THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Design Automation techniques for the accelerated design of aerospace components

An exploration of different approaches and challenges

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CHALMERS UNIVERSITY OF TECHNOLOGY

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ABSTRACT

The pace at which new technology and air transport system architectures need to be incorporated into the air fleet to compensate for its climate impact is ever increasing. Consequently, the speed at which the next generation of more sustainable products need to be designed is also increasing. Being complex and critical systems, their performance needs to be evaluated in detail, for which existing automation techniques have been traditionally applied to speed up the analysis. However, these technologies are limited by human in the automation challenges, and new techniques are required that can scale to the accelerated pace of design cycles. This research explores the different types of design automation approaches on the aerospace industry and academia, looking for strengths to build upon and challenges to avoid or consider in the next generation of automation frameworks.

Generative AI is a novel technology currently under intense development, along with high level expectations on LLM applicability into Engineering Design - yet there is no clear best practice, nor a sound theory basis available to guide developers of new/improved design methodologies and practices. Its applications for design automation opens up a new paradigm that presents both challenges and opportunities to the engineering practice and the design engineering community. This research identifies such factors through the development of use cases in collaboration with industry. In addition, it proposes models to position their novelty with respect the existing aerospace ecosystem of designers and tools, clarifying the novel technology role and contribution to the design activities.

Keywords: Design Automation, Knowledge Based Engineering (KBE), Enhanced Function-Means, Generative AI, Foundation Models, Large Language Models (LLM)

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APPENDED PUBLICATIONS

The following research papers form the foundation of this licentiate thesis. The work for each paper was distributed among the authors as described below.

PAPER A: DESIGN AUTOMATION STRATEGIES FOR AEROSPACE COMPONENTS DURING CONCEPTUAL DESIGN PHASES

Pradas Gómez A., Panarotto M. and Isaksson O., Aerospace Europe Conference 2023 – 10TH EUCASS – 9TH CEAS, Lausanne, Switzerland. doi: 10.13009/EUCASS2023-578
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PAPER B: FUSE: A NOVEL DESIGN SPACE EXPLORATION METHOD FOR AERO ENGINE COMPONENTS THAT COMBINES THE FUNCTIONAL AND PHYSICAL DOMAINS

Pradas Gómez A., Panarotto M. and Isaksson, Aerospace Journal 12(1), 51. Doi :10.3390/aerospace12010051
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PAPER C: LARGE LANGUAGE MODELS IN COMPLEX SYSTEM DESIGN

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PAPER D: EVALUATION OF DIFFERENT LARGE LANGUAGE MODEL AGENT FRAMEWORKS FOR DESIGN ENGINEERING TASKS.

Pradas Gómez A., Panarotto M. and Isaksson O., NordDesign Conference. Reykjavik, Iceland, 2024. Doi: 10.35199/NORDDESIGN2024.74
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PAPER E: A TEAM OF THREE: THE ROLE OF GENERATIVE AI IN THE DEVELOPMENT OF DESIGN AUTOMATION SYSTEMS FOR COMPLEX PRODUCTS.

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Distribution of work: Alejandro conceptualized the paper and offered Max Kretzschmar to co-author it. The two main authors divided the literature reviews and surveys at their respective companies.
Status: Submitted.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CAD	Computer Assisted Design
CAE	Computer Assisted Engineering
CFR	Code of Federal Regulations
CI/CD	Continuous Integration / Continuous Deployment
CO2	Carbon Dioxide
CoTS	Commercial off the shelf softwares
CS	Certification Specifications
DEFAINE	Design Exploration Framework based on AI for froNt-loaded Engineering
DNN	Deep Neural Networks
DRM	Design Research Methodology
EASA	European Union Aviation Safety Agency
ED	Engineering Design
EF-M	Enhanced Function-Means
EU	European Union
FAA	Federal Aviation Administration
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence
GPU	Graphics Processing Unit
IATA	International Air Transport Association
ICED	International Conference on Engineering Design
JSON	JavaScript Object Notation
KBE	Knowledge-Based Engineering
KM	Knowledge Management
LLMs	Large Language Models
NN	Neural Networks
OEMs	Original Equipment Manufacturers
PD	Product Development
PDP	Product Development Process
PLMs	Product Lifecycle Management
QMS	Quality Management System
RQ	Research Question
RSPs	Risk (and Revenue) Sharing Partnership
SAF	Sustainable Aviation Fuels
SEK	Swedish crowns
US, USA	United States (of America)
USD	United States Dollars
vRAM	video Random-Access Memory
WCED	World Commission on Environmental and Development

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1 INTRODUCTION

This chapter describes the societal, industrial and technological state of the aerospace industry, as well as an introduction to the research area of design automation for product development. A brief description of the Generative AI industry is provided. Together, they frame the current state of the industry and highlight the present challenges. Then the implications for the future are drawn and the research aim is described.

Design is a complex activity that involves artifacts, people, processes organizations and the environment in which take place (Blessing and Chakrabarti 2009). The topic of this thesis is the design automation process within engineering design. However, to understand the context in which it takes place, a general introduction to the societal challenges and aerospace civil industry is presented here.

On September 2024, the European Union (EU) released a report (European Commission 2024) called "The future of European competitions", commonly referred to as "the Draghi report". It this analytical report, the stagnation of Europe's economy – measured in Gross Domestic Product (GDP) compared to the United States (US) – was identified as a risk for keeping our societal and economic standards. Three focus areas for immediate action were identified to address this challenge: (1) Become a leader in technologies, with a primary focus on AI, (2) a beacon in climate responsibility and (3) an independent player in the world stage. The three areas are interrelated. We use them in this introduction to paint a picture of the environmental, technological, and socio-political situation that drives this research.

As an example, GKN Aerospace is a first-tier supplier designs and manufactures components jet engine manufacturers. Given the sustainability pressures, it needs to adapt their technologies in this accelerated environment and support shorter design cycles and unconventional design concepts. Not only the products need to evolve, the methods and processes used to design those products also need to transform to support their designers under ever higher pressures and more complex analysis processes. This research aims to support those engineers by novel automation techniques.

1.1 FROM WARNINGS TO REALITY: THE ESCALATING CLIMATE CRISIS

One main goal of commercial flight transport is to deliver payload (passengers and cargo) from point A to point B as safe as possible. This safety has made transport systems to continuously evolve towards ever more mature systems while addressing the secondary goal of making the flight as fuel efficient as possible, which in turn, is claimed to address the CO2 emissions. Climate change has shifted this approach, forcing aircraft and engine architects to take risks and consider alternative and innovative solutions that deliver a step change in performance and sustainability.

Global warming and sustainability have been in the global political agenda for over three decades (Bhamra and Hernandez 2021). A few highlights of the events are *The Bruntland Report* at The World Commission on Environmental and Development (WCED) in 1987 where the first definitions of sustainable development was internationally agreed. Passing through the adoption of Kyoto Protocol in 1997 (effective in 2005) where countries agreed to reducing emission particles to the atmosphere. A more recent event is the United Nations (UN) conference, Rio+20 in 2012, when the Sustainable Development Goals (SDG) were defined, and launched in 2015. Today, most research funding and private enterprise initiatives declare their alignment to these goals.

However, the willingness of most countries to tackle the climate change effort has not translated into effective measures. Industrial and societal practices are not changing fast enough. Already in the 1970's the first scientific correlations between carbon dioxide (CO_2), global warming and the effects the increase of extreme weather conditions were published (W. D. Nordhaus 1975; W. Nordhaus 1977). Two catastrophic scenarios involving extreme heat waves, droughts, water stress and extreme weather, were envisioned if the planet average temperature increased by 1.5 or 2.0 degrees Celsius from the pre-industrial era (1850-1900). In their latest report, The Intergovernmental Panel on Climate Change (IPCC) declared that *"Human activities, principally through emissions of greenhouse gases, have unequivocally caused global warming, with global surface temperature reaching 1.1°C above 1850–1900 in 2011–2020"* (Calvin et al. 2023). The European Centre for Medium-Range Weather Forecasts announced that 2024 is the first calendar year that has reached more than 1.5°C above the pre-industrial level (Copernicus EU 2025). The catastrophic consequences of global warning have already been experienced by many countries in Europe, including the severe raining in Spain in 2024 that caused hundreds of deaths and will require hundreds of millions investments to recover the public infrastructure and local businesses (Otto et al. 2024), similarly to other parts of Europe such as Germany in 2021. In Section 1.3, it will be described how the aerospace industry has organized to tackle dish challenge, manage the growing flight hours while tackling CO2 emissions.

Furthermore, CO2 emissions is only one dimension of the sustainability planetary boundaries (Rockström et al. 2009a; 2009b). Some researchers declare that planet earth is beyond six out of nine of the planetary boundaries identified (Richardson et al. 2023).

Given this pessimistic situation, could the latest advancements in Artificial Intelligence (AI) support humanity to find solutions to this crisis?

1.2 THE RISE OF ARTIFICIAL INTELLIGENCE: ECONOMIC, SOCIAL, AND ENVIRONMENTAL IMPACTS

Generative AI, and in particular, Large Language Models (LLMs) powered by the deep neural network architecture "Transformer" (Vaswani et al. 2017) have gained significant attention since OpenAI released the online application ChatGPT. The transformer attention layers are able to relate inputs in ways that previous architectures couldn't, widening the application of the same model to many use cases. This section touches the economic, social, environmental, political and legal factors related to artificial intelligence. Given the importance of the technological aspects of AI for engineering design, an expanded review is provided in Chapter 2.2.

The economic potential of this technology has been estimated by many consultancy companies to be in the trillion dollar figure worldwide, ranking for example between 2.6 and 4.4 trillion USD. (McKinsey 2023b) The key difference between previous automation technologies and Generative AI is the potential to automate complex task including decision-making, affecting knowledge workers the most. Only in Sweden, the potential automation accounts for 180-310 billion SEK by 2045 (McKinsey 2023a). A later independent report quantifies the impact in knowledge intensive tasks to 200 billion SEK. (Implement Consulting 2024). True figures are hard to estimate since the implementation of the technology is still under development for realistic cases. The Gartner AI hype cycle for Artificial Intelligence still classifies Foundation models in the "Peak of inflated Expectations", expecting to reach a plateau in 2 to 5 years. (Gartner 2024).

To measure the social impact of the technology, the adoption curve of some of the applications using LLMs. ChatGPT has adopted 100 million users in only 2 months, positioning itself as one of the products with the fastest user base growth since launch ("Chatgpt.Com Traffic Analytics, Ranking & Audience" 2024).

The environmental impact of the technology relates mainly to the massive computational efforts required to train and run the neural network models that exceed a billion parameters. (Luccioni, S 2024). The increase of computational resources originates from a new scaling law: more training data and compute delivers more performing models. The increased computational effort equates to an increased demand for power and water consumption.

In addition, only a limited number of companies are able to produce hardware able to execute those models fast enough at scale, giving NVIDIA a de-facto monopoly on GPU hardware. GPU hardware, and in particular a large enough virtual Random Access Memory (vRAM) is required to store all the parameters on a unified pool for the GPU to calculate the next token efficiently. As soon as some of the weights or calculations exit the GPU, the calculation time (for training or model execution) decreases significantly due to the loss of parallel computing that GPU enables. The limited production of capable hardware has created a race for acquiring resources for GenAI development. Due to the capital power, most of the production is being bought with months and years in advance mainly by large AI corporations such as Microsoft (OpenAI), Meta and X.ai. Still, some research institutes and national bodies are seeing these limitations and fighting for a share of the scarce hardware, such as NAISS at Sweden ("About Us | NAISS" 2024) or Denmark's Gefion supercomputer ("Danish Centre for AI Innovation" 2024).

Foreseeing the impact of this technology in society, the European Union is one of the first legislator to introduce ground rules for the use of AI in the "AI Act" ("Regulation - EU - 2024/1689 - EN - EUR-Lex," n.d.). The piece of legislation defines risks and limits the application of AI based on then. It imposes requirements and obligations on AI developers and providers to protect the general public. Examples include the prohibition ot use AI systems to matipulate or deceive, exploit human vulnerabilities, social scoring or General Data Protection Regulation (GDPR) adherence. Other legislative bodies, such as the US Senate committee on the judiciary, are also considering some sort of legislation ("Oversight of AI: Insiders' Perspectives | United States Senate Committee on the Judiciary" 2024). From the preliminary hearings, it is expected that the US senate will impose some basic legislation ("a light touch") compared to the EU, which is already clashing with Generative AI models. For example, the latest family models from Llama (3.2 vision models) are not licenced in the EU, and neither is available the latest Generative enabled features of the Apple iPhone operating system.

1.3 THE STATE OF THE AVIATION INDUSTRY

The aviation industry is estimated to contribute directly with 3.5% of the CO2 global emissions (Lee et al. 2021). Like other industries, the aerospace sector, especially the commercial passenger flight, is aligning with the sustainability goals and have set the objective to reduce their contribution to CO2 emissions by 2035 and offset completely by 2050. (European Commission 2011; 2022). Currently, the approach is to achieve net zero emissions while continuing at the current growth rate of aircraft operations. To enable this policy of "eat the pie and have it", there are several contributing approaches that together, can deliver net-zero. According to the latest International Air Transport Association (IATA) figures (McCausland 2021) those are: Sustainable aviation fuel (65%)

New technologies (13%) Infrastructure/operations (13%) and Offsetting or carbon capture (13%). These figures vary depending on the impact of the future new technology developments (Air Transport Action Group 2021). What is clear is that ideally, the new technology implemented in the development of aircraft and propulsion systems should provide efficiency improvements and/or the removal of hydrocarbon fuels. Everything else will have to be compensated through Sustainable Aviation Fuels (SAF) and offsets.

Although SAF has been declared as essential by the references above to achieve net zero aviation, it has significant implementation challenges. It has a lower carbon footprint (20% to 50% reduction) meaning that it will not reduce 80-50% its lifecycle emissions (Jarin et al. 2024). The raw materials and location of the SAF plants have a significant impact in their footprint (Dietrich et al. 2024), and there are doubts about the availability of biomass required to satisfy the needs of the aerospace industry (Grim et al. 2024). Therefore, this research does not focus on the SAF backup strategy and aims to solve the climate challenge using technological innovations, for which companies will have to design new components requiring accelerated evaluation loops.

Despite technological advancements, the airline and jet engine has reached a plateau of architectural innovation, and the forecasted technologies (Kellari, Crawley, and Cameron 2017) are not enough to cover the sustainability goals. Radical new technologies are required, that still need to comply with the strict airworthiness requirements. Those requirements for aircraft are defined by the European Union Aviation Safety Agency (EASA) in Europe Certification Specifications (CS)-25 and in the United States of America by the Federal Aviation Administration (FAA) in Title 14 of the Code of Federal Regulations (CFR) Part 25. For aircraft engines the regulations are respectively, CS-E and CFR Part 33. These regulations impose strict requirements on the design process to ensure flight safety.

Due to the flight dynamics, two main performance quantities of interest drive the development of aerospace products: weight and propulsive efficiency. The lighter the component, the lighter the plane and the further the range can be or accommodate more payload for the same range. The more efficient the plane, the less fuel or battery weight is required, reducing the propulsive system weight which in turn reduces the need for a big propulsive system. Together with the component manufacturing cost, these are the three main drivers for component development. The design systems making use of accelerated design and evaluation loops via simulations will use these quantities of interest in their evaluations.

From a stakeholder development perspective, the aerospace industry is driven by Original Equipment Manufacturers (OEMs) that capture the customer requirements (passenger, airlines), their market growth scenarios and align them with the Airworthiness authorities (EASA, FAA, etc). While OEMs are the integrators of the aircraft system, and developers of key technologies and components, they rely on suppliers to design and manufacture the components. Most civil airplane OEMs (Airbus, Boeing, Embraer) rely on this strategy as an alternative to a vertical integration strategy, mainly due to the cost of development and risk of a new aircraft or engine program. The supplier's responsibility can vary from purely a contractor role to a risk (& revenue) sharing partnership (RSP), depending on the experience, capability and capital expenditure provided to the programme. In addition, OEMs expect RSPs to propose new and more effective technologies, that govern the need for a coordinated approach and systems integration perspective, e.g. design studies to integrate sub system technologies into a whole engine system. To join the risk and revenue programme, OEMs nowadays require RSP to design and manufacture a percentage of the components equivalent to their share on the programme. With their own differences, the scenario of civil engine OEMs (Rolls-Royce, General Electric, Pratt & Whitney, Safran) is similar to the airframe OEMs. Given the importance of the aerospace sector to their national economies, USA airlines are encouraged to buy or lease Boeing aircraft and European airlines are encouraged to acquire Airbus. Airframers offer both EU or USA engines to offset that balance to airlines whose flight routes fit best the other side of the Atlantic airframe offer.

The OEM-RSP relationship makes the role of RSP the component developer, as opposed to the OEM which has a more systemic view. The design philosophy of the RSP (the component provider) follows more a traditional Product Development (PD) approach (K. T. Ulrich and Eppinger 2011; Pahl and Beitz 2007). The OEM, due to the complexity of the integration and verification requirements, follows a combination of traditional PD and Systems Engineering (SE) approaches (INCOSE (ed.) 2015; NASA 2006). In addition, due to RSP contributing to different engines and aircraft, need a generic product development that can adapt to their specific customers and is independently validated, and ultimately aligned with EASA's Design Organization Approval (DOA) or FAA Organization Designation Authorization (ODA).

RSPs develop products based on previous generation of products, therefore from a development strategy they typically follow a derivative development, rather than a new product development (K. T. Ulrich and Eppinger 2011). Due to the traditionally stable architecture (K. Ulrich 1995) the new product focus on incorporating similar requirements into similar manufacturing processes used as assets into the manufacturing platform. RSPs have a Global Product Development strategy, having several sites around the globe where manufacturing, design and OEMs need to coordinate on different time zones to develop the product. However, as discussed in Section **Error! Reference source not found.** the climate change and need for innovative solutions is challenging the traditional development approach, and this disturbance is one of the justifications for the need for accelerated design and evaluation frameworks.

To provide the airworthiness justification of new components, a fundamental part of the product design is the validation of the proposed product, which is recoded as analysis reports. For example, a structural product may be assessed against the manufacturing and airworthiness requirements, such as limit analysis (CS 25.303) or Damage tolerance (CS 25.571). Each of those reports, that undergo a quality process of author-reviewal-approval process can be considered the unit of work the design validation process. It is via the OEMs, who collect the justification of all components and requirements, that the aerospace systems are certified against the chosen airworthiness basis. The importance of this analysis activity is not only for the detailed verification, but also for the conceptual phases and conceptual system design. As the design margin is small in flying structures, new architectural concept needs to be assessed against those requirements (or a subset of them considered critical a priori by experienced designers) from the very early phases to ensure the proposed concept is valid.

Finally, on the AI front, new guidelines and future policies are being developed by EASA to leverage the power of AI while maintaining the safety of the aviation systems. (EASA 2023). The document categorizes AI systems based on the risk to safety and imposes increasing requirements as the risk to safety increases. Originally launched in 2019, the document was intended to cover the operational and on-board decision system, for example systems that support the pilot on real time (e.g. change altitude or heading). However, the ongoing effort has been expanded to include the support of Generative AI in design applications. These systems are preliminary called "non-embedded AI trustworthy tools" (EASA 2024), and could cover the tools used by engineers, such as the proposed accelerated design systems that this research will propose on Section 7. EASA is still defining the requirements, and it is planned that a preliminary list will be available in 2025.

1.4 Implications for manufacturers of aerospace components

Getting the right architecture configuration is important for the viability of the aerospace companies. The aerospace industry is risk adverse (Fragola, Putney, and Mathias 2003), specially stablished OEMs with a large market share and a backlog of orders that spans hundreds of aircraft and years of delivery wait for airlines.

At present, it is not clear what technology or combination of technologies is most effectively going to support the reduction of CO2. OEMs have launched research projects to investigate the use of alternative fuels (mainly in Europe), such as hydrogen, and the launch of new engine architectures prototypes, such as the RISE project (CFM International 2021). For RSPs, they need to prepare their technology and manufacturing processes in advance, approximately 3-7 years to develop the technology and another 3-5 to develop the products, making the entry into service of any future technology over a decade ahead.

However, the derivative concepts cannot longer deliver the expected sustainability goals, and there is no time to explore the design space of system and detailed component performance in a new product development scenario. Many aerospace companies have started with the goal of developing radical architectures such as Heart Aerospace, Lillium or Reaction Engines. The fact that Heart Aerospace has evolved their system several times in the past two years, or that Lillium and Reaction Engines have entered administration in late 2024 are three examples of how important it is to balance the right architecture with a detailed evaluation of the components performance.

Therefore, from a RSP design perspective, it is challenging to have an overall picture on how their component design can contribute to the overall system CO2 goals, and in what manufacturing technologies they should invest their development efforts. Internal development programs are being developed on a system level to judge what will be the system behaviour and have a notional concept to design the components against (GKN Aerospace 2024). It is critical that the RSP component technology is mature enough to be considered as a candidate during the next engine or airframe conceptual phase. This implies that several system architectures and components designs shall be explored in parallel, cascading the interface requirement to the component and evaluating its performance in detail.

1.4.1 SPECIFIC CHALLENGES TO BE ADDRESSED

The evaluation of the components is a time and resource intensive activity. Due to their complexity, customer specific methods and difficulty to automate, even harder to optimize (Elgh 2012; Simpson and Martins 2011). This leads to a lot of manual effort in validating each result manually or to configure the models and automations that generate the calculations. Over allocation of resources, report delays and the inability to respond on time to new system configurations are the usual implications for this environment. Therefore, there are missing opportunities to unlock design and manufacturing efficiency gains at early phases of product development, and project overruns at detail phases.

Many design automation techniques have been explored in the past to attempt to automate this design generation and evaluation of component designs. Knowledge Based Engineering is one of those technologies that promised significant gains, were initially adopted on the development of some airframe (Pardessus 2004) and engine products (Marra 1995), but have not been widely adopted by industry in subsequent products. The black box paradox and expertise level required to operate the system are some of the reasons why this technology has not been adopted (Kügler et al. 2023). Other sources claim that hostile takeovers of KBE companies contributed to the abandonment of the KBE technology. Could new open-source AI techniques support its adoption?

The aerospace industry has a high level of engineering capability; however, it is mainly specialized on system design or specific engineering disciplines such as mechanical engineering, aerodynamics or manufacturing. Artificial intelligence is not one of the core engineering capabilities. However, they are starting to evaluate the Generative AI capabilities for engineering tasks such as Saab or General Electric (Saab 2024). These platforms are explorative, and it is still unclear how the architecture of such systems could be best utilized. Each industry and company need to evaluate GenAI for their use case. Considering a report that states that approximately 90% of the pilot applications do not go into production (Bendor-Samuel 2024), there is a clear need to appropriately investigate the how to best adapt and practically implement this technology in the design automation of components.

1.5 RESEARCH AIM, FOCUS AND DELIMITATIONS

The aim of the research is to enable engineers to perform their design and validation activities as efficiently as possible. Efficiency is a measure of success that can be broken down into three different measures: Lead time, quality and cost. The area of contribution of this research is the Design automation, which ultimately aims to affect the three metrics. By automating some of the engineering tasks with computer programs, the time is significantly reduced to the speed at which machines can compute. By ensuring that the automation is implemented correctly, the quality of the results is guaranteed and free from user error, reducing iteration loops. Once these measures are addressed, the cost of designing a product is reduced due to the reduced engineering hours. (Cederfeldt and Elgh 2005).

Within the context of this research, complex products are defined as components that are usually part of complex systems that are difficult to describe, understand, predict, manage, design or change(Sellgren 2005), that additionally require the use of physical simulation models for the validation of the concepts.

The focus of the research is the design and verification of complex components. The complexity of a product can be defined from many perspectives, see Raja et al. (2019). The definition of component complexity is the more generic term defined by Sellgren (2005) s as components that are usually part of complex systems that are difficult to describe, understand, predict, manage, design or change. Given the support of GKN Aerospace, an RSP perspective has been taken to the design process, and the object of design is exemplified in structural aerospace component. Although the research is conducted in an aerospace domain, the generalization is clear for other neighbouring industries such as automotive, heavy machinery, is similar to the aerospace case and results could be extrapolated. The assumption has been confirmed via the industrial feedback in **Paper E** where both aerospace and automotive industries presented the same challenges, processes and tool types. Therefore, the context of predominantly considering the aerospace domain for the research studies is justified.

The efficiencies of the engineering process could be addressed from many perspectives. For example, from an organizational management it could be argued what is the most efficient team dynamics are: an agile approach vs a strong milestone and risk management (e.g. PRINCE2). It could also be explored from a Lean perspective: identifying value added and non-value added activities, removing the unnecessary engineering operations. Another perspective could be the Knowledge Management approach: how to maximize the relevance of the information available to engineers to do an efficient work and minimize the knowledge gaps to become a high performing engineer. In contrast, this thesis takes the **design automation perspective**. This perspective not only looks at the tools and methods to support engineers to perform such activities. It also considers the procedures and workflows in which those tools and methods are applied.

1.6 THESIS STRUCTURE

The chapters of this licentiate thesis are structured as follows:

Chapter 1 introduces the societal challenges, AI and aerospace situation today. It then presents then the aims and context of the research

Chapter 2 gives the research a reference framework and presents the state-of-the-art as extracted from the literature. The research gap is summarized.

Chapter 3 follows up with the presentation of the research questions that aim to clarify the research gap. The methodology to answer the research questions is presented and related to the papers presented. The method for data collection activities and data analysis is presented.

Chapter 4 compiles the summaries of the appended papers, and synthesis the outcome for the research question at the licentiate level.

Chapter 5 details the findings from the studies and logically link them together. Additionally, results from other research conducted by MSc students in the context of Generative AI and GKN Aerospace are added and linked to the results of this research.

Chapter 6 discusses the results from Chapter 5 as they relate to the research questions stated in Chapter 3.

Lastly, **Chapter 7** summarizes the previous chapters and outlines possible future work to be pursued.

Appendices collate the full-text versions of the four papers published during the research.

2 REFERENCE WORK AND STATE OF THE ART

This section explains the reference and perspective of this research, and highlights the relevant academic references and industrial state of this field

This thesis draws from its Chalmers foundations for the product development perspective and its neighbouring research influences. Particularly the vision of the Engineering Design in the Workshop Design-Konstruction group: Principles of engineering design (Hubka 2015) and Theory of Technical Systems (Hubka and Eder 1988), being particularly active since the early 80's. This perspective of product development and research has been carried forward by the Design Society (Eder 2008) and it is the primary lens in which this research is conducted for design automation. Aerospace components are the objects in which the engineering design theories are applied and bound the research to its industrial application. Similarly, Computer Science and AI is the automation technique. The research is not on the foundation models, neural networks, but in their application to solve problems identified by the engineering design research. See the Areas of Relevance and Contribution diagram in Figure 1.

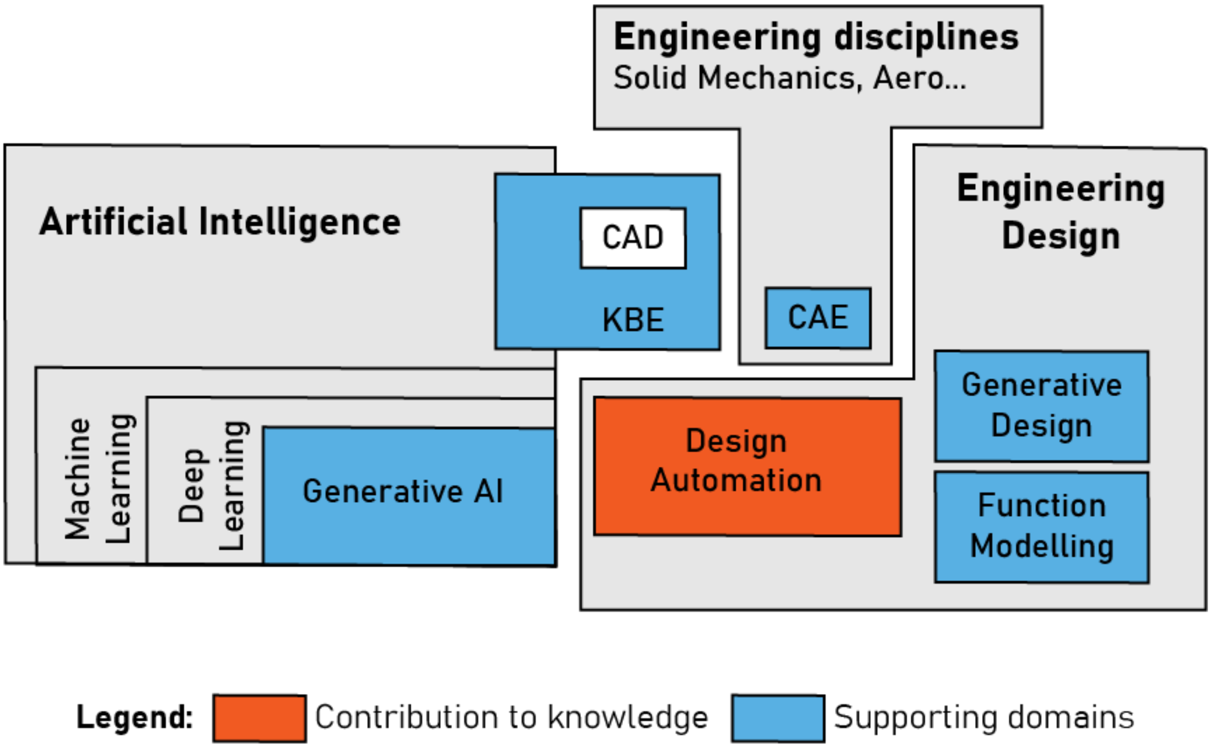

FIGURE 1 ARC DIAGRAM AS PER THE DRM SUGGESTION

2.1 PRODUCT DEVELOPMENT PROCESS: THEORY AND AEROSPACE PRACTICE

This chapter describes the theoretical perspectives that research have in the activity of designing products, and the practical perspectives used in the aerospace sector. It follows with an emphasis on three areas of research withing engineering design that are used in this thesis: functional modelling, generative design and design automation.

What is engineering design? And what is its relationship with product development? According to Urich and Eppinger (2011), the product development process is the set of activities beginning with the perception of a market opportunity and ending in the product sale, and delivery of a product. This definition could be expanded in many dimensions: expanding to services, not only physical products, or the activities: to the maintenance. However, this research choses to focus on physical products, in particular aerospace components that are part of a larger system. To design such products is to consider all the technical requirements and envision a definition of a product that can be effectively realized. Generating such definition requires a multi-disciplinary team of engineers that use their technical knowledge to evaluate and iterate the product definition. In this thesis, engineering design is this process. Although, for a wider perspective of engineering design and systems, the reader is directed to (Ola Isaksson, Wynn, and Eckert 2023).

Modelling this process of designing, or development of products is a complex process. There are as many theories and models as the perspectives for which they are developed. None of these process models is able to capture all its characteristics (Wynn and Clarkson 2018). In addition, all of these perspectives, models and theories can co-exist with equal validity, and the most helpful selection of those is dependent on the particular situation (Ola Isaksson, Wynn, and Eckert 2023). For dimensions are proposed by Wynn and Clarkson (2018) to group process models in design: abstract, procedural, analytical and management science/operations research. From them, the analytical (at its highest macro level perspective) is the one found most suitable to describe the design process at aerospace companies in the context of this research.

For aerospace engineering applications, the design process and the supporting organization resembles the structure defined in Pahl and Beitz (2007). Their description of the process and approach is generic, due to their objective of defining a systematic and general process valid for most industries. Given the different requirements and specific know-how required by companies (e.g. quality requirements and airworthiness certifications) to design aerospace components, in reality the development processes are governed by a Quality Management System (QMS) where detailed policy, procedures, activities and methods are described, and it is the primary definition of a product development process.

Depending on the nature of aerospace companies, their QMS may be influenced by a methodology or other. The nature of OEM companies as a System Integrator leads for those QMS to be inspired by a System Engineering approach, especially in the space and military sectors. On the other hand, RSPs receive delegation authority from their OEM customer and do not need to have a System Engineering Perspective. Although their QMS need to be aligned with the OEM, they design their own product development process in their QMS. This process is generic enough that can accommodate the different OEM partners they work with. Therefore a generic approach of product development (Pahl and Beitz 2007) combined with a project management gate-focused development (Cooper 1990) is the reported process in their respective QMS.

2.1.1 Function Modelling

The use of modelling products as a proxy for the physical design has been use for centuries in many product development activities. For example, the use of 2D drawings – the models – in the shipbuilding industry can be traced back to the 18th century to Fredrik Henrik af Chapman. Today, the models not only represent the physical product in CAD or CAE, but also their functional properties that they are supposed to fulfil. The use of "function" in product development has many definitions. In the context of this thesis "function" is defined as "the intended behaviour of the product" (Gero 1990).

A specific functional modelling techniques exists in the aerospace domain: Systems Engineering, which was developed at NASA (NASA 2006) after the insights gained from the space program Apollo. However, Systems Engineering can be argued to predominately provide a means to check consistency between requirements and their verification status and does not present a systematic guidance on the engineering design methodology level. More recently, a Model Based System Engineering (MBSE) philosophies have been developed that are tightly relates the systems, methodology to describe them (Arcadia) and tools used to model the system using the methodology (e.g. Capella). In this thesis however, we focus on the product development function modelling as described before by Hubka due to its simplicity and flexible application in the system conceptual phase.

This thesis looks at the connection between the functional domain and the physical domain. This overlapping of domains has also been explored by Buur and Andreasen (1990) and Suh (1990), the later defining the design activity as "zigzagging" between domains. The Function-Means structure (Hubka and Eder 1988) connects the need or function that the product needs to do with the concept of the physical means to do it. Schachinger and Johannesson (2000) combined Suh's first independence axiom into Hubka's Function-Modelling approach, defining the Enhanced Function-Means (EF-M) modelling approach, including also the dependency modelling between design solutions or means. The first independence axiom requires that only a single means or "Design Solution" can be connected to the Functional Requirement. Muller et al., (2019) highlighted the possibility of exploring the design space by exploiting the one-to-one association of design solutions to capture "variant" design solutions. Later, in (2020) and (2021), Müller et al., developed a method (OMFG) to connect the functional domain with CAD models in the physical domain. Their work and the lessons learned from it (Müller et al., 2020) is the state of the art from which this thesis continues further, specially the method developed in **Paper B**.

2.1.2 GENERATIVE DESIGN

In the context of product development, generative design is defined by Krish (2011) in the context of the conceptual design phase as the ability to generate designs by exploring a vast design space without conscious decision 0a-priory by the designer. Instead, boundaries (physical, parametrical, configuration alternatives) are defined, and an algorithm is allowed to search in that space. Some algorithms quantify the performance against some objective or metric, while other algorithms simply generate concepts and let it to the designer to choose. According to Krish, a generative design process shall include three things: "(i) a design schema. (ii) a means of creating variations and (iii) a means of selecting desirable outcomes". According to this definition, the OMFG method by Muller et al. (2021) is considered a generative design process as it automates the design schema and the generation of CAD models for analysis. The design exploration performed in **Papers A** and **B** are considered as per this definition of "generative design".

Other definitions of generative design exist within engineering product development. They are included below to describe them and position against the definition above of generative design in this thesis.

1. Generative design has been marketed by CAD/CAE software vendors as "*the process of using algorithms to help explore the variants of a design beyond what is currently possible using the traditional design process. Mimicking natures evolutionary approach, generative design uses parameters and goals to quickly explore thousands of design variants to find the best solution*" (McKnight 2017). As

such, it has been used as a marketing term, and in this thesis, it is considered a combination of topological optimization and design space exploration.

2. Genetic algorithms in the context of Design Space Exploration use the term generative to reflect the generation of offspring designs based on the previous generation.
3. Within the intersection of engineering design and deep learning research areas, there are other sub areas that also categorize themselves as generative design. The term generative comes from the output of the models. As the models learn from a dataset of possible designs and is able to generate new concepts that are not contained in the training dataset. Deep learning AI techniques have been applied in the conceptual design of automotive wheels (Oh et al. 2019; Jang, Yoo, and Kang 2022) or aircraft shapes (Shu et al. 2020).

As an evolution to deep learning and due to the recent deep neural network architectures, such as transformers or diffusion models, a new generation of AI is being referred as "generative AI" or GenAI. The key characteristic of the application of this Generative AI to the one mentioned in the third point above is that the above technique uses the deep neural networks to propose new concepts or to estimate their performance, while transformers models are used to generate a string of text that attempts to justify or use tools to generate or evaluate design concepts. This approach is described separately in section 2.2.3, and is the approached used for **Papers C, D** and **E**.

In summary, the generativity aspects in engineering design covers a wide array of techniques and processes. This research uses two approaches of "generative design". The traditional approach defined in this section for **Papers A** and **B**, and the Generative AI approach for design automation defined later in section 2.2.3.

2.1.3 Design Automation

This thesis claims to contribute to the research area of design automation, defined as the "*Engineering support by 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.*" (Cederfeldt and Elgh 2005).

The design automation support aims to increase the productivity by lead times, decrease and errors (Rigger and Vosgien 2018). Productivity is interpreted in this research as increasing the effectiveness of the design task, traditionally associated with automating the engineer activities to obtain results more consistently and faster than the manual alternative. The needs for this automation is driven by repetitive and laborious design tasks and desire for cost reduction (Cederfeldt and Elgh 2005). Note that the difference in between *effectiveness* – taking action to get closer to a goal – and *efficiency* – doing the task faster. The productivity gains expected are on both areas.

The application of design automation can be done through different methodologies, including automation *within* CAD or CAE software, bespoke Knowledge-Based Engineering frameworks or via standalone traditional scripting and coding languages. The experience with the participating aerospace companies shows that despite the level of automation that can be achieved in the Commercial off the shelf software (CoTS), there is always a bespoke step or activity needed at each company that CoTS cannot support. For example, CoTS application such as NX have automated methods to mesh components, or the ability to execute scripts that call their internal API functions (journalling). However, some pre- and post-processing of the design inputs and outputs is often required to connect and automate the design workflow, or often the design automation requires additional information that is not accessible directly by the CoTS automation capabilities. This thesis covers a generic view of the design automation of activities that cover all the design definition and verification, that can include none or several CoTS software.

2.2 ARTIFICIAL INTELLIGENCE

Long before the invention of computers and silicon chips, designers were already trying to offload their cognitive capabilities to analog computers. For example, the need to quickly and efficiently decompose a tidal wave into its harmonic components led Lord Kelvin to develop a machine that automated that process in 1873. As he described it, "*the object of this machine is to substitute brass for brain*" (Thomson and Kelvin 2011).

Alan Turing vision to build a "general-purpose computer" (Turing 1950) materialized by the construction of the Bombe machine in 1940, which embodied the theoretical works of Charles Babbage and Ada Lovelace on the Analytical Computer (Strawn 2023). The purpose of this machine was to de-cipher adversary communications rapidly. In a war scenario where real time information was critical, Bombe was able to decipher what humans couldn't do in the required timeframe. Since then, the use of electronic signals replaced mechanical devices, and with the development of the microchip the era of digital computers started in practice.

This example is an analogy to the need for a more powerful design automation technique in the development of aerospace products: engineers are running out of time to make an impact in the sustainability of the aerospace fleet. Can the new AI techniques speed up the design process?

To evaluate this recent AI developments and understand their characteristics it is worth to take a step back – in time. The first use of Artificial Intelligence (AI) has been attributed to the summer of 1956 in “A proposal for the Dartmouth Summer Research Project on Artificial Intelligence”. Since then, several periods of active research in the field have been followed by “AI winters”. The characteristics of each phase are defined by DARPA (“DARPA Perspective on AI” 2024) as waves. These waves are used in this research to inspire characterize each AI sub-technology, following the same qualitative criteria they use to characterize the waves:

1. **Perceive** rich, complex and subtle information.
2. **Learn** within an environment
3. **Abstract** to create new meanings
4. **Reason** to plan and to decide.

Each of the terms above would require its own definition and further quantitative analysis. Specially for the engineering design domain, which has been historically misunderstood for the scientific research (Eekels and Roozenburg 1991), and have within each research area the term may be defined differently. In particular, the term *reasoning* could be interpreted as *logic* in the mathematical domain. Eekels and Roozenburg categorize the patterns of reasoning as deductive and reductive, subcategorizing the later in induction, and abduction.

One critical difference with DARPA’s wave definition exists. In this thesis The perspective of the waves was intended to set the scene to a third wave of models supporting the “Explainable AI” paradigm (Barredo Arrieta et al. 2020; Geyer, Singh, and Chen 2024). It could not foresee back then the impact that generative models, created in the late 2010’s, had in the world in the early 2020’s. Therefore the third wave of AI has been considered in this thesis as the generative AI wave.

2.2.1 First wave: KBE

The exploration of Artificial Intelligence after the summer of 1956 led to the formation of the MIT Lab and the Stanford SAIL by Minsky and McCarthy, but in order to achieve progress in artificial intelligence, the focus was on a very “narrow” or specific domains.

An example of a narrow natural language by Winograd (1972) showcase an interaction between a human and a computer that seemed realistic as long as it was asked about a specific set of questions in a given environment. Later on, in order to advance the reasoning capabilities, engineers and researchers captured knowledge from the world and made it available to a "reasoning engine" to make conclusions about the inputs that had been received, launching the field of knowledge engineering and expert systems.

Knowledge-Based Engineering (KBE) is a descendant of this philosophy, and as La Rocca (2012) defines, it lays between CAD and AI. The key characteristic of the first wave of AI is that the knowledge of the world and rules have been derived by humans and coded in a machine-readable format. Based on the input provided by the user and following the rules, the reasoning engine computes an outcome deterministically. Therefore, the humans does the *perceiving* of the real world on behalf of the machine, giving a low score to this metric. Perceiving should not be underestimated, as the need for a knowledge expert to capture and codify the knowledge is a known bottleneck in this process, outside of the programming implementation. Knowledge management frameworks such as MOKA (M. Stokes 2001), ontology models and processes needed to be crafted and followed to implement and maintain such systems (Milton 2007). Such rule systems are unable to *learn* or *abstract* by themselves, scoring null on these metrics. But once the knowledge is in the system, its reasoning capability is high.

2.2.2 SECOND WAVE:

The second wave of AI is characterized by the ability to learn from data, as opposed to the first wave where a human had to interpret it. Models in this wave could be classified by Supervised, unsupervised and reinforcement learning process. Supervised learning takes data and corresponding labels and is trained to map the data to a label. Examples of supervised application are classification, regression, object detection or semantic segmentations. On the other hand, unsupervised learning is feed only data, and its goal is to learn hidden or underlying structure of the data. Examples are Clustering, feature or dimensionality reduction. Reinforcement learning has state-action pairs as data input, and their goal is to maximize future rewards over many time steps. AlphaGo is perhaps the most famous example (Silver et al. 2016).

In this generation of AI, the reasoning is not based on rules but purely on the data that the model is been able to observe and learn from it. Therefore, this generation has much higher capabilities to "perceive and learn" than to "reason". The models learn by being exposed to large amounts of data and a minimization objective, also known as training.

Due to its capability to learn from data, this wave is also called "Machine Learning". A compilation and automation of different *advanced statistical techniques* are also included here. Different model architectures exist, but one of the most famous and scalable architectures are Neural Networks (NN). The ability to learn from data allowed LeCun et al., (1998) to recognize digits from images, or for Krizhevsky (2012) to beat the ImageNet competition using a NN architecture.

Typical scenarios for engineer design are the classification of designs, similar to face recognition, or the prediction of a product performance (Baqué et al. 2018).

Since the models can read world directly (e.g. images, raw instrument data) they score high in the metric of *perceiving*. They find patterns in data directly and therefore have a high *learning* score also. However, their narrow scope of application and limited context awareness of the whole design process makes these models to have low *reasoning* scores. Although models trained using unsupervised learning are able to abstract concepts, this abstraction concept is not directly useful for the designer and therefore the *abstracting* score is still low. For example, unsupervised learning models can, with sufficient data, classify images of bolts and nuts, but they lack their design intent without further data outside the pictures.

The transition to the third wave of AI in engineering design is gradual. Some examples of deep learning approaches are the design of automotive wheels (Oh et al. 2019) or the exploration of the design space for variety (Chen and Ahmed 2021). These examples make use of the "latent space" or "embeddings" to extract knowledge from the design data itself. Sampling on these spaces, models can generate new designs using Variational Autoencoders (VAEs) or Generative Adversarial Networks (GANs), but they are still considered second wave generation models. For a review of these models application to the engineering design research area, see Song, Zhou, and Ahmed (2024).

2.2.3 Third Wave: Deep Generative Models for Reasoning

The third wave of AI has not been driven by a radical new idea, but the evolution of the second wave models and new domain applications. The enabling neural network architecture, the transformer (Vaswani et al. 2017) is the combination previous deep neural network techniques. However, the attention layer and the sequence prediction is the basic architecture from which the most Large Language Models (LLMs) derive from such as GPT-4 (Bubeck et al. 2023)

The key characteristic of this wave of models models is its ability to have a high level of observability: their domain is much wider than the first wave of AI, and at the same time can learn from data and reason – or *mimic* reasoning. These models have evolved their capabilities so much that they are no longer a tool that engineers use, but an active companion of the design process. Engineers can now offload low level cognitive processes to these models. A significant difference with respect to the first wave of AI is their non-deterministic nature of the output, which can be both a challenge in an aerospace context requiring repeatability, or an opportunity in the exploration of novel architecture definitions.

The purpose of the third wave is not to predict performance or a generate a novel design definition by itself. This is a significant difference from the previous waves. Focusing on a text only modality, the LLMs receive text and generate text. The input can be the need stated in natural language by an engineer to perform an engineering activity, and the outcome could be the specific steps and rationale to execute it. It could even be the calls to supporting tools to perform design or analysis activities. Other authors refer to the models able to perform these abilities as "NextGen-AI" (Alam et al. 2024). As discussed in this forward-looking review, there is a gap in the implementation of these technologies in a realistic design and product development processes. In addition, the performance of this technology is highly sensitive it's application environment, making the research of incorporating this technology rigorously in engineering design processes even more necessary.

This difference between performance prediction and reasoning prediction purpose of the new wave of AI has profound implications for the generation of innovative designs in aerospace. The sought designs may require departing from the available distribution of designs in the dataset and still requires to have a high confidence on their estimation for the quantities of interest needed to perform evaluations. Second wave of generative models (GANs, VAEs, etc) learned to interpolate new designs from the provided dataset, and the performance of those generated designs is weak if the dataset is not sufficient and diverse. Generating a good dataset to train the models is challenging. Therefore, learning how to perform the engineering steps to generate a new design, like a human engineer would do, becomes crucial if such design require an evaluation (stresses, pressure loss or life cycles) that is close to the actual results.

An example of a concatenation of multi-modal LLMs supporting designers can be found in Edwards et al., (2024), from stetch vision to description to the generation of 3D geometries. However, practical engineering applications in aerospace require the use of specific processes and tools. Conveniently, these models can also be instructed to follow those engineering steps. Is this ability to replicate human steps what makes it attractive for design automation activities. While first Generation KBE models required engineers to code the rules and pass on specific input parameters or files, the GenAI models are able to interpret the user input and refence previous natural language instruction to generate a response. These models can be therefore considered “translators” between human instructions and tools.

Other areas of the design process can be supported by this third wave of Generative AI models. For example, the use of Generative AI in early product development to support designers in innovating (Piller, Srour, and Marion 2024) or requirements management (Norheim et al. 2024). There is a consensus on the potential of these models to go beyond what traditional AI tools could provide, and at the same time highlighting the challenges of this technology.

Finally, it is worth mentioning the reasoning capabilities of these models, and the ongoing debate around it. Withing the AI and computer science domain, there is some consensus around enthusiasts of the technology that these models can imitate reasoning (Yao et al. 2022; Wei et al. 2023). They consider the reasoning capabilities as an emergent property of the escalation of the model in training data and number of neurons in the model (parameter size). The combination of memorization and task breakdown has effectively enabled a new paradigm on human-computer interaction (Mialon et al. 2023). However, other prominent figures in the field, such as Yan LeCun (2022) question this capability and the fundamental basis of the transformer architecture. Within the engineering design domain, this is still an ongoing debate: Are these models able to generate reasoning as per Eekels and Roozenburg? Or are they merely “pattern-matching” text that the models saw from the training data? (Mirzadeh et al. 2024; Wu et al. 2024)

The perspective of the third wave of generative AI has been used in **Papers C, D** and **E**.

2.2.3.1 CLASSIFICATION OF THE THIRD WAVE FOR ENGINEERING DESIGN AUTOMATION

As mentioned earlier, the third wave has been redefined from DARPA’s description, and therefore requires a new quantitative score for the criteria that is being used to consistently compare waves.

As discussed at the end of the previous section, there is no consensus to classify the model in the *reasoning* category in the computer science domain. Neither it is on the engineering design. The ability to reason, understood as the ability to plan and decide is linked to the ability to successfully perform the design activities. Therefore, the measure against this criterion depends on the design activity being performed, its performance, the inter-subjective definition of success, and the type of product being designed or evaluated.

Perceiving and abstracting are two easy categories to be quantified. Generative AI models use directly natural language and images; therefore, they have the highest score in *perceiving*.

The transformer attention layer good at finding relationships between tokens or words, and therefore can naturally abstract concepts, as long as they have been exposed to enough data during training. Therefore, generalist large language models, with extensive exposure to a wide amount of information in multiple modalities score very high at *abstracting*. However, specialized language models that have not been exposed to many concepts will have an intermediate score, but higher than first- and second-generation AI in comparison.

Given that the models learn to predict the next token or denoise an image from a vast amount of data, their *learning* score is highest, in accordance with the second wave rationale.

TABLE 1: SUMMARY OF THE ASSESSMENTS OF THE THREE AI WAVES AGAINST THE PREDEFINED CRITERIA

Criteria	**First wave: Rule Based**	**Second Wave: Machine Learning**	**Thrid wave: Agentic LLMs**
Perceive	Low	High	Highest
Learn	None	High	High
Abstract	None	Low	High
Reason	High	Low	Not clear consensus

2.3 Research Gap

The environmental challenges have been described in the introduction section. The speed at which we are moving towards a sustainable society is not fast enough. Long lead development times for new aircraft means that the solutions need to be developed at an even faster pace, for which design automation is needed. There is no obvious strategy for design automation, where there is an escalating industrial need of accelerated engineering studies. For example, a holistic design analysis of what are the automation techniques used today in industry is needed. For example, there is still a gap in methods that can generate generic concept architectures, and the approaches used in industry where detailed CAD geometries are expected for the product definition, even at earlier phases of the design (J. Müller 2020). Another example is the automation of a percentage only of activities. Engineers become the bottlenecks between different automated sub-steps, which limits the automation of end-to-end activities. For example, the need to capture knowledge (Pinfold, Chapman, and Preston 2008) or the need for these automation frameworks to define bespoke human created artifacts for setting up the geometrical and analysis processes required for the design space exploration of a particular problem. This research aims to explore this gap.

Incorporating novel technologies on aircraft systems rely also on the integration of the individual system component and technologies. New functionality will be required from traditional architectures, and therefore automation techniques are needed to be able to expand the design space exploration and connect the functional and physical domain. At present, there are limited methods with the ability to conduct system integration design studies (virtual integration) of novel technologies into e.g. engine architecture. For example, the research by Muller et al., (2021) proposes a functioning method, but there is still a gap between the capability of the proposed methods and the benefit expected in industry from using these specific methods.

The irruption of Generative AI applications to every part of the society has also reached the engineering design domain. The intense technology development efforts in the recent years have translated into a general-purpose technology, such as electricity or the internet. There is a high level of expectations of this technology in the Engineering Design Domain, yet there is no nor a sound theory basis available to guide developers of new or improved design methodologies and practices (Chiarello et al. 2024).

The LLM reasoning capabilities and their abilities are still under debate. It is necessary to investigate to what extent these so called "reasoning abilities" could be used to support designers and engineers. Given the LLM technology sensitivity to technical and implemented approaches, it is necessary to test in the field the capabilities of these models. At the same time, it is unclear what the negative effects of using this technology can be on the engineers, the products or the design ecosystem.

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3 RESEARCH APPROACH

This chapter describes the research questions, research approach methodology used in this thesis and the motivation for doing so.

3.1 RESEARCH QUESTIONS

In the two previous chapters the state of the industry and the different fields is described. The aim to increase automation in the design process to improve engineering efficiency is motivated. It is now time to define the Research Questions (RQs) that will guide the research effort.

3.1.1 FIRST RESEARCH QUESTION

If the purpose of engineering research is to provide support to designers and engineers, the existing support must be explored. The term *support* covers "*the possible means, aids and measures that can be used to improve design. This includes strategies, methodologies, procedures, methods, techniques, software tools, guidelines, information sources, etc.*" (Blessing and Chakrabarti 2009). Given the aim to increase efficiency of engineers via design automation tools, classifying and understanding the current automation techniques is the first step in the journey.

RQ1: What are the potential and limitations facing design automation strategies in engineering design and analysis processes for complex products?

Understanding each automation approach and classifying them through different dimensions can provide an overall picture. Highlighting the strengths and challenges will guide future automation efforts, exploiting characteristics that work well and being aware of challenges to address or avoid.

3.1.2 SECOND RESEARCH QUESTION

The design process of aerospace components and the convergence towards a valid solution is heavily influenced by the component's performance, for which physical models are required. Novel aerospace systems will impose new functional requirements on components, and automating the exploration of both functional and physical domains will be required to be able to explore the full design space.

RQ2: How can the design exploration of both functional and physical domains be combined and automated?

When researching to answer this question, the concept of expanding the design space should also be explored, as finding out new design solutions to existing or novel functional requirements can have a step change impact on the performance of the component and the overall aerospace system. In particular, the two hierarchy perspectives will be explored. From one side, the hierarchy between the system design and the component within that system that inherited the requirements. And from another hierarchical perspective, the functional hierarchy of requirements and design solutions present on the architectural alternative selection of the design space.

3.1.3 THIRD RESEARCH QUESTION

Generative AI has the potential to transform the design process, moving away from merely a tool that engineers use. If there is a design paradigm change, it is important to understand the unique characteristics of this technology, to build upon them and complement designers. In addition, the limitations and challenges shall be also understood to develop a reliable support system for engineers. The third question is therefore defined as:

RQ3: What are the potential opportunities and challenges of Large Language Models when applied to the engineering design of complex systems?

To answer this research question, it is required to get involved in the development of support tools, to really understand the technology in the context of engineering design and automation activities.

3.2 RESEARCH CONTEXT

The research is carried out as part of the author PhD studies at Chalmers University of Technology. It is performed in collaboration with GKN Aerospace, where the author worked as a structural engineer and later team lead for 10 years before starting the studies.

The funding mechanism is via VINNOVA and ITEA through the DEFAINE project, where large aerospace companies from Sweden and the Netherlands collaborate to reduce the lead time of concept design generation.

The total duration of the PhD is five years, which includes one year of departmental support in the form of teaching and supervising students, and another year of courses worth 60 ETCS credits. In addition, this research has been conducted during the execution of the DEFAINE project, including their milestone deliverables and workshop preparations.

This licentiate thesis is a milestone approximately halfway through the PhD journey, in which the two main objectives are evaluated:

1. The ability to perform quality independent research, and
2. The research scope refinement and direction definition for the second part of the PhD studies.

The research in Generative Artificial Intelligence has been performed between 2023 and 2024, a period of intense and rapid technological development in the field. The field of computer science and AI have different expectations on timelines, publication rigour and methodologies compared to Engineering Design. The application of Large Language Models for specific end user application has received billions in capital investments, leading to the development of an overwhelming saturation of frameworks that claim to provide reasoning capabilities and assistance support for tasks. Driven by market capture targets and economic incentives, these developments lack the rigorous evaluation to their optimistic claims. The consequence for the research is an overwhelming set of generic reasoning tools that keeps expanding and could be applied to support engineering activities, and the possibility to have missed critical information.

3.3 Design Research Methodology

The research to answer the questions was planned with the Design Research Methodology (DRM) approach (Blessing and Chakrabarti 2009). The DRM approach was developed to address three main issues: (i) the lack of overview of existing research, (ii) the lack of use of results in practice, and (iii) the lack of scientific rigour.

DRM divides the research into 4 distinctive stages:

3. **Research Clarification (RC)** stage: he researchers try to find some evidence or at least indications that support their assumptions in order to formulate a realistic and worthwhile research goal.

4. **Descriptive Study I (DS-I)** stage: with a clear goal and focus, the researcher conducts literature reviews or interviews to elaborate an initial description of the situation.
5. **Prescriptive Study (PS)** stage: Researchers now develop a further understanding of the existing situation to correct and elaborate an ideal vision of that the support tool should address. The support tool is developed.
6. **Descriptive Study II (DS-II)** stage: Investigation of the impact of the support via two empirical studies: its applicability and its usefulness.

The author attended the Engineering Design Research School, where among other teachers, Blessing presented the methodology and provided guidance in its application. One of the highlights is that while every research required a clarification phase, the entry point could be any of the other phases.

Another point raised in the methodology is the ability to be flexible and adapt DRM to the particulars for each research. Given the closeness to industry, it was decided to use it in combination with Action Research (Denzin and Lincoln 2011). Using a combination of different research methods is commonly used in practice (Marxen and Albers 2012). The benefits of the action research approach is the iterative nature and feedback from real use cases that enables a rapid iteration of the methods developed and problem understanding. In particular, the techniques used included a set of unstructured and semi-structured interviews, case studies and method co-development between researchers and industry experts.

While the DRM was used to define the main stages, the specific guidance of defining and applying the data collection methods was provided by the book on Research Methodology was used (Säfsten 2024).

The basis of the research is a set of interviews and papers for this licentiate thesis. They are related to the different research questions and phases of the DRM as follows:

TABLE 2: PAPER TO RQ AND DRM PHASE CONNECTION

Source	**Paper A**	**Paper B**	**Paper C**	**Paper D**	**Paper E**
RQ1	X	X			
RQ2	x	X			
RQ3			X	X	X
DRM Phase	*DS-I*	*PS, DS-II*	*DS-I*	*DS-I*	*DS-I/PS/DS-II*

3.4 DATA COLLECTION ACTIVITIES

Data is critical for good scientific research. The data obtained in this thesis is the combination of primary data (interviews, case studies, action research) and secondary data (literature reviews). The following table provides an overview on what collection methods were used. The following subsections argue for the suitability of those methods for the research questions.

TABLE 3 RESEARCH QUESTION-METHOD MAP

Data Collection	Literature Review	Interviews	Action Research	Surveys
RQ1:	X	X	X	
RQ2:	X		X	
RQ3:	X		X	X

3.4.1 LITERATURE REVIEWS

Literature reviews were used to answer every research question and published paper. Literature articles are useful secondary source for understanding the state of the art in the research community. Arguably, the state of the art in industry cannot be obtained from literature reviews, as companies often choose to keep in house their latest automation technologies, due to their advantages in their business.

With regards to the database consulted, two different sources were used. For engineering design related literature, Scopus was used as it is a source that includes peer reviewed articles. Web of Science was initially consulted as well, but it yielded the same duplicated results and therefore only Scopus was used moving forward for convenience. This source, however, was not considered sufficiently updated when it comes to the Large Language Models and Generative AI state of the art. Journal publication time average a year, and full paper submissions to conferences like DESIGN and ICED require the research activity to be performed and written about 9 months in advance. In addition, the computer science research community that drive LLM frameworks predominantly publishes in ArXiv.org, with only a limited number of papers making it to a conference or journal that is indexed in Scopus. To make it an obvious point, the seminal paper that defined the transformers architecture “attention is all you need”, by Vaswani et al. (2017) is not even listed in Scopus. Therefore, ArXiv was also used as a source of Generative AI and LLM techniques and architecture papers. Since the database contains draft, non peer-reviewed papers and can be added by almost any author, special care was taken while reviewing those papers. In addition to the initial scepticism, the quality of the paper was judged independently (method, biases, robustness), the number of citations and the affiliation of the authors also considered.

To conclude the on the sources on literature, Scopus was used as a source for design engineering research, and ArXiv as a source for technology development knowledge. Design Research has the purpose of understanding and building knowledge in Design Science, and the research of this paper focuses on bringing the latest technological advancements into this engineering design context.

When iterating on the query string, some key papers for engineering research were identified as a quality check to ensure that the literature search was returning relevant papers. Those key papers identified research peers and supervisors. For the computer science domain, they key papers were selected from a variety of sources, including domain news, tweets from relevant players, such as research institutes and lab, etc. As discussed in **Paper D**, the GenAI field is exploding with research so it is possible that relevant papers have been ignored and that the literature search field can be outdated in just a few months.

Some literature reviews were expanded from the initial selection with the use of literature tools such as Research Rabit, Connected Papers or LitMaps. The purpose was to connect similar research work that could have been missed due to using different names for similar effects.

Finally, while none of the literature reviews were claimed to be a systematic literature review, the PRISMA guidelines for such reviews were used to guide the process. (Page et al. 2021)

3.4.2 INTERVIEWS

Interviews provide a practical counterbalance to data collection to academic literature articles found by literature reviews. On those articles, authors interview and summarize their findings from a particular research perspective. They provide the reader access to their findings. For example, as part of answering RQ1 (*What are the potential and limitations facing design automation strategies in engineering design and analysis processes for complex products?*) KBE was identified as one of the potential technologies that can support designers. Challenges with KBE approaches have been reported by Verhagen et al., (2012) and La Rocca (2012) over a decade ago. The challenges have been evaluated recently from a literature perspective by Kügler et al., (2023). However, the journal articles found did not provide access to the full interview content, and therefore loosing valuable information for the research angle of this thesis. Challenges in automation are part of subjective perception and experiences. The context of this research as part of the DEFAINE project allowed to have access to people who used KBE in the 2000's and 2010's and their immediate network, providing a first hand experience on the challenges of KBE and other design automation techniques.

Although **Paper A** reported only a set of interviews within the DEFAINE project, an expanded set of interviews was conducted focusing only on KBE implementation in aerospace. The outcomes of those interviews are used for the discussion section.

Both interviews followed a semi-structured interview, allowing the researcher to stick to the topics as in a structured interview, but allow freedom to investigate challenges as part of an open interview process. There were five distinct phases on the interview process: interview planning, perform interview, transcribe, codify and summarize. Interviews were conducted face-to-face (in person or via online meetings), lasting between 45 and 90 minutes. One exception was a participant that requested the questionnaire to be sent via email, to think the answers without pressure. In that case, follow up questions were conducted via email as well.

Given the limited availability and access of engineers experienced with KBE, the interview sampling is based on non-probabilistic methods. In particular, the convenience of the participants on the DEFAINE project. In addition, snowball sampling was used to identify two more participants outside the DEFAINE project. This yielded a total of 5 participants, that together with the literature review challenges provided saturation. Interviewees had a background in both the European and American aerospace industries.

For the general interview of design automation challenges recorded in **Paper A**, four participants were selected. A fifth interview with a participant from the aerospace sector in the UK (OEM perspective) was also conducted, but not reported in Paper A due to the paper being already approved for the conference. The sampling was based on convenience primarily, but also provided a stratified sampling. Specifically, it included Engineers from both OEM and RSP perspectives, covering both sides of the aerospace industry. Geographically, it covered Sweden, USA, UK and the Netherlands. It also covered conceptual airplane design, airframe structures, jet engine components and wire and electrical harnesses.

3.4.3 Action Research

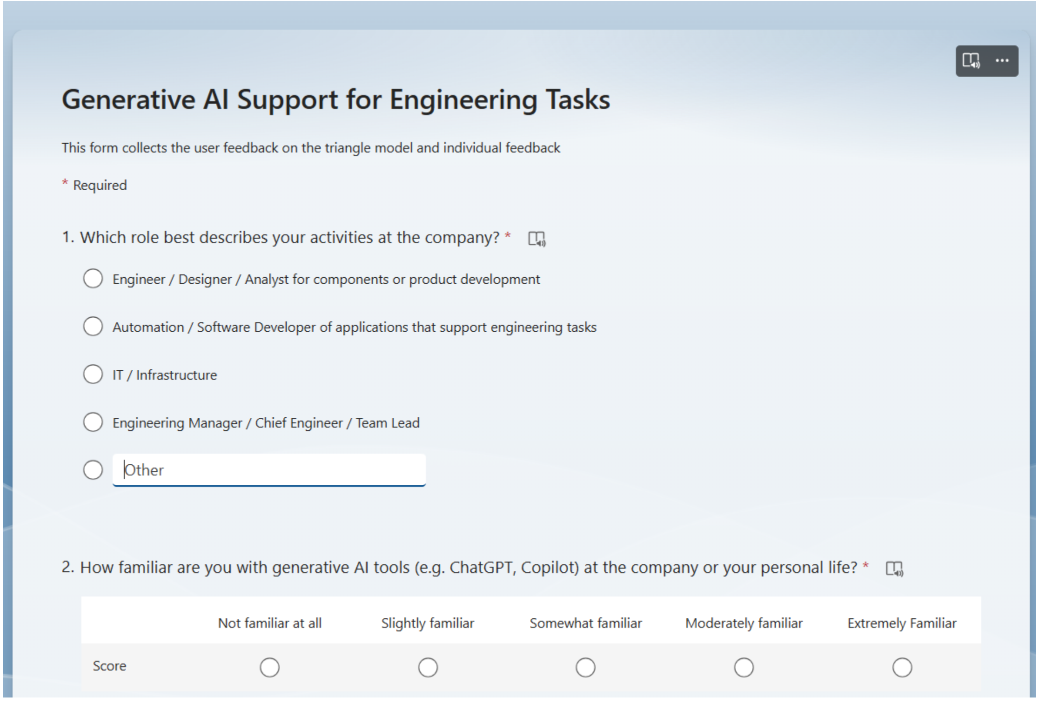
The action research took place between February 2022 and February 2023, involving primarily GKN AES with the support of Saab. Other participants also participated as part of the DEFAINE workshops conducted with all project participants. The researcher main working location was GKN offices for that period. This was possible due to the researcher previous employment at the company. 5 workshops were also conducted with the DEFAINE partners during that time, that allowed for the generation of a Use Case for testing the methodology. Action Research was the main data collection and influenced primarily the method development presented in **Paper B**. It also influenced the use case of **Papers C** and **D**.

3.4.4 Surveys

In the third research question (*What are the potential opportunities and challenges of Large Language Models when applied to the engineering design of complex systems?*), it was of interest to understand how industry would perceive those challenges and to what level the industry was familiar with the new technology. In the collection method "Survey", I include a group session feedback that followed the survey, resembling a focus group, for condensed exposition of the method chapter. To obtain this present and subjective information, the survey method was selected due to its relevance to capture the present situation and a wide range of perspectives. The structured format of the survey, which was a limitation for capturing all the potential challenges of the technology adoption, was complemented by the previously mentioned focus group straight after.

The survey, presented in **Paper E**, was used also to understand the acceptance and understanding of a model that derived from **Paper D**. In addition, it was also convenient to understand the industry perception of the usability of GenAI as a support automation tool, given that future research within the PhD, as it will be discussed on Chapter 7, will use this methodology for the development of an automation support in the design process.

The survey's results were collected online using Microsoft Forms. The Questions were carefully written and presented online to minimize the participant effort to answer the questions.



Generative AI Support for Engineering Tasks

This form collects the user feedback on the triangle model and individual feedback

* Required

1. Which role best describes your activities at the company? *

- Engineer / Designer / Analyst for components or product development
- Automation / Software Developer of applications that support engineering tasks
- IT / Infrastructure
- Engineering Manager / Chief Engineer / Team Lead
- Other

2. How familiar are you with generative AI tools (e.g. ChatGPT, Copilot) at the company or your personal life? *

	Not familiar at all	Slightly familiar	Somewhat familiar	Moderately familiar	Extremely Familiar
Score	○	○	○	○	○

FIGURE 2 SCREENSHOT OF SURVEY FORM ONLINE

The results outcome and visualization were designed concurrently with the question definition to ensure that the original research question, survey question, visualization and conclusion were straightforward. For more information, the reader is referred to **Paper E**.

3.4.5 Use case and Generative AI framework development

As part of the action research and the DEFAINE project, different use cases were selected to develop specific Generative AI applications and frameworks. Given the novelty and practical application of Generative AI, a hands-on perspective was chosen to complement the literature reviews to answer RQ3. The insights of the use cases and the frameworks developed were reported in **Paper C** and **D**.

3.5 Data Analysis

3.5.1 Literature analysis

Literature reviews were conducted to answer every research question, and the data analysis is presented in each paper. The articles were reviewed from the perspective of that research question and the implications for those were summarized with each paper.

Then, themes emerged from each summary and papers were grouped accordingly, highlighting their significance to each research question.

3.5.2 INTERVIEWS

Interviews were recorded for posterior analysis. In person interviews were recoded using a digital handheld recorder. Online interviews were recorded with a local software. The audio was then transcribed. Digital means were used to produce a first draft of the transcription (Otter.ai and an open-source model from OpenAI: whisper). With this draft, the audio was played again, and the author corrected the first draft to ensure that the transcription was accurate and literal. This previous step allowed to decrease the amount of time spent transcribing from the average x5-x10 reported by literature sources to only x2 of the original recording time. One interview was made though emails and therefore used directly. These transcriptions were the basis for which the KJ method analysis was performed (Scupin 1997; Boyatzis 1998).

A thematic analysis of the transcripts was conducted following (Säfsten 2024). An initial code was developed organically from which themes evolved (either explicitly or latent). Then an overview of the themes and codes were conducted after each interview to refine the coding in some cases or group themes. The software Nvivo was used to manage the transcripts and codes. A visualization of relationships between themes was then displayed and conclusions drawn. Participants were also provided with a summary of the interviews and key takeaways for them to confirm or comment on the conclusions.

3.5.3 SURVEYS

Surveys results were exported as Excel files directly from MS forms, and results translated to graphs directly. The figures were then refined using Adobe Illustrator to improve clarity, ensure consistent visual style and fit all results into a single A4 page. The open field in the survey, together with the information from the open discussion, was coded and thematically analysed. In the results of **Paper E**, the themes were then summarized using the survey feedback text as quotes.

4 RESULTS

This chapter summarises the five appended papers and their contributions to the research questions.

As part of the research that led to this thesis, five papers were published or submitted to high-quality peer-reviewed scientific fora and are included in the Appendix.

4.1 PAPER A: DESIGN AUTOMATION STRATEGIES FOR AEROSPACE COMPONENTS DURING CONCEPTUAL DESIGN PHASES

4.1.1 ARTICLE SUMMARY

The paper explores the different design automation techniques used in the aerospace industry. Through a combination of a literature review and interviews at aerospace companies, design automation methods are identified and categorized. The categorization involves the phase of the design process and their relationship to two relevant perspectives: design automation and their domain: functional vs physical. An initial approach is proposed to combine two of these technologies to cover the design space exploration for functional and physical domains. The approach is tested in a DEFAINE use case.

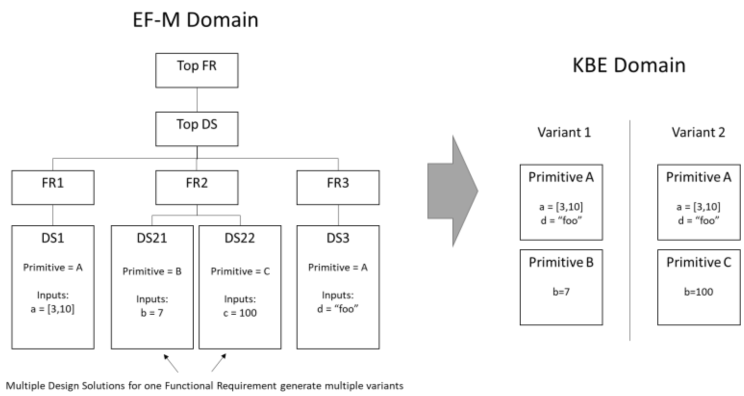


FIGURE 3 PROPOSED DESIGN EXPLORATION OF DIFFERENT ARCHITECTURES BY COMBINING FUNCTIONAL MODELS AND PHYSICAL KBE MODEL GENERATIONS. BOTH MAKE USE OF THE OBJECT ORIENTED PERSPECTIVES.

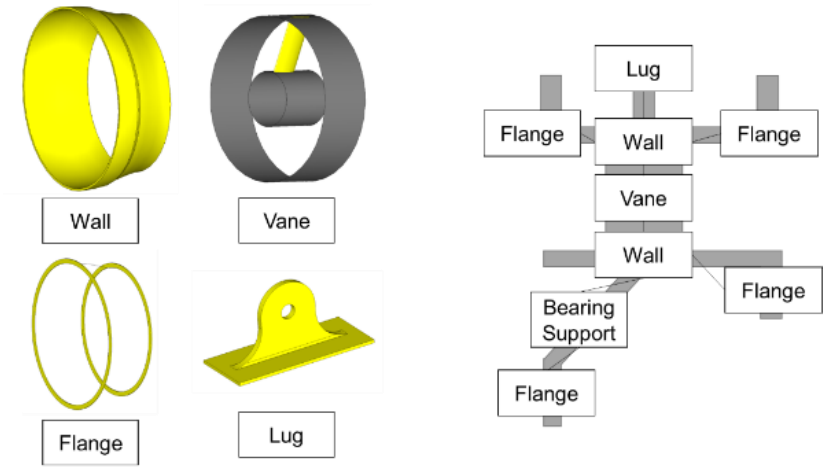


FIGURE 4 GEOMETRICAL REPRESENTATIONS OF PRIMITIVES TO THE RIGHT, AND THEIR MAPPING TO A 2D CROSS SECTION AREA OF A TRS COMPONENT.

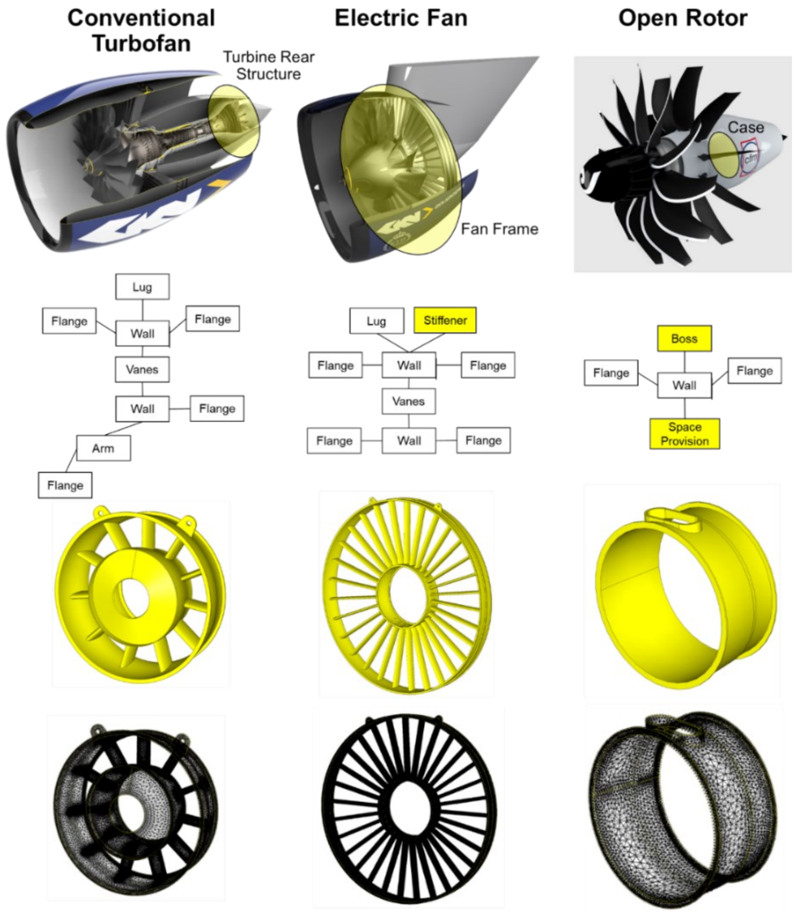


FIGURE 5 A GRAPHICAL EXAMPLE OF REUSABILITY STUDIES OF KBE PRIMITIVES FOR OTHER COMPONENTS OF JET ENGINES. REUSED PRIMITIVES IN GREY, NEW PRIMITIVES IN YELLOW.

4.1.2 RELEVANCE FOR THE THESIS

The research in this paper addresses RQ1 (*What are the potential and limitations facing design automation strategies in engineering design and analysis processes for complex products?*) The result of the paper uses the interviews with the companies to understand the landscape of the design automation support, and explore a method to combine functional modelling with KBE primitives.

This paper identifies three dimensions in which to quantify the design automation support: Domain to assess, storage of knowledge and the design phase in which the automation support happens.

The domain to assess refers to the assessment of the functionality domain vs the assessment of the product performance. The storage of knowledge refers to the ability to automate the know-how in a sequence of hard coded steps (e.g. KBE) vs an automation that is performed alternating or combining small automation steps with manual inputs using GUIs. This theme or domain will be used in **Paper E** to define one of the dimensions of the design ownership.

The interview highlighted that the design automation approach is multifaceted, sometimes driven by strategic actions and sometimes driven by reactive adaptations to the circumstances. The following are some of the factors that affect the selection of an automation strategy:

1. The **type of product** that the company manufactures: each product has different input and output requirements; it is difficult to define a superior strategy even for the same type of product.

2. The **organization and management**: A strategic management style contributes towards a design automation strategy. The preference may be implicit, by for example the limited budgeting for developing, maintaining and training for in-house applications may lead to use COTS solutions. Some companies have a clear strategy that supports the development, maintenance and deployment of in house design automation systems. Other companies rely on COTS solutions.

3. The **experience of the engineers**: Even if there was a superior design automation strategy, the experience of the engineer – especially the team lead – has a major impact on the design automation chosen.

4. The **tools** available: Engineers joining a project may have experience on more suitable design approaches, but the licenses may not be available and therefore the approach is discarded. Lead times to get the licenses are of the same order as some of the conceptual design projects.

5. The **legacy** of the team or project: Teams and projects have a history on how to do things, that may be even coded in the Quality Management System or agreed by contract with the customer. Changing the design automation approach is compared to “swimming against the tide”.

In addition, a challenge is identified: the need to evaluate physically every design alternative explored in the functional domain. Finally, The author gained the needed KBE development experience to generate the library of primitives and re-use them in different products.

4.2 Paper B: FUSE: A novel design space exploration method for aero engine components that combines the functional and physical domains

4.2.1 Article Summary

This paper presents a method that primarily addresses RQ2 (*How can the design exploration of both functional and physical domains be combined and automated?*) and provides additional context for RQ1 (*What are the potential and limitations facing design automation strategies in engineering design and analysis processes for complex products?*)

Society awareness and the environmental goals are forcing the aerospace industry to develop new sustainable system architectures. The components in the new system have to meet new functional requirements using alternative technologies and design solutions, while ensuring that the physical performance of the component is maintained. However, the design space exploration of both domains is challenging due to the intrinsic differences and nature of each: the functional domain exploration deals with alternative means to solve functions, while the physical exploration deals with parametric values, such as geometric dimensions and material types. Here, we present a method that enables concurrent exploration of the functional and physical design space. The method is based on a review of existing design space exploration methodologies. It has been developed in collaboration with industry and validated within a use case. We expect that this method will be useful for designers in conceptual phases where there are several functions containing multiple design alternatives and there are incompatibilities among them. The results of the method will allow designers to narrow down the design space to a few architectural candidates, including a baseline of physical dimensioning for each candidate.

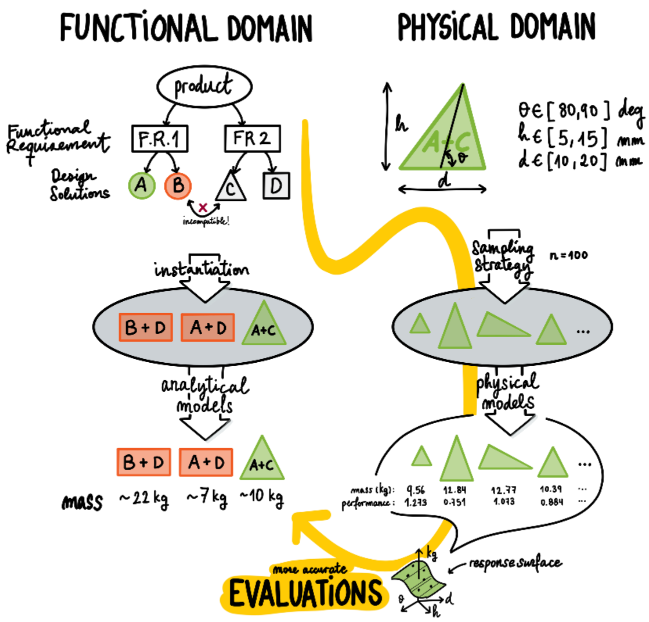


FIGURE 6 VISUALIZATION OF THE TWO DOMAIN SPACES, THEIR DESIGN EXPLORATION VARIABLES AND THE PATH IN YELLOW THAT THE PROPOSED METHOD FOLLOWS TO PROVIDE MORE ACCURATE EVALUATIONS

4.2.2 Relevance for the thesis

In this paper, the method proposed in Paper A is explained in detail. The challenge of exploring two design domains, the physical and functional are explained in detail. The method bridges the two domains as it is expected that the new technological changes in architectural configurations will need to be evaluated in detail, as discovered in **Paper A.** Therefore a methodology was created.

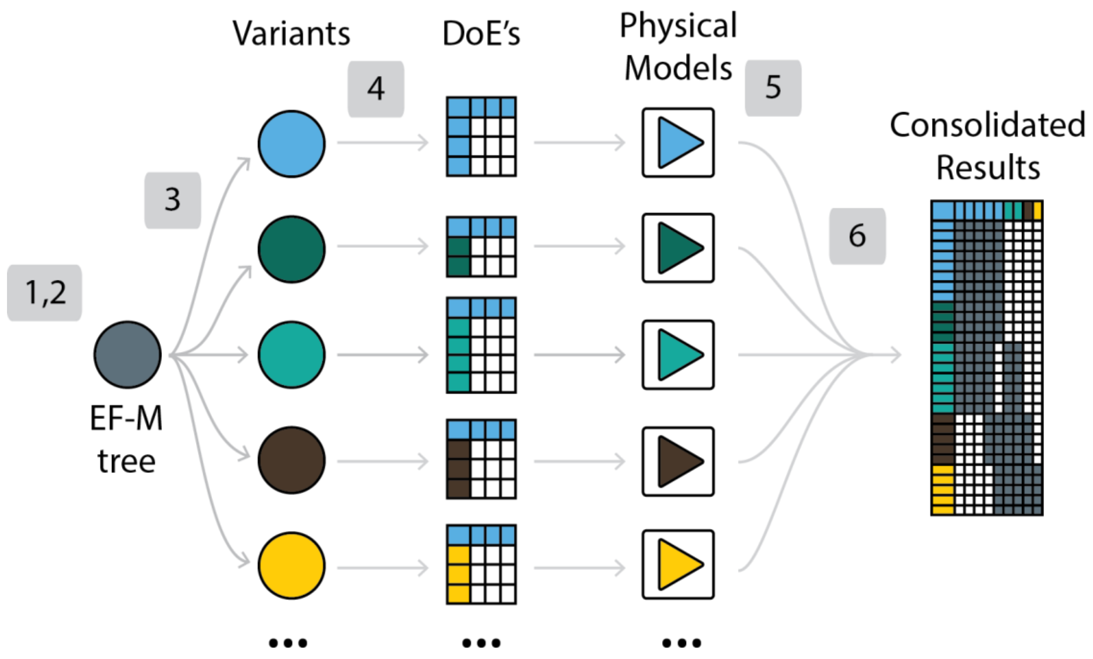


FIGURE 7 STEPS OF THE METHODOLOGY GRAPHICALLY REPRESENTED TO GENERATE DIFFERENT ARCHITECTURAL VARIANTS, THAT IN TURN CREATE THEIR OWN DOE TABLES, EXECUTED AND RESULTS CONSOLIDATED

This methodology is based in the original approach in **Paper A**, but further refined to consider industrial feedback. In particular, some companies do not use a KBE system as proposed originally. Relaxing this requirement, and allowing to use physical models built manually (different CADs with parameters, automatic meshing of FEM based on CAD tags, etc) making the applicability of the method valid for a wider range of companies.

This wider applicability meant however losing `the object-to-object connection (E-FM Design Solution to KBE Primitive). The implications are that the level of automation of the methodology had to be lower, and the designer and DoE had to be executed manually. On one hand, this reduces the level of expertise needed to execute the method, lowering the knowledge required to use this tools. In the other hand, a lower automation method requires more time to setup and develop the models, which is in contradiction with the overall objective of faster design evaluations of new architectural configurations.

The EF-M model here has proven to be useful again to manage the architectural variability. While Paper A used it to connect it to the different primitives and use it to automate the KBE tree, this paper uses it to define the variables to be used in each unique DSE.

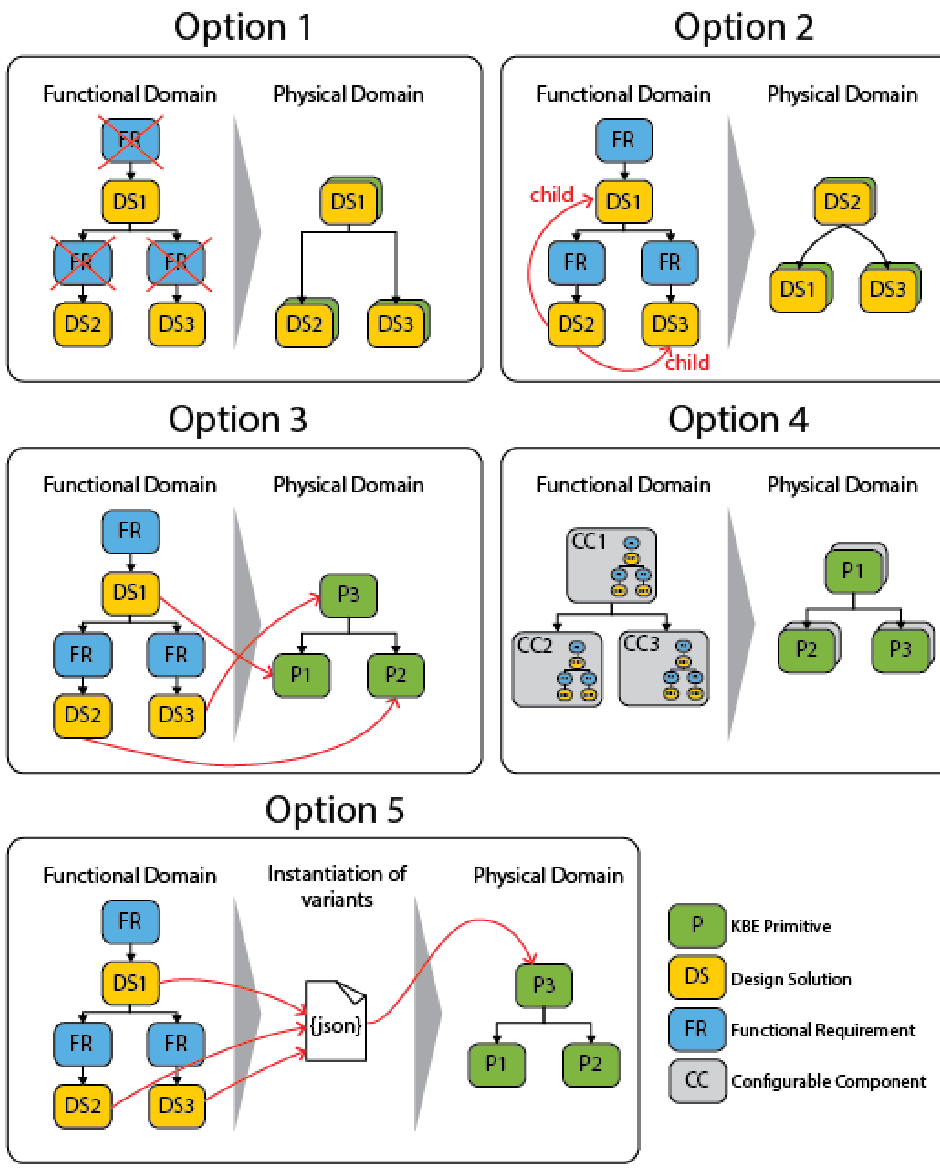


FIGURE 8 ALTERNATIVES CONSIDERED TO IMPLEMENT AN AUTOMATED CONNECTION BETWEEN FUNCTIONAL AND PHYSICAL ARCHITECTURES.

The original intention of this paper was to provide a fully automated means to connect the functional and physical domain definition and architectural configuration. The rationale was that with a bespoke EF-M tree configuration and prescribed procedure, an automated KBE primitive tree could be generated, removing the need to configure the KBE architecture. This serves two purposes: remove the need for manual intervention to speed up the configuration and remove the KBE expertise required to configure KBE architectures for different types of products. However, none of the different approaches to automate the domain connection was found satisfactory, and a JSON connection between the domains (Option 5 in Figure 8) was selected for the FUSE method presented in Paper B as the most flexible solution. Every approach to connect the two domains had significant drawbacks when implemented, concluding that the automation attempts stiffened the method to a point that would constringe engineers and the benefits that the two methodologies had separately: the EF-M lost the flexibility be adapted for each component and perspective (pure function-means, manufacturing system perspective, etc.) and the KBE system could lose all its configuration capabilities. Given the experience with the KBE adoption at some companies, the automated connection object to object was abandoned.

The implications of this automation dilemma between automation flexibility and efficiency are that some steps are best not to be automated using traditional methods: a full automation is not feasible, or at least very costly to achieve at 100% automated process. These gaps require designers to step in into the process, stopping the automation flow.

Looking it from a different angle, this dilemma sits at the core of the design automation process, and it is worth describing in more detail. On one hand, the design automation seeks to improve the design process, usually by selling faster development times, or automating a process where designers usually get it wrong. There are very powerful automation techniques, that require specific know how to be fully leveraged and taken advantage on the design process. And this adds a risk: in order to use these tools, it require the expertise to be always available. This is a risk that project leaders don't like to buy into, given their previous experiences with key resource availability (not only KBE specific, the expert availability being the bottle neck was a challenge in every discipline).

The possibility of the new wave of Generative AI technology was suggested as a support tool to bridge the design gaps that automation technology cannot cover, avoiding designers getting involved and therefore speeding up the design process. Engineers interact with automation tools in two different ways. There are low value added activities where the process is straightforward and necessary to evaluate a design characteristic. Those processes are the ones that could be highly automated. However, other design processes are exploratory, and engineers require to perform exploratory analysis and interact with the automation logic. LLM technology is prone to interaction, and LLM driving design automation, as it will be discussed in RQ3, has the potential to respond to those scenarios.

4.3 PAPER C: LARGE LANGUAGE MODELS IN COMPLEX SYSTEM DESIGN

4.3.1 ARTICLE SUMMARY

This paper contributes to answer RQ3 (*What are the potential opportunities and challenges of Large Language Models when applied to the engineering design of complex systems?*). This research explored the support of LLMs to support non-KBE experienced engineers to generate CAD using KBE technology.

This paper investigates the use of Large Language Models (LLMs) in supporting the design and engineering of complex systems. It exemplifies how they can support designers on detail design phases. The research reveals LLMs' challenges and opportunities to support designers, and future research areas to further improve their application in engineering tasks. It emphasizes the new paradigm of LLMs support compared to traditional Machine Learning techniques, as they can successfully perform tasks with just a few examples.

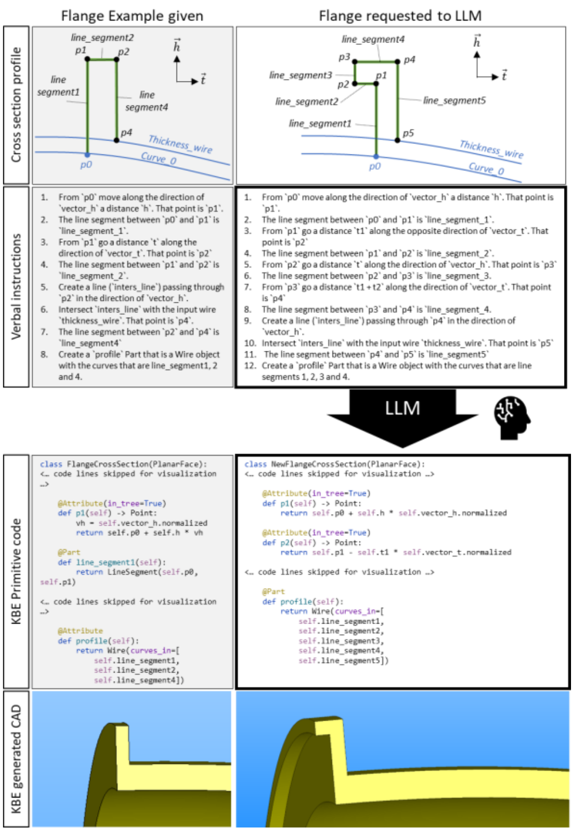


FIGURE 9 SHOWS IN THE LEFT COLUMN THE ONE-SHOT EXAMPLE THAT WAS GIVEN TO THE MODEL, IN ORDER TO GENERATE THE NEW KBE PRIMITIVE CODE (RIGHT COLUMN). THE FIRST ROW REPRESENTS VISUALLY THE INSTRUCTIONS PROVIDED TO THE MODEL IN THE SECOND ROW AS AN INPUT TO THE LLM. THE THIRD ROW IS THE MODEL RESPONSE, THAT IS MANUALLY EXECUTED IN THE KBE SYSTEM GENERATING THE 3D MODEL IN THE FOURTH ROW

4.3.2 RELEVANCE TO THESIS

Generative AI models were able to generate text, images and even 3D models. However, at the time, the amount of 3D shape generation was limited, consisting only in point cloud approaches. This implementation seeks to generate CAD based geometry on ruled surfaces. The LLM based implementation showed the potential of foundation models. The ability to generalize from a generic set of training data to be able to perform in a domain specific approach without the need of further training, with only an example given in the input prompt (one-shot-learning).

This Paper showed the capabilities of LLMs to perform domain tasks that before required an advanced level of expertise to be performed, not available to the average engineer. On one hand, algorithms exist to be able to identify 2D geometry and generate 3D shapes (Zhang et al. 2023). However, these algorithms are not available in commercial CAD suites and it is not straightforward to implement. In addition, this example showcased how new KBE code can be generated from a 2D model sketch. Since previous Papers A and B identified the challenges of needing a high level of automation expertise (KBE or other technologies), this paper demonstrates how an automation system can be modified without domain specific knowledge of KBE.

This paper introduced the author to the first automation applications of LLMs in engineering design. The first experiences showed the problems with hallucinations, limited capabilities to define the actions or the company-context issues. It also demonstrated how the model could be used as a chain of commands, and how it failed when not enough direction was needed, identifying the need to explore the different frameworks available for design automation, which was later performed in Paper D.

A clear distinction starts to emerge from previous AI waves. Now LLMs are used not to generate new CAD models or predictions themselves, but to use their reasoning capabilities to support the automation of the design steps using tools that were previously only managed by designers themselves.

4.4 Paper D: Evaluation of Different Large Language Model Agent Frameworks for Design Engineering Tasks

4.4.1 Article Summary

This paper evaluates Large Language Models (LLMs) ability to support engineering tasks. Reasoning frameworks such as agents and multi-agents are described and compared. The frameworks are implemented with the LangChain python package for an engineering task. The results show that a supportive reasoning framework can increase the quality of responses compared to a standalone LLM. Their applicability to other engineering tasks is discussed. Finally, a perspective of task ownership is presented between the designer, the traditional software, and the Generative AI.

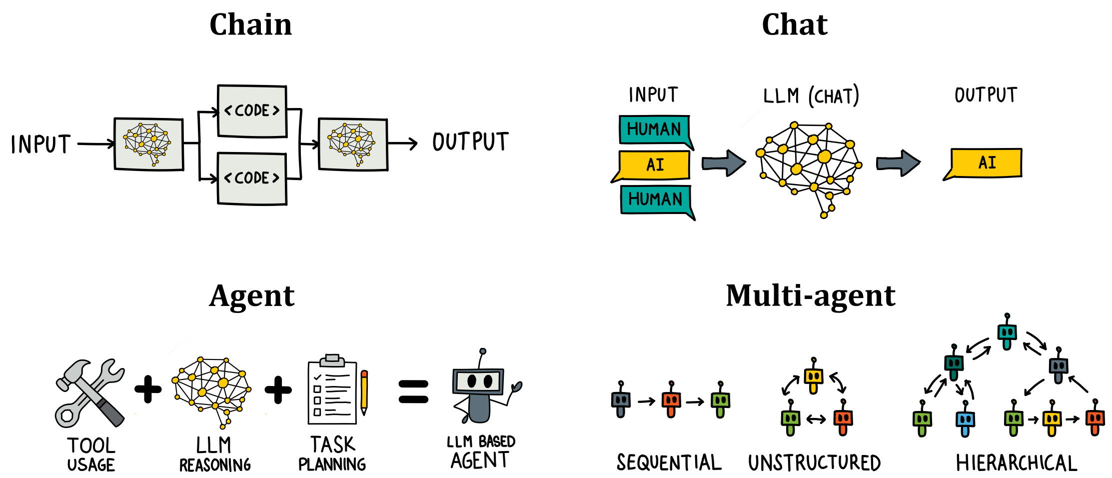


FIGURE 10 DIFFERENT GENERATIVE AI FRAMEWORKS EVALUATED ON A DESIGN ENGINEERING TASK

4.4.2 Relevance to Thesis

In the previous **Paper B**, it was identified that some design activities were not effective to be automated, due to the dilemma of automation flexibility vs efficiency. This paper picks up the research suggested to explore the use of the new wave of Generative AI to attempt to automate the design activity, by connecting the functional domain (E-FM model) with a KBE model in the physical domain.

The same EF-M and KBE models as **Paper A** and **B** were used to explore the efficiency of the models at merging those domains. This activity was chosen as it is an activity that is complex to automate with traditional tools.

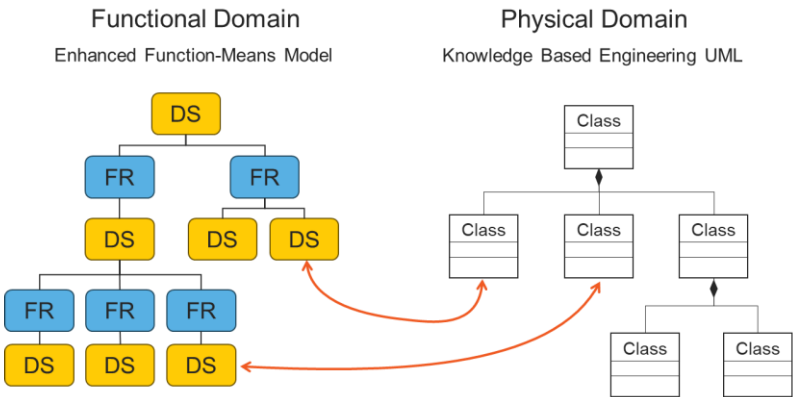


FIGURE 11 AUTOMATIONG THE FUNCTIONAL AND PHYSICAL DOMAIN CONNECTIONS WITH THE SUPPORT OF GENAI FRAMEWORKS

The results show that the bigger the model, the better it reasons. The different frameworks show interesting trends with respect to the approached followed. A chat framework is used as a baseline, that has 20% (gpt3.5) -30% (gpt4) efficiency on average. These models tend to fail at the task, due to the lack of structured expectations. A stricter framework – a chain – was used next, which implied that the LLM framework could not choose how to solve the problem. The steps on the chain were defined by the designer in his framework development role, as the results showed the inability of the model to perform effectively the task. It implied that the model was no longer orchestrating the steps. The efficiency increased to 60% (gpt3.5) to 90% (gpt4), but the model now was used as a tool only, not utilizing its agentic behaviour.

When more freedom was given in an agentic architecture, a different trend was observed in the different models due to their reasoning capabilities. The Agent using the gpt3.5 model was unable to reason properly to use the appropriate tools to retrieve the EF-M model, KBE Primitives and identify the parameters, failing at every attempt: 0%. However, the more capable model, gpt4, was able to use the tools correctly and connect the two domains on 90% of the repetitions. Finally, the multi-agent architecture raised the performance of both models to 90 and 100% respectively. This was due to the ability to not answer directly as a model, but give the framework the opportunity to reflect and correct its output via a do-review iteration. The performance of the model was increased significantly at the cost of generating more reflection tokens and iterative loops. This trade-off, identified in December 2023, was also used by OpenAI's o1 model announced a few months later, where they increase the model performance at inference time as well.

The consequences of this performance evolutions are that as they stand today and in the near future, LLMs on their own are not capable to perform moderate design tasks, or a collection of consecutive tasks. A framework or supporting scaffolding is needed for the models to access external tools and to plan and execute tasks following a workflow. The extend of how much the workflow needs to be defined (hard coded explicitly vs suggested) is very dependent on the model capabilities.

The research in this paper had additional contributions to the understanding of how to use LLMs and their characteristics. To start with, how to measure the efficiency of their performance and their repeatability. Due to their inherent variability in their probabilistic sampling, every response was different. Since we need to measure their performance consistently, a repetition strategy was followed (n=10 samples) leveraging that the models lack memory when their context window has been cleared. This was inspired by aerospace manufacturability inspection methods such as gauge repeatability & reproducibility in the measurement system analysis. The research also identified further prompt-engineering and model configuration sensitivities to the performance.

Finally, the development and testing of the different frameworks let to the realization that the model was being used with two purposes: to perform the automation steps (as a traditional tool) or to decide how to subdivide the goal that was given. Two types of errors were consequently identified: the model was performed the wrong step or performing the right step wrong. Identifying the LLMs as a new type of automation support was performed in previous papers. In this work the realization that 3 different entities are sharing the design responsibility now materialized by identifying the triangle of design responsibility.

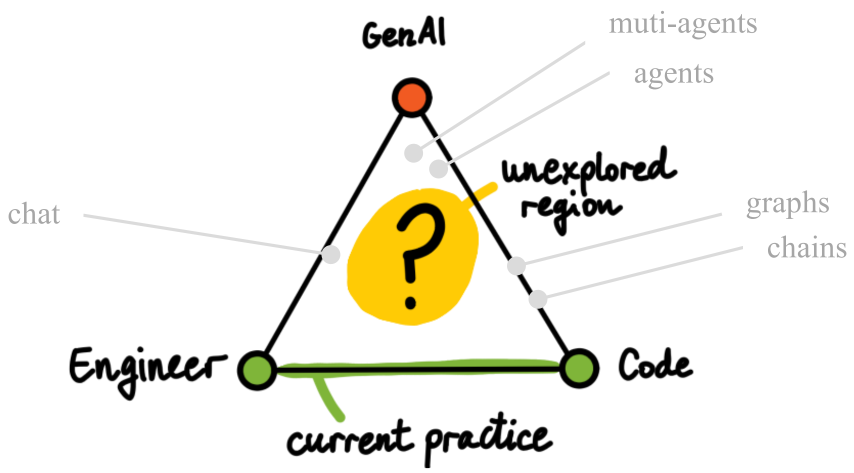


FIGURE 12 THE TRIANGLE OF SHARED RESPONSIBILITY THAT HAS BEEN CREATED WHEN GENAI AND LLMS ARE MAKING DESIGN DECISIONS. THE FRAMEWORKS USED IN THIS PAPER (IN GRAY) ARE PLACED IN THIS SPACE TAKING INTO ACCOUNT HOW MUCH DESIGN OWNERSHIP THEY ARE GIVEN.

4.5 PAPER E: A TEAM OF THREE: THE ROLE OF GENERATIVE AI IN THE DEVELOPMENT OF DESIGN AUTOMATION SYSTEMS FOR COMPLEX PRODUCTS

4.5.1 ARTICLE SUMMARY

Given the explosion of papers on the use of Generative AI and Large Language Models (LLMs) in different disciplines, there is a high interest in the use of this technology also in engineering design. Current approaches lack to leverage the models new opportunities and expose their inherent weaknesses. We present a conceptual model visualize the contribution of LLMs to design tasks and the delegation of design responsibility.

A literature review of design engineering papers presents its current uses in this community. The understanding of the triangle model is validated with industrial practitioners via a survey. We identify future research directions in the field of complex product design.

We hope that this model helps design automation developers, researchers and industry practitioners to position and assign responsibility effectively in their design automation implementation.

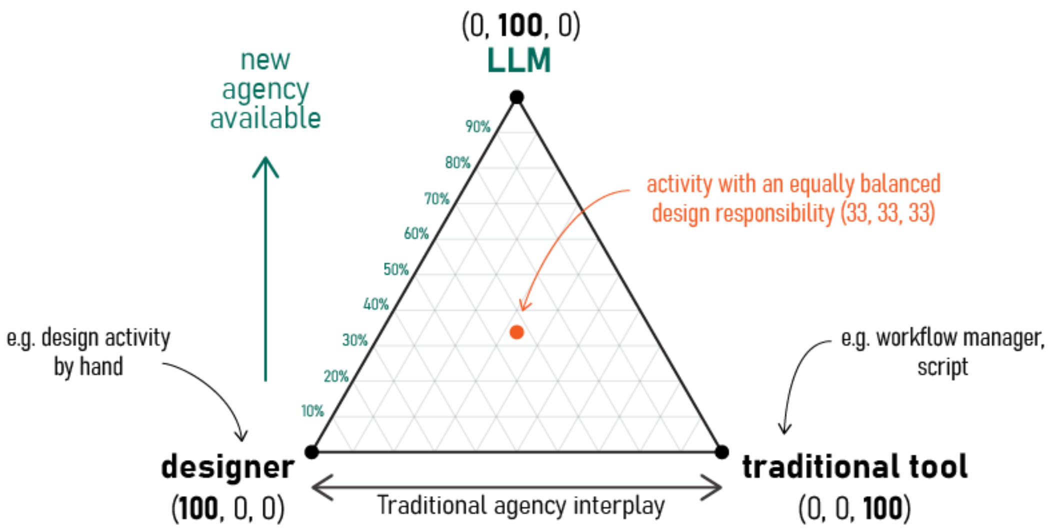


FIGURE 13 THE TRIANGLE OF DESIGN RESPONSIBILITY MODEL

4.5.2 RELEVANCE FOR THE THESIS

This paper is a cornerstone for the evolution of the thesis and sets the tone for the reminder of the PhD research, setting the scope for future research in Chapter 7. From **Paper D**, the triangle of responsibility was first proposed. In this **Paper E**, the model is further refined and tested against industry. It clarifies the contribution of the LLM in "doing the task" vs "orchestrating the task". This paper is relevant get the industrial perspective of the research question 3, as the survey and opportunities are discussed.

The literature review highlights the gaps in the Engineering Design community to treat the LLMs as agentic partners in the design process, justifying further research in the area. In addition, the combination of LLM and traditional tools is a necessary requirement for the adoption of these tools. In computer science terms, the grounding of the AI models is necessary for building confidence and therefore adoption in industry. In addition, the need for correct and reliable results is highlighted by the industry participants as a challenge by LLMs.

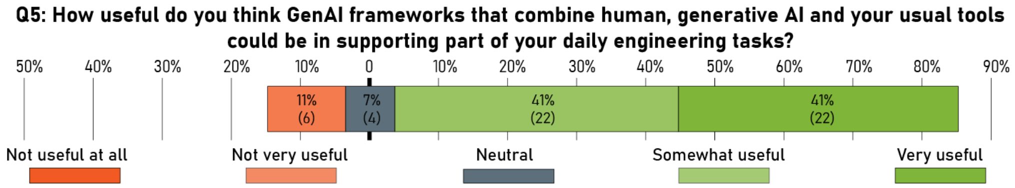


FIGURE 14 SURVEY RESULTS SHOWING THE OPINION OF INDUSTRIAL PRACTICIONERS ON THE USEFULNESS OF GENAI MODELS ON SUPPORTING THEM.

The industrial experience with LLMs is very varied. The survey and open discussion were intended to evaluate the triangle model proposed. However, this model seemed to be straightforward to adopt – see also its limitations in the paper. This resulted in the theme of discussion shifting towards the capabilities of LLMs to support their daily tasks. If was obvious from the feedback that the designers do not expect the activities to be fully automated, that they still wanted to be in control of the activities to be done, and how they were being done. Having the ability to take over at any given point, or to modify the LLM results when errors are found are important characteristics of future design automation systems. The ability to provide useful support was questioned, and concerns about hallucinations widely discussed.

In terms of opportunities, designers highlighted two scenarios in which automation support is needed. In the first scenario, where a known design space is being explored and minor changes are required, a high level of automation is needed. They also highlighted the need for exploratory evaluations carried out by design automation. In both cases, it was agreed that Generative AI support could be beneficial. In the first case, to configure properly the inputs and perform the activities independently within certain boundaries, removing labour intensive, non-value added tasks and leaving room for synthesis and analysis activities. In the second case, the GenAI benefit would be to iteratively generate new evaluations and automations. Having the ability to talk to the model in a natural language, rather than having to understand how the design automation system worked, was beneficial to some extent. Designers with entry level would welcome it, while experts in the automation systems argue that it is easier to automate the code.

5 FINDINGS

This chapter synthesises the findings relevant to this thesis into a coherent starting point for an informed discussion and for drawing up conclusions and future research plans.

5.1 ON THE DESIGN AUTOMATION OF COMPONENTS IN THE AEROSPACE INDUSTRY

The challenges to adopt KBE automation methodologies in industry has been well documented already a decade ago (La Rocca 2012; Verhagen et al. 2012)and recently again (Kügler et al. 2023). As an example, the definition of the MOKA Knowledge Management Framework to respond to KBE exploitation and scalability (M. Stokes 2001). The findings reported here complement the previous work. Gathering information first hand via interviews and during the DEFAINE project provided now a hands-on perspective to it. Not only for the author's experience developing KBE systems, but also for being able to interview first hand some of the people who actively researched and incorporated the systems in the 2000-2010's, and those who have developed and implemented in industry the latest KBE system available, ParaPy.

The KBE technology has not been adopted widely in industry, compared with others like CAD or FEM, despite the promises of efficiency and time savings claimed. Only one company of all the interviewed keeps using the technology, and it is applied mainly in the conceptual development of products. We focus mainly on the non-technical aspects, as the technical aspects have been discussed before.

Business and company strategies have large influence on the tools being used. For example, 3 participants mentioned the business move of Dassault systems buying the ICAD technology as one of the factors why KBE stalled. Interviewees believe that internal decisions that prioritised CAD automation features in decrement of a KBE system based on primitives was one of the reasons why it was not further adopted. Other interviewees highlighted the need for sponsorship from the higher management team, or as he called it, "believers" of it. The need to "believe" in the technology is because detailed expertise is required, in addition to time to develop the automations, which can take years to develop to a level that is good enough to provide useful support in real life applications. Others mention how despite a large effort being made in an OEM to have a comprehensive set of KBE tools available to design the system, the next airframe generation had the design responsibility offloaded to the RSPs. This lead the OEM KBE team without a product to design in detail, and since the tools were considered internal IP, were not shared with the RSPs, who chose simpler automation methods as they did not have time or budget to develop their own KBE systems.

Once a design automation system is in place, it is hard to change. A company that tried extensively KBE in their jet engine component design in the 2000's is a good example of it. The interviewees showed how the technology could be used to save time, but the strategic decision from management to ease the transition from conceptual phases to preliminary and detail phases had the unintentional consequences to abandon KBE techniques then, and possibly forever. Since the CAD and analysis models had to be stored in the PLM systems, and be editable in CAD, the KBE system back then did not allow for that. Therefore, the tools and methods used in detailed and preliminary phases were brought forward to the conceptual phase, and an automation framework was developed on top of them for the conceptual activities. Now, that cheaper licences of KBE systems are available, that there are a lot of programming techniques available to robustly generate primitives and deploy them to engineers (git, CI/CD pipelines, automated testing, KM methods…), traditional automation tools are still preferred. The reasons are not only due to the unsuccessful experiences from the past, but primarily because of the lack of KBE expertise and the investment made in other automation scripts and techniques around vendor CAE tools and PLMs. Any designer in the company can use the default CAD, but none of them can program in python to create KBE. The learning curve is too high to deploy a unfamiliar designer into a KBE based project and expect him to deliver without weeks and months of training. Therefore, it has currently been discarded.

The selection of an automation technology also has a historical context. Companies with a strong and stablished automation strategy may choose to keep their technology due to their investment made on them and risk of the new automation not working as expected, despite the probable efficiency improvement: Better the devil you know than the devil you don't. If a project has chosen an automation method, it tends to stay the same even if the development project last for more than 10 years. The project is focused typically on delivering design changes and evaluating those changes, and the design automation process is seen as secondary, time consuming and risky, as new method validation activities would have to be carried out. It is usually when new projects start when new automation techniques are allowed. In those cases, still, the personal experiences of the lead engineers is a critical factor: since the previous project automation techniques is what they know and feel comfortable with, it will be likely that that would be the technique to be used in the next project, unless a new technique is available that is mature enough to bet on it. Therefore, a 10 year old automation technology is the most likely candidate for the next 10 years of the future development programmes.

The seasonal and cyclic nature of the aerospace industry has also an impact on the adoption of the technology. Since the aerospace industry development times is long, employees move throughout the projects before they are finished, and sometimes it can take years between research and development projects to tackle design method development. This makes automation experts – who usually have another engineering discipline background – to be moved elsewhere, not being able to take their design automation experience with them. When the time for a new method development project appears, it is not guaranteed that they will be back, in the same role, or even at the same company, taking their tacit knowledge with them.

An additional factor is the design automation experience of the engineers, and their primary role. Engineers at aerospace companies are hired for their engineering capabilities, e.g. solid mechanics, aerodynamics or system engineering. Automation techniques is a skill that is not part of their academic curriculum, and it is learned "on the job". Interviewees agree that there are "curious" or "keen" engineers that are willing to adopt new methods, and those who don't, not even programming. This aversion to design automation is exacerbated in non-analysis engineering positions, such as CAD generating roles. The number of years of experience in aerospace was a factor that was proportional to the aversion to try new techniques, although not always. As an interviewee highlighted: *getting the right level of flexibility in an automation tool is a skill that is learned with time. You need both the experience in the thing you are automating, and the automation experience itself. You cannot say everything is an input, no one wants to fill in 20 parameters. You don't want to automate either exactly the problem of a given project, it will never be used in the next one.*

At this point, it looks to the me that for an automation technology to persist in a company it needs to *survive* to different factors. Much like how Homo sapiens spread from Africa to the rest of the world, waves of settlers were extinguished by harsh winters, diseases, or violence. In this case, the successful implementation of the technology in a sample product is not sufficient for a technology to last. Any external factor can produce a de-stabilizing situation that makes the evolution and stablishing of a technique to disappear. External factors that threat the technology adoption are company strategic decisions, employee turnover, KBE providers licences and contract, or IT infrastructure. Factors that help the technology survive are properly documented practices, good quality code, a critical mass of experience in the team, and company support at the management level. Previous success stories help also to anchor the technology in the company. If an automation technology disappears, experience employees eventually move on to other roles, and the new wave of designers find easier to use another automation technology and archive the old, strange automation method.

5.2 ON AUTOMATING THE LINK BETWEEN DIFFERENT DESIGN DOMAINS

In order to support the need for novel design configurations, it was promising to find a means for automating the connection between what the product should do (function) to what the product looks like (its definition). Both EF-M trees and KBE use objects to embed design concepts: Design Solutions and Primitives. However, as discussed during the result chapter, the author could not find an approach that could elegantly provide the flexibility and automation necessary to provide a meaningful support. Ultimately, the automation had the same challenges as the first generation KBE applications: becoming too static and cumbersome to adapt to future products and development programs.

The results showed that an equivalence and later automation would both restrict the freedom on both design spaces. Following from the previous section on challenges of automation, the equivalence was aimed at simplifying the connection between the domains for the ease of automation. The advantage of EF-M modelling techniques is its flexibility over other robust functional modelling, such as systems engineering. And the advantages of the KBE approach is the level of detail that they are able to codify, by using programming languages. Since they are meant for different domains, they have a different tree structure. And designers both use flexibly the hierarchy for practical reasons. On some occasions in KBE and physical domain, inheritance is better that composition, depending on the OOP paradigm that results in better code maintenance. Interfaces and slot management between KBE primitives are sometimes best managed with placeholder classes in the XML class hierarchy diagram (Tobie van den Berg et al. 2023). On the other hand, the structure of the EF-M adapts from the top first requirements to the bottom physical objects (Levandowski, Raudberget, and Johannesson 2014). Engineers use the hierarchy flexibly to represent requirements and variations on means to fulfil those requirements and apply them taking into account the design activity type, the product being design or the design phase. Implementing a traditional automation would imply creating a set of equivalence and rules in which the automation would exploit, restricting the flexibility that the different techniques enjoyed in their respective domains.

Even within the same physical domain, engineers use different structures to define products. Engineering Bill of Material (E-BoM) and Manufacturing Bill of Material (M-BoM) represent the same product, jet they have a different structure. The former focuses on they components and subsystems while the latter focus on the manufacturing assembly process.

In summary, the author was unable create a framework that could exploit the object oriented approach equivalence on both domains to exploit for automation. Two remarks on this statement are that (1) there could still exist a good framework and the author did not find it and (2) the traditional automation approach was too restrictive.

5.3 RESULTS OF THE MSC THESES SUPERVISED ON LLMS IN INDUSTRY

For the purpose of the author research into Generative AI, GKN Aerospace was supportive enough to let the author to define two MSc Theses that could complement the research and dive down into specific topics. In addition, a third MSc thesis was proposed from a different part of the company. The contribution of the author of this licentiate (Alejandro Pradas Gomez) was to set up the financing, frame the need of the research, supervise the students during 20 weeks in their methodological approach, LLM technology and report corrections. The MSc students were responsible to perform the research: select their methods, collect information, process it, extract insights and write the MSc Thesis report.

It was decided to include it as part of the licentiate thesis as it shows not only the author's capacity to supervise other MSc level research, but also, it provides specific insight into the characteristics of Generative AI when applied to real engineering tasks. The outcome of their MSc Thesis is used to pave the way of future.

As they are standalone pieces of work, a quick summary of the findings is presented here, highlighting only the arguments that complements the views of this Licentiate Thesis. The three theses followed a robust data acquisition and processing of the obtained information, both internally at GKN and externally.

The first thesis (Karlsson and Alfgården 2024) study on the extent of utilization of AI in GKN engineering design showed that it has not been used at GKN Aerospace for engineering design. As of May 2024, Generative AI was on the exploratory phase, not only GKN but also other engineering and pharmaceutical companies in the region.

The second thesis (Mare and Söderqvist 2024) incorporated the first LLM based framework to support the review and generation of analysis reports. It highlighted the need for test cases to test the performance of the LLM frameworks, and, similarly to **Paper D**, highlights the need of such frameworks to improve the performance of the bare LLMs. Their work was used as inspiration to propose that each company should not rely solely on the LLM public benchmarks as a measure of capability, but they should have internal benchmarks based on use cases where the LLM and surrounding framework need to be assessed as an application.

Finally, the third thesis (Naik 2024) highlighted the lack of spatial awareness of LLMs. The application developed gave a very good example of how an LLM could be embedded in a tool that engineers already know, NX, and complement their surface selection process.

However, the model failed at recognizing adjacent surfaces, showing the limitation of generalist foundation models that are not suited for geometrical recognition. It helped to understand the areas where foundation model reasoning in combination with tools could be used, and where they failed. They understand the concept and can provide basic language equivalences ("north" is "up"). Even Vision models struggled to understand geometries and basic orientation and rotation. The relevant insight is that LLMs on their own should not be used for activities that required spatial reasoning.

6 DISCUSSION

This chapter uses the results and findings from previous chapters to discuss the research problem and answer the research questions. Further discussion is provided regarding the novelty of the findings compared to the current state of the art, research quality, validation of the results, and the scientific and industrial contributions made by this licentiate thesis.

6.1 ANSWERING RESEARCH QUESTION 1

RQ1 *What are the potential and limitations facing design automation strategies in engineering design and analysis processes for complex products?*

Design automation techniques are dependent on the history and circumstances of the engineering company. It depends on the type of product they manufacture, and the role they have on the aerospace ecosystem (OEM vs component designer). The automation system chosen depends on the employee knowledge, and previous experience with the automation. The more capable the technology is, the more expertise is required to take advantage of it. The risk of not being able to update or run an automation due to lack of expertise makes companies to favour simpler techniques over more complex ones.

Desing automation techniques survive at companies. Sometimes they fail due to their own complexity, but external factors, such as company strategy, or cyclic economic workload, employee turnover and project priorities can jeopardize their survival. For example, the KBE technology showed clear benefits and successes at companies 20 years ago, and while it has thrived at some companies, it has been discontinued in others. Therefore a design automation technology that has a low barrier to entry, and can be modified to adapt to the specific product being designed has a higher probability of adoption.

6.2 ANSWERING RESEARCH QUESTION 2

RQ2 *How can the design exploration of both functional and physical domains be combined and automated?*

This thesis introduced the FUSE method in Paper B to **connect** both functional and physical domains. While the method can be beneficial in some circumstances, for example when designing similar products or derivatives of the same family, it is not a method that is widely transferable to other circumstances.

On the automation of the process, the author concludes that the method should not be automated. In addition to restricting the design process and freedom of the design, the zig-zagging process turned to be a useful step for the designer, expanding their knowledge of the design space, and an valuable exercise. Trying to automate the process using a traditional technique required a predefined equivalence between components (Design Solution and Primitives) that introduced complexity and restrained the freedom of the design space.

6.3 ANSWERING RESEARCH QUESTION 3

RQ3 *What are the potential opportunities and challenges of Large Language Models when applied to the engineering design of complex systems?*

Numerous challenges arise for the use of this novel technology on the engineering domain. The foundation models suffer from hallucinations and false confidence that can deceive engineers and a false sense of security. They require a supporting framework to correct for the inherent weaknesses of a transformed based deep neural network architecture, as discussed in **Paper D**. Developing products and automations using this technology is a new paradigm that remains essentially unexplored in industry. As discussed in **Paper C**, it requires a new mindset. In addition, they lack geometrical awareness, which is a crucial part on the development of physical engineering products.

The architecture of LLMs require large amounts of GPU vRAM, which is not available on many companies. As foundation models improve their reasoning capacity, it would be possible to run and fine tune them within the company premises with a modest investment on hardware. Alternatively, they could be exported if the export control and customer agreements are modified, as discussed in **Paper D**.

This technology could be used as a generic reasoning engine. As discussed **in Paper E**, it could be used as a reasoning agent to automate the sub-steps relevant to the design activity. It can effectively lower the barrier to entry into any traditional automation tool, which can increase the adoption of existing automation techniques, acting as a translator from novel engineers with expert systems. As the survey in Paper E shows, the technology has the potential to automate tedious tasks, making the engineer necessary only for higher level decision making, and automate larger parts of the design process, reducing the lead time for the design.

6.4 Scientific contribution

This research has several contributions to the academic research area. The interviews on KBE and automation experts in aerospace provides a new perspective that is complementary to the existing literature on the challenges of persistent adoption of this technology in undustry.

Within the design space exploration research area, the FUSE method in **Paper B** is another novelty presented to the community, although it is arguably only applicable to a group interested in architectural and physical performance evaluation.

Paper C provided an example of how off the shelf LLMs can be used for both system and component design, using their generic characteristics to provide useful results and save time. **Paper D** provided an overview of the different existing frameworks used in the computer science domain and presented them to the Engineering Design fora, exemplifying it with a design task example.

Finally, **Paper E** proposed a new conceptual framework to visualize and quantify the different types of automation contributions that a LLM can provide in a system, clarifying how the technology could be best used. The paper also highlighted a research gap in the use of this automation technology to orchestrate workflows and make use of traditional tools. Finally, the paper also pointed out the interest of industry in this technology.

6.5 Industrial contribution

The research within this thesis contributed directly to GKN Aerospace Engine Systems directly and indirectly to the DEFAINE partners involved.

To start with, it enabled the collaboration between different divisions of GKN to find common interest in automation technologies. It enabled the use of KBE technology and the creation of a library of primitives that could be used for the initial conceptual design of different products, and analyse them in the solid mechanics domain. Several analysis python modules were developed internally to execute the design cases covered in **Papers A, B and C**, that now form part of the internal library of analysis modules.

The research sparked the interest of the potential of Large Language Models to be used for automation. Initially the author fell it was a technology push from research, but as the

ChatGPT and LLM popularity increased, it started to be part of the 2024 and 2025 strategy to investigate the potential of this technology, which this thesis helped to scope.

To support the examples of LLM frameworks, a local LLM machine was set up internally that is now available for every employee within GKN aero engines. Example uses cases have been created and a new strategy is being defined for increasing the adoption in 2025. Other divisions of GKN, such as Foker Elmo, are now developing internal capabilities and asking for support to implement the technology. In addition, a group of different companies and researchers, spinning off the DEFAINE project, are starting a community of practice to talk about how LLMs can support design automation efforts.

6.6 Validity and transferability of results

As discussed on section 2, the research has been conducted methodically and according to the discipline best practices to ensure its validity. This section recaps the arguments for its validity and later it highlights some of the limitations. Each paper presented in the appendix has its own methodology justification and limitation section, this thesis covers the overall points.

Following the DRM methodology, *design research has two related objectives: the formulation and validation of models and theories about the phenomenon of design, and the development and validation of support founded on these models and theories, in order to improve design practice, including education, and its outcomes* (Blessing and Chakrabarti 2009). Since the research focuses on supporting methods and design tools, but not a developing of performance and simulation models (Sargent 2013). The criteria defined by Le Dain, Blanco, and Summers (2013) is used instead as suggested by Isaksson et al. (2020): Truth value, applicability, consistency and neutrality. Since the purpose of this research is empirical (Cantamessa 2003), the focus of the validation is on the research questions and the validity of the gaps identified. The two models proposed in the thesis, the FUSE method and the triangle of design responsibility, are addressed separately on the respective papers.

In empirical research truth value is defined by credibility. The methods chosen to answer the research question are supported by a triangulation of methods: different methods were answered to answer the same research question: literature reviews and case studies were common to all, and interviews and surveys were complementary to questions one and three, providing different perspectives to the problem. This approach strengthens the internal validity of the research and therefore, its truth value.

To argue for its applicability, the research was conducted closely with industry in case studies. The transferability or analytical generalization was achieved by involving more than one aerospace company, combining OEMs with RSPs, although GKN Aerospace Engine System perspective was dominant. This was demonstrated in **Papers A, B** and **C**. For **Paper E**, the automotive industry was also used as a complement to the aerospace perspective, confirming similar perceptions of Generative AI in industry and their feedback on the triangle of design responsibility model. Although only one case was used for the exemplification, the Turbine Rear Structure, the use case was generic enough to cover any structural aerospace component.

Consistency was achieved by following the methodology in the research methods for each paper and discussed already in section 2. By following an established design methodology (DRM) and a research method technique (e.g. interview recording, coding and summarization) a consistent and repeatable result was achieved.

Neutrality was the hardest of the trustworthiness dimensions to achieve, given my previous industrial experience. The definition of the research questions and design phenomena to study are influenced by the research angle, which in turn is influenced by the researcher experience. Being conscious of the personal bias, the data collection activities were set up to minimize it. For example, to identify automation challenges, questions like "Is the experience with the automation technique a factor that hinders the adoption of those systems?" were avoided and open-ended questions were asked instead, for example "What are the factors that hinder the adoption of automation techniques?". Summaries of the coded interviews were provided to the interviewees to ensure that it was indeed a fair summary of the conversation. In literature reviews, the papers were reviewed explicitly looking for counterfactuals to my initial hypothesis. Finally, papers were written with co-authors who provided alternative views and ensured that the summary and delivery of the discussion and conclusion were not biased by one author.

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7 Conclusions and Future Work

This final chapter summarizes the previous chapters of this thesis, providing final remarks on the research questions and outlining possible future work to be pursued.

7.1 Conclusions

Several internal and external factors challenge the adoption and persistence of design automation methods. The more potential the methods are, the more complex to use they are. In order to maintain and increase the automation capabilities, active development and sustain activities must take place, and the automation methods must be as simple as possible to use and to adapt to specific use cases by the engineers themselves.

The studies conducted in this thesis, and their findings, confirm the insight that developing automation frameworks requires significant efforts to develop, maintain, and update as the design practices and company knowledge gets updated. Interviews further suggest that the more capable and complex automation frameworks are constantly at risk of extinction due to external factors, such as employee and management turnover or industrial business or research cycles. Therefore the research suggest that the automation frameworks should be designed not only to be simple to interact with, but also easy to maintain and reuse its knowledge.

The third wave of AI and LLMs have the potential to orchestrate the engineering processes. However, there are several gaps, such as the actual performance on real design environments, their impact on the designer or the appropriate delegation of tasks, that need to be understood before their deployment in industry. In the latest paper (**Paper E**) the new role of LLMs in design has been explored, achieving agency that distinguish Generative AI frameworks from traditional tools. The triangle of design responsibility is a promising model to explore this interrelation yet still is premature and needs further refinements to position it against other theories and design situations. If this technology can deliver the expected interaction between designers and traditional tools, it is envisioned that they can enable faster analysis cycles and therefore support the novel configurations and rapid feedback needed for novel sustainable propulsion systems.

7.2 Future work

The research initially aimed to increase design automation to accommodate changes in aircraft configurations driven by sustainability goals. The original focus was on exploring wider design spaces, but it became apparent that this would not sufficiently impact support for new configurations. Challenges related to KBE adoption and sharing novel tools and methods with engineers highlighted the need for a more "user-friendly" interface, which is where Generative AI can provide a significant support. Their ability to interface and orchestrate are a paradigm shift in the design automation techniques.

According to Catic (2011), one way to categorize knowledge is to divide it into product and process knowledge (Sunnersjö, 1994; Wallace et al., 2005). Product knowledge relates to knowledge about e.g. relations between product parameters, while process knowledge is about activities – e.g. how a simulation is interpreted. Foundation models allow for the interpretation of these results, something that previous waves of AI could not perform.

This revised focus brings several advantages. Unlike the original approach, which targeted early conceptual phases, a revised approach shall be applied at any stage of the design process. Given that most engineering hours are spent in later phases, this shift has the potential for greater impact on industry practices. Thus, while functional modelling approaches using such as EF-M techniques will still play a role in future research, they are no longer the primary focus.

Expanding on this rationale, the new approach may benefit other industries, including for example automotive, naval, construction, architecture, or heavy industries. Any knowledge-intensive task requiring accurate tools for performance measurement and adherence to strict methodologies could gain from these developments.

The emergence of reasoning abilities in GenAI and the capability of GenAI agents to perform active tasks enable a shift in automation focus. Previously, scripts and workflow tools aimed to automate calculations as much as possible. Now, automation can extend to activities traditionally requiring human input, either directly or through codified decision-making processes. Given that humans are the slowest link in the automation chain, transitioning their role from active participation to review may facilitate broader exploration.

The potential of Generative AI is evident, but the best approach for engineering applications remains uncertain. Aerospace designers interact with numerous tools, and the integration of GenAI frameworks could offer significant advantages by combining the strengths of human designers, Generative AI, and traditional tools. The realization that Generative AI can be an active participant in the design process, rather than just a tool, emerged in Paper C. Future research must consider this perspective.

From interactions with engineers at GKN and a review of AI literature, the active subject of automation has revealed itself critical. Research questions should shift from "How can AI support the design automation process?" to "How can designers use AI to increase automation?" Stanford's Institute for Human-Centred AI (HAI) exemplifies this human-centred mission.

Finally, if the role of engineering design is to have an impact in design practice, the research should focus on finding effective support that does not fail the limitations of past automation support. It has been identified that the design automation using the first wave of AI, such as KBE, required the users to define in advance the design logic, and that ultimately led to a framework that was challenging to maintain and transfer to the next project. The future design automation framework should put an emphasis on reducing the burden to maintain and update it, ideally learning from the user interaction directly.

The next phases of the PhD research will focus on:

1. The development of a theoretical framework and its implementation on a realistic design scenario.
2. A further investigation on the different framework architectures and the best combination of foundation models for reasoning, and AI performance models based on datasets.
3. The impact of the proposed idea in industrial scenarios.

Specifically, the following questions are proposed to guide future research?

1. What is an appropriate evaluation criteria on the effectiveness of such framework on the design activities?
2. What type of activities should be delegated by designers to traditional tools and LLM agents, and what activities should be in control of designers?
3. How can the knowledge gained through the interactions with the framework be used to improve the accuracy of future interactions?

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9 APPENDICES

Paper A Design automation strategies for aerospace components during conceptual design phases

Paper B FUSE: A novel design space exploration method for aero engine components that combines the functional and physical domains

Paper C Large language models in complex system design

Paper D Evaluation of different large language model agent frameworks for design engineering tasks.

Paper E A team of three: The role of generative ai in the development of design automation systems for complex products.