

A Modular MDO Framework for Rapid Electric Aircraft Design

Álmos Quevedo Oross,^{*} Aaryan Lath,[†] and Thiago Guimarães[‡]
Purdue University, West Lafayette, IN, 47906

Conceptual aircraft design presents complex engineering challenges with demanding, often conflicting, requirements. Traditional, sequential design methods are often too slow for rapid design cycles, and the increasing use of electric propulsion introduces tightly coupled systems (e.g., batteries, structures, and aerodynamics) that are difficult to optimize manually. This paper proposes a robust Multidisciplinary Design Optimization (MDO) framework to facilitate rapid design space exploration. The framework is built on three core principles: it is 1) physics-based, rejecting reliance on unavailable historical data; 2) modular, allowing for rapid adaptation to new requirements; and 3) built for variable fidelity, balancing computational cost with accuracy. The proposed methodology features a suite of modular physics models that replace traditional statistical estimations with more accurate, physics-based sizing modules better suited to novel or unconventional designs. To maximize design efficiency, the framework employs a dual-mode optimization strategy. First, a Genetic Algorithm (GA) performs a broad, global search of the conceptual design space, allowing teams to explore discrete variables like motor count or tail configuration. Once the GA identifies a promising family of designs, the framework switches to an efficient, gradient-based optimizer. This second stage precisely refines continuous variables, such as wingspan and chord, to find the single-best aircraft within that concept. The proposed MDO framework provides a powerful, adaptable, and efficient tool for design teams, enabling them to confidently navigate a complex design space and develop more optimized aircraft.

I. Introduction

WHEN faced with an aircraft design challenge involving a multitude of requirements, constraints, and often various desired outcomes, traditional analysis procedures make the initial design exploration tedious and may in some instances overlook potential aircraft concepts [1]. Furthermore, with a shift toward electrification, the transition introduces new, complex design challenges, such as bulky and heavy electrical components that create spatial integration issues and a close coupling of disciplines. Thus, the outer mold line of the aircraft – a decision involving both aerodynamic analysis and payload requirements – together with aerodynamic and propulsive loads will directly impact structural design, which in turn will affect weight and balance and affect stability and performance. The result is a cycle of complex interactions between the various aircraft design disciplines that becomes difficult to navigate.

The ability to explore a large design space involving both continuous dimensions and categorical options has great value in such a situation. Thus, Multidisciplinary Design Optimization (MDO) emerged as an essential methodology to explore these new and complex design spaces. While the application of multidisciplinary approaches dates back to simple structural problems in the early 1960s, the field experienced significant development in the early 2000s due to increased computational availability [2]. The technological advancement has allowed the industry to transition from sequential processes, to integrated frameworks capable of solving complex interactions. This holistic approach has proven to yield optimal solutions far superior to those achieved by optimizing individual disciplines sequentially [2].

To navigate the conceptual and preliminary design phases of new electric aircraft, the optimization framework proposed in this study is built around three critical principles. First, it must not rely on historical data – given the relative lack of statistical precedence for electric powertrains, the system must analyze the aircraft using purely physics-based models. Second, to balance computational cost with accuracy, the framework must allow for variable fidelity, utilizing computationally efficient low-fidelity models for broad conceptual exploration and switching to high-fidelity models for preliminary design refinement. Finally, for ease of development and extensibility, the architecture must be modular and capable of seamless integration with existing optimization routines provided by software packages such as MATLAB.

This extended abstract introduces the architecture of this framework, which combines these principles into a novel, dual-mode optimization strategy. The methodology’s unique contributions are its pairing of a physics-based

^{*}Undergraduate Student, School of Aeronautics and Astronautics, 701 W. Stadium Ave.

[†]Undergraduate Student, School of Aeronautics and Astronautics, 701 W. Stadium Ave.

[‡]Associate Professor of Engineering Practice, School of Aeronautics and Astronautics, 701 W. Stadium Ave, AIAA Senior Member.

structural sizing module, which avoids the inaccuracies of traditional statistical methods for novel configurations, with a variable-fidelity aerodynamic analysis. This approach allows the framework to first efficiently conduct a broad conceptual search using a Genetic Algorithm before refining the design with a high-fidelity, gradient-based approach. The following sections detail this modular methodology and the validation of its integrated physics models.

II. Methodology

A. Constraint Handling

With this framework, we seek to encompass the entire breadth of constraints a designer could wish to impose on an aircraft concept [2, 3]. In particular, the framework is built to process any or all of the following constraints, each in its own separate block.

- 1) Mission requirements: these may come in various combinations. For example, in some cases, the target range and payload weight are known, while in others perhaps only a payload volume and intended endurance. The framework would allow effortless switching between different sets of requirements by treating them as independent constraints.
- 2) Performance requirements: these apply to specific maneuvers required as part of the mission. Examples include takeoff and landing distance, service ceiling, climb rate, turn radius, and cruise speed.
- 3) Geometric restrictions: these are often set by the operating environment (e.g. airports) or manufacturing.
- 4) Propulsion system requirements: the designer might need to address available propulsion system choices, number of powerplants, and so on. These would become categorical variables in the optimization problem.
- 5) Aerodynamic constraints: it is important to consider effects such as that of wing taper on stall progression to discard potentially dangerous or inefficient designs.
- 6) Aeroelastic constraints: In particular, the aircraft must remain within safe margins from its flutter and control reversal speeds during all points of its flight envelope [4].
- 7) Stability and control constraints: the ability to specify desired stability margins and handling qualities at the outset eliminates the need for a separate stability analysis later on in the preliminary design process, instead deferring the analysis to the detailed design phase when any control and navigation systems are implemented [4].

B. Physics Models

To evaluate the feasibility of a design against the constraints, the framework integrates a suite of modular physics-based models.

1. Aerodynamics

We propose two separate models – an approximate but light-weight analytical model for use during the broad conceptual search, and a higher-fidelity, computationally more intensive model for preliminary design optimization.

- 1) The light-weight model is based primarily on analytical and empirical relations provided in the USAF Stability and Control Datcom [5]. The corresponding module of the framework is responsible for approximating aerodynamic loads, stability and control derivatives, and linear dynamic response characteristics. While computationally efficient, this method is strongly dependent on past experimental data, limiting its reliability for truly novel configurations [6].
- 2) The higher-fidelity model used for preliminary design optimization obtains the same information by passing the aircraft geometry to the Athena Vortex Lattice (AVL) program through a custom MATLAB wrapper. AVL is a vortex-lattice model (VLM) that computes aerodynamic reactions on lifting surfaces, control surfaces, fuselages and engine pods at moderate angles of attack. While AVL results may capture geometry details ignored by the analytical model, the accuracy of a program is limited to quasi-steady inviscid flow, which presents a major drawback compared to the analytical models [7]. Viscous flow can be accounted for by implementing a nonlinear vortex lattice method (NL-VLM), which consists of providing viscous airfoil results to correct the potential flow solution and obtain more accurate estimates of drag and maximum lift [2]. This latter feature of our framework is currently in development. Figure 1 shows initial results from the development phase of the AVL wrapper.

Independently of the model chosen, the aerodynamics module serves to evaluate constraints on lift and drag characteristics, stability and control, and aerodynamic force distributions insofar as stall progression is concerned.

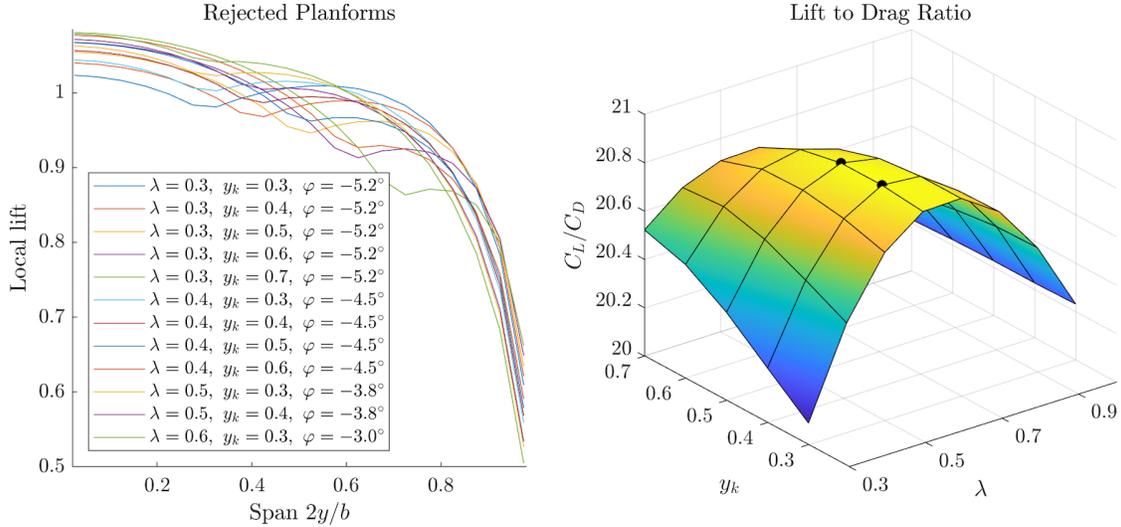


Fig. 1 Sample tapered wing optimization result from the initial testing of our AVL wrapper

2. Structures

The structures module conducts wing and fuselage sizing based on the distributed loads obtained from the aerodynamic analysis module. This analytical, physics-based approach is a deliberate departure from traditional "Class II" statistical weight estimations, such as those derived from Gudmundsson [8]. As demonstrated by Silva et al., such statistical methods can be highly inaccurate for the innovative designs and hybrid-electric architectures that this framework targets. Their study found that an analytical, physics-based sizing module estimated wing weight within 4% of a high-fidelity FEM analysis, whereas a statistical method was off by over 18% [2].

3. Propulsion

Propeller thrust, power, and efficiency at various airspeeds and RPM values are interpolated from publicly available performance tables. This approach allows us to obtain accurate thrust data for every phase of flight. As to batteries, we look at the charge available as well as its C-rating and impose those as an energy available constraint and a current draw constraint. We also use Peukert's law to verify we are able to draw current for the required time. We require further hardware testing and literature research to determine the best way to predict battery performance under load.

4. Performance

The framework includes a variety of performance calculations to account for different possible combinations of known and unknown quantities. For example, given an aircraft configuration, it is possible to either solve for takeoff shaft power knowing the allowed takeoff distance or the actual takeoff distance knowing the maximum shaft power. Dedicated functionality is included for a number of possible phases of flight. The performance module, along with the aerodynamics and propulsion module is ultimately responsible for obtaining and checking the feasibility of total mission quantities such as energy consumed, time elapsed, maximum current draw and propeller RPM, and so on.

C. Optimization Strategy

The current state of the framework executes a "blind search" of the entire design space, which is useful for initial validation but is not a formal optimization routine. It generates a comprehensive dataset that can be visualized in "carpet plots," allowing the designer to identify trends, understand multidisciplinary trade-offs, and visually locate regions of high performance. This process validates the coupling of the physics modules and provides a robust, feasible design point from which to launch a more formal optimization. The next step is to implement a formal, dual-mode optimization strategy that aligns with the dual-fidelity physics models described in the Methodology.

1. Conceptual Exploration: Genetic Algorithm

In light of the presence of discrete variables (e.g., number of powerplants) and categorical variables (e.g., tail configuration), we have identified the Genetic Algorithm (GA) as the optimal choice for the broad conceptual exploration.

Traditional gradient-based methods cannot handle discrete or categorical variables natively [9]. GAs, however, are exceptionally well-suited for these mixed-variable (combinatorial) problems, a capability that is critical in the conceptual design phase where such choices are paramount [10]. Furthermore, GAs are population-based search methods, allowing them to perform a global exploration of the design space to identify families of high-performing, non-intuitive solutions rather than converging on a single, local optimum. This approach is validated by frameworks like that of Silva et al., which successfully employs the NSGA-II (a GA-based algorithm) for a similar hybrid-electric MDO problem [2].

2. Preliminary Design Optimization: Continuous Approach

The high computation cost of the genetic algorithm can require 5 to 200 times as many function evaluations as a gradient-based method [11]. This makes it inefficient for high-fidelity design refinement.

Therefore, once the conceptual GA has identified a promising, narrowed design space (e.g., fixing the categorical choices for tail configuration and material), the framework will switch to a direct continuous approach. This gradient-based optimization is highly efficient for refining continuous variables (e.g., wingspan, chord, twist) with high precision. This strategy aligns with the strengths of each method: using the GA for global, mixed-variable *exploration* and the gradient-based method for local, continuous *exploitation* in a more narrowly defined and well-understood design space [11].

III. Final Paper

A. Framework

The final paper will present a detailed description, followed by the framework from model definition by the designer through physics simulation and optimization to selection of the winning configuration. The theory and logic behind the individual physics models will also be explained; supported by flowcharts and a case study encompassing the entire design cycle of an electric aircraft. The case study will be laid out to illustrate how our framework integrates with the broader aircraft design process. In particular, we will demonstrate translating system requirements and restrictions to a problem definition compatible with our framework and linking the results of the conceptual search to the inputs of the preliminary optimization.

B. Desired Features

The case study, in its current state, executes a blind search of the entire design space. As discussed in the methodology, a key desired feature of the framework is the ability to select between a conceptual or preliminary design mode. Due to the presence of discrete variables such as the number of powerplants or categorical variables such as the tail configuration or material selection, we have identified the genetic algorithm for conceptual exploration. However, given the high computation cost of the algorithm and randomness of the results, it is of key importance to ensure individual components of the framework are each implemented in the most efficient way possible. Thus, this will be another avenue the paper will focus on.

C. Outcomes

The initial conceptual blind search of the case study provided valuable outcomes, particularly in identifying computational bottlenecks and validating module-level efficiency gains. For example, our performance module includes a function for calculating required takeoff power by iteratively conducting a numerical simulation of the takeoff roll at different power settings and adjusting the power between iterations using the error e_d between the simulated and required takeoff distance:

$$P_{\text{new}} = P_{\text{old}} \cdot e_d. \quad (1)$$

The numeric simulation, besides being expensive in itself, calls the propulsion module to obtain thrust at each point of the simulation, thus requiring additional interpolations at each time step. To mitigate the high computational expense, we have ensured all tolerances are at their largest allowable value without hurting simulation results. More importantly,

we discovered that an adjusted power update formula of the form

$$P_{\text{new}} = P_{\text{old}} \cdot e_d^k \quad (2)$$

may reduce the number of power convergence loop iterations from 4–6 to 1–3 for an appropriate k determined experimentally. An example of this enhancement for a particular aircraft configuration is shown in Figure 2.

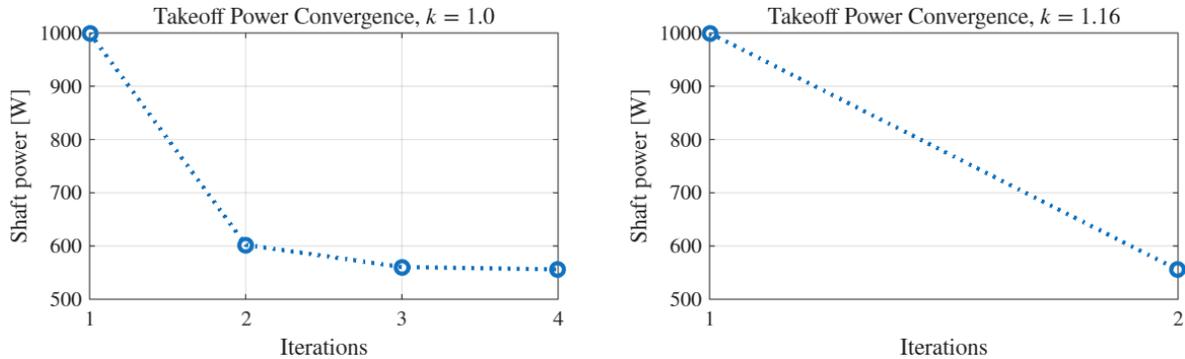


Fig. 2 Comparison of takeoff power convergence for different values of the parameter k

The final paper will present a detailed discussion of numerical testing conducted on all physics and simulation modules of the framework and on the top-level optimization algorithms themselves. In the case of the GA, the effect of user-defined parameters such as initial population size and continuous variable resolution will be thoroughly examined.

Based on the features highlighted, the paper should serve as both a guide to the design process as well as a template providing the tools for development based on the users mission or challenge.

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