ADVANCED MULTIDISCIPLINARY DESIGN OF NEXT-GENERATION GREEN AIRCRAFT

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Abstract

This study presents an advanced Multidisciplinary Design Optimization (MDO) tailored for the design of next-generation green aircraft, integrating innovative propulsion systems and advanced materials. The MDO is based on an advanced Class III weight estimation method. Traditional Class I and II methods were inadequate for contemporary green aircraft, necessitating a sophisticated approach to accommodate new concentrated masses and materials. The Asymmetric Subspace Optimization (ASO) method was employed to balance computational loads effectively across disciplines such as aerodynamics, structures, and propulsion systems. Preliminary results for a hybrid electric/traditional regional aircraft have shown significant performance improvements, including a notable reduction in fuel mass and an increase in lift-to-drag ratio.

Keywords: Multi disciplinary optimization, Structural aircraft design, Conceptual and preliminary design

1. Introduction

Currently, many major airlines, particularly those operating in the regional aircraft segment, are seeking replacements for hundreds of aging aircraft that are nearing the end of their commercial service life [1]. Additionally, the associated revenue, based on the calculation of passenger kilometers (RPKs), is projected to grow annually at a rate of over 4% within the next 20 years [2]. Moreover, climate change and the growing scarcity of resources call for a significant reduction in aviation's impact on citizens and the environment. Consequently, the integration of innovative *green* technologies into future aircraft will be essential for enhancing the appeal and benefits for both customers and airlines. Implementing design changes is most effective during the preliminary design phase, and it is essential to consider how the different disciplines interact, especially when designing next-generation aircraft. In addition to traditional areas such as aerodynamics, structures, and flight dynamics, it is more than ever necessary to include the modeling of novel propulsion systems during the initial stages of the design process.

Multidisciplinary Design Analysis and Optimization (MDAO) involves various architectures for integrating different disciplinary models in system optimization. Monolithic approaches like MultiDisciplinary Feasible (MDF) [3] solve the entire problem collectively, ensuring consistent design solutions but at the cost of a high computational intensity. In contrast, Individual Design Feasible (IDF) allows disciplines to operate independently, reducing computational complexity by eliminating direct communication. Distributed architectures like Asymmetric Subspace Optimization (ASO) balance computational loads by prioritizing less costly disciplines before invoking more resource-intensive ones. In Ref. [4], the ASO for aero-structural optimization was applied since aerodynamics typically requires an order of magnitude more time than structural analysis.

There are different examples in literature regarding MDAO on aircraft: in [5] the authors applied an optimisation strategy on a Blended Wing Body based on a multi-level approach with a multidisciplinary aircraft design task on the global level and a structural design task on the local level. Nonetheless, only a standard propulsive system was considered and a simple Breguet approach for the mission analysis was pursued.

Orefice et al. [6] proposed a design methodology for electric and hybrid-electric powered aircraft. Their approach integrates the unique challenges of electric propulsion systems, such as powertrain architectures, energy sources, and aerodynamic interactions, within the framework of traditional aircraft design practices. Their workflow involves defining a baseline design based on initial requirements, followed by the determination of energy needs and weight distribution while adhering to relevant aviation regulations. However, a limitation of their approach is the use of a simple Class I weight estimator for the aircraft structure, which is not directly coupled with the initial design phase.

Silva et al. [7] developed a general multidisciplinary design optimization method for the conceptual design of general aviation and hybrid-electric aircraft. Their framework uses efficient computational methods comprising modules of engineering that include aerodynamics, flight mechanics, structures, performance, and their integration. However, they also used a simple structural model with the structural idealization method proposed by [8], not suitable for composite materials nowadays used in aircraft primary structures such as Carbon Fiber Reinforced Plastic.

Weight estimation methods in aircraft design are typically classified into several categories. Class I methods, utilized in early conceptual phases, estimate Maximum Take-off Weight (MTOW), Operational Empty Weight (OEW), Payload Weight (PLW), and Fuel Weight (FW) based on statistical data and basic performance equations [9, 10, 11]. Class II methods, employed when baseline geometry is established, use semi-empirical relations to estimate component weights [9, 11, 12]. In contrast, Class III methods employ physics-based Finite Element Analysis (FEA) for detailed component sizing and weight estimation [13, 14, 15]. Class IV weight estimation methods also exist, but they are used beyond the scope of conceptual and preliminary design. These methods are typically applied during the detailed and pre-production phases, combining the results of more advanced FEM models than those used in Class III methods with weight calculations based on production CAD models and actual component weights from catalogs and suppliers.

Class I and Class II methods are typically used in the preliminary phase of the optimization process. However, several problems arise when applying this approach to innovative aircraft. Introducing

new concentrated masses, such as batteries or fuel cells and tanks, significantly impacts loads and requires detailed design considerations for the aircraft structures, ensuring they are adept at accommodating such new components while maintaining optimal performance and structural integrity. Furthermore, the transition to electric power sources, either in the form of batteries or fuel cells, facilitates the adoption of innovative propulsion systems such as distributed electric propulsion, which may significantly influence both loads and structural weight. Additionally, the integration of advanced materials, such as Carbon Fiber Reinforced Plastic, leads to a substantial reduction in structural weight, challenging the reliability of traditional empirical predictions for structural-weight estimates.
The incorporation of groundbreaking solutions, such as truss-braced wings or folding wing tips that enable high aspect ratio wings, and blended wing body configurations, further highlights the inadequacy of relying on Class I and II approaches for structural-weight estimates.
In this study, we introduce and employ an advanced Class III weight estimation approach. Our approach includes rapid automatic generation of a Finite Element Method (FEM) model for the entire aircraft in less than a minute of wall-clock time, facilitating its integration into a Multidisciplinary Design Optimization (MDO) loop. The algorithm and consequent software developed support automated aeroelastostatic analyses across different load cases and include buckling analyses. Moreover, it facilitates the modeling of composite structures, including sandwich components as well. Additionally, it can automatically generate an AVL input file [16] consistent with the aircraft geometry. AVL, an open-source Vortex Lattice Method code, allows for the estimation of the aircraft's lift-to-drag ratio.
The developed Class III weight estimation approach was previously applied by the authors in an open-loop analysis of a hybrid regional aircraft [17]. This method now serves as the basis for the innovative multidisciplinary approach proposed in this work. In particular, an Asymmetric Subspace Optimization (ASO) approach is considered. In the ASO architecture, a sub-optimization problem in the inexpensive discipline is solved for each call of the higher-fidelity discipline (refer to section 5.for more details). This results in a design space reduction of the main optimization problem that never includes design variables related to the faster disciplines (propulsion system) and in a reduced number of calls for the costly disciplines (aerodynamics and structure). Indeed, the propulsion system performances are included in the design process by defining further design variables such as engine power, fuel mass, and the mass of other propulsion system components in the case of innovative configurations like batteries, fuel cells, or tanks. To ensure the feasibility of the proposed propulsion system, a set of constraints is introduced. This encompasses a comprehensive constraint analysis, ensuring the aircraft's ability to adhere to have a takeoff compliant with the requirements, maintaining the designated cruise speed, and achieving the desired climb ratio, even in the event of an engine failure. Moreover, range constraints are imposed to satisfy the need of the assigned mission. In traditional propulsion cases, the analytical Breguet's solution can be employed; however, using innovative propulsion systems, in which the fuel mass depletion is not necessarily proportional to the energetic expense (e.g., because of batteries) the analytical solution is not available and therefore a time-marching approach is considered (see section 4.for more details). In section 2.the structural model employed within the developed MDO framework is presented. Next section 3.discusses various aerodynamic models employed, such as doublet lattice and vortex lattice methods, each chosen for their applicability in preliminary aircraft design phases. Then, section 4.details the modeling of the propulsion system. Subsequently, section 5.outlines the multi-disciplinary optimization approach adopted in this research. Finally, preliminary results are presented in section 6.highlighting improvements in aircraft lift-to-drag ratio and reduced fuel consumption achieved through the application of the MDO framework to a hybrid electric/regional aircraft design.

2. Structural modeling

In this study, we develop an advanced Class III weight estimation approach. A complete aircraft FEM model is generated using an in-house code named FUROR (Framework for aUtomatic geneRatiOn of aeRoelastic models), driven by a specified set of design variables. FUROR leverages the open-source geometric library OpenCasCade for automatic generation of wing boxes and fuselage geometries (refer to fig. 1), and utilizes the open-source software GMSH for FEM grid generation. The process of generating the aircraft FE model involves three main steps. First, the aircraft geometry is defined based on standard geometric characteristics such as wingspan, dihedral, sweep, chord, and fuselage length. Additionally, the geometries of key structural components like wing spars, ribs, and stringers are specified. Second, a hybrid structured-unstructured FEM mesh is generated using GMSH [18]. Finally, the complete FE model of the aircraft is established, with beam sections and shell thickness defined in a standard Nastran input file [19]. In this work, the structure is modeled in aluminum. However, FUROR is also capable of modeling laminated composite shells by automatically defining Nastran PCOMP cards, including sandwich structures. Additionally, aerodynamic doublet lattice surfaces are defined, incorporating control surfaces for trim analysis and aeroelastostatic analysis (Nastran sol144) across multiple load cases. Subsequently, a linear buckling analysis (Nastran sol146 [20]) considering the aeroelastostatic loads can be automatically performed and included in the MDO loop. Dynamic aeroelastic analyses, such as gust response (Nastran sol146 [20]), can also be automatically conducted and integrated into the MDO loop.

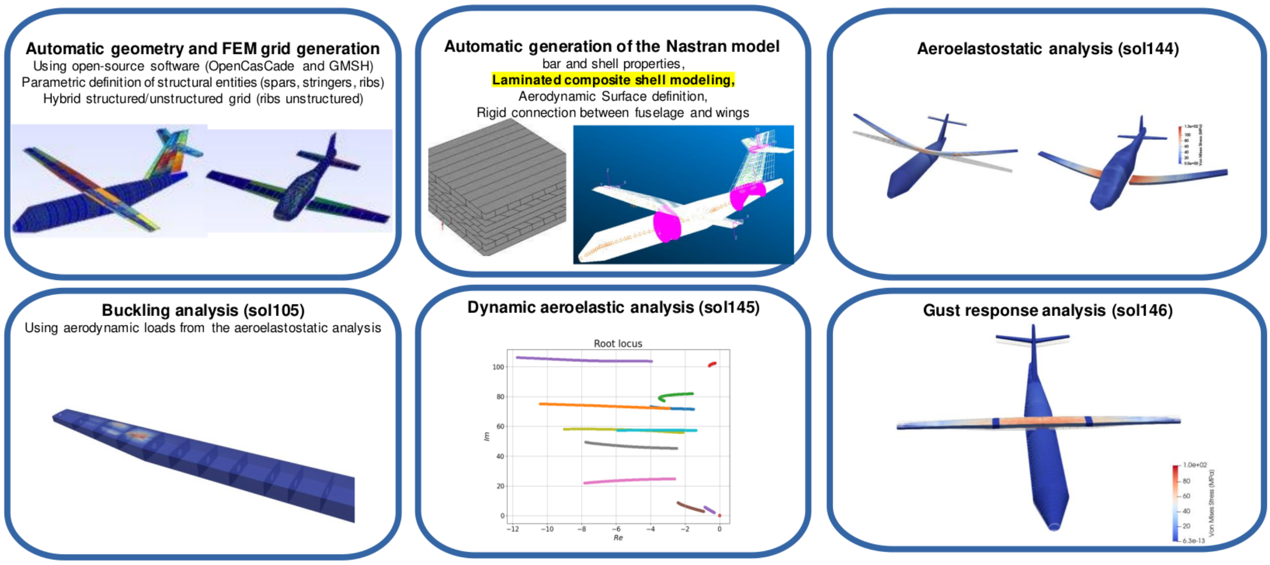


Figure 1 – Description of the in-house FUROR code (Framework for aUtomatic geneRatiOn of aeRoelastic models).

3. Steady and unsteady aerodinamic modeling

Aerodynamic modeling is crucial during the initial design stage for evaluating the forces acting on the aircraft structures and determining the aircraft's mission performance. Various aerodynamic models, each differing in accuracy and computational time, can be employed for this purpose. CFD methods relying on Navier-Stokes equations provide the utmost precision in analyses, effectively capturing the aerodynamic interaction among aircraft components and accurately estimating the overall drag of each component. In conceptual and preliminary aircraft design, the need to conduct multidisciplinary trade studies and optimizations with a wide range of variation parameters is crucial. Despite the recent developments in massive parallel computation on HPC platforms, RANS analyses are prohibitively expensive and are not yet utilized in this design phase. Hence, it is imperative to possess swift and resilient approaches easily accessible for every discipline engaged. Moreover, the constantly growing requirement for design effectiveness mandates a considerable degree of early-stage precision, encompassing both absolute and relative aspects.

Traditionally, statistical and semi-empirical methods are used for this task. They typically offer very high computational speed as well as robust runtime behavior, combined with accurate solutions for the calibrated parameter range. On the other hand, one major disadvantage of these tools is their strong limitation to the parameter range the underlying statistics are covering.

Simplified physical-based aerodynamics models such as strip theory, doublet lattice, or vortex lattice methods are crucial in the field. When employing the strip theory approach, the wing is divided into multiple sections, and the local angle of attack is evaluated for each section. By utilizing lookup tables, the lift and drag coefficients, along with the corresponding aerodynamic forces acting on each wing segment, can be determined. To ensure accurate predictions of the aerodynamic loads, a correction factor is applied to account for three-dimensional effects, also known as finite wing effects.

In preliminary design, the doublet lattice method [21] is commonly employed as a three-dimensional aerodynamic model. It offers enhanced accuracy in lift evaluation, making it suitable for aeroelastic analysis and accounting for finite wake effects. However, it is incapable of estimating drag, including both the induced and viscous components, thereby limiting the assessment of aerodynamic efficiency. The Vortex Lattice Method is more precise and computationally more expensive compared to the doublet lattice method [22]. In its standard nonlinear form, it simulates a free wake with non-linearities that account for wake deformation, resulting in a more accurate estimation of the induced velocity. Furthermore, this method has the capability to estimate induced drag. In the FUROR software, both the strip theory approach and the doublet lattice method are available, generating a Nastran input file [19] for aeroelastic analyses (Nastran sol 145 [20]) as well as trim and static analyses (Nastran sol 144 [20]) using these aerodynamic methods. Additionally, FUROR has the capability to generate an input file, which is coherent with the geometry of the structure, for the open-source Athena Vortex Lattice code.

In this study, the doublet lattice method is utilized for estimating aerodynamic loads in the aeroelastostatic analysis, where the aircraft is modeled as flexible. Moreover, the Vortex Lattice Method is employed for evaluating lift-to-drag ratio, with the aircraft considered as rigid. Additionally, a viscous correction is applied to estimate the zero lift drag coefficient (C_{D_0}).

Specifically, a drag correction based on the friction coefficient of a flat plate is adopted [9], the wetted surfaces are evaluated directly from the geometrical model generated with the in-house code FUROR.

4. Propulsion System Modeling

The propulsive model builds on *PhlyGreen* [23], an object-oriented Python code that, starting from the performance and mission requirements, returns a complete preliminary design of the target aircraft. The numerical code has been modified to account for the structural and aerodynamics model introduced in this paper. We consider a hybrid-parallel architecture in which a traditional kerosene-fueled gas turbine engine and a battery powered electric motor deliver torque to the propeller through a gear-box, as shown in Fig.2. We model the architecture using efficiency chains to relate input and output power.

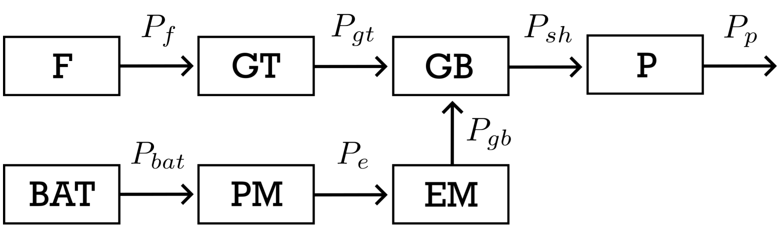


Figure 2 – Schematic model of a *parallel-hybrid* powertrain architecture.

Name	Component
F	Fuel
GT	Gas turbine
GB	Gearbox
BAT	Battery
PM	Power management and distribution system
EM	Electric motor
P	Propulsive element

Table 1 – Powertrain components

More specifically, we recast the algebraic relations between the powertrain components to form a linear system of equations of the form $\sum P_{out} = \eta \sum P_{in}$, that can be specified for the hybrid powertrain architecture as:

$$\begin{bmatrix} -\eta_{GT} & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\eta_{GB} & -\eta_{GB} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -\eta_{PM} & 0 \\ 0 & 0 & 1 & 0 & -\eta_{EM} & 0 & 0 \\ 0 & 0 & 0 & -\eta_{P} & 0 & 0 & 1 \\ \varphi & 0 & 0 & 0 & 0 & \varphi-1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} P_{fuel} \\ P_{gt} \\ P_{gb} \\ P_{sh} \\ P_{e} \\ P_{bat} \\ P_{p} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ P_{p} \end{bmatrix} . \tag{1}$$

The efficiency matrix elements are generally dependent on the flight conditions and engine operating conditions. Also, the parameter φ represents the instantaneous supplied power ratio [24], or power split, between the thermal and electric chain:

$$\varphi = \frac{P_{bat}}{P_{bat} + P_f} \in [0, 1] \, . \tag{2}$$

Solving the system of Eq. 1 allows us to determine the values of the required fuel and battery powers, given a certain flight condition. These values can subsequently be integrated along the mission profile to determine the cumulative energy contributions from fuel and battery:

$$E_i = \int_{t_s}^{t_e} P_{p,i} \left(W_{TO}, \varphi(t), \beta(t), h(t), V(t), C_D(C_L) \right) dt \qquad i = \text{battery,fuel} \tag{3}$$

where the propulsive power P_p depends on the aircraft instantaneous weight ($W(t) = \beta(t) \cdot W_{TO}$), the power split ratio φ, the flight condition in terms of altitude, velocity, and attitude, and the aircraft's drag polar. Once fuel and battery energies are known, their masses can be estimated using the fuel calorific power and the battery energy density.

The electric and thermal engines rating is finally determined based on instantaneous power requirements in the most critical flight phases, namely take-off and one-engine-inoperative (OEI) climb. To this end, we employ a canonical constraint diagram using requirements on the take-off field length and minimum climb gradient in OEI conditions [10].

5. Multi-Disciplinary Optimization approach

In this study, we adopt an advanced multi-disciplinary method focused on green propulsion systems. Our objective is to integrate considerations of structure, aerodynamics, and innovative propulsion systems directly into the initial design phase with a suitable level of precision, as detailed in previous sections. Our chosen framework for optimization is Asymmetric Subspace Optimization (ASO), which proves particularly effective when computational times vary substantially across disciplines [3, 4]. Specifically, structural and aerodynamic modeling (refer to section 3). demand computational times on the order of 10 seconds, while constraint and mission analysis (refer to section 4). require computational times on the order of 0.1 seconds.

Within the ASO approach, we aim to minimize the number of resource-intensive structural and aerodynamic analyses by integrating constraint and mission analysis within an optimizer as part of the external interdisciplinary analysis. Put simply, for each external assessment involving aerodynamic and structural analyses, we determine the optimal propulsion system for the given aircraft, assuming fixed geometry and structural properties.

The ASO framework is developed using the openMDAO open-source library [25]. However, several adaptations have been made. First, an interface was created to integrate the open-source library "pymoo: Multi-Objective Optimization in Python" [26], which provides implementations of state-of-the-art genetic algorithms for single and multi-objective problems.

Additionally, other modifications to openMDAO were made. Specifically, in the external optimization loop, the pymoo NSGAII algorithm is used, and the evaluation of the generation is parallelized using the Message Passing Interface (MPI), enabling evaluation across multiple nodes. For the internal optimization loop, a gradient-based algorithm is adopted, specifically the IPOPT implemented in the open-source "pyOptSparse" library [27].

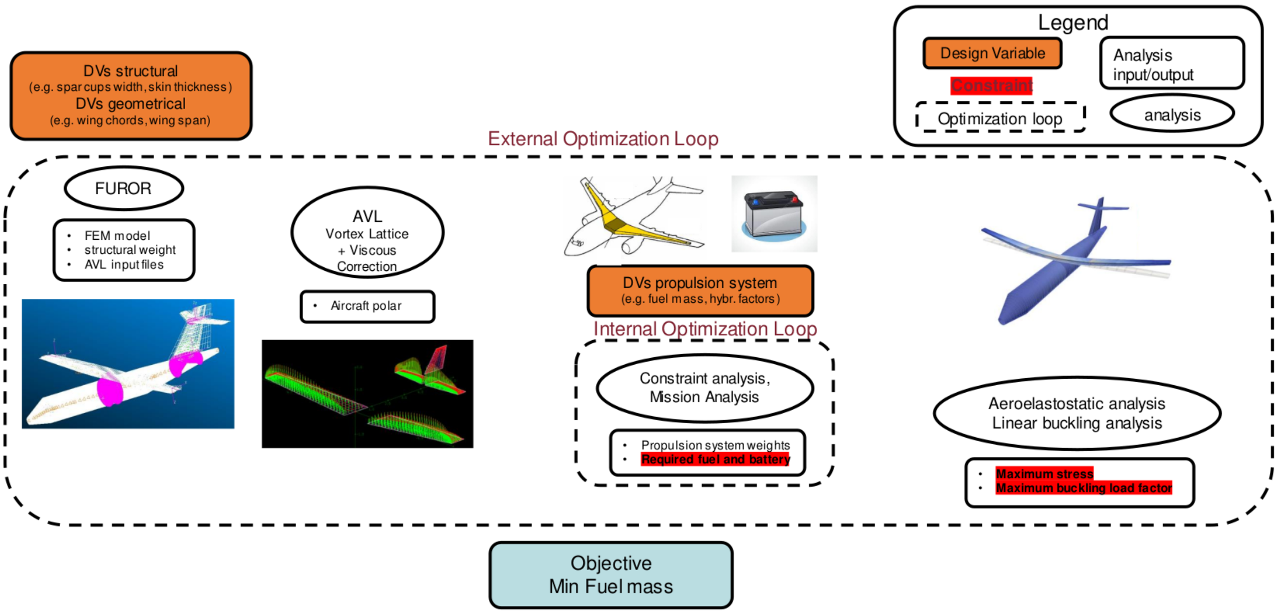


Figure 3 – Scheme of the multi-disciplinary optimization framework.

Figure 3 outlines the optimization loop. The chosen objective, for both the internal and the external optimization loops, is the minimization of the fuel mass for the assigned mission. This choice is motivated by its dual representation of both a significant portion of operational costs and the emitted CO_2, aligning with the goals of reducing environmental impact and operational expenses. The design variables (DVs) of the external optimization loop encompass both structural parameters (e.g., spar caps width and thickness, skin thickness) and geometric parameters (e.g., wing chords and wing span). Utilizing these DVs, the in-house code FUROR generates the aircraft FEM structural model and input files for the open-source Athena Vortex Lattice (AVL). Subsequently, with the aircraft model established, the Nastran weight estimator enables the estimation of the aircraft's structural weight. Additionally, while the payload remains fixed (as a top-level aircraft requirement), the masses of propulsion systems (such as batteries and fuel) are not yet known. These propulsion system masses are significant, and at this stage, it is not yet feasible to verify the structural integrity of the aircraft. However, given that the aircraft geometry is known, it is possible to conduct the aerodynamic analysis using AVL. By varying the angle of attack, the entire aircraft polar is estimated through AVL along with analytical corrections for evaluating viscous drag. It is important to note that the aircraft's aerodynamic polar, which is fundamental for constraint and mission analyses, thereby influences the subsequent sizing of propulsion systems, varies with changes in geometric design variables (e.g., an aircraft with a high aspect ratio will experience reduced induced drag compared to one with a low aspect ratio).
Given the aircraft's aerodynamic polar, the structural weight, and the fixed mission and payload requirements, propulsion system sizing can be carried out through an internal optimization loop. Design variables (DVs) of this loop include fuel and battery masses, maximum engine power, and hybridization factors.

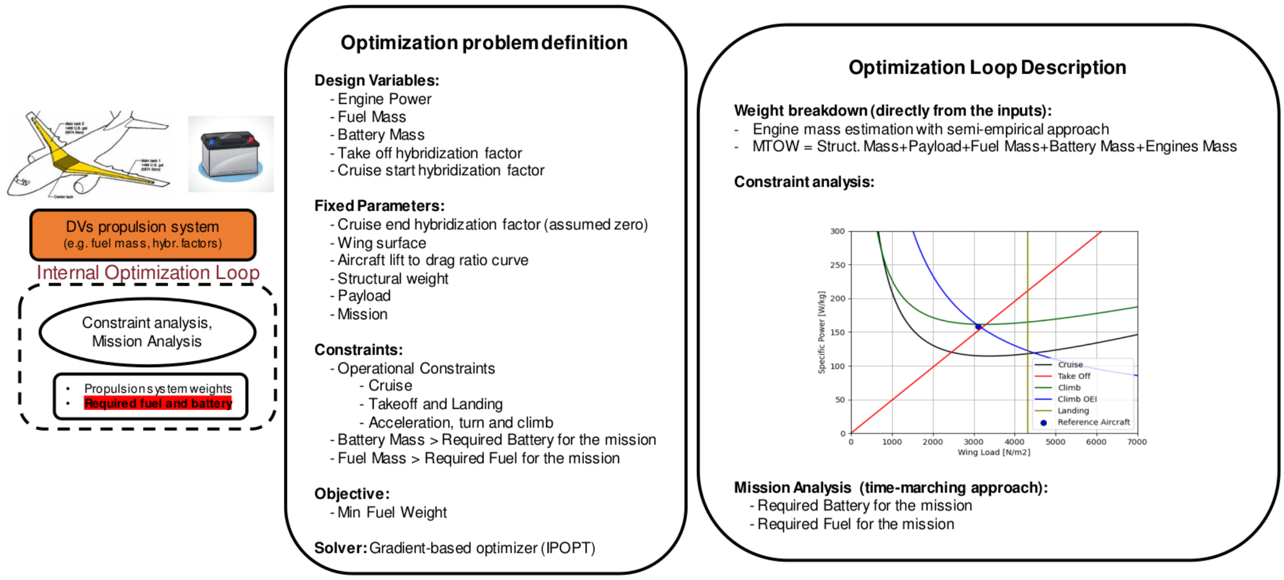


Figure 4 – Scheme of the internal propulsion system optimization.

Initially, weight estimation is performed considering the propulsion system DVs. Specifically, with knowledge of the maximum engine power and take-off hybridization factor (assuming take-off as the most power-demanding flight phase), semi-empirical relations are employed to determine the weights of thermal and electric engines. Subsequently, the Maximum Take Off Weight (MTOW) is estimated considering the engines' estimated weights, fuel and battery masses DVs, structural mass (derived from the Nastran weight estimator), and payload. Once the MTOW is estimated, constraint analysis (refer to section 4). is conducted to ensure the aircraft's capability to fly in all critical operating conditions, and mission analysis is performed to estimate the necessary battery and fuel masses for the considered mission.

Two constraints are then imposed to ensure the feasibility of the chosen fuel and battery mass DVs; these masses must exceed the required fuel and battery masses for the mission. Typically, towards the end of the propulsion system optimization loop, the required fuel and battery masses for the mission (output of the mission analysis) tend to match the fuel and battery masses DVs.

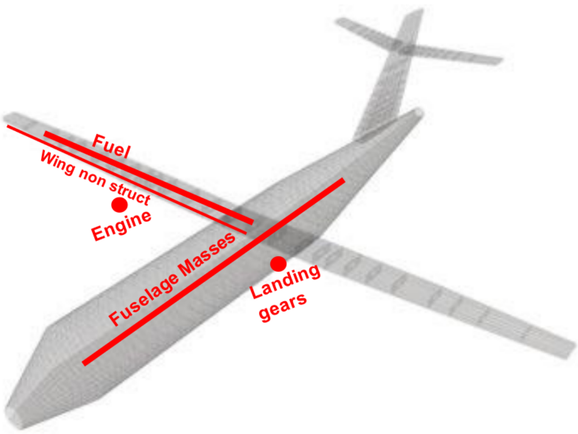
Finally, after determining the propulsion system in the internal optimization loop and acquiring all the aircraft masses, it becomes feasible to verify the structural integrity of the aircraft.

It is worth noting that the stability of the aircraft is significantly influenced by the positioning of the fuel and battery masses, which cannot be neglected. However, in order to reduce computational effort and considering that the chosen positioning of the masses ensures a certain level of stability, the comprehensive dynamic flight analysis using the AVL code to verify static and dynamic stability is conducted only for the optimized design.

As a consequence, the most critical load cases within the aircraft flight envelope are selected, and an aeroelastostatic analysis is conducted. This analysis imposes constraints to ensure the aircraft's structural integrity. For an aluminum structure, the maximum Von Mises stress is considered. Finally, considering both the aerodynamic loads from the aeroelastostatic analysis and the gravitational loads, a linear buckling analysis is performed with a constraint on the minimum buckling load factor.

6. Numerical results

The MDO approach described in section 5.is applied to a hybrid electric/traditional regional 40-seat aircraft. The first step involves defining a reference aircraft with a traditional propulsion system; a typical regional 42-seat configuration is chosen for this purpose. In fig. 5, the reference FEM with the mass breakdown is shown, and the weights of a typical regional 42-seat [28] are also reported for comparison. Then, the MDO is performed (refer to section 5). considering a hybrid electric/traditional propulsion system.



Description	Ref. [28]	Reference FEM	Unit
MTOW	16.70	16.70	ton
Payload	4.56	4.56	ton
Seats	400	400	kg
Crew	320	320	kg
Max Fuel	3.95	-	ton
Fuel at Max Payload	-	1.60	ton
Engine and nacelle	585	585	kg
Wing non struct	-	245	kg
Wing struct.	1496	1450	kg
Tail struct.	-	133.4	kg
Rudder struct.	-	244	kg
Landing gear	744	744	kg
Fusel. struct.	-	3.11	ton
Additional Fusel. Mass	-	2.72	ton

Figure 5 – Weight breakdown of the reference aircraft. The table on the right compares weights for a typical regional 42-seat configuration [28] (first column) with weights from the Finite Element Model (FEM) of the reference aircraft generated using FUROR (second column). On the left, the approximate distribution of non-structural masses on the FEM is illustrated.

To drive the external optimization loop, an open-source implementation of NSGA-II [26] is used, accounting for discrete design variables. To create a more realistic design and reduce computational time, the external loop design variables (DVs) are discretized. The discretization steps for each DV are detailed in Table 2; for example, the thicknesses are discretized with a step size of 0.05 mm to align with practical manufacturing constraints. Design variables are specified at the root, kink, and tip sections, and the thickness is linearly interpolated for each bay. For the ribs, the thickness is fixed at 4 mm. The number of stringers is fixed at 9 for all sections, though future developments will vary this number. Only the stringer section height is defined as a design variable. These stringers are assumed to be hat-type sections with a thickness equal to 10% of the height, a lower base width 20% of the height, and an upper base width 80% of the height.

Design Variable	Lower Bound	Upper Bound	Initial Guess	Optimized	Discretization Step
Wing Span [m]	12.3	49.1	24.6	37.1	0.025
Chord Root [m]	1.25	6.25	2.50	2.33	0.01
Chord Kink [m]	1.22	6.12	2.45	2.21	0.01
Chord Tip [m]	0.78	3.87	1.55	0.78	0.01
Rib Number Sec. 1	3	15	8	5	1
Rib Cosine Spacing Sec. 1	0.00	1.00	0.50	0.76	0.001
Rib Number Sec. 2	3	15	11	15	1
Rib Cosine Spacing Sec. 2	0.00	1.00	0.60	0.21	0.001
Spar Web Thickness Root [mm]	1.0	56.0	14.0	12.25	0.05
Spar Web Thickness Kink [mm]	1.0	15.0	5.0	8.05	0.05
Spar Web Thickness Tip [mm]	1.0	7.0	3.5	1.60	0.05
Spar Cap Width Root [%]	20.0	100.0	50.0	9.5	0.1
Spar Cap Width Kink [%]	20.0	60.0	30.0	4.5	0.1
Spar Cap Width Tip [%]	20.0	40.0	20.0	2.3	0.1
Spar Cap Thickness Root [mm]	1.0	100.0	25.0	39.85	0.05
Spar Cap Thickness Kink [mm]	1.0	54.0	18.0	26.2	0.05
Spar Cap Thickness Tip [mm]	1.0	20.0	10.0	1.55	0.05
Skin Thickness Root [mm]	1.00	11.20	2.80	7.60	0.05
Skin Thickness Kink [mm]	1.00	7.50	2.50	7.15	0.05
Skin Thickness Tip [mm]	1.00	3.00	1.50	1.15	0.05
Stringers Dimension Root [mm]	20.0	180.0	60.0	47.0	1.0
Stringers Dimension Kink [mm]	20.0	60.0	30.0	44.0	1.0
Stringers Dimension Tip [mm]	20.0	40.0	20.0	31.0	1.0

Table 2 – Design Variables (DVs) of the external optimization loop. The table includes DVs bounds, initial guesses, optimized values and discretization steps (a discrete genetic algorithm is adopted). Spar cap width is expressed as a percentage of the wing-box skin chordwise length.

To drive the internal optimization loop, the gradient-based IPOPT algorithm implemented in the open-source "pyOptSparse" library [27] is adopted. Table 3 summarizes the design variables, including their initial guesses and optimized values, with the ICE reference configuration serving as the initial guess. Although not strictly necessary, lower and upper bounds are provided to enhance the optimizer's convergence.
Regarding the hybridization factors, a linear behavior of the hybridization factor during cruise is hypothesized. At the start of the cruise, a design variable is defined to set the hybridization factor, while at the end of the cruise, the hybridization factor is assumed to be zero. Additionally, the take-off hybridization factor is treated as a design variable to reduce the peak ICE power required at take-off, thereby lowering the ICE weight.

Design Variable	Lower Bound	Upper Bound	Initial Guess	Optimized
Internal Combustion Engine Power [kW]	500	4000	1400	1548
Fuel Mass [ton]	0.00	3.00	1.60	0.85
Battery Mass [ton]	0.00	10.00	0.00	3.26
Hybridization Factor Cruise Start [%]	0.0	100.0	0.0	100.0
Hybridization Factor Take-off [%]	0.0	100.0	0.0	23.4

Table 3 – Design Variables (DVs) of the internal optimization loop. The table lists DVs bounds, initial guesses relative to the reference ICE aircraft, and optimized values.

The aircraft weight breakdown is shown in fig. 6. Note that these values are relative to the external

loop optimization. For each external loop design in the ASO architecture, the internal optimization loop on the propulsion system is converged. A significant reduction in fuel weight is achieved: compared to the reference configuration (1600 kg), the optimized design achieves a 47% reduction, resulting in a fuel weight of 851 kg with a battery mass of 3259 kg.
Regarding the geometry (see fig. 7), there is a substantial increase in the aspect ratio. The optimized configuration has an aspect ratio higher than 20, achieved by increasing the wing span and decreasing the tip chord. This results in reduced induced drag and an increased lift-to-drag ratio.

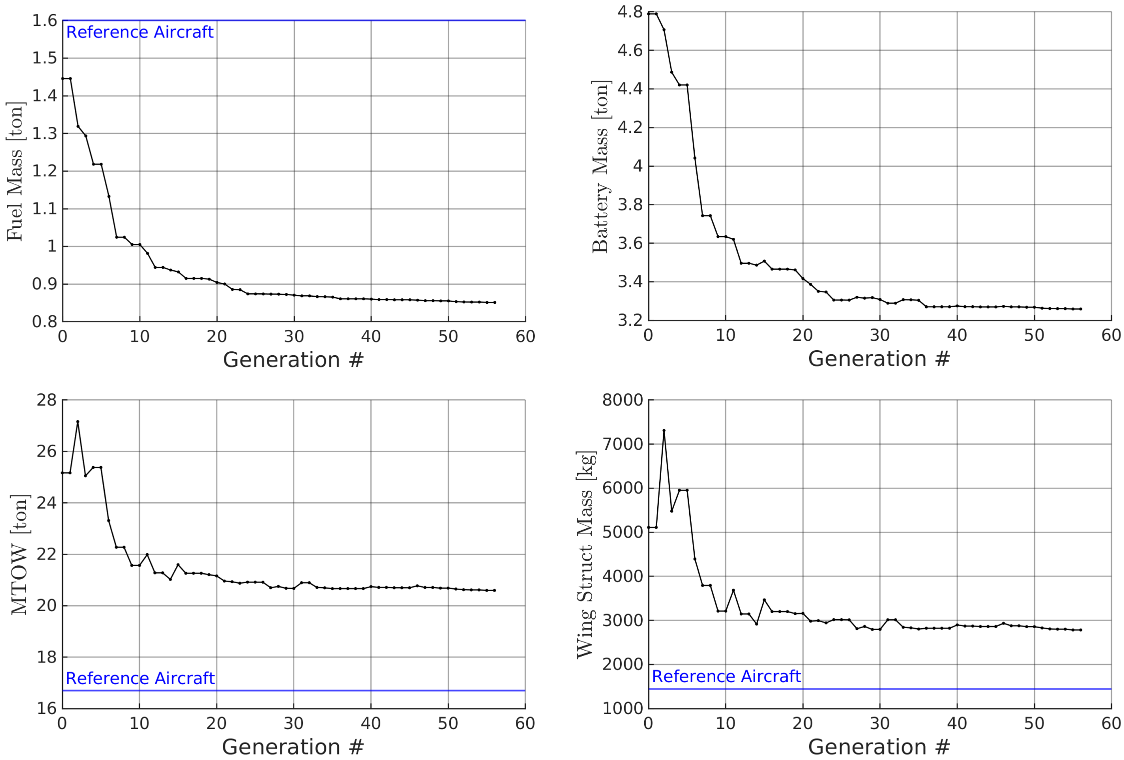


Figure 6 – Weight breakdown plot across iterations (generations) of the external optimization loop.

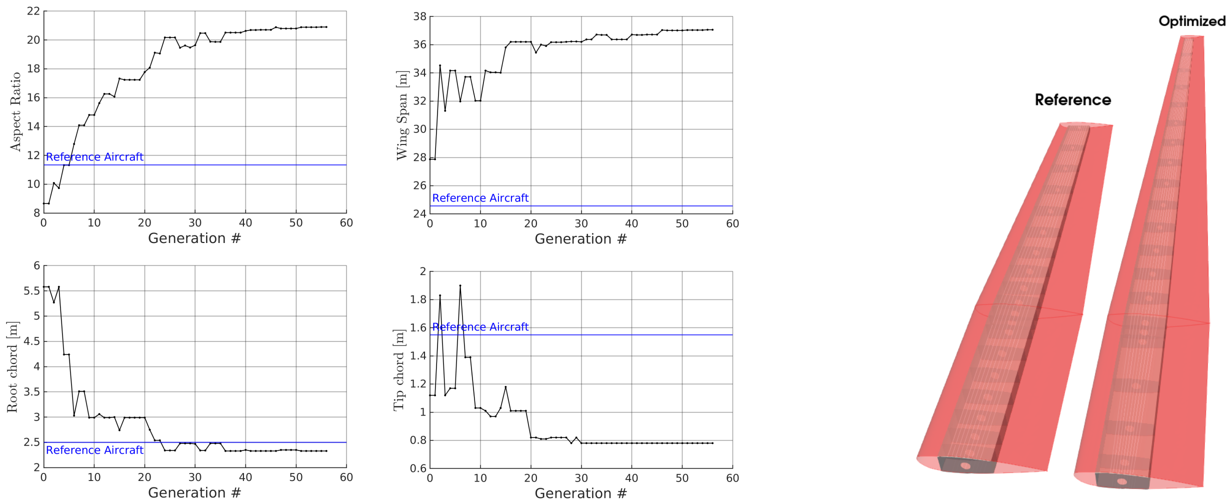


Figure 7 – On the left, the main wing geometric properties across iterations of the external optimization loop are shown, while on the right, the wing geometry in red (and the wing-box structure in grey) for both the reference and optimized configurations is depicted.

Regarding the propulsion system, fig. 4 shows the converged values of the inner optimization loop for each iteration of the outer optimization loop. Note that the fuel mass and battery mass reported in fig. 5 are also DVs of the inner optimization loop. The inner gradient-based optimizer aims to minimize the battery and fuel mass for the fixed mission (see section 5for details about the inner optimization loop). Additionally, a hybridization factor of more than 25% is achieved during the take-off phase to reduce the internal combustion engine (ICE) power peak and consequently the ICE weight. The optimizer also tends to use full electric power during the cruise phase start to save fuel, resulting in a hybridization factor of 100%.

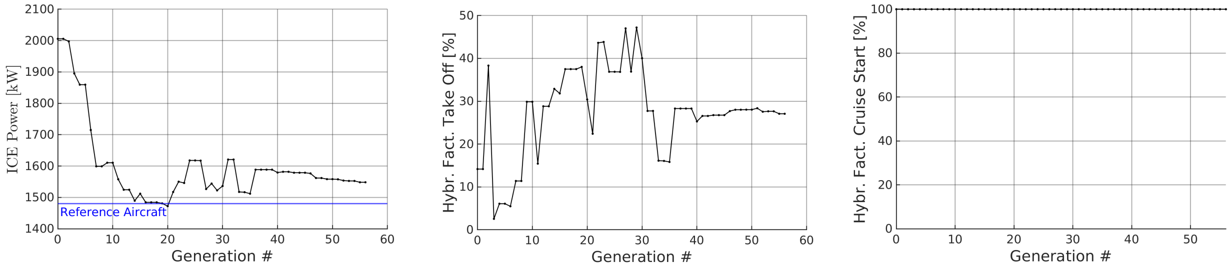


Figure 8 – Converged DVs of the propulsion system for each iteration of the outer optimization loop.

A structural weight increase compared to the ICE reference configuration is necessary to ensure integrity for the longer wing (see the wing structural mass in fig. 9), which experiences higher root bending moments exacerbated by the heavier fuselage housing the batteries. As depicted in fig. 9, both the structural constraints on maximum Von Mises stress and minimum buckling load factor are active in the optimization process, resulting in greater thicknesses of various components compared to the reference configuration.

For instance, the plot of spar cap thickness and skin thickness at the wing root in fig. 9 illustrates this increase. Additionally, design variables related to buckling constraints, such as the number of ribs, also increase compared to the reference configuration. A complete list of the structural DVs is reported in table 2.

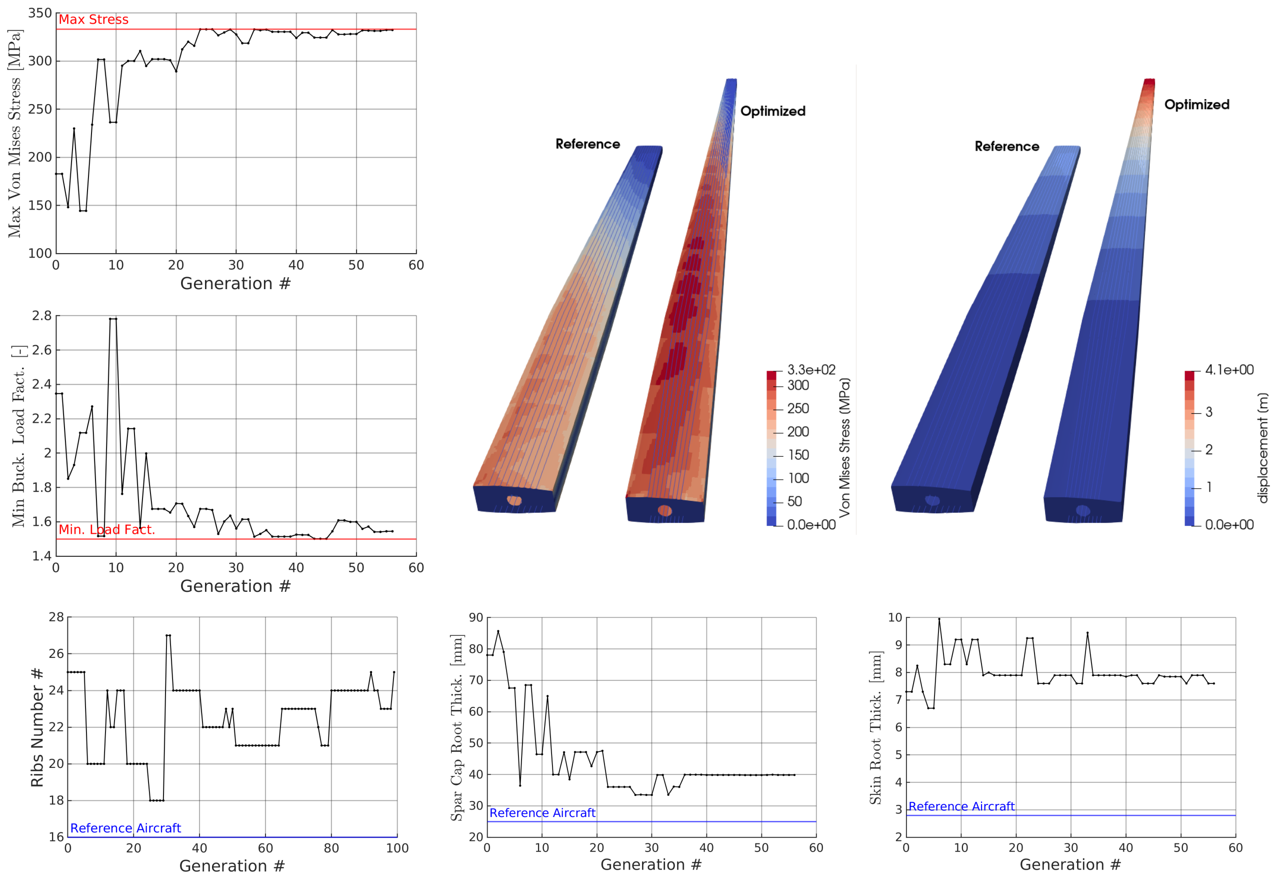


Figure 9 – Left: Structural integrity constraints (Von Mises stress and buckling load factor) across iterations of the outer optimization loop. Right: Contour plot of Von Mises stress and displacement for both the reference and optimized configurations. Bottom: Plots of key structural design variables (root spar caps and skin thickness, total rib number) across iterations of the outer optimization loop.

7. Conclusions and Future Developments

In this study, we want to address the critical need for accurate and efficient weight estimation methods in the preliminary design phase of next-generation green aircraft, emphasizing the integration of innovative propulsion systems and advanced materials. In this work is developed a sophisticated Class III weight estimation approach, facilitated by the in-house FUROR software, which enables rapid automatic generation of a Finite Element Method (FEM) model for the entire aircraft. This model can be created in less than a minute, significantly enhancing its integration into a Multidisciplinary Design Optimization (MDO) loop. Our proposed approach leverages the Asymmetric Subspace Optimization (ASO) method, which efficiently balances the computational loads by prioritizing less resource-intensive disciplines before more costly ones. This method is particularly advantageous given the significant computational disparities between disciplines like aerodynamics and structures versus propulsion system modeling.

The optimization framework, validated through preliminary results for a hybrid electric/traditional regional aircraft, demonstrated substantial improvements in aircraft performance. The optimized design featured a longer wing span and higher aspect ratio, resulting in a significant increase in the cruise lift-to-drag ratio. Despite the increased structural weight to ensure integrity for the longer wing and heavier fuselage, the fuel mass was notably reduced due to the enhanced lift-to-drag ratio and the inclusion of over 3 tons of batteries. This led to an overall increase in Maximum Take-Off Weight (MTOW), primarily driven by the additional battery weight and structural enhancements.

The study underscores the importance of integrating detailed and accurate weight estimation methods early in the design process to accommodate the complexities of modern green aircraft. Future developments will focus on including additional objective functions such as emissions and life cycle cost merit functions, which are critical for sustainable aviation. The inclusion of innovative propulsion systems, such as distributed electric propulsion, will also be considered from an aerodynamic perspective.

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9. Copyright Statement

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