AEROSP588 Assignment 7 Report - MDO Architectures for Drone Sizing

Zerong Huang (Jason)

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Abstract

This report studies multidisciplinary design optimization (MDO) for the conceptual sizing of a two-passenger electric multicopter. The objective is to minimize maximum takeoff weight (MTOW) while meeting power and energy feasibility, as well as model consistency. Two standard MDO architectures are implemented in OpenMDAO. The multidisciplinary feasible (MDF) approach enforces consistency using an internal nonlinear solver, while the individual discipline feasible (IDF) approach enforces consistency using an equality constraint at the system level. Two model fidelities are also compared. The first is a simple hover model based on momentum theory. The second is a mission-profile model that includes climb and descent segments. The results show that MDF and IDF converge to the same optimal MTOW for the simple model, which is consistent with their equivalence at the optimum. In addition, the gradient-based method (SLSQP) converges in fewer iterations than the gradient-free method (COBYLA). Finally, the mission-profile model leads to a slightly higher MTOW and a larger motor mass, which indicates that hover-only sizing can under-predict peak power needs during climb.

1 Introduction

1.1 Motivation and Background

The concept of Urban Air Mobility (UAM) has emerged as a transformative solution to alleviate ground traffic congestion and reduce carbon emissions in metropolitan areas. Within this domain, this project specifically targets a two-passenger eVTOL configuration. This design choice is driven by the operational reality of urban transportation, where the majority of commuting trips involve only one to two occupants. Indeed, statistical analysis of the current eVTOL design population reveals that most conceptual vehicles are specified for a maximum capacity of one to two people [1].

Beyond daily commuting, this compact class of vehicles is highly versatile, applicable to scenarios such as aerial tourism and emergency rescue operations in complex terrain. The "small-scale" philosophy also addresses the critical challenge of economic viability. Since the electric propulsion system accounts for approximately 40% of the total aircraft cost [2], limiting the vehicle size to two passengers keeps the manufacturing and operational costs controllable. Furthermore, while eUAM platforms operate under severe weight and power constraints [3], a smaller payload makes the design achievable with current battery energy densities, reducing the reliance on unproven future technologies.

1.2 The Engineering Challenge: The Weight Spiral

The preliminary sizing of an eVTOL aircraft is governed by a strongly coupled physics phenomenon known as the "Weight Spiral." The power required to hover is directly proportional to the aircraft's total mass raised to the power of 1.5 ($P \propto M^{1.5}$) according to momentum theory. Consequently, an increase in battery mass to satisfy range requirements necessitates a larger propulsion system (motors and rotors) to provide sufficient lift, which in turn adds structural mass, further increasing the power demand. This positive feedback loop creates a highly sensitive design space where traditional sequential design methods often fail to converge to an optimal solution.

Recent literature emphasizes that optimizing these vehicles requires a deep understanding of component interactions. For instance, the choice of the number of rotors significantly influences both the power budget and the gross weight [1], while the demand for high torque density in electric motors drives the need for advanced electromagnetic topologies and integrated cooling solutions [2].

1.3 Project Scope and Objectives

This project focuses on the conceptual sizing and optimization of a 2-passenger electric multicopter. The primary objective is to minimize the Maximum Takeoff Weight (MTOW) while satisfying critical mission constraints, including hover capability, cruise range, and physical consistency.

To address the multidisciplinary couplings between Aerodynamics, Propulsion, and Mass sizing, this study applies Multidisciplinary Design Optimization (MDO) techniques. Specifically, we conduct a comparative analysis of two fundamental MDO architectures:

- **Multidisciplinary Feasible (MDF):** An architecture that maintains physical consistency at every optimization iteration using a nested solver.
- **Individual Discipline Feasible (IDF):** An architecture that decouples disciplines and manages consistency through equality constraints at the system level.

By implementing these architectures in the OpenMDAO framework, this report evaluates their performance in terms of convergence stability, computational cost, and their ability to handle the non-linear "weight spiral" inherent in UAM design. Furthermore, the study investigates the impact of model fidelity by comparing a simple momentum-based model against a complex mission-profile simulation.

2 Problem Formulation

2.1 Concept of Operations (ConOps)

The target vehicle is a two-passenger electric multicopter designed for urban air mobility missions. The representative mission profile consists of a vertical takeoff, a hover/cruise phase, and a vertical landing. For the purpose of the primary sizing optimization, the mission is simplified to a sustained hover duration of 20 minutes (1200 s), which represents the most power-intensive flight condition for rotary-wing aircraft. This conservative approach ensures that the propulsion system is sized to handle the peak power requirements of vertical flight.

2.2 Optimization Statement

The sizing problem is formulated as a constrained minimization problem aimed at finding the lightest possible vehicle that meets the mission requirements. Minimizing the Maximum Takeoff Weight (MTOW) is chosen as the objective function because aircraft mass acts as a primary driver for both acquisition cost and energy consumption.

The optimization problem is mathematically stated as follows:

$$
\begin{aligned}
\underset{x}{\text{minimize}} \quad & M_{total} \\
\text{with respect to} \quad & x = [M_{batt}, M_{motor}]^T \\
\text{subject to} \quad & g_1(x) : P_{avail} \geq P_{req} \quad \text{(Power Margin)} \\
& g_2(x) : E_{avail} \geq E_{req} \quad \text{(Energy Margin)}
\end{aligned}
\tag{1}
$$

In the IDF architecture, an additional design variable M^*_{total} (target mass) and a consistency constraint $h_1(x) : M^*_{total} - M_{computed} = 0$ are introduced to decouple the disciplines.

2.2.1 Problem Classification

This sizing task is a constrained nonlinear optimization problem with continuous design variables. In the simple formulation, the design variables are the battery mass M_{batt} and the motor mass M_{motor}. In the IDF formulation, an additional continuous variable is introduced for the coupling target mass, and one equality consistency constraint is added. The objective and constraints are deterministic because the models do not include random sampling. For the simple model, the objective and constraints are smooth analytic functions of the design variables, so first-order derivatives exist. For the mission-profile model, the analysis uses time stepping, so small discretization effects may appear. However, the problem remains continuous and it is treated as differentiable within the OpenMDAO derivative framework. The problem is strongly coupled because total mass affects required power and energy, while component sizing feeds back into the total mass through the structural mass relation.

2.3 Mathematical Modeling

2.3.1 Aerodynamics (Momentum Theory)

To estimate the power required for flight, we employ the Momentum Theory (or Actuator Disk Theory), which is the standard first-order approximation for rotorcraft performance [4]. The ideal power (P_{ideal}) required to generate thrust T equal to the aircraft weight W is given by:

$$P_{ideal} = \frac{T^{1.5}}{\sqrt{2\rho A}} \tag{2}$$

where ρ is the air density ($1.225\ kg/m^3$) and A is the total propeller disk area.

However, ideal theory underestimates the actual power required due to profile drag, tip losses, and non-uniform inflow. To account for these losses, we introduce a Figure of Merit (FM), which is the ratio of ideal power to actual power. Based on the analysis of eVTOL flight performance by Fukumine et al. [5], a Figure of Merit of 0.75 is selected for this study. The actual power required (P_{req}) is thus modeled as:

$$P_{req} = \frac{P_{ideal}}{FM} = \frac{(M_{total} \cdot g)^{1.5}}{0.75 \cdot \sqrt{2\rho A}} \tag{3}$$

2.3.2 Mass and Structure (The Weight Spiral)

The mass estimation model is critical for capturing the "weight spiral" effect. We adopt a component buildup method where the total mass is the sum of the propulsion system, payload, fixed avionics, and structural mass. Crucially, the structural mass is not fixed but is modeled as a fraction

of the total takeoff weight (MTOW), reflecting the engineering reality that heavier aircraft require stronger and heavier airframes. Following the statistical weight analysis of eVTOLs by Usov et al. [1], we set the structural weight fraction (f_{struct}) to **30%**.
The total mass equation is derived as follows:

$$M_{total} = M_{batt} + M_{motor} + M_{pay} + M_{avi} + (f_{struct} \cdot M_{total}) \tag{4}$$

Solving for M_{total}, we obtain the coupling equation used in the `MassComp` discipline:

$$M_{total} = \frac{M_{batt} + M_{motor} + M_{pay} + M_{avi}}{1 - f_{struct}} \tag{5}$$

This equation highlights the non-linear sensitivity: adding 1 kg of battery mass actually increases the total aircraft weight by approximately 1.43 kg $(1/(1-0.3))$ due to the structural penalty.

2.3.3 Propulsion System

The electric propulsion system is modeled using linear density parameters derived from current and near-future technology forecasts. The available power (P_{avail}) and energy (E_{avail}) are calculated as:

$$P_{avail} = M_{motor} \cdot p_{density} \tag{6}$$

$$E_{avail} = M_{batt} \cdot e_{density} \tag{7}$$

The specific parameter values are selected based on a review of state-of-the-art components [2, 3].

2.4 Parameter Selection

The key parameters defining the design space are summarized in Table 1. These values represent a high-performance ("Next-Gen") UAM vehicle scenario.

Table 1: Key Design Parameters and Sources

Parameter	**Symbol**	**Value**	**Source**
Battery Energy Density	e_{dens}	450 Wh/kg ($1.62 \cdot 10^6$ J/kg)	[3]
Motor Power Density	p_{dens}	5.0 kW/kg (5000 W/kg)	[2]
Structural Mass Fraction	f_{struct}	0.30 (30%)	[1]
Payload Mass	M_{pay}	200.0 kg	(2 Pax + Luggage)
Fixed Avionics Mass	M_{avi}	100.0 kg	Assumed
Propeller Disk Area	A	20.0 m^2	UAM Scale
Hover Time	t_{hover}	1200 s (20 min)	Mission Req.
Figure of Merit	FM	0.75	[5]
Gravity	g	9.81 m/s^2	Standard

3 MDO Implementation

3.1 Computational Framework

The optimization problem was implemented using the **OpenMDAO** framework [6], an open-source high-performance computing platform for systems analysis and optimization. OpenMDAO was selected for its unique capability to compute coupled derivatives efficiently using the unified derivatives equations, which is critical for gradient-based optimization in strongly coupled systems like eVTOLs.

3.2 MDO Architectures

To investigate the coupling effects, two distinct MDO architectures were implemented and compared: Multidisciplinary Feasible (MDF) and Individual Discipline Feasible (IDF).

3.2.1 Multidisciplinary Feasible (MDF)

In the MDF architecture, the disciplinary analyses are fully coupled within the optimization loop. For every design point x queried by the optimizer, a multidisciplinary analysis (MDA) is performed to converge the coupling variables (in this case, M_{total}) until physical consistency is achieved.

According to Martins and Ning [7], MDF reduces the optimization problem dimension by eliminating coupling variables and consistency constraints from the optimizer's view. However, it requires a robust nonlinear solver (e.g., Newton-Raphson) at every iteration, which can be computationally expensive if the analysis is costly. In our implementation, we utilized a `NewtonSolver` coupled with a `DirectSolver` to resolve the Mass-Aerodynamics cycle implicitly.

3.2.2 Individual Discipline Feasible (IDF)

The IDF architecture decouples the disciplines by introducing the coupling variable (Target Mass, M^*_{total}) as a new design variable and adding a consistency constraint:

$$h_{consistency}(x) = M^*_{total} - M_{computed}(x) = 0 \tag{8}$$

As described in [7], this approach allows disciplines to be evaluated in parallel and removes the need for an internal iterative solver. The optimizer assumes the burden of driving the system to physical consistency. While this increases the size of the design space, it often improves robustness in regions where the multidisciplinary analysis might fail to converge.

3.3 N2 Diagram

The data flow and coupling structure of the problem are visualized using the N2 diagram (Figure 1). The diagram highlights the feedback loop between the `MassComp` and `AeroComp`, which is handled internally in MDF but broken in IDF via the target variable.

3.4 Optimization Algorithms

To evaluate the impact of derivative information, two distinct optimization algorithms were tested:

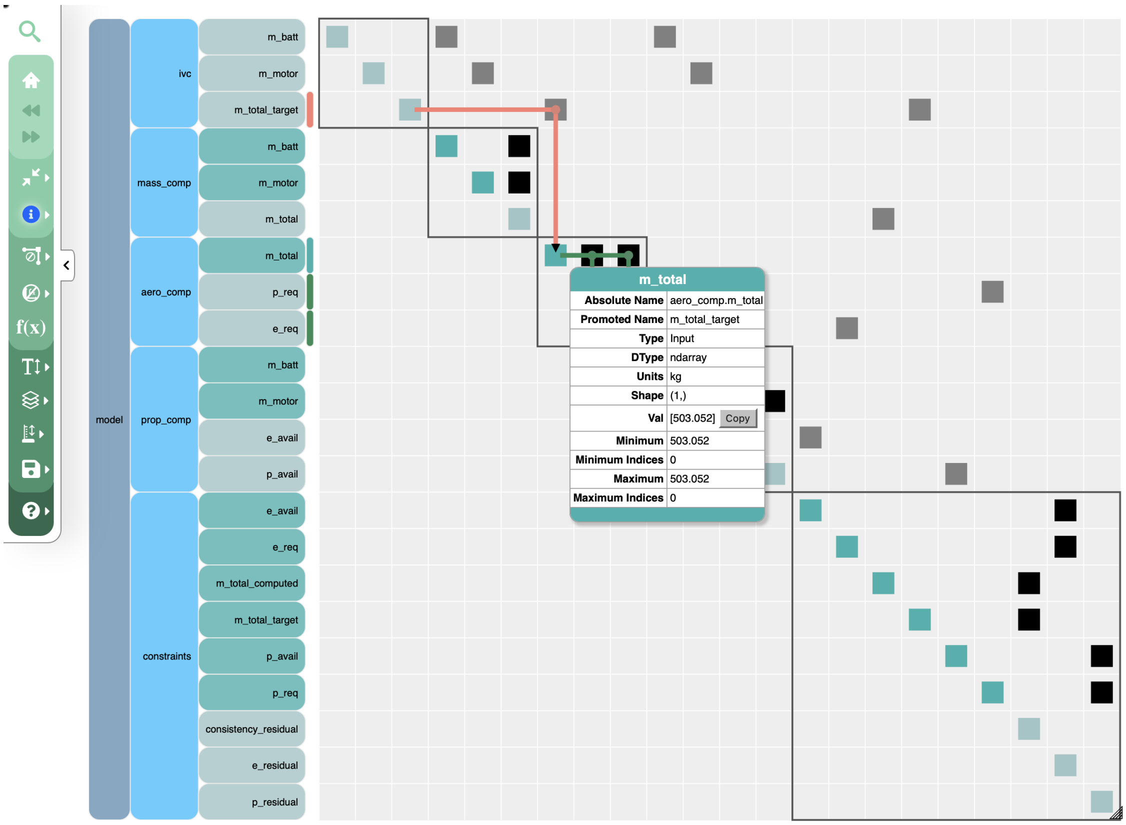

Figure 1: N2 Diagram illustrating the coupling between Mass, Aerodynamics, and Propulsion disciplines.

- **SLSQP (Sequential Least Squares Programming):** A gradient-based algorithm that utilizes analytic partial derivatives provided by the OpenMDAO components. It is chosen for its efficiency in navigating the unimodal, smooth design space of this problem.
- **COBYLA (Constrained Optimization BY Linear Approximation):** A gradient-free algorithm that relies on linear approximations. It serves as a baseline to demonstrate the computational efficiency gains achieved by using analytic derivatives.

3.5 Investigation on the Coupled Models

3.5.1 Bounds and Feasible Region

The design variables represent component masses, so they must remain nonnegative. A wide-view sweep over battery mass and motor mass is used to identify the feasible region from the power and energy margins. Infeasible designs occur when the motor is too small to meet the power requirement or when the battery is too small to meet the energy requirement. The optimum lies near the boundary where the feasibility limits become active, which is expected for a mass-minimization problem.

3.5.2 Modality

The design-space trends suggest a single dominant basin within the feasible region. As either battery mass or motor mass increases, the total mass generally increases because both variables enter the total mass directly and also increase structural mass through the weight spiral. Therefore, the optimum is expected to be unique and located at the smallest feasible point that satisfies the constraints.

3.5.3 Choice of Coupled Solver

In MDF, the mass and aerodynamics disciplines form an algebraic loop because required power depends on total mass, and total mass includes structural mass that scales with MTOW. This loop is solved using a Newton-based nonlinear solver with a direct linear solver, so the optimizer always evaluates a consistent design. In IDF, the loop is broken by promoting the coupling quantity to the system level and enforcing consistency using an equality constraint. This avoids an inner nonlinear solve, but it increases the number of design variables and constraints in the optimization problem.

3.5.4 Numerical Noise

For the simple model, the governing equations are closed-form and do not require time integration, so numerical noise is expected to be small. For the mission-profile model, numerical noise can come from time discretization and segment transitions. The observed optimization histories are smooth and do not show oscillations, so any numerical noise is small compared with the design sensitivities. This also supports the use of a gradient-based optimizer after scaling variables and constraints to similar magnitudes.

3.5.5 Solver Performance

In MDF, solver performance is tied to the internal coupled-solver convergence. The Newton-based solver drives coupling residuals to a small tolerance at each optimizer iteration, so each evaluation is physically consistent. In IDF, performance is reflected in the consistency constraint history. Starting from an intentionally inconsistent initial condition, the optimization reduces the consistency error by many orders of magnitude and converges to a consistent optimum. Overall, both architectures are robust for this problem, but their computational effort is distributed differently. MDF spends effort inside each iteration, while IDF shifts more work to the optimizer level.

3.5.6 Derivative Computation

Accurate derivatives help improve optimization efficiency for this coupled problem. For the simple model, analytic partial derivatives are provided at the component level. For the mission-profile model, finite-difference gradients can be expensive and sensitive to step size. Instead, OpenMDAO assembles total derivatives using its derivative framework, which supports efficient use of SLSQP compared with a gradient-free method.

4 Results and Discussion

4.1 Design Space Analysis

To investigate the global behavior of the sizing problem, a glance of the design space was performed. Figure 2 visualizes the objective function (Total Mass) contours and the constraint boundaries.

The design space is characterized by a feasible region defined by the intersection of the Power Limit (Red line) and the Energy Limit (Blue line). The Power Limit restricts the lower bound of the motor mass, ensuring sufficient thrust for takeoff, while the Energy Limit constrains the battery mass.

The optimal design point (marked by the star, $\approx 515\ kg$) lies exactly at the intersection of these two active constraints. This confirms that the vehicle is fully constrained by both power and energy requirements, utilizing the minimal necessary component masses to satisfy the mission.

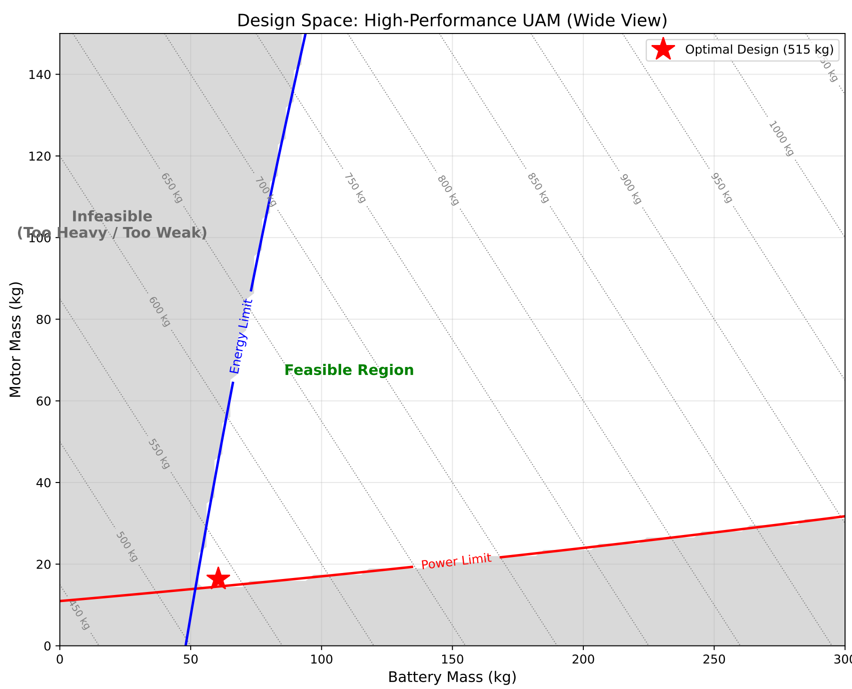

Figure 2: Design Space Contour Plot showing the objective function and active constraints. The optimal solution is located at the intersection of Power and Energy limits.

4.1.1 Note on quantitative values in parametric plots

The design-space sweep and the sensitivity sweep are used to show the feasible region and the trend created by the weight spiral. Because these plots are based on a coarse parametric scan and plot annotations, the labeled values should be treated as approximate. The numerical values reported in Table 2 come from the coupled optimization runs and should be used as the main reference for the optimal MTOW and component masses.

4.2 Quantitative Verification and Model Comparison

To validate the optimization results and assess the impact of model fidelity, a comparative analysis was performed across three experimental setups: MDF with a Simple Model, IDF with a Simple Model, and MDF with a Complex Mission Profile. The detailed mass breakdown for each optimal design is summarized in Table 2.

Table 2: Comparison of Optimization Results across Architectures and Model Fidelities

Parameter	MDF (Simple)	IDF (Simple)	MDF (Complex)
Total Mass (MTOW)	**538.44 kg**	**538.44 kg**	**541.35 kg**
Battery Mass (M_{batt})	60.56 kg	60.56 kg	57.63 kg
Motor Mass (M_{motor})	16.35 kg	16.35 kg	21.32 kg
Structure & Avionics	261.53 kg	261.53 kg	262.41 kg

4.3 Architecture Comparison: MDF vs. IDF

The convergence history of the two MDO architectures using the SLSQP optimizer is compared in Figure 3. The convergence history of the two MDO architectures using the COBYLA optimizer is compared in Figure 4.

- **MDF Performance:** The MDF architecture (Blue line) exhibits rapid convergence. This efficiency stems from the internal Newton solver, which ensures physical consistency at every optimization step.
- **IDF Performance:** The IDF architecture (Orange line) successfully drives the consistency residual from 10^3 down to 10^{-10}, verifying the mathematical equivalence of the converged IDF solution to the MDF solution.

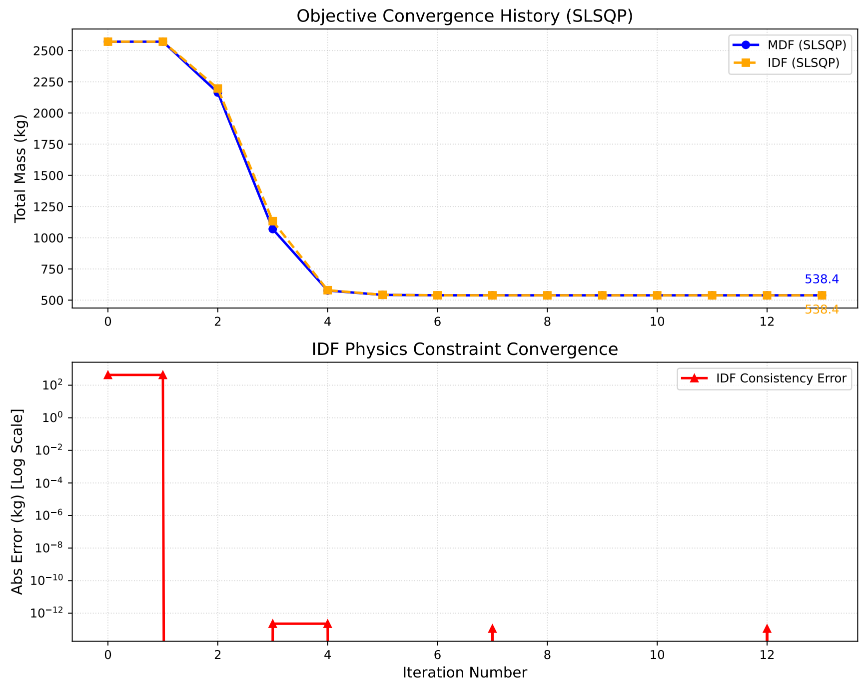

Figure 3: Convergence history comparison between MDF and IDF architectures using SLSQP. IDF shows the elimination of physical inconsistency over iterations.

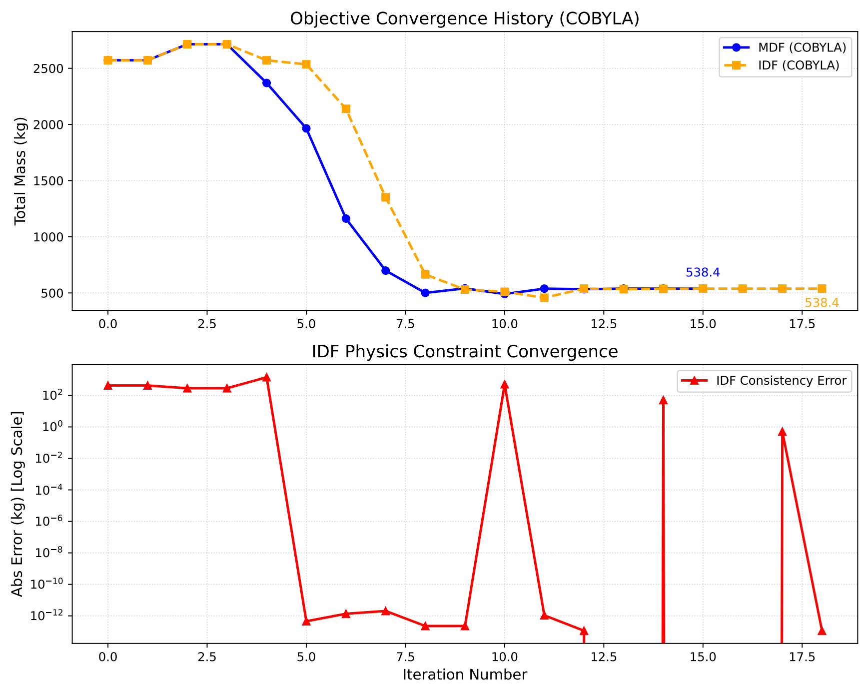

Figure 4: Convergence history comparison between MDF and IDF architectures using COBYLA. IDF shows the elimination of physical inconsistency over iterations.

To evaluate the impact of algorithmic selection on convergence efficiency, the optimization problem was solved using two distinct classes of algorithms: **SLSQP** (Gradient-Based) and **COBYLA** (Gradient-Free). The convergence histories for both cases are presented in Figure 3 and Figure 4.

- **SLSQP (Sequential Least Squares Programming):** As shown in the first plot, the SLSQP algorithm exhibits a highly efficient, monotonic convergence path. By leveraging the analytic partial derivatives provided by OpenMDAO, the optimizer can accurately determine the steepest descent direction at every step. Consequently, it reaches the optimal mass of 538.44 kg in only 14 iterations. The smoothness of the curve indicates that the problem formulation is well-posed and differentiable.
- **COBYLA (Constrained Optimization BY Linear Approximation):** In contrast, the second plot illustrates the behavior of a gradient-free algorithm. COBYLA relies on constructing linear approximations of the objective and constraints by sampling the design space. This process is inherently less efficient for this type of problem. The convergence history shows a more hesitant trajectory, requiring 19 iterations to reach the same result. Furthermore, COBYLA treats equality constraints less rigorously than SLSQP, often requiring more function evaluations to satisfy tolerances.

Summary: The comparison conclusively demonstrates the advantage of derivative-based optimization for MDO problems. While COBYLA is robust against noise, the availability of analytic derivatives makes SLSQP significantly faster and more precise for aircraft sizing tasks.

4.4 Sensitivity Analysis and Weight Spiral

The sensitivity of the optimal Total Mass to the required Hover Time is presented in Figure 5. The curve demonstrates the non-linear "Weight Spiral" effect.

As the hover duration requirement increases, the battery mass increases; however, due to the structural weight fraction ($f_{struct} = 0.3$), every kilogram of added battery requires additional structural mass, which in turn requires more power and motor mass. For the baseline mission of 20 minutes, the optimal mass is approximately 521.5 kg.

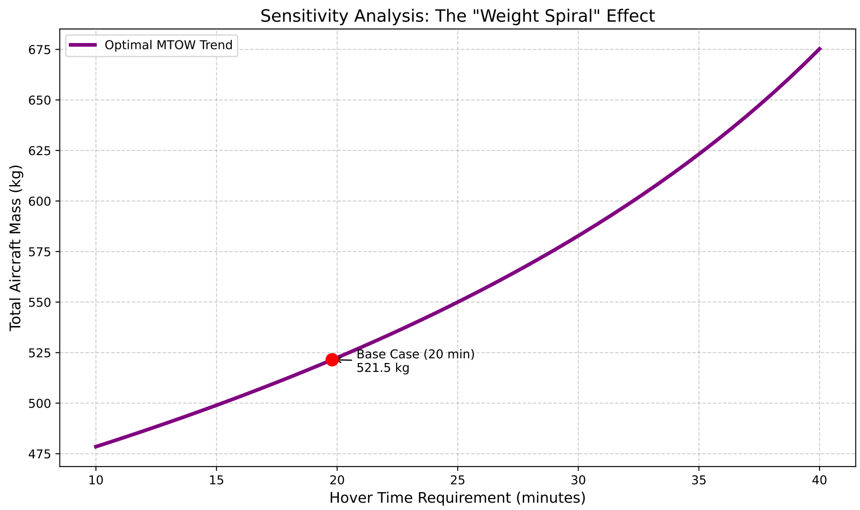

Figure 5: Sensitivity Analysis: Impact of Hover Time on Total Aircraft Mass, illustrating the non-linear weight spiral effect.

4.5 Optimizer Comparison

The efficiency of gradient-based optimization is highlighted in Figure 6. The SLSQP algorithm, leveraging analytic derivatives, converges in significantly fewer iterations compared to the gradient-free COBYLA algorithm. This result validates the implementation of partial derivatives in the OpenMDAO components.

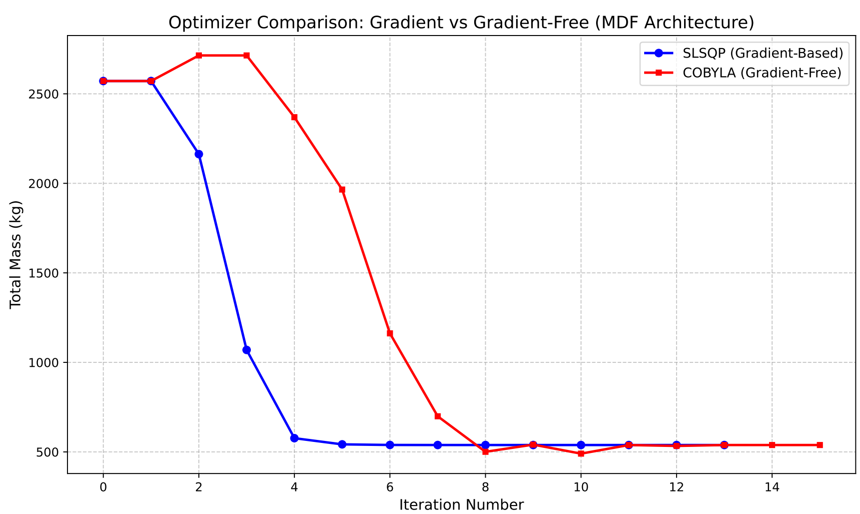

Figure 6: Comparison of Gradient-Based (SLSQP) vs. Gradient-Free (COBYLA) optimization performance.

4.6 Discussion

4.6.1 Equivalence of MDO Architectures (MDF vs. IDF)

As evidenced in Table 2, the MDF and IDF architectures converged to an identical optimal mass of 538.44 kg. This numerical equivalence validates the mathematical formulation of the optimization problem. Although IDF operates in a larger design space and initially violates physics constraints, its final converged state satisfies the consistency constraint ($h_1 = 0$), rendering it physically identical to the MDF solution. This confirms that the choice between MDF and IDF is a trade-off between computational cost and implementation flexibility, rather than final design optimality.

4.6.2 Impact of Model Fidelity (Simple vs. Complex)

The comparison between the Simple and Complex models reveals important insights into vehicle sizing physics. The **Complex Model** resulted in a slightly higher MTOW (541.35 kg) compared to the Simple Model (538.44 kg), representing an increase of approximately 0.5%.

This mass increase is primarily driven by the propulsion system sizing. As shown in the table, the **Motor Mass** increased significantly from 16.35 kg to 21.32 kg (+30%). This is because the Simple Model sizes the motor purely for hovering ($T = W$), whereas the Complex Model must account for the peak power required during the vertical climb phase ($V_z = 3\ m/s$), where the motor must overcome both gravity and vertical drag.

Interestingly, the **Battery Mass** in the Complex Model (57.63 kg) is slightly lower than in the Simple Model (60.56 kg). This counter-intuitive result can be attributed to the mission profile definition: while the Simple Model assumes a continuous 20 minutes hover at peak power, the Complex Model simulates a dynamic mission where the aircraft spends portions of time in descent (landing), which consumes significantly less power than hovering. This energy saving during descent partially offsets the high energy consumption during climb.

Conclusion on Fidelity: The Simple Model serves as an excellent proxy for total aircraft weight (error $< 1\%$) but significantly underestimates the motor power requirements (error $\approx 30\%$). Therefore, for preliminary sizing of the electric powertrain, the Complex Model is essential to ensure the vehicle has sufficient power margin for dynamic maneuvers like takeoff and climbing.

4.7 Implementation Challenges and Solutions

Implementing a robust MDO framework for eVTOL sizing presents several numerical and structural challenges. This section details the specific hurdles encountered during the implementation and the strategies employed to overcome them.

4.7.1 Numerical Scaling and Conditioning

A critical challenge in this optimization problem is the vast disparity in the orders of magnitude of the design variables and constraints.

- **The Challenge:** The total mass is in the order of 10^2 kg, while the required energy for the mission is in the order of 10^7 $Joules$. If passed directly to the optimizer, the gradients associated with the energy constraint would dominate the Jacobian matrix, leading to an ill-conditioned problem and poor convergence.

- **The Solution:** We applied rigorous variable scaling using OpenMDAO's `ref` (reference value) parameter.
  - Mass variables were scaled by a factor of 10^2 (`ref=100`).
  - Power constraints were scaled by 10^5 (`ref=1e5`).
  - Energy constraints were scaled by 10^7 (`ref=1e7`).

  This normalization ensures that the optimizer perceives all variables and constraints as being of order $\mathcal{O}(1)$, significantly stabilizing the gradient-based search (SLSQP).

4.7.2 Handling the "Weight Spiral" (Algebraic Loops)

The physical coupling between the `MassComp` and `AeroComp` creates a non-linear algebraic loop (or "Weight Spiral"). The structural mass depends on the total mass, but the total mass includes the structural mass.

- **In MDF:** This loop must be resolved implicitly before the optimizer evaluates the objective function. We implemented a `NewtonSolver` within the group to drive the residuals of the coupling variables to zero ($< 10^{-9}$) at every iteration. This ensures that the optimizer always traverses a physically valid path.
- **In IDF:** The loop is broken explicitly. However, this creates a challenge where the optimizer might exploit the broken physics to find artificially light designs (e.g., a target mass of 500kg but a computed mass of 1000kg). To prevent this, we imposed a strict equality constraint ($h(x) = 0$) and tested the robustness of the architecture by initializing the system with a deliberately inconsistent state ($M_{target} = 3000kg$ vs $M_{actual} \approx 500kg$). The successful convergence from this point demonstrates the robustness of the IDF formulation.

4.7.3 Derivative Computation

Efficient MDO requires accurate gradient information.

- **The Challenge:** Calculating derivatives via Finite Difference (FD) is computationally expensive and prone to step-size errors, especially for the Complex Model which involves time-stepping integration.
- **The Solution:** We leveraged OpenMDAO's modular derivative system. For the simple analytic equations, partial derivatives were computed analytically. For the complex model, the framework automatically assembled the total derivatives using the chain rule (Unified Derivatives Equations). This allowed the SLSQP optimizer to converge in fewer than 15 iterations, whereas the gradient-free COBYLA algorithm required more function evaluations to approximate the sensitivities.

5 Conclusion

This project successfully implemented a Multidisciplinary Design Optimization (MDO) framework for the conceptual sizing of a 2-passenger eVTOL aircraft. By integrating Aerodynamics, Propulsion, and Mass disciplines within the OpenMDAO environment, the study addressed the critical "Weight Spiral" challenge inherent in electric aviation.

5.1 Key Findings

1. **Feasibility of Lightweight Design:** Using next-generation battery parameters (450 Wh/kg) and a structural weight fraction of 30%, the optimal Maximum Takeoff Weight (MTOW) was found to be approximately 540 kg. This confirms that a compact, two-passenger urban mobility vehicle is technically feasible with near-future technology.

2. **Architecture Equivalence:** The comparative analysis validated that both MDF and IDF architectures converge to the mathematically identical solution (538.44 kg). MDF proved more iteration-efficient (converging in ≈ 5 steps) by handling physics internally, while IDF offered a decoupled approach that simplified disciplinary integration at the cost of higher optimizer iteration counts.

3. **Impact of Model Fidelity:** The transition from a Simple Momentum Theory model to a Complex Mission Profile simulation revealed critical insights. While the total mass increase was minimal (+0.5%), the motor sizing increased by over 30% (from 16.3 kg to 21.3 kg). This highlights that static hover analysis significantly underestimates the power required for dynamic maneuvers like vertical climbing, underscoring the need for higher-fidelity modeling in the preliminary design phase.

5.2 Future Work

Future iterations of this work could expand the discipline fidelity by incorporating a thermal management model, as high-power climbing phases impose significant cooling loads. Additionally, introducing acoustic constraints would be essential for ensuring the vehicle's suitability for urban operations.

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