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A COMPREHENSIVE REVIEW OF GENERATIVE DESIGN APPLICATIONS IN UNMANNED AERIAL VEHICLES

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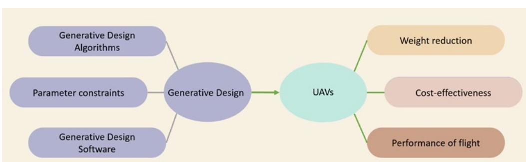
Graphical abstract



Abstract

The continuous progress in Unmanned Aerial Vehicles (UAVs) has spurred the exploration of novel design approaches to boost their effectiveness. Many drone configuration design methods have been used to enhance strength and reduce weight, such as topology optimization, high-modulus composite material, additive manufacturing, etc. One rapidly emerging technology with the potential to transform UAV design is generative design. This cutting-edge technology employs artificial intelligence to generate numerous design possibilities, assisting engineers in identifying optimal designs that align with precise requirements. Consequently, it has the potential to enhance UAV performance, efficiency, and cost-effectiveness significantly. This paper delves into various generative design approaches for drones, covering structural components, aerodynamics, energy efficiency, and payload distribution applications. Real-world case studies prove the benefits of integrating generative design into the UAV development process. These studies demonstrate the effectiveness of generative design and pave the way for significant advancements in UAV capabilities and applications, instilling confidence in its potential.

Keywords: Generative design, unmanned aerial vehicles, Challenges of Generative design

1.0 INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have transformed remarkably from their early military origins to revolutionize many industries. Initially designed for reconnaissance and combat missions, early UAVs like the U.S. military's MQ-1 Predator heralded a new era of long-range surveillance and precision strike capabilities [1]. In the past two decades, microelectronics, sensor technology, AI, and data processing advancements have given rise to smaller, more efficient, and highly autonomous UAVs [2]. This technological revolution has been accompanied by evolving regulatory frameworks and a surge in commercial interest, leading to a diverse range of applications in agriculture, delivery services, environmental monitoring, and beyond.

Amidst this rapid evolution, generative design has emerged as a game-changing innovation in UAV development. This computational design approach, powered by AI and advanced algorithms, is reshaping the future of UAVs [3]. Generative design is particularly significant for UAVs because it creates intricate, highly optimized structures that boost performance, efficiency, and durability. It accelerates the design process by swiftly exploring vast design spaces, fostering innovation, and enabling faster development cycles. Moreover, it allows the creation of customized UAV components tailored to specific missions, thereby enhancing mission effectiveness and resource efficiency [4]. By tackling the most complex design challenges and pushing the boundaries of innovation, generative design is set to significantly improve the capabilities and applications of UAVs in the modern era.

The convergence of generative design methodologies with drones presents a synergy that has the potential to reshape the very essence of aerial technology. However, a comprehensive literature review on generative design for drones needs to be included. The aim of this review is to fill this void by conducting a comprehensive examination of the diverse design methodologies employed in drone development. It encompasses their utilization across various facets of drone technology, highlights the difficulties linked to their implementation, and delves into the emerging trends with potential implications for the future of this domain.

This study aims to offer an all-encompassing examination of the approaches utilized in Generative Design for the field of drones. We will delve into the diverse applications of generative design in drone technology, covering structural components, aerodynamics, energy efficiency, payload distribution, and more. Analyzing real-world case studies will showcase the benefits of incorporating generative design into drone development processes.

2.0 METHODOLOGY

This paper examines existing research to assess how generative design can create unmanned aerial vehicle (UAV) structures. The authors conducted an extensive review of various databases to locate pertinent literature. Papers were chosen based on their alignment with the specified search keywords and citation count, without any limitations on publication dates. Figure 1 illustrates the essential keywords employed during the database search, shedding light on the current direction and volume of research on employing generative design in UAV development.

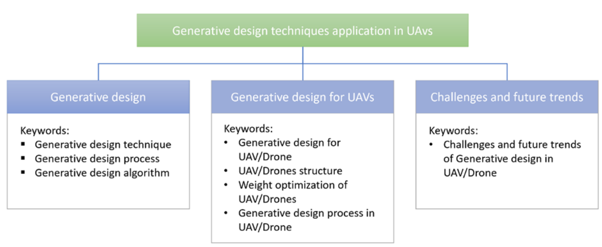


Figure 1 The essential keywords employed during the database search.

We employed a combination of keywords and phrases such as "Unmanned Aerial Vehicles", "Drones", "Generative Design", "Generative Design for UAV/Drone", "Generative Design Algorithms", "Weight optimization of UAV/Drone", and "Challenge and Future trends of Generative Design for UAV/Drone" Boolean operators were used to refine the searches, for instance, "Unmanned Aerial Vehicles" AND "Generative Design" or "Drones". The utilization of keyword searches enabled the identification of articles that explored the utilization of generative design techniques in unmanned aerial vehicles, shedding light on their capabilities, advancements, deficiencies, and hurdles.

Our inclusion criteria were designed to be comprehensive, encompassing all studies directly related to UAV technologies and generative design, published between 2000 and 2024 in English and available as full-text peer-reviewed journal articles, conference papers, patents, and significant industry reports. The selected time frame for the literature review was from January 2000 to May 2024, ensuring the inclusion of the most relevant and recent advancements in UAV technology and generative design. Exclusion criteria were also carefully considered, including studies not directly addressing UAV or generative design, publications before 2000, non-English works without translations, non-peer-reviewed articles, opinion pieces, and editorials. Furthermore, data analysis utilized the database search outcomes to discern trends and research priorities, gauged by the annual volume of published journal articles. The findings were graphically represented to illustrate the analytical impact, as shown in Figures 2 to 3.

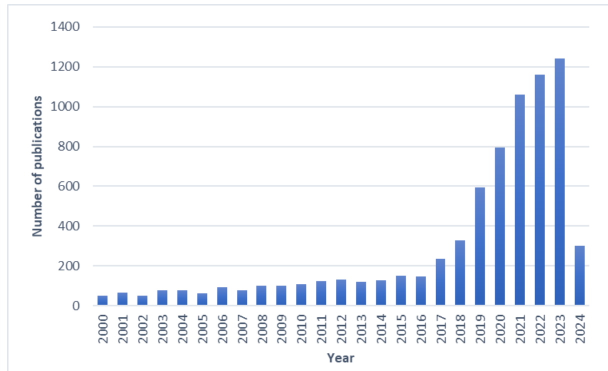


Figure 2 Publication outcomes per annum utilizing the search terms "generative design algorithm," "generative design technique," and "generative design process" (Search performed on June 12, 2024).

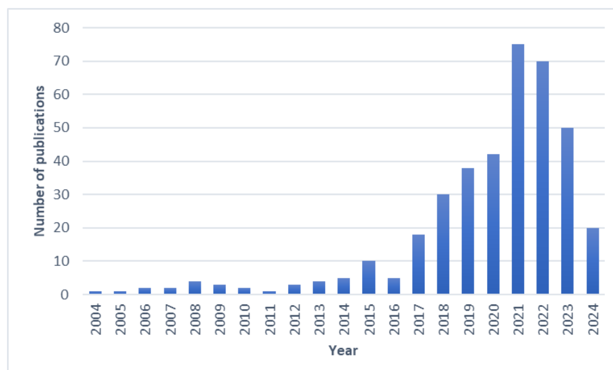


Figure 3 Publication outcomes per annum utilizing the search terms "generative design for UAV/Drones," and "weight optimization of UAV/Drones" (Search performed on June 12, 2024).

3.0 THE DEVELOPMENT OF GENERATIVE DESIGN METHODS

Generative design has evolved significantly over the past few decades, shaped by advances in computational power, algorithms, and integration with AI technologies. The timeline outlines the major milestones and technological shifts that have influenced the development of generative design methods, as shown in Figure 4.

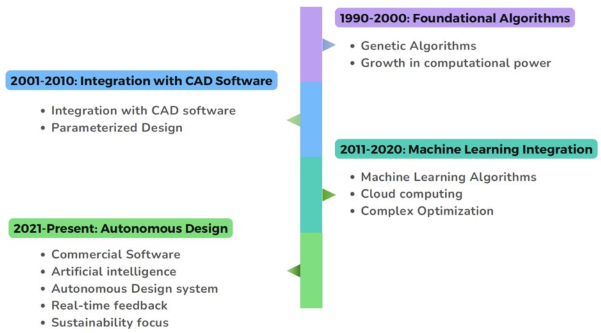


Figure 4 Timeline of Generative Design Evolution.

The exploration of Generative Design began during the 1980s, initially comprising theoretical publications with limited practical implementations [5]. Researchers sought to leverage these new resources as computer technology advanced to enhance their work processes. Initially, the most significant interest was observed in architecture [6]. Nonetheless, scholars from diverse fields started to investigate potential prospects and use arising from the fusion of computational methods and analogies drawn of evolutionary theory [7].

In the realm of design in engineering, Vajna and colleagues introduced the Autogenetic Design Theory, which explores the similarities between product progression and the natural developmental procedure [8]. The authors proposed that creating a product may be viewed as an ongoing refinement of a core solution, affected by beginning circumstances, restrictions, and other factors, including client requests, spontaneous ideas, and directions imitating environmental changes in the natural world. Even though Generative design is widely applied in various fields, a universally agreed-upon definition for it has not been established. According to Shea and colleagues, generative design can be characterized as systems that leverage modern computing and manufacturing capabilities to produce innovative, efficient, and feasible designs [9]. Krish offered a specific definition, "generative design" is a designer-led, parametrically constrained design inquiry approach used in history-based, parametric CAD process to support creation as an iterative process [10]. Nevertheless, engineering design applications now transcend parametric models and extend beyond conventional CAD programs.

Generative design can be described as a technique that involves the creation of multiple designs, incorporating a degree of automation and self-directed decision-making within the process [11]. It draws inspiration from the evolutionary approach found in nature's design process, starting with a single or several designs spread throughout the design space and gradually adjusting them to suit specific conditions better. Designs that fail to meet these conditions or align with the design objectives are discarded, and the evolutionary process continues in alternative directions. Engineers and designers primarily play a role in setting constraints and design objectives before the generation begins. Still, their involvement can extend to participating throughout the entire generation process, including customer input. Although generative design can be executed using defined rules with just a pen and paper, it is typically associated with computer-aided design. The generated outcomes can manifest in various forms, such as images, models, sounds, animations, and more [12]. Consequently, this method is used in various industries, including engineering design, building design, art, fashion, and numerous others.

Generative design is commonly associated with the application of algorithms to generate designs. Dedicated generative design modules have recently been integrated into various commercial CAD software packages for engineering design. These productive design tools initially draw upon algorithms utilized in topology optimization, expressly the level set method (LSM) [13]. Unlike topology optimization, which employs local density variables, these tools work with dynamic boundaries. Consequently, they exhibit mesh independence [14] and possess distinct requirements for setting up designs compared to topology optimization. LSM is known for its adaptability and ability to handle complex topological transformations. The subsequent sections will explore the similarities and distinctions between topology optimization and generative design tools.

Nordin's 2018 research [15] stands out for its successful application of generative design (GD) within a genuine industrial setting. The author provides an exposition of two case studies in which customized generative design techniques. The first case involved a disc-dispensing unit and specific engineering requirements, while the second focused on the industrial design of a camera. These projects utilized techniques incorporating parametric CAD models evolved through genetic algorithms (GAs) coupled with rigid body simulation and Finite element analysis. The resulting designs met engineering criteria optimally and garnered high levels of client satisfaction, demonstrating the effectiveness of GD in practical industrial scenarios.

While Tyflopoulos [16] aimed to create a perfect design for a piece of ski equipment by utilizing the Finite Element Method and Topology Optimization. However, there has been a shift in focus toward producing various design alternatives. This shift aligns with the recent rise of deep learning [17] made its way into generative design (GD) through the work of Oh et al. [18,19]. They combined Topology Optimization with Generative Adversarial Networks (GANs) to produce multiple wheel rim designs that met engineering and aesthetic criteria. GANs were employed to filter designs based on the assumption that existing designs are aesthetically superior to arbitrary Topology Optimization results. This presumption was implemented using a repository of pre-existing structures and a distance metric. The approach exemplifies Autodesk's preference for integrating different design phases. Khan's study method [20], which aims to aid beginner yacht hull builders in investigating numerous choices based on beauty and hydrostatic efficiency, exhibits a similar combination of aesthetics and engineering [21], Khan intentionally designed the generative system to be interactive rather than fully automatic, yet it still delivered options rapidly enough for practical use. This choice was likely due to the underwhelming results of the fully automated generation of parametric CAD models. However, Gunpinar et al.'s automotive profile design method integrates aesthetic judgement with performance data from Computational Fluid Dynamics (CFD), a comparable integrated strategy for generating numerous choices [22].

Dogan et al.'s research [23] emphasized 2D Bezier curves instead of complete 3D models. Their approach combined elements from Gunpinar and Khan to promote design diversity and incorporated a robust interface akin to the one developed in DreamLens for comprehensive design exploration. In this system, the initial setup requires manual input involving tracing a profile and incorporating constraints from existing designs. Subsequently, the system autonomously generates variations, which are then systematically explored using the interface. The system successfully produced profiles for ewers, glasses, and car sides, ultimately transforming them into 3D models.

The author in [24], they provided a hands-on depiction of the process and achievements associated with a particular software system designed to employ a generative approach in generating multiple alternative solutions for a static structural design challenge. The software analyzed is Autodesk's Generative Design and developed the fixed structure by following up input parameters and then analyzing model outcomes by FEA.

Table 1 summaries the progress of the generative design system according to the overall purpose, design stage application, interactivity, generative method, generative algorithm, and system evaluation.

Table 1 Summary of the progress of generative design methods

Ref	Year	**Objective**	**Generative design method**	**Generative design algorithm**	**Evaluation/Performance**
[5]	1998	Generate numerous conceptual designs interactively	Shape Grammar with 100 rules	Shape Grammar	Initial success
[6]	2001	Generate a multitude of architectural conceptual designs interactively	The Generative System utilizes a Genetic Algorithm that has been assessed within a limited scope or specific domain	Genetic Algorithm	The objective constraints have been satisfied, and designers and engineers have provided favourable practical assessments
[7]	2004	Generate a substantial quantity of integrated designs automatically	Evaluation based on physical equilibrium, vertical dimension, surface area, and the choice of materials	L-System with Genetic Algorithm	Initial success, demonstrating enhanced fitness compared to a non-generative approach.
[8]	2005	An evolution of the design process, aimed at instigating significant activity within the product development phase	By employing Autogenetic Design Theory, an examination was conducted to identify resemblances within the design process	Autogenetic Design Theory	They can manifest as directives, client specifications, impromptu concepts, and guiding principles
[9]	2006	Generate a significant quantity of fused designs automatically	Employing Shape Grammar consisting of 62 rules and utilizing a Genetic Algorithm to assess the fitness based on bottle volume	Shape Grammar and Genetic Algorithm	Initial success
[10]	2011	Generate a substantial quantity of conceptual designs automatically	Perform stochastic sampling on a parametric CAD representation	Genetic Algorithm	Initial success
[11]	2014	Generate numerous conceptual designs interactively, with guidance from objective data	Applying Shape Grammar to parametric CAD and enhancing it through Finite Element Analysis (FEM) optimization	Shape Grammar	Initial success
[18]	2016	Generate a multitude of architectural conceptual designs interactively	Leveraging an extensive collection of images and design characteristics from past designs, employing Generative Adversarial Networks (GANs), and focusing on car side images	The generative adversarial network (GAN) and Car side image	They transformed a statistical distribution into a mathematical model offering greater flexibility and realism than previously suggested representations
[15]	2018	Generate a substantial quantity of merged designs automatically	Utilizing parametric Computer-Aided Design alongside Genetic Algorithms, rigid body simulations, and Finite Element Analysis	Genetic Algorithm	Ideal designs and client approval
[23]	2019	Generate a substantial quantity of unique conceptual designs through automated processes	Using the Hausdorff distance metric to minimise the Audze-Eglais Potential when transforming a Cubic Bezier shape into parametric CAD	Shape Grammar	Enhanced variety in samples
[24]	2020	Apply GD tool to a static structural optimization	Using Generative design tool in Autodesk to generate and analysis by FEA	Artificial intelligence (AI) algorithms in Fusion 360	Satisfied with results, objective constraints met.
[40]	2021	Apply GD tool to reduce weight of a mechanical pedal	Using Generative design tool in Solid Edge to optimization of a mechanical pedal and analysis by FEA	Artificial intelligence (AI) algorithms in Solid Edge	Satisfied with results, objective constraints met.
[35]	2022	Generate a substantial quantity of conceptual designs automatically	Using Generative design tool in Autodesk to generate multiple mechanical-related products based on input parameters and analysis by FEA	Artificial intelligence (AI) algorithms in Fusion 360	Satisfied with results, objective constraints met.
[39]	2023	Generate a substantial quantity of conceptual designs automatically	Using Generative design tool in CogniCAD to generate and analysis by FEA	Artificial intelligence (AI) algorithms in CogniCAD	Satisfied with results, objective constraints met.

4.0 GENERATIVE DESIGN ALGORITHM

To establish a cohesive structure for generative design systems, Singh [25] identified four essential generative techniques: Swarm intelligence, L-system, Shape grammar, and Genetic algorithm. Their relevance to product design remains limited. Nevertheless, other generative techniques have been used successfully in creating products and are worth an overview exploration.

- Genetic Algorithm (GA): A meta-heuristic algorithm influenced by natural biological selection principles. These algorithms frequently use approaches similar to biological processes, including mutation, crossover, and selection, to find optimal solutions for optimization and search problems [26].
- Shape Grammar (SG) [27]: SG is a design production system comprised of a finite number of objects and an assortment of sequential transformation principles applied to a starting state. Unlike many other production systems, SGs operate inside a physical rather than a symbolic framework. When these shape rules are applied, designs are formed, and these rules define the generated strategies inside a design grammar. Shape grammars are frequently used as generative tools for formalizing existing configurations.
- L-system (LS) [28]: LS is a mathematical algorithm renowned for producing structures reminiscent of real-life forms marked by self-similarity, mirroring the attributes of biological growth. LSs have found applications in various design challenges, from straightforward computer graphics patterns to intricate city planning and simulation scenarios.
- Swarm intelligence (SI): SI is a systemic trait that occurs when many individual agents communicate with the environment around them, resulting in unified behavioral patterns at higher organizational levels [29]. The SI system is designed to solve problems requiring centralized control or a global-level framework.

Additional approaches are explicitly tailored for product design along with the methodologies described. Among these, parametric modelling is widely employed in contemporary CAD systems [30,31]. Parametric modelling symbolically represents solid models based on their features, involving defining a set of parameters and their interdependencies. Modifying a single parameter automatically leads to updates throughout the entire model. Parametric models provide a more natural experience for designers than the methods mentioned by Singh, and this approach is used in numerous existing design processes and applications, including modelling and evaluation tools., rely on this approach.

Nevertheless, it is critical to understand that parametric models are not intrinsically generative and must be adapted for such purposes. This adaptation involves the development of algorithms capable of directly manipulating the model's parameters. While converting from other generative representations like shape grammars is feasible, the process may not always be straightforward.

Table 2 is a comparative analysis table for various generative design algorithms used in UAV design. It highlights their advantages and disadvantages regarding computational efficiency, design precision, and Suitability for UAV Design Challenges.

Table 2 Summary of comparing the different algorithms of Generative design used in UAV.

Algorithms	Genetic algorithm	Shape grammar	L-system	Swarm intelligence	Artificial intelligence
Advantages	Good for complex, multi-objective optimization problems	Allows for the generation of a wide variety of design alternatives	Effective for modeling growth processes and fractal-like structures	Fast convergence, good for distributed problem-solving	Capable of learning and optimizing complex, dynamic systems
Disadvantages	It Can be computationally expensive and slow convergence	May require complex rule definitions and can be computationally intensive for complex designs	Limited applicability to highly functional designs, can be computationally heavy for detailed structures	It can get stuck in local optima and may require tuning of parameters.	Requires significant computational resources and large datasets
Computational Efficiency	Moderate to High	Moderate	Moderate	high	Low to High (varies by method)
Design Precision	High	High	Moderate to High	Moderate to High	High
Suitability for UAV Design Challenges	Suitable for optimizing multiple UAV design parameters but may require high computational resources.	Ideal for exploring innovative UAV designs and configurations through rule-based design generation	Suitable for biomimetic designs and structures that benefit from recursive and fractal patterns	Effective for collaborative UAV systems and optimization of flight patterns and formations	Suitable for predictive modeling, adaptive control systems, and real-time optimization in UAVs

5.0 GENERATIVE DESIGN SOFTWARE

Generative design is a method that employs software and algorithmic techniques to produce and explore many design choices depending on particular input parameters and limitations. Different software tools are available for generative design, each with advantages and disadvantages. As shown in Table 3, comparing the different software used in Generative design (GD) with advantages and disadvantages

5.1 Fusion 360

Generative design within Fusion 360 is a functionality that employs sophisticated algorithms to autonomously explore and create efficient 3D designs, considering parameters, objectives, and constraints defined by the user [32]. It utilizes topology optimization to identify optimal material distribution, resulting in unique and inventive design suggestions. Users can visualize and assess numerous design iterations, validate them via simulations, and make refinements as necessary [33]. This process ultimately leads to enhanced efficiency and cost-effectiveness in diverse industries, with the added benefit of reducing material waste and manufacturing expenses.

In the case study of researchers, the author in [34] optimized drone design using generative design principles and additive manufacturing techniques, focusing on material selection and testing. They identified and reduced unnecessary weight in the drone's structure, reducing mass from 705 grams to 586 grams (about 17%). This optimization enhanced the drone's take-off capacity. Balayan, A et, al. [35] focuses on developing a lightweight and robust chassis for a UAV using generative design and topology optimization in Autodesk Fusion 360. By leveraging 3D printing and materials like PLA, ABS, and Nylon 6/6, the study significantly improves structural efficiency and performance metrics for quadcopter designs. Results include nearly 50% weight reduction, improved power-to-weight and thrust-to-weight ratios by approximately 6%, and enhanced safety factors. The findings highlight the effectiveness of innovative design approaches in advancing drone technology, particularly for precision agriculture applications.

5.2 CogniCAD

CogniCAD was initially introduced in 2018 [36], and its launch garnered significant attention due to its unique software capabilities. Notably, CogniCAD is unable to provide the option to build geometries manually. It is instead intended to perform Generative Design and Additive Manufacturing activities. To create geometries for a project, such as bookends, users must employ a separate CAD system and then import the design as a STEP file into CogniCAD [37]. At this stage, decisions need to be made regarding whether to specify mechanical or thermal loads for a generation or include grid structures. The imported file is placed within one of these three areas, after which GD settings can be configured. As shown in the case study, the thesis in [38] investigates the use of generative design in aircraft development, highlighting its ability to generate optimized design solutions and reduce development times automatically. An engine mount for the Cessna 172R was designed using both traditional and generative design methods, comparing the results to identify the strengths and weaknesses of generative design. The study reveals the potential of generative design tools in the aerospace industry.

5.3 Solid Edge

Solid Edge's student edition only offers a limited generative design functionality. Thus, a licensed version of Solid Edge was utilized to make the artwork with full access to all features. The creation process is carried out while the data is locally recorded on the computer [39]. Within the CAD program, Solid Edge also produces geometry. To begin, a main body is needed as an initial sketch, representing the workspace and the desired geometries to be preserved, allowing for considering obstacles through cut-outs. As shown in the research, the thesis in [40] explores generative design techniques for jet engine brackets using Solid Edge software, focusing on computational structural optimization in aerospace engineering. It uses iterative design principles, structural simulations, and comparative analyses to improve structural integrity, weight efficiency, and flexibility. The study underscores the pivotal roles of material scientists and manufacturing experts in advancing aerospace and mechanical engineering methodologies.

5.4 Siemens NX

Iterate quickly through hundreds or thousands of possible optimized designs. Generative design automatically generates and compares multiple design options to find an ideal, best-fit solution [41]. Simcenter HEEDS is a generative design solution using NX CAD geometry with Simcenter CAE simulation to provide optimized designs. The result is a truly optimized solution that can then be 3D printed. As shown in the researches, the thesis in [42] evaluates additive versus subtractive manufacturing methods for suspension uprights from concept to validation through simulation. Additive manufacturing was applied to Global Formula Racing’s 2023 electric vehicle using Siemens NX, Nastran, Fusion 360, and Ansys Workbench. Structural analysis compared stress levels and safety factors, showing that additive manufacturing reduces design and manufacturing time significantly while offering innovative solutions to traditional design challenges in subtractive manufacturing and selection the materials. The author in [43] This paper investigates the impact of combining generative design (GD) with additive manufacturing (AM). Specifically, material extrusion (MEX) uses polylactic acid (PLA). It challenges the notion that GD automatically produces consistently high-performing designs, revealing substantial variability in outcomes influenced by initial conditions and AM's inherent unpredictability. Analyzing nine independently generated designs, the study shows performance variations up to 592%, underscoring the importance of improving GD setup understanding and training to achieve reliable and optimized designs, particularly in MEX processes of deign the model.

Table 3 Summary of comparing the different software of Generative design used in UAV with advantages and disadvantages

Software	Advantages	Disadvantages
Fusion 360	Integrated CAD and generative design. Cloud-based collaboration. User-friendly interface, Parametric and history-based modeling.	Limited generative design capabilities. Requires an active Autodesk subscription. Limited advanced simulation capabilities. May not be suitable for complex designs
CogniCAD	Cloud-based, accessible from anywhere. Automated design optimization. Quick generation of lightweight structures	Limited control over design parameters. Limited support for complex geometries. Limited export file formats
Solid Edge	Integration with Siemens PLM ecosystem. Comprehensive generative design tools. Robust simulation capabilities	Steeper learning curve. Requires a dedicated workstation. Higher cost compared to some alternatives
Siemens NX	Industry-standard CAD and CAE capabilities. Deep integration with Siemens PLM platform. Extensive generative design features	High cost, primarily for large enterprises. Complex interface for beginners. Resource-intensive for complex designs

6.0 CATGORIZATIONS OF UNMANNED AERIAL VEHICLES

Unmanned Aerial Vehicles (UAVs) are meticulously engineered with distinct attributes tailored to specific purposes, choosing the most suitable UAV a pivotal decision hinging entirely on the intended application [44]. UAVs are manufactured in varying sizes, including nano-sized (Figure 5a) [45], micro-sized (Figure 5b) [46], mini-sized (Figure 5c) [47], small-sized (Figure 5d) [48], medium-sized (Figure 5e) [49], and large-sized (Figure 5f) categories [50]. The decision regarding the size of the UAV should be aligned with the precise needs and objectives of the mission or task at hand.

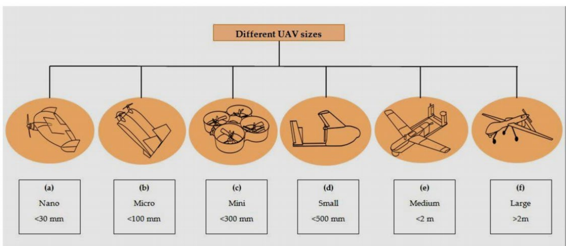


Figure 5 Categorizations based on size include [51].

Unmanned aerial vehicles (UAVs) are divided under two categories: fixed-wing and multi-rotor UAVs. As depicted in Figure (6a), Fixed-wing UAVs are traditional UAVs with stationary wings and can be controlled remotely or autonomously for sustained flight. In contrast, the Hybrid (VTOL) UAV type, shown in Figure (6b), is a versatile wing-based UAV often referred to as a fixed-wing jet, hybrid UAV, or VTOL aircraft. These Drones are adaptable across many circumstances, with the design of a multi-rotor that includes three or more propellers, providing a vertical landing and takeoff as well as forward flight capability, making them appropriate for various missions and operating environments [52].

Fixed-wing UAVs typically have a more aerodynamically efficient design compared to multi-rotor UAVs. Generative design can significantly benefit fixed-wing UAVs [53]. Generative design algorithms can optimize wing and fuselage shapes to reduce drag and enhance lift-to-drag ratios, which is crucial for extending flight range and endurance [54]. Additionally, these algorithms can iteratively refine structural designs to maintain robustness while minimizing weight, improving overall efficiency and payload capacity. Such optimizations are particularly advantageous in applications requiring long-range surveillance or mapping where maximizing flight time and operational range are paramount

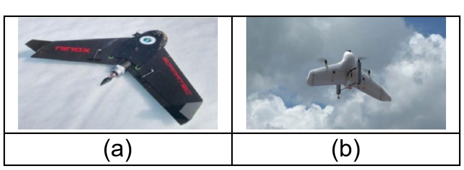


Figure 6 Types of UAVs: Fixed wings (a). Hybrid (VTOL) (b) [55].

Multi-rotors are drones that feature multiple rotors, typically four or more, arranged in a configuration similar to a helicopter. These rotor propellers operate like fixed-wing aircraft but come with unique advantages and limitations in their configurations. Rotary-wing UAVs can be divided into single-dual rotors as illustrated in Figure 7 and multi-rotors [56]. Among these, multi-rotor UAVs stand out as the most dependable wing-based UAVs, recognized for their speed and agility, enabling them to perform demanding tasks effectively. They represent a significant technological advancement of the past decade. Furthermore, several models of multi-rotor UAVs are available, including the Tricopter [57], Quadcopter [58], Hexacopter [59], and Octocopter [60].

Multi-rotor UAVs have different design considerations than fixed-wing UAVs. Generative design can enhance maneuverability and stability by optimizing the shape and configuration of the drone's frame and rotor arms. This includes minimizing vibrations and ensuring efficient weight distribution to improve responsiveness during flight. Moreover, generative design supports payload versatility. Unlike fixed-wing UAVs, multi-rotor UAVs can hover and perform vertical take-offs and landings (VTOL), making them suitable for applications requiring precise positioning or payload deployment [61]. Generative design can optimize the frame to accommodate various payloads while maintaining balance and stability. Additionally, generative design contributes to redundancy and safety [62]. Multi-rotor UAVs can incorporate redundancy in their design, such as redundant propulsion systems or batteries, to enhance safety and reliability. Generative design can play a role in optimizing the layout of these redundant systems to maximize reliability without compromising on weight or performance.

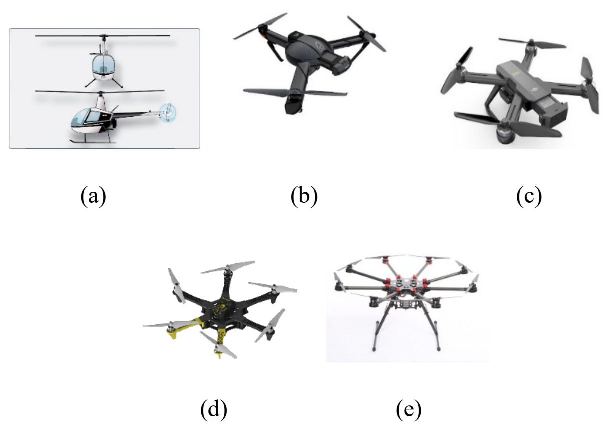


Figure 7. Categories of rotary wing configurations: (a) Single-dual rotors, (b) Tricopter, (c) Quadcopter, (d) Hexacopter, and (e) Octocopter [63].

7.0 APPLICATION OF GENERATIVE DESIGN IN UAVs

Generative design techniques have found extensive application in optimizing structures to meet specific performance objectives, and they have been utilized across various engineering domains. When applied to the design of structure of Drones, the generative design promises to deliver notable enhancements, including creating lightweight and highly efficient methods [64]. Generative design algorithms can explore various design possibilities and find optimal solutions. By optimizing the structural layout and material distribution, generative design can result in lightweight and efficient UAV structures. Structural strength and durability [65]. Generative design algorithms consider various load conditions, stresses, and constraints during optimization. As a result, they can produce structures with improved strength and durability. By redistributing material where it is needed most, generative design can assist the reduction of stress concentrations and increase the structural integrity of the Drone. These researchers present the concept of generative design for designing new drone structures as shown in Table 4, the techniques' design, and the problem's state.

The authors conducted a case study involving optimizing an assembly to simplify it for easier manufacturability [66]. They employed generative design, which utilizes automated computation to generate various design iterations. Autodesk's Fusion 360 was used to redesign the model and produce multiple outcomes. The study involved a comparison between aluminum and stainless-steel materials. This effort resulted in a final mass of 417 grams, representing a significant 27% reduction in mass.

In the study detailed in [67], the investigation focused on the design of a drone structure frame employing Generative design technique. Specifically, a structure frame of quadcopter was crafted utilizing Fusion 360. They evaluated the displacement results of the additively manufactured quadcopter compared to the DJI Flame and F450 drone frame. This comparison revealed substantial mass reductions, with the additively manufactured quadcopter weighing only 227g (a 31% reduction) and 267g (a 19% reduction) when compared to the original weight of 330g for the DJI frame, respectively.

Optimizes the frame of a drone to reduce its weight using generative design and allows for a larger battery to be installed in [68]. They used generative design software to create various frame designs based on specific criteria. They evaluated the methods based on weight, strength, and manufacturability. The final design was selected based on these evaluations. The drone frame was made from Acrylonitrile Butadiene Styrene (ABS) plastic. As a result, its overall weight was reduced by 25g.

The authors in [69] described the design of a small-sized UAV utilizing the 3DEXPERIENCE software. The methodology commenced by choosing materials, specifically ABS, PLA, and ASA, which were carefully selected and examined. Four main parts comprise the drone frame: the arm of 80g, the middle body cover of 50g, the centre top surface of 50g, and the side top cover of 10g. The design was subsequently realized through 3D printing using an ANYCUBIC I3 MEGA printer. The pieces were simulated using 3D design tools, with additional insights provided by a thorough evaluation of compromises and weight simulation of the drone.

The authors in [70] present a pioneering approach to designing the structural framework of a UAV drone. This strategy focuses on optimising material composition and production techniques, resulting in significant cost reductions for the industry through generative design. To accomplish this, they created a mechanical framework for the UAV drone within Autodesk Fusion 360. The optimized design yielded impressive results, with a maximum stress analysis indicating a value of 5.028 megapascals, signifying an 83.00% improvement. Additionally, the maximum displacement analysis showed a value of 0.666 millimeters, marking a 45.44% enhancement. Simultaneously, the production time was reduced to 15.5 hours, reflecting a 61.25% improvement. Collectively, these optimizations contribute to a heightened focus on weight reduction.

In their study as documented in [71], researchers investigate the application of generative design methods in conjunction with Additive manufacturing to access the outcomes of landing gear design. The authors delineate a three-stage process, commencing with Generative design: initiating 3D CAD modeling based on geometric parameters and creating the model using Fusion 360. The subsequent stage involves Outcome selection, where three key parameters are taken into consideration: component weight, cost, and component maximum displacement. In the final stage, Outcome optimization is realized through the utilization of additive manufacturing (AM) and validation via computer-aided engineering (CAE). The shape of the part is adjusted to meet the modified geometric requirements. As a result, the final product weighs approximately 67g. Considering that the analyzed assembly started off weighing around 148g, this suggests a sizable weight decrease, namely a 52% reduction.

The thesis discussed in [72] focuses on the development of a novel quadcopter frame through the utilizing generative design principles and 3D-printing fabrication methods. The design solution hinges on three key considerations: the quadcopter's geometric configuration, its ease of manufacturability, and the selection of materials, specifically ABS and PLA. The study used FEA to validate the model outcomes drone frame. he study found that the three-fourths prototype weighed 39.1g before post-processing and after finished model is 22.7g. This means that waste material accounted for 16.4 grammes of the total mass composition, accounting for roughly 42% of the entire mass composition.

The research in [73], the authors sought to increase performance by reducing the total mass of an aircraft's landing gear. They accomplished this by combining topological optimization and generative design methods. They used ANSYS for finite element analysis (FEA) to acquire critical data on several landing gear designs. This analysis included determining overall deformation as well as von Mises stress. The authors calculated the safety-to-mass ratio for each approach of the landing gear structure, which comprised the traditional design between Topology optimization design and generative design, a combination of two techniques. This process ultimately resulted in the development of a final main landing gear design that achieved a remarkable 30% reduction in weight compared to the conventional method.

The study outlined in [74] centers on a proposal involving the creation of a prototype for Drone using Generative design, a methodology concentrated on enhancing and generating multiple design alternatives from a single CAD model. Construction of the prototype is executed using PLA+ material, and they employ Finite Element Analysis to assess the model's performance. The core objective of their endeavor is to showcase that this approach can yield an optimized final design that not only upholds safety standards but also significantly enhances material efficiency.

The conference paper by Zaimis et al. [75] clarifies the distinctions between the conventional design for engineering methodology and generative design processes. The study accomplished by using a test case of the landing gear of a prototype drone, which is intended for low-volume manufacture. The work opens with describing the nose landing gear's design concepts. In the early phase, it employs the traditional Strength of Materials concept to compute stress distribution across components, yielding a design solution. A generative design investigation uses a readily accessible technology and the provided conceptual requirements. Both systems are theoretically evaluated for compliance with the STANAG 4671 standards, notably regarding strength requirements, utilising the finite element analysis technique. Finally, the final model outcome structure will be built with CNC machining, resulting in a 36% reduction in total mass while retaining its strength.

The authors in [76], they present a monobloc quadcopter design created using Generative Design techniques. The primary goal is to achieve a structurally superior design that not only reduces weight but also minimizes material consumption, leading to cost savings in both materials and manufacturing. Subsequently, they conduct an analysis of the results for this new design using the Finite Element Analysis tool. The results indicate that GD model 1 surpasses GD model 2 and the original model, boasting a significant reduction in mass, specifically 75.316 grams less.

Table 4 Summary of the existing research on generative design in unmanned aerial vehicles (UAVs**).**

Ref	Year	Key focus	Design tool	Material	Performance Improvement	Cost Reduction	Design Innovation
[66]	2021	Assembly optimization for easier manufacturability	Autodesk Fusion 360	ABS	Final mass reduced to 417 grams, 27% reduction in mass	Simplified manufacturing process	Multiple design iterations produced, optimized structural layout
[67]	2020	Design of quadcopter structure frame	Autodesk Fusion 360	Aluminum, stainless steel	Weight reduction to 227g (31%) and 267g (19%) compared to DJI Flame and F450 frame	N/A	Lightweight and efficient frame structure
[68]	2021	Frame weight reduction for larger battery installation	Autodesk Fusion 360	ABS	Weight reduced by 25g	N/A	Various frame designs evaluated for optimal weight, strength, and manufacturability
[69]	2021	Small-sized UAV design	3DEXPERIENCE software to design UAV. ANYCUBIC I3 MEGA printer	PLA, ABS and ASA	The drone frame's design resulted in four essential components: the center top cover of 50g, the side top surface of 10g, the middle body of 30g, and the drone's arm of 80g.	N/A	Detailed weight simulation and compromise evaluation, 3D printed realization
[70]	2022	Structural framework optimization.	Autodesk Fusion 360.	ABS	Max stress analysis improved by 83.00%, displacement improved by 45.44%	Production time was reduced by 61.25%	Material composition and production technique optimization
[71]	2022	Landing gear design with generative design and additive manufacturing	Fusion 360 and the Selective Laser Sintering (SLS) manufacturing technique.	polymeric material	Final product weight 67g, 52% reduction from original 148g	N/A	Three-stage process: 3D CAD modeling, outcome selection, optimization
[72]	2023	Quadcopter frame design and 3D-printing	Fusion 360, 3D printing (ORIGINAL PRUSA i3)	ABS, PLA	Prototype weight was reduced from 39.1g to 22.7g, resulting in a 42% reduction in waste material.	N/A	FEA validation, efficient geometric configuration, and manufacturability
[73]	2023	Landing gear performance improvement	Autodesk Fusion 360, FEA analysis (ANSYS)	Nylon polyamide 12 (PA 12)	30% reduction in landing gear weight	N/A	Combination of topological optimization and generative design, safety-to-mass ratio calculation
[74]	2022	Drone prototype creation	Fusion 360, FEA and CFD in ANSYS	PLA+	The result in an optimized final design that maintains safety standards and substantially improves material efficiency	N/A	Multiple design alternatives generated, FEA assessment for optimized final design
[75]	2021	Nose landing gear design for low-volume manufacture	Autodesk Fusion 360.	N/A	36% reduction in total mass while retaining strength	N/A	Comparison of traditional and generative design methodologies
[76]	2023	Monobloc quadcopter design	Autodesk Fusion 360.	ABS	GD model 1 reduced mass by 75.316 grams	Cost savings in materials and manufacturing	Superior structural design minimizing material consumption
[38]	2023	Engine mount design for light aircraft CESNA 172R	CogniCAD	Stainless Steel AISI 304, Titanium 6Al-4V , Cobalt Chrome,	Its safety factor is 18.62% higher, a considerable increase that demonstrates the potential of this technology	N/A	Reduced development times due to automated exploration of design solutions
[40]	2023	Jet engine bracket design	Solid Edge	Aluminium, Titanium Alloys	Improved structural integrity, optimized load distribution, weight minimization	N/A	Systematic iterative approach, balance between aesthetic and practical constraints

8.0 CHALLENGES OF GENERATIVE DESIGN IN UAV

Generative Design (GD) offers immense potential to revolutionize Unmanned Aerial Vehicle (UAV) design. However, it also presents a set of significant challenges. One of the primary issues revolves around the high computational demands of GD algorithms. These algorithms often entail intricate simulations and iterative procedures, which can consume substantial computational resources. This becomes particularly challenging for small, lightweight UAV systems with limited power and processing capabilities. Effectively optimizing designs within these constraints becomes a critical consideration. Researchers are exploring several innovative approaches to address the high computational demands of GD algorithms. Hybrid computing strategies [77], such as leveraging cloud computing and edge computing [78], can offload the computational burden from UAVs to remote servers or nearby network nodes, thus enhancing efficiency. Algorithm optimization through parallel processing and heuristic methods, like genetic algorithms, allows for faster design iterations by distributing tasks across multiple processors or GPUs. Reduced-order modeling (ROM) simplifies complex simulations, reducing computational demands while maintaining sufficient accuracy.

Furthermore, ensuring the validity and safety of designs generated through GD necessitates extensive validation and testing procedures [79]. UAVs operate in various environments and conditions, and their designs must adhere to stringent safety standards. Validating the outcomes of generative design algorithms to ensure compliance with these standards can be time-consuming and resource-intensive [80]. Robust testing protocols are indispensable to confirm that optimized designs perform well in simulations and real-world scenarios.

Integrating GD seamlessly into existing UAV design workflows poses another intricate challenge [81]. UAV design typically spans multiple disciplines, including aerodynamics, structural engineering, control systems, etc. Successfully incorporating GD into these multifaceted workflows requires meticulous coordination and adjustment of the design process. Ensuring that GD-generated output aligns with the specific requirements of each discipline and results in a coherent and functional UAV system is a formidable task. However, managing the selection process of Generative design model outcomes is another challenge and flight simulation of the new model-based design of UAV structures. Researchers are implementing advanced filtering and ranking mechanisms to manage the selection process of GD model outcomes [82]. These mechanisms use machine learning and artificial intelligence to evaluate and rank GD-generated designs based on how well they meet predefined criteria across various disciplines [83]. This approach helps streamline the selection process, allowing engineers to quickly identify the most promising designs for further development.

The inherent complexity of GD-generated designs can hinder human comprehension and collaboration with these systems. GD algorithms frequently produce intricate structures that may appear unconventional or challenging for human engineers to interpret. This lack of interpretability can complicate communication between engineers and automated design systems [84]. Striking the right balance between automation and human expertise is vital to fully exploit GD's potential without sacrificing human intuition and creativity.

Moreover, addressing regulatory compliance, design constraints, and the quality of input data within the GD framework is critical for UAVs. UAVs are subject to many regulations, encompassing weight limits, airspace restrictions, and safety standards. GD algorithms must consider these constraints to ensure the generated designs meet legal and safety requirements. Additionally, the quality and availability of input data, such as material properties or environmental conditions, can significantly affect the effectiveness of GD.

9.0 FUTURE DIRECTIONS AND TRENDS

The application of generative design techniques in drones is a rapidly evolving field marked by a plethora of emerging trends and future directions poised to influence its progress profoundly. These trends are fueled by technological advancements, evolving industry demands, and ongoing research endeavors.

One of the most notable impending developments is the seamless combination of artificial intelligence (AI) and machine learning (ML) into generative design framework procedures. This integration significantly enriches the intelligence and adaptability of generative design tools. AI-driven generative design systems can autonomously generate and evaluate numerous design iterations, optimizing for prescribed criteria such as weight, strength, and aerodynamics. Machine learning enhances this capability by enabling tools to learn from previous designs and adapt to new challenges, thereby improving the efficiency and effectiveness of UAV design. This adaptive learning process can lead to innovative solutions that human designers might not conceive, pushing the boundaries of UAV performance and functionality.

Future generative design techniques are set to accentuate multidisciplinary optimization. This comprehensive approach transcends traditional considerations of structure and aerodynamics, integrating crucial factors such as propulsion, energy efficiency, and mission-specific requisites. By concurrently optimizing across multiple domains, designers can create UAVs with a broader skill set that excels in a wider spectrum of tasks. AI algorithms can process vast amounts of data from various disciplines, finding the optimal balance between competing factors, thus enhancing overall UAV capabilities.

Furthermore, advancements in additive manufacturing and 3D printing technologies are opening new frontiers for generative design in the production of UAVs. The capacity to rapidly prototype and manufacture intricate, generatively designed components offers compelling advantages, particularly in reducing production lead times and costs. The path of future trends may see a seamless amalgamation of generative design tools with on-demand, locally situated manufacturing facilities. AI can further streamline this process by optimizing designs specifically for 3D printing, ensuring structural integrity while minimizing material usage..

With mounting global concerns about sustainability, the field of generative design in UAVs is expected to shift towards environmentally friendly solutions. Emerging trends encompass leveraging generative design to optimize UAVs for reduced fuel consumption, diminished emissions, and quieter operation.

Additionally, AI can aid in selecting sustainable materials and optimizing designs for recyclability, furthering the development of UAVs that exhibit greater environmental responsibility.

The future landscape of UAV design may also witness increased collaboration between human designers and generative design algorithms. Designers will progressively collaborate with AI systems, providing creative input and expertise, while the algorithms manage design's iterative and computationally intensive aspects. This synergistic human-machine partnership has the potential to yield innovative UAV designs that blend the best attributes of both realms. AI can assist by performing complex calculations and simulations rapidly, allowing human designers to focus on higher-level creative and strategic decisions.

10.0 CONCLUSION

Incorporating generative design techniques into various applications, particularly UAVs, has ushered in a transformative era of innovation, redefining how these aerial platforms are conceived, engineered, and deployed. This comprehensive review has illuminated the multifaceted applications, challenges, and promising future directions that characterize the integration of generative design in UAV development.

Generative design has proven invaluable for optimizing UAVs and enhancing structural efficiency, aerodynamic performance, and energy consumption. The ability to craft UAV designs that are not only high-performing but also customized to specific mission requirements is an achievement that holds great promise across various industries. This practical impact includes the potential for more efficient agricultural monitoring, enhanced environmental surveying, and improved disaster response capabilities, demonstrating generative design's broad applicability and benefit in real-world scenarios.

Nevertheless, we must recognize the challenges and limitations of this journey. Computational complexity, material constraints, and the need for interdisciplinary collaboration remind us of the importance of a measured and strategic approach to generative design implementation. While generative design empowers us to push the boundaries of what UAVs can achieve, responsible adoption and integration into established processes remain paramount.

Looking to the horizon, we witness various trends and innovations that promise to redefine the role of UAVs in our rapidly changing world. AI integration, multi-objective optimization, advanced materials, collaborative ecosystems, and biomimicry-inspired design are but a glimpse of the exciting developments ahead.

In these future directions, we find the potential for UAVs to evolve beyond our current conceptions. UAVs that adapt in real-time, swarms of cooperative aerial agents, user-friendly generative design tools, socially harmonious designs, and bio-inspired innovations offer a glimpse into a future where UAVs play increasingly pivotal roles in addressing complex challenges and driving progress in various fields. The practical impact of these advancements is immense, with potential applications in logistics, emergency services, environmental conservation, and beyond, underscoring the critical importance of generative design in shaping the future of UAV technology.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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