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Multi-Objective Optimization of Fleet-Level Metrics to Determine New System Design Requirements: An Application to Military Air Cargo Fuel Efficiency

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Panel 16. Defense Supply Chain Modeling Insights

Thursday, May 15, 2014	
11:15 a.m. – 12:45 p.m.	**Chair: Ken Mitchell Jr.,** Director, Research and Analysis, Defense Logistics Agency ***Mixture Distributions for Modeling Lead Time Demand in Coordinated Supply Chains*** Barry Cobb, Virginia Military Institute Alan W. Johnson, Air Force Institute of Technology ***Maintenance Enterprise Resource Planning: Information Value Among Supply Chain Elements*** Rogers Ascef, Naval Postgraduate School Alex Bordetsky, Naval Postgraduate School Geraldo Ferrer, Naval Postgraduate School ***Multi-Objective Optimization of Fleet-Level Metrics to Determine New System Design Requirements: An Application to Military Air Cargo Fuel Efficiency*** Parithi Govindaraju, Purdue University Navindran Davendralingam, Purdue University William Crossley, Purdue University

Multi-Objective Optimization of Fleet-Level Metrics to Determine New System Design Requirements: An Application to Military Air Cargo Fuel Efficiency

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Abstract

In many instances, yet-to-be-acquired military systems will, when deployed, operate alongside existing systems to provide a set of capabilities. The design requirements assigned to the yet-to-be-designed systems will impact the performance with which the resulting system of systems provides the desired capabilities. Identifying these design requirements for new, yet-to-be introduced systems is difficult, because quantifying the impact of these requirements on fleet level metrics must use some sort of analyses that recognizes the tight coupling of the system design problem (in this paper, a new aircraft design) and asset assignment problem (in this paper, aircraft fleet deployment to provide military cargo transportation). The methodology presented here addresses this by solving a combined platform design, fleet operations and acquisition-level decision-making problem wherein the design requirements of a new system (or systems) appear as design variables in an optimization problem formulation. The approach employs a decomposition strategy to describe the design requirements of the new, yet-to-be-acquired system so that the new system improves fleet-level performance. This fleet-level performance usually involves multiple, competing fleet-level objectives; the research investigates tradeoffs between objectives of fuel usage (cost) and fleet-wide productivity using a relatively simple example motivated by the USAF Air Mobility Command cargo carrying aircraft fleet. Solutions to the multi-objective optimization problem represent the best possible tradeoffs of these two objectives as functions of the new aircraft design requirements. Presenting these results as a Pareto frontier shows the relationship of fleet productivity to fuel cost; this has features of a "fuel cost as an independent variable" context for decision-making. From this, a decision-maker might select a desired balance of fleet-level fuel cost and fleet productivity, thereby identifying the corresponding new aircraft design requirements.

Introduction

Nomenclature

AR_X	=	aspect ratio of aircraft type X
B_p	=	maximum average daily utilization of each aircraft (20 hours)
$BH_{p,k,i,j}$	=	number of block hour for *k*th trip of aircraft *p* from base *i* to base *j*
$C_{p,k,i,j}$	=	cost coefficient for *k*th trip of aircraft *p* from base *i* to base *j*
$Cap_{p,k,i,j}$	=	number of pallet carrying capacity for *k*th trip of aircraft *p* from base *i* to base *j*
$Dem_{i,j}$	=	demand from base *i* to base *j* in number of pallets

DOC	=	direct operating cost
MTM/D	=	million ton-miles per day
$O_{p,i}$	=	indicates if airport *i* is the initial location(e.g., home base) of an aircraft *p*
$Pallet_X$	=	number of pallets carried by aircraft type X
$Range_X$	=	design range of aircraft type X (nm)
$Speed_X$	=	cruise speed of aircraft type X (knots)
S_{TO}	=	take off field length
$(T/W)_X$	=	thrust-to-weight ratio of aircraft type X
UTE	=	utilization rate
$(W/S)_X$	=	wing loading of aircraft type X, in lb/ft^2
$x_{p,k,i,j}$	=	Boolean variable indicating if the *k*th trip if flown by aircraft *p* from base *i* to base *j*
M	=	fleet-level DOC or fuel limit

Research Issue

The *Energy Efficiency Starts with the Acquisition Process* fact sheet (DUSD[AT&L], 2012) states, “Neither current requirements or acquisition processes accurately explore tradeoff opportunities using fuel as an independent variable.” The fact sheet also states, “Current processes undervalue technologies with the potential to improve energy efficiency.” Studies conducted by the Institute for Defense Analyses, the Defense Science Board, Energy Security Task Force and JASON Defense Advisory Group have all alluded to the significant risk and operational constraints that energy efficiency issues pose on military operational flexibility (DUSD[AT&L], 2012). The consumption and transport of fuel across a combat theater, throughout the lifecycle of operational systems, poses significant operational risk, strategic vulnerability and increased monetary cost in supporting forward-force assets. A significant portion of the Department of Defense’s fuel costs are attributed to aviation fuel, with the U.S. Air Force Air Mobility Command (AMC) being the largest single consumer.

AMC’s mission profile mainly consists of worldwide cargo and passenger transport, air refueling and aeromedical evacuation. Platforms in operation include C-5 Galaxy and C-17 Globemaster III for long range strategic missions, C-130 Hercules for tactical missions, KC-135 Stratotanker and KC-10 Extender for aerial refueling missions, and various VIP transport platforms including Air Force One. The logistics involved in cargo transportation across the AMC’s service network requires efficient deployment of cargo aircraft to meet delivery requirements. Aircraft are assigned to carry cargo on given routes while balancing the need for timely delivery with the goal of minimizing fuel consumption and related costs. The type of aircraft flown on each assigned route drives the fleet’s fuel use and cost; therefore, to reduce fuel use and cost, the process that allocates or assigns aircraft needs to consider fuel use and cost.

The aforementioned energy efficiency reports allude to the lack of a framework that captures the effects that fuel saving measures (i.e., new technologies, systems) can have on fleet-wide performance metrics. This lack motivated the authors’ prior work that simultaneously considers the design of a new aircraft and the assignment of this new aircraft, along with existing aircraft to meet cargo carrying demand. This perspective of providing the fleet-level capability of cargo transport using a collection of aircraft, which are independent in their own right, has several features of a “system of systems” (Maier, 1998).

The treatment of the new aircraft design requirements as governing decision variables, simultaneous consideration of aircraft design and fleet operations, and integration of the uncertainty nature of cargo demand, results in a stochastic mixed integer non-linear programming (MINLP) problem that is typically difficult, if not impossible to solve. However, the framework developed by the authors employs a decomposition strategy to address computational tractability and a naïve Monte Carlo sampling to address uncertainty. For some example problems, this approach has shown results with the potential to save fleet-level costs by suggesting, perhaps non-intuitive, design requirements for the new aircraft.

The research described in this paper demonstrates a framework that identifies optimal characteristics of new assets (here, aircraft) and investigation of trade-offs between fleet-level fuel usage and fleet productivity (as a measure of performance) as functions of the new aircraft requirements for an example problem motivated by the U.S. Air Force Air Mobility Command. The framework can examine how acquisition (or, perhaps, pre-acquisition) decisions describing the requirements for a new aircraft might directly reduce fleet-level fuel usage or cost, considering the operational network and other existing assets along with the potential new (or modified) platform. Consideration of the aircraft design and fleet assignment problems simultaneously presents many decision variables—a condition where the size of the problem rapidly exceeds the mental capability of the designer and a computational approach becomes necessary. Additionally, explicit consideration of uncertainty in operations better informs a new aircraft that improves the fleet-level performance.

Earlier work involving the authors (Choi et al., 2013) modeled individual aircraft trips within the context of a scheduling problem that explicitly account for flow balance constraints. Despite the computation complexity associated with solving scheduling problems, the “scheduling-like” formulation enables studies considering the time sensitive nature of the cargo transported in AMC operations. Cargo is tiered according to urgency of delivery, and thus poses implicit constraints on the routes traveled on (relating to the range of the aircraft used), and the capability (here, speed) of the aircraft. The optimization problem formulation describing the fleet operations incorporates “scheduling-like” features within the assignment problem to more closely represent recorded AMC operations. Fleet-fuel and fleet-operating costs have provided the performance metrics for our previous work (Choi et al., 2013) where the objective function of the assignment problem seeks to minimize the total amount of fuel burned or the fleet operating cost, resulting from cargo-carrying trips across the AMC network of operations. However, “fleet-productivity,” as referred to in prior studies (Tetzloff & Crossley, 2011) is a metric that combines speed and weight of cargo transported into a single metric that serves as the problem objective.

The work presented here demonstrates the ability to consider tradeoffs with fleet-level fuel consumption as one of the quantities of interest. The set of Pareto-optimal solutions obtained from the multi-objective analyses will allow acquisition decision makers to quantitatively determine the tradeoffs in fleet-level performance and fuel consumption, both of which are functions of design requirements assigned to the new platform.

Scope and Method of Approach

As suggested above, a desired approach for this study would maximize or minimize a fleet-level objective function by searching for a set of decision variables that describe the new system design and describe the assignment of the new and existing systems to perform operational missions. While a single, monolithic problem statement can reflect this kind of problem, solving the resulting mixed integer non-linear programming (MINLP) problem is difficult, if not impossible (Mane et al., 2007).

The decomposition strategy with a scheduling-like formulation under uncertainty, as notionally depicted in Figure 1, breaks down the computational complexity of the decision space into a series of smaller sub-problems controlled by a top-level optimization problem. The decomposition approach addresses the issue of tractability of solving a monolithic, mixed discrete non-linear programming problem and has yielded better “design solutions” across a set of aviation applications including commercial airlines, fractional management companies and air taxi services (Mane et al., 2006, 2007, 2012). The motivation of these prior works in identifying cost and fuel saving characteristics of a new, yet-to-be-acquired aircraft bears great similarity to the U.S. Air Force Air Mobility Command (AMC) problem. This paper presents a process that allows investigation of trade-offs between fleet-level fuel usage, performance metrics and acquisition alternatives for a conceptual problem that resembles missions of the AMC.

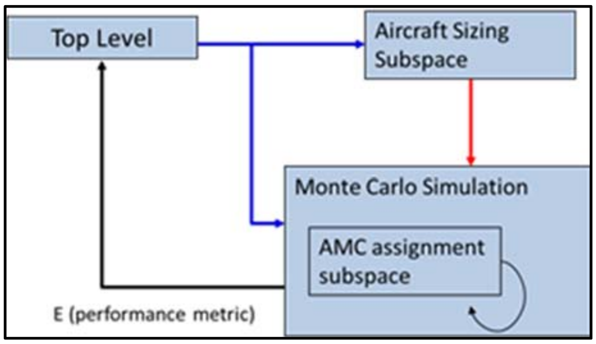

Figure 1. Decomposition Strategy for the Monolithic Optimization Problem

The research presented here extends the prior work (Choi et al., 2013) to encompass investigating tradeoffs between objectives of productivity/mission effectiveness and energy consumption. These two competing objectives often play a critical role in determining new system design requirements. Fleet productivity is a metric that combines speed of delivery and weight of cargo transported. Under the multi-objective formulation, an epsilon constraint approach addresses the two objectives—maximizing productivity and minimizing fuel consumed (or operating costs). Maximizing productivity subject to different fuel cost limits (enforced as constraints), and minimizing fuel as cost under different productivity constraints will lead to a Pareto frontier of optimal solutions representing the best possible tradeoffs between the two objectives. Payload capacity, design cruise speed, and range are common aircraft design requirements and serve as the top- or system-level variables.

To develop the example problem with relevance to Air Mobility Command, the Global Air Transportation Execution System (GATES) dataset provides historical route and cargo demand data. GATES contains very detailed information on palletized cargo and personnel transported by the AMC fleet. Cargo transported by the strategic fleet consisting of C-5 and C-17 aircraft, and chartered Boeing 747 Freighter (747-F) aircraft from the Civil Reserve Air Fleet (CRAF) for long range missions, are considered as a representative measure of typical cargo flow on the AMC service network. Each data entry in “GATES Pallet data” represents cargo on a pallet or a pallet-train that was transported. Each pallet data entry has detailed information of the pallet, such as pallet gross weight, departure date and time, arrival date and time, mission distribution system (MDS), tail number, aerial port of embarkation (APOE), aerial port of debarkation (APOD), pallet volume, pallet configuration, and so forth. These data enable the reconstruction of the route network, pallet demand characteristics and existing fleet size for our assignment problem

In this paper, the following assumptions are made on operations of the fleet, based on the available dataset:

1. The filtered route network from GATES dataset is representative of all AMC cargo operations.
    - **a.** Demand for subset served by C-5, C-17 and 747-F (75% of all pallets in GATES dataset)
    - **b.** Fixed density and dimension of pallet, representing the 463L pallet type
2. Aircraft fleet consists of only the C-5, C-17 and 747-F. The model is indifferent to variants of these aircraft types.

Monolithic Problem Formulation

The system-of-system level representation involves the combination of resource assignment (under uncertainty) and aircraft design perspectives that make up the monolithic problem. The resource assignment problem under uncertainty translates to a stochastic integer programming and the aircraft design problem is a non-linear programming problem. The combination of both problems results in a stochastic mixed integer non-linear programming problem. The resulting optimization problem is represented by the following equations:

Maximize

$$E\left[\begin{array}{l}\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot\left(Speed_{p,k,i,j}\cdot Pallet_{p,k,i,j}\right)+\\ \left(x_{p,k,i,j}\cdot\left(Speed_{p,k,i,j}\cdot Pallet_{p,k,i,j}\right)\left(\left(AR\right)_X,\left(W/S\right)_X,\left(T/W\right)_X\right)\right)_X\end{array}\right]$$

(Productivity – Speed x Capacity) (1)

Subject to

$$\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot C_{p,k,i,j}+\left(x_{p,k,i,j}\cdot C_{p,k,i,j}\left(Pallet_X,Speed_X,\left(AR\right)_X,\left(W/S\right)_X,\left(T/W\right)_X\right)\right)_X\leq M$$

(DOC or Fleet fuel limits) (2)

$$\sum_{i=1}^{N} x_{p,k,i,j}\geq\sum_{i=1}^{N} x_{p,k+1,i,j}\quad\forall k=1,2,3\ldots K,\ \forall p=1,2,3\ldots P,\quad\forall j=1,2,3\ldots N$$

(Node balance constraints) (3)

$$\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot BH_{p,k,i,j}\leq B_P\quad\forall p=1,2,3\ldots P$$

(Trip constraints) (4)

$$\sum_{p=1}^{P}\sum_{k=1}^{K} Cap_{p,k,i,j}\cdot x_{p,k,i,j}\geq dem_{i,j}\quad\forall i=1,2,3\ldots N\quad\forall j=1,2,3\ldots N$$

(Demand constraint) (5)

$$\sum_{i=1}^{N} x_{p,1,i,k}\geq O_{p,i}\quad\forall p=1,2,3\ldots P,\ \forall i=1,2,3\ldots N$$

(Starting location constraints) (6)

$$S_{TO}\left(Pallet_X,Speed_X,\left(AR\right)_X,\left(W/S\right)_X,\left(T/W\right)_X\right)\leq D$$

(Aircraft takeoff distance) (7)

$$14 \leq Pallet_X \leq 38 \quad \text{(Design pallet capacity bounds)} \quad (8)$$

$$2400 \leq Range_X \leq 3800 \quad \text{(Range at max. payload bounds)} \quad (9)$$

$$350 \leq Speed_X \leq 550 \quad \text{(Cruise speed bounds in knots)} \quad (10)$$

$$6.0 \leq (AR)_X \leq 9.5 \quad \text{(Wing aspect ratio bounds)} \quad (11)$$

$$65 \leq (W/S)_X \leq 161 \quad \text{(Wing loading bounds)} \quad (12)$$

$$0.18 \leq (T/W)_X \leq 0.35 \quad \text{(Thrust-to-weight ratio bounds)} \quad (13)$$

$$x_{p,k,i,j} \in \{0,1\} \quad \text{(Binary variable)} \quad (14)$$

$$(AR)_X, (W/S)_X, (T/W)_X \quad \text{(Continuous aircraft design variables)} \quad (15)$$

$$Pallet_X, Speed_X \quad \text{(Discrete aircraft design variables)} \quad (16)$$

Equation 1 is the objective function that seeks to maximize the expected fleet-level productivity where $Speed_{p,k,i,j}\ x\ Pallet_{p,k,i,j}$ indicates the productivity coefficient of the trip for k^{th} trip for aircraft p from base i to base j. Equation 2 limits the fleet-level fuel consumption or cost to a pre-defined limit; the limit is varied and the problem is re-solved for each varied value of limit to generate a set of Pareto-optimal solutions. The constraint Equation 3 is the balance and sequencing constraint that ensures that the $(k+1)^{\text{th}}$ trip of an aircraft out of a base occurs only after k^{th} trip into that base—this constraint ensures that an aircraft needs to already be at a base prior to completing a subsequent segment trip out of the same base. Equation 4 limits flights to only occur within daily utilization limit (assumption of 20 hours) of the aircraft where $BH_{p,k,i,j}$indicates the block hour for the k^{th} trip for aircraft p from base i to base j. Equation 5 ensures that carrying capacity of combined trip meets the demand where $Cap_{p,k,i,j}$indicates the pallet carrying capacity of the k^{th} trip for aircraft p from base i to base j. Equation 6 ensures that the first trip of each aircraft originates at the initial location (home base) which is randomly generated. The non-availability of the aircraft starting location information in the Gates dataset necessitates the random distribution of the starting location of each aircraft. Equation 7 limits the aircraft design based on maximum takeoff distance to ensure that the new aircraft can operate at bases in the network. Equations 8–10 describe bounds on the aircraft design variables of payload, design range (in nautical miles) at maximum payload and cruise speed (in knots) capabilities of the new aircraft. The chosen limits are within ranges exhibited by current military cargo aircraft. The continuous aircraft design variables of aspect ratio $(AR)_x$, thrust-to-weight ratio$(T/W)_x$ and wing loading $(W/S)_x$ (in lb/ft^2), describing the new aircraft are bounded within the range of values associated with current cargo aircraft; the bounds appear in Equations 11–13. Solving the aircraft design sub problem provides a solution that describes the features of the new aircraft with the lowest DOC (fuel cost) for the specified design range. The productivity and cost coefficients of the new aircraft for the various routes in the network are then estimated.

Subspace Decomposition Strategy

The subspace decomposition strategy, as shown in Figure 1, decomposes the MINLP problem into smaller optimization problems—each sub problem follows the natural boundaries of disciplines involved in formulating the original problem. The top-level problem helps explore the requirements space for the new yet-to-be introduced aircraft based on fleet-level metrics. In this research, top-level optimization problem is tackled using quasienumeration and seeks to maximize the expected fleet-level productivity using pallet capacity, range and cruise speed of the new, yet-to-be introduced aircraft type X.

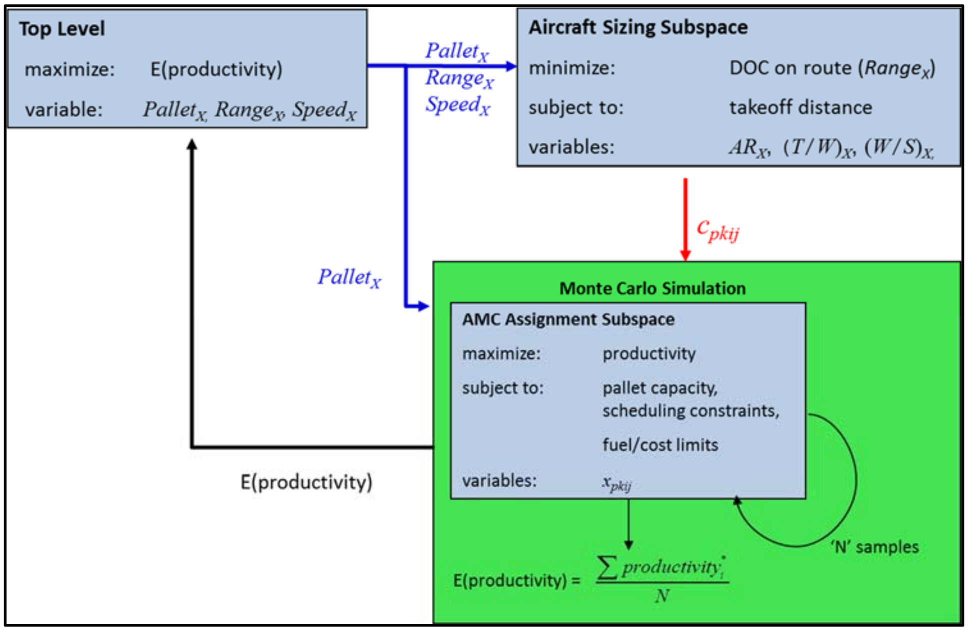

Figure 2. Subspace Decomposition of Monolithic Optimization Problem With Monte Carlo Sampling

The resulting pallet capacity (*Pallet*$_x$), design range (*Range*$_x$) and cruise speed (*Speed*$_x$) from the top-level problem then become inputs to the aircraft sizing problem. Here, the aircraft sizing problem seeks to minimize the direct operating cost of the new yet-to-be introduced aircraft for the value of range, pallet capacity and cruise speed from the top-level optimization problem. The aircraft design problem is also subject to constraints on take-off distance. The design variables are the main drivers of aircraft design, namely the aspect ratio $(AR)_x$, thrust-to-weight ratio $(T/W)_x$, and wing loading $(W/S)_x$. The outputs of the aircraft sizing problem and top-level optimization problem, namely the productivity coefficient and cost of operating the yet-to-be introduced aircraft X on individual routes, and pallet capacity, are then used as inputs in the aircraft assignment problem. Here, the objective is to maximize the fleet-level productivity using characteristics of the yet-to-be introduced aircraft (cost, pallet capacity, speed), subject to capacity, fleet-level cost and aircraft trip limits.

Aircraft Sizing Subspace

The problem formulation requires estimates of the cost, block time, and fuel consumed by each aircraft type in the fleet to determine the appropriate assignment of aircraft to the various routes in the network. A Purdue in-house aircraft sizing code, written in MATLAB, provides these estimates in the aircraft sizing subspace shown in Figure 2. Jane's Aircraft database (Jackson, 2004) provided the input parameters for the three existing aircraft types (C-5, C-17, 747-F) used in this study. The MATLAB sizing code's predictions of the existing aircraft size, weight and performance have been validated with published data.

DOC estimates include fuel costs, crew costs, maintenance, depreciation and insurance. DOC estimates are also dependent on the payload, route distance, empty weight, landing weight and takeoff gross weight. Figure 3 shows a typical mission profile used for the aircraft sizing and operating missions. To estimate the fuel weight necessary for flying the route distance, the fuel required for each mission segment is computed and aggregated. The fuel weight fractions for the different mission segments such as warm-up and take-off, climb, landing and taxi, and reserves are based on empirical data (Raymer, 2006). The Breguet range and endurance equations predict the fuel weight fractions for the cruise and loiter mission segments. The descent segment uses a no-range credit assumption. The reserve fuel fraction is assumed to be 6%, which also accounts for a small amount of trapped and unusable fuel.

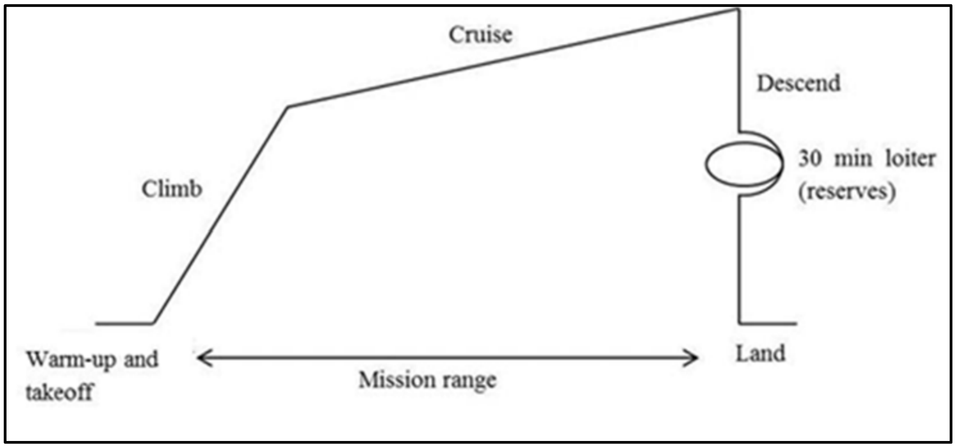

Figure 3. Mission Flight Profile

The payload-range curves for the existing aircraft fleet, depicted in Figure 4, indicate the maximum payload carrying capacity of the aircraft as a function of the distance flown by the aircraft. The payload-range curves for the existing fleet are constructed by using piecewise linear interpolation between specified points from published charts (Baker, 2002).

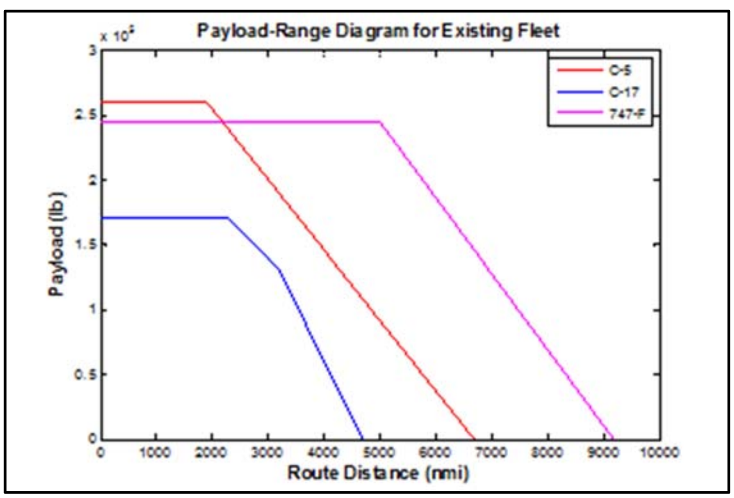

Figure 4. Payload Range Curves for Existing Fleet

The aircraft design variables are aspect ratio$(AR)_x$, thrust-to-weight ratio $(T/W)_x$ and wing loading$(W/S)_x$. There are many other design variables, but these three have significant impact on the size, weight, and performance of the aircraft. The aircraft sizing problem is a nonlinear programming (NLP) problem and is described using Equations 17–24.

$$\text{Minimize} \quad f = (DOC_{pallet,range,speed})_X \tag{17}$$

Subject to

$$S_{TO}\left(Pallet_X, Speed_X, (AR)_X, (W/S)_X, (T/W)_X\right) \le D \quad \text{(Aircraft takeoff distance)} \tag{18}$$

$$14 \le Pallet_X \le 38 \quad \text{(Design pallet capacity bounds)} \tag{19}$$

$$2400 \le Range_X \le 3800 \quad \text{(Range at max. payload bounds)} \tag{20}$$

$$350 \le Speed_X \le 550 \quad \text{(Cruise speed bounds)} \tag{21}$$

$$6.0 \le (AR)_X \le 9.5 \quad \text{(Wing aspect ratio bounds)} \tag{22}$$

$$65 \le (W/S)_X \le 161 \quad \text{(Wing loading bounds)} \tag{23}$$

$$0.18 \le (T/W)_X \le 0.35 \quad \text{(Thrust-to-weight ratio bounds)} \tag{24}$$

Equation 17 is the objective function that seeks to minimize DOC or fuel cost of the new aircraft X. The aircraft X design input variables are pallet carrying capacity of the aircraft, design maximum range at maximum loading condition, and cruise speed as described in Equations 19–21; these echo Equations 8–10 above. Equation 18 limits the aircraft design based on maximum takeoff distance to ensure that the new aircraft can operate at bases in the network within the bounds of modern day cargo aircraft descriptions shown in Equations 22–24.

Scheduling-Like AMC Assignment Subspace

Determination of Number Of New Aircraft

The number of new aircraft X to be introduced to existing fleet is unknown as capacity of the new aircraft is also unknown. However, the AMC strategic fleet is expected to be capable of servicing the maximum possible demand scenario, by requirement. Mobility Capabilities and Requirement Study (MCRS) 2016 (Jackson, 2009) illustrates three different scenarios which capacity of the strategic fleet must always meet. The peak for MCRS Case 1, which represents the highest level of modeled strategic airlift demand, required 32.7 million ton-miles per day (MTM/D). MTM/D values for each type of aircraft are calculated using empirical data. A C-5 carries 0.1209 MTM/D, while the newer C-17 carries 0.1245 MTM/D (Kopp, 2004).The 747-F carries 0.1705 but is not included in calculating the strategic airlift fleet MTM/D as the Civil Reserve Air Fleet (CRAF) is not operated by AMC. Hence, it does not affect the number of aircraft X required to meet the peak demand.

MTM/D of the new aircraft X is calculated using following equation.

$$\frac{MTM}{D} = \frac{BlockSpeed \text{ x } Avg.Payload \text{ x UTE Rate x Productivity Factor}}{1{,}000{,}000} \tag{25}$$

AMC force structure programmers use MTM/D when funding out-year aircraft purchases and many civilian agencies are accustomed to visualizing our fleet capability in terms of MTM/D. Utilization rate (UTE rate) of the new aircraft is assumed to be 12 hr/day and productivity factor of 4.8 is assumed for new aircraft, which is within the typical range of the strategic airlift fleet average value. However, the simple three-base problem is set such that only three new aircraft are introduced to the new fleet, as MTM/D calculation is not applicable for smaller route networks.

Assignment Problem Formulation

The monolithic optimization problem simultaneously considers the aircraft design and assignment (schedule-like) of the fleet's aircraft to meet demand obligations shown as AMC assignment subspace in Figure 2. The formulation considers inherent asymmetric demand nature (Choi et al., 2013) of the AMC network, and is given by the following equations.

Maximize

$$E\left[\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot\left(Speed_{p,k,i,j}\cdot Pallet_{p,k,i,j}\right)\right] \text{(Productivity = Speed x Capacity)} \quad (26)$$

Subject to

$$\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot C_{p,k,i,j} \le M \quad \text{(Fleet-level DOC or fuel limits)} \quad (27)$$

$$\sum_{i=1}^{N} x_{p,k,i,j} \ge \sum_{i=1}^{N} x_{p,k+1,i,j} \quad \forall k = 1,2,3\ldots K, \quad \text{(Node balance constraints)} \quad (28)$$
$$\forall p = 1,2,3\ldots P, \quad \forall j = 1,2,3\ldots N$$

$$\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j}\cdot BH_{p,k,i,j} \le B_P \quad \forall p = 1,2,3\ldots P \quad \text{(Trip constraints)} \quad (29)$$

$$\sum_{p=1}^{P}\sum_{k=1}^{K} Cap_{p,k,i,j}\cdot x_{p,k,i,j} \ge dem_{i,j} \quad \forall i = 1,2,3\ldots N \quad \text{(Demand constraint)} \quad (30)$$
$$\forall j = 1,2,3\ldots N$$

$$\sum_{i=1}^{N} x_{p,1,i,k} \ge O_{p,i} \quad \forall p = 1,2,3\ldots P, \forall i = 1,2,3\ldots N \quad \text{(Starting location constraints)} \quad (31)$$

$$x_{p,k,i,j} \in \{0,1\} \quad \text{(Binary variable)} \quad (32)$$

The aforementioned formulation is designed to adapt to the AMC fleet network, which is asymmetric in nature and is more reflective of actual AMC operations. Equation 26 describes of the objective of maximizing the fleet-level productivity, subject to cost limit, node balance, trip, demand and aircraft starting location constraints described in Equations 27–31; these echo Equations 1–6 of the monolithic problem formulation. The scheduling-like formulation used in the problem is a surrogate for cost and operation model, and it does not consider aircraft or pilot scheduling. However, the aircraft in the fleet are not required to return to their home base at the end of the day a round trip assumption is removed, and may continue servicing different routes. The Generic Algebraic Modeling System (GAMS) software package, accessed through a MATLAB interface is used to solve the assignment problem, using the CPLEX solver option (Ferris, 1998). The scheduling-like formulation using node balance constraints, more accurately models AMC operations, allowing for directional pallet cargo and tracking of aircraft tail numbers.

Monte Carlo Sampling Technique

The cost of operating a fleet is subject to the trip demand characteristics—a quantity that is typically uncertain. While passenger demand between origin-destination pairs is fairly constant for commercial or passenger airline route networks, the same cannot be said for AMC operations, which typically experiences high levels of uncertainty in demanded trips and cargo size (Choi et al., 2013). The GATES dataset reveals the variation in pallet demand (number of pallets transported on a route) over a year reflecting the uncertainty associated with pallet demand in AMC operations. Thus, it becomes imperative for any systems designer/planner, to consider the uncertainty in the network as part of the decision-making framework. Figure 5 shows the severity of fluctuation of the pallets transported daily between two popular bases in the GATES dataset. Figure 6, showing the histogram of the number of pallets transported per aircraft per day reveals that many of the days, aircraft are very lightly loaded. We address the issue of uncertainty through a Monte Carlo Sampling (MCS) approach from literature (Mane, 2012). The MCS technique solves an assignment problem for each simulated demand instance that is sampled from historical demand data distribution. MCS is a very simplistic, easy to implement and naïve approach. Generating high fidelity statistical correlations from the sampling would require large sample sizes, and hence, increased computational expense. The MCS technique can prove to be computationally expensive with increasing sample sizes, due to the computational complexity of solving an integer program for each realized sample of demand and starting location for each aircraft in the fleet. An assumption is made where the calculated fleet size of new aircraft entering into service, has feasible assignments for all realizations of demand instances sampled from distributions. The expected fleet performance metrics are then averaged across the entire solved sample instance assignments of demand.

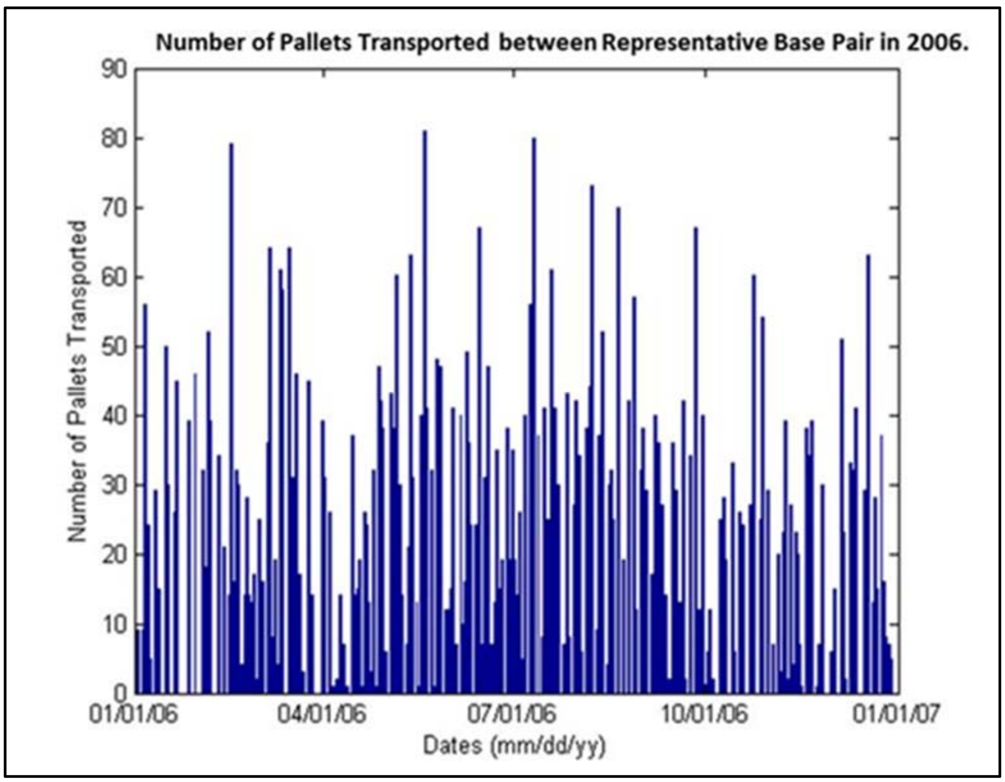

Figure 5. Distribution of Number of Pallets Transported by Date on a Sample Route From GATES Dataset

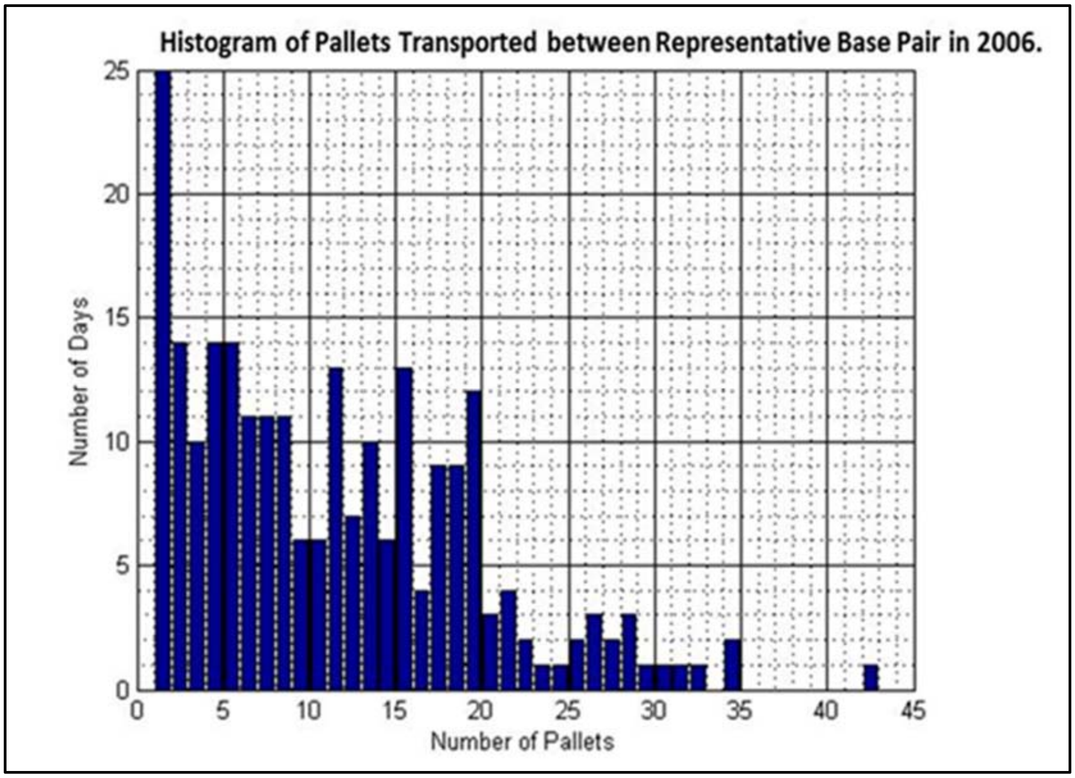

Figure 6. Histogram of Number of Pallets Transported Daily on a Sample Route From GATES Dataset

Three-Base Network Problem

A. Network Description

A simple, illustrative "baseline" problem for AMC operations, consisting of six directional routes between three bases is devised as an initial study. The motivation here is to illustrate the application of the subspace decomposition method, for the simple case of introducing a yet-to-be-designed aircraft to improve fleet-level metrics. The airbase locations and the route data is extracted from the GATES dataset. Figure 7 depicts the average daily pallet demand on these routes and the route distances of the network. The three bases in the network are ETAR, KDOV, and OKBK, which are the most flown routes in the GATES dataset for March 2006. The shortest distances between the routes are calculated using ICAO coordinate system. The intent is to assign aircraft to the three routes to satisfy the network cargo demand.

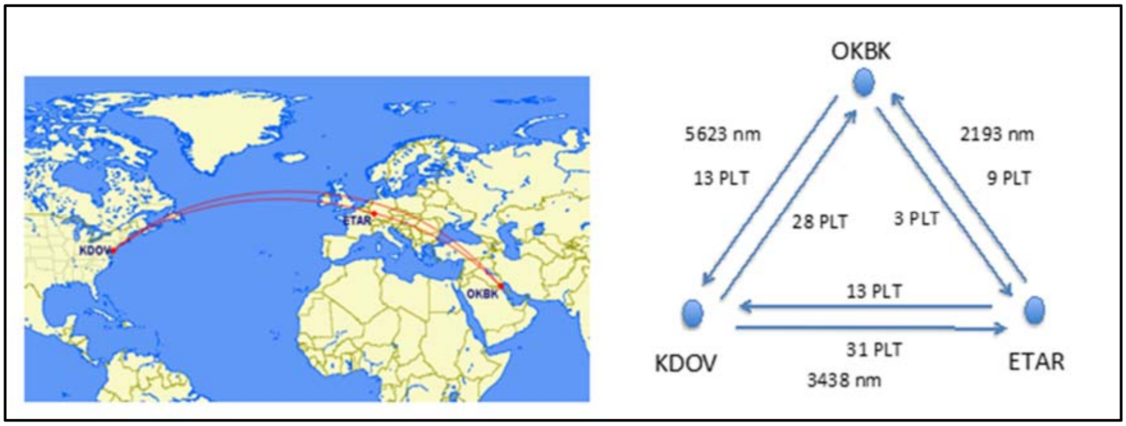

Figure 7. Schematic of Three-Base Network Problem

Three-Base Network Results

The actual size of the strategic airlift fleet dedicated to cargo transport is obtained from the GATES dataset by accumulating unique tail numbers resulting in a fleet composition of 92 C-5s, 145 C-17s and 69 747-Fs. The reduced exisiting fleet size for the three-base network problem consists of three of each aircraft type: type A representing the C-5s, type B aircraft representing the C-17s, and type C aircraft representing the 747-Fs, which is assumed to be operated as a chartered aircraft. Three of the new aircraft (aircraft type X) are introduced to the fleet. The new aircraft in addition to the existing fleet serve to satisfy the pallet cargo demand on various routes subject to the scheduling constraints.

The subspace decomposition strategy as depicted in Figure 2, is them employed, using pallet capacity, range at maximum payload, and cruise speed as the top-level design variables of the new aircraft X. The new aircraft X is optimized for minimum direct operating cost with the values for the top-level design variables as input parameters. The fleet assignment subspace then assigns the aircraft to the various routes to maximize productivity or minimize operating costs for the different sampled instances of demand. To address uncertainty, a MCS approach is used where the uncertainty in pallet demand is sampled from the historical distributions for each route. The intent is to obtain an aircraft description that is more robust to the uncertain demand network characterized by fluctuations as shown before in Figures 5 and 6. When sampling the demand, the MCS technique is set to calculate the probability of the number of pallets carried on an airplane on each route. Then a random number generated between 0 and 1 will select number of pallets carried on a route based on the probabilistic distribution. This process constructs a demand structure that is representative of the historical demand distributions for each route. The sequential subspace decomposition approach is solved sequentially until the top-level converges.

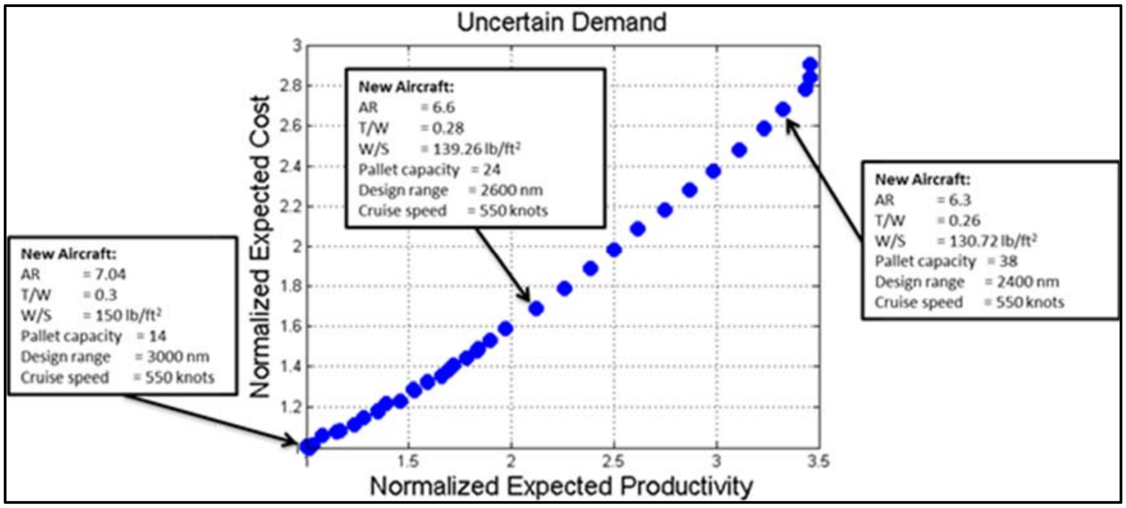

Figure 8. Pareto Front of Normalized Expected Fleet Productivity Versus Normalized Expected Fleet Costs for Three-Base Network Problem

Figure 8 depicts the Pareto front obtained from solving the multi-objective formulation using an epsilon constraint approach for the three-base network problem. The fleet productivity and cost values shown in Figure 8 have been normalized with respect to their respective minimum productivity and cost values. The Pareto front provides a quantitative measure of how the design of the new system varies, as a particularly objective is traded off with another objective. For instance, the optimal design of the new aircraft suggests a relatively smaller aircraft with a pallet capacity of 14, a high wing loading and thrust-to-weight ratio for a normalized expected fleet productivity and costs value of 1. Increasing the normalized fleet productivity by a factor of 2.15 increases the fleet costs by a factor of 1.7. However, the optimal design of the new aircraft required to achieve this also differs considerably. In this scenario, the optimal design of the new aircraft suggests a larger aircraft capable of carrying 24 pallets with a relatively lower thrust-to-weight ratio and wing loading. The general trend of the Pareto front is as expected, with fleet productivity increasing with increase in fleet costs.

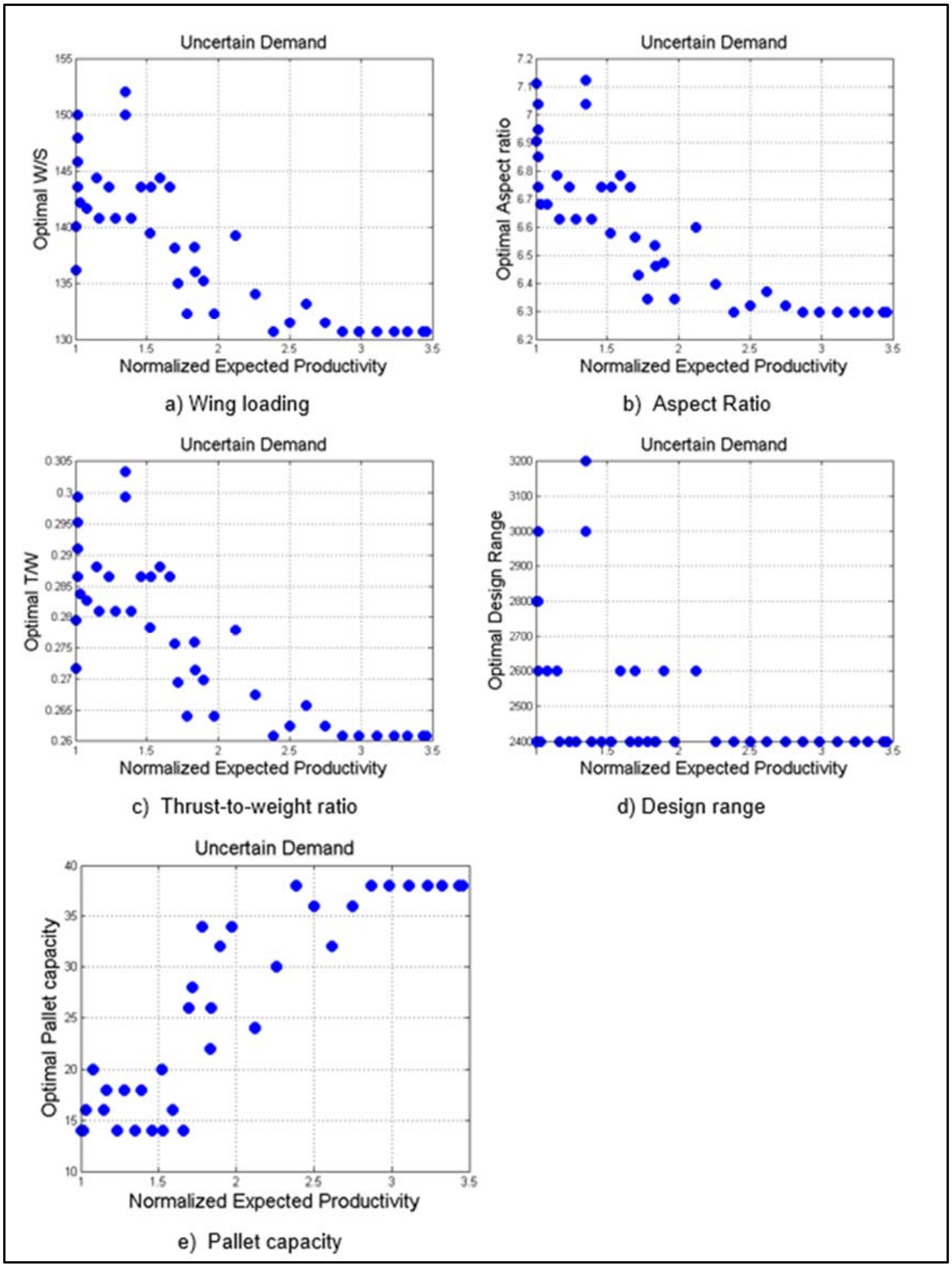

Figure 9. Trends of the Optimal Values of the Aircraft Design Variables Along Pareto Front

The optimal values of the design variables of the new aircraft X, as shown in Figure 9, illustrate some discernible trends. The pallet capacity of the new aircraft X increases with increase in fleet productivity, as pallet capacity is one of the main drivers for fleet productivity. The optimal cruise speed always reaches the upper bound of 550 knots. Faster cruise speeds offer increased productivity at the expense of increased system cost. However, for the three-base network, the increase in fleet-level costs is not limiting on the improved fleet-level productivity offered by a faster cruise speed. The relatively low demand in the network in comparison to the pallet capacity of the fleet causes the optimal design range of the new aircraft X to reach the lower bound of 2400 nm. The optimal design range increases to higher values when the sampled demand values are larger, thus enabling the fleet to more efficiently satisfy the demand in the network for those sampled demand instances. The optimal wing loading and the thrust-to-weight ratio show similar trends; these values are dictated by the single takeoff performance constraint. The optimal aspect ratio decreases with increase in fleet productivity and fleet costs. Higher aspect ratio leads to reduced fuel costs thus enabling the fleet to maximize productivity at lower fleet cost limits. The decrease in fuel costs owing to reduced drag in a higher aspect ratio configuration offsets the increase in fuel costs owing to increase in empty weight of the aircraft.

Conclusions and Future Work

The decomposition framework, adopted in this paper, presents a process that allows the identification of optimal design parameters of a military transport aircraft when trade-offs between fleet-level fuel usage, performance metrics and acquisition alternatives for a conceptual problem are considered under demand uncertainty in the route network. Although the method has been demonstrated for a very simple example motivated by Air Mobility Command, the method appears generalizable to acquisitions for other new platforms that are intended to work with other existing platforms to provide a set of overarching capabilities. The decomposition framework enabled the identification of a set of Pareto-optimal designs of the new yet-to-be introduced aircraft for two competing fleet-level performance metrics under uncertainty. The framework identifies the optimal design requirements of the new system, and the optimal utilization of the new system together with existing systems in the fleet. The new systems designed accounting for uncertainty in operations leads to optimal fleet utilization and consistent reliability levels.

The three-base problem provides a simplified example network to illustrate the decomposition approach and demonstrates its ability to generate plausible solutions. Given the modeling assumptions and assessment of the uncertainties in the model parameters, the subspace decomposition approach identified the optimal design requirement of the new aircraft for a set of fleet-level objective(s) for the three-base network problem. Figure 10 depicts the spread of the normalized objective function values for the three-base network problem, solved via the epsilon constraint multi-objective formulation for different demand samples. The authors would like to further investigate the possibility of any statistic correlations between the degree of dispersion due to the uncertainty in demand and the fleet-level objective tradeoff design space. The degree of dispersion can be correlated to the robustness of the new system in achieving a set of pre-determined fleet-level objective(s), accounting for the uncertainty in fleet operations. These correlations could identify new system design requirements that would provide fleet-level performances within specific threshold bands (e.g., between the 25th and 75th quartile fleet-level productivity for a pre-defined cost limit).

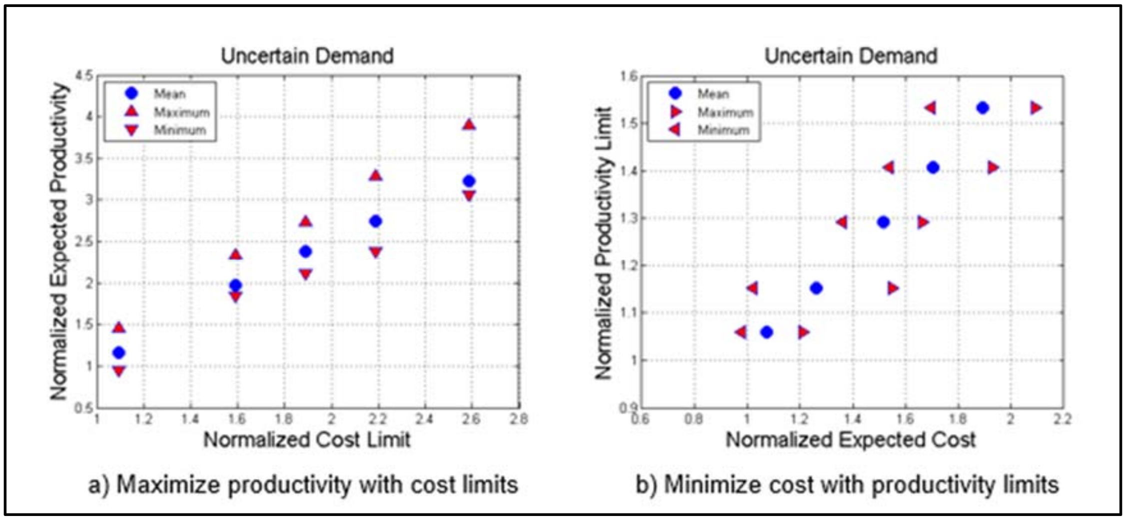

Figure 10. Spread of Objective Function Values for Different Constraint Limits

Future work will reflect a larger network from the GATES dataset (20+ bases) to investigate the ability of the subspace decomposition approach to solve larger, more interconnected networked systems. Recognizing the uncertainties in the cargo demand structure of the AMC fleet led the research to consider uncertainty via a comparatively naïve Monte Carlo Sampling technique. Multi-point design optimization techniques and control variate methods may be better suited for solving larger size problems, as computational cost associated with MCS grows exponentially with problem size. Future efforts will focus on reducing the computational cost associated with sampling the demand uncertainty in the network.

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