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Design Space Exploration Methodology including Aircraft Design, Industrial System, and Economic Considerations

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During high-level decisions for complex aerospace system designs, Top-Level Aircraft Requirements need to be implemented in a wide range of performance, industrial, and economic environments and under the same range of constraints. The trade-offs between the different range of environments are poorly reflected in traditional sequential design methods due to their nonlinear and interdisciplinary nature. In this paper, a Design Space Exploration methodology is discussed with an integration of Model-Based Systems Engineering and Multi-Disciplinary Analysis and Optimization. The goal is to identify, capture, and quantify key trade-offs across the constraint sets. The proposed framework allows rapid iteration in multiple design spaces with low- and medium-fidelity disciplinary models for aircraft performance, logistics modeling, and manufacturer economics. Surrogate modeling ensures traceability while supporting fast evaluation, and the methodology is validated on a derivative single-aisle commercial aircraft where multiple constraints in performance, logistics, and economics are analyzed. The approach demonstrates feasible design spaces, supports informed decision-making across stakeholders, and analyzes system-level feasibility early in the conceptual design phase using an interactive dashboard embedding metrics from performance, industrial, and economic domains.

I. Introduction

The aircraft design process tends to be challenging in various ways, involving multidisciplinary engineering analyses in a wide range of domains, specifically aerodynamics, structures, propulsion, manufacturing, and economics. For each discipline, a set of constraints, objectives, and trade-offs is introduced. Those requirements must be met for the final design to satisfy performance, regulatory, cost, and operational requirements. The overall design process is done in stages as follows: conceptual, preliminary, and detailed design, with the complexity and fidelity increasing and design freedom decreasing progressively [1]. In general, decisions made in the early conceptual phase commit the majority of program costs and restrict downstream design freedom [1].

The aircraft design process tends to be challenging in various ways, particularly in the coordination of multidisciplinary models and the management of interdependencies across engineering domains [2, 3]. Improper integration, uncertainty modeling, changes in future requirements, or coupling of system-level components can lead to infeasible configurations and trigger costly rework. To effectively resolve these challenges, a methodology that captures multidisciplinary interactions, propagates uncertainty, and maintains traceability to high-level requirements is necessary. The integrated analysis frameworks are key to aligning subsystem design with overall system feasibility early in the design process.

The allocation process requires the management of engineering analyses and tracing them back to the specific requirements imposed on the system. Systems engineering methodologies aim to achieve traceability using relationships such as inheritance, composition, aggregation, and satisfaction. Using such relationships, the system is broken down into subsystems and components, each with its distinct performance requirements and design objectives. Due to the subsystems and components decompositions that facilitate distributed analysis, there is a risk of decoupling the system from its goals without careful coordination. An example physical decomposition typically used in aircraft systems design is provided in Fig. 1.

Balancing aerodynamic efficiency against structural weight, aligning propulsion efficiency with noise and emission constraints, and integrating manufacturing feasibility with performance metrics and economic goals are examples of trade-offs that must be resolved. If such disciplinary interactions are not coordinated early, the resulting design may be infeasible, requiring further design iterations. Ultimately, the goal is to find a converged, consistent, and performant design that meets the requirements of all stakeholders involved. While Top-Level Aircraft Requirements (TLARs) define

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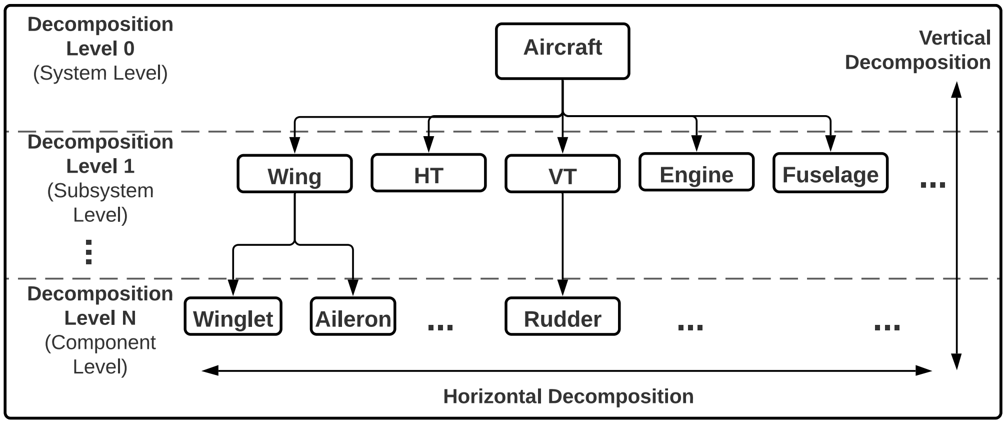


Fig. 1 Description of the decomposition levels [2]

global targets, disciplinary constraints that target more detailed phenomena impose additional feasibility conditions that are often nonlinear and interdependent. Thus, a central achievement in modern system design is the ability to explore the trade-offs and identify configurations that satisfy all constraints.

The work done in the paper builds on an integrated Model-Based Systems Engineering (MBSE) driven Multi-Disciplinary Analysis and Optimization (MDAO) design analysis and focuses on the details of the Design Space Exploration (DSE) step that completes the Analysis and Decision Support (ADS) loop. The overall methodology is described by Gautier et al. [4] and outlined in Fig. 2. The proposed methodology establishes relationships between the high-level requirements and disciplinary analysis models, enabling design trades across performance, economics, and industrial feasibility.

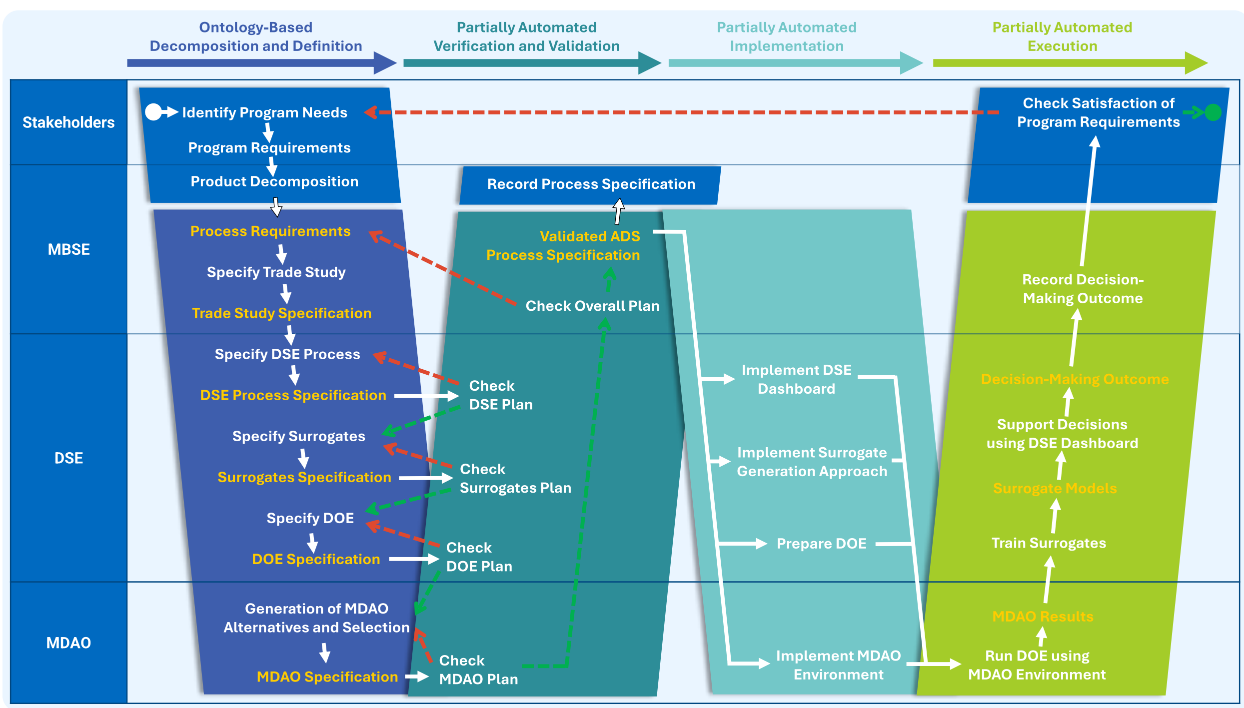


Fig. 2 Overall methodology follower during the design cycle [4]. This paper focuses on the DSE components of the methodology

The paper is organized into six sections. Sec. II discusses the evolution of aircraft design methodologies and the motivation for integrated frameworks. Sec. III reviews the technical formulation of the methodology and its integration of performance, economics, and logistics models. Sec. IV explains the analyses done on the application of the methodology to a derivative aircraft design use case. Sec. V presents the key results, including trade-off visualizations and feasibility analyses across multiple constraint sets. Conclusions and future research directions are provided in Sec. VI.

II. Background

Aerospace systems design and development have evolved through the decades. However, addressing the complexity, cross-disciplinary interdependencies, and adaptability required by modern aircraft continues to be a pain point during design. Integrating diverse constraints from performance, economics, and industrial domains is significantly difficult due to organizational barriers within a company as well. In this section, the conventional design methodologies, their technical limitations, and the need for integrated approaches capable of managing complexity through formalized models and exploratory frameworks are outlined. MBSE and DSE are then introduced as foundational enablers for integrated trade space analysis across aircraft design, manufacturing, and economic performance.

A. Traditional Approaches and Their Shortcomings

Historically, the "waterfall" model [5], including the conceptual, preliminary, and detailed design phases, has been followed for aircraft design. The process is a linear and phase-gated decomposition and allocation with integration of solutions at the end. As the design progresses through the phases, analysis model fidelity increases, and the design freedom decreases.

The *Conceptual Design* phase consists of engineers formulating high-level configurations based on TLARs driven by mission, regulatory, and market demands. Statistical models derived from historical databases on existing vehicle configurations are heavily used in the conceptual design phase. The data resources, while being computationally efficient, still lack the fidelity to capture nonlinear interdependencies among disciplines [6].

The *Preliminary Design* phase introduced refined analyses including low- to medium-fidelity aerodynamic, structural, and propulsion modeling. The aim of the preliminary stage is to identify subsystem feasibility and system integration. Even though the preliminary phase tends to be of medium fidelity, it lacks the iteration and alignment of models since engineering teams tend to operate in isolation and execute tasks in a sequential order [7].

The *Detailed Design and Production Baseline* phase focuses on converting subsystem definitions into logistics aspects. The definitions include specifications for manufacturing, requirements for tooling, and documentation for certification. The detailed design is the most precise phase of the traditional design method. However, any issue in earlier phases, specifically insufficient integration of constraints, results in manufacturability problems, production bottlenecks, and late-stage cost overruns [8]. Moreover, the inadequate agile feedback mechanisms in the traditional process make any requirements change infeasible without significant rework. In summary, the traditional design methodologies have the following key limitations:

Low Responsiveness to Change: Cascading rework is often caused by requirements shifts or technology insertions when the changes happen late in the process, which leads to increasing time and cost [9].

Isolated Disciplinary Optimization: Independent optimization of subsystems in the disciplinary optimization processes initiates globally suboptimal configurations because of inadequate subsystem consideration [7].

Heuristic-Driven Decision-Making: Experts' experiences and practices are the primary source of decisions without any formalized trade studies across the system lifecycle [6].

B. The Need for Efficient Design Methodologies

Design process methodologies must effectively evaluate complex trade spaces involving competing objectives. The design methodologies must also include efficiency in terms of time, computation, and cost due to the exponentially growing size and dimensionality of feasible spaces as a result of increasing fidelity. The second reason is the impracticality of remedying all interactions manually in a sequential design process. To reduce computational burden and increase accuracy, a structured exploration of the spaces is used, integrating modeling, simulation, and surrogate-based approximation [10, 11].

Example issues that must be considered in the early design decisions are production scalability, lifecycle cost, and supply chain risk. The example issues provided above necessitate frameworks that combine aircraft-level performance and economics modeling with industrial system simulation, enabling co-architecting of the product and its manufacturing environment [7, 8].

C. Modern Approaches: MBSE and DSE

Model-Based Systems Engineering (MBSE) is a formal modeling approach to replace the traditional document-centric approach that integrates digital representations of system architecture, requirements, behaviors, and interfaces [12]. The proposed approach improves traceability, reinforces decomposition of hierarchy, and facilitates consistency checks between disciplines by providing a centralized "single source of truth." For graphical and semantic representation of functional flows, Systems Modeling Language (SysML) is used to enable early validation of requirements and identification of architecture conflicts [13].

Design Space Exploration (DSE) serves as a complementary component to MBSE to allow quantitative evaluation of design alternatives in a defined multidimensional space. The use of sampling strategies (e.g., Latin Hypercube Sampling), surrogate modeling, and trade-off visualization is included in DSE to identify feasibility and optimality of a wide range of configurations under multiple constraints [7, 14]. While MBSE characterizes the design intent and system structure, DSE implements exploration of trade-offs and sensitivity analysis across the combined system space. As coupled components, MBSE and DSE form a framework with high-level requirements and architectures that are evaluated continuously against disciplinary models. The coupled components framework enables informed decision-making and iterative convergence toward feasible, cost-effective, and scalable designs.

D. Linking Industrial System Considerations to Aircraft Design

The industrial systems are composed of manufacturing flow, final assembly line capacity, supply chain logistics, and global transportation networks. Critical constraints on aircraft configuration and program feasibility are enforced by the composition of the industrial systems. Key decisions are related to numerous aspects of the logistics assumptions, such as the number of production sites, transportation modes for sub-assemblies, or the learning curve, that can affect cost and schedule. Infeasibility of the design during ramp-up or financial underperformance can be due to ignoring the logistics constraints during the early stages of the design [9].

The impracticality of complex composite layup techniques in a high-performance aerodynamic design is an example of the limitations in the tooling or labor skill availability in key facilities are not considered. Another example is the degradation of production rate or logistics efficiency due to optimizing airframe weight at the expense of modularity. Similarly, failing to account for geopolitical risks in the supply chain (e.g., reliance on materials with rare-earth elements or single-source suppliers) can lead to delays or redesigns [6].

Embedded industrial metrics directly into the design space through the MBSE-enabled DSE allows concurrent evaluation of trade-offs not only across technical performance but also across production feasibility and economic viability. The integration of logistics simulation, aircraft design model, and lifecycle cost estimators with aircraft weights and performance metrics creates a comprehensive co-architecture framework. The feasibility of the design under satisfactory constraints can be identified by engineers through the framework. The multiple constraints can be across all stakeholder domains: technical, industrial, and financial, which enables robustness and adaptability in program planning [8].

III. Design Space Exploration Methodology

The role of DSE within the overall design methodology given in Fig. 2 is to perform the trade-offs in a visual and interactive manner. The goal of the DSE team is to provide an environment that can be used to perform the trade-offs, but not make design decisions themselves. The stakeholders can change the design and assumptions about technologies on the design as well as the industrial system used to manufacture the aircraft within the DSE environment quickly. The DSE environment must then rapidly visualize the impacts of such changes on the way the system performs. The update time on the visualizations must also be reduced to a degree that the stakeholders can receive immediate feedback on their proposed changes. The short update time requires the DSE environment to work with surrogate models rather than the actual analysis models for visualizations.

Using intuitive plots, stakeholders can perform the trade-offs defined in the very first parts of the methodology shown in Fig. 2. The trade-offs involve many requirements such as aircraft performance, cost, production rate, and emissions. Therefore, the analyses must calculate the necessary metrics using sufficient fidelity analyses to be checked against the metrics defined in the requirements. The calculations are often multidisciplinary and coupled in aerospace systems; therefore, DSE requires the evaluation of potential design configurations in a complex trade space [10].

As described in II, the traditional design processes cannot efficiently explore interdependent relationships across subsystems [9]. To formulate an appropriate coupled MDA problem, MBSE methodologies can be used to trace requirements to metrics to analyses to couplings. In this work, Mission, Operational, Functional, Logical, and Technical

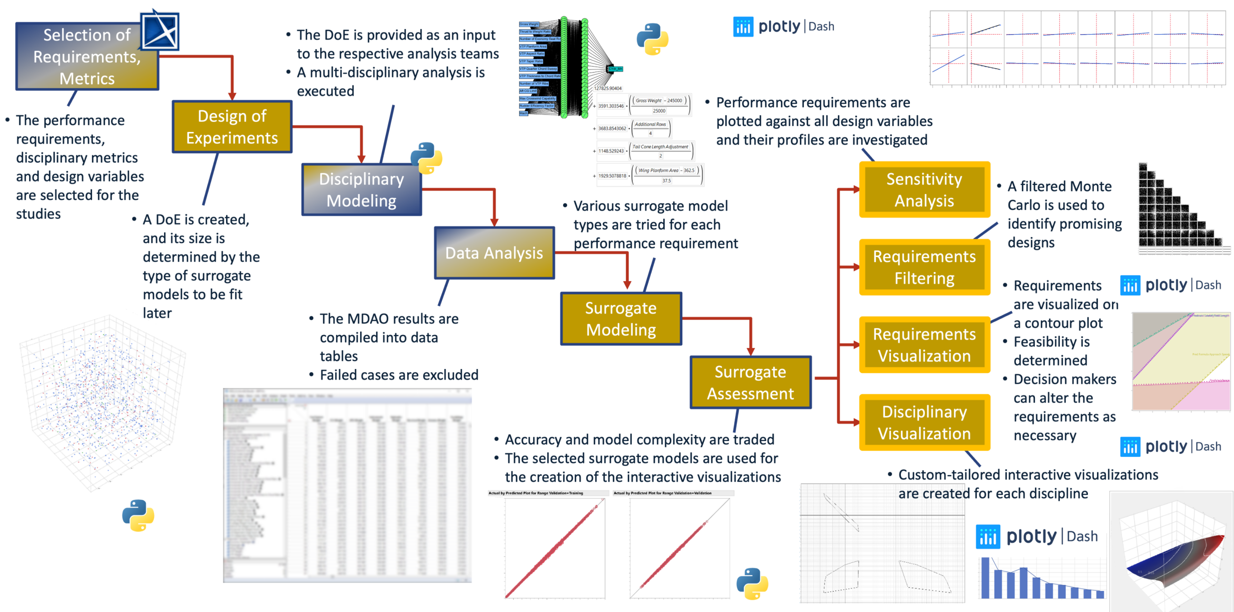


Fig. 3 Detailed description of the DSE Process

(MOFLT) is used as an MBSE process developed by Airbus [15]. MOFLT organizes system definition into layered domains where different requirements are applied. Using MOFLT, the system of interest is decomposed by its mission stages, functions required during each stage, and physical components those functions are allocated to.

The DSE methodology described in this paper supports the systematic exploration of feasible design regions by visualizing requirements as contour constraints and evaluating trade-offs between target objectives, also known as Figures of Merit (FOMs). The overall DSE methodology, as illustrated in Fig. 3, follows a structured process that integrates MBSE, disciplinary modeling, MDA, surrogate modeling, and decision-making. The process starts with the requirements being mapped to inequality constraints such as “aircraft mission range must be at least 3,000 NM,” or specific study assumptions such as “aircraft subsystem manufacture must be decentralized”. Through careful consideration, some of the requirements are mapped to MDA and others are mapped to DSE steps in the methodology.

Additionally, through subject matter expertise, design parameters that can be changed by the stakeholders in the final interactive and visual DSE environment are listed and provided as design variables. These variables will be used to create a design space and sampled using a Design of Experiments (DoE) method. The Design of Experiments (DoE) techniques are employed to generate samples across the multidimensional design space, ensuring coverage while limiting computational burden. DoE enables systematic evaluation of how variations in input variables influence system-level responses [16]. This step ensures that the surrogate models later used in the visual environment are built on statistically representative datasets spanning the entire design space. DoE is indispensable for generating high-quality datasets in surrogate-assisted MDAO frameworks [17]. In this work, a space filling design was used to sample the design space thoroughly to capture non-linear trends using neural network surrogate models.

To simulate aircraft mission performance, aircraft program and operation economics, and industrial system for its manufacture, individual disciplinary models are created after inputs are defined. An MDA framework is used to couple the disciplinary models to enable consistent and traceable data exchange and convergence of variables across domains. The baseline simulations are executed to validate model fidelity and ensure compatibility across interfaces. The inputs for the baseline aircraft and industrial system are fed to the necessary models. The coupling variables between the models are managed by the MDA framework and modified based on the outputs of each model and convergence as needed. Once the results are checked for quality and correctness, the DoE can be executed through the models.

The design space samples defined by the DoE provide the necessary inputs to this MDA in an outer loop, running through the list of each design point in the sample. For each design point, the MDA converges the necessary models based on their couplings. Outputs of the performance, industrial, and economic models are collected along with design variables and written into data tables as results.

The results can be directly visualized using multidimensional data visualization techniques such as scatter plot matrices and parallel plots. Scatter plots were used to interrogate analysis results initially, allowing the team to investigate outliers and suspicious trends. Once the results were accepted as reliable, the DSE effort shifted towards surrogate modeling activities. Surrogate models are needed for interactive exploration of the design space without needing to rerun computationally expensive computer models. They capture the trends within the DoE data and approximate the models that generated them using mathematical expressions such as polynomial, exponential, or similar functions.

Following the MDA execution phase in Fig. 3, surrogate modeling plays a critical role in enabling real-time visualization and trade space navigation. The surrogate models are trained on DoE-generated datasets to emulate each disciplinary response surface, enabling rapid evaluation of large numbers of configurations [14]. The data is always split between training, validation, and test portions to perform the fitting, check for generalization capability, and confirm the effectiveness of the surrogate model architecture chosen, respectively. Within the DSE process, surrogate models serve as efficient proxies for computationally intensive simulations, allowing stakeholders to interactively assess performance, economics, and logistics metrics with near-instant feedback.

To execute sensitivity analysis and trade space visualization, the surrogate models are a low-cost proxy for high-fidelity simulations. Surrogate models are checked for fit metrics such as the coefficient of determination (R^2) and mean squared and absolute errors for training, validation, and test sets of the data. As an example, for the use case described in Section IV, the surrogate models execute roughly 200 million times faster than the MDA. For the DSE environment, fewer than 20 surrogates are used in a single page; therefore, surrogate models were 10 million times faster than the analyses themselves. Using surrogate models, multiple trends in multiple dimensions can be computed within a few seconds at most, allowing the project to create a truly interactive design space exploration application, with the consequences of stakeholder inputs displayed immediately. Artificial Neural Networks were used in this work exclusively due to their ability to fit to many types of trends and the availability of sufficient data for their creation.

Finally, various visualizations are prepared for decision-makers to perform trade-offs and consider the pros and cons of alternative designs. These visualizations include profiler plots and contour profilers for trend and constraint analyses, bar charts and line charts are used for time series results, mathematical graph visualizations are used for logistics results, among others. Stakeholders can use the visualizations and user interface elements such as dropdown menus, check boxes, text boxes, and slide bars to interact with the visualization that update near instantaneously based on the inputs. Trade space navigation, constraint satisfaction evaluation, and multi-objective trade-off resolution are involved in the final DSE methodology phase. The computational burden of design iteration is significantly reduced by the surrogate models to allow engineers to explore broad regions of the trade space, identify feasible configurations, and converge toward optimal solutions under multiple stakeholder constraints [14, 17].

The reasoning behind the visualizations is to identify constraint violations across performance, logistics, and economics, quantify variable sensitivities with respect to system-level FoMs, and finally to support stakeholder-specific evaluations by enabling filtering on discipline-defined constraint sets. The MBSE framework receives insights from the decision-making process to update the architecture definitions, refine requirements, and ensure end-to-end traceability. Iterative convergence toward feasible and balanced system configurations is enabled through the closed-loop integration.

IV. Use Case: Designing an Aircraft with Performance, Industrial, and Economic Considerations

The use case presented in this research is for a single-aisle commercial aircraft derivative. It integrates various industrial systems factors like production ramp-up, learning rates, and logistics flow modeling with other performance and economic parameters like wing area, gross weight, labor rates, and lifecycle cost assessments. Overall, this use case intends to demonstrate the integration of MBSE, MDAO, and DSE to support trade studies across these disciplinary metrics. The collaborative architecture process is visualized through an eXtended Design Structure Matrix (XDSM) illustrated in Fig. 4. This MDAO tool captures the data flow and feedback mechanisms between the various disciplinary

Table 1 Models for Solution Sizing

Discipline	Model	Fidelity
Aircraft Performance	FLOPS	Low–Medium
Manufacturer Economics	ALCCA	Low
Industrial System	LOOMPA	Medium

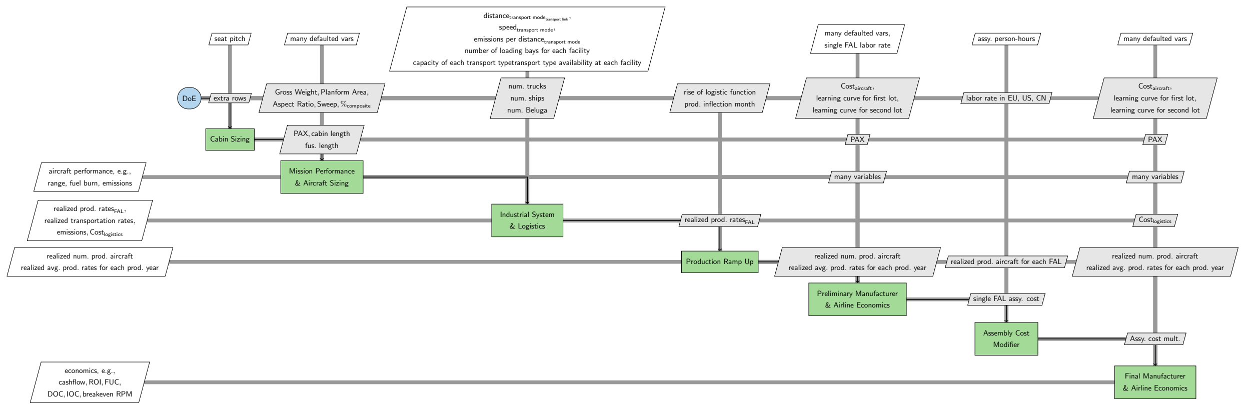


Fig. 4 Aircraft and industrial system design analyses used to generate data for design space exploration

models whose fidelity levels are given in Table 1. The design space is parameterized using a set of key input variables listed in Table 2, with allowable ranges considered to enable disciplinary trade-offs among various design points. The LHS technique is employed to generate the DoE with a uniform and stratified sampling of the design space [18]. The integrated workflow consists of the following disciplinary analysis models for the final coupled decision-making.

Aircraft Performance Analysis: Each DoE sample is first evaluated using the Flight Optimization System (FLOPS), which models the aerodynamics, propulsion, and weight breakdowns to estimate the mission fuel burn, payload capacity, range, and emissions [19]. FLOPS also includes parametric cabin sizing capabilities and accounts for high-level system trade-offs.

Industrial System Logistics: The performance outputs from FLOPS are fed into an industrial systems simulation model developed in the Aerospace Systems Design Laboratory (ASDL) called the LOgistical Operations and Management Platform for Analysis (LOOMPA), built using SimPy, a process-based discrete-event simulation framework based on standard Python [20, 21]. LOOMPA captures the industrial flows by modeling transportation logistics, production site throughput, and storage capacity constraints at Final Assembly Lines (FAL). Logistics-specific variables such as the assembly-line learning curve factors, logistic function parameters, and transport options are evaluated for their influence on production rates, emissions, and logistic operational costs. By doing so, this model examines the performance of the logistics network and its ability to meet delivery demands under constraints, assuming that the production facilities can keep up with continued operations. By treating the logistics network as the "customer," LOOMPA uses takt time, a key concept in lean manufacturing [22], to determine the rate at which a manufacturing facility needs to operate to meet downstream demand. This helps LOOMPA identify production bottlenecks and pinpoint underperforming stations in a production line, offering insight into how facilities must coordinate to sustain continuous operations.

Lifecycle Economic Analysis: The economic feasibility of each configuration is quantified using the Aircraft Life Cycle Cost Analysis (ALCCA) tool [23]. It uses probabilistic cost assessment techniques to estimate the Research, Development, Test & Evaluation (RDTE) costs, production costs, Direct and Indirect Operating Costs (DOC & IOC), and other key economic indicators such as net present value, Return on Investment (ROI), breakeven point, and annual and cumulative cash flows.

The disciplinary modeling tools are then integrated into a unified MDAO environment using GEMSEO [24], which manages data exchange, surrogate modeling, and trade-space filtering. This disciplinary coupling enables simultaneous evaluation of technical, economic, and industrial feasibility and facilitates system-level decision-making. The use case presented in this research is based on some controlled assumptions for simplification and traceability. These include modeling learning curves for production costs using fixed exponential rates, representing the failure probabilities in industrial systems as simplified discrete events, and predefining factory locations and transportation modes based on the current Airbus single-aisle production network.

Key results are then assessed through discipline-specific FOMs for each configuration to help design trade-offs. Logistics operation costs due to different transport modes and varying labor rates across production facilities are incorporated into economic analysis to capture the impact of industrial systems on total cost. Production ramp-up and throughput across final assembly lines are also modeled and visualized in order to identify bottlenecks in the supply

Table 2 Input Parameters for the Case Study

Variable	Baseline	Min	Max
Gross Weight (lb_f)	175,000	157,500	192,500
Wing Area (sqft)	1,331	1,198	1,464
Wing Aspect Ratio	9.1	8.2	10.0
Wing Sweep (deg)	24.92	22.43	27.41
Number of Extra Rows	0	−2	2
Percentage of Composites in Wing (%)	0	0	75
Number of Trucks	15	10	30
Number of Ships	4	2	6
Number of Beluga	8	4	12
Labor Rate US ($/hr)	37.18	33.46	40.90
Labor Rate EU ($/hr)	38.6	34.74	42.46
Labor Rate China ($/hr)	17.0	15.3	18.7
Production Inflation Month (Months)	108	96	120
Rise Logistics Function	0.1	0.08	0.12
Learning Rate (First Lot, %)	76	68.4	83.6
Learning Rate (Second Lot, %)	79	71.1	86.9
Target Price (Million $)	101	90	110

chain. Environmental impact is quantified via emissions from both mission performance and logistics transport. A comprehensive breakdown of the disciplinary FOMs across various categories is shown in Table 3.

Finally, the results are visualized in an interactive dashboard developed using Python-based Dash Plotly [25]. The *Sensitivity Profilers* help visualize individual design parameters' isolated effects on FOMs. By varying one parameter at a time while holding others constant, this visualization helps to identify the most influential input parameters and prioritize their modifications for design changes. The *Contour Profiler* shows the interactions between pairs of design parameters via contour lines representing constant FOM values. It reveals the constraint boundaries and current design point feasibility through contour mapping and guides design trade-offs to open up the feasible design space. The *Network Graph* maps interconnections within the industrial system, depicting transportation modes and facility linkages to optimize system-level logistics. Visualizing the flow of goods from various subassemblies to FALs helps identify

Table 3 Categorized Output Metrics for the Case Study

Category	Metrics
Aircraft Sizing	Wing Weight, Horizontal Tail Weight, Vertical Tail Weight, Fuselage Weight, Landing Gear Weight, Aircraft Empty Weight, Total Fuel Weight Used
Performance and Emissions	Wing Span, Operating Empty Weight, Payload, Mission Fuel, Design Range, Total NO_X Emissions
Economics	Assembly Cost Factor, First Unit Cost, First Unit Assembly Cost, First Airframe, Total RDTE (minus Propulsion Development), Avg. Unit Airplane Cost, Tooling Equipment, Max. Negative Cum. Cash Flow, Manufacturer's ROI, Avg. Yield/RPM, DOC and IOC per ASM, Breakeven Month
Logistics	Converged Production Rate (for Toulouse, Hamburg, Tianjin, Mobile), Production Size

the process bottlenecks, mitigate production delays, and minimize emissions. The *Cashflow Diagrams* depict the financial trajectory of design configurations over time via annual and cumulative trends. This visualization distinguishes income streams and cost categories and highlights break-even points, helping assess long-term economic viability. The *Parallel Plot* and *Scatter Plot* offer multidimensional insights by simultaneously displaying variable interdependencies and identifying trends, clusters, and outliers, which is particularly valuable in early-stage trade space exploration. Collectively, these visualization tools enable subject matter experts to trace trade-offs across disciplines, isolate regions of infeasible designs, and propose targeted refinements.

V. Results

The application of the MBSE-enabled DSE methodology for a single-aisle derivative aircraft is demonstrated through an integrated workflow combining FLOPS, LOOMPA, and ALCCA as described in Sec. IV. The analysis was conducted using a structured methodology that ensures requirements traceability through MBSE, uses MDAO for interdisciplinary coupling, and supports trade-space analysis via DSE. A representative design scenario was selected to showcase the framework's decision-making process.

The aim of the proposed methodology is the mitigation of costly redesign cycles and simulation reruns caused by simulation tool misalignment and inconsistent disciplinary assumptions. To ensure robustness of the results, a structured breakdown of the system was performed under MBSE, and the fidelity of each model was considered prior to setting up and launching full simulations. An ontology-based schema was developed in prior work [4] to explicitly define the specifications and relationships for each step of the design methodology. The objective of this work is to ensure knowledge and assumption integration of each system's inputs and outputs, and simultaneous consideration of aircraft design, industrial capabilities, and financial metrics, within the unified framework.

The inputs and constraints were controlled through an interactive DSE dashboard. Table 4 summarizes the input sliders available to the user, while Table 5 displays the stakeholder-defined feasibility constraints. Table 6 outlines the input-output mapping used for design evaluation and metric tracking.

Table 4 Input Parameters Set Using the Dashboard Sliders

Parameter	Value	Minimum	Maximum
Reference Wing Area (sqft)	1,355	1,200	1,450
Wing Sweep (deg)	24.7	20	30
Composites Fraction	0.38	0	1
Gross Weight (lb_f)	175,000	160,000	190,000
Aspect Ratio	9.1	8	10
Target Price (M$)	100	90	110
Assembly Learning Curve Factor First Lot (%)	76	68	84
Assembly Learning Curve Factor Second Lot (%)	79	72	86
Labor Rate US ($/hr)	37.2	30	45
Labor Rate EU ($/hr)	38.6	30	45
Labor Rate China ($/hr)	17.0	15	20
Extra Rows	2	−2	2
Logistics Function Rise	0.09	0.08	0.2
Production Inflection Month	97	96	120
Number of Trucks	20	10	30
Number of Ships	3	2	6
Number of Belugas	6	4	12

Table 5 Constraint Settings from the Dashboard

Constraint Parameter (Unit)	Lower Bound	Upper Bound	Range
Aircraft Produced	600	4,600	600–4,600
Average Unit Airplane Cost (Million &)	81.5	93.54	81.5–132.6
Average Yield RPM ($)	0.08	0.15	0.08–0.3
Manufacturer's ROI	0.16	0.3	0–0.3
Total RDTE (Billion $)	4.5	5.5	4.5–5.5
First Unit Cost, FUC (Million $)	280.0	323.8	280.0–366.0
DOC per ASM ($/ASM)	0.03	0.07	0.03–0.2
IOC per ASM ($/ASM)	0.02	0.04	0.02–0.06
Total Logistics Cost (Million $)	0.830	5.6	0.830–7.3
Total Logistics Emissions (Mt CO_2e)	0.061	0.797	0.061–1.900
Total Monthly Production Rate	30	65	13–65
Design Range (NM)	2,400	5,600	1,300–5,600
Block Fuel (lb)	16,000	38,560	16,000–63,000
Operating Empty Weight (lb)	90,000	103,350	90,000–105,000
Wing Span (ft)	95	118	95–120

Table 6 Selected Dashboard Input and Output Parameters

Surrogate Model Inputs	Design Space Exploration Outputs
Reference Wing Area	Aircraft Produced
Wing Sweep	Average Unit Airplane Cost (including spares)
Composites Fraction	Average Yield per Revenue Passenger Miles
Gross Weight	Manufacturer's Return on Investment
Aspect Ratio	Total Research, Development, and Testing Cost
Target Price	First Unit Cost
Assembly Learning Curve Factor First Lot	Direct Operating Cost per Aircraft Seat Mile
Assembly Learning Curve Factor Second Lot	Indirect Operating Cost per Aircraft Seat Mile
Labor Rate United States	Total Logistics Cost
Labor Rate Europe	Total Logistics Emissions
Labor Rate China	Total Monthly Production Rate
Extra Rows	Design Range
Logistics Function Rise	Block Fuel
Production Inflection Month	Operating Empty Weight
Number of Trucks	Wing Span
Number of Ships	
Number of Belugas	

A baseline configuration was then selected to assess feasibility across domains. Table 7 provides the corresponding inputs and outputs. The initial design failed to meet several feasibility constraints. Some of the violated metrics are:

Economic: Average Unit Cost, FUC, ROI, Total RDTE, Average Yield RPM.

Operational: Monthly Production Rate.

Logistics: Indirect Operating Costs per ASM (IOC/ASM).

Table 7 Baseline Inputs and Outputs for Initial Configuration

Input Parameters		Output Parameters	
Variable	**Initial Value**	**Metric**	**Value**
Gross Weight (lb_f)	175,000	Aircraft Produced	1,490
Wing Area (sqft)	1,355	Unit Cost (Million $)	106.9
Wing Aspect Ratio	9.1	Average Yield RPM ($)	0.15
Wing Sweep (deg)	24.7	Manufacturer's ROI (%)	−7.0
Number of Extra Rows	2	Total RDTE (Billion $)	4.956
% Composites in Wing	38	FUC (Million $)	326.0
Number of Trucks	20	DOC per ASM ($)	0.06
Number of Ships	3	IOC per ASM ($)	0.04
Number of Beluga	6	Logistics Cost (Thousand $)	168.2
Labor Rate US ($/hr)	37.2	Logistics Emissions (Mt CO_2e)	109
Labor Rate EU ($/hr)	38.6	Production Rate (A/C per month)	21
Labor Rate CN ($/hr)	17.0	Design Range (NM)	2,915
Inflation Start (Months)	97	Block Fuel (lb_m)	33,930
Logistics Rise Factor	0.09	OEW (lb_f)	99,250
Learning Rate 1st Lot (%)	76	Wing Span (ft)	107.3
Learning Rate 2nd Lot (%)	79		
Target Price (M$)	100		

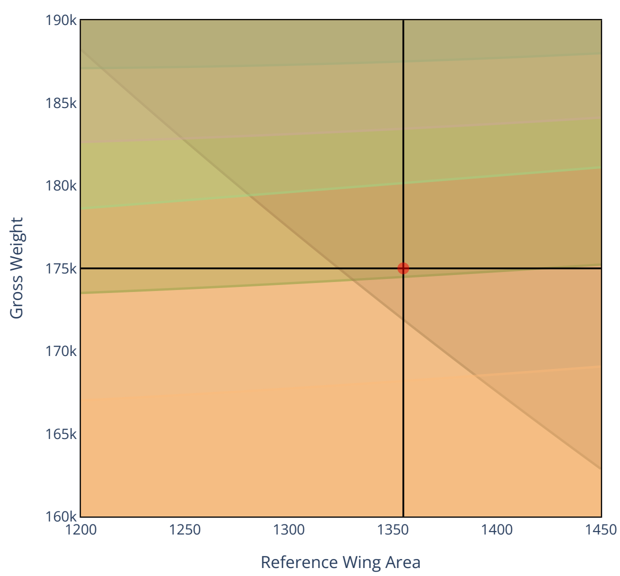


Fig. 5 Infeasible Design Space Contour Plot Visualization

This prompted a visual analysis of constraint satisfaction using contour plots. Fig. 5 highlights infeasible regions based on two key views of the multidisciplinary design space. More specifically, from the aircraft sizing perspective, gross weight and wing area were selected, along with the transportation logistics perspective, which includes settings such as the number of ships and the number of Belugas. The red-shaded areas mark combinations that violate stakeholder requirements. This confirmed that the baseline configuration was infeasible across multiple domains.

To navigate towards multidisciplinary feasibility, a recovery strategy was initiated by first modifying aircraft performance-related parameters. Further analysis was conducted using a sensitivity profiler, shown in Fig. 6. This profiler estimates the impact of input variables on target performance metrics by perturbing each input dimension while holding others fixed. The resulting plots allow for the ranking of variables by influence, providing valuable guidance for prioritizing design modifications. Using sensitivity analysis (see Fig. 6) and focusing on Average Yield RPM and FUC, the trends indicate feasibility for these metrics by making the aircraft lighter and thus also improving upon its

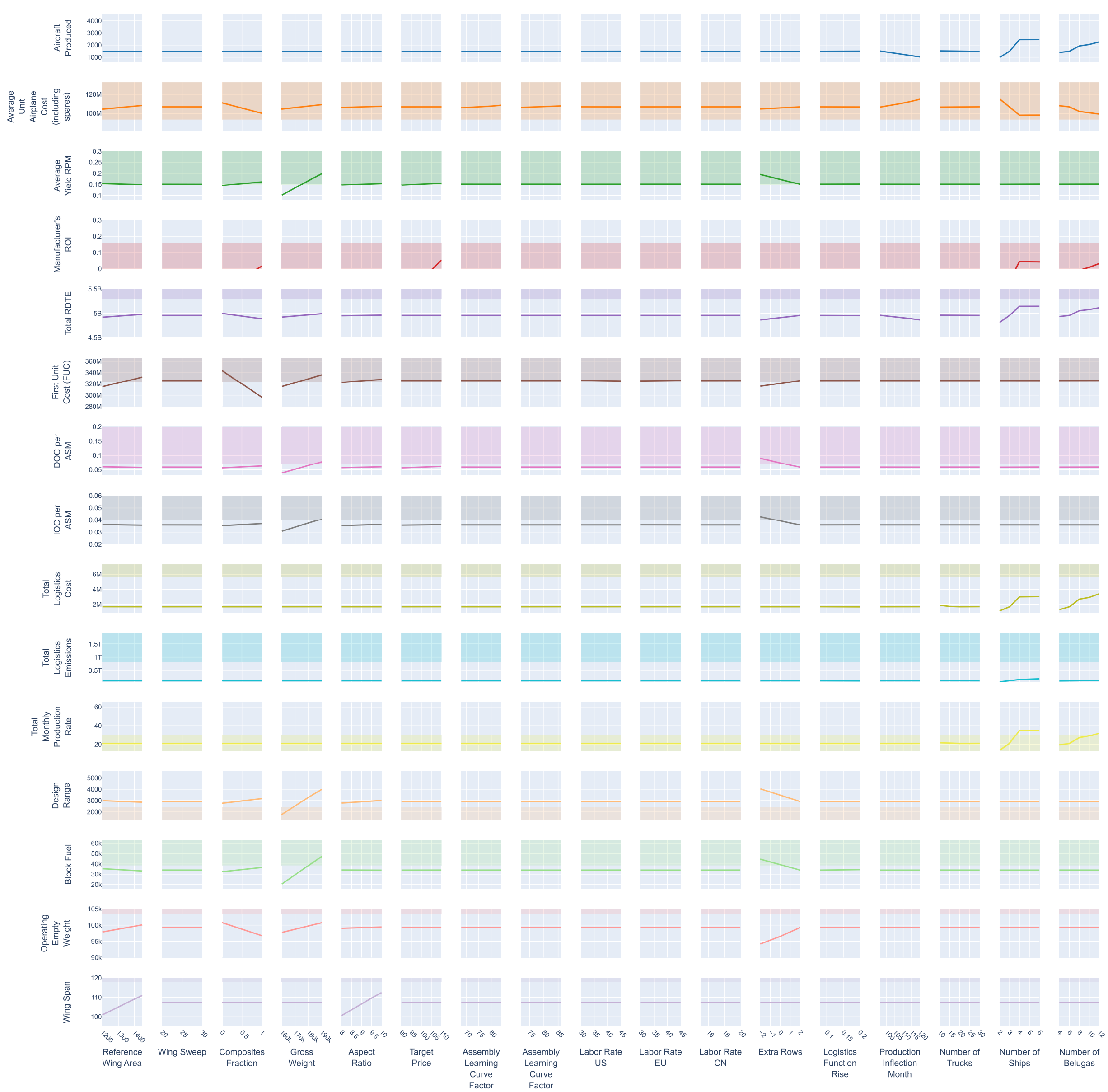
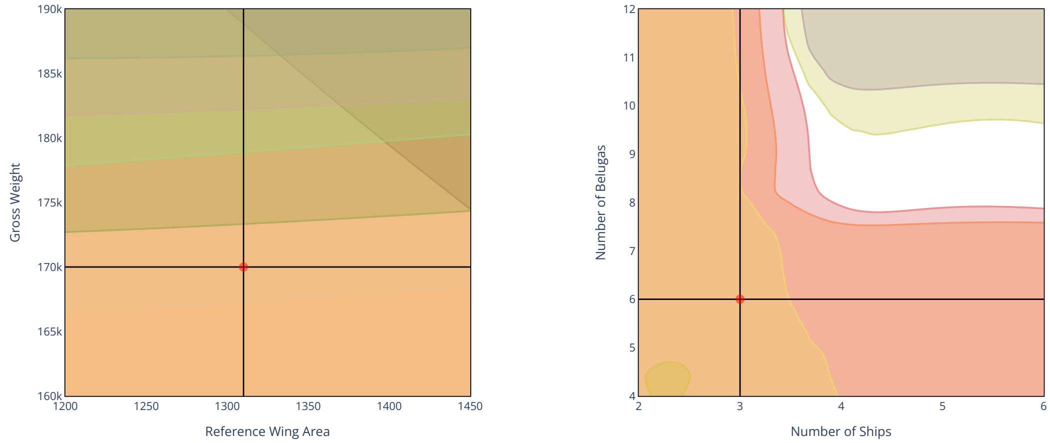
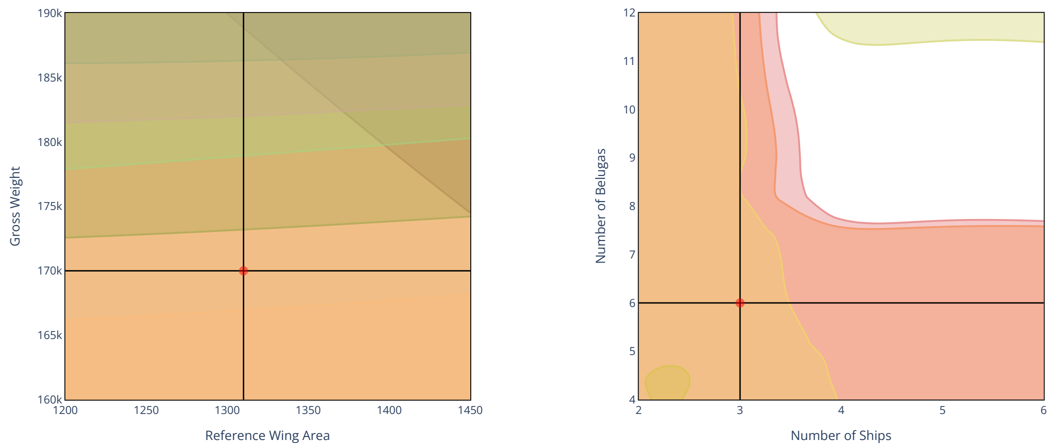


Fig. 6 Sensitivity Profiler as Mitigation to Infeasible Configuration

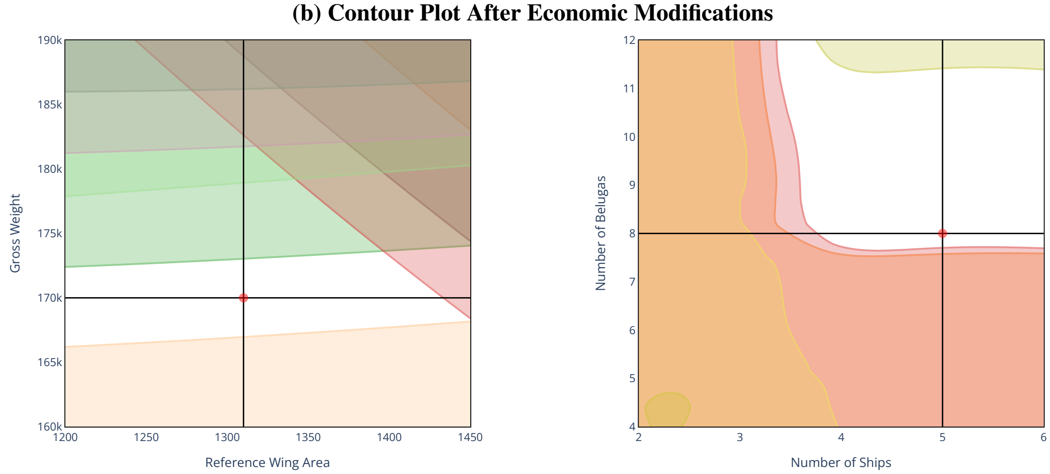
performance. Therefore, the wing area was reduced to 1,310 sqft, the use of composites for the vehicle increased to 55%, and gross weight decreased to 170,000 lb_f. The resulting design space is shown in Fig. 7a. This shift improved feasibility for the Average Yield RPM, IOC per ASM, and FUC, but did not fully meet all unmet constraints listed earlier.



(a) Contour Plot After Performance-Based Design Modifications



(b) Contour Plot After Economic Modifications



(c) Contour Plot After Logistics Modifications

Fig. 7 The progression of the design point towards the feasible space for aircraft and industrial system co-architecture

After the improvements made from the perspective of aircraft performance and design, additional considerations regarding the aircraft manufacturer's economics should now come into play. For the Average Unit Airplane Cost and ROI requirements, economic adjustments were suggested, including an increase of the aircraft market price to \$101M, a relaxed RDTE cap to \$5.4B, and a higher tolerance for logistics costs to \$6.7M. Such updates in the requirements are not always allowed and they depend on the type and source of each requirement. For instance, certification requirements are very strict and not up to reconsideration from the systems engineer. As seen in Fig. 7b, while these modifications expanded the feasible region within the design space, especially the market price per aircraft, RDTE, and logistics cost, the current design is still infeasible in terms of the Average Unit Airplane Cost and ROI requirements.

Since the constraints currently violated are the total monthly production rate, ROI, and average unit cost per aircraft, the next disciplinary view to examine is the logistics aspect. The final step was to modify the logistics to increase the number of Belugas from six to eight and the number of ships from three to five, in order to navigate towards a feasible area of the design space and meet the total monthly production rate programmatic constraint. The revised design space shown in Fig. 7c demonstrates a fully feasible configuration across the considered constraint sets. These results validate the use of interactive DSE using different views for the combined design space, to converge toward viable design solutions.

For the identified configuration shown above, Fig. 8 presents the annual and cumulative cash flow over the program timeline. Green bars represent annual income, red bars denote various costs (RDTE, manufacturing, sustaining), and the black line shows net cash flow. The breakeven occurs in Year 9, supporting the economic viability of the final configuration.

Production ramp-up and throughput across final assembly lines are illustrated in Fig. 9. Toulouse emerges as the leading contributor, with Hamburg, Tianjin, and Mobile coming next in the stated order. This output validates alignment between industrial feasibility and aircraft design.

To provide an aggregate view of variable interactions and design clusters for high-dimensional design spaces, the parallel coordinate plot in Fig. 10 maps feasible configurations across multiple disciplines, for the requirement values listed in Table 5. Each line represents a candidate design solution, and the axes display input variables and output metrics. This visualization allows engineers to simultaneously examine how trade-offs evolve across the design vector and quickly identify dominant trends or outliers.

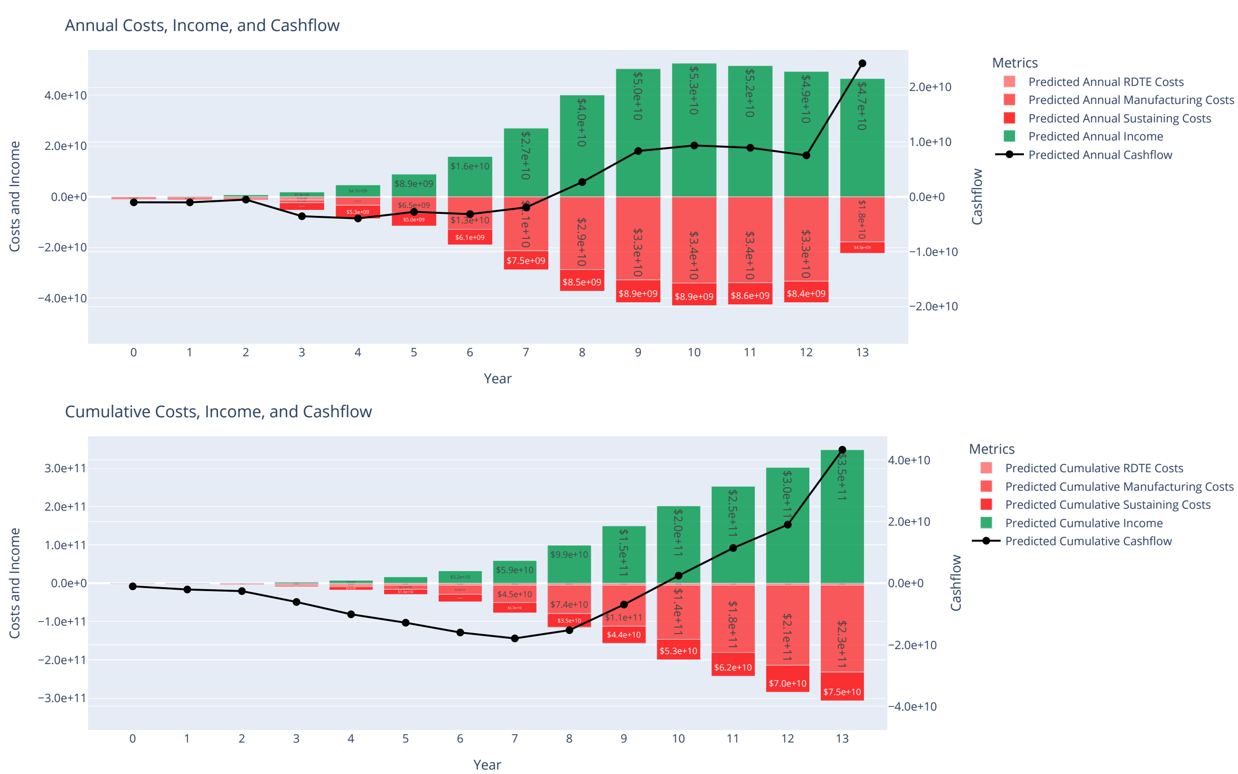


Fig. 8 Cumulative cash flow over the program timeline

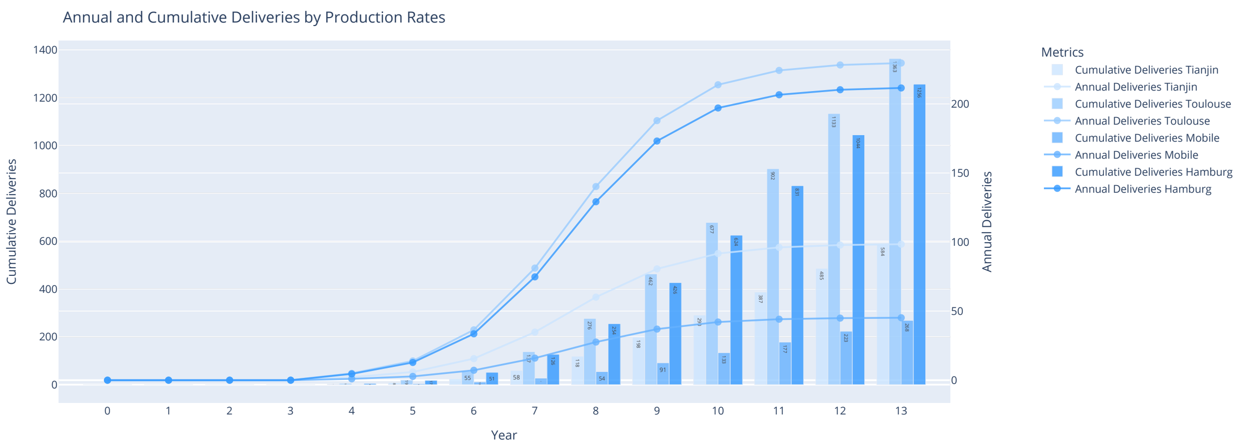


Fig. 9 Annual and cumulative aircraft deliveries across final assembly lines

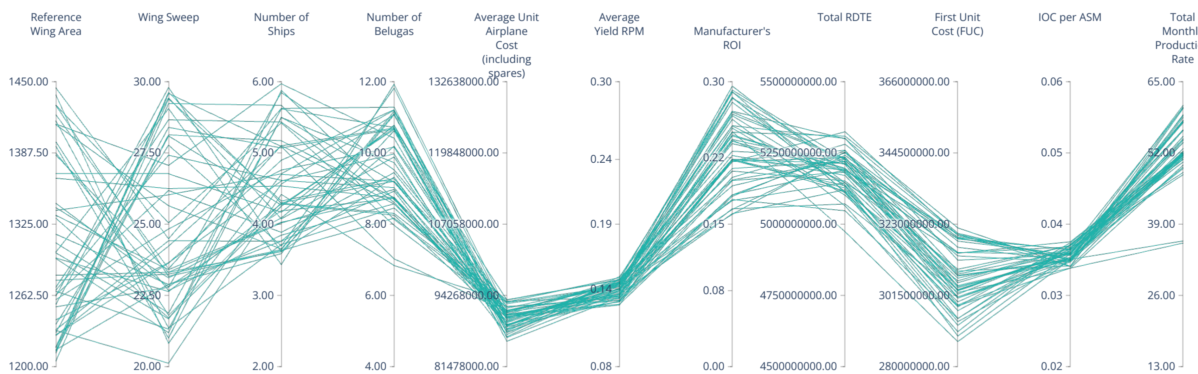


Fig. 10 Parallel plot illustrating input-output relationships and feasibility trends across design variables

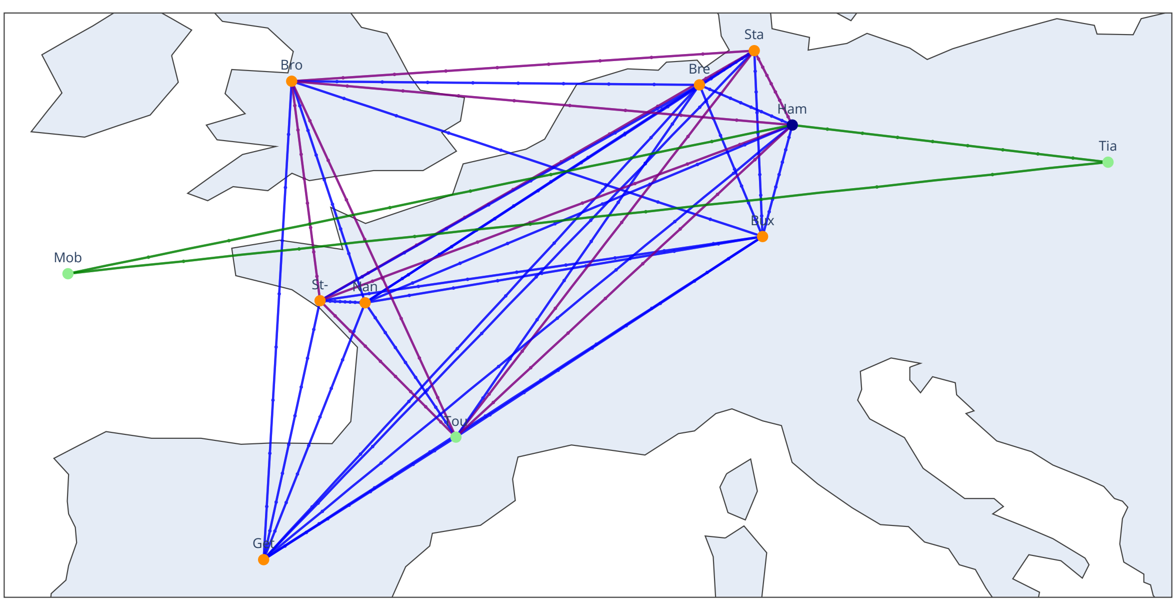


Fig. 11 Logistics network graph showing global Airbus facility interactions and transport modes

Lastly, Figure 11 presents the logistics network graph for the final configuration. Nodes represent global Airbus manufacturing and assembly sites, while colored edges denote transportation routes via ship, Beluga aircraft, or ground logistics. The map enables tracing of industrial flows and visual verification of transport feasibility within the chosen architecture. The final configuration maintains a robust global supply chain that aligns with production rates and minimizes bottlenecks. For readability, the nodes representing Mobile and Tianjin have been artificially moved closer to Europe in the map. When the real positions are used, the vertices and edges within Europe become difficult to distinguish.

The transition from an infeasible baseline to a validated configuration is enabled through the combination of parametric trade studies, visualization, and surrogate modeling. The multi-phase recovery strategy using performance refinement, logistics reallocation, and economical constraint relaxation refined the constraints and design variables to transmit a feasible configuration. The MBSE model must then be updated with the final design settings and any updated requirement values, to be reviewed by the systems engineer. Through the MBSE update, traceability is ensured, and the results of the different design scenarios can be stored in a database.

VI. Conclusions

The integrated MBSE-enabled DSE methodology presented in this paper links aircraft design with industrial systems and economic considerations on the manufacturer's side. The model-based systems, multidisciplinary simulations, and surrogate modeling were leveraged in the proposed approach to guide complex aerospace design decisions. The embedded design space with logistical and financial metrics enables a holistic view of feasibility that goes beyond traditional performance-centric analysis. This methodology was applied in the case study of a single-aisle aircraft derivative. It demonstrates an example of how disciplinarians can bring requirements' definition and validation earlier in the design process, to avoid costly redesigns that could be necessary if each disciplinary constraint were addressed later and separately, without requirements' communication and traceability. It also emphasizes the need to consider and create, whenever feasible, links between the different disciplines and implement them before the decision-making part, when each analysis level of fidelity and its metrics are determined, at the MDAO part. Finally, in this paper, one decision-making exercise was carried out for a set of requirements, to show potential pathways for efficient redesign, and when design and requirements reconsideration are feasible for the systems engineer.

Through the current framework, future development should include vertically and horizontally incorporating higher-fidelity disciplinary models for additional use cases, integrating real-time data streams into the design loop, and formalizing constraint relaxation strategies through interactive decision-support tools. The methodology can also be extended to incorporate broader system-of-systems applications to demonstrate scalability and impact.

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