number sequence frequently used. Quasi-random sequences are characterized by its low discrepancy. The discrepancy measures how in-homogeneous a set of vectors is distributed in a unit hyper-cube. Different quasi-random sequences have been published, such as Faure, Halton, Niederreiter or Sobol [14]. Sobol is the one used here due to the stable and straightforward implementation in the optimizer used.
Two samplings of the same design space have been done using a random and the quasi-random Sobol numerical sequences respectively. Both plots are shown in the figure below:

Figure 4.4: Representation of the Random sequence and the quasi-random Sobol sequence.

It can be observed that the quasi-random Sobol sequence presents a better sampling of the design space. As expected, the spreading is more effective than the one offered by a random distribution. That is why, the sampling of the so-called Design of Experiments (DOE) is generated using the quasi-random Sobol sequence.
Chapter 5

Route Optimization Model (ROM)

The Route Optimization Model (ROM) is the result of multiple parts working together. The key parts of ROM are the optimizer itself and two main algorithms: the route evaluation algorithm and the multi-objective algorithm. The different parts are developed in this chapter.

5.1 Functional structure

As mentioned above, the optimization process involves many different parts. In order to be able to explain all the mechanisms involved in ROM and all the parts that builds the model, its functional structure is firstly schematized in Figure 5.1 and briefly summarized after.

![Figure 5.1: Functional structure of ROM.](image)

It is composed by three main parts:

- Route Evaluation Algorithm
- Route Optimization Algorithm
- Optimizer
The optimizer randomly selects a set of free variables. The route optimization algorithm builds the route with the given free variables. The optimizer checks if the route is violating the constraints at any point of the route. In case it does, the route becomes invalid and, thus, discarded right away. In case the constraints are satisfied, the algorithm calculates the objectives according to the free variables selected. These objectives are feedback for the optimizer and the Non-dominated Sorting Genetic Algorithm II. A new selection of free-variables will is based on this feedback. This process is repeated until the Pareto-optimal set is found.

5.2 Route Evaluation Algorithm

The concept behind the route evaluation algorithm consists of perturbing the Orthodromic route in benefit of the the weather pattern to take maximum advantage of the sailing devices. The Orthodromic route represents the shortest distance between two points on the Earth surface, which is also known as Haversine or Great Circle line.

This perturbation approach consists of the deviation of the vessel from the Orthodromic route, therefore, from the shortest route in distance in order to find an different routes with known fuel consumption and sailing time. This approach also considers the non-constant speed of the vessel.

The methodology that this algorithm follows is explained in the following bullet points.

- **Orthodromic route definition**

  The shortest route in distance between the departure and arrival points is computed. This route is the one that aims to be perturbed in order to find the optimal one. Supposing departure and destination points given by Cartesian Coordinates, \((\phi_1, \lambda_1)\) and \((\phi_2, \lambda_2)\) where \(\phi\) represents the latitude of the coordinate and \(\lambda\), the longitude, the Haversine can be expressed according the following equation:

  \[
  \text{Haversine} = 2 \cdot R \cdot \arcsin\left(\sqrt{\sin(\Delta\phi/2)^2 + \cos(\phi_1)\cos(\phi_2)\sin(\Delta\lambda/2)^2}\right) \tag{5.2.1}
  \]

  Where \(\Delta\phi\) and \(\Delta\lambda\) are the latitude and longitude variations respectively and \(R\) represents the Earth radius.
• **Orthodromic route discretization**

In this step the Orthodromic route is discretized with a fixed number of equally spaced way-points. The number of way-points for a specific route is selected depending on the level of accuracy required to define the route and, therefore have more fine results regarding fuel consumption and carbon emissions. The number of way-points is a trade-off between the accuracy needed to find the optimal route and quantify savings in a precise way and the computational effort of the model. For each control point considered, a great number of interpolations are required regarding ship performance and weather patterns, what is highly costly in computational terms. Moreover, the number of free variables that the optimization faces is increased by two for each way-point considered.

• **Orthogonal shifts**

The route to be evaluated is created by perturbing the Orthodromic route. This model consists of an orthogonal deviation on each way-point, changing in this way the course of the vessel. The orthogonal shifts together with the ship speed for each leg will later be used as free variables for the optimization process.

![Figure 5.2: Sketch of the orthogonal shifts concept. The blue dots represent some of the potential orthogonal deviations from the Orthodromic route (represented by a non-continuous curve).](image)

This model deviates from [1], who used the *splines* in order to get a smooth course line. Contrarily to that approach (motor-ship), here the objective with the orthogonal shifts approach is to allow tacking into the wind. The pronounced course changes allow the vessel to set a sail configuration for each leg. The orthogonal deviation in each way point allows the Course Over Ground to have a less or more large variation. The maximum orthogonal deviation is also a variable that can be adjusted depending on how distant the vessel should be from
5.2. ROUTE EVALUATION ALGORITHM

the Orthodromic route.

Therefore, Course Over Ground plays a key role in route modeling for wind assisted vessels since it determines the True Wind Angle.

The True Wind Angle (TWA) is the relation between True Wind Direction (TWD) and Course Over Ground. TWD and COG are relative to the North direction. The Course Over Ground (COG) can be expressed as the heading in addition to the leeway which is the side-way drift of the desired course. However, the Performance Prediction Program already studies the leeway, thus, in this thesis, heading and Course Over Ground (in the following denoted as course) will not be differentiated.

In order to determine the course and distance between the way-points, the rhumb line equations are used:

\[
\text{course} = \arctan \left( \frac{\Delta \lambda \cdot \cos \left( \frac{\phi_1 + \phi_2}{2} \right)}{\Delta \phi} \right) \tag{5.2.2}
\]

\[
\text{distance} = \frac{60 \cdot \Delta \phi}{\cos(\text{course})} \tag{5.2.3}
\]

Where \( \Delta \phi \) and \( \Delta \lambda \) are the latitude and longitude variations respectively.

- **Compute the new positions**

Given the orthogonal deviation in relation to the Great Circle Line at each way-point, the new locations at each control point can be computed. As said previously, there are unlimited number of route combinations by changing the position of the control points. At this stage the exact position of the way points for each route will be known by making use of the orthogonal deviation in relation to the GCL.

After the exact position of the way-points are known, it is necessary to determine the distance between and the course between them. The distance is used to determine the time of arrival at each way-point as well as the total sailing time. The course, together with the time are key to compute the fuel consumption.
5.2. ROUTE EVALUATION ALGORITHM

• Weather interpolation (wind, waves and currents)

The weather data relevant for the development of the model (see Ch.5.3) needs to be known in order to evaluate the route. To proceed the weather data set acquired is interpolated for the exact latitude and longitude of each control point as well as the moment of time that the vessel will cross that coordinate. This is done by a multivariate interpolation with a uniformly spaced regular grid. As stated in Ch.5.3, the True Wind Speed, True Wind Direction, significant wave height and surface type will be known for the control points at a specific time.

By knowing the wind components, the True Wing Angle is extracted from the course of the vessel between two way-points previously computed. The True Wind Angle together with the True Wind Speed and the significant wave height (when considering seaway) are the parameters extracted from the weather data needed in order to apply the Performance Prediction Program at the control points.

• Performance Prediction Program application

At this stage, after knowing the weather data in the control points, the cargo vessel is introduced in the ROM by using its Performance Prediction Program (PPP). As said previously, this model is suitable for any cargo vessel with Wind Assisted Propulsion Systems. ROM is a broad model that can host any cargo vessel by making use of its Performance Prediction Program. In order to apply the Performance Prediction Program to the route, it is again used, a multivariate interpolation. The input information for the PPP is listed below.

- Ship speed
- True Wind Speed
- True Wind Angle
- Significant wave height

With these inputs at each control point, the model interpolates the corresponding delivered power and, thus, the fuel consumption can be approximated in each of the legs of the route.

\[ \text{fuel consumption} = SFC \cdot PD \cdot \text{time} \]  \hspace{1cm} (5.2.4)

This equation defines the fuel consumption in each leg of the route. Where \( SFC \) stands for Specific Fuel Consumption and \( PD \) refers to the Delivered Power.
• Time and Fuel Consumption computation

Eventually this algorithm calculate the total sailing time and the fuel consumption in order to evaluate the different routes. Both magnitudes are integrated over all the legs that constitute the route to find the total time and fuel consumption invested for each route evaluated.

5.3 Environmental conditions

In the route modelling topic is crucial to consider the environmental conditions. The decision process is totally influenced by the weather conditions. The most relevant environmental conditions for the route modeling are wind, waves and currents.

5.3.1 Weather data

As explained in the objective of this project (Ch.2), the Route Optimization Model is a tool to evaluate potential savings by studying the scenario where the vessel regularly sails. ROM is not meant to do a dynamic control of the route. If ROM would be used to suggest the best route for a planned journey, it would be advisable to use ensemble forecasts [2]. Which is used to calibrate the uncertainties in the initial weather conditions.

Historical Weather Data has been the solution used in order to evaluate the weather conditions relevant for the route building. Historical data sources are meteorological models calibrated with measurements. The weather data is obtained from Copernicus - Marine Environment Monitoring Service (CMEMS) [16] which has a regional domain of the entire global ocean. The data has a spatial resolution lower than 1 degree, both in latitude and longitude where an hourly-mean value is given. With this information it is possible to interpolate the weather data for the way-points defined on the route. Therefore, it is possible to simulate a route optimization for a certain period of time using historical results.

5.3.2 Wind pattern

The main consideration when thinking about route building for vessels with Wind Assisted Propulsion Systems is the wind pattern. The wind pattern together with the course will determine the orientation of the sailing devices.
The variables used in order to build the route with regards to the wind conditions are the following ones:

- Wind speed
- Northward wind component
- Eastward wind component

As mentioned above, it is essential to know the True Wind Angle that the vessel experiences at each leg of the route. As it is not included directly in the model data, it is calculated from the northward and eastward wind components, $v_o$ and $u_o$ respectively. $v_o$ and $u_o$ define the True Wind Direction which subtracted to the course of the vessel defines the True Wind Angle.

It could be possible the case where the wind speed is that high that the stability of the vessel is compromised. The Performance Prediction Program considers reefing of the sails in case of high wind speeds.

### 5.3.3 Wave pattern

Waves can be described as a disturbance of the free surface. They are commonly generated by local wind but also by atmospheric pressure gradients, gravitational attractions or underwater phenomena like seismic oscillations.

Sea waves are described by multiple parameters such as amplitude, wave length and phase velocity. It is considered a scenario with deep seas. The wave particulars relevant for this case are the wave height and the wave period.

For regular waves the wave height ($H_i$) can be defined as the surface elevation difference between the wave trough and the wave crest. The wave period ($T_i$) is defined as the time interval between two successive up-crossing points. However, in this case an irregular sea state is considered which is characterized by a significant wave height and a mean wave period.

The Performance Prediction Program calculates the added resistance in waves using as input parameters the significant wave height and wave period at each leg of the route. This calculation is done by a semi-empirical method used at DNV-GL for high level assessment of the added resistance in a seaway.
In order to separate the different waves in the recorded wave time series, the so-called zero up-crossing method is used which consists of localizing the zero up-crossing (or down-crossing) points. In the domain, two consecutive up-crossing points constitute an isolated wave. All the waves obtained by the zero up-crossing method are organized depending on their height in order to compute the wave scalars [16]. In this case, the relevant wave scalars for the route building are the spectral significant wave height and the wave period at spectral peak.

- **Spectral significant wave height.**

  The significant wave height $H_s$ is a term that defines the mean of the highest one third of the waves that arise in a wave spectrum. It is a way to define a standardized statistic that describes the height of the arbitrary waves. The reason behind is that higher waves are usually more compelling than the smaller ones. The way it is defined, coincides to the averaging of the waves that a sailor could do from on-board. As a rule of Thumb, the largest individual wave that can be confronted could double this significant wave height, even though this fact would be sporadic.

- **Mean wave period**

  The wave period is described as the time measured between two consecutive wave crests when observing from a fixed point. The mean period $T_m$ is defined as an average from the whole ensemble of wave components.

The significant wave height and the wave period are directly related to the added resistance and, thus, to the fuel consumption, which will be later treated as an objective for the optimization problem (See Ch.5.4). Since the objective functions aim to be minimized, the optimization favors the solutions with lower significant wave height and lower wave period. What is the same as avoiding large waves. That is the reason why $H_s$ and $T_m$ are not treated as constraints. ROM aims to be a generic tool that in a simple way predicts emission savings. The significant wave height and wave period that a cargo vessel can encounter depend on multiple factors. These factors could be the vessel itself or the loading conditions among others.

The consideration of $H_s$ and $T_m$ as constraints would increase the complexity of ROM. For the purpose of estimating fuel savings it is sufficient to consider the seaway by the added resistance. However, for practical applications, the wave height should be considered as a constraint.

The range of significant wave height and the wave period used for the generation of the Performance Prediction Program is extracted from IACS Recommendation No. 34, [9] for the example case studied (see Ch.7)
In Table 1 of that document appears the probability of sea-states in the North Atlantic described as concurrence per 100000 observations.

The significant wave height and wave periods with higher probability to develop are the ones considered in this optimization model. According to IACS Recommendation No. 34, the following intervals are the ones considered:

- \( 4.5 \text{s} < T_m < 15.5 \text{s} \)
- \( 0 < H_s < 11.5 \text{m} \)

However, it has been observed that when considering the sea state in the optimization process, the computational effort has been dramatically increased. The generation of the Performance Prediction Program with the five inputs stated is too costly for this early stage optimization tool. Moreover, the ranges under study of the significant wave height and the wave period are significantly broad. That is why the wave period is treated as a dependency of the significant wave height as shown in equation 5.3.1.

\[
T_m = \frac{2\pi}{g} \sqrt{\frac{g}{0.16} \cdot H_s} \tag{5.3.1}
\]

The performance Prediction Program delivers a wave period dependent on the significant wave height. Instead of having five inputs in the generation of the PPP, four are needed now. This modification decreases drastically the computational effort.

### 5.3.4 Currents

Ocean water is a system that continuously moves. Ocean currents are abiotic factors of the environment that significantly affects the seas in all water depths. Ocean currents are mainly caused winds, water density, water temperature and tides. The Coriolis effect also plays a key role in the current generation. Coriolis effect is caused by the
Earth rotation what forbids the ocean to water to follow a straight course while traveling along the rotating planet [17].

There are surface and deep currents, surface currents are the most relevant ones for this thesis since they will affect the course of the vessel. Global wind systems drive large-scale ocean surface currents which have a great impact on the international shipping routes. That is the reason why it has been considered crucial to acknowledge for currents in the Route Optimization Model.

Speed Through Water (STW) accounts for the velocity of the vessel with respect to the sea. The Speed Over Ground refers to the velocity relative to the ground, as illustrated by its name. The Speed Through Water can be derived from the Speed Over Ground and the current velocity components. The velocity components for the currents \((u_{curr} \text{ and } v_{curr})\) are obtained from CMEMS. The absolute direction of the currents and its speed can be obtained by using the following equations respectively:

\[
\begin{align*}
    r_{abs,curr} &= \arctan \left( \frac{u_{curr}}{v_{curr}} \right) \\
    V_{abs,curr} &= \sqrt{u_{curr}^2 + v_{curr}^2}
\end{align*}
\]

The direction and the velocity of the current relative to the vessel can be described by:

\[
\begin{align*}
    r_{rel,curr} &= r_{abs,curr} - \text{course} \\
    V_{rel,curr} &= V_{abs,curr} \times \cos(r_{rel,curr})
\end{align*}
\]

Eventually, the Speed Through Water can be obtained using the known Speed Over Ground of the vessel and the relative velocity to the vessel of the current as shown in the following equation:

\[
STW = SOG - V_{rel,curr}
\]

### 5.4 Optimization problem formulation

The route modeling consists of creating a track between the departure and destination harbour. Knowing the origin and arrival points, there is an uncountable number of tracks that can be built. One of them could be the shortest route in terms of distance i.e. Orthodromic route.

Great Circle Line navigation could be the optimal solution to the studied problem if the cargo vessel would purely sail with engine propulsion. Moreover, the Orthodromic distance is only optimal if environmental conditions are not considered. Even if the cargo vessel would not have sailing devices to assist its propulsion, considering environmental conditions such as wind, wave or current patterns would provoke a deviation from the shortest route in distance in benefit of time and possibly fuel consumption.
The wind, together with the wave pattern will play a key role in the route optimization for a vessel with wind assisted propulsion systems.

The optimization problem is defined according to Ch.4.1.

**Need for optimization**

Therefore, there is the need of optimization for the route between the departure and arrival coordinates. This optimization needs to be done according to an objective.

**Objective function formulation**

As mentioned previously, the main scope of this thesis is to reduce the carbon emissions of cargo vessels with wind assisted propulsion systems. This goal is achieved by reducing the fuel consumption of the vessel. The drawback with the mentioned objective is that it would be possible to indefinitely reduce the CO₂ emissions since the vessel could slowly sail using its sailing devices to the harbour of destination. This is not a feasible option since ETA (Estimated Arrival Time) is crucial to be competitive in the shipping industry. That is why the optimization needs a second objective, time, in order to stay competitive.

Therefore, the problem will be treated as a Multi-objective optimization problem with two clear objectives:

- **Fuel consumption.**
  
  The first objective function can be expressed as \( f_1(x) = \text{fuel consumption} \).

- **Time.**
  
  The second objective function is defined as \( f_2(x) = \text{sailing time} \).

Time could be also treated as a constraint instead of as a second objective. This would convert the Multi-objective optimization problem into a Single-objective optimization problem. Only one solution would emerge from the Single-objective problem rather than a set of Pareto-optimal solutions.

As mentioned in the Ch.2 this is an early stage design tool in order to predict potential savings. Therefore, Multi-objective optimization allows a greater number of solutions. There is a large number of optimal solutions depending on the fuel consumption limitations or the sailing time limitations which can be found in the same optimization.

Following this argument, the Ideal Multi-objective procedure (see Ch.4.2) is the one used in this optimization task. The optimal solution is selected with higher information level such as Estimated Time of Arrival. From a broad Pareto-optimal front, the optimal solution is selected depending on external needs.
Variables election

After defining the objectives of the optimization problem the free variables need to be established. As explained in (Ch.4.1.2), the free variables are the parameters modified within a certain range during the optimization process. A proper value or combination of values for an specific problem will mean the encountering of an optimal solution. The free variables in this problem are:

- **Position**
- **Speed**

in each of the control points located in the route. These control or way-points are equally spaced in the virtual curve that the vessel will follow. The exact position of those way points and the speed that the vessel will perform between the mentioned control points are the free variables in the optimization problem. An optimal solution will be represented by a proper combination of values.

The number of control points and thus, the number of free variables is chosen based on multiple factors such as the precision desired in the solutions of the optimization process or the computational effort among others. The number of free variables will be increased by two for each control point added in the route optimization. Therefore, the computational effort and time involved in the optimization process will be significantly increased.

Constraints determination

As mentioned in the previous chapter, the one studied here is a constrained optimization problem. This means that the optimization problem is bounded to a constraint that limits the design space. The only constraint considered in the optimization process is:

- **Land avoidance**

It is a logical a land avoidance constraint while building a route for vessels. The route at any point can approach the coast. In order to implement the land avoidance constraint it has been used a data base which differentiates the surface type in a global chart using a binary code from *Copernicus - Marine environment monitoring service*. The surface type is set to 1 if there is land on the chart and 0 in case there is water. Therefore, an equality constraint has been set. The constraint represents the addition of the surface type value in every control point defined in the route. No matter how
many control points exist, the sum of all values need to be equals to zero, what means that the vessel does not approach land in any case. Since there is only one constraint:

\[ h(x) = 0 \] (5.4.1)

In case the free variables that represent the position go on top of the land, this solution would be automatically dropped because it does not fulfill the constraint.

For shallow water an inequality constraint based on water depth would be necessary. For reasons of simplicity, only land avoidance is considered here.

Validity range arrangement

The design variables need bounds that define which is their freedom in the design space. This freedom is commonly stated as a validity range under which they can be tuned in order to find the optimal Parerto-optimal set of solutions to the optimization problem. In this case the bounds will be differentiated for the position ones and the speed ones.

- **Position free variables.** The range of validity of the position variables will depend on each specific problem. The default value has been set to an orthogonal deviation of 10% of the total Orthodromic distance (between arrival and destination points) on each side from the Great Circle Line. This is, the optimization process is allowed to build a route that deviates perpendicularly a 10% of the Haversine between departure and destination coordinates.

- **Speed free variables.** The validity range of the speed free variables are dependent on each specific cargo vessel. The range of velocities is the one compressed between the minimum and maximum speed that the cargo vessel can perform. The validity range is provided by the Performance Prediction Program.

Algorithm selection

Non-dominated Sorting Genetic Algorithm (NSGA-II) is the algorithm used to solve this optimization problem. The implementation of the optimization algorithm is further explained in Chapter 6 where its parameters are studied in order to have the the most suitable configuration to solve the optimization problem.

5.5 FS-Optimizer

The optimizer used in the development of this Thesis is FS-Optimizer provided by DNV-GL. FS-Optimizer is a generic optimization toolkit that enables the user to build up a process chain from a selection of algorithms and programs in order to generate new designs. The designs are improved by using controlling parameters and tools in
order to find superior designs and, eventually, the optimal solutions.

As mentioned previously, the optimization algorithm used due to its suitability with the problem under study is the Non-dominated Sorting Genetic Algorithm. FS-Optimizer allows a number of controlling parameters to evaluate the design features, the design space and to generate the new individuals in the more optimal way. The most important parameters are listed below:

**Parameters of the optimization**

- **Number of generations.** Describes the maximum number of generation within the population. (Default value equals to 100)

- **Population number.** Describes the number of individuals per generation. (Default value equals to 20)

- **Crossover rate.** Describes the percentage of population where two-bit crossover is applied. The remaining parents are mutated. (Default value equals to 0.2)

- **Perturbation.**
  - Standard deviation. Defines the deviation for parameter perturbation relative to the feasible domain. (Default value equals to 0.01).
Chapter 6

Systematic studies on optimization parameters

In this chapter it is shown how the optimization parameters have been set in order to have a better performance in the optimization process with the aim of having more accurate results or reduced computational effort. In order to do the systematic studies, an example route has been fixed. The route studied crosses the North Atlantic Ocean which allows to observe disparities on the parameter settings due to the considerable Orthodromic distance between the departure and destination coordinates.

Figure 6.1: Orthodromic distance between departure and destination coordinates for the example route.
CHAPTER 6. OPTIMIZATION PARAMETERS

The route departs from the north of Spain (43°00'00.0"N, 12°00'00.0"W) and crosses the Atlantic Ocean to the west coast of North America to meet the destination point (40°00'00.0"N, 70°00'00.0"W). The Orthodromic distance is equal to 2600 nautical miles. As mentioned previously, the orthogonal deviation allowed to model the route is 10% of the Orthodromic distance. Therefore, 260 nautical miles. In order to keep a relatively low computational effort the number of way-points has been fixed to 11. Thus, 10 legs are evaluated. The number of free variables ascend to 19. This is, 9 relative to the position (the initial and final way-points have fixed position) and 10 relative to the speed.

A simple Performance Prediction Program has been used at this stage of the project in order to find suitable parameters for the optimization in a fast way. The Prediction Performance Program considers the True Wind Speed, True Wind Angle and the speed of the vessel. The wave patterns are not added at this phase due to the complexity of the wave interpolation modules.

An optimization problem consists of finding the best solution with regards to a specific objective from all the feasible solutions. In this case two objectives are met at the time. The number of objectives together with free variables and the constraints make every optimization problem unique. Therefore, an iterative process has been followed in order to study the values that best suit the different optimization parameters. The most representative plots for the iterative process are the ones shown in this chapter.

In order to start analyzing the parameters to improve the optimization performance, a first optimization is run with the default values.

Each red circle in the diagrams in this chapter represents the evaluation of one route candidate, defined by one set of free variables.
Figure 6.2: *First optimization with default values and initial population number equals to 100, showing fuel consumption over sailing time.*

Figure 6.2 shows both objectives plotted against each other, the total sailing time on the horizontal axis for a route candidate versus the total fuel consumption for that candidate on the vertical axis. As both objectives shall be minimized in the process, the Pareto-optimal is the lower left boundary of the design space, according to figure 4.2.

It can be clearly seen that the generation of the Pareto-optimal front is not smooth. Even though a high number of solutions are evaluated.
6.0.1 NSGA-II - Perturbation parameter

Figure 6.3: Representation of one free variable, an example of position variable on the left and a speed free variable on the right, against the number of designs evaluated. First optimization with default values and DOE population number equals to 100.

Figure 6.3 shows a plot with an example of one position and speed free variable against the number of designs. Thus, illustrates the evolution of that variable during the optimization process. It can be seen that the free variables are clustered in a small number of values, both for the speed and the position variable.

With this plot it has been determined that the perturbation parameter is very relevant in the optimization process. The default standard deviation value used proves to be insufficient since a small number of values, within the range of the free variables, are used. The standard deviation is the parameter that controls how large the perturbations are with respect to the allowed range of a certain parameter.

By following an iterative process it has been determined that by enlarging the standard deviation parameter and, thus, allowing a greater deviation benefits the encountering of the Pareto-optimal set. When close to an optimum, the perturbation is the most effective trigger for the optimization.

The default value for the standard deviation parameter is 0.01. After completing the iterative process it has been seen that 0.2 is the value that better suits the optimization process for the given number of objectives, free variables and constraints. Figure 6.4 shows an optimization with default values, with standard deviation set to 0.2.
Figure 6.4: *Optimization with default values. Standard deviation equals to 0.2.*

It can be clearly seen the difference of the Pareto-optimal front only by enlarging the standard deviation parameter.

This parameter is set constant for the rest of optimization processes.

### 6.0.2 Initial population size - DOE

During the first phase of the optimization process, it has been observed that the initial population of the design space (DOE) is crucial to have a good performance of the optimization algorithm, in this case NSGA-II. As mentioned previously, quasi-random sequences present effective spreading of solutions in the feasible space. The number of designs that compose the initial population is essential. An insufficient number of designs and, therefore, a poor DOE table impedes the detection of a convenient starting point for a focused optimization problem. The default number for the initial population is set to 100. Nonetheless, this is a low value that offers a poor DOE. Thus, the initial population of the design space is not dense enough to guide the optimization. An iterative process has been followed in order to find a number that suits the problem. It has been discovered that between three thousand and eight thousand of evaluations...
in total are required in order to find the Pareto-optimal set of solutions for the studied cases. Thus an initial population number of 1500 designs suits any optimization within this range of evaluations. For the studies of parameters of NSGA-II in this chapter, the DOE can be saved and used in multiple optimization always that the objectives, free variables and constraints are maintained the same.

### 6.0.3 NSGA-II - Number of generations and population size

Two other relevant parameters for the optimization have turned to be the number of generations within the population and the population number in every generation. An empirical process has been followed in order to observe whether is better to increase the number of generations and decrease the population number of each generation or vice-versa.

In order to maintain the total number of designs, the same numbers have been used for both experiments. For the first case, the maximum number of generations within the population is set to the maximum allowed, i.e. 100. The population number allowed in each generation is fixed to the default value, i.e. 20. Both are the default values in the optimizer. The Pareto-front obtained can be seen in the following figure.

![Figure 6.5: Case 1: Optimization done for numbers of generations equals to 100 and population number equals to 20.](image-url)

The same optimization is visualized with the number of designs in the x-axis and the fuel consumption (left) and time (right) in the y-axis. The Pareto-optimal solutions are
represented by the green dots.

Figure 6.6: Case 1: Representation of the fuel consumption (left) and time (right) against the number of designs. Optimization done for numbers of generations equals to 100 and population number equals to 20. The green dots represent the Pareto-optimal solutions.

For the second case, the parameters have been reversed. Thus the maximum number of generations is set to 20 and there are 100 individuals in each generation. The same plots as in the first case are presented in order to compare both cases.

Figure 6.7: Case 2: Optimization done for numbers of generations equals to 20 and population number equals to 100.
CHAPTER 6. OPTIMIZATION PARAMETERS

Figure 6.8: Case 2: Representation of the fuel consumption (left) and time (right) against the number of designs. Optimization done for numbers of generations equals to 20 and population number equals to 100. The green dots represent the Pareto-optimal solutions.

The two cases are compared in order to see which combination of parameters better suit the optimization process. Firstly, a comparison between the plots where the two objectives are represented (Figures 6.5 and 6.7) is carried out. It can be seen that the first case (with large number of generations) the Pareto-optimal front appears to be smoother for the slower routes. On the other case (with large population number on each generation), the Pareto-optimal front presents better performance on the faster routes. On top of that, both cases present fairly similar results with reasonably good sampling of the Pareto-optimal front.

On the other hand, the plots where the fuel consumption objective is plotted against the number of designs (Figures 6.6 (left) and 6.8 (left)) show significant differences. In the first case, it can be seen that the design space is situated in a narrower space than in case 2. Nonetheless, the optimization in case 1 is able to find the firsts Pareto-optimal solutions between the 1500 and 2000 evaluations. These Pareto-optimal designs do not cover the entire fuel consumption range of solutions. Between 3000 and 3500 evaluation are needed in order to cover the entire fuel consumption range. To obtain the same amount of Pareto-optimal solutions in the second case, a number close to 3000 evaluations are needed. Nonetheless, these Pareto-optimal designs are distributed in the entire fuel consumption range of solutions.

The same tendency can be visualized for the time objective plotted against the number of designs (Figures 6.6 (right) and 6.8 (right)). The Pareto-optimal solutions are found with less number of evaluations in the first case. However, a better sampling of the design space is shown in the second case.
The convergence of the optimization process can be observed in the lower limit of the graphs where the objectives are plotted against the number of evaluations (Figures 6.6 and 6.8). In both cases it can be identified a clear convergence for both objectives.

In order to conclude, both cases present different benefits and drawbacks. In order to solve a route optimization problem where a low fuel consumption and therefore, spending more time sailing is not a dilemma, the first case (greater number of generations with a lower number of individuals within each generation) should be used. In the opposite and regular case where the time is a restraint, the second case (with a larger number of individuals for a lower number of generations) will be adopted.

Here, the second case, where the Pareto-optimal front presents better performance in the Pareto-optimal solutions for faster routes, has been further developed. Figure 6.8 shows that the Pareto-optimal solutions are found in the last evaluations of the optimization process. A greater number of evaluations are simulated in order to see how the performance of the population varies. To do so, the same tendency of case two is followed. The population number is maintained to 100 and the number of generations is duplicated to 40. Now for each generation, 40 individuals are evaluated.

![Figure 6.9: Optimization done for numbers of generations equals to 40 and population number equals to 100.](image)

The Pareto-front between the competing objectives of this new parameter setting proves to be smoother that the one presented in case 2 (with half number of generations).
Moreover, when observing the position of the Pareto-optimal front it can be seen that is located closer to both axes, thus, more optimal solutions are found when increasing the number of evaluations. The Pareto-optimal front displays a general improvement of 0.5 tonnes while having the same voyage time. Looking at a central point of the Pareto-optimal set, for example for a voyage time of 200 hours the fuel consumption is reduced from 6 to 5.5 tonnes if comparing Figure 6.7 and Figure 6.9. Which can be translated to an improvement of 10% of optimization performance.

![Figure 6.10](image_url)

**Figure 6.10:** Representation of the fuel consumption (left) and time (right) against the number of designs. Optimization done for numbers of generations equals to 40 and population number equals to 100. The green dots represent the Pareto-optimal solutions.

In Figure 6.10, where the objectives are plotted against the number of designs, show substantial differences when comparing to the ones from case 2 (Figure 6.8). The Pareto-optimal set of solutions, represented in green, are found in after larger number of designs are evaluated. The first optimal solutions appear after around 3000 design evaluations. However, more optimal solutions are found. The convergence of both objectives can be clearly observed in these plots.

Figure 6.11 shows a representation of one free variable (position on the left and velocity on the right) against the number of evaluations. There have been selected the same variables as in Figure 6.3. The aim of these plots is to show that with a wide initial sampling population and the appropriate parameter setting the entire free variable range is used, even though clear tendencies on the most favoured values can be seen.
6.0.4 NSGA-II - Crossover rate

In order to continue with the improvement of the optimization process, the crossover rate has been studied. This parameter studies the percentage of population where two-bit crossover is applied. The default value for the standard deviation is set to 0.2. An iterative process has been followed here in order to see which is the value that best suits this parameter with regards to the optimization process. All the optimizations processes shown so far have been done using the default value for this parameter. Figure 12 shows the Pareto-optimal front for the competing objectives for the most distinct crossover rate parameters.
6.1. COMPUTATIONAL EFFORT OF ROM

In an optimization process is essential to keep in mind the computational effort needed to run all the procedures in the ranges stated. Normally these procedures are substantially complex and the ranges of allowance of free the free variables are wide in order to ensure that the optimal solution is found.

The generation of solutions is done for the range of validity of the free variables. FS-Optimizer allows to tune the spacing (number of bits) within the range of validity. The default number of bits is 16. This means that for a cargo vessel that can sail between 0 and 20 knots, its validity range of velocity is compressed between 0 and 20 with a spacing of 16 bits. What is the same, within this range there are \(2^{16}\) potential speeds that are evaluated. Therefore the velocities are evaluated with a precision of 0.00031 knots. The same happens with the position free variables. There is an orthogonal deviation of the position in each control point of 10% of the Orthodromic distance. The Orthodromic distance in this specific case is equals to 2600 nautical miles. Therefore, there range of validity of the position free variables is equals to 260 nautical miles. Thus, there is a precision of \(2^{16}\) within a range of 260 nautical miles. The positions with this
configuration are evaluated with a precision of 0.004 nautical miles. Both numbers are senseless when optimizing Atlantic routes for a cargo vessel.

The number of bits within the range of the free variables, affects significantly the computational effort. A systematic study on the reduction of these parameters has been carried out.

A drastic reduction of these parameters has been implemented in order to evaluate the performance of the optimization process in relation to the computational time. The number of bits are reduced to 5 for both free variables. This means a resolution of 0.625 knots for the validity range of speed and 8.155 nautical miles for the range of position.

![Figure 6.13: Optimization done for 5 bits of resolution for speed and position](image_url)

Figure 6.13 shows that a resolution of 5 bits is not enough to perform a competitive optimization, even though the computational effort is drastically reduced.

The number of bits have been reduced to 7 bits for the speed free variables and 8 bits for the position free variables. What means a resolution of 0.156 knots and a resolution of 1 nautical mile. The computational effort has been reduced in more than a 50% and the sampling of the Pareto-optimal solution does not present relevant differences with the optimization done for the default number of bits in the free variables range.
Figure 6.14: Left: Optimization done with 7 and 8 bits of resolution for speed and position free variables respectively. Right: Optimization done with 16 bits of resolution for speed and position free variables.
Chapter 7

Route optimization evaluation

In this chapter different route optimizations are presented in order to evaluate the model. In order to be able to directly compare all the optimizations done, the vessel used for all of them is the same. The vessel under study is an hypothetical vessel which is not existing. The main particulars for this vessel are presented in the following table.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Length between perpendicu-lars (LPP)</td>
<td>70 m</td>
</tr>
<tr>
<td>Beam in water line (BWL)</td>
<td>8 m</td>
</tr>
<tr>
<td>Block coefficient (C_b)</td>
<td>0.6</td>
</tr>
<tr>
<td>Sail area (A_{sail})</td>
<td>1000 m^2</td>
</tr>
<tr>
<td>Windage area (A_{ref})</td>
<td>50 m^2</td>
</tr>
</tbody>
</table>

Table 7.1: Main particulars for cargo vessel studied.

A Performance Prediction Program is generated for this vessel. The final Performance Prediction Program generated in the Master’s Thesis: Performance Prediction Program for Wind-Assisted Cargo Ships done by Martina Reche, has not been applied due to the parallel development of both projects.

The Performance Prediction Program (PPP) considered here is based on a more complex model than the one used for the systematic studies on optimization parameters. The PPP considers windage force, sailing force and hull resistance. Seaway is considered in some of the evaluations using Kreitner approach [7]. The sail system has been simplified. The vessel does not have a real configuration for the wind propulsion systems but has an overall sail area of 1000 m^2 as stated in Table 7.1. The influence of the thrust that the sailing system can generate in relation to the total power demand the can be observed in Figure 7.1. The sailing force module applies a coefficient model, which is based on the True Wind Direction (TWD). Current patterns are considered in all optimizations.
The route is the same one which has been studied in Chapter 6. A route crossing the North Atlantic Ocean from East to West from North-West of Spain to the West Coast of the United States. Winter time has been considered a significant season to realize the route optimization evaluation due to the high seaways and large wind conditions that characterize the North Atlantic in this season. Therefore, the departure time of the vessel takes place the first of January of 2020. All the optimizations that are studied in this chapter have the same departure time.

Four different configurations are studied in order to evaluate the route optimization model:

- **Vessel without WAPS for calm waters.**
- **Vessel without WAPS considering wave pattern.**
- **Vessel with WAPS for calm waters.**
- **Vessel with WAPS considering wave pattern.**

Four polar diagrams are represented in order to observe the difference between the four configurations. The polar plots represent the power demand from the engine for a certain True Wind Speed in relation to the True Wind Angle. This is done for the range of velocities that the vessel can perform. For this case, the vessel has a maximum velocity of 16 knots (see legend in Figure 7.1).
Figure 7.1: Polar diagrams for the four different configurations with constant wind speed of 20 knots. Where the power demand is stated in KW. The plots on the top row are generated for the vessel without WAPS. The ones on the bottom row, for the vessel with WAPS.

The ones from the top row represent a cargo vessel without wind assisted propulsion systems, only motor. While the two bottom plots represent the same vessel with additional sailing devices.

It can be clearly seen the influence of the sailing devices on the power demand if the bottom plots. The delivered power is significantly reduced for True Wind Angles between 50 and 180 degrees. In special for the range comprised between 90 and 135 degrees, the so-called broad reach course. However, it can be seen that the influence of the sailing devices does not exceed 20% the fuel consumption for the most favorable True Wind Angles supposing a True Wind Speed of 20 knots.

When looking to the delivered powers, it can be clearly seen that the polar plots where
the seaway is considered have larger power demands. The added resistance is increased due to the waves and, therefore, the power as well. It can be observed that these also have an off-set center. The Performance Prediction Program considers the wave direction is the same that the True Wind Direction. The added resistance is lower for aft waves.

According to Ch.6, the parameters used for all the optimizations of this chapter are described in Table 7.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation</td>
<td>0.2</td>
</tr>
<tr>
<td>Design of Experiments (DOE)</td>
<td>1500</td>
</tr>
<tr>
<td>Number of generations</td>
<td>20</td>
</tr>
<tr>
<td>Population size</td>
<td>100</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 7.2: Optimization parameters used in Chapter 7.

## 7.1 Route comparison between Orthodromic distance and optimized route

The scope of this section is to test ROM. Different comparisons are done between non-optimized and optimized routes. In order to analyze the route optimization, the shortest route in distance i.e. Orthodromic distance is compared with the optimized route for a certain speed. For this case the positional free variables are assumed to be zero. There is no orthogonal deviation in any of the way-points. The velocity free variables are considered fixed to a certain value. A constant speed of 10 knots has been considered reasonable to study the optimization performance. It is a moderate speed which allows the study of other factors, in special wind influence. The Froude number of the vessel for 10 of speed is calculated by using the following equation:

\[
Fr = \frac{V}{\sqrt{g \cdot L}} = 0.196 \tag{7.1.1}
\]

The Froude number for merchant vessels commonly oscillate between 0.15 and 0.25 or even 0.28 for the faster ships. A constant speed of 10 knots represents a Froude number that does not deviate from this range.
7.1. ROUTE COMPARISON BETWEEN ORTHODROMIC DISTANCE AND OPTIMIZED ROUTE

CHAPTER 7. EVALUATION

7.1.1 Calm water

Vessel without WAPS for calm water.

The first route optimization has been done for the vessel without Wind Assisted Propulsion Systems, therefore it can only motor sail. The optimization does not consider seaway. Only wind pattern is considered in this case.

By using a constant speed of 10 knots, the shortest route in distance i.e. Orthodromic distance has been computed. The time and fuel consumption needed are listed in the following table:

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption</td>
<td>3.55 tonnes</td>
</tr>
</tbody>
</table>

Table 7.3: Time and fuel consumption for Orthodromic distance for vessel without WAPS for calm waters for constant speed of 10 kn.

An optimization is done for this case in order to find a better route with regards to the time and fuel consumption objectives. The aim here is to find a route that allows the vessel to reduce the fuel consumption while maintaining the Estimated Arrival Time by making use of the environmental conditions.

The Pareto graph between the competing objectives are presented in Figure 7.9.
Figure 7.2: Optimization done for vessel without WAPS and calm waters. Green: selected route evaluation with same sailing time as shortest distance and fixed speed.

The optimization presents a smooth Pareto-front with a wide range of optimal solutions. 3500 evaluations have been needed in order to achieve this Pareto-optimal set. According to the Ideal Multi-Objective approach, a solution is selected basing in a higher-level of information. In this case the ETA is known, therefore, an optimal solution is selected from the Pareto-optimal front based on that.

The green dot represents the Pareto-optimal solution for a voyage time of 260 hours. The fuel consumption used for a 260 hours of voyage, according to the optimal set of solutions, 3.52 tonnes.

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption for Orthodromic distance</td>
<td>3.55 tonnes</td>
</tr>
<tr>
<td>Fuel consumption optimized</td>
<td>3.52 tonnes</td>
</tr>
<tr>
<td><strong>fuel consumption reduction</strong></td>
<td><strong>1%</strong></td>
</tr>
</tbody>
</table>

Table 7.4: Objectives comparison between Orthodromic distance and optimization for vessel without WAPS for calm waters.

In Table 7.4 it can be seen the difference between fuel consumption for the shortest
route in distance and the optimized route. The optimization only benefits the fuel consumption in 0.03 tonnes of fuel in this first case. However, as mentioned above, this first optimization is done for pure motor sailing for calm water only considering the wind and current patterns. Therefore, the optimization in terms of fuel consumption is only dependent on the windage caused by hull and superstructure i.e. added resistance due to wind, and the current pattern. Both factors present residual impact on the optimization process. Nonetheless, despite not being significant, a reduction in the fuel consumption has been achieved.

Vessel with WAPS for calm water.

In this second case it is studied the vessel with Wind Assisted Propulsion Systems for calm water. The same systematic is used as in case one. Thus, the Orthodromic distance is calculated for 10 knots of constant speed. Equal conditions are applied here. However, the Performance Prediction Program includes a wind propulsion system in this second situation.

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption</td>
<td>3.22</td>
</tr>
</tbody>
</table>

Table 7.5: Time and fuel consumption for Orthodromic distance for vessel with WAPS for calm waters for constant speed of 10 kn.

If comparing Table 7.3 and 7.5 it can be observed that 9% of reduction in fuel consumption can be achieved by simply using the sailing devices where possible but without adapting speed and course.

The optimization for this case can be seen in Figure 7.3, where the confronted objectives are represented.
7.1. ROUTE COMPARISON BETWEEN ORTHODROMIC DISTANCE AND OPTIMIZED ROUTE

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Figure 7.3: Optimization done for vessel with WAPS and calm water. Green: selected route evaluation with same sailing time as shortest distance and fixed speed.

It can be seen that the Pareto-optimal front is slightly less smooth in this case than in the previous one. 3500 designs are also evaluated in this case. The addition of the Wind Assisted Propulsion Systems difficult the optimization process. More parameters need to be taken into account. Therefore, is more difficult to find the Pareto-optimal solutions.

The computational effort is intended to be maintained as low as possible that is why the number of evaluations has been kept to 3500 to maintain the balance between computational time and performance.

The green dot represents the optimal solution for a voyage time of 260 hours. If the route is optimized, the vessel consumes 2.76 tonnes of fuel, which is an additional saving of 14.2% of fuel consumption.
### 7.1. ROUTE COMPARISON BETWEEN ORTHODROMIC DISTANCE AND OPTIMIZED ROUTE

#### CHAPTER 7. EVALUATION

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<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Time</td>
<td>260 hours</td>
</tr>
<tr>
<td>Fuel consumption for Orthodromic distance</td>
<td>3.22 tonnes</td>
</tr>
<tr>
<td>Fuel consumption optimized</td>
<td>2.76 tonnes</td>
</tr>
<tr>
<td><strong>fuel consumption reduction</strong></td>
<td><strong>14.2%</strong></td>
</tr>
</tbody>
</table>

Table 7.6: Objectives comparison between Orthodromic distance and optimization for vessel with WAPS for calm waters.

The wind pattern plays a key role in this optimization. Wind Assisted Propulsion Systems can strategically use the wind conditions in their benefit. The power required by using the thrust generated by the sailing devices can be drastically decreased when cleverly use the wind resources.

Figure 7.4 shows the True Wind Angle for the Orthodromic and optimized routes in order to study whether the optimizer is able to exploit the sailing devices by the given weather conditions.

![True Wind Angle](image)

Figure 7.4: True Wind Angle in the different way-points. The blue curve represents the TWA that the vessel would experience if following the Orthodromic route. The orange curve represents the TWA the vessel would experience in the optimized route. Vessel with WAPS for calm water.

It can be clearly seen that the True Wind Angles is maintained within the range of angles that are more profitable in order to reduce the fuel consumption. According to Figure 7.1, this interval is TWA $\epsilon$ [70,150] deg.
A 14.2% of reduction has been achieved by making use of ROM for the configuration where the vessel has sailing devices only calm water is considered.

### 7.1.2 Seaway

**Vessel without WAPS considering seaway**

This optimization is done for pure motor vessel, which does not have any sailing devices installed. The seaway is considered in this case. Table 7.7 shows the fuel consumption if the Orthodromic route was followed by the vessel with a constant speed of 10 knots.

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption</td>
<td>16.35 tonnes</td>
</tr>
</tbody>
</table>

Table 7.7: Objectives for vessel without WAPS with seaway for constant speed of 10 kn.

An optimization is carried out for this specific case. Figure 7.5 shows the confronting objectives in each axis.

![Figure 7.5: Optimization done for vessel without WAPS and seaway. Green: selected route evaluation with same sailing time as shortest distance and fixed speed.](image-url)
This graph promptly shows a drastic general increase of fuel consumption. A significant increase of fuel consumption is to be expected due to the season and the high seas stated encountered (see Figure 7.7), thus the results are considered plausible.

It can be observed at first sight that the Pareto-optimal front presents some roughness. The addition of the wave pattern drastically increases the complexity of the optimization. The presence of steeper gradients due to the seaway inclusion difficult the encountering of optimal solutions. More designs need to be evaluated in this case. 5900 evaluations have been necessary in order to find the Pareto-optimal set of solutions illustrated in Figure 7.5. Which represents nearly twice the amount needed when the seaway was not considered. Therefore, the addition of seaway highly increases the computational effort of the optimization.

The green dot represents the Pareto-optimal solution for the sailing time of 260 hours. The optimized route for this optimal solution is represented in Figure 7.6.

Figure 7.6: Route optimized for vessel without WAPS and seaway.

The fuel consumption for the optimized route is shown in comparison with the fuel consumption for the Orthodromic route.
Table 7.8: Objectives comparison between Orthodromic distance and optimization for vessel without WAPS considering seaway.

<p>| | |</p>
<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>260 hours</td>
</tr>
<tr>
<td>Fuel consumption for Orthodromic distance</td>
<td>16.35 tonnes</td>
</tr>
<tr>
<td>Fuel consumption optimized</td>
<td>9.21 tonnes</td>
</tr>
<tr>
<td>fuel consumption reduction</td>
<td>43.6%</td>
</tr>
</tbody>
</table>

The route optimization shows high fuel savings when comparing the consumption with the one from the Orthodromic route.

The crossing of North Atlantic Ocean during winter time against prevailing wind direction can trigger the encountering of considerable wave heights above. Which is the case here. Figure 7.7 shows the significant wave height if following the Orthodromic route with the blue curve. Orange curve represents the encountered significant wave heights in the optimized route.

![Wave heights](image)

Figure 7.7: Wave height in way-points. The blue curve represents the wave height the vessel would encounter if following the Orthodromic route. The orange curve represents the wave height the vessel would encounter in the optimized route. Vessel without WAPS considering seaway.

It can be seen that there are two important peaks in the wave pattern for Orthodromic route. The vessel encounters huge waves that trigger the high demand of fuel consumption. However, the optimized route avoids the two large peaks. The optimization is able to find a route with reasonably low significant wave heights in order to diminish the added resistance and, therefore, the fuel consumption.
However, the added resistance due to waves considered in the Performance Prediction Program, as said previously on this chapter, has been calculated by using the Kreitner approach. It is possible that this approach overestimates the added resistance for the large wave heights observed here. Therefore, the fuel consumption could also be overestimated.

Figure 7.8 and 7.9 capture the most visible differences between the Orthodromic and optimized routes according to the wind speed.

Figure 7.8: Wind chart at way-point number 6. The direction of the arrow correspond to the True Wind Direction and the colors of correspond to the True Wind Speed. Comparison between Orthodromic route and optimized route. Vessel without WAPS with seaway. Where the dark blue represents a True Wind Speed of 7 knots and the intense red represents 50 knots of True Wind Speed.

In these captions it can be clearly observed that the optimized route avoids high headwinds while crossing way-point number 6. The vessel is able to navigate a relatively calm condition instead.
7.1. ROUTE COMPARISON BETWEEN ORTHODROMIC DISTANCE AND OPTIMIZED ROUTE

CHAPTER 7. EVALUATION

Figure 7.9: Wind chart at way-point number 9. The direction of the arrow correspond to the True Wind Direction and the colors of correspond to the True Wind Speed. Comparison between Orthodromic route and optimized route. Vessel without WAPS with seaway. Where the dark blue represents a True Wind Speed of 7 knots and the intense red represents 50 knots of True Wind Speed.

In these captions the most significant aspect is that the optimized route sails further north in order not to cross an area with high head winds that would be crossed if sailing along the Orthodromic route.

Vessel with WAPS considering seaway

In this last case, it is studied the route optimization for the vessel with Wind Assisted Propulsion Systems considering seaway. The fuel consumption when sailing at a constant speed of 10 knots following the Orthodromic route is stated in Table 7.9.

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption</td>
<td>16.05 tonnes</td>
</tr>
</tbody>
</table>

Table 7.9: Objectives for vessel with WAPS with seaway for constant speed of 10 kn.

If comparing Table 7.7 and Table 7.9 it can be observed that the reduction of fuel consumption by simply using the sailing devices without adjusting the course and speed is less than 2%.

In order to reduce this amount of fuel stated in Table 7.9, an optimization is carried out. Figure 7.10 represents the competing objectives.
Figure 7.10: Optimization done for vessel with WAPS and seaway. Green: selected route evaluation with same sailing time as shortest distance and fixed speed.

Is also visible in this case that the Pareto-optimal front has roughness. The computational effort is kept as low as possible in all the cases. After 7000 evaluations the optimization has been stopped in order to keep the balance between precision of results and computational effort.

The Pareto-optimal route according to the sailing time for a constant speed of 10 knots is represented by a green dot. The optimized route is represented in Figure 7.11.
The vessel deviates substantially from the Orthodromic distance in order to avoid non-desired weather conditions.

By optimizing the route it is possible to achieve considerable savings. The difference in fuel consumption for both routes is stated in Table 7.10.

<table>
<thead>
<tr>
<th>Time</th>
<th>260 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption for Orthodromic distance</td>
<td>16.05 tonnes</td>
</tr>
<tr>
<td>Fuel consumption optimized</td>
<td>8.65 tonnes</td>
</tr>
<tr>
<td><strong>fuel consumption reduction</strong></td>
<td><strong>46.1%</strong></td>
</tr>
</tbody>
</table>

Table 7.10: Objectives comparison between Orthodromic distance and optimization for vessel with WAPS considering seaway.

This amount of reduction when following the optimized route instead of the Orthodromic route is obtained since the vessel avoids large wave heights. In Figure 7.12 is it possible to see the significant wave heights the vessel encounters if following the shortest route in distance or the optimized route.
As well as for the vessel without sailing devices, the optimization proves to be able to avoid large waves. Therefore reducing the added resistance and the fuel consumption.

It is clear that during winter time and with the large waves encountered the main objective is to avoid large wave heights. However, the True Wind Angle that the vessel experiences has been studied in order to observe the capability of the optimizer to find routes suitable for the sailing devices according to the True Wind Angle. Figure 7.13 represents the different TWA that the vessel experiences in each leg of the optimization.
Figure 7.13: True Wind Angle in the different way-points. The blue curve represents the TWA that the vessel would experience if following the Orthodromic route. The orange curve represents the TWA the vessel would experience in the optimized route. Vessel with WAPS considering seaway.

Figure 7.13 shows that the main peak with head wind for the Orthodromic route is avoided in the optimized route. Moreover, the TWA is maintained within the range of angles where the sailing devices can generate more thrust, according to Figure 7.1 TWA $\epsilon [70,150]$ deg.

The weather systems can be visualized in the following figures between the Orthogonal route and the optimized route in the most relevant way-points. In this case with Wind Assisted Propulsion Systems it can be observed that the vessel also avoids head winds while avoiding large wave heights.
7.2 Route comparison between cargo vessels with WAPS and pure motor sailing

In the previous section, four cases have been studied. The fuel savings of the vessel when having sailing devices installed or not diverge substantially. Table 7.11 and 7.12 present the fuel consumption reduction in both cases for the chosen route.
### 7.2. ROUTE COMPARISON BETWEEN CARGO VESSELS WITH WAPS AND PURE MOTOR SAILING

#### CHAPTER 7. EVALUATION

**Calm water**

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<table>
<thead>
<tr>
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<tbody>
<tr>
<td><strong>Time</strong></td>
<td>260 hours</td>
</tr>
<tr>
<td><strong>Fuel consumption</strong></td>
<td></td>
</tr>
<tr>
<td>Motor sailing</td>
<td>3.52 tonnes</td>
</tr>
<tr>
<td>WAPS</td>
<td>2.76 tonnes</td>
</tr>
<tr>
<td><strong>fuel consumption reduction</strong></td>
<td>21.6%</td>
</tr>
</tbody>
</table>

Table 7.11: Objectives comparison between optimized routes for vessel without WAPS and vessel with sailing devices for calm water.

**Seaway**

<p>| | |</p>
<table>
<thead>
<tr>
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<th></th>
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</thead>
<tbody>
<tr>
<td><strong>Time</strong></td>
<td>260 hours</td>
</tr>
<tr>
<td><strong>Fuel consumption</strong></td>
<td></td>
</tr>
<tr>
<td>Motor sailing</td>
<td>9.20 tonnes</td>
</tr>
<tr>
<td>WAPS</td>
<td>8.65 tonnes</td>
</tr>
<tr>
<td><strong>fuel consumption reduction</strong></td>
<td>6.0%</td>
</tr>
</tbody>
</table>

Table 7.12: Objectives comparison between optimized routes for vessel without WAPS and vessel with sailing devices considering seaway.

The inclusion of the Wind Assisted Propulsion Systems in the optimization process has a high impact on the results. When observing fuel reduction due to the addition of sailing devices for calm water it can be clearly seen how the vessel deviates from the Orthodromic route in benefit of the sailing devices. The main objective is to find the most suitable course, so the vessel experiences True Wind Angles that allow to generate the maximum thrust according to Figure 7.1 and, thus, lower the total fuel consumption.

The reductions achieved have different magnitude when contemplating the wave pattern. It has been observed that if following the Orthodromic route the vessel would encounter large wave heights which radically increase the added resistance. The main aim of the optimizer is to avoid the large wave heights; Figure 7.12, in order to be able to reduce the added resistance and, therefore, the fuel consumption. However, the optimized route for the vessel with Wind Assisted Propulsion Systems proves to find suitable True Wind Angles for the vessel, Figure 7.13. The vessel is able to take profit of the thrust generated by sailing devices while avoiding high seaways.
7.2. ROUTE COMPARISON BETWEEN CARGO VESSELS WITH WAPS AND PURE MOTOR SAILING

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Figure 7.16: True Wind Angle comparison for vessel with WAPS for calm water condition on the left and considering seaway on the right.

It is important to observe that the True Wind Angles for the optimized route for calm water are clustered in a smaller range. This range is comprised between 70 and 140 degrees (with the exception of way-point number 10). According to Figure 7.1 they are the TWA for which more thrust can be generated.

On the other side, the TWA for the optimized route with seaway are still suitable for the thrust generation but not with the same magnitude. The optimizer prioritize the large wave heights avoidance over the thrust generation.

It is obvious that the seaway can not be neglected in route modeling since there is a substantial difference in the magnitude of the results. Therefore, for this case under study, the implementation of Wind Assisted Propulsion Systems can benefit the fuel reduction in terms of route optimization in a 6% when comparing to pure motor sailing.
Chapter 8

Conclusions

The main objective in this Master’s Thesis was to build a generic tool in order to predict fuel savings when optimizing a route for a cargo vessel with any Wind Assisted Propulsion System.

The model which has been developed is suitable for any cargo vessel with or without Wind Assisted Propulsion Systems. ROM has proven to be able to find optimal routes for both cases for a given sailing time. Moreover, the model can predict the fuel savings when comparing the optimized routes between pure motor sailing and sail assisted sailing.

Systematic studies for the optimization parameters have been developed in order to improve the performance of the optimization process. Proper settings for those parameters have been found which notably reduce the computational effort while giving reliable results.

Moreover, the route optimization model has been exemplified by applying it to a cargo vessel. Different optimizations have been carried out considering the same scenario for the case where the vessel entirely sails using its engines and the case where the vessel is provided with Wind Assisted Propulsion Systems. Significant reduction in fuel consumption has been achieved when optimizing the route for the motor sailing. However, even higher savings are obtained from the route optimization when installing wind-assisted sailing devices. The optimization proves to avoid high sea states while meeting the Estimated Arrival Time stated.

Furthermore, a significant reduction of fuel consumption has been shown when comparing the route optimizations between the vessel with and without sailing devices in benefit of the Wind Assisted Propulsion Systems.
CHAPTER 8. CONCLUSIONS

Further development

In order to further develop the route optimization model, some suggestions are stated in the following paragraph.

Computational effort has been the main issue in the thesis development. It is crucial to reduce the computational effort of the model in order to be able to achieve more precision in the obtainment of the results for practical applications. In order to keep the computational time reasonably low to test the model, only eleven way-points are evaluated in a route which crosses the Atlantic Ocean. Therefore, it has been considered that the environmental conditions are constant for the entire leg that separates two consecutive way-points. A larger number of way-points would trigger to have more reliable results.

A greater number of way-points, as mentioned, means the addition of two free variables per way-point. A possibility to avoid the extension in the free variable number could be to have control points in between the way-points in order to evaluate the weather conditions and the Performance Prediction Program at those points. The course would not be modified in the control points but the precision of the results would be highly improved. For all way-points and control points, weather and PPP interpolations will be carried out which are highly computational costly. However, the introduction of free variables could be avoided.

For this Master’s Thesis, it has been considered important to evaluate the entire set of solutions. In all the optimizations shown, the design space has not been constrained. However, for practical application of the Route Optimization Model, another suggestion could be to constraint the sailing time and the fuel consumption depending on specific needs. By doing that the Pareto-optimal front could be reduced in size and the optimization could be focused in a smaller area which would decrease the computational effort.
References

PAPERS


CHAPTER 8. CONCLUSIONS


BOOKS


WEB SITES

