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Extensions to a Gradient-Based MDAO Framework for Advanced Aircraft Conceptual Design

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Novel technologies have the potential to significantly improve aircraft energy efficiency via closer integration of propulsion, airframe and operations. The vehicles that incorporate these tightly coupled subsystems and innovative architectures require advanced design and evaluation tools. We extended our previously-proposed multidisciplinary design analysis and optimization (MDAO) framework to include new subsystem and performance models to accurately represent and determine the interactions between subsystems and the tradeoffs that drive design choices and system-level optimization. This framework is built on OpenMDAO and Aviary for modular gradient-based optimization with efficient coupled derivatives, allowing for the rapid evaluation of a wide design space. The subsystems represented include thermal engines, propulsors, electric machines, power electronics, thermal management, and batteries. Different levels of fidelity are available to add flexibility. Aircraft represented in this framework can be evaluated with conventional metrics such as fuel burn and energy consumption as well as more advanced metrics such as noise, emissions, contrail formation potential, and cost thanks to the addition of specialized models. With these performance metrics, the framework provides a more comprehensive evaluation of potential designs. The use of this framework is demonstrated for small single-aisle aircraft of different propulsion architectures. The framework will be made open source for the benefit of the wider aircraft design community.

I. Introduction

Commercial aviation faces internal and external pressures to increase aircraft efficiency while balancing other conflicting objectives, such as noise, cost, emissions, and overall sustainability. In traditional aircraft design processes, these factors are either not considered or are left for detailed design once the majority of the design is frozen. By

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bringing these considerations into conceptual design, a wide variety of novel technologies can be evaluated early in the design process to determine which show the most promise. With sufficient detail, this early assessment of technologies and designs reduces risk and increases confidence in moving to the next phases of design.

Aircraft are highly coupled systems and including novel technologies only compounds this. A complete evaluation of any new technologies not only requires capturing the behavior of those technologies, their impacts on the full aircraft through connections to other systems must also be included. Multidisciplinary design analysis and optimization (MDAO) captures this coupling between systems while efficiently exploring the full design space represented in the complete aircraft model. MDAO is especially important in the evaluation of novel systems where the interactions cannot be understood in the context of historical aircraft designs. This process also allows for the evaluation of designs for multiple metrics, such as energy usage, cost, environmental impact, and noise footprint.

Several research tools have been proposed to explore electrified aircraft at the conceptual design stage. NASA released Aviary [1, 2], a conceptual design tool for new aircraft configurations. Kruger and Uranga [3] presented the library for unified conceptual aircraft synthesis (LUCAS) and discussed design space exploration for electric commuter aircraft. Cinar et al.[4, 5] developed a tool for electrified propulsion architecture sizing and synthesis (E-PASS). Brelje and Martins [6] developed OpenConcept, an open-source tool for electric aircraft design and mission analysis using OpenMDAO [7].

This work contains extensions on the aircraft subsystem models and framework development previously presented by Kaneko et al. [8]. These additional models and development have the capability to model aircraft equipped with various advanced technologies that would enable ultra-efficient air transportation, such as the concept shown in Fig. 1. The newly added subsystem models are primarily higher-fidelity physics-based models to capture more detail in subsystem performance. We build our tool on top of NASA's Aviary [2] and OpenMDAO [7] and utilize their capabilities to perform fully-coupled, large-scale MDAO. Our tool will become open source for public use by the research community. This research effort is supported by NASA's Advanced Aircraft Concepts for Environmental Sustainability (AACES) 2050 Program.



Fig. 1 Concept aircraft illustrating the advanced technologies being modeled, including electrified propulsion, distributed propulsion, boundary layer ingestion, and blown lift. It serves as a research baseline and does not represent an optimized future configuration.

This paper is organized as follows. Section II provides an overview of the aircraft system-level MDAO integration, the underlying methodology, and the modeling approaches for aircraft performance and environmental impacts. Section III presents a brief overview of the new subsystem models. Finally, Section IV demonstrates the framework with electrified aircraft design optimizations.

II. Aircraft MDAO Framework: System Integration

A. Overview

Aircraft design is a highly coupled problem, especially when electrified powertrains and aeropropulsive effects are added. Individual systems have an impact on the overall mass of the aircraft as well as the power demand on the propulsion system, which themselves are coupled. Because of this, our MDAO framework models the system-level interactions of the subsystem models. Each system cannot be optimized in isolation because of the aircraft-level effects, so this fully connected optimization is necessary. Figure 2 shows how these subsystems are connected at the aircraft level and how the subsystems impact the performance and emissions metrics.

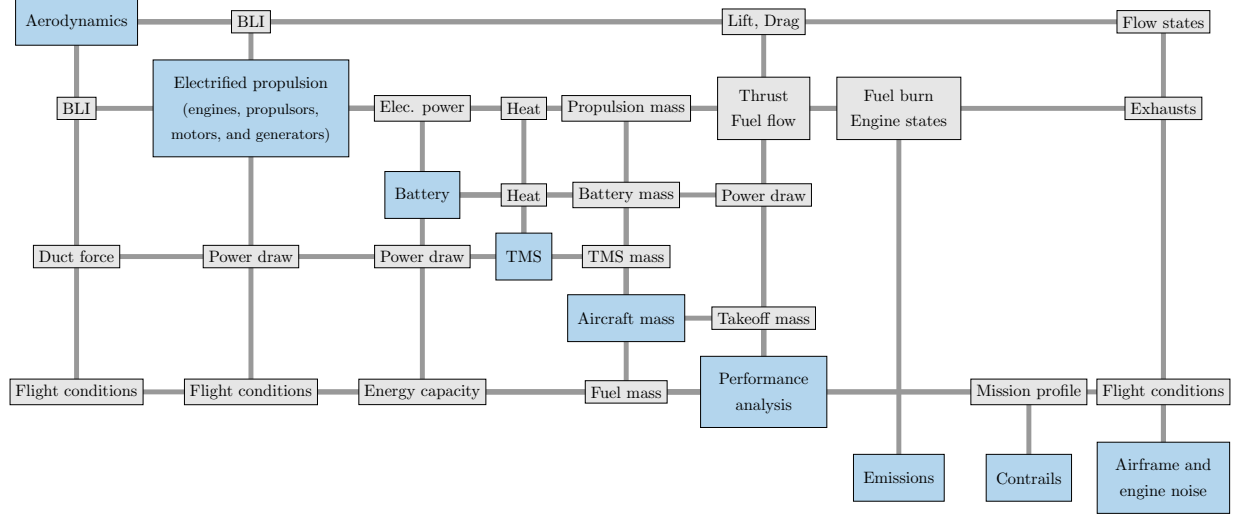


Fig. 2 Aircraft-level coupling of subsystems in MDAO framework. Diagonal blue blocks are major subsystems, and gray lines and off-diagonal blocks show interactions between subsystems.

B. Gradient-Based Optimization

Design optimization is a more efficient and comprehensive tool for exploring the large design space presented for advanced aircraft design than manually sweeping design variables or relying on historical trends. Optimization can automatically capture the effects individual systems have on the whole. That information can then be used to balance the competing forces of the design and drive each piece to find the maximum benefit overall.

In a large aircraft optimization made up of many subsystems each with their own inputs, the problem has a large number of design variable and constraints. Solving this is only made possible by efficient gradient computation to provide the optimizer an additional layer of information with which to navigate the large and complex design space.

C. Foundation: OpenMDAO, Dymos, and Aviary

Our framework uses OpenMDAO [7], Dymos [9], and Aviary [2], open-source Python packages developed by NASA for gradient-based optimization. Figure 3 shows this structure.

We implement our models for each subsystem and performance metric in OpenMDAO [7]. OpenMDAO is a general multidisciplinary design framework for gradient-based optimization developed by NASA. It computes derivatives based on the modular analysis and unified derivatives architecture (MAUD) [10; 11, Sec. 13.2] and the unified derivative equations (UDE) [12; 11, Sec. 6.9]. OpenMDAO also has an interface to gradient-based optimizers, including IPOPT [13] via its pyOptSparse wrapper [14].

Our framework extends Aviary [2], an aircraft conceptual design optimization framework developed by NASA. Subsystem models in Aviary— aerodynamics, propulsion, geometry, empty weight, and aircraft dynamics—are inherited from NASA’s two legacy aircraft design tools: Flight Optimization System (FLOPS) [15] and General Aviation Synthesis Program (GASP) [16]. Aviary adapts the legacy codes into OpenMDAO, enabling modular use of novel subsystems

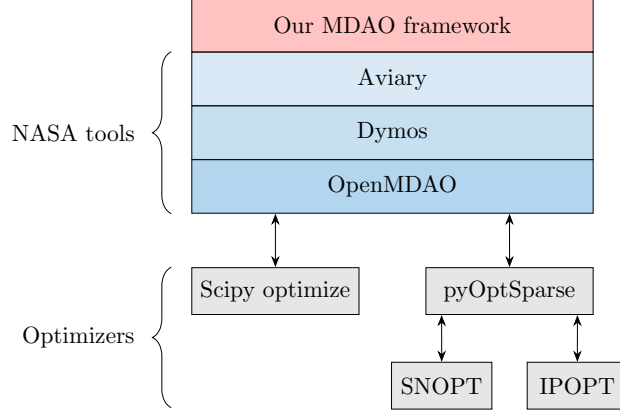


Fig. 3 Tools used to develop our aircraft MDAO framework.

alongside historically trusted methods. Using the flexibility of OpenMDAO, Aviary allows for the addition of new models. This allows us to add a new battery model for example and connect it to the existing aircraft design infrastructure.

Aviary uses Dymos [9, 17], a trajectory optimization library built on OpenMDAO, for mission analysis and optimization. In fixed-mission aircraft design mode, Aviary uses Dymos as an ordinary differential equations (ODE) solver to integrate time-varying quantities, such as aircraft dynamics, fuel burn, and battery energy usage. Aviary and Dymos allow the simultaneous optimization of aircraft design, mission profile, and dynamic controls, which could result in finding a better system design. For example, we can optimize the power management of electrified propulsion as an optimal control problem while concurrently sizing the motors, generators, and gas turbines for minimum weight.

Using these tools, we can build a framework on a trusted foundation. We have added models for electrified aircraft and aeropropulsive integration, increasing fidelity of models where necessary to capture more detailed tradeoffs in design. All of our models are differentiated, allowing for fully gradient-based optimization to quickly explore this large and complex design space. Section III describes the models newly added to the framework since the first set [8, Sec.III].

D. Performance Analysis and Environmental Impact Models

In addition to subsystems that represent aircraft components, our framework also has models to analyze the aircraft performance and impact. This includes a taxi model to capture the impacts of electrification, a new takeoff mission setup to improve computational efficiency and robustness, airframe and engine noise to capture certification and community considerations, emissions impacts from the propulsion system and aircraft operations, and the impact of contrail avoidance on aircraft design. These are in addition to the performance models described previously [8, II.D].

1. Taxi

Taxi consists of two segments: taxi out and taxi in. Taxi out was defined as the portion of the taxi that preceded the flight from the airport terminal to the departure runway. Taxi in was defined as the portion of the taxi following the flight from the arrival runway to the airport terminal.

Average taxi out and taxi in times were determined using historical 2024 taxi times from the FAA Aviation System Performance Metrics (ASPM) database. Taxi times and number of movements were used to calculate a weighted average of taxi times using data from the U.S. Core 30 Airports, the 30 busiest airports in the United States. Taxi out times were weighted by the number of departures at each airport, and taxi in times were weighted by the number of arrivals. The resulting averages were 19.8 minutes and 9.8 minutes for taxi out and taxi in, respectively.

The taxi model estimates the fuel burn and battery energy used for taxi operations. This model utilizes the existing Unified Propulsion System (UPS) to calculate fuel burn and battery energy directly from the required power during taxi. The taxi model assumes drag is negligible compared to friction, the runway is horizontal, and the rolling resistance coefficient is constant. With these assumptions, the only force to overcome is friction force between the aircraft and the ground. This can be calculated as:

$$T_r = F_f = \mu F_N = \mu M g, \quad (1)$$

where T_r is the required thrust, F_f is the friction force, μ is the rolling resistance coefficient, F_N is the normal force, M

is the aircraft mass, and g is the gravitational acceleration.

Once we have the required thrust, we can convert it to required power using the conversion for static conditions $1hp \approx 2.6lb$ thrust [18]:

$$P_r = \frac{T_r}{2.6\eta}, \quad (2)$$

where P_r is the required power in hp, T_r is the required thrust in lb, and η is the overall efficiency of the propulsion system.

The required power in taxi is input into the propulsion system. This returns fuel flow rate and battery energy used during taxi. Taxi fuel burn is calculated by fuel flow rate times taxi duration:

$$m_f = \dot{m}_f t, \quad (3)$$

where m_f is the total fuel burn during the taxi phase, $\dot{m}_f$ is the fuel flow rate, and t is the taxi duration.

These steps are for constant velocity. For each acceleration event (stop and go), we repeat these steps with a modification to required thrust calculation:

$$T_r = \frac{Mv}{\Delta t}, \quad (4)$$

where T_r is the required thrust to accelerate, M is the aircraft mass, v is change in velocity during acceleration event, and Δt is the duration of the acceleration event.

Taxi fuel burn and taxi battery energy used are summed up from all source (constant velocity and all acceleration events) and included in the sizing loop for aircraft optimization. For conventional taxi, only fuel burn is considered. For partial or full e-taxi, source electrification factor is used to decide how much power used in taxi from fuel burn versus how much comes from the battery.

2. Takeoff Mission

We adopt Aviary's solved two-degrees-of-freedom (2DOF) ordinary differential equations (ODEs) for takeoff trajectory analysis. For noise reduction and horizontal tail sizing studies, these takeoff ODEs are coupled to the general mission profile, which uses a height-energy approximation to describe the aircraft energy state throughout climb, cruise, and descent.

Because Aviary employs different state and time variable definitions for these mission phases, linking the trajectories between the 2DOF takeoff formulation and the height-energy mission formulation requires additional coupling constraints within the optimizer. To accomplish this, we employ an Individual Discipline Feasible (IDF) architecture in which consistency between the coupled mission phases is enforced through optimizer constraints. This allows the two ODE systems to converge independently during each optimization iteration.

The constraints take the form

$$h(y) = y_{2DOF} - y_{HE} = 0 \quad (5)$$

These are enforced between the final node of the takeoff phase and the initial node of the climb phase for the aircraft mass, time, and altitude states.

3. Airframe and Engine Noise

The noise component models engine and airframe noise using empirical and semi-empirical methods that link the acoustic source strength with the local flow and geometry parameters. This section provides a brief overview of the noise models; the details are presented in Hassanandani et al. [19].

We predict engine noise as the sum of fan, jet, and core contributions. For fan noise prediction, we use the Heidmann method with General Electric Aircraft Engines (GEAE) corrections [20, 21], which models broadband and tonal radiation in both the inlet and discharge directions as functions of fan tip Mach number, loading, and flow temperature. For configurations incorporating boundary layer ingestion (BLI), additional fan noise due to ingestion distortion and turbulence is assessed using the surrogate modeling approach developed by Clark et al. [22]. Fan liner suppression effects are also considered [21], with frequency- and direction-dependent attenuation applied to inlet and discharge components. For jet noise we use the Stone method [23], which relates turbulent-mixing noise to exhaust velocity, temperature ratio, and nozzle geometry. Core noise is modeled using the Emmerling method [24], which scales broadband combustion and turbine noise with flow properties and temperature gradients through the core. For electrified propulsion configurations, the framework additionally includes distributed electric propulsion (DEP) arrangements

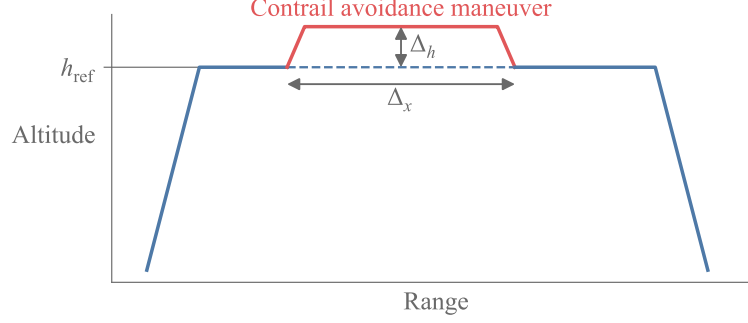


Fig. 4 Parametrization of mission profile for contrail avoidance maneuver.

with both ducted electric fans and open rotors. Open rotor DEP noise is represented using a surrogate-based approach developed from representative turboprop configurations as a function of propulsor count, thrust, and airspeed [25]. These models take the flow rate, temperature, and pressure from the propulsion module to provide physically consistent noise predictions across the flight envelope.

We compute the airframe noise using empirical and semi-empirical formulations for the major aerodynamic sources on the airframe. The noise of the landing-gear follows the Guo method [26], which is an empirical method based on broadband levels versus gear geometry and approach velocity. We compute flap noise using the Jiang-Filippone method [27], which models the boundary-layer interaction at the edges of the flap as a function of the deflection angle and chord length, with local flow properties. Slat noise is additionally included using a semi-empirical formulation based on deployed leading-edge device geometry and local flow conditions [28]. Shielding effects due to engine placement relative to the airframe are also modeled using a semi-infinite screen diffraction approach [29, 30]. Both models make use of geometry and flow information provided by the upstream component models discussed in Sec. III.

4. Emissions

Our framework provides an emissions cost model to account for the aviation’s environmental impacts in the aircraft conceptual design. The inputs to the emissions cost model are the mission histories of flight altitude, fuel flow rate, and combustor inlet stagnation pressure and temperature, which are provided by the upstream mission analysis and engine model. The emissions model computes the overall climate and air quality impacts from CO_2 , SO_x , and NO_x emissions using a simplified environmental model. We then monetize these impacts using damage functions and convert the future environmental damages to net present values using discount rates. Having both climate and air quality impacts in uniform, monetized metrics allows us to use them as an objective function of aircraft design optimization. The details of the emissions modeling are presented in Shukla et al. [31].

5. Contrails

We also provide a climate cost of persistent contrail formation, which can be used as a part of the design objective. Our model uses aggregated weather data across representative flight paths to estimate persistent contrail formation (i.e., intersection length of the flight path and ice supersaturated regions) for a representative mission. We then convert the length of the contrail formed in a flight to a representative and monetized environmental impact metric. The details of the contrail cost model are presented in Shukla et al. [31].

The contrail cost J_{cirrus} is a function of the mission profile, and we currently parametrize the contrail avoidance maneuver using the reference cruise altitude h_{ref} , horizontal length of contrail avoidance maneuver Δ_x , and the altitude change of the avoidance maneuver Δ_h , as shown in Fig. 4. The cost function is then

$$J_{\text{cirrus}} = f(h_{\text{ref}}, \Delta_x, \Delta_h) . \quad (6)$$

The mission parameters h_{ref} , Δ_x , Δ_h are design variables that can be optimized along with other aircraft design variables. Optimization then trades the contrail cost reduction for the fuel burn penalty resulting from flying a non-fuel-minimal mission profile.

E. Cost

The framework includes costs for conventional turbofan, conventional turboprop, hybrid-electric, and turboelectric aircraft. The models are described in more detail in [32]. These run in Aviary’s post-mission phase rather than in the loop of the optimization. Outputs of the optimization connect to the cost models to provide an estimate of each specific aircraft’s cost.

III. Updates to Aircraft Subsystem Models

This section describes the models added or updated since the original paper. All models are listed in Table 1. Models categories with no linked section had no changes or additions. Models not covered in another paper are described in detail here, otherwise the relevant paper is provided as a reference for additional detail.

A. Unified Propulsion System

The unified propulsion system (UPS) [3] implementation remains largely unchanged from the previously published description [8]. The main changes were architectural changes to allow for the pyCycle integration. Two new pathways were also added, a complete turbofan (rather than a combined core and fan) and a core with an embedded generator. These are shown in Figure 5.

B. Thermal Engine

Three levels of model fidelity are implemented for modeling thermal engines. The first two, a constant PSFC approach and engine decks, remain unchanged from the previous description [8, III.B]. The highest level, an implementation of pyCycle [33] within Aviary for both on-design and off-design sizing, has changed as development proceeded. These changes are briefly described here, additional details on the pyCycle implementation are in Tahiliani et al. [34].

Originally, two integration strategies were pursued [8, B.3]: a direct coupling method, evaluating pyCycle at each flight point, and a surrogate method, building an engine deck for off-design evaluations during the pre-mission phase. Though more time-intensive, this approach was thought to be more robust to the range of evaluations needed in off-design. With developments in the off-design initial guess methodology and bounding constraints presented in [34], the direct approach proved to be both more robust and computationally efficient, leading to the discardment of the surrogate approach.

The pyCycle implementation was originally proposed as a separate core and fan that could work together as a turbofan or individually, as the rest of models in the UPS are connected. Due to the complex and coupled nature of a turbofan model in pyCycle, handling this coupling outside of pyCycle itself was deemed impossible. Three pyCycle models are then implemented in our framework: turbofan, turboshaft, and fan. This adds a new mechanical pathway to the UPS (Figure 5).

The mechanical pathway routes shaft power to and from the pyCycle turbofan or turboshaft cycles. The shaft on-and-off take is upstream of the power balance inside the pyCycle models, allowing for positive (off-take) or negative (on-take) of power to the low or high pressure spools. The sign convention is based on the turbine’s reference to compressor power demand: an off-take of shaft power means the turbine must generate more power, while an on-take means it must generate less. Via this pathway, the UPS has a two-way routing of power to-and-from the mechanical turbofan or turboshaft cycles.

A detailed engine weight model based on properties from pyCycle was also added to the framework. This is based on a regression for gas generator based on takeoff power and additional buildups for the fan, low pressure compressor (LPC), low pressure turbine (LPT), and nozzles. Additional detail is presented by Tahiliani [35, Ch. 4.5, App. A].

C. Motor

After considering multiple potential motor technologies, we decided advanced permanent magnet and partially superconducting machines were the most viable for 2050 entry into service aircraft. Because motor properties and the differences between technology levels are more complex than scaling specific power and efficiency as captured in our lower fidelity model [8, III.D.1], we developed a higher fidelity model to capture detailed motor performance.

Our higher fidelity motor model consists of two modes: on- and off-design. On-design sizes a motor for the required power, shaft speed, and the motor properties. Off-design evaluates this motor at each operating point across the mission. This motor model was developed with subject matter expertise from AACES partner Hinetics.

Table 1 Summary of subsystem models

Section	Subsystem	Model	Aviary integration group(s)	Fidelity level
Sec. III.A	Propulsion system	Unified propulsion system	Pre-mission and Mission	-
Sec. III.B	Turboshaft/Turbofan core	Constant PSFC	Mission	Low
		Engine deck	Mission	Mid
		pyCycle	Pre-mission and Mission	High
Sec. III.B	Turbofan	pyCycle	Pre-mission and Mission	High
	Propulsor	Constant efficiency	Mission	Low
		Propeller	Mission	Mid
		Ducted fan deck	Mission	Mid
		pyCycle ducted fan	Pre-mission and Mission	High
Sec. III.C	Motor and generator	Constant efficiency	Mission	Low
		First principles model	Pre-mission and Mission	Mid
	Converter	Constant efficiency	Mission	Low
	Voltage limit	Safe operating voltage	Mission	Mid
Sec. III.D	Cables	Power loss	Mission	High
Sec. III.E	TMS	Lumped model	Pre-mission and Mission	Low
		Unified build-up	Pre-mission and Mission	High
		OpenConcept component build-up	Pre-mission and Mission	High
Sec. III.F	Battery	Constant efficiency	Mission	Low
		Equivalent circuit model	Mission	Mid
		PyBaMM SPMe, DFN models	Mission	High
Sec. III.G	Empty weight	Aviary build-up	Pre-mission	Mid
		Custom build-up	Pre-mission	Mid
		Aircraft-level regression	Pre-mission	Low
Sec. III.H	Aerodynamics	Aviary build-up	Mission	Mid
		Custom C_{D0} build-up	Mission	Mid
		High lift and stall	Pre-mission	Mid
Sec. III.I	Aero-propulsive integration	BLI	Mission	Mid
		Blown-lift	Mission	Mid
	Power off-take	Regression	Pre-mission	Mid
Sec. III.J	Geometry	Wing area	Pre-mission	Low
		Tail area	Pre-mission	Low
		Spatial integration	Pre-mission	Low
		Landing gear sizing	Pre-mission	Low
Sec. III.K	Stability	Static margin	Pre-mission	Low
Sec. II.D.3	Noise	Engine noise	Mission	
		Airframe noise	Mission	
Sec. II.D.4	Emissions	Climate and air quality costs	Missions	
Sec. II.D.5	Contrail	Climate cost	Mission	
Sec. II.E	Cost	Acquisition and operation	Post-mission	

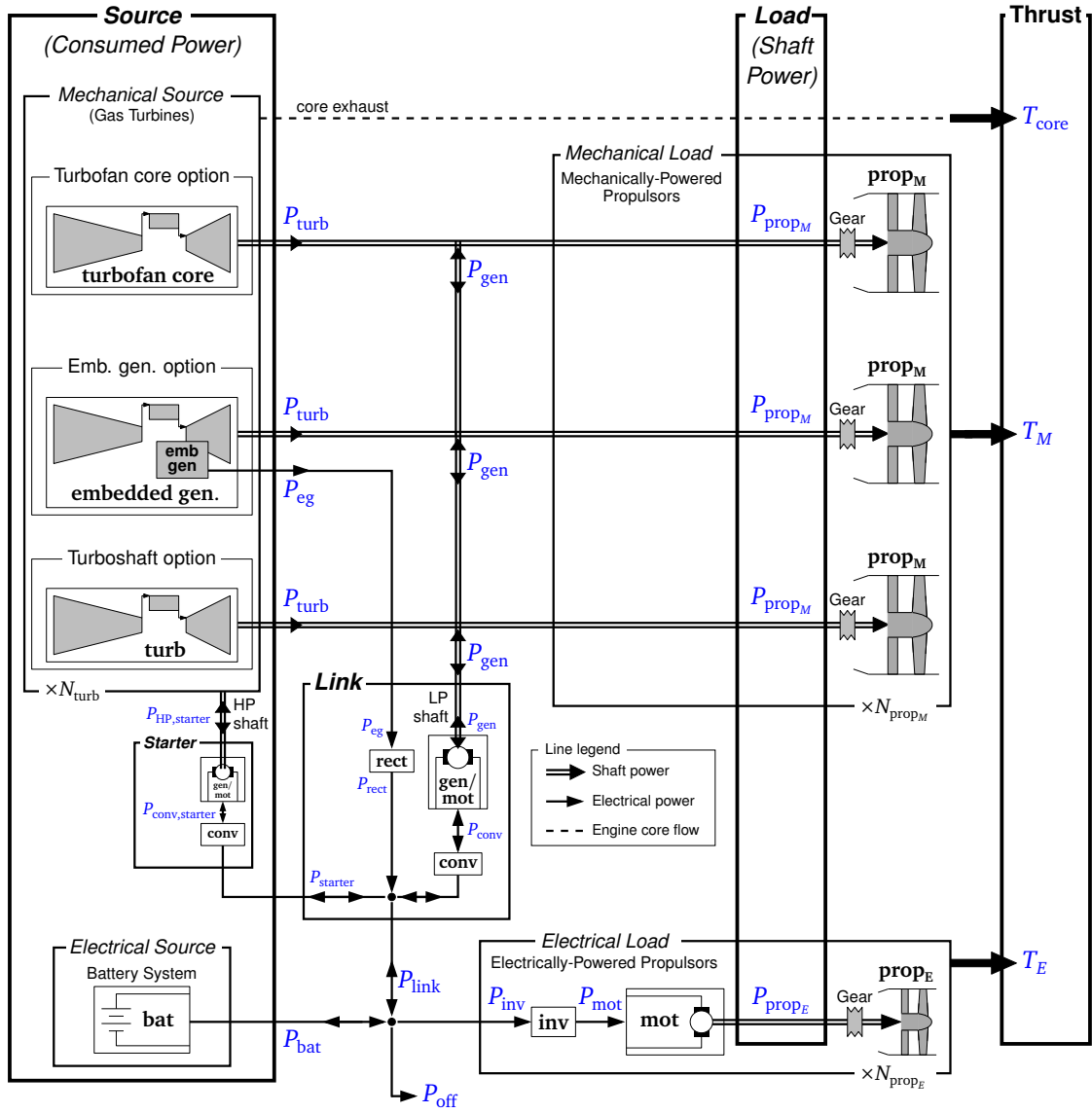


Fig. 5 New unified propulsion system (UPS) structure with added pathways for a turbopan and an embedded generator.

Necessary constraints include a limit on the length-to-diameter ratio, an upper bound on motor tip speed, and a limit on the heat produced by the motor. The length-to-diameter ratio constraint, typically around 5, avoids long and narrow motors that experience rotordynamic instability. The tip speed is constrained to avoid rotor Mach numbers approaching 1. The heat produced by the motor is bounded by a reasonable liquid cooling heat transfer coefficient and the maximum temperature increase $\Delta T_{\max}$ that can be sustained from the coolant to the heat sink surface based on the motor materials, generally such that the maximum temperature rise does not exceed 70°C .

For on-design, Aviary's pre-mission group sizes the motor based on the power and shaft speed requirement. As in the low-fidelity model, the optimizer sizes the power rating with power margin constraints. The design shaft speed is driven by the pyCycle fan model. For other propulsor models, this can be varied within a feasible range for a given fan diameter. Unlike the lower fidelity model, this model includes motor geometry specifications. Motor airgap diameter, copper slot depth d_{cu} , and copper current density J_{cu} are input to specify the motor geometry. From these inputs, the model determines the design torque, specific power, efficiency, length, volume, mass, and heat produced. User-set model parameters (not design variables) include the motor architecture, heat transfer coefficient h , and $\Delta T_{\max}$. The motor architecture sets a fixed value for peak airgap flux density B_{ag} , affects the mass model, and changes the assumptions on losses. The outer diameter D_{out} is estimated from the airgap diameter D_{ag} and d_{cu} as

$$D_{\text{out}} = D_{\text{ag}} + 7d_{\text{cu}}. \quad (7)$$

The length L is determined from the design torque τ and motor properties

$$L = \frac{\tau}{\frac{\pi}{8} B_{\text{ag}} D_{\text{ag}}^2 d_{\text{cu}} J_{\text{cu}}}, \quad (8)$$

and then the volume of copper V_{cu} in the motor is

$$V_{\text{cu}} = \frac{\pi}{4} \left((D_{\text{ag}} + d_{\text{cu}})^2 - D_{\text{ag}}^2 \right) L + 2A_{\text{ew}} L_{\text{ew}}, \quad (9)$$

where the end winding cross-sectional area A_{ew} is equivalent to the copper area and the end winding length L_{ew} is based on a logarithmic fit

$$L_{\text{ew}} = 0.0254 \left[\frac{2.5 \ln(P)}{3 \ln(10)} - 4 \right] + 0.5. \quad (10)$$

Power and losses also follow from the geometry and motor properties

$$P_{\text{loss}} = \rho V_{\text{cu}} J_{\text{cu}}^2 + P_{\text{core}}. \quad (11)$$

The core loss P_{core} is zero for partial superconducting machines and for permanent magnet machines is estimated as

$$P_{\text{core}} = 0.00704 m_{\text{core}} (12N/60)^{1.32} (B_{\text{ag}} + 1)^2, \quad (12)$$

where the core mass m_{core} is

$$m_{\text{core}} = \pi (D_{\text{ag}}/2 + 2.5d_{\text{cu}})^2 - 7650L (D_{\text{ag}}/2 + d_{\text{cu}})^2, \quad (13)$$

and heat losses can be calculated from power

$$\dot{Q} = \frac{P_{\text{loss}}}{\pi L (D_{\text{ag}} + 2d_{\text{cu}})}. \quad (14)$$

The mass model for the first principles motor is more detailed than the low fidelity model, which takes a user-provided specific power. This model estimates total motor mass from the auxiliary mass m_{aux} and the copper mass m_{cu} of the machine

$$m_{\text{tot}} = m_{\text{aux}} + m_{\text{cu}}, \quad (15)$$

where m_{aux} includes considerations of the structural mass that scales with torque, the mass of components that are required to establish flux for the motor architecture (iron yoke in permanent magnet machines or vacuums and cryogenic systems in superconducting machines), the cooling mass that scales with power loss, the rotor retention mass. This

mass model has fits to model two architectures: permanent magnet machines and superconducting machines. For a permanent magnet machine, m_{aux} is estimated from those four components as

$$m_{\text{aux}} = \alpha\tau + 6.1\beta\pi B_{\text{ag}}D_{\text{ag}}L + (0.3 \times 10^{-3})P_{\text{loss}} + 7.4\gamma\omega^2D_{\text{ag}}B_{\text{ag}}L, \quad (16)$$

where $\alpha = 6.5 \times 10^{-3}$ kg/N/m, $\beta = 10$ kg/T/m², $\gamma = 4.5 \times 10^{-5}$ kg/T/(rad/s)²/m², and ω is the design shaft speed.

The motor's specific power (SP) and design point efficiency η are often the most relevant properties at the aircraft system level. These are given by

$$\text{SP} = \frac{\tau\omega}{m_{\text{tot}}}, \quad \eta = 1 - \frac{P_{\text{loss}}}{\tau\omega}. \quad (17)$$

During Aviary's mission analysis, the off-design model takes the shaft speed and shaft power required at each flight point, the design shaft speed and efficiency, and the power rating. With this, it computes the new torque, the electric power required to run the motor, the heat rate, and the power margin for the corresponding constraint. The new torque τ^* is found from the instantaneous shaft power P_{shaft}^* and shaft speed requirements. The heat loss at the new point $\dot{Q}^*$ is calculated from the heat loss at the design point $\dot{Q}$ and the ratio of new torque to design torque, which is used along with the off-design shaft power to find the new efficiency η^* :

$$\dot{Q}^* = \dot{Q} \left(\frac{\tau^*}{\tau} \right)^2, \quad \eta^* = \frac{P_{\text{shaft}}^*}{\dot{Q}^* + P_{\text{shaft}}^*}. \quad (18)$$

D. Cables

Two cable models are implemented in our framework. The standard cable model had a mild change from its previous description [8, III.D.4].

1. Standard Cables

The fit of current to wire size in the previous cable model was adjusted to better fit a range of wire sizes:

$$a_{\text{cond}} = \frac{I}{3}, \quad (19)$$

where a_{cond} is the conductor area in millimeters and I is the current in Amps.

2. Superconducting Cables

Superconducting cables have potential to deliver significant system-level mass reductions and enable higher levels of electric power delivery than conventional cables. This section presents a model used to estimate the mass and cooling power requirements of superconducting cable systems. The model accounts for the masses of the cable core, cryogenic transfer line, cryocooler, cryopump, and reservoir containing cryogenic coolant:

$$M_{\text{SuperconductingCableSystem}} = M_{\text{CableCore}} + M_{\text{CryogenicTransfer}} + M_{\text{Cryocooler}} + M_{\text{Cryopump}} + M_{\text{CryoReservoir}}. \quad (20)$$

Cable core and cryogenic transfer line masses were modeled using data provided by Gemin et al. [36], which provided cable core mass as a function of ampacity, the maximum continuous current the cable could carry. An additional 4 kg/m was added to represent the mass of the cryogenic transfer line based on an estimate provided by Gemin et al. [36]. Combined cable core and transfer line mass is given as a function of ampacity in Figure 6.

A neon cryocooler was sized to maintain cryogenic temperatures along the transfer line. The cryocooler was assumed to operate at 30% of peak Carnot efficiency (η_{Carnot}) with a Carnot coefficient of performance (COP) of 1.31, based on assumptions for a notional supercritical liquid nitrogen system [36]. The total input power to the cryocooler was estimated using

$$P_{\text{Cooler}} = \text{COP} \frac{Q_{\text{Cold}} + P_{\text{Pumping}}}{0.3\eta_{\text{Carnot}}}. \quad (21)$$

The heat lift required to maintain cryogenic temperatures, Q_{Cold} , included the losses from transmission heat leakage, cable terminations, losses within the superconducting core, and losses from miscellaneous components, as given in the following equation:

$$Q_{\text{Cold}} = Q_{\text{CryogenicTransferLineHeatLeak}} + Q_{\text{Termination}} + Q_{\text{HTSLoss}}. \quad (22)$$

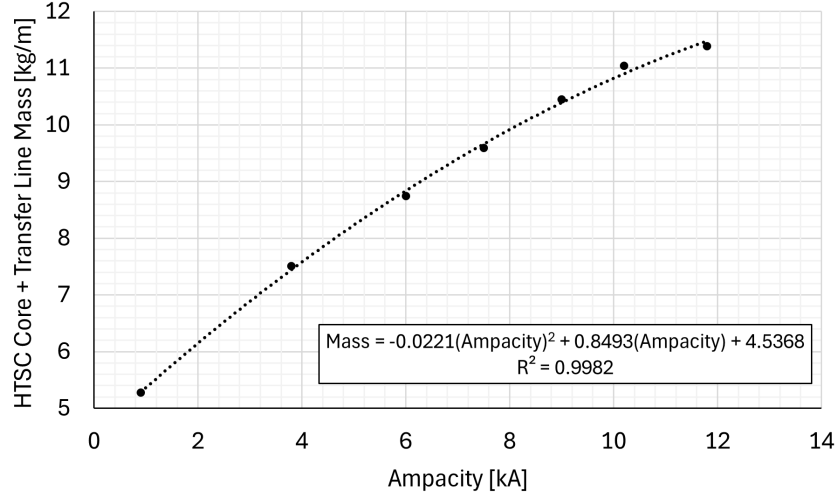


Fig. 6 High-temperature superconducting cable core and cryogenic transfer line mass per length

Transmission heat leak was estimated assuming a loss of $q' = 1.5$ W/m based on estimates provided by Deng et al. [37] [38] and e-volv, a technology company developing superconducting power delivery cables. $Q_{\text{CryogenicTransferLineHeatLeak}}$ was therefore taken as

$$Q_{\text{CryogenicTransferLineHeatLeak}} = q'L, \quad (23)$$

where L was the length of the cryogenic transfer line. Losses at the superconducting cable terminations were modeled by assuming a constant 2000 W were lost per cable end. $Q_{\text{Termination}}$ was therefore defined as

$$Q_{\text{Termination}} = 2 * N_{\text{Cable}} * 2000 \text{ W}. \quad (24)$$

Losses within the superconducting core were taken as 0.1% of the total power transmitted through the cable (P_{Elec}), based on assumptions made by Jankovsky et al. [39]. Q_{HTSLoss} was estimated as

$$Q_{\text{HTSLoss}} = 0.001 P_{\text{Elec}}. \quad (25)$$

This term accounts for miscellaneous losses including those at valves, sensors, and supports in addition to losses due to imperfect insulation.

Pumping power P_{Pumping} was expected to be small ($< 1\%$) compared to Q_{Cold} . This power was estimated as

$$P_{\text{Pumping}} = \frac{\dot{m}}{\rho} \Delta P, \quad (26)$$

where $\dot{m}$ was the mass flow rate of the cryogenic fluid, ρ was the density of the cryogenic fluid, and ΔP was the pressure loss across the transmission line. Cryogenic liquid nitrogen was assumed to move through transmission lines at a mass flow rate of 1.0 kg/s and maintain a density of 800 kg/m³. Pressure loss was estimated assuming a drop of 50 Pa/m.

Cryocooler mass was calculated using

$$M_{\text{Cryocooler}} = P_{\text{Cooler}} P'_{\text{Cooler}}, \quad (27)$$

where P'_{Cooler} was taken as 3 kg/kW, following the assumptions of Gemin et al. [36]. The masses of the cryogenic reservoir ($M_{\text{CryoReservoir}}$) and cryopump (M_{Cryopump}) were taken as 80 kg and 125 kg, respectively, based on input from e-volv. The 80 kg cryogenic reservoir mass was based on a 50 liter reservoir filled completely with liquid nitrogen.

E. Thermal Management System

Three thermal management systems are incorporated into our framework. The lumped model (a constant heat rejection per unit mass of TMS) and OpenConcept component buildup [6, 40] described previously both remain in the

framework. The third TMS model, called the “Unified Thermal Management System” (UTMS) model, is described in detail in [41]. This model captures the TMS impacts on aircraft weight, drag, and required power in flight. It is a modular system which sends heat between acquisition, transfer, and rejection modules. Each one is parameterized by subsystem performance parameters which have been outlined in the contemporary literature. These modules are connected in configurations which depend on the aircraft’s propulsion system architecture, but can vary in their exact design. This flexibility allows the framework to capture system level effects of varying not only subsystem performance parameters, but the effects of varying the thermal architecture itself.

The UTMS subsystem itself enforces a closed thermodynamic loop (i.e. the coolant temperature at the inlet of the first component must equal the temperature at the outlet of the heat rejecter). However, the framework interacts with the subsystem in a few ways, such as enforcing constraints on the UTMS or changing design variables at the optimization level. Directly exposing subsystem parameters to the optimizer improves robustness during design as it avoids poor behavior in local regions of infeasibility. The specific design variables the optimizer controls depend on the TMS architecture, however, as an example, the optimizer would vary air duct area and maximum coolant flowrate in a simple air-cooled configuration. It enforces sufficient heat is rejected to keep heat producing components below their maximum temperature limits while minimizing the weight, drag, and power deltas that the system level.

F. Battery

Three levels of fidelity are implemented in our framework: constant efficiency, equivalent circuit model (ECM), and a connection to PyBaMM [42]. The constant efficiency and ECM models remain as previously described [8, III.E], but an addition was made to the PyBaMM model, the highest fidelity model in our framework.

Previously only the Doyle-Fueller-Newman (DFN) model was connected to the framework, but the computational cost of evaluating this model was prohibitive to optimization. We added a connection to PyBaMM’s Single Particle Model with electrolyte (SPMe) [43] to reduce the computational cost while maintaining nearly the same level of model fidelity.

Both SPM and DFN are integrated into the framework in the same way, maintaining the IDF approach described in [8, III.E.3]. A more detailed description of the battery modeling, the importance of model fidelity, and aircraft case studies with the battery are presented in Sebastian et al. [44].

G. Empty Weight and Takeoff Weight Sizing

Our framework has multiple empty weight and structural weight buildups. These include the Aviary weight buildup from FLOPS, textbook weight buildups, and surrogate operating empty weight (OEW) buildup described previously [8, III.F].

A new model was added to compute the structural weight of a double bubble fuselage. We adapted the Julia version of TASOPT [45, 46] into an OpenMDAO component for use in Aviary. This only computes the fuselage weight, other textbook component weight buildups previously implemented are used to compute the weight of the wing, tails, and nacelles.

H. Aerodynamics

The takeoff aerodynamic model consists of full aircraft drag, wing lift and moment, and horizontal tail lift and moment. We use linear models for the wing lift and pitching moment. The wing lift and pitching moment coefficients are

$$C_{L,w} = C_{L0,w} + C_{L\alpha,w} \alpha, \quad (28)$$

$$C_{M,w} = C_{M0,w} + C_{M\alpha,w} \alpha, \quad (29)$$

where α is the aircraft angle of attack, $C_{L0,w}$ and $C_{M0,w}$ are the wing lift and moment coefficients at zero angle of attack, $C_{L\alpha,w}$ and $C_{M\alpha,w}$ are the wing lift-curve and moment-curve slopes. We estimate $C_{L0,w}$, $C_{M0,w}$, $C_{L\alpha,w}$, and $C_{M\alpha,w}$ based on available experimental or numerical data for similar aircraft in a takeoff configuration. Angle of attack bounds ensure that the wing stays in the linear regime during takeoff.

The horizontal tail lift is a linear function of angle of attack and elevator deflection. The tail lift coefficient is

$$C_{L,t} = C_{L0,t} + C_{L\alpha,t} \alpha_t + C_{L\delta_e} \delta_e, \quad (30)$$

where $C_{L_{0,t}}$ is the tail lift coefficient at zero angle of attack, $C_{L_{\alpha,t}}$ is the tail lift-curve slope, $C_{L_{\delta_e}}$ is the elevator lift increment, and δ_e is the elevator deflection. The tail angle of attack, α_t , accounts for wing downwash and is computed as

$$\alpha_t = \left(1 - \frac{\partial \epsilon}{\partial \alpha}\right) \alpha + i_t, \quad (31)$$

where $\partial \epsilon / \partial \alpha$ is the downwash derivative and i_t is the tail incidence angle. Similar to the wing, we use empirical values for $C_{L_{0,t}}$ and $C_{L_{\alpha,t}}$. We use methods presented by Raymer to estimate the elevator lift increment [47, Ch. 16.3.4] and the downwash derivative [47, Fig. 16.12].

The takeoff parasite drag models are the same as described by Kaneko et al. [8]. We pass the parasite drag, wing lift, and tail lift to Aviary's FLOPS-based induced drag and ground effect components to compute the total drag and lift. The total moment is the sum of the wing moment and the tail lift multiplied by the tail moment arm.

The horizontal tail can be sized based on takeoff trim constraints. The trim constraints enforce zero total moment for the rotation and liftoff phases of takeoff. We include elevator deflections as controls during these takeoff phases. For a given maximum allowable elevator deflection, the optimizer will determine the horizontal tail volume coefficient that satisfies the trim constraints and minimizes the objective.

The vertical tail can be sized as part of the balanced field length analysis. For a given maximum allowable rudder deflection, the optimizer will determine the vertical tail volume coefficient that produces a restoring moment equal to the engine yaw moment during engine-out takeoff. Raymer [47, Ch. 16.4.2] recommends a maximum rudder deflection of 20 deg. We estimate the rudder side-force increment the same way as the elevator lift increment [47, Ch. 16.3.4].

I. Aero-propulsive integration

Our aero-propulsive integration subsystems consist of blown lift and boundary layer ingestion. The boundary layer ingestion model remains unchanged and the blown lift model was added since the last publication.

1. Blown-Lift Model

For wings in propeller wash, a blown lift model is used instead of the linear model described in Sec. III.H. We use the 3D jet deflection model from Courtin [48, Sec. 3.5] to model the takeoff and landing performance of blown lift aircraft. This model is appropriate for propellers blowing over both upper and lower wing surfaces. We first calculate the total thrust coefficient C_T from the total thrust T , freestream velocity V_∞ , and wing area S_{ref} as

$$C_T = \frac{T}{\frac{1}{2} V_\infty S_{\text{ref}}}. \quad (32)$$

The jet velocity V_{jet} and momentum-excess coefficient ΔC_{jet} are then given by, respectively,

$$V_{\text{jet}} = V_\infty \sqrt{C_T \frac{S_{\text{ref}}}{A_d} + 1}, \quad (33)$$

$$\Delta C_{\text{jet}} = \frac{A_d}{S_{\text{ref}}} \left(\frac{V_{\text{jet}}^2}{V_\infty^2} \right) \left(\frac{V_\infty}{V_{\text{jet}}} + 1 \right), \quad (34)$$

where A_d is the propeller actuator disk area.

The lift coefficient C_L and the moment coefficient C_M are given by surrogate models whose values are tuned by computational fluid dynamics simulation in Courtin [48, App. B]. The induced drag coefficient C_{D_i} is then

$$C_{D_i} = \frac{C_L^2}{\pi e \text{AR} + 2 \Delta C_{\text{jet}}}, \quad (35)$$

where e is the Oswald efficiency and AR is the wing aspect ratio. The total drag coefficient is the sum of Eq. (35) and a zero-lift drag from one of the methods presented previously [8, III.G.2].

J. Geometry

1. Spatial Integration

To ensure the aircraft is properly sized for energy source and payload, we implement three spatial integration constraints. These are fuel volume, battery volume, and passenger cabin floor area.

Fuel Volume The fuel volume constraint ensures the available wing volume is greater than the required amount of fuel for the mission. This is implemented using the wing volume calculations in Aviary’s GASP implementation [16] and our internal wing geometry. This constraint is activated when resizing the wing. We do not consider any non-wing storage options for fuel with this model.

Battery Volume The battery volume constraint checks that the assumed pack volume fits within the fuselage. Pack volume V_{pack} is approximated as

$$V_{\text{pack}} = \frac{1}{b} V_{\text{cell}} n_{\text{series}} n_{\text{parallel}}, \quad (36)$$

where b is the volume burden factor, V_{cell} is the cell volume as set by the chemistry, and n_{series} and n_{parallel} are the number of cells in series and parallel. This is a simplistic approximation of pack volume as an actual pack layout code would be prohibitively expensive and complex to evaluate in the optimization loop.

The battery is assumed to be located in the fuselage and a user-specified percentage of the length is allocated for its storage. We then can constrain the computed battery volume to be less than this allowable fraction of the fuselage volume.

Cabin Floor Area The cabin area constraint is necessary for unconventional fuselage planforms or optimizations that resize the fuselage geometry. The cabin area is assumed to be some usable portion of the passenger compartment length times its width. The space taken up by passengers is set by an assumption on class layout and a constraint ensure the cabin area remains large enough for the space necessary for passengers.

2. Landing Gear Sizing

Nose and main landing gear load rating (R) were calculated for each wheel based on the total weight and the number of wheels (n_{wheels}):

$$R = \frac{\text{MTOW} \times \text{factor}}{n_{\text{wheels}}} \quad (37)$$

where R is the load rating, MTOW is the Maximum Takeoff Weight, factor is the weight load factor (1.0 for the main and 0.15 for the nose landing gear), and n_{wheels} is the total number of wheels. Using this rating, we estimate the size and weight of the tires using line fitting with tire data from [49]:

$$\begin{aligned} W &= 5.1 \times 10^{-3} R - 6.18 \\ r_{\text{wheels}} &= 1.86 \times 10^{-4} R + 11.2 \\ \text{width}_{\text{wheels}} &= 2.09 \times 10^{-4} R + 8.18 \end{aligned} \quad (38)$$

where W is the single wheel weight, R is the load rating for each wheel, n_{wheels} is the total number of wheels, r_{wheels} is the wheel radius, and $\text{width}_{\text{wheels}}$ is the wheel width.

The landing gear length is defined as a design variable optimized by the framework. It must be as short as possible to save weight, but long enough to satisfy tailstrike constraints ($\theta \geq 14^\circ$) and wingtip and/or nacelle clearance constraints ($\phi \geq 5^\circ$). The tailstrike angle determines how far the nose can lift before the tail hits the ground, determined by the following equation:

$$\theta = \arctan \left(\frac{S + r_{\text{LD}} - D * w_h}{L_c - S * \tan(\alpha)} \right) \quad (39)$$

where L_c is the longitudinal distance from the center of gravity to the aftmost section of the fuselage before the tailcone, D is the fuselage diameter, θ is the tailstrike angle, S is the strut length, r_{ld} is the tire radius, w_h is the wing height as a fraction of fuselage diameter (0 for a low-wing, 1 for a high-wing), and α is the strut angle as shown in Figure 7. In the case where an aircraft has a tail-mounted nacelle, θ_{nacelle} , the angle at which the nacelle scrapes the ground, is used, following the geometry shown in Figure 8.

$$\theta_{\text{nacelle}} = \arctan \left(\frac{s + r_{\text{LD}} - w_h D + w_{\text{nacelle,vert}} D - D_{\text{nacelle}}/2}{w_{\text{nacelle,long}} L - s * \tan(\alpha) + L_{\text{nacelle}}} \right) \quad (40)$$

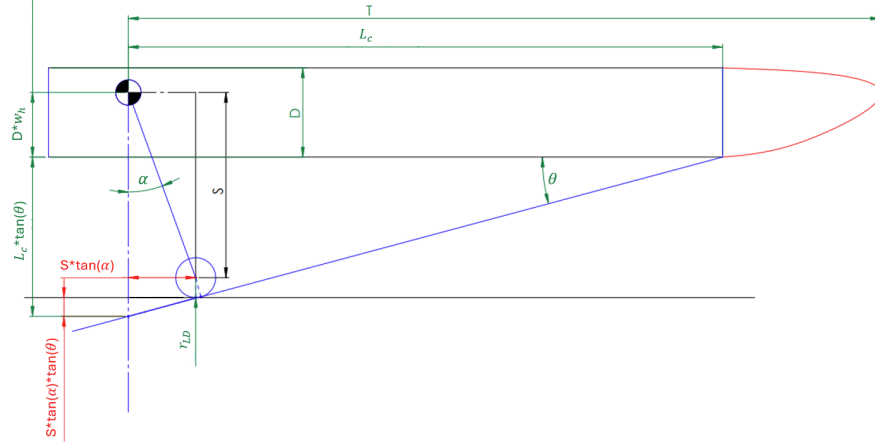


Fig. 7 Geometry used to determine tailstrike clearance

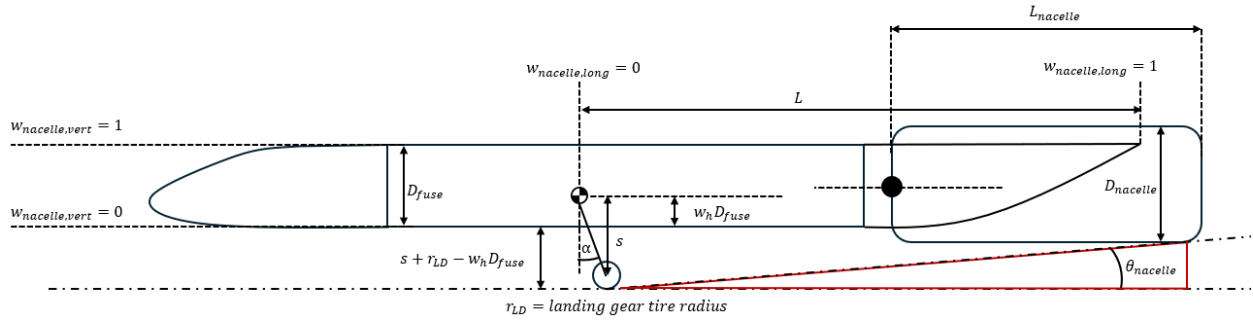


Fig. 8 Geometry used to determine nacelle tailstrike clearance

The wingtip clearance angle determines how much the airplane can roll before an engine nacelle scrapes the runway:

$$\begin{aligned}
y_{\text{LD}} &= (r_{\text{LD}} + S) * \tan(\beta) \\
B &= |d_{\text{OE}} - y_{\text{LD}}| \\
H_{\text{center}} &= S + r_{\text{LD}} - n \\
R_{\text{hyp}} &= \sqrt{H_{\text{center}}^2 + B^2} \\
\phi &= \arccos\left(\frac{r_e}{R_{\text{hyp}}}\right) - \arctan\left(\frac{B}{H_{\text{center}}}\right)
\end{aligned} \tag{41}$$

where d_{OE} is the engine lateral position, b is the wing span, y_{LD} is the gear lateral distance, r_{LD} is the tire radius, S is the strut length, β is the strut mounting angle, n is the vertical distance from wing to nacelle center, ϕ is the wingtip clearance angle, and r_e is the engine radius, as shown in Figure 9.

In the case of a clean wing without any nacelles, ϕ simply reduces to

$$\phi = \arctan\left(\frac{s + r_{LD}}{b/2 - (r_{LD} + S)\tan(\beta)}\right) \quad (42)$$

as shown in Figure 10. The tailstrike and wingtip clearance angles are then constrained to be greater than 14° and 5° , respectively.

The static margin can now be calculated as

$$SM = l_{np} - \frac{x_{CG}}{MAC} \quad (46)$$

Our framework allows the wing position to vary in order to meet a static margin constraint.

IV. Demonstrations of Electrified Aircraft Design Optimization

A. Model Setup

We previously demonstrated this framework on a version of NASA’s SUSAN concept and a hybrid commuter aircraft [8, IV]. Here we utilize the expanded framework to demonstrate two variations on two different aircraft configurations that demonstrate the flexible propulsion architecture and range of technologies, all for a small single-aisle aircraft. The two architectures considered are Tn , which has a single aft turbofan and n wing-mounted electrically driven fans, and Sn , which has two underwing turbofans and n electrically driven fans. The two T cases are $T2$ and $T16$, which each have a single aft turbofan and 2 and 16 electrically-driven fans on their wings. The two S cases are $S2$ and $S5$. Each has two underwing turbofans. $S2$ has two aft electrically driven fans and $S5$ has three aft electrically driven fans and two wing-mounted electrically driven fans.

Due to limitations in the framework, all components of a single type are sized together. This means all turbofans or all motors on a single aircraft are assumed to be the same size, regardless of location. Because of this, the $S5$ case with electrically driven fans on the wings and on top of the fuselage are all the same size.

These cases use the following models described in this work and the previous paper [8]:

- Scaled engine core deck with specific-power-based weight estimation
- BLI fan with RPM-based weight estimation
- First principles motor
- Constant efficiency generator, rectifier, and inverter with specific-power-based weight estimation
- Unified thermal management system (architecture tailored to specific case)
- Wing area sizing by a constant wing loading of $5600N/m^2$
- Aviary payload weight buildup
- OpenConcept structural weight model with systems weights from Aviary
- OpenConcept C_{D0} build-up and Aviary’s FLOPS induced drag model
- Tail area sizing by the volume coefficient methods

B. Optimization Setup

Table 2 describes the optimization setup for all four cases. Despite having different propulsive and thermal architectures, all have roughly the same optimization setup. This allows them to be evaluated against each other for potential energy savings.

Because takeoff is not explicitly modeled, we apply a fixed wing loading and a fixed sea level static T/W to ensure the aircraft remains sized for takeoff. Wing area is calculated from the current MTOW estimate and the fixed wing loading. Span is automatically calculated from the latest area and aspect ratio values. The full set of design variables for the motor is applied, allowing a customized motor for each architecture. The RPM is limited by an estimate of the maximum its associated fan is capable of based on the diameter. The load electrification factor (fraction of power to electrical propulsors) can vary linearly along each mission phase and can vary to meet the SLS T/W constraint, simulating using the electric powertrain for takeoff. These cases do not consider descent because it is not as impactful on the fuel burn and operations decisions as other phases for these cases.

C. Results

Figure 11 shows relevant mission outputs for each case. All four cases have about the same energy consumption. The load electrification factor varies significantly between the S and T cases, with both T cases decreasing electrification in climb but both S increasing electrification in climb. The S cases have a higher electrification in cruise than T . The larger single turbofan on the T cases is likely the reason for this, as its throttle level and performance will be different than the two separate turbofans on S . The motor power is higher on T , which lines up with the higher load electrification factor. The engine in the S cases throttles higher in climb, as the load electrification factor is lower.

Table 2 Multi-concept optimization problem setup.

Objective function	Minimize	Fuel consumption
Design variables	By varying	MTOW
		Wing aspect ratio
		Engine core sizing scaling factor
		All propulsor power ratings
		Motor power rating
		Motor RPM
		Motor airgap diameter
		Motor copper slot depth
		Motor copper current density
		Generator power rating
		Load elec. factor (takeoff, climb, cruise)
		TMS design variables (see [41] for details)
Constraints	Subject to	Sea-level static $T/W \geq 0.33$
		Component power margins in takeoff and climb
		Motor heat limit
		Motor length-to-diameter
		Motor tip speed
		Motor diameter restriction
		Wing fuel volume constraint

V. Conclusions

Aircraft design is a tightly coupled problem that continues to increase in complexity as novel technologies are proposed, subsystems become more tightly coupled, and competing objectives must be balanced. With this, the need to leverage design optimization has become more and more important. We previously presented a gradient-based MDAO framework built on OpenMDAO and Aviary with subsystems modeled at fidelity levels that are higher than typically used in conceptual design, in particular with regards to electrification of the propulsion system and more closely coupled airframe-propulsion-operations integration. This work presented further additions to subsystem models and performance metrics and incorporated them into this framework to add fidelity to aircraft components and allow for the evaluation of proposed designs for a range of considerations. These include not only fuel and energy consumption, but also environmental impact, noise, and cost. The enhanced framework was demonstrated on four propulsion system architecture variations, showing the benefits of a flexible and comprehensive framework design. Upcoming publications will describe detailed aircraft studies carried out with this framework to determine the most promising technologies for 2050 commercial aircraft.

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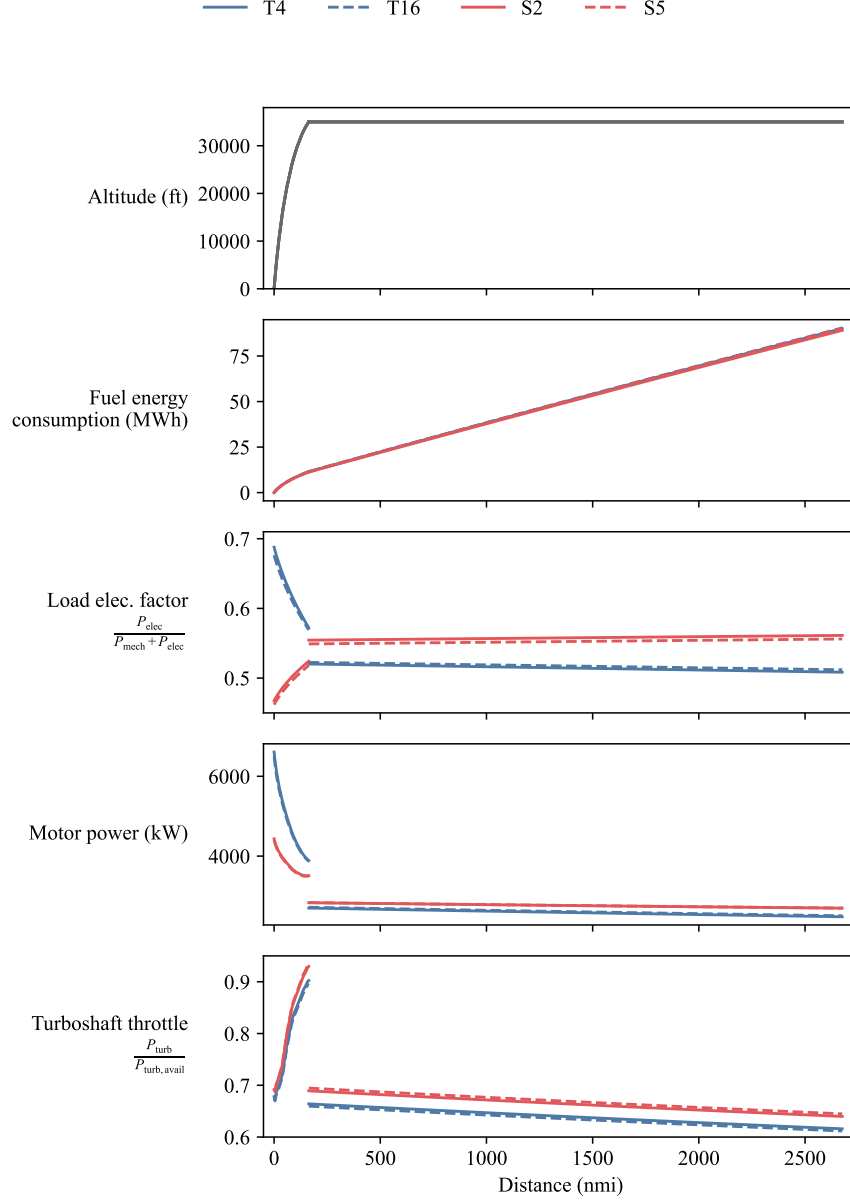


Fig. 11 Mission profile and relevant parameters for the four aircraft cases.

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