Generative design of light weight drone frame using FDM 3d printing – A Review

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Abstract. Endurance versus payload in UAVs is a direct trade-off governed by airframe mass and structural efficiency. Generative design (GD) and topology optimization (TO) are increasingly used to develop lightweight, high-performance drone structures optimized for additive manufacturing (AM). Among AM methods, fused deposition modelling (FDM) is the most cost-effective and accessible for producing polymer frames and substructures. This work reviews GD/TO-based UAV frame design using FDM, including design methods, materials, printing strategies, and validation approaches. Case studies show that incorporating AM constraints during optimization can reduce weight by 20–60% while maintaining or improving stiffness-to-mass ratio. A review of 57+ studies indicates GD can achieve 15–50% mass reduction compared to conventional designs. However, FDM still faces challenges due to anisotropic material behavior and fatigue limitations. Despite increasing demand for low-cost, robust, and lightweight UAV frames, current methods struggle to balance strength and weight effectively. Future work should focus on hybrid composites, multi-objective optimization, and real-world testing to enable reliable and certifiable FDM-based UAV structures.

1 Introduction

Drones as unmanned aerial vehicles represent one of the fastest growing industries in the modern age with application in military, logistics, agriculture, disaster management and surveillance. The weight of the structural frame is a major concern as it considerably affects UAV performance directly associated with payload capacity, manoeuvrability and endurance [1, 2]. Regular frames made of carbon fibre or aluminium alloys are stiff and strong but also expensive, providing a challenge for iterative prototyping and testing [3], [4]. [6].

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On the other hand, such generative design ideas combined with fused deposition modelling (FDM) 3D printing provide a low-cost and easily modifiable route for constructing lightweight UAVs [5], [6].PRISMA-based reporting for literature discovery, screening, eligibility and inclusion is adopted in this study to offer the transparency and repeatability stages necessarily required by a review article [3]. Unpublished works with similar content were also identified through systematic searches of major scholarly databases using combinations of keywords such as "UAV frame", "quadcopter", "generative design", "topology optimization," “DfAM,” and 'FDM'. Records were reviewed and screened in two rounds (title/abstract; full-text) against a pre-defined set of inclusion criteria: (i) UAV or multirotor frame/arm structures; (ii) additive manufacturing, emphasising Fused Deposition Modelling (FDM); (iii) topology optimisation or generative design approaches; and (iv) quantified mass, stiffness, stress, vibration, fatigue or manufacturability outcomes. Figure 3 lists the exclusion criteria that included non-structural UAV experiments, non-polymer AM techniques not addressing FDM limitations and publications that lacked measured performance data. The final eligible studies set (illustrated in the PRISMA flow diagram) serves as the foundation for synthesis across four key aspects: (i) algorithms design principles (goal-type generative design, density/component-based topology optimization, multi-objective optimization, and constraint management), (ii) FDM-oriented DfAM rules including overhang limits, wall thicknesses/build orientation control with anisotropy handling and infill/lattice selection excluding/include consideration.

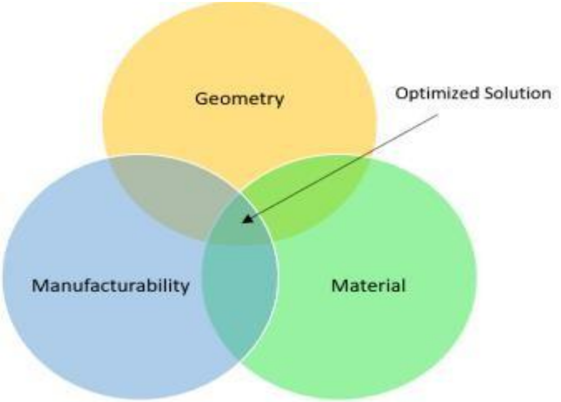


Fig. 1. Design Optimization framework

Generative design [7] is ensuring the usage of computer methods to explore a thoroughly wide variety of feasible geometries with respect to specified goals, constraints and loading cases. Contrary to classical topology optimisation, that largely removes material contained in the design space, for generative design multiple alternative topologies may be offered, where the material is placed more efficiently satisfying constraints [8], [9]. Previous studies have shown considerable mass reductions and performance benefits with frame weight decreases of 20% to 45% versus typical UAV frame configuration designs [10], [11]. The most accessible additive manufacturing process remains FDM, with rapid prototyping and the low-cost manufacture of optimised frames [12], [13]. Nevertheless, insufficient interlayer adhesion, anisotropy and low fatigue resistance still limit the real environment durability of FDM printed UAV structures [14], [15].

Optimisation in engineering design is based on the balance of manufactirability, materials and geometry. As shown in Figure [1], the optimised solution is where these elements intersect, trade off amongst production feasibility, and strength and performance. The properties that influence the lifetime and strength of the component are determined by the material, while its shape defines architecture and dynamics. Manufacturable ensures that the design is producible in a practical sense with currently available techniques. In today's generative and additive manufacturing processing, it is important to consider these three parts at once for designing cost, weight and efficient designs.

2 Fundamentals of generative design and FDM

Generative design is a computational technique for design-exploration which uses optimisations and AI-inspired search strategies to produce multiple potential geometries by repeatedly assessing engineering responses (e.g., stress, displacement, stiffness) subjected to defined load cases and constraints [16]. Designers define design space, keep-out regions, material properties, safety constraints, applied loads and boundary conditions; then the solver generates candidate topologies that satisfy constraints whilst optimizing objective functions (e.g. minimum mass at constrained deformation) [17]. While typical CAD application is mainly geometry call, generative design is performance driven and has been helpful to aerospace and automotive structures, therefore we apply that method to UAV frame components where weight and stiffness are closely connected [18]. Fused deposition modelling (FDM) is an additive manufacturing process in which thermoplastic filament is extruded from a nozzle and deposited on the build plate layer by layer, enabling low-timed, iterative frame design with common materials such as PLA, ABS, PETG, nylon and fiber-reinforced polymers to be rapidly fabricated through this method [19], [20]. FDM anisotropy limits UAV frames critically, with in-plane (X-Y) strength and stiffness generally higher than build direction (Z), which is due to interlayer bonding that encourages this. Several studies report very low Z-direction strength, indicating a general decrease of 30-60% depending on material and process parameters [21]-[23]. Manage through DfAM rules that inform generative results. With this in mind, drone arms and other high-bending members should be oriented such that the primary tensile/(compressive) loads are acting along the filament path in X-Y dimension as much as possible while concurrently avoiding Z-layer interfaces at arm roots or joint transitions.

Use raster strategies like ±45° in torsion-dominated areas to equilibrate shear transfer. Higher shell/perimeter counts and the application of locally thickened ribs imp All in all, uniting print-aware restrictions with generative design techniques enabled development of lightweight UAV's that were not just numerically optimised via simulation but also printed considerably more robust through FDM [24].

2.1 Design process and workflow

The generative design workflow generally involves four main stages:

1. Defining Constraints and Objectives – Designers input goals such as minimizing weight, maximizing stiffness, or achieving a specific natural frequency.
2. Material Selection – Appropriate materials compatible with the manufacturing process (e.g., PLA, ABS, or Nylon for FDM) are chosen.
3. Algorithmic Generation – Cloud-based or local software (like Autodesk Fusion 360, Siemens NX, or SolidWorks Generative Design) uses AI-based optimization to produce multiple geometry outcomes.

4. Evaluation and Selection – The generated results are compared based on performance parameters such as stress distribution, manufacturability, and cost efficiency [25].

2.2 Role of topology optimization

Topology optimization forms the mathematical foundation of generative design [26]. It determines the most efficient distribution of material within a defined design space to achieve the required stiffness and strength. In FDM-based applications, this ensures that the printed components are structurally sound yet lightweight. Generative algorithms apply iterative finite element analysis (FEA) to remove unnecessary material while maintaining load paths and strength requirements [27].

2.3 Selection of Material in PLA

TPLA has been used in this study primarily as a rapid prototyping filament, instead of the final flight ready material, since in FDM material attributes have significant impact on structural robustness upon the operational stresses experienced by UAVs. PLA is a biodegradable thermoplastic made from renewable feedstocks (such as corn or sugarcane). Due to its dimensional stability, low warpage, and ability to print without a heated chamber at very low nozzle temperatures (190-220 °C), it is the preferred material for 3D printing. Glass transition temperature is typically 55° to 65°, and in the previous draft, PLA thermal data has been mixed with PETG. Compared to PLA it has a very good ductility and thermal margin, prints in a higher temp range (≈230-250 °C) The primary zero of PLA for UAV frames is service durability: frames experience cyclic vibration and manoeuvre loads, with PLA being low in fatigue resistance, creep under sustained clamping loads, and heat softening near T_g affecting stiffness when exposed to warm outdoor conditions. Consequently, PLA is acceptable for indoor tests and geometry validation; on the other hand, PETG, nylon (PA), and fiber-reinforced nylons are recommended for outdoor and repeated-flight applications needing hardness together with vibration tolerance in addition to long-term stability.

3 Dynamic modelling and calculation

Aerodynamic lift is often explained by Bernoulli' s principle, which comes from the conservation of energy for fluid flow. Such an explanation is often associated with "longer-path" or "equal-transit" explanations of airflow over an airfoil. The lift force (L) can be described by the following expression:

Table 1. The components list and their weights [28].

Item	Count	Mass per Item (g)	Combined Mass (g)
RS2205S brushless motors	4 units	28.8 g	115.2 g
Pixhawk flight controller	1 unit	73 g	73 g
M8N GPS module	1 unit	32 g	32 g
5-inch propellers	4 units	4 g	16 g
BLHeli ESC modules	4 units	14 g	56 g
FC Hub / Power Distribution Board	1 unit	8.5 g	8.5 g
Camera module	1 unit	12 g	12 g
Telemetry unit	1 unit	15 g	15 g
iA6b receiver	1 unit	14.6 g	14.6 g
3S Li-Po battery	1 unit	200 g	200 g

Realistic loads were used to perform a structural response analysis with the help of finite element modeling on the selected outlined frame designs. Three-dimensional solid elements together with a varied mesh in joint and engine-mount locations were used to discretise the designs to capture local stress gradients. Element size was approximately 2–4 mm. Due to boundary limitations, the central hub/assembly interface could not fully represent the mains supports and loads were applied at the locations of the motor-mounts; these included thrust as well as payload transfer channels defined in the loading model. An isotropic ABS property set (linear elastic modulus, Poisson's ratio and yield strength for FoS reporting) was assigned to the material. Von Mises stress and global displacement were calculated using linear static analysis, while natural frequencies and mode shapes associated with vibration sensitivity were determined via modal analysis.

The materials and masses required for your modelling are given in Table 1. The total mass of the onboard components is 542.3 grams. To size the structure, the all-up mass (m) was conservatively estimated to be 1000 g when accounting for an expected frame mass (250 g) and additional 20% margin to account for wiring, fasteners, fabrication variability and payload margin. In hover, the lift generated by a rotorcraft is due to rotor thrust and is governed by momentum theory (the actuator-disk) and blade element theory, rather than Bernoulli "equal-transit-time" theories. So, total thrust required can oe approximated by vehicle weight as in (1):

$$\boldsymbol{T_{total} \approx W = mg} \qquad \textbf{(1)}$$

For a quadcopter, the thrust requirement per motor is given by (2):

$$\boldsymbol{T_{rotor} \approx mg/4} \qquad \textbf{(2)}$$

Under ideal hover conditions, momentum theory relates thrust to induced velocity as expressed in (3):

$$\boldsymbol{T = 2\rho A v_i^2} \qquad \textbf{(3)}$$

where $\boldsymbol{\rho}$ is air density, $\boldsymbol{A}$ is the rotor disk area, and $\boldsymbol{v_i}$is induced velocity. These relationships define the baseline thrust targets, which are applied to identify load cases and vibration excitation sources acting on the frame. The choice of propeller influences the characteristics of both efficiency and excitation: The two-blade propeller produces two dominant pressure pulses per revolution, whereas the three-blade propeller produces three pulses per revolution, leading to smoother thrust delivery and lower tonal noise at comparable operating conditions [29], [30].

4 Designing and selecting quadcopter structures through generative

The generative processes are now made up of a basic three-steps process composed of Generate-Define-Explore; defined together, the mediating factors in human-computer interaction design (HCID). At the Define stage, the designer communicates his or her vision of design to computer and sets goals or boundary conditions to describe a problem. In the Generate phase, there are detailed requirements submitted by a user, the system processes those, and from different engineering perspectives it generates diverse design options. At the Explore level, the system can generate an array of design options that meet defined parameters and constraints. Four key exploration mechanisms in RL inspired the development of techniques such as BESO and SIMP used extensively for structural topology optimisation, as stated by Hongbo Sun [31]. Sangeun [33] proposed a solution composed of an iterative design exploration system and a design evaluation module.

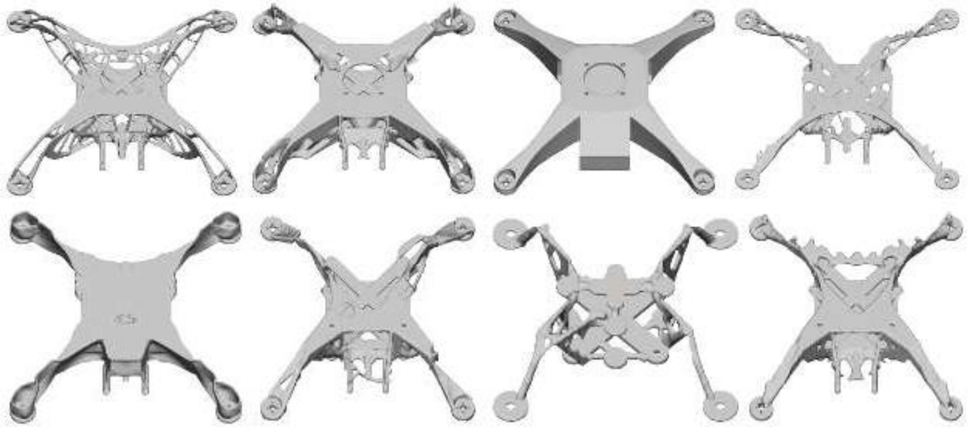


Fig. 2. Outcomes generated through the applied generative design process [33].

Table 1 provides an overview of the parameters employed in the generative design approach to develop the quadcopter frames. One such information measure is the entropy of the several possible outputs (Fig. 4), eight designs were selected that best meet the objectives of the project and feasibility of production. Subsequently, the stress-strain response, vibration behaviour, total frame mass and reported safety factor of selected variants were examined and compared to identify best configuration. Known as the generative solver, an iterative search engine reviews the evolving CAD representation in each iteration of evaluation and updates future candidates according to prior iterations until convergence on user-defined criteria and constraints [34]. However, most generative geometries are been created independent from procedural logic and are abstracted away from the user even though current CAD applications still depend on explicit geometric constraints and dimensions [35]. A particularly important aspect of generative design is its ability to grow a structure from an initial seed mass into a load-path-compliant shape while also remaining manufacturable in practice. Every iteration obeys boundary constraints, keep-out zones, interfaces and apertures while subtracting material in a regimented fashion to eliminate unnecessary weight, with a cloud-computing engine analyzing competing topologies and their physical performances. Any output that is created, but does not conform to the desired criteria/constraint gets discarded [36]. These optimised solutions selected for discussion are presented in Figure 3 along with their performance compared against the DJI F450 reference frame (Fig. 2) on information from the manufacturing status, experiment available data, material selection, single part cost, fully burdened cost, volume and mass ready condition at maximum von Mises stress under peak load conditions in addition to the minimum safety factor and maximum global displacement [37]. To increase its practical relevance beyond a single static scenario, the assessment accounts for representative UAV load cases (hover-thrust with cargo; hard-landing vertical shock; yaw-maneuver torsion on the arms; transient roll and pitch accelerations). These serve as lessons for possible failure modes for FDM frames: These mechanical loading scenarios may lead to arm-root delocation in the Z build direction, crack initiation at all joints and motors mounts due to fatigue, In addition creep deformation near the motors due coupled heating and cyclic vibration.

(a) Frame 1 (b) Frame 2

Fig. 3. Optimised design result derived through generative design [37].

Table 2. Comparative outcomes of generative design studies (reported metrics and interpretation constraints) [37]

Parameter	Frame 1 (Study 8 – Outcome 1)	Frame 2 (New Study 5 – Outcome 1)
Status	Analysis completed	Solution converged
Material	ABS (linear elastic model)	ABS (linear elastic model)
Build orientation	Not specified	X+ direction
Manufacturing route	No process restrictions	Additive manufacturing
Visual classification	Group 4 category	Unique geometry
Production quantity (pcs)	2500	2500
Part cost (USD)	303–624 (median 418)	272–524 (median 348)
Fully burdened cost (USD)	303–624 (median 418)	272–524 (median 348)
Volume (mm^3)	214,162.43	260,586.40
Mass (kg)	0.227	0.276
Maximum von Mises stress (MPa)	1.5	0.1
Maximum global displacement (mm)	6.22	0.01
Reported minimum safety factor (software output)	13.30	137.03
Safety factor used for interpretation (capped)	≥ 5 (reported as “high margin”)	≥ 5 (reported as “high margin”)

The very high FoS values reported by yield-based FEA post-processing (13.30 and 137.03) as listed in Table 2 represent an artefact known to appear when attempting to evaluate the operational margins of UAVs using this technique, and they should not be interpreted as reflecting accurate safety margins for application: if a computation returns von Mises stress that is much smaller than the assumed material strength, its value will inflate and unwieldy FoS values are returned which say little about realistic order-of-magnitude margins for operation. Thus, the FoS is used here only to verify that both designs remain well within the assumed elastic limit with respect to the imposed load case, using maximum von Mises stress and total global displacement as control comparison metrics. A modal of the results is interpreted based on the mentioned modelling assumptions (linear static response, isotropic ABS property set, idealised constraints) which applies thrust/payload induced forces across the motor-mount interfaces and constrain central hub/joint regions to represent assembly supports. Assuming far lower stress and displacement prediction under these conditions, Frame 2's greater mass implies a stiffness-dominant structural form, transferring more material that follows primary load paths and through connections. This describes the realistic trade-off: stiffening and reducing deformation generally yield increase in mass while inflating FoS under negligible stress. Design relevance: FoS (factor of safety) values above a practical threshold are limited in interpretation (e.g., FoS ≥ 5 →"high margin") and future optimisation should be directed at achieving an overarching control from FoS ≈ 2-3 with fatigue-aware constraints to depict cyclic vibration, manoeuvre loads and more realistic mission envelopes. The geometric (motor-to-motor) base distance was constant as the 450 mm wheelbase, and a circular envelope of this diameter was all adopted for comparing developed quadcopter frames with reference DJI frame with the same wheelbase to allow consistent comparisons between mass and load-carrying capability; this is seen in Fig. 3. A guided step-by-step graphical user interface leads the user with every phase of the generative workflow [38], while in engineering design optimisation supervised learning was often applied to train good estimations of feasible regions, improving evaluation cycles during exploration [39, 40]. The resulting node-based geometry from the design space exploration can be further refined for manufacturability through multi-stage structural optimisation processes incorporating specific additive-manufacturing constraints such as minimum feature size, overhang limits, and various build-direction considerations [41], [42].

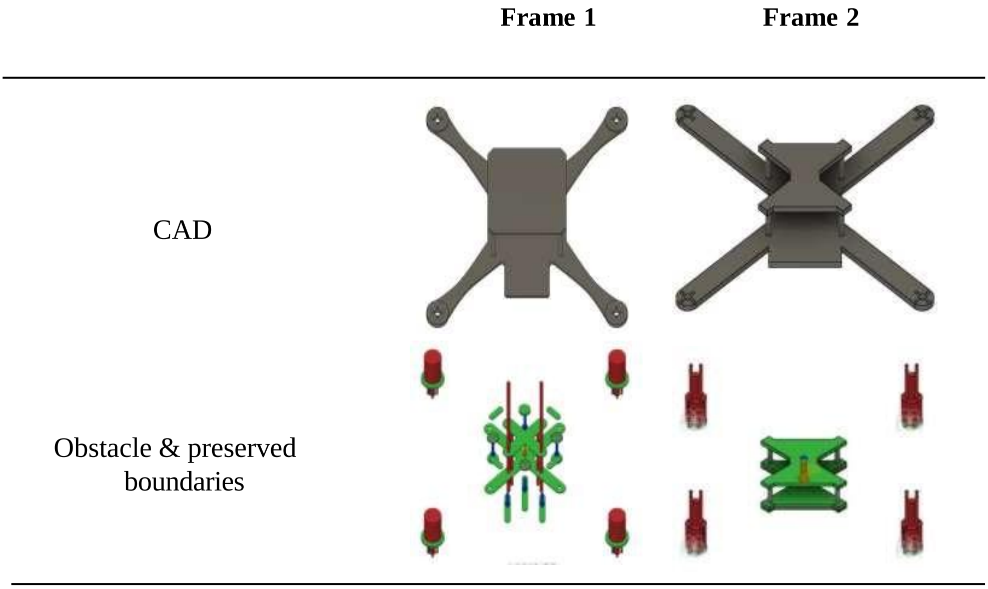


Figure 4. The schematic representation of DJI F450 drone frame [41]

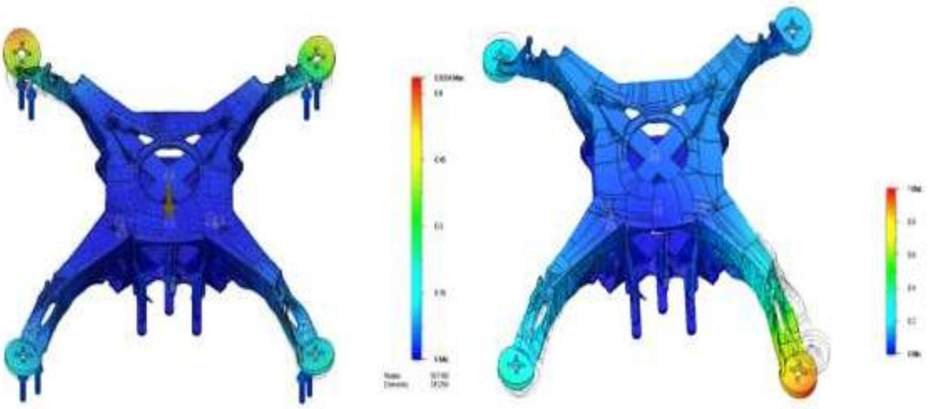


Fig. 5. Frame 1

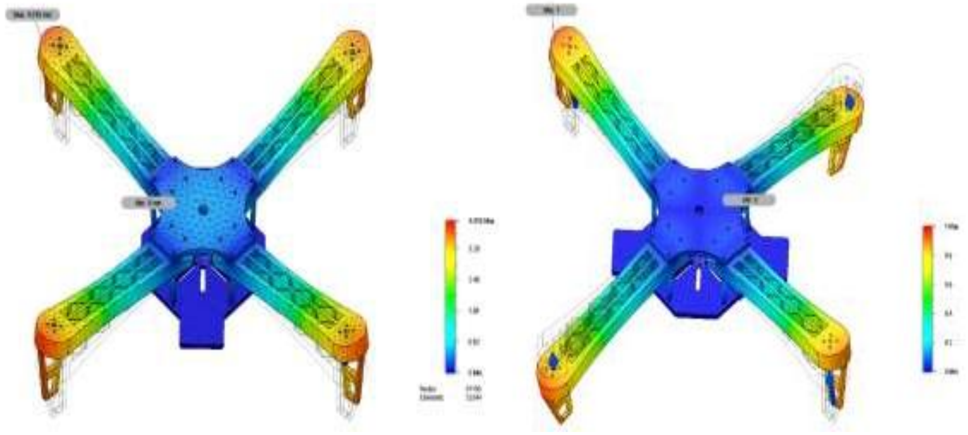
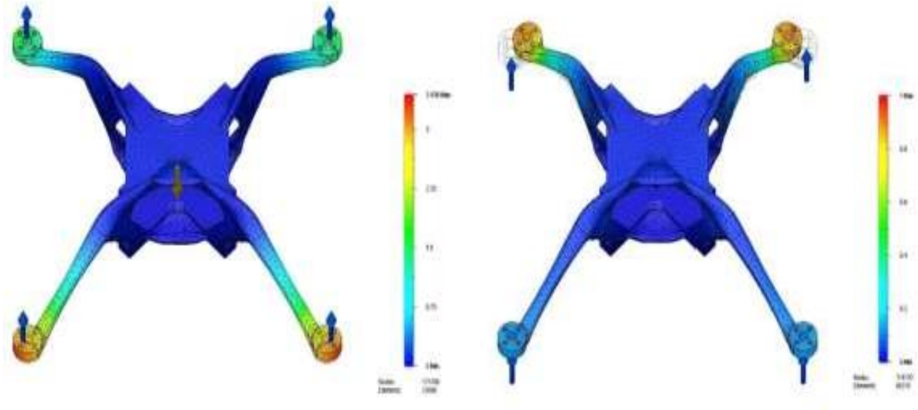


Fig. 6. Frame. 2



Fig,. 7. Frame. 3 [42]

Table 3. Comparison of displacement and modular frequency between different frames.

Parameter	**Frame 1**	**Frame 2**	**Frame 3**
Design Method	Traditional CAD	Semi-optimized Generative Design	Fully Optimized Generative Design
Stress Concentration	High at joints	Reduced	Minimum
Displacement (Deformation)	Moderate	Low	Very Low
Mass (Weight)	High	Reduced	Lowest
Safety Factor	Basic	Improved	Maximum

When comparing Frame 1, Frame 2, and the DJI reference structure (Figure 4), significant differences can be noticed in both of the trials [43]. Note that every frame remains at all times within the assumed safety margin. This demonstrates that for the given structural constraints, all models are able to carry the applied simulation load without breaking [45], [46]. As dictated by prior art setup practice, the axial compression gives rise to local stress zones in the standoff region at the edge of placement of drone arm termination 45 junction as depicted in Figure 4. This area may degrade print after print over repeated loading [47, 48]. The generatively designed frames are also able to endure cyclic and repetitive loads even with potential stress concentrations. The generative design algorithm reduces total mass, eliminates the material stress hotspots, and improves structure performance through gradually adjusting the material distribution in each iteration of the design process [49].

Symmetry is key to the design of a frame, as it ensures that the center of mass for the drone will line up with the desired location of its center of gravity. Most of the dozens of design options generated during the study exhibited greater material concentration in the standoff zone that linked the arms with the central body of dispatch. This is not surprising since the stabilizing mass in that region has to oppose the translated force coming out from the thruster/payload combination [50], [51], and [52]. Additional overhangs were added to alleviate the pressures in this region. Differences in the distribution of material over the standoff area, correlated with differences in safety factor and total frame mass, were present as well. For the most part, additional overhanging structures must be added to increase the MR so that the absolute mass of the frame may still increase to provide an adequate factor of safety. In contrast, compared to the mass-equivalent cases but with lighter standoff geometry, heavier standoffs decrease the safety factor [53]. The conventional F450 frame (as shown in figure 2(a)) has some structurally weak regions with triangle joints, and it weighs much more than the optimized ones in a generative sense [22].

There are 3 things that will make the difference in how they will be flying compared to a conventionally built F450: 1st comparisons Analysis of the optimized frames for the F450s, we find as follows: For instance, the safety factor of Frame 2 is more than forty times higher compared to the DJI frame in Fig. For the same material data and loading conditions, the probability of failure is likewise higher for the generatively created versions in the case of the DJI model. Von Mises values also help to determine whether a material will fail or creep with time. Since the stress of the DJI frame is about 11.4 times greater than lightweight aerospace-grade construction, tooth 1 shows quite a screen ratio of deformation or damage resistance. These features allow you to use these optimized frames in several applications, including the recreational. The upward displacement of Frame 2 at section AA is extremely small (compared to Figure 4, which was around 0.01 millimeter with load), and it's about four-hundredths of the DJI frame in this area. This indicates that the optimized geometry is stiffer and less deformable. The mass of the optimized frames is also sizably below the weight of the DJI S500: while that weighs 330 g, Frame 1 and Frame 2 (the lightest generative designs) only weigh in at 227 and 267 g, respectively. The following findings are derived from a large-scale data collection and analysis over all our experiments [56], [47].

5 Conclusion

This review evaluated the potential for generative design and topology optimisation, in combination with FDM 3D printing, to produce lightweight UAV frames through material redistribution along primary load paths while still satisfying stiffness and strength demands. Compared to traditional CAD-based frames, optimising additive manufacturing constraints (minimum feature size, overhang limits and joint manufacturability) can lead to weight savings of 15-50% (up to ~45% in some case studies). Material selection was concluded to be critical for serviceability: PLA and ABS suffice for testing geometric conformance through rapid prototyping, but outdoor operation and propeller-induced cyclic vibration require higher tolerance profiles for fatigue life and thermal stability; in the flight-capable context PETG is useful where increased toughness is desired, nylon dramatically inflates this envelope but if a very strong -stiffness-weight pack ratio is required then carbon-fiber-reinforced nylon becomes favorable. The most substantial limitation of FDM frames is still print-process anisotropy, and most studies report greater in-plane (X-Y) strength than Z-direction performance [60], highlighting the need for careful DfAM rules regarding build orientation, raster method, perimeter reinforcement, and joint design. Although simulation results show optimised frames will exhibit lower stress concentrations and displacement, repeatability is gained by limited FEA setup detail being reported, manufacturing variability and off-design load cases such as landing shock and yaw torsion.

Future work is warranted into fatigue-aware optimisation, comprehensive benchmarking with quantification of tolerance, and validation in the field to transfer optimised geometries into certifiable UAV structure.

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