

An approach for automatic design variation and assessment of technical and economic performance

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Abstract

Nowadays, designing component structures that meet highly demanding multi-criteria technical requirements holds the utmost significance, particularly in specialized industries like medical devices or construction industry. For example, high-dose radiation targets used in cancer therapy must be subjected to extreme thermal and substantial mechanical loads during operations. At the same time, in addition to customer satisfaction with mechanical performance, shorter lead times and reduced costs are among the industrial challenges to be addressed in the current environment [77]. However, when designing such components with fastidious mechanical design requisites, the consideration of economic characteristics, e.g., manufacturing costs, is often overlooked. The primary focus is on meeting restrictive technical specifications, such as excellent heat transfer or stable mechanical performance at high temperatures, and managing complex relationships between multi-criteria technical requirements, such as ensuring that high-speed rotation of a target wheel used to avoid local thermal overload does not cause damage due to spinning at high temperatures, which already pose significant challenges and consume valuable time and resources. In addition, further optimization of a feasible design that already meets challenging mechanical design demands to reduce the current manufacturing costs should be discouraged [101]. Such cost-based optimization requires additional time and effort and does not guarantee that the original mechanical performance will be maintained while cost-reduction measures are pursued. Therefore, it is necessary to consider both technical and economic performance simultaneously in the development process. However, due to the large number of design variables, experience-based design may lead to a suboptimal result. For this reason, a parametric approach is used, which integrates Design of Experiments (DoE), CAD modeling, numerical simulation, and manufacturing cost calculation. For fast assessment of many design variations from both technic and economics, an automatic design procedure is proposed that includes (1) a parametric CAD model that represents the design concept and automatically updates designs, (2) an automatic numerical-simulation-based assessment of the technical quantities of interests, (3) an automatic manufacturing cost calculation that does not determine all manufacturing costs, but only the design-dependent cost part to evaluate the economic perspective and (4) a systematic analysis based on Design of Experiments (DoE). This approach takes both the technical and economic aspects into account and aims to identify a design that not only meets the highly restrictive technical development requirements but also achieves cost-effectiveness. By basing the cost calculation on early manufacturing process planning, it facilitates quick design comparisons in product development to enable decision-making based on design and cost. The developed method is intended to increase the transparency, flexibility, and efficiency of the product development process. It can be applied to various areas of product development, including component design of aircraft, chassis, automobile, etc., and

be adapted to different development conditions, such as varying complexity of design tasks, varied challenges of design requirements, and various production processes. The developed approach is effectively demonstrated by designing a target wheel structure for an ultra-high power X-ray source used in cancer therapy and a rubber mount for a vibratory rammer, which acts as both a supporting part and a damper. The design improvements achieved in both use cases are presented to illustrate the effectiveness of the approach.

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1 Introduction

1.1 Initial situation

Industry is rapidly evolving, driven by a continuous quest for innovation and the complex tasks of component design that require adherence to restrictive technical specifications and economic considerations. In this challenging environment, reducing lead times, lowering costs, and increasing customer satisfaction are today's top priorities [77]. These demands challenge the development process, necessitating a balance between technical precision and cost-efficiency, while labor-saving strategies must also align with quality and performance expectations.

Currently, there is a high demand in industries such as medical devices and construction to design component structures with advanced technical performance, especially when these requirements cross multiple domains. For example, high-dose radiation targets used in cancer therapy must withstand extreme thermal stresses and high mechanical loads during operation. This situation is typical of the current climate where meeting customer satisfaction through robust technical performance is essential, along with challenges such as shortening delivery cycles, reducing manufacturing and development expenses, and maintaining agility for potential modifications.

However, focusing on complex technical design requirements, such as high-efficiency heat transfer or high-temperature stability, often neglects economic considerations, such as potential production costs. Balancing restrictive technical criteria with multi-domain considerations is a difficult task. In addition, incorporating economic relations into the design process requires significant additional time and resources. Achieving a technically and economically sufficient design is often not possible with current development approaches, especially in the detail design stages of product development. This difficulty is primarily due to the lack of information and know-how available to design teams for economic evaluation and the lack of appropriate methods. However, attempting to optimize a product with sufficient technical performance based on economic considerations is not recommended. It can compromise the product's technical integrity and may not yield the intended cost benefits.

Moreover, most current economic evaluation methods of products, especially before the production phase of product development, typically depend on historical data and similarities with existing products, which may fall short when applied to new product development. Consequently, it is rare to find transparent, straightforward, and quantitative economic evaluation methods

that can be effectively applied at a stages of new product development with limited available information. This gap highlights the need for more innovative approaches that simultaneously consider both technical and economic factors in product development.

1.2 Motivation

This initial situation establishes the foundation for the research motivation of this dissertation. Increasingly, it is being recognized that in today's context of escalating design requirements, an approach that concurrently addresses both technical and economic performance during the design process is necessary. However, traditional development methods, which are primarily experience-based, often fall short in this respect. This shortfall is particularly pronounced when the technical requirements span multiple domains and involve the complexity of a design with numerous design variables, leading to a longer development process and more efforts that may not provide the desired outcomes.

To meet these challenges, an approach to product development is required that integrates modules for various capabilities, such as automatic design modifications, automated technical evaluations, manufacturing cost calculations, and identification of optimal designs within a defined design space. These designs have to meet challenging technical requirements while being cost-effective.

The application of this approach aims to improve the general understanding, transparency, adaptability and labor-efficiency of product development process. It needs to be applicable to a wide range of development domains, including but not limited to the design of aircraft, automobiles, and machinery components. In addition, it provides flexibility to handle different levels of complexity, diverse design requirements, and various production strategies. The performance of this method should be validated through practical applications.

1.3 Research objectives and structure of the thesis

1.3.1 Research objectives

This research is focused on developing a parametric approach that effectively addresses today's product development challenges. It aims to improve product development by integrating various

methodologies, including DoE, CAD modeling, numerical analysis, and costing. The goals of this research are:

- **Develop a parametric approach:**
To create a methodology that integrates DoE, CAD modeling, numerical analysis, and production costing. This includes developing a parametric CAD model for automatic design modifications, allowing automated technical evaluations based on numerical analysis, and performing targeted manufacturing cost calculations that focus on design-related expenses.
- **Identify optimal designs for technical and economic performance:**
The application of DoE to identify optimal designs within a predefined design space that not only satisfy restrictive technical requirements but are also cost-effective. The goal is to balance technical precision with economic considerations in product development.
- **Improve the product development process:**
Improve the overall understanding, transparency, adaptability, and labor efficiency in the product development process. It should be applicable to a wide range of development domains and adapt to different design tasks.
- **Validate the approach through practical applications:**
Demonstrate the validity of the proposed approach through real-world examples. This includes the development of complex components such as a target wheel for an ultra-high power X-ray source and a rubber mount for a vibratory rammer.

1.3.2 Structure of the thesis

This dissertation is structured to systematically present the research, results, and contributions made in the field of product development. The thesis is organized as follows:

- Chapter 2 provides an overview of current methods for automatic design variation and evaluation, with a particular focus on the technical and economic performance of designs. This analysis identifies the challenges and establishes the foundation for developing a design approach.
- Chapter 3 delves into the background and fundamental principles of the methods applied in the proposed approach. The concepts of product design, technical evaluation, manu-

facturing cost calculation, and experimental techniques are discussed, highlighting their importance in the context of product development.

- Chapter 4 provides a detailed introduction to the developed approach, including its components, structure, and prerequisites for applying it. It also outlines the nine steps involved in product development, along with the details of each step and a potential guidance (with algorithms) that may be required.
- Chapters 5 and 6 demonstrate the practical application of the proposed approach in different development scenarios through two different design tasks derived from separate projects. These sections highlight the applicability of the approach in real-world settings, emphasizing its ability to simultaneously consider technical and economic aspects throughout solution exploration. The results of these applications provide substantial support for decisions on potential final designs.
- Chapter 7 presents a comprehensive discussion from four perspectives: quality of operation, applicability, adaptability, and computational performance, providing an in-depth analysis of the approach.
- Finally, Chapter 8 summarizes the the research work and discusses potential opportunities for further evolution.

Figure [1.1](#) illustrates the overall structure of this dissertation.

1.4 Supporting tools

The text of this thesis was developed with the assistance of editorial tools, including grammar checking and sentence rephrasing functionalities, provided by various platforms such as ChatGPT, DeepL, and Grammarly.

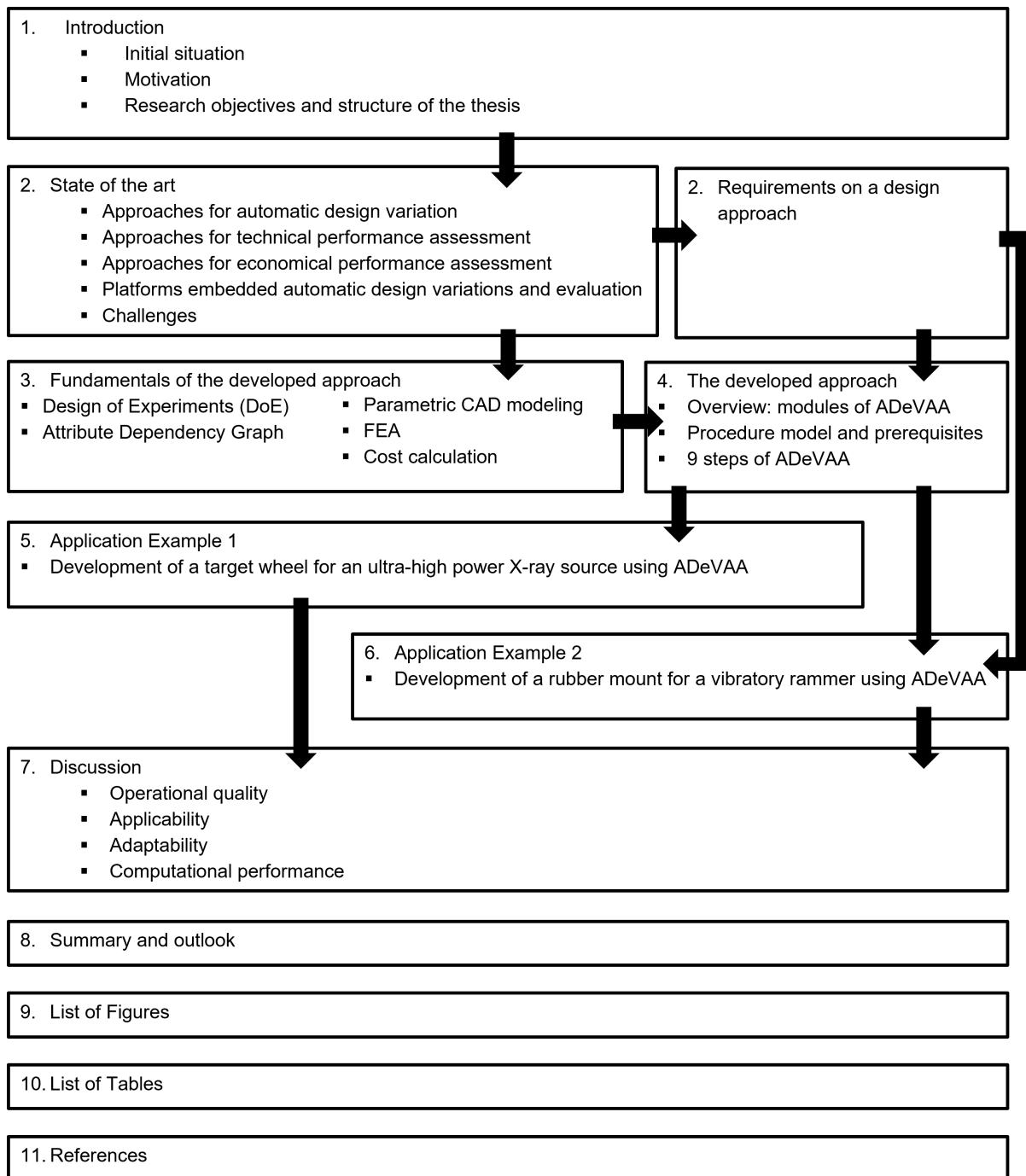


Figure 1.1: Structure of the thesis

2 State of the art

The modern industrial environment demands an increased focus on efficiency, with factors such as short lead times, cost reduction, and improved customer satisfaction occupying center stage [77]. As a result, product development has seen a surge in methodologies that emphasize both functional assurance and cost efficiency. Central to these methodologies is the ability to integrate and execute different tasks within the product development process concurrently. This contrasts with traditional sequential approaches and allows for a more comprehensive technical and economic performance assessment during the design phases.

In recent years, there has been a significant increase in strategies aimed at enabling concurrent tasks in product development. As industries continue to seek cost-effective, efficient, and innovative product designs, the development of automated optimal design identification methods has become more important. These methods utilize the power of advanced technology to deliver optimized designs within predetermined cost constraints. In this competitive and evolving environment, this thesis presents an integrated approach (the Automatic Design Variation and Assessment Approach (ADeVAA)) developed for completing a product development process that simultaneously addresses restrictive technical requirements and achieves cost-effectiveness.

Therefore, to fully understand the benefits of developing ADeVAA, it is essential to review the current design variation and evaluation strategies. First, the focus is on methods promoting an automated generation of design variation. In today's evolving design landscape, these methods form the foundational layer that enables the efficient creation of diverse design variations. Then, moving on to methods specifically focused on evaluating the technical performance of designs. In addition, the financial impact of these designs should not be overlooked. As they progress from concept to real-world production, companies need to perform early and reliable economic assessments and make a cost-effective decision of final design.

The review will discuss these methodologies' capabilities, recent advances, strengths, and limitations. It will also highlight the current relevance of these methods and their potential to redefine the field of cost-effective product development with restrictive technical design requirements. As the discussion progresses, the current challenges will be clarified. From that, the essential criterion that the to-be-developed approach attempts to meet will be identified.

2.1 Approaches for automatic design variation

In the constantly progressing engineering and design fields, finding "clever" ways to drive design variation and evaluate performance remains a key challenge. Generative Design (GD), Parametric Design (PD), and Topology Optimization (TO) stand out as prominent strategies to address this concern. GD algorithmically generates design solutions based on specified criteria, while PD uses adjustable parameters to provide the means for design variation. Conversely, TO is a mathematical method to optimally distribute materials within a given design domain subject to the physical boundary conditions [10], producing designs tailored to specific technical and even economic requirements [68]. Its primary strength lies in its ability to explore a large design domain (compared to size and shape optimization). In recent years, there has been a rapid growth of topology optimization to address a broader range of multi-disciplinary structural design challenges ([68], [113], [105]). However, the essence of TO does not lie in generating numerous design variations but focuses on optimization based on predefined constraints. Hence, its capacity for producing diverse design modifications is somewhat limited, making it less appropriate for scenarios that demand a wide range of design solutions. Furthermore, TO is more commonly applied in the concept development phase, where its focus is on determining the best possible topology or layout for a given set of design objectives and constraints at the very early stage of the design process (the conceptual and project definition phase) [32], rather than during the detailed design phase.

Conversely, both GD and PD provide multiple avenues for design variation and integrate with other technical performance evaluation tools. GD algorithmically generates designs based on predefined criteria, while PD provides the flexibility of variation through parameters that allow the design to be precisely customized. Both methods are suitable for the detailed design phase, with PD being particularly well-suited when further refinement and customization of the design are needed. This section explores the intricacies of these methods, highlighting their strengths and limitations within the context of automatic design variation.

GD is an innovative approach that is considered as an efficient method to explore a large design space by transforming the design problem into a configuration problem [66]. It utilizes iterative algorithms to autonomously produce a large number of designs while adhering to user-specified criteria and constraints [58]. These constraints include parameters such as material choices, manufacturing techniques, and cost constraints. At its core, GD fosters a collaborative relationship between designers and the computational system. While computer systems specialize in processing vast amounts of data, generating numerous design possibilities, evaluating them, finding optimal solutions, and refining them, designers use their expertise and creativity to guide and assess the process ([42], [94]). Therefore, they create a powerful

combination for efficient, optimized design generation and improvement, outperforming human engineering teams and revealing innovative and non-intuitive solutions that might otherwise go undiscovered with conventional design methods. According to Mukkavaara [75], GD is a new powerful approach to discover creative architectural design. Li [67] used GD to explore innovative bicycle pedal cranks with reduced invested development time. Thanks to the algorithms and artificial intelligence on which GD is heavily based, part geometry can be automatically adjusted during the simulation process, eliminating the need for manual adjustments. This system can explore potential solutions by comparing the results of thousands of mechanical evaluations through simulations to find the best design solution incorporating the desired properties [16].

While design generation tools rooted in GD facilitate the automated search for the preferred design, they are not free of limitations. First, the algorithms that support GD are often complex and inflexible, making them ill-suited for specialized needs and sometimes blind to specific real-world constraints. Second, the effectiveness of these algorithms is highly dependent on the initial setups, causing results to fluctuate based on these variables. Another obvious shortcoming is the lack of human intuition, a critical element in design processes. The computational demands of GD, combined with an over-reliance on software, may result in designs that are theoretically optimal but practically almost infeasible. This is evident when the "preferred design" can only be completed using a specific manufacturing technique, such as 3D printing, rather than a more conventional production method. The complex algorithms and extensive data processing associated with GD can also be challenging for designers familiar with more conventional design approaches, leading to slow adoption or misuse of the technology.

In contrast to GD, which starts from scratch and creates solutions with minimal human bias, PD focuses on improving existing initial designs by changing specific parameters, e.g., related to geometry. It allows designers to establish initial design models and their constraints, and then quickly generate multiple design variations by changing parameter values. This approach gives designers more precise control while still benefiting from automated tools that enable efficient evaluation of design variations. The adaptability and responsiveness to changing design criteria and requirements make PD especially useful for exploring with complex and dynamic design settings [27].

However, PD comes with its own set of limitations. While it offers detailed control over design modifications, its deterministic nature, rooted in a preset parametric framework that reflects the original design concept, means that the resulting design variations are often more or less similar to the original model. This limits the scope for discovering truly unique or unforeseen design solutions. This reliance on fixed models can potentially limit innovation by forcing designers into familiar patterns and binding them to basic assumptions. While it provides opportunities, screening through them is a difficult job that can lead to decision fatigue. The

large number of choices can sometimes hinder the designer's ability to see the big picture and focus on overarching design principles. In addition, constructing parametric models of intricate structures involves handling numerous design variables, demanding extensive expertise and diligence. Especially when these models are foundational to an automated design variation creation process, guaranteeing a seamless and error-free generation requires complex modeling and model-validation processes.

In evaluating automated design variation techniques, it is important to recognize the distinct suitability of TO, GD, and PD. Although TO is capable of generating optimal designs under various constraints, it is numerically quite expensive and produces only one distinct design, which limits its flexibility in adapting to design changes. In contrast, GD and PD are more suitable alternatives, especially when extensive design modifications and direct CAD integration are required. Consequently, this thesis will concentrate on GD and PD. The forthcoming analysis will be limited to exploring the possibilities of performance evaluation, specifically using GD and PD as the primary methods for generating design variations.

This research categorizes performance evaluations into two main areas: technical and economic. Technical evaluation identifies solutions with sufficient technical performance, even under complex constraints. Economic evaluation, on the other hand, evaluates the cost-effectiveness of design variations to find the most cost-effective designs.

2.2 Approaches for technical performance assessment

In today's engineering and design practices, adopting a comprehensive evaluation approach incorporating multiple technical criteria to efficiently complete product design tasks is critical. When considering aspects such as structural health, aerodynamic performance, or thermodynamic characteristics - either in isolation or in combination - it is essential to evaluate the technical performance of evolving design decisions methodically. Three primary methods emerge for this technical performance evaluation: Numerical methods rooted in design models like Finite Element Analysis (FEA) or Computational Fluid Dynamics (CFD); analytical model based methods anchored in predefined mathematical formulas, such as physics-based Surrogate Models; and data-driven model based techniques, including Neural Networks, Genetic Algorithms, Deep Learning, etc. In the following sections, we will review in detail how each method works, its practical application, and its respective strengths and limitations in the field of technical performance evaluation.

2.2.1 Numerical methods

In modern engineering, a numerical approach for evaluating a design's technical performance become an essential tool for predicting the behavior of real-world products. This approach is computationally oriented and uses numerical algorithms to solve complex problems that analytical methods may not solve. By discretizing the problem into manageable pieces, numerical models can deal with complex geometries, nonlinear behavior, and transient phenomena. Tools such as the FEA or CFD are examples of this approach. They break down complex problems into computationally tractable parts, focusing on structural behavior under various forces or fluid flow dynamics conditions. Integrating these tools with automated design variation approaches such as PD and GD realizes their transformative potential. This integration provides a robust framework for technical evaluations, accommodating restrictive and multi-domain design requirements, and enables the identification of optimal designs for specific technical performance criteria.

Numerical methods combined with PD

A technique using numerical methods for a technical assessment combined with PD has been adopted to identify optimal designs across various areas, each with distinct development criteria. The flexibility and ease of integration of PD with various numerical analysis platforms has enabled improvements in design development across a wide range of industries. For example, the combination of PD and CFD has led to design accuracy and efficiency advances.

Byrne [17] merged NASA's OpenVSP with evolutionary algorithms to create a parametric design tool that, along with CFD evaluations, resulted in a more aerodynamically efficient aircraft model. Benini [11] showed that coupling parametric methods with CFD provides efficient solutions for axial pump designs. Huang [49] introduced a parametric, automated CFD optimization process that improved the wave motion response of a buoy by 55.3%. Zhang [123] presented an optimal, lighter, and more efficient savonius blade design using a minimalist parametric wind turbine model and CFD transient simulations. Qian [90] used iSIGHT platform to integrate PD with CFD to improve brake rotor cooling by 35%. Guerrero [44] developed an automated, multi-functional design exploration framework integrating CFD and cloud-based parametric Computer-Aided Design (CAD) applications. Zhang [124] utilized a parametric model built in ANSYS to identify critical factors influencing the multichip module's thermal behavior, pinpointing optimal conditions for desired temperature reduction and enhancing thermal design. The study by Gholami [38] used this combination to optimize fin-and-tube compact heat exchangers with higher heat transfer efficiency and performance.

On the other hand, this combination has also demonstrated great effectiveness in applied mechanics, such as structural dynamics and vibration analysis, providing innovative ways to solve complex mechanical problems. Chen [18] enhanced iSIGHT platform for PD with DoE and FEA to determine the impact of crankshaft fillet radius on strength. Shah et.al [7] presented an improved parametric FEA model updating method using DoE with latin hypercubic sampling method to achieve higher efficiency and accuracy in analyzing complex welded structures. Park [80] developed an automated structural optimization framework that integrates parametric CAD-CAE software as well as meta-modeling techniques. This integration streamlines the development process, saving both time and computational resources. They confirmed its effectiveness in three design studies ranging from simple to complex scenarios. Vinjanampati [115] developed a knowledge-based preliminary optimal solution-finding method to analyze multi-mechanical aspects such as buckling, pressure, and vibration to obtain an optimal hydraulic actuator design.

After reviewing the application of numerical assessment combined with PD in various fields, it is clear that although its use and proven benefits are widespread across multiple industries, the lack of appropriate platforms that offer both automatic design variation via PD and professional-grade FEA remains a large challenge. Platforms from leading software companies, such as Siemens NX's SimCenter, Autodesk's Dynamo, ABAQUS, and ANSYS, typically specialize either in professional design variation, using their advanced parametric functionalities, or in advanced FEA. For example, ABAQUS and ANSYS are well known for their FEA capabilities and they provide basic parametric design features in their software mainly for FEA model preparation. However, compared to specialized PD platforms, such as Siemens NX, their PD capabilities are not as advanced. Moreover, they often lack the integration of these two core capabilities to enable simultaneous automatic generation of design variations and technical performance evaluation. This limitation forces designers into a labor-intensive process of switching between software and manual modifications, resulting in potential inefficiencies, risk of data misinterpretation, or even data loss.

Numerical methods combined with GD

In the field of design and engineering, numerical methods for technical performance evaluation of design variations have traditionally been integral to PD combined with numerical analysis methods such as FEA or CFD. Although GD has previously occupied an essential position only in architectural design [63], in recent years, with the development and application of commercial software, GD has made its way into the engineering field, especially in the structural area, presenting an excellent combination of time-tested methods and modern innovations [84]. By incorporating insights from FEA, GD enables performance evaluation at a design stage, avoiding

the need for a resource-intensive testing phase later on [59]. This integration can benefit the design process by identifying potential obstacles in advance, thereby reducing risk. A significant advantage of combining GD with numerical evaluation methods is the use of parallel engineering. PD typically develops into a linear iterative process when based on finite elements, whereas GD proposes a more comprehensive path. Generating the design while considering its impact on technical characteristics, supported by FEA, promises a more streamlined product development process, resulting in time and effort savings.

GD is centered on parametric computer-aided design (CAD), which serves as a conceptual anchor for designers and can generate a wide range of design outcomes [52]. Although the definition of GD is still not universally agreed upon, it can be appropriately described as "a design system that aims to produce spatially unique, efficient, and feasible constructions by evolving design techniques that result in novel design trajectories" [126]. The core of GD is the strategic use of evolutionary algorithms that fill the design space with variants [126]. These algorithms explore deep into the design space, evaluating everything from structural nuances to material choices while ensuring consistency with processing constraints. [82] explore how combining GD with Additive Manufacturing in the early stages of aerospace product development. In his study, a numerical-technical evaluation methodology is presented to guide designers in selecting the best design from various design solutions via GD, where the preferred solution must fulfill specific design requirements, including meeting predetermined deformation limits, achieving the required safety factor, or maintaining the allowed positional tolerance when deformed.

However, although the automation involved in this integrated approach delivers efficiency benefits, it is not without challenges. The biggest concern remains the limited impact of human interaction on the accuracy of FEA simulation results. In a traditional FEA environment, designers can customize the simulation model by specifying simulation settings such as mesh type to achieve sufficiently accurate technical evaluations. In FEA environments of the most GD platforms, however, these levers are often placed within the opacity of the software algorithms, locking the user into pre-configured settings. While this approach ensures program consistency and accelerates design progress, it can occasionally compromise the complexity or accuracy of the simulation model, especially when dealing with a complex or non-mainstream structure. In the same research [82], the author employed another professional FEA software for a more in-depth technical performance evaluation after selecting a preferred design. The software was chosen for its superior FEA simulation accuracy and flexibility in manually configuring simulation setups, including mesh and boundary conditions. This level of accuracy and controllability is far superior to the integrated FEA functionality found in GD tools. While the study highlights the effectiveness of integrating GD tools with numerical methods for technical assessment in the conceptual design phase, its reliance on software algorithms and selection standards suggests

potential areas for future refinement. The evaluative capabilities available in GD tools may not meet the expectation of technical evaluation that could be provided by specialized software.

Additionally, McKinsey's analysis highlights that the predominant application of GD algorithms is mainly in the area of structural-mechanical optimization [16]. The goal, for example, is to create components that harmoniously combine strength, stiffness, and wear resistance while efficiently using materials. This focus means that the applicability of a complete technical evaluation in GD tools to other domains, such as thermodynamics, is still limited.

2.2.2 Analytical methods

An analytical model is quantitative and used to answer a specific question or make a specific design decision [36]. It is rooted in mathematical equations derived from fundamental laws and principles. Different analytical models are used to address different aspects of a design, such as its technical performance, reliability, or mass properties. In analytical models, solutions are often represented by mathematical equations or formulas that can describe the behavior of the system with a high degree of accuracy.

Analytical models are widely used in the evaluation of technical performance. The authors used a multiphysics analytical model and rapid optimization to improve the VHS PM slotless motor's performance, with results aligning closely with 2D FEA [81]. Using MATLAB/Simulink, Liu analyzed the dynamic behaviors of vibration and control systems through analytical models [69]. Lobontiu and Garcia have presented an analytical method for evaluating the displacement and stiffness of compliant mechanisms with uniaxial flexure hinges. Strain energy and castigliano's theorem provide equations for these mechanisms, especially symmetric flexure hinge mechanisms. Optimization based on Lagrange multipliers improves the performance, and FEA simulations validate the results [70]. The research of Kirby [60] on automotive anechoic chambers concluded that analytical models outperform numerical models regarding simplicity and computational speed. This advantage stems primarily from their ability to bypass complicated calculations, thereby streamlining the computational process. However, there is a trade-off in terms of accuracy, where analytical models sometimes fall short. Increasing their accuracy requires the consideration of additional factors, adding layers of complexity to the modeling process. Moreover, when dealing with complex and unconventional models, analytical methods often struggle to meet the dual demands of rapid computation and high accuracy.

Analytical methods provide accurate solutions based on a deep understanding of fundamental principles, illustrate system behavior, and serve as reference points for other methods. However, their effectiveness is sometimes limited by the complexity of real-world situations. For example,

when designs require fine modifications, analytical model may be insufficient. They often start with simple structures and progress to more complex ones only when that complexity can be accurately described by mathematical formulas. In contrast to numerical methods such as FEA, analytical models do not integrate as effectively with CAD models, particularly in the technical evaluation of designs. This limitation results from the dependence on mathematical expressions that cannot consistently represent the adjustments required for different design variations when illustrating QoIs. In addition, when faced with complex evaluations-such as determining a structure's heat transfer capability or analyzing its response to thermal stress-analytical models can be limited. The difficulty lies in characterizing QoIs, such as temperature or thermomechanical stress, with Design Variables (DV)s that represent a complex structure in mathematical terms.

2.2.3 Data-driven methods

Data-driven methods are based on analyzing the data about a system, in particular, finding connections between the system state variables (input, internal and output variables) without explicit knowledge of the physical behavior of the system [108]. It focuses on extracting patterns, behaviors, and insights directly from data sets without initially imposing a predefined model or set of equations. Therefore, data-driven method can sometimes be applied as "black boxes," challenging understanding of underlying processes. These methods represent significant advances in conventional empirical modeling and include contributions mainly from Artificial Intelligence (AI), Computational Intelligence (CI), and Machine Learning (ML). Wang [116], for example, utilized the BP neural network to design and optimize petal-shaped auxetics based on mechanical properties, such as Poisson's ratio and Young's modulus, by training it with datasets from three auxetic structures [117]. These datasets were generated using random sampling and processed with the numerical model, namely the Isogeometric Analysis (IGA) based computation homogenization method [118]. This combination facilitated efficient auxetic design and analysis.

While data-driven models provide robust predictions and insights, they have inherent limitations, including a heavy dependence on original data, significant computational requirements, challenges with extrapolation, the need for large data sets, and constraints in adaptability across domains. These shortcomings are apparent when evaluating the technical performance of design variations with complex structures. Such intricate designs involve many DVs and interactions between them with QoIs that increase the risk of overfitting and require massive training data. Collecting extensive data from numerical models such as FEA simulations or physical experiments can be time-consuming or computationally expensive. Moreover, many data-driven models lack clear physical explanations, and their non-transparency reduces their trustworthi-

ness in technical evaluations. In particular, these models may not provide accurate performance predictions for novel design changes due to their general extrapolation challenges. Thus, while data-driven models offer significant advantages in various contexts, they may not be well suited for evaluating the technical performance of numerous design variations, especially when these designs involve complex geometries and are supposed to fulfill challenging multi-disciplinary design requirements such as excellent thermo-mechanical performance. The need for high accuracy for distinguishing the technical characteristics of design variations further compounds the challenge of such a data-driven evaluation method.

2.3 Approach for economical performance assessment

Adapting strategies to specific levels of environmental turbulence is the key to maximizing a firm's profits [51]. Therefore, in a competitive and cost-constrained market environment, companies must take the lead in managing the expected economical performance of their products [46]. Such kind of cost management is critical for many companies concerning offer generation and strategic evaluations [97]. As the most important part of economical performance assessment, it is essential for innovative product development, especially for products that push technological boundaries or face complex development challenges. Designing cost-effective products requires consideration of factors ranging from materials and manufacturing methods to production volumes, etc. Assessing a product's economics is critical before or in the design stages of product development. This assessment guides the efficient allocation of resources and locks in the design solution based on various conditions to ensure that the product remains financially beneficial to the company. It provides a clear insight into the cost structure to ensure the product remains viable and competitive after launch. Two fundamental types of this cost evaluation are "cost evaluation before design" (referred to as *Kostenabschätzung* in German) and "cost evaluation before production" (known as *Vorkalkulation* in German). While both assess the initial product's economic viability before the production stage, including the design concept, materials, manufacturing process, etc., they differ in definition, timing, prerequisites, and implementation complexity.

The cost evaluation before production, referred to as *Vorkalkulation* in German, aims to estimate the costs prior to the start of manufacturing or service delivery [61]. According to [30] and [61], the accuracy of these calculations is influenced by several factors, including the modularity of the product, the accessibility of data on materials, and manufacturing processes. This process can be particularly complex for new or highly customized products due to a lack of historical experience or comparable data for comparison. It involves gathering cost-related information from manufacturing plans, bill of materials, or other reference documents. Typically, product

models are used to develop manufacturing schedules that detail the required production steps and the time required for each step. These estimated production times are then converted into costs using predefined cost rates.

The cost evaluation before design, or *Kostenabschätzung* in German, provides a more general, early measure of potential costs based on preliminary data and assumptions [74]. It does not provide a detailed itemization but rather a rough estimate. This approach is notable for its versatility and is particularly suited to the very early stages, or the planning phase, of product development, especially before substantial design work or an order has been placed. This process is often based on experience or done without a specific design. Therefore, providing a comprehensive and objective estimate can be challenging when dealing with a novel product - without any direct reference, including potential designs or initial manufacturing processes. Conversely, the cost evaluation before production usually provides a detailed cost projection before the start of the service or determination of a final solution [61]. The method draws extensively on sub-detailed 3D design models or engineering drawings that can present the whole design, meticulous initial manufacturing schedules, and material lists to detail costs. In essence, this is a calculation based on planning data. The level of granularity, while increasing accuracy, can make this approach still challenging for novel or distinctive designs that lack prior data.

Ehrlenspiel [30] shows that early in the planning phase, a financial assessment with a cost estimate is obviously fraught with uncertainty and can be off by as much as 20% from the final cost benchmark of 100% accuracy (Fig. 2.1). However, post-design cost predictions based on cost calculation (*Vorkalkulation* in German) show a significant increase in accuracy, with the margin of error decreasing to as little as $\pm 5\%$. This increase in accuracy is due to the presence of a complex design with geometry details, fixed material lists, explicit manufacturing outlines, and a more crystallized project scope. Through this research, it becomes clear that there is a stronger tendency to evaluate cost before production compared to before design, in order to better assess economic performance when evaluating the technical and financial perspectives of design variations during the design and decision-making phase. As a result, further discussion will focus only on the actual situation of methods for cost evaluation before production (*Vorkalkulation* in German).

According to research from Möller, in traditional design-based engineering, the original intent was to clearly distinguish between design-based methods, which focus on optimizing product design, and cost-based methods, which emphasize the economic implications of design decisions. In practice, however, this clear distinction is often obscured. Design-based methods sometimes provide cost insights and sometimes vice versa, blurring the boundaries between the two. This overlap has been viewed positively, as it indicates an integration of both the technical and

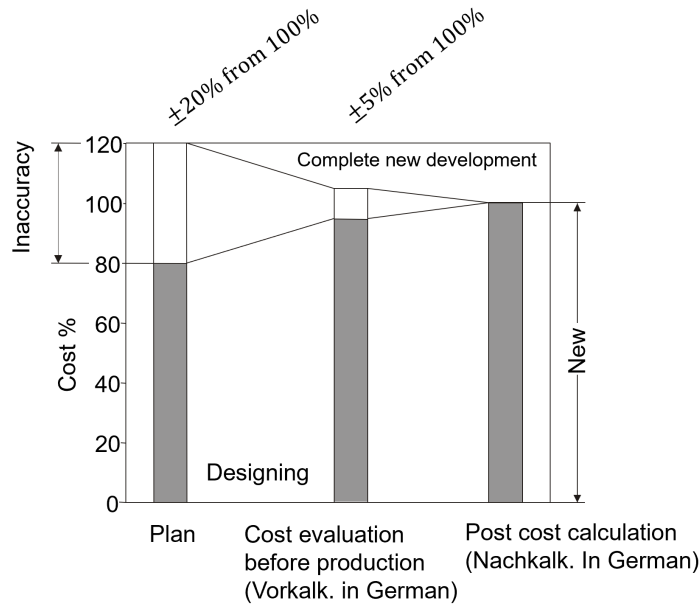


Figure 2.1: Accuracy of costing according to Ehrlenspiel [30]

economic facets of product design - an essential synergy for modern product development. Consequently, in their research, Niazi and Möller ([61], [78]) divide initial costing methods into two primary categories: qualitative and quantitative.

Qualitative methods [40] provide preliminary insights that help designers create cost-effective products, while quantitative methods numerically evaluate the costs associated with specific design proposals. The qualitative method applies a comparative perspective, comparing new products with historical counterparts to extract commonalities. This approach reduces the need for a cost analysis from zero by leveraging historical design and manufacturing data. Whether through experience or a system that codifies past expertise, qualitative approaches use experience data to provide rough costing in the early design stages. Conversely, quantitative methods [61] take a more in-depth look at a product's design, features, and related manufacturing processes. Rather than simply using historical data, these techniques accurately calculate costs analytically or as a collection of discrete units representing the various resources used to develop the product. To summarize: qualitative methods rely on experience and intuition, lacking explicit mathematical models and leaning heavily on human judgment, whereas quantitative methods employ mathematical models, data, and statistical techniques for predictions and analysis.

Given that our research focuses on developing new products without many reference sources with a concurrent economic evaluation during product development. Therefore, achieving an accurate and transparent economical analysis of design variations is imperative. In this case, quantitative methods are more appropriate for our study than qualitative approaches, which are the part of the following table that is in black.

Considering that our research is focused on new or technically demanding product development, there are limited references to the product development process and a lack of simultaneous economic evaluation. However, to be able to select a design solution that meets the technical requirements and is economical, it is imperative to conduct an accurate and transparent economic analysis of the design variations. For this reason, quantitative methods are more appropriate than qualitative ones, as shown in the Table 2.1 ([61], [78]).

	Cost evaluation before design (Kostenabschätzung)	Cost evaluation before production (Vorkalkulation)
Qualitative methods:	Intuitive techniques: Case-based methodology [92] Decision support systems: Fuzzy-logic approach [93] Expert systems [76] Role-based system [37] Analogical techniques: Regression analysis models [50] Back-Propagation Neural-Network (BPNN) [72], [102]	Design based methods: Heuristic rules [31] Good/bad examples [31], [47] Relative costs [33], [61]
Quantitative methods:	Parametric techniques [78] Analytical techniques: Operation-based approach [57] Breakdown approach [4] Tolerance-based cost models [107] Feature-based cost estimation [125] Activity-based cost estimation [20]	Design based methods: Weight cost method [5] Material cost method [40] Design equation [114] Cost-based methods: Quick cost calculation: Search calculation [30] Cost growth law [30] Neural networks [64] Cost functions [31] Cost tables [99] [41]

Table 2.1: Approaches to evaluate cost in product development according to [61] and [78]

2.3.1 Quantitative methods

The table shows three design-based methods for cost calculation: the weight-cost method, the material-cost method, and the design equation method. The weight- and material-cost methods, Gewichtskostenmethode and Materialkostenmethode in German, are intuitive yet widely used evaluation techniques [5]. They are based on fundamental proportional analysis, measuring the relationship between material and total manufacturing costs. These methods perform well when evaluating projects with significant material costs, whether due to physical weight (such as heavy castings) or the material's inherent value (such as precious metal components). However, its reliance on material costs may limit its adaptability to various applications. The design equation method [114], Bemessungsgleichungen in German, offers a more complex process combining technical aspects, such as strength analysis and cost calculations. This strategy combines technical and financial dimensions into a set of equations for an evaluation. While it is good at addressing more straightforward tasks both economically and accurately, it is challenged by increasing complexity and computational demands as practical cases become complex.

The "quick cost calculations" technique, or "Kurz kalkulation" in German [26], belongs to cost-based methods and is a set of cost-based approaches for quick and efficient cost calculating in product development. According to [61], it includes: 1) cost growth laws, Kostenwachstumsgesetzen in German [30], - Ideal for geometrically similar product lines where products have consistent length ratios. This method excels in accuracy for similar product variants, but its scope is limited to products with design similarities. 2) Search calculations, Suchkalkulation in German [30], - A comparative method that uses historical data. While it provides quick insights, its effectiveness is limited by the quality and relevance of the historical data used. It is especially useful for products with pre-existing analog designs. 3) Neural Networks, or "Neuronale Netze" in German [64] differ from traditional neural networks in the general sense. This approach represents a modern methodology that utilizes uses interconnected "neurons" trained on historical data. Its main strength lies in its adaptability and learning capabilities, making it suitable for a wide range of product portfolios where patterns can be identified from historical data. As a data-driven methodology, Neural Networks have limitations, as previously discussed.

In addition to the previously mentioned design-based and cost-based techniques, there are two other numerical strategies based on historical data and experience. Firstly, the cost table is a Japanese-originated cost precalculation tool based on a historical and experience database, designed to help designers and engineers predict costs when selecting materials, production methods, and design variations [99] [41]. Its main advantage is that it provides relatively accurate cost analysis based on a robust database, supporting cost-effective decision-making. However, its main disadvantages are high maintenance costs, high initial investment at the beginning,

especially when designing a new product, potential for rapid obsolescence, complexity of use, and increased dependence on the accuracy and completeness of historical data. Like cost tables, the cost function is also a quantitative, theoretical tool for decision-makers to predict expected costs under certain conditions [61]. It describes a mathematical model of the relationship between manufacturing cost and variable parameters such as production volumes, manufacturing possibilities, or product technical performance [31]. It provides decision-makers with a quantitative, theoretical tool to predict expected costs under specific conditions, which explicitly helps assess the economics of design variations or production strategies. The cost function can be empirically based, e.g., derived from statistical regression, or theoretically based, modeling specific cost-generating mechanisms. Its main drawbacks are that 1) it requires a large amount of accurate data to ensure its accuracy, 2) it may be oversimplified for complex production processes, and 3) it may not capture all relevant cost drivers.

2.3.2 Digitally supported methods

With the support of electronic data processing, traditional quantitative cost calculation approaches achieve greater accuracy, enabling design teams to assess cost implications early and take timely optimization measures [61]. According to Möller's study [61], several digitally supported techniques are available to assess the economic benefits of a product during its design phrase. Among these, KIS-XKIS-FEKIS, KOKOS, PICANT, LICCOS, and EVKS are fully capable of integrating with the design's CAD model to gather data for cost evaluation.

The Kosten-Informationssystem (KIS) is a cost information system that, when extended, becomes the Extendiertes-Kosten-Informationssystem (XKIS) and further evolves into the Featurebasiertes-Kosten-Informationssystem (FEKIS). XKIS, for example, is a software system that fully automates the integration of existing industrial costing methods based on overhead cost calculation, or Zuschlagkalkulation in German, into a CAD system [71]. It includes a module that facilitates the creation of preliminary work schedules and translates production durations into costs. Its main objective is to integrate data from CAD systems with cost information systems. The singularity of XKIS lies in its combination of knowledge-based processes, relational database technology, and conventional CAD systems. The system is based on two main components: a calculation module for various quantitative calculation methods and a feature for identifying identical or similar components. Designers can directly access this module after defining features, components, or assemblies in the CAD system. Firstly, create a unique manufacturing plan highlighting each component's key production phases using data from previous products. Then, the interrelationships between features of parts or assemblies are evaluated, and essential manufacturing steps, relevant machinery, and required production durations are determined based on preset guidelines, which will be translated into costs. In the

case of complex manufacturing processes without proper documentation, XKIS fills this gap by deriving concise formulas through Neural Networks.

Similarly rooted in overhead cost calculation or Zuschlagkalkulation in German, another costing method is the development-accompanying preliminary calculation system, known as Entwicklungsbegleitendes Vorkalkulationssystem (EVKS) in German. While XKIS incorporates industrial costing information directly into CAD systems, EVKS, conceptualized by Groner, adopts a broader strategy, merging seamlessly with a firm's PPS, CAD, and cost accounting frameworks. This comprehensive integration positions EVKS to efficient economical evaluation for multi-component products manufactured within a disconnected, multi-stage production process. EVKS uses overhead cost calculation to calculate unit costs and employer costing to show profitability over defined periods. In addition, its top-down approach provides stakeholders with a layered perspective on product development, from a comprehensive product view to specific component details. The basis for this is the formation of cost families (cluster analysis or Kostenfamilien in German) for individual parts, assemblies, and products based on the "technical requirement" criterion. The term "technical requirement" implies the same production methods in manufacturing. Within these cost families, regression analysis is used to identify the primary factors influencing cost causation, and their dependency on cost is documented in a concise calculation formula. However, a crucial requirement for the practical function of EVKS is that it must have available cost information at different levels. In particular, it requires access to the post-calculation results of products designed and post-calculated in previous periods. Moreover, it requires significant effort to set up, and the cost insights gained from regression analysis are not always universally applicable, potentially limiting its applicability to different industry cases ([71], [45]).

Unlike the first two methods, which are rooted in "overhead cost calculation," both LICCOS and PICANT operate on the fundamental principles of process and product models. LICCOS, which evolved as an advanced iteration of PICANT, incorporates software technology that facilitates resource-based costing throughout a product's life cycle. This technology was developed at the University of Karlsruhe in cooperation with the aerospace industry. At its core, PICANT is a resource- and process-driven cost model fine-tuned for preliminary manufacturing cost calculation. It recognizes different design categories and selects different costing methods based on the decision horizon. In particular, it can assimilate product models from CAD systems such as ProEngineer and quantify resource consumption determined by cost-driving characteristics. However, PICANT is tailored to manufacturing costs only, ignoring the use and post-use expenses of the product; it gives inadequate consideration to assembly-related costs; and, perhaps most importantly, it cannot allocate multiple production processes to a single component.

Compared with the above methods, KOKOS (cost information model for early cost assessment in product development) fully utilizes the principle of similarity, focusing on evaluating functional, conceptual, and structural similarities between new product concepts by comparing them with existing products. As a costing method, it leverages the power of fuzzy reasoning to handle uncertain and inaccurate data, making it particularly useful in the early stages of product development. It works in two ways: first, it accumulates current product and process details in an object-oriented database and then performs real-time cost analysis of evolving product concepts. One of KOKOS's particular strengths is its adeptness in dealing with uncertainty, providing flexible data analysis through the synergistic use of fuzzy inference, heuristic cost prediction, and Excel integration, among other methods. However, it cannot learn independently and relies on specialized heuristics, which can be a potential limitation in the absence of such expertise.

When looking at early computer-based costing methods that are directly integrated with design modeling, it is clear that KIS, XKIS, FEKIS, and EVKS primarily link traditional industrial costing approaches, particularly overhead cost calculation, with CAD systems. LICCOS and PICANT are based on the fundamental principles of process and product models and emphasize resource-centric costing over the entire product life cycle. In Addition, KOKOS uniquely uses the concept of similarity to compare new products with their existing counterparts. The ability to integrate costing with CAD systems, providing real-time feedback during product design for proactive decision-making. This combination ensures seamless data exchange, strengthens the decision-making framework, and improves the situation where designers make decisions without sufficient financial basis. Designers have limited access to cost information, which results in limited control over product costs, even though their choices impact these costs [1]. This problem can be attributed to insufficient and inappropriately formatted cost information. These tools help designers overcome these limitations by applying a meaningful cost model derived from collected data. However, these methods often depend heavily on an extensive repository of historical data and a completed model. They struggle with the complexities of manufacturing processes, may have difficulty adapting to different industry environments, and require specialized knowledge. As a result, these methods can be limited in their agility and effectiveness when faced with new product development challenges, hindering accurate and time-efficient economic evaluations.

2.4 Platforms embedded automatic design variation and evaluation

Besides the integration of digitally supported costing methods into CAD modeling, there is a clear trend toward the straightforward embedding of evaluation capabilities directly into CAD

modeling software. This integration manifests itself in software platforms that support design variation, including the ability to evaluate the economic feasibility of designs using quantitative economic evaluation techniques and to subject designs to evaluation using methods such as the FEA. This increased integration has led to a metamorphosis of CAD software from a primarily modeling-centric tool to a holistic platform that encompasses modeling, costing, and technical evaluation. This combination enables designers to gain a comprehensive perspective on both the technical and economic evaluation of design variations in design stages of product development. It represents a significant advancement in strengthening the link between technical capability and economic viability in the design of complex components. Following this path, specific popular CAD modeling software have ventured into embedding evaluation capabilities, paving the way for new avenues of design innovation. In particular, Autodesk Fusion 360, PTC Creo, Siemens NX, and CATIA 3D EXPERIENCE have taken this approach by integrating design evaluation capabilities into their GD or PD modules.

Table 2.2 shows a variety of platforms that include both automatic design variation and evaluation capabilities. The evaluation aspect includes the basic assessment of the economic and technical performance of the individual design based on the CAD model. What differentiates these software platforms is whether they provide design optimization capabilities based on the evaluation results. These insights are based on the current state of development of those platforms, with information sourced from official websites or user manuals. For example, cost-informed optimization involves calculating costs separately from the CAD modeling process and then utilizing these cost results to optimize the CAD model to achieve an economically efficient design while considering production constraints. This means determining whether these software options allow for modifications to the original design based on the evaluation results or automatically searching for more optimized design solutions within the design space.

The table shows that Fusion 360 from Autodesk offers GD capabilities that automatically generate design variations based on cloud-based algorithms. It combines CAD, CAM, and CAE to facilitate the simultaneous evaluation of multiple performances. Its unique manufacturing costing capability incorporates material prices, techniques, and tooling to give users a real-time cost perspective. As a result, users can change design criteria and immediately see the cost impact. PTC Creo is another powerful platform has GD tool that uses artificial intelligence to generate, evaluate, and optimize design variants. As a multi-functional software platform, PTC Creo separately offers manufacturing cost identification, which can include material costs, labor costs, overhead costs, etc., but these are not included in the GD capabilities. CATIA functional GD provides a single integrated solution that combines design, simulation, and optimization [106]. It also provides a separate but comprehensive manufacturing cost evaluation capability, similar to PTC Creo, which doesn't use this as a benchmark in searching for optimal solutions based on GD. NX Parametric Design from Siemens and CATIA's PD Study are two other software that embrace the potential of automatic design variation within the

2 State of the art

Platform (with design feature)	Automatic design variation		Technical performance evaluation			Economic evaluation		Requirements on skills	
	Generative Design	Parametric Design	Mech. performance informed optimization	FEA	Thermal analysis	Cost-informed optimization	User customization of materials	Detailed CAD model	Programming skills
Fusion 360 (Generative Design) from Autodesk [6], [52]	Yes	No	Yes	Yes	No	Yes	No	No	No
NX (Parametric Design) from Siemens [104]	No	Yes	No	Yes	Yes	No	No	Yes	No
NX (Generative Design) from Siemens [103]	Yes	No	Yes	Yes	Yes	No	No	No	No
Creo (Parametric) from PTC [86], [88], [87]	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No
CATIA (Generative Design) from Dassault [23], [24]	Yes	No	Yes	Yes	Yes	No	No	No	No
CATIA (Parametric Design Study) from Dassault [22]	No	Yes	Yes	Yes	Yes	No	No	Yes	No

Table 2.2: Platforms integrating automated design variation and assessment features

framework of PD. These platforms provide extensive evaluation capabilities on both technical and economic considerations, including the thermal analysis that isn't typically available in GD-based platforms. While these evaluations provide valuable insights, they may not automatically guide subsequent design optimization efforts, e.g., by including it into the objective functions.

Among the software platforms mentioned above, Autodesk Fusion 360's GD is the only platform that facilitates optimal product design through automated design variation and comprehensive evaluations of technical and economic performance. Through a strategic partnership, a co-developed costing feature with aPriori has been introduced, providing a manufacturing cost evaluation capability. This feature is distinguished from other similar platforms by its ability to import concurrent cost and manufacturing data from aPriori [52]. This collaboration leverages aPriori's customized regional data libraries and regular economic updates to ensure users can always access the current, region-specific information. The system incorporates critical determinants such as the factor of geometry, material selection, manufacturing techniques, production volume, and manufacturing location to provide a comprehensive cost view. In addition, by taking into account production volumes in a year, it is possible to distinguish between part cost (the cost of producing a part) and fully burdened cost (the sum of part cost and fixed costs associated with tooling). Autodesk GD provides robust toolsets for rapidly generating and optimizing a variety of design solutions. It evaluates design solutions from both technical performance and economic perspectives.

However, beyond GD's limitations, platforms such as Autodesk Fusion 360's GD that incorporate manufacturing costs into design decisions also face software-related challenges. These

include the limited range of manufacturing techniques they can consider, the accuracy of their cost evaluations, and their ability to handle complex designs or industry-specific requirements. For example, Autodesk's GD cost estimator is based on a data set focusing primarily on common materials, including only aluminum, steel, titanium, and plastics, and specific manufacturing techniques such as die casting, Addictive Manufacturing, and 2.5- to 5-axis milling. This data, owned by the partner company, is updated at fixed intervals and doesn't allow for user modification. Moreover, it only supports specific combinations of materials and production processes; for example, "AlSi10Mg" is incompatible with milling. Given these constraints, devising an optimal high-power X-Ray wheel design that involved more than one high-temperature resistant material via Autodesk's GD with a thermal stress analysis is unrealistic.

2.5 Challenges

After a detailed review of the current design variation and evaluation strategies, including the methods promoting automated design variation, the approaches focused on evaluating the technical and economical performance of a product design, and the platforms that aim to automate the design variation and evaluation processes to identify optimal solutions, we outline the general challenges of the current approaches:

1. **Over-reliance on limited historical data:** Many quantitative methods and software platforms heavily depend on historical data and established models. When dealing with new or innovative product designs, there can be a scarcity of relevant historical data, compromising the methods' accuracy and applicability. This echoes the concern that a lack of significant historical data makes it challenging to forecast or evaluate innovative designs using current tools and strategies.
2. **Lack of clarity:** Some strategies, especially those leveraging machine learning or specific algorithms, might not offer transparent insights into the creation or evaluation of design variations. This obscurity can complicate the decision-making process.
3. **Software-related limitations:** Platforms integrating design variation with evaluations restrict users to their inherent functionality and embedded data. Tailoring costing data, especially for unconventional materials, is often unfeasible. Furthermore, these platforms may not always be equipped with the latest tools or methodologies and may falter in producing intricate parametric CAD models or in confronting complex geometries. Setting up a FEA simulation with precise boundary conditions for optimal accuracy can also be challenging. Consequently, the derived model might either be too simple or have restricted

parameterization capabilities. This forces users into a dilemma: either conform to the platform's limitations, potentially compromising on detail and precision or juggle various specialized software tools. However, maintaining proficiency in numerous software tools, like CAD modeling, numerical analysis, and other evaluation techniques, can be inefficient, mainly due to fragmented workflows and automation. This fragmentation complicates the automatic generation and evaluation of multiple design variations, vital for initial decision-making in the product development.

4. **Limitations of cross-discipline design challenges:** Though the current design landscape is multifaceted, most methods or platforms are domain-specific. Tools considering both technical and economic performance across fields are rare. While multidisciplinary demands are crucial for comprehensive product evolution, they often remain unaddressed. This specialization implies that while a platform might excel in one domain, its relevance might wane when diverse disciplines are in play.
5. **Economic oversights in product development:** Designers often grapple with the absence of instantaneous, substantial economic evaluations during product development and innovation. While economic outcomes are pivotal in steering design decisions, contemporary tools and methodologies often neglect to offer timely and fitting economic insights. This void can result in technically proficient designs that may not be economically viable. Given today's design intricacy and diversity, the demand for prompt and reliable economic evaluations is even more pressing. This underscores the need for research into comprehensive systems and strategies that can bridge this gap, equipping designers with profound economic insights.
6. **Preliminary development unclarity:** During the detail design stage of product development, there may be numerous unknowns or uncertainties related to production methods and processes, especially when making important design decisions. These uncertainties can lead to inaccurate cost evaluations and hinder the decision-making process.
7. **Demand for automation:** As highlighted in the third point, designers face the challenge of operating multiple software tools for design and evaluation processes in a disconnected environment. This lack of consistent automation can interrupt development rhythms, requires manual intervention and poses challenges of switching between different software. These interruptions can hinder creativity. Instead of fully utilizing the software's capabilities, designers may feel limited by it. The current design environment highlights the importance of having integrated systems that easily combine automatic design modification with a wide range of advanced evaluation features.

2.6 Requirements on a design approach

This section summarizes the requirements extracted from the previous section summaries. The goal is to develop a design approach that supports decision-making through automated design variation and evaluation from both technical and economic perspectives.

Table 2.3: Requirements on the design approach.

Goal

Develop an approach that supports decision-making in the detailed design stage of product development, taking into account both technical and economic aspects concurrently

Functional requirements

Applicable in the design stages of the product development process.

Searches for optimal design with multiple design variables.

Builds a parametric CAD model with no constraints on geometric complexity or parameter count.

Automatically generates design variations within the entire design space.

Automatically evaluates the technical performance of design variations.

Evaluates the manufacturing cost of design variations.

Provides analysis and visualization for decision support.

Provides transparency throughout the complex product design and evaluation process.

Allows cross-discipline analysis, including for example thermodynamics and mechanics.

Provides automation, especially when transitioning between different software tools.

Application requirements

Guides and supports the user during application.

Applicable independently of problem and user.

Faster than existing methods.

Applicable more broadly than existing methods.

3 Fundamentals of the developed approach

This chapter serves as an introduction to the methods and approaches applied in the developed approach. It is particularly useful for readers who may not be familiar with the following sections: [3.1 Design of Experiments \(DoE\)](#), [3.2 Attribute Dependency Graph \(ADG\)](#), [3.3 Parametric CAD modeling](#) as well as [3.4 Finite Element Analysis \(FEA\)](#), and finally, [3.5 Cost calculation](#).

3.1 Design of Experiments (DoE)

Experimentation is one of the most common activities that engineers perform to understand and/or improve a technical product [\[121\]](#). It allows a researcher to find out what happens to the outcome or response when the settings of input variables in a system are purposely changed. The concept of DoE was initially introduced by Ronald Fisher, an English statistician, and was published in his work "The Design of Experiments." This publication in 1935 served as the foundation for the field of experimental design. In his book, DoE was defined as a science of experiments, and the three basic techniques of experimental design were introduced, namely replication and blocking, both of which can help to increase precision in the experiment, as well as randomization, which serves to decrease bias by preventing the experimenter from introducing systematic and personal biases into the experiment [\[34\]](#).

Since then, the term "Design of Experiments (DoE)" has encompassed multiple interpretations and has found application across diverse fields. Based on the research of Wu [\[121\]](#), the DoE is a collection of knowledge and techniques that enable a researcher to 1) conduct better experiments, 2) analyze data efficiently, and 3) make the connections between the conclusions drawn from the analysis and the original goals of the investigation. According to K. Telford's research [\[109\]](#), DoE is a series of tests in which purposeful changes are made to the input variables of a system or process, and the effects on response variables are measured. It is aimed to enhance the amount of information obtained from a study while minimizing the need for extensive data collection. It enables the assessment of the individual influence of a factor as well as the combined effect of multiple factors. While In the research report from Durakovic on "Design of Experiments application", DoE was defined as a statistical tool that deployed in various types of systems, process and product design, development, and optimization, as well as a multipurpose tool that can be used in various situations such as design for comparisons, variable screening,

transfer function identification, optimization and robust design [29]. DoE has been determined to be more effective than the spontaneous "trial-and-error" or "build-and-break" approach to engineering design.

In 2003, Anthony et al. [39] formally distinguished between modern and classical DoE in the study. Although both share the common goal of extracting the most information from a limited number of laboratory or computer experiments, modern DoE techniques are specifically designed for applications involving deterministic computer simulations, while classical DoE techniques were originally developed for laboratory and field experiments with random sources of error. This random error term ε , which is present in the measured response quantity of a classical DoE, can be described as 3.1:

$$\varepsilon = y_m(x) - y_t(x) \quad (3.1)$$

where $y_m(x)$ is the measured response and $y_t(x)$ is the true response. This random error term is assumed to be constant due to sources such as measurement error, inherent fluctuations in the response volume (e.g., turbulence), etc. Therefore, it is considered independent and identically distributed (i.i.d) [39]. However, in modern DoE, the determinism of computer experiments avoids the existence of the random error term. For example, if two computer simulations are performed with the same input data, both simulations will typically produce identical output data.

Classical DoE method, such as the full factorial design, can include all possible combinations of factors, providing extensive data and deep insight into factorial interactions. However, these methods are better suited to scenarios with fewer factors, as the number of experiments required grows exponentially with each additional factor. Although highly accurate, this approach requires more time and resources.

Modern DoE techniques, which often involve random sampling, are much more efficient for experiments with a large number of factors. This efficiency comes from not having to evaluate every possible combination of factors. Such methods are particularly advantageous for large or complex data sets. They offer greater flexibility in adjusting sample sizes and selecting different sampling strategies.

According to the research of Anthony et al. [39], quasi-Monte Carlo and pseudo-Monte Carlo approaches are the two more commonly used sampling techniques in modern DoE. They are both developed for multidimensional integration, aiming at uniform sampling in this multidimensional design space. Pseudo-random numbers, commonly used as a source

of randomness in the pseudo-Monte Carlo method, are generated by deterministic algorithms and appear random. However, compared to true-random numbers, such as those generated by radioisotope scattering, they lack the true randomness found only in nature. The quasi-random numbers used in the quasi-Monte Carlo method are also deterministic, although they are not designed to appear random but rather to be distributed as uniformly as possible to reduce integration errors in specific applications [54]. Pseudo-random number generation offers more flexibility and independence, while quasi-random methods are better suited to high-dimensional spaces, providing more uniform coverage. In addition, many pseudo-random number generators (PDNGs) are well-established and compatible with existing programming software, whereas implementing quasi-randomization algorithms can be more complex and time-consuming because of an additional setup that must be accomplished due to a lack of compatibility.

According to the research [39], no absolute method exists to determine whether pseudo-Monte Carlo or quasi-Monte Carlo is more appropriate for a given situation. Similarly, determining the optimal choice is not the main task for our case since both methods generate uniform sampling in a high-dimensional design space, which satisfies the requirement of DoE in our developed approach. After a thorough evaluation, considering time constraints and seamless compatibility with subsequent software, a decision was made to use Python's built-in `random()` function in the developed approach for generating pseudo-random samplings in the DoE. The `random()` function is based on the Mersenne Twister random number generation, which serves as its core generator. The Mersenne Twister is one of the most extensively tested random number generators in existence. It produces 53-bit precision floats and has a period of $2^{19937} - 1$. The underlying implementation in C is both fast and threadsafe [89].

A DoE with random samplings is analogous to the brute force method, providing a direct route to problem-solving by exploring every possible solution to find the right one. Although the DoE approach may seem exhaustive and at times less streamlined than other complex methodologies, its strength is that it does not require an objective function that might otherwise limit the choice of designs, allowing for a comprehensive global search. This is especially important when navigating a high-dimensional design space with multiple DVs. The application of DoE not only simplifies the problem definition compared to its complex counterparts but also consistently presents us with recognizable gradients in results. In contrast, local optimization is inherently constrained, carefully searching for the best solution within a particular region of the problem landscape. Although it is efficient within its boundaries, it may overlook optimal solutions outside its designated domain. This is similar to searching for the highest point on a mountain while only surveying a single hill. To ensure a broader perspective and avoid the limitations of a local focus, the DoE was chosen for this approach.

3.2 Attribute Dependency Graph (ADG)

Highly demanding, multi-criteria design requirements in product development increase complexity, especially in cases with a limited understanding of cause and effect. In these situations, the intricate interactions of various factors can make the design process more challenging and convoluted. In such a design process, according to the research of Rötzer et al. [95], designers struggle to effectively evaluate how a change to one attribute may affect other interconnected elements. This limitation often leads to a lack of transparency and unexpected system behavior, as designers may not fully understand and predict all of the potential effects of their changes.

In addition, the constraints imposed by some attributes that are not considered in the design requirements may limit the design process, resulting in the need to make assumptions about the values of these unknown attributes to fill in the gaps, potentially resulting in a constrained solution space from the start. To effectively navigate the complexity and maintain transparency during the design process of a highly demanding complex component, it is helpful to create a clear causal structure, called an ADG, that contains all the essential attributes needed for the design task and facilitates a clear distinction between what is realized and what is required. According to Rötzer [95], ADGs can assist engineers in the design process by supporting the analysis and decomposition of highly challenging design goals of complex components, such as a high-power X-ray target wheel. For design engineers, this involves breaking down the overall design requirements, such as mechanical and thermal performance, even from an economic perspective, into multiple technical design requirements, like ensuring that maximum stress or temperature stay within limits.

ADGs demonstrate the inter-dependencies among attributes that contribute to specific system behaviors, and they do not always require quantitative models or formulas to illustrate these dependencies. Therefore, in the early design phase, an abstract ADG is created that is essentially sufficient for engineers, but as the design process progresses, it is clarified by adding specific design variables for the required components. According to the graph theory classification by Diestel [25] and summarized in Kreimeyer [62] and Rötzer [95], an ADG has essential properties. It is a directed graph consisting of only directed edges and nodes, with no inherent weights, making it nonweighted. An ADG is a 'simple graph', meaning that nodes can not connect to themselves or form loops. Hyperedges are allowed (an edge connecting one node to several others), though an ADG is not a 'multigraph', allowing only one or no edges between any two nodes. Each edge must connect precisely two nodes; unconnected nodes are not allowed.

An ADG is a "node-labeled graph", where each node has a label, while edges stay unlabeled. "Complete" graphs or "cliques", where all nodes are connected, are impossible in ADGs due to

the restrictions on connections between nodes at the same hierarchical level. In short, ADGs represent a polyhierarchy because a source node can have multiple dependent nodes. The nodes in the ADG represent attributes and fall into three primary types: Design Variables (DVs), Design Parameters (DPs), and Quantities of Interest (QoIs), as defined by Papalambros and Wilde [79] and summarized by Rötzer et al. [95]. DVs are attributes that must be specified during the design process and are under the designer's control. They act as levers that can be adjusted to influence the design. For example, in the creation of an X-ray target wheel, DVs may include geometric DVs such as wheel diameter or focus track position. The design problem is to identify appropriate DV values that satisfy the requirements of the objective quantities [128]. Design parameters (DPs), on the other hand, are attributes that could potentially be changed but are considered fixed due to certain constraints or decisions made during the design process. For example, the thermal conductivity modulus becomes a design parameter once a particular material is selected. At the highest level of the ADG, we find QoIs, which describe the product's designed behavior but cannot be directly controlled. An illustrative quantity of interest would be the peak temperature on the focal track of a target wheel during operation. The requirements associated with the QoIs play a critical role in formulating the ultimate design goal. For example, ensuring that the peak temperature of the final design remains below the material's melting temperature becomes one of the essential design goals.

3.3 Parametric CAD modeling

CAD, or Computer-Aided Design, is the use of computers to design, model, analyze, and evaluate products while accurately documenting the entire design process [15]. CAD was developed as early as the 1960s, but the limited capabilities of computers hampered its progress at the time. It was not until nearly a decade later that the development and implementation of CAD began to enter the commercial marketplace. In the 1970s, the technology was still largely limited to 2D, producing drawings that resembled hand-drawn illustrations. Nevertheless, advances in programming and computer hardware, particularly the introduction of 3D solid modeling in the 1980s, facilitated the wider use of computers in design activities [96]. This technology provides engineers with a powerful and efficient tool for conducting research, driving innovation, and facilitating the design and development of new products. With CAD, engineers can easily conceptualize objects and create virtual models of products to ensure they meet intended functionalities before physical prototypes are built [66]. The flexibility of CAD enables engineers to explore and refine their designs in a virtual environment, making the design process more efficient [15].

A parametric model, as opposed to an explicit model with fixed attributes, is a geometrical representation of a design with some attributes or properties that can vary (parameters). Parameter is a term that has different meanings depending on the use. In design, it represents a non-geometric entity that can hold a value, aiming to control geometric components or their relationships [73]. Therefore, in a parametric model, because attributes (parameters) are dependent on parameter values, there is no need for erasure or redrawing during changes [73]. Figure 3.1 illustrates the same geometric structure represented by an explicit and a parametric model.

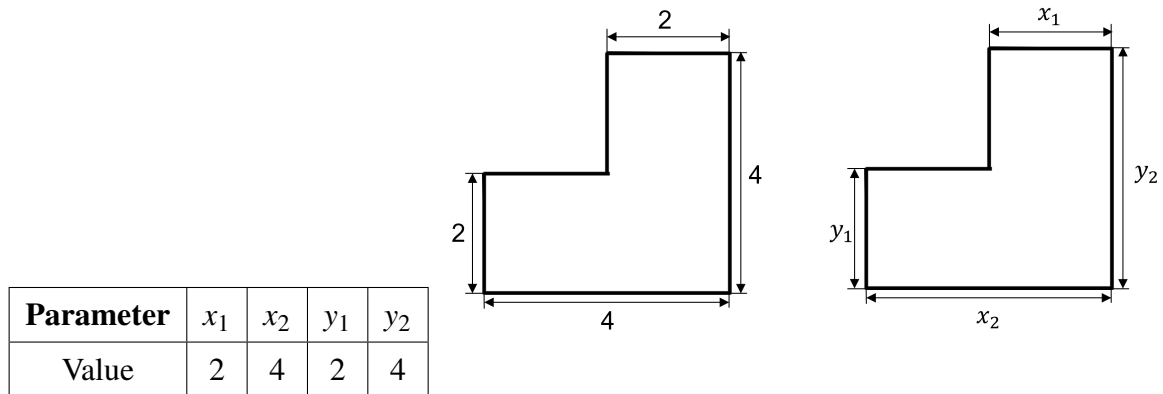


Figure 3.1: The explicit and parametric model describe the same geometry

With the increasing demand for flexible tools for CAD, parametric modeling is becoming mainstream in computer-aided design software, using "parameters" to accurately describe a geometric shape or form [96], simplifying the design referencing process. Traditionally known as PD, this approach fulfills the designers' demands for flexibility to make design variations by changing design parameter values without recreating the design on a computer. Design variations play an important role in the design process by enabling the exploration of better solutions to design problems. By providing a framework for improvement through optimization and adaptation, design variations enhance existing design solutions, increasing the quality of the final designed artifacts [73]. In the context of parametric design, as explained in references [73] and [96], parameterization is a fundamental step that involves the definition, execution, and assignment of parametric attributes to describe the geometric model, thereby defining the variations in geometric components. It is the process of transforming an explicit model into a parametric model by incorporating design parameters that include all the necessary elements to represent design features and their relationships. A successful parametrization of a CAD model requires careful consideration of the potential variations in geometry and an anticipation of the changes that the parametric model will introduce [96]. To accomplish this, the CAD model should maintain specific properties (such as tangency and parallelism, etc.) and defined dimensions, either explicitly or implicitly, to establish the necessary geometric relationships

[100]. Table 3.1 shows common design parameter types that could be applied in a parametric CAD model [15].

Table 3.1: Common design parameter types [15]

Parameter examples	Data type	Example
Dimensional variables	Numerical	(1) the height and diameter of cylindrical features, (2) the length, the height, and the width of a rectangle block (3) the radius of a fillet feature.
Constraints	Boolean	(1) parallel, perpendicular, angular relations of two lines (2) equal radii of two arcs (3) convert entities in sketching (4) the symmetric relations of two objects about a plane
Operations	Mixed data and logic	(1) the direction and instances of a pattern feature (2) drafting over existing face (3) the direction and the thickness of a rib feature
Equations	Mathematics expression	(1) the link value of multiple dimensions (2) the dependent relation of two or more dimensional variables

Designing complex components using parametric CAD models requires the parameter value management of a large number of design parameters. As a result, traditional manual design methods become laborious and time-consuming, especially when dealing with a mount of design variations, such as the more than thousands required for a DoE. The large volume of these modifications makes manual execution impractical. Therefore this underlines the need to use parametric CAD modeling for efficient and automated design processes. An API (Application Programming Interface) is a tool that allows a programming language to be used within different applications. This integration enables the creation of user-defined programs and facilitates communication between applications.

APIs allow various software components to interact and extend functionality, making the development process more flexible and efficient [85]. Automated parametric CAD modeling is enabled by the seamless integration of APIs with CAD modeling software. For example, when using CAD tools such as SolidWorks, which provides many API functions to simplify secondary development [55], APIs enable effortless communication with input data files (such as Excel or Text) where design parameter values are stored. With the help of programming and

APIs, CAD models representing various designs can be automatically generated. This process includes an automated collection of parameter values from input data and precise geometric adjustments. Engineers can efficiently explore numerous design variations by automating these tasks while ensuring accuracy and consistency. Seamless coordination between the CAD model and input data enables effortless modification of design variables, providing an easy-to-use and efficient parametric CAD modeling approach.

3.4 Finite Element Analysis (FEA)

Various engineering problems are defined by equations that include the design variables and their interactions with each other, called partial differential equations (PDEs). Typically, these PDEs come with specific initial or boundary conditions and can produce complex analytical results, even for simple structures. Conversely, discretization is an approximation technique that converts these differential equations into related algebraic equations [110], simplifying their solving. In 1941, A. Khrennikov proposed using the discrete element method to solve elastic-mechanical problems related to beam structures [48]. His innovative thinking set the stage for the birth of the FEA method. Since then, further attempts were made, and it was not until the 1960s that Clough presented the idea of finite elements [19]. However, with the limited computing capabilities of the time, the idea struggled to become widely accepted.

The FEA is a prominent discretization approach, segmenting the solution domain into several simple subdomains [14]. It has become an influential tool for solving complicated geometric problems [2] with the rise and advancement of computational methods in the 1970s. Since then, FEA began revolutionizing various fields, from architecture to aerospace. It expanded its scope from simple two-dimensional tasks to intricate three-dimensional challenges, moved from static to dynamic scenarios, and handled both simple linear and multifaceted nonlinear problems [110]. Due to its flexibility in modeling and investigating various structures, FEA has become a critical asset, especially in engineering design. Some of today's popular FEA software solutions are NASTRAN, ANSYS, ABAQUS, and COSMOS [43].

Using approximation techniques, the FEA transforms complicated analytical challenges into more approachable numerical tasks. As Amit [3] explains, a mesh in FEA refers to a discretization of a geometric domain into small subdomains formed by simple geometric shapes. These structures span the entire domain and ensure its boundaries are considered. Consequently, the mesh construction, known as meshing, is a key consideration in choosing the right numerical strategy. In particular, Pascal Frey emphasized that the structure of a mesh is crucial for the numerical simulation of any PDE problem [35]. Thus, mesh elements, which are the basic units formed during the meshing process, play a significant role in determining the efficiency of FEA method and ensuring the reliability of the simulation results. Selecting an appropriate mesh configuration is essential because it can influence simulation duration, result accuracy, and computational resources required.

Mesh types are typically classified according to two main criteria. The first is dimensionality, which can be two-dimensional (for surfaces) or three-dimensional (for volumes). The following distinction is based on the structural composition of the mesh, which is divided into structured and unstructured meshes.

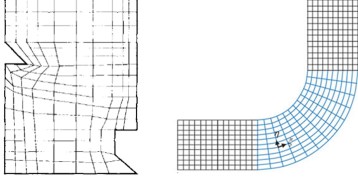
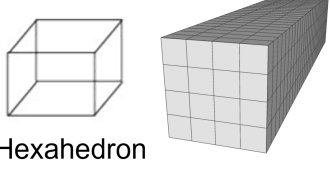
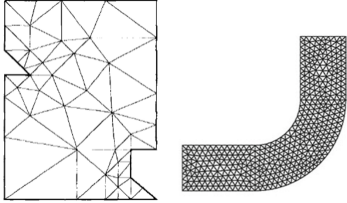
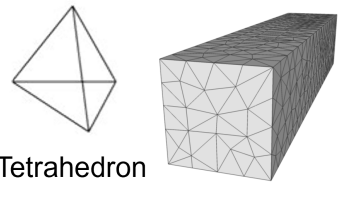
A structured mesh, in which all interior vertices are topologically alike and mainly derived from a consistent lattice topology [13], uses primarily hexahedra in three dimensions and quadrilaterals in 2D. This uniformity is beneficial for efficient memory storage and shorter simulation times due to its regularity. However, the simplicity of structured meshes can sometimes make them ill-suited for complex geometries, resulting in challenges such as skewness, non-orthogonality, and potential inaccuracies because of the unrealistic results and unphysical solutions [111]. While domain partitioning can provide a solution, it is often manual and time-consuming.

In contrast, unstructured meshes, which are primarily composed of tetrahedra in three dimensions and triangles in two dimensions, are highly adaptable. This flexibility is particularly evident when dealing with intricate meshing challenges of complex geometries, making it a defining characteristic of unstructured meshes. Their ability to quickly adapt to refinements and changes in element size is responsible for their widespread adoption across multiple industries. However, this adaptability comes at the cost of increased memory usage, longer simulation times, and higher computational requirements. Tetrahedra, unlike hexahedra, may struggle to preserve symmetries effectively. For symmetric designs, an asymmetric mesh may compromise the accuracy of the results. Furthermore, while tetrahedra are reliable in representing the internal facets of a model, their accuracy decreases at the boundaries [98]. Bern emphasized the tendency of errors to magnify in tetrahedral meshes. He emphasized that the errors resulting from triangular decomposition are influenced by the minimum angle and size of the element, observing that “errors grow with element size” [28]. Accurate results are often obtained with a more refined mesh. However, the balance between accuracy and simulation time is a dilemma that the researcher must address. The following Table 3.2 presents examples of structured and unstructured meshes in 2D and 3D ([13], [111], [98]), distinguishing between structured and unstructured configurations.

As the digital transformation of industry continues to grow, engineering simulation has undergone profound changes in both automation and efficiency. The FEA method, is a cornerstone in the industrial domain for solving complex engineering models. The fusion of FEA with Application Programming Interfaces (APIs) has established a new paradigm in simulation, increasing flexibility and refining the workflow. By leveraging the power of programming, engineers are now able to perform a wide variety of FEA simulation procedures. This ranges from preliminary pre-processing activities, such as customized setups and meshing, through the simulation phase to post-processing and presentation of results. This comprehensive automation not only reduces the time and computational resources spent on simulations but also reduces the susceptibility to human error, reinforcing a robust and repeatable framework.

However, behind this automation lies a significant challenge: ensuring the accuracy and reliability of FEA simulations with automated meshing. For highly complex geometries, using

Table 3.2: Examples of structured and unstructured mesh elements in 2D and 3D ([13], [111], [98])

		Dimensional classification	
		2D	3D
Structural classification	Structured mesh		 Hexahedron
	Unstructured mesh		 Tetrahedron

tetrahedral elements for automated meshing appears to be the simplest and most realistic approach. However, its ability to guarantee the accuracy of simulation results comparable to hexahedral meshing remains controversial. Therefore, in Chapter 4.7.4, a validation exercise is performed. A complex component is simulated using an automatic meshing process with unstructured 3D mesh element (tetrahedral element) and structured 2D shell elements. In this context, shell meshing refers to a technique in which a 3D model, which can be represented by a shell structure with a given thickness, goes through an initial planar meshing before being given depth to illustrate its full 3D configuration. Such an approach is emerging as an alternative to structured 3D meshing for complex 3D structures, especially in cases where a conventional structured 3D meshing (for example with hexahedral elements) requires extensive manual effort for segmentation or becomes impractical due to its complexity.

3.5 Cost calculation

As highlighted in Chapter 2.3.2, several EDP-supported methods exist for performing quantitative economic evaluation in the product development process. Many of these methods are rooted in differentiating overhead costing (of German: Differenzierende Zuschlagskalkulation),

particularly those incorporating the computer-aided design. The strength of these approaches is their ability to provide a comprehensive economic review of a product, regardless of the initial data available. This transparent assessment proves invaluable when making decisions about the final design. In addition, this approach works independently of existing data or previous designs, facilitating the creation of a cost model for a new design quickly and easily. This adaptability is especially beneficial when dealing with the complications of designing a completely new product.

Figure 3.2 shows the complete differentiating overhead costing model according to VDMA [5]. The segment focused on developing a quantitative costing model for ADeVAA, shown in green, starts with the manufacturing costs (MC). This includes various related costs such as material and production costs (MtC and PC). Detailed information on these costs and their specific calculation formulas is provided in Table 3.3.

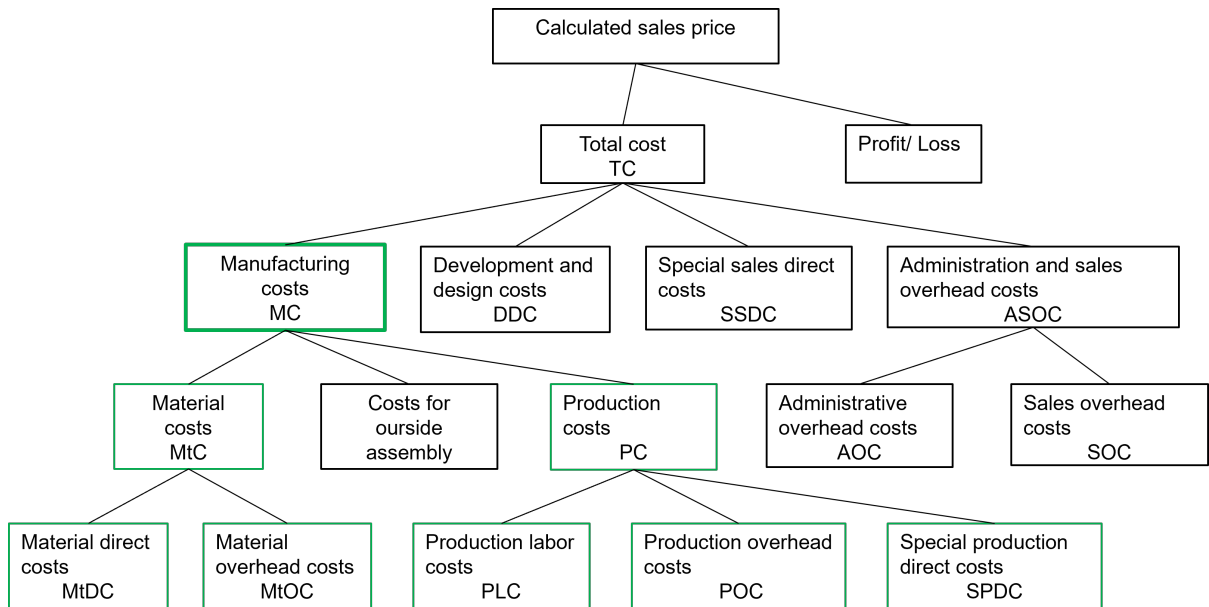


Figure 3.2: Differentiating overhead costing model according to VDMA [5]

From the formulas presented in Table 3.3, besides the predetermined intermediate quantities such as material cost per unit $mek(\text{€}/\text{kg}$ or $\text{€}/\text{piece}$), labor wage rate $flk(\text{€}/\text{h})$, tool cost per piece $fgk(\text{€}/\text{piece})$, and machine cost per hour $fgk(\text{€}/\text{h})$, two other critical factors significantly influence the production costs: machining time t and tool life h . The time is determined by machining speed and the total amount of machining work required, such as the volume of metal to be cut or the area of surface to be ground. For example, the production labor cost (PLC) is determined using the labor cost per hour and machining time ($PLC = flk \times t$), while the production overhead cost (POC) is calculated based on factors such as machine cost per hour,

machining time, tool cost per piece, and tool life. The material cost (MC) is determined by the material cost per unit, calculated once the quantity of material usage is established. The formulas for these calculations are available in Table [3.3](#).

Table 3.3: Overview of cost terms and formulas in the ADeVAA cost calculation model

Name (German Name)	Comment	Syms	Formulas and Examples
Manufacturing costs (Herstellungskosten)	The manufacturing costs are the sum of material costs and production costs.	MC	$MC = MtC + PC$
Material costs (Materialkosten)	The material costs are derived from the material direct costs and the material overhead costs.	MtC	$MtC = MtDC + MtOC$
Material direct costs (Material-einzelkosten)	The material direct costs refer to the direct costs of materials and are calculated from the consumed quantity of material multiplied by the value per unit of quantity (usually the cost price per unit).	MtDC	$MtDC = quantity \times \frac{value}{unit\ of\ quantity}$, for example: $MtDC = m_{raw} \times mek$; with mek (€/kg)
Material overhead costs (Materialge-meinkosten)	The material overhead costs include, for example, the storage space costs, interest for the capital tied up in the material warehouse, costs of goods receipt inspection, etc.	MtOC	Example: the company has a fixed cost of €50 per day to cover the storage space costs, interest for the capital tied up in the material warehouse, and costs of goods receipt inspection.
Production costs (Fertigungskosten)	The production costs are comprised of production labor costs and production overhead costs.	PC	$PC = PLC + POC$

Table 3.3 (Continued)

Name (German Name)	Comment	Syms	Formulas and Examples
Production labor costs (Fertigungslohnkosten)	The production labor costs are calculated from the wage rate and the time per piece.	PLC	$PLC = flk \times t$; with $flk(\text{€}/h)$
Production overhead costs (Fertigungsge-meinkosten)	The production overhead costs include, for example, the costs for machines, tools, halls (or factory buildings), supervisors etc.	POC	$POC = fgk \times t$ or $POC = fgk \times piece$; with $fgk(\text{€}/h)$, or $fgk(\text{€}/piece)$
Special production direct costs (Sondere-inzelkosten der Fertigung)	Special production direct costs are costs for jigs, models, and similar items, which are provided only for the production of a specific cost object.	SPDC	Example: A toy company needed a unique mold costing €15,000 for a special robot order.

In order to systematically calculate the required machining time for different machining methods, a crucial parameter is introduced: the Material Removal Rate (MRR). As defined by Jahan [53], MRR is the amount of material removed from the workpiece per unit of time. This quantity is important in determining the efficiency of the machining process. MRR directly impacts machining time because it determines the rate at which material is removed. Consequently, a higher MRR means faster material removal, reducing machining time and potentially lowering overall manufacturing costs. However, it is essential to balance MRR with tool life, as excessive MRR can lead to rapid tool degradation, reducing tool life and, eventually, the cost-effectiveness of production processes.

Typically, there are several ways to calculate MRR. For example, it can be determined from the volume of material removed or the difference in weight before and after machining [53]. Or it can be calculated based on specific parameters during the cutting process, such as depth of cut, width of cut, feed rate, etc., depending on different machining processes. Below are examples of how MRR can be calculated for different machining processes.

- **Turning:**

$$MRR(mm^3/min) = \pi \times D(mm) \times d(mm) \times f(mm/rev) \times RPM(rev/min)$$

where:

D :	initial diameter of the workpiece (mm)
d :	depth of cut (mm)
f :	feed per revolution (mm/rev)
RPM :	spindle speed (rev/min)

• **Milling:**

$$MRR(mm^3/min) = w(mm) \times d(mm) \times f(mm/tooth) \times RPM(rev/min) \times n$$

where:

w :	width of cut (mm)
d :	depth of cut (mm)
f :	feed per tooth (mm/tooth)
RPM :	spindle speed (rev/min)
n :	number of cutting teeth on the tool

• **Drilling:**

$$MRR(mm^3/min) = \pi \times r^2(mm^2) \times f(mm/rev) \times RPM(rev/min)$$

where:

r :	radius of the drill bit (mm)
f :	feed per revolution (mm/rev)
RPM :	spindle speed (rev/min)

• **Grinding:**

$$MRR(mm^3/min) = w(mm) \times d(mm) \times v(mm/min)$$

where:

w :	width of the grinding wheel (mm)
d :	depth of cut (mm)
v :	table feed or workpiece velocity (mm/min)

For the above manufacture methods:

$$RPM(rev/min) = \frac{1000 \times V(m/min)}{\pi \times D(mm)}$$

where:

V : cutting speed (m/min)
 D : initial diameter of the workpiece (mm) by turning
diameter of the cutter (mm) by milling
diameter of the drill bit (mm) by drilling

Normally, there are numerous factors involved in the calculation of the MRR, which depends on the material being machined, the tool material, the type of machine tool, the skill level of the operator, and many other variables. The costing phase in ADeVAA does not aim to provide an extremely precise total manufacturing cost. Rather, it provides a way to quantitatively calculate costs while leaving the specifics of each parameter to the user based on the actual situation. In the two usecases presented in this thesis, the factors such as feed and speed, as well as the approximate tool life under these conditions, are based on the general recommendations for different machining methods on different metals as suggested in [56]. These guidelines help to provide a framework for calculating machining time, although the exact values should be adjusted according to the individual situation of each machining process.

Tool life is influenced mainly by cutting speed. In general, a higher cutting speed leads to a shorter tool life. This specific relationship depends heavily on material condition, tool material, machine setup, and other factors [53]. Table 3.4, for example, shows the method of calculating tool life according to the training handbook of Sandvik about a selection of cutting parameters for turning [21]. The cutting parameters listed in the catalog are designed for a tool life of 15 minutes. This means that with these parameters, the tool must be replaced after 15 minutes. If a different cutting speed or MRR is desired, the tool life can be adjusted by multiplying it by an appropriate factor from the table.

Tool life [min]	10	15	20	25	30	45	60	90
Correction factor	1.11	1	0.93	0.88	0.84	0.75	0.7	0.6

Table 3.4: Tool life and correction factors for cutting speed [21]

4 The developed approach

4.1 Overview: modules of ADeVAA

The methodology presented is designed to efficiently generate and compute numerous design variations, especially in scenarios that require an automated workflow. Figure 4.1 uses the application of FEA to evaluate technical performance as an example to illustrate the various modules of the ADeVAA and their associated outputs. This approach supports the generation of design variations and ensures evaluations that includes both technical and economic aspects. The process begins from the left with well-defined DVs. These are then taken through a DoE that explores the entire design space encompassing all DVs. Through a series of modules, the DVs evolve from parametric CAD modeling to FEA engineering evaluations and cost prognosis, All facilitated by established tools for CAD modeling, numerical simulation, and programming (such as Solidworks, ABAQUS, and Python). On the right, the QoIs represent the evaluation process results.

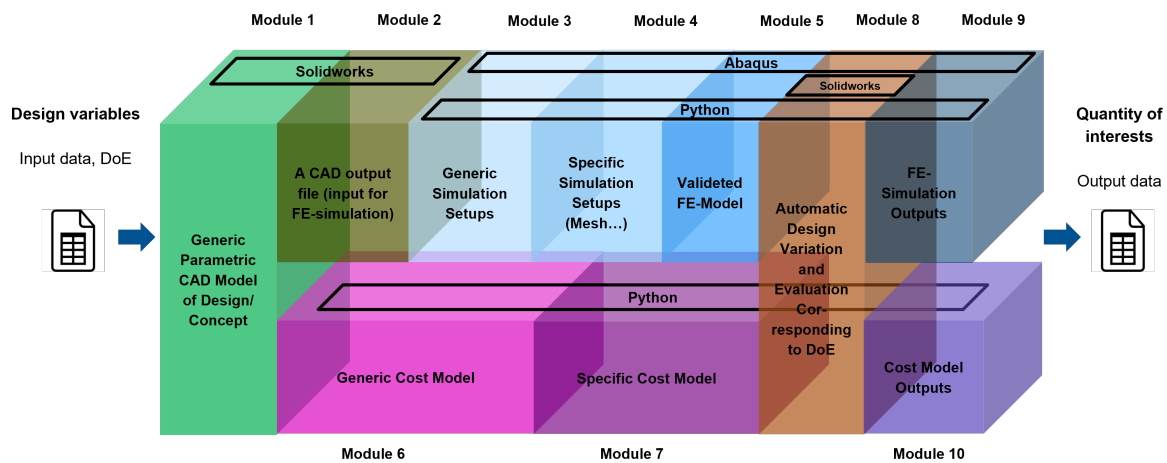


Figure 4.1: Overview: Modules of ADeVAA and their outputs

ADeVAA comprises nine modules, each representing a part contributing to the design modeling or evaluation. Python programming is used to automate most of them, so the modeling and evaluation process for a set of design modifications can be performed automatically. In module 1, a parametric CAD model is created that represents the initial design or concept. In module 2, the parametric CAD model is updated, and design variations are generated using various design variable values from the input data. At the same time, CAD files of design variations will be exported to FEA platforms (such as ABAQUS) in an appropriate form. This facilitates

the creation of an ADeVAA simulation model in module 3, which will be further refined in module 4 with specific computational setups, such as boundary conditions and meshing. The simulation model is validated in module 5 to ensure reliability, providing trustworthy engineering evaluations of design changes.

While modules 2 to 5 deal with the technical check, modules 6 and 7 take a different path, focusing on the economic evaluation of design modifications through a cost calculation model. Once the model building in modules 1-7 is complete, module 8 organizes an automated design variation and evaluation according to the DoE. Finally, the technical evaluation and cost analysis results are collected and archived in different modules: module 9 deals with the technical quantities of interest, while module 10 focuses on the economic aspects. A more in-depth exploration of each phase is provided in the following chapters.

4.2 Procedure model associated with the developed approach

The following section moves to a more general perspective after presenting the constitution of ADeVAA using a modular overview that emphasizes the interconnection between input data, work modules, and output results. The upcoming model [4.2](#), independent of specific software, provides a more general view. This procedural model describes the automatic design variation and evaluation process in a step-by-step format, capturing everything from the initial requirements to the analysis of the results and decision-making. Procedural models are designed to guide users through processes sequentially, ensuring that each step is clearly defined, interrelated, and logically leads to the next. With this model, the approach is universal and can be used across various platforms without relying on specific tools or software.

The diagram illustrates an automated design and evaluation process of nine progressive steps. It begins with the requirements collection process, where the QoIs at this early stage encapsulate the essence of the overall design task. Based on the QoIs established in this phase, the primary ADG can be created, which serves as a guide for the subsequent steps. With these QoIs already defined, it is possible to roughly identify which Design Parameters (DPs), DVs, and intermediate constants belong to which domains in consideration of a specific design task. Based on this, a "Parametric CAD Model" phase is developed for the initial design or concept, which brings the preliminary design scheme to the surface. Upon completing this parametric CAD model, the primary ADG (ADG I) is extended to a more detailed one that highlights technical dependencies and incorporates any defined DPs or DVs derived from the model.

Subsequently, this progression fulfills half of the next phase - the technical model dependency analysis, complemented by its counterpart, the economic model dependency analysis. This in-depth investigation, aided by the production process - the cost category dependency analysis - will begin to decompose the complex relationship between QoIs and DVs in economic performance. With the insights from both the technical and economic dependency analyses, a comprehensive ADG (ADG II) for this design task is established. This ADG serves as a

4.2 Procedure model associated with the developed approach

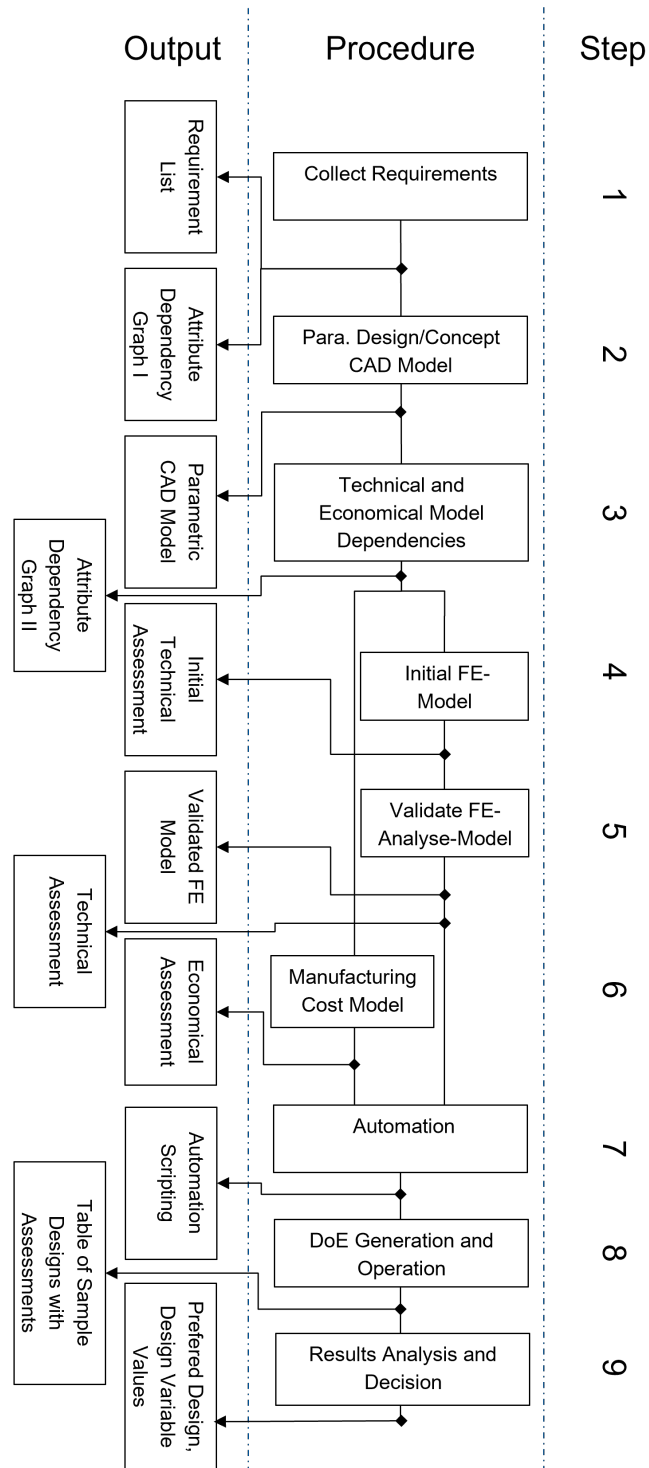


Figure 4.2: Procedure model of ADeVAA

roadmap that clarifies the complications of the design task, especially when faced with highly demanding, multi-criteria design requirements in product development that increase complexity and thus expand designers' previously limited understanding of causality.

After these planning and mapping phases (steps 1-3), the journey turns to model building to evaluate the design performance. This includes the "Initial FEA model" - focused on creating an FEA model for technical performance evaluation - and its following validation in the "Validate FEA model" phase, ensuring its accuracy and reliability. In parallel, a cost prognosis model is established during the Manufacturing Cost Model phase. Despite the uncertainties that occur before the production stage of product development, this model is capable of providing a quantitative cost evaluation.

Once the construction of the evaluation models between steps 4 and 7 is complete, the "automated scripting" phase increases the effectiveness. Through automation, the parametric CAD model can rapidly generate numerous design variations. It then performs performance evaluations of these designs, whether they're numerically integrated into ADeVAA simulation for a technical check or directly referenced to the analytical model for a cost forecast. Once the automated process is implemented, the platform is ready to identify the technically and economically optimal solutions within the defined design space. The next step is to complete an automated DoE configuration based on the predetermined feasible range for each design variable.

The "Results Analysis and Decision" step is the culmination of this entire procedure. Here, the data becomes more than just numbers. It turns into useful information that combines both technical and cost perspectives, with which a decision on an initial final design can be made. In the following chapters, each step of the whole procedure will be introduced in detail.

4.3 Prerequisites of the developed approach

Achieving optimal results depends on a harmonious collaboration of various elements: the technical skills of the personnel, the capabilities of the chosen software platforms, a precise definition of the tasks, and an appropriate understanding of the context.

Personnel technical skills: first and foremost, the people driving this initiative should have a solid technical background. This includes CAD modeling skills to translate abstract ideas into digital models accurately. In addition, a foundation in numerical simulation techniques such as FEA or CFD is necessary to assess the viability and performance of the design under various conditions. In addition, their toolkit should include robust programming skills that allow them to script and automate processes to streamline the design variation and evaluation phase.

Another key prerequisite is software capabilities: The software platforms selected for this approach play a critical role. For example, the CAD modeling tool should provide unrestricted ability to create complex parametric CAD models, regardless of their complexity. In addition, the software must be able to perform robust numerical simulations that provide insight into

potential design weaknesses. A key feature that ensures trouble-free implementation is the software's API support, which facilitates automation in a batch mode, making the entire process more efficient.

Last but not least is task definition and contextual understanding: Starting the development process with this approach requires a clearly defined development goal. From both technical and commercial perspectives, the design requirements must not only be defined precisely, but they must also be capable of being translated into mathematical terms that form the basis for establishing the QoIs. In addition, it is critical to understand the product's application environment. This means determining its potential operating scenarios and technical constraints for an accurate technical evaluation. At the same time, knowledge of possible production processes is required to ensure that the economic assessment has a foundation supported by practical considerations.

4.4 Step 1: Collect requirements

4.4.1 Formulating requirements with QoIs

The initiation or early phase in product development is critical in determining the overall development roadmap. During this phase, collecting product development requirements and formulation them with a language developers can understand becomes essential to successfully completing the development task. These requirements are often obtained through direct discussions with customers, providing a detailed understanding of their expectations and needs. Extensive market research can also provide valuable insights. Such analysis is critical for evaluating competitors' strengths and strategies and understanding market needs and trends. Since this approach usually begins in the early stages of product development, it builds on the initial design requirements already established. This thesis does not discuss the detailed methods of comprehensively collecting specific product development requirements. Instead, the focus is on formulation requirements with mathematical expressions that serve as a common language in the product development processes, particularly concerning technical requirements.

Technical requirements typically fall into two primary categories. The first category specifies exact values, like defined length, width, and height dimensions. An example of this could be mathematically expressed as

$$l \times w \times h = 50mm \times 100mm \times 200mm.$$

Such design requirements with a well-defined value can often be considered given conditions. Such constraints are rarely encountered in product development and will not be discussed here.

The second, more commonly used category that sets a feasible range for the requirements. This can be unilateral, such as specifying a length not exceeding 50mm, represented as

$$l \leq 50\text{mm or } l \geq 20\text{mm}.$$

Alternatively, it can be bidirectional, dictating a size that should not exceed 50mm but also not be less than 20mm, symbolized as

$$20\text{mm} \leq l \leq 50\text{mm}.$$

When a development task has multiple specifications, it is essential to have a consistent view to evaluate compliance with these requirements. The **normalized technical requirements violation** φ can be used to evaluate how well the design meets the requirements defined by the formula

$$\varphi = \max_j \{\varphi_j\}, \quad (4.1)$$

with

$$j = 1, 2, 3, \dots, m.$$

A set of φ_j could usually be defined as QoIs for multiple product development requirements. Therefore, the maximal count m of index j also corresponds to the number of design requirements. The following are examples of φ_j when dealing with different types of conditions.

- One-sided requirements:

$$\varphi_j = \left\{ \frac{y_{jl} - y_j}{y_{jn}} \right\}, \varphi_j = \left\{ \frac{y_j - y_{ju}}{y_{jn}} \right\} \quad (4.2)$$

- Two-sided requirements:

$$\varphi_j = \left\{ \frac{y_{jl} - y_j}{y_{jn}}, \frac{y_j - y_{ju}}{y_{jn}} \right\}. \quad (4.3)$$

Here:

- y_{jl} and y_{ju} represent the upper and lower limits and
- y_j is the actual value obtained from the design.

The normalization factor y_{jn} is chosen:

- For two-sided limits and $y_{ju} - y_{jl} > 0$:

$$y_{jn} = y_{ju} - y_{jl} \quad (4.4)$$

- For one-sided limits and $y_{ju} \neq 0$ ($y_{jl} \neq 0$):

$$y_{jn} = y_{jl} \quad (y_{jn} = y_{ju}) \quad (4.5)$$

- Otherwise: y_{jn} has to be chosen to “make sense” = contour lines of φ represent equivalent solutions.

Figure 4.3 illustrates contour limits for a particular choice of φ in the space of QoIs, here, y_1 and y_2 . On the contour limits, values of requirement violation are constant.

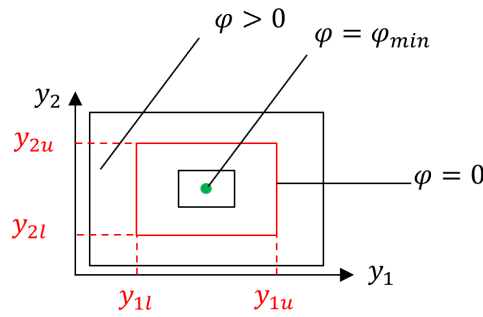


Figure 4.3: Worst-case objective meta function for requirements

Within this plane, there is a defined rectangle (outlined in red) with its corners at coordinates (y_{1l}, y_{2l}) and (y_{1u}, y_{2u}) . This rectangle represents an admissible region that meets the following requirements,

$$\varphi \leq 0$$

with

$$\varphi_1 = \left\{ \frac{y_{1l} - y_1}{y_{1u} - y_{1l}}, \frac{y_1 - y_{1u}}{y_{1u} - y_{1l}} \right\}, \quad \varphi_2 = \left\{ \frac{y_{2l} - y_2}{y_{2u} - y_{2l}}, \frac{y_2 - y_{2u}}{y_{2u} - y_{2l}} \right\}. \quad (4.6)$$

Three regions are labeled concerning the value of $\varphi = \max\{\varphi_1, \varphi_2\}$:

1. A value of $\varphi = 0$, indicates that the design is at the boundary of the rectangle, still barely satisfying all requirements.
2. When $\varphi > 0$, outside the rectangle suggesting violation of at least one requirement.
3. When $\varphi < 0$, indicating full compliance with all requirements.

4.4.2 First dependencies overview: ADG I

A set of QoIs is generated. This enables engineers to formulate a preliminary understanding using an ADG (ADG I) to guide subsequent design activities. This framework allows engineers to gain initial insight into potential DPs, DVs, and intermediate constants, particularly within specific domains such as material selection or operational strategies. ADG I is supposed to provide a clear and focused direction on the interactions of DVs and QoIs in the early stages of product development. This direction becomes especially important when faced with a wide range of options and considerations in the design process. The following figure 4.4 shows an example of ADG I with defined QoIs and possible DVs from different domains.

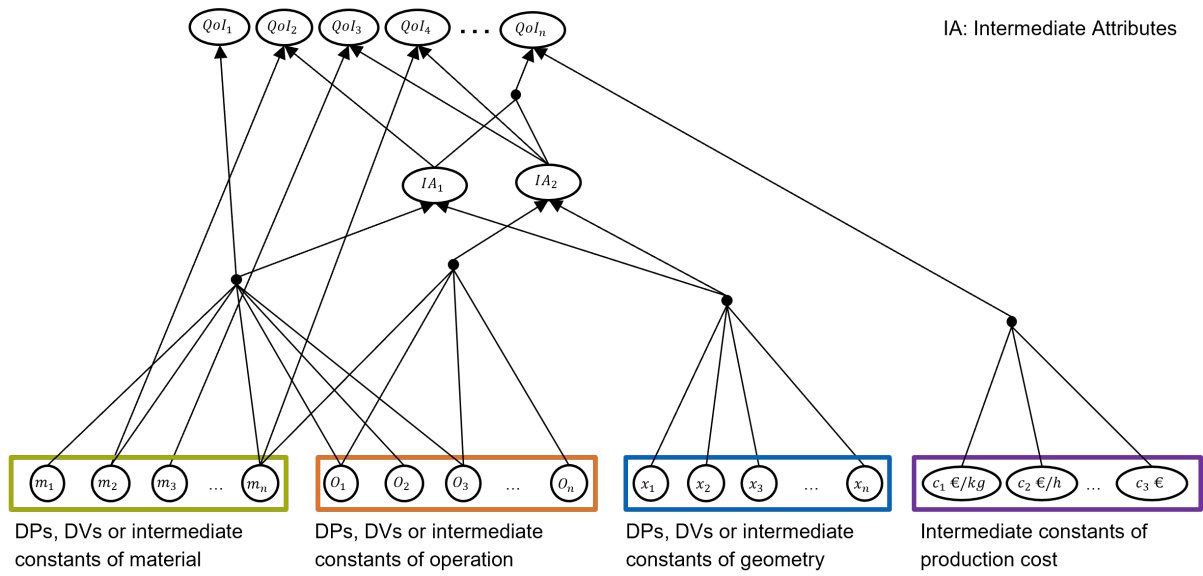


Figure 4.4: A preliminary ADG I

4.5 Step 2: Build a parametric design/concept CAD model

Creating a parametric CAD model means constructing a 3D design that allows for rapidly adjusting its features and dimensions through predefined parameters. To get started, it is essential to choose a suitable CAD software. Standard options on the market include SolidWorks, Autodesk Inventor, Creo Parametric, CATIA, and Fusion 360, with the ideal choice depending on the application's specific needs, the design's complexity, and the user's familiarity with the software. Once the software is in place, the process evolves into two primary phases. The first stage is creating a 3D CAD design incorporating the intended concept. The next step involves replacing fixed values in the initial model with parameters. By establishing relationships

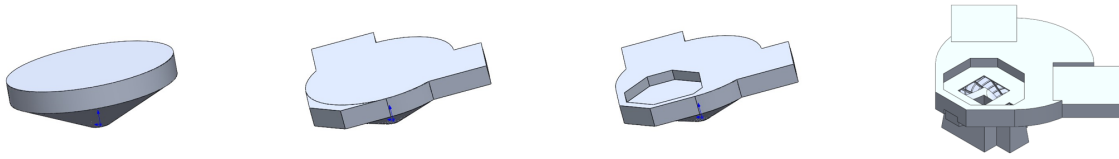


Figure 4.5: A satellite payload structure and its associated simplified CAD models, with details in [127]

between these parameters, the features and dimensions of the model can be modified later on by simply varying the set parameters.

1. **Understand basic design principles and decompose complex structures:** Start by understanding the design's core goals, operational requirements, and constraints. Next, identify the essential elements of the complex structure and understand how they relate to each other. Decompose an intricate design into multiple components with simple and symmetric structures. For example, a detailed satellite load configuration might be broken down into components such as the primary shell, secondary platform, structural supports, and buffers. For more complex designs, adopting a tiered decomposition strategy may be imperative, breaking down primary components into second or even third levels. This approach is illustrated by constructing the following satellite payload structure [4.5] and its associated simplified CAD models.
2. **Sketching: then, a basic 2D outline of the models is created.** This 2D representation serves as the basis for the subsequent 3D CAD model. Simplicity is maintained, and only half or a specific section is shown where symmetry is present, as in Figure [4.6] illustration of the X-ray target wheel section. As mentioned before, complex asymmetric structures often cannot be represented directly by a two-dimensional section. Typically, the model is simplified to a more basic symmetrical design, then detailed components are added incrementally.
3. **Define the parameters:** Parameters are set by introducing significant dimension variables into the 2D sketch. For a rectangular block, variables are specified for 2 dimensions like length width. Descriptive parameter names such as "Block_Length" are recommended over generic names such as "L".
4. **Create features:** Convert the sketch into the primary shape of the model using techniques such as extrude, revolve, or loft. This step specifies the parameters that transform the 2D sketch into its 3D representations, such as the extent and orientation of the extrusion for a cuboid or the rotation angle and the rotation axis for a revolving entity.

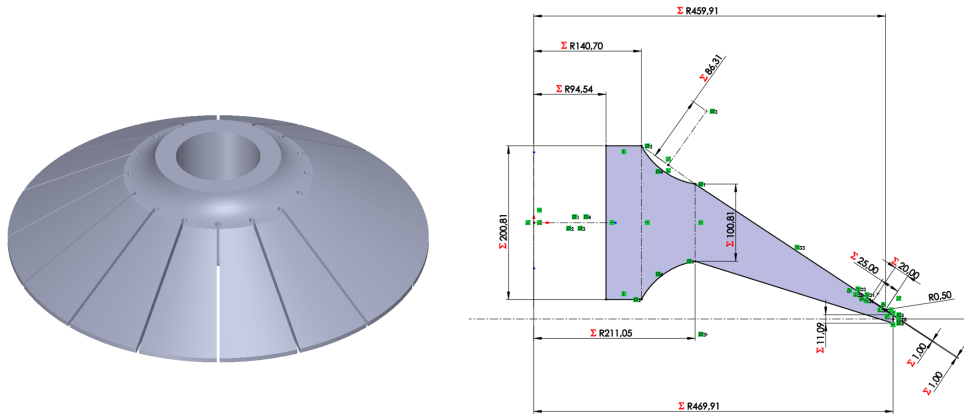


Figure 4.6: The 3D CAD representation and the 2D sectional drawing of an X-ray target wheel, with details in Section [6.3](#)

Repeat steps 2 through 4 above until all parts of the initial design are fully expressed.

5. **Establishing relationships:** It is a critical step when building a parametric CAD model. A parametric CAD model not only represents the geometry of a design but also embeds the interdependencies between different design elements. This allows for flexible adjustments and modifications refinement based on changing requirements or constraints. As geometric parameters change, the model updates automatically, ensuring consistency and reducing potential errors.
6. **Test the model:** Checking the model before incorporating the parametric CAD model into the automated design variation workflow is critical. This ensures its consistent performance and reliability, regardless of changes made to its parameter values. Start by visually inspecting the model, rotating and observing it from multiple perspectives to identify any apparent anomalies. Then, perform parameter range testing, stretching the design parameters to their maximum limits to evaluate the model's robustness and ensure no unexpected overlaps or mismatched geometries in the geometry. Finally, carefully check the model tree's order and relationship of features. The following is a sample model tree [4.7](#) showing the CAD model structure of a satellite payload design.
7. **Optimize and clean up:** Optimizing and cleaning up the parametric CAD model is necessary to perform the design variation part of ADeVAA efficiently. Start by carefully reviewing the feature tree and removing unnecessary features. Where possible, try to combine multiple sketches into one to simplify the model and reduce remodeling time. Next, ensure that constraints are applied reasonably, removing those that do not contribute

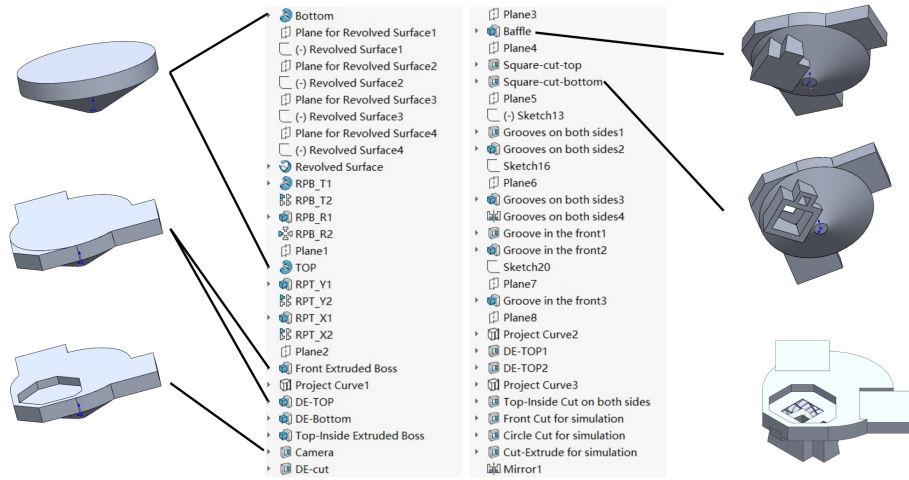


Figure 4.7: Satellite payload structure and its model tree

meaningfully to the model's functionality. Regularly remove unused or obsolete sketches, planes, or features. Finally, regularly test the model under varying parameter sets to confirm its robustness and functionality.

8. **Integration with other systems:** Depending on the development project, design options need to be imported into analysis platforms such as FEA or CFD for technical evaluation. Therefore, the parametric CAD model should be linked to automation programs to facilitate an automatic generation of design variations. Before a design variation is accepted as an evaluable design, it undergoes a testing phase linked to the parametric CAD model. A validation algorithm helps identify only those design variations that are free of errors as prime candidates for further evaluations.

Complete the previously mentioned eight steps to develop a parametric CAD model. In addition to achieving a robust model adaptable to generating design variations, this process also clarifies the available DVs and DPs associated with the geometry, helping to formulate a more comprehensive ADG. Details are presented in the following chapter.

4.6 Step 3: Establish technical and economical model dependencies

4.6.1 Technical model dependencies

Once the parametric CAD model is complete, the structure's DVs, DPs, and possible intermediate constants are identified. With this information, the technical aspects of the ADG I can be

fully expressed. The goal is to clarify and communicate the causal relationships between QoIs and DVs and to illustrate the technical model dependencies as clearly as possible in the final ADG (ADG II).

4.6.2 Economic model dependencies

Completing an economic analysis before establishing a detailed manufacturing plan in the production phase of product development, especially in the face of uncertainty, requires streamlining the use of available data without drowning it in irrelevant information. Central to this process is the critical step of performing a dependency analysis. It analyzes the relationship between the production process and various cost categories, with the goal of identifying where design-related costs occur within the production processes and their respective cost categories. In other words, this cost segment will change according to the design modifications. A clear mapping framework for the dependency analysis can be established, including different production processes and their associated cost categories. This method can quickly assess the cost impact of design modifications. For example, if a new material or technology is being considered, costs associated with material sourcing or production techniques may change.

Moving on to a more detailed introduction of the economic model dependency analysis, completing it requires a thorough analysis of potential production methods and the relationship between different cost categories. As described in section 3.5, "differentiating overhead costing model" (see Figure 3.2), a customized costing model 4.8 has been implemented in accordance with ADeVAA. This model, retaining all necessary cost items for calculating product manufacturing expenses, divides costs into five primary categories: material direct costs (MtDC) and material overhead costs (MtOC) - categorized under material costs (MtC); production labor costs (PLC), production overhead costs (POC), and special production direct costs (SPDC) - categorized under production costs (PC). The culmination of this cost calculation model is the manufacturing costs (MC).

After establishing the basics of the cost calculation model, it is imperative to explain how dependency analysis interacts with these identified cost categories. The below dependency analysis table details the processing classifications and their corresponding manufacturing parts. Under each processing category, there are a variety of specific processing contents and associated manufacturing methods. Vertically (row direction), various cost categories are presented, such as material direct costs (MtDC), production labor costs (PLC), production overhead costs (POC), etc. These represent the various costs incurred during the product manufacturing process.

After establishing the basics of the economic evaluation model, it is imperative to explain how dependency analysis interacts with these identified cost categories. The following dependency analysis table (see Figure 4.9) breaks down the processing categories and their manufacturing parts. Each processing category includes different processing types and their associated manufacturing techniques listed horizontally. Each column represents a separate processing category, detailing the processes and methods involved. For instance, the first column might

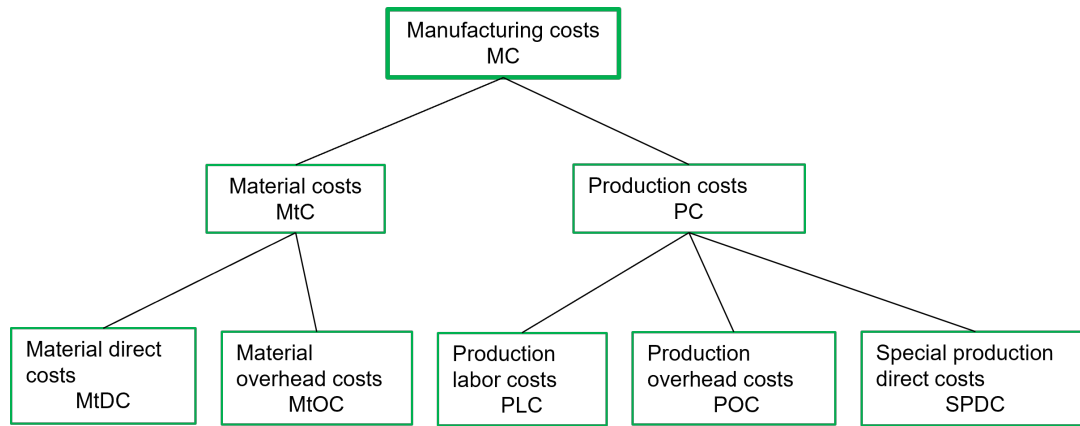


Figure 4.8: Cost model for ADeVAA from differentiating overhead costing model according to [5]

focus on "molding processes" for the part "rubber part" and include techniques such as "injection molding" or "compression molding". Vertically (row direction), various cost categories are presented, such as material direct costs (MtDC), production labor costs (PLC), production overhead costs (POC), etc. These represent the various costs incurred during the product manufacturing process.

To complete economic dependency analysis with the table, the following steps should be performed:

1. Identification of Processes:

- First, outline all the essential production steps required to complete the product. For each step, identify the specific part or component to be manufactured.
- Next, classify the step under a general manufacturing category, such as metallurgy or machining, and then specify the specific manufacturing techniques within that category, such as drilling or milling. It is important to note that because this analysis is in detailed design stage of product development, there may be a variety of potential production options to explore. Therefore, creating multiple parallel dependency analysis tables representing different production strategies may be beneficial to evaluate the design variations under different conditions.

2. **Cost-production dependency analysis:** Dependencies will be evaluated based on the five primary cost categories for every manufacturing step determined in the initial production process. These costs should be assessed using three criteria, each symbolized by a specific color.

4 The developed approach

	processing category 1 / manufacturing part 1				processing category 2 / manufacturing part 2			...	processing category n / manufacturing part n	
	Processing content 1 Manufacturing methods	Processing content 2 Manufacturing methods	Processing content ... Manufacturing methods	Processing content n Manufacturing methods	Processing content 1 Manufacturing methods	Processing content ... Manufacturing methods	Processing content n Manufacturing methods	Processing content ... Manufacturing methods	Processing content 1 Manufacturing methods	Processing content ... Manufacturing methods
Material direct costs MtDC										
Production labor costs PLC										
Production overhead costs POC										
Material overhead costs MtOC										
Special production direct costs SPDC										
There are no incurred costs. Cost independent of design variation K_f Cost depending of design variation K^* $MC_{total} = K_f + K^*$										

Figure 4.9: Cost-production dependency analysis table

- **Gray** indicates that there are no costs associated with the manufacturing step. For example, there will not be any associated material direct costs (MtDC) during machining processes like drilling.
 - **Light blue** indicates that while costs exist, changes in design variables (DVs) will not affect the costs. This segment of the cost is symbolized by K_f . For example, material overhead costs (MtOC), usually associated with storage expenses etc., do exist but remain consistent regardless of machining processes like drilling.
 - **Dark blue** represents situations where costs are directly affected by design modification, and these changes further affect the costs of subsequent processes. This cost is represented by K^* . Numerous examples exist, such as the material direct costs (MtDC) for producing the raw part or the time-related production labor costs (PLC) during the machining process.
3. **Identify the costs to focus on:** After finishing the first two steps, attention now focuses on the costs shown in dark blue. The design modifications directly influence these costs K^* , separate from the total manufacturing cost MC_{total} , which includes K_f and K^* . The cost component K_f is characterized as a fixed cost that remains constant across design variations. By avoiding the quantitative calculation of this fixed cost, the calculation process is simplified, and the information required is also reduced. This strategy allows for quantitative economic analysis of multiple design variations. Moreover, it minimizes

the dependence on large amounts of information, effectively overcoming the problem of the lack of production information at the detailed design phase of product development.

4.6.3 Combined dependencies: Attribute Dependency Graph II

After analyzing both the technical and economic model dependencies, the initial ADG (ADG I) could be refined into a more comprehensive version called ADG II. This enhanced ADG acts as a map that combines both technical and business perspectives. It provides a comprehensive view of the interrelationships among all participants in the product design process, including QoIs, DVs, DPs, and intermediate constants or attributes.

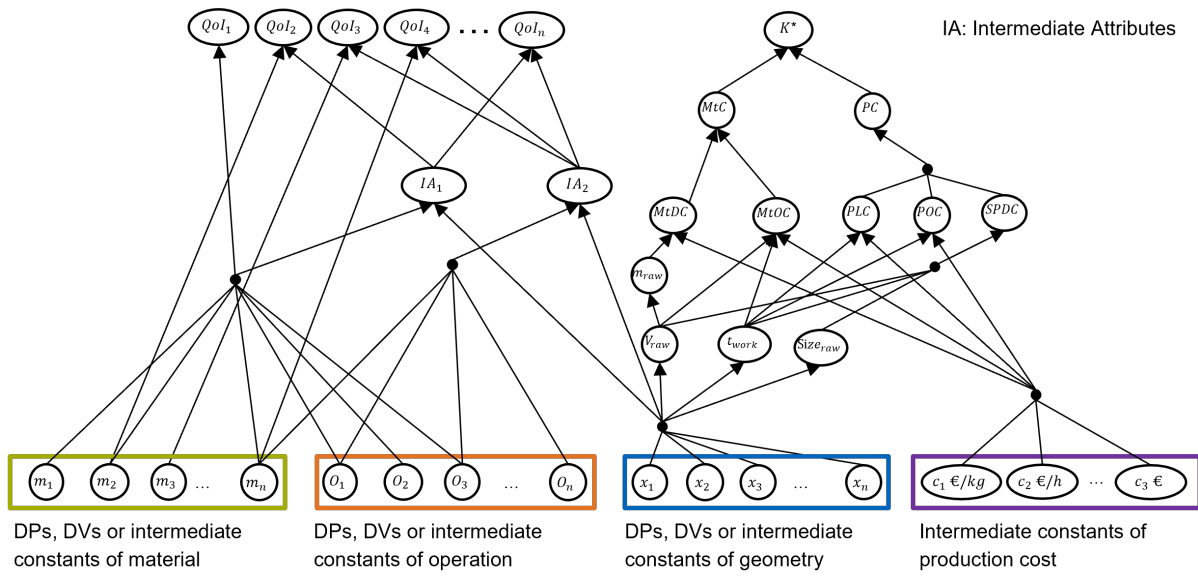


Figure 4.10: ADG for the entire model

4.7 Step 4: Complete the technical assessment of design variations via FEA

4.7.1 Overview

In the fourth step, numerical simulation (e.g., FEA, CFD) is used for engineering evaluation of various design options and can simulate and predict the behavior of a complex design under various conditions. In this thesis, the application cases use FEA method, so this section will use it as an example. The following section provides a general overview of how to set up a

FEA simulation in ADeVAA and discusses an important aspect of numerical simulation models: meshing.

While the sequence for setting up an FEA model may vary depending on the platform used for FEA, the primary steps include the following:

- **Problem definition:**

- Determine the specific problem or aspect to be analyzed (e.g., structural strength, heat transfer, fluid dynamics).
- Understand the real-world conditions the product will face.

- **Geometry creation:** In ADeVAA, 3D CAD models of design variations are directly imported into the analysis platform for technical evaluation.

- **Material properties:** Assign material(s) to the model. Make sure the material properties (such as Young's modulus, Poisson's ratio for structural analysis, or thermal conductivity for thermal analysis) are accurately defined.

- **Boundary and initial conditions:** Boundary conditions define how the model interacts with the outside world, like where it is fixed or where forces are applied. Initial conditions set the starting point for the simulation, like the beginning temperature or speed. In addition, boundary condition that simulates symmetry in ADeVAA simulations is often used. The reason is that symmetric designs can be represented by a segment of the whole, thus reducing computational requirements. By applying specific boundary conditions to the selected segment, the performance of the entire structure can be simulated.

- **Meshing:** Meshing is critical in the ADeVAA simulation process. It involves dividing the geometric model into smaller, discrete elements, commonly known as 'mesh elements' or 'finite elements'. These elements are interconnected at points called nodes. The mesh is essentially a discretized representation of the geometry, and the choice of mesh can significantly influence the accuracy and efficiency of the simulation.

Because of the importance of meshing, the following section [4.7.2](#) will discuss more details related to it.

- **Solution:** Select the appropriate solver based on the analysis required. For example, choose a linear static solver for a structural static analysis to determine displacements and stresses in a beam or a transient fluid dynamics solver for the dynamic response of a structure subjected to time-varying loads.

Run the simulation, and the solver will determine the model's response under the specified conditions.

- **Post-processing:** Post-processing also lays the foundation for validating the FEA model, primarily through intuitive checking of the results. In step 5 (section 4.8), the details of FEA model validation will be presented.

In conclusion, these steps provide a general guide for completing the engineering evaluation of design variations using numerical simulation, with ADeVAA as an example. However, it is important to note that each unique design task may require specific adjustments or considerations to achieve an accurate engineering assessment.

4.7.2 Meshing

After providing a general overview of FEA simulation setup in the previous section, this section focuses on the details of meshing. The choice of mesh type and the preparation of a meshing process can have a significant influence on the accuracy of the simulation results. This section discusses different mesh types, how to prepare structures to mesh them with a less computationally expensive mesh type, and a validation study as an example to ensure that the selected mesh type provides the expected accurate results.

As described in chapter 3.4, the main types of 3D meshing can be broadly categorized into structured meshes, represented by hexahedral meshes, and unstructured meshes, represented by tetrahedral meshes. Hexahedral meshes have notable advantages in computation time, CPU load, and accuracy. However, they tend to struggle when it comes to meshing complex structures. On the other hand, with its four-face structure, the tetrahedral mesh offers flexibility and adaptability for complex structures, making it the optimal choice for automated mesh generation in ADeVAA. However, the time consumption, CPU intensity, and potentially inconsistent accuracy of tetrahedral meshes require careful consideration before choosing them for FEA simulations.

The following sections discuss two situations involving complex structures unsuitable for direct hexahedral meshing. The first situation involves a structure that, despite its complexity, can be manually partitioned into simple components. The second situation is a highly complex structure resistant to all hexahedral meshing pre-processing strategies. Section 4.7.3 deals with the first scenario and illustrates the pre-processing of complex structures with a practical example: the structural partitioning of an X-ray target wheel. In treating the second scenario, the focus of section 4.7.4 is on an accuracy validation study that evaluates the accuracy of FEA simulations when using unstructured (tetrahedral) meshing elements.

4.7.3 Model partitioning and mesh refinement in complex structures

In FEA, dealing with complex models often requires a strategic approach of partitioning these models to make the analysis more manageable and accurate.

A basic approach in the early stages of ADeVAA is to partition the structure. This method breaks down the complex structure into more simplified substructures. By breaking down the detailed model into more fundamental geometries, it becomes much more manageable to address each segment's different attributes and requirements individually. Once a complex structure has been partitioned into several more superficial structures, performing hexahedral meshing or automated mesh using hexahedral elements is no longer challenging.

The figure below (see Figure 4.11) illustrates an example of a rotationally symmetric model representing the entire original X-ray target wheel in FEA simulation, partitioned into several meshing partitions. Each piece consists primarily of simpler shapes, such as hexahedrons. Structures like these are more easily meshed with structured meshing elements than the original one-part structure, allowing for an optimized ADeVAA.

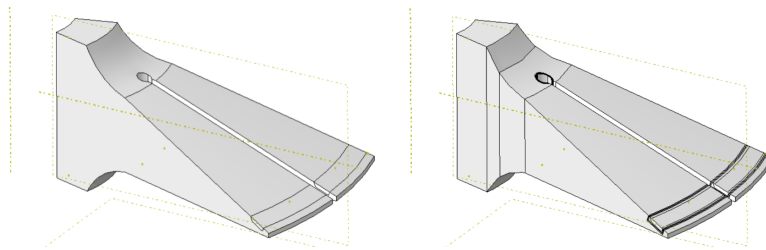


Figure 4.11: Original and modified structure with meshing partitions of the X-ray target wheel for FEA simulation

Another important technique is focused mesh partitioning.

Mesh partitioning considers the needs of the entire model and specific areas within the model that often require more detailed analysis. Due to their importance or unique function, these particular areas may require a denser and more detailed mesh than the broader model. Through targeted mesh partitioning, even in automated meshing processes without manual intervention, structural segmentation ensures mesh density and quality in priority areas. As illustrated in the Figure 4.12, in the FEA model of the X-ray target wheel, special attention is given to the focal track region, resulting in segmented structures and subsequent generation of a high-density mesh.

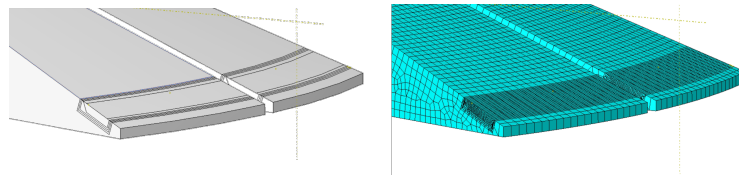


Figure 4.12: Focused mesh segmentation of the focal track on the X-ray target wheel

4.7.4 Validation study on the computational accuracy of unstructured mesh element

Chapter 3.4 highlighted the importance of automating mesh generation in numerical simulations (FEA) along with the pursuit of accuracy. The current chapter presents an analysis aimed at validating the performance of simulations performed with automated unstructured 3D (tetrahedral) meshes against those using the 2D shell mesh technique. According to [65], a 2D shell element can be considered a feasible alternative to structured 3D (hexahedral) meshing when dealing with complex shell geometries for both thick and thin structures, as it provides good accuracy, while requiring relatively low CPU time. The primary objective is to determine whether the accuracy offered by unstructured meshing is actually comparable to that provided by the structured equivalent.

For this analysis, a simplified satellite structure with intersecting longitudinal and transverse ribs was selected as the test model. This structure is characterized by a specific diameter and height, with ribs of uniform height extending orthogonally (see Figure 4.13). Such a model can be represented accurately in both shell and solid CAD formats, allowing its detailed configuration to be revealed.

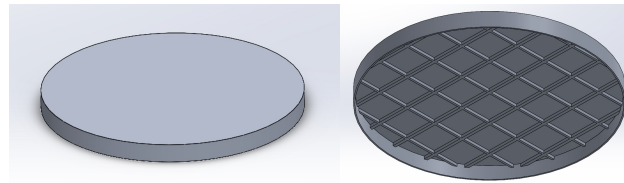


Figure 4.13: The test model (solid form) in two view directions

The design variables of the test model (see Figure 4.14) are the wall thickness (t) and the width of the ribs (b).

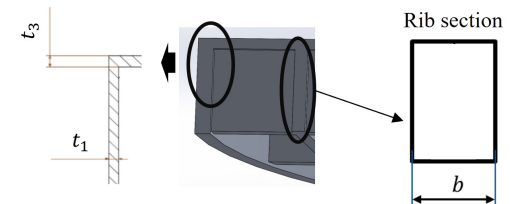
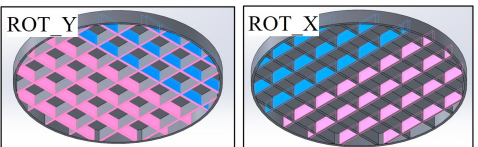
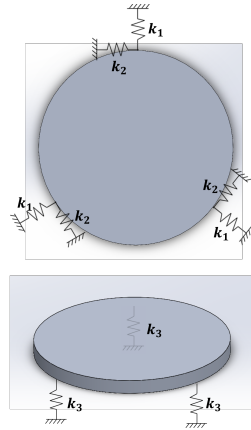
		Design Variables	
	t	t_1	wall thickness
		t_3	
	b	b_{ROT_Y}	widths of the ribs
		b_{ROT_X}	

Figure 4.14: The design variables of the test model

The test model is connected to the ground by three identical supports (see Table 4.1).

Table 4.1: The test model and its supports



Stiffness matrix $\mathbf{k}$ for each support:

$$\mathbf{k} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3.45 \times 10^7 \text{ N/m} & 0 & 0 & 0 & 0 \\ 0 & 0 & 2.1 \times 10^7 \text{ N/m} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

A total of one hundred solid 3D design modifications of the test model were generated with randomly selected design variable values. These samples were automatically numerically simulated for eigenfrequency and mass on an FEA platform (ABAQUS) using tetrahedral mesh elements. At the same time, the equivalent shell geometry of the test model was created manually in ABAQUS and then simulated using 2D shell elements. The randomly generated design variable values, which were used to create design variations in the solid form, were incorporated into the simulation setup parameters to establish the model's attributes.

Figure 4.15 shows the meshes of the test model with 2D shell elements and 3D unstructured solid elements in its shell and solid format, which represent the same structure but have different mesh distributions and shapes.

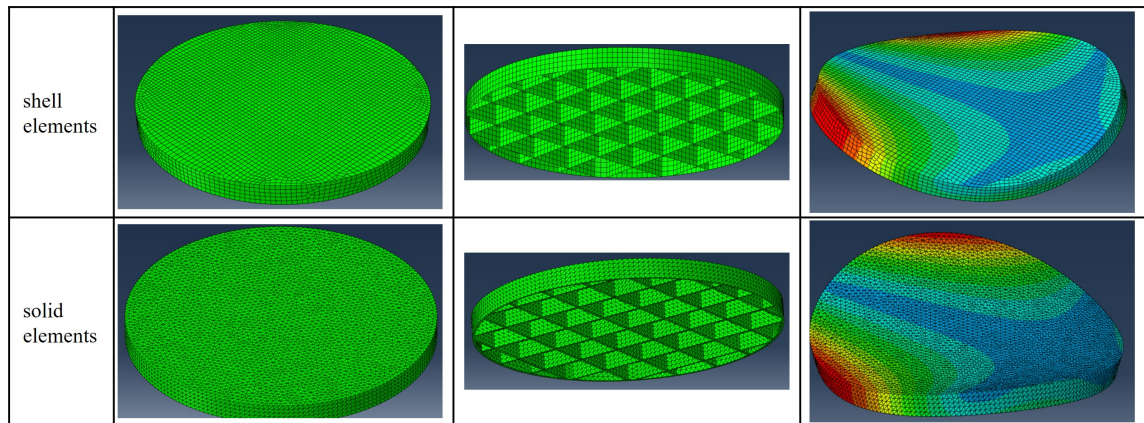


Figure 4.15: Mesh of the test model with shell structured elements and solid unstructured elements

After simulating the eigenfrequency and mass of the 100 test model samples with two different meshing elements, the mass-eigenfrequency values and the comparison of eigenfrequency are illustrated in the following diagrams (Figure 4.16 and 4.17):

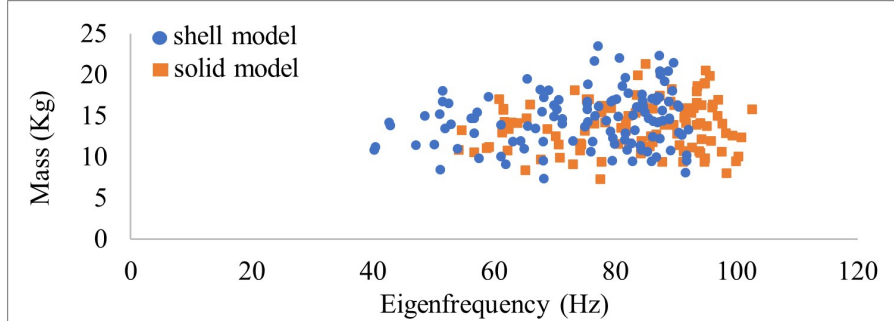


Figure 4.16: Mass and eigenfrequency values of the shell and the solid model

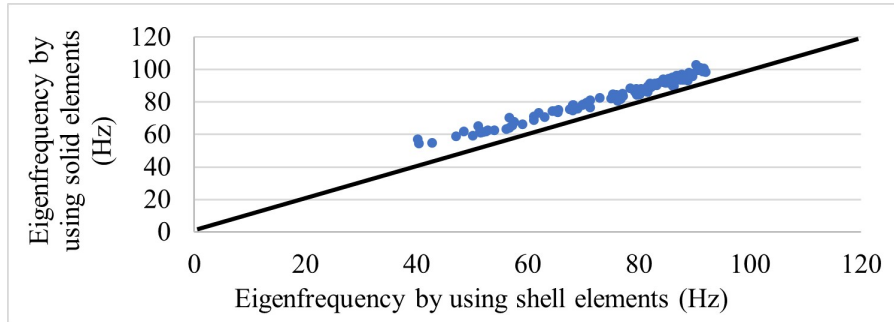


Figure 4.17: Correlation of eigenfrequency of shell and solid model

The results indicate that although the eigenfrequencies and masses derived from unstructured and structured elements are not identical, the variations are consistently small (<10%). Therefore, the solid unstructured (tetrahedral) element model is able to demonstrate a level of accuracy similar to that of the shell element model, proving that it can replace structured meshes in simulating complex geometries while still providing sufficiently accurate results.

However, in practical applications, several factors must be considered to ensure that using unstructured (tetrahedral) elements instead of structured (hexahedral) elements still guarantees sufficient accuracy in simulating complex structures. These include:

1. **Mesh quality:** those situations that degrade mesh quality should be avoided, such as overly elongated, flat, or irregular tetrahedral elements, as well as sudden changes in mesh size. It is important to ensure that the mesh transitions smoothly and naturally from fine elements to coarse elements, in order to maintain the accuracy of the results.

2. **Mesh refinement:** In complex geometries or regions with high gradients, tetrahedral meshes should be sufficiently refined to capture detailed features.
3. **Physical behavior of the model:** When replacing hexahedral elements with tetrahedral elements, the physical problem being simulated should have low sensitivity to mesh shape, such as in steady-state temperature analysis or linear static analysis. However, for problems that are highly sensitive to mesh geometry, such as stress concentrations, using tetrahedral meshes may reduce accuracy, and it is recommended to use hexahedral meshes instead.

Additionally, after the model is constructed, appropriate methods should be used for FEA model validation to ensure the accuracy of the simulation. For further details, please refer to Chapter [4.8](#).

4.8 Step 5: Validate FEA model

Validation is a significant step in the FEA process, ensuring that the computational results closely match the real-world consequences. Regardless of its complexity, the FEA model approximates the actual physical system. By validating the model, validation confirms its reliability and accuracy, ensuring that the predictions are relevant and reliable. This chapter discusses the possibilities for validating FEA models in ADeVAA.

Here are some common techniques to validate a FEA model:

1. **Theoretical validation:** For a geometrically simple model, FEA results in ADeVAA can be compared to established solutions derived from mathematical equations. For example, the displacement of a simple cantilever beam from FEA can be compared to predictions from the Euler-Bernoulli beam equation.
2. **Experimental validation:** This may be the simplest and most conclusive method. Build a real physical model, perform experiments on it, and then compare the experimental data with the FEA results.
3. **Mesh refinement/Optimization study:** This method involves running the simulation on the same model with different levels of mesh refinement or different kind of mesh, which has obviously a better computational accuracy. Theoretically, the results should converge to a certain value as the mesh is refined/optimized.
4. **Simplified model validation:** Simplify a complex model and validate the simplified model. If the simplified model is successfully validated, it can provide some confidence in the complex model.

4.9 Step 6: Establish economic assessment of design variations via cost calculation model

5. **Use previous data for validation:** For certain problems, previous simulation or experimental data may already be available. Although the conditions may be different, this data can be used as part of a preliminary validation.
6. **Expert review:** Review the model, boundary conditions, material properties, and results with colleagues or other experienced FEA analysts. They may be able to identify potential problems or errors that could have been overlooked.

The two use cases described in this thesis used different strategies to validate their FEA models. Only general guidance on the different possibilities for performing FEA model validation can be provided here, and no specific recommendations can be made for particular applications. ADeVAA users must independently decide which method or combination of techniques to use for model validation based on their design task.

4.9 Step 6: Establish economic assessment of design variations via cost calculation model

Step 6 provides a quantitative assessment of economic performance based on design modifications by calculating design-related costs derived from the dependency analysis of production processes and manufacturing costs. The relationship between intermediate values and QoIs with DVs from ADG II and fundamental mathematical formulas for calculating different costs from Section 3.5 are used to perform this step. This formulaic approach provides a cost calculation model adapted to a given design concept, considering specific initial manufacturing processes. The data used in the model comes from a variety of sources. Some cost-related figures come from data files, while others require extraction from design structures (such as a CAD file or an FEA simulation file). This requires the model to be synchronized with multiple data sources and systems. This integration will be elaborated on in the subsequent section 4.10. A main feature of the model is its flexibility. It adapts based on the selected design concept, different production processes, or results of the dependency analysis in step 3. However, its primary limitation is its focus: it can assess the cost-effectiveness of different design variations under a specific manufacturing strategy, but it isn't designed to compare the cost-effectiveness of different production methods for a same design variation.

4.10 Step 7: Automation

With ADeVAA's automation capabilities, this approach easily integrates various design and evaluation stages. It efficiently coordinates a range of processes, transforming tasks that previously required heavy manual intervention into a smooth workflow.

If the automation module of ADeVAA is categorized based on its functionality, it can be segmented as follows:

- **Design variation automation** This feature allows users to automatically generate multiple design variations suitable for FEA simulation using predetermined DVs values, eliminating the need for manual intervention. This capability can also be divided into several specific functions, including:
 - Entering values of DVs into a parametric CAD model with algorithm [A.1](#).
 - Saving configured CAD models of design variations in a format compatible with FEA simulations (algorithm [A.2](#)).
 - Performing checks on the CAD models to ensure its viability, including evaluating then based on specific criteria, such as file sizes, or checking specific parameters of a CAD model file representing a design variation, such as the surface area of a particular face (algorithm [A.3](#)).
- **ADeVAA simulation specification** This section focuses on automating the configuration and setup of numerical simulations (such as FEA simulations) to improve consistency and minimize manual effort. Everything can be done automatically, from importing CAD models to setting boundary conditions, meshing, and running the simulation. The main steps can be roughly categorized as follows:
 - **Importing and structural pre-processing of CAD models:** Before simulating, ensure that CAD files are available and that CAD models are complete. In some cases, importing assembly CAD models with parts made of different materials can cause errors, such as misidentifying mating surfaces. For example, by developing an X-ray target wheel, the "focal track" of the wheel body may be geometrically inaccurately recognized as a part made of another material. In such cases, these parts are adjusted or redesigned within the simulation platform to ensure accuracy (algorithm [A.4](#)).
 - **Establishing boundary conditions:** This section primarily deals with all the basic settings required for numerical simulations. First, material properties are defined to match real-world equivalents. External forces, pressures, and other loading conditions are then specified. Constraints such as boundaries (either fixed or movable) are also assigned. If necessary, initial conditions such as pre-existing stresses or deformations are integrated (algorithm [A.5](#)).
 - **Pre-meshing preparing and meshing:** Meshing is an important part of effective and accurate numerical simulations. It starts with identifying and marking regions that may require more detailed meshing, often for reasons such as potentially high-stress concentrations. In these areas, it is common to set seeds densely and to

create specialized partitions to ensure that the mesh quality remains satisfactory even during an automatic meshing process. In addition, partitioning the model is often a prerequisite for using structured mesh elements (for example, hexahedral element) that provide more accurate results. Finally, the mesh is generated, balancing mesh density and quality to ensure not only trustworthy simulation results but also acceptable computation time and CPU consumption (algorithm [A.6](#)).

- **Configuring and running the simulation:** To set up a numerical simulation in a platform (such as ABAQUS for FEA), select an appropriate type, whether static, dynamic, thermal, or others. Specify the simulation duration, time step intervals, and maximum/minimum increments allowed. Pre-select desired results, such as temperature distributions or von Mises stresses, to optimize calculation time. Then, specify a location for the results and assign the required CPU number. Once all settings are in place, run the simulation (algorithm [A.7](#)).

- **Cost calculation automation**

In the ADeVAA system, automated cost calculation begins with data collection from files. These data include labor rates, tooling costs, manufacturing speeds (which help determine material removal rates and tool life), and material costs. This data is regularly updated to meet the specific needs of different development projects. The process then obtains geometric details from files of design variable values - the same sources used to generate CAD models representing design variations. In addition, check for any one-time design-related costs, such as mold fees. With all the data, a comprehensive design dependent cost calculation (K^*) for an economic analysis could be built (algorithm [A.8](#)). Additionally, the cost calculation model incorporates a feature that employs linear regression for predicting tool life, as outlined in algorithm [A.14](#).

- **Automatic DoE with random sampling** An important step in an automatic DoE process with random sampling is that, for a given number of design variations, the DVs values are randomly generated within a predefined design space using a random number generation algorithm. Once all values have been generated, they are checked to ensure that there are no conflicts or inconsistencies within the dimensions of the design chain. If approved, these values are stored in a data file named by its design variation number for easy recall for future use (algorithm [A.9](#)).
- **Results processing automation** Results processing automation integrates three steps. First, it obtains relevant technical and economic evaluation outputs from the results file. It then translates these intermediate values into defined QoIs (such as the normalized technical requirements violation ϕ for technical assessment). Finally, these QoIs values are recorded in a comprehensive results file, providing an intuitive and solid basis for informed decisions (algorithm [A.10](#)).

- **Data extraction from result files:** Extract result values from numerical simulation results (such as FEA). For example, directly obtain unique displacements or stresses to calculate stiffnesses. Alternatively, it can be more complex by looking for potentially dangerous situations such as maximum stress or peak temperature across all time frames and nodes. This case will serve as an example to show the pseudo-code in algorithm [A.10](#).
- **Automatic QoIs calculation and documentation:** In the second step, the results obtained from the assessment model are formulated with desired QoIs. For example, for QoIs derived from technical performance, the normalized technical requirements violation φ is calculated using values extracted from the numerical simulation results. For economic performance, the QoIs are the K^* values obtained directly from the cost calculation model without any additional transformation (algorithm [A.11](#)).
- **Python-based integration** Integrating Python into ADeVAA's automation module exemplifies adaptability and efficiency in handling complex tasks. Python facilitates coordination among ADeVAA's various design and evaluation stages. It scripts repetitive workflows, such as entering values for design variables or initiating simulations. Additionally, Python's data manipulation capabilities ensure efficient data processing and documentation of results from multiple sources. Furthermore, Python's modularity simplifies the compartmentalization of each function, whether it is cost calculation or DoE configuration, aiding in debugging and updates.

In ADeVAA's automation module, users can combine multiple algorithms to create comprehensive functions. For example, integrating "automatic DoE with random sampling", "entering DVs values into a parametric CAD model", and "performing checks on the CAD models", establishes a pipeline that starts with DVs values creation, proceeds with generating CAD models representing design variations, and concludes with an initial model check. This combination allows for the efficient removal of nonconforming samples early in the experimentation phase.

However, this initial screening serves as a broad filter and does not guarantee that CAD models are error-free for numerical simulations. A CAD model that clears this first screening level may still encounter geometric errors during ADeVAA in FEA simulations because the filter may not meet the specific requirements of numerical analyses. Alternatively, the integration of "performing checks on the CAD models" in CAD modeling platforms and "importing and structural pre-processing of CAD models" within simulation platforms offers a more detailed screening.

The criteria for screening are highly dependent on the design task and the constructed intermediate models, precluding a universal standard. When users decide on a combination of basic functions, the algorithms within those functions often require customization to suit particular scenarios.

4.11 Step 8: DoE generation and implementation

Within the ADeVAA framework, the DoE procedure capitalizes on seven foundational procedural steps. The process is delineated as follows:

- **Objective specification:**

Identifying the output variables, known as QoIs, and the input factors, referred to as DVs, is the first step. These elements are well-defined from the beginning and thoroughly detailed in ADG II.

- **Approach to DoE:**

An appropriate DoE approach is selected to meet the defined objectives. For ADeVAA, a fully randomized experimental design is selected.

- **Factor definition:**

Define the design space of each input factor of the experiment (the range of each design variable), for example, a diameter range of 50 to 100 mm or a velocity of 0 to 200 m/s.

- **Experimentation:**

Samplings of DoE (CAD models of design variations) generation and experiments are performed automatically by utilizing ADeVAA's automation module. The experiments facilitate both technical evaluation through FEA and economic check via a cost calculation model.

- **Result collection:**

The results of each experiment will be collected and systematically documented, ensuring the completeness and accuracy of the result data set.

In the iterative process of DoE shown in Figure [4.18](#), a maximum number of experiments, referred to as m , should be determined for a given set of DoE conditions, such as within a predefined design space. The determination of m should take into account factors such as the restrictiveness of the design requirement and the estimated time required for the experiments etc. A value of n that is less than m is then chosen to start the first DoE. After generating design variations using a parametric CAD model and completing the technical and economic evaluations using FEA and a costing model, the results are documented and presented, for example, in a diagram. If at least one technically sufficient solution is identified, the DoE process is considered complete and further analysis and decision-making can proceed. Conversely, if no suitable solution is found, the sample size n is increased within the range of m for additional experiments. This loop is repeated until at least one technically sufficient solution is found. If the sample size n reaches m without identifying any technically sufficient solution, a re-evaluation and adjustment of the design space, based on the latest results, is required before starting a new round of experiments.

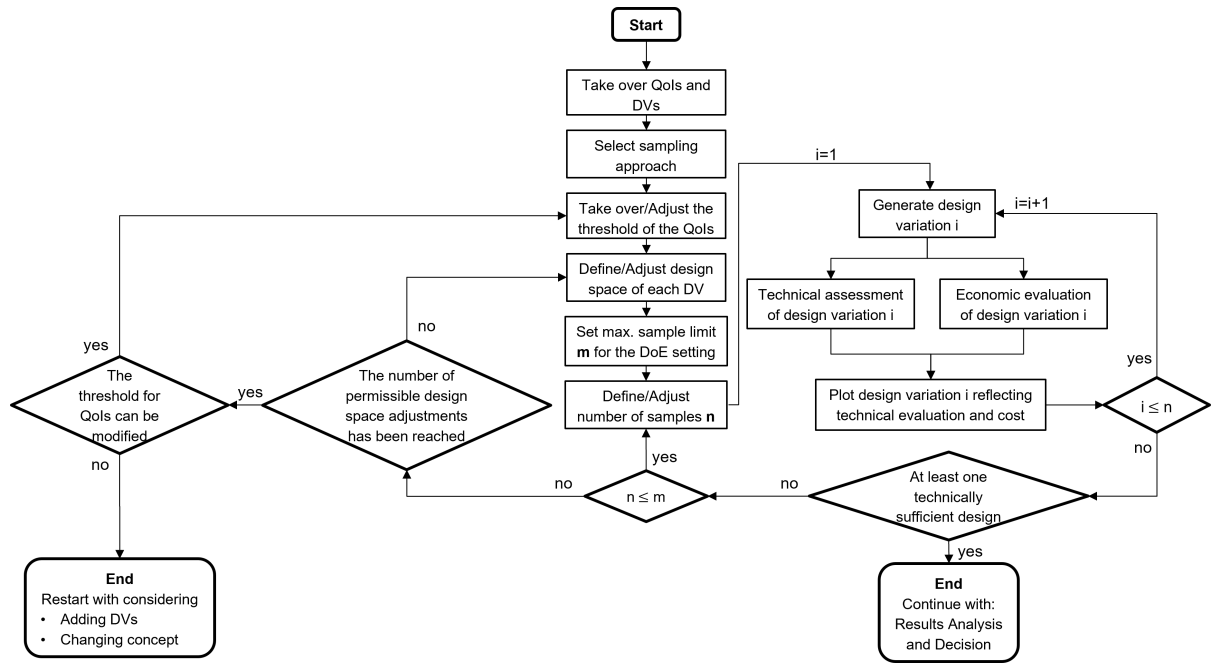


Figure 4.18: Iteration loop of DoE

When the limit of allowable design space adjustments has been reached, it may be necessary to adjust the QoIs threshold within the original settings. This adjustment will depend on the flexibility allowed in the project for changing the design requirement limits. If at least one technically sufficient solution is found, the DoE process ends and the project moves to the results analysis and decision phase (in Figure 4.2). However, if a number of adjustments to the DoE settings - from its size to the range of DVs and QoIs - still does not produce any technically sufficient solution, the DoE phase ends. The process should then restart from the beginning, referring back to steps 1 and 2 of the procedure model shown in Figure 4.2, considering adding new DVs or changing the design concept.

4.12 Step 9: Results analysis and decision-making

The final step in ADeVAA is step 9: results analysis and decision-making. At this point, a diagram summarizes the technical and economic assessments of all the design variations derived from the DoE results.

The technical performance expressed by QoIs are quantified into a single metric, called normalized technical requirement violation ϕ (formula 4.1), and plotted on the graph's horizontal axis. In parallel, the economic impact, measured as the design-related manufacturing cost from

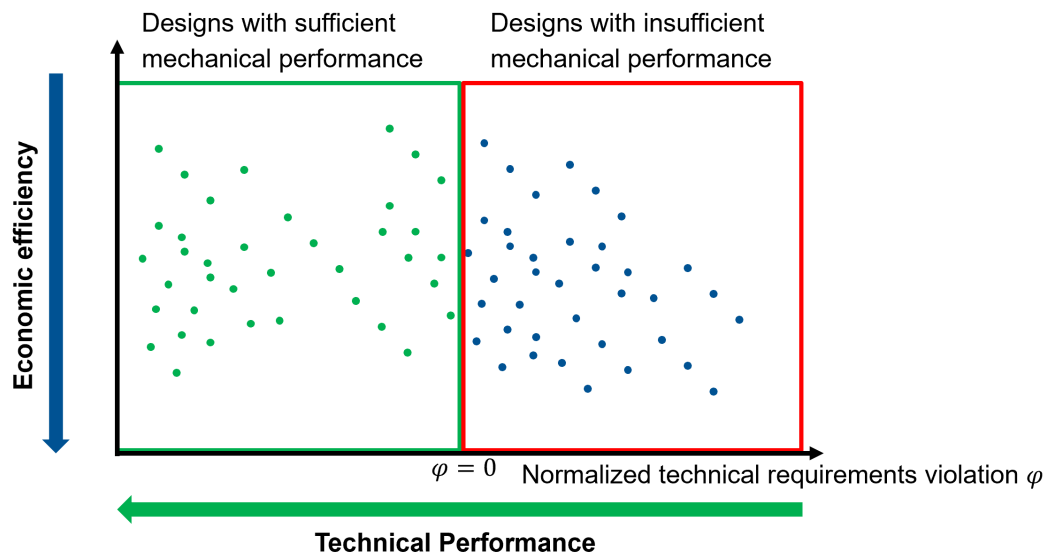


Figure 4.19: Plot of design variations reflecting economic and technical evaluation

the economic evaluation, is plotted on the vertical axis. This two-dimensional plot provides a comprehensive view of the outcome space for all design variations. An example of such a diagram is shown in Figure 4.19

By analyzing these plots, technically sufficient solutions emerge in the region where φ is less than zero. Within this defined range, attention is focused on identifying the design option with the lowest design-associated manufacturing cost. This step is important in isolating the design that best balances cost efficiency and technical performance, leading to a strategic and informed decision path.

After determining the optimal potential design variation, several additional analyses can also provide insights between QoIs and DVs to inform future product optimization.

- **Sensitivity analysis:**

This involves regression analysis of DVs against various QoIs to identify which DVs have a significant impact on performance and predict how DVs might affect future performance.

- **Design space analysis:**

By examining design spaces of different DVs and the range of sufficient mechanical performance, areas with a higher concentration of technically sufficient solutions can be identified. This knowledge can be used to narrow the design space in future DoE efforts, thereby increasing efficiency.

- **Specific QoIs observation:**

Observe the QoIs of technical requirements and the cost parts of design-related manufacturing cost, such as the material cost or the production cost of different processing steps. It helps users determine which technical requirements are more challenging to meet for all design variations and which costs determine whether the design variation is economically efficient, which is a guide for subsequent optimization.

- **Extreme variations study:**

By observing design variations at the extremes of the plot that reflect economic and technical evaluation (see Figure [4.19](#)), such as those with exceptionally high costs or poor technical performance, insight can be gained into why these variations meet or fail to meet the design requirements.

5 Application example 1: development of a target wheel for an ultra-high power X-ray source

5.1 Project background

There have been important advances in the treatment of cancer with radiation therapy, including innovative techniques such as microbeam radiation therapy (MRI) and FLASH X-ray scintigraphy. These techniques are designed to target tumors while protecting surrounding healthy tissue effectively. The challenge, however, is that these precise, high-quality beams have typically required the use of large synchrotrons. These machines are not only in limited supply but also costly and complex, limiting their use in clinical settings. Developing a compact line-focused X-ray tube (LFxT) suitable for hospital environments is critical in overcoming this limitation ([8], [91], [119]).

Such a device would be easier to fit into hospitals and allow more patients to benefit from the latest technologies. This new generation of X-ray sources must be both practical in terms of size and be capable of delivering significant power. Depending on the research of Winter [120], by innovating power converters that can quickly generate several megawatts of voltage and electron sources equipped with thermionic cathodes and quadrupole magnets, focused, high-energy electron beams can be produced. These beams accelerate toward the target, where their rapid deceleration releases powerful X-rays.

However, the process of producing these X-rays generates significant heat as the electrons slow down, so the target in the LFxT must be able to handle this intense power output - approximately 1 megawatt for one second - without sustaining damage. To dissipate heat and avoid hot spots, the target also spins at high speed, which means it must be exceptionally durable against high heat and mechanical loads while maintaining consistent performance over time. In the next section, following the developed ADeVAA, an X-ray target wheel development process will be presented. This process will follow a sequence of steps shown in the procedure model presented in Figure 4.2.

5.2 Step 1: Collect requirements

In developing an ultra-high power X-ray source, the design of the target wheel is a critical aspect that requires a balance between restrictive technical requirements and economic considerations. This section describes the design requirements essential for developing a target wheel that is functionally viable and economically efficient. The specifics are as follows:

- **Focal track heat limit:**

The target wheel design must ensure that the maximum focal track temperature does not exceed the melting point of the material used. This is critical to prevent structural failure and maintain the integrity of the X-ray generation process.

- **Overall temperature limit:**

Similarly, the entire body of the target wheel must be constructed of a material that will not exceed its melting point during operation. The wheel design should take into account the distribution of heat throughout the structure to ensure that no part of the target wheel body reaches a temperature that could compromise its form or function.

- **Strength limit:**

The maximum stress experienced by the target wheel during operation must be less than the yield strength of the material, which depends on the temperature. This prevents permanent deformation of the wheel and ensures long-term stability and reliability.

- **Hot spot temperature limit:**

Due to the depth of penetration of the electrons, the localized temperature increase in the focal track must not exceed 80% of the maximum allowable temperature of the material. This control of localized heating is essential to prevent thermal hotspots that could lead to premature material fatigue or failure.

- **Cost-effective manufacturing:**

While meeting technical specifications, the design must also consider the economics of manufacturing. The goal is to minimize manufacturing costs (MC) without compromising the quality and performance of the target wheel.

Once the design requirements have been defined, it is critical to formulate them with QoIs in a format engineers can easily understand and apply. As introduced in Section 4.4, the normalized technical requirements violation ϕ is used to express the QoIs corresponding to the technical design requirements. The QoIs are specified and listed in Table 5.1.

Table 5.1: Table QoIs for developing the X-ray target wheel

Category	Quantities of Interest	Symbol	Definition	Requirement
Technical performance	Focal track thermal violation	$\phi_{melt ft}$	$\frac{T_{peak} - T_{melt ft}}{T_{melt ft}}$	≤ 0
	Target wheel thermal violation	$\phi_{melt tb}$	$\frac{T_{tb} - T_{melt tb}}{T_{melt tb}}$	≤ 0
	Target wheel stress violation	ϕ_{yt}	$\frac{\sigma_{tb} - \sigma_{yt}(T)}{\sigma_{yt}(T)}$	≤ 0
	Focal track critical peak temperature violation	$\phi_{ft peak}$	$\frac{T_{ft peak} - 0.8 \times T_{melt ft}}{0.8 \times T_{melt ft}}$	≤ 0
Economical performance	Design-dependent manufacturing cost	K^*	The portion of the total manufacturing cost MC_{total} that varies due to modifications in DVs	minimal

With:

- T_{peak} - Max temperature of focal track
- $T_{melt ft}$ - Melting point of focal track
- T_{tb} - Max temperature of target body
- $T_{melt tb}$ - Melting point of target body
- σ_{tb} - Max stress of target body
- σ_{yt_b} - Yield strength of target body
- $T_{ft peak}$ - Peak temperature of focal track because of the localized thermal concentration from the penetration of electrons

The complexity of the FEA model for evaluating the technical performance of the target wheel design variations requires careful data extraction from the simulation results, so it is important to analyze each step of the simulation and the structural details involved. Table 5.3 lists the recorded temperature T and stress σ values at various possible critical locations during the

5 Application example 1: development of a target wheel for an ultra-high power X-ray source

simulation. This process is divided into three main phases: the initial spin-up of the wheel, the simultaneous electron beam radiation with high-speed spinning, and the final cooling phase. These potentially critical locations analyzed are listed in Table 5.2:

Table 5.2: Potentially critical locations of the target wheel

Positions

- 1.The center hole of the target wheel.
- 2.The relief hole at the split termination.
- 3.The focal track region of target wheel.
- 4.The unloaded backside of the target wheel.

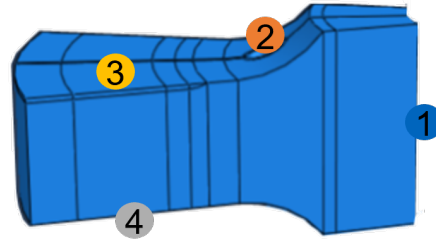


Table 5.3: Temperature and stress values at potentially critical locations during the whole process

Results from FEA		Step 1: Spinning (10s)	Step 2: Radiation and spinning (1.5MW 1s)	Step 3: Cooling down (40 Min)
$T(K)$	T_1			
	T_2			
	T_3		$T_{ft32}; T_{tb32}$	
	T_4			
$\sigma(N/(mm^2))$	σ_{tb1}	σ_{tb11}		
	σ_{tb2}	σ_{tb21}		σ_{tb23}
	σ_{tb3}		σ_{tb32}	σ_{tb33}
	σ_{tb4}			

In the indices, the first number indicates the observation point of the value, while the following number indicates the step from which the value is derived. For instance, T_{tb32} refers to the temperature at the third location during the second step on the target wheel. In contrast, T_{ft32} pertains to the temperature at the same third location on the focal track during the second step. Because the FEA simulation accounts for the temperature and stress conditions of the target wheel under high-speed rotation, the electron beam is uniformly applied across the entire focal track area. Consequently, the localized temperature rise $T_{ft_{peak}}$ due to electron penetration depth

and the associated stress cannot be captured in this FEA. Therefore, all the stress values σ_{tb_3} listed in the Table 5.3 pertain to the target wheel's body, particularly at contact surfaces affected by high-speed rotation and elevated temperatures.

Moreover, the temperature $T_{ft_{32}}$, obtained from the FEA, reflects the heat spread when power is evenly distributed across the entire focal track. After being subjected to radiation, the total temperature on the focal track, termed T_{peak} , is the sum of $T_{ft_{32}}$ and $T_{ft_{peak}}$:

$$T_{peak} = T_{ft_{peak}} + T_{ft_{32}} \quad (5.1)$$

Here, $T_{ft_{peak}}$ characterizes a local temperature increment on the focal track. This increment is inferred from thermal equilibrium calculations for infinitesimally small focal track elements, an approach propounded by Bartzsch [8]. The evaluation ensues at the electron's paramount absorption depth, as illustrated in formula 5.2.

$$T_{ft_{peak}} = \frac{P}{\rho \times b \times d \times v \times C_p} \quad (5.2)$$

where:

- P - Power
- ρ - Density of the focal track material
- b - Trackwidth
- d - Penetration depth
- v - Moving speed
- C_p - Specific heat capacity of the focal track material

The QoI "Target wheel stress violation" ϕ_{yt} in Table 5.1 are formulated with stress values at potentially critical locations described in the Table 5.3.

$$\phi_{yt} = \max \left\{ \frac{\sigma_{tb_{11}} - \sigma_{y_{tb}}(T)}{\sigma_{y_{tb}}(T)}, \frac{\sigma_{tb_{21}} - \sigma_{y_{tb}}(T)}{\sigma_{y_{tb}}(T)}, \frac{\sigma_{tb_{32}} - \sigma_{y_{tb}}(T)}{\sigma_{y_{tb}}(T)}, \frac{\sigma_{tb_{23}} - \sigma_{y_t}(T)}{\sigma_{y_{tb}}(T)}, \frac{\sigma_{tb_{33}} - \sigma_{y_{tb}}(T)}{\sigma_{y_{tb}}(T)} \right\} \quad (5.3)$$

Based on the defined QoIs, the intermediate attributes, and the potential DVs, the initial attribute dependency graph (ADG I) is shown in the following Figure 5.1.

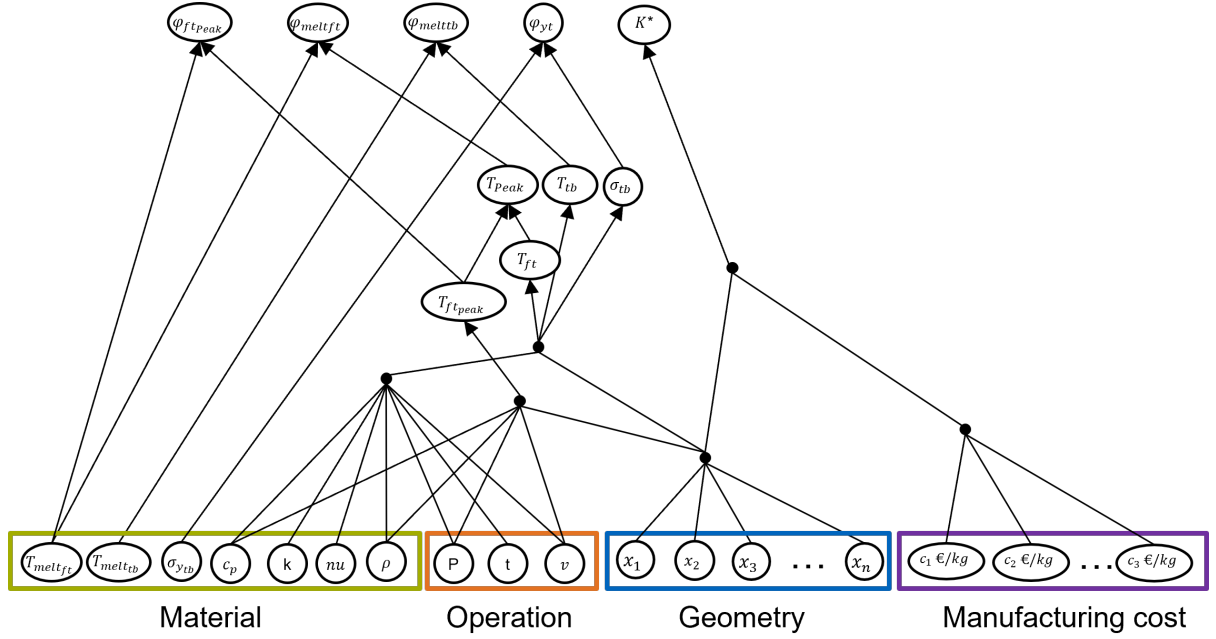


Figure 5.1: ADG I of the development task of a target wheel for an ultra-high power X-Ray source

5.3 Step 2: Build a parametric design/concept CAD model

5.3.1 The parametric CAD model and its main associated DVs

A parametric model for an initial design of the target wheel has been established based on the first-generation design, following the steps outlined in Chapter 4.5, as shown in the Figure 5.2.

The Figure 5.2 shows that a parametric CAD model represented the target wheel geometry. It includes all critical dimensions and parameters identified as essential to its performance, including but not limited to tip extensions, base dimensions, and radius at various locations on the structure.

In the parametric design of the target wheel, the radial dimensions related to R are basically based on the tip radius R_{tip} . These dimensions are modified by adding specific coefficients, such as $R_a = CR_{t-a} \times R_{tip}$. Such a methodical approach to defining the design space ensures logical consistency and coherence. It prevents the creation of a design space where inherently related dimensions are treated as independent, which could lead to structural errors or meaningless configurations.

Similarly, the thickness-related dimensions, denoted by t , are established based on the thickness t_{tip} . This systematic approach to building on a base dimension allows for creating a design space

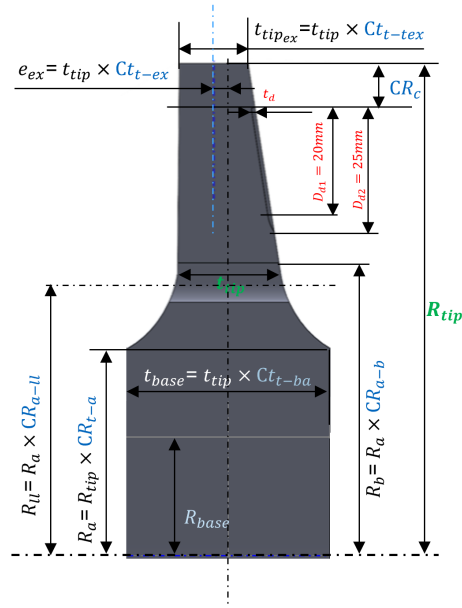


Figure 5.2: The parametric CAD model of the X-ray target wheel and its 12 geometric design variables

where changes are relational, ensuring that any changes in thickness maintain structural integrity and design intent. This strategic method of defining dimensions ensures that the relationships between different parts of the target wheel are maintained.

Table 5.4: Design variables of the X-ray target design with DoE.

Design Variable	Initial Value	Design Variable	Initial Value
CR_{t-a}	$R_a = CR_{t-a} \times R_{tip} = 55mm$	t_{tip}	$27mm$
CR_{a-b}	$R_b = CR_{a-b} \times R_{tip} = 74.21mm$	Ct_{t-ex}	$t_{tip_{ex}} = Ct_{t-ex} \times t_{tip} = 27mm$
Ct_{t-ba}	$t_{base} = Ct_{t-ba} \times t_{tip} = 45mm$	n_{st}	12
CR_c	$10mm$	Ct_{t-ex}	$e_{ex} = Ct_{t-ex} \times t_{tip} = 0$
R_{tip}	$120mm$	CR_{a-ll}	$R_{ll} = CR_{a-ll} \times R_{tip} = 65mm$
R_{base}	$30.5mm$	v_{ft}	$200m/s$

In Table 5.4, 11 out of the twelve DVs are associated with the geometry of the structure, while one DV pertains to the operational aspect, v_{ft} , which represents the linear velocity at the focal track. In addition, the width D_d and depth t_d of the focal track are defined constants that do not change with design modifications.

5.3.2 Other important intermediate quantities and modeling constraints

Figure 4.6 illustrates that the target is equipped with evenly-spaced thermal slits to deal with thermal expansion and relieve stress. The total number of these slits is defined as a design variable n_{st} , while the width of the slits t_s is an intermediate variable that depends on other DVs. This configuration is determined by considering the maximum expected deformation Δl_{max} under specified operating conditions.

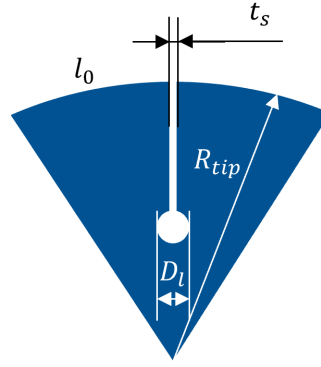


Figure 5.3: A schematic diagram of a thermal slit on the target wheel

The thermal deformation Δl of the target wheel at the slit from one side is as follows,

$$\Delta l = l_0 \times \Delta T \times \alpha, \quad (5.4)$$

where

- Δl is the displacement,
- l_0 is the initial length,
- ΔT is the change in temperature,
- α is the coefficient of linear thermal expansion.

In the worst-case scenario, where the metal undergoes maximum deformation at its melting temperature, the temperature difference ΔT is the melting temperature minus room temperature (25°C). The maximum deformation can be calculated using the following equation,

$$\Delta l_{max} = l_{0_{max}} \times \Delta T_{max} \times \alpha_{max} = \frac{2\pi R_{tip_{max}}}{n_{st_{min}}} \times (T_{melting} - 25^\circ C) \times \alpha_{max}. \quad (5.5)$$

The width of the slits, denoted t_s , is then supposed to be the sum of the maximum thermal deformation, Δl_{max} , at the radius on each side of the slit,

$$t_s = 2 \times \Delta l_{max} = 2 \times \left(\frac{2\pi R_{tip_{max}}}{n_{st_{min}}} \right) \times (T_{melting} - 25^\circ C) \times \alpha_{max}. \quad (5.6)$$

An essential limitation in the design is that the target wheel's radius $R_{tip_{max}}$ can not exceed 500mm due to spatial restrictions.

For focal track with tungsten	For target body with TZM
$R_{tip_{max}} = 500mm$	$R_{tip_{max}} = 500mm$
$n_{st_{min}} = 10$	$n_{st_{min}} = 10$
$T_{melting} = 3422^\circ C$	$T_{melting} = 2620^\circ C$
$\alpha_{max} = 5.1 \times 10^{-6}/K$	$\alpha_{max} = 6.45 \times 10^{-6}/K$
$\Delta l_{max_{ft}} = 5.024mm$	$\Delta l_{max_{ft}} = 4.75mm$
$t_s = 2 \times \Delta l_{max_{ft}} = 10.83mm$	$t_s = 2 \times \Delta l_{max_{ft}} = 10.165mm$

Table 5.5: The required slit width t_s for focal track (tungsten) and target body (TZM) to avoid thermal stress under the worst-case deformation.

Table 5.5 shows values for the required slit width t_s for the two materials used in the target wheel. This width ensures that there will be no contact between the two sides of the slit under the worst-case deformation condition within the given design variable value space and material properties provided by the company Plansee [83] (in Figure 5.4).

In the worst-case scenario, the tungsten focal track requires a larger permissible deformation Δl . Therefore, all subsequent calculations for t_s will be based on

$$t_s = 2 \times \left(\frac{2\pi R_{tip}}{n_{st}} \right) \times (T_{melting} - 25^\circ C) \times \alpha_{max}$$

$$D_l = 4 \times t_s,$$

where

$$T_{melting} = 3422^\circ C \quad \text{and} \quad \alpha_{max} = 5.1 \times 10^{-6}/K.$$

Another important design consideration is the angle between the plane of the focal track and the axis direction. As shown in the Figure 5.5, potential designs can be classified into four types based on the pinch angle α : $\alpha = 0^\circ$, $0 < \alpha < 90^\circ$, $\alpha = 90^\circ$ and $\alpha > 90^\circ$.

5 Application example 1: development of a target wheel for an ultra-high power X-ray source

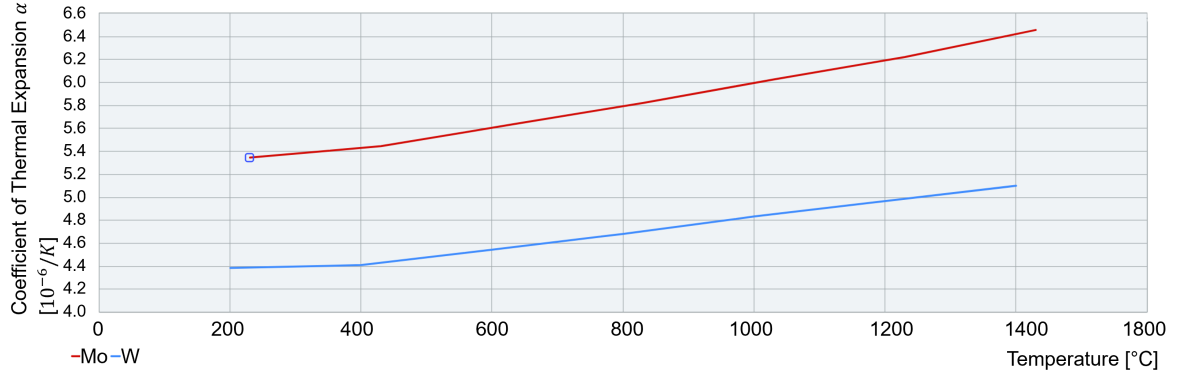


Figure 5.4: Linear thermal expansion coefficient of molybdenum (Mo) and tungsten (W) as a function of temperature [83]

Several considerations must be taken into account before determining a feasible design space:

- At an angle of $\alpha = 0^\circ$, the difference in expansion coefficients between the two materials could lead to failure during rotation due to potential separation of the tungsten alloy focal track from the target wheel body under conditions of high rotational speed and heat.
- At $\alpha = 90^\circ$, the heat distribution becomes suboptimal as the focal track surface area is reduced, which can worsen temperature conditions and stress at the interface.
- For angles $\alpha > 90^\circ$, the layout of the entire system could be problematic, for example in the positioning of the accelerator. Since the entry of the electron beam and the exit of the X-rays require an open space, such design variations are not feasible.

In summary, the optimal design space for the system requires that the angle α be set between 0° and 90° . A smaller angle α is advantageous for the design of the system because it increases the mechanical strength during operation. This is partly because a smaller angle results in less centrifugal force on the thinner outer edges of the wheel, reducing mechanical stress.

In this parametric CAD model, the control of the angle α is not defined as a direct design variable. It is modulated by the excentricity dimension e_{ex} , which is specified as the design variable C_{t-ex} . Consequently, in keeping with the previously defined design space for α , the allowable range for C_{t-ex} has been set from 0.2mm to 2mm.

In contrast to the radial position of the focal track on the target wheel CR_c , which is considered a design variable, the width of the target surface exposed to electron bombardment, designated d_{d1} , is consistently maintained at 20mm. To prevent electron impact outside the intended area, the width of the focal track, d_{d2} , is slightly larger than d_{d1} at 25mm. In addition, the thickness of

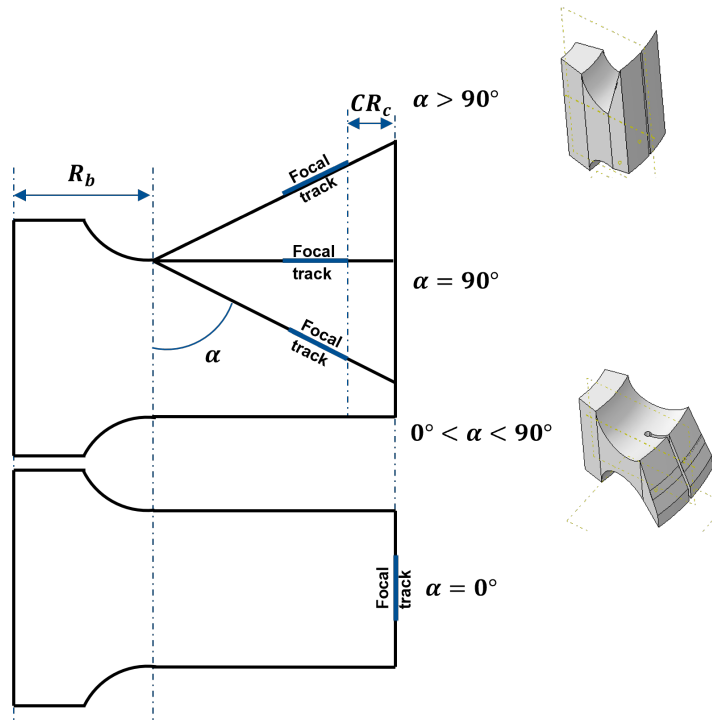


Figure 5.5: Design categories based on different α values and example design variations

the focal track, t_s , is a predefined design parameter that should be determined in the parametric CAD model. To determine the appropriate thickness, a series of comparative experiments were conducted in which t_s was adjusted to 3mm, 4mm, and 5mm within a same design variation. During these experiments, stress changes and stress distributions were observed and evaluated for compliance with the technical requirement for maximum stress. This test is also considered a way to validate the FEA model through expert review, which is shown in detail in Section [5.6.4](#).

5.4 Step 3: Establish technical and economical model dependency

Based on the DVs identified in step [5.3](#), along with the defined and potential relationships between DVs and intermediate quantities or QoIs, it is possible to establish the technical model dependency and represent it in the ADG II, as shown in the Figure [5.6](#). The details of this process will not be illustrated here.

The production of X-ray target wheels is a complex and specialized process that presents many manufacturing challenges. Currently, the most feasible production method available on the

5 Application example 1: development of a target wheel for an ultra-high power X-ray source

Table 5.6: Initial X-ray target wheel production processes at the company Plansee based on powder metallurgy

Powder Metallurgy	Mechanical Processing	Surface Treatment	Assembly
Oxide	Milling	Deburring & finishing	Cleaning
Reduction	Eroding	Cleaning & washing	
Mixing alloys	Turning	Polieren	
Pressing	Drilling		
Sintering	Polishing		
Forming	Grinding		
Heat treatment			

market is the powder metallurgy technique provided by the company Plansee. Therefore, our analysis focuses exclusively on this production method. The main production process for X-ray targets using this powder metallurgy technique are summarized in Table 5.6 provided by the company Plansee.

There are four main production steps:

- **Powder metallurgy:**
This initial stage involves converting metal oxides into fine powders, mixing them to form alloys, pressing them into shapes, sintering to bond the particles without melting, forming the desired final shape, and applying heat treatment to enhance material properties.
- **Mechanical processing:**
In this phase, the sintered parts are subjected to various machining processes, including milling to shape the material, eroding for precision details (for example, the slits), tuning for final dimensional adjustments, drilling for holes, and polishing for surface finish.
- **Surface treatment:**
Semi-finished targets are subjected to surface improvement processes such as deburring to remove sharp edges after the mechanical processing, finishing to improve surface quality to a higher level (for example, the focal track surface), cleaning and washing to remove residues, and other treatments to prepare the surface for its final use.
- **Assembly:**
The final step is to assemble the finished target wheel into its housing or package, which often involves additional cleaning to ensure that the target is free of contaminants before it is put into service.

5.4 Step 3: Establish technical and economical model dependency

	Powder metallurgy					Mechanical processing			Surface treatment		Assembly
	Blanks of powder-forged					Slits	Central hole	Relief holes	Fein surfaces	Rounding	Clean
											
Reduction	Mixing alloys	Pressing	Sintering	Heat treatment	Eroding	Turning Drilling Milling	Drilling	Grinding Polishing	Deburring Finishing	Clean & Wash	
Material direct costs MDC											
Production labor costs PLC											
Production overhead costs POC											
Material overhead costs MIOC											
Special production direct costs SPDC											
There are no incurred costs.											
Cost independent of design variation		K_f		Cost depending of design variation				K^*		$MC_{total} = K_f + K^*$	

Figure 5.6: Dependency analysis of production processes and different types of costs

Figure 5.6 displays a dependency analysis chart that aligns the various production processes for an X-ray target with the corresponding cost categories.

The company Plansee applies powder metallurgy to create the foundational shape of the target wheel, incurring material direct costs that vary with the design variations during the reduction and mixing phases. Production overhead costs arise during pressing, sintering, and heat treatment, yet these remain unchanged despite design changes. In the mechanical processing stage, the generation of center holes, relief holes, and slits primarily impacts production labor costs and production overhead costs, reflecting a dependency on skilled labor and flexible tooling (machining) that adjusts with design variations. The advanced forming capabilities of powder metallurgy allow no additional costs in shaping the target wheel — a contrast to other methods like subtractive manufacturing, where such costs would likely be required. Surface treatment, including grinding and polishing, incurs both production overhead and labor costs due to the necessity for exceptional surface quality on critical areas, such as the focal track surface, with expenses tailored to design specifications. Finally, assembly tasks like cleaning involve production labor and overhead costs, which are not affected by design modifications. Based on the results of the cost production dependency analysis, a more detailed ADG (ADG II) showing the relationship between QoIs and DVs in the development of a target wheel for the establishment of ultrahigh-power X-ray can now be completed as follows (Figure 5.7).

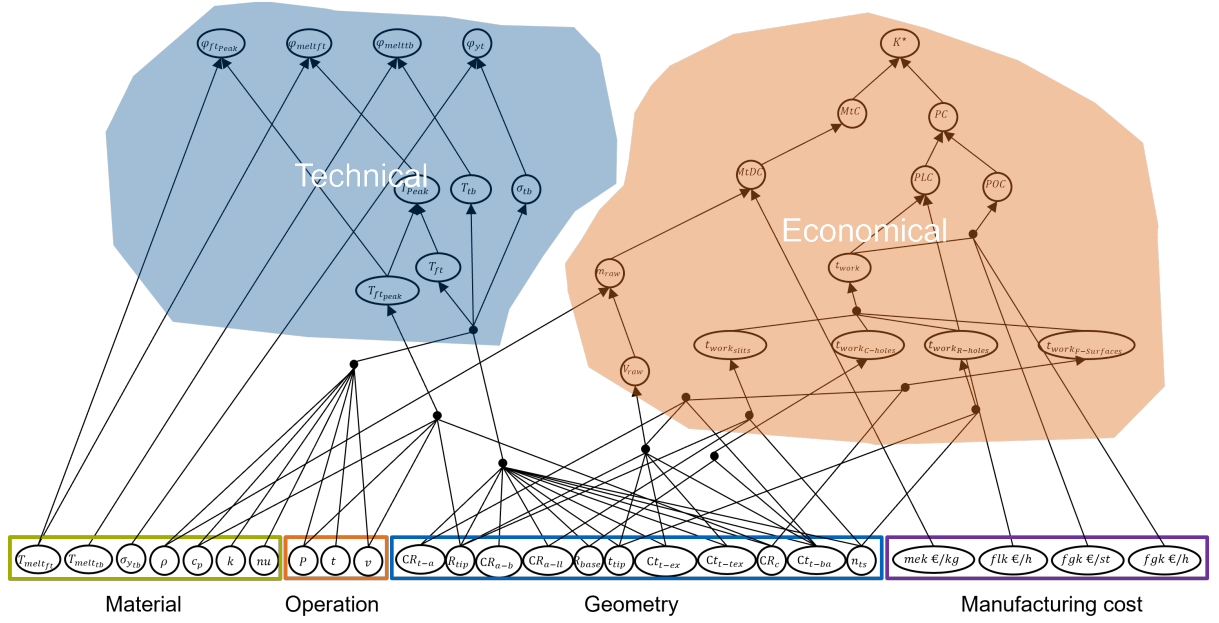


Figure 5.7: A comprehensive ADG II for the development of an X-ray target wheel

5.5 Step 4: Complete the technical assessment of design variations via FEA

5.5.1 Establish boundary conditions

The Figure 5.8 shows the boundary conditions for a FEA simulation of a segment of a target wheel divided into two components: the main body made of TZM and the focal track made of tungsten alloy. This particular segment is equal to $\frac{1}{n_{st}}$ of the entire target wheel. As the target wheel rotates around its core axis, there is a certain linear velocity on the focal track, referred to as v_{ft} . During a time frame of 1 second, the focal track undergoes a power application of 1 MW, resulting in a temperature rise from an initial temperature of 393.15K. The central aperture surface of the segment is cooled at a rate of $0.02 \text{ W}/(\text{mm}^2 \times \text{K})$, with the cooling fluid having a temperature of 296K. The twin sidewalls, which are attached to the rest of the structure rather than being open-ended, maintain boundary conditions that represent the inherent rotational symmetry of the segment. Specifically, the imposed constraints on displacements in the ϕ and z directions on these walls are represented as $u_\phi = u_z = 0$. At the segment's foundation, a highlighted red point has tangential u_ϕ and axial u_z displacements set to zero while radial motions remain unrestricted.

The linear velocity v_{ft} is a design variable of operation. It not only determines the local temperature increment on the focal track T_{ftpeak} (formula 5.2), but also dictates the rotational speed of the target wheel $\omega = \frac{v_{ft}}{r_{ft}} = \frac{v_{ft}}{R_{tip} - CR_C}$. The heat density of the load acting on the focal

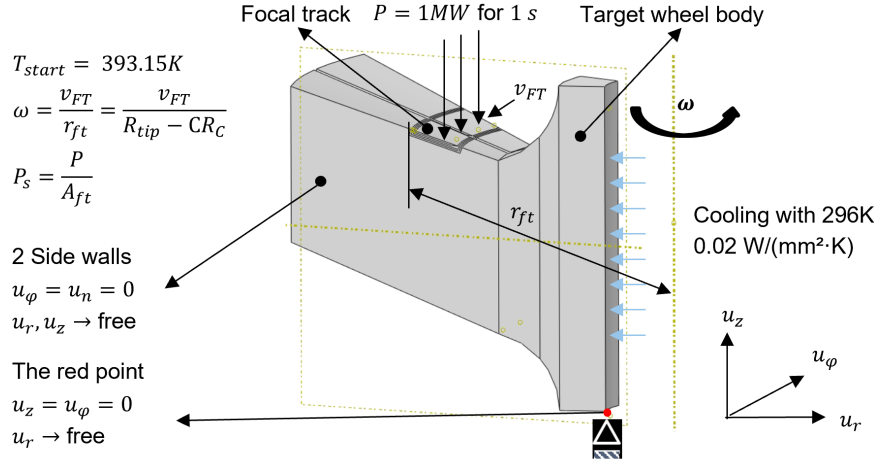


Figure 5.8: Boundary conditions of the FEA model

track can be calculated using the following equation: $P_s = \frac{P}{A_{ft}}$, where P is the total power of 1 MW and A_{ft} is the surface area of the focal track, which varies with changes in geometric DVs.

5.5.2 Meshing

The Figure 5.9 shows a finite element mesh generation of the segmented part of the target structure, meshed with structured (hexahedral) elements, which are always recommended for use in 3D structural simulations because it means less memory requirements, shorter time, and the guarantee of accuracy. As mentioned in Chapter 4.7.3, the original target wheel is segmented into several basic geometric forms, mostly hexahedrons, which facilitates the use of structured mesh types for mesh generation. The mesh size, denoted by $\frac{60}{R_{tip}} \text{ mm}$, plays an important role in the simulation's accuracy and computational efficiency. The aspect ratio AR , which is the ratio of the longest to the shortest dimension of the mesh, varies throughout the model: it is capped at 5 at the focal track area, peaks at 15 at the edges, and reaches a maximum of 5 in the relief holes located at the beginning of the slits. This metric is essential for assessing mesh quality, with appropriate values ensuring accurate results and avoiding computational problems. The consistent uniformity of the mesh, especially in critical areas such as the focal track and relief hole, is fundamental to the reliability of the simulation results. Overall, the FEA simulation model achieves an optimal balance between simulation accuracy and computational efficiency while paying particular attention to the unique areas and features of the target structure.

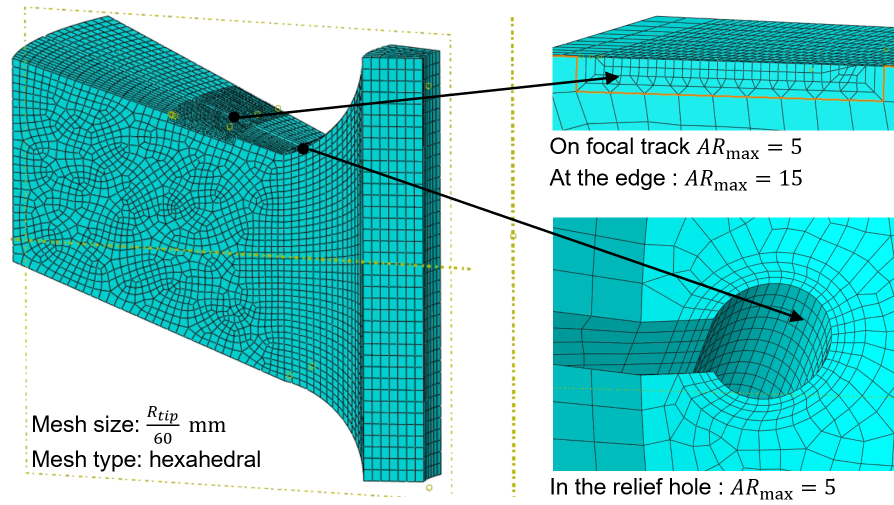


Figure 5.9: Meshing of the FEA model

5.6 Step 5: Validate FEA model

Chapter 4.8 highlights the importance of validating the FEA model within a FEA workflow to ensure that the simulated results closely match the actual behavior. This validation step certifies the reliability and accuracy of the model and ensures that the predicted results are both relevant and reliable. Using some of the commonly used validation techniques presented in Chapter 4.8, we have identified a subset that applies to validating the FEA model used in ADeVAA for the technical evaluation of X-ray target wheel development. It includes:

- **Theoretical validation**

A target wheel with a specific geometry, for which mathematical formulas can determine stress and temperature, is used as a reference to evaluate the accuracy of the FEA model results.

- **Mesh refinement study**

In this validation, the mesh of the FEA model is improved to a near-ideal form for computational accuracy, but very time and CPU-consuming, and compared to "standard meshes" in the FEA model to assess whether the standard meshes provide sufficient accuracy in the simulation results.

- **Simplified and previous model validation**

The use of historical, simplified models allows current simulations to be compared to

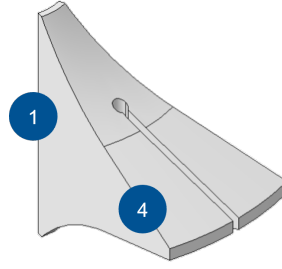


Figure 5.10: Target model used to validate the FEA model through theoretical analysis

previous FEA models from previous X-ray target projects, which provide substantial accuracy.

- **Expert review**

This validation involves a collaborative review of the simulation boundary conditions and results by experts, providing an assessment of the accuracy of the simulation based on the logical consistency and plausibility of the results.

5.6.1 Theoretical validation

A specific target wheel, characterized by a particular geometry (Figure 5.10) that allows the determination of stress and temperature through mathematical formulas, serves as a benchmark to evaluate the accuracy of the FEA model results. In this segment, the analysis focuses on estimating the pressures at points 1 and 4 of the rotating wheel. This is accomplished by applying the predefined FEA model, and basic stress calculation formulas are for uniform thickness disks, as DUBBEL's handbook for mechanical engineering [9] quoted. These formulas are the only mathematical approximation for evaluating stresses in non-uniform thickness disks. They include calculations for radial 5.7 and tangential 5.8 stresses and the von Mises stresses 5.9 derived from these stresses,

$$\sigma_r(r) = c_1 \rho \omega^2 r_a^2 \left(1 + \frac{r_i^2}{r_a^2} - \frac{r_i^2}{r^2} - \frac{r^2}{r_a^2} \right) \quad (5.7)$$

$$\sigma_t(r) = c_1 \rho \omega^2 r_a^2 \left(1 + \frac{r_1^2}{r_a^2} + \frac{r_a^2}{r^2} - c_3 \frac{r^2}{r_a^2} \right) \quad (5.8)$$

$$\sigma_{vonmises} = \sqrt{\sigma_r^2 + \sigma_t^2 - \sigma_r \times \sigma_t}, \quad (5.9)$$

where

- c_1 and c_3 are constants functions of Poisson's ratio of the target body,

- ω is angular speed of spinning,
- r_a is inner radius and r_o is outer radius.

The results show that the discrepancies between the numerically and analytically derived stress measurements at points 1 and 4 are modest, at 2.9% and 0.5%, respectively. This reflects the agreement between the simulated stress values and the theoretical predictions, indicating that the simulation accurately captures the expected stress distribution.

On the other hand, validation concerning temperature calculations is conducted similarly to stress, with temperatures at the focal track of different design modifications calculated through FEA simulation and mathematical formulas. It is assumed that the target body receives all power on the surface just below the focal track as a uniform heat flux input. Assuming the target body has the same thickness as the focal track, the solution for the disk receiving heat flux input around its circumference (from [12]) is used to calculate the maximum temperature at the outer radius of the target body T_{ft} (5.10),

$$T_{surf} = \frac{flux \times r_o}{k \times q'} + Initialtemperature \quad (5.10)$$

with

$$q' = 0.5 \sqrt{\frac{\pi}{F_o}} - \pi \times \frac{1}{8.0}$$

and the Fourier number

$$F_o = \frac{\alpha \times t_{op}}{(r_o)^2}$$

Here

- r_o is maximum outer radius,
- t_{op} is time of operation,
- α is thermal diffusivity of target,
- k is thermal conductivity of target, and
- $flux$ is power flux on focal track.

Similar to stress evaluation, the Table 5.7 shows that FEA simulations can provide temperatures comparable to those obtained from the analytical model, demonstrating that the FEA model in ADeVAA used for the technical assessment of the target wheel has been proven substantially accurate by theoretical validation.

Design Variation	T_{ft} from FEA [K]	Analytical T_{ft} [K]	Difference %	r_o or R_{tip} (mm)
165	1421	1493	5	463
128	1511	1609	6	428
71	1436	1520	6	486
184	1530	1628	6	406
180	1907	2024	6	332

Table 5.7: Validation through numerical and analytical models

5.6.2 Mesh refinement study

During the validation phase, the mesh in the FEA model is carefully refined to approach what might be considered ideal computational accuracy. As shown in the Table 5.8 below, this model uses a 1mm mesh size, which provides high accuracy but requires significant time and CPU resources. This finer mesh is compared to the "default" mesh, which is rougher but is assumed to balance computational detail and resource consumption. This comparison aims to evaluate whether the standard mesh can provide the necessary accuracy for simulation results while maintaining efficiency in computational performance. The Figure 5.11 illustrates the mesh configuration of the focal track area using various meshing approaches.

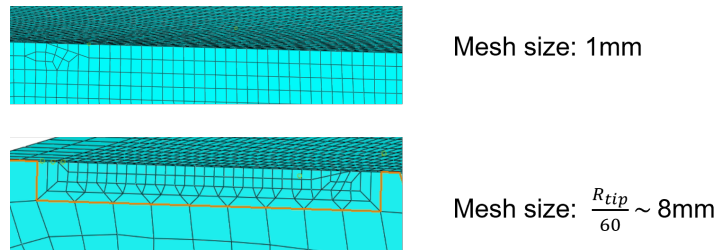


Figure 5.11: Mesh construction of focal track region under different mesh strategies

The Table 5.8 shows that the "fine" mesh strategy, fine-tuned manually, ensures a high mesh quality with an average aspect ratio below 2 (which is better than the software's recommendation) and a maximum aspect ratio around 4 across two design variations. In contrast, the "default" mesh applied by automatic meshing is selectively refined in critical regions, leaving the main part of the target wheel with a rougher mesh, resulting in a maximum aspect ratio close to 40. Nevertheless, the comparative analysis shows that the largest deviation in all QoIs is about 8%. This suggests that the meshing approach used in the FEA model is sufficiently accurate. It also offers advantages in terms of automation and computational efficiency.

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Mesh strategy (mm)	Design var.	Hex Average AR	Hex Worst AR	Wedge Average AR	Wedge Worst AR	Element number	Max. Deviation of QoIs ϕ %	Running time
Fine	1	1.42	3.18	1.58	3.01	473436	8.57	120h
Rough		2.85	39.46	3.83	24.98	48034		20min
Fine	2	1.94	3.09	1.79	4.19	480762	6.67	150h
Rough		2.33	29.17	2.86	15.71	42470		25min

Table 5.8: Validation through different mesh properties

5.6.3 Simplified and previous model validation

In this validation study, the geometry of the simplified variant of the X-ray target wheel was technically evaluated using the ADeVAA FEA model and then compared to the results of the earlier model, as shown in the figure. The Figure 5.12 shows the stress distribution at the focal track interface within the two FEA models. The comparison shows that both models have virtually identical stress distributions and comparable scaling.

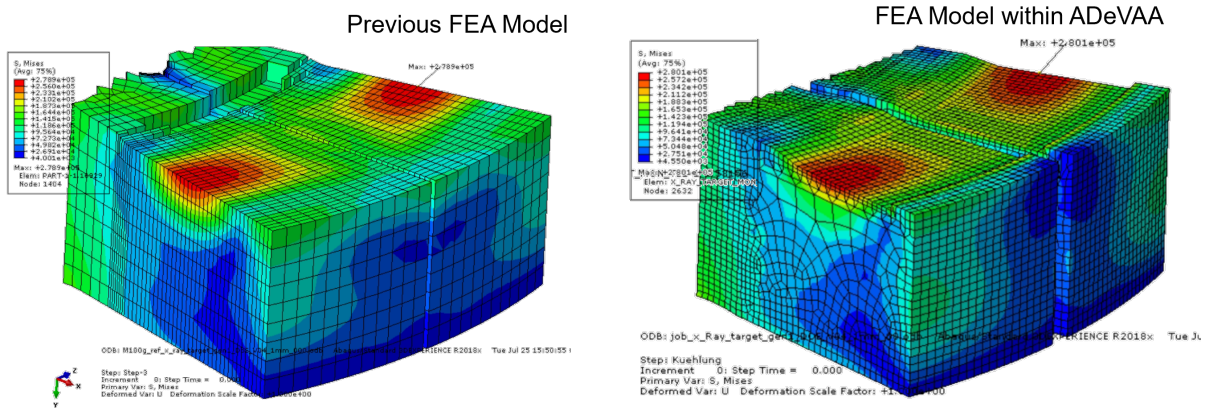


Figure 5.12: Mesh construction of focal track region under different mesh strategies

A careful examination of the data from two different simulation models operating under identical conditions (see Figure 5.9), which include the temperatures across different material layers at the focal track (T_{ft} and T_{tb2}) and the stresses caused by rotation in the relief holes σ_{tb21} , as well as the thermal stresses within the target at the focal track σ_{tb32} during electron beam radiation, shows that the results of the two models are nearly equivalent. The largest discrepancy is less than 10%, demonstrating the reliability of the FEA model within ADeVAA.

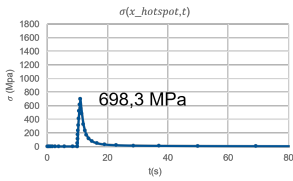
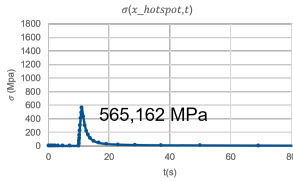
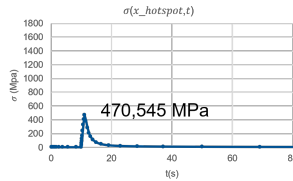
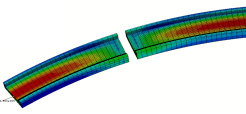
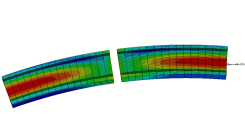
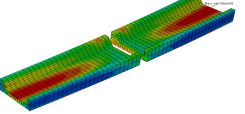
Simulation Model	Design Nr.	T_{ft}	T_{tb_2}	$\sigma_{tb_{21}}$	$\sigma_{tb_{32}}$
Previous FEA model	M100	1282K	1250K	325MPa	278MPa
FEA model of ADeVAA	M100	1249K	1211K	298MPa	280MPa
Difference %		2	3	8	1

Table 5.9: Validation through simplified and previous model

5.6.4 Expert review

As described in Section 5.3, a study was conducted to determine the appropriate focal track thickness t_s by examining the same design variation with t_s sets at 3mm, 4mm, and 5mm. This study involved observing stress variation over time at the point on target wheel of maximum stress, observing the stress distribution in the most critical area - the focal track region - at the peak stress moments, and assessing whether the maximum stress values met the design requirements for stress. The results of this study are shown in the Table 5.10.

Table 5.10: Review of (1) stress vs. time at maximum stress points under varying focal track thicknesses t_s , and (2) focal track stress distribution at peak stress moments $t_p = 11s$, (3) along with yield stress at that temperature and (4) technical requirement violation of stress ϕ_{yt} of the design variation

	$t_s = 3$	$t_s = 4$	$t_s = 5$
$\sigma(x_{hotspot}, t)$			
$\sigma(x_{hotspot}, t_p)$			
$\sigma_{yt}(x_{hotspot}, t_p)$	490MPa, $T = 462^\circ\text{C}$	520MPa, $T = 559^\circ\text{C}$	560MPa, $T = 490^\circ\text{C}$
ϕ_{yt}	0.42	0.0112	-0.159

The Table 5.10 shows that in three different scenarios, the stress at a particular point below the focal trace of the target wheel, where the stress is maximum, increases quickly at the 10th second and peaks at the 11th second. This increase is initiated by the beginning of electron radiation at

the 10th second and is completed after 1s of continuous radiation. As the thickness t_s increases, the peak stress value $\sigma_{(x_{hotspot_{max}})}$ shows a decreasing trend. At 11s, in all three scenarios, the stress distribution at that region remains uniform. In particular, the stress decreases progressively as one moves closer to the slit where displacement is allowed, eventually dropping to zero while remaining comparatively higher around the symmetry axis, suggesting a gradient in stress intensity towards the slit. Since the yield strength σ_{yt} of the material changes with temperature - decreasing as the temperature increases - the yield strength also increases with the increasing t_s in all three cases. Finally, it is concluded that in terms of the design requirement for the stress of the target wheel, this scenario meets it only when t_s is 5 mm. Therefore, our DoE is based on the CAD model with t_s set to 5mm.

5.7 Step 6: Establish economic assessment of design variations via cost calculation model

This section demonstrates how to construct a cost calculation model based on the results of the dependency analysis presented in Section 5.4. This involves translating the identified dependencies between QoIs and DVs into a quantitative model that calculates the design-related manufacturing costs. The model aims to provide an economic assessment that helps compare different design options.

Based on the results presented in Figure 5.6, the cost model consists of various design-related costs. These include the material direct costs incurred during the powder metallurgy process, as well as the production labor costs and production overhead costs associated with the machining processes for the center hole, relief holes, slits, and the application of surface treatments to specific high quality required surfaces. The calculation of these costs can be performed by applying the DVs of the structure along with the cost related variables using the formulas described in 3.5.

It should be noted that cost variables such as material prices and labor costs are subject to change due to time and geographic variations. As a result, it is inadvisable to create a static database of these expenses. Users are therefore encouraged to conduct their own research to determine costs relevant to their particular application. The data used in this research, presented in Table A.1, was compiled by taking into account factors such as local labor market salaries, material costs, tooling prices, and other relevant considerations.

5.7.1 Material direct costs (MtDC)

Since the whole target wheel is manufactured using powder metallurgy techniques, the material cost is only dependent on the type and amount (volume) of material used.

$$MtDC = m_{tb} \times mek_{TZM} + m_{ft} \times mek_{WRe} = V_{tb} \times \rho_{TZM} \times mek_{TZM} + V_{ft} \times \rho_{WRe} \times mek_{WRe} \quad (5.11)$$

The volume of focal track V_{ft} and target wheel body V_{tb} can be mathematically determined from the geometric DVs.

5.7.2 Production labor costs (PLC)

Production labor costs are driven primarily by four key processes: (1) the labor to machine the large center hole, (2) to machine the slits, (3) to create the relief holes at the end of each slit, and to (4) finish the special surfaces.

$$PLC = \sum_i (t_{machining_i} \times flk_{machining_i}) \quad (5.12)$$

When machining the center hole, it is important to note that the machining time is influenced by both the radius R_{base} and the depth t_{base} of the hole. Since the diameter of most commercially available drills is less than 50 mm, holes larger than this diameter typically require pre-drilling prior to turning. Consequently, the calculation of machining time varies depending on these factors (A.12).

Slits are typically produced using wire electrical discharge machining (EDM), where the machining time depends on the radial length of the slit $R_{tip} - R_{ll} - \frac{D_l}{2}$, the feed rate, and the number of slits n_{st} .

Similarly, for each relief hole at the end of every slit, the machining time is determined by the axial depth of the hole t_{tip} , the drilling speed, and the number of holes n_{st} .

For high quality surface treatments, this process requires two specific surfaces: the focal track surface and another surface A_{ab} for assembly that is perpendicular to the axial direction, on the distinct side against the focal track. This perpendicular surface is a cylindrical section with inner and outer radius R_{base} and R_a . The area of focal track A_{ft} can be obtained from FEA model or calculated using mathematical formulas based on DVs (A.13). The processing time for this procedure depends on the size of surface areas to be treated and the polishing speed.

5.7.3 Production overhead costs (POC)

Production overhead costs include the cost of tools, such as cutting tools, and the cost of the cutting machines. Tooling costs primarily include the number of tools required during the machining process, which depends on the machining time and the life of each tool. Typically, tool life is inversely proportional to cutting speed, as discussed in Chapter 3.4. Although the cost

of machining machines is a function of machining time, in actual manufacturing a particular machining operation may block an entire segment of machine time. Therefore, variations in machine costs due to design modifications are initially ignored here.

5.8 Step 7 and Step 8: Automation, DoE generation and implementation

After all preliminary work, including model preparation and validation, has been completed, the workflow moves on to the following steps: step 7 and 8, which include automation, DoE generation and implementation.

In step 7 for automation, we construct automation program codes following the algorithm guidelines provided in 4.10. As a result, a comprehensive automated process for the X-ray target wheel design task is established. This process integrates various individual program codes, from the generation of design variants to technical and economic evaluations. Due to the diversity of development cases, the algorithmic code can vary well, making it difficult to provide a consistent and straightforward guideline. Users are, therefore, encouraged to adapt the automation programs of their specific design tasks and the functionalities offered by different platforms.

After completing step 7, which lays the groundwork for automated computational experiments within the DoE, we approach a very important part of the entire development process: step 8. This step focuses on generating and implementing the DoE. Before starting this large experimental initiative, it is necessary to establish the its setups. This includes defining the design space for each design variable. Table 5.11 presents the design spaces for each of the 12 DVs involved in the development.

Table 5.11: Design variables of the X-ray target wheel development with their design spaces

Design Variable	Design Space	Design Variable	Design Space
CR_{t-a}	0.25–0.6	t_{tip}	90-200mm
CR_{a-b}	1.3–1.5	Ct_{t-ex}	0.2-2
CR_c	1–20mm	Ct_{t-ba}	1.3-2
R_{tip}	200–500mm	n_s	10-18
CR_{a-ll}	1.1-1.4	Ct_{t-ex}	-0.5-0.5
R_{base}	$(27 - (R_a - 5))mm$	v_{ft}	50-250m/s

In the subsequent stages of the DoE, a high-dimensional overall design space is explored almost indiscriminately by generating different design variations through random combinations of

values for each DV within its design space. This exploration is not aimed at understanding the impact of varying each DV within its range on overall performance. On the contrary, given the large number of DVs, such exploration is considered unworthy and overly complex, risking inconclusive results. Instead, randomly changing each DV value to generate and evaluate design variations allows us to bypass the study of individual design variables. The focus is simply on identifying the optimal design variation across the full range of samples. This sample range is supposed to comprehensively cover all possible combinations within the design space, maximizing the probability of identifying the best possible configurations.

As mentioned above, performing a DoE using FEA in a complex, high-dimensional design space with many DVs can be both time-consuming and CPU-intensive. This is especially true in this case, where thermal-mechanical simulations for complex geometry are required. To minimize these challenge, we have established two preliminary screening stages to filter out design variations that do not meet specific criteria before entering the resource-intensive DoE phase. The first screening is based on $T_{ft_{peak}}$, which is defined by the formula [5.2]. Since $T_{ft_{peak}}$ is calculable through a mathematical formula, this criterion - which specifies that $T_{ft_{peak}}$ should not exceed 80% of the melting temperature of the material - was applied as a filter in the first round of screening after the generation of design variants.

The second screening is based on the density of the heat flux distribution, P/A_{ft} , on the focal track surface. Although this criterion is not defined as one of the QoIs, it is closely related to many of them, such focal track thermal violation $\phi_{melt_{ft}}$ or target wheel stress violation ϕ_{yt} . Since this density is directly calculable by a mathematical formula, many design requirements become impossible to satisfy when it exceeds a specific limit. Therefore, a rough estimation based on this is performed during the design variation and filters out non-compliant solutions, saving both time and CPU resources in subsequent processes.

5.9 Step 9: Results analysis and decision-making

In this section, we aim to complete the analysis of the results and make decisions based on the results: determine which design variation emerges as the most prospective final design candidate. First of all, the technical performance summary in the QoIs represents various technical capabilities obtained from the numerical simulation phase and quantified into a normalized technical requirement violation ϕ (see formula [4.1]). The maximal violation ϕ_{max} then combined with the economic impact measured by the design-related manufacturing costs from the economic evaluation to construct a plot. The diagram [5.13], as shown below, provides a comprehensive view of the results for all design samplings. It shows which designs have sufficient mechanical performance, which do not, and which have higher economic performance than those with relatively higher costs.

The results presented in Figure [5.13] show that with ADeVAA, numerous solutions with sufficient mechanical performance were identified in developing the X-ray target wheel. Achieving this is

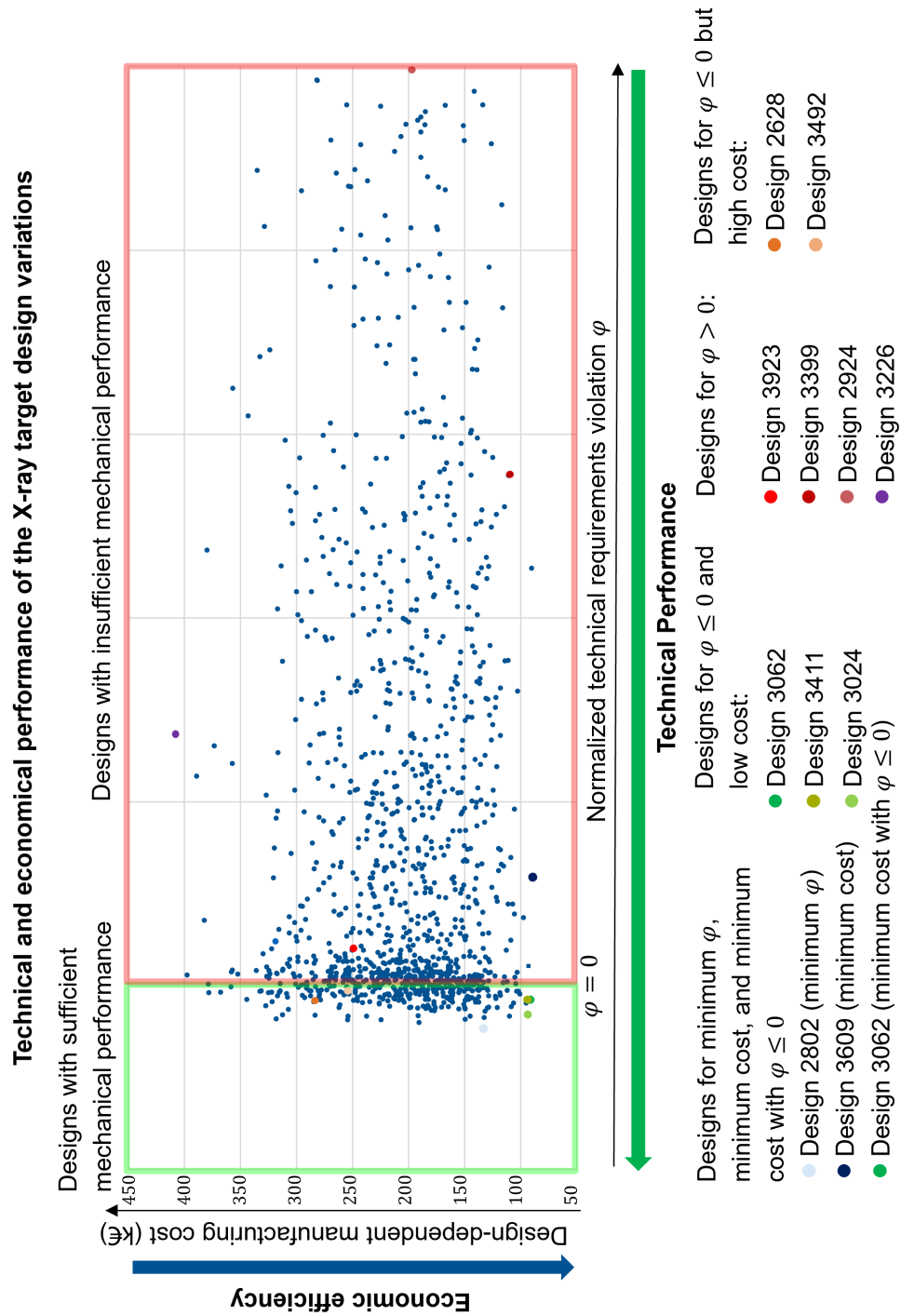


Figure 5.13: Design variations of the X-ray target wheel reflecting economic and technical evaluation, with highlights of some specific solutions

not simple for design tasks that are subject to restrictive technical requirements. Based on the results shown in Figure 5.13, it was observed that among all solutions where the normalized technical requirement violation $\varphi \leq 0$, design 3062 (Table 5.12) was noted for having the lowest cost. Therefore, it can be concluded that among all these samples, it not only complies with the restrictive technical design requirements, but also represents the most economically beneficial variation.

Two other specific designs, 2802 and 3609, stand out in the series of design samples (see Table 5.12). Design 2802 is recognized as having the best technical performance of all the samples, while design 3609 has the lowest production cost. Analyzing their structures, it is clear that the minimal 3mm eccentricity of design 2802 provides a virtually symmetrical shape that skillfully reduces the additional stress at the relief holes during high-speed rotation due to asymmetry. However, maintaining the ideal focal track area for heat dissipation requires a larger radius, resulting in a larger diameter and central volume, thus increasing material costs and reducing its economic benefits. Design 3609, with its thinner center section and significant eccentricity, minimizes material usage but fails to meet the technical requirement due to yielding at the relief holes at high rotation as a result of its inappropriate material distribution.

These cases illustrate that a lack of global perspective in product development can lead to a dilemma where a technically superior design does not necessarily translate into economic superiority, as is the case with design 2802. Conversely, as highlighted in the introduction (Chapter 1.1), attempting to reduce manufacturing costs by modifying design (such as the change the usage/distribution of materials) can compromise technical performance, as is the case with design 3609.

Among all solutions with sufficient mechanical performance, we identified the top three by checking their economic efficiency, as shown in Table 5.13.

These three design solutions are structurally different, with some having a thicker central area and other having greater eccentricity at the edges. The most critical areas in terms of technical design requirements also differ among these three design variations, i.e., their maximum technical requirement violations φ_{max} occur at different locations in different steps. For design 3062, the most critical point is the stress at the relief hole (position 2) caused by high-speed rotation (step 1), while for some other designs (design 3062 and 3024), it is the thermal stress at the focal track position (position 3) during electron radiation (step 2). The detailed DVs values of these three designs, which describe their geometries, are shown in Table A.2.

Compared to the technically and economically optimal solutions, the result set also includes some designs with insufficient technical performance, as shown in Figure 5.13. We have selected a few representative examples from them. For example, design 3399 does not satisfy the required technical requirements, but is relatively cost-effective. Design 2924 has very poor technical performance. Design 3226 represents a possible design that fails to achieve the required technical performance and is also very expensive to produce. In addition, design 3923 was randomly selected as an example of a technically "poor" design (with $\varphi > 0$), but its geometry is significantly different from the three technically optimal solutions (with $\varphi \leq 0$).

5 Application example 1: development of a target wheel for an ultra-high power X-ray source

Table 5.12: The technically best design (left) (with minimal φ), the economically best design (middle) (with the lowest cost) from all the samplings, and the one (right) with minimum cost from designs with sufficient technical performance ($\varphi \leq 0$)

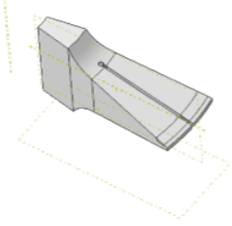
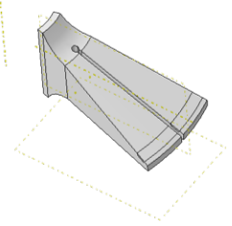
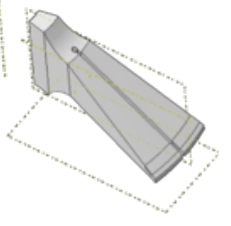
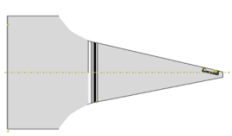
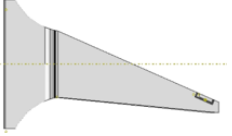
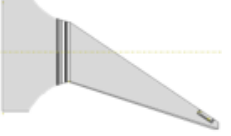
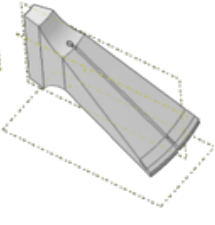
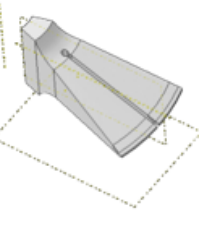
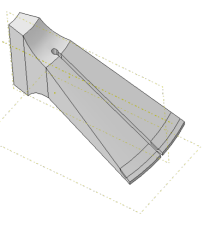
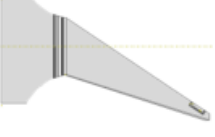
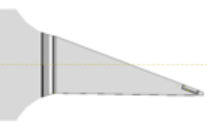
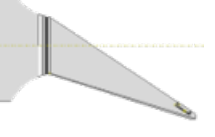
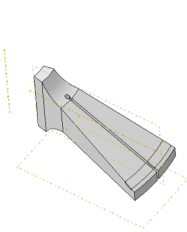
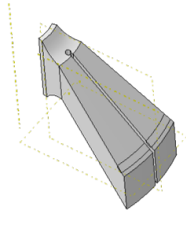
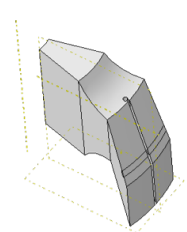
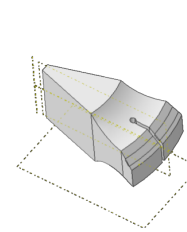
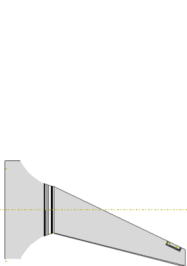
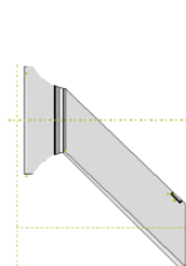
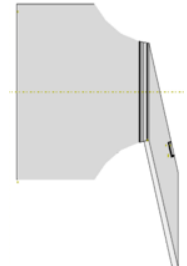
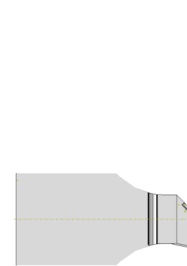
Design variation	2802 with the best technical performance	3609 with the lowest cost	3062 minimum cost with: $\varphi \leq 0$
Segment part			
Sectional view			
$\varphi_{yt_{max}}$	-0.23 ($\varphi_{yt_{32}}$)	0.58 ($\varphi_{yt_{21}}$)	-0.0734 ($\varphi_{yt_{21}}$)

Table 5.13: Three designs with sufficient technical performance (with $\varphi \leq 0$ and low cost) from all the samplings

Design variation	3062	3411	3024
Segment part			
Sectional view along axis			
$\varphi_{yt_{max}}$	-0.0734 ($\varphi_{yt_{21}}$)	-0.079 ($\varphi_{yt_{32}}$)	-0.15 ($\varphi_{yt_{32}}$)
Ranking of economic assessment	1	2	3

When we observe those designs with insufficient technical performance, their structures vary a lot. Looking more specifically at the locations and steps where yielding occurs, we see that most of the critical points are around the relief hole (position 2) during high-speed rotation (step 1). When comparing them with the designs that resist high-speed rotation without yielding, we see that they have more material at the edges, away from the axis. This increase in material is not only in the thickness at the edges but also in their larger off-center distances. In addition, designs 3226 and 3923 show yielding at the focal track area (position 3) during electron radiation (step 2) due to thermal stress, likely caused by insufficient focal track surface area resulting in an excessively high heat flux density.

Table 5.14: Examples of designs with insufficient technical performance (with $\varphi > 0$)

Design var.	3399	2924	3226	3923
Segment part				
Sectional view				
$\varphi_{yt_{max}}$	2.27 ($\varphi_{yt_{21}}$)	11.699 ($\varphi_{yt_{21}}$)	1.36 ($\varphi_{yt_{21}}$) and 1.31 ($\varphi_{yt_{32}}$)	0.17 ($\varphi_{yt_{32}}$)

Within the solutions with sufficient technical performance, another category should be considered: those that meet the technical requirements but are less economically efficient. For example, designs 3492 and 2628 in Figure 5.14, as shown in design variations 5.13, have design-associated manufacturing costs that are much more higher than some other solutions. The figure for designs illustrates that other structural configurations can also perform sufficiently from technical aspect.

In contrast to the more economically efficient solutions, these designs are characterized by their much more massive central areas and steeper focal track surfaces, as shown by the reduced angle α in Figure 5.5. Such structures are beyond conventional expectations for X-ray target

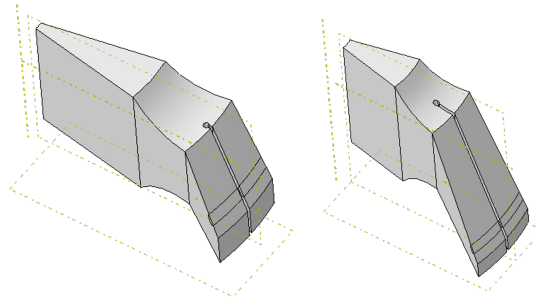


Figure 5.14: Examples of solutions with sufficient technical performance (with $\varphi \leq 0$) but are economical inefficient

designs. Although they require more material - making them heavier and more expensive to manufacture, especially when material costs are high - they provide a very open X-ray emission face and a wider entrance angle for the electron accelerator. This is in contrast to designs with bigger α , close to 90° . These design variations become the optimal choice when design-making criteria change, such as the need for a more open focal track surface due to electron accelerator settings.

Considering that all design variable values are changed simultaneously, it is challenging to quantitatively attribute and define the exact effects on technical or economic performance. However, based on the analysis provided, the following conclusions can be made:

- A relationship exists between a larger focal track radius and improved thermal stress distribution.
- There is a correlation between the thinness of the outer edges and the reduction of mechanical stresses, which are typically amplified by rotational speed.
- Minimal eccentricity is associated with reduced material usage, which in turn is associated with reduced mechanical stress during rotation and a reduction in both weight and further production costs.
- Material costs represent a significant portion of production costs, especially for this massive component. Therefore, reducing material consumption is key to reducing overall production costs.

Following the analysis, design 3062 was identified as a potential candidate for the final design due to its robust technical performance and cost-effectiveness. It stands out among comparable high-performance options for its advantages in terms of lighter weight and improved cost savings, in keeping with the goal of efficient material use while maintaining the technical functionality.

6 Application example 2: development of a rubber mount for a vibratory rammer

6.1 Project background

Following Xu [122], the project's background is optimizing vibratory rammers, which are an integral part of soil compaction in construction. These machines use a combination of pistons, motors, and crank mechanisms to apply rhythmic pressure through a foot pedal, achieving vertical and forward compaction due to a 12-degree shaft tilt. The development task is to redesign the vibratory rammer to reduce vibration at the control point, thereby improving operator comfort and safety and increasing possible operating time - factors critical to gaining competitiveness.

The rubber mount, shown in the Figure 6.1, plays a critical role in the functionality of the rammer, requiring a balance between being stiff enough to provide support and elastic enough to absorb vibration. System-level research has shown that the mount's planar stiffness in two axial-perpendicular directions and its rotational stiffness around the axis must fall within a precise (narrow) range to meet system requirements, a criterion not met by the existing initial design. Therefore, the design challenge is to explore the design space beyond the initial concept to find a technically appropriate and cost-effective solution.

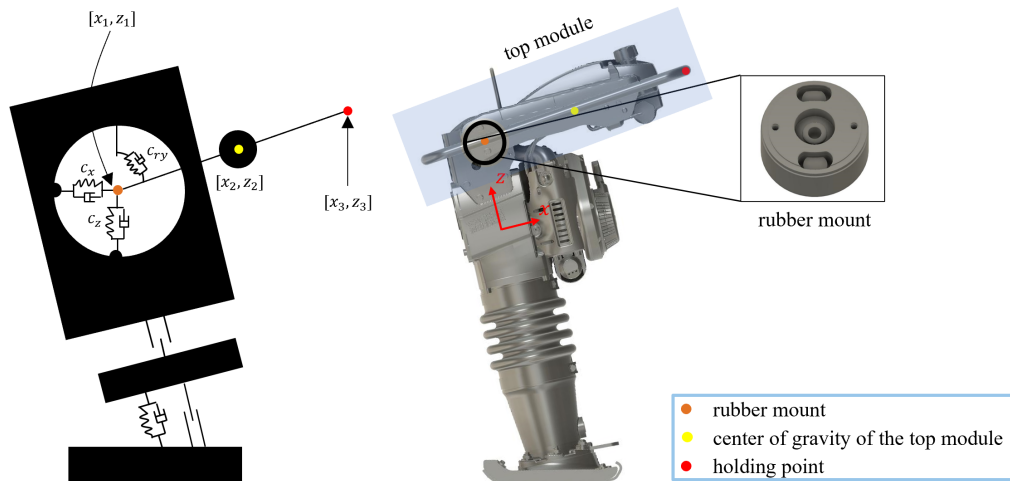


Figure 6.1: Vibratory rammer and its rubber mount

6.2 Step 1: Collect requirements

Based on the results of system-level development, the technical design requirements for the rubber mount specify that its stiffness in three directions must be within a specified range, as shown in Table 6.1.

Table 6.1: Component design requirements for rubber mounts on stiffness

Number	Symbol	Name	Unit	Lower Limit k_{lower}	Upper Limit k_{upper}
1	k_x	Stiffness x	kN/mm	0.532	0.836
2	k_z	Stiffness z	kN/mm	0.77	1.21
3	k_{ry}	Stiffness ry	Nm/deg	5.85	6.05

As mentioned in Section 4.4, the normalized technical requirements violation ϕ is used to express the QoIs relevant to the technical design criteria of the rubber mount. These QoIs are detailed and listed in the table 6.2 specifically for the rubber mount.

Table 6.2: Table of QoIs for redeveloping the rubber mount

Category	Quantities of Interest	Symbol	Definition	Requirement
Technical performance	Lateral stiffness violation in X-axis	ϕ_{kx}	$Max\left(\frac{k_{xlower}-k_x}{k_{xupper}-k_{xlower}}, \frac{k_x-k_{xupper}}{k_{xupper}-k_{xlower}}\right)$	≤ 0
	Lateral stiffness violation in Z-axis	ϕ_{kz}	$Max\left(\frac{k_{zlower}-k_z}{k_{zupper}-k_{zlower}}, \frac{k_z-k_{zupper}}{k_{zupper}-k_{zlower}}\right)$	≤ 0
	Rotational stiffness violation in Y-axis	ϕ_{kry}	$Max\left(\frac{k_{rylower}-k_{ry}}{k_{ryupper}-k_{rylower}}, \frac{k_{ry}-k_{ryupper}}{k_{ryupper}-k_{rylower}}\right)$	≤ 0
Economical performance	Design-dependent manufacturing cost	K^*	The portion of manufacturing costs MC_{total} that is affected by changes in DVs that impact subsequent process costs.	minimal

Based on the defined QoIs, the clarified intermediate attributes, and the potential DVs, the initial ADG (ADG I) is shown in the following Figure 6.2.

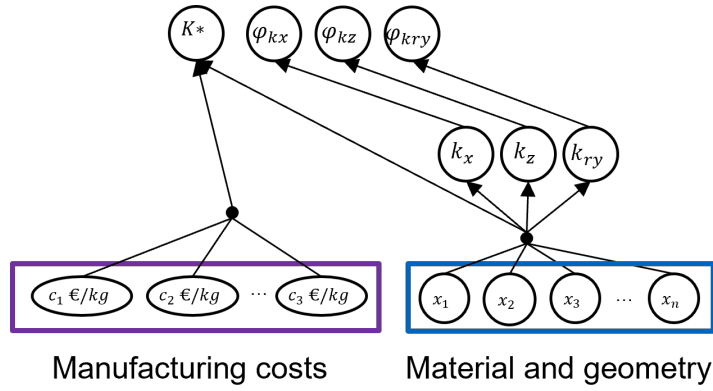


Figure 6.2: ADG I of the development task of a rubber mount

6.3 Step 2: Build a parametric design/concept CAD model

The rubber mount is composed of three segments (Figure 6.3): the top and bottom metal components, known as the upper and bottom part, respectively, and the central rubber component, which is the focus of the optimization task. The complex internal structure of this rubber part is primarily responsible for the overall stiffness of the whole rubber mount. Therefore, this design effort will use a CAD model to represent the configuration of the rubber part.

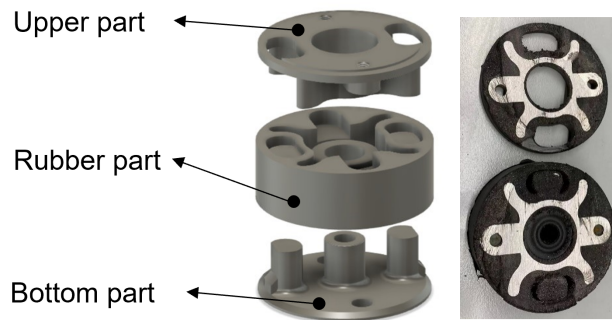
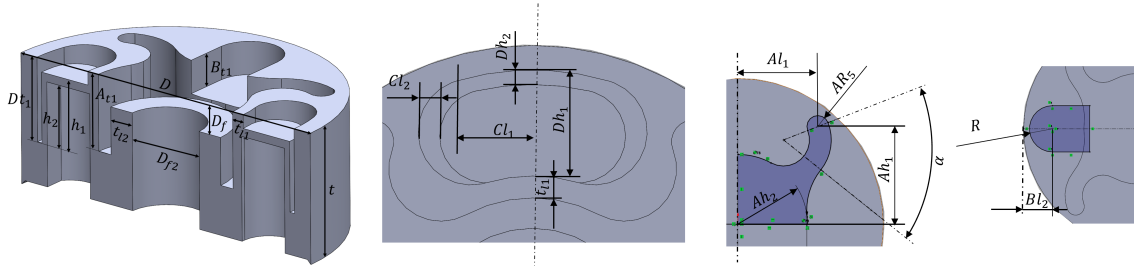


Figure 6.3: A rubber mount

A parametric CAD model representing the rubber part structure was created using 22 geometry DVs. These DVs are shown in the Figure 6.4. This parametric CAD model is based on the

original reference design, which does not meet the stiffness requirements in three directions necessary for optimization, as shown in Figure 6.12 . The box in there represents the required solution space, and the red dot indicates the initial design, clearly showing that it does not fall within the expected solution space. Table 6.3 lists all the geometry DVs and their values based on the reference design. Design variations can be generated by modifying these values. The initial dimensions were taken from a reference design. To determine the intricate geometry inside the rubber mount, several samples were profiled from different directions (as shown in Figure 6.3, right).



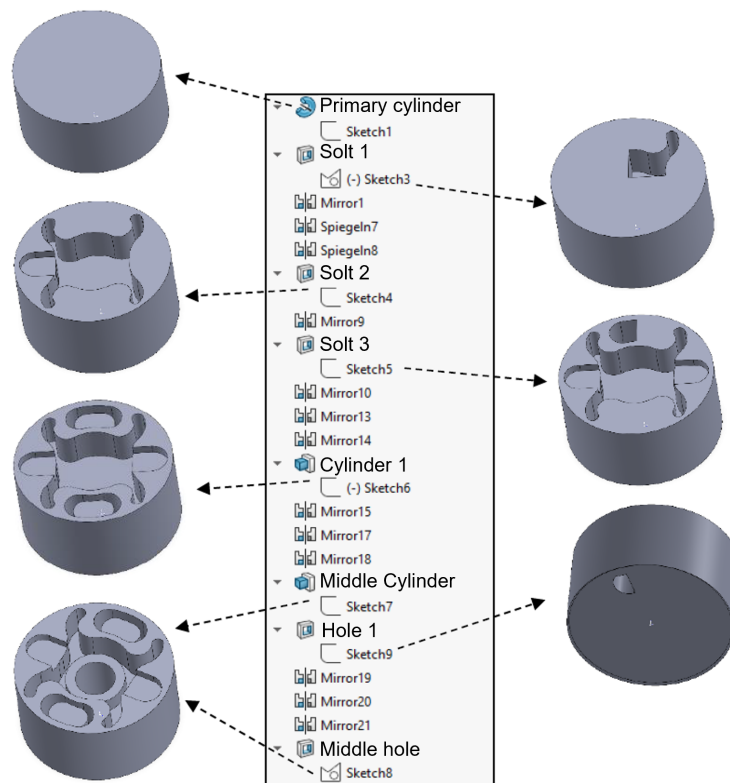


Figure 6.5: Processes for creating a 3D CAD model of a rubber mount

by injection or compression molding. The production process begins with fabricating the metal parts, assembling them, and then injecting the rubber to represent the actual manufacturing steps of the rubber mount.

In the machining process, the upper metal part undergoes surface profile milling to define its outer contour, followed by milling a center hole for alignment. The sides of the part are then hollowed out by milling or drilling, and threaded holes are drilled to facilitate assembly with a vibratory hammer. Similarly, the bottom metal part is formed by surface profile milling. A center hole is drilled for mounting, and additional holes are drilled on each side, with threads added where necessary.

In another production strategy, the upper and bottom metal components are produced through metal casting. This approach allows most of the part features, such as the overall shape and major holes, to be shaped directly during the casting process. The primary expenses in this method include the cost of the casting molds (special production direct costs), the materials for metal parts and the rubber part. As the casting process creates most of the necessary features,

Table 6.3: Values of DVs of the rubber mount for initial design

Design Variable	Value (mm)	Design Variable	Value (mm)	Design Variable	Value (mm)
D	80	t	40	Ah_2	19.15
AR_5	3	Al_1	22	Ah_1	26.82
α	60 deg	R	8	Bl_2	10
Cl_1	5.84	t_{l1}	3	Cl_2	0.96
Dh_1	14.5	Dh_2	1.5	t_{l2}	5
Df_2	20	At_1	20	Bt_1	5
h_1	20	Dt_1	25	h_2	25
Df	10				

only a limited amount of post-casting machining is required, primarily for tapped holes. These additional machining costs are relatively unaffected by design modifications, leading to their classification as design-independent costs. Furthermore, since the molds used in casting are prebuilt, the time taken for casting, along with the related labor and tools or machinery costs, show minimal fluctuation in response to design variants. Therefore, these production labor costs and overhead costs during the casting process are not considered design specific.

The assembly and molding phase begins with grinding and polishing to smooth the corners and, if necessary, achieve the desired surface texture. The metal parts are then assembled with the molds designated for the rubber element. The core rubber part is formed by injection molding, where the rubber material is injected into the mold consisting of the metal parts to create a complete rubber mount. The mold is then removed, and any residues are cleaned off, leaving a finished rubber mount ready for application.

The cost-production dependency analysis for both the machining and casting processes of the rubber mount is shown in Figure 6.6 and 6.7. This analysis serves as the basis for the economic evaluation of the rubber mount design variations, taking into account the different potential manufacturing processes.

Following the results of the cost-production dependency analysis and the DVs of the parametric CAD model of a rubber mount, a detailed ADG (ADG II) can be created (6.8 and 6.9).

6.4 Step 3: Technical and economical model dependency

	Machining processing upper part				Machining processing bottom part				Assembly and molding			
	Surface profile 	Center hole 	Hollowed out sides 	Threaded Hole 	Surface profile 	Center hole 	Holes on both sides 	Threaded Hole 	Rounded corners and surface roughness 	Assembly of metal parts and molds 	Rubber Injection Molding 	Mold removal and cleaning 
	Milling	Milling Drilling	Milling or Drilling	Threaded - Drilling	Milling	Drilling	Drilling	Threaded- Drilling	Grinding Polishing			
Material direct costs MDC												
Production labor costs PLC												
Production overhead costs POC												
Material overhead costs MIOC												
Special production direct costs SPDC												
There are no incurred costs. Cost independent of design variation K_f Cost depending of design variation K^* $MC_{total} = K_f + K^*$												

Figure 6.6: Dependency analysis of production processes and different types of costs for production strategy machining

	Casting processing		Machining processing		Assembly and molding			
	Whole profile of upper part 	Whole profile of bottom part 	Threaded hole of upper part 	Threaded hole of bottom part 	Rounded corners and surface roughness 	Assembly of metal parts and molds 	Rubber injection molding 	Mold removal and cleaning 
	Casting	Casting	Threaded- Drilling	Threaded- Drilling	Grinding Polishing			
Material direct costs MDC								
Production labor costs PLC								
Production overhead costs POC								
Material overhead costs MIOC								
Special production direct costs SPDC								
There are no incurred costs. Cost independent of design variation K_f Cost depending of design variation K^* $MC_{total} = K_f + K^*$								

Figure 6.7: Dependency analysis of production processes and different types of costs for production strategy casting

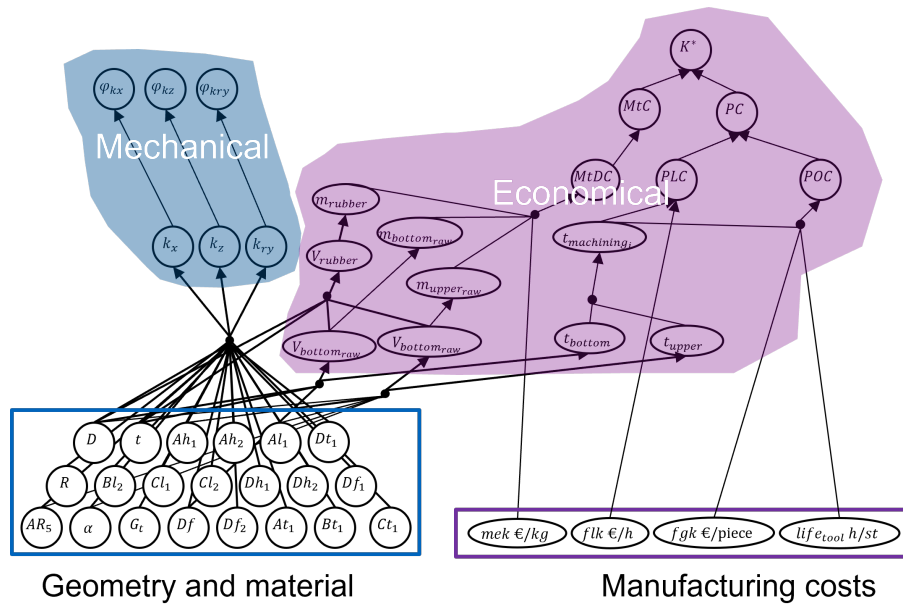


Figure 6.8: A comprehensive ADG II for the redevelopment of a rubber mount with production strategy machining

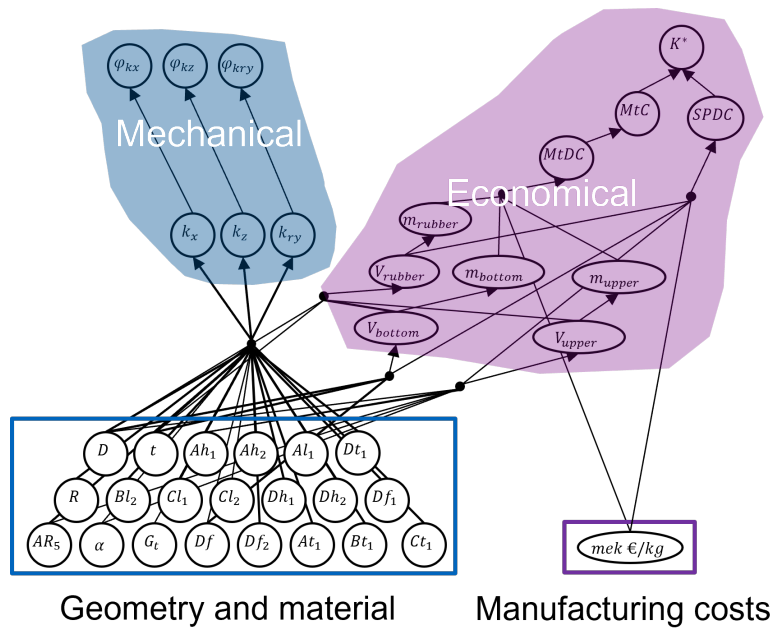


Figure 6.9: A comprehensive ADG II for the redevelopment of a rubber mount with production strategy casting

6.5 Step 4: Complete the technical assessment of design variations via FEA

6.5.1 Boundary conditions

Figure 6.3 and the injection molding technique used to produce the rubber mount show that the surface of the rubber component is in close contact with the metal parts. This means that any force or displacement applied to the metal part is evenly distributed across its contact surface with the rubber, which can provide an even better damping effect, especially when the contact surface is intricately shaped. As shown in Figure 6.10, only the rubber component is simulated in the FEA model to reduce computational expense. A rigid connection is made between the contact surfaces and a reference point, which is supposed to represent the mass point of the upper part. The forces or displacements originally applied to the metal part are applied directly to this point to achieve a simulation effect that mirrors reality. The surface in contact with the lower part is directly fixed.

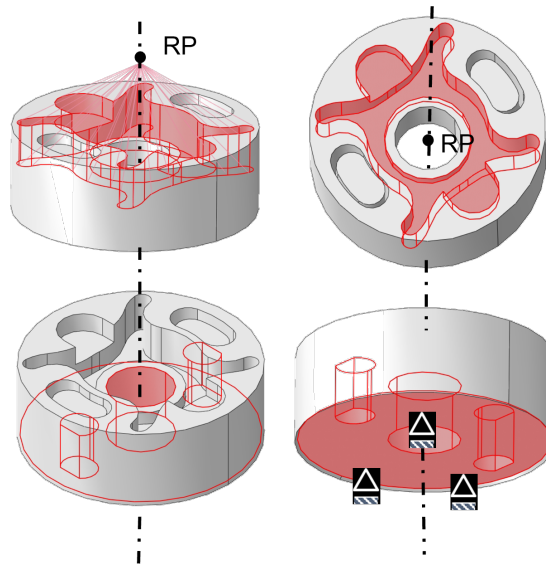
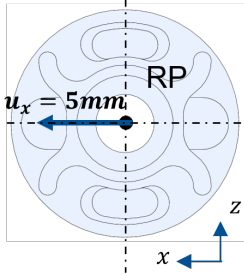
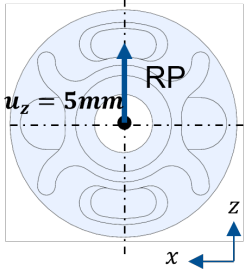
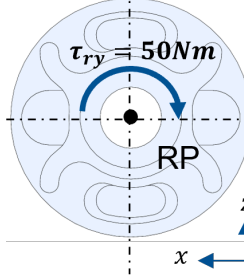


Figure 6.10: Boundary conditions of the FEA model

In order to accurately determine the stiffness values k_x , k_y , and k_{ry} in the simulation, three different loading scenarios were established. In each scenario, one side of the rubber (specifically the bottom surface) is fixed, while the other side is subjected to a unit force or torque in the x , z , or y directions, as shown in Table 6.4. Stiffness is calculated based on the response to applied external forces or displacements. The calculation depends on the corresponding output - either the resultant displacement, angle of rotation or the reactive force generated. Throughout this evaluation, the rubber is consistently modeled as an isotropic material.

Table 6.4: Loads of the rubber mount in three directions

Steps	Step1 Horizontal x	Step2 Horizontal z	Step3 Torsion ry
			

6.5.2 Meshing

Due to the complex internal configuration of the rubber mount, pre-processing steps such as segmentation into single pieces for structured meshing prove to be difficult. As a result, a tetrahedral unstructured 3D mesh element was used to generate meshes for the design variations of the rubber mount. This type of mesh is particularly suitable for complex structures. Chapter 4.7.4 discusses the general validation of unstructured meshes and confirms that they can maintain the required accuracy under certain conditions, such as the use of sufficiently small mesh sizes. In this case, a 2-mm mesh size was chosen to mesh the CAD model of the design variations. It effectively balances computational efficiency and the accuracy required for the FEA simulation.

6.6 Step 5: Validate FEA model

Since the rubber mount is available as a finished product, the validation stage of the FEA model adopts a direct and practical method: experimental testing. As detailed in Xu's research [122], the stiffness measurements of the rubber mount are shown in Figure 6.11. In this setup, the rubber mount is mounted to a test fixture and subjected to either forces or torques along the x, z, and y directions. The resulting displacements or angles of rotation are measured. This experimental data is then used to determine the stiffness of the rubber mount in each of these three directions.

Improving the accuracy of the FEA model is achieved by refining it using the experimental data collected. This refinement involves adjusting various parameters to match the stiffness values obtained in the simulation for the x, z, and y directions with those obtained from the experimental measurements, as detailed in Table 6.5. Through this iterative adjustment, key material properties such as a Young's modulus of 2.06 MPa and a Poisson's ratio of 0.422 are accurately determined. The reliability of the FEA model is further established by the minimal

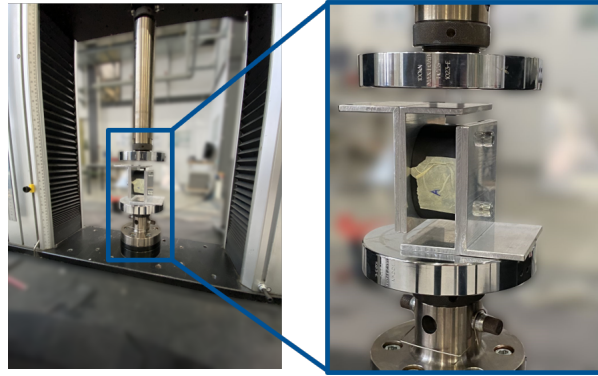


Figure 6.11: Measurement of the rubber mount stiffness [122]

discrepancy between the experimentally and computationally derived stiffness values, with an absolute variation kept below 4%, as shown in Table 6.5. Therefore, the FEA model is considered to be both trustworthy and effective in simulating the response of the rubber mount under different loading scenarios.

Table 6.5: Measured and validated stiffness of the rubber mount [122]

	k_x (kN/mm)	k_z (kN/mm)	k_{ry} (Nm/deg)
Measurement	0.76	1.1	5.12
Simulation	0.731	1.144	5.08
Percentage derivation	−3.77%	3.97%	−0.86%

6.7 Step 6: Economic assessment of design variations via cost calculation model

The section dedicated to constructing a costing model for the development case of rubber mount adapts the results outlined in Section 6.4. This involves translating the identified dependencies between QoIs and DVs into a quantitative framework for calculating the manufacturing costs associated with designing rubber mounts. This model aims to facilitate an economic evaluation that helps compare different design variations from economic perspectives.

Cost calculation models are created to adapt according to the specific production strategies chosen for the rubber mount, including machining and casting technologies. The costing model is adjusted for each production strategy to reflect the specific cost factors and variables

associated with that strategy. In the case of machining, from the conclusions in Figure 6.8, the costing model includes material direct costs for raw materials, such as the metal blanks for the upper and lower components and the rubber used in injection molding. It also includes production labor costs and the overhead costs associated with machining processes such as shaping, drilling, and other necessary operations. For the casting process, as shown in Figure 6.9, the model is adjusted to include the cost of the metals and rubber used in a casting process, which are included in material direct costs, and the cost of making the molds, which is included in special production direct costs. These adjustments ensure that the costing model correctly reflects the economic implications of each production strategy, providing a comprehensive tool for economic analysis across different potential manufacturing scenarios.

6.7.1 Cost calculation model for production with machining

Material direct costs (MtDC)

The material direct costs for the rubber mount are primarily associated with the metal and rubber materials used. The cost calculations consider the types and volumes of materials required for both the upper and bottom metal parts, as well as the rubber element.

$$MtDC = (m_{upper_{raw}} + m_{bottom_{raw}}) \times mek_{steel} + m_{rubber} \times mek_{rubber} \quad (6.1)$$

$$= (V_{upper_{raw}} + V_{bottom_{raw}}) \times \rho_{steel} \times mek_{steel} + V_{rubber} \times \rho_{rubber} \times mek_{rubber} \quad (6.2)$$

The cost of the metal parts is calculated based on their respective volumes and the price of the metal (steel), while the cost of the rubber material is determined by the volume of rubber used and its market price.

Production labor costs (PLC)

The design-related production labor costs are primarily influenced by five machining processes, three of which are for the upper part and two of which are for the bottom part. For the upper part, these include (1) profiling the surface, (2) drilling the center hole, and (3) hollowing the sides. Similarly, for the bottom part, the machining processes include (1) profiling the surface and (2) drilling the center hole. While other machining steps, such as creating a threaded hole or drilling holes on both sides of the bottom component, are part of the manufacturing process, they are treated as design-independent costs due to their consistent conditions, such as uniform hole diameter or hollow thickness, and are therefore not included in the costing model. According to the design-related manufacturing labor cost, which is significantly affected by the five machining processes for the upper and bottom parts, we can calculate the manufacturing labor cost for each part based on equation 5.12. The focus of this calculation is to determine the machining time required for each part. This determination is made primarily by calculating the

volume of metal to be removed in the machining and the material removal rate (MRR) according to Section 3.5, which is derived from the cutting speed.

Production overhead costs (POC)

In this case, production overhead costs consider the cost of tools used in the production of rubber mounts. The calculation of these costs is based on the usage time of each machining tool, taking into account its life and purchase price. Since there is an interaction between machining speed, production time, and production overhead costs, higher cutting speeds can reduce labor costs by shortening production time. However, they can also reduce tool life, thus increasing production overhead costs for tool purchase or maintenance. In this use case, we use the relationship between cutting speed and tool life from Table 3.4 and observe two cutting speeds to determine if the optimal economic design variation changes at different speeds within the same machining scenario.

6.7.2 Cost calculation model for production with casting

Material direct costs (MtDC)

Material direct costs in molding include the raw materials used for the metal components - both upper and bottom - and the rubber element. The materials selected for these components directly influence the total material cost. The part dimensions and the density of the metal determine the weight of the metal material used in the casting. Similarly, the amount of rubber material is calculated based on the volume needed to fill the mold for the rubber component, considering the density and current market price of rubber.

$$MtDC = (m_{upper} + m_{bottom}) \times mek_{steel} + m_{rubber} \times mek_{rubber} \quad (6.3)$$

$$= (V_{upper} + V_{bottom}) \times \rho_{steel} \times mek_{steel} + V_{rubber} \times \rho_{rubber} \times mek_{rubber} \quad (6.4)$$

Special production direct costs (SPDC)

Special production direct costs primarily refer to the molds required to cast the metal parts. The price of these molds depends mainly on the material used for the mold and its size. The molds are generally made of a metal that is proportional in size to the metal components but with a wall thickness of 15cm to ensure durability and quality in the casting process. The cost of material for the mold is calculated based on the volume of metal required, which is derived from the dimensions of the mold and the thickness of its walls. This cost estimate primarily considers the material cost of the mold, which is determined by the various design variations and their impact on the amount of mold material required. It does not include costs associated with machining and finishing the mold.

6.8 Step 7 and Step 8: Automation, DoE generation and implementation

Once the preliminary stages of model building and validation are complete, the process moves on to the next stages: steps 7 and 8. These steps are dedicated to automating processes, generating and implementing design of experiments (DoE).

In step 7, dedicated to automation, we developed scripts in line with the algorithms referenced in Section 4.10, resulting in an automated program adapted to the development of rubber mounts. This program includes scripts for generating design variations and performing both technical and economic evaluations. A special feature is a flexible cost calculation model for evaluating rubber mount design variations based on different production techniques and processing speeds. Unlike the more fixed X-ray target costing model, which focuses on a single manufacturing process, the rubber mount cost model is more flexible, which is essential to ensure accurate and reliable economic evaluations and provides more detailed decision support for a potential final design by considering a wide range of different production characters.

Continuing with Step 8, after establishing a foundation for automated computational experiments for DoE, move on to the phase of generating and performing the DoE. Before starting this large experimental program, it is necessary to configure its settings. This involves defining the design space for each of the design variables. Table 6.6 will detail the design spaces for each of the 22 DVs involved in the rubber mount development.

Table 6.6: Design variables of the rubber mount development with their design spaces

Design Variable	Design Space (mm)	Design Variable	Design Space (mm)	Design Variable	Design Space (mm)
D	50–95	t	38–50	Ah_2	16–26
AR_5	1–5	Al_1	16.5–24	Ah_1	21–28
α	20–90 deg	R	5–10	Bl_2	7–25
Cl_1	2–7	t_{l1}	1.5–3.5	Cl_2	0.4–3
Dh_1	12–18	Dh_2	0.9–2.2	t_{l2}	2–10
Df_2	18–40	At_1	15–27	Bt_1	1–25
h_1	5–35	Dt_1	5–35	h_2	1–30
Df	1–40				

6.9 Step 9: Results analysis and decision-making

In this case, we used ADeVAA to perform the variation and evaluation of 10,000 random samples in DoE automatically. Figure 6.12 shows the initial design of the rubber mount and the solution space defined by the system-level design requirements. The red dot in the diagram represents the initial designs that need to be redesigned, with their position in this space determined by the stiffness values in three directions. Clearly, the initial design does not fall within the solution space we have defined. The graph on the right shows 10,000 random design samples within the design space, marked by blue dots. Within the solution space, six solutions with sufficient technical performance are identified, indicated by green dots.

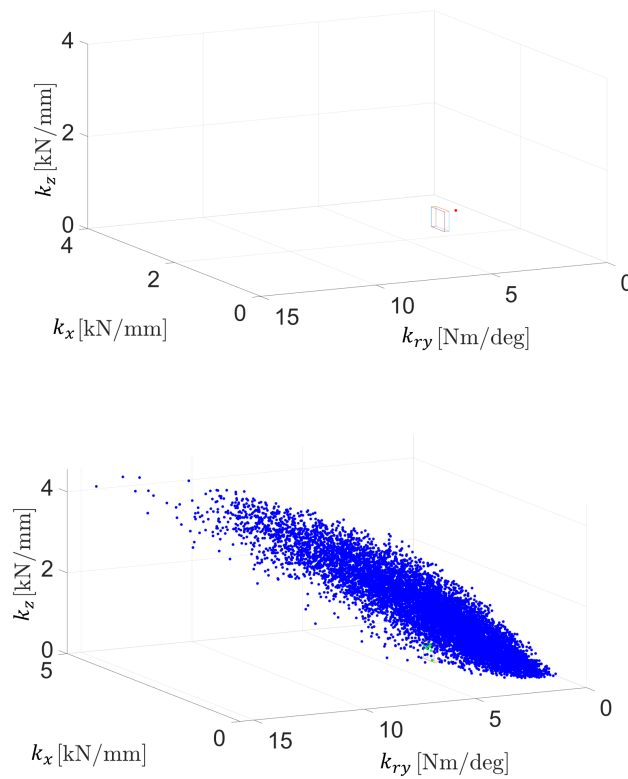
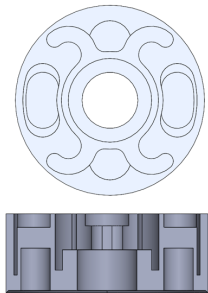
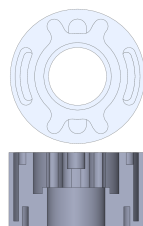


Figure 6.12: Design of Experiment: (a) solution space and the initial design; (b) solution space and the 10,000 design variations

By translating the stiffness requirements from three directions into a single metric known as the normalized technical requirement violation ϕ , and considering this in combination with the

Table 6.7: The design with lowest φ (indicates the most technically robust) and also is the most cost-effective among those with sufficient technical performance ($\varphi \leq 0$) (left) and the economically best design (with lowest cost) from all the samplings (right)

Design variation	22	9422
	with the best technical performance and the lowest cost among designs that meet technical requirements	with the lowest cost among all the design variations
		
φ_{max}	-0.4	23.41
$k_x[kN/mm]$	694.1	442.27 ↓
$k_z[kN/mm]$	1000.09	429.87 ↓
$k_{ry}[kN/mm]$	5.93	1.17 ↓

economic performance over 10,000 samples, we arrive at the conclusions shown in Figure 6.13. These results take into account the economic analysis conducted under normal recommended machining speeds within a machining process.

As shown in Figure 6.13, design 22, detailed in Table 6.7, not only performs robustly from the technical perspective out of all 10,000 samples, but is also the most economical among those that meet the technical requirements. This design successfully balances technical and economic aspects, making it superior in the analysis.

In contrast, the most cost-effective design, 9422, had a more decentralized structural configuration and compact dimensions: for the same height, its diameter is half that of design 22. This smaller size contributes to its reduced stiffness and inability to meet technical requirements despite its lower production cost. It fails to meet the stiffness requirements in all three directions, with values well below the required lower bound. In other words, its structural stiffness was too weak. Although this design used less material and was also cheaper to produce, it failed to meet the requirements in terms of functional viability.

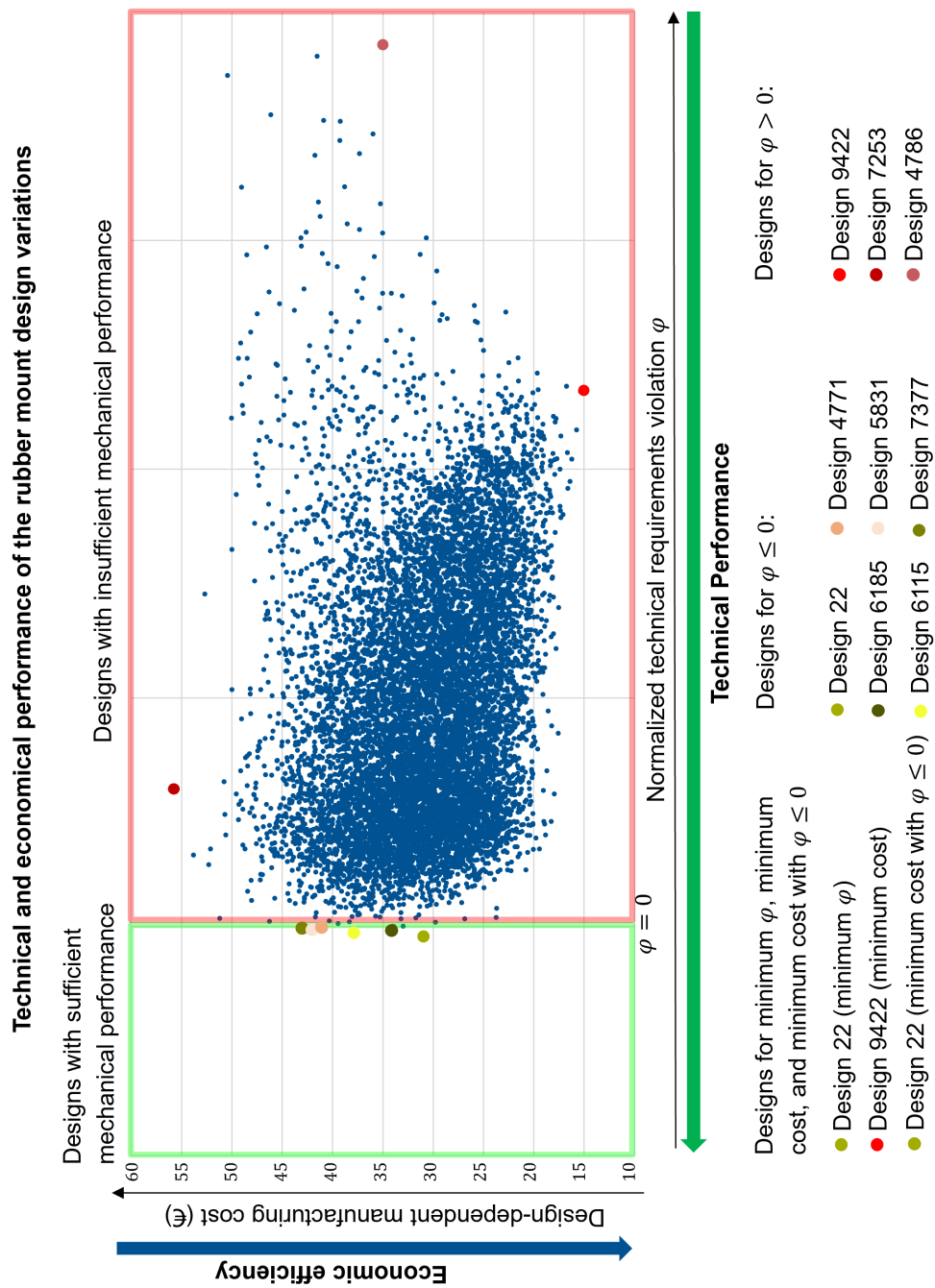
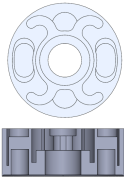
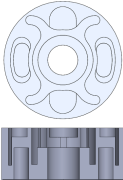
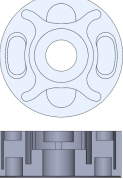
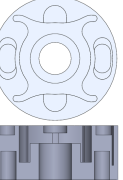
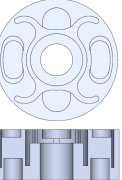
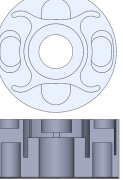


Figure 6.13: Design variations of the rubber mount reflecting economic and technical evaluation, with highlights of some specific solutions

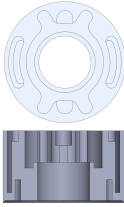
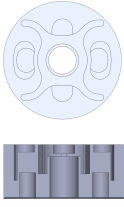
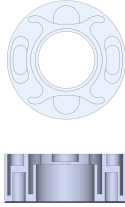
Table 6.8: Six designs with sufficient technical performance (with $\varphi \leq 0$ from 10,000 design samplings)

Design var.	22	6115	6185	4771	7377	5831
						
φ_{max}	-0.404	-0.259	-0.050	-0.034	-0.012	-0.010
$k_x[kN/mm]$	694.1	725.5	625.64	825.63	832.31	766.81
$k_z[kN/mm]$	1000.09	1096.02	792.06	1088.08	1011.42	1099.08
$k_{ry}[kN/mm]$	5.93	5.976	5.99	6.03	5.92	5.85
Ranking of lower cost	1	3	2	4	6	5

In the Figure [6.13](#), the six designs that satisfy technical requirements are marked. Notably, their economic effectiveness varies significantly. A review of the six design variations, as detailed in Table [6.8](#), reveals that each has distinctive features with no easily identifiable commonalities. Within the design space, each exhibits individual characteristics such as extended lengths along the axial direction or a more concentrated structure in the central region. For details on their specific dimensions, namely the values of each design variable and comparisons with the initial design, see Table [A.3](#) in appendix.

Looking at three example designs with insufficient technical performance from the whole set of samples, as listed in Table [6.9](#) - for example, the cheapest design 9422, the most expensive design 7253, and the design 4786, which is the furthest from meeting the technical requirements- it is clear that these designs have no structural similarities. The cheapest design significantly under-performs in stiffness in all three directions, and while it saves on material usage, it does not achieve the desired stiffness values. Conversely, the most expensive design exceeds the lateral stiffness requirements but falls below the torsional stiffness requirement. The design with the poorest technical evaluation has stiffness values that far exceed the required range in all directions, but its cost does not exceed that of the most expensive design variant.

Table 6.9: Examples of designs with insufficient technical performance (with $\varphi > 0$)

Design var.	9422	7253	4786
			
φ_{max}	23.41	3.14	38.48
$k_x[kN/mm]$	442.27 ↓	1791.7 ↑	4114.38 ↑
$k_z[kN/mm]$	429.87 ↓	1840.66 ↑	4547.64 ↑
$k_{ry}[kN/mm]$	1.17 ↓	5.67 ↓	13.74 ↑
The character of the design	the cheapest	the most expensive	with the worst technical performance

This case demonstrates that the complexity of the structures makes it difficult to intuitively identify clear trends through a straightforward analysis. This highlights the advantage of ADeVAA, which indiscriminately searches for optimal solutions within a predefined design space without considering the individual impact of each design variable on the overall result.

Nevertheless, by reviewing the technical performance of a wide range of design variations and performing regression analysis, a tentative trend can be identified: The stiffness of the central cylindrical section has a significant impact on the overall stiffness of the rubber mount. In this context, "stiffer" refers to the idea that for a given wall thickness, greater stiffness can be achieved by increasing the length or increasing the inner diameter.

When developing the cost calculation model for the production of rubber mounts, the potential for multiple production strategies was taken into account. This included the possibility that the upper and bottom metal components might be finished in different ways, and also how varying speeds of machining might influence the economic assessment results. The economic evaluations of the design samples are shown in Figure 6.14, categorized by the method of manufacturing.

The analysis evaluates cost-effectiveness of different design variations based on their production strategies, whether machining or molding. Each manufacturing approach uses a different cost model based on its specific economic model dependencies. As a result, it is impractical to directly compare the economic performance of a design across different manufacturing methods based solely on the total cost values from their respective cost calculation models. This is because each model contains a unique set of cost components specific to the manufacturing

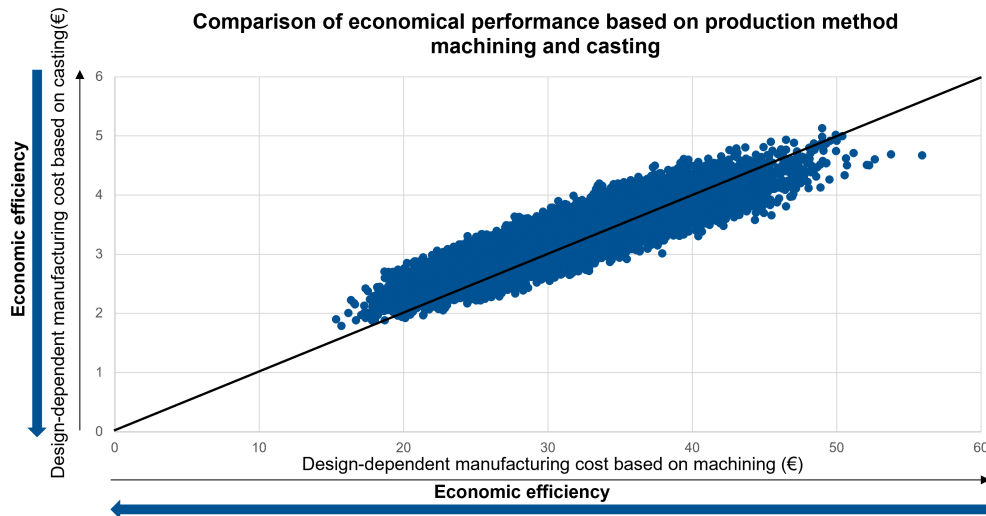


Figure 6.14: The economic performance of technically feasible designs was assessed based on different manufacturing methods

process under analysis. Therefore, the analysis is visualized in Figure 6.14, where points lying on the diagonal line indicate that the economic evaluation results for a design are the same for both manufacturing methods. Points below the line indicate that casting is more economical, while points above the line indicate that machining is more economical.

Overall, points closer to the origin represent designs with better cost-effectiveness. A general trend observed is that almost all points are almost uniformly distributed on both sides of the diagonal, indicating that designs with good economic performance under one production method tend to have similarly good performance when produced under a different production method. A probable reason for this trend is that material costs are an important part of design-dependent costs in the costing model, regardless of the production method. As a result, designs that use less material tend to be more economical.

When considering the effects of different cutting speeds within the same machining process, choosing a relatively slower cutting speed can increase tool life and reduce tool replacement and service costs. However, in this case, when the cutting speed is reduced by 20%, the overall cost increases by an average of 75% due to the extended machining time and labor costs, which are substantially higher than the cost of the tools. This illustrates that while slower cutting speeds may extend tool life and minimize costs associated with tool service and replacement, the resulting increase in labor costs significantly reduces the economic advantage. Therefore, even with the potential for longer tool life at reduced speeds, the increased labor costs suggest that higher cutting speeds may be more cost effective in this case. However, in situations where

the tools are extremely expensive, such as specialized cutters for machining ultra-hard materials, choosing slower cutting speeds to extend tool life becomes more economically viable. The high cost of such specialized tools can make their life a more critical factor in the cost calculation, making slower speeds more economical even with potentially higher labor costs.

In summary, after a comprehensive evaluation that included both technical performance and economic assessments using two different costing models adapted to different manufacturing methods, design 22 is highlighted as the preferred choice of a potential final design. Not only does it meet the technical design requirements, but it does so more economically. This balance makes it a wise choice in scenarios where both technical performance and cost-effectiveness are important.

7 Discussion

In recent years, product development has become much more advanced, especially when it comes to designing component structures that meet a wide range of restrictive, multi-criteria requirements. These requirements have become more than just technical. They now cover much broader issues, including economic viability, development time efficiency, and the essential goal of minimizing labor costs in an increasingly competitive global marketplace.

In this evolving environment, the research presented here presents an advanced parametric methodology designed for use in the detailed design phase according to Eppinger's generic product development process [112], as illustrated in Figure 7.1. Based on the results of earlier phases, such as the design requirements identified in the planning phase, the concepts formulated in the concept development phase, and the detailed specifications from the system-level design phase, this methodology advances the detailed design process of product development. It facilitates the identification of designs that are both cost effective and technically sufficient within a high dimensional design space. Typically, accurate manufacturing cost calculations require the completion of detailed design and a detailed manufacturing plan derived from it. However, ADeVAA is able to perform quantitative cost analysis with minimal information in the detailed design phase, ensuring that potential final design decisions are made based on a consideration of technical and economic perspectives. ADeVAA integrates several common but powerful techniques: the reliability of DoE, the precision of CAD, the evaluative capabilities of the numerical analysis model, e.g. FEA, and the cost insights of manufacturing costs calculation model.

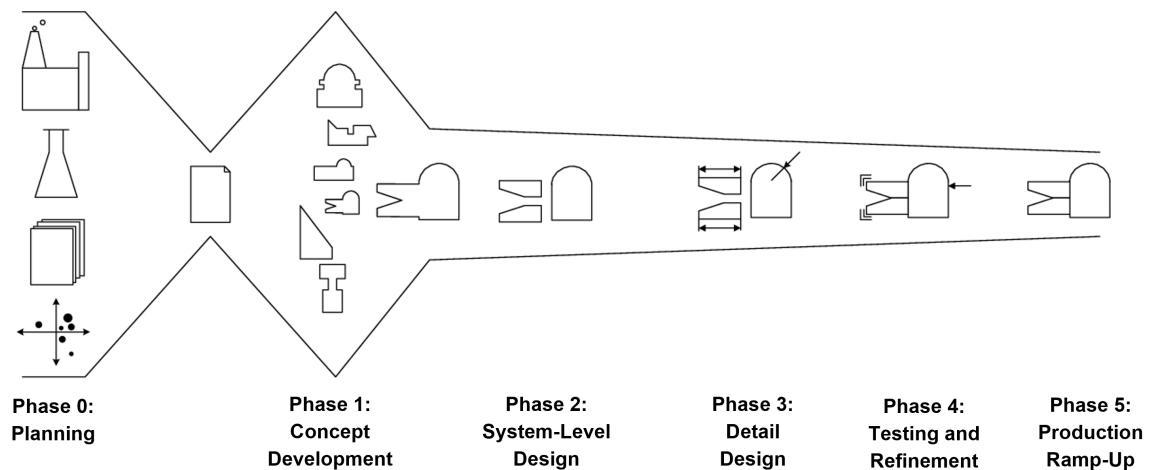


Figure 7.1: The generic product development process according to [112]

However, the power of this approach is not just in its integration. It lies in its automation and comprehensiveness. Rather than confining engineers to a limited design space, this methodology allows them to generate many design variations automatically. It ensures that amount of potential solutions could be considered so that most of the design space is covered. However, automatically generating design variants for a design space exploration is only part of the story. The real innovation is in the approach's ability to evaluate these numerous design variations from different perspectives. Integrating technical criteria with economic considerations provides a complete evaluation matrix and seeks to optimize technical specifications with economic viability. This ensures that engineers are not only technically sound, but also grounded in real-world economics.

This research is not just about introducing a design approach. It is about developing an approach to a more efficient product development that will recognize the complexity of today's industries and meet their diverse challenges. Based on this, the discussion will explore the dissection of this approach, breaking it down into four dimensions critical to understanding its potential and implications. The specific facets that will be discussed are:

- **Operational Quality:**

The effectiveness of a methodology depends on its ability to deliver high-quality results consistently. How does it compare to the standards for producing accurate results? Does it fully meet the criteria for method development? And how does it compare to alternative approaches in terms of operational benefits?

- **Applicability:**

While innovative methods are valuable, the practical application is the key evaluation. Considering the complex design variation and evaluation process, it is critical to identify the situations in which the approach performs well. Is this method flexible enough to be implemented across different domains or industries, or is its use limited to a specific industry area? To what extent can its application be widespread?

- **Adaptability:**

In a rapidly evolving environment, any approach must be able to adapt to changing requirements and challenges. It is important to assess the long-term value and sustainability of an approach. The flexibility of this approach and how it can be adapted or modified to meet different requirements or new challenges will be explored.

- **Computational performance:**

The computational power of a method, especially when coupled with the DoE, is critical to the functionality of the overall approach. How well does this approach work with DoE? Is there a notable improvement or compromise in computational performance when implementing DoE? The ability of the method to interact efficiently with DoE speaks not only to its technical sophistication but also to its potential applicability to complex design challenges.

7.1 Operational quality

The challenge of ADeVAA lies in its ability to balance precision and operational efficiency. In an industry increasingly focused on innovation and efficiency, reducing labor expenses, improving product technical performance, and increasing economic benefits through efficient design methodologies while maintaining the quality of the product intended for final selection is critical to success. ADeVAA addresses this by automatically generating and evaluating design variants with minimal manual effort.

Precision and reliability

Evaluating engineering performance is a major part of the whole approach, and ensuring its accuracy and credibility is critical to its overall effectiveness. In finite element simulations, automating the meshing process, especially when dealing with complex geometries, is essential to achieve consistent and scalable evaluation of design variations. While unstructured meshing (tetrahedral mesh) is optimal for generating automatic meshes for complicated structures, it can raise concerns regarding accuracy. Chapter 4.7.4 described a comprehensive comparison between 3D unstructured meshing (tetrahedral mesh) and 2D structured meshing techniques, which is often suggested as an alternative to 3D structured meshing (hexahedron mesh) for specific complex designs with structures that can be converted from 3D to 2D, promising consistent accuracy in finite element simulations. Through this study, it could be determined whether FEA simulations with unstructured elements are also accurate and reliable enough for technical evaluation compared to those with structured elements.

The intricate structure of the test model - a simplified satellite structure is characterized by intersecting longitudinal and transverse ribs (as shown in Figure 4.13). The validation results confirmed that FEA simulations with automated unstructured (tetrahedral) meshing can achieve sufficient accuracy. This study uses a suitably fine tetrahedral mesh to ensure an acceptable range of computation times. The results showed a less than 10% deviation when comparing results derived from tetrahedral elements with those derived from structured shell elements. In addition, finite element simulations using the tetrahedral element were compared with results from actual physical tests. Precisely, to determine the stiffness of the rubber mount, its complex design allowed only unstructured (tetrahedral) meshing to perform the FEA simulation. Chapter 7 includes a physical experiment to measure its three stiffnesses. The comparative study showed that the maximum discrepancy between the FEA simulation and physical experiment results was less than 4%.

Validation of FEA simulations using unstructured mesh elements against those using structured mesh elements, as well as physical experiments, has shown that FEA simulation using unstructured mesh (tetrahedral), which is ideal for handling complex geometries, has the ability to provide accurate results for various structures, which gives confidence in its reliability. However, achieving such an accuracy depends on a well-specific initial FEA model, which includes factors

such as mesh density and mesh seed distribution. Defining what is "well specific" is not a straightforward task. Therefore, after creating the initial FEA model in Step 4, it is essential to continue with model validation in Step 5, as suggested in Chapter 4.8. This ensures a technically accurate and reliable assessment to guide further analysis and support decision-making.

Satisfaction of requirements

ADeVAA as an approach to provide robust decision support in product development. The following Table 7.1 shows the compliance of ADeVAA with the specified requirements for its development, considering both its functional and application aspects.

Table 7.1: Comparison of the developed approach with the predefined requirements

Requirements		Compliance
Fully satisfied: ✓; Partially satisfied: ✓; Not satisfied: ✗		
Functional	Applicable in the design stages of the product development process.	✓
	Searches for optimal design with multiple design variables.	✓
	Builds a parametric CAD model with no constraints on geometric complexity or parameter count.	✓
	Automatically generates design variations within the entire design space.	✓
	Automatically evaluates the technical performance of design variations.	✓
	Evaluates the manufacturing cost of design variations.	✓
	Provides analysis and visualization for decision support.	✓
	Provides transparency throughout the complex product design and evaluation process.	✓
	Allows cross-discipline analysis, including e.g. thermodynamics and mechanics.	✓
	Provides automation, especially when transitioning between different software tools.	✓
Application	Guides and supports the user during application.	✗
	Applicable independently of problem and user.	✓

Faster than existing methods.



Applicable more broadly than existing methods.



ADeVAA performs well when evaluated according to functional requirements, demonstrating its ability to address essential functionality in the product development process. Guided by the DoE, ADeVAA is adept at facilitating extensive design modifications and exploring most of the design space. Utilizing advanced CAD modeling capabilities, it is able to create parametric CAD models without limitations of geometric complexity or parameter constraints. An independent generation and evaluation of design variations ensures that no corner of the design space is left unchecked to find the optimal design. ADeVAA does not just focus on technical evaluations but also takes the economic implications of design modifications into account. Moreover, It provides decision-making support analysis and clean visualizations that promote transparency throughout the process. Its multidisciplinary capability is demonstrated by integrating multi-domains such as thermodynamics and mechanics. In addition, its automation is highlighted by smooth transitions between different software platforms. Finally, it provides users with a forward-looking cost prognosis, enabling them to assess economic values in the uncertainty of development.

Among the application requirements that ADeVAA meets is its universal applicability to product design tasks. Regardless of the design domain, its complexity, or the availability of historical data and examples, ADeVAA can independently navigate the design space by generating and evaluating design variants to help engineers find the most promising solutions.

Compared to many existing approaches, which may be limited by their inability to provide essential functionality such as mechanical performance evaluations or cost assessments that aren't based on historical data, ADeVAA offers a broader scope. As long as the software can be defined and run automatically via an API, it can be integrated into ADeVAA, making it an integral part of the system. For example, in the two use cases presented, one focuses on mechanical performance only, while the other focuses on thermodynamics coupled with mechanical aspects.

However, ADeVAA is not without its shortcomings. A key limitation is its inability to guide and support users during the application effectively. This is primarily due to the lack of a well-developed user interface. In addition, the fact that the tools that makeup ADeVAA are flexible and interchangeable depending on the design task makes the guidance process difficult. ADeVAA can only provide general guidance for each step and falls short of more specific and intuitive guidance. Therefore, this requirement remains unfulfilled.

Another application requirement that ADeVAA only partially meets is speed. While ADeVAA offers a significant advantage over fully manual methods of identifying feasible designs in terms of time and labor savings, it still falls short of some algorithm-based optimization software. ADeVAA's approach of unfiltered, pure random sampling via DoE can be time-consuming, especially when navigating high-dimensional design spaces with multiple and

restrictive design requirements. In these situations, some optimization programs can deliver results faster. Therefore, when evaluating the "faster than existing methods" criteria, instead of a "fully satisfied" rating, it can only be "partially satisfied".

Comparison against other comparable approaches

Based on the comparison presented in Table 2.2 in Chapter 2, an analysis can be conducted on ADeVAA in relation to various platforms that integrate both automatic design variation and evaluation capabilities. Table 7.2 provides a functional comparison between ADeVAA and these platforms.

Platform (with design feature)	Generative Design	Parametric Design	Mech. performance informed optimization	FEA	Thermal analysis	Cost-informed optimization	User customization of materials	Detailed CAD model	Programming skills
Fusion 360 (Generative Design) from Autodesk [6], [52]	Yes	No	Yes	Yes	No	Yes	No	No	No
NX (Parametric Design) from Siemens [104]	No	Yes	No	Yes	Yes	No	No	Yes	No
NX (Generative Design) from Siemens [103]	Yes	No	Yes	Yes	Yes	No	No	No	No
Creo (Parametric) from PTC [86], [88], [87]	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No
CATIA (Generative Design) from Dassault [23], [24]	Yes	No	Yes	Yes	Yes	No	No	No	No
CATIA (Parametric Design Study) from Dassault [22]	No	Yes	Yes	Yes	Yes	No	No	Yes	No
ADeVAA	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7.2: Platforms integrating automated design variation and assessment features

When ADeVAA is compared to the modern GD-integrated design variation and evaluation platforms, distinct differences and strengths. One notable difference is ADeVAA's lack of generative design capabilities, which sets it apart from competitors. This absence suggests that ADeVAA may lack the ability to automatically generate design modifications based on algorithms, which could be technically and economically superior to design variations generated from a parametric CAD model. However, while advanced, the complexity of GD's algorithms also poses the most significant challenge to create design variations. This complexity requires additional investment in human resources, training, continued refinement, and understanding of these algorithms. In addition, parametric CAD modeling brings ADeVAA more transparency in generating design modifications. But in this case, ADeVAA shines in its comprehensive performance evaluation. Unlike most GD-based approaches focusing primarily on technical performance evaluation only in the mechanical domain, ADeVAA has a broader functional FEA

framework that ensures enhanced analysis. In addition, what sets ADeVAA apart from them is its economic evaluation with a manufacturing costs calculation model.

While approaches based on parametric CAD models may seem comparable in their technical assessments, ADeVAA differs in its customized economic analysis. It has the capability to calculate manufacturing costs across various cost categories. This ensures a quantitative and transparent economic evaluation of design variations in the detailed design stage of product development, even amidst numerous uncertainties.

ADeVAA is in a different category than numerical simulation-based optimization platforms, which are primarily divided into global and local optimization techniques. Local optimization, while efficient, requires the user to define the optimization parameters and the target region precisely. This specificity can limit optimization to a limited area, potentially missing out on a broader, more holistic view. In contrast, both ADeVAA and global optimization methods search the entire predefined design space to identify technically superior solutions with a comprehensive technical performance evaluation.

Where the two methods differ, however, is in their basic methodology: while global optimization relies heavily on complex algorithms, ADeVAA uses a DoE approach, providing a more transparent and user-friendly path for designers. In addition, while a numerical simulation-based (e.g., FEA-based) global optimization approach is excellent at refining the technical prowess of a design, it often sidelines economic analysis. ADeVAA shines here by providing an assessment combining technical and economic aspects. In addition, global optimization aims to find a unique solution in the target solution space. However, its frequent overlooking of cost implications could render its unique algorithmically derived solution economically suboptimal. In contrast, ADeVAA's DoE framework often identifies multiple technically viable solutions, allowing the selection of the most economically advantageous one.

In the race against time, the efficiency of optimization is primarily determined by the platform's underlying algorithm and the parameters set. Local optimization can provide solutions quickly if the initial conditions and parameters are well-defined. However, it requires deep engineering expertise to reduce the iterative trials, and the results, while optimal in a localized setting, may not represent the global best. In contrast, ADeVAA's DoE method unbiasedly explores the design space. It may not be the most rapid, but its key strengths lie in 1) It automates the entire process of design variation and evaluation to identify the best solution, minimizing manual intervention; 2) as the sample volume grows, ADeVAA's derived solutions get progressively closer to the absolute global best.

Conclusion: ADeVAA demonstrates comprehensive features that make it attractive to other comparable approaches. Its requirements for programming skills show that it is aimed at users who want more flexibility and control over their product development process.

7.2 Applicability

ADeVAA is a versatile design approach that can be used in a variety of fields. Its primary target task consists of product development projects that have at least an initial design or can articulate their design concepts through CAD models, no matter how geo-complex, especially those with complex and restricted design requirements. Whether these technical requirements are interdisciplinary or cross-industry, as long as they can be mathematically evaluated in platforms that support API integration, they can be incorporated into ADeVAA's automatic technical evaluation module. From optimizing aerospace designs for aircraft wings to achieve minimum weight, maximum stiffness, the best aerodynamics, and optimal economics to adjusting automotive strategies to reduce aero-resistance, maintain stiffness, and lower production costs. Even in medical engineering, where the challenge might be to design medical devices to achieve specific therapy goals while ensuring safety operations and cost-effectiveness, or in machine part design, where there's a need to meet rigorous design requirements, find feasible solutions within a tiny solution space, and further define the most cost-effective among them, ADeVAA offers efficient solutions. Its adaptability and flexibility make it an invaluable method for various cases that require iterative design modifications and evaluations.

In this research, the applicability of ADeVAA was validated through two use cases. The first case was in the field of medical devices, specifically the design of an ultra-high power X-ray target. The starting point was an initial concept design, along with dimensions and a series of challenging design requirements, including thermodynamics and mechanics. The design had to ensure robust mechanical and thermal performance even under high temperature and speed conditions. With ADeVAA's support, various designs were developed that met these demanding technical requirements. Not only were they technically sound, but an economically optimal design was selected as the initial final design. The second design challenge was to optimize a critical component within a dynamic rammer - the rubber mount. Due to its unique application, the rubber mount had to be simultaneously stiff for support and soft enough to act as a damper, resulting in a tiny solution space. The existing initial design did not fall within this specified space. With the application of ADeVAA, several feasible solutions were found within this constrained space, and the most cost-effective solution was identified.

Both use cases had a common starting point: an initial design or design concept and specific design requirements. ADeVAA's steps, from 1-9, facilitated the generation of design variations, evaluations of technical and economic performance, and finally, the achievement of the desired outcomes. One of the benefits of ADeVAA is its transparency. Not only can the optimal solution be easily identified, but unexpected designs that were overlooked or beyond the initial human consideration can be brought to light. While they may not always be the final choice for some reasons, they can provide invaluable insight and expand the designer's vision. In addition, with the support of advanced FEA software and multiple validations, ADeVAA provides a

technically accurate and credible assessment that provides a solid foundation to support final design decisions.

However, the application of ADeVAA also identified some limitations. For example, there's an apparent lack of robust validation methods for the cost model. However, the transparent computational model allows engineers to see where costs are derived and get a clearer understanding of the costs incurred in the production process. In addition, while ADeVAA can, in principle, integrate any numerical engineering assessment, the use cases in this research were performed only with FEA, with no use case implemented with other methods such as CFD.

7.3 Adaptability

ADeVAA's adaptability lies in its integrated framework, which allows it to be flexible and adaptable. As design requirements change across industries, the ability to incorporate different computational platforms makes ADeVAA a future-proof application. Its modular architecture allows for integrating other CAD modeling tools or evaluation platforms for technical and cost checks as needed, making it relevant across various sectors and industries.

For example, although ADeVAA was primarily demonstrated using FEA in this research, its framework can easily be extended to include computational fluid dynamics (CFD), thermodynamics, and even customized algorithms. The only requirement is that these evaluations are based on CAD models of design variations, whether in shell or solid form. This adaptability ensures that the current capabilities of the approach do not limit designers and engineers and can freely extend its functionality in response to changing needs.

ADeVAA's adaptability is not limited to its computational capabilities but extends to the design modeling process. The platforms' easy-to-use CAD parameter modeling interface allows users to effortlessly modify design parameters and incorporate constraints without requiring extensive technical expertise. Users can choose any modeling software they are comfortable with; the only requirement is that the software can intuitively create CAD models for complex design without limitations and support automation via API to ensure the automatic generation of design variations. While this study used only SolidWorks to create parameterized CAD models, many other CAD modeling tools, such as CATIA and ProE, can also be integrated with ADeVAA. In addition, should generative design (GD) become more intuitive to modeling tasks through innovative algorithms, it may also find its place in ADeVAA modules. The system's adaptability in creating design variations ensures that as the industry introduces new design concepts or methodologies, ADeVAA can integrate them, positioning it as a continuously developing platform.

In addition, ADeVAA's adaptability allows for multidisciplinary design challenges. Whether it is mechanics, aerodynamics, thermodynamics, or other engineering domains, this platform can adapt its algorithms and tools to provide integrated development solutions. This study presents the design of an ultra-high power X-ray target wheel, integrating both thermodynamic and

mechanical aspects along with economic considerations. Products are becoming more integrated, and financial concerns are increasingly important in determining competitiveness. Therefore, a design approach considering multiple perspectives is essential, making such adaptability even more relevant.

In conclusion, ADeVAA's adaptability ensures it remains relevant, efficient, and essential in the ever-evolving engineering world. Whether addressing industry-specific needs, tackling interdisciplinary challenges, or adapting to new computing platforms, ADeVAA stands out as a flexible and adaptable design solution.

7.4 Computational performance

ADeVAA is characterized by its automated design and evaluation capabilities. At first sight, these facets may seem similar to traditional CAD modeling and other numerical simulations in terms of computational power, primarily because ADeVAA also integrates these components. However, what sets ADeVAA apart is its use of DoE for design variations as samplings. DoE enables unbiased exploration of the entire design space without being constrained by its dimensionality.

When combined with numerical assessment methods such as FEA, this extensive exploration increases ADeVAA's computational requirements. Each sample passes through a comprehensive process, from design generation to technical and economic evaluation. The computational intensity is significant, both in terms of runtime and CPU consumption.

While ADeVAA based on DoE is computationally demanding, it is not without benefits. ADeVAA's design exploration, powered by DoE, avoids pitfalls such as local optimizations at the expense of global considerations often associated with cheaper computational alternatives. The thorough design discovery process ensures that every feasible solution derived from ADeVAA is equally credible. Instead of the singular solutions typically produced by optimization methods, ADeVAA's approach can produce multiple feasible alternatives. In addition, the high degree of automation within ADeVAA eliminates the need for manual intervention after the first seven steps have been established, resulting in substantial savings in human effort and cost.

To address the high computational cost of ADeVAA, several strategies can be employed: more intelligent algorithmic sampling techniques, rather than pure random sampling, can be used in DoE to search the design space with minimal sampling comprehensively. Also, CPU-efficient methods can be used without compromising the accuracy of FEA simulations. For example, choosing hexagonal meshes over tetrahedral meshes can result in computational savings. Although this requires additional effort in decomposing complex structures into simpler ones and their subsequent automation, such methods have been successfully implemented in specific design cases, such as the development of an X-ray target wheel.

8 Summary and outlook

The research introduces an integrated automated approach to product development called the Automatic Design Variation and Assessment Approach (ADeVAA). This approach integrates DoE with random sampling, parametric CAD modeling, numerical simulation, and cost modeling. Applied in two different development tasks, its main function is to automatically generate design variations based on a concept or initial design, and then to evaluate these variations. This evaluation focuses on both technical performance and economic efficiency, particularly in the detailed design stages of product development. The goal is to support the decision for a potential final design with sufficient technical performance and is economic efficiency.

In this research, the two development cases in which ADeVAA was applied have different characteristics. The development task of a target wheel for an ultra-high power X-ray source is challenging due to its demanding technical requirements, which cross multiple disciplines (thermal and mechanical) and are highly restrictive. Such complexity makes traditional or experience-based design approaches less effective in quickly identifying the optimal solution. In addition, The lack of a physical product requires significant effort to validate the numerical simulation model to ensure reliable technical assessments. However, the task is somewhat simplified regarding cost modeling, as manufacturing challenges and developing production technologies limit the range of feasible production strategies and parameters that can be considered.

The development of a rubber mount for the vibratory rammer is based on an existing product from a previous generation, whose technical performance can be evaluated through feasible physical experiments. Consequently, the process of validating the technical evaluation model in this case benefits from more straightforward and intuitive experimental approaches. While establishing the technical evaluation model in this case does not require much effort due to the relatively uncomplicated technical design requirements (only mechanical), the economic evaluation does have to deal with uncertainties in the production process. These include selecting the possible and appropriate production strategies, determining the suitable manufacturing tools, and setting key process parameters such as machining speed. Considering these variables, performing a detailed and quantitative economic analysis in the development process becomes necessary. This involves analyzing multiple production strategies, tooling and production process setups then establishing the cost calculation model.

Applying ADeVAA to these two use cases demonstrates its adaptability to cross-disciplinary development challenges. ADeVAA is not limited by the complexity of the design and offers the potential for large reductions in human resources. An experienced engineer can complete the preliminary model preparation within a few days or weeks, depending on how complex the development task is, after which the process transitions to a fully automated DoE, initiating the process of identifying an optimal solution.

For technical evaluations, ADeVAA ensures models' accuracy and reliability through various validation options. For economic evaluation, it is capable of building economic evaluation models in product development, taking into account different potential production strategies and balancing information gaps. This is achieved by performing dependency analysis between manufacturing costs and design modification to leverage limited information and facilitate quantitative economic analysis of different design variations.

In summary, ADeVAA is proving to be a highly flexible and efficient tool capable of handling diverse design challenges, facilitating both technical and economic evaluations in product development, and streamlining the path from initial design concept to a final optimal solution. However, it is also apparent that there is still greater potential to be realized in the development of ADeVAA.

In the two development cases within this research, ADeVAA uses SolidWorks for CAD modeling and Abaqus for numerical simulation (FEA). However, the main idea of ADeVAA is its broad applicability to different design domains and its compatibility with varying tool platforms. This includes applying other numerical simulation techniques, such as CFD, for technical evaluations in different industries. Regarding platform diversity, ADeVAA is designed to allow users to choose the tools they prefer, whether for numerical simulation or CAD modeling. Recognizing the wide range of user preferences for tool platforms, such as in CAD modeling, where numerous alternatives with similar capabilities to SolidWorks could be preferred, ADeVAA provides flexibility in integrating different platforms.

This multi-faceted adaptability is important to ensure that ADeVAA meets the diverse needs of its users. However, this research did not take full advantage of the broad design scope and flexibility of tool selection. Therefore, future implementations should include design tasks in a broader range of domains and use varying platforms for CAD modeling or numerical simulation. Such an expansion would contribute to the continuous development and refinement of ADeVAA, extending its applicability and adaptability to a wider range of development challenges and tool selections.

In addition, both use cases in the thesis implemented random sampling for their DoE, a simple sampling method in DoE. While Python provides readily available code for this method, there's still potential for improvement in efficiency, especially when dealing with design space consisting of many DVs. An alternative direction would be to investigate more efficient, yet similarly indiscriminate, sampling techniques for DoE. As discussed in Chapter 3.1, such advanced sampling methods may not be available as ready-to-use codes or programs, requiring custom development. Nevertheless, adopting a more efficient sampling strategy could improve the overall efficiency of ADeVAA's process, potentially reducing product development time.

Looking ahead, an important area for ADeVAA to focus on is improving its user support and guidance capabilities. Developing a user-friendly interface or guide that provides step-by-step guidance, especially for inexperienced users, through CAD modeling and numerical simulation would be highly beneficial. In addition, for users without programming experience, an algorithm

that allows for intuitive operations and can be directly translated into generic automated code would be very helpful.

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A: Appendix

Appendix

Algorithm A.1: Entering DVs values into parametric CAD model

Data: Design Variables (DVs) values form file (DVsFile), path to parametric CAD modeling(CADPath)
Result: Updated CAD model
Start CAD Modeling Software at CADPath
for each DV in DVsFile **do**
 Read DVs values from DVsFile
 Enter DV value into the CAD model parameter
end for
Save and close the CAD model

Algorithm A.2: Saving configured CAD models

Data: Path to the loaded CAD model, Desired file format for FE simulations (Format, e.g., .STEP)
Result: CAD model saved in the desired format
Open CAD Modeling Software
for each design variation i **do**
 Check if the CAD file (.STEP file) for variation i already exists
 if STEP file exists **then**
 Proceed to design variation $i + 1$
 Notify "CAD (.STEP) file already exists"
 else
 Load the configured model with DVs values for variation i
 Save the model for variation i in the desired Format
 end if
end for
Close CAD modeling software

Algorithm A.3: Checking CAD models

Data: Path to saved CAD models (ModelPath), Thresholds for checks (Threshold, e.g., minimum CAD file size)

Result: Results of the checks

Access the saved CAD model (e.g., .STEP file) from ModelPath

Check the file size of the CAD model

if size < Threshold **then**

 Delete the CAD file (.STEP file)

 Notify "CAD file is with error"

else

 Notify "CAD File is ok for size"

end if

Algorithm A.4: Importing CAD model and structural pre-processing

Data: Path to CAD files, required DVs values for CAD model Pre-processing

Result: Model is ready for simulation

if CAD file exists at specified path **then**

 Load the CAD model into the simulation environment.

else

 Move to the next file. **return**

end if

if model is incomplete **then** ▷ E.g., missing the 'focal track' in x-ray target wheel

 Reconstruct or adjust missing parts within the simulation platform.

end if

Ensure all parts are correctly identified and mapped.

Algorithm A.5: Detailed setting of boundary conditions

Data: Model geometry, list of materials, list of external forces, list of boundary constraints, list of initial conditions
Result: Model with boundary conditions

Load model geometry

for each material in List of materials **do**
 Define physical properties of material
 for each component associated with material **do**
 Assign material properties to component
 end for
end for

for each force in List of external forces **do**
 Specify type (e.g., point load, distributed load)
 Assign magnitude and direction
 Apply force to respective model region or node
end for

for each constraint in List of boundary constraints **do**
 Specify type (e.g., fixed, hinge, slider)
 Determine affected model region or node
 Apply constraint
end for

for each condition in List of initial conditions **do**
 Specify type (e.g., pre-stress, temperature)
 Assign values or distribution pattern
 Apply initial condition to respective model region or node
end for

Validate all conditions and constraints for conflicts

Algorithm A.6: Meshing and pre-meshing preparations

Data: Model geometry, list of critical regions, meshing parameters (e.g. seeds density, element types), model geometric parameter values
Result: Quality meshed model

for each region in List of critical regions **do**
 Mark region for refined meshing
 Partition region to improve mesh control
 Calculate ideal seed density for the region
 Deploy seeds in the region for refined meshing
end for

Assess entire model to determine if it can be partitioned into simpler structures
if model can be partitioned easily **then**
 Partition model into individual sub-structures
 for each partitioned sub-structure **do**
 Deploy seeds uniformly across the sub-structure
 Generate hexahedral-elements mesh for the sub-structure
 end for
else
 Deploy seeds uniformly across the entire model
 Use tetrahedral elements to mesh the entire model
end if

Algorithm A.7: Configuring and running the simulation

Data: Prepared model (with boundary conditions and meshing completed), Simulation parameter (simulation type, time steps etc.)
Result: Completed simulation with stored results

Choose simulation type (static, dynamic, thermal etc.)
Specify static analysis parameters
Define simulation duration
Set time step intervals
Define maximum allowable increment
Define minimum allowable increment
Select desired results for output
Specify location for saving simulation results
Set number of CPUs for computation
Run simulation
Store final results to specified location

Algorithm A.8: Automated cost calculation

Data: Data files with labor rates, tooling costs, processing speeds, material cost, DVs values
Result: Design dependent manufacturing cost K^* for each design variation
Fetch data from the database: labor rates (flk [€/h]), machine/tool costs (fgk [€/h or €/piece]), machining speeds (v [mm/min]), material cost (mek [€/kg])
Calculate material removal rates (MRR [mm^3/min]) and tool life (l [h])
for each design variation i **do**
 Extract geometric details for design variation i from DVs values files
 Calculate machining time t_i based on geometric details and material removal rates
 Calculate required number of tools n_i based on machining time t_i and tool costs
 Determine material volume V_i required for the design variation

 Check if there are other one-time design-related costs C (for example $SPDC$ or $MtOC$).
 if other costs exist **then**
 Determine the value of each cost ($SPDC_i$, $MtOC_i$).
 Determine the sum of one-time design-related costs C_i .
 $MC_i^* \leftarrow f(t_i, n_i, V_i) + K_i^*$
 else
 $K_i^* \leftarrow f(t_i, n_i, V_i)$
 end if
 Store K_i^* for current design variation in MC^* list.
end for
return K^* list

Algorithm A.9: Automatic DoE with randomization

Data: Predefined design space for each design variable, total number of design variations n
Result: Values of DVs stored in data files named after design variation numbers
for each design variation i from 1 to n **do**
 for each design variable DV_j **do**
 $DV_{j_value} \leftarrow$ random value within design space of DV_j
 Check for dimensional conflicts:
 while there is a conflict **do**
 Adjust the values of conflicted DV_j to resolve conflicts
 end while
 end for
 Save the values of each DV_j to a file named "design_variation_ i "
end for

Algorithm A.10: Data Extraction from Result Files

Data: numerical simulation result file (.obd file of FEA) for each design variation, cost calculation model

Result: Output data of technical and economic assessment results for each design variation

▷ Technical Assessment

for each design variation **do**

 Initialize $maxStress \leftarrow 0$

 Initialize $maxTemperature \leftarrow 0$

for each time frame in FEM result file **do**

for each node in the time frame **do**

$currentStress \leftarrow$ Extract stress value from the node

$currentTemperature \leftarrow$ Extract temperature value from the node

if $currentStress > maxStress$ **then**

$maxStress \leftarrow currentStress$

end if

if $currentTemperature > maxTemperature$ **then**

$maxTemperature \leftarrow currentTemperature$

end if

end for

end for

▷ Economical Assessment

$HK^* \leftarrow$ Extract HK^* value for the design variation from the cost calculation model

$detailedCost \leftarrow$ Extract detailed cost values if needed from the cost calculation model

 Store $maxStress$, $maxTemperature$, HK_{star} , and $detailedCost$ for the design variation

end for

Algorithm A.11: Automatic QoIs calculation and documentation

Data: Results from assessment models, intermediate values for QoIs calculation
Result: QoIs values for each design variation in a result file
for each design variation **do**
 if technical performance assessment result file exists **then**
 Extract values for calculation from simulation results
 Calculate Normalized Technical Requirements Violation ϕ with corresponding intermediate values
 Store ϕ for current design variation in the result file
 end if
 if economic performance assessment exists **then**
 Extract K^* from cost calculation model
 Store K^* for current design variation in the result file
 end if
end for

Algorithm A.12: Calculate production labor cost (PLC_mb)

if $R_{base} \leq 25\text{mm}$ **then**
 $PLC_{mb} \leftarrow \frac{t_{base}}{v_{drill}} \times flk_{drill}$
else
 $PLC_{mb} \leftarrow \frac{t_{base}}{v_{drill}} \times flk_{drill} + \frac{V_{toturning}}{v_{turning}} \times flk_{turning}$
end if

Algorithm A.13: Calculate focal track area A_{ft}

Define the function $f_2(y)$ through the start and end points of the focal track $FT_1 (x_{ft_1}, y_{ft_1})$ and $FT_2 (x_{ft_2}, y_{ft_2})$
 $(x_{ft_1}, y_{ft_1}) = \left(\frac{t_{tip}}{2}, R_b \right)$ and $(x_{ft_2}, y_{ft_2}) = \left(\frac{t_{tip_ex}}{2} + e_{ex}, R_{tip} \right)$
Set $f_2(y) = k_2 \times y + c_2$
Calculate $k_2 = \frac{R_{tip} - R_b}{\frac{t_{tip_ex}}{2} + e_{ex} - \frac{t_{tip}}{2}}$
Calculate $c_2 = R_{tip} - k_2 \times \left(\frac{t_{tip_ex}}{2} + e_{ex} \right)$
Calculate $A_{ft} = \int_{y_{ft_2}}^{y_{ft_1}} 2\pi \times f_2(y) dy$ (Figure A.1)

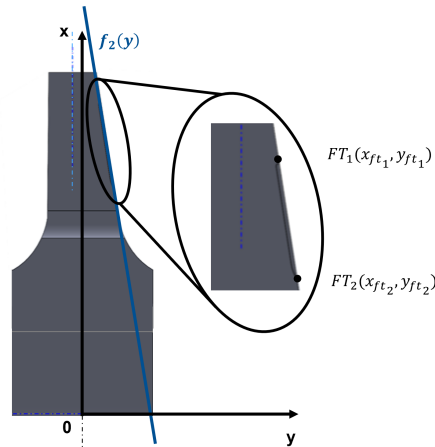


Figure A.1:: Calculate focal track area A_{ft} with formulas

Algorithm A.14: Calculate tool lifetime

Input: factor - the ratio of actual to recommended machining speed

Output: tool life - the adjusted tool lifetime in hours

function LINEEQUATION(factor, tool life)

return the slope and y-intercept of the line equation between factor and tool life

end function

function GENERATEEQUATIONS(factor and tool life)

return a list of line equations for each segment defined by factor and tool life

end function

function CALCULATELIFETIME(x, equations)

return the corresponding y value (lifetime) for a given x (factor) within the piecewise linear equations

end function

factor_drilling $\leftarrow$ Calculate factor based on actual and recommended speeds for drilling

lifetime_drilling $\leftarrow$ CalculateToolLifetime(factor_drilling)

factor_milling $\leftarrow$ Calculate factor based on actual and recommended speeds for milling

lifetime_milling $\leftarrow$ CalculateToolLifetime(factor_milling)

Table A.1.: Cost and operation data used for the use cases in the research work

Name	Syms	Price	Source
Material costs	$mek_{WRe}[\text{€/kg}]$	189	https://www.metallpulver24.de
	$mek_{TZM}[\text{€/kg}]$	200	https://www.pyropowders.de
	$mek_{steel}[\text{€/kg}]$	1.13	https://tradingeconomics.com
	$mek_{rubber}[\text{€/kg}]$	1.5	https://tradingeconomics.com
Tool costs	$fgk_{drill_{hardmetals}}[\text{€/piece}]$	92 ($D < 12mm$)	https://www.kemmler-shop.de
	$fgk_{drill_{hardmetals}}[\text{€/piece}]$	330 ($D = 50mm$)	https://cuttingtools.ceratizit.com
	$fgk_{drill_{steel}}[\text{€/piece}]$	22.6 ($D = 12mm$)	https://eshop.wuerth.de
	$fgk_{edm_{wire}}[\text{\$/piece}]$	62.2 ($D = 0.25mm$)	https://eshop.wuerth.de
	$fgk_{milling_{cutter_{hardmetals}}}[\text{€/piece}]$	150 ($D = 12mm, n = 4$)	https://www.fraeser-shop.de/vhm-fraeser
	$fgk_{milling_{cutter_{steel}}}[\text{€/piece}]$	52	https://www.avantec.de
	$fgk_{turning_{tool_{hardmetals}}}[\text{€/piece}]$	200	https://cuttingtools.ceratizit.com
	$fgk_{turning_{tool_{steel}}}[\text{€/piece}]$	26.7	https://toolineo.de

Table A.1 (Continued)

Name	Syms	Price	Source
	$fgk_{grinding_{tool}}$ [€/piece]	17	https://tooling. weinigusa.com/
Labor costs (in a 35-hour week)	$flk_{CNC_{grinder}}$ [€/h]	22.3	https://www. stepstone.de/gehalt
	$flk_{CNC_{milling}}$ [€/h]	21.9	https://www. stepstone.de/gehalt
	$flk_{machinist}$ [€/h]	21.75	https://www. stepstone.de/gehalt
	$flk_{erosion}$ [€/h]	21.53	https://www. stepstone.de/gehalt
	$flk_{CNC_{cutting}}$ [€/h]	21.26	https://www. stepstone.de/gehalt
	$flk_{general_{machining}}$ [€/h]	22.37	https://www. igmetall.de/tarif/ tariftabellen/ metall-und-elektroindustrie

Table A.2.: Values of DVs of the X-ray target wheel for concept design and the 3 designs with sufficient technical performance

DV	Values (mm)			
	Concept design	3062	6411	3024
R_a	55	140.7	140.7	143.7
t_{tip}	27	100.8	104.05	101.17
R_b	74.21	211.05	211.38	215.55
t_{tipex}	27	11.0891	6.243	8.0936

Table A.2 (Continued)

DV	Values (mm)			
	Concept design	3062	6411	3024
t_{base}	45	200.81	204.05	201.17
n_{st}	12	16	11	14
R_c	10	10	10	10
e_{ex}	0	125.77	53.37	128.89
R_{tip}	120	469.91	475.73	479.7
R_{ll}	65	12.8	18.8	14.8
R_{base}	30.5	94.54	85.34	96.1
$v_{ft}(m/s)$	200	128	106	123

Table A.3:: Values of DVs of the rubber mount for initial design and the 6 designs with sufficient technical performance

DV	Values (mm)						
	Initial design	22	6115	6185	4771	7377	5831
D	80	82.45	84.32	85.12	85.96	85.90	84.18
t	40	32.19	36.12	31.26	38.27	35.58	39.73
Ah_2	19.15	21.17	21.7	22.37	24.81	21.38	22.21
AR_5	3	3.41	3.28	3.22	2.26	2.04	1.79
Al_1	22	26.39	28.63	28.41	27.81	27.43	25.21
Ah_1	26.82	24.21	23.25	24.23	26.94	27.6	28.83
α	60°	113.13°	54.8°	34.39°	37.69°	82.22°	62.18°
R	8	9.35	9.63	10.08	8.02	9.87	10.12
Bl_2	10	16.02	13.42	16.68	14.13	16.2	15.35

Table A.3 (Continued)

DV	Values (mm)						
	Initial design	22	6115	6185	4771	7377	5831
Cl_1	5.84	10.66	12.11	11.25	9.93	11.46	8.88
t_{l1}	3	2.01	1.95	3.17	2.8	2.38	2.89
Cl_2	0.96	3.8	4.35	2.82	3.91	3.4	4.1
Dh_1	14.5	14.81	12.77	13.39	12.18	14.98	14.88
Dh_2	1.5	1.33	2.24	1.46	1.19	1.74	1.31
t_{l2}	5	6	7.05	7.82	6.05	7.08	7.44
Df_2	20	24.34	21.6	21.62	22.38	22.6	23.54
At_1	20	22.93	24.96	22.16	25.18	24.82	25.55
Bt_1	5	4.91	6.39	7.26	5.04	6.17	8.83
h_1	20	19.41	19.36	19.57	20.88	20.94	17.95
Dt_1	25	24.93	25.52	25.66	27.32	26.21	23.96
h_2	25	10.95	11.96	7.95	9.79	6.5	8.34
Df	10	14.66	13.4	12.4	12.19	9.33	12.26