UNIVERSITY OF TURKU

Artificial intelligence-driven design

How AI will change design in the industry

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This thesis explores the transformative potential of artificial intelligence in enhancing additive manufacturing design processes. By integrating AI in design for additive manufacturing, designers can overcome traditional constraints and innovate at an unprecedented pace. The study focuses on the use of generative design and topology optimization, which utilize AI to automate and optimize design parameters, thereby enhancing the creation of complex, functionally superior, and customized products in less time.

However, the integration of AI in design for additive manufacturing also presents challenges, including the dependency on high-quality data and the need for extensive training datasets to avoid biases. Future directions suggest further integration of AI to refine design processes, enhance the predictability of material properties, and reduce the iterative nature of traditional design methodologies. The research discusses how AI-driven methods not only streamline the design-to-production cycle but also improve material utilization, reduce waste, and increase the sustainability of manufacturing practices.

The thesis highlights AI's crucial role in revolutionizing design capabilities in the AM industry. AI-driven optimization is expected to become standard practice, enhancing both efficiency and sustainability of manufacturing processes.

Keywords: Additive manufacturing (AM), design for additive manufacturing (DfAM), artificial intelligence (AI), machine learning (ML), deep learning (DL), generative design (GD), topology optimization (TO)

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1 Introduction

Artificial intelligence (AI) has become increasingly integrated into our day-to-day lives, transforming how we interact with the world around us. From smart home devices to sophisticated data analysis tools, AI's capabilities are expanding at an unprecedented rate. This rapid growth is not just confined to the traditional field of computing or robotics but has also started to make a significant impact in creative and design-oriented domains. Among these, the field of additive manufacturing, also known as 3D printing, stands out as a particularly exciting area of application.

1.1 Additive manufacturing

Additive manufacturing (AM) techniques create three-dimensional (3D) objects by successively layering material on top of the previously deposited material according to a computer-aided design (CAD) model. This approach enables the direct fabrication of complex or tailor-made items without waste material and the necessity for costly tools or moulds, streamlining the manufacturing process. It allows for the creation of complex parts that can bypass the restrictions posed by traditional manufacturing methods. Moreover, AM can significantly reduce the number of parts needed by minimizing or eliminating the assembly of multiple pieces. Additionally, it facilitates the on-demand production of parts, cutting down on the stockpiling of spare parts and shortening the lead time for essential or hard-to-find replacement parts [1]. However, the AM process is recognized as a complex system that integrates various technologies such as materials science, mechanics, electronics, optics, and computer science. Production of high-quality parts is dependent on various factors, such as material properties, processing parameters, process stability, and operational conditions. The state-of-the-art of AM and its different processes are further expressed in [2].

In the past decade, AM has seen rapid growth and is now used in diverse areas such as aerospace, automotive, maritime, and medicine. As AM technology continues to evolve, its applications across these fields have also expanded. To make sure that AM products meet design standards in terms of mechanics, materials, and functionality, it's crucial to not just rely on the unique benefits of AM but also to choose the right processes and materials, and to optimize the parameters of the chosen processes accordingly. As a result, numerous strategies have been developed to effectively enhance AM technology's application. Notably, the integration of AI through Machine Learning (ML) and Deep Learning (DL) has transformed the way we understand and navigate complex physical phenomena in AM, providing substantial support.

AI's role in AM can be viewed from four angles. First, AI helps in design for AM, simplifying the design and optimization process. Second, it plays a significant role in materials design for AM and analyzing their properties. Third, AI is crucial in process selection, control, and optimization through real-time monitoring. Lastly, AI is being used to predict the quality of AM products, aiming at ensuring quality standards [3]. This thesis will explore the first two proposed roles of AI in AM.

1.2 AI, ML, and DL in AM

AI and its subsets, ML and DL, are revolutionizing the field of intelligent manufacturing and systems design. In a broader sense, AI represents a variety of computational strategies that replicate human intelligence. ML can learn from provided datasets autonomously, using them as input to predict future outcomes. ML possesses the capability to explore unexploited areas of the design space, thereby significantly broadening its limits. ML is emerging as a potent and flexible tool in the hands of material researchers, offering a different approach to tackle optimization challenges, allowing the design of high-performance materials without needing to thoroughly search the entire design space, and uncover unique mechanical properties. The integration of ML with 4D printing (4DP) is anticipated to significantly speed up the process of materials design and discovery. For ML in AM, the use of ML extends beyond its conventional role of data-driven prediction. Researchers are exploring how to integrate ML and AI into AM to improve product quality, reduce costs, and optimize manufacturing processes.[4]

DL is a subset of ML that employs neural networks (NN) with multiple layers to gradually identify more complex patterns from unprocessed data. These NN mimic the human brain's functioning by integrating data inputs, weights, and biases to effectively identify, categorize, and interpret features in the data. The main distinction between ML and DL lies in human involvement in the algorithm's learning stage. For instance, in identifying solidification defects, such as porosity and hot cracking, ML needs human insight to pinpoint the features that differentiate these defects. In contrast, DL automates this process of feature differentiation, although it demands a more substantial data volume to enhance its precision. [5]

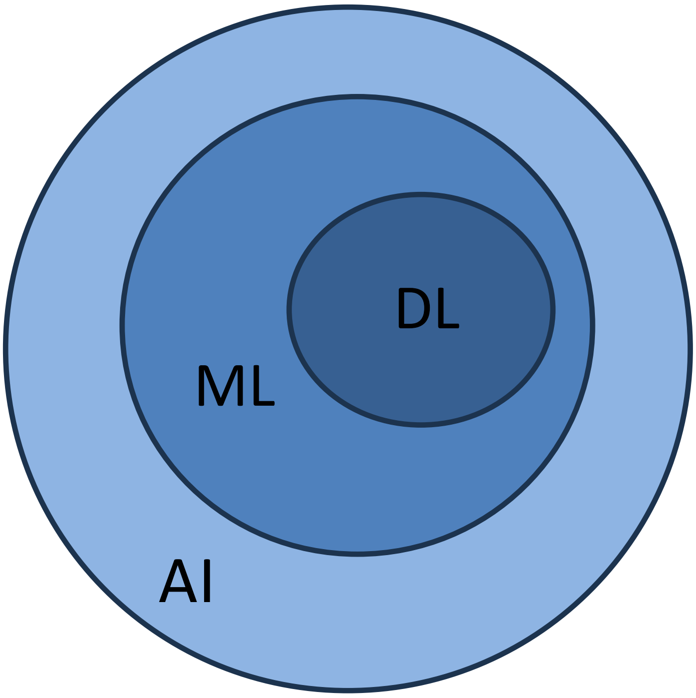


Figure 1. Artificial intelligence (AI) and its subsets machine learning (ML) and deep learning (DL).

1.3 Design for AM

AM has opened the door to innovative design possibilities and enhancements in product functionality, offering capacity for unrestricted geometric shapes and the integration of complex structures [6]. This innovative method of production unique to AM brings variations in production volumes, timelines, and cost considerations compared to conventional manufacturing methods. Furthermore, it requires specific strategies for measuring and ensuring product quality. In response, the concept of Design for Additive Manufacturing (DfAM) has been developed, providing designers working with AM a comprehensive set of tools to address the complexities of advanced component designs and AM processes' specificities.

DfAM refers to the specific design principles and practices tailored to leverage the unique capabilities and constraints of AM technologies. Unlike traditional manufacturing methods, which often impose significant design limitations due to their subtractive nature and tooling requirements, AM offers unparalleled freedom in design complexity and customization. DfAM optimizes this potential to create parts and products that are excessively expensive or almost impossible to make with traditional methods Central to DfAM are two key focuses: the creation of parts and design optimization (DO) [7]. In terms of part creation, AM allows the fabrication of tailor-made shapes and geometries, facilitating the development of complex internal structures that enhance the functionality and efficiency of components, thereby significantly expanding the creative horizon for designers. On the optimization front, those engaged with AM design are challenged to identify the most effective strategies for production paths, positioning of parts, orientation during building, and the configuration of supports, all aimed at improving the quality of the end product and overall efficiency. The evolution of artificial intelligence and the proliferation of data have led to the growing application of ML technologies in DfAM, marking a significant trend in recent years [8].

Despite the advantages of DfAM, it also presents several challenges. Designers must thoroughly understand the capabilities and limitations of AM technologies, including issues related to material properties, surface finish, and the need for support structures during printing. Additionally, there is often a need for post-processing steps to achieve the required surface quality or mechanical properties. Therefore, AI is being researched and implemented to help designers with these challenges.

1.4 Thesis structure

By providing a literature review of the state-of-the-art AI-driven design in the AM industry, this thesis explores the current use of AI in the design process for AM, highlighting the applications of AI made in the AM industry by covering studies and real-world examples, and going through the advantages and challenges of the subject matter.

The study is structured into three chapters. The initial chapter focuses on presenting the theoretical background of AM, AI, ML, and DL for the reader. The second chapter undertakes a comprehensive literature review of the state-of-the-art applications of AI-driven design for AM. Finally, the third chapter covers the conclusions of the research, the advantages and the challenges of AI-driven design in AM, and potential future developments.

In this thesis artificial intelligence was leveraged in grammar-checking (via Grammarly), and for information retrieval (via GPT-4).

2 Applications of AI-driven design

Leveraging AI in the pre-processing phase of AM can help capture accurate geometry and functionality details. This approach reduces the risk of unsuccessful outputs and saves time in production. It also optimizes performance and material utilization in part creations, while meeting user constraints. As a result, it makes AM technologies more accessible to individuals without extensive expertise in the field. [8]. This part of the thesis covers the various applications of AI in the design phase of AM, including generative design, topology optimization, shape deviation, and more.

2.1 Generative design

Traditionally, design processes have been largely constrained by human intuition and experience, limited exploration of the design space, and the practicalities of manufacturing capabilities. Generative design (GD) shatters these boundaries by employing AI and ML to systematically explore thousands of design alternatives, evaluating each against a set of performance criteria and constraints to identify optimal solutions. This not only accelerates the design process but also unveils creative, efficient, and sometimes unexpected solutions that might not have been considered through conventional design methodologies.

GD is a design exploration process that uses the power of computational algorithms to generate a wide array of design options based on specific input criteria such as materials, manufacturing methods, budget constraints, and performance requirements. It uses AI and ML to iterate through countless possibilities, quickly identifying solutions that might not be immediately apparent through traditional design methods. This approach allows designers and engineers to explore a broader design space to find the most efficient and innovative solutions. GD algorithms can create optimized structures that make better use of materials, reduce weight, and enhance performance in ways that were previously unimaginable.

GD, especially when combined with AM, represents a future where the constraints of traditional design and manufacturing processes are overcome, leading to more efficient, sustainable, and customized products. As technology advances and becomes more accessible, the potential applications of GD are expected to expand, further revolutionizing how we approach design and manufacturing across industries.

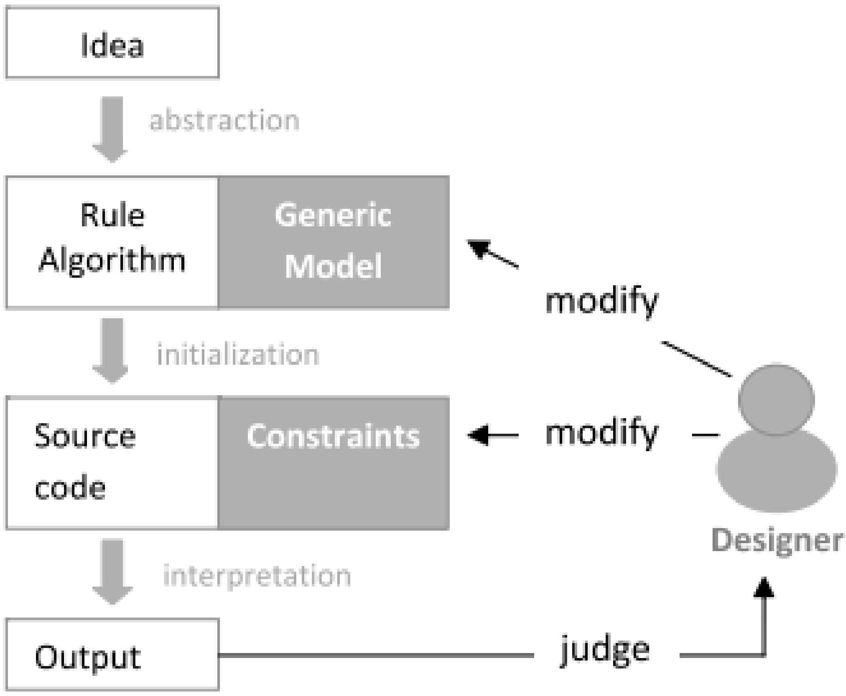


Figure 2. Generative design process [9].

2.2 Topology optimization

Topology optimization (TO) answers the fundamental engineering question of finding the optimal way to distribute material within a given design space for a given set of constraints [10]. TO is a computational approach used to design structures by efficiently arranging material within a designated space, taking into account specific forces and limitations. Traditional TO processes can be time-consuming, requiring many rounds of design adjustments and prototypes, especially for large or complex structures. This makes it a resource-heavy task. ML models, particularly those involving deep neural networks, encounter similar challenges during their initial training stage. However, when these ML models are trained, they are able to rapidly produce optimized designs, bypassing the need to start from the beginning every time. This allows ML to complement traditional TO methods effectively.

To tackle mechanical design challenges, Convolutional Neural Networks (CNN) have been trained using data from the midway points of TO processes. For example, the process might be paused after just a few iterations to use the CNN to predict the final, optimized structure [11]. This approach has shown that a well-trained CNN can generate the end design up to 20 times faster than the traditional method, with only minor differences in detail. This technique has been proven not just for mechanical issues but also for thermal ones, outpacing traditional methods in both speed and accuracy, demonstrating CNN's broad applicability without needing specific problem expertise. Banga et al. [12] took this a step further by applying it to 3D structure generation, where a trained model could almost instantly predict final designs with high accuracy and a significant reduction in time compared to using the Finite Element Method (FEM) based traditional method alone.

While ML does not replace the traditional TO method as a whole, it enhances the process by reducing the number of iterations required and accelerating the optimization process. Additionally, ML can offer quick, initial predictions of design outcomes, which can be particularly useful in the early stages of a project. However, it's important to note that these innovative ML applications have not yet been widely adopted in AM.

2.2.1 GD using TO

Recent studies on GD have shifted from changing design parameters to using TO as the main way to create designs. This new approach allows for the creation of many designs at the same time using cloud computing [13]. In this process, a designer sets various boundary conditions for TO, leading to different optimized designs based on those conditions. Matejka et al. [14] explain that GD changes the problem's parameters, while parametric design directly alters the geometry's parameters. GD's goal is to explore various design possibilities that meet structural requirements and to select the most appropriate designs based on the specific needs of different designers. This contrasts with traditional TO, which focuses on identifying the single best design solution.

The overall process of GD can be broken down into four stages [13]:

- 1: Set the design parameters and objectives for TO.
- 2: Generate designs by executing TO across various parameters.
- 3: Explore alternatives, refine through iteration, and choose the optimal design.
- 4: Produce the design with AM.

Specifically, the advancement of AM technology has enabled the creation of complex geometric designs, thereby enhancing the applicability of GD in practical scenarios.

Several limitations have been identified in the current approaches to GD. To begin with, it is important to note that although GD is often associated with AI, it does not make use of the full potential of advanced AI technologies like DL. As a result, GD's potential for innovation and optimization is limited.

Secondly, GD has been criticized for its tendency to prioritize engineering functionality over aesthetic appeal. This can lead to designs that may not be visually pleasing to consumers. However, it is important to consider aesthetics alongside engineering performance, as it plays a crucial role in consumer satisfaction.

Lastly, there is a lack of variety in the optimized designs produced by GD. Although these designs may vary in technical specifications such as material distribution or density, they often appear similar in terms of human perception.

2.2.2 Difference between TO and GD

Both of the tools mentioned use algorithms to design structures. However, they have different approaches. TO uses mesh-dependent optimization methods like SIMP, which are well-researched and refined to deliver effective results. However, the initial shape required for analysis can restrict the final design. To address this, users can start with a larger initial model, although it can be challenging for complex parts with multiple components. One limitation of TO is that it generates only one design per analysis. Future studies could explore running multiple analyses simultaneously with varied parameters such as initial shape or goals for reducing material use.

In contrast, GD does not require a fully defined initial design space, offering more flexibility for design changes. However, it requires engineers to adopt a new mindset for setting up designs, which can be a hurdle. These tools are relatively new, and their algorithms require more refinement to deliver high-quality results. Current limitations include designs with thin, non-functional areas, seldomly added holes that lead to uneven material use, and limited compatible manufacturing processes. GD tools also demand high computational resources, often taking hours to produce results, but they could reduce the need for specialized equipment.

Currently, neither tool takes into account material and manufacturing costs, which is a significant concern for engineers. Future versions should consider these factors. More research is needed to understand how these tools could impact the early stages of the design process. [15]

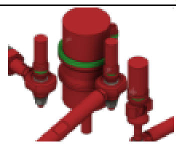
	Topology optimization	Generative design
Initial geometry	 Solid part of a rocker	 Suspension assembly
Materials	Al 7075-T6	Al 7075-T6, AlSi10Mg, Titanium 6Al-4V, Stainless steel AISI 304
Manufacturing methods	Not considered	2-axis cutting, 3-axis milling, additive manufacturing, unrestricted
Objectives	Mass reduction up to 50%	Minimize mass, $S_f \geq 1$
Study result	1 optimal design, mesh body 	>100 designs, 8 diverse groups 
Mass reduction	45 %	Max. 32%
Duration of a study	2 minutes	2.5 hours
Parallel design comparison	Not available within the tool	Available, mass and stress comparison
Additional design editing	30 minutes, required	Not required in some cases

Figure 3. Comparison of TO and GD parameters and results of a study conducted by D. Vlah, R. Žavbi, and N. Vukašinović [15].

2.3 Support structure design

To make sure products made by AM meet high-quality standards, it's crucial to optimize the design beforehand [16] the part is taken to the manufacturing stage. This preparation phase involves making several important decisions, such as figuring out the best layout and direction to build the part, which affects significantly the process and fabrication attributes [17]. For example, a study [16] used a method called K-means clustering, along with a specific criterion for evaluating clusters, to find the efficient build orientations by analyzing the surfaces of models. This method breaks down the model into clusters, with the best orientation chosen through a detailed analysis.

To avoid issues like unsightly marks or damage to delicate details after removing support structures needed during the printing process, a study was introduced by Zhang et al. [18]. The authors created a model that picks the printing direction based on factors like support area, visual importance, preferred viewing angles, and smoothness conversation. Support structures themselves are crucial in AM for parts of the model that hang over without anything underneath. If support structures aren't incorporated into certain designs, the part can't be fabricated, and the print will fail due to the lack of support.

Huang et al. [19] introduced an approach to determine the least amount of support structures required for a successful fabrication of a model. They utilized a unique neural network technique known as the surfel convolutional neural network (surface element – CNN), designed to enhance the identification of necessary support locations. The surfel CNN involves taking detailed points on a surface that include direction information, using a special technique called LDNI (Layered Depth-Normal Image) [20]. This technique creates a bunch of lines (rays) that pass through the CAD model to record where they hit the model and at what angle. From this information, pictures of the surface points that need support during printing are made and then used by the surfel CNN to figure out where supports are needed. The test showed that this new method is better at finding where supports should go compared to the normal-based method and image-based method. This study points out that the surfel CNN is especially good at identifying supports for parts of the model with unusual shapes or features, making it a stronger option than the traditional image-based method.

2.4 Lattice structure design optimization

Lattice structures, characterized by their repetitive, interconnected network of nodes and struts, present a unique opportunity in AM to achieve high strength-to-weight ratios. However, the design of these complex geometries poses significant challenges due to their complex interrelationships between form, function, and fabrication constraints. The design process for lattice structures in AM traditionally involves substantial manual intervention, limiting the exploration of the design space and potentially leading to suboptimal configurations. The integration of AI, specifically through 3D Generative Adversarial Networks (3DGANs), automates and enhances this process. 3DGANs learn to generate and evaluate numerous lattice configurations by training on datasets of designs known for their superior mechanical properties. This method not only accelerates the design process but also uncovers innovative solutions that might not be intuitively apparent to the designer.

3DGAN operates on the principle of competition between two neural networks: the generator and the discriminator. The generator aims to produce new lattice designs that are indistinguishable from real, high-performing structures, while the discriminator assesses their authenticity. Through iterative training, the generator improves its ability to create feasible, innovative lattice designs optimized for specific load-bearing requirements and material efficiency.

LPBF, which constructs objects by melting and fusing metallic powder using a laser, is particularly suited to realizing complex lattice designs produced by 3DGAN. The AI-generated designs are directly translatable into LPBF processing paths, allowing for the fabrication of components with tailored mechanical properties such as improved tensile strength and fatigue resistance. This direct digital-to-physical translation underscores the potential of AI-driven design in reducing development time and material waste, thereby enhancing the sustainability of manufacturing processes.

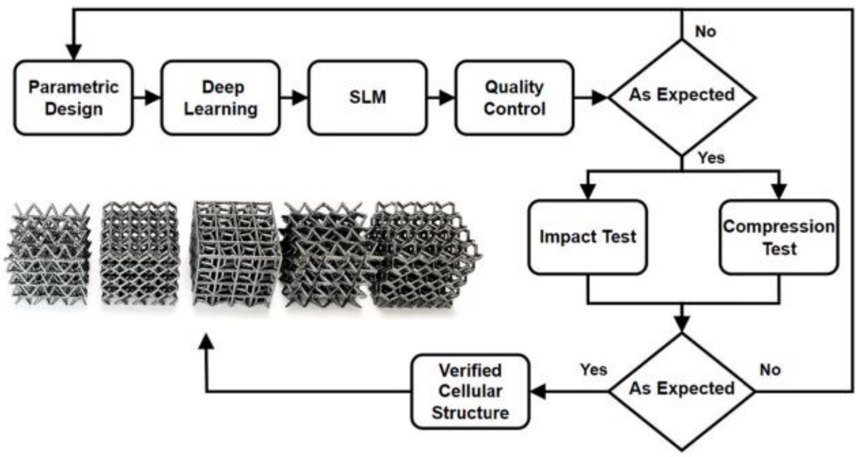


Figure 4. The process flowchart for the design and development of lattice structures [21].

While the AI-driven design of lattice structures offers considerable benefits, there are several challenges that need to be addressed. For example, the quality of the generated designs heavily depends on the diversity and comprehensiveness of the training datasets. To address this, ongoing efforts are focused on enriching these datasets with a wider range of high-performance designs. Moreover, computational resources and training time remain significant constraints. Advanced algorithmic improvements and hardware optimizations are being explored to mitigate these issues.

The integration of AI, particularly 3DGAN, into the design of lattice structures for AM represents a significant advancement in the field. Looking forward, the potential of AI in the design of lattice structures extends beyond generative design to include predictive analytics and real-time adaptation during the manufacturing process. By incorporating sensors and feedback mechanisms within the SLM systems, AI could dynamically adjust processing parameters to compensate for any deviations from the expected outcomes, thus ensuring higher accuracy and consistency in the final products. [21]

2.5 Shape deviation

In the field of DfAM, making sure that the shapes of final products are accurate is very important. This process is about minimizing the differences between the intended design and the actual product [22]. During the AM process, many factors can change the shape of the final product, such as the material used, how heat is distributed, and the direction in which the product is built. These changes can make the final product differ from its intended design, which poses a challenge in predicting these shape differences and finding ways to correct them.

To address these challenges, many studies have shown that ML models can help with issues related to shape accuracy. These models can predict shape changes, classify and measure how accurate the shapes are [23] [24], and adjust for any deviations [25]. For example, artificial neural networks (ANN) have been used to understand how different printing settings can lead to errors in the shape of the product in various AM processes. Zhu et al. [22] proposed a machine learning-based method to model in-plane deviation and random local variant in AM. The approach aimed to capture the global trend of shape deviations by generating a relationship between the design and the final shape from a transformation perspective. However, due to the presence of complex and unexplained variations, a multi-task Gaussian process (GP) algorithm was utilized to learn from the unexplained deviation data and model the local deviation. The experimental results showed that the effectiveness of the proposed method obtained prediction accuracies of over 90%.

2.6 Case study

The case study conducted by a team from the Department of Mechanical Engineering at Guru Gobind Singh College of Engineering and Research Centre presents a comprehensive analysis and application of GD and AM techniques to optimize the landing gear of a Boeing 747 aircraft [26]. This research highlights the integration of advanced AI-driven tools and manufacturing processes to enhance aerospace component design.

The primary focus of the study was to explore the potential of GD in optimizing the structural efficiency and material usage of landing gear components. Utilizing software such as SolidWorks and Fusion 360, the research team applied evolutionary algorithms combined with AM techniques. These tools enabled the exploration of new material approaches and the creation of optimized design configurations that were previously unattainable with conventional methods.

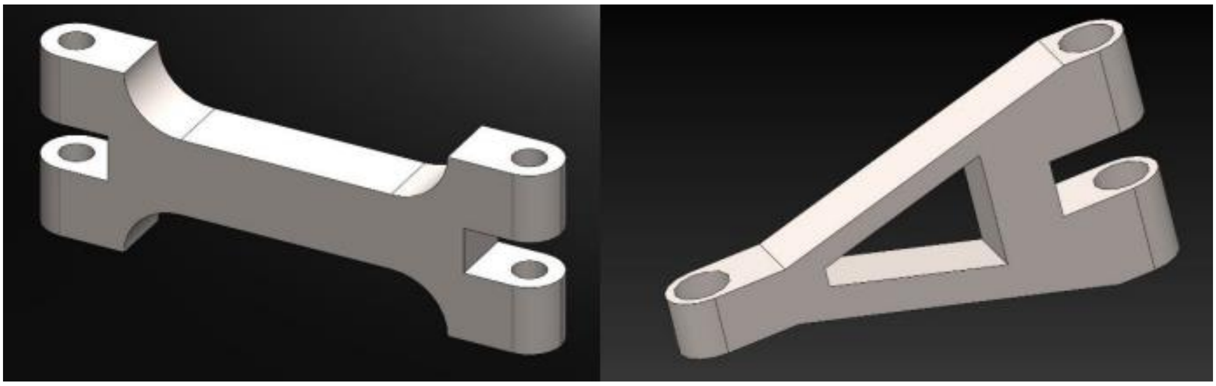


Figure 5. Oleo strut link and Torsion link.

AI played a crucial role in this research through the use of GD algorithms. These algorithms automate the design process by generating optimal structures based on predefined objectives and constraints, such as weight reduction, material properties, and load-bearing capabilities. This AI-driven approach allowed for the rapid iteration of designs, where each iteration improved upon the previous by optimizing the material distribution and structural integrity.

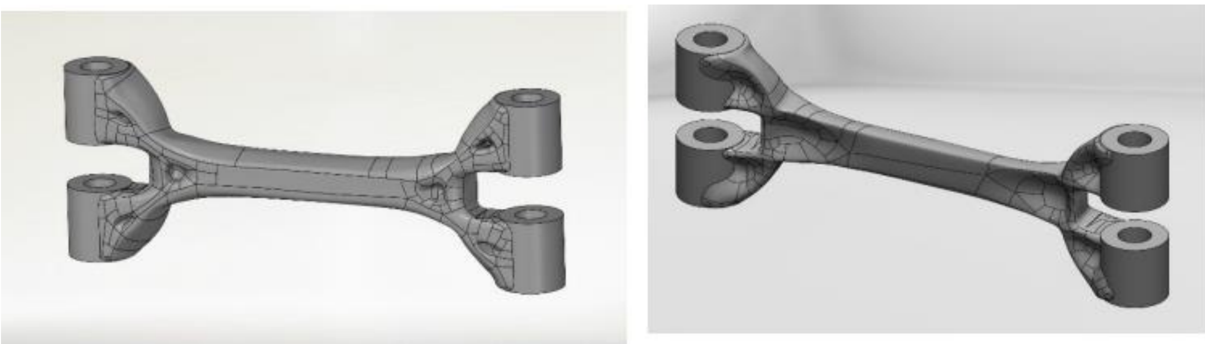


Figure 6. Generative design – Oreo strut link front and back.

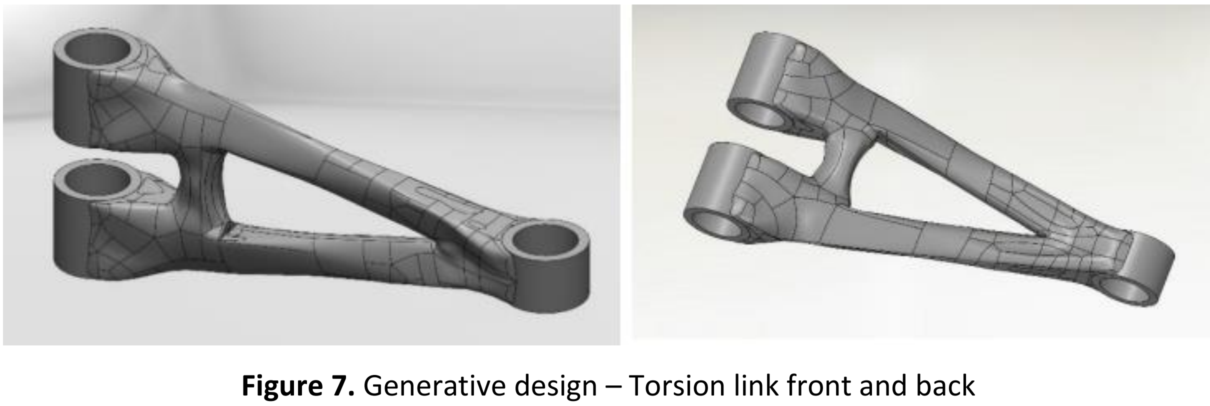


Figure 7. Generative design – Torsion link front and back

The case study led to several benefits for the team. Firstly, they were able to achieve significant weight reductions in the landing gear components by utilizing GD. For instance, the weight of the oleo strut link was reduced by about 50% from 106.27 kg in the traditional design to approximately 50.297 kg in the generative design. Similarly, the torsion links saw a reduction from 60.88 kg to around 35.928 kg, marking a 41% decrease in mass. These weight reductions contribute significantly to the overall efficiency of the aircraft, as lighter components can lead to reduced fuel consumption and lower operational costs. Additionally, the study ensured that these lighter components could still meet all required load-bearing and stress parameters, which is crucial for maintaining safety and performance standards in aerospace applications.

The study demonstrated the use of AM techniques to produce complex geometries that optimize the entire design space of aerospace components. This leads to improved functionality and better structural performance of the landing gear. The optimized components were tested under various simulated load conditions to ensure they meet the demanding requirements of aerospace operations. The results showed improved performance and durability, which is critical for the safety and efficiency of aircraft operations. Additionally, GD significantly shortened the design cycle, allowing for faster development and testing of multiple design variations. This accelerates the innovation cycle in aerospace engineering, providing a more competitive edge in rapidly evolving markets. The study validates the practical applications of GD in aerospace applications and serves as a benchmark for other industries exploring similar technologies for complex, high-performance components.

The case study effectively demonstrates how AI can transform traditional engineering processes, resulting in smarter, faster, and more efficient manufacturing outcomes. The integration of GD and AM represents a significant leap forward in design, offering substantial advantages in terms of cost, performance, and environmental impact. In conclusion, AI has the potential to revolutionize the way engineering is performed and bring about positive changes in the manufacturing industry.

3 Conclusions

The integration of AI in AM represents a transformative shift in how design processes are conceptualized and executed within the industry. This thesis outlines the core aspects of AI in enhancing AM design processes, highlighting its pivotal role in GD, TO, support structure design, and the management of shape deviations. Through GD and TO, AI-driven approaches have shown remarkable efficiency in navigating the complexity of design parameters, thus enabling the creation of optimized, functional, and innovative designs that exceed traditional manufacturing constraints.

3.1 Advantages of AI-driven design in AM

Incorporating AI, particularly ML and DL, into AM design processes significantly enhances design efficiency, creativity, and innovation, making parts more lightweight and efficient, as seen in the case study. AI algorithms excel at predicting material behaviour, optimizing design parameters, and generating new structures using GD methodologies. These capabilities allow AI to quickly produce multiple optimized models, giving designers a variety of viable options tailored to specific requirements. Also, the use of DL technologies like CNN in TO has drastically reduced design cycle times by efficiently predicting optimal material distribution early in the design process.

The integration of AI in AM not only streamlines the entire design and manufacturing process but also contributes to sustainability. By optimizing material use, minimizing waste, and making products more energy efficient through reduced weight, AI leads to more sustainable manufacturing practices. The precision of AI algorithms reduces excess material use and energy consumption, notably minimizing the need for support structures in complex parts, thereby cutting down on post-processing waste. This approach not only conserves resources but also enhances overall production efficiency, highlighting the benefits of environmental sustainability and operational efficiency.

Overall, the implementation of AI with AM is transforming the field by reducing the time and cost associated with iterative design processes, driving forward sustainable practices, and unlocking new possibilities for creative and innovative solutions in manufacturing.

3.2 Challenges of AI-driven design in AM

While the integration of AI in AM has brought remarkable advancements, several challenges limit its full potential and necessitate careful management. Advanced AI technologies like DL face complex integration issues due to the unique demands of AM, often resulting in a focus on engineering functionality that may neglect aesthetic appeal. This functional bias can lead to products that, while structurally sound, fail to meet consumer expectations for visual aesthetics. Balancing technical and aesthetic considerations is crucial to satisfy both structural integrity and consumer preferences.

A significant limitation of AI-driven AM is the heavy reliance on data. The effectiveness of AI models depends on the availability and quality of data, which impacts the development, scalability, and adaptability of these systems to new materials and processes. Gathering comprehensive and high-quality datasets for training AI is both challenging and costly, potentially holding back innovation.

Moreover, the training of AI models introduces its complexities. AI systems must be trained with diverse datasets to avoid generating designs that are technically distinct but perceptually similar, a current limitation that reduces the variety and appeal of produced designs. Additionally, there is a risk of over-reliance on AI, which could lead to vulnerabilities in the production process if AI systems do not adapt well to evolving manufacturing contexts or if they encounter data that fall outside their training parameters. Expanding the training datasets to include a wider range of design outcomes could reduce some of these issues. This expansion would not only enhance the models' ability to generate varied and visually appealing designs but also increase the resilience and versatility of AI applications in AM.

3.3 Future directions and additional considerations

The future of AI-driven design in AM is set to significantly enhance design capabilities, efficiency, and sustainability. The integration of advanced DL techniques will refine AI's predictive capabilities and optimization processes for AM, allowing for quicker, more accurate model generation and adaptation to new materials. As for now, this hasn't reached its full potential and further research on this is suggested.

Addressing challenges like data dependency and the potential over-reliance on AI will be crucial. Ensuring robust, diverse training datasets will be essential to prevent biases and improve AI model generalizability. There will also be a need to balance AI-driven automation with human expertise and intuition, especially in complex design decisions where for example aesthetics are to be considered.

Future developments may also include collaborative AI systems where AI algorithms and human designers work together, combining computational power with creative human insight. Predictive analytics and real-time monitoring integrated through advanced sensors and IoT will likely become standard, enabling real-time adjustments during the manufacturing process to improve product accuracy and consistency.

Overall, as AI technologies mature, their integration into AM is expected to revolutionize the design and manufacturing landscape, offering unprecedented precision, efficiency, and customization capabilities.

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