Development and Application of

Robust Design Optimization

Methods for Turbomachinery

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STUDENT REPORT

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Abstract:

The influence of manufacturing variations on product performance shows that manufacturing uncertainties should be considered already in the development phase. One way of doing this is by combining numerical optimization and sensitivity analysis. This unification is referred to as Robust Design Optimization (RDO). RDO methods can be applied to any type of product, but the aim of this project is to develop and apply RDO methods for turbomachinery applications that use inverse design methods. Existing RDO methods are used to inspire new approaches that are tested on a representative case. The RDO methods revolve around a CFD model created to successfully facilitate RDO. Results show that while none of the tested methods are successfully able to produce a more robust design than conventional optimization in this case, designs performing similarly can generally have different performance variations and hence sensitivities. In addition to this, the hydraulic sensitivity of the blade has also been investigated through a sensitivity analysis. This shows the trailing edge to be the most sensitive part of the blade, and the tolerances should therefore be tighter at the trailing edge in this design. Since the sensitivity analysis is performed on a single nominal design, it cannot be extrapolated to apply to all impellers. Until more studies are performed and potential general tendencies are identified, it is therefore recommended to always investigate the hydraulic sensitivity of a design before specifying tolerances.

Pages, total: 63
Appendices: 3

Executive Summary

Presently, pumps and other turbomachinery applications are developed without considering the impact that manufacturing deviations have on the performance. This often results in the increase of costs, performance variation and time-to-market. Therefore, this thesis provides an analysis and evaluation of the potential improvements that Robust Design Optimization (RDO) methods can provide to the current development methods. The thesis seeks to answer the following research question:

Can Robust Design Optimization be used to improve existing pump design methods and to specify tolerances for pump manufacturing?

RDO is a relatively young term that covers a wide range of combinations of methods that generally seek to locate a robust optimum with low performance variation. The common denominator for these methods are the combination of numerical optimization and uncertainty quantification. To investigate if RDO can improve the current development methods, two new methods named One-Design-At-a-Time (ODAT) RDO and hybrid RDO are developed and applied to a representative case. By comparing how these methods perform to how the conventional methods perform, the RDO methods can be assessed. The best design from these methods is then subject to an uncertainty quantification, which can be used to determine how tolerances are best specified to reduce performance variation and costs and to ease manufacturability.

Results show that ODAT RDO is the most promising of the two RDO methods in terms of improving the existing methods, however, there is no significant difference between the design obtained using ODAT RDO and the one obtained through conventional methods. In fact, the two methods produce the same design, which is likely caused by the global optimum also being the most robust in this case. While ODAT RDO is unsuccessful in this case, it is evident from the results that the performance variation of two designs with equal mean performance can differ significantly. Hence, ODAT RDO or a similar method may be successful in other cases.

Investigations into the sensitivity of the blade show that different regions of the blade have different sensitivities in terms of their impact on the performance variation. The results find the trailing edge to be the most sensitive part, which means variations in this part have the largest impact on variations in efficiency, power consumption and head gain. The leading edge is of less importance, but still influences the efficiency, while the middle part of the blade are the least important region in terms of all three parameters. The study also shows that it is advantageous to tighten tolerances in regions with high sensitivity, while they can be loosened in regions of low sensitivity.

The results of this study are limited to the case to which they have been applied. Therefore, more studies are recommended to determine the extent to which the conclusions drawn here can be applied to other impeller types, design cases and potentially other turbomachinery applications. Considering the limitations of this study, the following recommendations are made:

- More studies applying ODAT RDO and similar methods to different cases are recommended as there is a large potential in successfully locating robust designs.
- Investigations into how broadly the knowledge produced in this thesis can be applied are also recommended. Eventually, this might remove the need for a uncertainty quantification of all future designs.
- Considering the sensitivity of the design in the tolerance specification is strongly advised. Until it is determined how broadly the current knowledge can be applied, this requires an uncertainty quantification of the design.

Preface

My name is Michel Noaparast, and I am currently writing my Master's thesis in Thermal Energy and Process Engineering at Aalborg University. The thesis is titled "Development and Application of Robust Design Optimization Methods for Turbomachinery" and is carried out as a collaboration between Grundfos and Aalborg University. Prior to this thesis, I did a report named "Assessment of Robust Design Optimization Methods (RDO) on CFD Applications". Here, preliminary investigations were performed to test the different methods within Robust Design Optimization on CFD. The findings were promising and substantiates the need for more investigations into RDO.

Grundfos is a pump development and manufacturing company, and their knowledge and methods are the product of decades of working with pumps. Due to the collaboration, I will have access to world-leading commercial software and tools that are currently used at Grundfos. Taking full advantage of the powerful commercial software means that some of the underlying methods cannot always be modified, and some of these will therefore not be treated in details. The thesis is carried out using an arbitrary design case and as such, the results in this thesis do not reflect the performances of any of Grundfos' pumps.

The report presupposes a certain level of knowledge within numerical optimization, CFD and fluid mechanics. Basic knowledge with centrifugal pumps is also recommended.

This thesis deals with applying Robust Design Optimization (RDO) to the development phase of an impeller for a centrifugal pump, which requires combining RDO and Computational Fluid Dynamics. All results in the thesis are based exclusively on numerical simulations and the thesis contains the following parts:

- Nomenclature containing lists with explanations of abbreviations, commonly used terms, symbols and subscripts. Figures showing key parts and view angles of the pump can be found here as well.
- Introduction to the challenges of the current design methods followed by a problem statement and a description of different RDO methods.
- Description of the design case and how the geometry is parametrized.
- The set-up for the CFD model and investigations into how to find the best trade-off between accuracy and calculation speed.
- Description of the application and execution of RDO methods. The results are presented and the best design is used for a robustness evaluation, where the sensitive parts of the geometry are highlighted for future tolerance specification.
- Evaluation of the findings and future perspectives within RDO.
- Three appendices describing the inverse design method, the method used to perturb the geometry and the underlying methods in RDO.

Nomenclature

List of abbreviations

Abbreviation	Explanation
3D	Three dimensional
app	Appendix
ALHS	Advanced Latin Hypercube Sampling
ARSM	Advanced Response Surface Method
BC	Boundary Condition
BEP	Best-Efficiency-Point
CAD	Computer-Aided-Design
CAE	Computer-Aided-Engineering
CFD	Computational Fluid Dynamics
CoP	Coefficient of Performance
DoE	Design of Experiments
EA	Evolutionary Algorithm
eq	Equation
FF	Full Factorial
gv	Guide vane
imp	Impeller
K	Kilo (Thousand)
LHS	Latin Hypercube Sampling
LE	Leading Edge
MCS	Monte Carlo Simulation
MLS	Moving Least Squares
MOP	Meta Model of Optimal Prognosis
NLPQL	Non-Linear Programming by Quadratic-Langrangian
ODAT	One-Design-At-a-Time
PDF	Probability Density Function
RDO	Robust Design Optimization
RFR	Rotating Frame of Reference
RMS	Root-Mean-Square
SST	Shear-Stress-Transport
std	Standard
SVR	Support Vector Regression
TE	Trailing Edge

List of terms

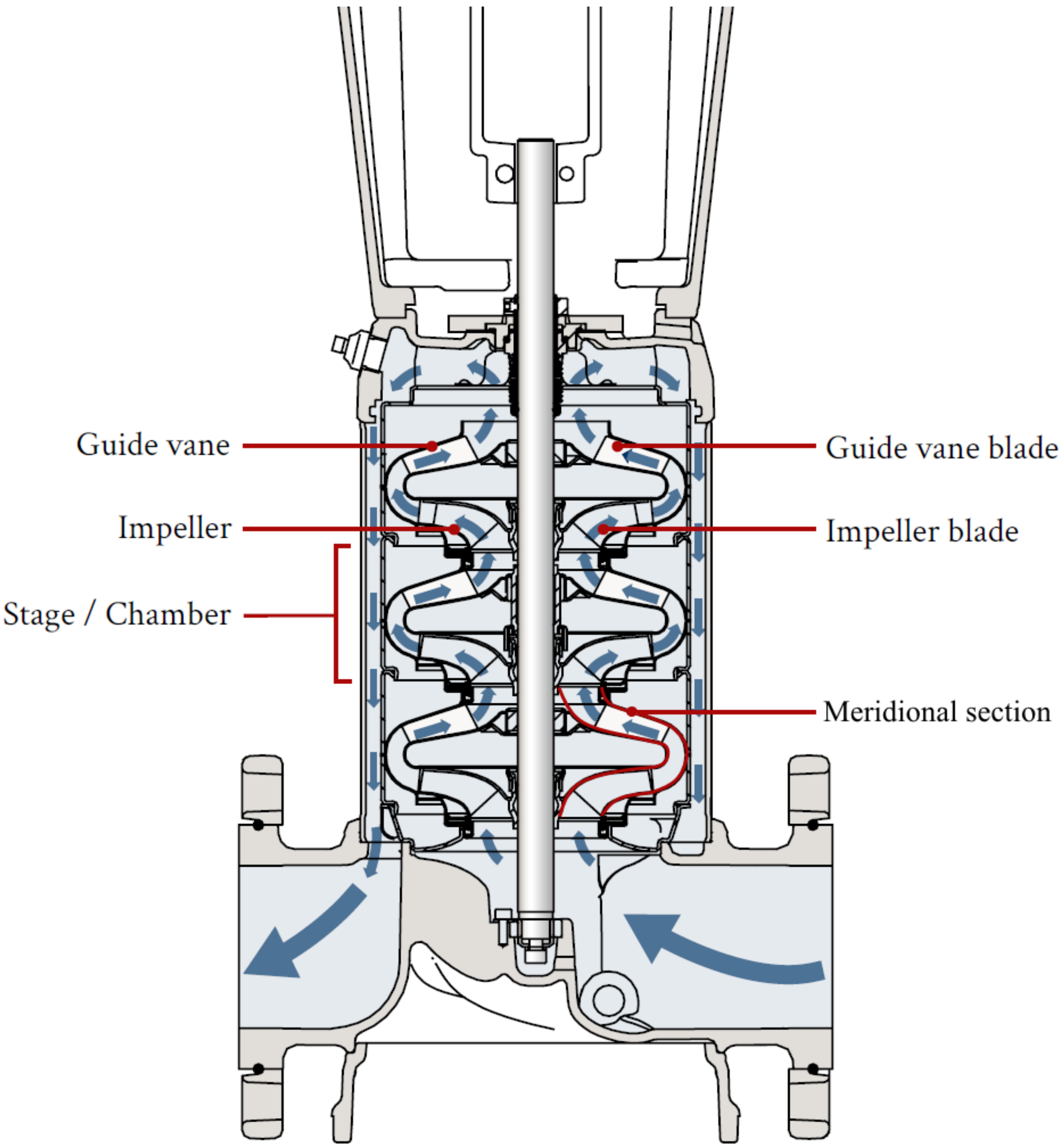
Term	Explanation
Best-Efficiency-Point (BEP)	The flow rate and rotational speed at which the pump operates at highest efficiency.
Constraint	Limitation on the optimization domain.
Design of Experiments (DoE)	Range of methods used to investigate a parameter space through sampling.
Failure limit	Limit that determines if a design fulfils the requirements or not.
Global optimization	Optimization across the entire domain.
Latin Hypercube Sampling (LHS)	A quasi-random DoE method based on Monte Carlo Simulation.
Leading edge	The front edge of the blade.
Local optimization	Optimization where the optimization domain is only searched locally.
Meridional cut	Cross-sectional view of a component.
Meta model	A model consisting of analytical functions that can be used as a substitute for more expensive models.
Nominal design	Refers to the design created from the design process. Differs from the manufactured component due to manufacturing variations.
Perturbation	Deformation of something. Used to replicate manufacturing variations.
Response	The output of the solver.
Robustness	The sensitivity of a design. High robustness means a lower variation in the response.
Robustness evaluation	Sensitivity analysis showing the response variation and the sensitivity of the design.
Robust Design Optimization (RDO)	The combination of numerical optimization and uncertainty quantification in the design phase.
Trailing edge	The rear edge of the blade.
Uncertainty quantification	The investigation of the uncertainties affecting the nominal design due to variations in the real world. It will be carried out through the robustness evaluation.

List of symbols

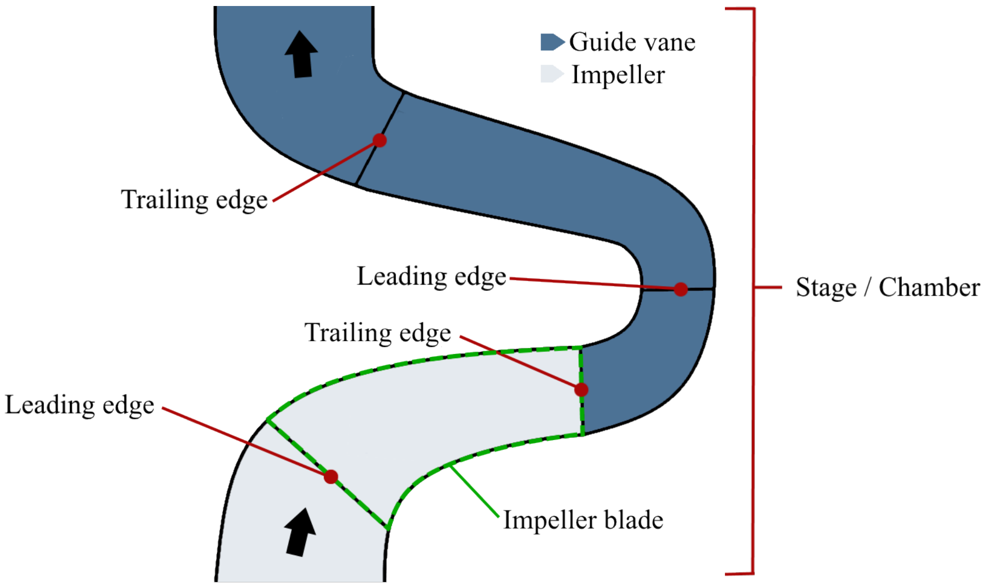
Symbol	Explanation	Unit
β	Blade angle	[°]
C	Absolute flow velocity	[m/s]
C_P	Reduced pressure coefficient	[–]
ΔH	Head gain	[m]
η	Efficiency	[–]
inv	Inverse	[–]
P	Pressure	[Pa]
P_2	Hydraulic power consumption	[W]
pert	Perturbation	[–]
ρ	Density	[kg/m^3]
r	Radius	[m]
rVt	Relationship between C_{2U} and U_2	[–]
U	Refers to x-direction of a 3D coordinate system	[–]
U_2	Tangential blade velocity	[m/s]
V	Refers to y-direction of a 3D coordinate system	[–]
W	Refers to z-direction of a 3D coordinate system	[–]
ω	Rotational speed	[°/s]
Q	Flow rate	[m^3/h]
Z	Axial height of the front plate	[m]

List of subscripts

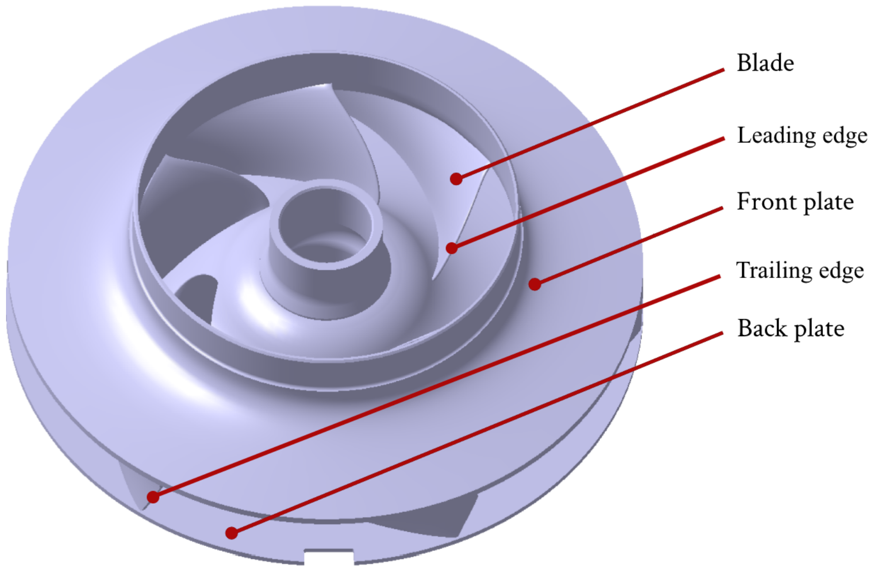
Script	Explanation
0	Stagnation
1	Inlet
2	Outlet
d	Design target
F	Front plate
B	Back plate
nom	Nominal
opt	Optimum
rot	Rotational
tang	Tangential



Cross-sectional cut of the multi-stage pump. [Grundfos R&D, 2008]



Meridional shape of an impeller and a guide vane in a single stage.



Impeller consisting of a front plate, a back plate and six blades.

Contents

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First Chapter

Introduction

The global pump market is highly competitive and the demand for better and cheaper pumps is therefore ever-increasing. At the same time, simulation capabilities have increased significantly in the recent decades. As a result, CAE-based (Computer-Aided Engineering) optimization combined with numerical simulation is now widely used within the pump industry as part of the development process [Li and Zheng, 2017]. By doing CAE-based optimization a highly optimized nominal design can be obtained. This design will often perform near the boundary of the requirements in order to reduce the costs, and therefore even small geometric deviations from the nominal design could mean that the component no longer meets the requirements. Challenges can therefore occur when the nominal design is to be manufactured. Geometric deviations will occur between the nominal design and the manufactured component, and thus the component will perform poorer and may no longer fulfil the design requirements.

An example of how a manufactured component can deviate from a nominal design is shown in Figure 1.1. As seen, the geometric deviations are especially large for the impeller blades, and these are therefore of significant interest in an RDO process. In the example shown, the geometric deviations are more than 0.5 mm and as seen in Figure 1.2, this heavily affects the power consumption. This calls for an improvement of the existing design strategy, where the variation in the output is considered.

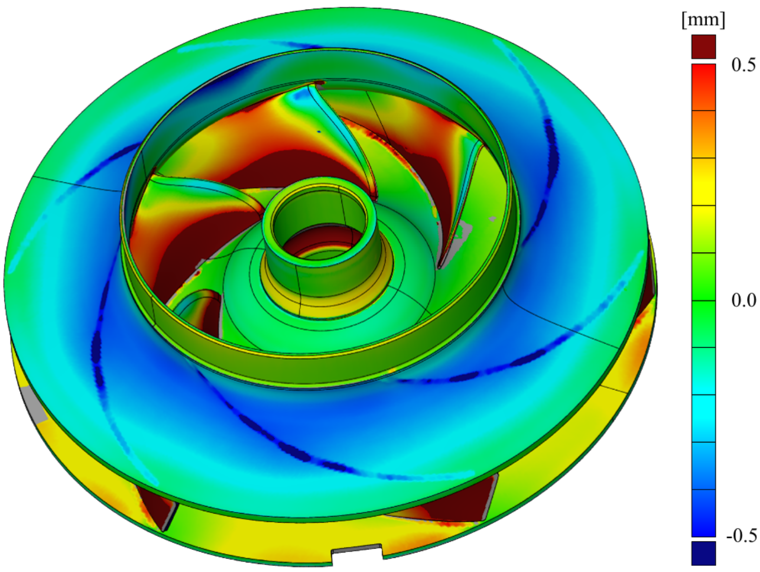


Figure 1.1: Deviations between a nominal design and a manufactured component. Units are normalized with blade thickness.

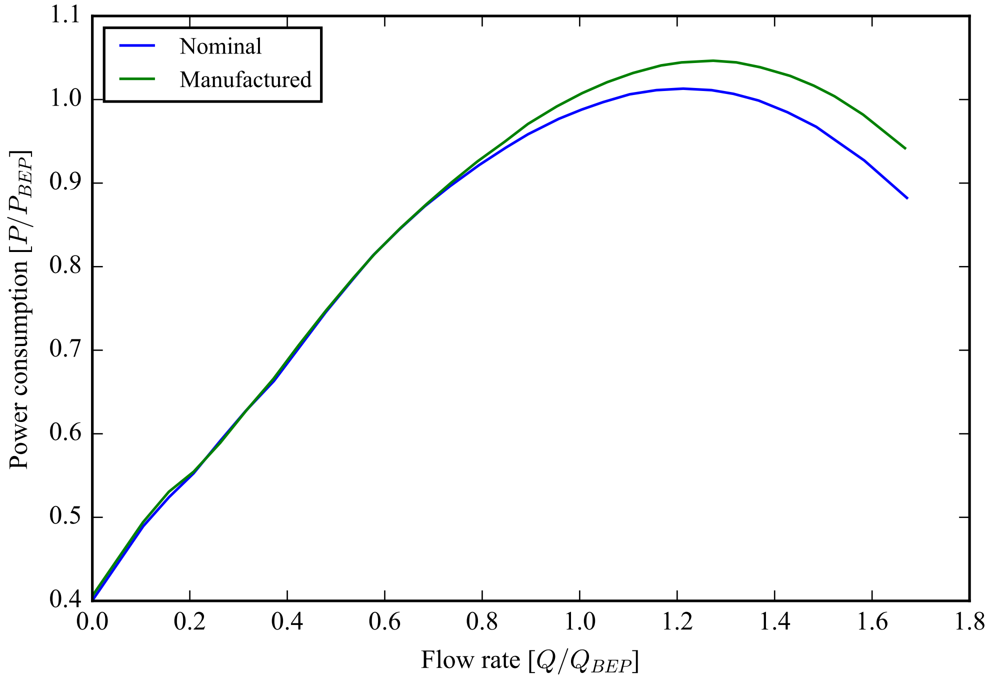


Figure 1.2: The power consumption for the nominal design and the manufactured component from Figure 1.1. The power consumption are calculated from a CFD model. The blade thickness is 1 mm.

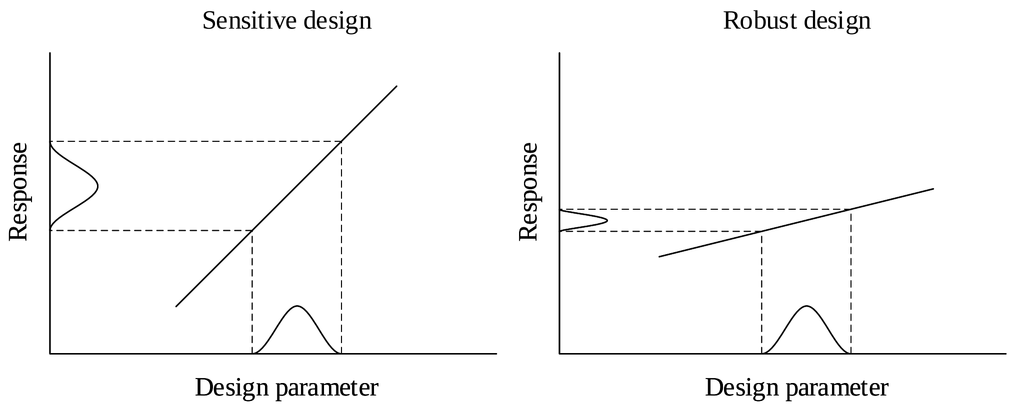


Figure 1.3: An illustrative example of the difference between a sensitive design and a robust design.

Taguchi [1987] introduces the concept of Robust Design Optimization (RDO) as a way of handling these geometric deviations in manufacturing. Taguchi believes that by combining traditional optimization with uncertainty quantification, a design can be developed where the uncertainty sources have minimum influence on the response. The uncertainty can for example be quantified through an evaluation of the design sensitivity using a robustness evaluation. The robustness evaluation is a type of sensitivity analysis that focuses on determining the response variation and identifying what parameters cause the variation. A design with low impact from the uncertainty sources is referred to as a robust design based on Taguchis definition of robustness. The concept of robustness is defined by Taguchi [1987] as being resilient towards factors that cause variations in for example performance. An example of such a factor is geometric variations of a component as a result of manufacturing. The robust design may therefore have lower nominal performance than a design obtained from traditional optimization, but the robustness ensures that the performance is preserved in manufacturing, which may not be the case with a traditional design. Figure 1.3 illustrates the difference between a robust design and a traditional design.

"Robustness is the state where technology, product, or process performance is minimally sensitive to factors causing variability (either in manufacturing or in the user's environment) and aging at the lowest unit manufacturing cost."

- [Taguchi, 1987]

Turbomachinery literature generally uses the direct design method in the RDO process [Einzinger, 2014] [Roos et al., 2009]. One of the drawbacks of this approach is that the direct method contains a large number of design parameters, making optimization and hence also RDO difficult. Therefore, this thesis proposes using the inverse design method in the RDO process, where fewer design parameters are required. The inverse design method is described in app. A.

As mentioned, RDO seeks to combine traditional optimization methods and uncertainty quantification. A large number of approaches towards achieving this can be found in the literature [Arora, 2017] [Yaping and Chuhua, 2016] [Chakraborty et al., 2017] [Yi et al., 2018]. Common for all these methods and the original methods suggested by Taguchi [Schwarz, 2017] [Taguchi, 1987] are that they perform RDO using the same parametrization of the geometry in both the optimization process and the uncertainty analysis. While it is often correct to assume that the design parameters are quantifiable, geometric dimensions, this is not the case with the inverse design method. When investigating the influence of manufacturing variations through simulations, the geometry parametrization must be able to mirror the actual variations that occur in manufacturing in a quantifiable way, however inverse design parameters cannot be directly linked to parameters that describe geometric variations. Hence, the traditional parametrization of an RDO problem, where the same parametrization is used for all steps, is insufficient in this case as two different parametrizations are required.

Furthermore, RDO is often applied to create a design that does not exceed some prescribed failure limit [Schwarz, 2017], which is something that can also be obtained through conventional optimization using a safety margin. When applying RDO that way, the resulting design is not necessarily less sensitive towards geometric variations. Instead, the design may simply have a sufficiently large safety margin for the variations not to cause a violation of the limit. While such a design is often referred to as a robust design, this is not the interpretation of robustness that Taguchi [1987] expresses in the quote above nor the interpretation used in this thesis. Robustness means low sensitivity towards input variations, which can be translated directly as having the lowest possible variation in the output given a defined input variation. An appropriate robustness property therefore describes the variation and can for example be the standard deviation of a normal distribution.

As a result of this interpretation of robustness, new RDO methods that consider the robustness of multiple designs are developed. This is used to determine if it is possible to locate designs with varying robustness properties but similar performance. If that is the case, the methods can also be used to locate the most robust of the designs. These methods will also be able to handle both inverse and geometric parametrizations making them suitable for the inverse design method.

Once a robust design is found, the next step is to investigate how to set the tolerances for manufacturing. By employing parts of the RDO process, it is possible to not only determine the output variation caused by the inputs, but also determine what input parameters contribute most to the variation. Hence, stricter tolerances can be specified in selected areas of the component, where the sensitivity is high. Such an investigation is a natural extension of any RDO process and will therefore be performed on the best design from the RDO processes.

Second Chapter

Problem Statement

This thesis investigates the use of Robust Design Optimization (RDO) in the design phase of turbomachinery applications, where CFD simulations are used. Previous RDO methods do not facilitate cases where the design parameters are not directly linked to the geometric parameters. This makes it impossible to investigate the influence of manufacturing variations when the inverse design method is used, despite the inverse design method being well-suited for numerical optimization as a result of the small number of design parameters. Due to the advantages of the inverse design method, a new RDO methodology capable of handling both inverse and geometric parameters is desired.

Furthermore, the advantage of RDO over conventional optimization is the consideration of manufacturing variations. A big part of these manufacturing variations are controlled by the manufacturing tolerances specified by the designer. Hence, investigating how to set the manufacturing tolerances is a natural extension of an RDO process. This leads to the research question:

Can Robust Design Optimization be used to improve existing pump design methods and to specify tolerances for pump manufacturing?

The question will be answered by developing and testing new RDO methods and applying them to a real pump case to attempt to locate a robust design. The case should reflect real life design tasks and will therefore be to develop a sheet metal impeller for an existing pump using CFD modelling. Furthermore, the RDO methods should account for two types of parametrizations, namely the inverse parameters and geometric parameters. The geometric parameters will be limited to cover the blade variations, since this is where the most significant variations are observed. Once the methods have been applied, the resulting designs can be compared to a design obtained using traditional design optimization, and thus the new RDO methods can be evaluated with respect to their ability to produce robust designs as well as the additional calculation time that they require.

The tolerances will also be investigated using RDO methods to improve the performance of the final manufactured component. The purpose behind this approach is to specify stricter tolerances in the parts of the design, where geometric variations have the highest impact on the responses. This will result in a final component with smaller response variations, while maintaining low manufacturing costs.

2.1 Comments and remarks

The RDO methods are presented with a focus on sheet metal impellers, but can generally be applied to both composite and moulded impellers with the right parametrizations and tolerance considerations. The robustness is evaluated with respect to variations in the blades, since these are subject to the most significant geometric deviations during manufacturing for this impeller type, but once again this can be changed for other cases. Hence, this thesis presents generalized RDO methods that can be used in many different cases to find designs that are less sensitive towards geometric variations.

The CFD model is a crucial part of the RDO process in this thesis, and a computationally expensive CFD model will make RDO impossible. Therefore, a significant part of this thesis also focuses on finding the set-up that provides the best trade-off between accuracy and calculation speed. This ensures the most favourable surroundings for the RDO processes to be successful.

One of the drawbacks of RDO and optimization in general are the high computational costs. The traditional design process for pumps focuses on the performance curves from 0 % to well-above 100 % of the Best Efficiency Point (BEP) flow rate. This is not realistic when combining any type of optimization with CFD, and the focus of an optimization process is therefore typically on a single flow point. In this case, the BEP flow rate will act as the design point, but any flow point can in principle be used. This limitation of optimization methods means that optimization and hence also RDO cannot be used alone as a design tool. It is necessary to also investigate how the entire performance curves look. Hence, RDO should be used to locate robust designs that can then be further investigated over the entire flow domain, however, this thesis will focus only on developing and applying RDO.

A wide range of optimization algorithms exist, many of which are well-suited for this thesis. It is therefore not straight-forward to select one method as the best. However, different algorithms will not be tested as this is a time-consuming investigation and are not within the scope of this thesis. Instead, appropriate methods will be used based on the optimization formulation, case and recommendations found in the literature.

It is common practice within optimization that algorithms are tested and benchmarked with respect to some known benchmark optimization problems, typically known analytical functions [Jain et al., 2018]. However, the main focus of this thesis is to perform RDO on CFD applications, and doing RDO on analytical benchmark functions will not elucidate all challenges that arise when doing RDO on CFD. These are challenges such as a varying responses due to solver noise (for example due to mesh variation), to some extent the calculation time, verifying that CFD can actually detect small geometry variations and so on. As such, doing benchmark tests becomes a time consuming process without sufficient reward. For these reasons, the RDO methods will not be benchmarked with respect to a known optimization problem.

THIRD CHAPTER

Development of Robust Design Optimization Methods

Robust Design Optimization (RDO) refers to a number of different approaches that combine optimization and uncertainty analysis. The main goal of this thesis is to determine the best RDO approach to handle a CFD solver and both inverse and geometric parametrizations. The following sections will therefore describe the different RDO approaches that are investigated in this thesis. Relevant underlying methods within RDO are explained in greater detail in appendix C. The appendix covers the Design of Experiments (DoE) method, the optimization methods and the method of uncertainty quantification, which is referred to as a robustness evaluation.

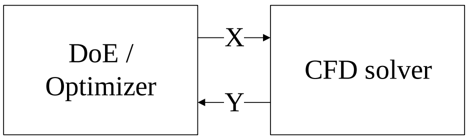


Figure 3.1: The two fundamental blocks of a design development process that uses a numerical optimization loop and CFD simulations.

The flow chart in Figure 3.1 shows the fundamental blocks of any optimization loop. Both blocks contain a number of steps that can vary depending on the case, but all methods presented in this thesis can generally be summarized into those two blocks. The RDO method dictates the contents of the left-hand block in Figure 3.1, and hence this block is the focus of this chapter.

3.1 Conventional optimization

To evaluate the performances of the different RDO approaches, it is necessary to compare the results to a result from a conventional optimization process. Therefore, this section will present how the conventional optimization process in this thesis will look. Conventional optimization is characterized by not considering the robustness of the designs.

Since the solver is a CFD model, it can be an advantage to adopt a variant of optimization that uses the optimization of a meta model to estimate the optimum. This is done as a preliminary optimization step as shown in Figure 3.2. A meta model is a surrogate model that can be used as a substitute for an expensive solver call. The meta model aims to mimic the real solver and is typically an analytical function that is fast to evaluate. The meta modelling method is described in appendix C. The preliminary optimization of the meta model is followed by a local optimization with direct solver calls. The purpose of this approach is to reduce the calculation costs by minimizing the number of real solver calls needed.

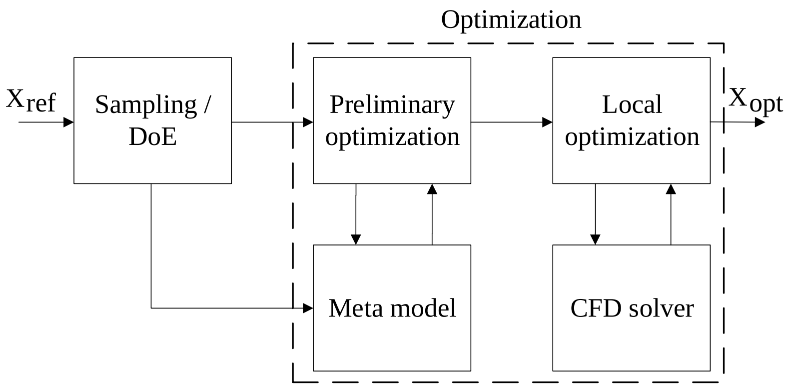


Figure 3.2: A flow chart of a numerical optimization process that uses meta modelling as a preliminary optimization step.

As seen in Figure 3.2, the first step is to investigate and describe the design space by employing a Design of Experiments (DoE) method, which is then used to produce a meta model. The best design from the DoE is used as the starting point for a preliminary optimization step, where the meta model is called rather than the actual solver. This is followed by a local optimization with real solver calls, where the actual optimum is found. The optimization flow in Figure 3.2 is used as the fundamental optimization work flow in all the following RDO processes.

3.2 Iterative and simultaneous RDO

In simultaneous RDO, a robustness evaluation (see app. C) is performed for each iteration in the optimization as shown in Figure 3.3. The robustness evaluation then returns the performance variation and mean value for the design in the current optimization iteration. This makes it possible to include robustness directly into the optimization by using it as either an objective or a constraint. However, doing that many robustness evaluations results in a large number of solver calls. With a CFD solver, the calculation time can therefore easily exceed a week even with a cheap CFD model and significant computer power.

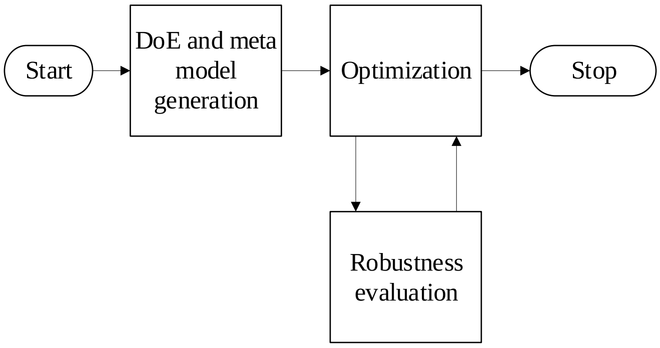


Figure 3.3: A flow chart of a simultaneous RDO process.

Iterative RDO is a cheaper alternative to simultaneous RDO that only requires few robustness evaluations. Initially, iterative RDO performs a conventional optimization without considering the robustness. After the optimization, the robustness of the optimum design is found through a single robustness evaluation. If the design violates the robustness requirements, a new optimization is performed, where either the constraints, the input variations or both are adjusted. A new design is then obtained through the optimization, which may or may not fulfil the requirements. This continues until a satisfactory design is obtained. The work flow is shown in Figure 3.4.

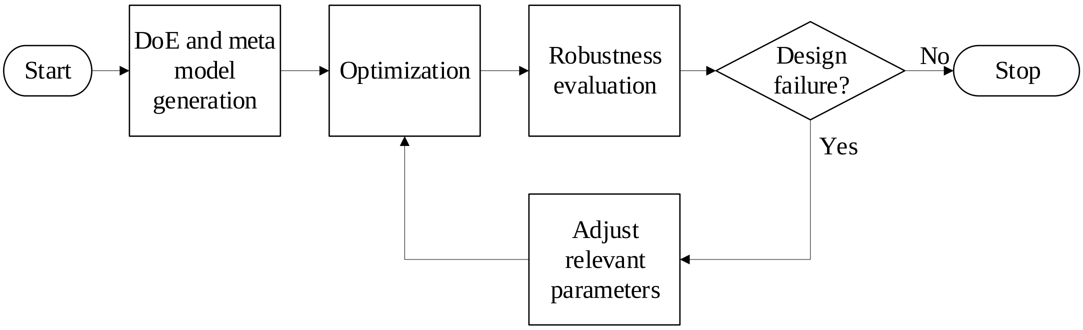


Figure 3.4: A flow chart of an iterative RDO process.

Iterative RDO is often preferred over simultaneous RDO due to the computational costs [Most and Will, 2017] [Wanzek et al., 2015] [Niemeier et al., 2015] [Schwarz, 2017]. However, iterative RDO does not include robustness directly into the optimization and does not produce a more robust design. At the same time, simultaneous RDO is computationally expensive, and it is therefore necessary to develop alternative methods that seek to combine the advantages of the two methods. This is presented in the following sections.

3.3 ODAT RDO

The first method to be investigated is inspired by iterative RDO, where the robustness evaluations are only performed a few times. The disadvantage of iterative RDO is that the design in each robustness evaluation will be similar to the previous design, and hence the robustness in terms of output variation will likely be similar. Therefore, the One-Design-At-a-Time (ODAT) RDO approach presented in this section is a method, where the robustness of different designs is considered. The fundamental idea is to systematically constrain a selected input parameter at for example three different levels corresponding to three different designs. The remaining inverse parameters are then used for an optimization for each level, which will produce three optimized designs with different geometries that all fulfil the design requirements with respect to head gain and flow rate. Each design can then be evaluated in terms of their robustness. This will indicate whether or not different designs actually have different robustness properties. This method is therefore superior to iterative RDO in terms of both the knowledge gained and the potential for obtaining a robust design, while still remaining cheaper than simultaneous RDO. The ODAT RDO work flow is shown in Figure 3.5, and as seen it will require multiple optimizations and robustness evaluations, however ODAT RDO is not significantly more expensive than iterative RDO, where multiple optimizations and robustness evaluations can also be expected.

Prior to the optimizations, it is necessary to determine a reference design from which the constrained parameter can be decided. This is obtained by doing a DoE to create a meta model, which can then be optimized to obtain a reasonable reference design. From the meta model optimization it can be decided what input parameter to constrain, how many designs are desired and what values to constrain the parameter at.

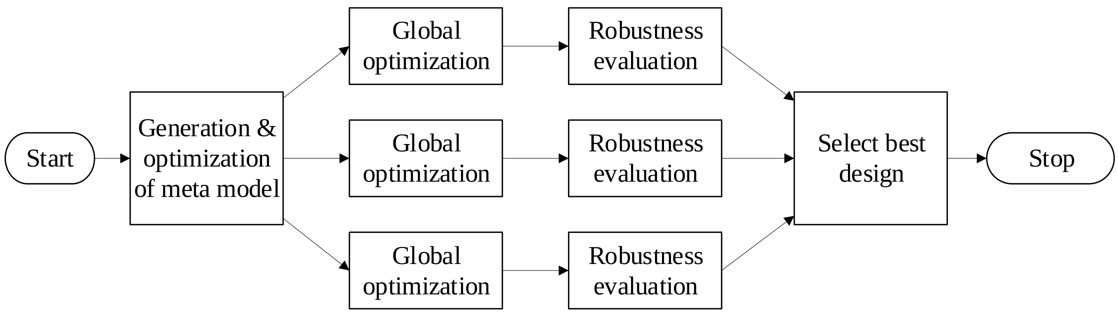


Figure 3.5: A flow chart of the ODAT RDO method evaluating three designs.

The optimizations are performed using inverse parameters, while the robustness evaluations are performed using blade perturbation parameters as explained in app. C. This method is therefore capable of handling the two different parametrizations as required.

3.4 Hybrid RDO

The advantages of simultaneous RDO are significant and including robustness directly into the optimization can be especially advantageous, when the purpose is to locate a design that is insensitive towards geometric variations. Therefore, a hybrid method is developed which will make it possible to include robustness directly into the optimization, while at the same time attempting to reduce the computational costs compared to simultaneous RDO.

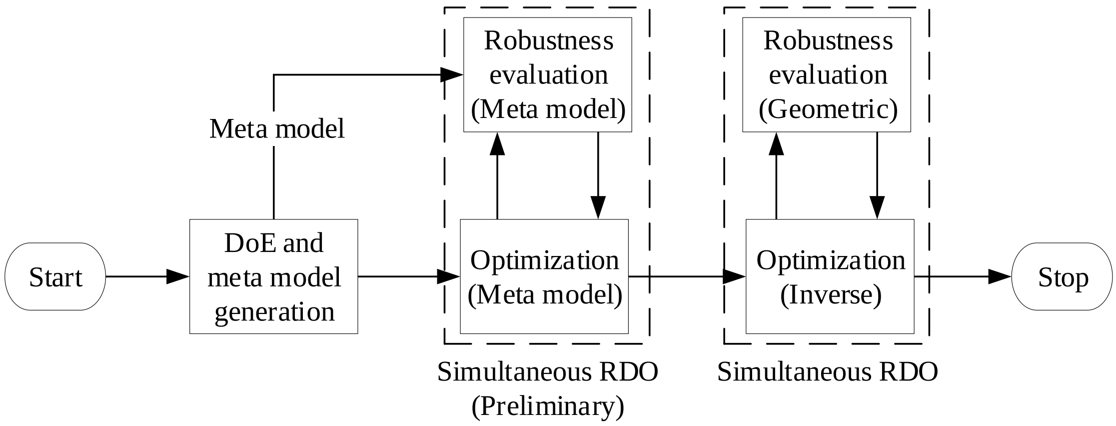


Figure 3.6: A flow chart of the hybrid RDO method.

To reduce the costs, the hybrid method finds inspiration in the optimization flow described in Figure 3.2, where a meta model is used initially in the optimization. However, the extent to which meta models are used is increased with the hybrid method. In addition to using the meta model for optimization, a robustness evaluation will also be performed on the meta model to estimate the robustness of the given design. This corresponds to doing simultaneous RDO using only meta models. The first step of the hybrid method is therefore to do a DoE and to generate a meta model. The second step will be performing simultaneous RDO on the created meta model. The purpose of this step is to do a preliminary study that can estimate how a robust design should look. This will be followed by a final step, where simultaneous RDO is now performed using CFD solver calls with the best design from the previous step as the starting design. Hence, this method uses simultaneous RDO twice; once on the meta model and once with CFD solver calls. This is done with the purpose of lowering the total number of required solver calls by substituting the solver with the meta model. The entire work flow is illustrated in Figure 3.6.

The meta model is based on inverse design parameters, and hence the robustness evaluation on the meta model will not be performed on geometric parameters. This is implemented to reduce the costs related to generating a second meta model and to significantly reduce the complexity of the set-up. The decision of using only inverse parameters for the first simultaneous RDO step is based on the assumption that if the same variation in the inverse parameters produces different standard deviations in the output, then this information will indicate the robustness of the designs relative to one another. Since this step is a preliminary investigation, knowing the robustness relative to other designs are sufficient.

In the final step, where simultaneous RDO is performed with CFD solver calls, the optimization uses inverse design parameters, while the robustness evaluation uses the blade perturbation parameters described in app. C. Hence, both the inverse and the geometric parametrizations are considered using this method.

3.5 Summary

Two alternatives to the existing RDO methods have been presented. One-Design-At-a-Time (ODAT) RDO constrains chosen parameters at different levels and performs optimizations for each level to forcefully produce different optimum designs with different robustness properties. However, ODAT RDO still does not include a robustness property directly into the optimization. Hybrid RDO seeks to do just that by expanding the usage the meta model and performing simultaneous RDO on the meta model as a preliminary study. The best design from this process is then used in simultaneous RDO with direct solver calls.

Case Description and Parametrizations

The purpose of this project is to develop and apply RDO methods to CFD applications such as pumps. The methods should focus on developing robust designs with a low performance variation. In chapter 3, two methods referred to as One-Design-At-a-Time (ODAT) RDO and hybrid RDO are suggested as potential improvements to the existing RDO methods. In this chapter, the optimization case is described followed by a description of the parametrization of the geometry in terms of both inverse and geometric parameters and the set-up for the solver call.

4.1 Case description

The design task is to develop a stainless steel sheet metal impeller that can be used in a multi-stage centrifugal pump, where the guide vane and inlet are already defined. A sheet metal impeller is created from sheets of metal and consists of the front plate, back plate and blades. These are all separate parts that are created separately and welded together at a later stage during manufacturing. An example of a sheet metal impeller is shown in Figure 4.1.

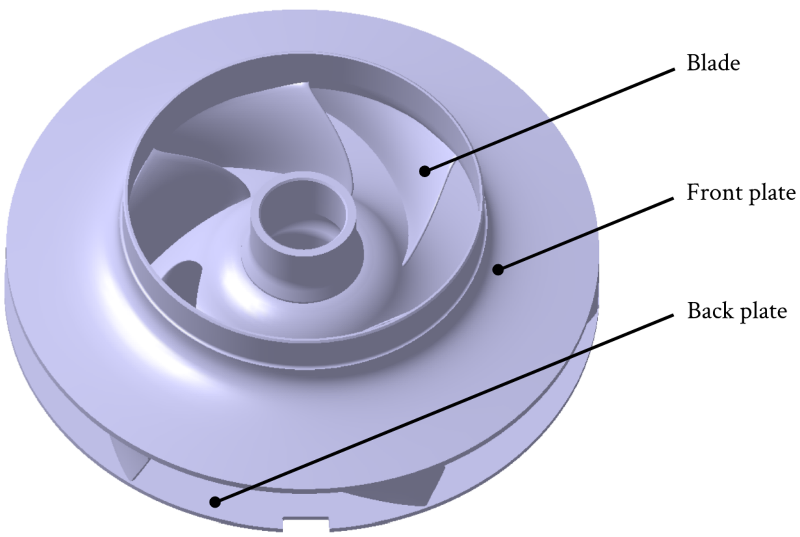


Figure 4.1: A typical metal sheet impeller consisting of front plate, back plate and blades.

As mentioned, the task is to develop an impeller that is feasible with the current inlet and guide vane design. A meridional cut of the pump geometry is shown in Figure 4.2, where the dashed line shows the impeller, which is to be designed, and the dotted line shows the connector, which is used to connect impeller and guide vane but is not part of the design task. The only change that can be made to the inlet and guide vane is translation in the inlet flow direction if necessary. Therefore, the new impeller design is constrained by a fixed inlet diameter, and the performance will be affected by how well the impeller outlet matches with the guide vane inlet.

The objective of the design task is to minimize the mean value and variation of the hydraulic power consumption while maintaining a head gain of at least 28 m for the nominal design. There are no requirements towards the variation of the head gain. High robustness must be prioritized to ensure that geometry variations in manufacturing has minimum influence on the hydraulic performance. The pump should have a nominal speed of 2955 rpm and a nominal flow rate of 95 m^3/h.

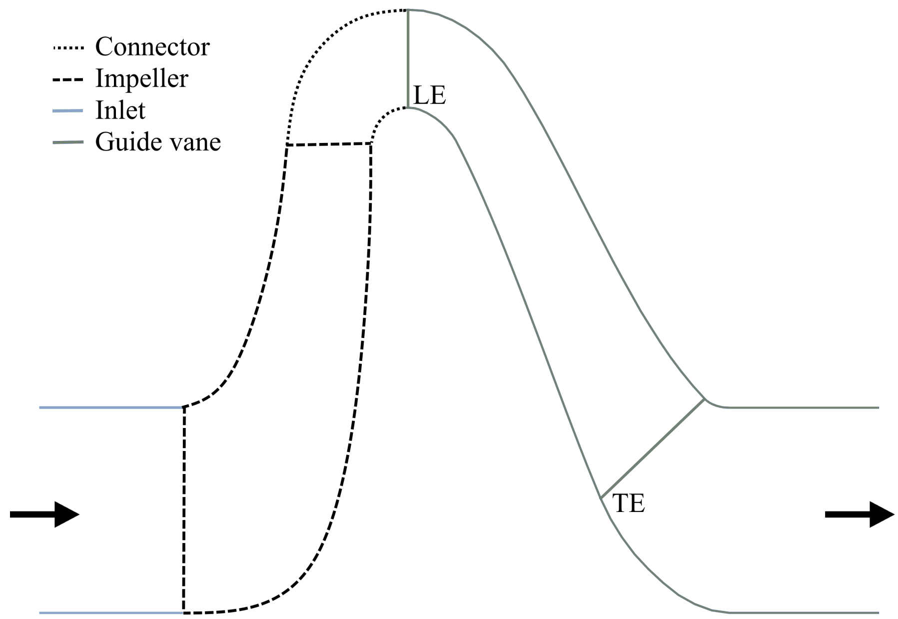


Figure 4.2: The meridional cut of the inlet, the guide vane and an arbitrary impeller with connector. An impeller that fits the space between inlet and guide vane is to be designed. LE refers to the guide vane leading edge, and TE refers to the guide vane trailing edge.

Tolerances must also be considered in order to assess the robustness of the design. As previously mentioned, the blades are subject to tolerances, while the remaining parts of the geometry are assumed to always be nominal. The variations on the blade due to manufacturing can currently be assumed to be normally distributed with a standard deviation corresponding to 20 % of the blade thickness for all control points, and hence this value is used for all parameters in the robustness evaluations during the design phase. Once a final design is chosen from the different RDO processes, the tolerances must be investigated further for the selected design. This information can be used to specify tolerances in way, where the impact from the manufacturing variations is minimized.

4.2 Parametrizations

As previously mentioned, two different sets of parameters are required for the optimization and the robustness evaluation. Inverse design parameters are used for the optimization, whereas the robustness evaluation is based on a geometric parametrization of the blade. The parameters used are described in this section.

The inverse method is characterized by the fact that the geometry is generated from the desired operating conditions and loading profiles and not the other way around. This means that the target flow rate Q_d, head gain ΔH_d and rotational speed n_d are parameters that can be supplied in the inverse design method, and the method will then attempt to reach these values with the generated design. The rotational speed and flow rate are specified in the CFD model and are used to describe the design point and hence will not be used as optimization parameters. The loading profiles will not be used in the optimization and will take on the default shape for centrifugal pump impellers.

In addition to the design point parameters, a number of other parameters are used in the optimization. These are the outlet flow angle β_2, the position of the leading edge of the blade on front and back plate (LE_F and LE_B, respectively), the axial height of the front plate Z and rVt. rVt is defined from from the velocity triangles on Figure 4.3 as

$$rVt = \frac{C_{U_2}}{U_2} \tag{4.1}$$

where C_{U_2} is the tangential component of the absolute flow velocity at the outlet and U_2 is the tangential blade velocity at the outlet.

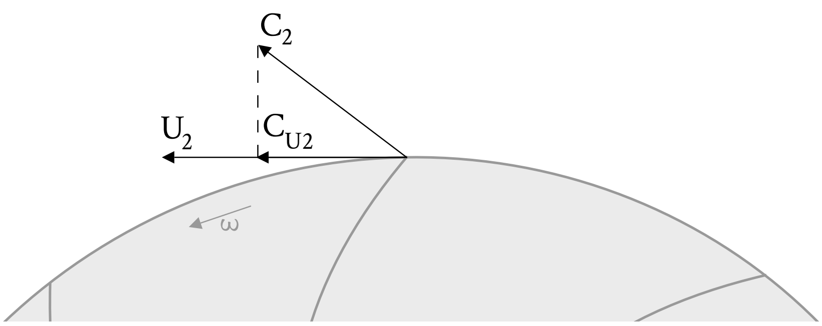


Figure 4.3: The velocity vectors used to calculate rVt.

To do a robustness evaluation, it is necessary to use some parameters that can be linked directly to a known geometrical change. In this project, focus is on the blade variations, and hence a parametrization of the blade using geometric parameters are required. The blade variations will be produced by perturbations on the blade as explained in appendix B. The perturbations are controlled by 25 points evenly distributed across the blade surface as shown in Figure 4.4. These points form a matrix whose values dictate a translation of the points the direction normal to the blade surface. Five cubic splines are used both in the span- and streamwise direction to connect the control points.

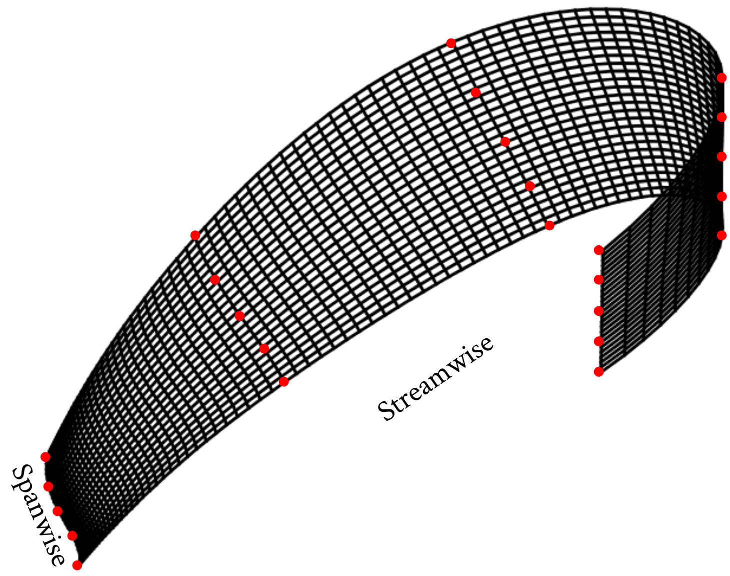


Figure 4.4: The distribution of the control points. In this case, five splines in the spanwise and five splines in the streamwise direction results in 25 control points.

4.3 Summary

The design task is to develop an impeller that fits the existing geometry of a pump. The impeller should be optimized in terms of power and robustness, while maintaining a head gain of at least 28 m. The impeller will be optimized using the inverse parameters and evaluated in terms of robustness using the geometric parametrization. These two parametrizations mean two different solver calls, which have also been described in this chapter.

Fifth Chapter

CFD Set-up

Any Robust Design Optimization (RDO) process is built around a solver, which in this case is a CFD solver. The CFD model is therefore an essential part of this thesis, and since RDO requires a large number of solver evaluations, the CFD model is also the part of the entire process that has the highest impact on the total execution time. Furthermore, the accuracy of the CFD model is not paramount in an RDO process, since the purpose is to compare different results from the same CFD model. Hence, the CFD model to some extent only needs to maintain the same shape of the model response surface. This means that it can be acceptable and even necessary to sacrifice some accuracy, if this increases the total calculation time.

The case that the CFD model must handle is described in chapter 4. The task is to design a sheet metal impeller for an existing pump. A reference geometry has been generated on which the findings in this chapter will be based.

5.1 Flow domain

When developing the flow domain, it is important to consider what parts of the pump to include and what parts to neglect. This is especially true in this case, where a fast CFD solver is desired, and hence the model should be as simple as possible. Furthermore, the main purpose in this thesis is still to investigate and develop the best possible RDO methodology, which makes a simpler, cheaper model more acceptable.

To reduce the computational costs, the flow domain will only consider a single stage of the multi-stage pump, neglecting the fact that the flow will change from stage to stage in reality. Cavities, leakage flows and modifications made to the design to facilitate manufacturing are assumed to be the same for all designs and are therefore neglected as well. The guide vane is included in the flow domain, since this will introduce more losses. This has two main advantages. Firstly, the impeller design will be tailored to the existing guide vane, increasing the overall performance of the pump. Secondly, doing CFD on an impeller alone can result in efficiencies well-above 95 %, which can make it difficult to distinguish different extrema from each other. Hence, the extra losses help improve the optimization process.

In addition to the impeller and guide vane, it is necessary to include an inlet and outlet pipe to ensure a fully developed flow at the impeller inlet and at the outlet boundary of the domain. The inlet has a length of three times the diameter, while the outlet has a length of six times the diameter.

To reduce the number of cells significantly, the flow domain will take advantage of the periodic symmetry that occurs in an impeller and guide vane. By applying a periodic boundary condition, the domain is reduced to include only one channel in impeller and guide vane. The flow domain is shown in Figure 5.1.

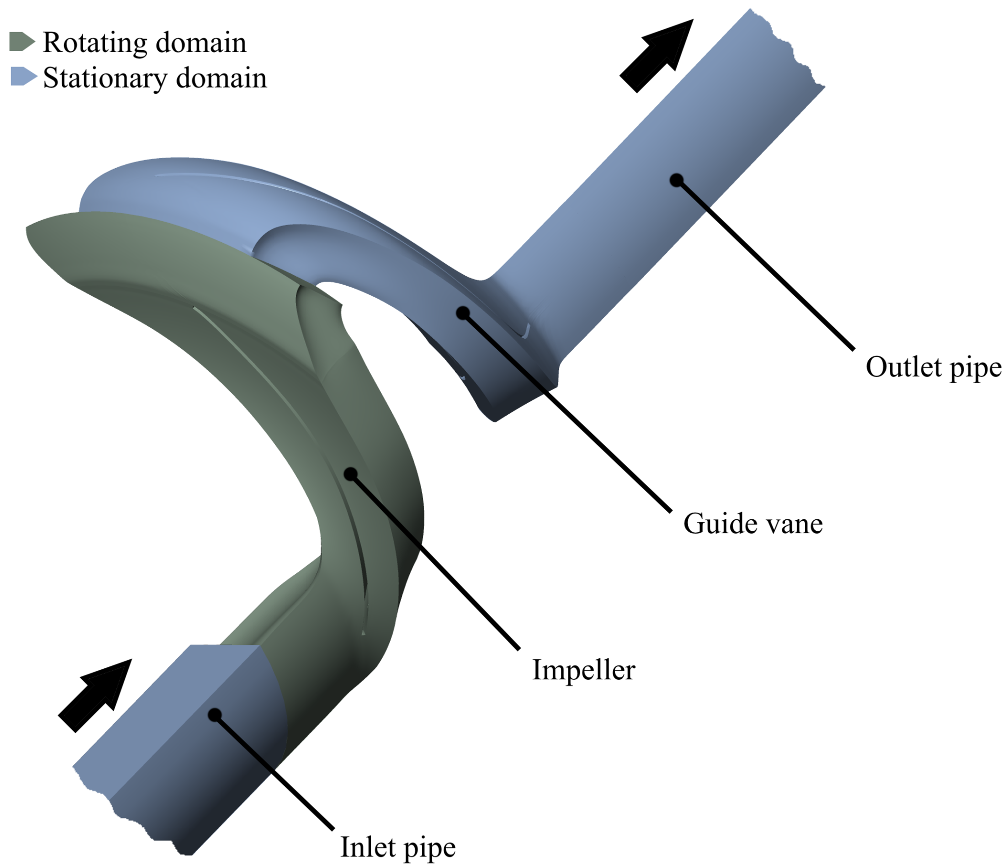


Figure 5.1: The flow domain used in the CFD model with the initial impeller design.

5.2 CFD set-up

The CFD model is set-up and evaluated using the commercial software ANSYS CFX 18.1. The set-up used in CFX will be described in this section.

The entire flow domain has a high order or rotational symmetry, and since the CFD model is to be as computationally cheap as possible, the CFD model will be solved as a steady-state problem. Water at a temperature of 25 ^{o}C is used as the fluid, and a Rotating Frame of Reference (RFR) is specified for the impeller with a value corresponding to the design requirement speed. The RFR is specified to include the impeller motion into the CFD model.

A turbulence model is required to capture the effects of the turbulence occurring in the flow. The two most common methods are the k-ϵ and the k-ω or variants of the two methods. The k-ω Shear-Stress-Transport (SST) method is often recommended for high accuracy in the boundary layer, however, in order to benefit from the k-ω SST method, requirements must be met. The main requirement is that a resolution of 10 cells in the boundary layer is required with the first cell at y+=1 [ANSYS, 2017]. The geometry in this thesis will vary during the RDO work flow, and the meshing process is therefore automated, which makes it impossible to fulfil the requirements. Instead, the k-ϵ method will be used as a compromise, since this method is more robust and insensitive towards y+ [ANSYS, 2017]. Furthermore, an accurate CFD model is not paramount in this case, where calculation speed has to be prioritized. This decision has been tested using the two turbulence models on a mesh with around 900,000 cells, where the difference in head, power consumption and efficiency between the two models were 0.7 %, 0.6 % and 0.1 %, respectively.

Boundary Conditions (BC) also need to be specified in the CFD model. A mass flow rate is therefore specified at the inlet, and a static pressure is specified at the outlet. This configuration is used, because it results in the most robust model [ANSYS, 2017]. In addition to the inlet and outlet boundary conditions, a no-slip wall boundary condition is specified for the walls of the inlet and outlet pipe as well as for the hub, shroud and blades of both guide vane and impeller. The walls are assumed to be smooth for the inlet and outlet pipes, since the losses in these are of no interest. The walls in impeller and guide vane have a sand-grain roughness of 40 μm, corresponding to the surface roughness of the sheet metal used to manufacture the components.

As previously explained, the flow domain only consist of parts of the full geometry due to the rotational symmetry of the impeller and guide vane. By specifying rotational symmetry as a boundary condition, it is sufficient to calculate the flow in a single channel of each component. Furthermore, interfaces also have to be specified between the inlet pipe, impeller, guide vane and outlet pipe to connect each domain. The interfaces can be supplied with either a frozen rotor or a mixing-plane averaged boundary condition. The frozen rotor approach maps the value from one side of the interface onto the other side directly, while the mixing-plane approach maps the circumferential average across bands on the interface. The mixing-plane approach is advantageous when rotational symmetry boundary conditions are used, because it uses the average across the entire circumference, which means the position of the impeller domain relative to the guide vane will not influence the result. With the frozen rotor, on the other hand, changing the position would change the result. Hence, the mixing-plane approach is used.

Since CFX uses a pseudo-transient solver, it is possible to specify a time step over which the calculation takes place. Typically, a large time step will increase the convergence speed, but also increase the risk of the model diverging. Based on a number of tests, a time step corresponding to a 90° rotation has proven to be well-suited for the current model and is used for the first 150 iterations. Afterwards, the time step is changed to correspond to a 3.6 $^{\circ}$ rotation to ensure a stable result.

Best-practice for high accuracy	**Custom practice for RDO**
Steady-state (or transient)	Steady-state
Water at 25 ^{o}C	Water at 25 ^{o}C
Rotating impeller	Rotating impeller
Static pressure BC at the outlet.	Static pressure BC at the outlet.
Mass flow rate BC at the inlet.	Mass flow rate BC at the inlet.
Pipes: No-slip wall (Smooth)	Pipes: No-slip wall (Smooth)
Impeller/Guide vane: No-slip wall (40 μm roughness)	Impeller/Guide vane: No-slip wall (40 μm roughness)
Mixing-plane interfaces	Mixing-plane interfaces
k-ω SST turbulence model	*k-ϵ turbulence model*
Full domain	*Single channel (Rotational symmetry)*

Table 5.1: A comparison of the best-practice CFD settings and the CFD settings used here. The differences are displayed in the bottom in italic.

5.3 Mesh development

In this thesis, the mesh generation needs to be automatic in order to do the design evaluation loops in an RDO process. For this purpose, GridPro is used. GridPro is a multiblock grid generator that produces a structured hexahedral mesh based on a defined topology. The same topology can be applied to similar geometries automatically, making it well-suited for an RDO process.

While the mesh quality is of importance, it can also be a time-consuming process to generate a good quality mesh. Since it is still necessary to reduce the computational time as much as possible, a compromise is once again necessary between accuracy and calculation time. GridPro uses an iterative approach, where it uses a specified number of iterations to generate the mesh. Therefore, the following two sections will present a mesh independency analysis as well as an analysis of how many iterations are necessary to obtain a converged mesh of reasonable quality.

5.3.1 Mesh independency study

The mesh independency study is used to verify the validity of the mesh as well as to determine the coarsest possible mesh that still provides reasonable accuracy. The properties of these meshes are shown in Table 5.2.

Cells in mesh	**Max skewness**	**Max aspect ratio**	**Max warpage**
20K	0.99	187	136
60K	0.97	101	99
150K	0.97	116	107
220K	0.97	145	94
400K	0.96	118	66
870K	0.95	140	49

Table 5.2: Quality properties of the meshes in the mesh independency study

While the mesh properties in 5.2 are relatively poor when compared to typical mesh properties in other applications, they are acceptable in this case. The impeller and guide vane are complicated geometries with a lot of curvature, and a structured mesh will therefore often possess such quality properties. Especially when the mesh has to be automatically generated, which is the case here.

Figure 5.2 shows the accuracy of the efficiency for the different meshes as a function of the normalized execution time of a single solver call. The head gain and power consumption accuracies are similar to the efficiency, and hence they are not shown in the plot. Since both speed and accuracy are required, it is necessary to make a trade-off between the two when selecting a mesh. As seen, the deviation from the best mesh decreases exponentially as a function of the execution time, and as such there is only a small benefit from increasing the cell density once the number of cells pass 150,000. Adding 130,000 cells to the mesh with 20,000 cells reduces the deviation by 1.1 %-points, whereas adding 250,000 cells to the mesh with 150,000 cells only reduces the deviation by 0.15 %-points. Based on this, the mesh with 150,000 cells appears to provide a reasonable accuracy (0.2 % of the best mesh), while keeping the execution time as low as possible.

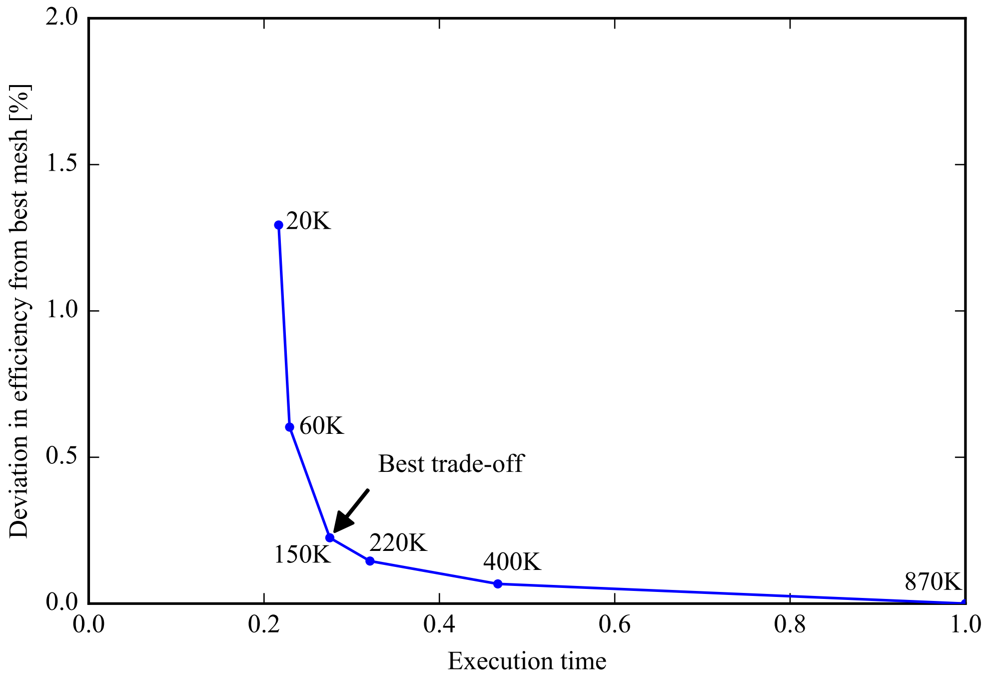


Figure 5.2: The deviation in efficiency relative to the best mesh as a function of the execution time. The annotation shows the number of cells in the mesh at each point.

In addition to considering the accuracy and execution time of each mesh, it is also necessary to test if the mesh is able to react to small geometry changes. For that purpose, two geometries are calculated using the same mesh resolution. The first geometry is the reference design and the second is a design, where the blade has been perturbed to resemble a real manufactured component. The mesh with 150,000 cells determines a deviation in efficiency between the two designs of 0.62 %, while the finest mesh with 870,000 cells results in a deviation of 0.65 %. Hence, the mesh with 150,000 is roughly as good at determining the difference between designs as the finest mesh. This comparison has been replicated with different designs showing the same tendency.

Based on the findings in the section it is clear that the mesh with 150,000 provides a reasonable trade-off between accuracy and execution time, while also maintaining the ability to detect deviations between different designs. Therefore, this mesh resolution is used in the CFD model.

5.3.2 No. of iterations in the mesh generation

As previously explained, the mesh is generated using GridPro. GridPro is an iterative mesh generator, which means the mesh is generated through iterations. The number of iterations should be sufficient for the mesh to converge without spending valuable time on unnecessary iterations. Therefore, the mesh will be evaluated in a CFD solver after a different number of iterations to investigate whether the mesh produces a converged result. The head gain, power consumption and efficiency relative to the fully converged solution are shown in Figure 5.3. As seen in Figure 5.3, the solution starts converging at around 2000 iterations, suggesting that this is the minimum number of iterations required. If less iterations were to be used, two results from the CFD model with the same inputs might be different, since the mesh has not converged and will vary between each run. This is undesirable, especially when investigating small geometry changes. Furthermore, the number of iterations has a low influence on the total execution time, making 2000 iterations acceptable.

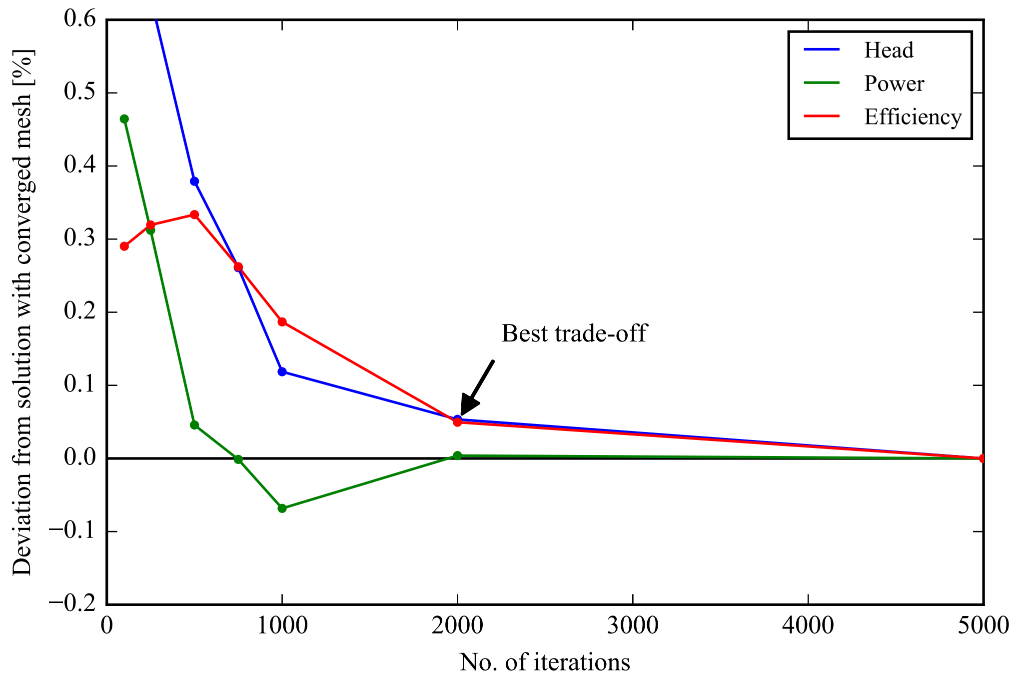


Figure 5.3: The deviation in head gain, power consumption and efficiency relative to the best mesh.

5.4 Convergence criteria and maximum no. of iterations

The convergence criteria is another important aspect of the CFD model. Once again, this is something that affects both accuracy and execution time. The convergence criteria is described by a minimum residual that needs to be fulfilled, and the residuals of the different model equations are therefore shown in Figure 5.4. As seen, the residuals level out after approximately 500 iterations, however doing 500 iterations would significantly increase the calculation time and fewer iterations would be preferable. Figure 5.5 on the following page shows the head gain and power consumption stabilizing after approximately 100 iterations, however this is too few iterations according to the residuals in Figure 5.4, where a significant drop in the residuals occurs at around 150 iterations. Therefore, the residual values are set to 10^{-5} to capture the biggest drops in the residuals, while still focusing on keeping a fast calculation time. To further ensure a fast solver, the maximum number of allowed iterations are set to 250.

5.5 Summary

The purpose of this chapter has been to develop a CFD model that favours RDO by having the best trade-off between calculation time and accuracy. As such, a flow domain with 150,000 cells and rotational symmetry is used to minimize the calculation time. Furthermore, some additional trade-offs have been made to reduce the calculation time. This has resulted in a slightly reduced accuracy when compared to the most accurate settings, but the ability to detect geometry variations remain intact.

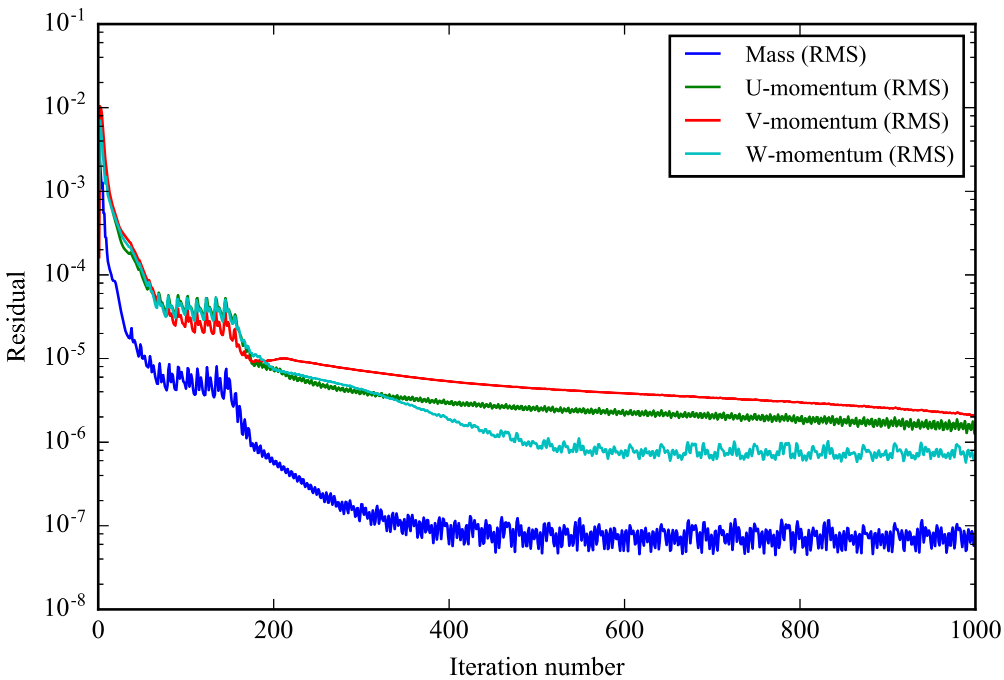


Figure 5.4: The residuals of the CFD model.

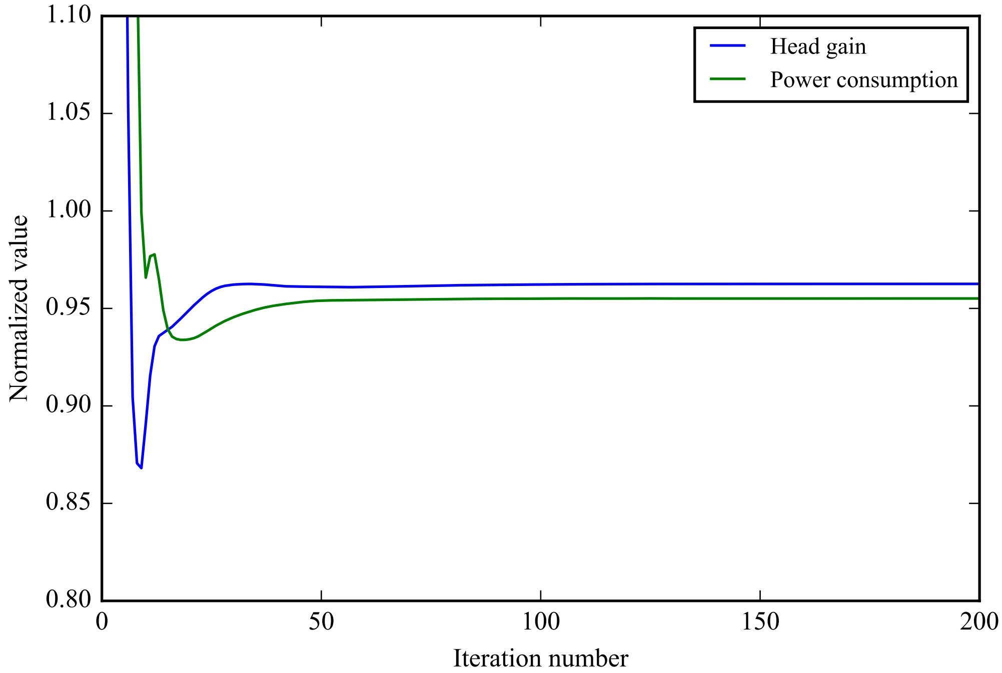


Figure 5.5: The progress of the head gain and power consumption as a function of the number of iterations.

Sixth Chapter

Application of Robust Design Optimization Methods

With the RDO methods developed and prerequisites completed, it is now possible to apply RDO. Once the solver flow has been described, conventional RDO is performed followed by One-Design-At-a-Time (ODAT) and hybrid RDO. Conventional RDO is performed to ensure that the results from the RDO methods can be assessed not only in relation to each other but also in relation to conventional methods.

6.1 Solver flow

In any optimization process, it is necessary to set up a solver, which can be called by the optimization. Each time the solver is called, a series of commands are executed producing a response, which the optimization process receives. In this case, the solver is called differently depending on whether inverse or geometric parameters are used. The following two sections will therefore present the solver call for an optimization, where inverse parameters are used, and for a robustness evaluation, where geometric parameters are used to perturb the blade.

6.1.1 Optimization call

The optimization solver call is shown in Figure 6.1 and is identical to the call used in the Design-of-Experiment (DoE) to generate the meta model. It uses the inverse design parameters to generate the main impeller dimensions, which are the meridional shape of the front and back plate and the position of the leading and trailing edge of the blades. The blade shape is then generated followed by the meshing of the flow domain. Finally, a CFD model is set-up and solved producing the response.

6.1.2 Robustness evaluation call

The robustness evaluation requires a different solver call as shown in Figure 6.2, because the parametrization is different. Instead of the inverse design parameters which affect the entire geometry, geometric parameters describing a perturbation of the blade are used.

The robustness evaluation is based on an already generated design. The first step is therefore to import the geometry whose robustness is to be evaluated. This is then followed by the blade perturbation. The mesh is generated from the same topology as for the optimization call, and a CFD model is solved using the same settings.

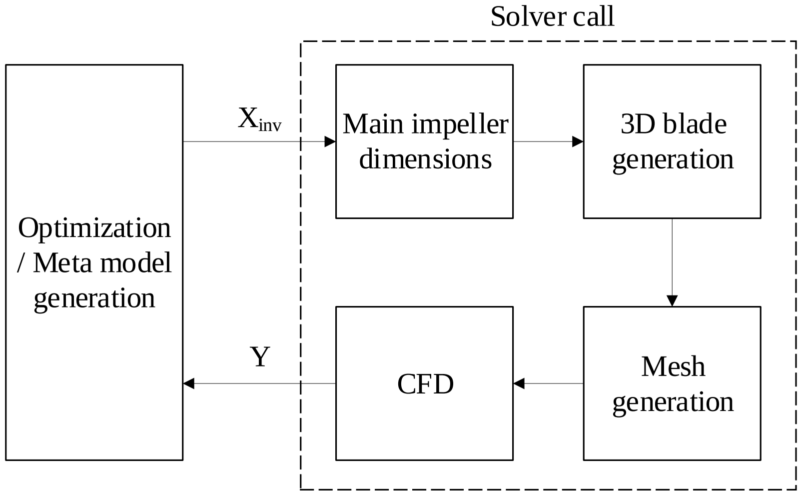


Figure 6.1: The flow of the solver call with inverse design parameters.

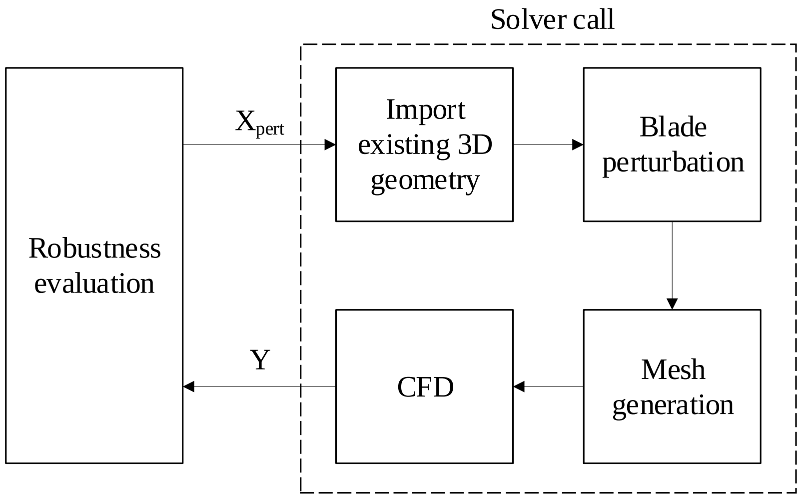


Figure 6.2: The flow of the solver call with geometric blade perturbation parameters.

6.2 Evaluation criteria

Any type of optimization process has the purpose of locating the best design in terms of a given set of objectives and constraints. This optimum design is referred to as the nominal design and the responses of the nominal design are referred to as the nominal responses. With RDO, the goal is to consider the actual responses and corresponding standard deviations when including deviations during manufacturing into the analysis. This means the introduction of two additional ways of describing the responses; the mean value of each response and the respective standard deviation taken across all designs in a robustness evaluation. Hence, each response parameter can be described in terms of its nominal value, mean value and standard deviation. When considering robustness, the mean value and standard deviation are typically of greater interest than the nominal value.

6.3 Conventional optimization

The work flow of conventional numerical optimization is shown in Figure 3.2 on page 8. Initially, a meta model is generated and optimized as a pre-optimization step. This is followed by an optimization using direct solver calls and a final design is then selected based on the hydraulic performance.

6.3.1 Objective formulation

The design objectives are to consider both power consumption and robustness, however, in conventional optimization the robustness is not included, and hence the robustness will not be considered during the design process. Instead, it will be used as a benchmark later on to compare if the RDO methods are able to produce more robust designs. The optimization objective is therefore to minimize the nominal power, while keeping the head gain above 28 m;

$$\text{minimize} \quad \mathrm{P_2}(\beta_2, \mathrm{LE_F}, \mathrm{LE_B}, \mathrm{Z_2}, \mathrm{rVt}, \Delta\mathrm{H_d}) \tag{6.1}$$

$$\text{subject to} \quad \Delta\mathrm{H_{nom}}(\beta_2, \mathrm{LE_F}, \mathrm{LE_B}, \mathrm{Z_2}, \mathrm{rVt}, \Delta\mathrm{H_d}) \geq 28 \text{ m} \tag{6.2}$$

The optimization approach is described in Figure 3.2 on page 8. A meta model generated by a DoE is used to do a cheap preliminary optimization before performing an optimization with direct solver calls.

6.3.2 Design development

The meta model is created from 100 samples generated by Latin Hypercube Sampling (LHS). It is then optimized using the Non-Linear Programming by Quadratic Lagrangian algorithm (NLPQL), which is a local gradient-based search algorithm. The best design from the DoE is used as a starting point for the NLPQL, since the search algorithm is local [Dynardo GmbH, 2017]. The optimal design from the meta model is used in a real solver call to confirm whether the estimated performance is reasonably close to the real values or not. As seen from Table 6.1, all performance parameters deviate by less than 1 %.

	ΔH	$\mathbf{P_2}$	η
Meta model deviation [%]	0.97	0.22	0.15

Table 6.1: The deviation between meta model response and the response from a real solver call. The real solver call is used as reference for the calculations here.

The optimum design from the meta model is then used as the starting point for the optimization with real solver calls. Here, specific requirements must be met by the algorithm. Since a CFD solver is used, there is a risk of solver noise and evaluations may fail due to computational errors. To overcome these challenges, the Adaptive Response Surface Method (ARSM) is used. ARSM uses a number of supporting design points to generate a response surface from which it estimates the optimum. Because ARSM uses more points for the response surface than what is needed for the regression, it smooths out the solver noise and is capable of handling some failed calculations [Dynardo GmbH, 2017].

The algorithm converges towards a final design, where the constraint stating that the head gain must be 28 m or above is fulfilled. The design obtained has a nominal head gain of 28 m, a nominal power consumption of 9134 W and a nominal efficiency of 79.3 %. To investigate the robustness of the design, a robustness evaluation is performed using Latin Hypercube Sampling (LHS). This results in both a mean value and a standard deviation for each performance parameter. The performance parameters of the optimum design are found in Table 6.5 on page 33.

6.4 ODAT RDO

The One-Design-At-a-Time (ODAT) RDO work flow is depicted in Figure 6.3. The figure shows three different design optimizations, however this number can be either increased or decreased depending on the case. As seen, this approach begins with the generation and optimization of a meta model. The obtained design is then used as the reference design in a number of optimizations. In each optimization, one or more parameters are constrained at different values to forcefully create different designs. Each design is then evaluated in terms of robustness and the best design in terms of both hydraulic performance and robustness is used as the final design.

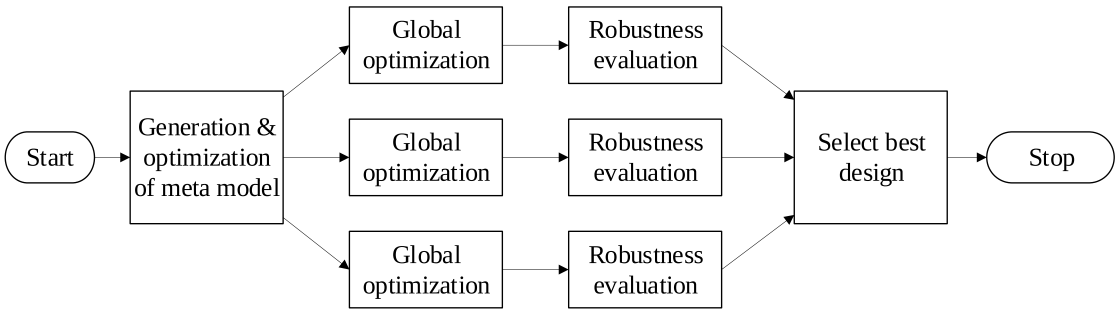


Figure 6.3: A flow chart of the ODAT RDO method evaluating three designs.

6.4.1 Objective formulation

In this case, the rVt parameter is held constant at four levels during the corresponding four optimizations. Among other things, rVt affects the diameter, and hence the diameter between each design will be different. This will ensure significant differences between the designs.

ODAT RDO is similar to the conventional optimization approach in the sense that the robustness is not used directly as an optimization objective, since the optimization and the robustness evaluation are separated completely. This also means that the optimization problem is described by the formulation given in equation 6.1. ODAT RDO differs from conventional optimization in the sense that multiple optimizations are performed followed by robustness evaluations. This allows for a comparison of the robustness of the obtained designs to select the best overall design as the final design.

6.4.2 Design development

The constrained parameter rVt is held constant at four levels; 0.41, 0.44, 0.47 and 0.50, and the best design for each of these levels will be referred to as rVt41, rVt44, rVt47 and rVt50, respectively. The values are used because they cover the range in which the impeller can be assumed to perform most efficiently.

The first step, where a meta model is generated and optimized to locate a start design, is identical to the first part of the conventional optimization and hence the same algorithms are used. Nonetheless, due to the stochasticity of the Design of Experiments (DoE) used to generate the meta model, the results from optimizing the meta model is slightly different in this case. However, the meta model response is still within less than 1 % of the actual response at the estimated optimum.

	ΔH	$\mathbf{P_2}$	η
Meta model deviation [%]	-0.33	-0.75	-0.05

Table 6.2: The deviation between meta model response and the response from a real solver call. The real solver call is used as reference for the calculations here.

The optimum design from the meta model is used as the reference design with rVt having different values in each of the four optimizations. The optimization algorithms then use a maximum of 180 iterations each to determine the optimum. Once optimized, each design is evaluated in terms of robustness using LHS to determine what the mean values and standard deviations are for the response parameters. The responses all resemble normal distribution and hence they can be described by a mean value and a standard deviation. These are summarized in Table 6.3.

		rVt41	**rVt44**	**rVt47**	**rVt50**
ΔH [m]	Mean	27.98	27.97	27.98	28.01
	Std. deviation	0.164	0.165	0.154	0.156
P_2 [W]	Mean	9175	9141	9114	9210
	Std. deviation	59.5	59.6	55.8	62.1

Table 6.3: The means and standard deviations of the responses for the different designs obtained using ODAT RDO. The results are visualized in Figure 6.4.

The results from Table 6.3 are visualized in a parallel plot in Figure 6.4. Each vertical axis represents a response parameter and the range of each axis is defined by the minimum and maximum values of the respective parameters. The values are expressed in terms of the difference from the smallest parameter value.

From the parallel plot, it is possible to quickly identify what designs are best and worst in terms of each response parameter. This is advantageous, since selecting the best design will depend heavily on what parameters are considered most important. In this case, the highest priority is to minimize the mean value and standard deviation of the power consumption P_2. The parallel plot clearly shows rVt47 as having both the lowest mean value and standard deviation and it is therefore the best overall design. The performance parameters of rVt47 are summarized in Table 6.5 on page 33.

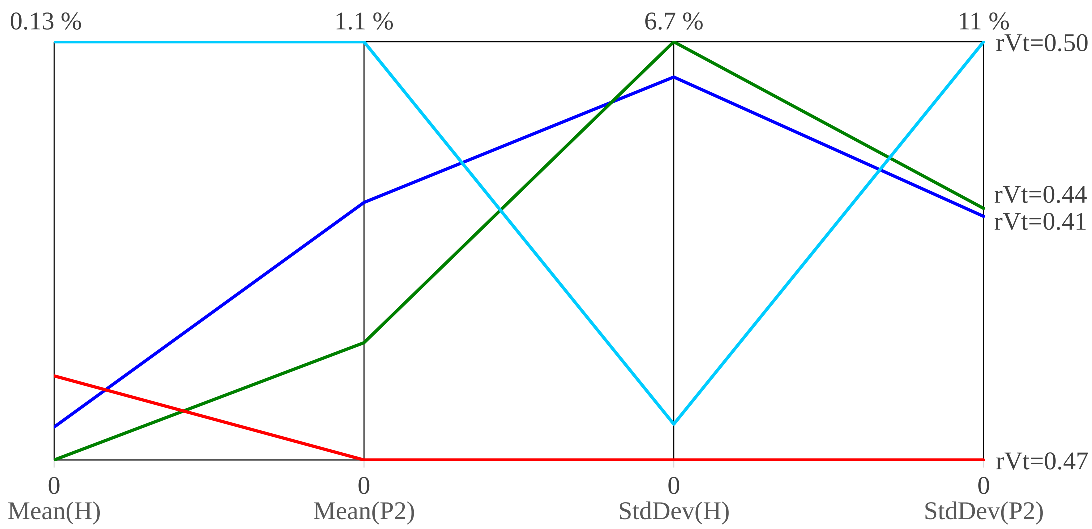


Figure 6.4: Parallel plot of the responses from Table 6.3 expressed as the difference from the smallest value for each parameter.

6.5 Hybrid RDO

The hybrid RDO work flow is shown in Figure 6.5. As in the other methods, the first step is to create a meta model. Simultaneous RDO is then performed on the meta model followed by simultaneous RDO with direct solver calls.

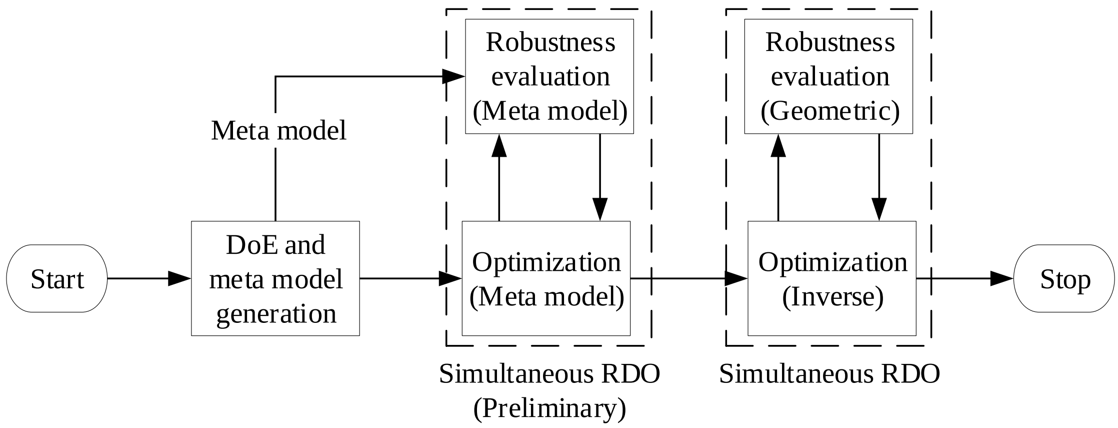


Figure 6.5: A flow chart of the hybrid RDO method.

6.5.1 Objective formulation

In conventional and ODAT RDO, the optimization has been single-objective, because the power is only described by the nominal value obtained from the calculations. With hybrid RDO, a robustness evaluation is introduced in each optimization iteration, which means the power is described by three values; the nominal value, the mean value and the standard deviation. This makes it possible to do multi-objective optimization, and the objective is therefore to optimize both the mean value and the standard deviation of P_2, while still maintaining a head gain of 28 m or above.

$$
\begin{aligned}
\text{minimize} \quad & \mathrm{Mean}(\mathrm{P_2}(\beta_2, \mathrm{LE_F}, \mathrm{LE_B}, \mathrm{Z_2}, \mathrm{rVt}, \Delta\mathrm{H_d})) && (6.3)\\
& \mathrm{StdDev}(\mathrm{P_2}(\beta_2, \mathrm{LE_F}, \mathrm{LE_B}, \mathrm{Z_2}, \mathrm{rVt}, \Delta\mathrm{H_d})) && (6.4)\\
\text{subject to} \quad & \Delta\mathrm{H_{nom}}(\beta_2, \mathrm{LE_F}, \mathrm{LE_B}, \mathrm{Z_2}, \mathrm{rVt}, \Delta\mathrm{H_d}) \geq 28 \text{ m} && (6.5)
\end{aligned}
$$

6.5.2 Design development

Once again, the meta model is created from 100 samples generated by LHS. The meta model is used as the solver in a simultaneous RDO set-up, which means it will be subject to multiple robustness evaluations. The optimization parameters are used as the geometric parameters for the preliminary simultaneous RDO.

The purpose of doing a preliminary simultaneous RDO is that it should lower the necessary number of required optimization iterations in the subsequent simultaneous RDO with real solver calls. However, as shown in Table 6.4, the deviations between the meta model optimum design and the values from a CFD simulation of the same design are significant. In fact, the meta model overestimates the head gain by 10.1 %, resulting in a significant violation of the constraint according to the CFD solver call.

	ΔH	**P_2**	η
Meta model deviation [%]	10.1	12.7	-2.1

Table 6.4: The deviation between meta model response and the response from a real solver call. The real solver call is used as reference for the calculations here.

Due to the constraint violation, the design obtained from performing simultaneous RDO on the meta model is unsuited as the initial design for simultaneous RDO with real solver calls. Instead, the best design in terms of nominal power consumption from the DoE is used as the initial design, which corresponds to skipping the preliminary simultaneous RDO entirely.

The optimization algorithm for hybrid RDO must be able to handle multi-objective optimization problems, while also being able to deal with the occasional failed design due to computational errors and solver noise. An Evolutionary Algorithm (EA) is therefore used. Some predefined EA methods are available in the optimization software. One of these are a genetic algorithm developed for expensive solvers. The algorithm uses exactly 100 design evaluations to find a pareto front. Doing 100 design iterations are the absolute maximum allowable number of iterations due to the computational costs caused by each design iteration requiring a robustness evaluation.

The robustness evaluation is performed using LHS with 100 samples. This is necessary to ensure reasonable computational costs. With 100 optimization iterations that each require a robustness evaluation of 100 design evaluations, the total number of solver calls will reach 10,000. For comparison, the conventional optimization approach used a total of 280 solver evaluations.

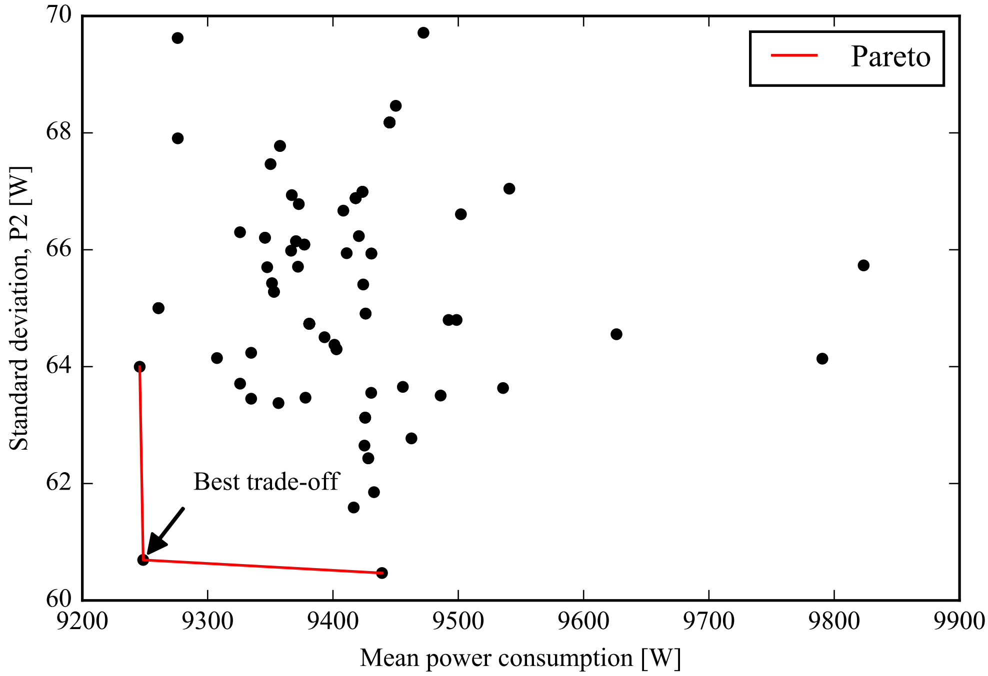


Figure 6.6: The designs from the optimization complying with the constraint. The pareto front is shown as well.

All optimization designs not violating the constraint are shown in Figure 6.6 along with the pareto front. It is evident from the plot that designs with similar performances can have different standard deviations. In fact, vertical lines can even be drawn between some of the designs. This shows that several of the designs in this case have similar mean power consumptions, but significantly varying standard deviations. The design point marked by an arrow on Figure 6.6 is considered the best trade-off between the two objectives and is selected as the best design from this optimization. The performance values of the design is shown in Table 6.5 on the facing page.

In this case it is evident that using the meta model for an initial simultaneous RDO process in the hybrid RDO approach provides no benefits compared to simply doing simultaneous RDO with direct solver calls from the start. As such, the expected advantages from hybrid RDO are non-existent in this case, and using the simultaneous RDO approach described in chapter 3 would therefore have provided the same results as the hybrid method at a lower number of solver calls. In other words, the hybrid RDO method applied here now corresponds to the original simultaneous RDO methods. Nonetheless, it will still be referred to as the hybrid RDO methods for the remainder of this thesis.

6.6 Comparison of best designs

Three RDO methods have been tested; conventional optimization, ODAT RDO and hybrid RDO. Each method has resulted in a design and these corresponding three designs will be evaluated and compared in this section. The designs are summarized in Table 6.5.

		Conventional	ODAT RDO	Hybrid RDO
Cost	Solver evaluations	280	1220	10100
ΔH [m]	Mean	28.0	28.0	28.1
	Std. deviation	0.154	0.154	0.160
P_2 [W]	Mean	9111	9114	9249
	Std. deviation	54.1	55.8	60.7

Table 6.5: The best designs from conventional optimization, ODAT RDO and hybrid RDO.

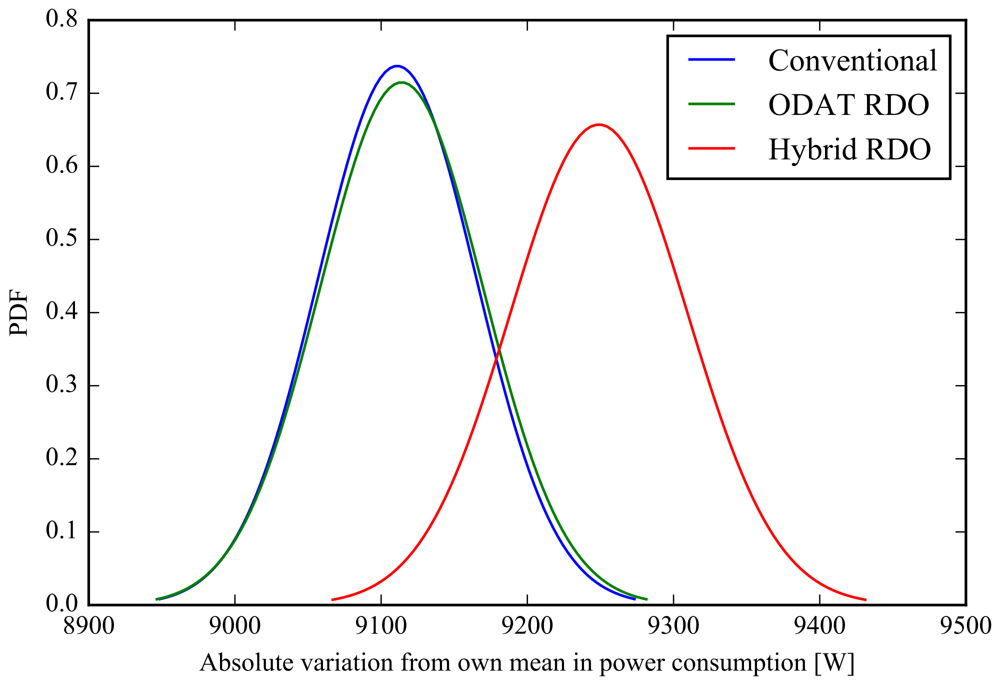


Figure 6.7: The normal distribution of the power consumption based on the mean values and standard deviations of the best designs from the conventional optimization, ODAT RDO and hybrid RDO.

Figure 6.7 shows the normal distribution of the power consumption for the three designs. A robust design is characterized by low variations in performance, and having a narrow normal distribution curve is therefore preferable. As seen, the hybrid RDO method in this case struggles to provide a design that performs as well as both the conventional method and ODAT RDO in terms of both mean value and the amount of variation. Despite several attempts at tweaking the optimization algorithm, the hybrid RDO method has not been able to produce results that perform as well as the other two methods. Whether this is caused by the limited number of optimization iterations, the choice of optimization algorithm, mere coincidence or a combination of the three is unclear. However, it is evident that additional optimization steps are necessary in order for hybrid RDO to have a chance at being successful in cases such as this one. This requires a significant amount of additional solver evaluations, which will increase the development time. The results from this case therefore indicate that the hybrid and by extension also the simultaneous RDO method are inferior methods compared to conventional optimization methods and ODAT RDO.

The ODAT RDO design and the design from conventional optimization perform similarly. In fact, the two designs are close to identical as seen in Table 6.6. Hence, ODAT RDO method is unable to produce a design with lower performance variation than the design from conventional optimization. This could in principle suggest that designs with different robustness properties do not exist. However, from Figure 6.6 on page 32 it is evident that designs can have the same mean performance while having different robustness properties. Therefore, the fact that the two methods produce the same design actually indicate that the global optimum and robust optimum happen to be the same in this design case, which can also be seen in Table 6.6. Whether the robust and global optimum being the same is a coincidence is unclear, but it might indicate that there are no advantages towards including the robustness into the numerical optimization. However, more case studies, which could be performed in future projects, are necessary before concluding this.

Since the design from ODAT RDO is the most robust design obtained from the applied methods, ODAT RDO is actually able to locate the most robust design, however it is unclear whether this is due to the robust design also being the global optimum. In this case, the robust optimum just happens to also be the global optimum, and ODAT RDO and conventional optimization therefore produce the same design by coincidence. Whether or not ODAT RDO had been able to locate a robust optimum if one had existed can therefore not be concluded. However, it is evident that none of the tested RDO methods have managed to improve the design so far. Using RDO methods as a substitute for conventional optimization in the design phase therefore do not seem to result in a significant advantage, but once again more studies are needed before this can be concluded with certainty.

	Conventional	**ODAT RDO**
rVt [-]	0.467	0.470
Z [mm]	19.8	20.0
LE_F [-]	0.101	0.100
LE_B [-]	0.290	0.285
β_2 [^{o}]	18.0	18.0
ΔH_d [m]	22.4	22.5

Table 6.6: The design parameters of the best design obtained from conventional optimization and ODAT RDO. The two designs are close to identical.

While the combination of numerical optimization and robustness evaluation is unsuccessful in this case, it can still be advantageous to consider the robustness of a developed design to understand what performance variations to expect as a result of manufacturing deviations. This knowledge can be used to specify the tolerances for manufacturing and is demonstrated in chapter 7.

6.7 Summary

Three different approaches towards design development are tested; conventional optimization, ODAT RDO and hybrid RDO. Hybrid RDO fails to produce a design better than what is obtained from conventional optimization. As such, hybrid RDO is not recommendable based on the results from this case. ODAT RDO produces the same design as conventional optimization, suggesting that the global optimum and robust optimum happen to be the same, and hence a more robust optimum does not seem to exist for this case. Whether ODAT RDO would have been able to locate a robust optimum if one had existed cannot be concluded with certainty. If other cases have different robust and global optimums, ODAT RDO might be able to locate the robust optimum. However, none of the tested RDO methods have managed to improve the design so far, which is an indication that using RDO as a substitute for conventional optimization provides no advantages.

Tolerance Investigation

An important part of minimizing the influence of manufacturing variations on the hydraulic performance is to investigate the tolerances. A variation in some parts of the geometry will have a higher impact on the performance variation than in other parts, and it can therefore be an advantage to specify tighter tolerances for the more sensitive parts. At the same time, tolerances can be loosened in less sensitive areas, which can both reduce manufacturing costs and ease the manufacturing process itself. Tolerances are investigated using robustness evaluations, which is a type of sensitivity analysis.

The tolerances used in manufacturing today should ideally be specified based on knowledge about the hydraulic sensitivity of the different parts of the geometry, however, this is not currently the case as mentioned in chapter 6. Instead, the tolerances are often the same for the entire blade. The reason for this is lack of knowledge regarding these hydraulic sensitivities. Hence, they will be investigated in this chapter. Based on the results, recommendations will be made regarding how to set the tolerances. Once again, focus will be on the blades with 25 points controlling the perturbations as described in appendix B. The blade is shown in a meridional view of the impeller and guide vane in Figure 7.1.

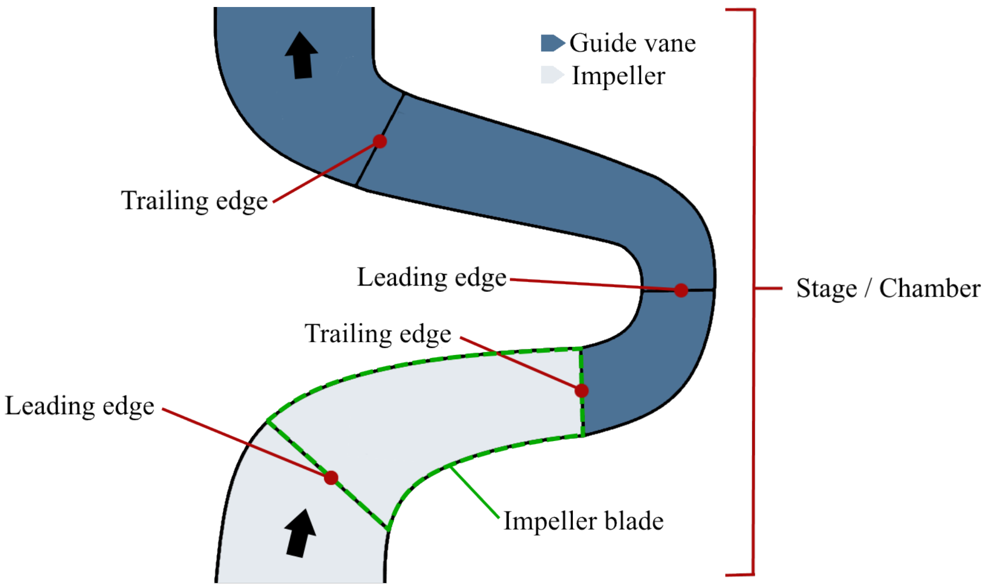


Figure 7.1: Meridional shape of the impeller and guide vane shown for a single stage. The impeller blade is marked by the dashed green line and the Leading Edges (LE) and Trailing Edges (TE) are marked as well.

The design obtained through conventional optimization will be analysed, since this design had the best performance. Initially, the blades will be subject to a robustness evaluation, which will determine the performance variation and the importance of the different control points with respect to the performance variation. Based on this, changes are made to the tolerances and new robustness evaluations will be performed. This will further elucidate how the tolerances influence the variation.

7.1 Hydraulic sensitivity of the geometry

The first step of investigating how to set the tolerances is to determine the hydraulic sensitivity of the geometry, which is the blade in this case. Hence, a robustness evaluation is performed to determine which points along the blade affect the performance the most.

The control points for the robustness evaluation are given a uniform distribution with a range. The variations are uniformly distributed to reflect that they in fact tolerances and that the designs can end up anywhere within the prescribed tolerance ranges. There are no linear dependencies between the control points, and two adjacent control points can therefore be displaced in opposite directions. The settings used for the initial robustness evaluation are shown below:

- Design of Experiments (DoE) method: Latin Hypercube Sampling (LHS)
- Number of design samples: 100
- Tolerance distribution: Uniform
- Tolerance range: +/-0.3 mm

The sensitivities of the blades in terms of how geometry perturbations affect performance are shown by the color plots in Figures 7.2, 7.3 and 7.4. The sensitivities are plotted directly on the blade. The colors show how much of the total variation each control point accounts for. Linear interpolation between the points are used to colorize the blades between the points to assist in visualizing the results.

Based on Figures 7.2, 7.3 and 7.4, it is evident that the trailing edge is the most critical part of the blade in terms of minimizing the performance variation. The trailing edge determines the outlet flow angle β_2, and this therefore indicates that β_2 is an important parameter to consider during manufacturing to minimize unwanted variations.

Maintaining the same position and outlet angle of the trailing edge is especially important for the power consumption and head gain, whereas the efficiency is affected by perturbations all across the blade as well. This makes it harder to control the variations in efficiency compared to the variations in power consumption and head gain, although the trailing edge remains the most important part even for the efficiency.

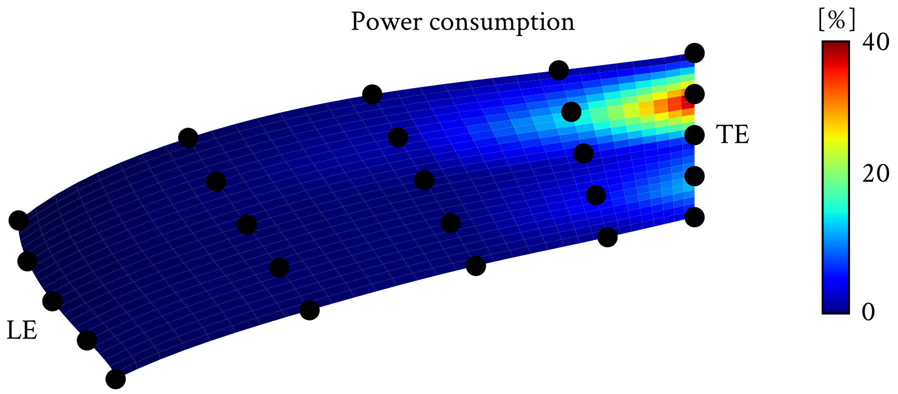


Figure 7.2: The sensitivity of the blade with respect to variations in the power consumption. The colors explains how much of the variation each point is responsible for. The black dots are the control points.

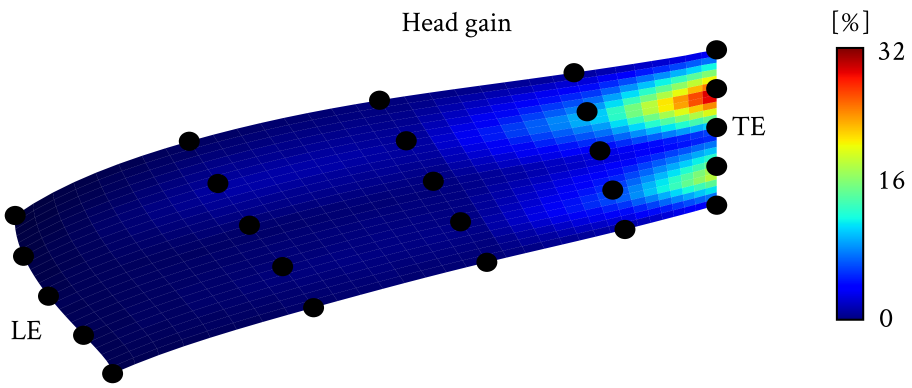


Figure 7.3: The sensitivity of the blade with respect to variations in the head gain. The colors explains how much of the variation each point is responsible for. The black dots are the control points.

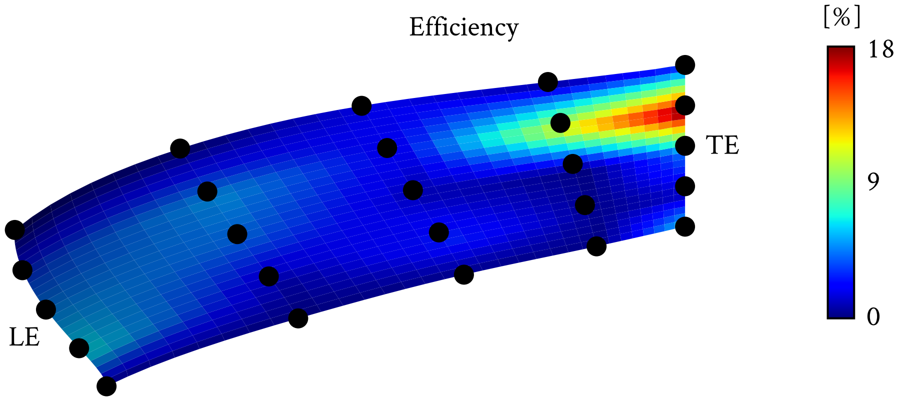
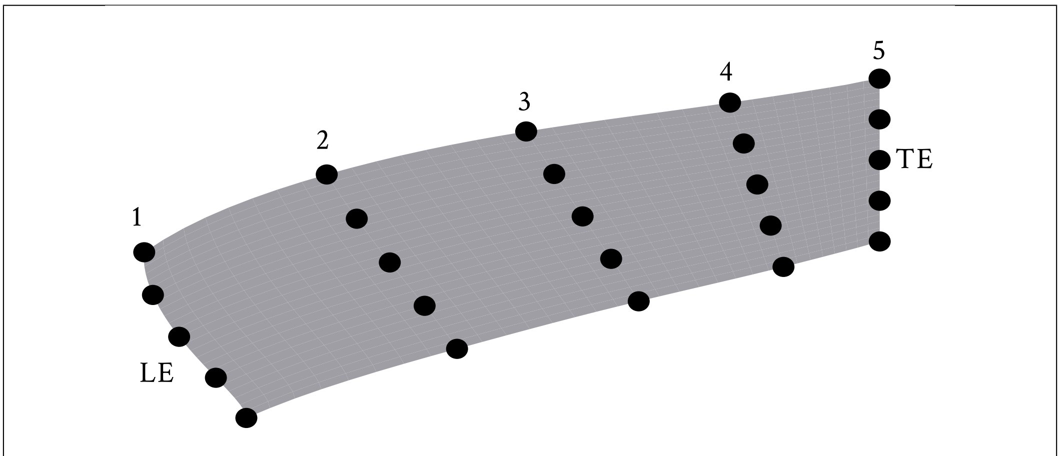


Figure 7.4: The sensitivity of the blade with respect to variations in the efficiency. The colors explains how much of the variation each point is responsible for. The black dots are the control points.

7.2 Specifying tolerances based on the hydraulic sensitivity

With the most important parts of the blade determined, it is now possible to investigate how the performance variation is affected by local tolerances on different parts of the blade. The purpose of this is to investigate how the performance variation will be affected if local tolerances are used. With the current manufacturing methods, it is logical to prescribe the same tolerances for the same column of control points, and as such there are five tolerances to specify. Three cases with different tolerance specifications are investigated.

The first case is the reference case from section 7.1, where all columns are given a range of +/-0.3 mm. Case 2 differs from case 1 by having the tolerances at the trailing edge tightened to a range of +/-0.1 mm, and case 3 differs from case 2 by also having the tolerances of column 2 and 3 loosened to 0.5 mm.



Column	1	2	3	4	5
Case 1	+/- 0.3 mm	+/- 0.3 mm	+/- 0.3 mm	+/- 0.3 mm	+/- 0.3 mm
Case 2	+/- 0.3 mm	+/- 0.3 mm	+/- 0.3 mm	+/- 0.3 mm	+/- 0.1 mm
Case 3	+/- 0.3 mm	+/- 0.5 mm	+/- 0.5 mm	+/- 0.3 mm	+/- 0.1 mm

Table 7.1: The three different tolerance specifications.

The performance variations resemble normal distributions, and they can therefore be described by a mean value and a standard deviation. This is shown in Figures 7.5 and 7.6, where the mean value for each case is shown with a confidence interval of 99.73 % corresponding to three times the standard deviation. A large confidence interval bar means a large variation, and hence a small confidence interval bar is desired. Figures 7.5 and 7.6 show the mean and confidence interval for the power consumption and head gain, respectively.

The tendencies for the variations in both head gain and power consumption are the same, which can be seen on Figures 7.5 and 7.6. This is not surprising considering that the same parts of the blade are important for both two performance parameters. Going from case 1 to case 2, where the difference is tighter tolerances on the trailing edge, the confidence interval is reduced by 40 % and 35.7 % for the power consumption and head gain, respectively. Hence, a significant reduction of the performance variation can be achieved by tightening the tolerances on the trailing edge of this design.

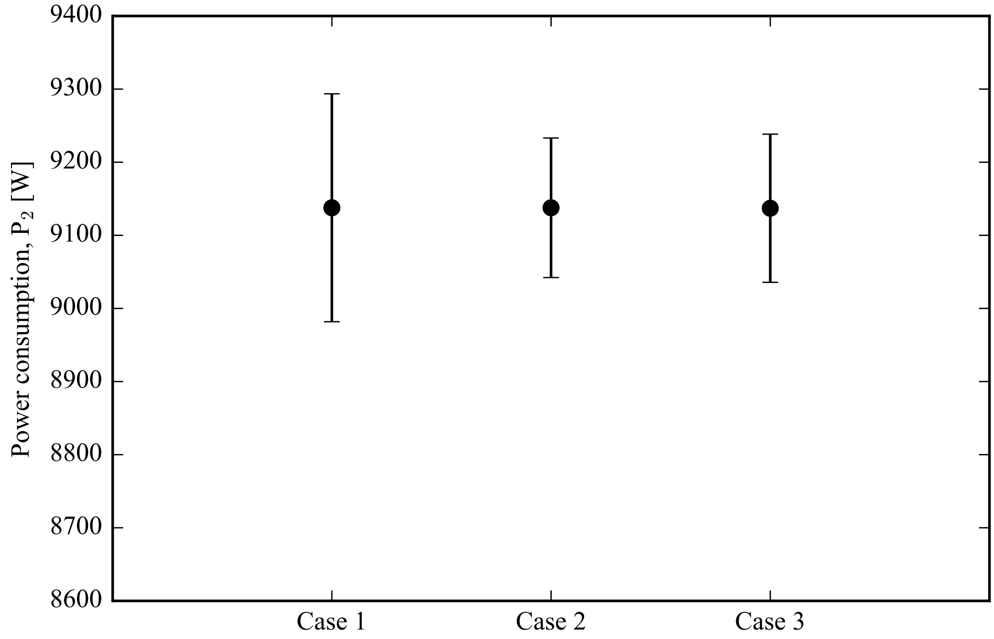


Figure 7.5: The mean value of the power consumption for the three cases. The bars designate a confidence interval of 99.7 % corresponding to three times the standard deviation.

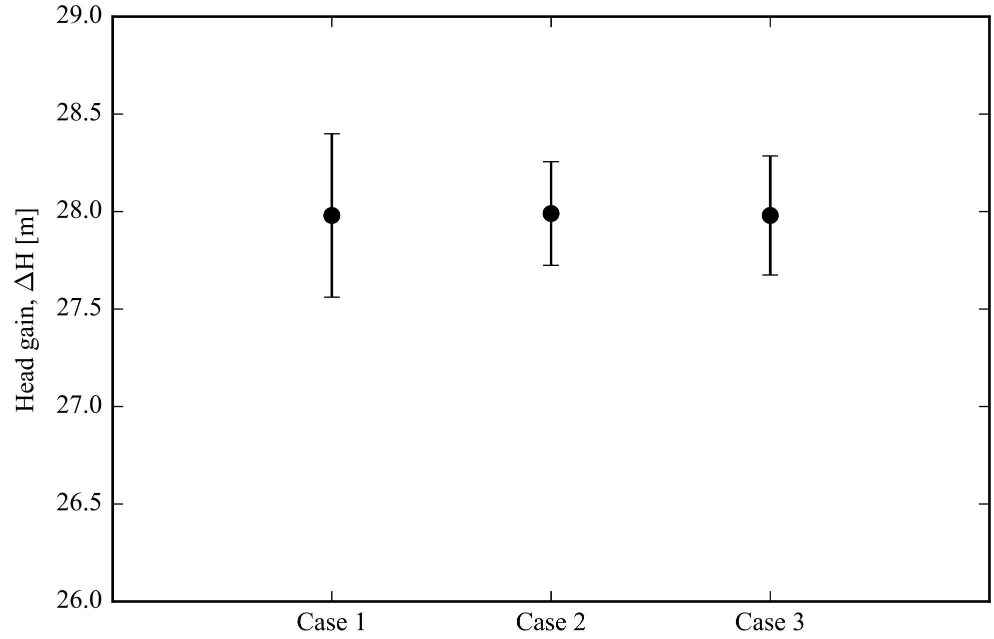


Figure 7.6: The mean value of the head gain for the three cases. The bars designate a confidence interval of 99.7 % corresponding to three times the standard deviation.

Following the tightening of the trailing edge tolerances in case 2, the next step is to loosen the tolerances in the less sensitive regions of the blade to ease manufacturing and potentially reduce the manufacturing costs. The less sensitive regions are mainly the control points in columns 2 and 3. Here, both columns of points have their tolerances increased by the same amount that the trailing edge was tightened with in case 2. This increases the confidence interval in case 3 slightly compared to case 2. However, comparing case 3 to case 1 shows that the confidence interval is still reduced significantly. The new confidence interval corresponds to a reduction of 35.0 % and 27.1 % in power consumption and head gain compared to case 1, despite case 3 actually having looser average tolerances.

So far, the impact from changing the tolerances have only been considered in terms of power consumption and head gain. However, the variations in efficiency are also affected by these changes. Compared to the power consumption and head gain, the reduction in variation for the efficiency is smaller when going from case 1 to 2. In fact, the confidence interval is reduced by only 23.4 % compared to 40 % for the power consumption. However, this is consistent with the sensitivity plots in Figures 7.2, 7.3 and 7.4, where the trailing edge is of less importance for the efficiency variations than for the power consumption and head gain variations.

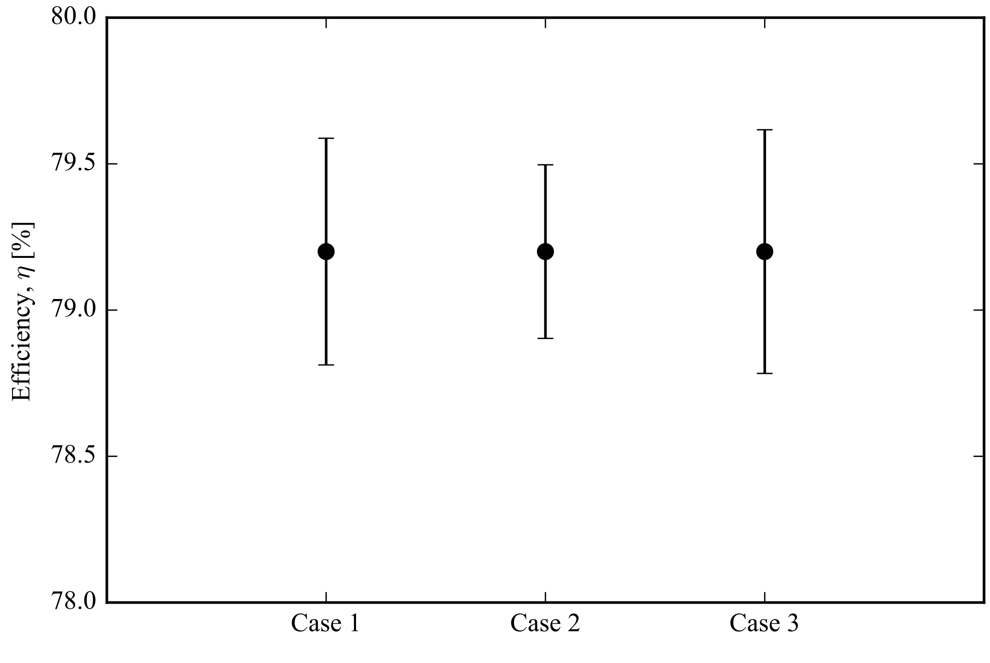


Figure 7.7: The mean value of the efficiency for the three cases. The bars designate a confidence interval of 99.7 % corresponding to three times the standard deviation.

While the efficiency variation is less affected by case 2, loosening the tolerances in case 3 actually has a larger impact on the efficiency variation than with the power consumption and head gain. For the efficiency, case 3 even has a 7.5 % larger confidence interval bar compared to case 1. Hence, the efficiency variation actually increases going from case 1 to 3, despite a reduction of the variation in power consumption and head gain.

It is evident from the study that it is not always possible to loosen tolerances significantly without also increasing the variation of one or more performance parameters as seen in case 3. Here, the efficiency variation is increased from case 1 to 3 despite the reduction in the variation of the remaining performance parameters. How to specify the tolerances will therefore depend on a prioritization of the performance parameters as well as the magnitude of the variation. In this case, the slight increase in the variation of the efficiency is worth it when also considering the improvements to the variation of both the power consumption and head gain.

As demonstrated in the three cases, it is possible to reduce the performance variation by specifying the tolerances in a way that takes into account the hydraulic sensitivities. This means tightening the tolerances in areas that are critical towards performance and loosening them in less critical regions. Doing so can ease manufacturing, reduce costs and minimize the performance variation depending on how and with what purpose the knowledge on hydraulic sensitivity is applied. Hence, knowledge on the hydraulic sensitivity should always be considered when specifying tolerances for manufacturing.

7.3 Summary

The hydraulic sensitivity of the blade of the best impeller design is investigated. The trailing edge is found to be the most critical region in terms of contributing to the performance variation, and as such tightening the tolerances in this region is especially beneficial. At the same time, it is possible to loosen the tolerances in some of the less critical regions without significantly increasing the performance variation. Thus, using the knowledge on hydraulic sensitivity when specifying tolerances for manufacturing are recommended.

Eighth Chapter

Conclusion

The purpose of this thesis has been to investigate if Robust Design Optimization (RDO) can be used to improve existing pump design methods and to specify tolerances for manufacturing. This means successfully improving the robustness of the design by locating alternative optimums as well as determining how to best specify the tolerances. This purpose is described by the following research question and will be answered in this chapter.

Can Robust Design Optimization be used to improve existing pump design methods and to specify tolerances for pump manufacturing?

None of the investigated RDO methods manage to locate a better design point than the one obtained through conventional optimization methods, however, the methods are successfully able to determine the sensitivity of different regions of the blade, which can be used to specify tolerances more effectively. The implications of these findings are presented below.

The two RDO methods are evaluated by comparing the best designs from each method to the best design obtained from conventional optimization. The hybrid method locates a poorer design point and is therefore not recommended, while the One-Design-At-a-Time (ODAT) method locates the same design point as the conventional optimization. This is likely caused by the fact that the global optimum and the robust optimum happen to be the same, which raises the question whether this is a coincidence or always the case. If this is always the case, then RDO becomes trivial in the design development and provides no improvements to the current design methods. That this should always be the case is unlikely, since examples that indicate the existence of robust optimums can be found in the literature [Dynardo GmbH, 2017] [Yaping and Chuhua, 2016]. However, further studies are perhaps required to clarify with certainty whether and when robust designs exist. If it is merely a coincidence then it is not possible to evaluate ODAT RDO with certainty based on the current findings, since the method might be able to locate a robust design if such a design exists.

The robustness evaluation of the blade shows the trailing edge to be the most sensitive region for the current design. In this region, the deviations occurring during manufacturing have the highest impact on the performance variations of all three performance parameters. Furthermore, the efficiency is affected significantly by the leading edge as well. This type of knowledge is incredibly useful when specifying tolerances for manufacturing, since it enables the designer to specify tighter tolerances in critical regions and looser tolerances in less important regions. This means that the performance variations can actually be reduced even if the average of the tolerances are loosened. Therefore, using the robustness evaluation to specify tolerances can both ease manufacturing and reduce performance variations at the same time, making it a powerful tool in any development process. It is currently not possible to say with certainty whether the location of the sensitive regions apply to all cases across impeller design and type, and it is therefore recommended to always do a robustness evaluation of a new design before specifying tolerances.

The CFD model is a critical part of successfully including RDO methods into the design development of centrifugal pumps as well as other turbomachinery applications. How to set up the CFD model and how to decide on a trade-off between calculation speed and accuracy therefore affects the outcome of the RDO process. The CFD model in this case has been set up with the knowledge that some of the investigated RDO methods require a significant amount of solver calls, and hence calculation speed has been prioritized heavily. Based on the results in this thesis, future design methods may be likely to only include a single robustness evaluation. In such a case, the computational costs are reduced significantly through the reduced number of solver calls, and it can therefore be acceptable to use a finer and more accurate mesh and more expensive CFD settings.

Ninth Chapter

Future Work

It has already been mentioned in chapter 8 that new questions have arisen as a result of the findings in this thesis. It is necessary to further investigate if and how frequently robust optimums occur as an alternative to the global optimum. A promising approach towards investigating this could be to apply ODAT RDO to other turbomachinery cases and compare the results with what can be obtained from conventional optimization. This corresponds to repeating this study on several other cases. By doing this, the results can be generalized in a way, where it becomes possible to assess RDO as a design method with more certainty.

Another question is regarding the sensitivity of the blade. It is unclear whether the results from the robustness evaluation are unique for the current design or something that can be generalized to include all centrifugal pump impellers. Repeating the robustness evaluation on both similar and significantly different types of impellers will help clarify this and produce more general guidelines for tolerance specification. It is therefore the next logical step towards understanding how to specify tolerances with hydraulic sensitivity in mind.

So far, the robustness evaluation has been limited to include only perturbations of the blade, and the front and back plate have therefore been assumed to be nominal. While these are less critical than the blade, they still influence the performance variations. A study similar to the one performed on the blades should therefore be performed on the front and back plate to further increase the understanding of how tolerances should be specified. The study could also be extended to include other parts such as the guide vane.

The perturbations in this investigation have been completely random to prioritize working on the RDO methods. Alternatively, the perturbations can be chosen randomly from a set of predefined shapes that describe mechanisms that occur in manufacturing. This could for example be spring back and over bending of the blade and will show what mechanisms are most critical during manufacturing. This information could also be very useful, but it should be noted that this method will require careful consideration on how to define the predefined shapes to avoid bias and wrong results.

Appendix A

The Inverse Design Method

A.1 Motivation behind the inverse design method

Modern turbomachinery design methods typically include numerical CFD simulations to evaluate designs prior to testing [ADT, 2006]. Design methods that include CFD are typically classified as being either direct or inverse. Direct design methods are the conventional approach, where the blade geometry is specified and modified iteratively by trial and error as shown in Figure A.1. This approach relies heavily on the experience of the designer and often requires many iterations, which makes it computationally more expensive as well as slower compared to the iterative approach [Li and Zheng, 2017] [ADT, 2006]. In the inverse design method, the blade geometry is generated from a specified pressure distribution along the blade. The pressure distribution controls the desired flow and shapes the blade accordingly, and because the optimum pressure distribution is often the same or similar for the same applications, it only needs to be developed once [ADT, 2006].

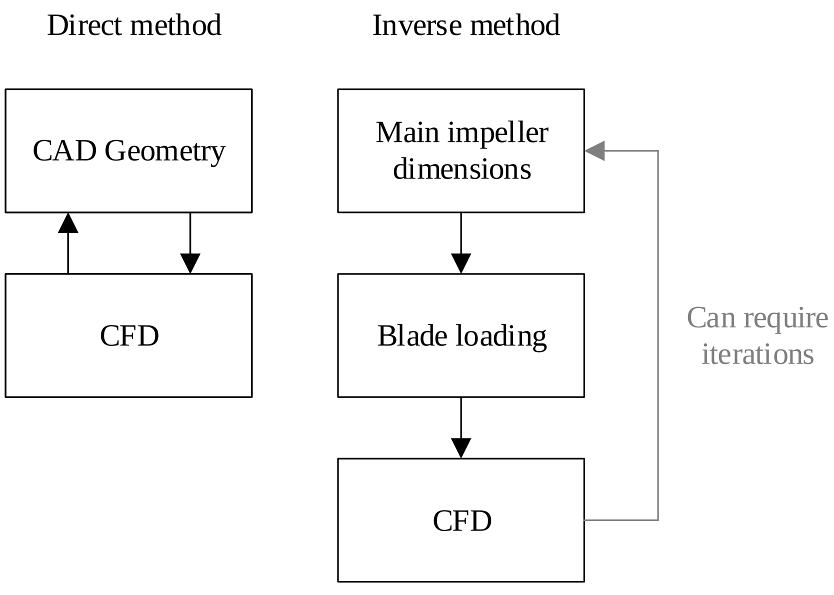


Figure A.1: Comparison between the direct and inverse method.

The issue with the direct method relying heavily on the designer's experience can to some extent be solved by applying an optimization loop to the direct method. However, the direct method uses geometric parameters to parametrize the blade, which results in a large number of parameters and hence a highly complicated optimization problem. The inverse design method relies on fewer parameters, which makes the inverse method better-suited for an optimization loop [Yang, 2013]. The fact that the inverse method is well-suited for an optimization loop is further substantiated by [Bonaiuti and Zangeneh, 2009], [He and Shan, 2012] and [Li and Zheng, 2017].

A.2 Description of the inverse method

The inverse design method aims to reduce the occurrences of secondary flows by specifying a pressure distribution along the blade. Secondary flows are generated when there is a reduced static pressure gradient between the hub and shroud of an impeller [Zanganeh and Goto, 1998]. The reduced static pressure is defined as:

$$\mathrm{P_{red}} = \mathrm{p_{static}} - \frac{\rho\omega^2 \mathrm{r}^2}{2} = \mathrm{p_{static}} - 0.5\rho \mathrm{U_{tang}^2} \tag{A.1}$$

where $\mathrm{p_{static}}$ is the static pressure, ρ is the density, ω is the angular velocity of the impeller, r is the radius and $\mathrm{U_{tang}}$ is the tangential velocity. This can be rewritten as a reduced pressure coefficient to make it dimensionless:

$$\mathrm{C_p} = \frac{\mathrm{P_{0,rot}} - \mathrm{P_{red}}}{0.5\rho \mathrm{U_{tang}^2}} \tag{A.2}$$

where $\mathrm{P_{0,rot}}$ is the rotational stagnation pressure.

The goal is now to develop a design, where the pressure difference between hub and shroud $\Delta \mathrm{C_p}$ is minimized in the parts of the impeller that is most sensitive towards secondary flows. The secondary flows are stronger in areas with a thick boundary layer, which is in the aft part of the impeller [ADT, 2006]. This means that it is better for $\Delta \mathrm{C_p}$ to be larger in the inlet part of the impeller, while it should be as small is possible in the aft part.

With the traditional method, it is difficult to control these pressure distributions along the blade. Therefore, the inverse method has been developed. In the inverse method, the pressure distribution is specified, and from that a blade geometry that fulfils the specified pressure distributions is generated.

Using pressure distributions have additional advantages. The optimal distributions are similar for the same applications, which means that the same pressure distribution can be reused over and over again. Furthermore, fewer parameters are required as inputs to the design flow, making optimization easier. Therefore, the inverse method is used in this thesis.

Appendix B

Geometry Perturbation

Current Robust Design Optimization (RDO) methods assume that the design parameters are directly related to geometry parameters and hence can be used to describe manufacturing variations. This is not the case when using the inverse design method and hence an RDO method capable of handling two different parametrizations are required; a parametrization using inverse design parameters and one using geometric parameters. The geometric parameters describe the variation in manufacturing through perturbations of the geometry.

Creating a tool to perturb an existing geometry as complicated as the impeller is a comprehensive task, and the same method cannot be used for the perturbation of all parts of the geometry. Hence, the blade, hub and shroud will all require different approaches. Creating this tool is not the main focus of this thesis, and a tool will only be developed for the blade, which is the most critical part of the impeller. This appendix therefore presents and discusses possible methods to perform these perturbations on the blade.

Perturbations can be performed in different ways such as for example mesh morphing, manipulation of the CAD geometry or by manipulating some of the text files that describe the geometry. Mesh morphing is based on free-form deformation making it ill-suited for parametrized perturbations [Eggenspieler, 2012] [ANSYS, 2018]. Parametrized modifications of a CAD geometry is possible, but this is a computationally expensive approach that would significantly increase the execution time of each iteration. Modifying a text file, on the other hand, is faster, more robust and applicable in a wider range of applications. In this approach, all blades are described by the same geometry file, which means any geometry variation will be applied to all blades. While this means it is not possible to investigate periodic variations in production, it also enables the use of periodic boundaries on the CFD model, which significantly reduces the calculation time. Hence, the blade shape will be modified through direct modifications of the text file describing the geometry.

The existing blade shape is described by splines in the stream- and spanwise direction. These splines are controlled by points located at the intersections between the splines. Figure B.1 shows the stream- and spanwise splines of an arbitrary blade geometry. As seen, the number of points on the blade is large and varying all points would make it impossible to replicate actual, realistic deviations through the DoE. Therefore, the number of splines that are actually modified must be reduced. This can be achieved by specifying a desired number of splines n and m in the stream- and spanwise direction, respectively. Then, n times m points can be distributed evenly on the existing surface as shown in figure B.2.

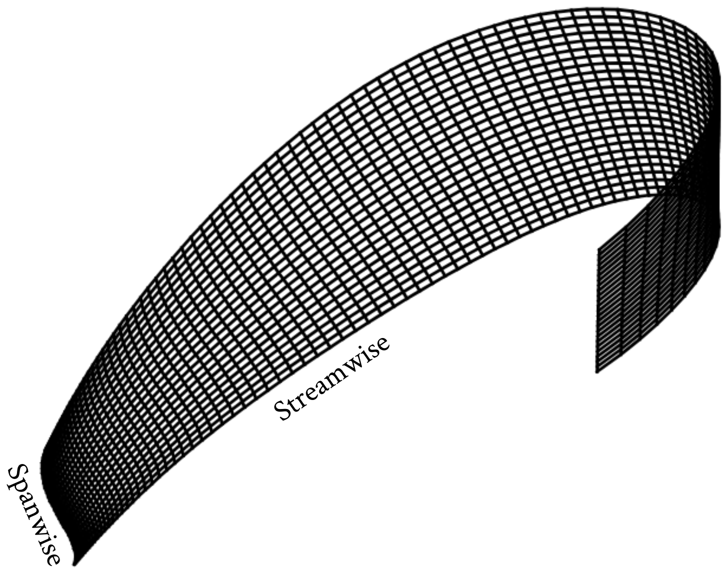


Figure B.1: The blade geometry is described by stream- and spanwise splines. A control point is located at every intersection between the splines.

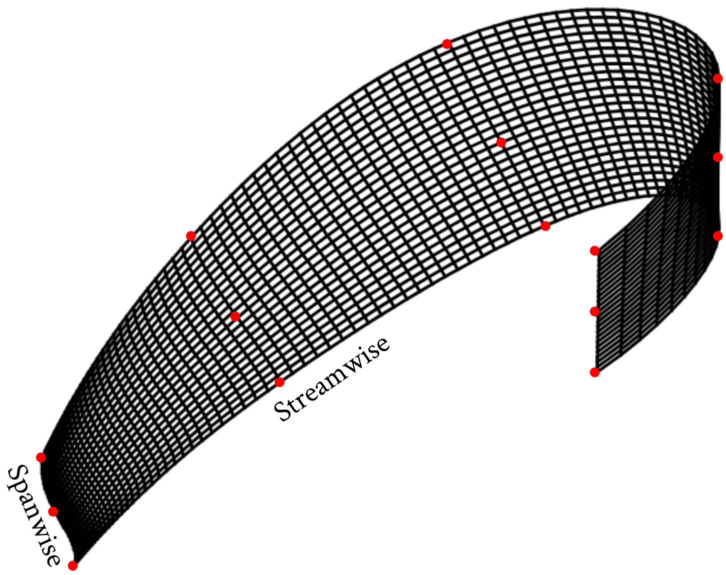


Figure B.2: This shows the distribution of the reduced number of points. In this case, five splines in the spanwise and three splines in the streamwise direction results in 15 control points.

With the reduced number of control points defined, it is now possible to define the splines. Cubic splines are used, since these ensure that the spline curves pass through all the required points, which is necessary to generate the blade. This will produce a replica of the existing blade geometry, whose shape can be perturbated by changing the position of the control points. The control points are varied in the direction normal to the blade surface. The displacement is specified by a deformation matrix containing a scalar value for each point.

When using cubic splines, there is a risk that extraneous inflection points will be generated on the curve resulting in unwanted geometry perturbations. This is shown in Figure B.3, where the deformations are based on matrix B.1. While these inflection points may influence the results of the RDO, the impact will be less random due to the large number of evaluated designs in a robustness evaluation compared to if only a single design is considered. This can be explained by the fact that moving a point will sometimes create an extraneous inflection point and sometimes not. Hence, the error due to extraneous inflection points will to some extent be reduced by the designs, where no inflection points occur.

$$\begin{bmatrix} 0 & 0 & -0.5 & 0 & 0 \\ -0.5 & -0.5 & -0.5 & -0.5 & -0.5 \\ 0 & 0 & -0.5 & 0 & 0 \\ 0 & 0 & -0.5 & 0 & 0 \end{bmatrix} \tag{B.1}$$

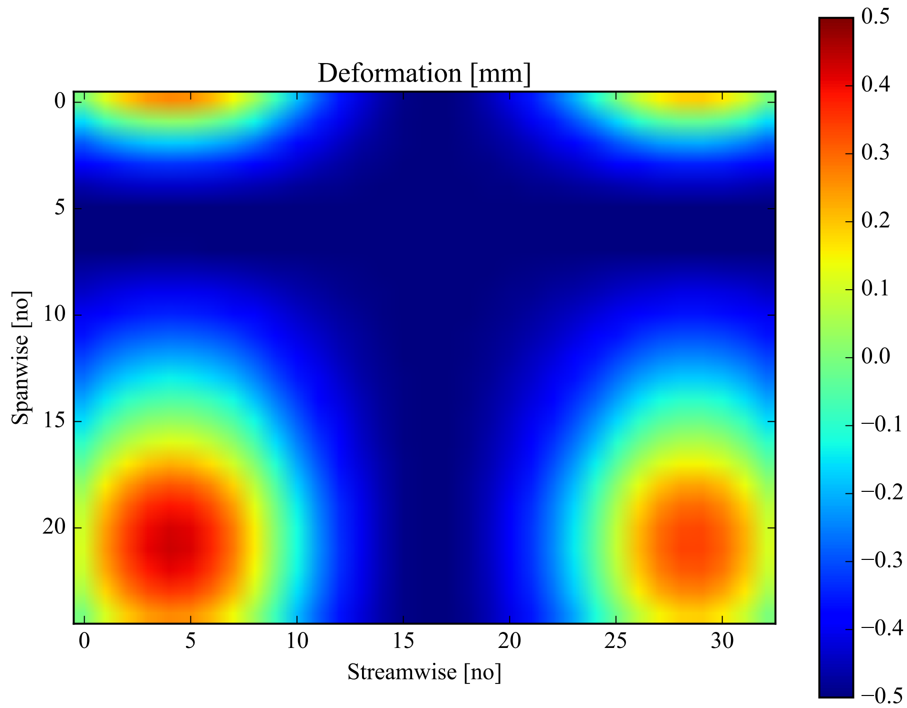


Figure B.3: Heat map of the deformations of the surface of the blade. Extraneous inflection points are created in the red zones, despite the fact that no deformation was specified in this area. This example is exaggerated to illustrate the occurrences of extraneous inflection points. The deformations are defined in equation B.1.

In an attempt to avoid or minimize the occurrences of extraneous inflection points, an alternative method can be used. Here, no control points in the deformation matrix are allowed to vary independently. Instead, deformation mechanisms that are observed in production can be replicated by different predefined deformation matrices, and a scalar can then be used to define the extent of the specific mechanism. This makes it possible to minimize the occurrences of extraneous inflection points, since the deformation matrix will be predefined in a way, where this is unlikely to happen.

An example can be shown for the blade, which is produced by forming sheet metal, and an example of a mechanism that can be observed in this type of production is springback. Springback occurs when the forces shaping the sheet metal are released, resulting in deviations in the curvature of the blade. Springback can be described by the deformation matrix in equation B.2, and by multiplying the matrix with a scalar, the degree of springback can be changed. Figure B.4 shows the heat map of the deformations of the blade surface, and as seen no extraneous inflection occur.

$$\begin{bmatrix} 0 & 0.05 & 0.1 & 0.2 & 0.4 \\ 0 & 0.05 & 0.1 & 0.2 & 0.4 \\ 0 & 0.05 & 0.1 & 0.2 & 0.4 \\ 0 & 0.05 & 0.1 & 0.2 & 0.4 \end{bmatrix} \tag{B.2}$$

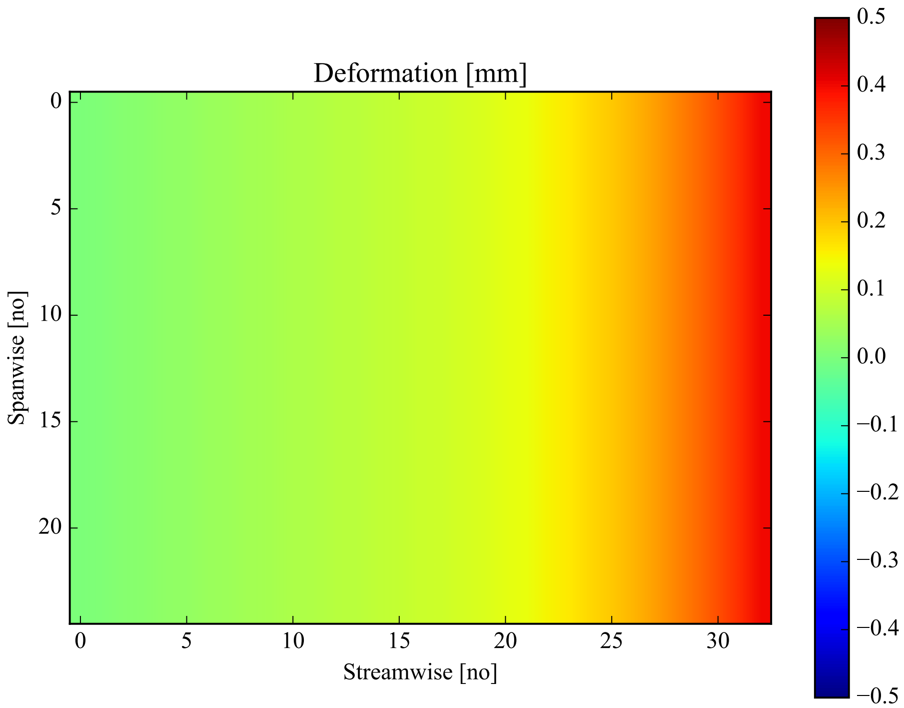


Figure B.4: Heat map of the deformations of the surface of the blade. The deformations correspond to springback during manufacturing. No extraneous inflection points are created in this case. The deformations are defined in equation B.2.

The issue with using deformation mechanisms is that it requires an extensive investigation into exactly how to describe observed deviations. This is not something that is possible with the current data, but rather something that is planned for the future. Furthermore, if several mechanisms are applied to the same design, there is a risk that extraneous inflection points may still occur. Varying the points individually may therefore be an equally sufficient method, and choosing what method to use should perhaps depend on whether the robustness evaluation should investigate what importance the mechanisms have or what importance each geometric point has. However, since this thesis focuses on the RDO methodology, and since it is not clear what perturbation method is best, the geometry will be perturbed with the method that is simplest to implement, which is using random variations in the control points.

Appendix C

Underlying methods in RDO

Robust Design Optimization is a term that covers a range of different methods such as different Design of Experiments (DoE) methods, meta modelling methods and uncertainty quantification methods. These are explained in this appendix.

C.1 Meta modelling and optimization

An essential part of the RDO process is the optimization process. An extensive amount of numerical optimization algorithms can be found in the literature [Arora, 2017] [Li and Zheng, 2017] [Schwarz, 2017], however, the number of required solver calls is generally higher than what is acceptable for CFD cases. As a result, optimization based on meta models have attracted significant attention in the recent decades [Wang and Shan, 2006]. Meta models are analytical functions that mimic the response of more computationally expensive models such as CFD models.

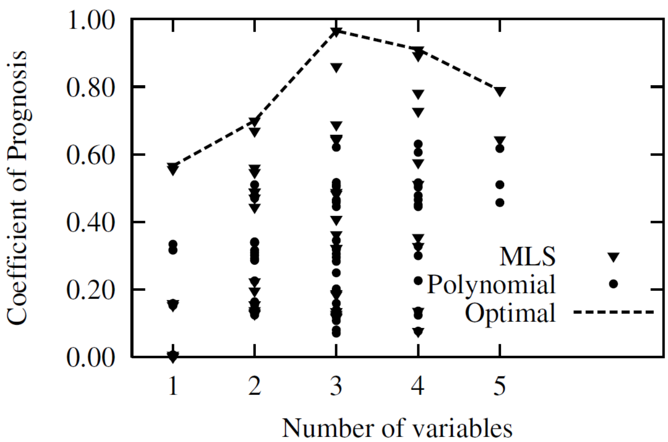


Figure C.1: Evaluation of different combinations between input parameters and meta models. The Coefficient of Performance shows the accuracy of each method, where 1 is a perfect match. [Dynardo GmbH, 2017]

Many meta modelling methods already exist, however, it is often not clear which ones are best-suited for which problems [Roos et al., 2007]. While Clarke and Griebsch [2004] and Li [2010] find that the Support Vector Regression (SVR) is often the best method, they do not consider the option of reducing the space to disregard insignificant parameters, which can be a necessity if a large number of parameters are used. A meta model typically performs better with few parameters, which means that it can be an advantage to disregard insignificant parameters [Schwarz, 2017]. Hence, different combinations of meta models and significant input parameters should be compared each time a meta model is generated. An example of this is shown in Figure C.1, where the Coefficient of Prognosis (CoP) refers to the accuracy of the model and 1 is a perfect match. This approach, where multiple meta models are investigated, is referred to as finding the Meta model of Optimal Prognosis (MOP).

In order to use the meta model approach, a set of design points must be evaluated using direct solver calls, which can be generated using different sampling methods. This is known as Design of Experiments (DoE). Many DoE sampling methods such as the Monte Carlo Simulation (MCS) and the Full Factorial (FF) method exist. These methods can generally be distinguished as stochastic models or deterministic models [Li and Zheng, 2017]. Deterministic models such as FF are limited to few dimensions [Yaping and Chuhua, 2016], making stochastic models such as the MCS better-suited for turbomachinery applications. Unfortunately, MCS requires a huge amount of solver evaluations due to the random sampling, which means MCS is also a poor choice for CFD applications [Yaping and Chuhua, 2016] [Schwarz, 2017]. Therefore, an alternative DoE method must be applied. The MCS-based Latin Hypercube Sampling (LHS) is a quasi-random DoE method proposed by [McKay et al., 1979] that performs well with few samples, making it well-suited for CFD applications. Advanced LHS (ALHS) is a variant of LHS that is available as an alternative sampling scheme and is well-suited for cases with less than 50 parameters [Dynardo GmbH, 2017] [Huntington and Lyrintzis, 1998].

The meta modelling approach does not change the fact that a wide range of optimization algorithms are available. These include methods based on response surfaces, gradient-based methods and so on. Each of these methods will not be tested, since this is time-consuming and not within the scope of this thesis, and hence an optimization method will be chosen based on existing recommendations and the current case.

C.2 Latin Hypercube Sampling

Latin Hypercube Sampling (LHS) is a Design of Experiments (DoE) method. DoE methods are used to scan the space of input variables by discrete realizations and are often also referred to as sampling methods. Deterministic DoE methods such as the Full Factorial (FF) are common [Antony, 2003], however, they are limited to few dimensions [Yaping and Chuhua, 2016], because the number of samples increase exponentially with the number of parameters [Dynardo GmbH, 2017]. Stochastic DoE's such as LHS are therefore often preferred as they are less dependant on the number of parameters.

LHS is a quasi-random sampling method that has its origins in Monte Carlo Simulation (MCS). MCS randomly selects points to evaluate and therefore requires a large number of samples to avoid clustering of results and undesired correlations betweens input variables [Dynardo GmbH, 2017]. This makes it ill-suited for CFD applications, and therefore LHS is better-suited for the problem at hand. The distribution of the samples in MCS and LHS are illustrated in Figure C.2 and as seen, the LHS sample points are more evenly distributed [Schwarz, 2017].

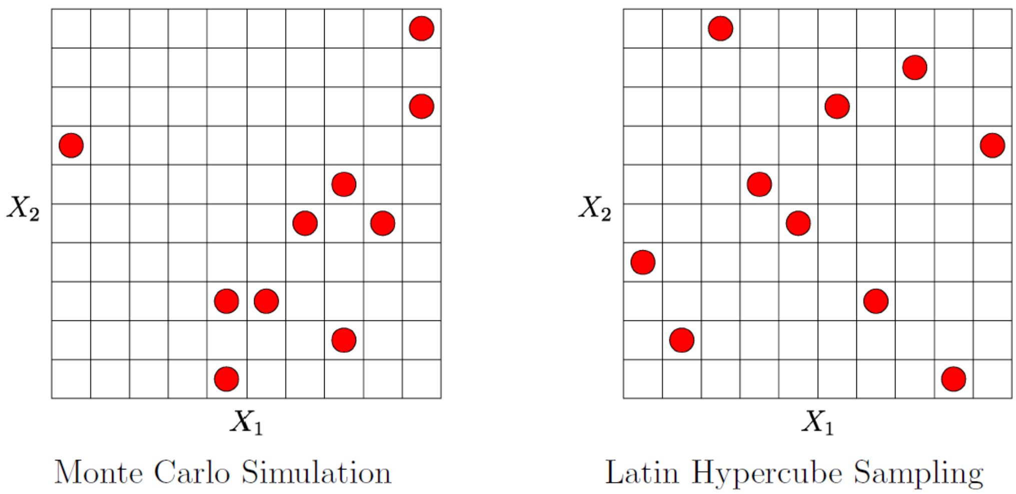


Figure C.2: Distribution of the sample points using MCS and LHS. [Dynardo GmbH, 2017]

In statistics, a latin square is an n·n array with a sample point in each row and column. This is also what is shown to the right in Figure C.2. The generalisation of a latin square to more dimensions is referred to as a latin hypercube, and hence this sample point distribution is what characterizes LHS [McKay et al., 1979]. Since LHS was first proposed by McKay et al. [1979], modifications have been made [Iman et al., 1981] [Sheikholeslami and Razavi, 2017] and methods such as Advanced LHS (ALHS) have been derived. Common for all these methods are that they are all based on the latin hypercube described in appendix C.

C.3 Robustness evaluation

The robustness evaluation is a method that has the purpose of determining the robustness of a design. In the framework of this thesis, variance-based robustness evaluation is used. A DoE generates a set of design samples from a number of geometric parameters. The geometric parameters are described by a distribution type, a mean value and a standard deviation.

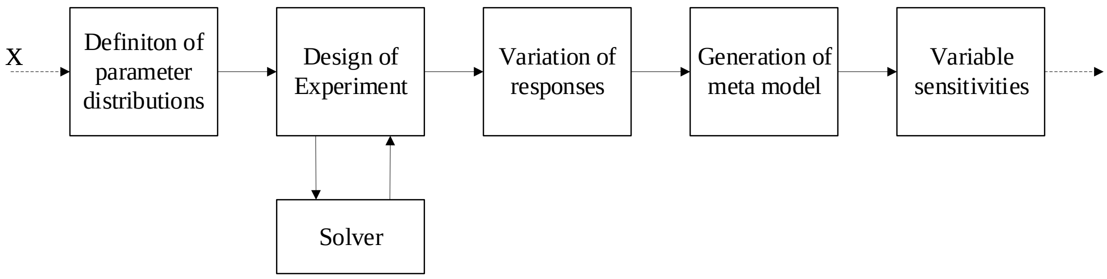


Figure C.3: Flow chart of a robustness evaluation.

Figure C.3 shows the flow chart of a robustness evaluation. Once the parameters and their corresponding distributions have been defined, a DoE is used to obtain a set of samples and responses. This is used to determine the statistical properties such as variance and mean of the responses. Then, a meta model is generated from the DoE, which is used to determine what input parameters have the greatest influence on the variations in the model response. The robustness can then be quantified by for example the variance, the number of failed designs or the Taguchi loss equation.

The variance-based robustness evaluation described here is a type of reliability analysis, however, the robustness evaluation relies on fewer samples than the reliability analyses. As a result, this method is faster but also less accurate than other methods [Schwarz, 2017], which is a necessary trade-off due to the expensive CFD solver.

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