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Platform Design For Fleet-Level Efficiency Under Uncertain Demand: Application For Military Cargo Aircraft And Fleet

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PLATFORM DESIGN FOR FLEET-LEVEL EFFICIENCY UNDER UNCERTAIN DEMAND: APPLICATION FOR MILITARY CARGO AIRCRAFT AND FLEET

A Thesis

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Special feeling of gratitude to my loving parents, Whan-Sub Choi, Bo-Nyung Kim who has supported me throughout my life and has never doubted me, and to my brother, Jee-Hoon Choi, and his family.

I dedicate this dissertation to my wife Wonkyung Kim.

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TABLE OF CONTENTS

Page

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

NOMENCLATURE

AFSAA	=	Air Force Studies and Analyses Agency
AMC	=	Air Mobility Command
AMOS	=	Activitiy Mobility Simulator
APOD	=	aerial port of debarkation
APOE	=	aerial port of embarkation
AR_X	=	aspect ratio of aircraft type *X*
B_p	=	maximum average daily utilization of each aircraft
$BH_{p,k,i,j}$	=	number of block hour for k^{th} trip of aircraft p from base *i* to base *j*
BTS	=	Bureau of Transportation Statistics,
$C_{p,k,i,j}$	=	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*
CONOP	=	Concept of Operations
CRAF	=	Civil Reserve Air Fleet
$Dem_{i,j}$	=	demand from base *i* to base *j* in number of pallets
DOC	=	direct operating cost
DUSD	=	Deputy Under Secretary of Defense for Acquisition and Technology

GA	=	Genetic Algorithm
gal	=	gallon
GATES	=	Global Air Transportation Execution System
ICAO	=	International Civil Aviation Organization
LP	=	Linear Programming
MCRS	=	Mobility Capabilities and Requirement Study
MCS	=	Monte Carlo Sampling
MDO	=	multidisciplinary design optimization
MDS	=	mission distribution system
MINLP	=	mixed integer, non-linear problem
MOM	=	Mobility Optimization Model
MRC	=	major regional conflict
MTM/D	=	million ton-miles per day
MTOW	=	maximum takeoff weight
nmi	=	nautical miles
NPS	=	Naval Post Graduate School
NRMO	=	NPS/RAND Mobility optimizer
$O_{p,i}$	=	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*
S_{TO}	=	takeoff field length
SA	=	Simulated Annealing

USTRANSCOM = United States Transportation Command

$(T/W)_X$ = thrust-to-weight ratio of aircraft type *X*

USAF = United States Air Force

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 kth trip if flown by aircraft p from base i to base *j*

ABSTRACT

Choi, Jung Hoon. M.S., Purdue University, December 2013. Platform Design for Fleet-Level Efficiency under Uncertain Demand. Major Professor: William Crossley.

The aircraft system's role in the United Stated Air Force is crucial. For the U.S. Air Force to maintain its air superiority in the world, the constant maintenance, upgrade, and acquisition of the systems must follow. As the cost of fuel rises and with the recent budget situation, the emphasis is on both running the Air Force fleet more efficiently and acquiring the platform that can reduce the fleet level operating cost and the fuel usage and yet brings same capabilities. The approach presented in the thesis combines approaches from multidisciplinary design optimization and operations research to improve energy efficiency-related defense acquisition decisions. The work focuses upon problems that are relevant to the U.S. Air Force-Air Mobility Command (*AMC*), which is the largest consumer of fuel in the Department of Defense. To reflect *AMC* problems, the approach must consider the uncertainty in cargo demand; historical data shows that the cargo demand for *AMC* varies on a daily basis. The approach selects requirements for a new cargo aircraft; predicts size, weight and performance of that new aircraft; and allocates the new aircraft along with existing aircraft fleet to meet the cargo transportation demand. The approach successfully provides a description of a new

cargo aircraft that, given the abstractions and assumptions used, will reduce the fleet-level operating cost and / or the fuel needed to meet air cargo demand. The allocation problem incorporates scheduling-like features to account for time driven operational constraints. The results of this study demonstrate the approach for a simple three-route network and 22-base network, using the Global Air Transportation Execution System (*GATES*) dataset. With addition of uncertainty in demand and random home base generation, the simulation result will suggest an aircraft design that is more flexible to the fluctuations in demand. The 22-base network represents one day of operation of the *AMC* randomly selected from the *GATES* data. The result from the 22-base network simulation under uncertain demand scenario for the strategic fleet suggests the introduction of five new aircraft that are capable of 24 pallets and 3,300 nautical miles of unrefueled design range. The existing fleet with new aircraft introduced will save 1.10 percent in the expected direct operating cost and 4.20 percent in expected fuel usage compared to the baseline allocation result without introduction of the new aircraft.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Aviation fuel contributes the largest percentage of energy consumption in the Department of Defense (*DoD*).[1] The Air Mobility Command (*AMC*) has the largest fleet of the biggest airframes in the Air Force, and they are the *DoD*'s largest aviation fuel customer consuming 28 percent of *DoD*'s energy use.[2]

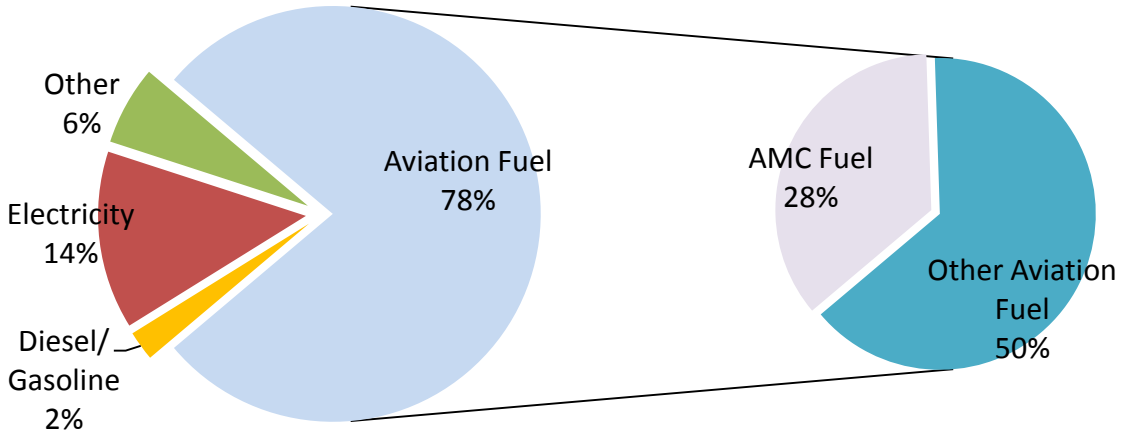

Figure 1.1 *AMC* Fuel Usage in Relation to the *DoD* Energy Usage in Percentage[2]

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. *AMC* also charters aircraft from the Civil Reserve Air Fleet (*CRAF*) during peacetime via contractual commitments with U.S. airlines.[3]

The complex logistics involved in the transportation of various cargos across the *AMC*'s service network requires efficient deployment of the *AMC* fleet of cargo aircraft to daily cargo delivery requirements, while minimizing fuel consumption and subsequent costs. The choice of aircraft used and the individual flights flown by the aircraft drive operating and fuel costs. To meet the cargo delivery operations within a prescribed schedule timeframe, *AMC* uses multiple aircraft systems in a manner that fits the description of a 'system of systems'. Maier[4] describes five characteristics of System-of-Systems (*SoS*) as,

- Operational Independence of the Elements
- Managerial Independence of the Elements
- Evolutionary Development
- Emergent Behaviour

- Geographic Distribution

If the *AMC* is disassembled, aircraft in the system, which are component systems, can usefully operate independently. The aircraft in the *AMC* not only can operate independently, they do operate independently if necessary. The *AMC* constantly update and modify functions and purposes with experience showing evolutionary traits of *SoS.* Operating together, the collection of aircraft produces capabilities not produced or fulfilled by the elements alone. Finally, *AMC* has very distributed network in the geographic extent.

One of the important traits of the *AMC* as a *SoS* is the evolutionary behavior of the system and component systems. In the *AMC*, aircraft are constantly being managed and upgraded to be more efficient and effective. The *AMC* is in the process of modernizing the current strategic fleet, consisting of C-5s and C-17s, by incorporating new avionics systems, materials and engines on existing airframes to operate the current fleet more efficiently and extend the service life of these aircraft[5]. While upgrading existing aircraft will provide some efficiencies, the design of new, more fuel efficient aircraft may provide the biggest fleet operations cost savings and fuel consumption savings, if those are primary concerns. The C-5 will phase out of the inventory around 2040, *AMC* needs to begin pursuing a C-X that might potentially replace both the C-17 and C-5[6], as development of an aircraft is times taking task.

The uncertain nature of *AMC* operations, coupled with its complex logistics results a stochastic mixed integer non-linear programming problem which makes it difficult to identify a fuel efficient aircraft design that achieves target performance, while simultaneously minimizing fuel consumption across the range of day-to-day operational scenarios. An approach that can help determine the design requirements and design description of a new aircraft to meet the required cargo delivery performance while also minimizing cost on day-to-day operations is needed. There are a large number of variables when addressing this sort of problem – the design requirements for the new aircraft (e.g., payload, range), the design variables of the new aircraft (e.g., thrust-to-weight, aspect ratio, wing loading), and decision variables describing how the aircraft are assigned or allocated to different cargo routes. With the many variables available to a systems designer, a computational approach becomes necessary to determine which variables to change and determine the magnitude of change to satisfy constraints while achieving an objective (or multiple objectives). The solutions obtained from properly formulated optimization problems provide insight into decisions about new systems and help to inform acquisition decisions. This thesis presents an approach, built upon previous research efforts, that can simultaneously determine design requirements for the new aircraft, a set of optimal design variables describing the new aircraft, and representative allocations of this new aircraft along with existing aircraft, to meet demand scenarios typical of the *USAF AMC* with the objective of minimizing fleet-level operating costs or fleet-level fuel consumption.

1.2 Previous Relevant Research

Previous research relevant to this thesis can be found in several different topical areas. This includes studies in commercial domain using the decomposition strategy to solve a large monolithic optimization problem, and transportation and asset allocation studies from the military domain research.

1.2.1 Decomposition Strategy Studies

Several previous research efforts have examined a decomposition strategy that address the design of aircraft for commercial airline and air taxi operations. When the problem size increases to the point where the traditional mixed-integer, nonlinear programming approaches cannot obtain a solution, the decomposition approach can find solutions for these larger problems. Mane, Crossley and Nusawardhana (2007)[7] used the decomposition method to break down a large monolithic optimization problem into an allocation domain and an aircraft sizing domain. In 2009, similar decomposition method is used to assess the fleet level environmental impact of new aircraft by Tezloff and Crossley[8]. Then in 2012, this decomposition method is applied to Allocation and Design of Aircraft for On-Demand Air Transportation with Uncertain Operations by Mane, Crossley[9]. In that research, the authors implement a trip assignment method in the allocation subspace. The research tackles the uncertain demand nature of on-demand air transportation with a Monte Carlo Sampling (*MCS*) technique. The research allocates each aircraft design to an uncertain demand case constructed using the *MCS.*

The formulation used in this thesis designs an aircraft, then fleet with the newly designed aircraft is allocated to multiple possible demand networks. The decomposition method is borrowed from previous research done by Mane, Crossley and Nusawardhana[7], which uses the decomposition strategy to solve a large monolithic mixed integer linear programing problem. This research addresses the uncertain scheduling of the *AMC* network using the scheduling-like formulation similar to that from Mane, Crossley[9], which introduces the scheduling-like formulation to address the flight characteristics of on-demand air transportation network. In this research, *MCS* constructs the possible demand network each iteration, and then finds the average expected operating cost or expected fuel usage of the fleet.

1.2.2 Mobility Allocation Studies

In the military domain, Naval Post Graduate School (*NPS*), RAND corporation and the U. S. Air Force lead similar research effort to model military air transportation and asset allocation. In 1991, Mobility Optimization Model (*MOM*) [10], a linear programming (*LP*) optimization model, used a time-dynamic model that includes both airlift and sealift. In 1994, Air Force Studies and Analyses Agency (*AFSAA*) introduced another LP optimization model specific to airlift, *THRUPUT*[11] which was a time-static strategic airlift model on a general routing network. Then *AFSAA* asked NPS to combine the *MOM* and THRUPUT models into one model that would be time dependent and would also capture the specifics of airlift operations; this resulted in *THRUPUT* II[12]. In 1997, RAND developed a model similar to *THRUPUT* II called *CONOP* (CONcept of OPerations)[13].

CONOP was a large linear optimization model of the air mobility system to minimize a function representing the delivery dates of cargo. However, *CONOP* had features that THRUPUT lacked and vice versa. In 2002, Baker, Morton, Rosenthal and Williams introduced the NPS/RAND Mobility optimizer (*NRMO*)[14], which has been designed to provide insight into several types of mobility questions concerning investment using Time Phase Force Deployment Data (*TPFDD*). A more recent and widely-used model at the *AMC* is Activity Mobility Simulator (*AMOS*), which is a rule base discrete-event worldwide airlift simulation model used in strategic and theater operations to deploy military and commercial airlift assets[15]. But, the military domain research concentrates on the scheduling and allocation of the assets and none of the previous research considers the design of a new aircraft to be introduced to the existing fleet. Furthermore, previous military domain researches lack considerations of cost efficiency, specifically fuel efficiency of the platforms and the overall fleet.

Table 1.1 shows the different previous researches and features of those researches compared to this research. The table shows that there has not been a research that solved fleet allocation problem with the introduction of new aircraft, for the military fleet with uncertainty in demand using decomposition strategy, and this research will address such problem.

Table 1.1 Different Features of Previous Research and This Research

	Fleet Allocation	New Aircraft	Military Fleet	Uncertainty in Demand	Decomposition Strategy
Mane, Crossley and Nusawardhana	X	X			X
Mane, Crossley	X	X		X	X
MOM	X		X		
THRUPUT	X		X		
THRUPUT II	X		X		
CONOP	X		X		
NRMO	X		X		
AMOS	X		X	X	
This Research	**X**	**X**	**X**	**X**	**X**

1.3 Research Objective / Research Question

The Acquisition Process factsheet[16] states, "Neither current requirements or acquisition processes accurately explore tradeoff opportunities using fuel as an independent variable." The factsheet also states, "Current process undervalue technologies with the potential to improve energy efficiency." The objective of this research is to develop a tool and problem formulation that suggests a new aircraft

design that can minimize the fleet-level objectives of operating cost and fuel consumption. This tool, focused on the military cargo aircraft and fleet, will aid assessment of acquisition-relevant decisions about requirements and design choices about a new aircraft impact fleet-level metrics (e.g., fleet cost or fuel consumption) under conditions of operational uncertainty. The research will enhance understanding about what features this kind of process should entail.

CHAPTER 2. RESEARCH BACKGROUND / MOTIVATION

2.1 Air Mobility Command Network

The Air Mobility Command (*AMC*) is one of three service components comprising U.S. Transportation Command (*USTRANSCOM*) together with Navy's Military Sealift Command and the Army's Surface Deployment and Distribution Command. *AMC*, located at Scott Air Force Base provides global reach through strategic airlift. The aircraft assets include: C-17 Globemaster III, C-5 Galaxy, C-130 Hercules, KC-135 Stratotanker, KC-10 Extender C-37, Gulfstream V, C-21 Learjet, C-40 Clipper, Boeing C-32A, Boeing C-40B, Boeing C-40C, and Boeing VC-25. *AMC* also operates contracted Civil Reserve Air Fleet (*CRAF*), a fleet of commercial aircraft committed to support the transportation of military forces and material. *CRAF* is critical to national defense and military operations; the *CRAF* provides transportation for 93% of passengers[17] and 47% of cargo for *AMC*[18].

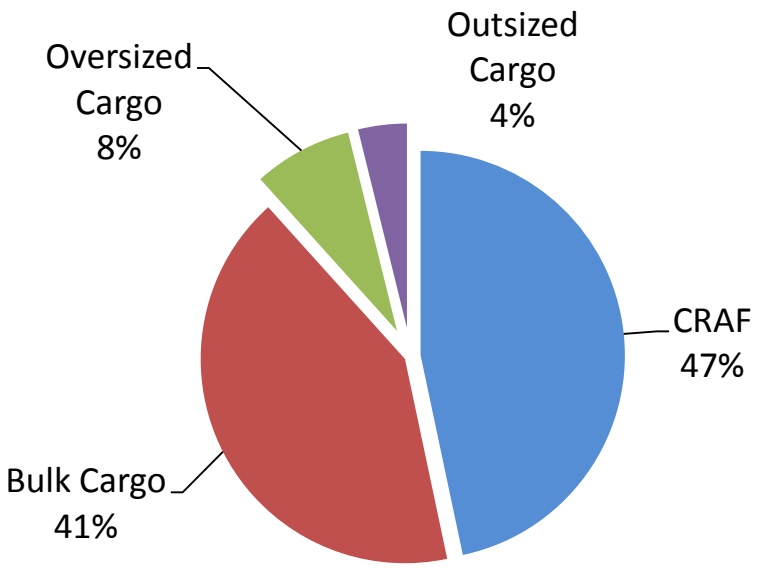

Figure 2.1 Amount of cargo types transported by *AMC* fleet and *CRAF*[18]

The *AMC* cargo mobility fleet is divided into two specific fleets: the strategic fleet and the tactical fleet. A strategic airlift aircraft is defined as an aircraft with a cargo capacity of at least 150,000 pounds and a capability to transport outsized cargo over an unrefueled range of at least 2,400 nautical miles. The current aircraft types that meet this definition are the C-5 and C-17[19]. The strategic fleet focuses on inter-theater transportation whereas the tactical fleet focuses on intra-theater transportation. A tactical airlift aircraft is typically turboprop-powered and has features such as short takeoff and landing distance and low pressure tires allowing operations from unpaved airstrips. Currently in the *AMC*, Lockheed Martin's C-130 Hercules variants are considered the main platforms of tactical airlift aircraft.

The *AMC* demand network is different from that of the commercial airline or parcel service networks, because it does not have a hub-and-spoke network structure. Often in the *AMC* network, cargos will be embarked from a site (a depot) and make multiple stops embarking and debarking cargos. This requires a new formulation relative to previous commercial airline fleet allocation problem[8], because the round trip assumption is no longer valid. The round trip assumption assumes that the number of passengers flying from airport A to airport B on a given day is nearly equal to the number of passengers flying from airport B to airport A on the same day. The round trip assumption is typically used for commercial airline network, and the flights in the round trip assumption are considered to be non-stop flight segments.

In the *AMC* network, not only does the cargo often have multiple stops, but the cargo is often consumable, so that it never returns. In other cases, it may be military hardware that will move to an "in theater" location and remain for a long time. Neither of these situations would fit the round trip assumption.

2.2 *AMC* Strategic Fleet Platforms

As stated before, a strategic airlift aircraft has a cargo capacity of at least 150,000 pounds and a capability to transport outsized cargo over an unrefueled range of at least 2,400 nautical miles. Outsized cargo is any cargo that exceeds 1,000 inches in length, 117 inches in width, 105 inches in height in any one dimension. Examples of this might include the Bradley Fighting Vehicle or the AH-64 Apache helicopter[20]. Table 2.1

describes the dimensions and restrictions of the three common cargo classifications used by the *AMC*.

Table 2.1 Dimensions and Restrictions of Cargo Size Classifications Used in the *AMC*

Classification	**Dimension (inches)**			**Restrictions**
	L	W	H	
Bulk	104	84	96	Weight Limit: Max 10,000 lb
Oversize	1000	117	105	
Outsize	>1000	>117	>105	In any one dimension

As mentioned previously, *AMC* currently operates two types of aircraft for the strategic fleet: C-5 and C-17. Figure 2.2 illustrates the size comparison between the two aircraft types.

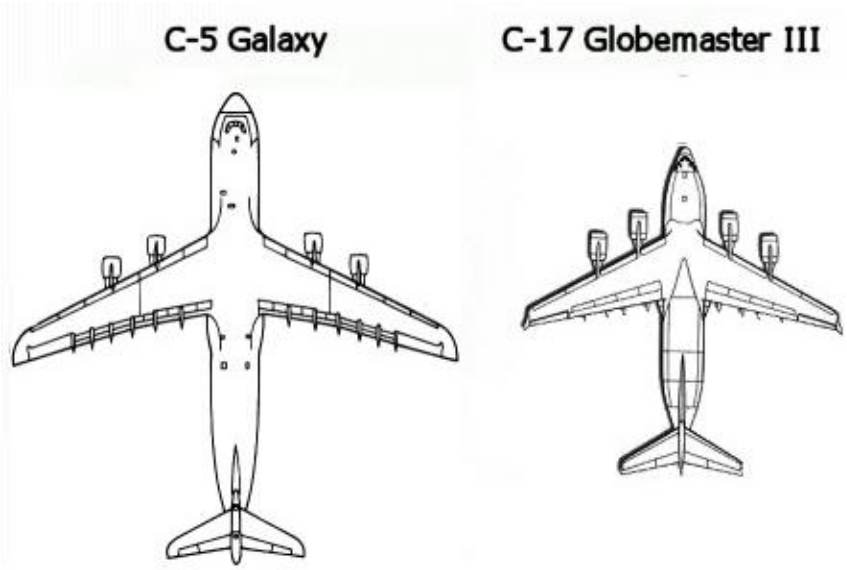

Figure 2.2 Size Comparison of the *AMC* Strategic Airlift Platforms: C-5, C-17[21]

The C-5 Galaxy is the second largest aircraft of its kind after Russia's Antonov 124. The C-5 is capable of carrying outsized cargo or up to 36 standardized 463L palletized cargos. The C-5 can carry nearly all of the Army's combat equipment. It is the only aircraft capable of carrying the 74-ton mobile scissors bridge. It is also capable of loading cargo through both the front and rear-loading ramp. This capability enables fast unloading and loading, because cargo unloading can take place through one end of the fuselage while loading takes place through the other end. There are four variants of C-5s: C-5 A, B, C, M. Currently, the C-5 is under ongoing a modernization process to the C-5M Super Galaxy as the C-5 A, B, C airframes age. The aging aircraft require more maintenance and as a result has low mission capability rate. C-5Ms will have more powerful engines to have a higher climb rate, increased cargo load and range, and shorter takeoff field length. In addition, the C-5s will have upgrades to airframe and skin,

avionics, and the autopilot system. As of September 2012, there are 79 C-5s in service[22]. However, the C-5 is one of the older aircraft platforms in the U.S. Air Force, with an average age of 32.7 years and average age of C-5 variant A and C more than 41 years[22].

The C-17 Globemaster III was introduced as a replacement to the C-141 Starlifter cargo aircraft. The C-17 is also capable of transporting outsized cargo or 18 standardized 463L palletized cargos. One outstanding characteristic of the C-17 is its ability to take off and land on runways as short as 3,000 ft and land in 3,000 ft or less. These capabilities allow it to deliver cargo directly to more airfields doing away with the need for a portion of the intra-theater tactical airlift[23]. The C-17 has two major variants: C-17A, and C-17B. The C-17 fleet is also under a modernization process. As of September 2012, *USAF* operates 217 C-17s in the fleet[22]. The C-17 is *AMC*'s primary military airlift aircraft. Compared to C-5, C-17 is a very young platform with average age of 9.3[20]. Table 2.2 compares detailed specifications of C-5[24, 25] and C-17[25, 26].

Table 2.2 General Specifications of C-5 and C-17[27]

		C-5	C-17
Payload		36 Pallets 270,000 lb	18 Pallets 170,900 lb
Cargo Compartment Dimension	L	1,725 in	1,056 in
	W	228 in	216 in
	H	162 in	148 in
Length		247 ft	147 ft
MTOW		840,000 lb	585,000 lb
Engine		4 x 43,000 lbf each	4 x 40,440 lbf each
Cruise Speed		M 0.77 496 kn	M 0.76 450 kn
Range		2,400 nmi (w/ 263,200 lb PL)	2,420 nmi (w/ 160,000 lb PL)
Wing loading		120 lb/ft^2	150 lb/ft^2
Thrust-Weight		0.22	0.277
Fuel Capacity		51,150 US gal	35,546 US gal

In addition to the strategic fleet, Boeing 747 freighter versions (747-F) from the *CRAF* conduct a significant portion of *AMC* operations. Although the 747-F cannot carry outsized cargo (cargo with exceptionally long dimensions), it is capable of carrying oversized cargo (heavy cargo) or 29 palletized cargos. The B747-F's long range capability is a valuable characteristic in the *AMC* because, with an unrefueled range of over 7,200 miles[28], this aircraft does not require aerial refueling or need to make refueling stops on many of the long distance routes in the *AMC* network reported in *GATES*. Table 2.3 illustrates the cargo carrying capacity, capability and range of the three aircraft used in the *AMC* strategic fleet.

Table 2.3 Comparison of Cargo Capacity, Unrefueled Ranges of the Three Aircraft Types in the Strategic Fleet

	C-5	**C-17**	**747-F**
Cargo Capacity	261,000	164,900	248,300
Capability	Outsized	Outsized	Oversized
Unrefueled range	2,982	2,420	7,200

2.3 Uncertainty

The global presence of U. S. Armed Forces requires constant transportation of troops and cargos. However, unlike the airline fleet problem, the *AMC* network consists of very inconsistent demand structure and the priorities of cargoes.

Figure 2.3 shows a bar graph describing the number of pallets transported between LTAG (Incirlik Air Base, Turkey) and KCHS (Charleston Air Force Base, South Carolina, US) for each day during 2006 and a histogram showing frequency of number of pallets transported per day. The bar graph suggests that this route has rather consistent minimum demand; at least 40 pallets travel this route almost every day. This is not directional demand; therefore, 40 pallets could imply 30 pallets one way from KCHS to LTAG and 10 pallets on the return flights from LTAG to KCHS. The histogram shows that the demand distribution has peaks around 40 pallets, 80 pallets, or 120 pallets transported with few heavy demand days with more than 140 pallets. This histogram does not follow any single distribution of the well-known probability distributions (e.g., normal, beta, etc.).

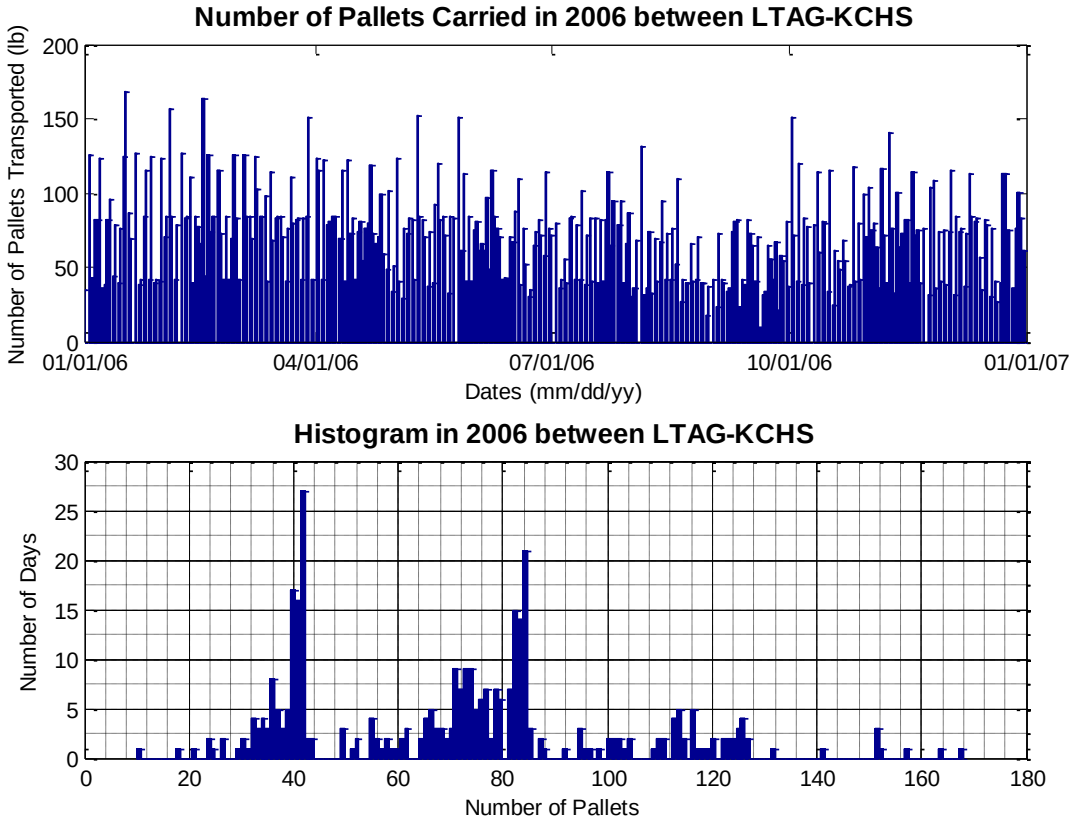

Figure 2.3 Number of Pallets Transported per Day and Histograms Showing Number of Pallets Transported between LTAG and KCHS

Figure 2.4 shows the same types of graphs as Figure 2.3, but these (Figure 2.4) show palletized cargo demand between OTBH (Al Udeid Air Base, Qatar) and ETAR (Ramstein Air Base, Germany). In this origin-destination pair (O-D pair), the demand does not show cargo transportation every day, and amount of pallets transported fluctuates greatly when cargo does travel on this route. The histogram shows what might approach a uniform distribution, when cargo does travel on this route, which suggests that the demand fluctuates greatly. In addition, there are many days when the demand is less than 10 and as low as two pallets. This suggests the priority cargo

situation when two pallets need to be transported even if the aircraft is not loaded to its normal capacity. This fluctuation in demand causes the uncertainty in demand, as one demand scenario or deterministic demand scenario is not sufficient to fully describe the *AMC* network demand structure.

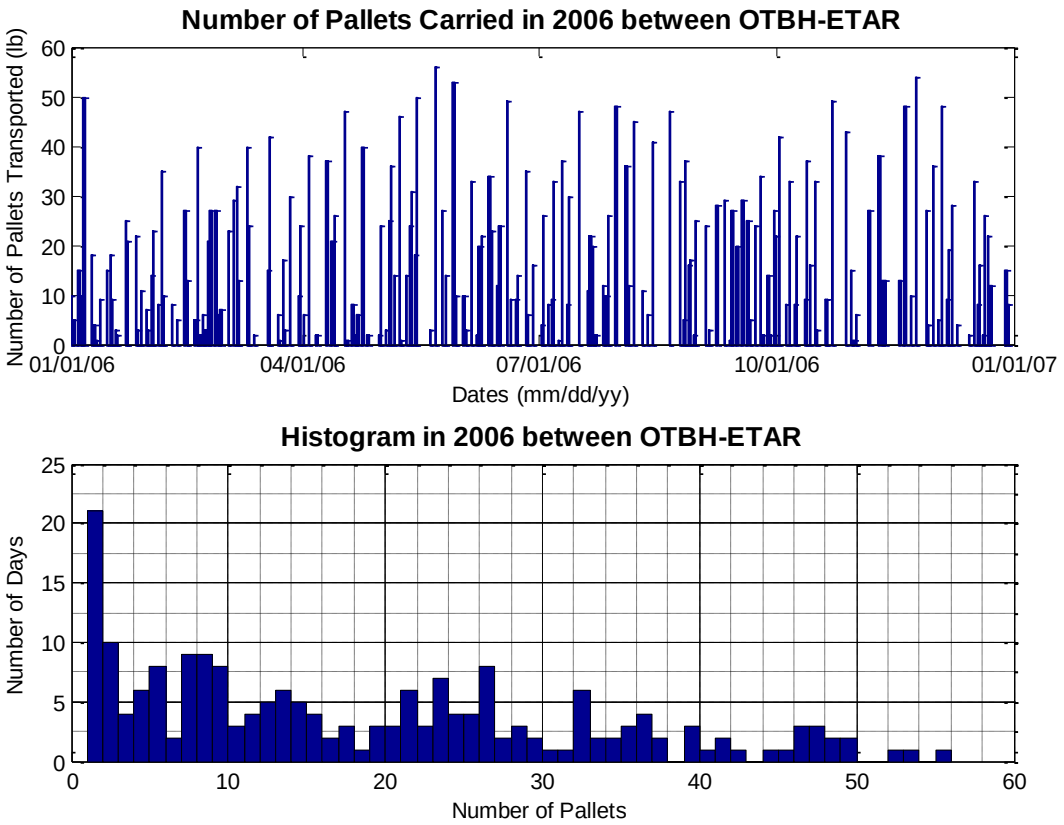

Figure 2.4 Number of Pallets Transported per Day and Histograms Showing Number of Pallets Transported between OTBH and ETAR

Because the United States cannot predict when and how often war or other high volume cargo demand (like humanitarian relief) might occur, it is important to have the flexibility to meet fluctuating demand[29]. This would allow *AMC* to meet the

comparatively rare, high-demand situations. Similarly, to address fuel efficiency, the *AMC* fleet also needs to serve typical demand effectively. Further, the next generation of strategic airlifter capability and cost related study is needed now to avoid a degradation of capability in the future.[23]

This research uses the 2006 *GATES* data that was during a time when U. S. military operations were still active in Iraq and Afghanistan. Peacetime demand continues to exhibit wide fluctuation but the wartime requirement for air mobility is on the rise, generating more asymmetry in both wartime and peacetime demand[29]. Lately the conflicts had become more of suppressing insurgencies rather than large-scale operations. This trend can result in more irregular scheduling of cargo delivery missions with fewer payloads carried per mission. For prolonged, low-level conflicts in the future, the demand scenario considered in this research would be appropriate to use when considering the design of a new military cargo aircraft.

CHAPTER 3. SCOPE AND APPROACH

3.1 Description of the Global Air Transportation Execution System Data

To gain a network that resembles Air Mobility Command (*AMC)'s* operational network, this work uses data from the Global Air Transportation Execution System (*GATES*). *GATES* is *AMC*'s automated air transportation management system, which is managed by *USTRANSCOM* and has very detailed information on palletized cargo and personnel transported by the *AMC* fleet. Cargo transported by C-5 and C-17 aircraft and chartered Boeing 747-F aircraft from the *CRAF* for long range missions are considered to represent typical cargo flow using the *AMC*'s strategic fleet. Each data entry in the field '*GATES* Pallet data' represents cargo on a pallet or a pallet-train the *AMC* 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 of aircraft carrying the cargo, aerial port of embarkation (APOE), aerial port of debarkation (APOD), pallet volume, pallet configuration, etc. These data enable the reconstruction of the route network, pallet demand characteristics, and existing fleet size of the allocation problem that will represent *AMC* operations. Table 3.1 shows the fleet size, number of flights, average pallet weight per flight and average number of pallets carried per flight for each aircraft type reconstructed from the *GATES*. The

average pallet weight and average number of pallets per flight are averages computed from the entire calendar year 2006 operations recorded in *GATES*.

Table 3.1 Fleet Size and Mission Data Reconstructed from the *GATES* Data Set

Aircraft Type	**C-5**	**C-17**	**747-F**
Fleet Size	92	145	69
Number of Flights in 2006	3330	14990	4825
Avg. Pallet Weight	4262.9 lb	3825.9 lb	2590.4 lb
Avg. Pallet per Flight	10.35 Pallets	7.77 Pallets	21.33 Pallets

The setup of the allocation problem required calculation of additional values. These have been assigned "field names" that are similar to the current field names used in *GATES*. Because *GATES* records data for each pallet (or pallet train) carried, the number of pallets carried on the same flight, assigned to field name NUM_PAL, was calculated by summing *GATES* entries with same APOE and APOD with the same departure date and time (DEP_DT_TM) and arrival date and time (ARR_DT_TM). Table 3.2 shows a sample of the GATES raw data, where APOE of the three entries are the same, but the APOD are different. This does not indicate three separate flights, but as indicated in the MDS (aircraft type) and TAIL_NUM (aircraft tail number) fields, they are individual pallets flown in a same aircraft that made multiple stops.

Table 3.2 Sample GATES Data Entry for a Specific Flight Servicing Multiple Locations

DEP_DT_TM	MDS	TAIL_NUM	ARR_DT_TM	APOE_ICAO	APOD_ICAO	NUM_PAL
02/02/2006 21:20	C005A	00448	02/03/2006 04:35	KNGU	LERT	7
02/02/2006 21:20	C005A	00448	02/05/2006 15:02	KNGU	LICZ	5
02/02/2006 21:20	C005A	00448	02/06/2006 23:14	KNGU	OBBI	7

When GATES dataset is extracted, all the entries that originate from same APOE, same DEP_DT_TM and have a same aircraft tail number are collected. Then, all of the pallets are assumed unloaded at the end of every flight segment, and only the pallets traveling connecting flight segments are reloaded on aircraft. This results adjustment of APOE_ICAO and NUM_PAL as shown in Table 3.3.

Table 3.3 Adjustment of APOE_ICAO and NUM_PAL Field

DEP_DT_TM	MDS	TAIL_NUM	ARR_DT_TM	APOE_ICAO	APOD_ICAO	NUM_PAL
02/02/2006 21:20	C005A	00448	02/03/2006 04:35	KNGU	LERT	19
02/02/2006 21:20	C005A	00448	02/05/2006 15:02	LERT	LICZ	12
02/02/2006 21:20	C005A	00448	02/06/2006 23:14	LICZ	OBBI	7

The following assumptions are made on operations of the fleet, based on the available data set:

1) 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, and the aircraft performance parameters (thrust-weight, aspect ratio, wing loading) are indifferent to variants of these aircraft types.

In addition to the assumptions, an abstraction is made that the filtered route network from *GATES* represents all *AMC* strategic fleet operations. This abstraction is a reasonable because, the demand for subset served by C-5, C-17 and 747-F (75% of all pallets in *GATES* data)

3.2 Monolithic Problem Formulation

Previous research efforts have addressed the issue of simultaneously designing the 'assets' and 'operations' of a platform – in this case, the design of yet-to-be introduced aircraft, and the consequent allocation of the fleet (incorporating the new aircraft design along with current aircraft) across a service network. The simultaneous consideration of the design of an asset (here, aircraft), and its operations (here, allocations) as a comprehensive platform has been demonstrated to show potentially significant cost savings for airline, fractional ownership and air taxi operations[7,9]. The result of the integrated perspective is an approach that can 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 allocation 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. The decomposition strategy with an allocation formulation under uncertainty in demand, as notionally depicted in Figure 3.1, breaks down the computational complexity of the decision space into a series of smaller sub-problems controlled by a top-level optimization problem.

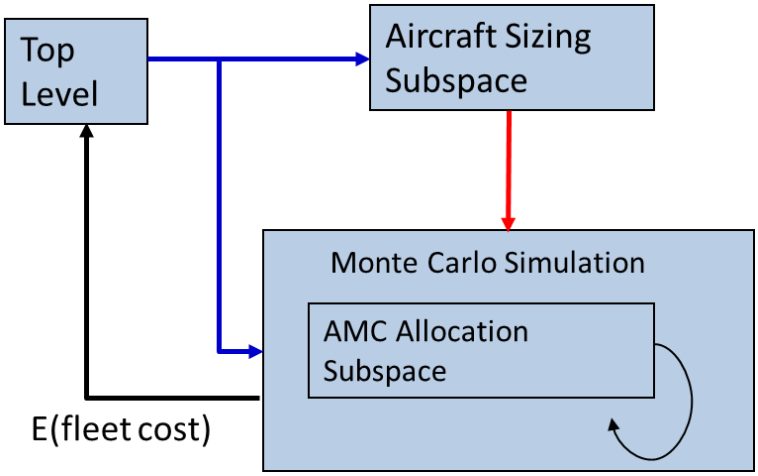

Figure 3.1 Decomposition Strategy of the Monolithic Optimization Problem

The decomposition approach addresses the issue of the 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[7, 9]. The motivation of these prior works in identifying characteristics of a new, yet-to-be-acquired aircraft that reduces fleet-level operating cost has relevance to the U. S. Air Force *AMC* problem of designing a new aircraft that reduces fleet-level operating cost and / or fleet-level fuel consumption.

The objective of the allocation problem in the decomposition seeks to minimize fleet level Direct Operating Cost (*DOC*) by allocating the available fleet to the given route network, using the information provided on the aircraft flight costs (including fuel costs) from the aircraft sizing sub-problem describing the new aircraft, or from other information describing existing aircraft. These cost coefficients appear in the formulation of the following mathematical programming problem.

Mathematical programs have two important aspects of the formulation: the objective function that reflects the metric being minimized or maximized, and constraints that reflect resource limitations in the problem. The decision variables can be manipulated to optimize the objective while satisfying constraints. The allocation problem statement is:

Minimize

$$\text{Fleet DOC} = \sum_{i=1}^{3} \left\{ \sum_{\substack{A \in C\text{-5}, \\ C\text{-17}, 747\text{-}F}} \left[C_{Ai} x_{Ai} \right] \right\} \tag{1}$$

Subject to

$$\sum_{i=1}^{3} x_{Ai} \le B_{Ai} \quad A \in \{\text{C-5}, \text{C-17}, 747\text{-F}\} \qquad \text{(trip limits / aircraft count)} \tag{2}$$

$$\sum_{\substack{A \in C\text{-5}, C\text{-17}, \\ B\text{-747}}} Cap_{Ai} x_{Ai} \ge C_i \qquad \text{(capacity)} \tag{3}$$

$$x_{Ai} \in \text{int}, \; x_{Ai} \ge 0 \tag{4}$$

In the case of a traditional aircraft allocation problem, in which the characteristics of all the available aircraft are known, the objective function Equation (1) seeks to minimize the Fleet *DOC* where C_{Ai} is the cost coefficient of an aircraft of type A on route i. The decision variable is given by x_{Ai} (with subscripts for aircraft type and route) and is an integer, making the allocation problem an integer programming problem. The total fleet *DOC* is the sum of the costs associated with the number of round trips an aircraft of type A flies on route i. The constraints expressed in Equations (2) and (3) are the aircraft trip limit and cargo capacity limits on each route i, where B_{Ai} is maximum number of trips by an aircraft of type A on route i. The trip limit constraints account for the number of aircraft available; the limiting values for number of trips operated by a given aircraft type in one day are based upon information from the *GATES* data set.

3.2.1 Fleet Allocation including Design of New Aircraft

Here, the *AMC* aircraft allocation problem is extended to consider the potential addition of a new, yet-to-be designed aircraft, and its impact on fleet wide operating costs and fuel consumption. The optimization problem now needs to consider the aircraft operating costs of the new aircraft as a function of the variables describing the new aircraft. The monolithic optimization problem simultaneously considers the aircraft design and allocation of the fleet's aircraft to meet demand obligations and is given by the following equations.

Minimize

$$\text{Fleet DOC} = \sum_{i=1}^{3} \left\{ \left[\sum_{\substack{A \in C\text{-}5,\\ C\text{-}17, 747\text{-}F}} C_{Ai} x_{Ai} \right] + C_{Xi} \left(Pallet_X, (AR)_X, (W/S)_X, (T/W)_X \right) \right\} \tag{5}$$

Subject to

$$\sum_{i=1}^{3} x_{Ai} \le B_{Ai} \quad A \in \text{C-5, C-17, 747-F, } X \qquad \text{(trip limits / aircraft count)} \tag{6}$$

$$\sum_{\substack{A \in C\text{-}5,\ C\text{-}17,\\ 747\text{-}F,\ X}} Cap_{Ai} x_{Ai} \ge C_i \qquad \text{(capacity)} \tag{7}$$

$$S_{TO}\left(Pallet_X, (AR)_X, (W/S)_X, (T/W)_X \right) \le D \qquad \text{(aircraft takeoff distance)} \tag{8}$$

$$14 \le Pallet_X \le 42 \tag{9}$$

$$6.0 \le (AR)_X \le 9.5 \tag{10}$$

$$65 \le (W/S)_X \le 161 \tag{11}$$

$$0.18 \le (T/W)_X \le 0.35 \tag{12}$$

$$x_{Ai}, Pallet_X \in \text{int}, \ x_{Ai} \ge 0 \tag{13}$$

Equation (5) is the objective function that seeks to minimize fleet *DOC*. For alternate objectives, this equation could reflect the minimization of fuel use and would then replace the cost coefficients with trip fuel consumption coefficients. Equation (6) preserves the aircraft trip limits for a typical year from values calculated from existing flight data; this represents utilization rate so that any given aircraft is limited to service up to three trips per day. From 2006 *GATES* data, there were 21,664 flights by C-5, C-17

and 747-F, and more than 99% of the flights flew less than three one way trips per 24 hour period. Equation (7) ensures sufficient pallet capacity for cargo traveling on route i. Equation (8) limits the aircraft design based on maximum takeoff distance to ensure that the new aircraft can operate at bases in the network. Pallet capacity of the aircraft X in Equation (9) is selected to design aircraft matches in the strategic airlift aircraft description[19]. The change in pallet carrying capacity affects the fuselage size. The smallest possible aircraft shall carry 14 standardized 463L pallets. The aircraft loads two pallets in a row, so even number pallet capacity that is close to the strategic airlift aircraft requirement is chosen. The largest aircraft that can be designed can carry 42 pallets, which would be an aircraft larger than AN-124. In Equation (10), the shortest range is 2,400 nmi, which is the minimum unrefueled range in the strategic airlift aircraft description[18]. 4,000 nmi is set as the longest unrefueled range, which can accommodate trans-continental and inter-continental flights. The continuous new aircraft sizing variables are set to remain near but not limited to the values of current cargo aircraft such as C-5, C-17, 747-F, AN-124, etc.

As in the "traditional allocation" problem, the number of trips of each aircraft type, x_{Ai}, in the monolithic problem are integers. The combination of the integer fleet allocation variables with the continuous aircraft design variables makes the monolithic problem a mixed-integer, non-linear programming (*MINLP*) problem. *MINLP* problems are sometimes impossible to solve for even moderately sized problems due to the high

computational expense. However, the decomposition approach developed in previous work and adapted here for the air cargo problem uses a Multidisciplinary Design Optimization (*MDO*) informed approach that breaks the monolithic *MINLP* problem of Equations (5-13) into a coordinated sequence of more tractable problems, which appeared as the individual boxes in Figure 3.1 above

3.3 Decomposition Strategy

The subspace decomposition strategy, as shown in Figure 3.2 with additional detail, decomposes the *MINLP* problem into smaller optimization problems – each sub problem follows boundaries of disciplines involved in 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. The top-level problem seeks to minimize the expected fleet level *DOC* using pallet capacity and range of the new, yet-to-be introduced aircraft type X. The expected fleet level *DOC* is calculated using the arithmetic mean of some number of samples using solutions to the allocation subspace problem.

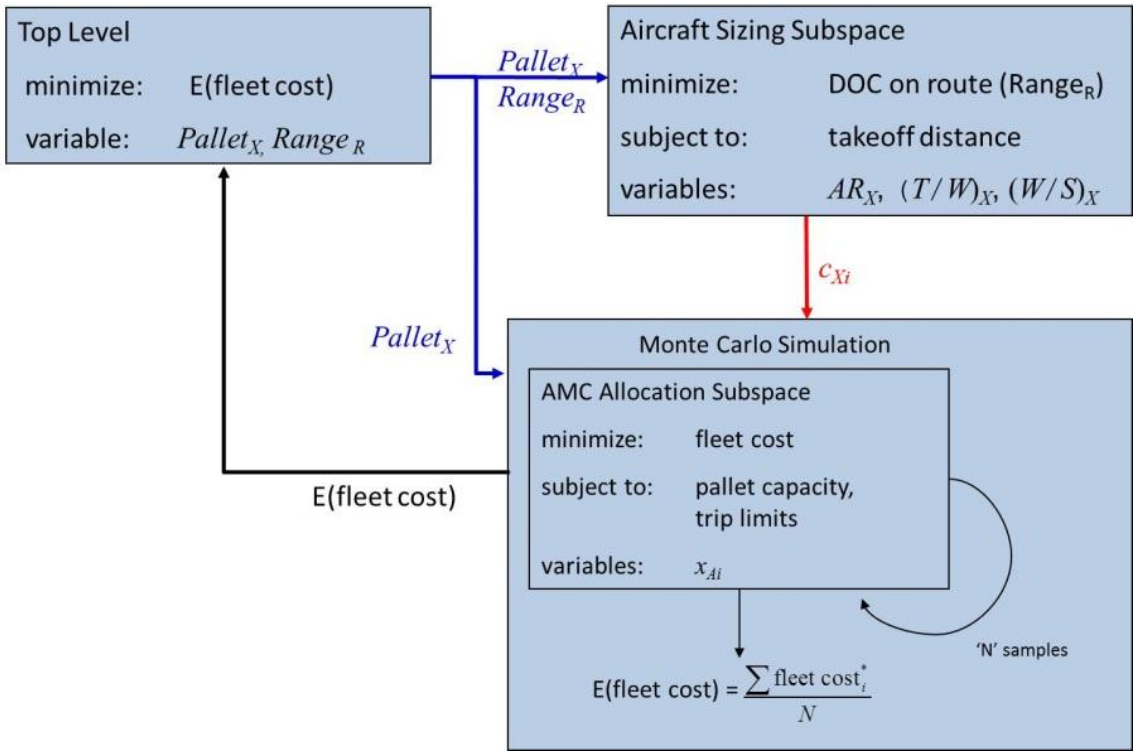

Figure 3.2 Subspace Decomposition of the Monolithic Optimization Problem with Monte Carlo Sampling for the Allocation Subspace

The resulting pallet capacity ($Pallet_x$) and range ($Range_x$) 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 on the "design mission" described by $Pallet_x$ and $Range_x$, subject to constraints on take-off distance.

The outputs of the aircraft sizing problem and top-level optimization problem, namely the cost of operating the yet-to-be introduced aircraft X on individual routes and pallet capacity now become inputs to the aircraft allocation problem.

As depicted in Figure 3.2, a Monte Carlo Sampling (*MCS*) technique allows calculation of an expected fleet-level direct operating cost over some set of non-deterministic scenarios; each sample requires solution of the integer programming allocation problem. Chapter 4 will explain the details of *MCS* as implemented in this work. The objective of each allocation problem is to minimize the fleet-level direct operating costs, subject to capacity and aircraft trip limits; the decision variables here are the number of aircraft of each type assigned to each route.

3.4 Aircraft Sizing Subspace

In the aircraft sizing subspace, aircraft sizing code is used for the analysis of new and existing aircraft. Then the optimization problem that uses the sizing code to determine the best combination of the aircraft design variables.

The problem formulation requires estimates of the cost, block time, and fuel consumed by each aircraft type in the fleet to determine the appropriate allocation of aircraft to the various routes in the network. A Purdue in-house aircraft sizing code, written in MATLAB, provides these estimates. *Jane's All the World's Aircraft*[27] provided the input parameters for the three existing aircraft types (C-5, C-17, 747-F) used in this study, as shown in Table 3.4.

Table 3.4 Existing Strategic Aircraft Characteristics Used in the Modeling

Parameter	**C-5**	**C-17**	**747-F**
Range at MTOW (nmi)	2,982	2,420	4,445
Pallet Capacity	36	18	29
***W/S* (lb/ft^2)**	135.48	161.84	137.34
T/W	0.205	0.263	0.286
AR	7.75	7.2	7.7

The problem formulation also requires calculation of aircraft operating costs. Because cost-estimating relationships exist and were readily available for commercial transport aircraft, this work uses these commercial aircraft *DOC* estimators, even if they may not directly match the costs of *AMC* operations. *DOC* estimates for commercial aircraft 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 3.3 shows the basic 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, 30-minute loiter, landing and taxi, and reserves are based on empirical data presented in

Raymer's textbook[31]. 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. In addition to the 30-minute loiter fuel, 6% reserve fuel is assumed, which accounts for a small amount of trapped and unusable fuel.

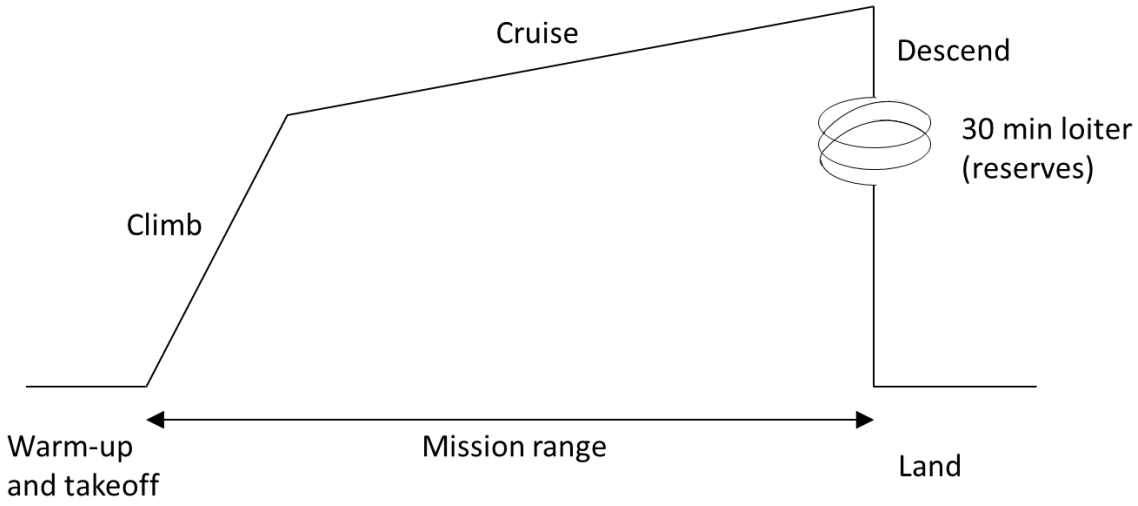

Figure 3.3 Mission Flight Profile

The payload-range curves for the existing aircraft fleet, depicted in Fig. 3.4, indicate the maximum payload carrying capacity of the aircraft as a function of the distance flown by the aircraft. Superimposed on this figure are symbols indicating the combination of payload carried and range flown per trip in the *GATES* data set. The payload-range curves for the existing fleet are constructed by using piecewise linear interpolation between specified points from charts used in *NRMO*[14]. The reason that some operated routes that are outside of the payload-range envelope of the corresponding aircraft is not clear; it is plausible that these flights that made

intermediate refueling stops without unloading or loading cargo, or that used aerial refueling (the C-5 and C-17 are capable of receiving aerial refueling). *GATES* data does indicate neither refueling stops nor aerial refueling.

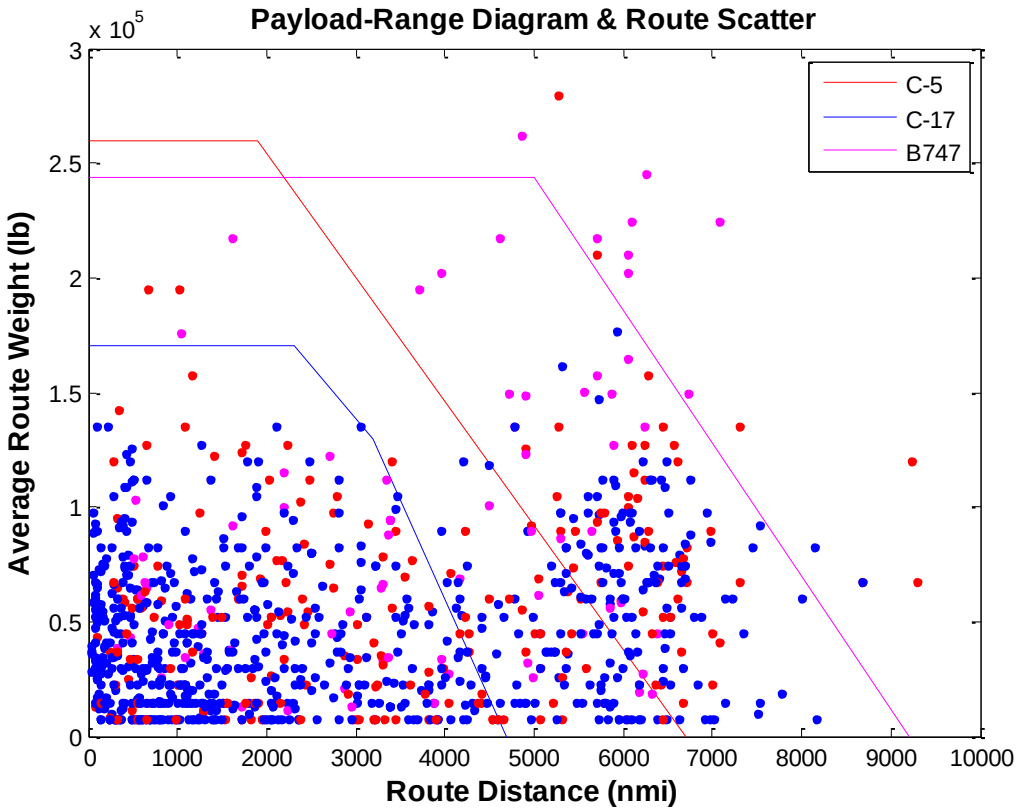

Figure 3.4 Payload Range Curves for Existing Fleet and Scatter of the Demand Routes in the *GATES*

The pallet capacity and design range of the yet-to-be introduced aircraft from the top-level problem then becomes an input 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, subject to constraints on minimum take-off distance. The aircraft design variables are aspect ratio, thrust-to-weight ratio and wing loading. There are many other design variables, but these three have significant impact on the size, weight,

and performance of the aircraft. The objective function can be altered to minimize alternative objectives such as fuel burn, and be subject to additional constraints as required. Equations (14) to (18) describe the nonlinear programming aircraft sizing problem.

Minimize

$$f = (DOC_{pallet,range})_X \tag{14}$$

Subject to

$$S_{TO}\left(Pallet_X, (AR)_X, (W/S)_X, (T/W)_X\right) \le D \quad \text{(Aircraft takeoff distance)} \tag{15}$$

$$6.0 \le (AR)_X \le 9.5 \quad \text{(Wing aspect ratio bounds)} \tag{16}$$

$$65 \le (W/S)_X \le 161 \quad \text{(Wing loading bounds, lb/ft}^2\text{)} \tag{17}$$

$$0.18 \le (T/W)_X \le 0.35 \quad \text{(Thrust-to-weight ratio bounds)} \tag{18}$$

Equation (14) is the objective function that seeks to minimize *DOC* for the mission described by the combination of $Pallet_x$ and $Range_x$ provided by the top-level problem. Equation (15) limits the aircraft design based on maximum takeoff distance to ensure that the new aircraft can operate at bases in the network close to the bounds of modern day cargo aircraft (e.g. C-5, C-17, 747-F, AN-124, etc.) descriptions shown in Equations (16) to (18).

3.5 Determination of Number of New Aircraft Needed

Formulating the problem that introduces the new aircraft along with the existing aircraft in the *AMC* strategic fleet requires knowledge of the number of new aircraft type X that are available for allocation. An approach using the metric of million ton-miles per day (MTM/D) enables a way to compute the number of new aircraft available for the allocation problem as a function of the pallet capacity of the new aircraft. By requirement, the *AMC* strategic fleet must serve the maximum possible demand scenario by requirement; this uses MTM/D to describe the scenario. In addition, AMC force structure programmers use MTM/D when funding out-year aircraft purchases and many civilian agencies are accustomed to visualizing the strategic airlift fleet capability in terms of MTM/D[32]. Mobility Capabilities and Requirement Study (*MCRS*) 2016[33] illustrate three different scenarios that the capacity of the strategic fleet must always meet. The peak for *MCRS* Case 1 required 32.7 MTM/D. *MCRS* Case 1 represents the highest level of modeled strategic airlift demand, which is to win two nearly simultaneous Major Regional Conflicts (*MRCs*) plus conduct smaller operations[34].

The value of MTM/D per aircraft uses the following equation.

$$MTM/D = \frac{(Block\ Speed) \times (Avg.Payload) \times (UTE\ Rate) \times (Productivity\ Factor)}{1,000,000} \tag{19}$$

MTM/D values for the existing strategic fleet aircraft are calculated using historical data, which informs the average payload, utilization rate (UTE rate), and productivity

factor for the C-5, C-17 and 747-F. A C-5 carries 0.1405 MTM/D, while the newer C-17 carries 0.1314 MTM/D[35]. A 747-F carries 0.1705 MTM/D, but this is not included in calculating the strategic airlift fleet MTM/D, because *AMC* does not directly operate the CRAF and cannot rely on these aircraft in the peak scenarios. Hence, having B-747Fs operate on a daily basis does not affect the number of aircraft X required to meet the peak demand scenario.

Table 3.5 MTM/D Values of Aircraft in the *AMC* Strategic Fleet.

Aircraft Type	**C-5**	**C-17**	**B-747**
MTM/D per a/c	0.1405	0.1314	0.1705

By counting unique tail numbers from the 2006 *GATES* data, 92 C-5s, and 145 C-17s are identified. If there were aircraft that were not recorded in the 2006 *GATES* or if aircraft never carried a palletized cargo in 2006, such aircraft tail number may not appear in the *GATES.* Thus, the identified fleet may not represent all the aircraft in service. The strategic fleet identified from the *GATES* results in a combined MTM/D of 31.98, which is less than the capability described in *MCRS* 2016.

To compute MTM/D for the new aircraft, the UTE rate is assumed to be 12 hr/day and productivity factor of 0.48 is assumed for the new aircraft, which is within the typical range of the strategic airlift fleet average value. The productivity factor describes the gross measure of an aircraft's expected useful ability to move cargo and passengers

to a user, expressed in percentage. If an aircraft makes a repositioning flight, the productivity factor is zero for that flight. Thus, newer aircraft does not necessarily have higher productivity factor. In the problem formulation, the existing fleet size and MTM/D value are reduced in proportional to the described demand. The number of new aircraft is calculated to satisfy the reduced MTM/D value with the reduced existing fleet.

3.6 Scheduling-Like Aircraft Allocation Subspace

There has been previous fleet allocation researches[7, 8] that have approached the issue of demand as being symmetric, due to the inherent nature of the observed demand (e.g. airline transportation return trips as published in Bureau of Transportation Statistics (*BTS)* data). By treating demand as being symmetric, it simplifies the allocation problem by reducing the number of decision variables needed. Given that the previous work for the simultaneous aircraft design and fleet allocation problem, a logical starting point for the AMC application, the formulation used in the deterministic demand model[36], used the symmetric demand / round trip assumption. However, while symmetric demand / round trip assumption may be acceptable for the simplified commercial passenger airline work, where the daily passenger demand from one specific airport to a second airport is nearly equal to the daily demand between the second airport and the first, many of the routes in the *AMC* network do not have symmetric demand. It is because *AMC* transports most cargos one way, and aircraft service a different base-pair segment instead of returning to its original base. To

investigate this issue, this research explored the demand asymmetry of the *GATES* data set using a developed metric, shown in Equation (22).

$$\text{Demand asymmetry} = \frac{\sum_{O=1}^{N}\sum_{D=1}^{N}\left|Demand_{O,D} - Demand_{D,O}\right|}{\sum_{O=1}^{N}\sum_{D=1}^{N}\left[\max(Demand_{O,D}, Demand_{D,O})\right]} \tag{20}$$

The equation calculates the demand asymmetry between bases where O is an origin base and D is a destination base. $Demand_{O,D}$ is the cargo demand from O to D measured in the number of pallets; $Demand_{D,O}$ is the demand from D to O. A fully symmetric demand route with the same number of pallets moving in both directions will have a measure of 0 demand asymmetry whereas a fully asymmetric demand network with demand flowing only in one direction will have a measure of 1.

The average of this measure for every base O-D pair in the *GATES* network gives an idea of how well or how poorly the symmetric demand and round trip assumption is for AMC operations. The demand network reconstructed from the *GATES* dataset shows 0.652 demand asymmetry, which means that the round trip assumption is poor. In comparison, from the 2006 Bureau of Transportation Statistics (*BTS*) data[37]using equation (20), the asymmetry results 0.0316. Thus, an alternative formulation that tracks individual aircraft in a more scheduling-like formulation appears better suited for *AMC* operations.

The AMC demand network is not a typical hub-and-spoke structure; the flight data also describes missions without any cargos, which indicate repositioning flights of an empty aircraft. Figure 3.5 depicts a simple network example where the round trip assumption is no longer applicable.

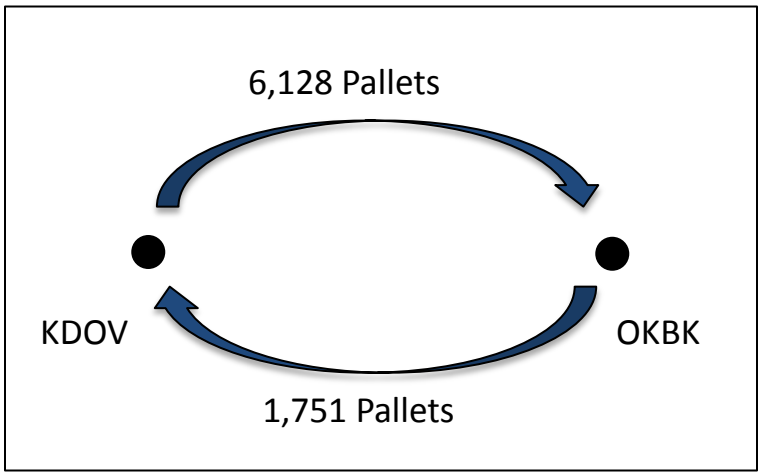

Figure 3.5 Change from the Round Trip Assumption to Scheduling-like Formulation is Necessary for the *AMC* Network

In the example route shown in Fig. 3.5, there are total of 6,128 pallets transported from KDOV (Dover Air Force Base, Delaware, US) to OKBK (Al Mubarak Air Base, Kuwait), and only 1,751 pallets transported from OKBK to KDOV in 2006. If the round trip assumption is applied, the flight from OKBK to KDOV will have same cost coefficient as the flight from KDOV to OKBK, although, in reality, the cost coefficient of the flight from OKBK to KDOV will be much lower. To address this issue of asymmetric demand, the round trip assumption is removed, and the cost coefficients are set up differently from that of allocation with the round trip assumption, where the cost coefficient of a flight originating from A to B is same as the cost coefficient of flight from

B to A. There are several cases to consider: base pairs with asymmetric demand, base pairs with one-way demand, and base pairs without any demand.

To demonstrate the cost coefficient calculation for these cases, a simple network consisting of three bases is devised; this appears in figure 3.6. In this network, the route from A to B has demand of 6 pallets and the route from B to A has demand of 5 pallets; this represents a base pair with asymmetric demand. The route from A to C has no demand, while the route from C to A has 10 pallet demand, and the routes between B and C has no demand in either direction.

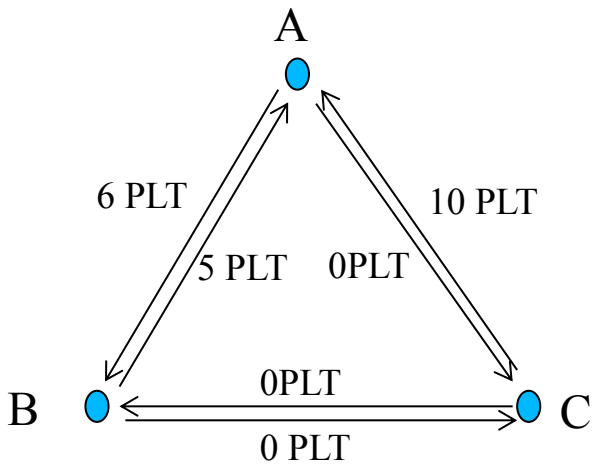

Figure 3.6 Simple Network to Consider Possible Cost Coefficient Cases in Scheduling-like Demand Network.

First, a very large number (VLN) is assigned as the cost coefficient for flights originating and arriving at the same base such that the allocation does not assign such a flight. For routes with asymmetric demands, the function calculates the cost coefficients depending on the amount of cargo carried on the individual flight. The

amount of cargo carried on the flight depends on the demand value of that day. This uses the same performance predictions as in the aircraft sizing code to predict the direct operating cost for each route. For routes with one way demand, the route with demand will have cost coefficient calculated individually similar to asymmetric demand case, and for returning flight, the function calculates the cost coefficient of flying aircraft with no cargo. It is computationally more expensive to calculate cost coefficient for individual flights depending on the amount of cargo and route distance, but this will calculate the flight cost more accurately because payload weight affects the amount of fuel consumed, which directly affects the operating cost of that segment. Which this formulation, a repositioning flight with no payload will have a lower operating cost. For routes with no demand, both routes will have the cost coefficient of flying aircraft with no cargo. This case is specific to the scheduling-like formulation, because routes without demand do not appear in the formulation using the round trip assumption. This allows flights that originate from B to carry payload from A to C then return to its original location B when necessary without backtracking its routes. The sample cost coefficient, shown in Fig 3.6, represents a possible calculation result for the network and demand. The numbers in Table 3.6 here are selected to illustrate the issues associated with the demand shown and might indicate dollars per flight.

Table 3.6 Cost Coefficient Result of the Simple Network

Origin \ Destination	A	B	C
A	VLN	3,000	500
B	2,500	VLN	200
C	5,000	200	VLN

The scheduling-like monolithic optimization problem simultaneously considers the aircraft design and allocation of the fleet's aircraft to meet demand obligations. This scheduling-like formulation addresses asymmetric demand nature of the *AMC* network, which the allocation problem with round-trip assumptions cannot. The system-of-system level representation involves the confluence of resource allocation (under uncertainty) and aircraft design perspectives that make up the monolithic problem; this encompasses the resource allocation problem under uncertainty (stochastic integer programming) and the aircraft design problem (non-linear programming) resulting in a stochastic mixed integer non-linear programming problem, which is typically very difficult to solve. The following equations represent the resulting optimization problem:

Minimize

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

(*DOC* or Fleet fuel usage) (21)

Subject to

$$\sum_{i=1}^{N} x_{p,k,i,j} \geq \sum_{i=1}^{N} x_{p,k+1,i,j} \quad \forall k = 1,2,3...K, \quad \forall p = 1,2,3...P, \quad \forall j = 1,2,3...N$$ (Node balance constraints) (22)

$$\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{p,k,i,j} \cdot BH_{p,k,i,j} \leq B_P \quad \forall p = 1,2,3...P$$ (Trip constraints) (23)

$$\sum_{p=1}^{P}\sum_{k=1}^{K} Cap_{p,k,i,j} \cdot x_{p,k,i,j} \geq dem_{i,j} \quad \forall i = 1,2,3...N \quad \forall j = 1,2,3...N$$ (Demand constraint) (24)

$$\sum_{i=1}^{N} x_{p,1,i,k} \geq O_{p,i} \quad \forall p = 1,2,3...P, \forall i = 1,2,3...N$$ (Home base constraints) (25)

$$S_{TO}\left(Pallet_X, (AR)_X, (W/S)_X, (T/W)_X\right) \leq D$$ (Aircraft takeoff distance) (26)

$$14 \leq Pallet_X \leq 42$$ (Design pallet capacity bounds) (27)

$$2400 \leq Range_X \leq 4000$$ (Range at design capacity bounds) (28)

$$6.0 \leq (AR)_X \leq 9.5$$ (Wing aspect ratio bounds) (29)

$$65 \leq (W/S)_X \leq 161$$ (Wing loading bounds, lb/ft^2) (30)

$$0.18 \leq (T/W)_X \leq 0.35$$ (Thrust-to-weight ratio bounds) (31)

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

$$(AR)_X, (W/S)_X, (T/W)_X$$ (Continuous aircraft design variables) (33)

Equation (21) is the objective function that seeks to minimize the expected fleet-level direct operating cost (*DOC*) by altering the pallet capacity and maximum payload

range of the new aircraft X, where $C_{p,k,i,j}$ indicates the cost coefficient or fuel cost coefficient of the trip for k^{th} trip for aircraft p from base i to base j. This equation can be modified to study alternate objectives such as directly minimizing fuel consumption, etc.; there is nothing in the overall approach that limits this objective. The constraint Equation (22) is the balance and sequencing constraint that ensures that the $(k+1)^{th}$ trip of an aircraft out of a base occurs only after k^{th} trip into that base. Equation (23) limits flights to only occur within daily utilization limit (20 hours) of the aircraft where $BH_{p,k,i,j}$ indicates the block hours needed for the kth trip of aircraft p from base i to base j. Number of flights is also limited to 3 segment flight per day. Equation (24) ensures that carrying capacity of combined flights meets the demand, where $Cap_{p,k,i,j}$ indicates the pallet carrying capacity of the kth trip of aircraft p from base i to base j. Equation (25) ensures that the first trip of each aircraft originates at an initial location to start the time period the allocation problem covers. This could be the home base of the aircraft. When incorporating uncertainty these initial locations are randomly generated. Equation (26) limits the aircraft design based on maximum takeoff distance to ensure that the new aircraft can operate at bases in the network; as before, this is simplistic, but demonstrates how other aircraft design constraints might be implemented. Equations (27-28) describe limits on the payload and range (in nautical miles) capabilities of the new aircraft. The continuous design variables-aspect ratio, thrust-to-weight ratio, and wing loading (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 (29-31). Solving the aircraft design sub problem provides a solution that describes the features of the new aircraft with the lowest *DOC* (fuel usage) for the specified design range. The cost coefficients of the new aircraft for the various routes in the network are then estimated. The formulation represents minimizing operating cost while meeting demand for a given time period, such as one day of operations, or for the entire year of operations depending on the setup of demand data.

This formulation is designed to adapt to the *AMC* fleet network, which is asymmetric in nature and is more reflective of actual *AMC* operations. The aircraft in the fleet are not required to return to their home base at the end of the day. The Generic Algebraic Modeling System (*GAMS*)[38] software package, accessed through a MATLAB[39] interface solves the allocation problem, using the CPLEX solver option.

CHAPTER 4. MODELING UNCERTAINTY

4.1 Limitations of Deterministic Model

When considering an uncertain demand network in which the number of packages on a given route or segment can vary on a day-to-day basis, an aircraft design optimized for one specific demand scenario may not be optimal for other demand scenarios. As stated before, the demand network and size fluctuates very much in the *AMC*. To design a tool that suggests an aircraft design and evaluates fleet level performance of this new aircraft along with existing aircraft under the uncertain demand, a deterministic scenario is not suitable. Another important characteristic of the *AMC* network, in addition to the fluctuating demand, is the uncertain initial location of aircraft. Unlike the commercial hub-and-spoke model used in Refs. 7and 8, in which initial location of the aircraft could be the hub airport, the origin location of aircraft are not fixed to represent *AMC* strategic fleet operations. The priorities associated with the cargo makes it even more difficult suggesting that aircraft cannot have a regular schedule for cargoes with higher priority, and that the aircraft often cannot be fully loaded (i.e., they need to leave for their destination before cargo demand reaches a level that would fill or nearly fill the aircraft).

4.2 Monte-Carlo Sampling Technique

The cost of operating a fleet is subject to the trip demand characteristics – a quantity that is typically uncertain. Future demand can only be predicted, and historical demand used to inform those predictions can show significant fluctuations in the level of demand. While passenger demand between origin-destination pairs is fairly constant on a day-to-day basis for commercial or passenger airline route networks, this is not the case for the *AMC* operations, which typically experiences high levels of variation in demanded trips and cargo size[9]. 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. Any systems designer/planner needs to consider the uncertainty in the network as part of the decision-making framework about a new cargo aircraft. Figure 4.1 shows the fluctuation of the pallets transported daily from ETAR (Ramstein Air Base, Germany) to KWRI (McGuire Air Force Base, New Jersey, US), two bases that appear frequently as origins and destinations in the *GATES*.

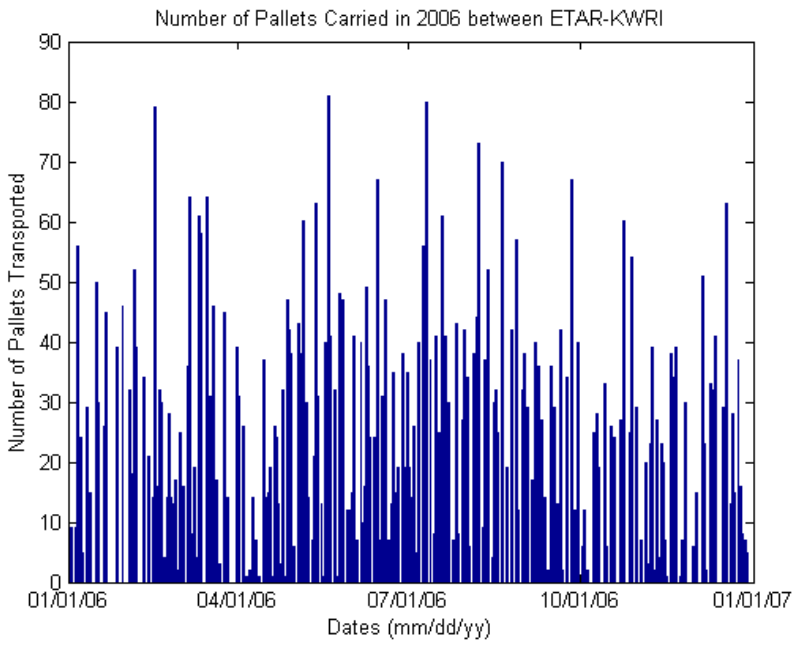

Figure 4.1 Distribution of Number of Pallets Transported by Date on a Sample on the ETAR to KWRI Route from *GATES* Data Set for 2006

Figure 4.2, showing the histogram of the number of pallets transported per aircraft per day reveals that many of the days, the aircraft are very lightly loaded. This research addresses the issue of uncertainty through a MCS approach, following from a concept that appears in Ref. 9 for air taxi and fractional aircraft management operations. The MCS technique samples one-day route demand from a historical demand data distribution of each route using information like that in Fig. 4.2 and then solves an allocation problem for each set of sampled route demand. The approach here uses the segment demand for pallets, so that the demand between two base pairs may actually be correlated to demand between other base pairs. The work presented here, however, assumes that the daily demand between bases is independent of each other.

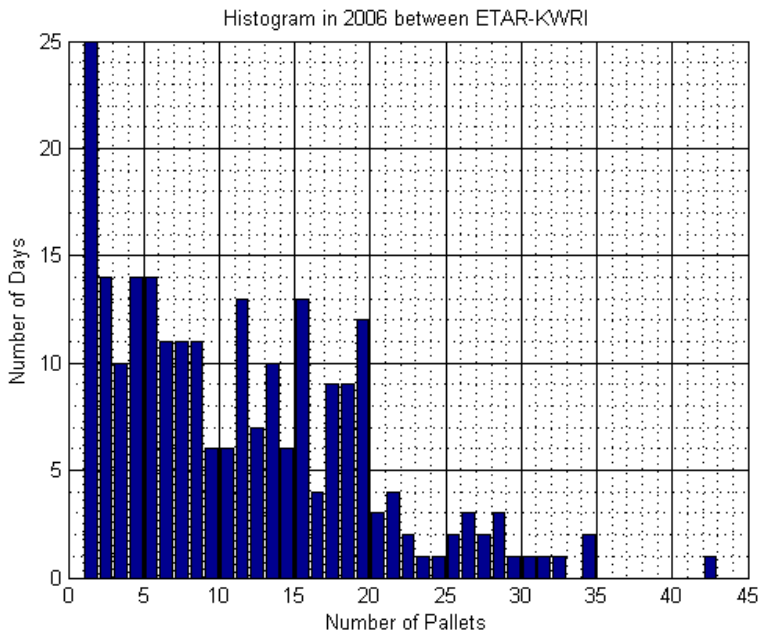

Figure 4.2 Histogram of Number of Pallets Transported Daily on the ETAR to KWRI Route from 2006 *GATES*

For the AMC problem, the initial location of each aircraft to start the day of operations is also sampled from a distribution. The MCS technique is computationally expensive, because this requires solution of an integer programming problem for each sample of demand and aircraft starting locations. The expected fleet DOC used as the objective in the top-level problem is then the average fleet cost across all the sample instances that have different allocations of demand and fleet aircraft starting home bases.

4.3 Random Initial Aircraft Location Generation

Without the hub-and-spoke network and a round trip assumption, the scheduling-like assignment problem requires a starting location for each aircraft. Therefore, the

initial locations of aircraft in the *AMC* network needs to be properly modeled, because *AMC* network does not have a hub-and-spoke network nor use a round trip assumption. However, due to the computational expense associated with MCS and lack of clear aircraft starting location information in the *GATES* data, a simple selection method generates random starting locations for the *AMC* aircraft as part of considering uncertainty. In the random starting location selection, each aircraft in the fleet is randomly distributed to the demand network with uniform distribution – each air base is equally likely as a starting location. This may require the first flight of aircraft to be a repositioning flight in order to load demanded pallets. The random starting location selection may assign an aircraft to a remote base with distance to the nearest base greater than the maximum range of the aircraft. In this case, an infeasible cost coefficient (i.e., a very large cost coefficient) discourages repositioning of the aircraft from the remote base. In the instance when the random initial location selection assigns too many aircraft to a remote base unable to satisfy the demand network, the starting location is regenerated.

CHAPTER 5. RESULT

5.1 Three-Base Problem

A very simple, illustrative 'baseline' problem reflective of *AMC* operations for an initial study consists of six directional routes and a single period of demand between three bases. Figure 5.1 depicts the network for the baseline problem. 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 in minimizing fleet-wide direct operating costs; this scenario uses a deterministic demand for simplicity. The airbase locations and the route data are extracted from the *GATES*.

Figure 5.1 Locations of Bases in the Three-base Problem Network

Figure 5.2 shows the demand size and the network structure of the three-base problem. The three bases in the network are ETAR (Ramstein Air Base, Germany), LTAG (Incirlik Air Base, Turkey), and OKBK (Al Mubarak Air Base, Kuwait); the routes connecting these bases are amongst the most popular routes in the GATES dataset. The shortest distances between the routes are calculated using ICAO coordinate system. The maximum distance of the three chosen routes is 2,193 nautical miles, which means that all three types of current strategic airlift aircraft to provide service on these routes without refueling. The intent is to allocate aircraft to the three routes to satisfy all cargo demand. For this initial study, the average weight of each pallet is assumed 7,500 lb because more than 95% of pallets in *GATES* weigh less than 7,500 lb. The route from

LTAG to OKBK has no pallet demand, which indicates a directional demand route with route asymmetry of 1.0.

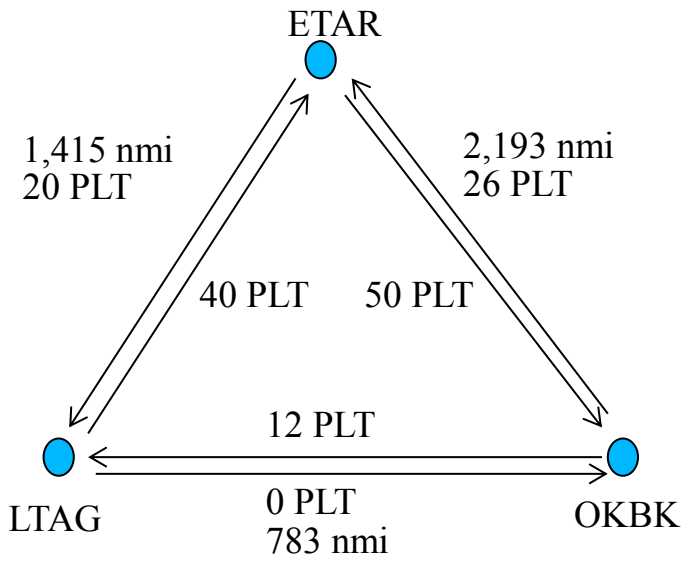

Figure 5.2 Schematic of Three-Base Allocation Problem

5.1.1 Baseline Scenario Allocation

The baseline scenario describes the current fleet operation without the introduction of the new aircraft type X. In the baseline scenario, the fleet size consists of five of each aircraft types: 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 supporting the AMC strategic fleet. The baseline allocation results $ 1,892,400 for fleet level DOC and 535,831 gallons of aviation fuel consumed to satisfy the demand. The allocation result provides a baseline to measure the impact of introducing the yet-to-be-designed aircraft into the fleet mix.

5.1.2 Introduction of New Aircraft

Three of the new type X aircraft are introduced to the existing baseline fleet in this scenario. The number of the new aircraft to be introduced is pre-determined for the three-base scenario, because the size of the demand network is too small to meaningfully calculate MTM/D of the fleet. The subspace decomposition approach of Figure 3.1 is then employed, using range and pallet capacity as the top-level design variables for the new, yet-to-be designed aircraft X. The range is a continuous variable and pallet capacity is an integer variable, thus the top-level problem is a MINLP problem. However, because the size of the problem is small, partial enumeration approach can solve this problem without high computational cost. The top-level optimization problem for the problem is addressed using a simple, partial enumeration scheme. Using partial enumeration scheme, 182 combinations or design range and capacity were considered with range varying from 2,400 nmi to 3,800 nmi in increments of 200 nmi, and pallet capacity varying from 14 to 40 in increments of 1 pallet. In this particular scenario, the demand is deterministic, and the simulation allocates aircraft for various routes in the network once for each top-level function evaluation. The descriptions of the aircraft type X, which are the design variables determined by the aircraft sizing optimization sub-problem, along with the DOC and fuel cost savings compared to the baseline scenario appear in Table 5.1. Also appearing in Table 5.1 is the time required for the enumeration.

Table 5.1 Optimal Aircraft Design and Allocation Result of the Three-Base Fleet Allocation Problem

Variables, Parameters, Objectives	**Enumeration**
Computation Time	37 hr 30 min
# of Aircraft X used in Allocation	3
Design Range (nmi)	2,400
Pallet Capacity	14
Wing Loading (lb/ft^2)	134.52
T/W	0.27
Aspect Ratio	6.93
Baseline Fleet DOC	$ 1,892,400
Baseline Fleet Fuel (gal)	535,831
Allocation with New Aircraft Fleet *DOC*	$ 1,883,100
Allocation with New Aircraft Fleet Fuel (gal)	528,302
Δ *DOC*	-0.49 %
Δ Fuel Usage	-1.41 %

The result suggests the introduction of three aircraft type X with a design range of 2,400 nmi, and pallet capacity of 14. The addition of three aircraft X to the three-base

network will save 0.49 % in fleet-level DOC and 1.41 % of fleet-level fuel consumption compared to the baseline scenario. The optimal solution suggests a small pallet capacity aircraft – at least relative to the other aircraft in the AMC strategic fleet that takes advantage of the low pallet demand in the network. The smaller pallet capacity aircraft has a higher load factor compared to existing aircraft thus resulting in a lower cost per pallet transported. The enumerated design space for the top-level problem is shown appears in Figure 5.3.

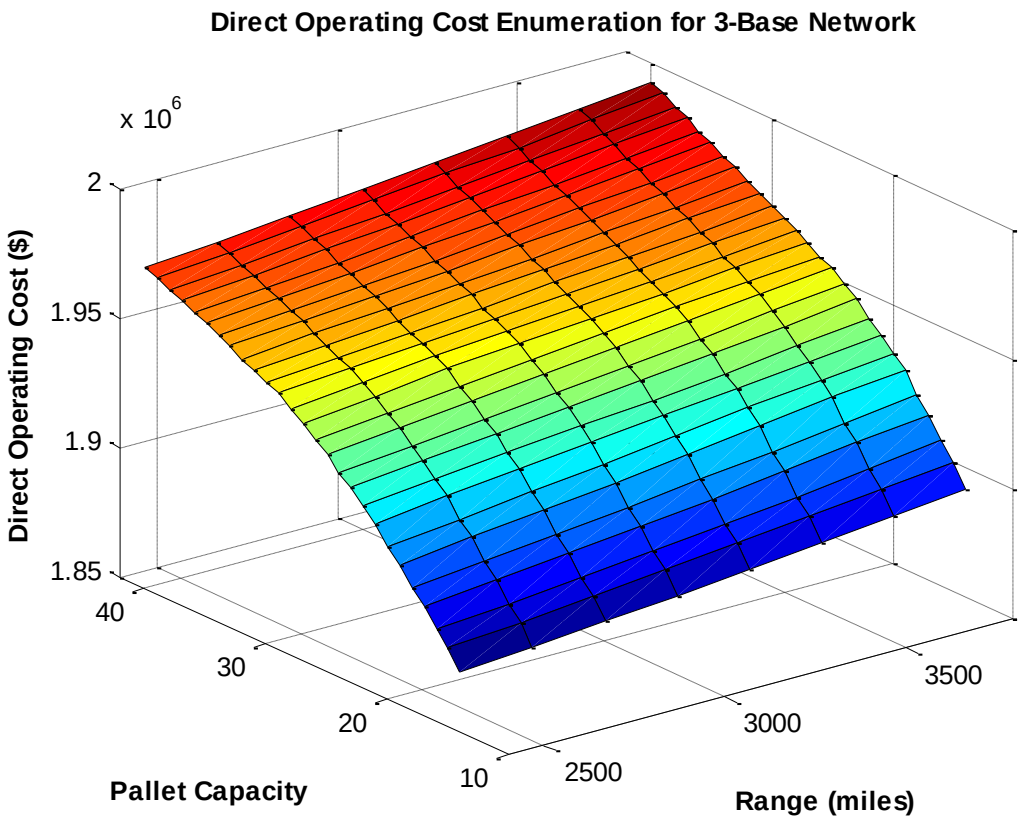

Figure 5.3 Enumeration Result from Three-Base Demand Problem

The enumeration result suggests that the smaller and shorter-range aircraft is best suited for the three-base demand network. In addition, the surface in Fig. 5.3 is very

smooth because the demand network is deterministic and the lower bound on range of 2,400 nmi is sufficient to fly all of the routes in the three-base network.

The three-base problem provides a simplified example network to illustrate the decomposition approach and demonstrate its ability to generate plausible solutions. Increasing the size of the network to investigate the ability to solve larger and more complex network system using decomposition is appropriate.

5.2 Extended Results for 22-Base network from GATES

The increased size problem is selected from one day of operation from the GATES dataset. Total of 310 pallets are transported amongst 22 bases in the network. The very sparse nature of the AMC network results in only 23 routes between 22 bases. The longest route in the network is 5,711 nmi, which only type A aircraft, representing C-5, can service at the full capacity, and the mean distance is 1,947 nmi. The weight of each pallet is assumed 7,500 lb. Figure 5.4 depicts the 22-base network used in this scenario.

Figure 5.4 Geographical Locations of Bases and Demand Network in the 22-Base Route Network

The actual size of the strategic airlift fleet dedicated to cargo transport is obtained from the *GATES* by accumulating unique tail numbers; this results in a fleet composition of 92 C-5s, 145 C-17s and 69 747-Fs that operated in 2006. In this 22-base problem, which is a subset of the entire network of bases served by AMC's strategic fleet, the fleet size is reduced from the entire 2006 in proportion, such that the combined capacity of the existing fleet can easily meet the demand. The reduced existing fleet consists of 6 type A aircraft representing the C-5s, 9 type B aircraft representing the C-17s, and 5 type C aircraft representing the 747-Fs. Number of new aircraft to be introduced to the existing fleet depends on the size of the new aircraft. Figure 5.5 presents the top-level optimization problem design space as a function of pallet capacity and design range for the new aircraft; these results were obtained through partial enumeration. Using partial enumeration scheme, 364 combinations or design range and

capacity were considered with range varying from 2,400 nmi to 3,800 nmi in increments of 100 nmi, and pallet capacity varying from 14 to 40 in increments of 1 pallet.

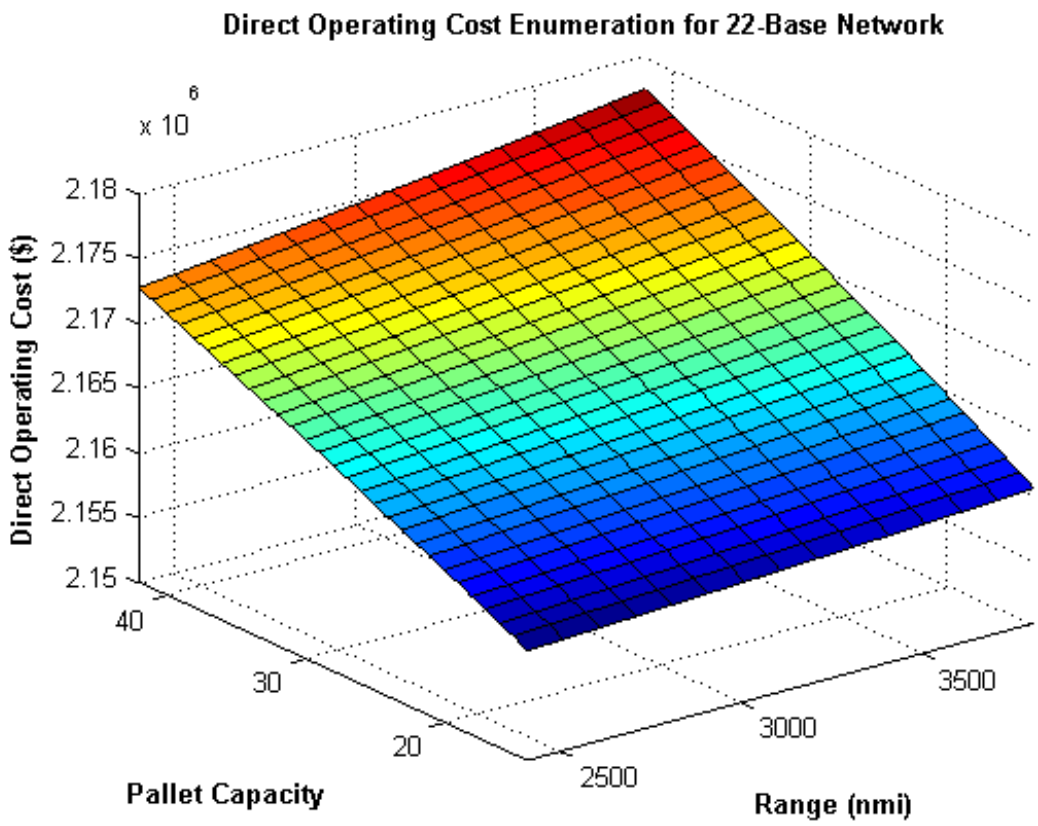

Figure 5.5 Enumeration Result from 22-Base Demand Problem

The result from enumeration suggests introduction of 7 aircraft type X to the existing fleet. The new aircraft have a maximum pallet capacity of 14, using the design pallet weight of 7,500 pounds, and design range at MTOW of 2,400 nmi. The wing loading of the aircraft X is 134.52 lb/ft^2, the thrust-to-weight ratio is 0.268, and aspect ratio is 6.94. The introduction of the new aircraft will result in 1.59 % *DOC* savings, and 1.17 % fuel savings compared to the baseline allocation using only existing aircraft. The

enumerated surface suggests that a small, short-range aircraft is best suited to reduce the fleet-level operating costs for the deterministic demand network.

The top-level problem combines integer (pallets) and continuous (range) variables, which cannot be solved with gradient-based methods. The partial enumeration scheme of the top-level design variables can search the discontinuous design space, as demonstrated above. Additionally, heuristic optimization techniques such as Genetic algorithm (GA) and Simulated Annealing (SA) are candidates for solving the top-level optimization problem. The next investigation using the 22-base problem assesses the computational efficiency and tractability of solving the top-level problem using GA and SA schemes. The GA is set such that it has resolution of 100 nmi between discretized values of design range and a resolution of a single pallet by controlling the bits describing the top-level design variables. Design range at MTOW uses 4 bits, while the pallet capacity of the new aircraft uses 5 bits for encoding the design variables. The implementation of SA used here treats both the pallet capacity and design range as continuous variables, possibly resulting in a design with fractional pallet capacity. Table 5.2 compares the results from top-level optimization techniques with the partial enumeration technique. This comparison includes the computational time to obtain the results.

The aircraft X descriptions obtained through GA are identical to that of the enumeration, because the variables describing the new range and payload capacity are

the same. The allocation result obtained through GA matches the enumeration solution resulting in 1.70 % DOC savings and 1.26 % fuel savings compared to the baseline scenario. The small demand size of the 22-base network is the primary reason for the low *DOC* and fuel savings.

The results from using simulated annealing to solve the top problem result in the assignment problem using seven new type X aircraft with maximum pallet capacity of 14.09, design range at MTOW of 2,469 nmi, the wing loading of 124.40 lb/ft^2, the thrust-to-weight ratio of 0.248, and aspect ratio of 6.57. This very closely matches the description of aircraft X from enumeration result. However, SA converged to an optimal pallet capacity value of 14.09, which is not suitable for the aircraft description because this should be an integer value. Rounding the pallet capacity is not always a reasonable option, given the discrete nature of the allocation problem. The allocation of the aircraft in the network could differ significantly for a unit change in pallet capacity of the new aircraft. In addition optimizing the variables in the continuous domain, SA required additional computational expense to reach the optimal solution. Hence, of the three options investigated here, the GA is chosen as the top-level optimization technique for its relative computational efficiency and ability to treat the number of pallets as an integer.

Table 5.2 Optimal Aircraft Design and Allocation Result of 22-Base Fleet Allocation Problem from Enumeration, GA and SA

Variables, Parameters	**Enumeration**	**GA**	**SA**
Computation Time	8 hr 54 min	3 hr 30 min	3 hr 48 min
# of Aircraft X used in Allocation	7	7	7
Design Range (nmi)	2,400	2,400	2,469
Pallet Capacity	14	14	14.09
Wing Loading (lb/ft^2)	134.52	134.52	124.40
T/W	0.268	0.268	0.248
Aspect Ratio	6.94	6.94	6.57
Baseline Fleet DOC	$2,193,400		
Baseline Fleet Fuel (gal)	598,140		
Allocation with New Aircraft Fleet *DOC*	$ 2,158,400	$ 2,158,400	$ 2,167,700
Allocation with New Aircraft Fleet Fuel (gal)	591,116	591,116	593,161
Δ *DOC*	-1.60 %	-1.60 %	-1.17 %
Δ Fuel Usage	-1.17 %	-1.17 %	-0.83 %

The payload-range diagram of the aircraft X with a design range of 2,400 nmi and a capacity of 14 pallets is shown in Figure 5.6 compared to the existing aircraft in the fleet.

From the design result, the new aircraft will sever shorter, low demand routes in the network.

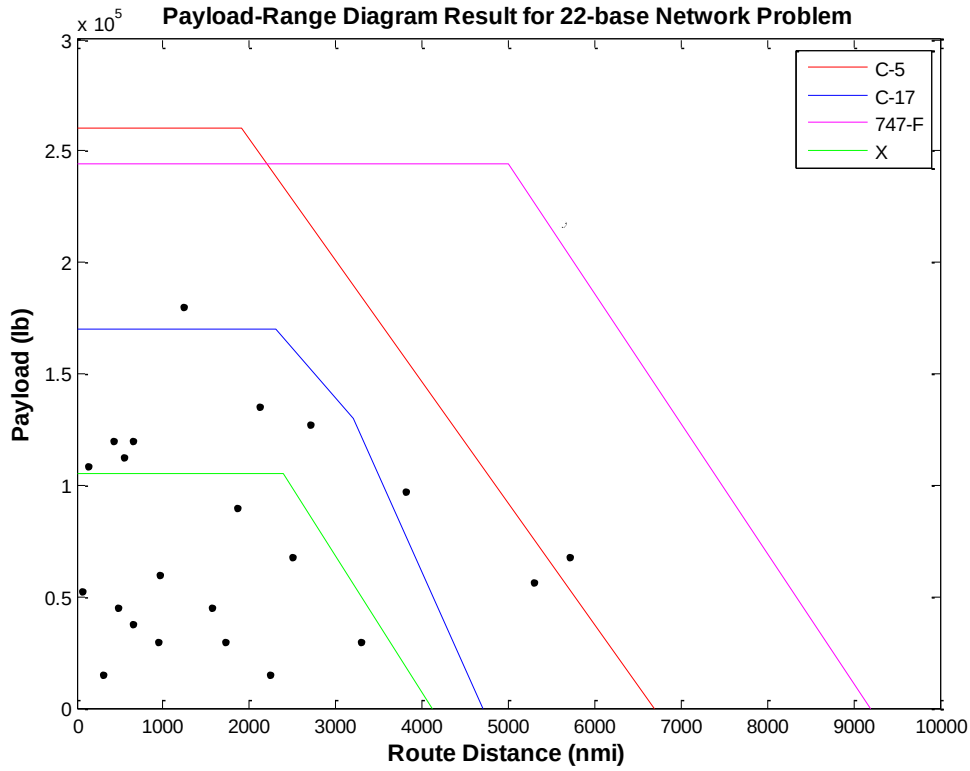

Figure 5.6 Payload-Range Diagram Result and Demand Network Scatter from *GATES* for 22-base Network Problem with Aircraft type X

5.3 Uncertain Demand Scenario

With GA selected as the top-level optimization technique, the same 22-base network with uncertainty in demand is considered. The number of bits describing the design range is set to 4 bits to have a resolution of 100 nmi and 5 bits for pallet capacity at MTOW to have a resolution of a single pallet. To address uncertainty, a MCS approach is used where the initial location for each aircraft is sampled from a uniform distribution, and the uncertainty in pallet demand is sampled from the historical

distributions for each route (see, for example, Figure 4.2). The approach here assumes that these segment demand distributions are independent of each other.

Because of the computational cost, the sampling strategy results in 30 different allocation problems solved in the allocation subspace of the decomposition strategy. The average value of the objective function, which is fleet *DOC* in this case, for each description of the new aircraft from aircraft sizing subspace, provides the top-level objective function value. The relatively small number of Monte Carlo samples limits the accuracy of the average fleet *DOC* value, but this does show the basic approach used to address some of the uncertainties in the network. The intent is to obtain an aircraft description that is more robust to the uncertain demand network and the random initial aircraft location, because fluctuation in demand is high in the *AMC* network as shown before in Figures 4.1 and 4.2.

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 based on the historical distributions for each route for each demand-sampling loop changing the demand size. Table 5.3 shows the GA optimized description of the aircraft X in the 22-base fleet allocation problem and its savings compared to the baseline solution.

Table 5.3 Optimal Aircraft Design and Allocation result of 22-base Fleet Allocation Problem with Uncertainty in Demand.

Variables, Parameters, Objectives	**GA**
Computation Time	37 hr 30 min
# of Aircraft X used in Allocation	5
Design Range (nmi)	3,300
Pallet Capacity	24
Wing Loading (lb/ft^2)	136.00
T/W	0.271
Aspect Ratio	7.0
Baseline Fleet DOC	$ 2,182,700
Baseline Fleet Fuel (gal)	604,079
Allocation with New Aircraft Fleet *DOC*	$ 2,158,700
Allocation with New Aircraft Fleet Fuel (gal)	578,698
Δ *DOC*	-1.10 %
Δ Fuel Usage	-4.20 %

GA allocation with new aircraft results in $ 2,158,700 fleet *DOC* and 578,698 gallons of fuel used for the 22-base network, a saving of 1.10 % in fleet *DOC* compared

to the baseline result of $ 2,182,700, and 4.20 % saving in fuel from the baseline result of 604,079 gallons with the introduction of 5 of aircraft type X. The aircraft type X description results in a design range of 3,300 nmi, capacity of 24 pallets, wing loading value of 136.00 lb/ft^2, thrust-to-weight ratio of 0.271 and aspect ratio of 7.00.

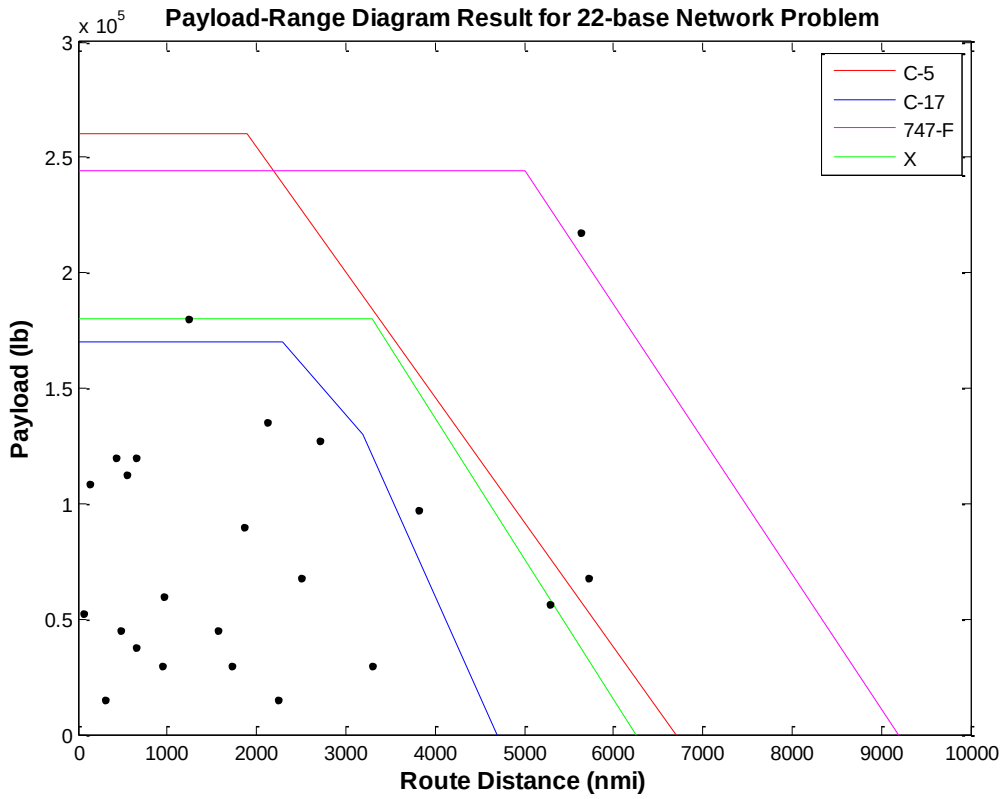

Figure 5.7 Payload-Range Curves for Existing Fleet and the Aircraft Type X from the 22-base Network Problem

A very coarse design space with a resolution of 4 pallets between evaluated values of design capacity and 200 nmi between evaluated values of design range was enumerated to investigate the impact of uncertain demand and uncertain home base. The Monte Carlo sample size is only 30 because larger sample size becomes computationally too expensive. The result suggests very different aircraft compared to

the result from deterministic scenario. The aircraft X description result from enumeration suggests the design range of 3,000 nmi, capacity of 18 pallets. The resulting aircraft design from the enumeration may be different from that of GA due to the very coarse grid as well as uncertain demand and random home base constraint.

The enumerated space shown in Figure 5.8 illustrates the non-smooth topology of the Fleet DOC solution space in the case of uncertainty in demand and aircraft initial location. The surface topology uses the mean value of fleet *DOC* based on the 30 samples taken for each combination of design range and pallet capacity. As in the case when the GA provided the search for the top-level problem, the results using an enumeration approach while incorporating uncertainty in demand suggests a longer design range and slightly larger aircraft compared to the deterministic case. The arrow indicates the optimal result from the GA optimization. The optimal solution from the GA does not match the enumeration result, largely because the enumeration does not have the same resolution. The fleet *DOC* result from enumeration was $ 2,142,000 with new aircraft, which is a saving of 3.19 % from $ 2,212,700 baseline scenario.

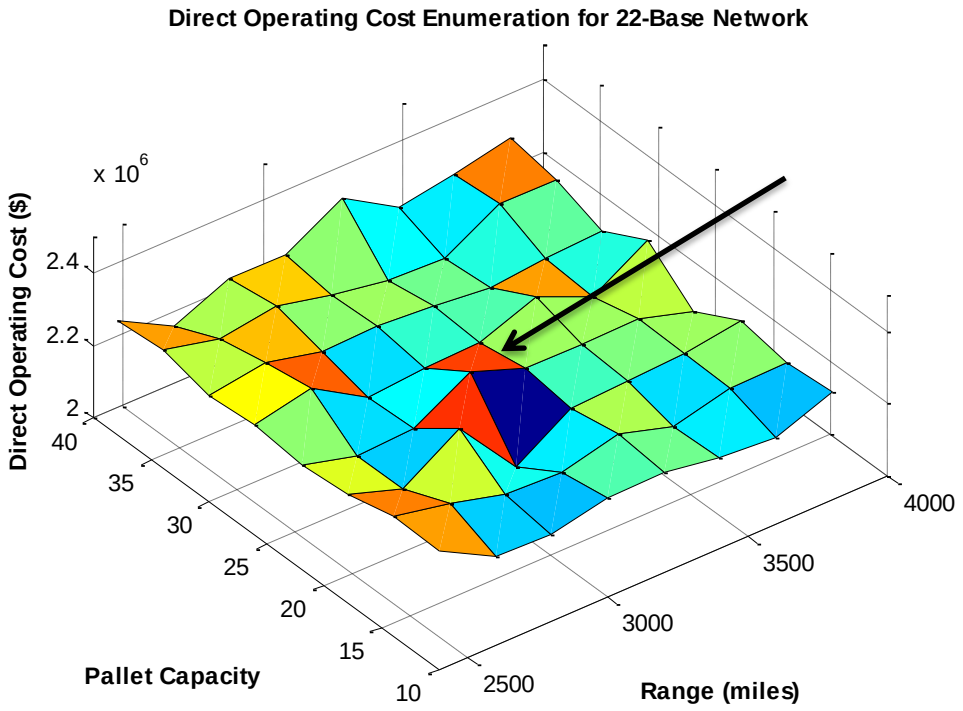

Figure 5.8 Enumerated Surface and GA Aircraft Design Results (shown with arrow) from 22-base Network with Uncertain Demand and Home Base

Table 5.4 shows the decomposition approach result of the aircraft design from the deterministic demand scenario with decomposition approach result of the aircraft design using the uncertain demand scenario. While the aircraft designed considering uncertain demand scenario resulted a 1.10 % DOC saving and 4.20 % fuel savings, the aircraft design from the deterministic demand scenario, but evaluated using an uncertain demand, had *DOC* cost increases of 2.03 % and only 0.94 % fuel savings. While this outcome may be expected, this comparison shows that aircraft design optimized for a single deterministic scenario may not be an optimal solution for different demand scenarios.

Table 5.4 Aircraft Design X from the Uncertain Demand Scenario and the Deterministic Demand Scenario Allocated in the Uncertain Demand Network

	Aircraft X design result from uncertain demand	**Aircraft X design result from deterministic demand**
Expected Baseline *DOC*	$ 2,182,700	
Expected Baseline Fuel (gal)	604,079	
Expected *DOC* from Allocation Including New Aircraft X	$ 2,158,700	$ 2,227,000
Expected Fuel from Allocation Including New Aircraft X (gal)	578,698	598,416
Δ *DOC* compared to Expected Baseline *DOC*	-1.10 %	2.03 %
Δ Fuel Usage compared to Expected Baseline Fuel	-4.20 %	-0.94 %

Using the optimal aircraft design description, acquisition decision practitioners can benefit by assessing the impact of the new platform integrated into the existing fleet under uncertain operational scenarios. With addition of uncertainty in demand and random home base generation, the simulation result suggests a design that is more flexible to fluctuations in demand; compared to a design that does not incorporate uncertainty in demand. However, the current formulation and implementation is computationally very expensive even for a network consisting of only 22 bases, and 30 Monte Carlo samples to address uncertainty. The simulation tool will need improvements to make it computationally less expensive before extending the framework for the full-scale *AMC* network with 170+ bases as described in the *GATES*.

5.4 Uncertain Demand Scenario with Relaxed Design Constraint

Many of the missions in the *AMC* network are short range and have demand for a small number of pallets as shown from figure 3.4. The representative 22-base network also has many routes that are short range with small demand. The design of an aircraft that is outside of strategic airlift aircraft definition could possibly save more fuel for day-to-day operations. Currently, very large aircraft are allocated to carry missions with short range and low demand. In this scenario, the aircraft design subspace allows the design of aircraft that is not limited to the strategic airlift; the result might illuminate what kinds of fleet-level operating cost efficiencies are available.

Again, GA is selected as the top-level optimization technique, for the same 22-base network with uncertainty in demand. The number of bits describing the design range is set to 5 bits to have a resolution of 100 nmi between 1,000 and 4,100 nmi and 5 bits for pallet capacity at MTOW to have a resolution of a single pallet varying from 10 to 41 pallets. This design range and pallet capacity can result in smaller aircraft compared to the traditional *AMC* strategic airlift aircraft. The *AMC* allocation subspace is sampled 30 times to address uncertainty in a manner consistent with the previous scenario.

Table 5.5 Solution to 22-Base Fleet Allocation Problem with Uncertainty in Demand with Relaxed Design Constraint

Variables, Parameters, Objectives	**GA**
Computation Time	57 hr 24 min
# of Aircraft X used in Allocation	11
Design Range (nmi)	1,100
Pallet Capacity	10
Wing Loading (lb/ft^2)	121.63
T/W	0.243
Aspect Ratio	6.13
Baseline Fleet DOC	$ 2,161,800
Baseline Fleet Fuel (gal)	594,265
Allocation with New Aircraft Fleet *DOC*	$ 2,096,600
Allocation with New Aircraft Fleet Fuel (gal)	559,412
Δ *DOC*	-3.01 %
Δ Fuel Usage	-5.86 %

GA allocation with new aircraft results in $ 2,096,600 expected fleet *DOC* and 559,412 gallons of expected fleet fuel usage for 22-base network, a saving of 3.01 % in

expected fleet *DOC* compared to the baseline result of $ 2,161,800, and 5.86 % saving in expected fuel usage from the baseline result of 594,265 gallons. The aircraft type X description results in a design range of 1,100 nmi, capacity of 10 pallets, wing loading value of 121.63 lb/ft^2, thrust-to-weight ratio of 0.243 and aspect ratio of 6.13. The result suggests the introduction of 11 of aircraft type X. Because the size of the newly designed aircraft is small, the fleet requires more aircraft to satisfy the required MTM/D of the fleet. The description of the aircraft type X suggests the introduction of much smaller, short-range aircraft with the aircraft X description of 1,000 nmi design range and capacity of 11 pallets compared to the fleet that is strictly composed of strategic airlift aircraft.

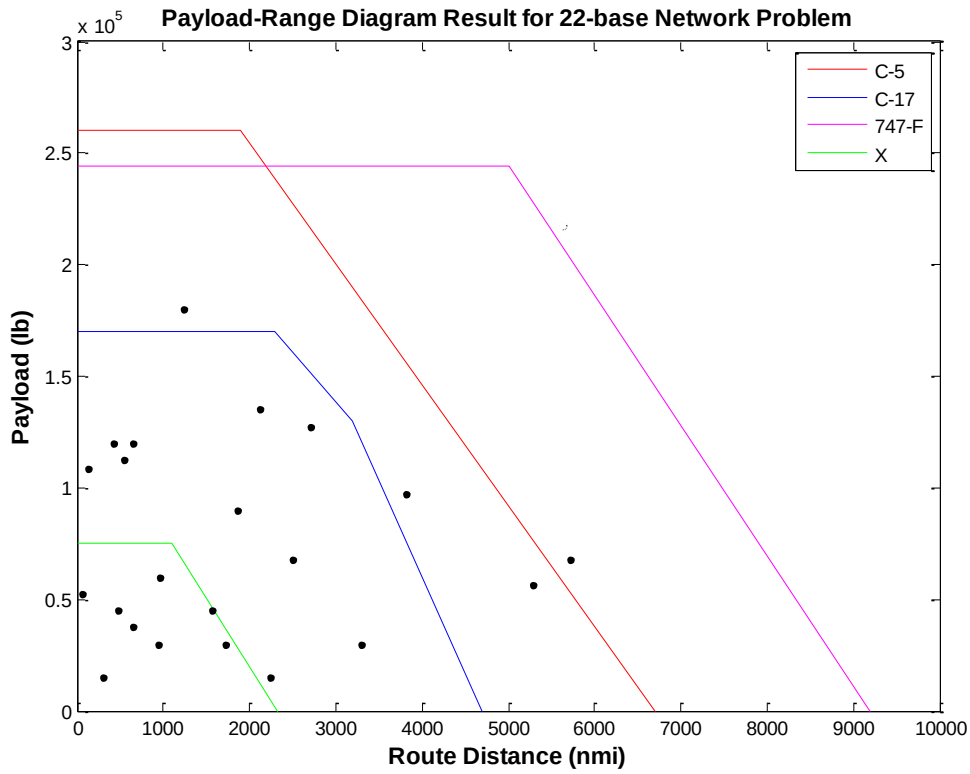

Figure 5.9 Payload-Range Curves for the Existing Fleet and the Aircraft Type X from the 22-base Network Problem with Relaxed Design Constraint

The result suggests that this platform will be even more efficient as many of the routes in the network are short and low demand cargos. The fuel saving in all cases are directly related to the expected *DOC* saving as fuel cost is driving factor in *DOC*.

CHAPTER 6. CONCLUTIONS

The work presented here demonstrates the viability and applicability of the decomposition approach in better informing acquisition decisions for *AMC* fleet acquisitions. The *AMC* operations typically involve highly uncertain and asymmetric cargo demand operations, in contrast to the commercial or passenger airline operations where routes and cargoes are relatively consistent. The round trip assumption, though valid for the studies with the symmetric demand route network, appears to be a weak abstraction of the entire *AMC* network. Subsequent versions of the decomposition framework incorporated “scheduling-like” formulations of the resource allocation problem by implementing node balance constraints to address this issue. By implementing the scheduling-like formulation using node balance constraints, representative *AMC* operations are more accurately modeled, allowing for directional pallet cargo and aircraft tail number tracking.

The studies presented here also use direct operating cost as the objective function. This follows from the previous work for commercial airline related investigations, but here this allows the chartered 747-F aircraft to be part of the problem. If a formulation sought to minimize fuel consumed by AMC, it is possible that one solution would lead to

carrying all cargo on the chartered 747-F aircraft. As demonstrated in the thesis, fleet-level fuel values are readily available and minimizing DOC has a strong relationship to minimizing fuel consumption.

Uncertainty in demand and starting fleet aircraft location characteristics are considered via a *MCS* technique, resulting in a new, yet-to-be introduced aircraft design that is tailored to minimize fleet level cost (fuel/direct operating) under prescribed uncertainty. From the result, the newly designed aircraft descriptions suggests aircraft that is slightly larger and have longer unrefueled range than the existing C-17 aircraft in the strategic fleet.

The aircraft design from the deterministic demand scenario is allocated in the uncertain demand scenarios. The result suggested clearly that the aircraft design optimized for single demand scenario might not be sufficient for the uncertain demand network. This indicates the uncertainty in demand must be addressed in such a network with high fluctuation in demand and route network that is not hub-and spoke structure.

The new aircraft design with relaxed capacity and range restriction enable the allocation of the aircraft that are designed to carry only a small number of palletized cargos on short routes. This diversifies the size of the aircraft, and tries to exploit the fact that existing large-size aircraft generally carry only a small fraction of their maximum weight (and in some case volume) capacity. The smaller aircraft introduced

to the strategic fleet will predominantly be used on routes that are short and will carry a comparatively large number of pallets per flight.

CHAPTER 7. FUTURE WORK

An acquisition support issue is the selection of the top-level design variables that represent some of the requirements for a new platform. Payload capacity, design cruise velocity, and range are common aircraft design and are logical choices for these top or system level variables.

Current investigations have considered a design range and the maximum number of pallets as top-level variables as palletized cargo data was available in the *GATES* data. However, one of important roles of the strategic fleet is to transport oversized and outsized cargos. While palletized cargo has well defined geometric dimensions (particularly length and width), the pallet density (weight per pallet) of cargo carried has a wide variation. Further, outsized or unusually dimensioned payload often set cargo bay dimensions for new aircraft; for instance, the large size of the C-5's cargo bay allowed air transport of the 74-ton mobile scissors bridge. To improve the credibility of the aircraft design portion of the decomposition approach, the payload capacity requirements must incorporate both weight and volume (or dimension) as two distinct, but not wholly independent, aspects. One potential approach to this is to select a discrete set of potential outsized payloads to set the dimensions, recognizing that the

aircraft will most often carry palletized cargo, and then use maximum payload weight as one of the top-level design variables/new aircraft requirements. The resulting values for these requirement variables can inform acquisition decisions about what new platform requirements will lead to a more successful fleet. The decomposition framework also informs how the new platform needs to be used to improve the fleet-level objective(s).

Another important future improvement is to capture *AMC* operations through considering the time sensitive nature of cargo. Cargo is tiered according to urgency of delivery, and thus poses implicit constraints on the routes travelled on (relating to the range of the aircraft used), and the capability (here, speed) of the aircraft. The previously developed tools, *AMOS* or *NRMO,* explicitly consider the Time Phase Force Deployment Data and scheduling of the *AMC* assets. The current model is not capable of addressing the priorities associated with cargos and *GATES* data set does not clearly show the priorities of cargos, although 97 % of the cargo is listed as Priority 1.

LIST OF REFERENCES

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1. Allardice, Lt. Gen. R. R. (2012, March 5). AMC vice commander: Saving fuel secures the future – one gallon at a time. *Inside AMC,* http://www.amc.af.mil/news/story.asp?id=123292555, [accessed March 2013]

2. McAndrews, L. (2010, June 29). Aviation fuel savings: AMC leading the charge. *Air Mobility Command Public Affairs*, http://www.mcconnell.af.mil/news/story_print.asp?id=123211757, [accessed March 2013]

3. Air Mobility Command. (2007). US Air Force Fact Sheet: Civil Reserve Air Fleet. *Air Mobility Command,* http://www.amc.af.mil/library/factsheets, [accessed September 2013]

4. Maier, M. W. (1998). Architecting principles for systems-of-systems. Systems Engineering, 1(4), 267-284.

5. Knight, W., & Bolkcom, C. (2008, April). Strategic Airlift Modernization: Analysis of C-5 Modernization and C-17 Acquisition Issues. Library of Congress, Washington DC., Congressional Research Service.

6. Tirpak, J. A. (2012, June). Mobility Maturation. *Air Force Magazine.* Vol 95, No. 6.

7. Mane, M., Crossley, W. A., & Nusawardhana, A. (2007). System-of-systems inspired aircraft sizing and airline resource allocation via decomposition. *Journal of Aircraft*, *44*(4), 1222-1235.

8. Tetzloff, I., & Crossley, W. (2009, September). An Allocation Approach to Investigate New Aircraft Concepts and Technologies on Fleet-Level Metrics. In9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)

9. Mane, M., & Crossley, W. A. (2012). Allocation and Design of Aircraft for On-Demand Air Transportation with Uncertain Operations. *Journal of Aircraft, 49*(1), 141-150.

10. Wing, V. F., Rice, R. E., Sherwood, R., & Rosenthal, R. E. (1991). Determining the optimal mobility mix. *Joint Staff (J8), Force Design Division, The Pentagon, Washington, DC*.

11. Yost, K. A. (1994). The THRUPUT strategic airlift flow optimization model. *Air Force Studies and Analyses Agency, The Pentagon, Washington, DC*, *120*, 100.

12. Lim, T. W. (1994). Strategic Airlift Assets Optimization Model. Naval Postgraduate School, Monterey, CA

13. Killingsworth, P. S., & Melody, L. (1997). Should C-17s Be Used to Carry In-Theater Cargo During Major Deployments? (No. RAND-DB-171-AF/OSD). RAND National Defense Research Inst., Santa Monica CA.

14. Baker, S. F., Morton, D. P., Rosenthal, R. E., & Williams, L. M. (2002). *Optimizing military airlift. Operations Research, 50*(4), 582-602.

15. Wu, T. T., Powell, W. B., & Whisman, A. (2009). The optimizing-simulator: An illustration using the military airlift problem. ACM Transactions on Modeling and Computer Simulation (TOMACS), 19(3), 14

16. DUSD (A&T) (2012) *Energy Efficiency starts with the acquisition process*, http://www.acq.osd.mil/asda/docs/fact_sheets/energy_efficiency_starts_with_the_acquisition_process.pdf, [accessed March 2013]

17. Eisenhut, J. A. (2003). Strategic Air Mobility: Meeting the Demands of the 21st Century. Army War Coll Carlisle Barracks, PA

18. Graham, D., Bracken, J., Dalfonzo, J., Fedorochko, W., & Hilton, R. (2003). Sustaining the Civil Reserve Air Fleet (CRAF) Program (No. IDA/HQ-P-3819). Institute for Defense Analyses, Alexandria, VA

19. Gertler, J. (2010). *Air Force C-17 aircraft procurement: Background and issues for Congress*. DIANE Publishing.

20. Lambert, G. R., Barnes, J., & Van Veldhuizen, D. A. (2007). A tabu search approach to the strategic airlift problem. Military Operations Research, 12(3), 59-79

21. Military Transport Aviation Command. http://www.globalsecurity.org/military/world/russia/av-transport.htm, [accessed October 2013]

22. Journal of the Air Force Association. (2013). *Air Force Magazine*: 2013 USAF Almanac, 2013. *Vol. 96, No. 5, p.45,49.*

23. Warner, D. W. (1998). Strategic Airlift: Can the C-17 Fill the Requirement?. Army war coll carlisle barracks, PA

24. Air Mobility Command. (2007). US Air Force Fact Sheet: C-5 Galaxy. Retrieved from [http://www.af.mil/factsheets/factsheet.asp?fsID=84]

25. Journal of the Air Force Association. (2007). *Air Force Magazine*: 2013 USAF Almanac, 2013. *Vol. 90, No. 5,*p. 146.

26. Air Mobility Command. (2007). U. S. Air Force Fact Sheet: C-17 Globemaster III., http://www.af.mil/factsheets/factsheet.asp?fsID=86, [accessed October 2013]

27. U. S. Air Force. (2013). Air Force Fact Sheets, http://www.af.mil/AboutUs/FactSheets, [accessed October 2013]

28. Harris Jr, J. D. (1997). Civilian Reserve Air Fleet: Should The USAF Use It Routinely? (No. AU/ACSC/0519/97-03). Air Command and Staff Coll Maxwell AFB., AL

29. Chow, B. G. (2003). The Peacetime Tempo of Air Mobility Operations: Meeting Demand and Maintaining Readiness (No. 1506). Rand Corporation. p. 2.

30. Jackson, P. A., Munson, K., & Peacock, L. T. (Eds.). (2004). *Jane's All the World's Aircraft 2003-2004*. Janes Information Group.

31. Raymer, D. P. (2006). *Aircraft design: A conceptual approach*. Reston: American Institute of Aeronautics and Astronautics.

32. Air Force Pamphlet. (2010). 10-1403. *Air Mobility Planning Factors*.

33. Jackson, J. (2009). *Mobility Capabilities and Requirements Study 2016 Accreditation Report. Volume 1: Summary* (No. IDA-P-4475). Institute for Defense Analyses, Alexandria, VA.

34. Goure, D. (2013). The Measure of a Superpower: *A Two Major Regional Contingency Military for the 21st Century*. Heritage Foundation.

35. Kopp, K. W. (2004). *Improvement of Air Mobility Command Airlift Scheduling* (No. AFIT/GMO/ENS/04I-01). Air Force Institute of Technology Wright-Patterson Afb Ohio School of Engineering and Management.

36. Choi, J. H., Govindaraju, P., Davendralingam, N., & Crossley, W. A. (2013). *Platform Design for Fleet-Level Efficiency: Application for Air Mobility Command (AMC)*. Monterey, California. Naval Postgraduate School

37. Bureau of Transportation Statistics (BTS), (2006) U. S. Department of Transportation, online database, http://www.bts.gov, [accessed December 2013]

38. Brooke, A., Kendrick, D., Meeraus, A., Raman, R., & America, U. S. (1998). The General Algebraic Modeling System. GAMS Development Corporation

39. MATLAB, Version 7.10. 0. R2010a. (2010). The MathWorks Inc., Natick, Massachusetts

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