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Subject review

A Comprehensive Review on Generative and Parametric Approaches in Cloud - Based CAD/CAM Platforms for 3D Printing Applications

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Abstract: The integration of parametric and generative design approaches into cloud-based computer-aided design (CAD) and computer-aided manufacturing (CAM) platforms is transforming contemporary product development, especially in 3D printing applications. Parametric design prioritizes constraint-driven, feature-based modelling that embodies designer intent, facilitating editable, reusable, and changeable CAD models. Advanced datasets like WHUCAD, which include attributes such as fillets, chamfers, grooves, and shells, enhance deep learning and replication of human-computer interaction for 3D form development. Prominent parametric cloud systems, like Onshape, Autodesk Fusion 360, Siemens NX, and PTC Creo+, utilize server-side kernels and APIs to provide real-time collaboration and feature mapping. In contrast, generative design utilizes artificial intelligence and algorithmic methods - such as topology optimization, implicit modelling, and large language model (LLM)-assisted script generation - to independently investigate extensive design spaces and enhance products for performance, weight, and manufacturability. Innovative pipelines like ZOO text-to-CAD and GPT-enhanced FreeCAD scripting exemplify this approach. Parametric processes thrive in customization and precise assembly control, whereas generative approaches facilitate structural optimization and innovation from exploration, especially when combined with additive manufacturing. Future hybrid design methodologies seek to integrate parametric accuracy with generative creativity; however, obstacles persist in geometric fidelity, computing requirements and manufacturability verification. This study provides a thorough examination of parametric and generative design processes for 3D printing applications, evaluating their techniques, industrial uses, benefits, problems and future potential.

Keywords: 3D printing; CAD/CAM; cloud-based platforms; generative; parametric

1 INTRODUCTION

CAD and CAM are the backbone of modern engineering and production, helping improve productivity, accuracy, and creativity in design and manufacturing. With the shift from traditional desktop software to cloud-based platforms, CAD and CAM have become more collaborative, scalable, and compatible with advanced tools like Artificial Intelligence (AI) and Machine Learning (ML). These new technologies have changed the way CAD/CAM systems work, especially through the use of parametric and generative design methods in additive manufacturing, such as 3D printing. Parametric design is featuring oriented CAD modelling methodology in which geometry is delineated by a series of parameters and constraints, encapsulating the designers intend via an adjustable modelling history. This enables designers to produce models that are both accurate and configurable while also being rapidly adjustable through parameter modification. Contemporary parametric CAD system integrates sophisticated engineering functionalities such as fillets, chamfers, grooves, shells, and revolve operations under pinned by human computer interaction (HCI) meta-Deta that documents section methods and editing sequences. This comprehensive parametric history maintains design semantics, facilitating straight forward modifications, reuse and compatibility among CAD systems [1]. Parametric Modelling offers a solid base for integrating product development and production processes. Conversely, generative design signifies a transformative change in design process.

Generative design uses smart algorithms and AI-based methods such as topology optimization, voxel or implicit modelling, and Large Language Model (LLM)-assisted script generation. These techniques enable the system to explore a wide range of design possibilities independently, rather than relying solely on manually created models. The algorithms automatically generate and refine shapes to achieve key goals such as reducing weight, maintaining strength, optimizing material use, and improving manufacturability.

Generative design enables the identification of organic, light weight and novel geometries that conventional approaches cannot efficiently create especially when combined with additive manufacturing. By integrating computational optimisation with design objectives, generative methodologies expedite product creation while improving material efficiencies and sustainability [2-4].

3D printing, often known as additive manufacturing, is a crucial facilitator for parametric and generative design methodologies. Its versatility in producing elaborate geometries - such as lattice structures and topology-optimised components renders it particularly effective for actualising the sophisticated results of generative algorithm. Parametric models facilitate the regulations and enhancements of printed components, guaranteeing accuracy in fit, configurability, and consistency. Simultaneously, the capacity of generative design to optimise for printing limitations, process parameters and support structures is directly congruent with the capabilities of additive manufacturing [5]. The intimate integration of cloud-based CAD/CAM system with 3D printing workflows facilitated a seamless transition from digital design to physical production, allowing for rapid prototyping, customisation and dispersed manufacturing.

Numerous prominent Cloud based CAD/CAM software platforms have been adopted to generative design paradigm, incorporating advance algorithms that facilitate collaborative real time- online processes. Autodesk FUSION 360 exemplifies leading software, proving generative design tools that integrate topology optimisation with manufacturability constraints, specifically designed for the use of additive manufacturing. Siemens NX offers convergent modelling technology enabling designers to directly manipulate mesh-based topologies derived from generative design outputs hence streamlining editing and validation within a cohesive parametric and prismatic geometry framework.

Onshape, a leader in entirely cloud-based CAD, facilitates collaborative parametric modelling via web browsers, whereas Dassault Systèmes' 3DEXPERIENCE platform amalgamates generative design with social collaboration, simulation, and manufacturing process planning. Emerging open-source programs have started to utilise LLM-assisted scripting to facilitate generative design workflows for a wider audience. This cloud-based platform utilises server-side kernels, web APIs and macro parametric exchange standards (such as STEP AP-242) to facilitate persistent naming, feature mapping and efficient data interchange among distant team and software ecosystems. Their integration of AI and ML techniques including massive language modelling for script creation, error correction, enhances both parametric and generative design capabilities, diminishing the necessary human labour while broadening design originality. This paper provides a detailed review of parametric and generative design approaches within cloud-based CAD/CAM platforms, emphasizing their integration with 3D printing. It discusses the core principles, methodologies, and tools that enable these approaches, while also addressing their advantages, challenges, and industrial adoption. Special attention is given to leading platforms such as FUSION 360, Siemens NX, Onshape, and 3DEXPERIENCE, which are actively incorporating AI- and ML -driven enhancements [6]. Finally, the paper highlights emerging trends and future directions, underscoring how these technologies are driving innovation, efficiency, and sustainability in modern engineering and manufacturing.

This study offers an extensive assessment of parametric and generative design methodologies inside cloud-based CAD/CAM systems, focusing on applications in 3D printing. It contrasts their ideas, processes, benefits and limits while emphasising applications in aircraft, medicinal fields, consumer items and architecture. Prominent platforms like Autodesk FUSION360, Onshape, Siemens NX and Dassault 3DEXPERIENCE are analysed to demonstrate the integration of these methodologies into contemporary design ecosystems. The study provides unique insights into contemporary difficulties and prospects by synthesizing research and industry case studies, making it a comprehensive overview for both scholars and practitioners.

2 PARAMETRIC DESIGN

Parametric design is an approach in which the structure and form of a model are dictated by a defined set of parameters, rules and restrictions rather than by manual manipulation. Parametric design fundamentally employs algorithmic approaches to define relationships among design elements. These interactions are articulated through parameters that can be adjusted to dynamically and automatically refresh the overall design. This method prioritises the acquisition of design intent, namely the fundamental logic and interdependency inherent in the design via constraint system and history-based modelling. History based modelling documents each stage or characteristic of the design as a sequential procedure (including sketches extrusions, revolutions, fillets and chamfers) culminating in the final form. As parameters fluctuate, the model reconstructs its geometry by reassessing this history tree, enabling designers to swiftly investigate changes without starting over [7].

The notation of associative logic on parametric design guarantees propagation of adjustments, for instance, if a hole's location is specified in relation with centre of a block altering the block's length results in an automatic adjustment of the hole's position while preserving its relative placement. This paradigm not only optimises design interaction but also facilitates the creation of groups of linked components derived from a single parametric template. Widely used tools for Parametric design encompass SolidWorks, Autodesk FUSION 360, Siemens NX, CATIA and Onshape. These software applications offer comprehensive environments for creation, management and modification of parameters and constraints via human interfaces such as a feature trees or parameter tables. SolidWorks utilises a feature manager tree to document dimensional and relational data; FUSION 360 combines parametric and direct modelling with adaptable history tracking; Siemens NX provides extensive parametric functionalities in conjunction with advanced modelling tools; CATIA specialises in industrial grade parametric modelling featuring design tables and formula based relationships. Onshape a cloud centric CAD tool enables web parametric modelling with shared histories that promote collaborative engineering, parametric design tools, prioritise accuracy, consistency and regulated customisation, rendering them essential for mechanical assemblies, architectural modelling and production preparations. For graphical representation refer to Fig. 1 [2, 8].

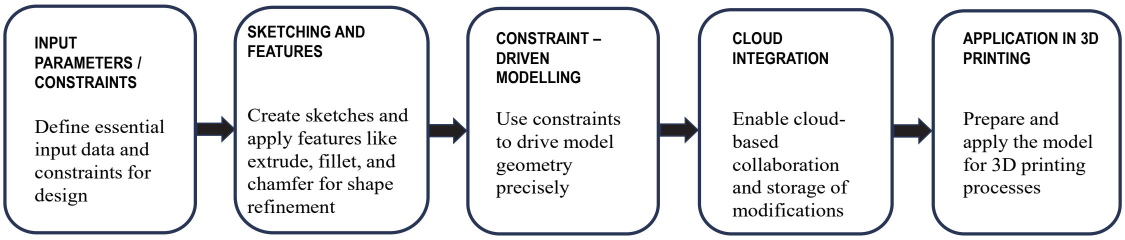

Figure 1 Flowchart for parametric design approach

3 GENERATIVE DESIGN

Generative design is a sophisticated design exploration method that fundamentally contrasts with parametric design by assigning the creation of design alternatives to computer algorithms. Instead of a designer manually modifying geometry, generative design receives high level design objectives, restrictions (including material usage, load conditions, and manufacturing techniques) and performance requirements, subsequently generating a multitude of optimised design alternatives through iterative processes [9]. It is fundamentally a computer-generated process in which the software independently investigates the design space to discover innovative, high-performance solutions some of which maybe counterintuitive or excessively intricate for conventional design methodologies [10].

Generative design generally uses methods including topological optimisation, genetic algorithms, swarm intelligence and artificial intelligence methodologies. Topology optimisation mathematically reallocates material within a specified design space to enhance structural efficiency or reduce weight while maintaining functional integrity. Genetic algorithms replicate evolutionary mechanism to develop candidate design via mutation and selection. Artificial neural networks and other AI models can enhance and expedite design generation by assimilating insights from previous examples or user's Feedback [3, 11].

In contrast to designer driven and historically influenced approach of parametric design, generative design workflows commence with the establishments of objective rather than the direct generation on geometry. Designers delineate problem parameters, goals, limitations and permissible manufacturing methods [12]. The generative engine there after produces, evaluates and enhances design in an iterative cycle until an optimal or suitable solution is achieved. Subsequently designers pick, validate and may adjust the outcomes. This approach facilitates the investigation of solutions that transcend human intuition, particularly advantageous for light weight structures, intricate organic geometries and components prepared for additive manufacturing [13].

Prominent software platforms that incorporate generative design functionalities within parametric frameworks comprise Autodesk FUSION 360, Siemens NX featuring convergent modelling and topology optimisation, Dassault Systèmes 3D experience and nascent AI enhanced workflows utilising large language models (LLM) for automated CAD scripting. These platforms frequently integrate parametric accuracy with generative innovation, facilitating hybrid methodologies that utilise advantages of both paradigms [14]. The flowchart of the generative design approach is depicted in Fig. 2 below.

Figure 2 Flowchart for generative design approach

4 COMPARISON OF GENERATIVE AND PARAMETRIC DESIGN

The comparison between parametric and generative design highlights the fundamental differences as well as the complementary nature of both methodologies. Parametric design follows a constraint-based approach, ensuring precision, reusability, and control, which makes it suitable for mechanical assemblies and regulated industries. In contrast, generative design relies on artificial intelligence and algorithmic exploration to generate optimized, lightweight, and innovative solutions, often addressing complex shapes that traditional methods cannot easily achieve. The table provides a structured overview of these distinctions in terms of methodology, flexibility, computational requirements, and practical applications, offering a clear understanding of how each approach contributes uniquely to modern CAD/CAM systems [15, 16].

Table 1 Comparison of generative and parametric design [20]

Criteria	Generative Design	Parametric Design
Definition	Uses algorithms (often driven by AI) to explore many design alternatives automatically, optimising toward specified performance goals.	Relies on user-defined parameters and relationships to drive model geometry; designer explicitly builds the feature tree.
Exploration of Design Space	Very broad: generates hundreds of unique concepts within prescribed "design space".	Limited by the modeler's foresight and manual setup of parameters; explores variations on existing geometries.
User Control	High-level: user defines objectives (goals, constraints); algorithm handles geometry generation.	Low-level: user directly controls dimensions, relations, and feature order; fine-grained control.
Learning Curve	Moderate: must learn new workflow and interpret algorithmic outputs, but no deep CAD skills needed.	Steep: requires mastery of CAD tool's feature set, sketch constraints, and relational logic.
Speed of Concept Generation	Very fast: evaluates hundreds of options in minutes via cloud or local compute.	Slower: each variant must be manually created or updated in the feature tree.
Optimization Targets	Multi-objective: mass, stiffness, cost, printability, etc.	Single or multi-objective only if manually integrated with simulation tools.
Iteration Workflow	Automatic: algorithmic refinement loops until goals are met.	Manual: designer edits parameters or features and reruns analysis.
Geometry Output	Faceted (mesh) or hybrid (via convergent modelling), often requiring clean-up for CAD.	Precise B-Rep/NURBS geometry, immediately editable in CAD.
Typical Use Cases	Topology optimization, light weighting, complex lattices, 3D-printed parts, early concept exploration.	Detailed mechanical parts, assemblies, engineering drawings, documentation, manufacturing-ready models.
Integration with Simulation	Built-in AI-driven FEA/CFD feedback loops	Uses external simulation modules or plugins; requires manual linking of parameters.

5 EVOLUTION OF CLOUD-BASED SOFTWARE

Over the past four decades, CAD/CAM has transitioned from independent desktop applications, requiring each designer to possess a high-performance workstation, local file storage, and manual version control to cloud based platforms offered through software- as- a-service (SaaS). During the 1980s and 1990s, companies made substantial investments in on-premise CAD/CAM, utilising costly servers and acquiring desktop licenses; design teams were geographically isolated, and the exchange of large model files frequently required shipping tapes or FTP uploads, resulting in version discrepancies and increased IT burden. The mid-2010s saw the emergence of "CAD in the Cloud", a system that centrally stores all design data on remote servers. Mid-2010s enhanced internet and dependable data centres facilitated "CAD in the Cloud", wherein all the design data is centrally stored on remote servers. Pioneers such as Onshape (2015) and Autodesk FUSION 360 (2016) introduced real time, browser-based modelling that seamlessly synchronises edits and maintains version histories, thereby obviating the need for expensive local infrastructures and intricate setups. Three fundamentals enablers rendered cloud CAD/CAM feasible: ubiquitous high-speed internet facilitating seamless streaming of 3D models; established SaaS billing that transitioned the cost from capital expenditures to predictable subscriptions; and integrated collaborative tools (chat, comments, simultaneous editing) allowing multiple users to congruently design the same model. The advantages are revolutionary [14].

Scalability enables teams to provision more computing resources for graphics, simulations or generative design as needed, without the necessity of acquiring new hardware. Remote access enables engineers to login from any device - PCs, tablets, Smart phones and collaborate on the newest design in real time, facilitating scattered or hybrid work forces [17].

Genuine real time collaboration - contrary to desktop file sharing, every keystroke or sketch modification is instantly observable by all participants, hence everting redundant rework and version discrepancies. Unrestricted computational capacity - Cloud servers manage intensive studies (FEA, CFD, ray-trace rendering) that would incapacitate the majority of local workstations, facilitating closer integration between design and validation [18-21].

Transitioning CAD/CAM to cloud enables organisation of all sizes to democratise access to sophisticated design tools, significantly decrease IT costs, and expedite innovation cycles - transforming CAD/CAM from a cost-centre investment into a versatile, collaborative, business-enhancing resource [15, 19, 23, 24].

Table 2 Comparison of different software [22]

Tool Name	Core Domains	Platform(S) Supported	Standout Feature	Pricing (EUROs) /Year	Rating (G2/Trustpilot)
AutoCAD	Designers, Engineers	Web, Desktop	Precision and drafting tools	1337 / year	4,5/5
SolidWorks	Mechanical Engineers	Desktop	3D modelling and simulation	2574-4301 / year	4,6/5
FUSION 360	Startups, SMBs	Web, Desktop	Cloud-based design & manufacturing	506 / year	4,7/5
Rhino 3D	Designers, Architects	Desktop	Flexibility and organic shapes	909 (Perpetual)	4,3/5
CAM Works	Manufacturers	Desktop	CNC toolpath generation	3255 / year	4,5/5
Tinker CAD	Beginners, Hobbyists	Web	Simple 3D printing design	Free	4,4/5
FreeCAD	Engineers, Designers	Desktop	Open-source, customisable	Free	4,2/5
Solid Edge	Engineers, Product Designers	Desktop	Synchronous technology	(Foundation): 1610 / year (Premium): 2570 / year	4,5/5
Onshape	Remote teams, Startups	Web	Real-time collaboration	(Standard): 1370 / year (Professional): 2283 / year	4,6/5
SolidCAM	Manufacturers, Engineers	Desktop	CNC machining integration	Custom pricing	4,4/5

6 APPLICATIONS OF PARAMETRIC AND GENERATIVE DESIGN

6.1 Aerospace Applications

The aerospace sector has been one of the most significant beneficiaries of parametric and generative design integrated with 3D printing. By leveraging cloud-based CAD/CAM platforms, engineers can create lightweight unmanned aerial vehicle (UAV) frames and optimize complex geometries under realistic load conditions. These approaches enable rapid design iterations, material-conscious evaluations and improved performance while reducing weight, cost and development cycles [11].

6.1.1 Lightweight, mission specific, UAV air frames

Generative design approaches allow aerospace engineers to develop mission specific unmanned aerial vehicle (UAV) structures that save the weight while meeting rigorous strength and stiffness criteria in a single workflow a user delineates the fundamentals [7]. The CAD geometry of a quadcopter frame retains critical regions such as motor mounts and payload bays, while restricting obstacle zones around electronic components. A thrust load of 49.3 N per rotor, along with gravitational forces, is applied, with an algorithm aimed at reducing mass in ABS or PLA materials for 3D printing. The cloud-based solver in Autodesk FUSION 360 evaluates numerous possibilities and each assists based on mass, maximum von mises stress and global displacement. Outcome 1 for ABS (6,37 kg, 0,49 MPa, 0,45 mm deflection) and outcome 3 for PLA

(7,73 kg, 0,51 MPa, 0,29 mm deflection) are identified as the premier solutions. Finite element study confirms that Outcome 3 endures a thrust of 50 N with peak stress of only 1,55 MPa and deflection of 0,22 mm. Through the automation of the design exploration and evaluation, OEMs can provide the ideal frame version within hours, facilitating swift customization for endurance, payload or manoeuvrability specifications without need for manual CAD modification [24].

6.1.2 Material-Conscious Investigation of Octocopter Architecture

The dual-layer rotor layout of an octocopter provides payload benefits but complicates the design of the frame. Engineers utilize generative design to build a preliminary CAD model of an octocopter, with maintained hubs, delineated barrier sections for stories bays and applied motor thrust loads of 50N/arm. Two materials - ABS and PLA - yielded 30 potential geometries apiece. The optimal ABS frame (outcome 1) had a mass of 6,37 kg, exhibiting a stress of 0,49 MPa and defection of 0,45 mm: the optimal PLA frame (outcome 3) weighed 7,73 kg, demonstrating a stress of 0,51 MPa and a deflection of 0,29 mm. Finite Element Method (FEM) analysis was conducted in this study to evaluate the stress and displacement responses of the generatively designed octocopter frames under 50 N/arm motor thrust loading. The approach enables aerospace companies to evaluate materials and load scenarios - interchanging carbon-fibre composites or aluminium - within a single automated process, guaranteeing that each produced structure is functional and optimal for materials prior to prototyping [25].

6.2 Biological Applications

In biomedical and pharmaceutical fields, generative approaches combined with AI and deep learning have accelerated innovation in drug discovery and molecular design. Techniques such as conditional GANs and infoGAN allow the exploration of vast chemical spaces, enabling the creation of novel drug candidates with desired properties. These methods significantly reduce time and resources while expanding possibilities for precision medicine and therapeutic innovation [26-29].

6.2.1 Innovative Lead Generation Utilizing Conditional GANs

In the first stage of drug discovery, the identification of new chemical scaffolds exhibiting target activity and advantageous dynamics is essential but tedious. Conditional generative adversarial networks, trained on extensive bio activity datasets - such as ABL1 enzyme inhibitors encompassing wild-type and 5 clinically significant n = mutants - facilitate DiNovo drug creation. The generator creates SMILES-encoded structures based on specified activity ranges (example plC50 between 0,05 and 10 μM), whereas the discriminator eliminates implausible chemo types.

Following creation, compounds are subjected to computational docking and ADMET prediction. In a particular investigation GAN achieved a 65% hit rate against the ABL1-F317l mutant, significantly reducing the candidate synthesis list from 1000 s to 100 s compared to random library screening. By including potency conditioning physiological filters into GAN's latent space, medicinal chemists can navigate unchartered chemical territories and rapidly refined potential lead series.

6.2.2 Expansion of chemical space driven by properties via infoGAN

Standard GAN's frequently amalgamate many molecular characteristics, complicating control design. infoGAN improves interpretability by optimizing mutual information between latent codes and produced molecules. By allocating latent variables to target attributes - such as lipophilicity (XlogP), polar surface area (TPSA), and projected solubility - chemists can precisely tune desirable ranges and generate diverse structures that meet specified criteria. An InfoGAN trained on DrugBank and PubChem data produced novel quinoline scaffolds with XlogP values ranging from 2-4 and TPSA below 90 Å^2, suitable for CNS penetration. Subsequent in vitro testing confirmed 70% of these as moderate enzyme inhibitors. This separated latent method enhances the iterative optimization of multi-parameter drug profiles, expediting the transition from hit to lead [30].

6.3 Product Design Applications

Product design has been transformed by the synergy of parametric and generative methods with 3D printing, allowing for both customisation and creativities. From prosthetic components optimised through topology and FEA for strength, comfort, and rapid production, to jewellery concepts generated using grammar-based parametric rules, these applications highlight efficiency, innovation, and adaptability. Such workflows enable scalable mass customization and faster product development cycles.

6.3.1 Prosthetic Components Optimized via Topology and 3D Printing

The integration of topology optimisation, finite element analysis (FEA) and additive manufacturing (AM) has transformed the design of custom prosthetic components [28]. In a study, researchers delineated preservation regions for socket interfaces and load bearing struts in a transtibial prosthetic foot, established goal loads simulating heel striking (1,2 × body weight) and toe-off cycles, and restricted maximum displacement to under 1 mm. Topology optimisation with Opti Struck eliminated 62% of non-essential materials, resulting in skeletal structure with enhanced load pathways FDM printing with TPU with metal-reinforced areas, resulted in a 50% reduction in bulk compared to conventional polymer sockets, enhanced comfort via regulated compliance and decreased production time from weeks to 48 hours. Clinics in resource-constrained environments can now produce customised prosthetics for patients on demand, significantly reducing expenses and enhancing fit [28].

6.3.2 Exploration of a Grammar-Driven Jewellery Concept

In consumer product and apparel design, swift conceptualisation of organic shapes is crucial. A Rhino/VBScript plugged in utilizing shape grammar encodes affine transformations - bend, split, mirror, scale, and combined - as parametric rules. Designers commence with a foundational ring design and thereafter apply iterative rules (e.g.: "Divide band into 3 segments", "curve outer segment into a wave", and "reflect and replicate segmentations") to produce 200 distinct ring geometries in less than 2 minutes. Each version is capable of being 3D printed in resin for high-fidelity prototyping. This generating approach inspires innovative form factor while incorporating manufacturing limitations, such as minimum feature thickness and closing clearances, to guarantee that the final designs are readily producible. Jewellery houses utilise this strategy to investigate experimental collections while conforming to swift seasonal cycles.

7 EMERGING TRENDS AND FUTURE PROSPECTS

The development of cloud-based CAD/CAM platforms is increasingly influenced by the integration of parametric and generative design approaches bolstered by advancements in artificial intelligence (AI), machine learning and cloud computing. A significant trend is the incorporation of AI-driven design assistance and large language models (LLMs) into CAD systems, facilitating the use of natural language or multimodal instructions to create, modify, or enhance models [31]. Innovative pipelines like ZOO text-to-CAD and GPT-assisted free CAD scripting demonstrate how designers can circumvent significant learning curves by immediately converting design intent into parametric or generative models. A crucial focus is on real-time generative feedback loops, in which surrogate machine learning models expedite optimisation cycles by approximating resource-intensive simulations, thus tackling issues of combinatorial complexity in generative workflow [31]. Moreover, the industries are advancing towards a hybrid design framework that integrates the accuracy and modifiability of parametric methods with the exploratory and optimisation capabilities of generative algorithms. These systems seek to maintain the design intent while facilitating algorithmic exploration, resulting in processes that are both designer-driven and machine-enhanced. The emergence of collaborative cloud ecosystems like Autodesk Fusion 360, Onshape, Siemens NX, Dassault 3DEXPERIENCE significantly improves the scalability and accessibility, allowing distant teams to co-create and test models in real time. A notable trend is growing advocacy for interoperability standards (e.g., STEP, IFC), facilitating the easy sharing of parametric and generative models between Platforms and diminishing data silos [31].

In the future, quantum computing and high-performance cloud clusters have the potential to significantly enhance generative optimisation by addressing large-scale multi-objective issues that are presently insurmountable. Simultaneously, open-source ecosystems like free CAD and Grasshopper are expected to gain traction, promoting community-driven innovation and transparency. Future research will prioritise manufacturability validation, ensuring that generating outputs are both performances optimised and practical within the limits of industrial additive and subtractive manufacturing [32, 33].

The trajectory indicates the emergence of intelligent, hybrid and collaborative CAD/CAM platforms that integrate human creativity with computational efficiency. These advancements are said to transform product design by integrating parametric accuracy, generative creativity and cloud scalability, thereby enhancing the adaptability, accessibility and sustainability in next generation 3D printing processes [34].

8 CASE STUDY

This case study aimed to evaluate the advantages of generative design over conventional parametric design by analyzing a lifting bracket subjected to static loading conditions. Both models were designed in Autodesk Fusion 360, maintaining identical loading and boundary parameters, with the goal of comparing performance in terms of weight reduction, strength, and manufacturability. A linear static structural analysis was performed to assess stress, displacement, and safety factor distribution. A vertical load of 500 N was applied on the upper lifting eye to simulate real operating conditions, while the two mounting holes were constrained with fixed supports to restrict translational and rotational motion. The analysis used tetrahedral elements with adaptive mesh refinement, with an average element size of 1,5 mm. Two materials were considered: ABS plastic, with a density of 1,050 kg/m³, Young's modulus of 2,3 GPa, Poisson's ratio of 0,35, and yield strength of 40 MPa; and Aluminium AlSi10Mg, with a density of 2,670 kg/m³, Young's modulus of 70 GPa, Poisson's ratio of 0,33, and yield strength of 230 MPa. Both materials were considered isotropic for simplicity, despite potential anisotropic behavior in additively manufactured aluminium. The baseline parametric ABS bracket had a volume of 25,315 mm³ and a mass of 0,027 kg. Under the applied load, the maximum Von Mises stress was 27,41 MPa, resulting in a safety factor of 1,46 and a maximum displacement of 0,97 mm, indicating a stable but not weight-efficient design. Generative design optimization was then performed to minimize mass while maintaining a minimum safety factor of 1and a maximum displacement of 1,5 mm, preserving the bolt holes as fixed geometry. The optimized ABS bracket achieved a volume reduction to 16,704 mm³ (33,9%) and a mass of 0,018 kg, with a maximum stress of 28,45 MPa, a safety factor of 1,41, and a maximum displacement of 1,407 mm. The generative aluminium bracket achieved even greater efficiency, with a volume of 5,890 mm³ (76,7% reduction) and a mass of 0,016 kg (40,7% lighter), while exhibiting a maximum stress of 106,1 MPa, a safety factor of 2,17, and a maximum displacement of 0,219 mm, demonstrating superior stiffness and load resistance. The ABS brackets were designed for Fused Deposition Modeling (FDM), whereas the aluminium bracket, with its complex organic geometry and internal lattices, was suitable for Selective Laser Melting (SLM). Notably, a higher stress value does not necessarily indicate a lower safety factor, as the aluminium bracket, despite having a higher stress than ABS, benefits from its much higher yield strength. Overall, the study demonstrated that generative design can significantly reduce mass - up to 76,7% in the aluminium case - while maintaining structural reliability, with the aluminium bracket offering the highest safety factor and least displacement, and the ABS models providing acceptable performance for low-load, cost-sensitive applications. This highlights the critical role of material strength in determining safety factor and underscores the efficiency of generative design in optimizing load paths while minimizing material usage.Overall, these results show that generative design greatly improves the performance-to-weight ratio when compared to traditional parametric design [35, 36].

Table 3 Comparison of approach (baseline generative ABS and generative aluminium)

Parameter	Baseline (Parametric ABS)	Generative ABS (Additive)	Generative Aluminium (Alsi10mg)
Volume / mm^3	25,315	16,704 (↓33,9%)	5,890 (↓76,7%)
Mass / kg	0,027	0,018 (↓33,3%)	0,016 (↓40,7%)
Max von Mises Stress / MPa	23,6 (Within safe range < yield strength of ABS)	27,417	110,687
Min Safety Factor (baseline is 1)	> 1,5	1,407	2,168
Max Displacement / mm	< 1	1,407	0,219

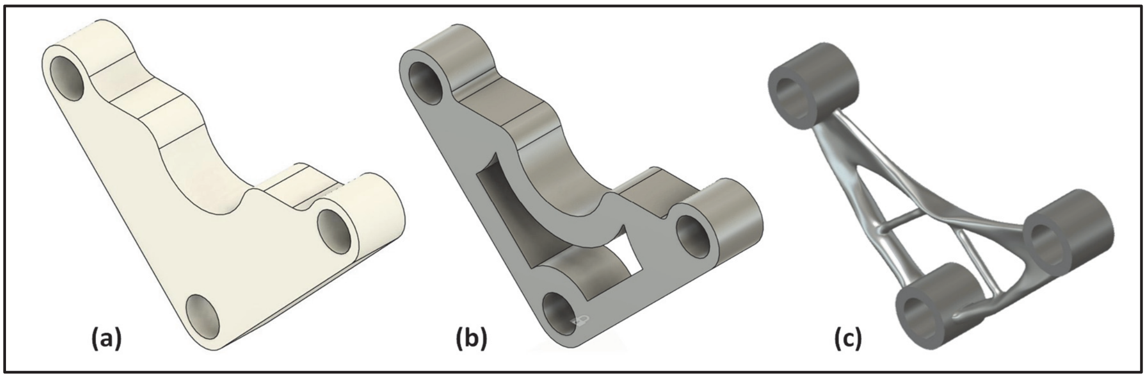

Figure 3 (a) Baseline geometry (b) Optimized design using a shape optimization tool (c) Optimized design employing a generative technique

9 LIMITATIONS AND CHALLENGES OF GENERATIVE DESIGN AND PARAMETRIC DESIGN

While parametric and generative design methodologies offer significant advancements in modern CAD/CAM systems, they are not without limitations. Each approach faces unique challenges related to usability, computational demand, and practical implementation. Highlighting these constraints is essential to understand their current drawbacks and to identify areas where further development is needed for broader industrial adoption.

Parametric design, although providing exact control and modifiability, encounters several problems in both research and industry applications. A significant disadvantage is its reliance on intricate constraint management and history-based modelling, where changes to prior parameters may lead to mistakes or inconsistencies within the design model. Research indicates challenges related to steep learning curves, software dependence and significant processing requirements for managing complex models with sophisticated feature like chamfer, fillet, groove and revolve. In practical processes laborious when modifying models to accommodate non-standard or extremely organic shapes. Conversely, generative design presents distinct obstacles despite its efficacy in optimisation and creative inquiry. Generative approaches often encounter computational complexity and combinatorial explosion owing to the extensive design space, necessitation rigorous simulation and optimisation cycles that are both time and resource consuming.

Moreover, interoperability across simulation environments is restricted and produced designs may not consistently conform to manufacturability restrictions, resulting in geometries that are challenging to create using current additive or subtractive technologies. Moreover, generative outputs sometimes depend on surrogate or AI-driven models that mimic performance but may lack precision relative to conventional physics-based approaches. This prompts apprehensions about validation and industry acceptance. These challenges collectively suggest that although parametric approaches demonstrate superiority in precision and repeatability and generative methods in exploration and structural efficiency both encounter obstacles in scalability, usability and industrial integration - underscoring the necessity for hybrid frameworks in cloud-based CAD/CAM systems for 3D printing applications [37, 38].

10 CONCLUSION

The integration of parametric and generative design methodologies into cloud-based CAD/CAM systems signifies a pivotal advancement in engineering and product development, especially for additive manufacturing. Parametric design guarantees precision, constraint-based correctness and reusability, making it essential for regulated sectors and mechanical assembly. Conversely, generative design employs artificial intelligence, topological optimisation and algorithmic exploration to reveal lightweight, innovative and very efficient geometries that surpass human intuition. Collectively, these techniques underscore as an emerging tendency towards hybrid processes that reconcile designer purpose with computational ingenuity.

Notwithstanding their advantages, each method encounters unique obstacles. Parametric design is limited by significant learning curves, rigidity in managing highly organic shapes and interoperability issues, while generative design requires substantial computer resources and often yields complicated geometries that complicate manufacturability.

These constraints underscore the need for enhanced integration with validation tools, superior interoperability standards and user-friendly interfaces to provide broader access.

The integration of artificial intelligence, large language models, and real-time cloud collaboration is anticipated to transform the CAD/CAM environment. Innovative hybrid techniques will integrate the precision of parametric systems with the investigative capabilities of generative algorithms, bolstered by scalable cloud infrastructures and augmented by forthcoming advancements like quantum computing.

This trend signifies a shift towards intelligent, collaborative and sustainable design ecosystems, facilitating accelerated innovative cycles reduced costs and enhanced accessibility.

The integration of parametric and generative design in cloud settings is set to be fundamental to the future of 3D printing and digital manufacturing.

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