AN ANALYSIS OF TIME SERIES FORECASTING METHODS FOR THE AIRLIFT OF PALLETIZED SUSTAINMENT CARGO

GRADUATE RESEARCH PAPER

Brian A. Surdyk, Major, USAF
AFIT/IMO/ENS/10-14

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT/IMO/ENS/10-14

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Brian A. Surdyk, BS, MSME

Major, USAF

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Major, USAF

Approved:

//SIGNED//	10 JUNE 2010
Dr. James T. Moore (Advisor)	Date

AFIT/IMO/ENS/10-14

Abstract

In the Department of Defense (DOD) supply chain for sustainment cargo, over 45,000 pallets were transloaded at Incirlik Air Base (AB), Turkey from April 2008 to December 2009 with ultimate destinations in the USCENTCOM AOR, making Incirlik the largest transshipment node for airlift in the DOD by over two-fold. Current methods of forecasting follow-on transportation requirements are based on the number of pallets on hand at the aerial port as well as short-term visibility of pallets currently in the channel system destined for Incirlik, yielding a forecast horizon of only 2-3 days for planning subsequent airlift missions.

Post-sample forecasts of historical pallet data from the Global Air Transportation Execution System (GATES) were analyzed to determine if significant results could be obtained to forecast follow-on transportation requirements from airlift transshipment nodes. In addition, both daily and weekly aggregation of pallet data was obtained to determine the best means to analyze the data. Daily pallet groupings with forecast methods that considered the aircraft type into the transshipment node yielded the most consistent results.

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To My Wife and Children

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Brian A. Surdyk

Table of Contents

List of Figures

List of Tables

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I. Introduction

Background, Motivation, & Problem Statement

Recent conflicts have highlighted deficiencies in the Department of Defense's (DOD) management of the supply chain. Since 1990, the US Government Accounting Office (GAO) has maintained the DOD's supply chain management processes on their list of high-risk areas "needing urgent attention and fundamental transformation to ensure that they function in the most economical, efficient, and effective manner possible" (US GAO 2007, ii). Despite recent process improvements in supply chain coordination, logistical gaps exist that the GAO continues to emphasize.

The main contributors to the DOD supply chain are the Defense Logistics Agency (DLA) and the United States Transportation Command (USTRANSCOM). DLA is the prime acquisition, storage, and packing source for the millions of line items required by DOD customers. In this vein, it operates a number of supply centers, distribution centers, and several specialized field activities. Transportation, however, is not one of its core logistics functions. This responsibility falls to USTRANSCOM.

USTRANSCOM is one of 10 Combatant Commands listed in the Unified Command Plan. Of the 10, it is one of 4 commands organized under a functional construct, meaning it is not limited to a geographic area of responsibility. Like DLA, it reports directly to the DOD, and is further divided by service components in the distribution process: Military Surface Deployment and Distribution Command (Army), Military Sealift Command (Navy), and Air Mobility Command (Air Force). The functional components reflect the modal managers and force providers for surface transportation, sealift and airlift.

Complicating their role in the supply chain, in 2003 the Secretary of Defense named USTRANSCOM the Distribution Process Owner (DPO), shifting their focus from solely the "fort to fort" segment of the supply chain to "end to end." This statement effectively increased USTRANSCOM's stake in the role that DLA plays in distribution. Prior to 2003, DLA and USTRANSCOM's relationship was at best arm's-length, leaving the supplier, warehousing and order processing functions to DLA and the transportation of goods to the service arms of USTRANSCOM through organic capability or contracts with commercial carriers. On the surface this declaration seemed very straightforward. However, the GAO has identified several problems with this edict. As of 2007, no executive orders had been published defining the authority of USTRANSCOM over DLA's processes. Furthermore, there has been concern over the USTRANSCOM exceeding its core competencies by taking on this role (US GAO 2007, 11).

Despite the DOD having a vertically structured supply chain, the arm's-length relationships between DLA and USTRANSCOM historically have caused gaps in planning transportation requirements, despite DLA knowing of these requirements (on some level) weeks, sometimes months in advance. To alleviate some of these problems, DLA and USTRANSCOM have partnered on several initiatives to improve their level of supply chain coordination. The first, and arguable the most successful, is the development of the Joint Deployment and Distribution Operation Center (JDDOC).

Based off of the test program in US Central Command (USCENTCOM), the JDDOC provides an in-theater presence of logistical expertise from DLA, the services and USTRANSCOM that enhances in-transit visibility (ITV) and the prioritization of intratheater movements.

Particularly relating to this study is the myriad of information technology (IT) systems through which the DOD manages its supply chain. Although process improvements have led the charge in advancements in DOD logistics, IT still presents a major hurdle to the overall efficiency of the DOD supply chain. It is apparent from the literature that there is no consensus on the exact number of logistics applications that exist, only that there are far too many. The estimates range from 500 major systems (Heise 2009) to over 2000 sub-applications (US GAO 2006, 5). With the sheer volume of information to be processed, it is no surprise that these systems lack the integration necessary for end to end visibility or seamless transition from order to receipt (Hauser, et al. 2004).

The fundamental problem with IT solutions in DOD logistics is that their architectures are largely service-based and service-funded. As part of their Business Management Modernization Program, the "DOD recognizes that achieving success in supply chain management is dependent on developing interoperable systems that can share critical supply data" (US GAO 2006, 7). While some legacy systems have been eliminated, bridge applications have attempted to band-aid the gaps. One such system is USTRANSCOM's Global Transportation Network (GTN). GTN bridges the myriad of distribution management solutions from the services as well as their contract partners to provide a common portal for ITV once a shipment enters the Defense Transportation

System (DTS). Despite its success in providing a common interface, it is limited by its focus on the transportation system alone.

DLA, as the prime distributer of material consumed by the DOD, maintains the systems through which orders are placed from its DOD customers. Like the transportation side of the supply chain, DLA also receives feeds from numerous service and DOD agency requisition systems. Their system to combine these systems into a parent database is the Integrated Data Environment (IDE). The goal of DLA in creating IDE is “to make the data for which it has stewardship responsibility available to authorized users on an on-demand basis and in a useable format” (DLA J-6 n.d., n. d.).

IDE and GTN form the basis of a recent partnership between DLA and USTRANSCOM in an effort to improve the end-to-end supply visibility. IDE/GTN Convergence, or IGC, will provide a single platform for the entire DLA-USTRANSCOM supply chain, enabling common users a medium in which to track their orders from “factory to foxhole.” As these individual systems serve many commercial partners as well as the services, the individual platforms will be phased out in a spiral approach to allow a seamless transition (Heise 2009). While it remains to be seen whether IGC will truly be an overarching supply chain enterprise resource planning (ERP) system, its design promises to reap some of the benefits that have been achieved in commercial industry.

In their study on the strategic supply industry, Hauser, et. al. (2004) found that band-aided legacy ERP systems had a much higher failure rate. Their focus expanded the common reference to ERP, including the processes and planning functions in addition to the information systems aspect that comprise commercial supply chains. Their research found that the proprietary nature of ERP information systems often made them ill-prepared to adapt to future systems integration. Furthermore as a planning function, they noted that organizations which conducted joint planning had more efficient supply chains. However, they are quick to admit that it is naïve to assume that a complex organization can adopt a single ERP information system.

Despite the promise that IGC offers in the realm of transportation requirements planning, it still is a work in progress and no official date has been identified for its release. Hauser, et. al. (2004) also bring into question the operability of a band-aided approach. The question then becomes what we can do today to enhance the visibility of down-range transportation requirements, given that a requirement to move something at some time is already known by DLA. USTRANSCOM attempts to alleviate the uncertainty of the demand for transportation assets by using Time Phased Force Deployment Data (TPFDD). In theory, the advantage of the TPFDD is that it provides readily available data for unit moves in the form of availability for shipment, required delivery date and priority. This information is essential to the planners that forecast and plan requirements down the supply chain. However, the vast majority of cargo validated for air shipment to the USCENTCOM area of responsibility (AOR) is that for sustaining combat operations procured through service-specific supply procedures not included in the TPFDD. Most of this sustainment cargo is picked and packaged at distribution centers operated by DLA and then transported to aerial ports for shipment via organic channel airlift or via contract carriers to a transload port.

At the present time, transload ports such as Incirlik Air Base (AB), Turkey can only predict the follow-on transportation requirements in terms of the number of pallets and time of arrival at the aerial port. They cannot identify beyond 2-3 days (at best) where the final destination will be, information that is critical to airlift planners for planning the follow-on missions into the AOR. This shortened horizon forces mission planners to sacrifice efficiency for effectiveness often at expense to the customer. Austere airfields with low maximum on ground (MOG) capabilities limit airlift throughput. This scarce ramp space makes it imperative that aircraft cargo capacity is utilized at near peak levels to ensure that current operations can be sustained.

The purpose of this research paper is to analyze different forecasting methods based on their ability to identify requirements in the distirbution of sustainment cargo. Pallet level data from the Global Air Transportation and Execution System (GATES) is used to determine whether they can expand the current 2-3 day horizon that planners face in planning follow-on requirements for cargo shipped to transload locations for the USCENTCOM AOR via the channel system The study is limited to the transload operations that occur at Incirlik AB, with the proposal that similar methodologies could be applied to other transload ports once steady state operations have been achieved. The ultimate goal of such forecasting efforts would be to yield similar effects to the predictability of TPFDD movements, thus enhancing the efficiency of the airlift planning process and ultimately provide more predictable deliveries to the customer.

In that vein, the next chapter presents a review of the literature as it pertains to the "as-is" framework airlift transload operations as well as published research on forecasting. Chapter 3 describes the time series forecasting methodologies that were used in this study to determine their ability to forecast different types of sustainment operations. Chapter 4 discusses the results of the forecasting methods applied to transload operations at Incirlik AB, Turkey. Finally, Chapter 5 forwards conclusions based on the results of the forecasted series to provide insights as to how planners could use these methods to streamline mission flows subsequent to transload operations.

II. Literature Review

Transportation is a service based on derived demand. That is, the demand for transportation is necessitated by the demand for a product that must travel from one point to another. As such, in order to accurately size capacity (organic capability) and write contracts for excess capability (contract carriers), it is essential that forecasting measures be in place to measure this demand.

One of the more recent changes to the airlift system, in its application to the USCENTCOM AOR, is the two Expeditionary Airlift Squadron (2-EAS) system. In this system, two C-17 squadrons deploy to provide a theater presence of dedicated heavy lift-capability for the combatant commander. Instituted in May of 2006, this system represented a doctrinal shift that in recent years had only been applied to C-130 aircraft. While the achievements of this system are outside of the scope of this research paper, its development laid the groundwork that is the foundation of this study.

Prior to 2006, C-17s operated primarily in a direct delivery role, transporting material directly from the continental United States (CONUS) to the theater. The great distances involved necessitated crew changes at enroute stages due to limitations on the amount of time that a single crew could remain on duty. To facilitate these crew changes, personnel from a single C-17 squadron deployed at enroute bases. The deployed squadron acted as an enabler in the process by managing the crews at the stage location, but did not fly the missions themselves. Furthermore, the enroute stages did not possess aircraft, ground times were limited to the minimum amount required to generate an additional crew and to meet any additional restrictions in the follow-on segments for the mission. The result was often aircraft flying great distances simply to recover the mission to a CONUS location.

Under the 2-EAS construct, 2 squadrons of aircraft and crews are now forward deployed to the AOR and direct delivery missions are flown by exception. Instead, most missions originating from outside the USCENTCOM AOR fly to intermediate bases such as Al Udeid AB, Qatar; Kuwait International, Kuwait; or Incirlik AB, Turkey; where cargo shipments are transloaded for follow-on movement to the final destination by C-17 and C-130 aircraft. In this sense, the system operates in a two loop system, with the open loop operating similar to the trunk lines of a commercial airline hub and spoke system. The closed loop system, operated by the assets in place at the transload points, functions as the smaller feeder routes in the hub and spoke system (Buschur 2007).

The 2-EAS construct is in-line with other USTRANSCOM-led programs, as the DPO, that have contributed to an increase in the velocity of cargo throughput to the warfighter. However, this increase in velocity also creates additional challenges. While TPFDD cargo typically has long lead times and advance notice of shipment, the supply-distribution gap of sustainment cargo is not as seamless. In fact, USTRANSCOM Handbook 60-2 establishes distribution forecasting and planning as the second largest technological gap behind in-transit visibility (USTRANSCOM 2008).

The current hub system that manifested under the 2-EAS construct relies on capability forecasts from the aerial ports at the transshipment nodes to plan follow-on missions in the post-channel, closed loop system. However, the improved velocity in the open loop system has led to a decrease in the lead time with which capability forecasters have visibility over sustainment movements. In the case of Incirlik AB, Turkey, the average time from pallet build time to delivery at Incirlik AB is only 3 days. This does not account for any delays in manifesting a particular pallet to a mission, which most likely decreases this visibility even further. In reality, the capability forecaster realistically only knows of follow-on requirements of sustainment cargo about 2-3 days in advance of a mission's arrival. Given the restrictions arising from MOG in theater, this places airlift planners in a reactionary position, essentially basing closed loop requirements on port levels.

Forecasting Transportation Demand

Studies have been published on the forecasting of transportation requirements for nearly every mode. In the commercial sector of transportation, these models can make or break a company and provide the basis for strategic directions such as markets to enter and fleet mixes. As such, their forecasts focus more on the long term to help make these decisions and changes made to infrastructure, equipment and schedules are rarely completed on a less than quarterly basis.

With the advent of containerization, the forecasting of waterway traffic lends itself to the comparison to airlift demand, based on the nature of palletized movement. Hui, et al. (2004) and Lam, et. al (2004) highlight the importance of forecasting in their studies of Hong Kong's sea port. As a vital node in the trade lanes of the Pacific, these studies attempt to improve those accomplished by the Hong Kong Port and Maritime Board. Each study utilized several years of historical data to produce and then validate their models. As is the case with many forecasts used in commerce, the methodologies in their forecasts do not lend themselves well to military airlift as they rely heavily on econometric data. However, the importance of their studies to this research is how they validated their methods. Historical data was used first to develop the model, and then subsequent validation was achieved by using a post-sample forecast. That is, they used historical data subsequent to that used in developing the model to validate its results. This method is used to evaluate the methodologies used in this paper and is discussed further in the results section.

The forecasting models used in the Hong Kong studies, while focused on a particular mode, are generally applicable to other modes of transportation. Similarly, other studies, while focusing on a particular mode, have universal take-aways. Al-Deek (2002) used data from inbound shipments from ocean vessels to forecast requirements for surface shipments from the seaports to the destination. In this sense, he effectively studied the same framework that exists in the open and closed loop system of military airlift.

Additionally, Peng and Chu (2009) in their study on container volumes through the port of Taiwan, identified that container volumes through the port of Taiwan were best forecast using classical time-series decomposition and that more complex models did not necessarily produce more accurate results. Two additional studies (Babcock and Lu 2002, Babcock, Lu and Norton 1999) also identify methods of forecasting on a per unit basis. Common to these studies is that they identified that there are few explanatory variables published for the modes of interest. As such, demand levels on a per-unit basis are forecasted using time series methods.

Forecasting Airlift Demand

As a tool, forecasting is probably used more widely as a demand predictor than for any other means, whether used for services or goods. For various industries, it provides a means to make strategic decisions based on the substance of predicted values. That said, the accuracy of forecasts have very measurable consequences, and considerable development is given to establishing novel forecasting methods to predict demand.

Wilson and Keating cite several examples of industries that use forecasts to streamline their operations (2009). While they outline that forecasting is a key component in ensuring customer expectations are met in a profitable manner, they limit their description of forecasting in supply chain management to the supply segment of the chain, neglecting the importance of forecasting in transportation planning. In the DOD context, demand forecasting systems play an integral role in the acquisition of the line items needed by its customers. Dussault (1995) examined the Air Force and Navy forecasting systems' ability to forecast different demand patterns for products. While he provided an in depth look at the systems themselves, as was the case with Wilson & Keating, he offered little insight into how these forecasts could be used effectively by USTRANSCOM in their operations.

Surprisingly, there is very little published research on demand forecasting for the DOD transportation system as a whole. What does exist is rather dated in its application. A RAND study in 1968 represents one of the first mathematical attempts to model airlift scheduling as a function of demand. In their analysis, RAND used linear programming to develop route scheduling for the then Military Airlift Command (today, Air Mobility

Command (AMC)) both by month and by day (Midler and Wollmer 1968). In both models, the demand is based on what is already known regarding supply on hand at aerial ports. In this sense, it provides little more than what is already done in capability reports—everything else that it achieves has already been streamlined through the development of various IT systems.

In contrast, Billion and Regan (1966) attempted in very general terms to describe an econometric method to forecast demand for cargo to overseas destinations. While the RAND study did not examine the demand for supplies, Billion and Regan's method uses the demand for supply as the core part of their method. However, their method focuses more on the prediction of demand for airlift in relation to other modes for the purpose of acquiring organic systems. In this sense, their methodology focuses on the long term acquisition process rather than the tactical level scheduling of individual flights.

More recent studies in solving airlift problems almost unilaterally focus on capacity-level restrictions based on throughput, rather than the scheduling of missions based on demand at the pallet level. They examine the ability of airlift to occur, not whether or not and in what quantity it will be demanded. Koepke, et al. (2008), focus primarily on MOG values in their model, establishing a method by which the channel system can be rescheduled according to variances in available MOG. Many other studies have been published in an effort to determine strategic mixes required to accomplish the mobility effort of a conflict (Koepke, et al. 2008). While these efforts serve their purpose well in establishing the airlift requirements for troop movement into an operation, the level of detail for sustainment operations is less robust.

The topic of scheduling Air Mobility Command's channel cargo missions has been very well covered in the literature. Fitzsimmons and Walker (1994) and Rau (1993) developed methodologies to improve the channel route scheduling systems in use at the time, the Strategic Transport Optimal Routing Model (STORM), CARGPREP, and CARGOSIM. In a similar fashion, Del Rosario (1993) developed a model to minimize the delay enroute for the channel system, given movement requirements and flight schedules. While their focus was on the channel system, the goal was to enhance efficiency by updating the long range channel plan with near term requirements. Although it is difficult to extend their models to the post-channel system, the nature of the research alone highlights the complex nature of predicting airlift requirements in the DOD system. Additionally, like several other studies, these studies focused on a *modeling* approach versus a *forecasting* approach, the difference being that the forecasting approach narrows its focus to a particular per-unit variable.

While not a published portion of the literature, it is worth noting the as-is framework of the forecasting efforts that are currently in place. USTRANSCOM identifies planning as one of the functions of the Joint Deployment and Distribution Enterprise. Demand forecasting is one of the core competencies of the planning function, using quantitative and qualitative forecasts to improve the overall distribution of material in the DOD (Ford 2008). However, the capability forecasts produced at Incirlik AB are not predictive in nature. They simply identify what cargo has been manifested on the missions coming to Incirlik AB. The Hub Cape Report, shown in Figure 1, identifies the outbound missions as well as the short timeframe for inbound missions. According to Lanier (2009), occasionally the Dover Air Force Base (AFB) utilization logs are obtained in addition to the cape report in order to identify further requirements; however, it was apparent in his research that only visibility further into the supply chain would give the forecasters greater ability to predict demand in the closed loop system (Lanier 2009). While IGC may offer this ability, it remains to be seen whether the variability of this information will be of use in forecasting aggregate demand at the pallet level and is discussed in greater detail in the Conclusions chapter.

HUB MISSIONS

MSN#	ICAO	APOD	Pro	Att	ETD/Z	DEP/Z
10/026						
ABR20X7C1026	OAZI	AZ1		12	0615	0648
ABR20Y7C3026	OAKN	KDH		18	0830	
ABR20X7C5026	OAZI	AZ1		16	0845	
ABW2063C7026	ORBD	OR9		18	1400	
ABR20Y7C9026	OAKN	KDH		18	1630	
ABW20N7C8026	ORQW	O6R		16	2130	
10/027						
ABW2063YT027	ORBD	OR9	18		0530	
ABR20Y7D1027	OAKN	KDH	18		0530	
ABR20X7D3027	OAZI	AZ1	18		0615	
ABW2045D7027	ORSH	O2R	17		1100	
ABR20Y7D9027	OAKN	KDH	18		1130	
ABW2059D8027	ORBI	SDA	14		1745	
10/028						
ABR20X7E1028	OAZI	AZ1	18		0615	
ABR20Y7E3028	OAKN	KDH	18		0745	
ABR20X7E5028	OAZI	AZ1	16		0845	
ABW2045E7028	ORTL-ORSH	TA8-O2R	13		1030	
ABR20Y7E9028	OAKN	KDH	18		1300	

THIS COLOR IN PRO COLUMN IS NOT WAITING ON ANY INBOUND INFO & HAS LESS THAN 10 PALLETS

THIS COLOR IN PRO COLUMN HAS LESS THAN THREE PALLETS FOR ONE STOP OF A TWO STOP

THIS COLOR IN PRO COLUMN IS WAITING ON INBOUND CARGO INFO

THIS COLOR IN PRO IS 100% UTILIZED A/C

OEF MISSIONS HIGHLIGHTED IN YELLOW

KIK, O6R, & OSM IS AUTHORIZED TO BE MOVED TO OR9

FEEDER CARGO

MSN#	ETA/Z	ATA/Z	KIK	O2R	O6R	OR9 (BSR, O8R, OR7)	OSM	SDA	TA8	KDH/TE2	AZ1	Totals
10/026												
BBW1D390J025	0830		4.9	0.0	1.0	8.0	0.0	4.0	2.0	17.0	4.0	40.9
BBWWX390A024	1225		1.0	0.0	0.0	11.0	0.0	0.0	1.0	14.0	7.0	34.0
BBWKD390C026	2030		1.0	7.0	2.0	7.8	3.0	3.0	3.0	14.0	1.0	41.8
10/027												
BBW6D390C026	0430											0.0
10/028												
BBWKX390D027	0030											0.0
JBWGF390K026	0430											0.0
BBW6X390L027	0830											0.0
BBWYD390E028	2030											0.0
TOTALS			6.9	7.0	3.0	26.8	3.0	7.0	6.0	45.0	12.0	116.7

BACKLOG OF PALLETS IN PROCESSED STATUS (NOT MANIFESTED/LOAD PLANNED OR FRUSTRATED)

	ORKK/KIK	ORSH/O2R	ORQW/O6R	ORBD/OR9	ORBM/OSM	ORBI/SDA	ORTL/TA8	OAKN/KDH	OAZI/AZ1
$	0.0	10.0	0.0	26.0	5.0	7.0	7.0	112.0	35.0
T-1 ADS									
T-1 LOG								1.1	3.3
T-2 ADS									
T-2 LOG									
T-3									
T-4									
RSS									
TOTALS	0	10	0	26	5	7	7	113.1	38.3

17 PLT POS TO ACCOMMODATE FOR RAVENS REQUIREMENTS

UPDATED AS OF	026/0800Z	DTAL SINGLE PALLETS ON HAN	206.4
		DTAL EPP's for TRAINS ON HAI	0.0

HIGH LINE SPACE	
AVAILABLE	30
USED	0
OPEN	30

GRID LOCATIONS	
AVAILABLE	500
USED	209
OPEN	291

C-17 TAILS	OP WEIGHT	MOMENT	STATUS	ETIC	REMARKS
33127	286618	25929	NMCM	026/1000	ACOUSTICAL LINER HAS FRAYE
44129	286922	25947	PMCM		
44135	285987	25911	PMCM		PP 2L BROKE RAIL
44136	286112	25896	PMCM		
33126	282500	25805	PMCM		

MOC AT 6464 // ATOC AND CAPE ARE NOT RESPONSIBLE FOR TRANSLATING MOC'S SITREP

Figure 1 Incirlik AB Hub Cape Report (Farris 2010)

General Forecasting

Despite a gap in forecasting the airlift demand problem, the literature on forecasting in general is vast. Of particular interest to this study is a series of forecasting competitions that were performed over the course of several decades beginning in 1982. In these competitions, experts from the forecasting field were given hundreds of data sets with which to apply forecasting methods of varying complexity. The ultimate goal was to determine the type of forecasts most appropriate for a given type of data. The first competition identified three general conclusions. In terms of significant improvements in forecasting accuracy, judgmental methods are not necessarily more accurate than objective methods; causal methods are not more accurate than extrapolation; and more complex methods are not necessarily more accurate than simple methods (Makridakis, et al. 1982, 112). These conclusions were also re-affirmed in the most recent competition (Makridakis and Hibon 2000). The concept presented here forms the basis of the methodologies that were explored in this research. That is, that simpler forecasting methods developed without the use of forecasting software can produce results with statistical significance.

III. Methodology

Scope

While forecasting methods can be applied to any component of the Defense Transportation System (DTS), their utility arises when applied to problems more narrow in scope. In 2008 and 2009 alone, over 625,000 pallets were catalogued in GATES. Given that that the movement of units is known through the TPFDD process, the necessity of short range forecasts for these goods is questionable. However, the movement of sustainment goods, those required to continue combat operations, represents an area that lacks sufficient study.

In the airlift portion of the DTS, these goods are transported primarily through a two part system. The first part of the system represents the long haul, strategic segment, operating aircraft capable of larger economies of density such as commercial Boeing 747s. Following transportation to a transshipment node, these goods are then transferred to smaller aircraft such as the Boeing C-17 and the Lockheed C-130 for shipment to the pallet's Aerial Port of Debarkation (APOD).

The transshipment nodes often are airfields with robust aircraft and materiel handling capabilities. In contrast, the follow-on APODs often lack such features and are constrained by MOG due either to physical limitations or the ability to service multiple aircraft. The planning of follow-on missions from the transshipment node, thus becomes a delicate act, balancing inbound missions that generate requirements with the capability of the subsequent airfields. While this aspect is not limited to sustainment cargo, the notice that is given to airlift planners of these requirements is often very short.

While it is known that an aircraft will arrive with a certain capacity, it is not known until approximately three days prior to arrival how that capacity will be utilized. For instance, a channel mission is scheduled to arrive at a transshipment APOD and has a B-747-400 dedicated to it. Planning factors from AFPAM 10-1403, *Air Mobility Planning Factors*, indicate that it has 34 pallet positions available (although in practice, as discussed in the results section, it is higher). However, it is not until pallets are loaded against this mission in GATES at the Aerial Port of Embarkation (APOE) that final destinations represented by the B-747's capacity are known. Furthermore, recent advances in supply chain coordination have reduced the port hold time, the time that a pallet sits in the APOE/APOD awaiting follow-on transportation. While this synergy has undoubtedly increased the velocity of palletized goods in the DTS, it also compresses the time in which airlift planners have to identify follow-on requirements.

Given this problem, the nature of the transshipment activity lends itself to forecasting methods, which in turn would serve to reduce the uncertainty of follow-on requirements from the transshipment APODs. The purpose of this research is to compare the ability of different forecasting methods in their ability to forecast requirements in advance of the present 3-day window.

Selection of Data

Of all the pallets that were catalogued in GATES between 23 April 2008 and 31 December 2009, over 118,000 were subject to transload operations. That is, all of these pallets were offloaded at an intermediate APOD that was not their final destination. Some of these pallets were transported by intermodal means to the final destination; however, the vast majority was airlifted subsequently by other aircraft. Table 1 contains a list of the three-letter airport codes (APCs) from GATES for those airfields described in this research. For brevity, these codes will be referenced in lieu of the full airfield name.

Table 1 APC Identifiers

APC	Airfield	APC	Airfield	APC	Airfield
3OR	Al Asad AB, Iraq	KWI	Kuwait Intl., Kuwait	OSM	Mosul Airfield, Iraq
ADA	Incirlik AB, Turkey	IUD	Al Udeid AB, Qatar	RMS	Ramstein AB, Germany
AZ1	Camp Bastion, Afghanistan	O2R	Al Sahra Airfield, Iraq	SDA	Baghdad Intl., Iraq
DOV	Dover AFB, DE	O6R	Qayyarah West Airfield, Iraq	SUU	Travis AFB, CA
KDH	Kandahar Airfield, Afghanistan	OA1	Bagram AB, Afghanistan	TA8	Ali AB, Iraq
KEZ	Ali Al Salem AB, Kuwait	OR5	Al Taqqadum AB, Iraq	WRI	McGuire AFB, NJ
KIK	Kirkuk Airfield, Iraq	OR9	Balad AB, Iraq		

23 April 2008 was selected as the starting period for this analysis as Incirlik's runway had been closed for repairs for several months prior to that time. Figure 2

describes the activity of the top ten transshipment aerial ports during this period. As shown in this figure, Incirlik dwarfs the other aerial ports in terms of its transload operations, accomplishing over triple the next higher port, IUD. Furthermore, Incirlik operations accounted for 39% of the total volume of airlift transloads DTS-wide. As such, Incirlik offers the advantage that, while it is not unique in these operations, it has a large data set that can be studied.

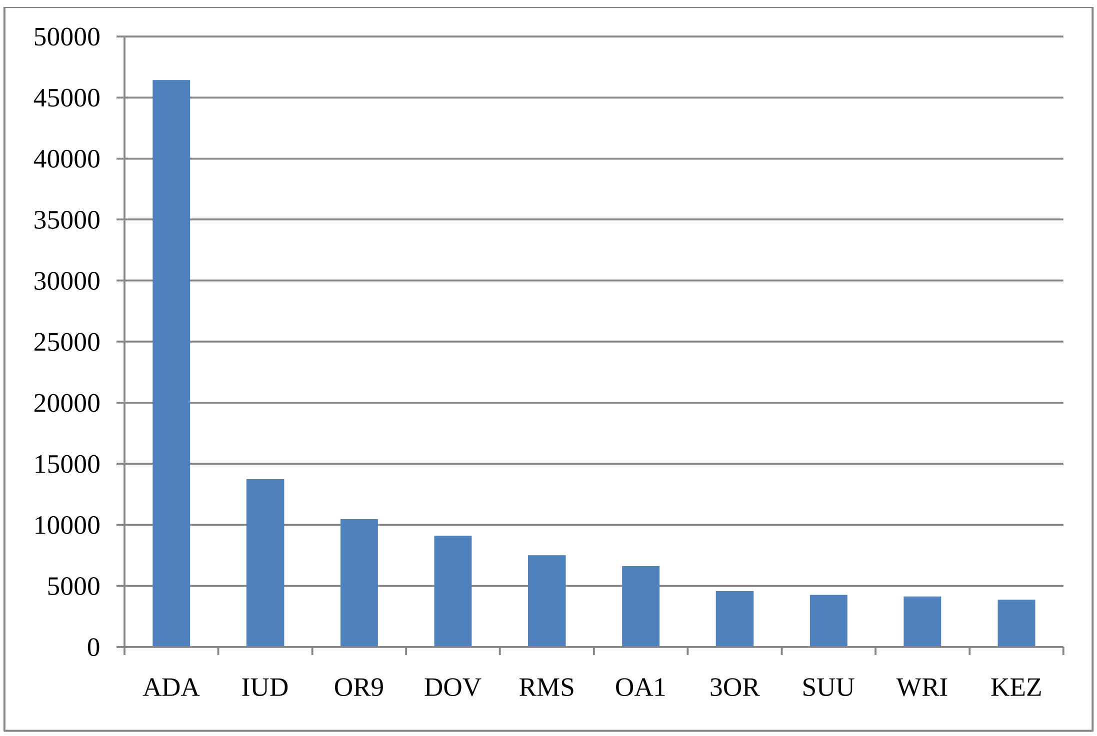

Figure 2 Pallet Position Equivalents by Transload APOD
23 April 2008 – 31 December 2009

As the goal of the forecasting effort is to define the follow-on requirements of pallets arriving at a transshipment location, it is necessary then to determine what the primary pallet destinations are during the studied period. Figure 3 illustrates those destinations that received greater than 2000 pallets during the study period.

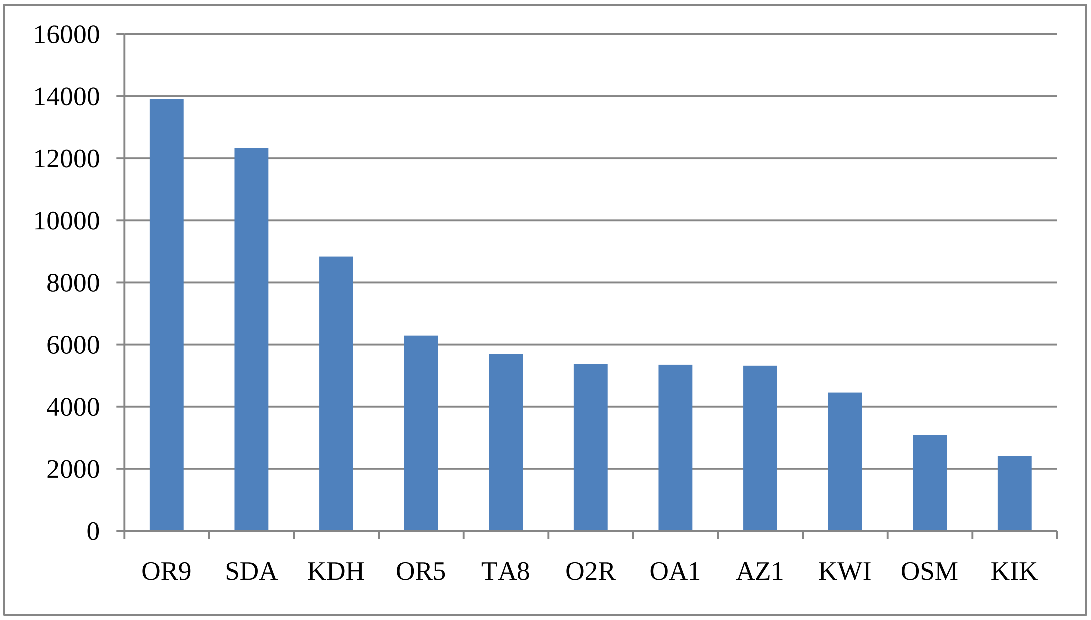

Figure 3 Pallet Position Equivalents for Final Destination APODs
23 April 2008 – 31 December 2009

It comes as no surprise that all of these locations are in the USCENTCOM AOR, given the weight of effort in the DTS to support that theater. Since only transload operations at Incirlik AB are studied in this paper, Figure 4 illustrates the breakdown of final pallet destinations by APOD that were first offloaded at Incirlik AB for subsequent movement by intratheater airlift.

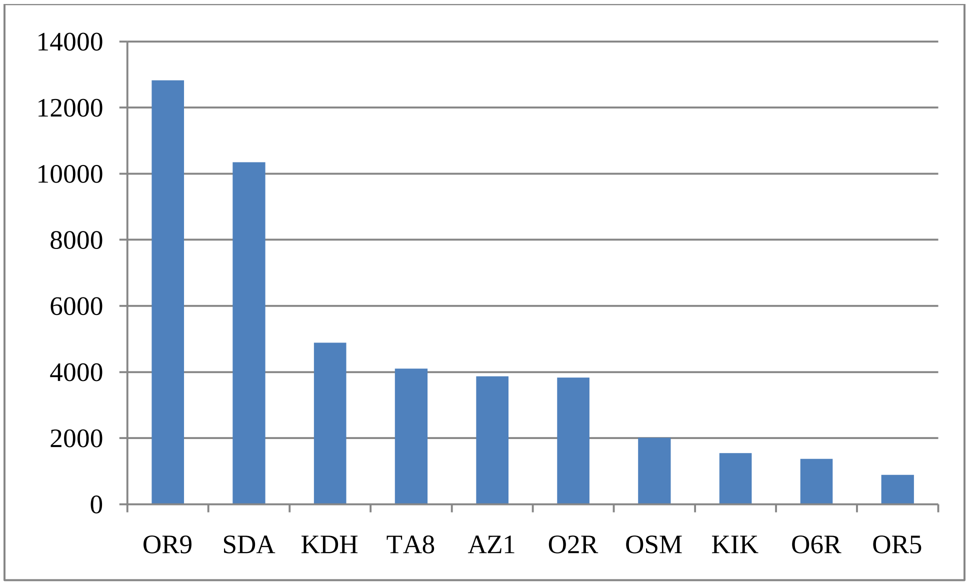

Figure 4 Pallet Positions for Final Destination APODs Transloaded at Incirlik AB 23 April 2008 – 31 December 2009

It should be noted that 98% of Incirlik AB's transload volume was destined for the 10 ports in Figure 4. The remaining 2% was allotted to 14 other ports at various intensities. In terms of forecasting models, these 10 ports in addition to OA1 present 4 different scenarios.

Routine Sustainment: operations that, while varying with time, are relatively stable with respect to the frequency of transload occurrences. This characteristic applies to KIK, O2R, O6R, OR9, OSM, SDA and TA8 during the study period.

Declining Operations: operations that, during the study period, experienced a significant decline in transload operations. This characteristic is demonstrated by OR5.

Escalating Operations: operations that, during the study period, experienced a significant increase in transload operations. This applies to KDH as well as AZ1.

Random Operations: operations that do not show a discernable pattern in frequency or volume. While the unstudied pallet APODs also fall into this area, OA1 only is analyzed here as it has enough volume to be worth discussion.

Sources of Data

All data in this study is obtained from GATES and provided by Air Mobility Command's Analysis division (A9) in the form of Microsoft Access databases. These two data sets, from 2008 and 2009, contained all of the pallets registered in the GATES system during that time. Pallets to be analyzed in this study were identified by two factors. The first was the mission APOD, identifying that the mission was offloading pallets at Incirlik AB. Second, the data was filtered to include only those pallets that had pallet APODs (versus mission APODs) other than Incirlik. This produced a database of pallets that were subject to transload at Incirlik AB. This filtered set was then exported to Microsoft Excel for ease of manipulation. Due to a runway closure prior to 23 April 2008 at Incirlik, only those pallets arriving on or after are considered for this analysis. Finally, occurrences where pallets were returned to Incirlik after initial transload were filtered from the data so that inflated demand would not be predicted. Of the over 45,000 pallets contained in the set, 0.1% contained inconsistencies in the data that excluded them from analysis in this study.

Forecasting methods

Several methods were used to forecast the demand for airlift to the 10 APODs from 1-31 December 2009. In order to effectively compare the forecasting methods, pallet arrivals were grouped both on a daily and weekly basis by the pallet APOD. The forecasting methods for daily arrivals included moving averages, simple exponential smoothing, Holt's method, Winter's method, multiple regression and novel methods. The treatment of weekly data also included these methods as well as Adaptive Rate Exponential Smoothing (ADRES). For each of the methods described, Microsoft Excel was used for its universal availability to the Air Force forecaster.

Mean square error (MSE) was used as a basis of comparison for each of the models based on a forecast period of t + 7 days for daily forecasts or 1 week for weekly forecasts. An explanation of the methods used in this study as well as MSE follows. For brevity, explanation of the variables is limited to those instances where the symbology differs.

<u>Naïve forecast</u>

The naïve forecast is the simplest method in that the forecast demand is simply equal to the previous period's observed value as illustrated by Equation (1). It is worthy to note that ADRES forecasts with a β parameter equal to 1 produce the same results as the naïve forecast. The naïve forecast was used as a baseline for determining the significance of the results of the other models.

$$F_{t+1} = X_t \tag{1}$$

where

$$F_{t+1} = \text{Forecast value for } t+1$$
$$X_t = \text{Observed value at time t}$$

Moving Averages

The moving average is a simple technique often used to forecast data that exhibits substantial randomness. It is easily described as an equally weighted average of recent data, calculated by Equation (2):

$$F_{t+1} = \frac{\sum_{t-n}^{t} X_i}{n} \tag{2}$$

where n is equal to the number of periods in the moving average.

Simple Exponential Smoothing

Simple exponential smoothing is best applied to data when there is no seasonal or trend components in the data. It uses past data to forecast future data by smoothing the recent data by a smoothing constant, α. Values of α closer to zero will be more representative of moving average models with large values of n, while those with α values closer to 1 are similar to moving averages with smaller values of n. However, due to the exponential decay of the past data, it differs from the moving averages in that it gives greater weight to more recent data. Its general formula is:

$$F_t = F_{t-1} + \alpha\left(\mathrm{X}_{\mathrm{t-1}} - F_{t-1}\right) \tag{3}$$

where α represents a value between 0 and 1.

<u>Holt's Method</u>

Holt's method is an extension of simple exponential smoothing that accounts for trends in the data. Named for its originator, C. C. Holt, the Holt method uses an additional constant, β, here optimized through solver, to identify an increasing or decreasing linear trend.

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{4.1}$$

$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \tag{4.2}$$

$$F_{t+k} = S_t + kT_t \tag{4.3}$$

where

S_t = Smoothed value
T_t = Trend Estimate
β = Smoothing constant for the trend estimate $(0 \le \beta \le 1)$
k = Number of forecast periods

<u>Damped Trend Forecast</u>

In the Holt model, the smoothing value is considered constant over the course of the model. The damped trend forecast adds a third parameter, φ, which specifies the decay of the trend over time.

$$S_t = \alpha A_t + (1-\alpha)(S_{t-1} + \varphi T_{t-1}) \tag{5.1}$$
$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)\varphi T_{t-1} \tag{5.2}$$
$$F_{t+k} = S_t + \sum_{i=1}^{k} \varphi^i T_t \tag{5.3}$$

where

$$\varphi = \text{Smoothing constant for trend decay } (0 \le \varphi \le 1)$$

Winter's Method

Winter's method, also referred to as the Holt-Winter's method, is best used when data exhibits seasonal patterns with respect to time. That is, there are periodic increases and decreases in the demand measured that have a predictable pattern. It combines the basic features of Holt's method, biased by a seasonal index . The seasonal index is a unitless multiplier that accounts for variations in the data which can be attributed to the time frame over which the events are considered. To allow for seasonal variability in the model, the multiplicative form of the Winter's method is used:

$$S_t = \alpha\, X_t / I_{t-p} + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{6.1}$$
$$I_t = \gamma\, X_t / S_t + (1-\gamma) I_{t-p} \tag{6.2}$$
$$T_t = \beta(S_t - S_{t-1}) + (1-\beta) T_{t-1} \tag{6.3}$$
$$F_{t+k} = (S_{t+1} + kT_{t+1}) S_{t+k-p} \tag{6.4}$$

where

I_t = Seasonality estimate
γ = Smoothing constant for the seasonality estimate $(0 \le \gamma \le 1)$
k = Number of periods in the forecast lead period
p = number of periods in the seasonal cycle

Multiple Regression

Multiple regression forecasting models used in this paper were limited to those that could be performed using Microsoft Excel's Data Analysis Toolpak. As such, no programming was required; however, Equation (7) describes the process used in Excel to arrive at the coefficients in the regression models. The regression models were limited to using aircraft type and quantity as the sole independent variables in the models.

$$F_t = f(Y_1, Y_2, \ldots Y_n) = \beta_1 Y_1 + \beta_2 Y_2 + \ldots \beta_n Y_n + \varepsilon \qquad (7)$$

where

Y_i = Number of aircraft of a certain type
β_i = Coefficients of independent variables solved by the least squares method
ε = Error term representing the difference between actual and forecast data

The coefficients of the regression term are solved by minimizing the sum of squares (Equation (8)) of the error term. In each of the models, the value of *F(0,0..0)* is constrained to zero, resulting in no constants in the regression equation.

$$\sum \varepsilon^2 = \sum (X - F)^2 \qquad (8)$$

Adaptive Rate Exponential Smoothing (ADRES)

The ADRES model functions very similar to simple exponential smoothing, except that the smoothing constant varies over the forecast period in response to the observed error of the forecast. Like simple exponential smoothing, it is best used for instances in which the data does not display trends or seasonality.

$$F_{t+1} = F_t - \alpha_t \left(X_t - F_t \right) \tag{9.1}$$

$$\alpha_t = \left| \frac{S_t}{A_t} \right| \tag{9.2}$$

$$A_t = \phi e_t + (1 - \phi) A_{t-1} \tag{9.3}$$

$$M_t = \phi \left| e_t \right| + (1 - \phi) M_{t-1} \tag{9.4}$$

$$e_t = X_t - F_t \tag{9.5}$$

where

$$\begin{aligned} A_t &= \text{Smoothed error} \\ \phi &= \text{Smoothing constant} \\ M_t &= \text{Absolute smoothed error} \\ e_t &= \text{forecast error at time t} \end{aligned}$$

Novel Methods

The three additional methods used in this paper differ from the previous forecasting methods in that they also consider aircraft type to determine an expected number of pallets to be transloaded at Incirlik AB. These values are independent of the actual destinations of the pallets contained on the aircraft. As the type of aircraft assigned to a particular channel mission should be known in advance of the forecast period, these expected values can then be used in conjunction with one of the methods above to estimate a pallet quantity for a particular airfield. These methods are labeled "novel" simply to differentiate them from the classical time series methods.

The Novel 1 method estimates the amount of transloaded pallets for a particular mix of aircraft by first using 85% of the planning values identified in AFPAM 10-1403, shown in Table 2. As actual arrivals occur, the transload values for a particular type aircraft are updated as a running average from 23 Apr 08 to the preceding 7 days for any given time in the study period. This provides a realistic measure as the baseline figures would not be known at the outset of a contingency.

Table 2 Expected Transload Values

Aircraft	Pallet Capacity	85% Capacity
C-130	6	5.1
C-17	18	15.3
C-5	36	30.6
KC-10	23	19.55
B-747	34	28.9
B-757	15	12.75
B-767	24	20.4
DC-10	30	25.5
L-1011	26	22.1
MD-11	34	28.9

In order to determine the proportions of the transloaded pallets that are destined for a particular airfield, the Novel 1 method used moving averages of the actual arrival data optimized through Solver on the basis of MSE. Therefore, for any given period, the forecast was calculated by Equations (10.1) and (10.2).

$$E_t = \begin{bmatrix} x_1 & x_2 & \ldots & x_n \end{bmatrix} \cdot \begin{bmatrix} TP_1 \\ TP_2 \\ \vdots \\ TP_n \end{bmatrix} \tag{10.1}$$

$$F_t = (E_t) \cdot A_t \tag{10.2}$$

where

x_i = The number of planned arrivals of an aircraft type at period t
TP_i = The running average of transloaded pallets from a particular aircraft type
E_t = The total number of pallets expected to arrive for transload operations at period t
A_t = The moving average of the proportion of total pallets for a given airfield
F_t = The forecast for pallets destined to a particular airfield to arrive at period t

The Novel 2 method uses the same methodology as Equation (10.1) to determine the expected number of pallets to arrive for transload operations in a given period. However, rather than using moving averages, Novel 2 forecasts the proportions through Holt's method. The Novel 3 method uses multiple regression to first determine the total number of pallets to arrive for transload operations as a function of the mix of aircraft arrivals at a given time period. Subsequently, it uses Holt's method to determine the proportion of the expected pallet arrivals that will be destined for a particular airfield.

For all of the methods above, the Evolutionary Solver subroutine was used to identify optimum parameters in each model. This method was selected over the other non-linear options in Solver due to its ability to evaluate objective functions containing “lookup” and “if” statements   Solutions for the parameters were calculated by minimizing the MSE for the periods prior to the forecast periods. For example, if the forecast period was 1-31December 2009, the parameters of the model would be calculated through solver by minimizing the MSE of the model from 23 April 2008 to 30 November 2009. These parameters would then be the basis of calculation for the 1-31 December 2009 forecast by the selected measure. A MSE for the post sample forecast was then calculated in order to compare the method’s accuracy for the given airfields. The calculation of the MSE is depicted by Equation (11):

$$MSE = \sum_{i=1}^{n} \frac{\left(X_i - F_i\right)^2}{n} \tag{11}$$

where *n* represents the number of cycles (days or weeks) in the forecasted period.

Limitations

Pallet data in GATES is often not provided in whole number increments due to pallet sizes that exceed the dimensions of a 463L pallet. In the cases where pallets were larger than a single pallet position, the pallet size was simply determined to be the fractional multiple of a single pallet. By this measure, it is possible that aggregation of the pallets on a daily or weekly basis would produce levels that would not be transportable by simple dividing the aggregated total by the pallet capacity of a given aircraft.

In addition, while the goal of this research is to identify a forecast methodology that best identifies airlift requirements for post-transload operations at any aerial port, it only examines operations at one transshipment node (Incirlik AB, Turkey). As such, there may be other factors not measured in this study that skew the results. Furthermore, the methods discussed above are not causal models, and therefore, do not take into account external factors that could cause abrupt shifts in requirements. It is important for any forecaster to take these factors into account when basing decisions on the models used in this research.

IV. Results and Analysis

The first set of trials examined the forecast methods using all of the data available from 23 April 2008 to 30 November 2009. For each model, the parameters determined through Solver were used to forecast 1-31 December 2009. Pallets were aggregated on a daily basis. Date values were determined by the Greenwich Mean Time (GMT) values as reported in arrival time field reported in GATES. The MSEs for 1-31 December 2009 of the model applied to the airfields identified in Figure 4 are reported in Table 3, with the exception of OR5 and OA1. Since the deliveries to these airfields ended prior to December 2009, their results are discussed separately.

Table 3 Daily Forecast Results for 1-31 December 2009 Using 23 April 2008 – 30 November 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	61.0	260.6	397.9	9.4	43.3	10.4	70.1	68.3	4.5
Simple Exponential	32.3	204.2	182.7	5.6	24.6	5.9	86.3	61.8	6.3
Moving Average	32.4	226.6	187.1	5.5	26.7	5.9	82.5	42.7	4.3
Holt's	32.3	217.0	188.6	5.6	24.6	6.0	86.3	56.0	6.3
Damped Trend	32.5	204.2	189.4	5.5	24.6	5.9	86.3	61.9	6.3
Winter's	33.9	212.1	266.0	5.2	24.7	6.4	77.9	44.8	3.9
Multiple Regression	24.0	194.8	107.0	4.0	18.0	3.6	143.4	116.0	4.9
Novel 1	23.6	89.4	71.2	3.9	16.8	4.2	22.0	17.8	2.9
Novel 2	24.4	87.7	62.1	4.2	16.6	3.6	18.4	13.7	3.7
Novel 3	25.4	86.1	62.4	4.4	17.0	3.6	17.6	13.1	3.6

The MSE values reported in the table reflect the accuracy of the forecasts compared to the actual data. Adopting the approach by Makridakis and Hibon (2000), significance of the forecasts was determined by performing F-tests at the 5% level by comparing the forecasts to a common benchmark, in this case the naïve forecast. The highlighted values indicate the forecasts which pass the F-test and are statistically significant (that is, not the result of chance). This convention is used throughout the reporting of the results.

The same date convention was used to aggregate the transloaded pallets at the weekly level. For this treatment, weekly periods were constructed beginning on 23 April 2008, ending on 1 December 2009. Solver was used to determine the model parameters, minimizing MSE for the first period. These parameters were then applied to the four weeks beginning 2 December 2009. The results of this weekly grouping are reported in Table 4.

It is apparent from the results that for daily forecasts, the novel models that took into account the type of aircraft delivering the pallets to Incirlik AB had the greatest consistency of significant forecasts when compared to the naïve model. Aggregating the pallets at the weekly level had decidedly different results. While the novel forecasts performed better than the traditional time-series methods, in most cases, the forecasts did not produce results with greater significance than the Naïve forecast baseline. An explanation for this can be found from an examination of the variance of the daily and weekly transloads volumes.

Table 4 Weekly Forecasts for 2-29 December 2009 Using 23 April 2008 – 30 November 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	460.5	1055.5	2295.5	67.1	441.5	128.9	89.8	666.8	17.2
Simple Exponential	335.7	1265.4	1224.8	40.7	262.5	40.8	334.4	844.7	39.4
ADRES	299.8	1218.9	1757.9	39.8	256.8	40.9	89.8	943.2	52.2
Moving Average	356.9	1528.3	1113.2	29.4	308.8	40.1	655.4	712.5	89.0
Holt's	335.7	1570.1	1287.0	40.7	262.5	40.8	334.4	727.3	39.4
Damped Trend	335.7	1575.8	1324.7	40.7	262.5	40.8	334.4	727.3	39.4
Winter's	310.0	772.6	2166.1	42.1	388.6	109.3	815.2	419.4	18.9
Multiple Regression	214.8	12369.7	7059.7	24.0	430.3	29.1	3133.7	6650.1	105.2
Novel 1	334.3	1265.1	802.3	15.5	200.6	49.3	317.6	374.0	55.4
Novel 2	205.1	1071.9	236.8	16.9	179.1	41.7	160.6	217.5	91.2
Novel 3	200.2	1090.4	238.9	16.7	186.2	41.6	157.4	205.2	86.4

As shown in Table 5, the relative standard deviations (as a percentage of the mean transload volumes) for a particular airfield were much higher for the daily transload volumes than in the weekly volumes. In fact, in most cases the daily standard deviation percentages were more than double the weekly standard deviation percentages. As a result, by aggregating the pallets to the weekly level, the performance of the naïve forecast was improved. As this was the baseline in determining the significance of the other models, the standard of performance to establish significance of the other forecasts was also increased.

In order to determine if the post-sample forecasts for 1- 31 December 2009 would be better predicted by using only near term-data, model parameters were calculated using

Table 5 Variation of Daily Versus Weekly Transload Volumes

	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Daily Mean	6.8	6.4	7.9	2.6	6.4	2.3	20.9	17.0	3.3
Daily Std Dev	6.0	11.3	11.8	2.6	6.4	2.9	16.9	14.2	3.6
%	90	180	150	100	100	120	80	80	110
Weekly Mean	47.5	44.5	55.6	17.9	44.7	16.4	146.6	119.0	23.1
Weekly Std Dev	17.0	58.7	62.4	7.0	20.7	7.9	63.3	49.7	10.2
%	40	130	110	40	50	50	40	40	40

only the data during 1 Jun to 30 November 2009. Table 6 and Table 7 report the daily and weekly results, respectively. The results of this analysis are inconclusive. Of the 81 model combinations, 54 showed an improvement, 5 showed no change and 22 actually declined. Furthermore, of the 37 forecasts that were significant using the entire data set, 24 produced lower MSEs. While a distinct positive conclusion cannot be drawn from these findings, further research may be able to identify an optimum timeframe with which to establish the forecasts.

The last treatment of the forecasts was performed to determine if the presence of lower than average transload volumes had a significant effect on forecast performance. As shown in Figure 5, the transload volumes for December were 16% lower than the average for the year and 21% lower than the average for the previous 7 months which had been relatively stable.

Table 6 Daily Forecasts for 1-31 December 2009 Using 1 June 2009 – 30 November 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	61.0	260.6	397.9	9.4	43.3	10.4	70.1	68.3	4.5
Simple Exponential	31.6	202.5	179.3	5.6	24.2	5.9	116.9	54.0	5.8
Moving Average	35.5	228.7	191.5	5.5	26.9	5.9	78.3	42.7	4.5
Holt's	31.6	190.9	214.8	5.5	23.6	5.9	116.9	42.2	5.8
Damped Trend	31.6	190.9	186.2	5.5	23.6	5.9	116.9	42.2	5.8
Winter's	34.4	212.2	216.0	5.4	25.4	6.4	62.4	46.8	6.5
Multiple Regression	24.4	194.8	107.0	4.2	29.9	4.7	65.4	90.4	3.8
Novel 1	23.5	85.5	61.8	3.8	16.6	4.2	19.8	17.5	2.9
Novel 2	23.6	83.2	69.5	4.4	15.9	4.7	16.8	13.0	3.4
Novel 3	24.3	81.2	65.8	3.7	16.2	3.7	16.6	12.9	3.3

Table 7 Weekly Forecasts for 1-31 December 2009 Using 1 June 2009 – 30 November 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	460.5	1055.5	2295.5	67.1	441.5	128.9	89.8	666.8	17.2
Simple Exponential	354.0	1184.1	1155.2	27.8	277.7	48.4	343.0	884.6	16.6
ADRES	465.9	1218.9	1998.2	19.8	429.7	128.9	776.9	529.9	61.5
Moving Average	347.1	1687.9	1685.9	43.0	308.8	40.1	574.2	948.9	89.0
Holt's	364.8	1317.1	2280.0	17.7	217.8	128.7	516.9	946.0	45.1
Damped Trend	364.8	1317.1	2075.9	18.4	217.8	128.7	516.9	946.0	45.1
Winter's	256.4	953.4	3417.7	35.0	389.2	47.4	1420.6	575.6	112.8
Multiple Regression	311.2	9670.9	15668.5	48.5	990.0	65.7	538.3	1376.4	107.9
Novel 1	305.6	1286.3	391.5	15.5	193.2	49.3	264.9	364.2	55.4
Novel 2	319.3	1003.8	257.2	15.9	149.8	41.8	184.4	856.0	12.1
Novel 3	324.3	1045.7	250.7	15.6	154.7	41.7	164.4	808.1	10.2

In order to eliminate the selection of December as a possible bias, 1-31 October 2009 was used as the basis of comparison, as its volume was in line with the average of the preceding months. As in the first forecasts, all of the parameters for the daily models were solved based on the full data set, from 23 April 2008 – 30 September 2009. The MSE for the weekly forecasts is calculated from the 5 weeks following 30 September 2009 to capture all of October. Table 9 and Table 8 report the results for the daily and weekly forecasts, respectively.

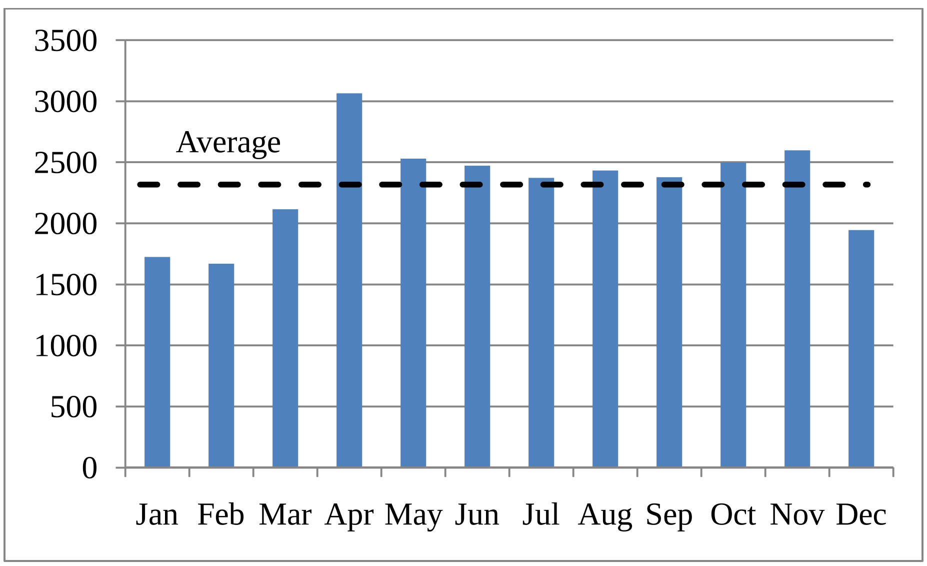

Figure 5 Transload Volumes at Incirlik AB During 2009

Table 9 Daily Forecasts for 1-31 October 2009 Using 23 April 2008 – 30 September 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	35.0	173.4	158.8	5.1	63.2	5.3	213.9	187.8	14.5
Simple Exponential	21.5	152.9	120.4	2.8	25.8	2.3	112.7	97.1	9.2
Moving Average	24.3	204.9	131.0	2.8	26.4	2.3	116.0	99.1	10.1
Holt's	13.1	120.9	61.9	1.4	13.1	1.3	57.2	49.3	4.7
Damped Trend	12.1	120.9	63.5	1.4	13.1	1.1	57.2	49.4	4.7
Winter's	20.2	212.5	126.2	2.8	26.7	2.8	107.5	95.7	10.4
Multiple Regression	22.3	80.5	81.7	3.2	23.8	2.7	110.1	84.8	8.8
Novel 1	18.3	114.1	97.1	2.5	20.4	2.7	51.1	60.0	9.7
Novel 2	21.3	185.9	100.5	2.3	19.7	3.0	47.7	61.9	8.5
Novel 3	22.1	184.8	141.6	2.5	20.0	3.0	49.0	65.0	8.7

Table 8 Weekly Forecasts for 1-31 October 2009 Using 1 June 2009 – 29 September 2009 Data

Forecast Method	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Naïve	112.6	1445.8	4545.4	74.5	140.4	51.3	274.8	971.2	127.5
Simple Exponential	92.9	2408.4	3061.8	48.5	71.4	18.3	232.8	430.4	111.1
ADRES	98.7	2452.2	4092.7	50.6	70.1	17.9	318.0	412.3	115.6
Moving Average	127.9	4398.5	2804.6	51.6	84.5	18.7	449.9	404.9	110.7
Holt's	270.0	4983.4	3006.5	48.5	71.4	20.3	232.8	462.2	111.1
Damped Trend	270.0	5391.3	3057.7	48.5	71.4	22.8	232.8	430.1	111.1
Winter's	115.2	3856.2	2469.9	38.5	96.2	50.2	379.0	562.2	133.9
Multiple Regression	40.3	20393.9	3724.1	82.4	699.6	88.4	3244.0	2146.6	62.5
Novel 1	95.3	1389.9	2371.7	40.3	77.3	22.5	383.4	453.9	130.2
Novel 2	143.3	7882.9	2170.3	37.3	68.4	18.9	254.7	402.5	61.9
Novel 3	136.4	8360.5	2175.0	34.3	74.5	20.4	278.0	411.4	56.9

Similar to the examination of the daily versus weekly aggregation, in analyzing the results of the October 2009 forecasts compared to the December 2009 forecasts, the variance in the transload volumes of the forecasting periods also played a role in the significance of the forecast results. When the volume was higher and the relative deviation was lower as shown in Table 10, all of the models performed better in October than they did in December.

Table 10 Variation of December 2009 Versus October 2009 Transload Volumes

	TA8	AZ1	KDH	KIK	O2R	O6R	OR9	SDA	OSM
Dec Mean	6.1	14.9	17.9	2.0	4.9	2.0	9.5	6.7	1.4
Dec Std Dev	5.5	13.8	12.9	2.3	4.9	2.4	7.8	6.0	1.7
%	90	90	70	120	100	120	80	90	120
Oct Mean	5.8	14.5	18.0	2.2	5.3	2.0	14.6	13.5	3.6
Oct Std Dev	4.5	10.8	10.5	1.6	5.1	1.5	10.6	9.8	3.0
%	80	70	60	80	100	70	70	70	80

The two airfields omitted from the tables above were OA1 and OR5. The pallet data for OA1 exhibited a very random pattern accounting for only 4 deliveries of pallets for transload operations. These 4 deliveries were also spread out over 34 days at inconsistent intervals. The performance of all of the forecasting methods discussed here for OA1 were insignificant and therefore, not shown.

Table 11 reflects the results of the forecasts for OR5. Deliveries to OR5 from the transload operations at Incirlik AB continued as a routine operation until 31 May 2008, after which steady deliveries began to decline and occur with greater and greater randomness. Operations from Incirlik AB to OR5 ceased altogether on 23 October 2008. In order to examine the effect of the forecasts on a declining operation, the period from 23 April 2008 to 31 May 2008 was used to determine the model parameters for the daily and weekly forecasts.

Table 11 Daily and Weekly Forecasts of OR5 Transloads for June 2008

Forecast Method	Daily	Weekly
Naïve	159.9	724.9
Simple Exponential	98.2	4058.0
ADRES	N/A	1357.4
Moving Average	94.6	1316.7
Holt's	98.2	1073.1
Damped Trend	N/A	1242.2
Winter's	122.2	N/A
Multiple Regression	73.0	1242.2
Novel 1	79.0	627.1
Novel 2	99.0	822.5
Novel 3	95.7	771.7

The purpose of examining forecasting the transload volume for OR5 was to determine which methods would be adequate for forecasting an airfield that exhibited declining operations. As was the case with the forecasts for the previous airfields, aggregating the pallets at the weekly level did not produce significant results when compared with the naïve forecast. For the daily models, it was expected that Holt's method or the damped trend model would produce significant results, since these account for the decreasing nature of the trend. However, the results of both of these forecasts yielded worse results than the naïve model. Figure 6 shows the decreasing linear trend (not to be confused with the trend forecast) of OR5's deliveries. In this instance, while there was clearly a decrease as shown by the trend line in black, the sporadic deliveries during June 2008 and beyond could not be accounted for in the classical time-series models. As was the case with most of the airfields, the models that took into account the aircraft delivering the transload shipments performed the best.

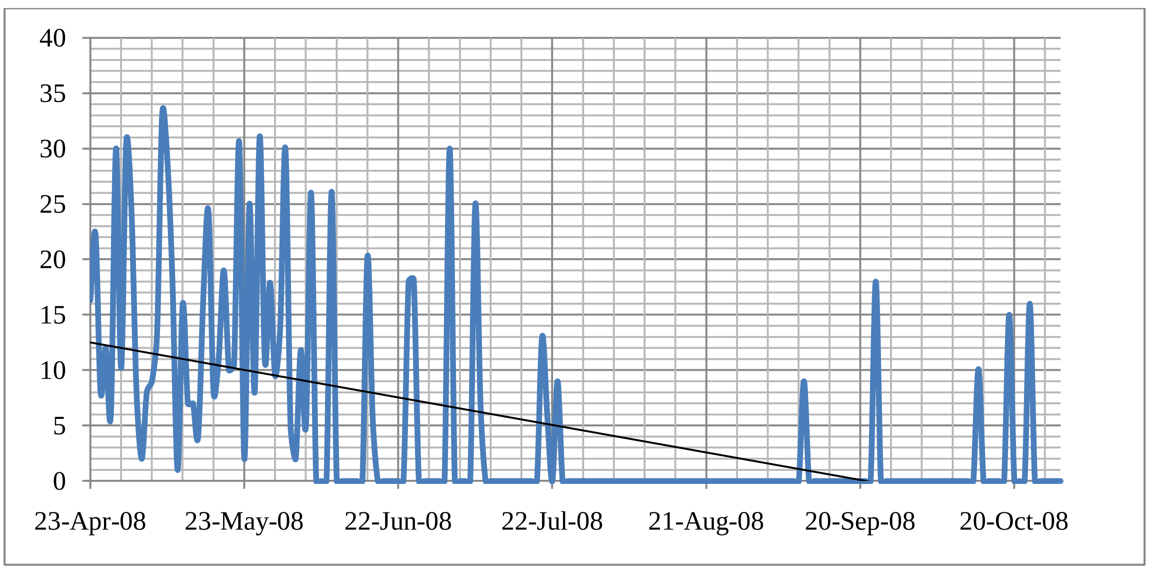

Figure 6 Transload Volumes for OR5 23 April 2008 – 23 October 2008

In contrast to the results for OR5, the two airfields with increasing transload operations, AZ1 and KDH, demonstrated positive results with Holt's method and the damped trend model. The difference in the results is mainly explained by the forecasted period. During October and December 2009, AZ1 and KDH did not exhibit the same gaps in deliveries that OR5 did during June 2008. Figure 7 shows the linear trends of both AZ1 and KDH during the study period that illustrate this occurrence.

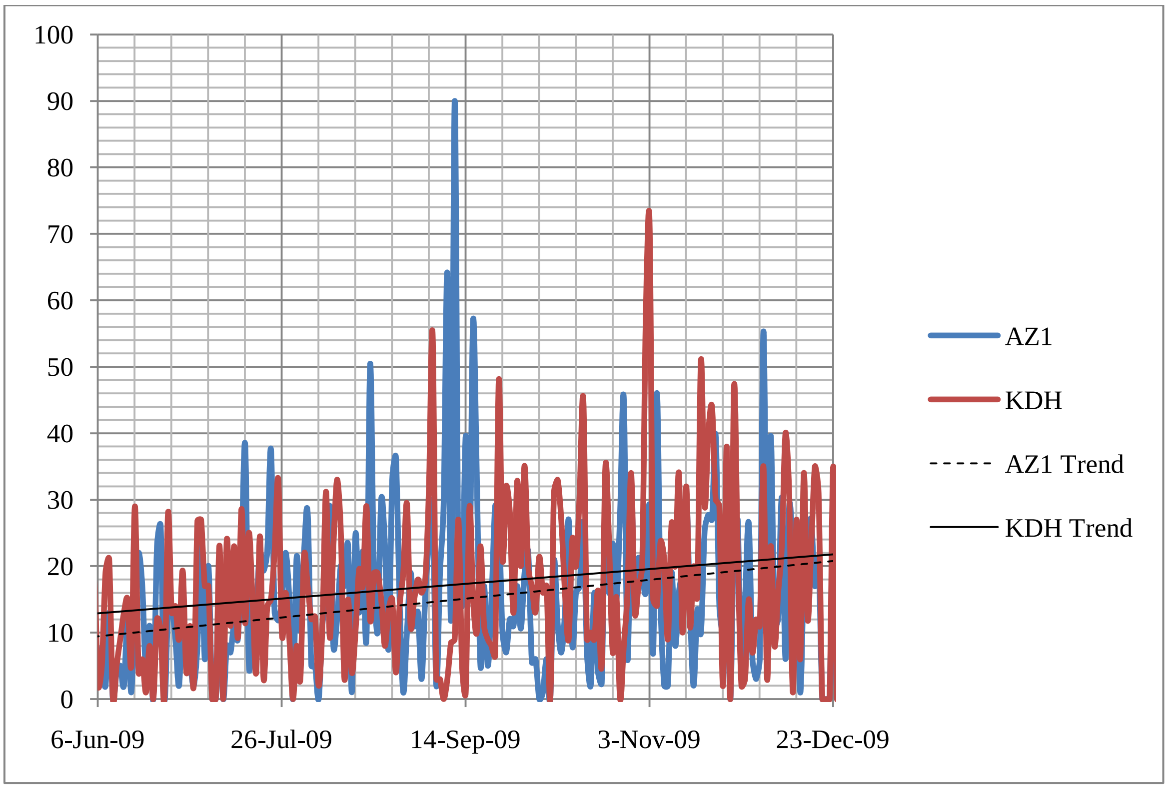

Figure 7 AZ1 and KDH Transload Volumes

It should also be noted that for daily models, no forecasts produced significant results for OSM. While the novel models did exceed the performance of the naïve forecast in all cases, the low daily volume paired with a regular delivery schedule caused the performance of the naïve forecast to be relatively higher than when it was applied to other airfields.

For all four scenarios (routine sustainment, declining operations, escalating operations, random operations) studied, the only methods producing consistent results were the four models that forecasted transload volumes based on inbound aircraft type. Of the 28 airfield and forecast period scenarios considered in daily forecasting, multiple regression had significant results for 16 of the 28 scenarios, novel 1 had significant results for 23 of the scenarios, and both novel 2 and novel 3 produced significant results for 20 of the scenarios. In terms of weekly forecasting, the performance of the naïve forecast was improved through aggregation, resulting in less significant results for the all of the forecasting methods. In this case, multiple regression had significant results for 6 of the 28 scenarios, novel 1 had significant results for 12 of the scenarios, and both novel 2 and novel 3 produced significant results for 16 of the scenarios. Considering both daily and weekly aggregation of the data in this study, novel 2 and 3 were marginally better at producing significant results for any scenario. However, each of the novel models performed better than one another at different times, depending on the specific destination airfield.

V. Conclusions and Recommendations

The results of this research indicated that the performance of forecasts taking into account the aircraft type was better than classical time-series forecasts for transload operations at Incirlik AB, Turkey. Furthermore, aggregation of pallet deliveries at the weekly level caused an increase in performance of the naïve forecast, resulting in no clear conclusion on a specific forecasting method that is best for weekly forecasts.

Recommendations for Current Initiatives

In the sustainment pipeline, the focus of current initiatives is to synchronize the flow of material between DLA and the airlift system that supports its movement (Lanier 2009). While these initiatives will undoubtedly create linkages that will foster enhanced efficiency between supply and distribution, there appears to be some neglect in the latter phases of distribution. While the transition from warehouse to APOE becomes more seamless, under the current framework, these efficiencies serve to compress the visibility window in the supply chain under which transload ports like Incirlik AB operate.

Current methods in determining follow-on missions for transload operations are based on real-time data from GATES. Although not without error, this method produces a *relatively* error-free approach in identifying follow-on requirements. The drawback to the as-is framework is that it gives airlift planners little time to plan missions to destinations that are constantly constrained by MOG and other restrictions. In the opinion of the researcher, forecasting these requirements in advance would provide an adjustable baseline to smooth aircraft and materiel flows from the transshipment node to the pallet's APOD.

While the capability forecasts completed at Incirlik AB are a step forward, they are still only a reflection of what is, not what will be. In order to boost the efficiency of the movement to the final destination, other means need to be implemented. Whether it be forecasting methodologies like those discussed in this paper or enhanced linkages between supply and distribution, the tail of the supply chain requires equivalent attention as has been given to the earlier stages.

Additionally, while the focus of this research was on the final phases of distribution, sharing this information with earlier phases in the distribution pipeline may yield even greater results. As part of the overall supply chain management process, Lambert (2008) identifies demand management as one of the eight key supply chain management processes. In this framework, demand management is a key synchronizer between procurement and distribution. In the cases where demand uncertainty is high (which is arguably the case here), Lambert forwards decreasing flexibility and reducing variability as the two primary means to handle the problem.

In military airlift, the ability to build in flexibility is low. Airfields are constrained by parking limitations and organic intratheater airlift is further constrained by infrastructure and political sensitivities of the host nation where they are based. However, there are methods to decrease the variability of distribution. The forecasts presented in this paper identify the volumes for specific airfields based on arrival at Incirlik AB as a transshipment node. As a corollary, however, they also identify the throughput from several other APOEs. If these forecasts were used by the APOEs (primarily CONUS east coast locations), the pallets could be held at the APOE until an appropriate level was reached to support a follow-on mission from the transload port. The same effect could also be obtained by holding them at the transload location. This would limit the subsequent additional transloads at other ports in theater for the sole sake of reducing port hold time. For the airfields studied in this paper, KIK had the lowest average daily volume at 2.6 pallets per day. Therefore, the average hold time to generate an entire C-17 load for KIK would increase to 6 days. The other APODs studied here would require even less port hold time. Pagh and Cooper (1998) identify this concept as logistics postponement—a strategy that is used today in commercial sectors to reduce overall logistics costs. In the case of the DOD, this would limit secondary transload operations, saving fuel and manpower.

This would, of course, entail a paradigm shift in the way port hold time is used as a measure of efficiency. Through a balanced strategy of analyzing the total pallet port time under current operations with the proposed concept of holding pallets at a single port longer, it is the opinion of the researcher that the cost efficiencies gained may outweigh any delays (if realized at all) to the customer. Proper analysis of forecasted pallet deliveries is an avenue to accomplish this task.

Recommendations for Future Initiatives

Soon IGC will come on-line as a replacement to GTN, combining supply side data and distribution data accessible under a single interface. While this is certainly a huge step in achieving end-to-end visibility, the ability to use this supply side data effectively to forecast transportation requirements deserves additional study. While this study did not limit its focus to DLA-produced pallets only, an initial attempt was made to establish a relationship between the supply side data from DLA's warehouse at Susquehanna, Pennsylvania (DDSP) and the arrival time of a given order at the transshipment port. The goal here was that looking back in the supply chain, there would be enough materiel data at the transportation control number (TCN)-level to forecast requirements effectively at least a week in advance of a pallet's arrival. DLA tracks their orders through many steps in the acquisition process from order placement, receipt at the warehouse and departure from the warehouse. While order placement was the earliest visibility in the sustainment flow, on average being 40 days in advance of the shipment from the warehouse, the variance was too large to be of any use at 522357 days^2. Much more consistent was the receipt of the order at the warehouse. From this date to the date that a shipment arrived at the transload APOD was 6 days with a variance of 13 days^2. Yielding a standard deviation of over 3 days, it is doubtful that this measure would produce more accurate results than forecasting at the pallet level.

Complicating the usage of TCN data for forecasting airlift requirements is that a single pallet TCN is often made up of several hundred individual orders. With the establishment of the pure pallet program, it is difficult to identify in advance when an order will be received and subsequently what orders will be combined to form the pure pallet. In this sense, the pure pallet program, in terms of forecasting transportation requirements is a victim of its own efficiency.

It is no secret that many successes in commercial logistics have come from establishing linkages between different nodes in the supply chain. The promise of a system like IGC is that it will provide the linkage that has been missing in the DOD between supply and distribution to improve visibility in the supply chain. When used to forecast transportation requirements, it is essential that the enhanced data set provide more than just a combination of the two systems that comprise it. In that vein, further analysis is necessary to correlate what variables contained within IGC will be of interest to the transportation forecaster. If information can be gleaned from the data such that when an order is placed, it triggers a notional delivery date and, therefore a transportation requirement, transportation planners can use this information to plan missions weeks and sometimes months in advance. The ripple of such an action would be felt all the way to the final APOD. When given exact requirements with such a long lead time, there would be less juggling of missions at the last minute to get priority cargo to its destination.

Recommendations for Further Research

The research discussed in this paper focuses on the forecast methodologies themselves. What may be of greater importance is developing bounds to their accuracy. In order to effectively implement any method, it is essential that the model produce results that are usable. It would do little good if the forecasts produced results that created more effort without greater gains in efficiency and effectiveness. For this reason, a further area of research in forecasting transload requirements should focus on the acceptable level of error of the forecast. If the tolerance is zero, then the as-is framework is the only method that will work.

Furthermore, the forecasting methods in this paper were judged based on their MSE. However, Yokum and Armstrong (1995) identified that accuracy of a forecast may not be the only, nor the most important, measure of interest to decision makers. Their study reported a meta-analysis of several studies, to include their own, on the importance of accuracy and other measures. While they did find that accuracy was consistently ranked as the most important measure, other measures were nearly as important such as ease of implementation. Such a study is warranted to determine what measures would be used as the criterion for selecting forecasting methodologies in the DOD.

Additionally, the models presented in this paper are by no means all-encompassing. There may be other variables not examined in this research that may produce better forecasts. For this reason, continued analysis of metrics within GATES and IGC is needed to discern their ability in forecasting requirements for missions subsequent to transload operations.

Final Thoughts

It is true that forecasts are always wrong; however, doing nothing goes against every planning effort that the DOD undertakes. This paper demonstrated that forecasting methodologies can be used to produce results that are quantifiable and useable. We can synchronize flows of transportation from the warehouse to the APOE, but neglecting the tail end of the supply chain can undo any efficiencies gained by such action. As we are further constrained on the use of a finite organic fleet of airlifters, we cannot afford to do less.

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Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Street, Building 642
WPAFB OH 45433-7765

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14. ABSTRACT

In the Department of Defense (DOD) supply chain for sustainment cargo, over 45,000 pallets were transloaded at Incirlik AB, Turkey in from April 2008 to December 2009 with ultimate destinations in the USCENTCOM AOR, making Incirlik the largest transshipment node for airlift in the DOD by over two-fold. Current methods of forecasting follow-on transportation requirements are based on the amount of pallets on hand at the aerial port as well as short-term visibility of pallets currently in the channel system destined for Incirlik AB. This process yields a forecast horizon of only 2-3 days for planning subsequent airlift missions. An analysis several time series forecasting methods using post-sample pallet data from the Global Air Transportation Execution System (GATES) was accomplished to examine their ability to forecast different sustainment scenarios at least 7 days in advance of arrival at Incirlik AB, Turkey. Recommendations on how to implement forecasting methodologies in a general framework were proposed.

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