Scalable multifidelity design optimization: Next-generation aircraft and their impact on the air transportation system

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Commercial aircraft designs have begun to plateau in fuel efficiency.

Figure 9.1: The fuel burn per passenger per unit distance of new aircraft over time, as a percentage of the value in 1960. The last 5 decades have seen a 50% reduction, but progress has stalled in the last 2 decades. Source: the International Council on Clean Transportation. 

Unconventional aircraft configurations

Over the last five decades, the fuel efficiency of commercial aircraft has approximately doubled through advancements in technology and design. However, as Fig. 9.1 shows, this trend has stagnated in recent years, as each aircraft becomes more optimized and further improvements become more technically challenging to achieve. This concern is compounded by the fact that air traffic is expected to outpace efficiency improvements in the next two decades, in the face of rising fuel costs and growing environmental concerns.

The National Aeronautics and Space Administration (NASA) has identified the need for new concepts for commercial aircraft that significantly improve efficiency and environmental compatibility. To this end, NASA has outlined aggressive targets for the N+3 (2025) generation of aircraft, including a 71 dB noise reduction, an 80% reduction in NOx emissions, and a 60% reduction in fuel consumption over mission. These reduction targets are relative to a baseline represented by the Boeing 737-800, which was first flown in 1997. One approach to achieving these target metrics is through discipline-specific improvements such as increased use of composites for reduced structural weight, higher bypass ratios (BPR) for increased propulsive efficiency, and improved high-lift systems for reduced noise and drag. On the other hand, Figure 9.1 suggests that the 50-year-old tube-and-wing design may.

[Efficiency trends for new commercial jet aircraft. ICCT, 2009]
Commercial aircraft designs have begun to plateau in fuel efficiency over the last 5 decades, as shown in Figure 9.1. The fuel burn per passenger per unit distance of new aircraft has approximately doubled through advancements in technology and design. However, this trend has stagnated in recent years, as each aircraft becomes more optimized and further improvements become more technically challenging to achieve. This concern is compounded by the fact that air traffic is expected to outpace efficiency improvements in the next two decades, in the face of rising fuel costs and growing environmental concerns.

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The tube-and-wing configuration has been perfected over the last 50 years.
Breakthrough improvements require unconventional aircraft configurations

- Truss-braced wing
- Blended wing body
- Joined wing
- Double bubble
Low-fidelity and empirical design tools do not adequately model the tradeoffs:

- Additional wave and interference drag
- High aspect-ratio composite wings
- Continuous descent and low Mach number flight

Diagram:
- CFD analysis
- Aeroelastic tailoring
- Mission analysis
Adjoint-based design optimization algorithms can accelerate the design process.
Adjoint-based design optimization algorithms can accelerate the design process.
The challenge problem:
How can we design a new configuration while considering the impact at the airline level?
We chose to focus on the truss-braced wing.
The approach is to find the best design that maximizes profit for the airline. 

Aircraft design

Aerostructural analysis

CL, CD, Cm at each point in the mission

Mission analysis

Fuel burn, block time on each route

Allocation analysis

Profit
To do this, we perform simultaneous allocation-mission-design optimization.
To do this, we perform simultaneous allocation-mission-design optimization.

Aerostructural analysis and mission analysis are coupled…

One mission analysis per airline route
To do this, we perform simultaneous allocation-mission-design optimization.

Aerostructural analysis and mission analysis are coupled…

… but aerostructural analysis is computationally expensive
Our proposed solution is to use surrogate modeling.

We can use a surrogate model at lower cost.
Subprojects for Year 1

1. Parallel matrix-free optimizer
2. Parallel computational framework
3. Aerostructural modeling and optimization of the TBW
4. Mission and allocation modeling and optimization
5. Uncertainty quantification for multifidelity design
Subproject 1
Parallel numerical optimization

- Optimizer
- Aircraft design
- Aerostructural analysis
- Training points
- Mission profiles
- Flights per day
- Aerostructural surrogate
- Lift, drag, moment
- Flight conditions
- Mission analysis
- Fuel burn, block time
- Allocation analysis
- Airline profit
Gradient-based optimization takes a more direct route to the optimum
Gradient-based optimization is the only hope for large numbers of design variables.

**Figure 3:** Study 1: Dimension analysis for 2-D Rosenbrock function.

**Figure 4:** Study 1: Local minimum of 8-D Rosenbrock function.

Methods reflect in their better ability to find global minimum. As the increasing of problem size, gradient methods tend toward the local minimum while non-gradient methods can still find the global minimum. However, consider their performance at high dimension, we cannot take fully use of this advantage.
The adjoint method computes gradients with respect to large numbers of variables efficiently.

\[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1} \frac{\partial R}{\partial x}
\]

- \frac{dy}{dx}

Large numbers of design variables
... but the adjoint method cannot handle large numbers of variables and constraints simultaneously

\[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1} \frac{\partial R}{\partial x}
\]

Large numbers of design variables

Large numbers of design variables and constraints
Current state-of-the-art optimizers do not scale well with problem size...

...they solve the optimality conditions using Newton’s method

\[
\begin{bmatrix}
W_k & A_k^T \\
A_k & 0
\end{bmatrix}
\begin{bmatrix}
p \\
d
\end{bmatrix}
= -
\begin{bmatrix}
g_k \\
c_k
\end{bmatrix}
\]

This requires the matrices $W$ and $A$ explicitly, which are costly to compute for large problems.
We developed an all new algorithm for numerical optimization that uses a matrix-free approach. Instead of requiring the matrices explicitly, our optimizer requires only matrix-vector products:

\[
\begin{bmatrix}
W_k & A_k^T \\
A_k & 0
\end{bmatrix}
\begin{bmatrix}
p \\
d
\end{bmatrix}
= -
\begin{bmatrix}
g_k \\
c_k
\end{bmatrix}
\]

This saves memory and computational time, enabling the solution of very large problems.

RSNK: Reduced-space Newton—Krylov

[Hicken and Dener, SIAM J.Opt., 2015 (submitted)]
We benchmark this new algorithm on an aerodynamic shape optimization problem.

Minimize the drag coefficient with respect to airfoil shapes subject to the following constraints:

- Lift constraint
- Moment constraint
- Volume constraint
- Thickness constraints
Previous results with conventional optimizers show that this is a challenging problem.

\[ C_D = 0.019967, \quad C_L = 0.5000, \quad C_M = -0.1779 \]

\[ C_D = 0.018277, \quad C_L = 0.5000, \quad C_M = -0.1700 \]

[Lyu, Kenway and Martins, 2015]
A matrix-free interface was developed for our CFD solver and adjoint

- SUMad (based on SUmb)
- Parallel, finite-volume, cell-centered, multiblock solver for RANS equations
- Spalart–Allmaras turbulence model
- Implemented adjoint using automatic differentiation to evaluate partial derivatives
- Developed both frozen-turbulence and full-turbulence adjoint
- New: matrix-free interface
RSNK was shown to be more efficient than a state-of-the-art optimizer for large problems.

[Dener, Hicken, Kenway, Lyu and Martins, AIAA 2015-1945]
Summary for Subproject 1

Year 1 achievements:

- Developed a novel parallel optimizer
- Develop a matrix-free RANS CFD adjoint
- Demonstrated scaling on a high-fidelity aerodynamic shape optimization problem

Next steps:

- Perform RANS-based aerodynamic shape optimization
- Implement inequality constraints
- Implement matrix-free aerostructural interface
Subproject 2
Parallel computational framework

- Optimizer
- Aircraft design
- Mission profiles
- Flights per day

- Aerostructural analysis
- Training points
- Aerostructural surrogate
- Lift, drag, moment
- Flight conditions
- Mission analysis
- Fuel burn, block time

- Airline profit
- Allocation analysis
Combining many types of models and computing their gradients is challenging.
Combining many types of models and computing their gradients is challenging.
We recently developed an equation that unifies the methods for computing derivatives:

\[
\frac{\partial R}{\partial u} \frac{du}{dr} = \mathcal{I} = \left[ \frac{\partial R}{\partial u} \right]^T \left[ \frac{du}{dr} \right]^T
\]

- Finite differences \( \frac{df}{dx} = \frac{\partial F}{\partial x} \)
- Chain rule \( \frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{\partial F}{\partial y} \frac{dy}{dx} \)
- Direct method/adjoint method \( \frac{df}{dx} = \frac{\partial F}{\partial x} - \frac{\partial F}{\partial y} \frac{\partial R^{-1}}{\partial y} \frac{\partial R}{\partial x} \)
- Algorithmic differentiation

[Hwang and Martins, AIAAJ, 2013]
Using this theory, we developed a parallel framework that computes coupled gradients. Each discipline computes its partial derivatives; the framework computes the total derivatives. Handling many disciplines, a unified theory is acquired through a modular framework.

Each component computes its local derivatives; the framework computes coupled gradients automatically.
The framework uses efficient numerical linear algebra

Block Gauss-Seidel

Preconditioned Krylov subspace methods

The built-in solvers are used extensively in the mission analysis component

[Hwang and Martins, 2015 (to be submitted)]
This algorithmic framework has been implemented in NASA’s OpenMDAO

Several other applications have been handled:

- Satellite design and operation optimization
- Wind turbine optimization

[Gray, Hearn, Moore, Hwang, Martins, and Ning, AIAA 2014-2042]
Summary for Subproject 2

Year 1 achievements:

• Developed a novel algorithmic framework for coupled analysis and gradient computation
• Implemented framework numerical methods in OpenMDAO
• Successful spin-offs through OpenMDAO

Next steps:

• Benchmark framework in other problems
• Continue supporting OpenMDAO team
Subproject 3
Aerostructural modeling and optimization of the truss-braced wing aircraft

- Optimizer
  - Aircraft design
    - Aerostructural analysis
    - Training points
      - Aerostructural surrogate
      - Flight conditions
    - Lift, drag, moment
      - Mission analysis
      - Fuel burn, block time
  - Mission profiles
  - Flights per day

- Airline profit
  - Allocation analysis
To model the TBW, we use GeoMACH, which was developed in an earlier NASA effort.

GeoMACH models aircraft geometries and structures using a differentiable parametrization.
To investigate the aerodynamics near the strut, we performed Euler-based shape optimization.

minimize \( \text{drag coefficient} \)

with respect to \(\text{angle of attack} \quad 1 \)
\(\text{fuselage shape variables} \quad 25 \)
\(\text{wing shape variables} \quad 200 \)
\(\text{strut shape variables} \quad 128 \)
\(\text{v. strut shape variables} \quad 50 \)
\(\text{tail shape variables} \quad 128 \)
\(\text{532} \)

subject to \(\text{lift coefficient constraint (0.5)}\)
Shape optimization eliminates the shock and reduces the drag by 58%
Shape optimization eliminates the shock and reduces the drag by 58%
We obtained similar results with the RANS equations
We also developed a structural model for the truss-braced wing using GeoMACH
Summary for Subproject 3

Year 1 achievements:

‣ Developed geometries for the wing & struts and for the full TBW configuration
‣ Performed aerodynamic shape optimization to eliminate the shock
‣ Began development of a structural model for the TBW

Next steps:

‣ Perform detailed shape optimization
‣ Perform aerostructural optimization
‣ Develop an aerostructural surrogate model
Subproject 4
Mission and allocation modeling and optimization

Optimizer

Aircraft design

Aerostructural analysis

Training points

Mission profiles

Flights per day

Aerostructural surrogate

Lift, drag, moment

Flight conditions

Mission analysis

Fuel burn, block time

Allocation analysis

Airline profit
We developed a unique mission analysis tool within the parallel framework. This tool is dependent on the number of quantities of interest rather than the number of variables. Therefore, for gradient-based optimization problems with large numbers of design variables, computing total derivatives using the adjoint method is advantageous. Both direct and adjoint methods have been implemented in a prototype of the computational framework, and the total derivatives are automatically calculated with the specification of the partial derivatives.

The other important feature of the prototype framework is the ability to hierarchically decompose the problem, which enables the implementation of different solution strategies. For example, block Gauss–Seidel solvers can be used on certain parts of the problem while Newton–Krylov solvers are used to solve other parts monolithically. For large systems, Newton’s method is the only tractable solution method. The lack of robustness of Newton’s method can be addressed by implementing a line search or trust region method for selecting the sizes of the Newton steps. Gauss–Seidel methods can be useful by acting as preconditioners, as well as for solving a series of explicit systems.

The basic component of the framework is a mathematical system. A system is defined as a compound system if it contains subsystems, or an elementary system otherwise. Compound systems can be further classified into serial and parallel systems. For the mission analysis problem, only serial systems are used, since the problem size is generally not large enough to possess obvious advantages for parallel computing. Elementary systems can be distinguished between independent systems, explicit systems, and implicit systems. Independent systems consist of variables that are not dependent on other variables. Explicit systems include variables that can be determined exactly by an expression involving only variables from other systems. Implicit systems depend on both variables from within the system as well as variables from other systems.

The objective here, as motivated by previous sections, is to develop a modular mission analysis tool capable of performing the proposed simultaneous optimization of aircraft design, airline allocation and flight trajectories. Therefore, the three driving goals for the development of this tool are: efficiency, robustness, and modularity. Due to the anticipated large size of the overall problem, a gradient-based optimization scheme must be used to keep the problem tractable, which results in the need for total derivatives. Many existing tools utilize finite-difference or complex-step methods to compute such derivatives, but with the anticipated size of the overall coupled optimization problem, the adjoint method must be used.

The hierarchical structure of the mission analysis problem will now be explained. As shown in Figure 2, the overall problem is contained within a serial system named mission. Mission contains 5 separate subsystems, and solves them in sequence using one Gauss–Seidel iteration. The first subsystem is composed of input variables such as altitude and Mach number control points. These are implemented as independent systems, and are initialized with a single block Gauss–Seidel iteration. The second subsystem uses these inputs to generate B-spline interpolants, which allow us to reduce the number of input variables (which are design variables during optimization) while maintaining the accuracy of the collocation method. The B-spline implementation is similar to the approach taken by Hwang et al. for a small satellite design optimization problem. The third subsystem takes the parameterized input profiles, and computes the corresponding flight conditions at each collocation point explicitly. This is done by solving explicit systems sequentially once using the block Gauss–Seidel solver.

The fourth subsystem contains the nonlinear coupled system of equilibrium equations, as well as the aerodynamic relations, and the fuel-burn equation. The ordering of subsystems within the coupled analysis block is determined in order to compute the total derivatives efficiently. The framework automatically computes derivatives using the adjoint method.
The mission analysis solves the flight equilibrium equations

\[ L + W \cos \gamma - T \sin \alpha + \frac{W}{g} v^2 \cos \gamma \frac{d\gamma}{dx} = 0 \]

\[ T \cos \alpha + D + W \sin \gamma + \frac{W}{g} v \cos \gamma \frac{dv}{dx} = 0 \]

\[ \frac{dW_f}{dx} = \frac{SFC \frac{1}{2} \rho v^2 S C_T}{v \cos \gamma} \]
The altitude and Mach profiles can be optimized using a B-spline parametrization.

The remaining variables are computed by solving a system of equations.
Multiple trajectories can be optimized quickly

[9000 NM] 100 NM mission never
reaches a steady cruise

classic cruise-climb result
appears for longer missions

more fuel needed for
longer missions

[Kao, Hwang, Martins, Gray, and Moore, AIAA 2015-0136]
The allocation problem seeks to maximize profit

\[
\text{maximize} \quad \text{profit} \\
\text{with respect to} \quad \text{flights/day for each route and } a/c \quad \text{pax/flight for each route and } a/c \quad \text{altitude profiles for each route and } a/c \\
\text{subject to} \quad \text{mission profile constraints} \quad \text{route demand constraints} \quad \text{aircraft availability constraints}
\]
We tested allocation-mission optimization on a 3-route test problem

This section presents a suite of allocation-mission optimization results obtained using Algorithm 1. We start by describing the routes and the types of aircraft in the problem we solved, and present 4 results. First, we show the predicted increase in profit for an airline if it purchases new aircraft instead of existing aircraft. Second, we show that there is a difference between the results of allocation-only optimization (MILP-a) and allocation-mission optimization (MINLP-a-m). Next, we explore the presence of local optima in (NLP-a-m) and show that (MINLP-a-m) is highly sensitive to the starting point. Finally, we discuss the numerical performance of the allocation-mission analysis and optimization algorithm.

A. The problem

The results in this paper solve a 3-route problem with ranges of roughly 7000 nmi, 5500 nmi, and 2500 nmi. The routes have been chosen to represent a network with a hub in Newark, New Jersey and the following destinations: Hong Kong; Kuwait City, Kuwait; and Quito, Ecuador. The routes are summarized in Tab. 1 and shown graphically in Fig. 4.

<table>
<thead>
<tr>
<th>Route</th>
<th>Range [nmi]</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Newark, New Jersey (EWR) Newark, New Jersey (EWR) Newark, New Jersey (EWR) Hong Kong (HKG) Kuwait City, Kuwait (KWI) Quito, Ecuador (IQT)</td>
<td>6998 5546 2509</td>
<td>1200 550 700</td>
</tr>
</tbody>
</table>

Table 1: The 3 routes considered in the allocation-mission optimization.

We consider 6 aircraft types, 4 existing ones and 2 hypothetical next-generation aircraft. The Boeing 737-800 (B737), Boeing 777-200ER (B777), Boeing 747 (B747), and Boeing 787 (B787) have been chosen as the existing aircraft to cover a variety of design ranges and seating capacities. The two new aircraft are a notional advanced conventional design based on the Common Research Model [46] and a blended wing body concept based on Liebeck [47] with a reduced seating capacity. The aircraft types are summarized in Tab. 2 with seating capacities shown after applying an 80 % load factor. Table 2 also shows the 4 allocation-mission optimization problems we solved, representing 10 of 17 different scenarios in which the hypothetical airline chooses to buy different aircraft.

<table>
<thead>
<tr>
<th>Aircraft</th>
<th>Boeing 737-800</th>
<th>Boeing 777-200ER</th>
<th>Boeing 747-400</th>
<th>Boeing 787-8</th>
<th>CRM: advanced conventional</th>
<th>BWB: blended wing body</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category Capacity</td>
<td>Existing 122</td>
<td>Existing 207</td>
<td>Existing 294</td>
<td>Existing 200</td>
<td>New 300</td>
<td>New 400</td>
</tr>
<tr>
<td>Scenario</td>
<td>S-base 20</td>
<td>24</td>
<td>24</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>S-CRM 20</td>
<td>24</td>
<td>24</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>S-BWB 20</td>
<td>24</td>
<td>24</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>S-both 20</td>
<td>20</td>
<td>20</td>
<td>8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The cost, ticket price and the performance data of the existing aircraft for the different routes in the network are obtained using the simulation tool FLEET [29, 30]. For the new aircraft, the ticket price, no-fuel direct operating cost and the indirect operating cost are also obtained from an equivalent aircraft modeled in FLEET. The current model does not account for airline competition and assumes the ticket prices are fixed across types of aircraft on a given route.

B. Profit increase with new aircraft

Figure 5 shows the profit after optimization for each of the 4 scenarios. The results agree with intuition because the CRM and BWB both represent an improvement over the existing aircraft. The CRM design is based on the B777, but it is assumed to have a larger seating capacity and higher aerodynamic efficiency since it is a next generation aircraft. The B787 has the range of the CRM but a lower seating capacity, while the B747 has the seating capacity but a lower range and lower efficiency as it is a much older design. Thus, the S-CRM scenario provides a 192 % improvement in profit over the baseline S-base, the S-BWB scenario provides a 323 % due to its larger seating capacity, and the S-both scenario provides a further improvement with 414 % compared to the baseline.

Figure 5: Comparison of profit for the four scenarios at the solution to (MINLP-a-m). The results show an increase in profit when the hypothetical airline purchases the next-generation aircraft.
Allocation-mission optimization yielded large profit increases with next-generation aircraft.

Table 2: The types of aircraft considered in the allocation-mission optimization. The bottom four lines show the number of each aircraft type available in each of the four scenarios.

<table>
<thead>
<tr>
<th>Category</th>
<th>Existing</th>
<th>Existing</th>
<th>Existing</th>
<th>New</th>
<th>New</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity</td>
<td>122</td>
<td>207</td>
<td>294</td>
<td>200</td>
<td>300</td>
</tr>
<tr>
<td>Scenario</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>8</td>
<td></td>
</tr>
<tr>
<td>S-CRM</td>
<td>20</td>
<td>24</td>
<td>24</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>S-BWB</td>
<td>20</td>
<td>24</td>
<td>24</td>
<td>8</td>
<td></td>
</tr>
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<td>20</td>
<td>20</td>
<td>8</td>
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B. Profit increase with new aircraft

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![Graph showing profit increase](image)

Figure 5: Comparison of profit for the four scenarios at the solution to (MINLP-a-m). The results show an increase in profit when the hypothetical airline purchases the next-generation aircraft.

[Hwang, Roy, Kao, Martins, and Crossley, AIAA 2015-0900]
Summary for Subproject 4

Year 1 achievements:

- Developed an efficient mission analysis & optimization tool with analytic derivatives
- Implemented allocation-mission optimization
- Developed a method for solving the mixed-integer nonlinear optimization problem

Next steps:

- Parallelize the allocation-mission optimization
- Solve the problem with larger networks
- Perform allocation-mission-design optimization
Subproject 5: Uncertainty quantification for multifidelity design

- Optimizer
- Aircraft design
- Aerostructural analysis
- Training points
- Aerostructural surrogate
- Flight conditions
- Mission analysis
- Lift, drag, moment
- Mission profiles
- Flights per day
- Fuel burn, block time
- Allocation analysis
- Airline profit
We cast the multidisciplinary system design as an estimation problem
To demonstrate the approach, we solve an aircraft sizing problem using TASOPT
We focus on quantifying the sensitivities to the uncertainty of future engine performance.

- **Tt4CR** total temperature at turbine inlet in cruise
- **OPR** overall pressure ratio
- **PFEI** fuel energy consumption per payload-range
Our approach to global sensitivity analysis yields design insights.

There are no interaction terms in this case.
The results also provide insight into how we can satisfy cost and uncertainty budgets.
Using these tools, we can quantify the tradeoffs between cost, standard deviation, and risk.
Summary for Subproject 5

Year 1 achievements:

• Developed UQ approach for managing risk in early stage aircraft design

• Demonstrated approach by quantifying effect of engine technology uncertainty on fuel burn

Next steps:

• Extend UQ approach to consider nonlinear interactions

• Complete and demonstrate multi fidelity approach
This project has yielded 7 publications so far


Summary of novel contributions so far

1. A new modular, scalable, and general numerical optimization algorithm that handles parallel problems
2. A new parallel, scalable algorithmic framework for multidisciplinary analysis and gradient computation (now implemented in OpenMDAO)
3. A matrix-free CFD adjoint
4. An adjoint-based mission analysis and trajectory optimization code
5. A method for simultaneously optimizing aircraft trajectory and allocation
6. A framework for performing aircraft design optimization under uncertainty
Thank you!