THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Marine propeller optimisation tools for scenario-based design

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Abstract

The marine propulsion system is one of the most important components of a ship in order to cover the demanding operating needs of propulsion nowadays and to increase performance in a wide range of operating conditions. Marine propellers are designed with the purpose of matching the hull and machinery system, create the required thrust for the entire operational profile, and fulfil the techno-economical requirements that depend on the decision-making of several stakeholders. The final product must represent a unique propeller, designed for a specific vessel, and is a trade-off between all requirements. In an industrial framework, the marine propeller design process should therefore be straightforward and well-developed. The limited time under which the design process must be performed, plays a decisive role in the methods utilised to carry it out, as for example in the selection of the analysis tools, which must be fast and they usually involve semi-empirical evaluations. Since blade design is a multi-objective and multidisciplinary problem, automated optimisation has been used with the aim to search good solutions in the design space efficiently. However, automated optimisation has failed to be used in industrial applications due to obtaining solutions with high performance but with infeasible geometries, and as a method it proved to be inferior to the manual design process, something that shows the importance of the designer's expertise. The main research question of this thesis is therefore related to incorporating optimisation in a systematic way in order to improve the propeller design process and assist the blade designers to obtain feasible and high-performing propellers in strict time constraints. A methodology is proposed that combines interactive optimisation with machine learning and in parallel new objectives are implemented for more complex scenarios. The designer is enabled to manually evaluate cavitation nuisance during the optimisation and guide the algorithm towards areas of the design space with satisfactory cavitation characteristics. Several scenario-based situations have been investigated by using the proposed methodology, that involve different propeller types, design and off-design conditions, several objectives and constraints, cavitation nuisance on the suction and the pressure side of the blade, and applications within conventional and wind propulsion. The results have shown that by involving the blade designer's expertise in the design and optimisation process systematically, competitive propeller designs with feasible geometries can be obtained efficiently.

Keywords: marine propeller design, interactive optimisation, user-code interaction, machine learning, cavitation nuisance, scenario-based design, wind propulsion.

Στην οικογένειά μου.

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Ioli Gypa
Göteborg, November 2022

LIST OF PUBLICATIONS

The thesis consists of an extended summary and the appended papers listed below.

Paper I	I. Gypa, R. Bensow, K. Wolff & R. Gustafsson. Interactive evolutionary computation for propeller design optimization of wind-assisted vessels. In AIAA AVIATION 2020 FORUM (p. 3162).
Paper II	I. Gypa, M. Jansson, K. Wolff, & R. Bensow. Propeller optimization by interactive genetic algorithms and machine learning. Ship Technology Research (2021), 1-16.
Paper III	I. Gypa, M. Jansson, R. Gustafsson, S. Werner & R. Bensow. Propeller design procedure for a wind-assisted KVLCC2. Proceedings of the 15th International Symposium on Practical Design of Ships and Other Floating Structures, Dubrovnik, Croatia, 2022.
Paper IV	I. Gypa, M. Jansson & R. Bensow. Cavitation nuisance identification through machine learning during propeller optimisation. Proceedings of the Seventh International Symposium on Marine Propulsors, Wuxi, China, 2022.
Paper V	I. Gypa, M. Jansson, R. Gustafsson, S. Werner & R. Bensow. Controllable-pitch propeller design process for a wind-powered car-carrier optimising for total energy consumption. Manuscript under review in Ocean Engineering.
Paper VI	I. Gypa, M. Jansson & R. Bensow. Marine propeller optimisation through user interaction and machine learning for advanced blade design scenarios. Manuscript submitted to Ships and Offshore Structures.

ABBREVIATIONS

BEM	Boundary Element Method
CFD	Computational Fluid Dynamics
CPP	Controllable-Pitch Propeller
FPP	Fixed-Pitch Propeller
GA	Genetic Algorithm
GHG	Greenhouse Gas Emissions
IEC	Interactive Evolutionary Computation
IGA	Interactive Genetic Algorithm
IMO	International Maritime Organisation
MCR	Maximum Continuous Rating
ML	Machine Learning
MLP	Machine Learning Pipeline
NCV	Nested-Cross Validation
NN	Neural Network
NSGA-II	Non-dominated sorting genetic algorithm II
PS	Pressure Side
PSO	Particle Swarm Optimisation
RANS	Reynolds Average Navier-Stokes
SS	Suction Side
SVM	Support-Vector Machine
VLM	Vortex Lattice Method
WASP	Wind-Assisted Ship Propulsion
WPSP	Wind-Powered Ship Propulsion

CONTENTS

Chapter 1

Introduction

The waterborne transport is the most cost-efficient way of transport and accounts for 90% of the world's trade nowadays. Thousands of ships travel daily and their design must be carried out with safety as the most important requirement, while efficiency is another essential requirement that drives the ship design process. However, due to the significant environmental impact of shipping, a new goal has been added: designing vessels in a sustainable manner with the aim to significantly reduce greenhouse gas (GHG) emissions and achieve the decarbonisation of the industry.

The transport industry alone was accountable for 27% of global GHG emissions in 2019, a percentage which was temporarily reduced by 10% in 2020 due to the pandemic situation and thus the reduced need for transport [8]. However, in 2021 the transport demand rebounded, and the predictions showed a continuing demand for passenger and cargo transport [9]. The CO_2 emissions of each industry of the transport sector are shown in figure 1.1.

The International Maritime Organisation (IMO), in order to be in line with the ambitions of the 2015 Paris agreement [10], set a goal of reducing GHG emissions by 50% by 2050 compared to the emissions of 2008 [11] in the shipping industry. During the years 2008-2012 there was an increase in GHG emissions of 4.7% though, according to the Fourth Greenhouse Gas Study 2020 [12] and in 2012 the shipping industry was accountable for 2.2% of the global anthropogenic CO_2 emissions, with a projection of growth between 50% and 250% until mid-century [11]. In 2021, the Clydebank Declaration for Green Shipping Corridors was signed by 22 countries during COP '26, which handles the establishment of six green shipping corridors by 2050, where zero-emission routes between two or more ports will be created [13], with the goal to achieve a global net zero by mid-century. It is therefore clear that focusing on the development and the active utilisation of more efficient and green technologies in all stages of the ship design process contributes towards achieving the decarbonisation of the industry.

The selection of the propulsion system is an important part of the ship design process and the overall goal is to design a unique, efficient propeller, which matches the hull and machinery system, creates the required thrust, covers all operating needs of the vessel and fulfils the requirements that have been set by the stakeholders. The requirements from each stakeholder are different and

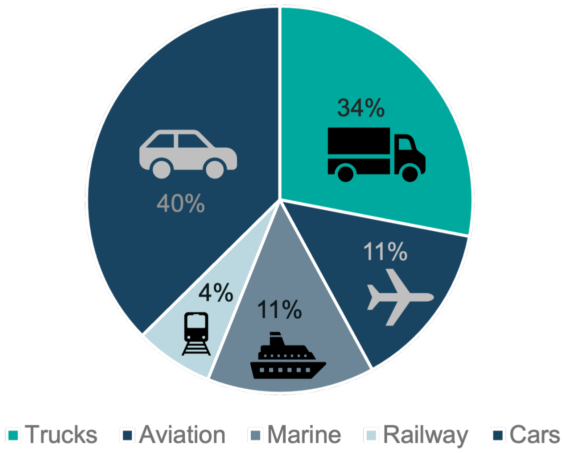


Figure 1.1: CO_2 emissions of the transport sector [14]

often contradicting and the blade designers need to consider them and decide on a geometry that is the best compromise between all these requirements. Except propeller efficiency, other crucial requirements are fuel consumption, overall cost, comfort, cavitation, propeller-hull induced pressure pulses, classification regulations etc. All things considered, the blade design process in an industrial framework has to be straightforward, well-developed and be completed under strict time limitations. This has become harder to achieve, due to the increasing demands on performance over a wider range of operating conditions. Therefore there is an increasing need to improve the design process and help the designers in developing blades of higher performance.

1.1 Challenges in the blade design process

The marine propeller design process is complex; it is multidisciplinary, combining disciplines like hydrodynamics, strength, acoustics etc., and multi-objective, with objectives related to the requirements of the stakeholders. In addition to the objectives, the constraints play an important role in perplexing the design process further. The blade geometry is also very complex and its several design characteristics need to be considered for the fulfilment of the objectives for each specific problem. By alternating the values of the design characteristics, new propeller geometries are obtained that fulfil the objectives up to a certain degree and are within the constraints. The more objectives and constraints, the harder it is to design a propeller geometry that will achieve those satisfactorily. Therefore, it appears necessary to iterate through the design characteristics in order to find the geometry that is the best trade-off of the problem's objectives.

This iteration can be performed by the blade designers, who based on their knowledge and experience, change the values of those design characteristics that affect the performance of the objectives the most, in order to create a suitable geometry. Although competent results are obtained through manual design processes, they often are very laborious due to the extensive design space and the contradicting objectives. An alternative is to use optimisation algorithms with the aim to automatically produce a high number of propeller geometries. The optimisation algorithms search the design space in a smart manner and alternate the values of the design characteristics systematically. This type of optimisation is referred in this thesis as automated optimisation.

In recent years several research groups have developed automated or semi-automated optimisation procedures [15, 16, 17, 18,19, 20, 21, 22, 23, 24, 25, 26, 27, 28], in order to support the blade designer during the design process and find good propeller geometries. Most of these studies regard constrained multi-objective propeller design problems and they follow different design and optimisation approaches by utilising various stochastic optimisation algorithms and different hydrodynamic analysis tools in their process. Note that the analysis tools must be fast, which means that high-fidelity simulations or experiments are not feasible. In some of the studies, high fidelity simulations are used after a good geometry has been found through the optimisation. A general approach involves combining a stochastic population-based optimisation algorithm with a mollified constraint handling using semi-empirical analysis of cavitation nuisance. Although promising results have been obtained, the fully automated optimisation processes have failed to be useful in an industrial framework for the following reasons:

- The optimisation algorithms are difficult to set-up to reach a converged solution; this involves the definition of the design space and the parameters that control the optimisation process.

- The different requirements on each scenario-based design situation are difficult to formulate into a single well-posed optimisation problem; e.g. several operating conditions may need to be considered, with different cavitation nuisance requirements in each.

- The constraint handling fails due to the fact that: a) the physics involved in some constraints (e.g. erosion risk, radiated sound) is too complicated to be represented by semi-empirical evaluations within the strict time limitations b) the number of feasible designs developed during the optimisation is very low to be useful.

- The performance prediction of the tools have high uncertainty in some regions and guide the optimisation in the wrong area of the design space.

Consequently in an industrial framework the traditional manual design process has been considered more reliable and efficient compared to the automated one [23, 29]. The main disadvantage of manual design is that it is labour-intensive though, especially in complex problems.

1.2 Objectives and scope of this thesis

Most of the above-mentioned studies have as a common denominator the involvement of the blade designers in the optimisation process in some way. The knowledge and experience of the blade designers appears to be of major importance in order to obtain good and feasible propeller geometries. In parallel, time is a crucial constraint of the propeller design process, making the optimisation an essential tool for the blade designers.

The challenge is therefore to develop an optimisation process, which involves the blade designer more systematically. This could be a key solution towards supporting the blade designers in order to obtain good and feasible propeller geometries. The primary research question in this thesis is formulated as:

> How can optimisation be incorporated in a systematic way to improve the propeller design process and assist the blade designers in order to obtain feasible and high-performing propellers within strict time constraints?

This gets especially important for complex scenarios with multiple conditions and objectives. Subsequently in this thesis we have worked towards developing optimisation tools that support the blade designers in the marine propeller design process with the goal to obtain good and feasible geometries efficiently. The tools have been developed based on the limitations of a commercial design system and time frame. The aim is to empower the blade designers and involve them more in the optimisation process, instead of substituting them. For this purpose, several scenario-based situations have been investigated, with various objectives, propeller types, design and off-design conditions and applications within both conventional and wind propulsion. The proposed methodology involves an investigation towards the following objectives:

- Develop an interactive optimisation process where the blade designer is enabled to interact with the design tools during the optimisation systematically, assess design characteristics and later input this information back to the optimisation with the aim to have a control over the quality of the designs.
- Investigate in which way machine learning (ML) could be part of the process with the aim to accelerate and support the interactive optimisation.
- Investigate the use of new objectives in the optimisation in order to be able to carry-out more complex scenarios with off-design conditions.

1.3 Thesis Outline

This thesis consists of an extended summary and six papers, which are appended in chronological order of publication. In the paragraph below and in figure 1.2 it is explained how the papers relate to the objectives and to each other. The extended summary is organised as follows: In chapter 2, the marine propeller design process is described, with focus on an industrial design task, along with the limitations of the process. Chapter 3 presents the optimisation procedures and algorithms used in this thesis, a discussion on the interactivity by the blade designer together with a background on interactive optimisation processes, the machine learning pipeline (MLP) and the proposed methodology of the thesis. In chapter 4 the scenario-based design is described for both conventional and wind propulsion. The summary of the six appended papers can be found in chapter 5.

All appended papers touch upon the first objective because the interactive optimisation process is the core of this thesis and is utilised everywhere. Papers I, II and VI are directly linked to the first objective. Paper I is the first step towards the development of the interactive optimisation methodology, which has been exemplified with a simple blade design optimisation problem and in paper II the methodology is further developed by enabling the designers to evaluate cavitation. In addition to this, an ML model was introduced in paper II as part of the optimisation process. This aspect was further developed in paper IV where more ML algorithms are investigated, along with their hyperparameters, in order to build an MLP with the aim to find the best ML model depending on the given input data. Papers II and IV are therefore connected to the second objective. In paper VI the complete interactive optimisation process is combined with the MLP of paper IV and is investigated on two advanced propeller design scenarios. This paper is connected to both the first and second objectives. Papers III and V are mainly linked with the third objective and regard scenarios within the area of wind propulsion. More specifically, a methodology is presented on how to design and optimise propellers for wind-assisted/powered vessels, where the interactivity is utilised up to a certain degree, and in parallel new objectives have been implemented in the methodology in order to cover the demanding operating needs of wind propulsion. A diagram of the thesis outline is presented in figure 1.2.

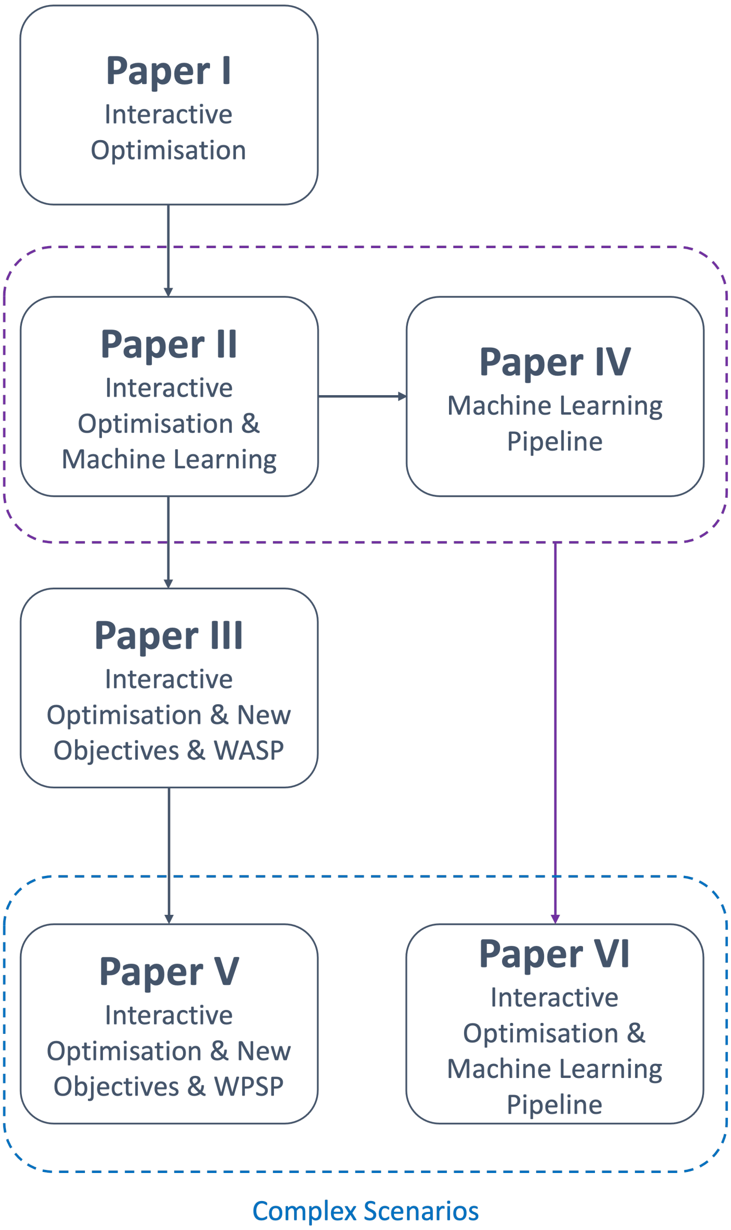


Figure 1.2: Diagram of thesis outline

Chapter 2

Marine propeller design process

2.1 Industrial design task and current procedures

The complexity of the marine propeller design process is related to its multidisciplinary and multi-objective nature, which makes it a challenging problem to solve. The decision on the right geometry of the propeller is directly linked to the mission profile of the vessel, which is usually very specific. The final geometry represents a unique propeller which is the trade-off of all the techno-economic requirements, objectives and constraints of this demanding problem. The design process can be summarised by three stages, the concept, preliminary, and detailed design, and they are described in the following sections. The activities performed within the different stages can be repetitive, and in most cases it is needed to reiterate between them.

2.1.1 Concept Design

The propeller selection and design process starts with the concept design stage. The goal of this stage is to translate the mission requirements into realistic propulsion characteristics, in order to select the correct propeller type and design point. The decisions taken at this stage are very important, because a change or lack of the right input, means that the entire process needs to be repeated. The customer (shipping company, ship owner, shipyard etc.) informs the propeller supplier on the vessel's mission along with its propulsion needs. The customer sets also the requirements that are usually related to efficiency, fuel consumption, costs, comfort, etc. and based on this information the blade designers will consider additional requirements, such us cavitation, propeller induced pressure pulses, classification regulations etc. Necessary input here is the vessel type along with its main dimensions and hull characteristics, the mission profile that includes operating conditions, ship route and service life. Experimental data from model tests for the resistance are essential and they usually have been defined or collected in earlier stages of the ship design spiral. However, it is possible that some important data are lacking, hence empirical formulas can be used or simulations might be performed, in order to extract the missing information.

The selection of the propeller type and the engine-gearbox system is mutually dependent and directly linked to the aforementioned techno-economical requirements. Fixed-pitch propellers (FPPs), whose only operational variable is the rotational speed, are usually preferred for scenarios where the vessel sails mainly in one condition. The most common goal for those cases is the maximisation of the propeller efficiency, something that can easily be achieved. In parallel, significant cost savings can be attained in terms of downtime, maintenance and repairs. For more demanding operational profiles, controllable-pitch propellers (CPPs) are usually selected, who have one additional degree of freedom, the blade pitch control. By changing the pitch, higher efficiency can easily be achieved for varying operational points, depending of course also on the engine selection. There is also the advantage of full power utilisation in various functions, such as accelerating and stopping, quick manoeuvring and dynamic positioning among others. In parallel, the cost is higher than FPPs and the designers should take into consideration some practicalities, like avoiding blade collision, proper positioning of the blade on the blade foot between the bolt holes and preventing stress concentration by avoiding the blade overhang at the blade foot [30]. In addition, the entire system (engine-gearbox-propeller) should cover powering needs for all operating conditions.

Matching the propeller towards the hull and the machinery system is essential in order to fulfil the power requirements and attain the desirable performance. The majority of the conventional cargo ships operate for the most part of their voyages under one condition (design condition) with a specific speed. However, for the design of the propeller, the most important operational conditions need to be taken into consideration and the designer has to select a suitable design point that will lead to good performance of the engine even for off-design conditions that the vessel will encounter during its service life. The propeller performance assessment can be carried out with the aid of PDn (propeller power - propeller speed diagrams) for the various conditions. Figure 2.1 shows an example of a PDn diagram, where the engine curve, the design point at the design condition (Des), the design pitch curve and a condition A at a given ship speed are presented. Aim of the designers is to achieve high efficiency, but at the same time maintain a torque margin to the engine curve. This is very important especially for CPPs, where by adjusting the pitch, higher efficiency can be achieved easily, but staying within the limits of the engine curve is a requirement. A sea margin of 10-25% is usually applied, in order to take into account conditions with increased resistance due to the vessel's loading, harsh sea state, hull and propeller roughness, shallow waters, trimming etc; this leads to having more than one propeller demand curve. In addition to this, an engine margin of 10-15% of the maximum continuous rating (MCR) is applied, in order to decrease fuel costs and enable increased power for off-design conditions.

Different blade designers might select different design points for the same problem, something that will eventually lead to a different final propeller design. Therefore, the selection of the right design point requires great attention. For commercial propeller suppliers that have large databases with designs from older projects, it is common practice to use this information as guidance for the

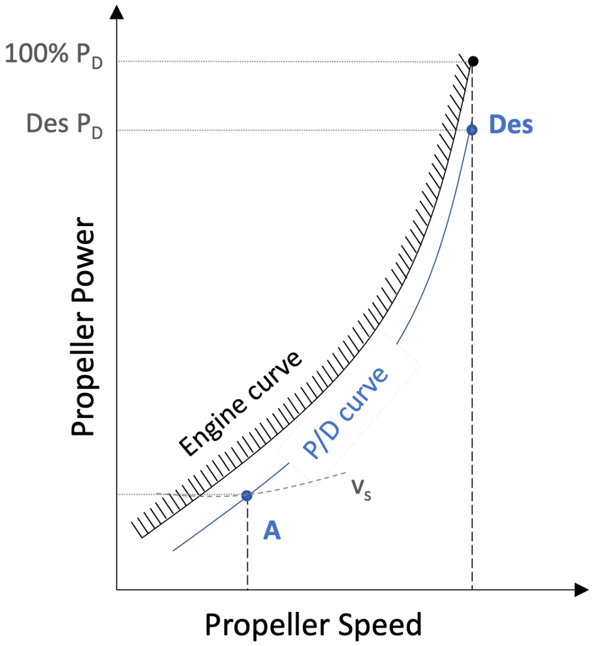


Figure 2.1: PDn diagram

selection of the design point for projects/vessels with similar geometry and mission requirements.

2.1.2 Preliminary Design

Once the propeller type and design point have been selected, the next stage is the preliminary design of the propeller, where the aim is to define the main propeller particulars: the propeller diameter, number of blades, mean pitch, blade area ratio and the sectional ratios of pitch, camber, thickness, skew, rake and chord length. The main characteristics of the hub are selected in this stage too. The selection of the main particulars is directly linked to the requirements set on the previous design stage. For example, if high efficiency is the goal, then the blade designers would choose a large propeller diameter with less blades and decreased blade area ratio. In yacht design, where usually comfort is the goal, meaning less noise and vibrations, larger propeller – hull clearance is preferred in order to achieve lower hull pressure pulses, in combination with a higher number of blades. If low risk of cavitation erosion is a requirement, blades with higher blade area ratio would be preferred [31]. Note that there is more focus on cavitation during the next design phase, as the more detailed design parameters have a greater effect on cavitation.

Circulation theory and the use of systematic propeller series are the tools that aid the designers during this stage to choose the main particulars [23]. The designers choose some initial values for the blade area ratio, thickness at the midchord and the tip, as well as the skew and the rake distributions. It is

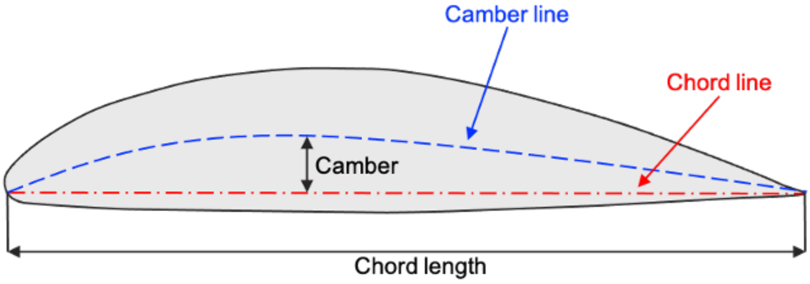


Figure 2.2: Blade section with camber and chord lines

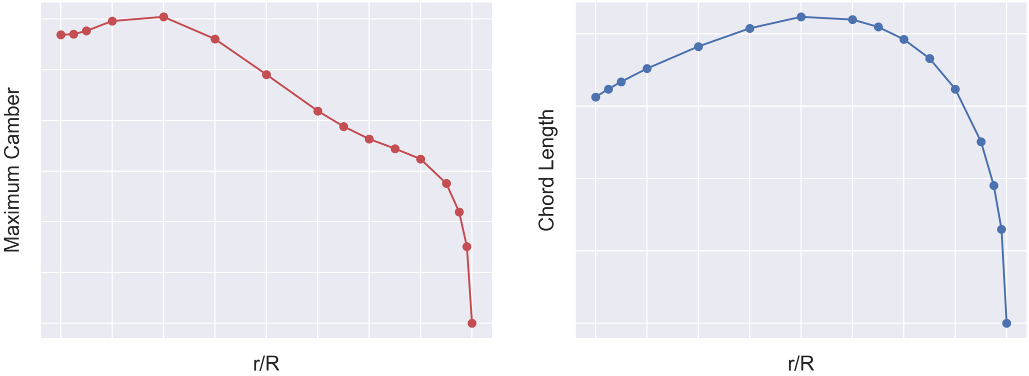


Figure 2.3: Maximum camber and chord length distributions

common practice at this point to reduce the tip loading of the blade, in order to obtain reduced pressure pulses later. Then, the optimal pitch and camber distributions are calculated with the aid of lifting line and lifting surface methods respectively. The aforementioned distributions are represented by spline curves along the radius of the propeller and the designers should always check how the curvature of the splines is formed. In figure 2.2 a blade section with the camber and chord lines is shown and in figure 2.3 the maximum camber and chord length distributions in different radial positions are presented. A means to check if the designer goes towards the right direction in selecting the main particulars is for example to verify that the midchord bubble cavitation is within the required limits that have been set out of experience. The whole process is iterated until the cavitation requirements are met. If this is not possible, then the designers return to the concept design stage, redefine the design point and then restart the preliminary design process with the new input.

2.1.3 Detailed Design

The purpose of this stage is to determine the final detailed geometry of the propeller that will later be manufactured, along with the detailed information about the hub. Selecting correctly all the detailed design parameters will lead to successfully fulfilling the requirements that were set during concept design. The final outcome is a unique propeller, tailored for the specific vessel and operational scenario that achieves all objectives as effectively as possible.

The output parameters of the preliminary design, together with the information about the wake from the model tests or the simulations, constitute the input of the detailed design stage. As a first step, the designers need to select the suitable design parameters in order to achieve a fitting position of the blade on the flange of the hub and to avoid blade collision. The visualisation of the geometrical characteristics in plots is beneficial and it speeds up the design process. Small alterations in the design parameters are done iteratively until the correct position is achieved. The next step involves the calculation of the static and dynamic strength of the blades. This can be accomplished by utilising different numerical methods, such as beam theory, or finite element method (FEM) tools. Moreover, the blade's thickness is defined by following the rules of classification societies. Finally, the designers need to analyse the hydrodynamic performance of the propeller in order to calculate the propeller forces and as a result the power consumption. This analysis can be done through different types of numerical methods, but at this stage potential methods are usually preferred, due to the strict time constraints. Except the efficiency prediction, an important part of this analysis is the evaluation of sheet cavitation, since it can lead to potential erosion damages. The designers visualise graphically how the cavitation has been developed, usually on the suction side of the blade, and assess whether it is within the satisfactory limits or not. For scenarios where off-design conditions are involved, the designers have to consider pressure side cavitation as well. Additionally, according to the mission requirements, the propeller-induced pressure pulses can be calculated either through empirical methods like Holden [32] or through the above-mentioned numerical methods. If one of these requirements/objectives are not fulfilled or if the designers are not fully satisfied with the results they receive, then they iterate the procedure of the detailed design until the desirable results are obtained. If this is not possible, then the designers need to return to the preliminary design or in some cases even to the concept design and redefine the important design parameters.

At the end of the design process, the designers obtain a number of designs that are good alternatives, based on the objectives. Depending on the project, additional evaluations might be needed and some of these designs will be further investigated with tools of higher fidelity. The design that is considered the best trade-off will later be manufactured.

2.2 Limitations during the blade design process

The most important limitation is that the entire design process runs under very strict time constraints. This is repeated throughout the thesis, since if the parameter of time would not exist, the approach and methods used towards solving the blade design problem would be very different.

From the description of the design stages, it is evident that several parts of the process are iterative, until a geometry is designed that fulfils the objectives and is within the limits of the constraints. There are parts of the the design stage, where the contribution of the blade designer is of significant importance (e.g.

definition of the design point), other parts where it is possible to alter geometrical parameters systematically until the specific objectives are attained (e.g. detailed design stage) and finally other parts, where designers need to visualise and manually evaluate some characteristics of the propeller (e.g. cavitation). The blade designers have the control of the whole procedure when they follow a manual blade design process and this is the most common practice for the industry nowadays. However, manually producing many design alternatives becomes significantly labour-intensive, especially in complex scenarios, and this is connected to the limitation of time again.

For those parts, where systematic parameter alterations is an option, it is possible to use automated optimisation, with the aim to produce a large number of designs. However, for the parts that the involvement of the blade designer is necessary, automated optimisation can be considered insufficient. Chapter 3 describes how the involvement of the designer can become part of the optimisation in a more systematic and effective way, in order to support the designer in the design process.

Chapter 3

Blade design optimisation methodology

Optimisation is nowadays utilised in most engineering problems as a support tool, with the aid of various optimisation algorithms. The aim is to use the optimisation in order to search for solutions in the design space efficiently and give a set of diverse optimal solutions as an output to the engineers that they would not be able to produce manually, due to the time limitations.

With the aim to describe our optimisation methodology, we first describe each part of it separately. The current status in blade design optimisation from various research groups is first presented, together with the limitations, and then the background of the interactive optimisation is discussed, which is the basis of the proposed methodology, along with the limitations of it. The implemented MLP (machine learning pipeline) is then described and eventually the entire methodology is discussed.

3.1 Background in blade design optimisation

Most research on blade design optimisation has focused on automated or semi-automated optimisation processes that utilise stochastic population-based optimisation algorithms, as they quickly offer a set of optimal solutions, spread in a wide design space [33]. Due to the time limitations, the optimisation algorithms are usually combined with fast analysis tools (e.g. lifting line, vortex lattice method (VLM), boundary element method (BEM) etc.) and some semi-empirical evaluation of cavitation nuisance constraints. Some of the studies use surrogate models and machine learning as support to the optimisation methodology.

A two-stage optimisation methodology for full-scale propellers working behind a ship was presented by Berger et al. in [17]. In a first stage, an evolutionary algorithm coupled with a panel code was utilised for a multi-objective optimisation problem and in a second stage, some of the best propeller designs of the first stage were chosen in order to be investigated further by a hybrid Reynolds Average Navier-Stokes (RANS) and BEM approach for the hull and propeller flow, respectively. The choice of the optimal designs was executed manually as an intermediate step between the two stages. Although better designs were obtained at the end of the optimisation, some of these optimal solutions led to infeasible geometries.

Foeth and Lafeber presented a propeller parametrisation method in [18] for the optimisation of a propeller geometry in an effective wake, where the non-dominated sorting genetic algorithm II (NSGA-II) [34] was utilised combined with a BEM tool. The distribution curves of pitch, chord, camber, thickness, skew and rake were fully parameterised by Bezier curves. The objective of the optimisation of the case study was to maximise in-behind efficiency and no cavitation was included. A constraint was set in order to not deviate 0.1% from the required thrust at the design rpm. According to the results, the optimisation did not lead to a large improvement in the efficiency. This work was further developed and presented in [19], where the parametric geometry model was used together with the NSGA-II for solving two propeller optimisation problems with different objectives and constraints in each case, while a BEM tool was utilised for the calculation of the hydrodynamic performance in behind condition. The results obtained for the first optimisation problem showed a quantified trade-off between the tip vortex noise and the efficiency. The designs obtained for the second optimisation problem, where ice-class rules were considered, represented very high-skew propellers that although they met the ice-class requirements, they would be infeasible in practice. The authors mentioned the importance of having a robust engineering environment for the automated optimisation to be performed efficiently. They also emphasised that the manual design is still part of the process, but the result of the automated optimisation can be utilised as a starting point for obtaining a competitive final design.

Gaggero et al. [20] worked on a multi-objective optimisation problem of a cavitating propeller of a high-speed craft , where a genetic algorithm (GA) was combined with a BEM tool. After the optimisation, a number of designs was manually selected by the blade designer for further evaluation by a RANS-based computational fluid dynamics (CFD) tool. In addition to this, one of the designs was validated by cavitation tunnel tests. The optimisation was set-up in the ModeFRONTIER environment and the design variable distributions were parameterised and described by B-spline curves. Objectives of the optimisation were the efficiency maximisation and the cavity volume minimisation. Since the problem regarded a high-speed propeller and bubble cavitation is hard to be predicted by BEM, non-cavitating pressure distributions were utilised instead. It is mentioned by the authors that during the optimisation, some criteria were monitored, and at the end of the optimisation those designs that did not fulfil the criteria were discarded manually. Two different baseline geometries were optimised and for one of the two, there was good agreement between the BEM and CFD tools, according to the results. In [21], a simulation based design optimisation method is presented. More specifically, a metamodel is suggested that can be utilised for global design space exploration and as part of optimisation procedures. Both low fidelity data from a BEM analysis tool and high fidelity data from a CFD tool are utilised as input to the co-Kriging metamodel. The results showed that by combining the low with the high fidelity data, less CFD computations were needed than by using solely CFD-based metamodels.

A practical optimisation tool for the hydro-acoustic optimisation of naval propellers was presented in [22], where the optimisation was done in three different levels and GAs were utilised. At first, a large design space was explored with the performance in open water as the main objective. The obtained designs from the first step defined the design space of a second round, where more objectives were set and the performance was assessed in behind conditions. Finally, a specific number of designs was chosen by the users and evaluated using a CFD solver of higher fidelity. Main priority of this optimisation tool has been the low computational time and the good usability of the tool and this becomes more achievable when the users are included in the optimisation process.

The automated propeller and propulsion system optimisation process of Caterpillar was presented in [35]. Specifically for the propeller optimisation part, the authors mention the importance of optimisation processes (automated in their case) in propeller design due to the labour-intensive manual design. In their process they combined the NSGA-II with a BEM tool. The case study regarded the optimisation of a CPP for a twin-screw vessel, and for a scenario with several conditions, most of which are off-design, where many objectives and constraints were included. The results gave a well-defined Pareto frontier. However, when the feasible designs were plotted, it was evident that almost all the Pareto designs were not feasible. A number of feasible non-Pareto designs proved to be better than the manual design though. Eleven feasible designs were manually selected by the blade designers for further evaluation by a RANS-based CFD tool. The tool gave a significant cost improvement compared to the time that the manual design required. Another industrial application study was presented in [36], where a competitive multi-objective particle swarm optimisation (PSO) algorithm was combined with a BEM tool for the optimisation of a propeller geometry, and some Pareto designs were further evaluated by a RANS-based CFD tool. The case study regarded a complex scenario for the optimisation of a single screw CPP, involving three operating conditions: a design, an MCR, and a slow-steam manoeuvring condition with high rpm. Bezier curves were utilised for the representation of geometrical distribution curves, such as chord, pitch, skew and camber. The objectives of the optimisation were the maximisation of the efficiency, the minimisation of the first order harmonics of pressure fluctuations on the hull above the propeller and the minimisation of the pressure side cavitation. Two cavitation-related constraints were applied, together with some geometrical constraints. The results of the optimisation showed a detailed, diverse and well-converged Pareto frontier. However, more than half of the high efficiency solutions had pressure side cavitation. Three Pareto designs were selected by the designers manually, and were evaluated by CFD. The difference between the CFD and BEM results were similar for the three designs, thus it was concluded that a similar Pareto frontier would be obtained if it would be possible to perform the same analysis with CFD tools.

Doijode et al. [27, 28] approached the marine propeller optimisation problem by combining a dynamic optimisation method with supervised and unsupervised machine learning methods and a BEM analysis tool. Instead of using the conventional design variables, such as pitch, camber, skew etc., an orthogonal parametric model was proposed where the parameters were directly derived from the propeller mesh. This was done in order to solve the multicollinearity problem that is linked with the conventional design variables. The goal was to separate the designs in different clusters of satisfactory and unsatisfactory performance. The method was investigated with a single-objective optimisation problem [27], where the aim was to maximise efficiency in a non-cavitating scenario. The results showed that by using dynamic optimisation and machine learning, designs of higher efficiency and with lower computational cost were obtained when compared to a Wageningen model baseline. A similar method was used for a multi-objective, constrained optimisation problem [28]. Since this was a more complex scenario, soft explainable classifiers with online training were additionally utilised. The classifiers were trained to identify the location of the Pareto frontier and later exclude designs, which were predicted to be away from the frontier. It is not clear how the online training was performed and how labour-intensive or how high the computational cost was though. The results showed a 30% computational cost reduction compared to the NSGA-III algorithm, and Pareto frontiers with diverse solutions were obtained.

Attempts at developing fully automated blade design optimisation processes were presented in [23, 24, 25, 26] by Vesting et al. The focus was on different optimisation algorithms, such as the NSGA-II and PSO, including extensions with metamodels. Different geometrical modifications and constraint-handling methods, mainly related to cavitation, were implemented in their process. The proposed processes were evaluated for several commercial design cases, and while the outcome was satisfactory, it was still considered inferior to the manual design. It was concluded though that the manual design requires a large number of labour hours, making it difficult to obtain more than a few different designs. These designs were however of higher quality than the ones generated by the automated process that suffered from a large number of infeasible designs.

In most of the above-mentioned studies, the automated or semi-automated optimisation is supported either by the blade designers who aid the different processes by manually selecting interesting designs or beneficial areas of the Pareto frontier for further evaluation, or by metamodels and machine learning methods, which are utilised for reducing the computational cost of the optimisation and for searching the design space more efficiently. However, this has not been implemented in the optimisation procedure systematically. In the following sections, the proposed methodology on the implementation of support tools within the optimisation procedure, by involving the blade designers and machine learning systematically, is presented.

3.2 Interactive optimisation

The more complex the engineering systems get, the need for involving the designers as a part of those systems grows [37]. Multidisciplinary and multi-objective processes can be simplified by integrating the human thought and knowledge in the optimisation loop of the systems and in parallel find solutions more efficiently. Interactive evolutionary computation (IEC), which is defined as an optimisation method that is based on evolutionary computation and utilises subjective human evaluation in its process [38], can enable the integration of the code - user interaction. IEC has been the basis of the proposed interactive optimisation methodology, which has been described in [7] in detail.

3.2.1 Brief Background in IEC

IEC is utilised in complex optimisation problems where objectives or constraints cannot be expressed through quantitative objective functions and the system users interact with some features of the system, judge them and return their input into the system. This guides towards solutions that fulfil the objectives or constraints based on the preference of the system user.

IEC has been used over the years in several disciplines, like design, music, graphic arts, virtual reality, image processing and data mining among others [39]. In recent years, it has started being utilised for engineering, but mostly in applications where there are objectives related to engineering aesthetics, for example in car design [40]. Similarly as in non-IEC optimisation processes, different types of stochastic population-based optimisation algorithms can be utilised. Examples of these algorithms are the interactive GAs (IGAs) [41, 42], interactive PSO [43, 44] and interactive ant colony optimisation [45]. Results from these studies showed that it is indeed possible, in different levels, to guide the optimisation algorithm towards areas of interest of the design space through user interaction.

A key parameter in IEC is the population size of the optimisation, which differs in the various applications and algorithms. Deciding on whether the population size is small or large, depends a lot on how the user interface of the application has been developed, i.e. how many designs are being presented simultaneously, if there is a reference design for comparison, if the users are able to alternate the geometry of the designs etc. For small population sizes, the users evaluate characteristics of the entire population manually [40, 46]. For problems that large populations of individuals are required, the users have to do numerous manual evaluations, and after a point of visualising and assessing designs via a graphical user interface, human fatigue is caused and the users cannot evaluate the designs objectively anymore. Human fatigue is the main disadvantage of interactive optimisation [38].

A solution or improvement on the user fatigue issue is considered the use of surrogate models [47], where the users train a surrogate model by evaluating a subset of the entire dataset and the model approximates the performance of the remaining non-evaluated set. Several surrogate models have been used as parts of IEC processes, such as neural networks (NNs) [48, 49] and support-vector machines (SVMs) [50, 51] among others.

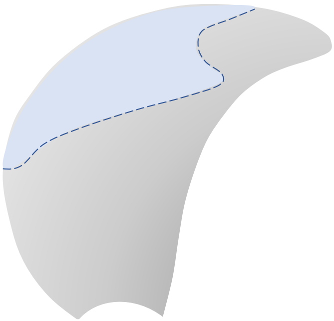


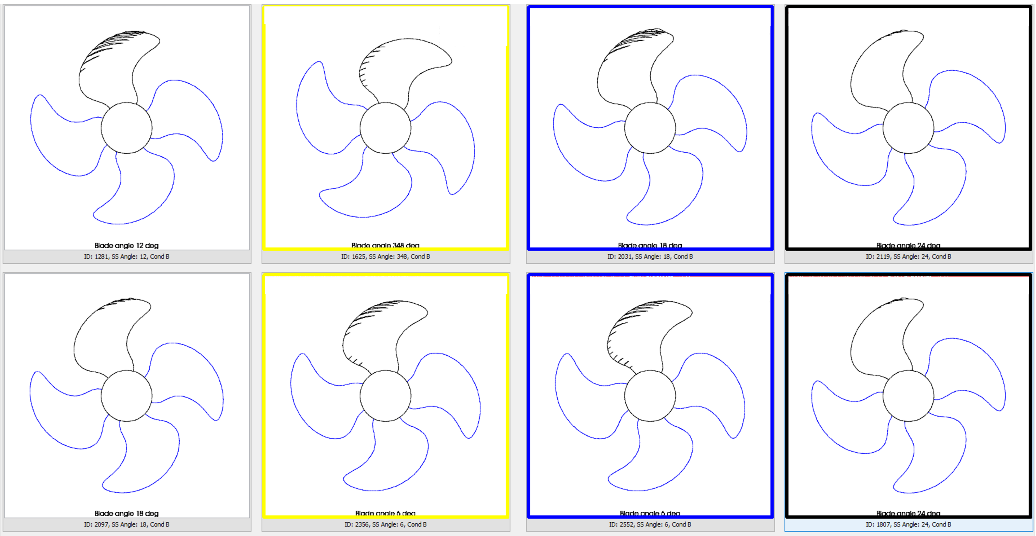
Figure 3.1: Cavity on blade [2]

3.2.2 IEC in the proposed methodology

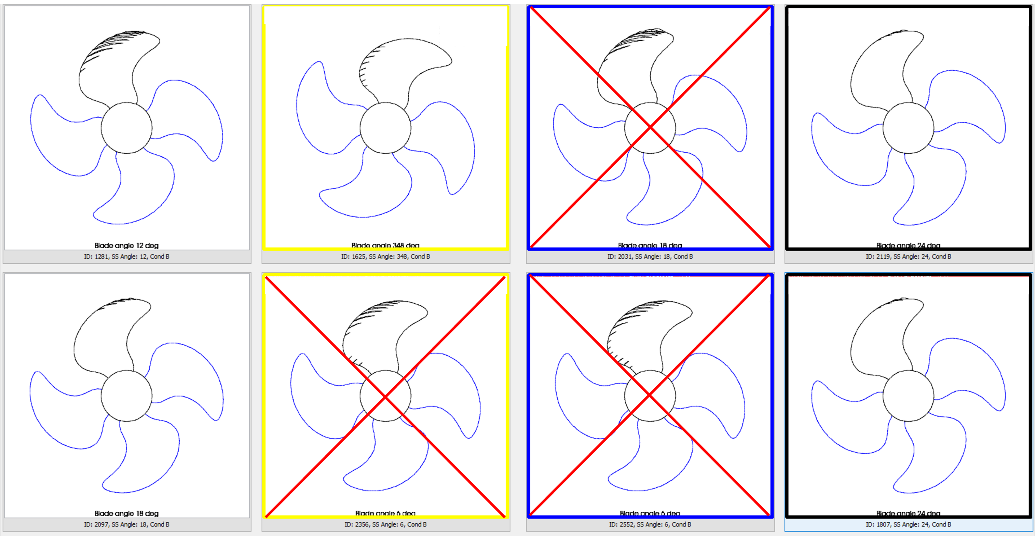
Cavitation is usually encountered in blade design optimisation as a quantitative constraint, and the designs should not exceed a specific value. Vesting [23] did an extensive investigation on various cavitation parameters (maximum non-dimensional cavity volume, chord-wise centroid harmfactor, maximum non-dimensional length of each cavitating blade section, cavity closure line harmfactor, cavitation thickness at the three outermost blade radii and non-dimensional cavity change), which were set as constraints in his research.

However, the evaluation by an experienced designer, who assesses cavitation characteristics by looking and observing cavitation images, is considered more reliable than the outcome of constraining those proxy parameters. Therefore, IEC is utilised in our process in order to enable designers to evaluate the cavity shape that has been formed on the blade of every propeller of the optimisation, as shown in figure 3.1. The designers reject the designs where the cavity shape is not satisfactory, according to their own judgement. After communication with the designers [29], it was decided that it is sufficient to present the blade with the cavity shape at the time step of the most critical angle, when there is maximum cavity volume.

One of the first steps towards solving the problem of user fatigue has been the implementation of a user interface for evaluating the cavitation of the designs. The implemented cavitation evaluation dialogue box is presented, where the designs are first presented to the designer, as in figure 3.2a, who rejects those designs with non-satisfactory cavity shape, depending on the project, as in figure 3.2b. This enables the designers to judge several designs simultaneously and compare them with each other. By comparing the user fatigue from paper II, where there was no user interface, to papers III-VI that it was implemented, the user fatigue reduced significantly, with regards to the usability of the tool.



(a) Designs with cavity shape presented to the designer



(b) Rejected designs by designer

Figure 3.2: Cavitation Evaluation Dialogue Box

3.3 Machine learning in optimisation

The other step towards solving the user fatigue problem of IEC has been the use of ML as surrogate model. Instead of presenting the cavitation images of the entire population to the designers, only part of those are presented. The designers perform the manual evaluations and this information is utilised as training of the ML model. The accepted and rejected designs are assigned with the values 1 and 0 respectively. After the training and when a new dataset is available through the optimisation, the ML model is used for prediction of the cavitation evaluation, instead of performing manual evaluations. This speeds up the entire optimisation process.

Since this is a classification problem with the two classes of accepted and rejected designs based on satisfactory or non-satisfactory cavity shapes, ML classification algorithms have been utilised. In paper II, SVMs were used with linear and polynomial kernels as hyperparameters. Hyperparameters are defined as parameters whose values are used to control the learning process of the algorithm. Considering that it regarded a simple blade design scenario, satisfactory predictability was achieved. In paper IV, four additional ML classification algorithms were investigated, the k-nearest neighbours [52], NNs [53], decision trees [54] and XGBoost [55]. For each algorithm, various hyperparameters were also investigated. Nested-cross validation (NCV) and grid search method have been utilised to perform the hyperparameter tuning and an MLP has been set up with the aid of scikit-learn [56], in order to implement the entire process. The MLP was implemented as part of the optimisation process for two more advanced scenarios in paper VI.

In any ML process, the importance of the input is significant. Two different sets of input have been investigated in the various studies. The first set of input features involves the aforementioned cavitation parameters and the second set regards the design variables of the optimisation problem. The reason that both sets of input features have been utilised is that the different cavitation shapes of the designs might be produced by other means, except through optimisation, and by using other analysis tools.

3.4 Proposed Methodology

The selected optimisation algorithm in the proposed methodology is the NSGA-II and when used in combination with the interactive optimisation, it is mentioned as IGA. In short, the NSGA-II is an evolutionary algorithm, which involves three special characteristics: elitism, crowding distance and for multi-objective problems a method to separate and promote the non-dominated solutions. Elitism gives the opportunity to the best individuals to pass to the next generation and crowding distance ensures diverse solutions. In multi-objective optimisation, the solutions are split into different ranks based on their performance, with the non-dominated solutions belonging to rank 1, and the ranks are updated with every new generation. Outcome of the last generation is one Pareto frontier that includes all non-dominated solutions with rank 1.

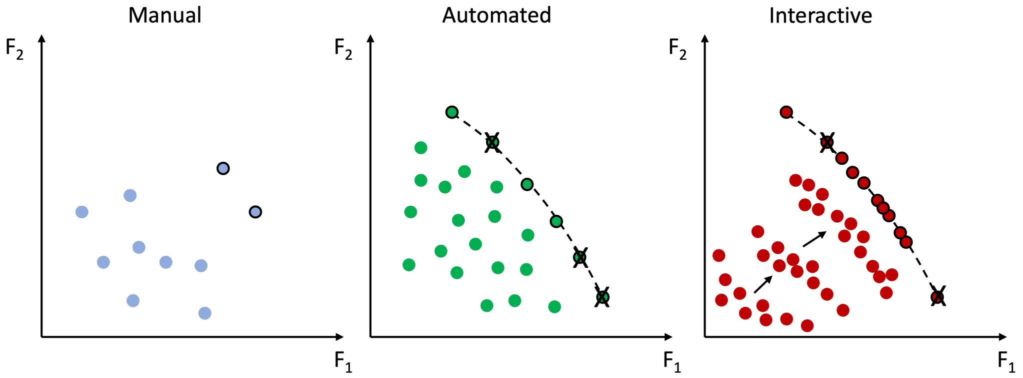


Figure 3.3: Performance in manual, automated and interactive Optimisation

In the proposed optimisation methodology the NSGA-II is combined with IEC and ML. The aim is to obtain the Pareto frontier, where most of the designs have accepted cavitation characteristics, according to the designer, and the process is carried out within the limited time constraints. As shown in figure 3.3, with the manual design process a small number of designs are created by the designer manually, with only few non-dominated options, but with all the designs having satisfactory cavitation characteristics since the designer has the control over the entire process. With the automated optimisation, a more detailed Pareto frontier is obtained, but several designs have non-satisfactory cavitation characteristics, shown with the 'x' marker. With the interactive approach, several optimisation runs are performed and the designer evaluates the cavitation manually, in a number of intermediate steps. The expectation of the final Pareto frontier is a detailed Pareto frontier, with a performance that is similar as in the manual and automated processes, but with designs that have cavitation characteristics that are closer to the preference of the designer. This means that the performance of the objectives is guided by the NSGA-II and depends on how well the design space is being searched, while the designer guides the algorithm towards solutions that have satisfactory cavitation characteristics. Also, the Pareto frontier ends up being more detailed in those areas that the designer has selected as more beneficial. The MLP is utilised when necessary, depending on the size of the population of the optimisation problem.

The framework of the proposed methodology is presented in figure 3.4. A baseline geometry is created by the blade designer, who sets up the optimisation problem, along with the design variables, objectives, constraints and defines the various important optimisation parameters (e.g. crossover, mutation, number of generations etc.).

The optimisation starts by running the NSGA-II and the first stage is the interactive optimisation, where the designers evaluate the cavitation images interactively. Depending on the problem, the designer decides on the amount of runs that are necessary in order to guide the algorithm towards a beneficial area of the design space. Smaller runs are preferred at this stage so that human fatigue is not caused. Except using the manual evaluations as part of the interactive optimisation, the data are saved in order to be used later as input of the MLP (or an ML model).

A new optimisation run is performed, which usually includes a larger population. In parallel, the MLP is used for finding the most suitable ML model for the prediction of the cavitation evaluation of the new run. Input of the pipeline is the dataset that was previously saved. The dataset includes the input features (cavitation parameters or design variables) together with the user evaluation. Output of the pipeline is an ML model that combines an ML algorithm with the best fitting hyperparameters. This model is then trained again with the entire dataset and a prediction of the cavitation evaluation of the designs of the new optimisation run is done.

One final optimisation run is performed and for this the designers evaluate only the designs of the Pareto frontier manually. They can eventually conclude towards one or a small set of non-dominated designs with satisfactory cavitation characteristics.

The proposed methodology is flexible and in the different scenarios of the appended papers, it is used in a different way. The exact same framework is used in paper VI. In paper II, the evaluations are all manual and the option of ML has only been investigated as an optional solution. In papers III and V that regard wind propulsion, the interactive part was utilised only at the end to ensure that no extreme cavitation appeared. More details on the framework for wind propulsion applications can be found in chapter 4 and in papers III and V. In paper IV two runs are performed, one for ML training and one for prediction of the cavitation evaluation of the new run.

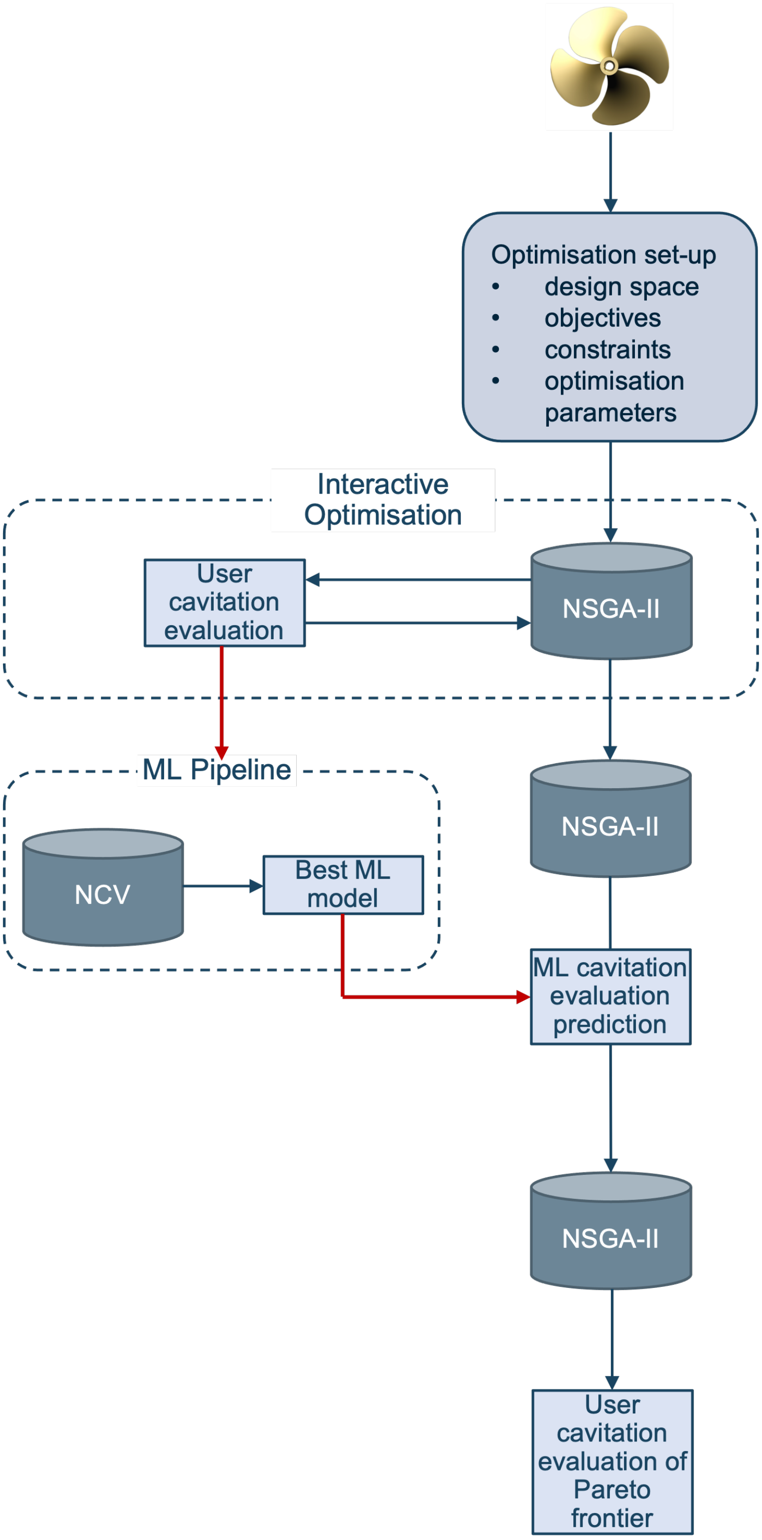


Figure 3.4: Framework of proposed methodology

Chapter 4

Scenario-based design

The work that has been done in this thesis regards several design scenarios, with different propeller types for various types of vessels and with optimisation problems that included conditions with many objectives and constraints. The applications have been separated in two categories, those of conventional propulsion and of wind propulsion. Papers II, IV and VI regard scenarios of conventional propulsion, while papers I, III and V regard wind propulsion. Conventional propulsion is related to ships where the main source of powering comes 100% from the engine, while in wind propulsion the main or auxiliary source of power comes from the wind. In this thesis, the concept of wind propulsion regards both wind-assisted ship propulsion (WASP) and wind-powered ship propulsion (WPSP), and the difference lies on the percentage of powering provided by the wind.

4.1 Conventional Propulsion

The majority of the conventional cargo ships sail for the most part of their voyages under the design condition with a specific speed. Therefore, the blade design work is performed primarily based on this design condition. This means that already from the concept design, the aim is to improve the performance at the design condition and then later at the stage of the optimisation, most of the objectives and constraints are set based on this condition.

In several scenarios (e.g. with twin engines or twin propellers), it is common to consider also some off-design conditions. Off-design conditions are also very common in wind propulsion applications, something that is discussed later in section 4.2. The designers perform the blade design work based on the design condition, but when they create new geometries, they investigate whether the performance of the off-design conditions is within the required or desired limits. If the geometry that gives optimal performance in the design condition does not fulfil the requirements of the off-design conditions, a new geometry should be designed. As a result a trade-off is found that covers both design and off-design conditions. With the proposed methodology of chapter 3, it is easier for the designers to control the design and optimisation process, in scenarios where there are several conditions, because cavitation for example can be evaluated manually, instead of constraining the problem too much by setting several quantitative constraints.

The MCR condition is also an important condition that the designers must investigate, since most of the strength-related criteria are checked for the MCR and changes in the geometry can affect the blade strength. Moreover, in scenarios where cavitation is involved, even if the operational probability at the MCR is very low, one should always check the cavitation in this condition. For example with one geometry the design condition might have an acceptable cavity shape with high cavity volume, but then the cavity volume at the MCR would be too high, and a new geometry should be found.

The selection of the propeller type and the propeller function (windmilling, feathering, etc.) combined with the engine, the gearbox and the operational profile of the vessel affect the design and the optimisation procedure. The two advanced scenarios of paper VI regarded the design and optimisation of two different CPP designs for two ROPAX vessels. For both cases, the blade design work was based on the design condition, but also one off-design condition was investigated, set at approximately 40% of the MCR, which was the point before switching to operating with one propeller only. The objectives for the one scenario were related to the efficiency and pressure pulses of the design condition, the cavity volume of both conditions, while the quantitative constraint was related to the blade strength at the MCR condition. Also, when the cavitation characteristics of the designs on the Pareto frontier were evaluated by the designer, also the cavitation characteristics at the MCR were checked. More information on the two scenarios can be found in chapter 5 and in paper VI.

Each blade design scenario plays a significant role on how to set-up the entire design and optimisation process. Also, as the complexity of the scenarios increases, the harder it becomes for the designer to create good propeller geometries manually and manage to control all the objectives. The proposed methodology from chapter 3 can therefore function as support tool for the designers.

4.2 Wind propulsion

The need for decarbonising the shipping industry was highlighted in the introduction. In order to achieve this goal, the shipping community has focused on research and development for utilisation of cleaner fuels, like biofuels, methanol and hydrogen, [57, 58, 59], and alternative sources of energy, like wind or solar power. Wind propulsion, often combined with solar power technologies and cleaner fuels, is a concept preferred more and more by shipping companies, as a means to reduce emissions and save fuels costs. The advantage of utilising the wind as the main source of thrust is that these vessels have less exhaust pollutants, something that leads to GHG emission reduction and in parallel to fuel savings. Since it is hard to use the wind for the full powering of the ships, all of the existing commercial adoptions of wind propulsion technologies are combined with conventional propulsion [60].

Plenty of research in wind propulsion has been published in recent years and the main focus has been on the improvement of wind propulsion technologies, hull design and optimisation and weather route optimisation. When it comes to wind propulsion technologies, there are several ways to exploit the wind for propulsion of a ship, with the main focus on kites and different types of sails. Examples of sails are rigid sails, with a large variation in foil section profile or plan form, and active devices such as Flettner rotors. In most of the research studies [61, 62, 63, 64, 65, 66, 67, 68, 69], different arrangements and sail area sizes of wind propulsion technologies have been investigated, and they are often combined with other alternative sources of energy or fuels. Also, different weather conditions based on either real weather measurements or weather simulations were examined. The studies have shown a fuel cost reduction of 1-50%, which is a wide range, but the results depend on the weather conditions, the type and route of the vessel and the WASP technology, thus each case is very specific. Also, the emission reduction calculation, if performed, is done in a different way in each study, by considering either the CO_2, or NO_x or SO_x emissions or all simultaneously.

Although most of the research studies and the existing commercial adoptions concern WASP, WPSP is also a very interesting solution, although it is harder to achieve. A well-known WPSP case is the Oceanbird [70], which is under commercial launch, and the vessels adopting this concept will be equipped with wing sails combined with a specially optimised sailing hull, with the overall goal of cutting emissions by up to 90%.

4.2.1 Propeller performance

Despite the fact that there is such amount of research and development related to wind propulsion, together with some commercial applications, there is little published research, to our knowledge, related to the design and selection of propellers for wind-powered/assisted vessels. The traditional propulsion system (engine-shaft-propeller) is however necessary for the propulsion of wind-powered/assisted vessels. In addition to this, the challenges connected to the selection of the propulsion system for wind propulsion are several and should be considered early in the ship design process. These challenges are discussed in section 4.2.2.

Some interesting results were however presented by Molland and Hawksley [71], who made an assessment of the propeller performance for two different types of WASP vessels, a coaster and a cargo ship. More specifically, the performance of each vessel was assessed by either setting constant speed or constant power, combined with different types of engine/gearbox and propeller arrangements. According to the findings for both vessels, when they operated at a constant speed mode, for a single engine and a single screw installation, an FPP gave satisfactory results on the efficiency. For twin engines and a single screw installation, it was preferable to install a CPP or a two-speed gearbox. However, by considering the costs, a single engine and an FPP gave a better trade-off overall in both cases. Regarding the constant power operation mode, engine power limits cannot be reached as easily as in the constant speed operation mode, so an FPP was used in that case as well. At the same time, engines with small power margins can easily result in revolution limits and subsequently in lower effective thrust, when higher ship speed is required. A solution to the thrust decrease was the use of a CPP or the use of a single engine with larger power margin.

Tillig and Ringsberg [65] emphasised the high risk of potential pressure side cavitation for propellers that operate with a varying load and it was advised by the authors that for vessels with large sail areas, it is beneficial to equip them with a CPP, in order to avoid pressure side cavitation problems.

4.2.2 Challenges in the propeller design process of wind propulsion

The main difference between conventional and wind propulsion is that although the weather conditions are always unpredictable, for wind propulsion the power of the wind must be exploited. When designing vessels for conventional propulsion, as described in section 4.1, we typically perform the propeller design work based on the design condition. With wind propulsion there is a broader range of operating conditions for the vessel and a wide load span for the propeller and the engine. Especially for wind-powered vessels, this span can be from 0 to 100% of the engine power. This results in a series of challenges.

The first thing to decide during the design process is what engine - gearbox and which propeller type are needed, based on the mission profile of the vessel. This selection is mutually dependent and is a task that takes place simultaneously. The selected engine and gearbox should cover all powering needs of the vessel, including high wind-powering, high sea state and normal calm water conditions. Then, the selection of an FPP or a CPP depends on several techno-economical factors, and each type is connected to different challenges.

Moreover, during the propeller-engine selection, one should bear in mind that in high sea states, the engine should offer sufficient powering and the propeller should have a margin to the engine's upper torque limits for the specific operation. In very light conditions, there is a risk that the system will reach the engine's lower torque limits. An additional limitation during the light conditions is that the low shaft speed is connected to bearing lubrication issues on the shaft.

Depending on the size of the variation of the propeller load, the mission profile of the vessel, and the overall cost, the blade designers and the ship owner have to decide between an FPP and a CPP. When the wind powering is considerably high, to the point that the propeller does not operate, the propeller will be either windmilling or be in a feathered position (if a feathering CPP is selected), in order to reduce drag. The added resistance from the windmilling/feathering propeller should be considered and estimated early in the design process, so that the most suitable propeller-engine selection is done. Note that this mostly regards ships that are fully wind-powered, where the power is provided by the wind propulsion technology and the propeller is in windmilling or feathered position. Another option is the harvesting operation of the propeller, where energy is harvested through a generator coupled to the windmilling propeller. This option would add further resistance but in parallel it would generate electricity. For harvesting propellers the frictional losses should be minimised, since otherwise a significant part of the generated power could be lost.

Another challenge is related to the optimal combination of propeller diameter and propeller speed. Although for conventional vessels the largest possible diameter is usually chosen, since we aim for the highest propeller efficiency, for wind-assisted/powered vessels that operate in several conditions with different loads, the aim is not necessarily the high propeller efficiency at a single design point, but a low total energy consumption of all operating conditions combined. Therefore, the largest diameter might not fulfil the objective for those vessels. According to [72], a higher loaded propeller with 3-4% smaller diameter, when studied together with the rudder system, it could perform better than with a larger diameter, for a conventional vessel. Thus, how to select the right combination of propeller diameter and propeller speed should be investigated for wind propulsion as well.

Finally, a phenomenon that is connected to more lightly loaded propellers is the pressure side cavitation that potentially can occur; a type of cavitation that should generally be avoided. For wind-assisted/powered vessels, the designers have to evaluate whether the pressure side cavitation is within the acceptable limits, in the cases that it cannot be eliminated and at the same time, suction side cavitation must be evaluated for the normal and more highly-loaded conditions.

4.2.3 Propeller design optimisation process in wind propulsion

The aforementioned challenges clearly show that the propeller design and optimisation process of wind-powered/assisted vessels should be approached in a different way than in conventional propulsion. The operational profile plays a significant role in the design process, while new objectives for blade design optimisation have to be considered. Overall, propellers for wind-propulsion are often lightly loaded and should operate well in off-design conditions.

In papers III and V, two case studies on wind propulsion were presented, where common goal was to develop a methodology for the design and optimisation of propellers for ships that are assisted or powered by the wind. The case study of paper III regarded the design and optimisation of a propeller for the KVLCC2 vessel, which was retrofitted with six Flettner rotor sails and sailed between two fixed destinations with constant speed. In more detail, it was investigated whether the existing propeller covered the demanding needs of wind propulsion or a retrofit of a better design was needed. The case study of paper V regarded the design and optimisation of a propeller for a wind-powered car-carrier, which was equipped with four rigid wing sails and sailed between two fixed destinations with constant speed. This vessel was a newbuilding and it was investigated how to design the propeller in order to reduce the vessel's propeller energy consumption as much as possible. Paper I also regarded a scenario on wind-propulsion, but it was at a very early stage on the development of the methodology, and it was just considered that the vessel operated in two conditions with constant speed.

Operational profile

The unpredictable weather conditions suggest a wide operational profile for the ship and the propeller in wind propulsion. The operational profile of a vessel can defined by either route simulations, which is a very common input, or actual measurements. Based on the available input, the blade designer selects those conditions that can affect the blade design the most and off-design conditions.

There are specific conditions, off-design or not, with high operating probability during the route and the designer should certainly consider them. At the same time, there are several off-design conditions that should be considered as well. For example, when the wind propulsion technology offers a significant amount of thrust to the vessel, even if the probability for this weather condition is low, the designer should check whether reducing the power considerably, would lead to reaching the engine's lower torque limits. In parallel, in high sea states, the upper torque limits should be checked as well.

Optimisation objectives and constraints

The objectives and constraints in blade design optimisation processes are usually related to efficiency, cavitation, pressure pulses and strength among others. Most of these objectives are relevant in wind propulsion, but now there are several conditions that represent the operational profile with varying propeller loads, which affect the blade design work. All these conditions have to be considered in the optimisation and therefore, the following two objectives are proposed for blade design optimisation within wind propulsion:

$$total\ energy\ consumption = \sum_{i=1}^{n} P_{Di} * t_i, \tag{4.1}$$

where P_{Di} is the delivered power to the propeller for each condition and t_i is the operating time for each condition.

When there is detailed engine information with specific fuel consumption available, it is possible to calculate the TFC, according to:

$$total\ fuel\ consumption = \sum_{i=1}^{n} P_{Di} * t_i * SFC_i, \tag{4.2}$$

where SFC_i is the specific fuel consumption for each operating condition.

An important constraint in blade design optimisation problems within wind propulsion is related to cavitation. In lightly loaded conditions, there is high probability of having pressure side cavitation and in middle and highly loaded suction side cavitation appears. This is the case also in conventional propulsion, but in wind propulsion there are more conditions for which the cavitation should be controlled. The final design should be such so that the cavitation is within the acceptable limits in all conditions. The results from case study III showed that cavitation appeared in almost all conditions, and it was indeed within the limits. Since the scenario of case study V was complex with several off-design conditions, the expectation was that there would be cavitation issues and that interactive cavitation evaluation would be necessary. However, no cavitation appeared, most probably due to the specially optimised sailing hull, something that did not give us the opportunity to use the developed interactive optimisation methodology extensively.

Chapter 5

Summary of papers

In this chapter, the summaries of the six appended papers are described. For each paper, the division of work, the aim, the summary and discussion are presented.

5.1 Paper I

I. Gypa, R. Bensow, K. Wolff & R. Gustafsson. Interactive evolutionary computation for propeller design optimization of wind-assisted vessels. In AIAA AVIATION 2020 FORUM (p. 3162).

Division of work
All authors participated in reviewing the paper and provided me with feedback throughout this work. Robert Gustafsson provided the baseline propeller that was used. Rickard Bensow and Robert Gustafsson set up the user scenario. I developed the code for the optimisation methodology, performed the optimisation runs, post-processed the results and wrote the paper.

Aim
Paper I is the first step towards the development of the interactive optimisation methodology, which has been exemplified with a simple blade design optimisation problem. The overall goal has been to investigate how interactive optimisation works when selecting specific areas of the Pareto plots, and whether it is possible to guide the optimisation towards a particular direction within the preference of the blade designer.

Summary and Discussion
The flowchart of the methodology is shown in figure 5.1. The interactive part in the optimisation process is that the blade designer evaluates the Pareto plot of the objectives that is displayed. The designer at the end of one optimisation run selects interesting designs, which form the first run of the next optimisation run. This process can be carried out as many times as the designer thinks it is necessary. In between the optimisation runs, it is possible to change some optimisation parameters, such as the crossover and mutation operators, with the aim to pass from the exploration stage to the exploitation.

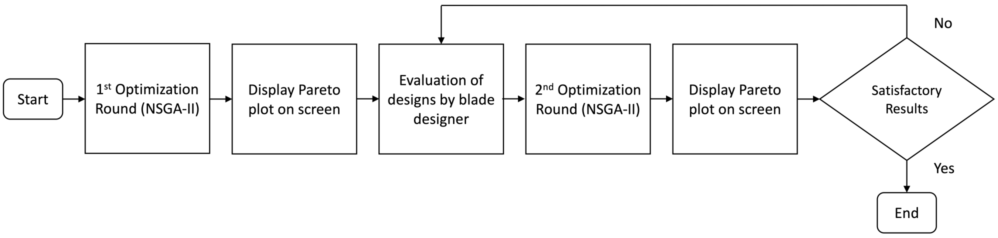


Figure 5.1: Flowchart of IEC Algorithm for Blade Design Optimisation

The user scenario regards the design of a CPP for a wind-assisted vessel and two conditions are investigated which have the same ship speed and the objective of the optimisation is to increase the efficiency in both conditions.

At the first part of the study, and after the completion of the first optimisation run, the designer selects a small and a large area of the Pareto frontier to see how the algorithm will evolve. The results showed that by selecting specific areas of interest, the algorithm searches solutions in a more targeted manner. During the second run, both areas were examined with different combinations of crossover and mutation, and the optimisation was repeated several times. According to the results, with the mutation set to 0, the best results were obtained with regards to the size of the final Pareto frontiers. At the second part of the study, the designer is asked twice to evaluate the frontier and it is shown after the end of the three runs that by starting from a coarse frontier, with the aid of the interactive evaluation by the designer, a detailed frontier is obtained eventually, focused on the area of interest.

The method of paper I was the first step towards interactive optimisation for blade design problems, based on which the methodology of papers II and VI developed. These initial results showed that it is indeed possible to guide the optimisation to a specific direction and the blade designer managed to obtain a detailed Pareto frontier with several alternatives.

5.2 Paper II

I. Gypa, M. Jansson, K. Wolff, & R. Bensow. Propeller optimization by interactive genetic algorithms and machine learning. Ship Technology Research (2021), 1-16.

Division of work

All authors participated in the development of the methodology, provided me with feedback throughout this work, set-up the user scenario and reviewed the paper. Marcus Jansson developed the code for the optimisation methodology and provided the baseline propeller that was used. I developed the code for the ML methodology, performed the optimisation runs, post-processed and analysed the results and wrote the paper.

Aim
In Paper II the interactive optimisation was developed further by enabling the designers to evaluate cavitation and by using an ML model as part of the optimisation process. The purpose of the study is to investigate the behaviour of a user-guided interactive optimisation method as one component in an improved industrial propeller design process.

Summary and Discussion
The methodology is shown in figure 5.2. The interactive part of the optimisation involves the assessment of a cavitation related characteristic, which is the cavity shape at the most critical angle, as shown in figure 5.3. During the optimisation, images of the cavity shape are shown to the blade designer and the designer selects the ones that are considered accepted for the specific project, whereas the remaining ones are considered rejected. The accepted ones form the first generation of the next optimisation run, and the optimisation resumes with the aim to obtain a Pareto frontier that has designs with high performance, following the objectives, and good cavitation, following the preference of the designer. Similarly as in paper I, the interactive part can be carried out as many times as it is considered necessary by the designer, and in parallel it is possible to change the optimisation parameters. The main disadvantage of interactive optimisation processes is the user fatigue, which is caused when the designers have to perform numerous manual evaluations, due to the large populations of the generations in the optimisation. Since it is not possible to reduce the size of the populations for blade design problems, due to the large design space involved, we tried to solve this problem by using an ML algorithm as part of the optimisation process, the SVMs. More specifically, instead of presenting the whole population of individuals to the designer, only a part of the designs is presented, the designer evaluates their cavitation, and based on this evaluation, the SVM algorithm is trained. When a new optimisation run finishes, the evaluation of the cavitation of the designs is predicted by the SVM, instead of requesting manual evaluations by the designer.

The user scenario regards the design of a fixed pitch propeller for a single-screw car-carrier vessel. The optimisation has two objectives, the maximisation of the efficiency and the minimisation of the maximum cavity volume at the MCR condition.

Through the proposed methodology the results showed that it is indeed possible to obtain a detailed Pareto frontier with designs of high performance in terms of objectives, and satisfactory cavitation characteristics, following the preference of the designers. A comparison with an automated approach was done, where there is no interactivity, and both approaches gave almost the same fitness in the objectives. The design space was searched more broadly with the automated approach, but most of these diverse solutions were rejected due to unsatisfactory cavitation, whereas with the interactive approach, solutions were found in a more targeted manner. Regarding the SVM model, it was clearly needed for improving the user fatigue issue caused by the large populations, and its predictability accuracy proved to be high. The sensitivity analysis on the training size of the SVM showed that good accuracy was achieved even with

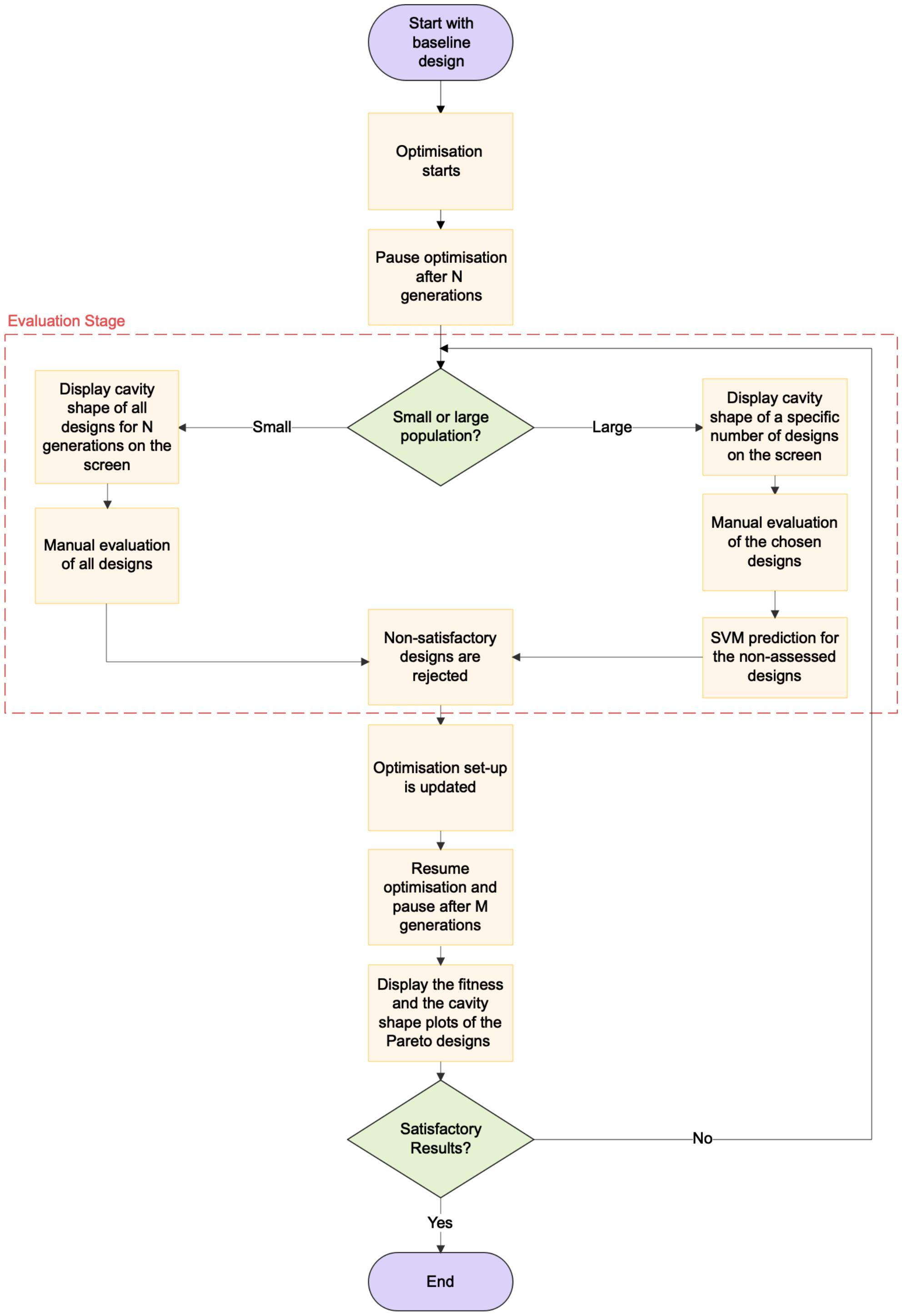


Figure 5.2: IGA Methodology Flowchart

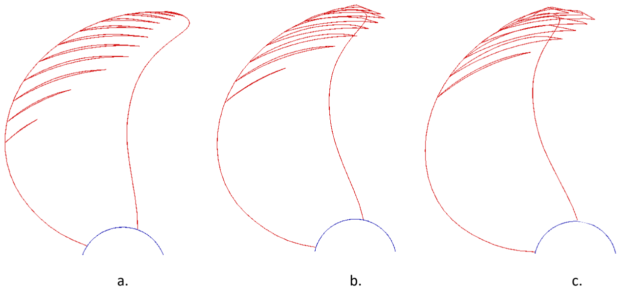


Figure 5.3: Cavity shape of three propellers at their most critical angle

small training sizes of 10-20%. However, with training sizes of 50% and above, the standard deviation was lower, therefore a training size of 50% would be preferred.

Although the method gave overall satisfactory results, the specific blade design was simple, with cavitation only on the suction side, and with only two objectives for the optimisation problem. In addition to this, the designs were presented to the designers one-by-one for assessment, something that increased the user fatigue and the evaluation time. However, this study was a good base for the more complex scenario of paper VI, where the same optimisation methodology is used, with additions on the ML methodology and with a user-friendly cavitation evaluation interface.

5.3 Paper III

I. Gypa, M. Jansson, R. Gustafsson, S. Werner & R. Bensow. Propeller design procedure for a wind-assisted KVLCC2. Proceedings of the 15^{th} International Symposium on Practical Design of Ships and Other Floating Structures, Dubrovnik, Croatia, 2022.

Division of work

All authors participated in the development of the methodology, provided me with feedback throughout this work, set-up the user scenario and reviewed the paper. Marcus Jansson and Robert Gustafsson provided the baseline propeller that was used. Marcus Jansson implemented the new objective in the optimisation tool. I performed the optimisation runs, post-processed and analysed the results and wrote the paper.

Aim

Research and development in WASP, together with actual applications adopting WASP technologies, have increased in recent years as a means for emission reduction. However, there is a research gap in this topic when it comes to the design and optimisation of propellers for such vessels. The aim of paper III has been to present the challenges of the propeller design process in WASP and propose a methodology on how to design and optimise propellers for WASP vessels.

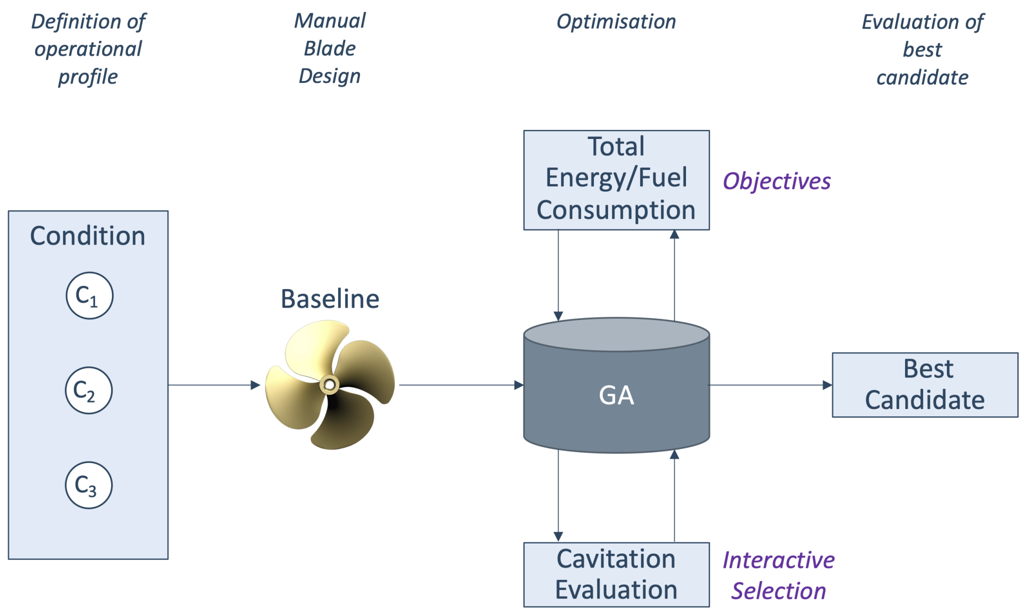


Figure 5.4: Flowchart of optimisation methodology

Summary and Discussion

The main challenge connected to propeller design for wind propulsion is that the vessel operates in a wide range of operating conditions and the propulsion system in a broad load span. For conventional vessels the propeller design work is based on one main operating condition, something that is not possible in wind propulsion, since the design point is not obvious. This suggests that a propeller is needed that operates well in all conditions, including off-design conditions and more lightly loaded propellers. With this in mind, it was concluded that the following are of great importance for the propeller design and optimisation of propellers in wind propulsion:

- Input data for the operational profile.
- To optimise the propeller with an objective that considers all important conditions of the operational profile.
- Control cavitation in all conditions.

In order to deal with this, a methodology is proposed that is shown in figure 5.4. According to it, after receiving as an input route simulations, the blade designer defines the operational profile, by deciding which conditions are the most important ones, and that will affect the blade design. The optimisation is driven by two new objectives, the TEC and the TFC, depending on the provided engine information, and these two objectives are calculated by taking into consideration the conditions that the designer has selected as important. In parallel, the designer controls the cavitation of the designs in all selected conditions through the interactive evaluation that was presented in paper II.

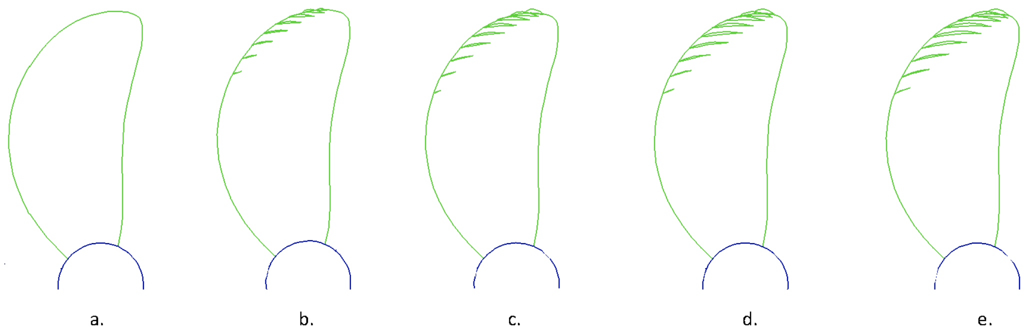


Figure 5.5: Suction side cavitation at critical angle for five conditions

In the case study of this paper, the KVLCC2 vessel is investigated, where six Flettner rotor sails are retrofitted and its operational profile is explored for a route between two fixed destinations. It is explored whether the existing propeller is sufficient for the operating profile of the retrofitted KVLCC2 and in parallel through the optimisation methodology, it is examined whether a new propeller design can offer a significantly lower TEC for the route compared to the existing propeller. Note that the objective of TFC was not utilised in this case, because detailed engine information were not provided.

The baseline blade design geometry of the optimisation is the existing propeller of the vessel. However, independent optimisation runs are performed by having each of the selected conditions as the design condition in each run respectively. When the design is based on one condition, the others are referred as analysis conditions. Although the baseline design is the same, the required K_T is different, because it corresponds to the value of the design condition (and for each run there is a different design condition), and the GA evolves towards different areas of the design space in the search of the optimal TEC.

According to the results, the optimal propeller design offered approximately 0.9% reduction in TEC with the proposed methodology, and it was achieved with the optimisation run driven by the low condition. This suggested that the existing propeller was sufficient and a new propeller should not be retrofitted. Moreover, although some cavitation issues were expected, especially in the off-design conditions, no particular issues appeared at the end. The suction side cavitation for the five conditions, from very lightly loaded to very highly loaded, of the optimal design, is shown in figure 5.5. Also, pressure side cavitation did not appear at all.

The proposed methodology proved to be fast with improved usability and increased reliability. By implementing the new objectives of TEC and TFC, the selected operational profile was considered and post-processing was not needed. Regarding cavitation, the blade designer controlled it interactively, something that ensured designs with cavitation within the acceptable limits during the optimisation. The same methodology is used in paper V, for a more complex scenario for the design and optimisation of a CPP for a wind-powered vessel.

5.4 Paper IV

I. Gypa, M. Jansson & R. Bensow. Cavitation nuisance identification through machine learning during propeller optimisation. Proceedings of the Seventh International Symposium on Marine Propulsors, Wuxi, China, 2022.

Division of work
All authors provided me with feedback throughout this work and reviewed the paper. Marcus Jansson provided the three baseline propellers that were used. I developed the methodology and code for the MLP, performed the optimisation runs, post-processed and analysed the results and wrote the paper.

Aim
In paper II, support vector machines were used in order to reduce the manual evaluations of the blade designer during the interactive optimisation. In this paper more ML algorithms are investigated, along with their hyperparameters. The aim is to build an MLP, which will be used as part of the interactive optimisation methodology, and for every propeller design project the pipeline will find the best ML model. This model can be used later for prediction of cavitation evaluation.

Summary and Discussion
The general concept of the ML methodology is that a dataset is created, which is inputted in the MLP, NCV is used for investigating various hyperparameters of different ML algorithms and the output is the best model for each algorithm. The best model is the one that has the hyperparameters that give the highest accuracy; this is then selected as the final model. When there is a new dataset, this model is used for cavitation nuisance prediction.

In this study, the dataset is created through the optimisation and the prediction is done for a new optimisation run. Three propeller geometries have been used, where propellers I and II have both suction and pressure side cavitation, and propeller III has only suction side cavitation. Since a different model is built for each combination of propeller and cavitation type, there are in total five propeller cases, the I-SS, I-PS, II-SS, II-PS and III-SS, where SS and PS are the suction and pressure sides respectively. Five ML algorithms are investigated and various hyperparameters.

Two different sets of input have been used as input features for the MLP separately: the design variables, such as pitch over propeller diameter, camber, chord length, skew, etc. and the cavitation parameters. This means that two different models are built, based on the two different input sets. The reason that both sets of input features are being used is that the different cavitation shapes of the designs might be produced in different ways, except through optimisation that the blade geometry is known.

According to the results, the prediction accuracy proved to be high (above 90%) for almost all propeller cases. Higher accuracy was generally achieved when the cavitation parameters were the input features. The investigation on the training size of the best models showed that for the three propeller cases, training sizes of 20% provided satisfactory accuracy, while for the two cases, training sizes of 30-50% of the dataset were more satisfactory. In addition to investigating the predictability of the different models, the output of the models was explained by using and presenting the SHAP values. More specifically, variable importance plots were utilised in order to show which input features contributed to the model the most and directionality plots, in order to show which values of the input features had positive or negative impact on the prediction of the model.

Using ML as part of the proposed interactive optimisation method proved to be beneficial in order to identify cavitation nuisance faster, since less manual evaluations by the blade designer were required. Note that the specific pipeline does not necessarily have to be part of the optimisation, but it can be used for cavitation evaluation prediction independently. This pipeline is used in paper VI as part of the optimisation for two advanced design scenarios with contradicting objectives and with cavitation both in the SS and in the PS.

5.5 Paper V

Gypa, I., Jansson, M., Gustafsson, R., Werner, S. & Bensow, R. (2022). Controllable-pitch propeller design process for a wind-powered car-carrier optimising for total energy consumption. Manuscript under review in Ocean Engineering.

Division of work

All authors participated in the development of the methodology, provided me with feedback throughout this work, set-up the user scenario and reviewed the paper. Marcus Jansson and Robert Gustafsson provided the baseline propeller that was used. I performed the optimisation runs, post-processed and analysed the results and wrote the paper.

Aim

WPSP is the concept where the wind is the main source of thrust for the vessel, a type of propulsion that can lead to considerably reduced emissions. The aim of paper V is to present a methodology for designing and optimising a suitable propeller for a wind-powered car-carrier (wPCC), in order to cover the demanding operating needs of WPSP.

Summary and Discussion

WPSP has similar challenges as WASP, but the wind-powered vessels operate in a wider operation, where it is common to have very light loads for the propeller, due to the capability of exploiting the wind more. In parallel, the propeller can often be highly loaded, when there are harsh weather conditions. Therefore, a CPP has been selected for this type of vessel and operation, since CPPs have the advantage of full power utilisation among others. However, the parameter of pitch has to be considered early in the design process, something that increases the complexity

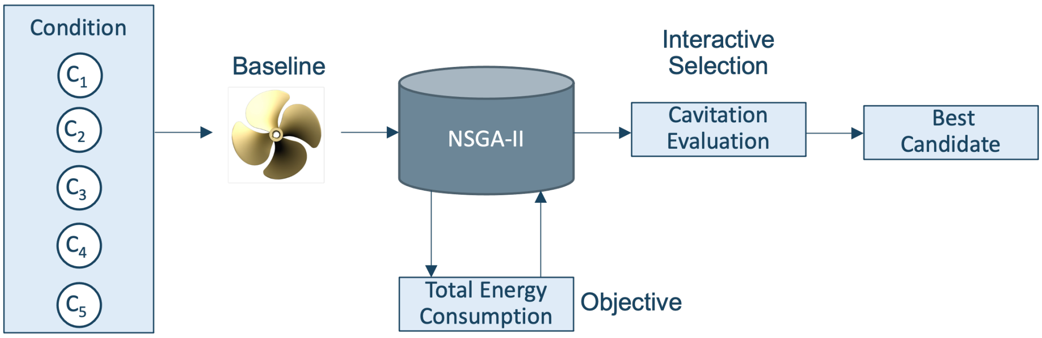


Figure 5.6: Flowchart of optimisation methodology

of the problem.

The case study regards the design and optimisation of a CPP for a wPCC, which is equipped with four rigid wing sails and does a transatlantic crossing between two fixed destinations and operates at a constant speed. A similar design and optimisation methodology has been followed as in paper III, which is shown in figure 5.6. Based on this, first the designers define the operational profile of the vessel, with the aid of results from route simulations that are a necessary input to the design process. The designers select the most important operating conditions, which are five in this study, and for each condition, they create a baseline blade design. The suitable pitch settings for each condition are selected by using the Wageningen C-series with the goal to have high efficiency, which are then corrected in order to have a 5% torque margin to the engine curve. The designer defines the design variables and the optimisation starts with the objective to minimise the TEC. After evaluating the cavitation characteristics of the designs interactively, the best candidate is found.

Since 50% of the time the vessel is sailing and not using the propulsion system, the windmilling, feathering and harvesting functions of a CPP are investigated. The results showed that a feathering CPP offered the lowest drag over ship resistance compared to a windmilling FPP and CPP. Regarding the harvesting operation, it was demonstrated that the shaft losses affected the efficiency of the propeller significantly and should be considered early in the design process. These results were the outcome of open water model test data.

Several optimisation runs were performed for two operational profiles and the lowest TEC for both profiles was obtained from the optimisation runs that had as a starting point the baseline design of the most highly loaded condition. It seems that the reason for this is that although the least time was spent in that condition, the delivered power was very high, which resulted in high energy consumption. Therefore it was more advantageous, for this case study, to optimise the blade design, based on the highly loaded condition, since the effect of the more lightly loaded conditions was not as important for the calculation of TEC. When the starting point of the optimisation was the baseline of a lightly loaded condition, the efficiency in the highly loaded conditions was not that high, something that increased the delivered power of the more highly loaded conditions and this had a negative impact on the TEC.

Regarding the geometry of the optimal designs, they had decreased pitch values at 0.7R, high camber values at 0.7R and 0.95R and minimum chord length. Also the optimisation runs that were carried out with wider limits in the design variables led to lower TEC, but the variable curves should be controlled by the designer so that the result is not infeasible geometries.

Moreover, similarly as in paper III, the expectation here was that there would be cavitation issues, at least in some of the off-design conditions. However, no cavitation was predicted, almost at all.

The proposed methodology proved to be fast and reliable, and it seems that it fulfilled the goals of WPSP along with WASP. Performing independent optimisation runs, based on different baseline designs corresponding to the selected conditions, found to be time-consuming though. However, it is suggested to start the optimisation by having as a starting point the baseline that offers the lowest TEC (based on the selected operational profile), even if this baseline represents a condition that has a stand-alone high energy consumption.

5.6 Paper VI

Gypa, I., Jansson, M. & Bensow, R. (2022). Marine propeller optimisation through user interaction and machine learning for advanced blade design scenarios. Manuscript submitted to Ships and Offshore Structures.

Division of work

All authors participated in the development of the methodology, provided me with feedback throughout this work, set-up the user scenarios and reviewed the paper. I performed the runs for the optimisation and the MLP, post-processed and analysed the results and wrote the paper.

Aim

In paper VI, the methodology of paper II is completed, by combining the interactive optimisation with the MLP of paper IV. The aim of this study is to investigate how the design and optimisation of advanced design scenarios is performed through the proposed methodology.

Summary and Discussion

The framework of the proposed methodology is presented in figure 3.4 and has been described in detail in chapter 3. The case studies regard two advanced design scenarios for CPPs for two ROPAX vessels, involving several design variables, objectives and constraints, and the last are both quantitative and qualitative. In addition to this, operating conditions with cavitation on either the SS or the PS are investigated, something that makes the entire process more complex. The mission profile for each vessel/propeller is different, but in both cases the optimal designs, obtained from the optimisation, are compared to the delivered designs that the blade designers performed manually without using any optimisation tools. The challenge with the specific advanced designs is that except improving the performance of the objectives, when most of them are contradicting, the cavity shape should be controlled as well, based on the preference of the designer.

The results for both designs showed that the proposed method works well towards finding advantageous areas in the design space. Both Pareto frontiers were well-converged, detailed and diverse. There were several competent designs that were considered superior to the manual design, offering the designers a wide selection of designs to choose from.

The ML predictability was lower than in papers II and IV, 79.5% for design I and 72% for design II. SS and PS cavitation of different conditions were both evaluated simultaneously by the designers, thus it was harder to decide which designs should be accepted or rejected, something that led to inconsistent cavitation evaluation. Since the evaluations together with the design variables were used as input for training the ML models, it was reasonable that the prediction accuracy dropped.

Overall, the proposed methodology found to be a good support tool of the entire optimisation process, according to the results and the blade designers.

Chapter 6

Concluding Remarks

The multidisciplinary and multi-objective nature of marine propeller design makes it a challenging problem to solve. In an industrial framework, the marine propeller design process has to be straightforward, well-developed, and be completed under strict time constraints, which is hard to achieve due to the increasing demands on high performance for a wide operational profile. Therefore, this thesis involves several steps taken towards incorporating optimisation in a systematic way to improve the propeller design process and assist the blade designers in order to obtain feasible and high-performance propellers under limited time.

The first objective of the thesis was to develop an interactive optimisation process where the blade designer is enabled to interact with the design tools during the optimisation systematically, assess design characteristics and later input this information back to the optimisation with the aim to have control over the quality of the designs. This method was first developed in paper I, where the designers assessed areas of the Pareto frontier manually, and the results showed that through user-code interaction it is possible to steer the optimisation towards areas of the design space that the designer prefers. The method was further developed in paper II, where the designers manually assessed cavitation characteristics during the optimisation and by comparing the results of the interactive process to an automated optimisation, it was shown that the frontier obtained from the interactive optimisation was more detailed and with more designs that had cavitation characteristics that followed the designer's preference. In paper VI, interactive optimisation was utilised for two advanced design scenarios with several objectives. The results of the interactive optimisation were compared to the delivered design that the blade designers created manually. For both designs the method proved to be very useful and the optimisation offered detailed Pareto frontiers with designs that were superior to the manual design.

From the work done especially in paper II, it was concluded that manually evaluating high number of designs is very laborious. This is related to the primary disadvantage of interactive processes, the human fatigue. A solution to this problem was to create a user interface, which enabled the blade designers to evaluate several designs simultaneously. The user interface was used in papers III-VI and proved to accelerate the evaluation procedure. However, for optimisation runs with very large populations of individuals, the process found to be slow.

Therefore, the second objective was to investigate in which way machine learning (ML) could be part of the design process with the aim to accelerate and support the interactive optimisation. This objective is directly linked to the human fatigue drawback of interactive optimisation. In paper II support-vector machines (SVMs) were investigated and had very satisfactory accuracy with low to normal training sizes. In paper III, more ML algorithms and hyperparameters were investigated with the aid of a machine learning pipeline (MLP) that found the best ML model for each propeller design scenario. The accuracy was satisfactory in this paper as well. In paper VI, the MLP was utilised as part of the interactive optimisation process. For the two advanced design scenarios, conditions with either suction side or pressure side were investigated and ML was used for cavitation evaluation prediction of both types of cavitation. The prediction accuracy of the cavitation evaluation for Design I dropped to 79.5% and for Design II to 72%. However, this was related to the fact that due to the complexity of the scenarios, it was hard for the designers to decide whether some designs were accepted or rejected. Since this information is used for training the ML model, it means that the input to the model was inconsistent and the relatively low predictability is related to that. However, since ML has been used as part of the optimisation process, the predicted cavitation evaluation is utilised as guidance for the algorithm. If some outliers have passed to the next generations during this process, this will not affect the result much. The non-dominated sorting genetic algorithm II (NSGA-II) will find more solutions in the area that has been guided and designs with the highest performance will be promoted to the next generations. Therefore even with lower predictability than in the other scenarios, ML proved to be a useful support tool for the optimisation process.

The third objective of the thesis was to investigate the use of new objectives in the optimisation in order to be able to carry-out more complex scenarios with off-design conditions more efficiently. This was done in papers III and V that represented two complex scenarios for blade design and optimisation of a wind-assisted and a wind-powered vessel. We developed the objectives of total energy consumption (TEC) and total fuel consumption. The objective of TEC proved to be a very useful tool that increased the usability and the reliability of the process, since the entire operational profile was considered with one objective. Although the objectives were developed with wind-propulsion scenarios in mind, we believe that they could be used for the design and optimisation of controllable-pitch propellers in more complex scenarios.

By using the proposed methodology in different scenarios throughout this thesis, it is shown that it is possible to make the optimisation and the designer work together and to yield better results with less manual labour than a pure manual process. We believe that the proposed methodology can be a useful support tool for the designers and enable them carry out the design process more efficiently.

However, in order to better understand the further needs for the specific tool, more information is needed by the designers after utilising it for their everyday design tasks. A human factor research with the participation of blade designers could aid towards that direction. There are several questions that need to be answered, such as after how many user evaluations do the blade designers feel fatigued, if they should be enabled to alternate the geometry of the designs during the optimisation and for which design scenarios should the MLP be used. This process could also create ideas on more new interactive steps that could lead to faster convergence and to more efficient solutions.

Several supervised ML classification algorithms have been utilised in this thesis for the predictability of the cavitation evaluation, for classifying the designs as accepted or rejected, based on their cavitation characteristics. As a next step, clustering methods could be utilised as well, for clustering the designs into different groups based on the performance of the objectives. In this way, the manual evaluations of the cavitation would be focused only on the clusters of high performance, something that could reduce the human fatigue further.

With the more complex design scenarios, the number of the design variables increases, something that makes the search of the design space more laborious. Traditionally, design space exploration, such as exhaustive-search method, is utilised, in order to select the most suitable variables and their ranges, that will constrain the search in the most beneficial areas of the design space. Since this is a time-consuming process, various ML methods could be utilised instead, more efficiently.

References

[1] I. Gypa, R. Bensow, K. Wolff, and R. Gustafsson. *Interactive Evolutionary Computation for Propeller Design Optimization of Wind-Assisted Vessels*. 2020. doi: 10.2514/6.2020-3162. URL `https://arc.aiaa.org/doi/abs/10.2514/6.2020-3162`.

[2] I. Gypa, M. Jansson, K. Wolff, and R. Bensow. Propeller optimization by interactive genetic algorithms and machine learning. *Ship Technology Research*, pages 1–16, 2021. doi: 10.1080/09377255.2021.1973264.

[3] I. Gypa, M. Jansson, R. Gustafsson, S. Werner, and R. Bensow. Propeller design procedure for a wind-assisted KVLCC2. In *15th International Symposium on Practical Design of Ships and Other Floating Structures*, Dubrovnik, Croatia, 2022.

[4] I. Gypa, M. Jansson, and R. Bensow. Cavitation nuisance identification through machine learning during propeller optimisation. In *Seventh International Symposium on Marine Propulsors*, Wuxi, China, 2022.

[5] I. Gypa, M. Jansson, R. Gustafsson, S. Werner, and R. Bensow. Controllable-pitch propeller design process for a wind-powered car-carrier optimising for total energy consumption. Manuscript under review in Ocean Engineering, 2022.

[6] I. Gypa, M. Jansson, and R. Bensow. Marine propeller optimisation through user interaction and machine learning for advanced blade design scenarios. Manuscript submitted to Ships and Offshore Structures, 2022.

[7] I. Gypa. Interactive optimisation in marine propeller design, 2021. Licentiate Thesis.

[8] IEA. Greenhouse gas emissions from energy: Overview, 2021.

[9] IEA. Tracking transport, 2021.

[10] `https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement`. The paris agreement. Accessed: 2022-08-01.

[11] IMO Resolution MEPC.304(72). Initial IMO strategy on reduction of GHG emissions from ships, 2018.

[12] IMO. Fourth IMO GHG study, 2020.

[13] COP26 Declaration. Clydebank Declaration for Green Shipping Corridors. https://ukcop26.org/cop-26-clydebank-declaration-for-green-shipping-corridors/, 2021.

[14] IEA. Transport, 2022.

[15] Mishima S. *Design of cavitating propeller blades in non-uniform flow by numerical optimization*. PhD thesis, 1996.

[16] R. Puisa and H. Streckwall. Prudent constraint-handling technique for multiobjective propeller optimisation. *Optimization and Engineering*, 12(4): 657–680, 2011.

[17] S. Berger, M. Druckenbrod, M. Pergande, and M. Abdel-Maksoud. A two-stage optimisation method for full-scale marine propellers working behind a ship. *Ship Technology Research*, 61(2):64–79, 2014. doi: 10.1179/str.2014.61.2.001. URL `https://doi.org/10.1179/str.2014.61.2.001`.

[18] E. J. Foeth and F. Lafeber. Systematic propeller optimization using an unsteady boundary element method. In *Fourth International Symposium on Marine Propulsors (SMP15); Austin, TX, USA*, 2015.

[19] J. Huisman and E. J. Foeth. Automated multi-objective optimization of ship propellers. In *Fifth International Symposium on Marine Propulsors SMP'17*, Espoo, Finland, 2017.

[20] S. Gaggero, G. Tani, D. Villa, M. Viviani, P. Ausonio, P. Travi, G. Bizzarri, and F. Serra. Efficient and multi-objective cavitating propeller optimization: An application to a high-speed craft. *Applied Ocean Research*, 64:31–57, 03 2017. doi: 10.1016/j.apor.2017.01.018.

[21] S. Gaggero, G. Vernengo, and D. Villa. A marine propeller design method based on two-fidelity data levels. *Applied Ocean Research*, 123: 103156, 2022. ISSN 0141-1187. doi: https://doi.org/10.1016/j.apor.2022.103156. URL `https://www.sciencedirect.com/science/article/pii/S0141118722001031`.

[22] F. Valdenazzi, F. Conti, S. Gaggero, D. Grassi, C. Vaccaro, and D. Villa. A practical tool for the hydro-acoustic optimization of naval propellers. In *Proceedings of the 8th Conference on Computational Methods in Marine Engineering (Marine 2019)*, Gothenburg, Sweden, 2019.

[23] F. Vesting. *Marine Propeller Optimisation - Strategy and Algorithm Development.* PhD thesis, Chalmers University of Technology, 2015.

[24] F. Vesting, R. Bensow, R. Johansson, R. Gustafsson, and N. A. Costa. Procedure for application-oriented optimisation of marine propellers. *Journal of Marine Science and Engineering*, 4, 2016.

[25] F. Vesting, R. Gustafsson, and R. Bensow. Development and application of optimisation algorithms for propeller design. *Ship Technology Research*, 63:50 – 69, 2016.

[26] F. Vesting and R. Bensow. Particle swarm optimization: an alternative in marine propeller optimization? *Engineering Optimization*, 50(1):70–88, 2018. doi: 10.1080/0305215X.2017.1302438. URL `https://doi.org/10.1080/0305215X.2017.1302438`.

[27] P. S. Doijode, S. Hickel, T. van Terwisga, and K. Visser. A machine learning approach for propeller design and optimization: Part i. *Applied Ocean Research*, 124:103178, 2022. ISSN 0141-1187. doi: https://doi.org/10.1016/j.apor.2022.103178. URL `https://www.sciencedirect.com/science/article/pii/S0141118722001213`.

[28] P. S. Doijode, S. Hickel, T. van Terwisga, and K. Visser. A machine learning approach for propeller design and optimization: Part ii. *Applied Ocean Research*, 124:103174, 2022. ISSN 0141-1187. doi: https://doi.org/10.1016/j.apor.2022.103174. URL `https://www.sciencedirect.com/science/article/pii/S0141118722001183`.

[29] Kongsberg hydrodynamic design team. Private Communication, 2022.

[30] J. Dang, HJJ Van Den Boom, and J. Th. Ligtelijn. The wageningen c-and d-series propellers. In *12th International Conference on Fast Sea Transportation FAST*. Citeseer, 2013.

[31] J. Tornblad and KaMeWa AB Marine Laboratory. *Marine Propellers and Propulsion of Ships*. Marine Laboratory, KaMeWa, 1987.

[32] K. O. Holden, O. Fagerjord, and R. Frostad. Early design-stage approach to reducing hull surface forces due to propeller cavitation. Technical report, 1980.

[33] G. Wu, R. Mallipeddi, and Suganthan P. N. Ensemble strategies for population-based optimization algorithms – a survey. *Swarm and Evolutionary Computation*, 44:695 – 711, 2019. ISSN 2210-6502. doi: https://doi.org/10.1016/j.swevo.2018.08.015. URL `http://www.sciencedirect.com/science/article/pii/S2210650217300445`.

[34] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002. doi: 10.1109/4235.996017.

[35] T. Huuva, E. Cerdier, S. Törnros, and O. Klerebrant-Klasson. Propeller and propulsion system optimization. In *SNAME 15th Propeller and Shafting Symposium*. OnePetro, 2018.

[36] S. Törnros, O. Klerebrant, E. Korkmaz, and T. Huuva. Propeller optimization for a single screw ship using bem supported by cavitating cfd. In *Proceedings of the Sixth International Symposium on Marine Propulsors SMP*, volume 19, 2019.

[37] T. W. Simpson and J. Martins. Multidisciplinary design optimization for complex engineered systems: report from a national science foundation workshop. *Journal of Mechanical Design*, 133(10), 2011.

[38] M. Wahde. *Biologically inspired optimization methods: an introduction*. WIT press, 2008.

[39] H. Takagi. Interactive evolutionary computation: fusion of the capabilities of ec optimization and human evaluation. *Proceedings of the IEEE*, 89(9):1275–1296, 2001.

[40] B. Yannou, M. Dihlmann, and R. Awedikian. Evolutive design of car silhouettes. In *DAC 2008*, 2008.

[41] B. Filipič and D. Juričić. An interactive genetic algorithm for controller parameter optimization. In R. F. Albrecht, C. R. Reeves, and N. C. Steele, editors, *Artificial Neural Nets and Genetic Algorithms*, pages 458–462, Vienna, 1993. Springer Vienna. ISBN 978-3-7091-7533-0.

[42] J. H. Lee and M. L. Chang. Stimulating designers' creativity based on a creative evolutionary system and collective intelligence in product design. *International Journal of Industrial Ergonomics*, 40(3):295–305, 2010.

[43] A. Lewis and T. Kipouros. Methods of interactive optimisation in engineering design. 02 2015. doi: 10.13140/2.1.1706.8320.

[44] J. Felkner, E. Chatzi, and T. Kotnik. Interactive particle swarm optimization for the architectural design of truss structures. In *2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES)*, pages 15–22, 2013. doi: 10.1109/CIES.2013.6611723.

[45] C. Simons, J. Smith, and P. White. Interactive ant colony optimization (iaco) for early lifecycle software design. *Swarm Intelligence*, 8:139–157, 2014. ISSN 1935-3812. doi: 10.1007/s11721-014-0094-2. URL `https://uwe-repository.worktribe.com/output/817012`.

[46] J. Madar, J. Abonyi, and F. Szeifert. Interactive evolutionary computation in process engineering. *Computers & chemical engineering*, 29(7):1591–1597, 2005.

[47] X. Sun, D. Gong, and W. Zhang. Interactive genetic algorithms with large population and semi-supervised learning. *Appl. Soft Comput.*, 12:3004–3013, 2012.

[48] M. Ohsaki and H. Takagi. Improvement of presenting interface by predicting the evaluation order to reduce the burden of human interactive ec operators. *SMC'98 Conference Proceedings. 1998 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No.98CH36218)*, 2:1284–1289 vol.2, 1998.

[49] J. Biles, P. Anderson, and L. Loggi. Neural network fitness functions for a musical iga. 1996.

[50] Y. Ren and P. Y. Papalambros. A design preference elicitation query as an optimization process. *Journal of Mechanical Design*, 133(11), 2011.

[51] X. Llorà, K. Sastry, D. Goldberg, A. Gupta, and L. Lakshmi. Combating user fatigue in igas: partial ordering, support vector machines, and synthetic fitness. In *GECCO '05*, 2005.

[52] E. Fix and J. L. Hodges. Discriminatory analysis. nonparametric discrimination: Consistency properties. *International Statistical Review/Revue Internationale de Statistique*, 57(3):238–247, 1989.

[53] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, 79(8):2554–2558, 1982.

[54] J. R. Quinlan. Induction of decision trees. *Machine learning*, 1(1):81–106, 1986.

[55] T. Chen and C. Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 785–794, 2016.

[56] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[57] J. Carlton, J. Aldwinkle, J. Anderson, et al. Future ship powering options: exploring alternative methods of ship propulsion. *London: Royal Academy of Engineering*, 2013.

[58] P. Balcombe, J. Brierley, C. Lewis, L. Skatvedt, J. Speirs, A. Hawkes, and I. Staffell. How to decarbonise international shipping: Options for fuels, technologies and policies. *Energy conversion and management*, 182:72–88, 2019.

[59] A. D. Korberg, S. Brynolf, M. Grahn, and I. R. Skov. Techno-economic assessment of advanced fuels and propulsion systems in future fossil-free ships. *Renewable and Sustainable Energy Reviews*, 142:110861, 2021. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2021.110861. URL `https://www.sciencedirect.com/science/article/pii/S1364032121001556`.

[60] T. Chou, V. Kosmas, M. Acciaro, and K. Renken. A comeback of wind power in shipping: An economic and operational review on the wind-assisted ship propulsion technology. *Sustainability*, 13(4), 2021. ISSN 2071-1050. URL `https://www.mdpi.com/2071-1050/13/4/1880`.

[61] R. Leloup, K. Roncin, G. Bles, J. B. Leroux, C. Jochum, and Y. Parlier. Kite and classical rig sailing performance comparison on a one design keel boat. *Ocean engineering*, 90:39–48, 2014.

[62] R. Leloup, K. Roncin, M. Behrel, G. Bles, J. B. Leroux, C. Jochum, and Y. Parlier. A continuous and analytical modeling for kites as auxiliary propulsion devoted to merchant ships, including fuel saving estimation. *Renewable Energy*, 86:483–496, 2016. ISSN 0960-1481. doi: https://doi.org/10.1016/j.renene.2015.08.036. URL `https://www.sciencedirect.com/science/article/pii/S0960148115302366`.

[63] M. Traut, P. Gilbert, C. Walsh, A. Bows, A. Filippone, P. Stansby, and R. Wood. Propulsive power contribution of a kite and a Flettner rotor on selected shipping routes. *Applied Energy*, 113:362–372, 2014.

[64] L. Talluri, D. K. Nalianda, and E. Giuliani. Techno economic and environmental assessment of Flettner rotors for marine propulsion. *Ocean engineering*, 154:1–15, 2018.

[65] F. Tillig and J. W. Ringsberg. Design, operation and analysis of wind-assisted cargo ships. *Ocean Engineering*, 211:107603, 2020. ISSN 0029-8018. doi: https://doi.org/10.1016/j.oceaneng.2020.107603. URL `https://www.sciencedirect.com/science/article/pii/S0029801820306077`.

[66] I. S. Seddiek and N. R. Ammar. Harnessing wind energy on merchant ships: case study Flettner rotors onboard bulk carriers. *Environmental Science and Pollution Research*, 28(25):32695–32707, 2021.

[67] I. M. Viola, M. Sacher, J. Xu, and F. Wang. A numerical method for the design of ships with wind-assisted propulsion. *Ocean Engineering*, 105: 33–42, 2015. ISSN 0029-8018. doi: https://doi.org/10.1016/j.oceaneng.2015.06.009. URL `https://www.sciencedirect.com/science/article/pii/S0029801815002528`.

[68] R. Lu and J. W Ringsberg. Ship energy performance study of three wind-assisted ship propulsion technologies including a parametric study of the Flettner rotor technology. *Ships and Offshore Structures*, 15(3):249–258, 2020.

[69] E. Lindstad, T. Stokke, A. Alteskjær, H. Borgen, and I. Sandaas. Ship of the future–a slender dry-bulker with wind assisted propulsion. *Maritime Transport Research*, 3:100055, 2022.

[70] `https://www.theoceanbird.com/the-oceanbird-concept/`. The oceanbird concept. Accessed: 2022-07-10.

[71] A. F. Molland and G. J. Hawksley. An investigation of propeller performance and machinery applications in wind assisted ships. *Journal of Wind Engineering and Industrial Aerodynamics*, 20:143–168, 1985.

[72] J. Andersson, R. Gustafsson, A. Eslamdoost, and R. E. Bensow. On the selection of optimal propeller diameter for a 120-m cargo vessel. *Journal of Ship Research*, 65(02):153–166, 2021.