JÖNKÖPING UNIVERSITY
*School of Engineering*

Licentiate Thesis

# Data-driven and Real-time Prediction Models for Iterative and Simulation-driven Design Processes

Mohammad Arjomandi Rad

Jönköping University
School of Engineering
Dissertation Series No. 071 • 2022

JÖNKÖPING UNIVERSITY
*School of Engineering*

Licentiate Thesis

# Data-driven and Real-time Prediction Models for Iterative and Simulation-driven Design Processes

Mohammad  Arjomandi Rad

Jönköping University
School of Engineering
Dissertation Series No. 071 • 2022

Licentiate Thesis in Machine Design

Data-driven and Real-time Prediction Models for
Iterative and Simulation-driven Design Processes

Dissertation Series No. 071



Published by
School of Engineering, Jönköping University
P.O. Box 1026
SE-551 11 Jönköping
Tel. +46 36 10 10 00
www.ju.se

Printed by Stema Specialtryck AB, 2022

SVANENMÄRKET
Trycksak
3041 0234

ISBN 978-91-87289-77-4

七転び八起き

*Fall Down Seven, Stand Up Eight.*

# Contents

## Acknowledgements

This work has been carried out in the Department of Industrial Product development, Production, and Design from 2019 to 2022. I would like to acknowledge the financial support from the Swedish Knowledge Foundation (KK-Stiftelsen) and Jönköping University without which I could not have been able to start and finish this journey.

I would like to especially thank my former main supervisors, Dr. Joel Johansson for trusting me and choosing me for the project, Professor Fredrik Elgh for the warm welcome and showing patience with a lost naive researcher, and my current main supervisor Dr. Roland Stolt for always encouraging me and giving me the ability to drive and follow my passions.

Countless people supported me, mentored me, and taught me along the way, and I can not stop being grateful for each one of them. But among all, I would like to express utmost appreciation to other supervisors Dr. Dag Raudbergt for the helpful attention and well-needed stops at my room, Dr. Mirza Cenanovic for the continuous exchange of ideas and insightful hints along the way, Professor Kent Salomonsson for the giving the best feedback and reassurance that one can wish for, and my former roommate Dr. Tim Heikkinen who has been like an unofficial but vital supervisor for me up to the midway and all the other Ph.D. students and colleagues of the department for all the intuitive tips and fruitful discussions.

Last but not least, I would also like to offer my heartfelt gratitude to my wife, Maryam, who has given me everything unconditionally and unexpectationally, and my mother, my sister and her family for their unending support, patience, and understanding despite the distance.

## List of publications

This thesis is based on the following publications:

I **Data-driven and Real-time Prediction Models for Highly Iterative Product Development Processes**
**Arjomandi Rad, M.**, Raudberget, D., Stolt, R.
*In 29th ISTE International Conference on Transdisciplinary Engineering*, 2022, MIT, MA, USA
(Accepted for publication)

II **Correlation-based feature extraction from computer-aided design, case study on curtain airbags design**
**Arjomandi Rad, M.**, Salomonsson, K., Cenanovic, M., Balague, H., Raudberget, D., Stolt, R.
*Computers in Industry*, 2022, 22(24), 138, 103634.
(https://doi.org/10.1016/j.compind.2022.103634)

III **A CAD-based image regression database enabling real-time prediction during the design process, a case study on the airbag design process**
**Arjomandi Rad, M.**, Cenanovic, M., Salomonsson, K.
*ASME Journal of mechanical design*, 2022,
(Submitted)

Additional publications that are not appended to this thesis:

IV **System properties to address the change propagation in product realization**
**Arjomandi Rad, M.**, Stolt, R., Elgh, F
*In 27th ISTE International Conference on Transdisciplinary Engineering*, Warsaw, Poland, 1-10 July 2020 (Vol. 12, pp. 343-352). IOS Press.
(https://doi.org/10.3233/ATDE200093)

V **Design science meets engineering design**
**Arjomandi Rad, M.**, Stolt, R., Salomonsson, K.
*Clean Design conference*, 2022, The 10th international design symposium, Thailand
(Submitted)

# Author contributions

The contribution of authors is defined based on the guidelines provided by ICMJE.[1].

| | Paper I | | | Paper II | | | | | | Paper III | | | Additional | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mohammad Rad | Dag Raudberget | Roland Stolt | Mohammad Rad | Kent Salomonsson | Mirza Cenanovic | Henrik Balague | Dag Raudberget | Roland Stolt | Mohammad Rad | Mirza Cenanovic | Kent Salomonsson | Mohammad Rad | Roland Stolt | Fredrik Elgh | Mohammad Rad | Roland Stolt | Kent Salomonsson |
| | 1 | 2 | 3 | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Conceptualization | ■ | | | ■ | | | | | ■ | ■ | | | ■ | | | ■ | | |
| Methodology / Study design | ■ | | | ■ | ■ | | | | | ■ | | | ■ | | | ■ | | |
| Software | ■ | | | ■ | | ■ | | | | ■ | | | ■ | | | ■ | | |
| Validation | ■ | | | ■ | | | ■ | | | ■ | | | ■ | | | ■ | | |
| Formal analysis | ■ | | | ■ | | | | | | ■ | | | ■ | | | ■ | | |
| Investigation | ■ | | | ■ | ■ | | | | | ■ | ■ | | ■ | | | ■ | | |
| Resources | | | | | | ■ | ■ | ■ | | | ■ | | | | ■ | | ■ | ■ |
| Data curation | ■ | | | ■ | ■ | | | | | ■ | | | ■ | | | ■ | | |
| Writing – original draft | ■ | | | ■ | | | | | | ■ | ■ | | ■ | | | ■ | | |
| Writing – review and editing | ■ | ■ | ■ | ■ | | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |
| Visualization | ■ | | | ■ | | | ■ | | | ■ | ■ | | ■ | | | ■ | | |
| Supervision | | ■ | ■ | | ■ | ■ | | ■ | ■ | | ■ | ■ | | ■ | ■ | | ■ | ■ |
| Project administration | | ■ | | | | | | ■ | | | | | | | ■ | | | |
| Funding acquisition | | ■ | ■ | | | | | ■ | ■ | | | | | ■ | ■ | | | |

[1] http://www.icmje.org/recommendations/browse/roles-and-responsibilities/defining-the-role-of-authors-and-contributors.html

# Sammanfattning

Utvecklingen av mer komplexa produkter har ökat beroendet av virtuella/digitala modeller och ökat betydelsen av simuleringar för att validera en produkt inför produktion. Ett stort beroende av digitala modeller och simulering tillsammans med den individuella anpassningen och kontinuerliga kravförändringar leder till ett stort antal iterationer i varje steg i produktutvecklingsprocessen. Forskningen som presenteras i denna avhandling studerar denna typ av produkter som har multidisciplinära, mycket iterativa och simuleringsdrivna designprocesser. Det har visat sig att dessa tekniska produkter på hög nivå, som vanligtvis tillhandahålls av underleverantörer, vanligtvis har en lång ledtid för utveckling. Litteraturstudien pekar på flera forskningsspår, exempelvis designautomation och datadriven design, eventuellt med stöd. Efter att ha studerat fördelarna och nackdelarna med varje spår, väljs det datadrivna tillvägagångssättet och studeras genom två fallstudier som leder till att två stödjande verktyg tas fram. De förväntas förbättra utvecklingsledtiden i tillhörande designprocesser. Feature extraktion i CAD som ett sätt att underlätta metamodellering föreslås som det första verktyget. Detta stöd använder medial axis för att hitta korrelerade features som kan användas i regressionsmodeller. När det gäller det andra stödjande verktyget används ett automatiserat CAD-skript för att producera ett stort bibliotek med bilder som är associerade olika designvarianter. Dynamisk relaxation används för att märka varje variant med dess finita elementlösning. Slutligen används detta bibliotek för att träna ett konvolutionerande neuralt nätverk som kartlägger skärmdumpar av CAD som indata till finita elementfältsvar som utdata. Båda stödverktygen kan användas för att skapa modeller för förutsägelser i realtid i de tidiga konceptuella faserna av produktutvecklingsprocessen för att utforska designrymden snabbare och minska ledtid och kostnader.

# Abstract

The development of more complex products has increased dependency on virtual/digital models and emphasized the role of simulations as a means of validation before production. This level of dependency on digital models and simulation together with the customization level and continuous requirement change leads to a large number of iterations in each stage of the product development process. This research, studies such group of products that have multidisciplinary, highly iterative, and simulation-driven design processes. It is shown that these high-level technical products, which are commonly outsourced to suppliers, commonly suffer from a long development lead time. The literature points to several research tracks including design automation and data-driven design with possible support. After studying the advantages and disadvantages of each track, a data-driven approach is chosen and studied through two case studies leading to two supporting tools that are expected to improve the development lead time in associated design processes. Feature extraction in CAD as a way to facilitate metamodeling is proposed as the first solution. This support uses the concept of the medial axis to find highly correlated features that can be used in regression models. As for the second supporting tool, an automated CAD script is used to produce a library of images associated with design variants. Dynamic relaxation is used to label each variant with its finite element solution output. Finally, the library is used to train a convolutions neural network that maps screenshots of CAD as input to finite element field answers as output. Both supporting tools can be used to create real-time prediction models in the early conceptual phases of the product development process to explore design space faster and reduce lead time and cost.

# Chapter 1

# Introduction

The core aim of the product realization is either economic success or addressing a need or a combination of both which is carried on by satisfying requirements like quality, cost, sustainable goals, etc. Since designers are responsible for the technical and economic properties of a product, timely and efficient development results in the commercial success of a product realization process. Therefore, designers strive to improve the Product development (PD) procedure to achieve successful products (Pahl & Beitz 2013). The complexity of the products, the competitiveness of the markets, and also the demands for more variety in shorter times have forced companies to outsource the design and manufacturing of their complete systems or components to suppliers (Liker et al. 1995). Nevertheless, development outsourcing forces communication with suppliers to be focused on the fulfillment of certain functional requirements rather than the manufacture of a design solution (Sutinen et al. 2004). Over the past years, some high-level technical products have emerged with a transdisciplinary design process that are following strict requirements from various stakeholders. Companies with such products work very closely with their customers to satisfy requirement specifications when developing new products. Their products are of high precision and complex and subsequently depended on digital engineering tools. For these products, virtual models and simulations are primary means of validation before production for reducing physical prototyping costs. As a result of this reliance on digital models and simulations, these products often have a highly iterative design process that leads them to suffer from a long development time. Long developing lead time makes requirements susceptible to change because often the customers vaguely know about their needs at the beginning of the development stage which is known as the *design paradox* in the literature (Ullman 1992). The ever-changing and intertwined requirements associate with customers and various other stakeholders such as standard or safety organizations make the design exacerbates iterative nature which adds up to the development lead time. Computer simulations exist from the early phase of the request for quotation (RFQ) phase and play a major role in determining the developing path and final state of these products. Literature confirms that iterations are historically considered a major source of increased PD lead time (Eppinger et al. 1994). Additionally, for these products, it can be said that most of the developing time is spent on iterative manual work of verifying design changes.

## 1.1 Background

Product development is a challenging and costly part of product realization. It takes a lot of time to develop a product and a lot of developing people on board. Modeling PD stages and interactions between them have been a subject of studies for decades. A generic PD process with a handful of methods and guidelines is described in (Ulrich & Eppinger 1995) with six phases which are depicted in Figure 1.1.

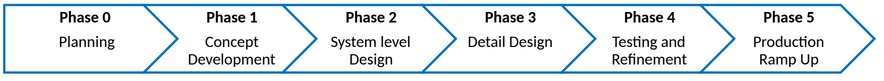


**Figure 1.1:** Generic PD process model by (Ulrich & Eppinger 1995)

Activities that need to be covered in each phase are elaborated in detail, at different levels (Marketing, Design, Manufacturing, and other functions). Emphasizing the generic nature of the exhibited process, the authors argue that each company needs to adapt these steps based on the context of the company and the challenges of the projects. Also, the process might not follow such a sequential fashion, as many factors could cause overlapping between phases, step-backs, or iterate activities. Pahl and Beitz define the PD process as a general problem-solving process, or as a general decision-making process (Pahl & Beitz 1984). They propose a practical and procedural Product development process (PDP) as illustrated in Figure 1.2, and mentioned that any process model has to be considered as operational guidelines for activities based on the patterns of technical PD and the logic of stepwise problem-solving.

One can identify several other development process models, for instance (Hubka & Eder 1988), (VDI 1993), (Stauffer & Ullman 1991), and (Suh 1998) and each of them is established to describe the PD process in one way. These process models can give intuition to the flow of work or activities, but they can also conceal one aspect or part of the work. For instance, even though the early linear stage-gate methods (Cooper 1990) have received great appreciation in terms of saving devel-

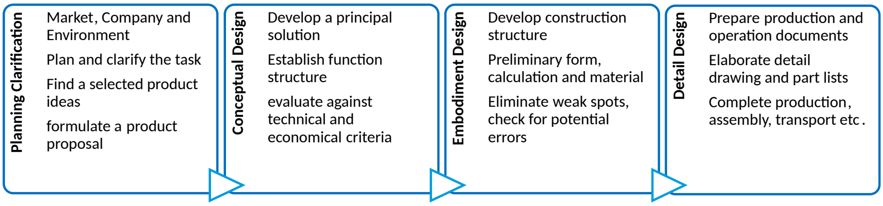


**Figure 1.2:** Generic PD process model by (Pahl & Beitz 1984)

opment time, at the same time, many failures are also reported by various industries. Some of the process models are criticized for being too rigid to handle, too planned to be innovative or dynamic, too controlling, and bureaucratic, with too much nonvalue-added work (Cooper 2014). Choosing the best process model for a design process is not trivial and needs attention to multiple factors. The degree of formalism is one of the factors to consider when choosing from a wide range of processes. A structured design method increases design transparency and helps achieve complex objectives by preventing unnecessary iterations. On the other hand, too structured methods reduce the clarity as well as creativity and make it prone to longer development lead time. A simplified process leaves tasks for interpretation which can cause chaos when the objective involves several stakeholders. Controlling the level of formalism (granularity) of the design process models, is one way to adjust model transparency and traceability and consequently its efficiency. Examples of this can be found in design automation (Heikkinen 2021) and engineering knowledge management (Johansson et al. 2018).

PD process models are categorized differently in the literature. Wynn et al describe four main groups of models (Wynn & Clarkson 2018) where each group can range from a detailed micro-level model with a focus on individual process steps to a macro-level with a focus on project structure. The first group (Management/Operation) is on the conceptual level and describes overall recommended design strategies. The second group (Procedural) is more systematic and supports the execution of design steps. The design process models in this research will be of this type. The third set of models (Analytical) is more focused on providing procedures or solving problems encountered during the design and development process and the fourth group of models (Abstract) focuses more on describing the interaction processes between different stakeholders in the design process. Common ground for all PD models is to have iterations of analysis, synthesis, and evaluation steps as their core.

### 1.1.1 Iterative design

Intuitively and historically in PD, the creation of design follows its physical evaluation and then modification and validation iteratively until th,e desired requirements are met (Vellathottam et al. 1997). Almost any model for PD is following an iterative cycle of designing, building, and testing. This traditional Design-Build-Test cycles are performed at different development levels (system, subsystem, component) at each stage of the product realization process (concept, engineering, pilot production). In the early conceptual phases and late pre-production level, the iterations are at the higher system level but in the middle engineering phases, they are performed at the lower component level. As illustrated in Figure 1.3 the process which is referred to as prototyping is a basic building block of any development activity (Wheelwright & Clark 1992).

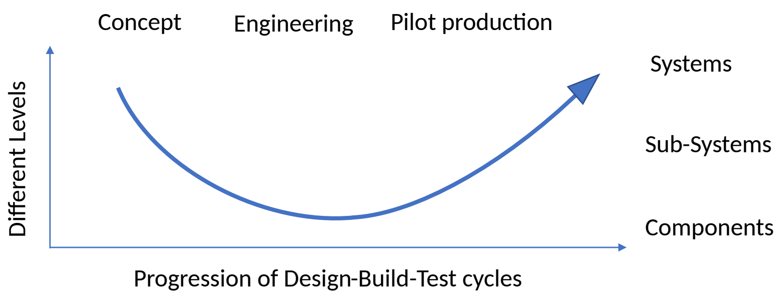


**Figure 1.3:** The traditional path of Design-Build-Test cycles (Wheelwright & Clark 1992)

Repeating certain tasks to improve the design is one way of defining the iteration in the design process. Some authors defined iteration as the process by which a solution is approached step by step (Pahl & Beitz 1984). And others as repeating an already completed task to incorporate new information (Ulrich & Eppinger 1995). There is another definition that is less concerned with the repetition of a task and more focused on the thought process that justifies the need to perform that activity, named the heuristic reasoning process. Other researchers consider iterations as cognitive cycles for designers to gather knowledge, process them, make revisions and execute them with the goal of improvement (Adams & Atman 1999). Thus, the definition of iteration ranges from simple repetition to a pattern of a designer's behavior. This classification is expanded to three type of iteration called, rework, design, and behavior, based on design process attributes such as activity, abstraction level, and scope (Costa & Sobek 2003).

Iterations are an inherent and unavoidable characteristic of any development process (Pahl & Beitz 1984), (Ullman 1992). This is because breaking down a problem and solving it in iterative and smaller steps is a good way of attacking complex and intertwined design problems. The more iterations need to be performed, the more duration and cost the project will have. On the other side, with iteration comes accuracy and highly iterative design processes are favored for high precision and complex products. The design process, in general, is a form of problem-solving and all forms of problem-solving follow a similar cycle of activities. General problem solving can include, Problem definition, Design value system, Synthesis of system, Analysis of system, Choosing the system, and Implementation planning (Bellgran & Säfsten 2010). Each phase in the model depends on the outcome from the previous phase. Several of the phases are strongly connected and it is necessary to iterate back and forth between the phases.

### 1.1.2 Simulation-driven design

The goal of simulations is to validate a concept idea or design. Simulations are usually considered where observing or testing the real-world experiment is expensive or impossible, and where analytical solutions are too complicated, or costly to be validated (Maria 1997). Many simulation analysis methods can be used in the design phase to improve design variants and respond to changing requirements. Simulations utilize models (defined as simpler representations of systems) to study the behavior and performance of a system, mainly to reduce the chances of failure in meeting requirements. More detailed models are more effective in addressing the occurrence and consequence of unplanned iterations. However, due to the simplified nature of models, some researchers argue that no modeling framework or simulation model can capture the full complexity of iterations in PD (Wynn et al. 2007).

Simulation-driven design (SDD) (Sellgren 1999) has been defined as a design process where the majority of the detailed design is performed with computer-based product models. SDD uses studies on the behavior and performance of a system as the primary means of design evaluation and verification in all major phases of the PD process, (Shephard et al. 2004). This evaluation is concerning various properties of a system for example mechanical, electrical, chemical, software, control engineering, etc. SSD aims to move simulation technology from the middle and the late cycles of a design process to the very front cycles and in this way, lower the time it takes for companies to develop products. Introducing simulation analysis very early in the design process (Roth 1999) is called front loading which prevents the back and forth between stages and saves a lot of time in PD but it also makes the process highly dependent on these simulations. Today, the role of simulation design has evolved beyond just validating Computer-aided Design (CAD) models (Lockwood 2009). Just as it was speculated by Bossak nearly two decades ago, SDD has evolved into a shared, highly flexible, information-based, responsive design environment with plug-and-play interoperability across dispersed and dissimilar environments (Bossak 1998). An integrated design environment such as SDD can allow virtual prototyping and therefore increase manufacturability, lower lifecycle costs, and improve the quality and performance of future products.

Simulations in PD have grown to be an umbrella for a diverse range of methods. For instance, in the mechanical design field, computer-aided engineering (CAE) was first introduced in 1980 by J. Lemon as a way to provide analytical information in a timely manner in the PD process. But Lemon's proposed concept was later differentiated with CAE as a new concept and named Virtual prototyping (Kojima 2000). CAE today is a way to address the use of computer software to simulate a physical phenomenon in which the application of software may include validation and optimization of a product or a process (Merkel & Schumacher 2003). CAE analysis in commercial software commonly consists of three major steps: preprocessing (creating a model by idealization), processing (physics-based system of equation is solved), and postprocessing (the results are graphically presented to the stakeholders for review and analysis or decision making). With advances in computers and modeling techniques and the need for more focused products, many commercial tools have been developed with a focus only on one of the mentioned three steps. Strategic implementation of CAE analysis is vital for the success of the product, meaning that it should be thoroughly and appropriately integrated into the PD process (King et al. 2003).

## 1.2 Problem description

Iterations are considered a major source of increased development lead time (Eppinger et al. 1994). Some researchers (Will 1991) suggest that a major decision on the cost (85%) of a product is incurred directly due to decisions made before the product design is released to manufacturing. Similarly, Osborne (Osborne 1993) reported that iterations accounted for 13 to 70% of the total development effort for nine projects. Other researchers (Ulrich & Pearson 1993) argue differently by creating a methodology to evaluate the question "Does design determine 80% of the manufacturing cost?". They analyze a coffee maker's total production cost and conclude this percentage is lower than common belief, but it is still significant. Aside from the exact percentage, iterations lead to a lot of manual work with CAE and CAD that can take up a significant amount of total engineering man-hours in a company. Thus, it can be argued that design iterations are taking up a lot of time in development and overall they increase the total cost of a product, making them the cause for the lead time problem.

Considering a problem-solving definition for PD, iterations can be seen as "bundles of problem-solving cycles" that each consist of activities for designing, building, and testing phases (Fujimoto 2000). In this definition, the managers and engineers aim to resolve the bundles of problems by compressing, simplifying, front-loading, or overlapping the activities at each of the phases to achieve a shorter lead time. As a result of this approach, problems are easier to address in the early phases. It takes more cost and time to solve problems later in the development projects, while the fidelity of the early simulation models tends to be lower (Clark 1991). A lesson learned from 1990s Japanese automaker companies and the lean movement is introducing improved technologies which can eliminate irrational waste in different PD stages (Sei 2000). For instance, during 80s, applying lean approaches resulted in rapid development that gave the leading Japanese firms significant advantages in forecasting consumer preferences and offering newer designs (on average), faster paybacks, and more innovative products incorporating newer technologies (Wheelwright & Clark 1994, Clark 1991).

Total lead time for a product realization process (also known as the time to market) consists of development lead time and process lead time with start of the production as the separation point. The trend in the automotive industry over the last decades has been to utilize digital PD tools such as CAD and CAE to decrease the amount of necessary physical testing. For instance, the lead time from styling freeze to start-of-production in the Audi motors company has been decreased from five years to only two years and still shows to have some room for improvement (Roy et al. 2006). Waste in any form (waiting time, iterations, etc.) consumes critical technical resources and a process's lead time is proportional to its amount of waste (Garcia & Drogosz 2007). However, it should be also noted that shorter lead time does not necessarily result in a successful product or PD process, but it does result in fewer engineering man-hours, which means more competitiveness for the companies. Undoubtedly, with the development of digital tools and their increased capabilities over the last two decades, the total lead time has been reduced especially in physical prototyping and testing. However, the change has resulted in increase for the lead time for digital evaluation of a product. This has resulted in a long development lead time to be one of the main problems in product realization today.

The problem area of the current research is development lead time. An example of typical development work for a digital evaluation of a product as well as waste in form of the waiting times and iterations that take to solve the problem is shown in Figure 1.4. This model also shows different forms of waste can be coupled with each other. For instance, reducing the number of iterations can cause a reduction in total waiting time, however, reducing the waiting time between iterations does not contribute to any reduction in terms of the number of iterations. As discussed, earlier iterations are generally considered good for the development and optimization of a product. Thus, aims is to offer solutions for the problem area with a focus on reducing the waiting time between iterations and not eliminating them.

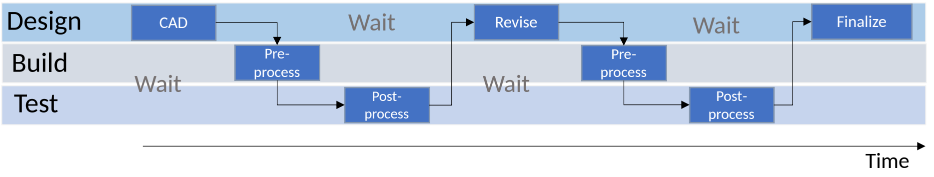


**Figure 1.4:** Workflow for digital evaluation loop (Adapted from Neural concept SA)

The requirement specification aims at describing product functions and constraints in the PD process as well as giving a unified impression to all stakeholders involved in the project (Pahl & Beitz 1984). However, due to the described long development lead time, these requirements change all the time and are rarely fixed during the development life cycle. Requirement management tries to capture, disseminate, maintain, share, and validate product requirements (Fiksel & Dunkle 1990) to address fluctuations. A large body of literature exists that aims to model and understand how this management can address requirement fluctuations. From a development lead time point of view, the fluctuations are not a reason for the long development time, but it is the cause of it. Because suppose the lead time problem is addressed by a supporting tool that could cover up for it by accelerating iteration exploration, then the fluctuation of the requirements will no longer be an issue in the PD since they will not affect the lead time anymore. As discussed, iterations are resented for creating a long lead time but if they can be covered fast, then the development will not take so long. Effectively addressing the problems of the outlined design process is challenged in both executing iterations rapidly or efficiently, and linking individual iteration cycles so that solutions are coherent. Moreover, for high-level technical products, cost and quality are two conflicting requirements that obstruct the improvements in lead time, resulting in a wide variety of methods to improve the execution and linkage of problem-solving cycles. To narrow down, the scope of the attacking problem is limited to only a long-developing lead time which is believed to be a common problem among high-level technical products. For summarizing Figure 1.5 shows the design processes and their associated problem area addressed in this research.

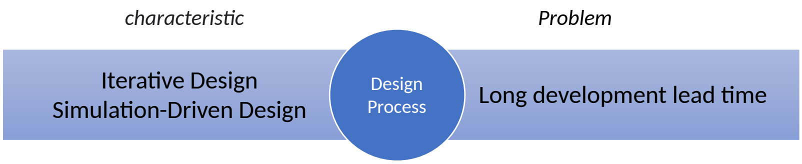


**Figure 1.5:** The design process with several characteristics and a problem

## 1.3 Motivation and purpose

Prototypes reduce the risk of costly iterations by reducing the possibility of making an error in downstream stages which expedites the development steps and improves the lead time. Prototyping in product design and development ranges from physical to analytical and aims to answer questions like ‘How well does it work?’ (Eppinger & Ulrich 2015). Analytical prototypes are mathematical approximations and therefore are highly flexible. They will generally contain parameters that can be varied to represent a range of design alternatives. Within this definition, the analytical prototypes are analogous to building models or simulations. Intuitively, changing a parameter in an analytical prototype is easier than changing an attribute of a physical prototype. Thus, the purpose of this research is to provide supports that improve the efficiency (with respect to development lead time) of the analytical prototype in a group of products that have iterative and simulation-driven design process. However, since analytical prototypes are merely approximating models and fail to completely represent all the aspects of the physical phenomena (just as discussed about simulations) and therefore, often physical prototypes are needed at later stages to validate early analytical prototypes.

After the third industrial revolution which aimed to initiate the use of computers for digitalization and automation, the latest and fourth industrial revolution, so-called Industry 4.0, is marked by large scale and integrated digitalized assets, Artificial Intelligence (AI), Big Data, Cloud Computing technologies, predictive analyses & maintenance, Internet of Things, etc (Keleko et al. 2022). Integration of designing and testing (i.e. systems like CAD and CAE) which is the aim of the presented supports in this research is one of the major goals for Industry 4.0 that can facilitate communication, accelerate design iterations and in turn, reduce the development lead time. Meanwhile, engineering design has an undeniable role in the current industrial revolution (Tatipala et al. 2021). For achieving its purpose, this research is utilizing assets from industry 4.0 such as automation and artificial intelligence.

The digital twin is a concept developed in recent years and refers to a virtual environment with assets that carry the footprints of a physical system. It aims to reduce the time to market lead time by enabling real-time data gathering, real-time processing, as well as real-time decision-making in a transdisciplinary environment (Boschert & Rosen 2016). In this sense, the data-driven and real-time prediction model proposed in this research is contributing to the same goals of achieving an integrated real-time development process. This research is narrower in the case studies as they only address simulation of mechanical properties of a product, but richer and broader and more like a digital twin in the envisioned design process models as it can potentially connect different value chains from different disciplines.

Most of the economic, environmental, and societal impacts of a product are related to the decisions that are taken during the design process (He et al. 2020). Designing a product means deciding on the product's lifecycle, and consequently, product design can play an important role in addressing sustainability-related problems. Therefore, sustainable development has become one of the core global concepts for many countries and international organizations and lead to a huge focus on the issue. The Sustainable Development Goals (SDGs) are a collection of 17 global goals (Desa et al. 2016) designed to be a "blueprint to achieve a better and more sustainable future for all" July 2017 (UN resolution A/RES/71/313). Sweden aims to be a leader in the implementation of the 2030 Agenda -both nationally and globally (n.d. 2018). The 2030 Agenda involves a process of gradual transition and further development of the Swedish social model as a modern and sustainable welfare state. These goals are concerned with integrating different parts of PD, so as to have an overall more sustainable process. This research is directly contributing to goal *n.9. Industry, Innovation, and Infrastructure*. This is because reducing the long lead time will free up resources that can be invested elsewhere. Additionally, *n.12. Responsible consumption and production* because the application of the support and achieving the aims of the research will result in much responsible production. For instance, reducing the need for physical testing means less material and energy will be wasted. Also, this research is indirectly contributing to goal *n.3. Good health and well-being*, in the sense that the application of the study is on a safety-related product that has a great environmental impact and contributes to its efficient lifecycle, is also a contribution to the environment.

## 1.4 Research Questions

This research aims to study the problem of long development lead time. The design process studied is transdisciplinary, highly iterative, and simulation-driven, therefore these characteristics need to be considered when developing support. To this end the following research questions have been formulated:

**RQ1:** What current strategies and support exist to respond to long developing lead time and changing requirements in iterative and simulation-driven design processes?

By answering this research question, the current and existing supports in the literature that deal with the same type of problem will be explored to find out their advantages and disadvantages.

**RQ2:** What criteria are important for faster development and requirements management in iterative and simulation-driven design processes?

By answering this research question, affecting factors for long lead time will be identified. Identified best possible solutions will be developed to identify the limitations and possible success factors for proposed solutions will be discussed.

**RQ3:** What models, methods, or tools can be used for faster development and requirements management in iterative and simulation-driven design processes?

By answering this research question, the solution will be further refined and applied to an in-house developed prototype. The effectiveness of the solutions in satisfying the objective will be studied concerning success factors.

## 1.5 Scope and Delimitation

By iterative design processes, we imply to refine and improve concepts incrementally and avoid excessive physical testing. So, iterations in this research are of a positive character that enables improvement, therefore should not be eliminated. The focus of this study is not to reduce the dependency of the product design on simulations and thus not to do fewer iterations but instead to do them smarter and more efficiently.

Simulation-driven design is a broad knowledge area that entails a lot of disciplines. Mechanical, electrical, chemical, software, and control engineering disciplines all use simulations in various forms and sizes to help the development process of complex products. However, the interviewed case company in this research uses mostly the term CAE equivalently and interchangeably for simulations and their design process is driven by computer-based finite element analyses for testing and validation. Consequently, the case studies performed in the current study are confined to this meaning and not on the other types of simulations such as the agent-based, the discrete event, multimethod, etc. that are also widely performed in PD.

# Chapter 2

# Research Methodology

This research is conducted according to Design Research Methodology (DRM) which is one of the many methodologies that exist in design science. The difference between Design Science and Engineering Design is one of the important distinctions that need to be pointed out for in this research. Design Science is about developing and improving the know-how of the design process by scientifically performing research on it and Engineering design is about developing and improving a product or a service by engineering tools and methods. However, one cannot neglect the similarities between these two as well (Eekels & Roozenburg 1991). The current research does not contribute to the development of some products. Although in the performed case studies, product's performances and properties are studied, yet the proposed support intends to change the way these products are being designed. Thus, it contributes to the design process of a group of products and the proposed tools in this research contribute to the design process of those products by making them faster and consequently efficient.

## 2.1 Design Research Methodology

This section is based on (Blessing & Chakrabarti 2009) methodological framework on DRM. The framework consists of four stages as displayed in Figure 2.1.

*Research Clarification (RC)* is all about clarifying the work which is about to be done and finding some information to back up the assumptions. It can be done by looking up literature or other means of information gathering that helps to explain the research. The outcome of this stage is a description of the existing and desired situation. Also, a success criterion is formulated so that the outcome of the research

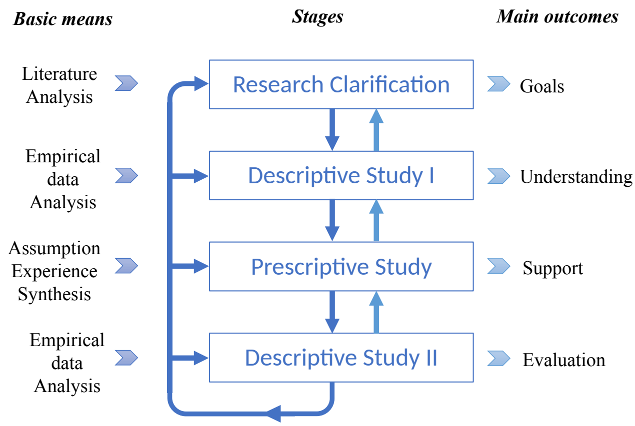


**Figure 2.1:** DRM framework (Blessing & Chakrabarti 2009)

could be evaluated. What is measured for success criteria should be aligned with the subject under investigation. For example, when investigating timeframe, an increase in profit cannot be used but the reduction in time-to-market is a more useful criterion.

By *Descriptive Study I (DS-I)*, the researchers know about the goal and focus, but more literature study is needed to investigate influencing factors and to shed light on the current situation. Some gap analysis might be done and areas that literature does not have any answer to it is identified. Other methods to increase knowledge about the problem like interviews, field observation, etc. could be used, and then gathered data should be analyzed to determine which factor(s) improve task clarification and our understanding of the situation.

Blessing & Chakrabarti use the term 'support' to represent possible means for improving the process (Blessing & Chakrabarti 2009). A support can include "strategies, methodologies, procedures, methods, techniques, information sources, software, tools, guidelines, etc., addressing one or more aspects of design". *Prescriptive Study (PS)* is about finding the support and evaluating it. The researcher should have a complete understanding of the existing situation when moving on with this phase. Their description will guide them into identifying factors or ways that get them from existing to the desired situation. Several supports could be developed in a systematic way to address different scenarios as long as they verify underlying assumptions. Whether the support has the desired effects, is investigated in the next phase.

*Descriptive Study II (DS-II)* is about finding out how well the support works and if it can satisfy the desired situation. To this end, more empirical studies could be done to find out the usability of support. If the study shows that the support is applicable but it is less useful than it was intended, then further investigations of the existing situation are needed and the picture of the desired situation needs to be adapted accordingly before the tool can be improved this recommends a revisit to the DS-I stage. The double arrows in the picture show the fact that the researcher is allowed to revisit the stages to make sure the foundation of research is on solid ground.

## 2.2 Research design and quality

In this section, some issues considering how the research has been designed and what could contribute to its quality will be discussed.

### 2.2.1 Data type

From a data type perspective, this research can be divided into two main parts. The first part which includes Research Clarification and Descriptive study One (DS-I) involves scoping many improvement areas in companies. There are a lot of interviews done with different people/roles and all of these interviews are studied. This qualitative data is then analyzed, which means qualitative research is performed at this stage. Clearly, qualitative research is a kind of research that relies on unstructured and non-numerical data. According to (Hammarberg et al. 2016) qualitative research is appropriate to answer questions about experience, meaning, and perspective, most often from the standpoint of the participant. It is used when there is no single answer to the problem. The second part of the project which includes Prescriptive Study (PS) and Descriptive Study II (DS-II) includes building support to address raised problems. The work includes working with programming languages and mathematical equations explicitly or implicitly through commercial simulation software. Thus, lots of quantitative data are validated and improved through quantitative methods.

### 2.2.2 Reasoning

In different sections of this research different types of reasoning, and methods are used, mainly dependent on what was aimed to accomplish. *Inductive reasoning* is characterized by the inference of general laws (conclusion) from one or more instances (premises). *Deductive reasoning* is characterized by the inference of premises from a general conclusion. *Abductive reasoning* inference to the best explanation differs from deductive reasoning by the direction of the reasoning relative to the conditionals. Deductive reasoning goes in the same direction as that of the conditionals, whereas abductive reasoning goes in the opposite direction of the conditionals. Some researchers (Summers 2005, Lu & Liu 2012) map these definitions to design science. According to them, Inductive reasoning seeks to generate appropriate design knowledge based upon the given set of design variables and design specifications (patterns of observed phenomena). Deductive reasoning is where the design variables (grounds) and the design knowledge (warrants) are given and the design specifications (conclusions) are derived. In abductive reasoning, the design specifications and the design knowledge are given, and the design variables are derived. Figure 2.27 is a schematic example of what a deductive pattern can look like in a design problem. Clearly, abductive, and inductive also could be derived with flipped arrows. In design research also, design variables can be mapped to clarify research elements, design knowledge to support, and the design specification to research evaluation results.

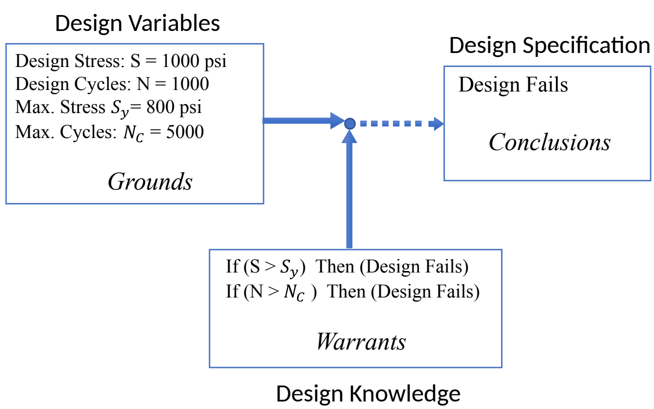


**Figure 2.2:** Deductive Pattern in design science (Summers 2005)

### 2.2.3 Semi-structured interviews

In essence, Semi-structured interviews are conversations in which the interviewer allows the respondent to express his or her own feelings and give distinct examples instead of solely shallow answers and add in-depth insight into the challenges. Some characteristics of the semi-structured interview are; questions to be used flexibly, specific data required from all respondents, the largest part of the interview guided by a list of questions or issues to be explored, and no predetermined wording or order exist (Merriam & Tisdell 2015). This is important to remember, as the main purpose of a semi-structured interview is to make it feel more like a conversation rather than questioning.

Many researchers in the product and production development discipline use semi-structured interviews to gather information about how companies work and what processes they follow. A typical process that is also being used in this study can be viewed in Figure 2.3 in the adopted form (Flankegård et al. 2019). In this process, first keywords and phrases were noted when reading the transcripts and then categorized into themes. Next, all quotes exemplifying the codes were copied to a spreadsheet together with the keywords and phrases indicating different themes, and the naming and categorization of the challenges were developed. In the next phase, these categories will be presented at a workshop with the management team and interview respondents at the studied company to receive feedback on the categories.

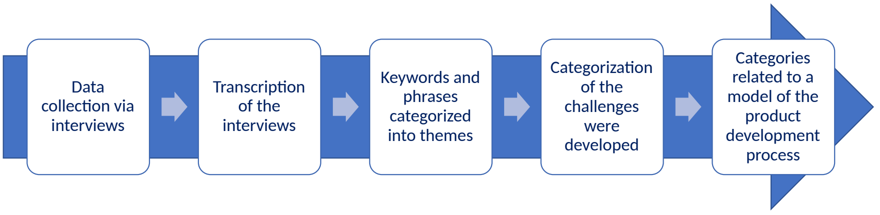


**Figure 2.3:** Interview process and the analysis afterward (Flankegård et al. 2019)

## 2.3 Validity and Reliability

The willingness of respondents to be good informants has implications for the validity of the data in semi-structured interviews. Therefore, in this study for validating data, triangulation is proposed. This has been done by not relying on one source of the data for acquired information and facts and trying to validate them through multiple sources of data. This is a way of assuring the validity of research through the use of a variety of methods to collect data on the same topic, which involves different types of samples as well as methods of data collection (Yin 2011). This has been achieved by participating in some of the internal meetings of the companies and also some observation sessions with different actors that are working on the same tasks and also combining observations and interviews and enabling a data collection with triangulated insights, which provided great evidence and trustworthiness for the research. As for the Reliability of proposed support during Prescriptive Study (PS) and Descriptive Study II (DS-II), the final solution that is applied to the designed prototype is validated by acceptance.

# Chapter 3

# Theoretical Framework

In the introduction section, a prevalent problem is identified within design processes characterized as being iterative and simulation-driven. As mentioned in the introduction, the wide scope of methods addressing the development lead time problem does not allow for discussing all the existing methods here. However, this chapter propels through some of the methods in knowledge-based engineering and data-driven design as two mainstream topics on top of which this research is built.

## 3.1 Knowledge-Based Engineering

Knowledge-Based Engineering (KBE) is the use of advanced software techniques to capture and re-use product and process knowledge for several goals, among others, to reduce lead time. The use of KBE allow complex rules, heuristics, artificial intelligence, and agents to be embedded in the system. In addition, some KBE systems provide more direct control over geometry and topology and feedback to the system. These systems leverage the reuse of design knowledge to eliminate mundane tasks within the design iteration.

Unlike traditional CAD, KBE systems can capture the intent behind the product design by representing the 'why' and 'how' of a design, in addition to the 'what' of a design (Saxena & Irani 1994). The geometric description is only one piece of information about the total product model. Moreover, CAD is a tool for generating geometry while KBE goes further and deals with both geometric and non-geometric knowledge (Stokes et al. 2001), which makes KBE essentially an extended form of CAD models. Numerous methodologies for building KBE applications have been developed, and most tend to be complex modeling tasks, with emphasis on knowledge acquisition and modeling processes. KBE systems aim to capture product and process information in such a way as to allow businesses to model engineering design processes and then use the model to automate all or part of the process (Pinfold & Chapman 2001).

By storing knowledge to assist the design process, KBE enables computers to take the dull routine. Therefore, KBE is most effective when handling iterative design processes that are performed manually and take a lot of development time (Stokes et al. 2001). The product design process as a model connects the information to the know-how and companies pursue to transform the implicit tacit knowledge into explicit and sharable information resources (McMahon et al. 2004). From an academic viewpoint, KBE aims to study implicit and explicit knowledge in the PD process of a company and provide opportunities for reuse, modification, or improvement, but from an industrial viewpoint, KBE should meet more tangible benefits such as reduced lead time or resource use (Van der Velden 2008).

Another definition for KBE, considers it as the application of knowledge-Based System (KBS) technology in the domain of manufacturing design and production (La Rocca 2012). For example, in the same way, that Artificial Neural Networks (ANNs) attempt to simulate the human brain's ability to learn, KBS represents the ability of artificial intelligence in problem-solving. KBE systems aim to capture and systematically reuse product and process engineering knowledge with the final goal of reducing the time and cost of the product development through automating iterative tasks and optimization of the design process (La Rocca 2012). In this definition, KBE is a shared concept between AI and CAD and programming where captured knowledge and reasoning mechanism are augmented by geometry handling capabilities to provide engineering design solutions.

### 3.1.1 Requirement Management

For any developed system, correctly capturing user requirements plays a central role in the effectiveness and flexibility of the delivered system. A customer specification is a document that describes the requirements of the desired system from the customer's point of view. For many products, managing customer specifications and requirement is essential and can reduce the design loops as it contributes to clarity in the process.

A four-step process for defining and managing stakeholder requirements has been proposed (Nilsson & Fagerström 2006) to provide a common understanding of different stakeholders, requirements, functions, and systems during the design of a product, especially management of different stakeholders that affect the product. The proposed model supports the iterative and evolutionary nature existing between function and solution by using a function-means structure. This co-evolution between function and form supports Value Analysis and assists in the distribution of appropriate functional and constraining requirements to each sub-supplier. André, et al (Andrè et al. 2014) studied four different companies to find out how they handle fluctuating requirements and proposed a model for the interface between technology development and product development. A need for strategies on how to be flexible when engaging in product and technology development is identified. This would likely improve the companies' ability to manage fluctuating requirements. And later (André et al. 2016) developed a support system called Design Platform Manager to utilize platforms to efficiently meet product customization demands and applied a platform approach for a supplier active in the automotive industry.

Additionally, agile and flexible design is used as a means of handling changing requirements and variations (Thomke & Reinertsen 1998). The authors propose keeping requirements simultaneously frozen and liquid as an analogy for the way a newspaper is structured to allow different time horizons for completion. Some parts of the newspaper are planned and written weeks in advance, while others are not finalized until the last minutes before printing. This comparison implies that the requirements are planned to be frozen in succession, rather than all at once. This way, designers do not have to predict an uncertain future.

### 3.1.2 Design Automation

Design Automation (DA) systems have a history of application and research for several decades and are considered a subset of knowledge-based engineering. DA has been defined (Cederfeldt & Elgh 2005) as "engineering support by the implementation of information and knowledge in solutions, tools, or systems, that are pre-planned for reuse and support the progress of the design process. The scope of the definition encompasses computerized automation of tasks that directly or indirectly are related to the design process in the range of individual components to complete products". Four aims are mentioned for DA including a cut on lead time and the ability to adapt to different customer specifications which make DA a suitable approach for the problem area of current research. DA has been divided into two major categories: Information handling and Knowledge processing which makes DA not only a means for improved efficiency but also a method to reduce lead time, improve offer precision, quality assurance, and an enabler for higher degree of customer adaptation (Elgh 2007).

Notwithstanding the broad theoretical definitions and considering only the practical applications, DA boils down to using programming to connect design tools/assets to and facilitate the design process by letting the computers map design requirement inputs to design objective outputs. The argument can be exemplified through the DA in the different automation levels of the CATIA, shown in Figure 3.1, which includes support on several different levels of varying capability and complexity (n.d. 2006).

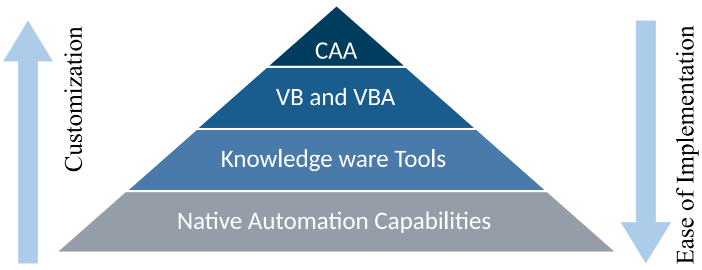


**Figure 3.1:** Different levels of CATIA automation tiers (n.d. 2006)

*Native Automation Capabilities* is the first, and most rudimentary, level of automation through the specification of parameters, formulas, design tables, templates, or power copy and is available in the native CATIA environment. Tools such as *Knowledge Ware Tools* come in the second row and usually require a separate license to run. They turn implicit design methods into explicit knowledge for obtaining the optimum design by supporting the specification of design intent into product models. The other tier is *VB and VBA* which consists of macros (.CATScripts) which is a great tool for rapid deployment of simple automation applications but it is difficult to debug. VBA (.CATvba) offers increased flexibility and complexity through the implementation of a user interface. VB6 & VB.NET run outside of CATIA and is advantageous in the implementation of the components and type libraries and individual modules which also makes collaboration and sharing easier. The last tier is *CAA* which is the most powerful level of automation in CATIA and is the hardest to implement but also the most capable in customization. It provides access to the core CATIA framework which extends functionality further from the API described in the previous level to operations on topology and underlying geometry, through libraries that can be accessed in C++ development environments.

The mentioned practical viewpoint also reveals the limitations associated with DA systems. Some of the limitations are related to the nature of the design (it is only a part of the development work like processing information still needs to be performed) and some are related to the nature of automation (Just supports repetitive and non-creative design tasks and can not handle creative work) and others reveal themselves in the context where DA is applied. This is for example concerning the development of DA applications that is generally undertaken by domain engineers who may not have formal knowledge of engineering or software development training, with subsequent development processes lacking the structure of formalized methodologies, and important principles can be neglected (Van der Velden 2008). A mapping between approaches in DA eases the understanding in the industry about what type of tasks can be automated and which approaches in DA are suitable for what kind of tasks (Rigger et al. 2016). Other researchers indicate that the application of DA has been limited (Rigger et al. 2018) most notably in configuration systems in realizing solutions of interest for the user.

### 3.1.3 CAD-FEA Integration

Integration of CAD and CAE has been a challenge for a long time mainly because of design intent loss, data inconsistency, the difference in mathematics description, etc. In the traditional sequential up-to-down design process, the idealization of the geometric model (simplification and modification) is implemented before mesh and simulation. Figure 3.2 shows such a process in which tedious manual work must be implemented by designers or engineers. The initial design model usually contains log history, tolerance information for manufacturing, and detailed features for downstream applications, which are redundant information for finite element simulations (Feng et al. 2020).

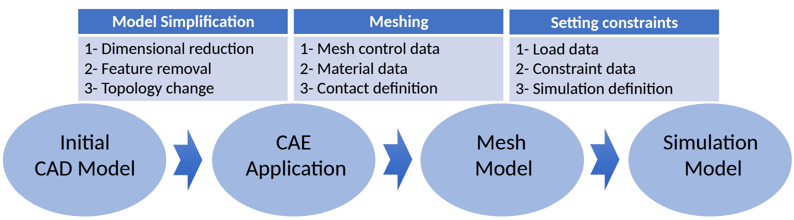


**Figure 3.2:** Traditional sequential up-to-down design process (Feng et al. 2020)

CAD and FEA integration is where basic analysis tools for first-pass studies are tightly coupled with CAD software. This allows designers and engineers to quickly iterate back and forth in performing basic conceptual "what-if?" studies to evaluate the merit of different ideas, compare alternatives, and filter out design weaknesses before more detailed analysis, prototype testing, and production planning. Advances in CAD technology can reduce CAE modeling time to only a few percent of the total. One of the early examples of this integration is 'Meshable CAD' in which users were required only to provide minimal input such as general meshing density as a guide for the software transforming the solid model into an analysis model (Roth 1999). As a result of this integrated technology, processing time was reduced and almost 55% of the development lead time was saved, as illustrated in Figure 3.3.

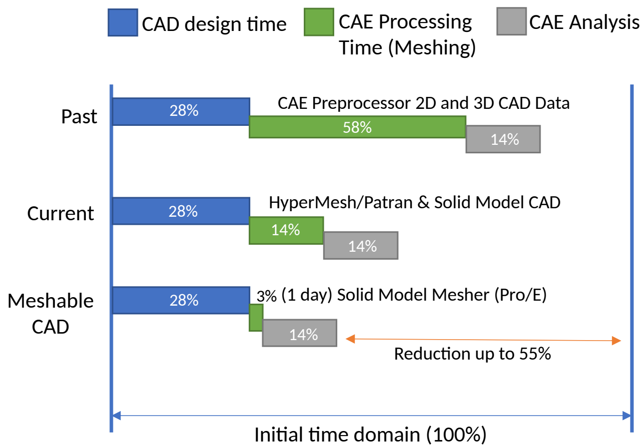


**Figure 3.3:** The Meshable CAD technology (Roth 1999)

The intelligent advisory system called PROPOSE, for design improvements considering FEA results, is an example of another successful integration system (Novak & Dolšak 2008). The idea was to encode the knowledge and experiences and build an intelligent advisory system to help the designer to perform an analysis-based design improvement process. Regarding any question, the system provides help to the user in the form of explanation or advice to inexperienced designers as to how to change/improve the design in critical areas of a structure after stress-strain or thermal analysis. Recently, Heikkinen et al. proposed a simulation-ready CAD model that essentially integrates pre-processing with CAD work (Heikkinen et al. 2016). It has been argued that this kind of support can address time-pressured technology development in small-sized companies, where building extensive KBE systems are not feasible.

### 3.1.4 Design Structure Matrix

Design structure matrix (DSM) and DSM-based tools have been used to improve iterative product development processes and therefore are highly relevant from this research's point of view. Based on DSM, researchers presented two different iteration models for engineering design. The first model (Smith & Eppinger 1997*b*) called the *sequential iteration model* supposed that each design activity is of deterministic duration and probabilistic repetition where the repeat probabilities are defined by the strength of task coupling. They use modeling to compute the expected duration of the iterative solution process and to suggest an initial ordering of coupled design tasks to minimize the expected solution process. The second model (Smith & Eppinger 1997*a*) called the *parallel iteration model* which provides managers with information as to which activities in a complex and coupled process may be contributing the most to the iterative development process. This information can be used to predict convergence of iteration within a project and prediction of those coupled features of the design problem which will require many iterations to reach technical solution.

Johansson and Elgh presented three ways that a design structure matrix can help engineering DA (Johansson et al. 2013). It has been shown that DSM can be used to accommodate communication by better visualization or as an inference mechanism, to sequence the execution of the design process, and lastly to assist the knowledge object selection at runtime. To make the product design specification process more explicit by graphically representing the specification through the expansion of its characteristics and logical relations. Loureiro et al. proposed a method called design structure network (DSN) based on DSM to allow visualization of the design variables as nodes of a network and the relations of interdependence as links and the specification reasoning as a path that connects the nodes in a network (Loureiro et al. 2020). For the management of network complexity, they implemented ten principles based on cognitive processes. By applying their proposed method to the geometric specification of a surfboard as a case study, they showed that the systematization of the principles can reduce the complexity up to twelve times.

## 3.2 Data-Driven Design

Artificial intelligence is contrary to natural intelligence and the analogy is often made with mimicking the human brain where senses gather data and human reasoning draws a conclusion on them. Machine learning (ML) is "A form of applied statistics with increased emphasis on the use of computers to statistically estimate complicated functions and a decreased emphasis on proving confidence intervals around these functions" (Goodfellow et al. 2016). In this definition, computers are considered able to learn complicated response surfaces and identify patterns or make decisions in an iterative learning process and the decreased emphasis is on how much the utilized functions are verifiable. Thus, as Figure 3.4 is illustrating, machine learning belongs to a family of artificial intelligence (AI).

Data-driven is a term that became popular with the advent of AI and ML and it refers to analysis and decision-making which used such statistical methods (as a reasoning engine) to interpret the gathered data. Frameworks for data-driven

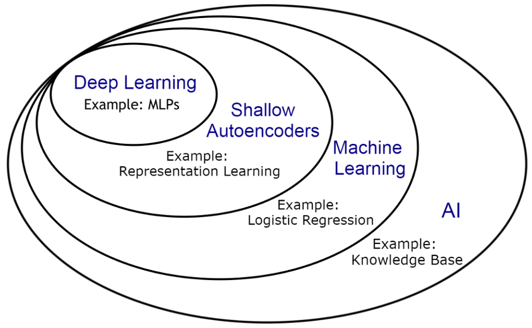


**Figure 3.4:** A Venn diagram showing AI categorization with examples (Goodfellow et al. 2016)

design usually consist of real-time data sensing and acquisition coupled with data processing and storage units which then input the developing model and perform data mining on results and knowledge (Zhang et al. 2017). AI is a big umbrella for many practices and as discussed, the knowledge-based method is also considered one application of AI. Hence, data-driven design can be defined as a multidisciplinary science that extracts, and handle structured and unstructured data from domain knowledge of product design and development and uses statistical and computer science methods to draw conclusions on them, assisting domain engineers and managers to interpret data and make a decision. With the rise of data science, data-driven products and data-driven design are increasingly evolving. Data may be used to identify patterns and trends to drive innovation, monitor product performance, and progressively enhance the product experience under the data-informed design paradigm (Li et al. 2019). The aim of data-driven design ranges from being sustainable in the design process by optimizing logistics, process, or shop floor scheduling or being able to improve service, online diagnosis, and maintenance, or saving on energy and resources by reusing or remanufacturing.

Synergies between engineering design and data science have been reviewed recently (Chiarello et al. 2021). Through identifying tools and algorithms, the authors refer to challenges in this field, among the others is the necessity of the novel use of CAD as a source of input for data-driven methods Search for meaningful feature representation, automatic data labeling, and speeding up the prototyping process. Another article (Feng et al. 2020) specifically reviews data-driven product design based on the conventional design process stages (requirement analysis, conceptual design, detail design, and knowledge support). For requirement analysis, data-driven methods are used to predict outputs and explore design space. For conceptual design, it helps to map from customer requirements to solution output by iterative reasoning and decision making. For detailed design, it supports the design tasks and verifying the simulation results. And as design knowledge support tools it used for data extraction and design realization. Each of the application areas discussed has its challenges and there is a gap in the literature for more studies. For instance, taking detailed design, machine learning, and AI models can help the design task by optimizing the product. In this case, the gap exists in building the database that is needed for this task. For some products with financial and business nature, there is a huge amount of data that can be easily harvested. However, for mechanical design applications, this is not the case and this has opened a new challenge and research field on how to acquire big data in the solid mechanics field (Ramnath et al. 2019). Researchers raise the question "How to teach solid mechanics to artificial intelligence" and assert the application results in a fast solver that can potentially accelerate the calculation of stress distribution in highly nonlinear mechanical systems, an achievement that can unlock many important more complicated simulations, materials, loading scenarios, and optimization problems, which previously was avoided (Mianroodi et al. 2021).

### 3.2.1 Case-Based Reasoning

Companies strive not only for considering and reusing past solutions but to go further and generate new alternatives, the ones that never existed, in a feasible design space. Case-based reasoning (CBR) is one of the methods that helps to find a good starting point for design by searching among past solutions and finding the closest alternative to the problem at hand therefore it is considered among decision support systems (DSS) (Dutta et al. 1997). Representation of the design knowledge and acquisition of the optimal solution are two initiatives of the design process that are facilitated if past design knowledge is available and reusable.

CBR initially originated in ML science and sometimes the learning part of the system is independently referred to as case-based learning. The objective of a CBR system is similar to any other AI system, which is to automate solution acquisition for the problem (Aamodt & Plaza 1994). In short, a CBR system automatically retrieves the most similar case between previous cases which is called retrieving, and then the designer reused this old case as a starting point to suggest a solution for the problem at hand which is often included revising the case. Then the new solution is tested is added to the general knowledge database which is called retain. Overall, four pillars of a CBR system namely retrieve, reuse, revise, and retain are illustrated in Figure 3.5.

Examples of the application of a CBR system in the product development field exist in the literature. Contributing to each of the described pillars has been the topic of many papers. For instance, in the case of the retrieval pillar, many new algorithms have been developed. Unlike conventional parameters search, shape

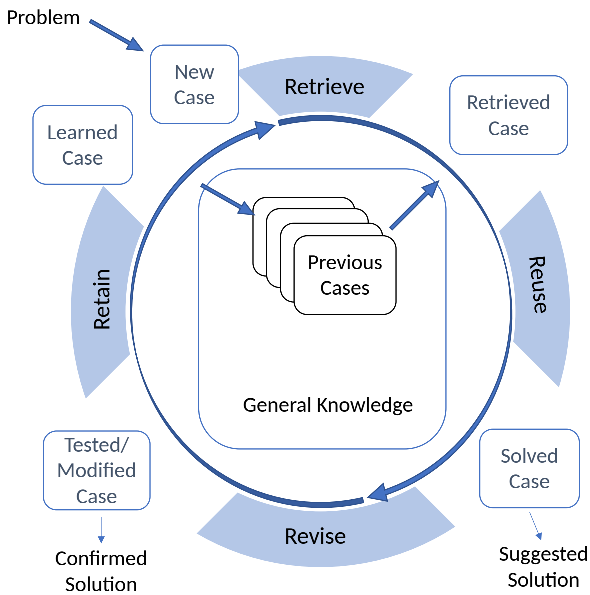


**Figure 3.5:** Case-based reasoning cycles (Aamodt & Plaza 1994)

retrieval by matching new problem shapes with existing solutions shapes for minimum clearance is proposed (Johansson 2012). The target component was a car roof rack and the system is implemented in the usual CAD to aid designers to retrieve the closest shape possible for further modifications. Reusing past solutions to develop new ones helps to reduce development lead time for developing new products (Feng et al. 2020).

### 3.2.2 Meta/Surrogate Modeling

Many statistical approximating methods such as Response surface methodology, Taguchi methods, ANNs, Inductive learning, and Kriging have been used to predict the output of the computation-intensive design problems (Simpson et al. 2001, Wang & Shan 2007, Sun & Wang 2019). These methods by building meta models or surrogate models prevent costly computations which result in cutting the total development lead time. However, the approach's goal is restricted in the sense that the application area has been limited exclusively to the computational analysis stage of the development process. As a result, these technologies are unable to span a larger range of product realization processes. For instance, the capacity of these methodologies, to capture tacit knowledge from downstream production and make it available to front row decision-makers is underexplored in the literature.

Most of these methods have been challenged by the curse of dimensionality which implies that the performance or accuracy of a system is reduced by an increased number of dimensions. Some of the high-level technical products, such as vehicle body structure and aircraft designs, can have up to hundreds of design variables which results in a highly nonlinear problem. Designers expand design dimensions to address such concerns, resulting in so-called high-dimensional, costly, and black-box (HEB) issues (Shan & Wang 2010). Another way to attack this problem is to break down the problem into several subproblems but the drawback is that each of the subproblems can have a different correlation with output and optimizing weights is not a trivial practice due to coupled and complex relations and lack of knowledge (Li et al. 2017). Although this field is couple of decades old, and there are lots of papers on the subject, there is still a gap in literature on the solutions for limitations like dimensionality and parameterization.

One main approach in literature as a solution for HEB is dimensionality reduction. For instance, creating simple shapes that have just enough important inputs during the SLA 3D printing process (Wang et al. 2018) or simplified geometry for the road wheel design process (Yoo et al. 2021), or simple design geometry with only three design parameters as well as a less computationally expensive CAE method, modal analysis (Du & Zhu 2018). Another approach to overcome dimensionality is to increase the size of the database. For example, up to 60,000 design samples for a study on automotive hoods (Ramnath et al. 2019, 2020) and 100,000 design samples for predicting aerodynamic coefficients of transport airplanes (Secco & de Mattos 2017).

Recent advances in image processing have opened up new opportunities in metamodeling. A group of metamodeling techniques that uses images as input for predicting the performance or property of the system has been developed (Li et al. 2017, Cunningham et al. 2019). For instance, images of a 2D linear cantilevered beam as input have been used with convolutional neural networks (CNNs) to predict the stress field as a picture in an end-to-end surrogate model (Nie et al. 2020). In another example images of automotive wheels are used in a model to predict modal analysis response from finite elements (Yoo et al. 2021).

### 3.2.3 Generative Design

Another example of the contribution of soft computational methods to design science is the use of AI with a combination of generative design. Generative design is one of the integrated design processes involving CAD, solid modeling, and a range of performance analysis tools. The subject of generative design is very broad and shows up in a range of different applications and fields such as art, architecture, and product development. Shea et al. define generative design as systems that aim to create new design processes that produce spatially novel yet efficient and produce-able designs through the exploitation of current computing and manufacturing capabilities (Shea et al. 2005).

Deep generative models are other examples of research that fit into this category. Burnap et al. have used deep generative models in the automotive styling domain, where automotive styling design samples of the last two decades are used to generate new styles (Burnap et al. 2016). Moreover, the end-to-end AI systems in the previous section can also be discussed from their second end, generative, point of view. For instance, Yoo et al. used generative design to explore design space and create a big library of design samples as input for surrogate models for automotive road wheels (Yoo et al. 2021). Most of the applications used with these methods are immature. This is currently a hot topic in data-driven design and the algorithms can generate new realistic and novel design samples but the picture that is resulted from the networks are not clear or ready to use.

## 3.3 Summary

There is many tools for combating development lead time than what has been presented. Some of the ongoing successful trends are not captured such as lean practices and concurrent engineering and requirement management. The selection criteria have been the relevance of the methods to proposed supports (current and future) as results of the research. An overview of some of the relevant and practiced tools and methods as well as the contribution area in this research is presented in Figure 3.6.

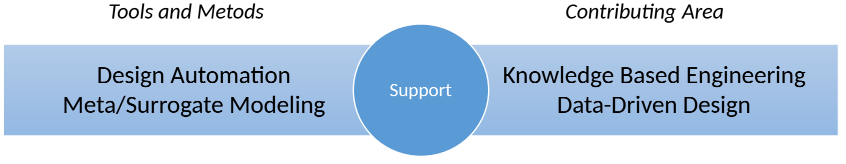


**Figure 3.6:** Contribution area of this research with utilized tools and methods

As shown in the figure, two major contributing area of this research namely, Knowledge Based Engineering and Data-Driven Design have been discussed in two sections. For each category several examples of tools and methods is presented separately in subsections. The figure represents one example from each category that is most relevant for the proposed supports in this research.

Despite the prevalence of the solutions that exist for shortening different stages of the design process, many of these solution areas are hindered by different shortcomings. For example, metamodeling methods are hindered by dimensionality problems. Several novel areas for addressing such problems are also under development and need to be further investigated. For example, with AI algorithms new possibilities for training on unconventional data types have emerged that can be studied further. The proposed supports in this research will try to fill out these identified gaps through next chapters.

# Chapter 4

# Summary of papers

This chapter first describes planned studies and their connection to utilized methodology as well as how each of them answers the defined research questions. Next, a summary of each paper as outcome of the studies will follow in the rest of the chapter.

## 4.1 Performed studies

The workflow that connected DRM to performed studies and associated papers until licentiate is illustrated in Figure 4.1. The figure also shows how different studies contribute to answer the defined research questions.

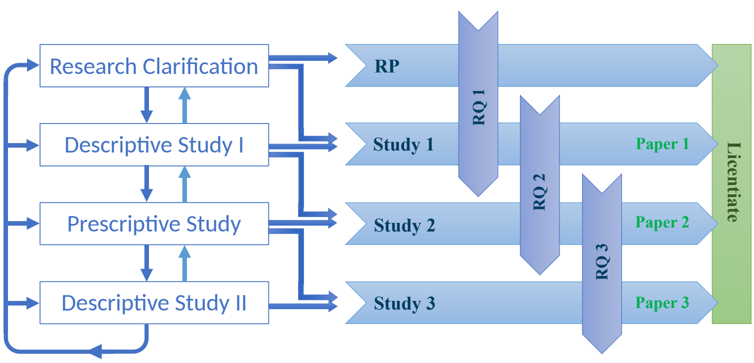


**Figure 4.1:** Mapping the methodology, research questions, and the planned studies

**Research Proposal** (RP) aligned with research clarification and tried to answer the first research question partially. It was an explorative attempt to understand the problem from an academic perspective by searching different research fields as well as industrial perspectives by interviewing the case company and outlining the problem area. The result is reflected in the RP to increase the understanding of the problem and plan for further studies. This study also identified success criteria which in short is development lead time. Finally, the existing literature is investigated to find relevant strategies and supports that can be used to further develop or address the identified problem and achieve the objective.

**Study 1** extended the investigations of previous research by narrowing down the list of potential supports to find out the final possible contribution area. Several methods and tools from selected areas are studied on a trivial basis to get familiarized with their capabilities and limitations. Company interviews finalized, and practical knowledge documented. A generalized design process model is developed which increased the grip on the identified problem. An envisioned support in form of another design process model showed real-time prediction model can be a supporting tool to solve the problem. Based on the findings that are published in a conference paper the first research question was fully addressed by the end of this study. Moreover, as an initiation to the second research question, and as a part of the contribution to the paper, several rough schemes for future case studies are suggested and critically discussed.

**Study 2** continued to answer the second research question by identifying the most influencing factors on the development lead time (success criteria). This was done by implementing the identified tool(s) in an actual case and evaluating this with the help of company specialists and based on the improvements that were achieved. The implemented method was successful but showed limitations that needed to be addressed. Moving on from this study required a full understanding of the problem mechanism and influencing factors as stated in the second research question. The fact that the created support was tested on a case showed that the mentioned incentive was achieved. The results and findings are published in the Computers in Industry journal. The demonstration of the support and its limitations creates the need for another case study which was performed in the next study.

**Study 3** was a revisit to the prescriptive study and re-formulation of new support to address limitations experienced in previous support. The new support is evaluated by its contribution to the success factor through feedback from company specialists and observing how much the utilized prototype is different in the realization process from the real case curtain airbag. Although this new support successfully addressed the previous shortcomings but in essence, showed other kinds of limitations. All advantages and disadvantages of the proposed supports are discussed in the associated papers but ultimately it is up to the design engineers in different industries to decide which support is best for their needs. The finding of this study together with a summary of the problem and the systematic procedure for how it was achieved is submitted to the ASME Journal of mechanical design.

## 4.2 Summary of paper 1

This paper addresses RQ1 on what current strategies and supports are currently being used to address long developing lead time in iterative and simulation-driven design processes. The result of the interviews and the workshops presented helped to envision a process model which can potentially address the issue. Moreover, this paper shows two major research areas that deals with the same lead time problem and also studies the advantages and disadvantages of each research area.

In this paper, a group of high-level technical products with common characteristics in their design process are defined. Semi-structured interviews were used to study the design process which allowed the interviewer to express their true ideas and give distinct examples. It was found that these products with transdisciplinary, iterative, and simulation-driven design processes suffer from long development lead time. This was because the design process for these products is experiencing 50-60 loops in the design process.

Iterative and simulation-driven products experience iterations on two levels. The first iteration point is just before the gate where digital models and simulations are verified in collaboration with the customers. This is the inner loop shown in Figure 4.2 where the designers iterate the work from design space constraints to objective requirements. This can be due to the complexity of the product, and difficulty in satisfying all the design requirements or both simultaneously. There can be several requirements connected to different disciplines and sometimes the order of their satisfaction becomes important. As the development work goes forward the digital verification loops become mature and able to address all the existing requirements. It is only then, that the concept moves to the next out loop in the second level.

The second level for iterations happens when the work between prototype testing and the development process is also iterative (outer loop) which is usually due to the dynamic nature of the customer requirements or lack of correlation with physical tests. Overall, the two loops constitute a highly iterative process for the case company which is a common property among those groups of products under study in this research. In high-level technical products, developers strive for flawless launch by continuously correlating design with physical testing. Therefore, products with iterative processes might take years to be launched. This iteration continues until a highly reliable product is realized. During this process design and testing as two separate processes interact with each other. This is done by the

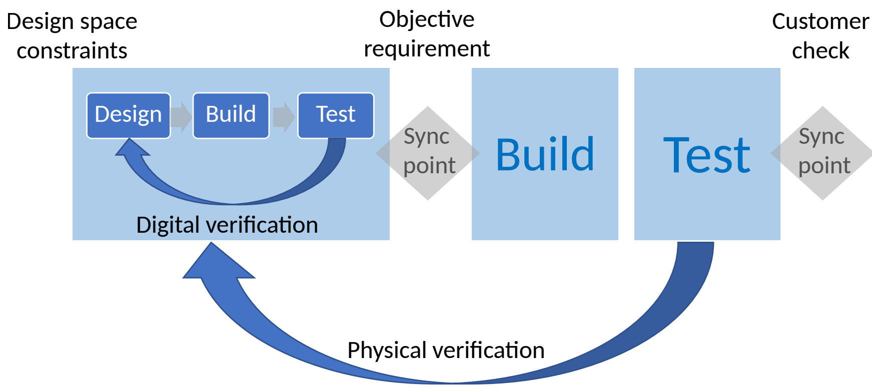


**Figure 4.2:** The generic PD model for iterative and simulation-driven products

feedback that testing provides for design and leads to its refinement.

However, the possible, and feasible solution is to do the iterations faster and/or smarter. As a realistic example, consider a company with a product having 60 inner loops in the design phase where each of them takes several hours to resolve. Additionally, there is a need for 7 correlations, which means 7 outer loops that take place every two-month following a sync meeting with the customer. Together, this makes up to a 20-month lead time only for developing work. The main problem lies with the 60 iterations in the design process because the loops for correlations are dependent on customers and they are usually fixed as described.

The idea was to provide theoretical background and investigate the state of practice by process modeling. To this end, the design process at hand is modeled in a generic way to point out its associated bottleneck which turned out to be the large number of iterative loops that happen in the conceptual phase. Two major solution areas for solving such problems have been identified as 1- Design automation to perform the iterations automatically as well as 2- Data-driven approaches to avoid the iterations. It was discussed that even though the design automation can free designers from doing manual design loops it will not solve the issue completely. This is due to design process characteristics such as being simulation-driven in which computational run time creates major lead time rather than manual work. Several workshops with simulation experts were performed to understand how the problem can be addressed. Literature was explored to find out existing data-driven approaches that combat development lead time. As a result of studies and interviews, a generic design process model is envisioned to address the lead time problem by employing an embedded *real-time prediction model* in the design phase. This process model is illustrated in Figure 4.3.

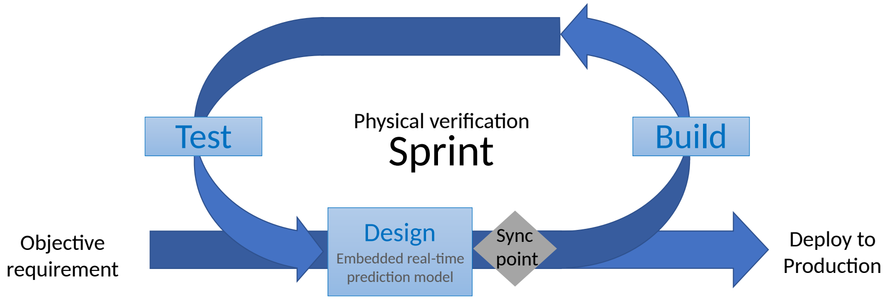


**Figure 4.3:** Envision PD with embedded real-time prediction model

Using such models in the design process can help to map the design inputs to outputs through performing the digital verification. In the proposed model digital verification is embedded design which will enable real-time prediction up until the concept is ready for physical verification. By practicing only physical verification coupled with design/analysis the process will enable agile sprints for building and testing the product in each iteration. This will potentially reduce the lead time as it will prevent many iterations in the design loop. Asking the company representatives about the proposed method, they confirmed that this can help them "avoid all the simulations" and "reduce the number of iteration loops" and therefore reduce the development lead time in the conceptual design phase.

Through the literature review and the workshops hindrances to applying a prediction tool in the design process namely Dimensionality and Parameterization are identified. Examples of the solutions that can addresses these hindrances are identified in the literature and categorized. The shortcomings of each category are discussed, and further improvements were suggested for future studies.

1. **Oder reduction** emphasizes using better quality parameters for building data-driven approaches. Principle component analysis and Analysis of variance (ANOVA) are among the methods that deal with selecting the parameters by statistically analyzing their effect on the objective outputs. It was proposed that to avoid the direct use of CAD parameters as input for data-driven approaches, feature extraction on CAD can be a solution for mapping design inputs to output and make the data-driven approach independent from parameterization.

2. **Avoiding parameterization** emphasizes using other kinds of inputs instead of the usual scalar parameters. Examples of this exist in literature such as using CAD log files and images from the built prototype or performed testing. To be able to produce a lot of labeled data, it was proposed to use

screenshots from CAD as input for novel Convolutional Neural Network (CNN). In this way, designers will be able to predict the consequences of the decisions in the design phase in real-time. Using image processing machine learning as a prediction model embedded into a button in CATIA it is possible in every design loop to evaluate roughly any simulation output.

For a data-driven solution, which is the envisioned support, a more in-depth literature analysis was performed which resulted in two potential solutions for addressing the hindrances that exist in applying them. By clarifying the limitations of each research area and also proposing potential solutions, this paper touches upon RQ2 to some extent.

## 4.3 Summary of paper 2

This paper is a mix of *descriptive study I* and a *prescriptive study* in DRM which leads to study2 and paper2. It was an attempt to answer RQ2 partially by showing the importance of fast evaluation in the design process which directly affects the success criteria which is reducing the long development lead time. This paper also answers RQ3 by demonstrating support for conceptual design by which designers can shorten the design process.

The paper used a curtain airbag prototype to study the possibility of using correlation-based feature extraction in CAD for regression-based machine learning algorithms. Figure 4.4 shows the chosen geometry for the curtain airbag which holds most of the characteristics of a real size curtain airbag.

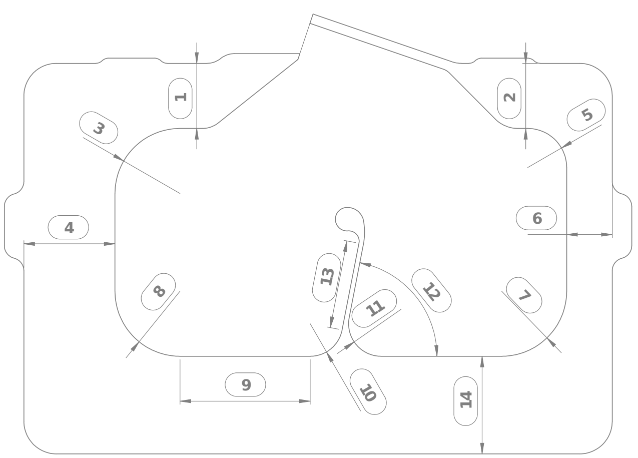


**Figure 4.4:** The curtain airbag prototype used in this research

It was shown that for fully defining a CAD model requires to use a lot of parameters which in most cases will lack correlation with the objective output. The problem of parameterization and dimensionality in using data-driven approaches and the reason why they are happening was comprehensively discussed at the beginning of the paper. Details of the performed finite element simulation to calculate the volume of the airbag were presented and then a parametric study was performed on the CAD parameters to show a great amount of difference in each parameter's effect on the volume as objective output. Thus, this clarified the coupled and complex nature of this effect between CAD parameters. Using the latin hypercube sampling method, 100 design samples were generated and studied for their volume output. This is performed with one fully automated Python script that created geometries in CATIA, meshed them in ANSA pre-processor and solved the generated key file in Ls-Dyna, and then read the volume in META post-processor, and then saved the final volume number to an excel file. It was determined that none of the CAD parameters correlate with the final output, which is shown in three first rows of Table 4.1.

**Table 4.1:** Comparison of the correlation between CAD and Sleeping parameters

| Name of the parameter (refer) | R2 Correlation with the output (Volume) |
|---|---|
| No. 1 (CAD parameter) | 0.037 |
| No. 13 (CAD parameter) | 0.0183 |
| No. 12 (CAD parameter) | 0.0441 |
| Area | 0.829 |
| Length of the medial axis | 0.752 |
| Sum of circumferences of all circles inscribed | 0.8816 |

In the next phase, the medial axis of the geometrical 2D shape of the airbag was calculated. Figure 4.5(right) shows how the medial axis was generated in Rhino/Grasshopper. The Vonronoi component used to generate circles on equal distance on the edge of the geometry and then by increasing the radius of these circles and making them to create boundary, the medial axis is generated. The meidal axis is a geometric entity like other entities such as area, circumference, etc. These geometric entities as new parameters, referred to as *sleeping parameters*, are defined and studied as a performance indicator for the inflated curtain airbag.

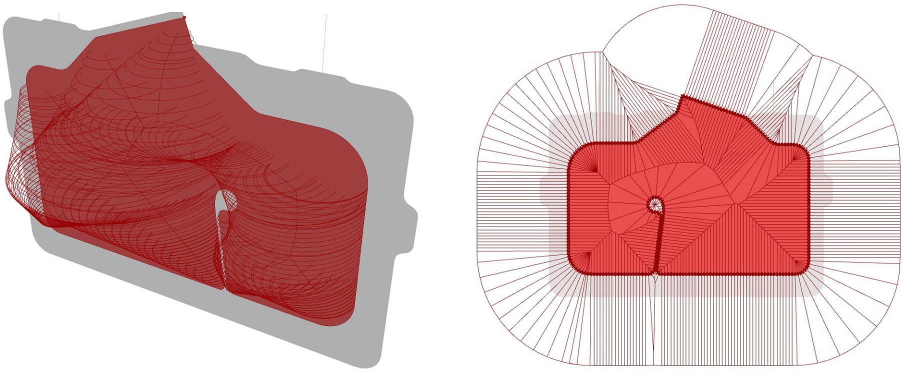

**Figure 4.5:** Feature extraction; Flipped inscribed circles (left), Representation of medial axis (right)

4.5 (Left) shows how rotating inscribed circles on the medial axis represent an inflated airbag. By similar reasoning, it was found that the sum of circumferences of all circles inscribed shows an even better correlation with the volume output. The correlation of these parameters These two parameters together with the area of the geometry are depicted in Table 4. It was demonstrated that new features have better correlations with the volume. And they can be extracted from geometry without any need for model parameterization which maintains freedom in design.

Through a comparison of the correlation between CAD and sleeping parameters (Table 4.2), it was shown that CAD parameters alone, do not lead to an effective prediction. Regression analyses were performed to compare and validate the performance of extracted parameters in a regression model by showing the ability of these parameters in more effective predictions. The result of this paper can allow designers to build simple but accurate regression models with a low number of features and sample points. To maintain a high level of interpretability and to further demonstrate the effectiveness of the proposed approach a Support Vector Regression model (SVR) was also trained. This shows that moving from simple linear regression to such sophisticated algorithms does not address the prediction accuracy issue to the degree that sleeping parameters can address. Sleeping parameters by increasing the quality of training features have made it possible to get an acceptable result with MLR and there is no need for advanced and complicated regression algorithms such as SVR. This shows the effectiveness of the sleeping parameters, such as the ones studied in this paper.

**Table 4.2:** Comparison of the correlation between CAD and Sleeping parameters

| | **Multivariate Linear Regression** | | **Support Vector Regression** | |
|---|---|---|---|---|
| Accuracy of the regression model among predicted and expected sets | All 14 CAD model parameters | Selected 3 Sleeping parameters | All 14 CAD model parameters | Selected 3 Sleeping parameters |
| R2 | 0.6318 | 0.9505 | 0.8027 | 0.9544 |
| MSE | 14.7304 | 1.8802 | 14.3419 | 1.7784 |

The calculated simple regression will empower designers in the early stage of airbag design to have a real-time prediction model and therefore potentially will reduce the development lead time. This model can be added to a CAD environment so when designers change a length and/or a radius and/or an offset they can quickly see the impact of their decisions on the volume of the bag without any need to perform a complex finite element analysis. Moreover, independence from conventional parametrization in CAD will provide the flexibility for being creative with new solutions since they will not be forced to follow one standard parameterization in complex geometries which is very much needed in today's industry.

The proposed methodology is transferable to all volume simulations in airbag models that are using 2D geometries as inputs such as knee and side airbags that deploy from the passenger seat. Additionally, this methodology can be utilized by other simulations that use 2D shapes as inputs such as the design of wire patterns for seat heaters in the automotive industry. Other inflatable structures that require volume simulation can benefit from the finding of this paper, such as high-pressure vessels, inflatable tunnel plugs, inflatable rubber dams, different kinds of inflatable boats, etc. The methodology is also scalable to any performance evaluation that requires good enough accuracy but fast evaluation for decision-making in the early stages of the design process.

This framework is not applied to the case company's design process and the information for its effectiveness comes from the presentation of the support to the CAE engineers and also held workshops with them. However, according to the engineers dealing with such problems, it is obvious that the design lead time will decrease. However, more studies need to be performed to be able to quantify the actual improvements in time.

## 4.4 Summary of paper 3

This paper a combination of *prescriptive study* and a *descriptive study II* in DRM which leads to study3 and paper3. The proposed support satisfies the success factor completely but there are limitations and disadvantages to it. The paper builds on top of the metamodeling techniques and attempts to address the same identified problems namely, dimensionality and parameterization. It does not directly refine the previous papers' results, unlike what it mentioned in Descriptive Study 2 and RQ3, However, it attempts to address the same problem as the previous paper which is the long development lead time with another approach.

It was argued and supported by a literature review that metamodeling techniques can reduce development lead time during a design process. However, most existing techniques face limitations in producing the needed amount of training data. A computational method called dynamic relaxation existed in the literature and it has been mainly used for simulating unstable structures previously in the literature. The method takes some iterations to converge but the iterations are computationally cheap as no stiffness matrix is needed to be assembled. However, discretization and some of the steps are still time-consuming. In this paper, an implemented version of dynamic relaxation in a component called Kangaroo in Rhino/Grasshopper is used for producing labels for 60,000 CAD models. A methodology to create a large amount of labeled data using dynamic relaxation is proposed that can be used on a wide range of simulations but not any simulation. Figure 4.6 shows volume visualization in Rhino which is achieved by using the Kangaroo component in Grasshopper.

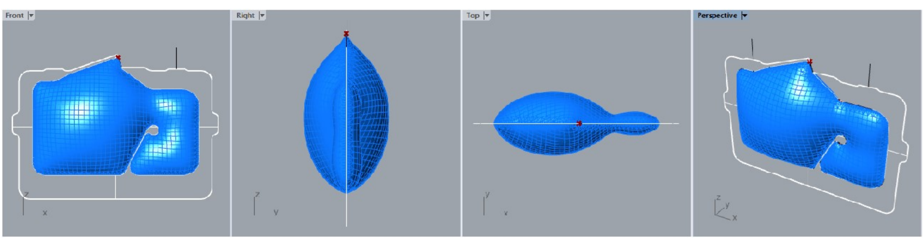


**Figure 4.6:** Volume simulation visualization in Rhino

It has been argued that engineering-based datasets have special characteristics and therefore need special treatments in terms of machine learning algorithms used with them. One character is that the picture of the airbag as an input creates skewed training data because a little change in the dimension of the bag produces very little difference in the image's pixels but the output may be affected drastically. There are advantages to the engineering databases as well. For example, because all the images are created digitally, a lot of pre-processing that is common with databases can be saved. By cropping all the images in the same way by a script, it is possible to lay all the constant pixels in one position which can save a lot of time training in the learning process. This is something that takes a lot of time to process for other datasets.

Figure 4.7 shows the schematic of the database created from two sizes of images as well as their labels which are volumes of the associated geometry. This database has been made available to the public in an online repository (Arjomandi Rad 2022). Most of the machine learning databases today are based on real-life problems and literature can benefit from engineering databases like the one presented here for benchmarking purposes.

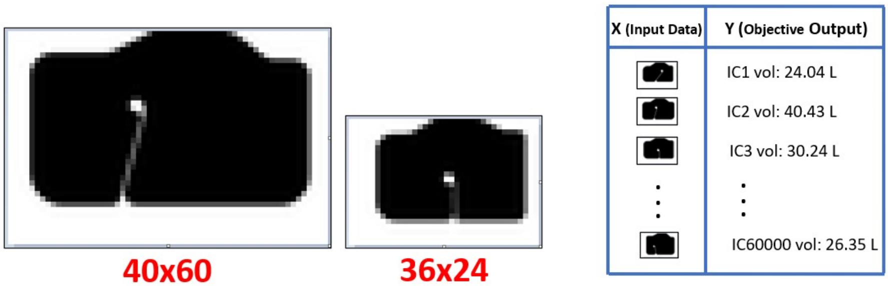


**Figure 4.7:** The database consists of 60,000 labeled images with two sizes

Moreover, an off-the-shelf implemented CNN with three layers for convolutions and pooling that each goes through the ReLU activation function. Dropout at each layer secures overfitting and prevents the network from memorizing the images. Other hyperparameters such as (such as kernel size, alpha, pool size, activation, and padding type) in the network are default values and the other parameters (such as dropout rate, input shape, and layer density) are chosen based on trial and error and best practices from the literature. The training was performed with 128 as batch size and 50 as epoch number.

As shown in Figure 4.8 the loss value which is representing the summation of the errors in our model (calculated from the cost function) for each case in the testing database is shown on the left. And in the right, the figure presents the accuracy which is the percentage of the correct prediction and it is a concept that can only be applied to classification tasks. As it can be concluded from the picture, in the accuracy there is not much gap between training and validation and converging to roughly 90%. Also in the loss graph, both training and validation are decreasing good and in a stable manner with an acceptable gap between them (known as generalization gap) with every epoch and converging to the 0.2 which shows a successful model.

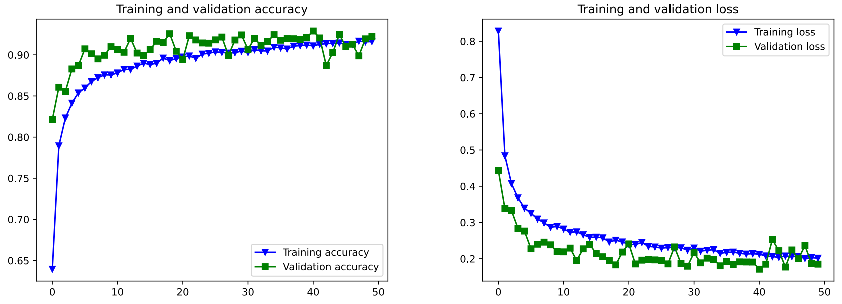


**Figure 4.8:** Accuracy (Left) and loss (Right) of training and validation database

Later the network accuracy was tested using 10000 new samples that were acquired separately within a similar but separate sampling process. The testing showed 89.42% accuracy and 0.26 loss which means that from 10000 testing cases, 8943 cases were predicted correctly and 1057 cases were placed in the wrong bin.

The result of the paper shows a promising way of using novel types of input data for state-of-the-art machine learning algorithms and predicting simulation outputs. However, according to the company engineers and specialists, the framework is more likely to be applied in the practice in case its limitations are deposed. Thus, more studies are required to achieve this goal. However, according to the company engineers and specialists, the framework is more likely to be applied in the practice in case its limitations are deposed. And more studies are required to achieve this goal.

# Chapter 5

# Discussion and Conclusion

This section elaborates on how the results from this work answers the research questions stated at the beginning of this thesis. The aim is to review the research outcome by discussing the limitations of the proposed supports.

## 5.1 State of the art and practice (RQ1)

**RQ1:** *What current strategies and support exist to respond to long developing lead time and changing requirements in iterative and simulation-driven design processes?*

The long development lead time as a prevalent problem in a group of products was identified in the Introduction, *chapter 1*, and related topics in literature dealing with this problem were studied and the findings are presented in the Theoretical Framework, *chapter 3*. Some characteristics of these products that are suffering from this problem pointed out to the existence of a group of special products that share similar characteristics and similar problem. These products have transdisciplinary, highly iterative, and simulation-driven design processes and they suffer from a long lead time in the development phase that can take up to several years. Some of the causes for this long development lead time were identified and discussed. This work resulted in a process model for such design processes which shows a lot of the iterations are happening in what is named digital verification. In each iteration, the product requirements are satisfied and the product is synchronized with the customer before it moves either to the next iteration or to the production phase. Digital models used through this verification process resemble digital twins and the work can be positioned in the context of industry 4.0. It has been argued that iterations are part of development nature and are beneficial for optimizing and refining every product. However, through the literature study, two major research approaches dealing with the same problem, in general, have been identified, namely, the design automation and the data-driven design approach.

The pros and cons of each track have been studied through the interviews and workshops within the companies. The result shows having fully automated systems have undeniable advantages, yet it does not satisfy the industrial needs for fast design exploration. On the other hand, data-driven approaches such as metamodels and sophisticated AI algorithms require a large amount of training data that needs an automated CAE simulation process. Furthermore, the design automation and data-driven approach (separately) require scripting competence which domain engineers in the industry usually lack. Design automation is usually more transparent but it has a slow process and requires the same expensive simulations as manual work. Whereas data-driven algorithms lack transparency but once the training has been performed, the speed is almost considered real-time. Which makes them exceptionally suitable for early phases of the design process where high accuracy is not necessary. Overall, literature analysis together with performed interviews and workshops with a specialist in the company directed this research toward metamodeling and soft computational techniques.

## 5.2 Challenges and support requirements (RQ2)

**RQ2:** *What criteria are important for faster development and requirements management in iterative and simulation-driven design processes?*

Analysis performed to answer RQ 1 showed dimensionality and parameterization as the bottleneck for a data-driven design approach to a wide range of design processes. It was shown that CAD model parameters are not always good features for training datasets because they lack a correlation with the simulation output. Also following a parameterization convention limits designers' creativity in the sense that they are required to follow that convention when they overcome a new design case. This challenge was shown with the prototype airbag design which was developed together with the case company. In the second paper, for designing a shape for the airbag 14 parameters are used and the question was raised what if the designers want to introduce a new angle or a new radius somewhere in the geometry. Answering this question helped to identify the requirement for support. It was concluded that any utilized feature in the data-driven design approach should be independent of the parameterization convention that is used for the design process. Designers should be able to create any shape with their creative mind and address customer requirements without this affecting the support's performance.

Dimensionality was another identified challenge for data-driven approaches. As shown in Table 4.2, the number of the utilized parameters in a data-driven design approach affects the accuracy of the prediction model. In general, complex products require a lot of parameters to be designed. Historically, the meta/surrogate modeling research field has been hindered by the high dimensional and nonlinear problems which require hundreds of inputs to be fully defined. This challenge shows us another requirement for support. Due to this requirement, the support should use a minimum number of important features rather than a pile of unnecessary ones.

## 5.3 Developed supports (RQ3)

**RQ3:** *What models, methods, or tools can be used for faster development and requirements management in iterative and simulation-driven design processes?*

Both identified challenges were studied in the literature to find out about supporting solutions. There are several methods in the literature for selecting the best features based on several different criteria, however, this is not providing a solution as there is no guarantee that there will be a high-quality feature between known inputs. Therefore, feature extraction independently from geometrical parameterization has been developed through medial axis theory. The proposed sleeping parameters, not only are independent but also are correlating with the output, and therefore as shown in Table 4.1 a few of them can constitute a higher accuracy of the metamodel than 14 CAD parameters. This support, by satisfying the requirements defined in the response of RQ2 shows that data-driven approaches can benefit a lot from feature extractions methods such as the one presented in paper 2.

As another solution to overcome the dimensionality issue, and at the same time to keep the models independent from parameterization, image regression has been proposed as an alternative support to overcome the defined problem. This novel approach uses screenshots of a CAD design as input for training an off-the-shelf CNN model with three layers. For labeling the images dynamic relaxation method has been used which is much faster in comparison to finite element. The results show a roughly 90% accuracy rate for the training dataset. This study fills the support requirements, and contributes to the research as it provides a library of engineering-based labeled images for benchmarking purposes. Simultaneously, it contributes to the industry by providing a methodology to achieve real-time prediction model. This methodology can be applied to a wide range of simulations that dynamic relaxation can provide an answer. However, it is limited in this aspect, since many simulations (that for example have stress as their output) are not suitable for this method.

An advantage with metamodeling is that once the implementation of the model is done at the companies, it should allow for more design engineers to do structural analysis fast and efficiently in the early stages which usually tend to be done at later stages when design changes become expensive. However, the necessity of building training data has been considered as a downside because it is time and labor-consuming and methods like dynamic relaxations does not always exist for every simulation. For some companies or some products, the gain from building such models could not be worth the pain and for others, this might open a door for fast design exploration in the early phases. Through the interviews, the company specialist acknowledged the fact that the proposed support can be an ideal tool for simulations that are performed for quotation purposes. As the accuracy demand is not high and the designers and sales department are only searching for a rough estimate to conclude a reasonable price.

## 5.4 Validation of the results

The design of the used airbag prototype model and also both of the two developed supports are presented to the company specialist and asked them about the applicability of the solution in the real case for daily use of the employees. Since the supports are already working successfully on a close case and it shows a drastic change in time to calculate the volume output, the company specialist have confirmed the useability and validity of the proposed support (validation through acceptance). To apply envisioned PD into a real environment in the company, the developed supports need to be integrated into their design process. So they can use it as an embedded system in the design environment. This part of the application requires deep programming support from CAD software architectures and thus remains to be addressed by companies themselves. Overall, it can be said that the achievement from the lead time point of view is certain but the applicability of it as a daily used support for designers needs to be implemented, studied, and verified in future studies.

The other aspect of verification for envisioned support is its applicability of it to any simulation in the design phase. Although several limitations exist that are mentioned in the discussion sections will prevent the application of this process to any simulation and any product. However, this is ongoing research, and there are plans for broadening the scope by studying other simulations and other products in other companies after licentiate.

## 5.5 Conclusion

While design automation has been successfully used in product development to free engineers from mundane tasks and reduce the development lead time, the continuous growth of product complexity and unexpectedness of customer requirements necessitates new smart ways to explore product design space. More recently AI algorithms and data-driven design have shown great potential to take up design automation to the next level and use machines to learn, generate and analyze design variants. This study proposes a real-time prediction model for analyzing product performance in early phases. The solution process model is implemented on a case product of a car curtain airbag in close collaboration with an industrial partner through two studies. The first study extracts some features from CAD that are independent of the parameterization. In this way, the proposed real-time prediction model can be used freely by the designer right after shape modification, irrespective of which parameterization convention has been used. The second study includes novel convolutional neural networks that use CAD screenshots as input to predict the simulation output. This implementation of the real-time prediction model does require a pre-built database. Through the studies, limitations associated with each support were demonstrated and discussed which opens up for further investigations. Despite this limitation, the company specialist believed that the solutions are ready to be implemented in actual design processes. The industrial contribution of this research will hopefully help not the case company alone but also other companies with high level, technical products characterized by iterative, simulation-driven design processes to reduce their development lead time or successfully handle their fluctuating requirements in a shorter time.

## 5.6 Future work

Extractable information from geometrical and simulation models can be explored as the input for building an AI model. Cloud-based or voxel-based representation of an object has shown promising results in the literature. These geometrical representations could provide a new data type for training AI models. Moreover, physics informed neural networks (PINNs) have emerged which include the physical laws (for example a differential equation) governing the behavior under study in the cost function. Since there are analytical solutions for crash simulation, these equations can be tested on PINNs to improve the learning and reduce the training size. Testing several data types on different models will determine what kind of data works best with which AI method. The final support will also consider the requirements from companies about the applicability of the proposed solution to a wide range of simulations.

Explored data types can increase the sophistication level of databases which results in better-benchmarking tools. Other sampling methods can be explored to generate design variants that efficiently cover design space. The simulation runs can be performed for each variant by the automated scripts or new alternative and iterative methods such as dynamic relaxations and then the training, testing, and validation databases will be created. The selected AI method will be further studied. Most of the implemented AI methods are designed for classification problems and therefore need to be modified for engineering regression solving. Network architecture will be designed, training epochs will be carried out within higher and real scale ranges, hyperparameters will be optimized with a relevant method, and accuracy will be reported on testing sets. The final network will be measured for extrapolating performance.

If the development of the metamodels is successful and valid, new software tools with a graphical user interface can be implemented at the companies and utilized by the design engineers. This will make the use of such sophisticated AI algorithms much easier for non engineers. In future studies we expect to find out what kind of data types are more suitable for which types of simulations and geometries, be it solid models, sheet metal, etc. Finally, moving from real-time predictions to real-time analysis, a generalized framework for performing performance analysis in real-time can be developed and validated with relevant validation methods.

# References


Aamodt, A. & Plaza, E. (1994), 'Case-based reasoning: Foundational issues, methodological variations, and system approaches', *AI communications* 7(1), 39–59.

Adams, R. & Atman, C. (1999), Cognitive processes in iterative design behavior, *in* 'FIE'99 Frontiers in Education. 29th Annual Frontiers in Education Conference. Designing the Future of Science and Engineering Education. Conference Proceedings', Vol. 1, pp. 11A6/13–11A6/18 vol.1.

André, S., Stolt, R. & Elgh, F. (2016), A platform model for suppliers of customized systems: Creating an ability to master fluctuating requirements, *in* 'Proceedings of the ASME, International Design Engineering Technical Conferences and Computers and Information in Engineering Conference', pp. 21–24.

Andrè, S., Stolt, R., Elgh, F., Johansson, J. & Poorkiany, M. (2014), Managing fluctuating requirements by platforms defined in the interface between technology and product development, *in* 'Moving Integrated Product Development to Service Clouds in the Global Economy', IOS Press, pp. 424–433.

Arjomandi Rad, M. (2022), 'Airbag cad to cae volume', https://www.kaggle.com/mohammadrad/airbag-cad-to-cae-volume. Data files.

Bellgran, M. & Säfsten, K. (2010), *Production Development over Time*, Springer.

Blessing, L. T. & Chakrabarti, A. (2009), *DRM: A design reseach methodology*, Springer.

Boschert, S. & Rosen, R. (2016), Digital twin—the simulation aspect, *in* 'Mechatronic futures', Springer, pp. 59–74.

Bossak, M. A. (1998), 'Simulation based design', *Journal of Materials Processing Technology* **76**(1-3), 8–11.

Burnap, A., Liu, Y., Pan, Y., Lee, H., Gonzalez, R. & Papalambros, P. Y. (2016), Estimating and Exploring the Product Form Design Space Using Deep Generative Models, Vol. Volume 2A: 42nd Design Automation Conference of *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

Cederfeldt, M. & Elgh, F. (2005), Design automation in smes–current state, potential, need and requirements, *in* 'DS 35: Proceedings ICED 05, the 15th International Conference on Engineering Design, Melbourne, Australia, 15.-18.08. 2005'.

Chiarello, F., Belingheri, P. & Fantoni, G. (2021), 'Data science for engineering design: State of the art and future directions', *Computers in Industry* **129**, 103447.

Clark, K. B. (1991), 'Product development performance: Strategy', *Organization, and Management in the World Auto Industry* .

Cooper, R. G. (1990), 'Stage-gate systems: a new tool for managing new products', *Business horizons* **33**(3), 44–54.

Cooper, R. G. (2014), 'What's next?: After stage-gate', *Research-Technology Management* **57**(1), 20–31.

Costa, R. & Sobek, D. K. (2003), Iteration in engineering design: inherent and unavoidable or product of choices made?, *in* 'International Design Engineering Technical Conferences and Computers and Information in Engineering Conference', Vol. 37017, pp. 669–674.

Cunningham, J. D., Simpson, T. W. & Tucker, C. S. (2019), 'An investigation of surrogate models for efficient performance-based decoding of 3d point clouds', *Journal of Mechanical Design* **141**(12).

Desa, U. et al. (2016), 'Transforming our world: The 2030 agenda for sustainable development'.

Du, X. & Zhu, F. (2018), 'A new data-driven design methodology for mechanical systems with high dimensional design variables', *Advances in Engineering Software* **117**, 18–28.

Dutta, S., Wierenga, B. & Dalebout, A. (1997), 'Case-based reasoning systems: From automation to decision-aiding and stimulation', *IEEE transactions on knowledge and data engineering* **9**(6), 911–922.

Eekels, J. & Roozenburg, N. F. (1991), 'A methodological comparison of the structures of scientific research and engineering design: their similarities and differences', *Design studies* **12**(4), 197–203.

Elgh, F. (2007), Computer-supported design for producibility: principles and models for system realisation and utilisation, PhD thesis, Chalmers University of Technology.

Eppinger, S. D., Whitney, D. E., Smith, R. P. & Gebala, D. A. (1994), 'A model-based method for organizing tasks in product development', *Research in engineering design* **6**(1), 1–13.

Eppinger, S. & Ulrich, K. (2015), *Product design and development*, McGraw-Hill Higher Education.

Feng, Y., Zhao, Y., Zheng, H., Li, Z. & Tan, J. (2020), 'Data-driven product design toward intelligent manufacturing: A review', *International Journal of Advanced Robotic Systems* **17**(2), 1729881420911257.

Fiksel, J. & Dunkle, M. (1990), Principles of requirement management automation, *in* 'Combined Proceedings of the Leesburg Workshops on Reliability and Maintainability Computer-Aided Engineering in Concurrent Engineering', IEEE, pp. 231–236.

Flankegård, F., Johansson, G. & Granlund, A. (2019), Challenges with supplier involvement in product development: A supplier' s perspective, *in* 'Proceedings of the Design Society: International Conference on Engineering Design', Vol. 1, Cambridge University Press, pp. 2179–2188.

Fujimoto, T. (2000), Shortening lead time through early problem-solving—a new round of capability-building competition in the auto industry, *in* 'New product development and production networks', Springer, pp. 23–53.

Garcia, P. & Drogosz, J. (2007), 'Lean engineering-best practice in the automotive industry', *SAE Technical Paper* pp. 01–0532.

Goodfellow, I., Bengio, Y. & Courville, A. (2016), *Deep learning*, MIT press.

Hammarberg, K., Kirkman, M. & de Lacey, S. (2016), 'Qualitative research methods: when to use them and how to judge them', *Human reproduction* **31**(3), 498–501.

He, B., Li, F., Cao, X. & Li, T. (2020), 'Product sustainable design: a review from the environmental, economic, and social aspects', *Journal of Computing and Information Science in Engineering* **20**(4).

Heikkinen, T. (2021), 'Transparency of design automation systems using visual programming–within the mechanical manufacturing industry', *Proceedings of the Design Society* **1**, 3249–3258.

Heikkinen, T., Johansson, J., Elgh, F. et al. (2016), Assessment of simulation ready cad models in a set-based concurrent engineering context, *in* 'DS 84: Proceedings of the DESIGN 2016 14th International Design Conference', pp. 649–658.

Hubka, V. & Eder, W. E. (1988), 'Theory of technical systems: A total concept theory for engineering design', *Berlin and New York* .

Johansson, J. (2012), Combining case based reasoning and shape matching based on clearance analyzes to support the reuse of components, *in* 'International Design Engineering Technical Conferences and Computers and Information in Engineering Conference', Vol. 45028, American Society of Mechanical Engineers, pp. 603–610.

Johansson, J., Contero, M., Company, P. & Elgh, F. (2018), 'Supporting connectivism in knowledge based engineering with graph theory, filtering techniques and model quality assurance', *Advanced Engineering Informatics* **38**, 252–263.

Johansson, J., Elgh, F. et al. (2013), Three examples of how dsm enhances engineering design automation, *in* '15th International Dependency and Structure Modelling Conference', pp. 3–10.

Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H. & Tongne, A. (2022), 'Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis', *AI and Ethics* pp. 1–25.

King, G., Jones, R. & Simner, D. (2003), 'A good practice model for implementation of computer-aided engineering analysis in product development', *Journal of Engineering Design* **14**(3), 315–331.

Kojima, Y. (2000), 'Mechanical cae in automotive design', *R&D Review of Toyota CRDL* **35**(4), 1.

La Rocca, G. (2012), 'Knowledge based engineering: Between ai and cad. review of a language based technology to support engineering design', *Advanced engineering informatics* **26**(2), 159–179.

Li, Y., Roy, U. & Saltz, J. S. (2019), 'Towards an integrated process model for new product development with data-driven features (npd3)', *Research in Engineering Design* **30**(2), 271–289.

Li, Y., Wang, H. & Liu, J. (2017), 'Can cnn construct highly accurate models efficiently for high-dimensional problems in complex product designs?', *arXiv preprint arXiv:1712.01639* .

Liker, J. K., Liker, J. K., Ettlie, J. E. & Campbell, J. C. (1995), *Engineered in Japan: Japanese technology-management practices*, Oxford University Press on Demand.

Lockwood, A. (2009), 'Simulation-driven product development: Will form finally follow function', *CAE White Paper* .

Loureiro, G. B., Ferreira, J. C. E. & Messerschmidt, P. H. Z. (2020), 'Design structure network (dsn): a method to make explicit the product design specification process for mass customization', *Research in Engineering Design* **31**(2), 197–220.

Lu, S. C.-Y. & Liu, A. (2012), 'Abductive reasoning for design synthesis', *CIRP annals* **61**(1), 143–146.

Maria, A. (1997), Introduction to modeling and simulation, *in* 'Proceedings of the 29th conference on Winter simulation', pp. 7–13.

McMahon, C., Lowe, A. & Culley, S. (2004), 'Knowledge management in engineering design: personalization and codification', *Journal of Engineering Design* **15**(4), 307–325.

Merkel, M. & Schumacher, A. (2003), 'An automated optimization process for a cae driven product development', *J. Mech. Des.* **125**(4), 694–700.

Merriam, S. B. & Tisdell, E. J. (2015), *Qualitative research: A guide to design and implementation*, John Wiley & Sons.

Mianroodi, J. R., H Siboni, N. & Raabe, D. (2021), 'Teaching solid mechanics to artificial intelligence—a fast solver for heterogeneous materials', *npj Computational Materials* 7(1), 1–10.

n.d. (2006), 'Approaches in automation, catia v5 automation'.
**URL:** *https://catiatutor.com/approaches-in-automation*

n.d. (2018), 'The global goals and the 2030 agenda for sustainable development'.
**URL:** *https://www.government.se/government-policy/the-global-goals-and-the-2030-Agenda-for-sustainable-development/*

Nie, Z., Jiang, H. & Kara, L. B. (2020), 'Stress field prediction in cantilevered structures using convolutional neural networks', *Journal of Computing and Information Science in Engineering* **20**(1), 011002.

Nilsson, P. & Fagerström, B. (2006), 'Managing stakeholder requirements in a product modelling system', *Computers in Industry* **57**(2), 167–177.

Novak, M. & Dolšak, B. (2008), 'Intelligent fea-based design improvement', *Engineering Applications of Artificial Intelligence* **21**(8), 1239–1254.

Osborne, S. M. (1993), Product development cycle time characterization through modeling of process iteration, PhD thesis, Massachusetts Institute of Technology.

Pahl, G. & Beitz, W. (1984), 'Engineering design, the design council', *London, Springer* **12**, 221–226.

Pahl, G. & Beitz, W. (2013), 'Engineering design: A systematic method'.

Pinfold, M. & Chapman, C. (2001), 'The application of kbe techniques to the fe model creation of an automotive body structure', *Computers in Industry* **44**(1), 1–10.

Ramnath, S., Haghighi, P., Kim, J. H., Detwiler, D., Berry, M., Shah, J. J., Aulig, N., Wollstadt, P. & Menzel, S. (2019), Automatically Generating 60,000 CAD Variants for Big Data Applications, Vol. Volume 1: 39th Computers and Information in Engineering Conference of *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

Ramnath, S., Haghighi, P., Ma, J., Shah, J. J. & Detwiler, D. (2020), Design Science Meets Data Science: Curating Large Design Datasets for Engineered Artifacts, Vol. Volume 9: 40th Computers and Information in Engineering Conference (CIE) of *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

Rigger, E., Münzer, C., Shea, K. et al. (2016), Estimating the potential of state of the art design automation-tasks, methods, and benefits, *in* 'DS 84: Proceedings of the DESIGN 2016 14th International Design Conference', pp. 421–432.

Rigger, E., Vosgien, T. et al. (2018), Design automation state of practice-potential and opportunities, *in* 'DS 92: Proceedings of the DESIGN 2018 15th International Design Conference', pp. 441–452.

Roth, G. (1999), 'analysis in action: The value of early analysis', *ANSYS, Canonburg, PA* .

Roy, R., Kerr, C. I. & Sackett, P. J. (2006), 'Requirements management for the extended automotive enterprise', *Advances in Design* pp. 269–279.

Saxena, M. & Irani, R. K. (1994), 'A knowledge-based engineering environment for automated analysis of nozzles', *Concurrent Engineering* **2**(1), 45–57.

Secco, N. R. & de Mattos, B. S. (2017), 'Artificial neural networks to predict aerodynamic coefficients of transport airplanes', *Aircraft Engineering and Aerospace Technology* .

Sei, S. (2000), Reduction of development lead time through improvements in the development process and innovations in production technology—reconfirmation of japanese-style supplier relations. evidence from a case study, *in* 'New Product Development and Production Networks', Springer, pp. 341–355.

Sellgren, U. (1999), Simulation-driven design: motives, means, and opportunities, PhD thesis, KTH.

Shan, S. & Wang, G. G. (2010), 'Metamodeling for high dimensional simulation-based design problems'.

Shea, K., Aish, R. & Gourtovaia, M. (2005), 'Towards integrated performance-driven generative design tools', *Automation in Construction* **14**(2), 253–264.

Shephard, M. S., Beall, M. W., O'bara, R. M. & Webster, B. E. (2004), 'Toward simulation-based design', *Finite Elements in Analysis and Design* **40**(12), 1575–1598.

Simpson, T. W., Poplinski, J., Koch, P. N. & Allen, J. K. (2001), 'Metamodels for computer-based engineering design: survey and recommendations', *Engineering with computers* **17**(2), 129–150.

Smith, R. P. & Eppinger, S. D. (1997*a*), 'Identifying controlling features of engineering design iteration', *Management science* **43**(3), 276–293.

Smith, R. P. & Eppinger, S. D. (1997*b*), 'A predictive model of sequential iteration in engineering design', *Management Science* **43**(8), 1104–1120.

Stauffer, L. A. & Ullman, D. G. (1991), 'Fundamental processes of mechanical designers based on empirical data', *Journal of Engineering Design* **2**(2), 113–125.

Stokes, M. et al. (2001), *Managing engineering knowledge: MOKA: methodology for knowledge based engineering applications*, Vol. 3, Professional Engineering Publishing London.

Suh, N. P. (1998), 'Axiomatic design as a basis for universal design theory', *Universal Design Theory* pp. 3–24.

Summers, J. D. (2005), Reasoning in engineering design, *in* 'International Design Engineering Technical Conferences and Computers and Information in Engineering Conference', Vol. 4742, pp. 329–340.

Sun, G. & Wang, S. (2019), 'A review of the artificial neural network surrogate modeling in aerodynamic design', *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering* **233**(16), 5863–5872.

Sutinen, K., Gustafsson, G. r. & Malmqvist, J. (2004), Computer support for requirements management in an international product development project, *in* 'International Design Engineering Technical Conferences and Computers and Information in Engineering Conference', Vol. 46962, pp. 189–200.

Tatipala, S., Larsson, T., Johansson, C. & Wall, J. (2021), 'The influence of industry 4.0 on product design and development: Conceptual foundations and literature review', *Design for Tomorrow—Volume 2* pp. 757–768.

Thomke, S. & Reinertsen, D. (1998), 'Agile product development: Managing development flexibility in uncertain environments', *California management review* **41**(1), 8–30.

Ullman, D. G. (1992), *The mechanical design process*, Vol. 2, McGraw-Hill New York.

Ulrich, K. & Eppinger, S. (1995), *Product design and development*, Tata McGraw-Hill Education.

Ulrich, K. T. & Pearson, S. A. (1993), 'Does product design really determine 80% of manufacturing cost?'.

Van der Velden, C. (2008), Application of knowledge based engineering principles to intelligent automation systems, PhD thesis, RMIT University.

VDI, V. (1993), '2221. design handbook 2221, systematic approach to the development and design of technical systems and products'.

Vellathottam, G., Perumalswami, P., Iliankamban, R. & Sankaranarayanan, S. (1997), 'An upfront analysis driven design process for product development', *SAE transactions* pp. 2367–2371.

Wang, G. G. & Shan, S. (2007), 'Review of metamodeling techniques in support of engineering design optimization'.

Wang, J., Das, S., Rai, R. & Zhou, C. (2018), 'Data-driven simulation for fast prediction of pull-up process in bottom-up stereo-lithography', *Computer-Aided Design* **99**, 29–42.

Wheelwright, S. C. & Clark, K. B. (1992), *Revolutionizing product development: quantum leaps in speed, efficiency, and quality*, Simon and Schuster.

Wheelwright, S. C. & Clark, K. B. (1994), 'Accelerating the design-build-test cycle for effective product development', *International Marketing Review* .

Will, P. M. (1991), 'Simulation and modeling in early concept design: An industrial perspective', *Research in Engineering Design* **3**(1), 1–13.

Wynn, D. C. & Clarkson, P. J. (2018), 'Process models in design and development', *Research in engineering design* **29**(2), 161–202.

Wynn, D. C., Eckert, C. M., Clarkson, P. J. et al. (2007), Modelling iteration in engineering design, *in* 'DS 42: Proceedings of ICED 2007, the 16th International Conference on Engineering Design, Paris, France, 28.-31.07. 2007', pp. 693–694.

Yin, R. K. (2011), *Applications of case study research*, sage.

Yoo, S., Lee, S., Kim, S., Hwang, K. H., Park, J. H. & Kang, N. (2021), 'Integrating deep learning into cad/cae system: generative design and evaluation of 3d conceptual wheel', *Structural and Multidisciplinary Optimization* **64**(4), 2725–2747.

Zhang, Y., Ren, S., Liu, Y., Sakao, T. & Huisingh, D. (2017), 'A framework for big data driven product lifecycle management', *Journal of Cleaner Production* **159**, 229–240.

## Data-driven and Real-time Prediction Models for Iterative and Simulation-driven Design Processes

The development of more complex products has increased dependency on virtual/digital models and emphasized the role of simulations as a means of validation before production. This level of dependency on digital models and simulation together with the customization level and continuous requirement change leads to a large number of iterations in each stage of the product development process. This research, studies such group of products that have multidisciplinary, highly iterative, and simulation-driven design processes. It is shown that these high-level technical products, which are commonly outsourced to suppliers, commonly suffer from a long development lead time. The literature points to several research tracks including design automation and data-driven design with possible support. After studying the advantages and disadvantages of each track, a data-driven approach is chosen and studied through two case studies leading to two supporting tools that are expected to improve the development lead time in associated design processes. Feature extraction in CAD as a way to facilitate metamodeling is proposed as the first solution. This support uses the concept of the medial axis to find highly correlated features that can be used in regression models. As for the second supporting tool, an automated CAD script is used to produce a library of images associated with design variants. Dynamic relaxation is used to label each variant with its finite element solution output. Finally, the library is used to train a convolutions neural network that maps screenshots of CAD as input to finite element field answers as output. Both supporting tools can be used to create real-time prediction models in the early conceptual phases of the product development process to explore design space faster and reduce lead time and cost.

MOHAMMAD A. RAD holds a B.Sc. in mechanical engineering with a focus on solid design and an M.Sc. in Automotive engineering with a focus on vehicle body and structure. In the licentiate, he is working on bringing data science and design science together. Applying machine learning in the design process can help a lot of industries with technical and complex products to explore the design space faster and more efficiently and also reduce the prototyping costs and lead time.

ISBN 978-91-87289-77-4