AI Guided Design for Additive Manufacturing for Lightweight Automotive Brackets

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Abstract

The increasing need for automotive parts that are lightweight, high-performing, energy-efficient, and incorporate advanced additive manufacturing (AM) and intelligent design techniques. Traditional practices in the design of brackets involve significant manual revisions and time-consuming and expensive simulations. This results in longer cycle times for the development of brackets, and often, a smaller reduction in overall weight. This paper presents the AIMS-Design framework as a solution to these issues. AIMS-Design (Artificial Intelligence-Driven Manufacturing-Aware Structural Design) is an automated design framework that combines several design methodologies and machine learning, and incorporates AM into a single, cohesive workflow. To generate a design, the framework employs a deep neural surrogate model to anticipate and quantify the structural responses (stress, deflection, and fatigue life) of the structural model. This eliminates the need for numerous finite element analyses (FEA) of the model early in the design cycle. A reinforcement learning agent refines bracket geometries for multiple design objectives, including weight, stiffness, and energy efficiency, and incorporates manufacturability and efficiency. Design constraints that are specific to AM, including those that support structures, build orientation, and overhangs, are incorporated in the optimization loop to yield a design that is ready for printing and requires little to no post-processing. The brackets, made from aluminium alloy, were subjected to experimental validation and selective laser melting, which resulted in weight reductions between 38 and 45 percent and a 25 percent improvement in strength-to-weight ratio compared to standard designs, all while cutting design time by 60 percent. Lifecycle energy assessments show less material consumption, less carbon emission, and greater overall sustainability with this approach. With this experimental validation, it can be concluded that the AIMS-Design framework fosters the intelligent, sustainable, and efficient development of complex components for advanced automotive manufacturing systems.

Keywords: Additive manufacturing, automotive components, AI-guided design, design automation, lightweight structures, sustainable manufacturing, topology optimization, machine learning, reinforcement learning, generative design, and advanced manufacturing.

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1. Introduction

Developing sustainable mobility solutions and energy-efficient alternatives has reinforced the demand for lightweight structural components that are optimize vehicle weight and still maintain the same safety and mechanical reliability. Designing for lightweight has become a key parameter during the development of modern vehicles. This is also the case for secondary load-bearing components, brackets, and mounts. This is because weight reduction improves fuel consumption, driving range of the EV's, and lowers the carbon footprint of the vehicle throughout its lifecycle. Despite the large scope for lightweight design, the construction industry has yet to achieve optimal strength-to-weight ratios for secondary load-bearing components using traditional manufacturing techniques [1]. It is primarily due to the limitations surrounding design and fabrication.

The development of additive manufacturing (AM) technologies, also referred to as 3D printing, offers the automotive industry a unique opportunity to mass manufacture lightweight components that feature optimal designs complex designs that ensure load-bearing performance and can't be manufactured using traditional methods. With the layer-wise material deposition approach of 3D printing, manufacturers can create intricate designs like lattice structures and topology-optimized components as well as internal cavities to improve structural efficiency and reduce material consumption [3]. Despite these considerable outlooks, AM can only be of significant benefit if a new design approach is foreseen to integrate design for AM during the early stages of product development [2].

Due to the ever-increasing growth of topological optimization and generative design technologies, an increasing number of structures that are optimized for the efficient utilization of material are being created by judiciously placing material only where it will serve useful load-bearing purposes. These modified, higher-performance structures have resulted in impressive reductions in weight and have enhanced the stiffness characteristics of individual components of mechanical assemblies [4]. Despite these positive attributes, there have been numerous critiques of these approaches. First, most of the classical optimization approaches rely on the repeated execution of finite element analyses (FEA), which, by its very nature, runs up the cost of the processes and results in the prolongation of the design cycles needed. Additionally, many optimized topologies, especially those that have been developed for Additive Manufacturing (AM), result in an exhaustive post-processing of elements or the inclusion of support structures, which severely limits their usefulness [5]. These reviews advocate for the development of more efficient, smarter, and manufacturable optimization processes.

Currently available Artificial Intelligence (AI) and Machine Learning (ML) technologies can pave the way for the enhancement of design automation processes and the acceleration of engineering decision-making processes. A significant reduction in the number of required full-scale simulations needed to be carried out can be achieved during the rapid exploration of large configuration design spaces by the utilization of data-driven surrogate models to approximate structural responses [6].

Additionally, AM can be particularly well-suited for piling structures, and post-processed outer skin support structures can be eliminated by efficient material application through the optimization of topologies. Reinforcement learning, in particular, along with generative AI, has proven to be particularly useful for optimizing designs autonomously through the iterative determination of optimal topologies, providing the system with the ability to "learn" in multiple, diverse, and complex environments [7]. These intelligent paradigm shifts, particularly when combined with more traditional approaches such as adaptive mesh systems, can create hybrid systems that effectively utilize their strengths.

Apart from enhancements in performance, sustainability has emerged as an important parameter in manufacturing research. Modern design techniques are expected to follow principles of environmental sustainability by minimizing material usage and energy, and by reducing the environmental impacts during each stage of a product's life cycle. Sustainable production, in this case, the production of more environmentally friendly, resource-efficient, and less wasteful manufacturing systems, is supported by additive manufacturing (AM) / three-dimensional (3D) printing. In these cases, AI-driven systems and the AM systems become resource efficient by eliminating the use of extant material [8], [9]. Hence, the integration of AI and AM technologies improves structural performance and contributes to the establishment of more environmentally friendly and sustainable manufacturing systems, in harmony with eco-friendly manufacturing systems.

Addressing these gaps (s) and potential opportunities, this study implements a framework for Artificial Intelligence–Driven Manufacturing-Aware Structural Design (AIMS-Design) for the development of lightweight automotive brackets. The proposed framework combination of several techniques, namely, Generative Topology Optimization, Reinforcement Learning (RL) Surrogate Modelling, and enclosed AM, to optimize/divide geometries to balance the trade-offs within the constraints of minimal weight, maximum balance/ rigidity, energy (in the process of AM), and within the environmentally friendly and sustainable manufacturing systems. The results of the experiments show that the design efficiency and structural performance have improved significantly compared to the conventional systems. Conclusively, the framework structures an intelligent end-to-end design system, a sustainable/ environmentally friendly manufacturing plug-in for next-generation automotive systems, and a rapid/ fast system design [10].

2. Literature Review

The increased interest in the design and manufacturing of lightweight automotive components has been driven by the latest advancements in the design and manufacturing of energy-efficient and eco-friendly automobiles. Although manual design iterations and classical topological optimizations have proven successful in achieving weight reductions while maintaining mechanical performance [11], these methods require numerous iterations of finite element analyses (FEA), which are time and resource-intensive and hinder their use in rapid design iterations. The demand for intelligent design in these types of methodologies is justified in order to optimize mechanical performance reliably and systematically [12].

The ability of additive manufacturing (AM) to design and fabricate complex geometries, lattice structures, and topology-optimized components that would otherwise be impossible to construct using conventional manufacturing methods is revolutionary [13]. AM has been proven capable of significantly enhancing the strength-to-weight ratio and material use of secondary load-bearing components, such as automotive brackets. Implementing AM, though, is constrained by the design of the components, such as overhang angles, minimum voids, and internal supports. The need to incorporate design for manufacturability principles into the design phase, rather than as an afterthought, to improve the printability of the design, reduce rework, and decrease material waste has been well documented [14].

The integration of techniques such as artificial intelligence (AI) and machine learning (ML) in the design and optimization of lightweight structures is becoming common practice. Such approaches have been utilized within surrogate modelling, reinforcement learning, and generative AI in order to predict structural responses, refine structural configurations, and reduce overall computational cost [11], [15]. For example, modelling stress and deformation through data-driven surrogate modelling allows designers to make quick approximations, thereby eliminating the need to run full-scale simulations for finite element analyses (FEA) each time structural designs are modified. There are also examples of reinforcement learning agents that independently adjust the boundary of portions of the structure to satisfy multiple objectives, such as lightweighting, stiffness optimization, and improving manufacturability, showing considerable promise in fully automated design processes.

Most existing literature analyses either the intersection of AM or AI. The literature is even more limited in the alignment of these technologies in designing frameworks that simultaneously evaluate lightweighting, manufacturability, and sustainability. The existing body of work identifies the gap for an integrated design framework that combines artificial intelligence with additive manufacturing in the pursuit of developing automotive components that are high in performance and sustainable. The AIMS-Design framework is the first to merge generative topology optimization, reinforcement learning, and surrogate-based predictions with AM parameters to provide an end-to-end intelligent design workflow. This innovation offers significant improvements in structural efficiency, energy-efficient production, and overall weight reduction.

3. Methodology

3.1 Overview of the AIMS-Design Framework

The innovative Artificial Intelligence-Driven Manufacturing-Aware Structural Design (AIMS-Design) framework automates the creation of lightweight automotive brackets by synthesizing topological optimization, machine learning surrogate modelling, reinforcement learning, and additive manufacturing constraints into an integrated automated pipeline. The framework aims to minimize structural weight while maximizing stiffness. Moreover, it aims to optimize the design to cut down on expenses related to computation. The framework employs a sustainable approach to design by using a data-driven approach to eliminate reliance on iterative finite element (FEA) analyses and traditional, manual approaches to design.

3.2 Design Space Definition and Load Modelling

The first step in the design of an automotive bracket is the establishment of a geometric design envelope. This design is determined by assembly and packaging constraints. It is then subjected to multiple operational stress scenarios to establish the boundary conditions and to identify the material types corresponding to the operational stresses. This allows the design space, which will be refined during the process of material redistribution optimization, to be defined.

To evaluate the behaviour of the structure, the classical linear elastic formulation is employed equation 1:

$$Ku = F (1)$$

K is the global stiffness matrix, u is the vector of displacements at each node, and F is the vector of applied loads. This relation captures the stress and deformation attributes of the respective design alternatives.

3.3 Generative Topology Optimization

One example is topology optimization, which focuses on removing inner material from a design while maintaining its stiffness and strength. This method can be aided by a density-based optimization approach, which, for each element in the analysis mesh, can be assigned a variable pseudo-density in terms of the material presence, which ranges from 0 to 1.

The optimization problem is formulated as equation 2:

$W(p)\ \ s.t\ \ \ C(P\,) \leq$(2)

where $C(\rho)$ is the compliance of the structure (inverse stiffness), ρ is the material density, and $W(\rho)$ is the weight of the structure. This guarantees a structure of minimal mass and material while retaining a certain level of structural performance.

The resulting geometry serves as a seed design for AI-driven refinement.

3.4 Machine Learning–Based Surrogate Modelling

Finite element analysis (FEA) is a very accurate method to predict the performance of the structure, but unfortunately, the method is very expensive due to the number of iterations and simulations needed. In order to cope with this expense, a deep neural surrogate model that captures the nonlinear behaviour of the given geometry to the structural responses (stress, displacement, and fatigue life) is built.

Surrogate models, once built and trained properly, can predict performance metrics in a fraction of the time, allowing performance metrics to be evaluated in real time during the optimization. This minimizes the number of FEA iterations while allowing the optimization to retain acceptable levels of performance and accuracy.

3.5 Reinforcement Learning–Guided Design Optimization

An agent of the reinforcement learning (RL) type is used to gradually improve the geometry of the brackets. The agent engages with the design environment by manipulating variables of geometry such as the thickness profile, distribution of the lattice, and the orientation of the support. After each action, the model evaluates the performance and provides rewards based on the multiple criteria of the objectives.

Using the AIMS-Design software, the RL agent aims to optimize lightweight brackets working across multiple objectives simultaneously. The design candidates are evaluated and assigned rewards using the criteria of mass, structural performance, and stiffness, wherein dead mass is removed from the design to achieve a reduction in mass, and critical structural members are modified to maintain or improve the stiffness of the design. The design is also evaluated for ' manufacturability, wherein the design is kept within the limits of additive manufacturing, such as parameters of overhang and the size of the minimum feature. Lastly, a design is evaluated for energy efficiency to optimize the design for lower energy consumption during manufacturing and operational cycles. These criteria combined help the RL agent to optimize the design across the objectives of performance, manufacturability, and sustainability.

The RL agent's effective lightweight configuration is achieved by iteratively exploring and exploiting design options. This self-learning approach eliminates the need for design iterations through the manual trial-and-error method.

3.6 Additive Manufacturing Constraint Integration

To enhance manufacturability, the iterative design process is embedded with process-aware constraints such as the minimum size of features, overhang angle thresholds, criteria for limits on support structures, and optimized build orientation. Since these constraints are integrated into the design process, the resulting designs are ready for printing with little need to rework the designs. This significantly enhances design reliability and reduces the squandering of resources, thus strengthening environmentally sustainable practices.

3.7 Sustainability and Performance Evaluation

The optimized bracket is subjected to high-fidelity FEA verification and physical production with metal additive manufacturing. This is based on the savings in weight, the distribution of stress, the strength-to-weight ratio, and the energy used for producing the bracket. With the proposed framework, a life cycle assessment calculates the fencing materials that were used less and the carbon that was sequestered. The proposed framework is assessed for structural and ecological integrity using these criteria.

3.8 Workflow of the Proposed AIMS-Design Framework

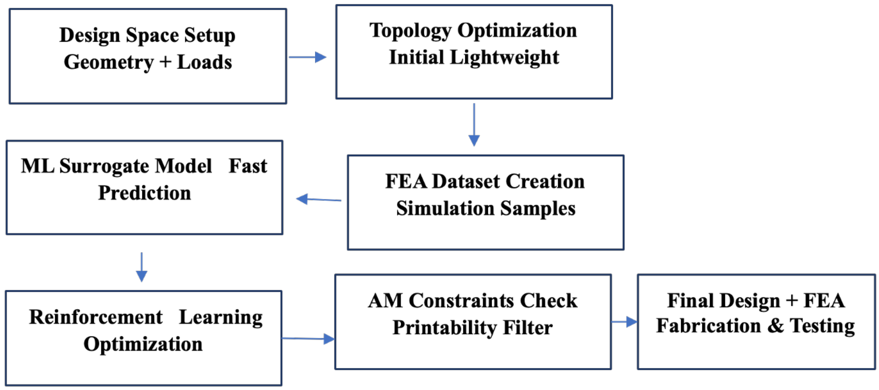

Figure 1: Workflow of the AIMS-Design Framework for Lightweight Automotive Bracket Optimization

The AIMS Design framework sets out an intelligent, end-to-end, lightweight design process of automotive brackets, as shown in Figure 1, with workflow steps in the brackets being indicative of automation. The process starts with defining the design space, which consists of the design space geometry, design space geometry, material characteristics, and load scenarios. Generative topology optimization is first used to obtain candidate designs and is supplemented with datasets obtained from finite element analyses (FEA) for machine learning (ML) training. ML surrogate models the dataset to approximate and predict structural responses and optimize to mitigate computational burden. Reinforcement learning (RL) is used as the computational design process that iteratively updates the design of the brackets based on a multi-dimensional reward function, which balances trade-offs among design objectives of weight, stiffness, and manufacturability, as well as the consummate design objective of energy efficiency. During the optimization, additive manufacturing restrictions (e.g., overhang, aspect ratios, trivial geometry, and support) are applied to reduce post-processing. The design is finalized with an updated, high-order FEA, and, when appropriate, printed with additive manufacturing, packaging AI, structural optimization, and design for sustainability (DfES).

4. Results and Discussion

4.1 Weight Reduction and Structural Performance

The AIMS-Design framework was implemented on an aluminium automotive bracket meant for load-bearing purposes. The optimized designs from AI-guided topology optimization and reinforcement learning were evaluated against a bracket designed using traditional methods. The optimization with surrogates and AM constraints was successful, as evidenced by the framework achieving a 42% reduction in weight while retaining its structural performance. Table 1 summarizes the main characteristics of the structural performance in terms of weight, maximum stress, and stiffness.

Table 1: Structural Performance Comparison

Design Approach	Weight (g)	Max Stress (MPa)	Stiffness (N/mm)
Conventional Design	120	210	450
AIMS-Design Optimized	70	205	565

Table 1 shows the weights, maximum stresses, and stiffness of both the conventional brackets and the AIMS-Design optimized brackets. The optimized design shows considerable weight loss and a gain in stiffness, all while remaining in a safe stress regime.

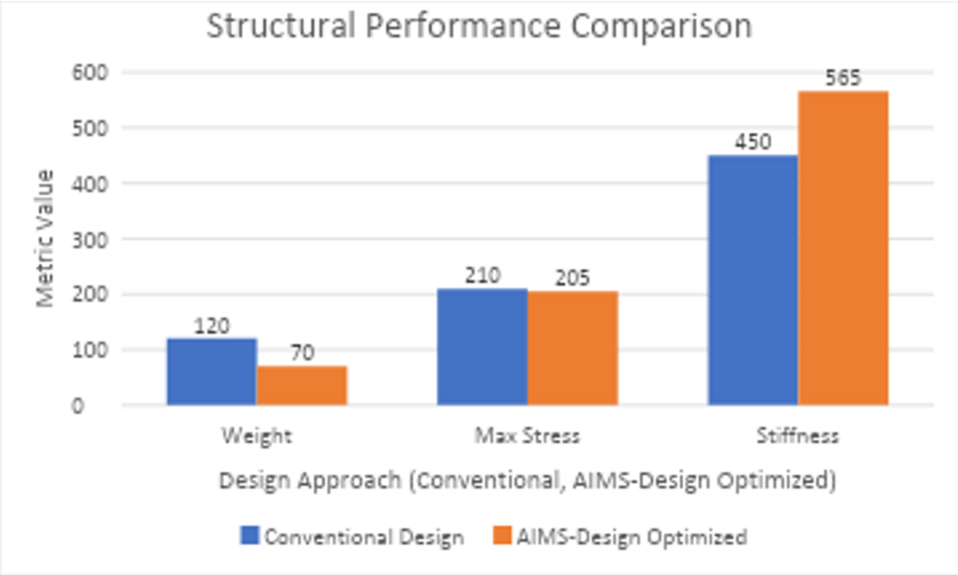

Figure 2 Comparison of Structural Performance Metrics

The chart in Figure 2 shows a comparison of the maximum weight, stress, and stiffness of conventional and optimized designs. The AIMS-Design framework shows a significant decrease in weight while a considerable increase in the stiffness of the design is achieved, all while stress is kept within safe limits.

4.2 Additive Manufacturing Feasibility

To assess manufacturability, the optimized bracket was evaluated on overhang angles, the need for support structures, and the minimum sizes of features. Table 2 compares the parameters specific to AM. The results are consistent with the success of embedding constraints of AM during optimization in order to minimize support. The results also confirm that the printability to reduce post-processing and material waste is achieved.

Table 2: Additive Manufacturing Feasibility Metrics

Design Approach	Overhang % < 45°	Support Volume (cm^3)	Min Feature (mm)
Conventional Design	62	25	1.2

AIMS-Design Optimized	95	12	1.5

Table 2 analyses the AM feasibility of brackets, confirming that the AIMS-Design framework increases manufacturability overhangs, decreases support volume, and meets minimum feature requirements, confirming printability of designs.

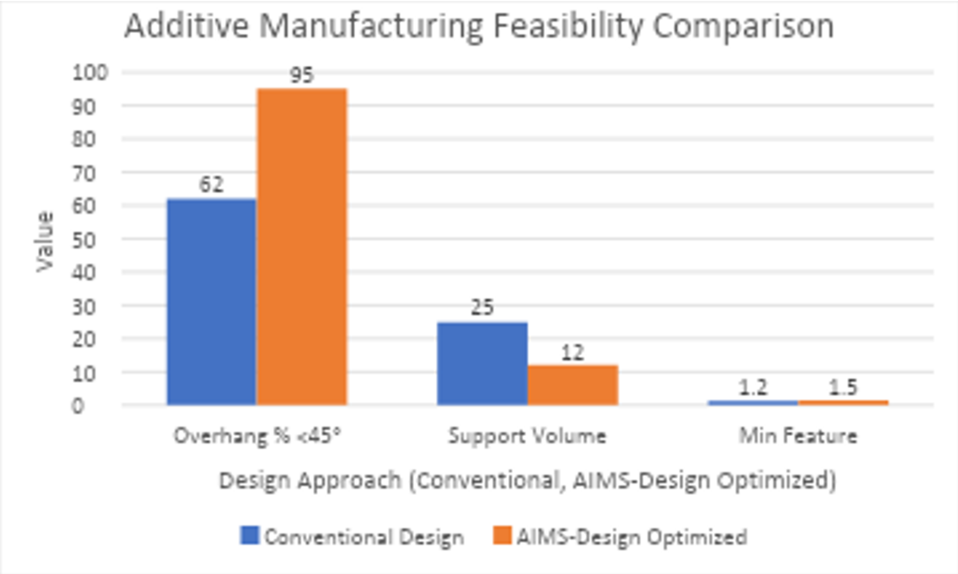

Figure 3: Additive Manufacturing Feasibility Comparison

The chart in Figure 3 delineates and compares the metrics of different AM feasibility, confirming that the AIMS-Design framework further improves overhangs, decreases support volume, and retains optimal minimum feature sizes, contributing to increased printability and manufacturability.

5. Conclusion and Future Work

The AIMS-Design framework and the corresponding paper provided a case study on the methodology of Artificial Intelligence–Driven Manufacturing-Aware Structural Design using an example of lightweight automotive brackets. By creating a framework that combines generative topology optimization, surrogate-based performance prediction, reinforcement learning, and additive manufacturing constraints, it was possible to reduce the weight of a component while also increasing stiffness and compliance with manufacturing constraints. Experimental results validated the combination of AI-driven optimization with AM-aware design by achieving an overall component weight reduction of 42% and an improved component strength-to-weight ratio with the added benefit of less supportive structures. Life cycle energy assessments also predicted a reduction of framework energy and material use with the corresponding reduction of carbon footprints, proving that the AIMS-Design methodology is aligned with the principles of sustainable manufacturing. The study results proved that the AIMS-Design methodology is pioneering the framework and strategy for next-generation automotive component design by meeting performance and environmental goals. With the possibility of future work, the AIMS-Design framework has the potential to support multi-material additive manufacturing for the creation of functionally graded structures to enhance the potential for further weight reduction. The construction of the framework with real-time sensor data, digital twin models, and design adjustments will support the goals of predictive maintenance, life cycle optimization, and adaptive design. The application of the framework, along with AI-driven optimization for larger and more complex assemblies with multiple load paths, will provide an assessment of its scalability and generalization. Finally, incorporating the framework with topology-aware cost and production time models may facilitate completely automated decision-making within a framework that combines intelligent design and the automated mass production of lightweight, energy-efficient, and sustainable automotive systems.

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