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Roy, Satadru; Davendralingam, Navindran; Crossley, William A.; Govindaraju, Parithi

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Satadru Roy—is a PhD student of Dr. William Crossley in the School of Aeronautics and Astronautics at Purdue University specializing in the field of Aerospace Systems. His research interests center on design optimization and systems engineering. [roy10@purdue.edu]

Navindran Davendralingam—is a Research Scientist in the School of Aeronautics and Astronautics at Purdue University. He received his PhD from Purdue University in Aerospace Engineering in 2011. He is currently conducting research in the Center for Integrated Systems in Aerospace (CISA) led by Dr. Daniel DeLaurentis. [davendra@purdue.edu]

William A. Crossley—is a Professor in the School of Aeronautics and Astronautics, Purdue University, where he has been on the faculty since 1995. His research and teaching interests focus on design and optimization of aerospace vehicles and systems of systems. [crossley@purdue.edu]

Parithi Govindaraju—is a PhD student of Dr. William Crossley in the School of Aeronautics and Astronautics at Purdue University specializing in the field of Aerospace Systems. His research interests center on design optimization and systems engineering. [pgovinda@purdue.edu]

Abstract

Traditional approaches to design and optimize a new system often do not consider how the operator will use this new system alongside the other existing systems. This "handoff" between the designs of the new system and how this new system operates with the group of systems leads to the sub-optimal performance of the new system when measured with respect to system-level objective. Aircraft design choices made to meet a set of requirements dictate the performance of the aircraft, and the aircraft performance influences how the operator might use the aircraft. Further, the presence of uncertainties in predictions of the new aircraft performance and costs and uncertainties in the amount of payload to transport further exacerbate the problem of determining these requirements. Recent efforts have posed approaches to address this problem, but generally with a deterministic perspective. This research adopts a previously developed subspace decomposition approach and integrates features from robust/reliability based optimization to address the uncertainties and solves two application problems—a military and a commercial airline application. The result demonstrates the ability of the framework to identify the design requirements for the new aircraft, and a posterior analysis indicates that the framework acceptably handles the uncertainties.

Research Issue

The *Better Buying Power 3.0* document (Kendall, 2014) states, "Defining requirements well is a challenging but essential prerequisite in achieving desired service acquisition outcomes." Traditional acquisition processes focus on development of requirements at the system-level. Current acquisition analyses of design alternatives are disjointed from considering operations (the way an end user operates these new systems alongside existing ones), resulting in inefficiencies at the higher aggregate level (Taylor & Weck, 2007; Mane, Crossley, & Nusawardhana, 2007). Typical design practice for new systems assumes a "handoff" between the design of the new, yet-to-be introduced system, and the operations on how the system impacts top-level performance.

The authors proposed an approach that would include top-level requirements for a new system as decision variables in an optimization problem. With the objective to maximize (or minimize) a fleet-level performance metric, then an optimization algorithm should determine the "right requirements" as part of finding the optimal set of decision variable values. Using aviation examples, one can pose the optimization problem that included top-level requirements as decision variables along with new system design variables and operational decision variables. The resulting formulation is a mixed-integer nonlinear programming problem that is very difficult if not impossible to solve in reasonable time. The authors and their colleagues have developed a decomposition approach that allows solution of this problem, with a few minor modifications from the original problem.

The initial efforts concentrated on demonstrating that solving the decomposition approach was practical and that the results were useful; however, those initial efforts could not address data uncertainties in the problem. The recent work has identified and demonstrated how to include consideration for various types of data-driven uncertainties as well. With the focus on aviation examples, the work first considered an application of the decomposition approach under uncertainty to military air cargo transportation using actual data from the U.S. Air Force Air Mobility Command (AMC) as the basis for a set of example problems. Then, to explore the flexibility of the decomposition approach under uncertainty, data from the Bureau of Transportation Statistics provided the basis for another set of example problems representative of commercial airlines.

This paper presents how the approach applies to both military air cargo problems and to commercial airline problems and how the approach handles uncertainties in the aircraft design sub-problem, propagates those uncertainties to the allocation (commercial airline) or assignment (military air cargo) sub-problem, and additionally considers demand uncertainty in the allocation or assignment sub-problem. While the overall decomposition framework can address these two different aviation problems under uncertainty, there are some specific modifications necessary to represent these two different problems.

The approach is able to identify the best requirements for a new aircraft for both the commercial airline and military air cargo problems. *A posteriori* analysis of the resulting design shows the advantages that the approach under uncertainty has over deterministic approaches to the same problems.

Subspace Decomposition Approach

This section describes in details the methodology that uses the previously developed subspace-decomposition approach (Mane et al., 2007; Govindaraju, Davendralingam, & Crossley, 2015). The approach serves as a 'meta-algorithm' framework within which specific choices in performance metrics and resource constraints can be made for each of the two problem instantiations we have solved (AMC and Commercial Airline) in prior work (Roy et al., 2017; Govindaraju et al., 2015). The description of each subspace and the information flow between subspaces appears in Figure 1.

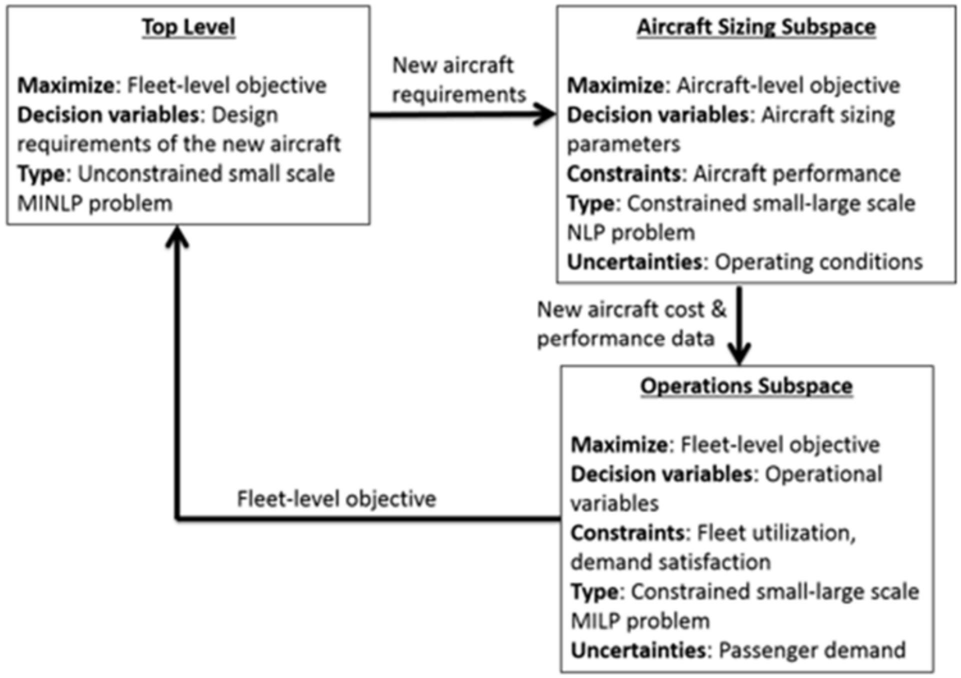

Figure 1. Overview of the Sequential Decomposition Framework

Top-Level Subspace

The top-level problem seeks to maximize the fleet-level objective of the operator, based upon the choice of the design requirement of the new yet-to-be-designed aircraft. These top-level requirements include design range, payload-carrying capacity, etc. of the new yet-to-be-designed aircraft. This level is a small-scale Mixed Integer Non-Linear Programming (MINLP) problem and is solved either using an MINLP solver or by performing a pseudo enumeration.

Maximize Fleet level objective

Design variables Design range **Top: MINLP**

Payload carrying capacity

Aircraft Sizing Subspace

The decision variables from the top level appear in the aircraft sizing sub-space as parameters. Starting from these top-level requirements, this subspace solves an aircraft design optimization problem with the objective that minimizes the design mission direct operating cost. The decision variables for this sub-problem are the variables that defines the wing geometry such as aspect ratio, taper ratio, sweep, etc. and the engine parameters like static thrust, bypass ratio, fan pressure ratio, and so forth. Further, the portion of the aircraft conceptual design phase known as “aircraft sizing,” usually uses empirical equation and simplified physical models to predict the cost and performance of the aircraft. The limited knowledge available at this phase of the design process combined with the modeling fidelity results in high uncertainty.

Minimize Design mission expected direct operating cost

Design variables Wing design variables

Engine design variables **Size: NLP**

Subject to Aircraft performance constraints (using RBDO)

For instance, an aircraft is sized for its design mission based on a set of nominal values for operating conditions (e.g., cruise altitude). However, when evaluating the operating missions to determine block time and fuel consumed on the flight, there might be a variation in winds aloft, which would alter the block time and fuel consumed. Additionally, predictions of the aircraft performance and characteristics, like parasite drag, that use low-fidelity models will have associated uncertainty. It is therefore necessary to simulate the effect of uncertainties on the design parameters, in the absence of closed form mathematical expressions, for subsequent inclusion in the resulting aircraft sizing optimization problem. We employ a reliability-based design optimization (RBDO) formulation on the new aircraft that is subject to a collection of uncertain parameters. This sub-problem is a Non-Linear Programming (NLP) problem that can be solved using a choice of NLP solver such as the *fmincon* function in MATLAB.

Maximize Expected Fleet-level objective

Design variables Allocation (integer type)

Payload (continuous type) **Alloc: MILP**

Subject to Aircraft utilization constraints (nominal and worse case)

Demand constraints

Operations Subspace

Operations subspace seeks to solve how the operator uses the new yet-to-be-designed aircraft alongside the existing fleet of aircraft. This is an allocation problem that allocates the new aircraft together with the existing aircraft with the goal to maximize the fleet-level objective. The strategy involves assigning or allocating the fleet on various routes. This sub-problem is posed as a Mixed Integer Linear Programming (MILP) problem with both integer (allocation variables) and the continuous (payload) type variables and is solved using the CPLEX solver available within the GAMS (Brooke et al., 1998) software package. This sub-problem is subjected to operational constraints such as aircraft utilization, demand, and so forth. Further the demand in this subspace is uncertain. The amount of payload to carry across the various routes is an uncertain parameter. Thus, we have two levels of uncertainties that interact and need some strategies to address the propagation of uncertainty from one domain to the other. The new aircraft coming out of the aircraft sizing subspace has uncertain performance and cost coefficients. Our approach employs an Interval Robust Counterpart (IRC; Lin, 2014) formulation to address this uncertainty propagation from the sizing sub-space to the allocation subspace. We size the aircraft at two cases of the uncertain parameters of the aircraft sizing subspace: a nominal case and a worse case and use the IRC formulation to enforce the worse-case performance and cost in the allocation constraints using some tolerance limit. An overview of the operations sub-problem (Alloc: MILP) appears below.

In the following two sections, we detail application of the subspace decomposition approach for the case of setting optimal requirements for military air cargo, and, for commercial airline systems. We mainly highlight key differences in the modeling approach for each subsection to illustrate flexibility of the framework in accommodating unique problem characteristics of each case.

Applications of Subspace Decomposition Approach

Case 1: Military Air Cargo

The subspace decomposition approach in the prior section is used to determine the optimal requirements of a new, yet-to-be introduced system (here, strategic airlift aircraft), which will operate alongside other strategic military airlift aircraft of the United States Air Force Air Mobility Command (AMC). The problem was motivated by the USAF AMC's emphasis on reducing fleet-wide fuel consumption. The objectives are to maximize expected fleet productivity and minimize expected fuel consumption. As these are competing objectives, the problem is posed in a multi-objective sense where fleet-wide fuel consumption is minimized and a minimum acceptable fleet productivity level is set as a constraint that is varied to generate a series of non-dominated Pareto solutions. Data on cargo demand is obtained from the Global Air Transportation Execution System (GATES) dataset for the year 2006. Figure 2 illustrates the subspace decomposition of the AMC problem statement.

Differences in Top Level Subspace

The top-level optimization problem does not include any nonlinear constraints and only has bounds imposed on the top-level decision variables. Equations (1) to (4) describe the deterministic formulation of the top-level problem; the formulation incorporating uncertainty appears in latter subspaces.

$$Minimize \quad Fleet\ fuel\ (Pallet_x, Range_x, Speed_x) \quad (1)$$

$$Subject\ to \quad 14 \le Pallet_x \ \le 38 \quad \text{(Design pallet capacity bounds)} \quad (2)$$

$$2400 \le Range_x \le 3800 \quad \text{(Range at max. payload bounds in nmi)} \quad (3)$$

$$350 \le Speed_x \le \quad \text{(Cruise speed bounds in knots)} \quad (4)$$

$$Pallet_x \in Z^+ \quad Range_x, Speed_x \in R^+$$

Equation 1 describes the objective function that seeks to minimize the fleet-level fuel consumption using pallet capacity, range and cruise speed of the new, yet-to-be-introduced aircraft type X as decision variables. Equations 2–4 describe the bounds for the top-level design variables. The values for the bounds were based on strategic airlift requirements, and characteristics exhibited by current cargo transport aircraft (Gertler, 2010; Graham et al., 2003). Here, the design requirement decision variable describing payload capacity uses an integer number of pallets, while the design range and design speed decision variables are continuous.

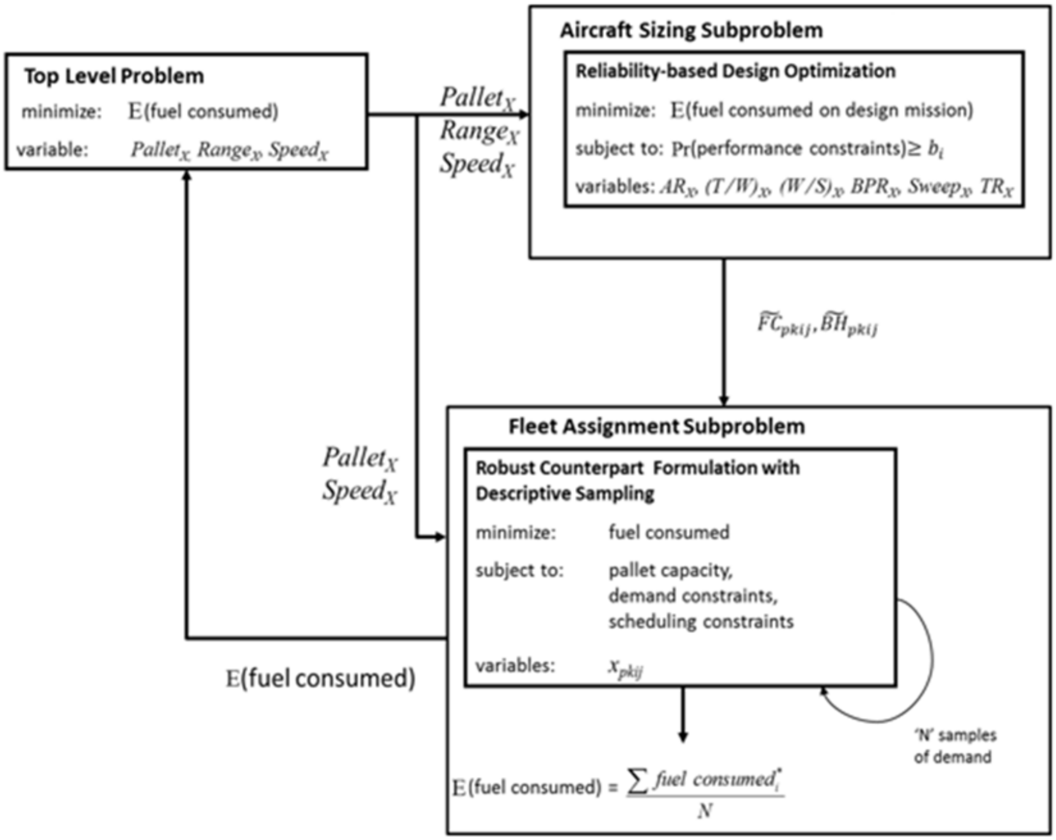

Figure 2. Subspace Decomposition strategy for the USAF AMC Application

Differences in Aircraft Sizing

Uncertainty in Design Parameters

The conceptual phase of the aircraft design process relies upon semi-empirical equations and simplified physics models. The limited knowledge available about the system definition at this phase of the design process combined with the usage of low-fidelity modeling tools results in high uncertainty. Aircraft sizing typically determines the size, weight and performance of an aircraft to meet its design mission based on a set of nominal values on operating conditions (e.g., cruise altitude). However, when evaluating the operating missions to determine block time and fuel consumed on the flight, there might be a variation in assigned altitude, routing, speed, and so forth, which would alter the block time and fuel consumed. For instance, there is uncertainty in the prediction of the parasite drag coefficient. In this example, a scaling factor k_{C_D} follows a distribution to represent the uncertainty in the parasite drag prediction, so that the "actual" coefficient relates to the "predicted" coefficient in the following manner:

$$C_{D_0\,actual} = k_{C_D} \text{x} (C_{D_0\,predicted})$$

To address the uncertainty related to operations and predictions of the new aircraft performance in the aircraft sizing subspace with reasonable computational expense, the Analysis of Variance (ANOVA) technique, a sensitivity analysis method, determined the subset of the most important parameters that influence the outputs under consideration

(Montgomery, 2008). This investigation assumes triangular distributions for the scaling factors of identified parameters listed in Table 1.

Table 1. Triangular Distributions of the ANOVA Identified Uncertain Parameters in the Aircraft Sizing Subspace

Uncertain Parameters (ξ)	Lower limit	Mode	Upper Limit
C_{D_0}multiplier, k_{C_D}	0.90	1.0	1.10
Specific Fuel Consumption, SFC [hr^{-1}]	0.45	0.5	0.55
Oswald efficiency multiplier, k_{e_0}	0.95	1.0	1.05
Cruise altitude [ft]	32000	35000	38000
Pallet mass [lbs]	7200	7500	7800

The aircraft sizing sub-problem seeks to minimize the fuel consumption of the new, yet-to-be-introduced aircraft for the values of design range ($Range_x$), pallet capacity ($Pallet_x$), and cruise speed ($Speed_x$) from the top-level problem. With the top-level objective to minimize fleet-level fuel consumption and the aircraft-sizing objective to minimize the fuel consumed by the new aircraft for its prescribed design range, pallet capacity, and cruise speed, a slight disconnect exists between the objectives of these two levels. The difference in the objectives is that at each aircraft sizing iteration the minimization of fuel consumption uses a single combination of fixed values for design range, pallet capacity, and cruise speed—this is the typical case in aircraft design where these quantities are set as requirements for some "representative design mission." However, the top-level optimization problem drives the question of "What requirements do we need to set in the first place?" by searching through the decision space of the top-level variables to find aircraft requirements that optimizes fleet-level operational aspects of how the aircraft is used.

For example, consider the dimension of design range—as the top-level problem searches across values of range, this naturally changes the set of feasible routes that the new aircraft can fly, thereby changing how the fleet comprised of existing and new aircraft serves the overall route network. By doing so, the top-level problem seeks additional fleet-wide fuel savings that these operational aspects reflect as a function of the decision variables. Therefore, the aircraft sizing objective can be viewed as a subset of the top-level problem objective. Because the type of aircraft assigned on individual flight segments drives the total amount of fuel consumed by the fleet, an aircraft designed for minimal fuel consumption will lead to improved fleet utilization that reduces fleet-level fuel consumption when compared to fleet operations using only the fleet of existing aircraft. The approach in this work poses the aircraft design sub-problem in the context of Reliability Based Design Optimization problem to account for uncertainty in the design phase.

The Reliability-Based Design Optimization (RBDO) formulation (shown below) represents the aircraft design under uncertainty problem.

$$
\begin{aligned}
&\underset{x}{Minimize}\ \ \mathrm{E}\left[f(x,\xi)\right] \\
&Subject\ to\ \ \mathrm{P}\left[g(x,\xi)\le 0\right]\ge b_i \qquad \forall\ i = 1, 2, \ldots, m \\
&x:\ \text{set of decision variables} \\
&\xi:\ \text{set of uncertain parameters} \\
&b_i:\ \text{desired probability of satisfying the } i^{th} \text{ constraint}
\end{aligned}
$$

Aggregating the outputs for each realization (sample) of the uncertain parameter allows for the estimation of statistical measures such as expectation and probability, which the objective and constraint function evaluations require. The objective of the aircraft sizing subspace is to minimize the fuel consumption of the new aircraft X using the decision variables listed in Table 2. For each function evaluation of the top-level problem, the current values of $Pallet_x$, $Range_x$, and $Speed_x$ become fixed parameters for the aircraft sizing problem. Table 2 summarizes the decision variables, uncertain parameters, and constraints in the aircraft sizing optimization problem.

Table 2. Decision Variables and Constraint Limits in the Aircraft Sizing Optimization Problem

Decision Variables, (x)	Lower Bound	Upper Bound
Wing Aspect Ratio, AR_x	6.00	9.50
Thrust-to-weight Ratio, $(T/W)_x$	0.18	0.35
Wing Loading [lb/ft^2], $(W/S)_x$	65.00	161.00
Engine Bypass Ratio, BPR_x	4.50	14.50
Wing Leading Edge Sweep [deg], $Sweep_x$	10.00	35.00
Wing Taper Ratio, TR_x	0.10	0.40
Constraints	**Value**	
Takeoff Distance [ft]	≤ 8500	
Landing Distance [ft]	≤ 5500	
Second segment climb gradient	≥ 0.025	
Top-of-climb rate [ft/min]	≥ 500	

The aircraft sizing sub-problem includes performance constraints such as limits on takeoff and landing distances and upper and lower bounds for the decision variables. The RBDO formulation optimizes the expected performance metric of interest and ensures that the probability of satisfying the performance constraints is greater than or equal to the user-defined reliability level, b_i, considering the uncertainty present in this sub-problem.

Differences in Fleet Operations

This subspace mathematically represents the AMC's operations where the AMC fleet flies cargo missions to deliver pallets of supplies on an "as-needed" basis without a predetermined, long term schedule. The fleet allocation model here considers the multiple destination nature of the flight path for each aircraft, where an aircraft may fly from point A to B and then on to C—this in contrast is different to the airline case where airline aircraft are assigned to fly back and forth on specific segments points. This multiple destination travel path prompts the need to include tracking of tail numbers in the fleet operations subspace. Furthermore, the unscheduled and uncertain nature of demand for cargo transportation includes unknown origin and destination pairs of trips as well—this is modelled using random sampling of starting points for aircraft where the random sample mimics the end of the previous day's flight termination point of the aircraft. The Interval Robust Counterpart (IRC) formulation addresses uncertainty in parameters within AMC fleet operations model; in this case the uncertainty associated with the fuel consumption rate $\widetilde{FC}_{p,k,i,j}$, and in the flight block hours $\widetilde{BH}_{p,k,i,j}$, on given routes in the service network. The optimization problem of the fleet operations model seeks to minimize the fleet-level fuel consumption while enforcing a constraint on productivity.

Case 2: Commercial Airline

We apply the subspace decomposition approach, as a modified version of the AMC case, to the case of a commercial airline application. These modifications arise from the statistical differences in cargo demand between the AMC case study and passenger demand for a commercial airline and from the underlying business model where airlines will set and publish a schedule from which the traveling passengers select flights and purchase tickets. The highly uncertain nature of demand in the AMC case, versus the more symmetric and seasonal nature of demand in commercial applications, prompts different computational strategies within the approach presented here. The detailed subspace decomposition framework for the commercial airline application appears below (also appears in Roy et al., 2017). For the commercial airline application, the airline operation subspace is further sub-divided into two subspaces—airline allocation and a profit evaluation block.

Top-Level Subspace

The top-level optimization problem for the commercial airline application, seeks to maximize the expected fleet-level profit of a representative airline based on the choices made about the design requirements for the new, yet-to-be designed aircraft; here, the range and passenger seating capacity are the design variables in this top-level problem. Like the AMC formulation, the top-level optimization problem is unconstrained except for bounds imposed on the decision variables. The following equations describe the formulation of the top-level problem; consideration for uncertainty, as reflected in the expectation of profit appears later in the aircraft sizing and airline operations subspace.

$$\begin{aligned} \underset{x}{\text{Maximize:}} \quad & E[Fleet\ Profit] \\ Subject\ to: \quad & 75 \leq SeatCapacity_x \leq 250 \\ & 500 \leq Range_x \leq 2600 \\ & SeatCapacity_x \in \mathbb{Z}^+, Range_x \in \mathbb{Z}^+ \end{aligned}$$

The objective function here seeks to maximize fleet-level profit using passenger seating capacity and range of the yet-to-be-introduced aircraft type X as decision variables. The two constraints describe the bounds for the top-level design variables of aircraft passenger seating capacity and range. The values for the bounds on these design variables were based on typical characteristics of current class of aircraft. Here, the design requirement decision variable describing passenger seating capacity and the design range are both integer variables. While the expectation term appears in the objective function of the top-level formulation, the source of uncertainty associated with the expectation term comes from the aircraft design and fleet allocation subspaces. Our discussion in these latter sections will make clear the evaluation of the expectation term for the top-level objective function.

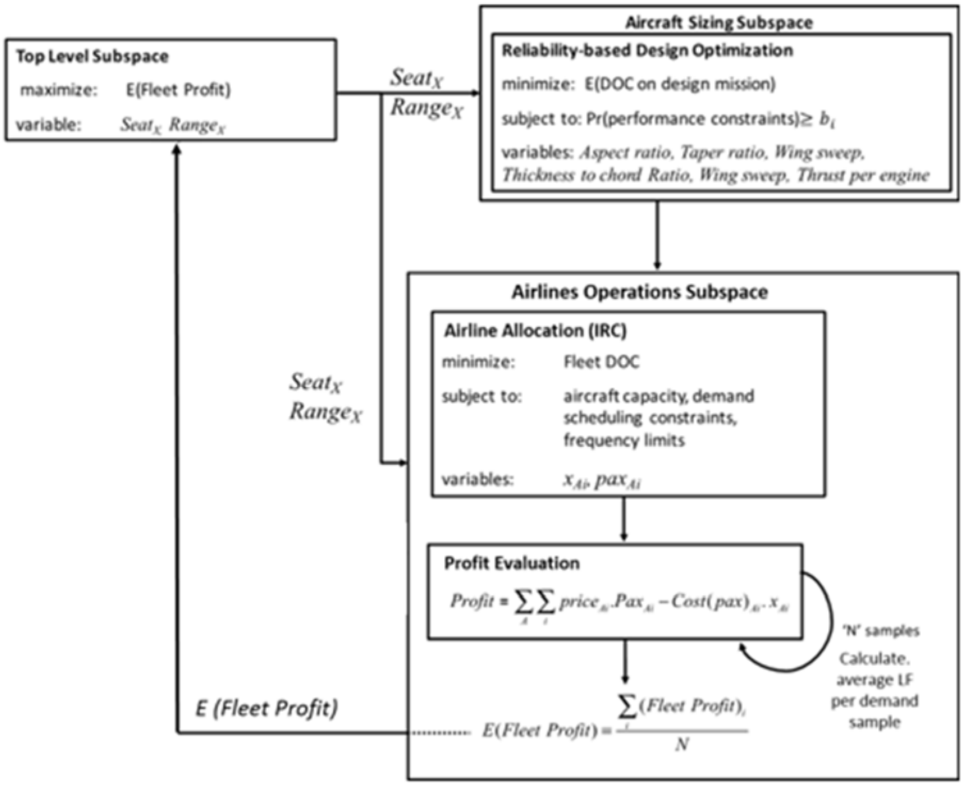

Figure 3. Subspace Decomposition Strategy for the Commercial Airline Application

Aircraft Sizing Subspace

This subspace is similar to the AMC work as described before. However, to accommodate different number of seats as required by the top-level problem formulation for the commercial applications, the sizing code needs to vary the size of the fuselage and the tail using an empirical relation established using the existing aircraft data. For this work, the uncertain parameters of choice, as appears below in Table 3, are selected based on subject matter expert opinion for illustrative purposes. A more formal approach of identifying most relevant factors would involve an Analysis of Variances (ANOVA) and a Design of Experiments (DOE) approach to identify the most statistically relevant design parameters influencing the aircraft design.

Table 3. Uncertain Parameters in the Commercial Aircraft Sizing Optimization Problem

Uncertain Parameters (ξ)	Lower Bound	Default	Upper Bound
C_{D_0} Multiplier [non-dim]	0.95	1	1.05
Oswald Efficiency Factor Multiplier [non-dim]	0.95	1	1.05
Thrust Specific Fuel Consumption Multiplier [non-dim]	0.95	1	1.05
Passenger Weight [lbs]	90	165	220

The RBDO formulation optimizes the expected performance metric of interest and ensures that the probability of satisfying the performance constraints is greater than or equal to the user-defined reliability level, considering the uncertainty present in this sub-problem. Here, we assume a triangular distribution for the uncertainties in each parameter; this will facilitate demonstration of the method, but better characterization of these distributions would improve the quality of the results. The aircraft sizing sub-problem includes performance constraints such as limits on takeoff and landing distances, second segment climb gradient, top of climb rate, and upper and lower bounds for the decision variables.

As mentioned earlier, at the solution of the RBDO problem, the resulting aircraft design has uncertain responses because of the input uncertainties (Table 3). Of interest for the airline operations subspace—the cost to fly the new aircraft on any route, the block hours needed to fly any route, the maximum number of passengers that the aircraft can carry on each route, and the takeoff distance of the aircraft—all follow probabilistic distributions.

Airline Operations

This subspace mimics an airline's operational behavior. The Interval Robust Counterpart (IRC) formulation recognizes and obtains the performance characteristics of the uncertain aircraft for the nominal and worst-case values of the uncertain aircraft design parameters of Table 3. We use these performance data in our allocation formulation to minimize the airline's fleet-level direct operating cost, while satisfying maximum predicted passenger demand on the route network. Here, the maximum predicted passenger demand comes from historical data available from the Bureau of Transportation Statistics; this provides a credible demand distribution for the problem, as if this historical demand were actually a prediction of future demand. Solving the allocation solution represents setting the airline's schedule, and then the approach samples the uncertain passenger demand that would fly on the set schedule and evaluates an expected profit considering the uncertain demand. To further capture seasonal variation in passenger demand, we set four different quarterly allocations. The purpose of considering each quarter's worth of data is to capture better the impact that seasonal fluctuations will have on the observed maximum number of passengers traveling on each route for a representative travel day. Average profit (or the expected profit) over all sampled demand for all the quarters then returned to the top level and appears as the top-level objective function.

Summary of Subspace Decomposition Approach in USAF AMC vs. Commercial Airline Applications

The main difference between the use of the subspace decomposition approach to the AMC and commercial airline cases are dictated by the nature of the payload for each aircraft type (pallets vs. passengers) and the statistical nature of the demand for transport (uncertainty, unstructured cargo vs. scheduled commercial flights). The details of differences in subspace modelling in both cases are summarized in Table 4.

Table 4. Differences in Subspace Formulations Between AMC and Commercial

	Subspace Decomposition Approach Application	
	USAF AMC Military Cargo	**Commercial Airline**
Subspace Level		
Top-Level	Requirements are number of pallets and range of aircraft.	Top level requirements are number of seats and range of aircraft
	Use of Global Optimizer (NOMAD) to search design space	Perform Pseudo enumeration to search the design space
Aircraft Sizing	Fuselage sizing rules based on number of standardized pallets	Fuselage sizing rules based on number of seats
Fleet Operations	USAF AMC flight operations based on "as needed" basis for demand for cargo transport	Fleet operations based on BTS (BTS, 2015) data to model future prediction of demand (assumes demand in symmetric)
	IRC formulation minimizes fuel consumption and enforces constraint on productivity. External demand sampling loop. Single IRC solution for each sampled demand set. Average fuel consumption of sampling returned to top level problem	IRC formulation minimizes operating cost while meeting the ever recorded maximum demand on a route for travel
	Use of aircraft assignment that tracks tail numbers of aircraft	BTS data on historical airline data used to predict future demand distribution
	Demand sampling done by random sampling of starting locations for aircraft	Scheduling done to meet maximum demand on all routes at same time
		Profit calculated through statistical sampling schemes on demand, and, includes ticket pricing model

Representative Results and a Posteriori Analysis

Military Air Cargo

Figure 4 shows the results from the multi-objective analyses of the 25-base network problem, using the subspace decomposition approach for the AMC case study (refer to

Figure 2). The plot shows the normalized expected values of the fleet-level metrics. Using normalized fleet-level responses help to identify the trends, and help to show the relative variations in fleet-level responses for different solutions to the multi-objective optimization problem. The fleet-level responses have been normalized with respect to the lowest expected values from the results of the scenario labeled “Fleet with five new A/C.” Each point in the “Fleet with five new A/C” scenario describes the optimal design of the new aircraft required to meet the specific fleet-level objectives. These results show the collection of optimal aircraft designs that would meet the fleet’s operational needs at each level of permitted fuel consumption or at each level of required fleet-wide productivity.

For three different solutions from the “Fleet with five new A/C” results, Figure 4 contains callout boxes that describe the values of the new aircraft requirement decision variables along with the values of the aircraft design variables. The trends in the fleet-level responses are as expected, with fuel consumption increasing as productivity increases. There appears to be a trend in the size of the optimal aircraft along the Pareto frontier for increasing productivity/fuel consumption values. For a normalized expected productivity and normalized expected fuel consumption value of 1.0, the optimal requirement decision variables of the new aircraft X are at the lower bounds for pallet capacity (16) and design range (3800 nmi). Moving from this point on the tradeoff plot towards solutions with increasing fleet-level productivity, the results suggest that larger pallet capacities for the new aircraft X can best meet the fleet-level objectives. There is not substantial evidence to determine whether these trends would generalize to other route networks or other similar design problems; however, the behavior is not unexpected, because the aircraft pallet capacity strongly drives the fleet-level productivity metric. Though it is intuitive that a larger aircraft would increase productivity, the optimal design features of the new aircraft X, such as the aspect ratio (AR_x), the wing loading $((W/S)_x)$, the thrust-to-weight ratio $((T/W)_x)$, and so forth, are reflective of the specific existing fleet and demand characteristics of the service network. For each solution in the plot, the assignments of the fleet of aircraft to routes are different to meet the actual demands better. The introduction of the five new aircraft (of type X) results in fleet-level fuel savings between 2.79% and 6.48% for the same normalized expected fleet productivity values, when compared to the case where only the existing fleet operates in the network.

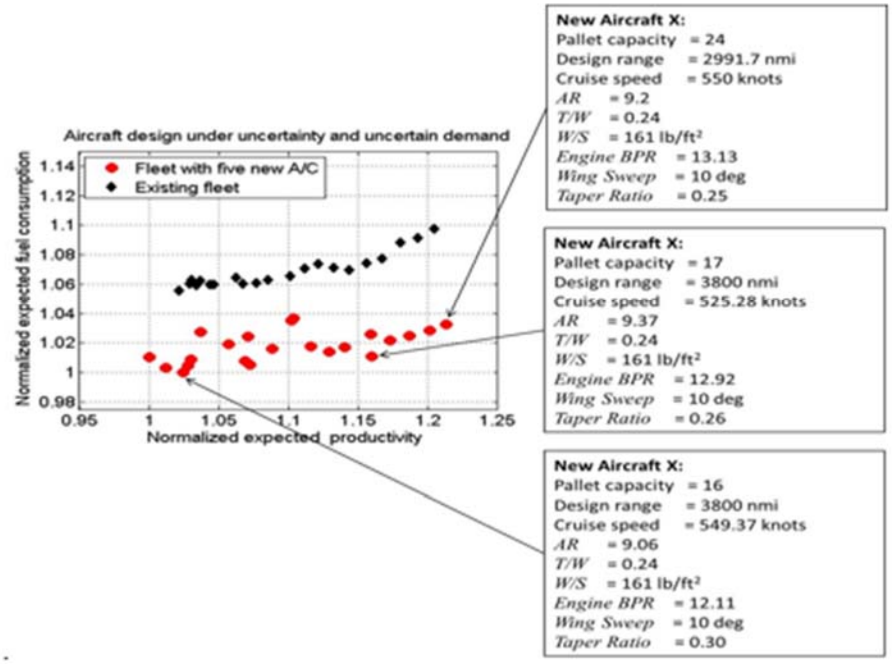

Figure 4. Results From Multi-Objective Analyses of 25-Base Network Problem

The solutions to multi-objective analyses present a way to perform “fuel/cost as an independent variable” type of trade-space analysis; this might be more obvious by switching the axes in the plot from Figure 4. These types of plots can help decision-makers/acquisition planners to analyze the trade-space and select the optimal requirements and design of the new aircraft that would achieve the desired level of fleet fuel consumption and productivity. For instance, a decision-maker can determine the level of fleet productivity available for a specific level of fleet fuel consumption; this fleet-level productivity value can then be translated to a specific (or bounded) level for the mobility airlift requirements that are set by the DoD in terms of tonnage of cargo transported per day. Having established the goals for the fleet-level productivity and fuel consumption, the collection of optimal aircraft designs required to achieve these fleet-level goals can be determined from plots such as those shown in Figure 4.

Posterior Analysis

Figure 5 shows the results from a posteriori analysis (200 samples) of a few solutions from the multi-objective analyses of the 25-base network problem. The dispersion in fleet-level fuel consumption does not show any discernible trend. However, the degree of dispersion in fleet-level productivity appears to decrease for solutions with increasing fleet productivity and fuel consumption values.

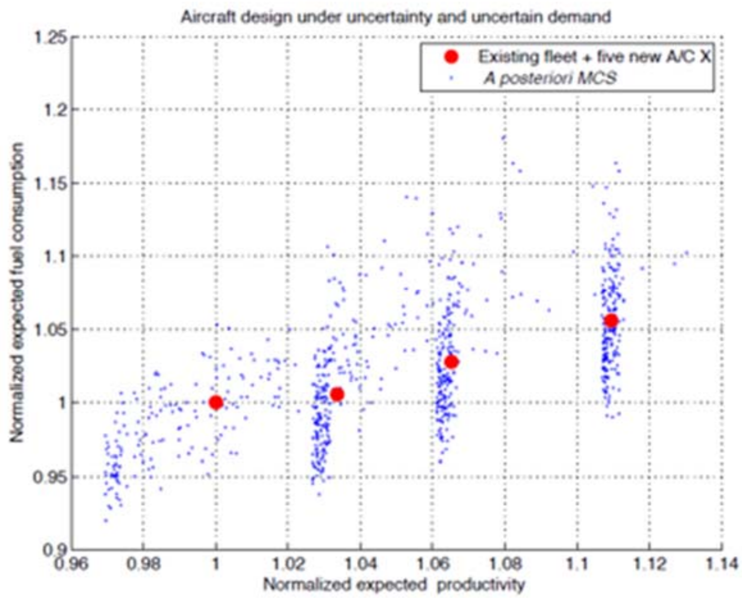

Figure 5. A Posterior Analysis for 25-Base Problem

Solutions with higher normalized fleet fuel consumption, in Figure 5, are more "robust" (less variance) in terms of fleet productivity. A possible explanation for this behavior is because the multi-objective analyses (using the e-constraint formulation) vary the limit value of the fleet productivity constraint, while minimizing fleet-level fuel consumption. If solutions that are more "robust" (less variance) to fuel consumption are desired, then the multi-objective analyses should vary the limit on the fleet-level fuel consumption constraint, while maximizing fleet productivity.

Decision-makers/acquisition planners can use such results to perform comprehensive exploratory analysis of the design space and identify regions in this design space that present significant viable or opportunities to reduce the fleet fuel consumption. For instance, AMC may need to incur "switching costs" (additional cost for training, maintenance and infrastructure due to the addition of a new aircraft type into the fleet) of integrating a new aircraft type into the fleet for relatively small decrease in fuel burn; however, the trade-space analysis (Figure 5 can help identify promising designs and inflection points, if they exist, where the decision to acquire a new aircraft type could provide significant benefits.

Commercial Airline

In the case of the commercial airline application problem, we solve a 31-route representative airline network as appears below. This network resembles a portion of the Northwest Airlines network before the merger with Delta and has its hub at Memphis.

Figure 6. A 31-Route Network of the Example Airline Problem

The representative airline has the following fleet composition (Figure 7) and seeks to include five new yet-to-be-designed aircraft (from the aircraft sizing sub-space).

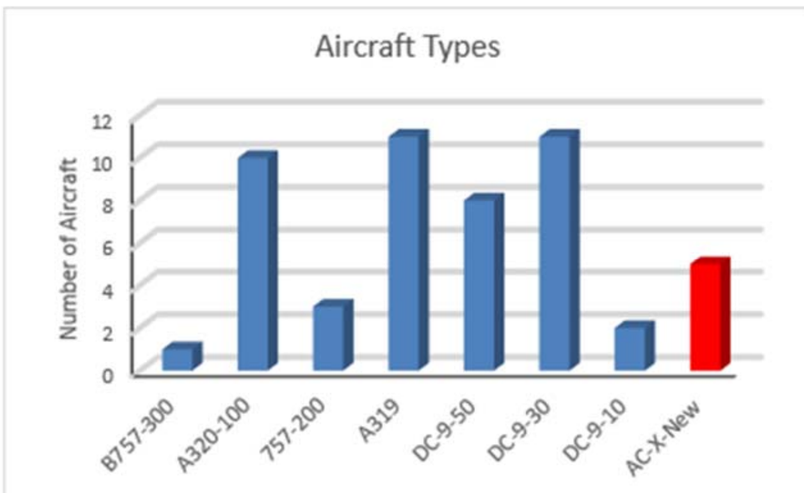

Figure 7. Fleet Composition of the Representative Airline

In this conceptual study, we used a pseudo-enumeration approach to address the top-level problem that uses the following range of discrete choices, as shown in Table 5. The interval values within the range for each of the variables is selected to more rapidly generate reasonable solutions at this stage of development in our approach—refinements in the grid space for the top-level enumeration scheme can be selected as required for more realistic problems.

Table 5. Design Variable Values of Top Level Problem for Enumeration

Range [nmi]	Seat Capacity
500	75
1200	150
1900	250
2600	

For each combination of design variables (4 range variables × 3 seat capacity variables = 12 enumerations points), we execute the overall subspace decomposition methodology shown in Figure 3. Figure 8 shows the profit data for all possible combinations of the enumerated top-level design variables from Table 5.

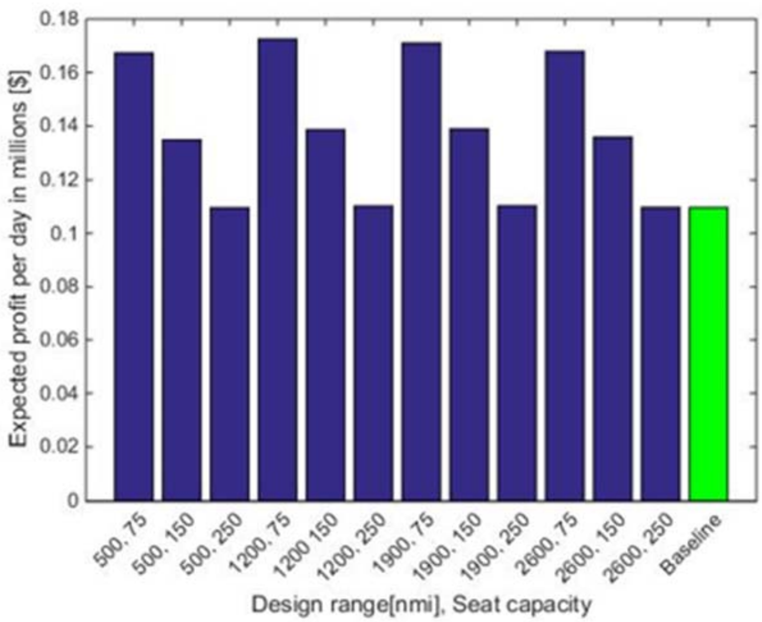

Figure 8. Expected Fleet Profit Values for the Combination ("Test Cases") of the Top-Level Design Variables (Green Denotes Baseline Fleet With No New Aircraft Type X Use)

The results show that the optimal seating capacity is 75 seats for the new aircraft, because the new aircraft is allocated on routes with average passenger demand of less than 110 passengers. Also, because the route distances of these routes in which the new aircraft is allocated are less than 1000 nmi (the longest route in the network is 1626 nmi), the optimal design range of the new aircraft corresponds to a distance of 1200 nmi. Further physical details of the optimal aircraft are retrieved from the aircraft design subspace problem that corresponds to the optimal range and passenger capacity values [1200nm, 75seats] and appear in Table 6.

Table 6. Optimal Aircraft Design

Optimal Aircraft Design Variables	
Aspect Ratio	12
Taper Ratio	0.3
Thickness-to-chord ratio	0.095
Wing Sweep [deg]	10.43
Wing Area [sq.ft]	664.76
Thrust per Engine [lbs]	9351
Passenger Capacity	75
Range [nmi]	1200

Figure 9 shows the utilization of each aircraft type in the fleet, over each quarter. In these plots, we note that most flights of the new aircraft design are allocated around the 500nmi range to fill in the travel needs. Given the number of aircraft available for each aircraft type, it is desired (as seen from the allocation results) to have a 1200nmi range aircraft, as it provides the option to be used on fewer long-range routes.

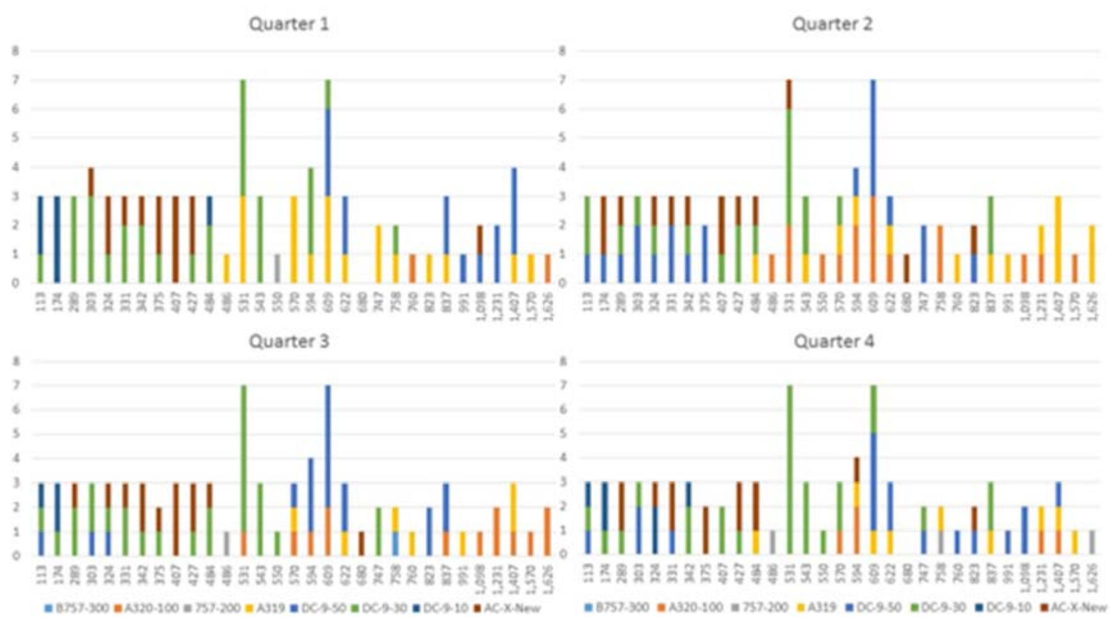

Figure 9. Distribution of Fleet Allocation Over Route for Each Quarter

Posterior Analysis

To validate the application of our framework, we performed a posterior analysis with a different set of 1000 samples. To generate this set of 1000 samples, we pick one sample for each uncertain parameter in the aircraft design subspace and performed an off-design mission analysis across all the routes in the network, keeping the aircraft design variables fixed to values obtain from the RBDO formulation. We then evaluate the performance characteristics of the aircraft and determine how many occasions these performance constraints are satisfied. Figure 10 below shows out of these 1000 samples how many times the aircraft performance constraints are met. Take-off distance seems to violate the most, as 78 of the 1000 samples did not meet the take-off distance criteria. The take-away from this plot is all the constraints are satisfied well within the 10%, which is our tolerance settings in the RBDO formulation at the time of designing the aircraft.

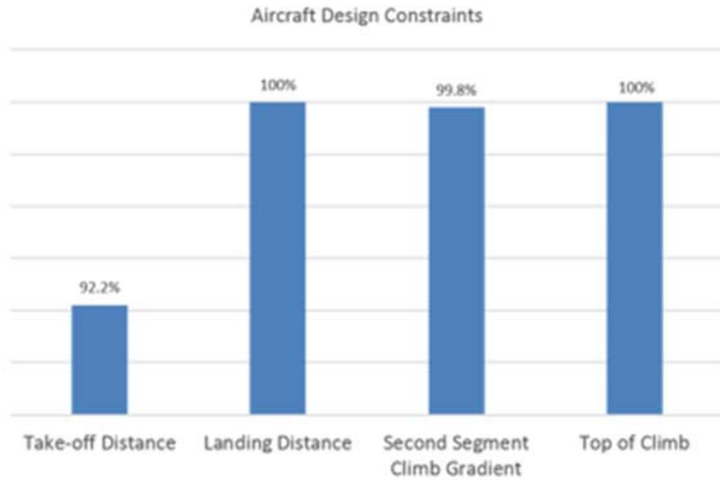

Figure 10. Percentage Satisfaction of the Aircraft Performance Constraints in Posterior-Analysis

Similarly, we performed a posterior analysis of the expected profit calculation, by sampling one instance of demand for every route and appears below in Figure 11. This demand sample combined with the extrinsic sample of the aircraft design subspace, both drawn independently, constitutes one sample for the posterior analysis. We repeat this step 1,000 times. Intuitively, one can say the expected profit from the posterior analysis should be around the same value as the original RBDO-IRC formulation run, if both of these methods handling the associated uncertainties well. This is confirmed in the plot below. We feel confident of our framework to address this type of problems, as attested via posterior analysis with 1000 independent samples.

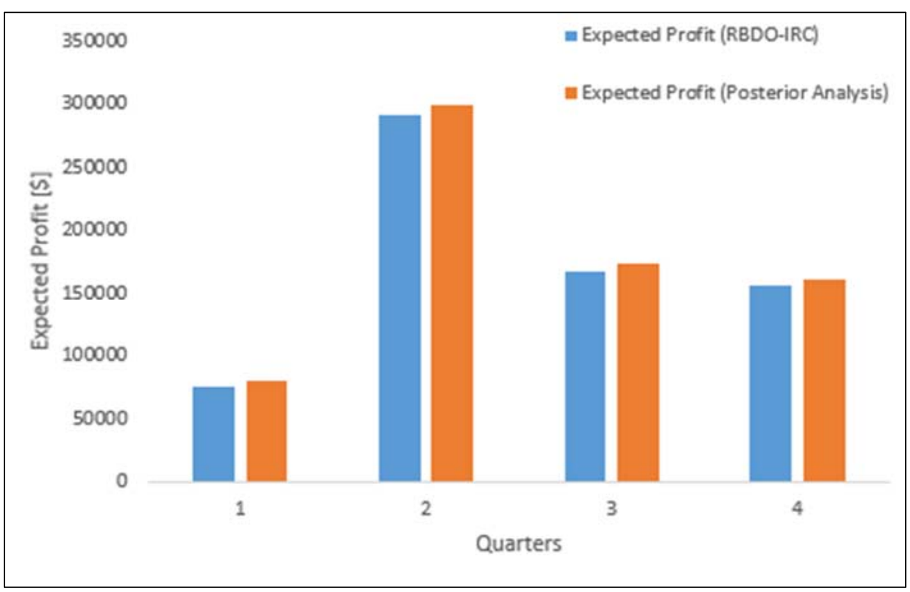

Figure 11. Expected Profit Comparison [Posterior Analysis]

Conclusions and Recommendations

In this paper, we have presented application of a subspace decomposition approach that better enables identification of design requirements of a new, yet-to-be introduced system (here, aircraft) towards improving fleet-wide performance metrics. The approach explicitly accounts for the impact that the new system will have on fleet-wide performance when used alongside existing systems within a fleet and also accounts for various data uncertainty that manifest in the problem. We have presented an application of the approach for commercial airline and military cargo airlift cases, demonstrating domain agnosticism of the approach. The approach is envisioned to be useful to relevant decision-makers within the general acquisition community (government, military, commercial) by enabling trade-off analyses between performance metrics of interest, and, under conditions of data uncertainty, thereby enabling a framework for robust decision-making on setting design requirements of a new, yet-to-be introduced system. Future work may encompass an extension of the approach to include additional relevant forms of domain-driven data uncertainty and further improvements in computational efficiency.

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Acquisition Research Program
Graduate School of Business & Public Policy
Naval Postgraduate School
555 Dyer Road, Ingersoll Hall
Monterey, CA 93943

www.acquisitionresearch.net