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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MBA PROFESSIONAL REPORT

CONSOLIDATED AUTOMATED SUPPORT SYSTEM (CASS) EFFICIENCY AND ALLOCATION COST IMPROVEMENT

By: James L. Rorer, and
Luis F. Asifuinagomez
December 2013

Advisors: Kenneth Doerr,
Noah Myung

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REPORT DOCUMENTATION PAGE		*Form Approved OMB No. 0704–0188*

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1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE December 2013	3. REPORT TYPE AND DATES COVERED MBA Professional Report
4. TITLE AND SUBTITLE CONSOLIDATED AUTOMATED SUPPORT SYSTEM (CASS) EFFICIENCY AND ALLOCATION COST IMPROVEMENT		5. FUNDING NUMBERS
6. AUTHOR(S) James L. Rorer, Luis F. Asifuinagomez		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943–5000		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A		10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB protocol number ____N/A____.

12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public use; distribution is unlimited	12b. DISTRIBUTION CODE A

13. ABSTRACT (maximum 200 words)

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14. SUBJECT TERMS Consolidated automated support system, CASS, eCASS, non-linear programming, resource allocation, discrete stochastic capacity allocation, queuing congestion, utilization, operational availability, readiness	15. NUMBER OF PAGES 61
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU

NSN 7540–01–280–5500

Standard Form 298 (Rev. 2–89)
Prescribed by ANSI Std. 239–18

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Submitted in partial fulfillment of the requirements for the degree of

MASTER OF BUSINESS ADMINISTRATION

from the

NAVAL POSTGRADUATE SCHOOL
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LIST OF ACRONYMS AND ABBREVIATIONS

A_o	operational availability
CASS	consolidated automated support system
CNI	communication, navigation, identification CASS
DoD	Department of Defense
DON	Department of the Navy
EO3	electro-optical CASS
ETE	end to end (run time or number of runs)
EXREP	expeditious repair
FCFS	first come, first served
FRC	Fleet Readiness Center
HYB	hybrid CASS
I-Level	intermediate maintenance level
MTBF	mean time between failure
MTOS	mean time on station
NALCOMIS	Naval Aviation Logistics Command Management Information System
NAMP	Naval Aviation Maintenance Program
NAVAIR	Naval Air Systems Command, Patuxent River, MD
O-Level	organizational maintenance level
OPTS	operational test program set
OR	operations research
PMA	program manager activity
RF	radio frequency CASS
RFHP	radio frequency and high power device test set CASS
RT	reconfigurable transportable CASS
SRA	shop repairable assembly (circuit card)
SRU	serviceable repairable unit
TAT	turn-around time
TPM	test program medium
TPS	test program set

T/M/S	type/model/series
TYCOM	type commander
USN	United States Navy
UUT	unit under test
WUC	work unit code
WRA	weapons repairable assembly
63E	APG-65/73 CASS WRAs and related TPS work center
63X	Fire Control Radar Branch
64C	Electronic Warfare Deceptive Electronic Countermeasures (DECM) Shop
64D	Forward Looking Infrared (FLIR)/Optical Shop
650	Integrated Weapons System Branch

ACKNOWLEDGMENTS

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I. INTRODUCTION

A. BACKGROUND

The U.S. Navy supply chain system faces the same challenges that any other supply chain system may encounter. However, demand is the most challenging aspect of a supply chain system; its unpredictability generates fluctuations that stimulate the development of strategies that aim to achieve a sustainable supply chain system. Battling demand's variability requires organizations to maintain an adequate inventory of safety stock which will significantly help prevent a stockout. A stockout has the potential to produce costly outcomes that may impact the Navy's mission.

In the U.S. Navy, command activities do not always have the option to acquire the services of an alternate merchant should a stockout occur. In some situations the incapability to acquire a component or service means that the command must wait and put on hold its current operation, but in other circumstances placing a mission on hold is not a possibility.

Naval Air Systems Command (NAVAIR) provides full life-cycle support of naval aviation aircraft, weapons and systems. Within the NAVAIR command structure is the Program Manager Air (PMA) 260, Aviation Support Equipment office. PMA-260's mission is to manage common aviation support equipment and automated test systems throughout the entire acquisition process for the U.S. Navy and U.S. Marine Corps. Additionally, PMA 260 ensures sufficient capacity of support equipment and automated test systems exists to maintain every type/model/series aircraft in the naval aviation inventory.

In our research, we will concentrate on the consolidated automated support systems (CASS) test equipment that diagnoses electronic equipment for weapons systems ranging from aircrafts, ships and submarines. In this instance, a stockout may be caused by the unavailability of required CASS test equipment station to fix a reparable part. The utilization of these stations follows the pattern formed by the operation cycle of aviation

squadrons which generate variability in demand peaks. Generally, these demand peaks harmonize with a command's preparation to an unforeseen or modified deployment schedule.

B.   THE CASS TEST EQUIPMENT FAMILY

The Navy currently possesses 713 stations of CASS, which operate in intermediate, depot and factory maintenance levels (Naval Air Systems Command, n.d.). The prominence of these stations ashore and afloat is critical in order to achieve mission readiness. To provide a better understanding of each of these CASS stations, a brief description is provided.

Hybrid–this station provides the core test capabilities needed for general purpose electronics, computers, instruments and flight controls.

Electro-optic (EO)–Provides hybrid station capabilities plus support capabilities for the forward looking infrared, lasers/designators, laser range finders and visual systems.

Radio frequency (RF)–Provides the same capabilities of the hybrid station in addition to the ECM, ECCM, EW support measures, the fire control, navigation &tracking radars, as well as radar altimeter support capability.

High power–provides RF station capabilities plus the capability to test high power RADAR systems (i.e., APG-65 & APG-73).

Communications/ navigation/ interrogation (CNI)–Provides RF station capabilities plus communication, navigation, interrogation and spread spectrum system support capability.

Reconfigurable Transportable CASS (RTCASS)–Provides as man-portable CASS configuration using COTS hardware and software to meet USMC V-22 and H-1 support requirements as well as to replace mainframe CASS stations at USMC fixed wing aircraft (EA-6B, F/A-18 & AV-8B) support sites.

eCASS–This station will replace the five mainframe CASS configurations (Hybrid, , EO, RF, CNI and HP). This station entered system design and development in 2009 and Low Rate Initial production started in 2012, its full rate production decision is scheduled for 2014. (Naval Air Systems Command, n.d.)

C. UNANTICIPATED FACTORS

The unpredictability of world events has a great impact on the dynamics, or changing variability of demand. The increased involvement of the United States with these world events produces a surge in battle group deployments that quickly disturb the programmed operation cycles of many commands. This disruption places a stress that generates overuse of current CASS test equipment.

The sequestration challenges caused the U.S. Navy to encounter unforeseen challenges while trying to support these battle groups. These struggles forced NAVAIR offices to reexamine the allocation methodologies required to ensure that CASS stations are utilized to the maximum extent.

D. RESEARCH OBJECTIVE

In 2010, Akturk and Beckham analyzed the allocation of CASS test equipment. They compared NAVAIR PMA-260's current method of allocating CASS stations to a method utilizing linear and nonlinear mathematical models. In their models, they compared demand at two thresholds of 50% and a peak period of 95%. The approach of using a peak demand of 95% allowed them to allocate a sufficient number of CASS stations that significantly reduced the probability of stockout at most demand levels (Akturk & Beckham, 2010).

This project will focus on the U.S. Navy's CASS test equipment and its allocation to Intermediate maintenance level repair sites. We will specifically look at the impact of the deployment cycle on utilization rates, extending the static analysis of Akturk and Beckham (2010). The project goals are to offer improvements to the allocation process, as measured by both the allocation cost and the impact the allocation has on readiness.

E. ELEMENTS TO BE CONSIDERED

Naval aviation assets take on many forms; these assets have an intrinsic value and carry an operating cost. Assets that are underutilized still incur preventive maintenance, operating and manpower costs. In the instance of support equipment, aviation managers may choose to place an underutilized asset into a preservation condition to reduce cost. In

either scenario, this underutilized piece of support equipment drains scarce funding resources. A better way to maintain its significant value may be to utilize it at another command where it will generate the productivity and value intended for the equipment.

Since the number of CASS stations is limited, identifying the underutilized stations is a key element that will facilitate the goal to support an intermediate maintenance level command before it will encounter an upcoming high demand peak. Once this classification of work stations by utilization level is obtained, the station allocation process will need to be taken into consideration, leading to the achievement of our proposed project objective of leveling utilization and increasing the value of scarce stations.

F.   RESEARCH QUESTIONS

CASS provides a critical capability to ensure the readiness of air forces in the Navy. As demand for CASS stations fluctuates over time, moving CASS stations in anticipation of demand changes can improve overall utilization despite the costs to move the stations.

1.   Primary Research Question
What is the most efficient allocation method for CASS test equipment to Intermediate maintenance level repair facilities located within the United States?

2.   Secondary Research Question
How can those allocations be made to be more robust against a Fleet Response Plan (deployment cycle)?

II.   LITERATURE REVIEW

We have reviewed articles from both inside and outside the DoD that deal with *discrete stochastic capacity allocation*. In discrete capacity allocation problems, capacity must be added in discrete amounts (a certain number of CASS stations, a certain number of hospital beds, etc.). In stochastic capacity allocation problems, either the demand for capacity, or the amount of capacity, is random. Many of the models reviewed dealt with goal programming or multi-objective models. Although we will not examine the multi-criteria nature of the CASS station allocation in this paper (we will treat cost as the sole and primary criteria), our model is a type of goal program, in which two of the objectives (utilization and operational availability) are constrained (from above and below, respectively), and the model could be used in an iterative fashion to examine the efficient frontier between criteria, or to achieve any feasible cost/utilization/readiness tradeoff. Finally, we used knowledge obtained from several courses taught at NPS, specifically Operations Management, Business Modeling and Analysis, Logistics Risk Assessment and Control and Logistics Engineering. The concepts acquired helped us to explore other methods of CASS station allocation.

There have been a few studies that examined CASS station allocation. Allocation of CASS stations has remained an issue since the Navy began using CASS stations. Test equipment originally was designed for specific platforms. As such, allocation was not an issue; test equipment went where the weapon systems assets were located. CASS stations were designed to operate across different types of aircraft.

The question the Navy faced in 1996 was how many CASS stations did the Navy need to purchase to meet its requirements at a shore-based facility (Lynn, 1996)? The research also examined which specific types of CASS stations to purchase and allocate. In developing initial allocation numbers for shore based maintenance activities, the Navy utilized a system that did not account for actual failure rates. Additionally, the Navy used a high operational tempo rate, in other words a very high demand rate. In Lynn's study,

Lynn proposed utilizing data from maintenance action forms (MAFs) that not only tracked actual failure rates, but gave the analysis a more realistic operational tempo rate for a shore based activity.

In Lynn's study, it was found that at an A_o of 80%, the Navy had overestimated by as many as seven CASS stations (Lynn, 1996). The study estimated that the Navy would save $11 million over the course of a 20-year life-cycle. Additionally, instead of assuming A_o to be only 80%, the study was able to conclude through the MAFs that A_o was actually in the range of 80–90%. Running the data for analysis at A_o of 90% the study determined that the Navy overestimated by 11 CASS stations.

Akturk and Beckham (2010) presented research on optimizing CASS station allocation. They focused on mathematical models utilizing integer, linear and non-linear programing. Akturk and Beckham examined an optimal solution to allocate CASS stations based on several factors; demand, cost of the station, and aircraft availability. A significant contribution from their research showed that the Navy's current method of allocation using a workload formula was static and did not account for variation. Applying management science and operations research methodology gave the Navy better utilization of the stations, specifically where to allocate any spare stations. However, their research was limited with regards to demand. Akturk and Beckham (2010) utilized predetermined demand thresholds as their input, for example 50% and 95% of demand.

Akturk and Beckham (2010) argued that the Navy's method of using a basic linear algebraic equation to solve a more complex problem led to possible under or overutilization of CASS stations. Overutilization of CASS stations meant that a queue would develop and potential customers would have to wait for repairable parts. Waiting for a repairable part, sometimes forces an organizational unit to cannibalize a part, which increases maintenance man-hours and decreases morale (GAO, 2001). On the other hand, underutilization causes idle time on test equipment, which makes expensive assets unused. We contend that although using a static demand rate of 95% ensures a high service level, that demand is cyclic. Demand rarely reaches 95% and by portraying a more accurate demand level in the model a better allocation of CASS stations can be

determined. In this study, we replicate the Akturk and Beckham (2010) study, but apply actual demand data derived from MAFs to their model.

Ross (2003) wrote an article on the subject of the future of automated test equipment. As the DoD moves towards joint capabilities and weapons systems, test equipment must also be inter-operable among the services but maintain low acquisition and support costs. A critical factor of future test equipment is that the test equipment must usable from the field to the factory (Ross, 2003). CASS stations, normally utilized on a ship or naval air station were deployed in expeditionary logistics units (ELUs). The ELUs allowed Navy E/A-6B Prowler squadrons to support a forward deployed NATO mission away from naval maintenance facilities. The article failed to mention how many CASS stations were used for this specific example or how that specific number was derived. The article concludes with the summary that test equipment will operate throughout all levels of maintenance organization and in a joint environment.

A paper written by Armstrong and Cook (1979) addressed the allocation of search and rescue (SAR) aircraft to Canadian military bases. Armstrong and Cook (1979) used a goal programming model but specifically determined the number of aircraft that should be sent to each type of base. As they developed the model, they understood that historical data was the best predictor to making an assessment to demand, since a SAR event was completely random. A complaint of historical data was that the data was not completely or accurately tracked (Armstrong & Cook, 1979). In 1979, automated data collection systems were rare. Despite the historical demand data or sophisticated computational equipment capable of running the massive calculations required for such a model, the solutions Armstrong and Cook obtained received positive feedback from managers of the bases.

Numerous nonmilitary applications of discrete stochastic capacity allocation models exist in literature. Mild and Salo's (2009) research centered on building a model to allocate resources across different road and highway maintenance activities. The local government's fixed budget had to be properly allocated across multiple divisions. Within

the local department, each division had specific needs to satisfy. One of the mangers' concerns in conducting this research was the interest in allocating funds outside the constraints of past budgets.

As Mild and Salo (2009) began the project, a serious challenge was not to make the model too big or too difficult. Adding constraints to a project of this magnitude could quickly overcome the capabilities of the software readily available. Also, the model had to remain simple enough for the managers to manipulate for the model to be a useful tool. Finally, the managers had to understand the results of the model and the steps on how those results were calculated. The output of the model cannot be the final solution to the decision on how to allocate funds.

The resultant model was actually three models, a preference model, a life-cycle model and an optimization model (Mild & Salo, 2009). In the end, the model was capable of producing useful analysis. The model developed was capable of producing diagrams that showed a yearly allocation based on changes over time, instead of one fixed number year after year (Mild & Salo, 2009). Each specific activity received a minimum amount of funding to ensure operation throughout the fiscal year. Once intact, the model showed how changes in budget cuts would affect allocation. The model's outputs allowed managers to better predict how the cuts would affect the future of the divisions; thereby resulting in better planning decisions (Mild & Salo, 2009).

Hospitals require a standard solution to properly assign beds for surgery and minimize length of stay of patients. Insurance providers scrutinize over patients charts and will not pay for time wasted due to inefficiency of the hospital. In research conducted by Zhang, Murali, Dessouky and Belson (2009) a mixed integer programming model was developed to maximize the allocation of operating room capacity across various medical specialties. As a result hospital costs were reduced because the queue wait for operating room space was reduced, improving the overall efficiency of the hospital.

Typically, hospitals utilize a block scheduling method of scheduling operating time. Time slots are developed at the start of a week. Doctors decide which patients in their specific specialty will have surgery the following day. Outpatients are given a few

slots, but the majority of the slots are given to inpatients due to the penalty of inefficiency placed on inpatient wait time (Zhang et al., 2009). Emergency room patients represented unknown demand. Due to the urgency of the necessity of surgery, emergency room patients tended to move to the head of line in front of the known waiting patients. In the model developed by Zhang et al. (2009) the focus was specifically on reducing the inpatients' length of stay in the hospital. Severe penalties were incorporated into the model to reflect postponement of surgery.

Zhang et al. (2009) used simulation modeling to assess the quality of their mixed integer programming model. In this case, Zhang et al. (2009) determined that surgery demand is discrete since the surgeries are not measure by the amount of time they take but the actual number of surgeries. However, in the template of the model created by Zhang et al. (2009) surgery was measured in hours. Simulation hoped to demonstrate the effectiveness of the model despite this difference.

The Zhang et al. (2009) study concluded that a model could reduce overall patient wait time by efficient allocation of operating room space. They did note that the model may not obtain accurate optimization in situations where surgery length and patient arrival rates widely fluctuated. They further note that "future research can focus on incorporating uncertainty" into the model they designed (Zhang et al., 2009, p. 671).

Research conducted by Abdelaziz and Masmoudi (2012) examined allocation of hospital beds between hospitals. They focused on a goal programming model that minimized the cost of creating new beds and the cost of medical staff, specifically nurses and doctors. As stated in their review, the current research had not explored the idea that in moving beds between hospitals, nurses and doctors may need to be added to accommodate the increase in demand (Abdelaziz & Masmoudi, 2012). This article provided us with an interesting thought, CASS stations could be moved between naval air stations but manpower would be needed to operate those stations. Manpower may be acquired from within a command, possibly from an underutilized work center within the division. If that manpower did not exist, it would be unlikely to gain additional manpower from outside the command and therefore an added CASS station would remain idle. Finally, Abdelaziz and Masmoudi (2012) identified that they considered

yearly demand, which they admittedly assume to be uniform throughout the year. They acknowledge that demand can vary throughout the year and in some cases be seasonal.

Further examples of advantages to the type of mathematical model that we propose for CASS station allocation can be found in a paper written on allocation of test equipment of circuit cards (Goentzel, Manzione, Pibernik, Pruett, & Thiessen, 2007). This article described a company that explored three different options for testing circuit cards; allocating test equipment to manufacturing sites based on demand, developing a central test site, or investing in research and development programs into an idea of circuit cards capable of self-testing (Goentzel et al., 2007). Despite the complexity of the problem, the researchers created a mathematical model that produced an optimal solution. Similar to our research, the model provided leaders with a tool to formulate strategy. The model accomplished this solution, considering all the variables and constraints in a quick, unbiased manner.

Another example that the Goentzel et al. (2007) article relates to our research is that with a predictable cyclic demand schedule, allocation plans executed prior to changes in the demand cycle will maximize utilization of the available test benches (Goentzel et al., 2007). However, two critical factors exist in the decision making process that was a part of the Goentzel et al. (2007) model. First, a defined time-period is required for installation of test equipment prior to the desired operational time and must reflect in the organization's planning schedule. Next, the organization incurs a fixed cost during the disassembly, transport and reassembly of the test equipment assigned for allocation. The article suggested that budgeting of the capital required to move the identified equipment occur in advance of the move.

III. METHODOLOGY

Our methodology will center on extensions to a model built by Akturk and Beckham. Our model will examine how dynamic demand (demand which is both variable and non-stationary), affects a capacity plan. In particular, we will examine two capacity plans: the current solution based on the PMA260 model, and the solution proposed by Akturk and Beckham. Both these solutions are based on stationary demand. The PMA260 model is based on average demand. The Akturk and Beckham model attempts to control for variability via a set of constraints on peak utilization, and another set of constraints on minimum availability. But the variability in the Akturk and Beckham model is assumed to be stationary, and hence, may not be robust to changes in demand structure caused by the fleet readiness plan or unforeseen conflicts.

Finally, the Akturk and Beckham methodology centered on the development of a 'proof of concept' model. The limited testing they performed was based on hypothetical data, loosely based on field data for demand at Oceana and Norfolk, but entirely hypothetical in terms of the existing capacity plan at those sites. Our testing will use actual demand and capacity data from Lemoore, and constitutes the first empirical test of their model on field data.

A. PMA 260 ALLOCATION FORMULA

This formula is currently used to calculate the number of CASS stations along with the required test program set (TPS) and operational test program set (OTPS) needed for a specific unit under test (UUT). The formula was generated to calculate the requirements per the work unit code (WUC) of each UUT. Currently, there are 2,884 unique part numbers over the 52 Navy and Marine Corps command activities that consist of 40 different aircraft combinations (Cervenak, 2010). The formula states that:

$$\text{Workload} = \frac{(\text{Number of aircraft}) \; X \; (\text{Monthly flight hours}) \; X \; (\text{MTOS})}{(\text{CASS A}_o) \; X \; (\text{Site monthly operational hours}) \; X \; (\text{MTBUM})}$$

- Number of aircraft: The number of specific type/model/series aircraft at a specific site.

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- Monthly flight hours: Average monthly flight hours for each aircraft.

- MTOS: Mean time on station. The end to end run time (ETE) and other times for WRA.

- CASS A_o: Operational availability of the CASS station in a given month

- Site monthly operational hours: Operational hours at a maintenance facility for a given month.

- MTBUM: Mean time between unscheduled maintenance (Cervenak, 2010).

Two major discrepancies of this model is that it does not account for a queuing congestion or variability in demand (Akturk & Beckham, 2010).

B.   AKTURK AND BECKHAM MODEL

As previously mentioned, Akturk and Beckham's research centered around four mathematical models that attempted to account for the lack of queuing theory or variability in demand from the PMA-260 formula. Our research will apply changes to their fourth model, a non-linear program model that constrains demand, utilization, readiness and congestion (Akturk & Beckham, 2010). Additionally, the Akturk and Beckham model examined four sites, we will focus only on one I-Level site, but will examine the impact of changes to demand over time at that one site. Consolidation of the I-level sites by the U.S. Navy (USN) to Fleet Readiness Centers (FRC) has significantly reduced the number of available sites. Also, by focusing on only a single site, we can examine the quality of the capacity plans in more detail. These are the reasons we chose to examine data from one FRC.

1.   Queuing Congestion

The application of arrival and service rates made the basis for the queuing theory calculations. The arrival rate is simply the number of UUTs arriving to the FRC in one hour. The service rate consists of the combination of all the CASS stations that a particular FRC has available. Since CASS station service times vary, Akturk and Beckham utilized "the mean and standard deviation of all UUTs for the CASS configuration network" (Akturk & Beckham, 2010, p. 26). Finally, an I-level adopts

many different queue disciplines. For simplicity purposes, Akturk and Beckham (2010) focused only on the first come, first serve queue discipline.

2. Demand Constraints

Akturk and Beckham utilized the expected number of failure formula to calculate the demand of WRAs at a given site. This demand represents a calculated mean.

$$\text{Number of failures} = k \cdot \lambda \cdot t$$

where:

k=number of total components requiring same CASS

$$\lambda = \frac{1}{\text{MTBF}}$$

t=monthly flight hours

Many of the CASS stations provide the capability to share testing functions. The hybrid (HYB) CASS station provides core test capabilities. All of the four remaining test stations can also preform the core test capabilities that the HYB station provides. The radio frequency (RF) test station provides RF test capabilities. Both the CNI and RFHP test stations provide RF test capabilities. For some UUTs in some work centers, a technician has the ability to decide which station to use. To account for the sharing capability, Akturk and Beckham added 60% of the CNI and RFHP CASS excess capabilities to the HYB CASS capacity. Also, they added 40% of the CNI and RFHP CASS excess capacities to the RF CASS with the additional constraint that excess capacity "must be greater than or equal to RF CASS station demand" (Akturk & Beckham, 2010, p. 29). CNI, EO3 and RFHP CASS capacity had to be greater than or equal to their respective CASS station demand (Akturk & Beckham, 2010).

3. Utilization Constraints

Akturk and Beckham's model included a utilization constraint to reduce the impact of congestion which might be caused by bottlenecks in the system. Since we are only examining one site, we have modified their original formula to the following:

$$\text{Average utilization} = \frac{\text{Total demand for CASS}}{\text{Total available CASS hours}}$$

4. Readiness Constraints

Introduction of the readiness constraints into the model forced Akturk and Beckham to use a nonlinear program. Simply stated, the queuing delay provides a change in the turn-around time in a nonlinear manner as the number of CASS stations change (Akturk & Beckham, 2010).

Readiness in warfighting equipment remains a top priority of USN leadership. The Chief of Naval Operations (CNO) has established an aircraft material readiness goal of 73% for all of USN aviation (Commander, Naval Air Forces (COMNAVAIRFOR), 2013). Aviation readiness is essentially the same idea as operational availability (A_o). In examining A_o, there are two main factors; total time available, and non-mission capable time (NMCT). NMCT is a function of three variables; the mean corrective time (MCT), the mean preventative time (MPT), and the administrative and logistics delay time (ALDT) (Jones, 2006).

MCT accounts for the amount of time on average an aircraft is unavailable to perform a mission due to a failure of a component (Jones, 2006). In Akturk and Beckham's model, the MCT was based upon the calculated number of failures (Akturk & Beckham, 2010). The MPT estimates the number of hours that an aircraft is unavailable for a mission due to preventative maintenance. Finally, the ALDT tracks the amount of time spent that the aircraft is unavailable but due to non-maintenance related issues (Jones, 2006). This is the equation used to calculate A_o.

$$\text{Operational availability} (A_o) = \frac{\text{Total time - (MCT+MPT+ALDT)}}{\text{Total time}} \quad \text{(Jones, 2006)}$$

Availability of spares plays a factor in calculating overall A_o. When a component fails, the length of time in obtaining the spare depends on whether or not supply has that part. Spare parts that are retrieved from off-station take considerably more time than parts that are on-hand. Akturk and Beckham accounted for this time by establishing ready for issue levels (RFI) for spare UUTs. The numbers were based on their experience and not

on actual data. They concluded that the RFI rates were beyond the scope of their research (Akturk & Beckham, 2010). We will conduct our research within the same scope and assumptions, and hence use the same rates, as listed in Table 1.

	HYB	RF	CNI	EO3	RFHP
Site	0.9	0.9	0.8	0.85	0.9

Table 1.   Spare Part Factor for UUTs (from Akturk & Beckham, 2010)

In the table, a spare probability means for that CASS station, the spare UUT will be available and not obtained from off-station. For example, 90% of the time the spare components for HYB are on-station. Otherwise, the component has to incur the off-base fill time (Akturk & Beckham, 2010). Note that this assumption means that lead time will be treated as a single number, the weighted average of RFI and back-order lead times; hence the impact of variability in lead time, the impact that variability can have on A_o, is not fully represented in the model.

5.   Congestion Constraints

In Akturk and Beckham's model, UUTs arrive for service at the various CASS stations. As the UUTs enter the FRC, the UUTs enter a distinct line structures based on the type CASS station, a multichannel single phase line. Akturk and Beckham made an assumption that all the CASS stations operate under one organizational unit. In using a UUT failure number based on a calculation, Akturk and Beckham determined that their arrival and service rate numbers followed a unknown distribution. In their analysis, they followed a waiting time approximation for a G/G/s queue, in which the "G" stands for general and the "s" stands for servers.

$$L_q = \left(\frac{\rho^{\sqrt{2(s+1)}}}{1-\rho}\right) \times \left(\frac{C_a^2 + C_s^2}{2}\right)$$

L_q = Expected number of UUTs waiting

ρ = Utilization of the CASS stations $= \dfrac{\lambda}{s\mu} = \dfrac{\text{Demand/Arrival}}{\text{Capacity}}$

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$$\lambda = \text{UUT failure rate} = \frac{1}{\overline{X}_a}$$

$\overline{X}_a$= Mean UUT interarrival time

$$\mu = \text{UUT service rate} = \frac{1}{\overline{X}s}$$

$\overline{X}_s$= Mean UUT service time

$$C_a = \text{Coefficient of variation of UUT interarrival time} = \frac{S_a}{\overline{X}_s}$$

S_a = Standard deviation of the UUT interarrival time sample

$$C_s = \text{Coefficient of variation of UUT service time} = \frac{S_s}{\overline{X}_s}$$

S_s = Standard deviation of the UUT service time sample

$$W_q = \text{Expected time UUT waits for an available CASS station} = \frac{L_q}{\lambda} \text{ (Akturk \&}$$

Beckham, 2010)

In order to obtain total W_q, Akturk and Beckham needed to use the expected failure formula to multiply with the W_q (2010).

$$\text{Total } W_q = (k \cdot \lambda \cdot t) \cdot W_q$$

C. CONSTRUCTION OF ADJUSTED MODEL UTILIZING ACTUAL DEMAND

Using the previously described model as a basis, we will construct a variation of that model so that we could apply actual demand data from an I-Level FRC.

1. Notation

i = CASS station type (HYB, RF, CNI, EO3, and RFHP)

j = WRA type (HYB, RF, CNI, EO3, and RFHP)

X_i = number of CASS stations of type i to install at the FRC

d_j = demand by WRA type j

r = readiness level at the site

u_i = utilization of CASS station type i

C_i = unit cost of each type of CASS station

Z = Available CASS station hours per month

2. Assumptions

- CASS stations are assigned to one FRC and not dispersed in multiple work centers. (This reflects the reality of the installation at Lemoore.)
- Aircraft numbers do not fluctuate month to month.
- Aircraft flying hours do not fluctuate month to month.

3. Nonlinear Program

$$\text{Min} \sum_i X_i * C_i \tag{1}$$

Subject to:

$$X_1 + (X_2 - d_2) + 0.60 * [(X_3 - d_3) + (X_5 - d_5)] + (X_4 - d_4) \geq \frac{d_1}{Z} \tag{2}$$

$$X_2 + 0.40 * [(X_3 - d_3) + (X_5 - d_5)] \geq \frac{d_2}{Z} \tag{3}$$

$$X_3 \geq \frac{d_3}{Z} \tag{4}$$

$$X_4 \geq \frac{d_4}{Z} \tag{5}$$

$$X_5 \geq \frac{d_5}{Z} \tag{6}$$

(1) The objective function is to minimize the total cost of the CASS stations given that all constraints are satisfied.

4. Application of Non-stationary Demand

UTTs tested on a CASS station require an issued maintenance action form (MAF). To account for demand on each CASS station, this project will focus on using actual demand as indicated by MAFs as recorded in the Naval Aviation Logistics Command Management Information System (NALCOMIS). A shore based I-level FRC provided 18 months of MAFs from a period of January 2012 to June 2013. Unfortunately, MAFs do not identify the type of CASS station utilized to test or repair the component. To attempt to identify the type of CASS station, we will use the master UUT list. The master UUT list provides a list of the part numbers and type of station required for each UUT. We will isolate only the MAFs that had corresponding part numbers to the master UUT list.

CASS stations for the facility are distributed among five work centers. The Naval Aviation Maintenance Program (NAMP) determines the work center designation and as a result, this sends groups of UUTs to a work center based on the UUT associated system. The five work centers that utilize CASS stations are: APG-65/73 CASS WRAs and Related TPS (63E), Fire Control Radar Branch (63X), Electronic Warfare Deceptive Electronic Countermeasures (DECM) Shop (64C), Forward Looking Infrared (FLIR)/Optical Shop (64D) and Integrated Weapons System Branch (650) (COMNAVAIRFOR, 2013). The maintenance facility studied in this project allocates available CASS stations as per Table 2.

Distribution of CASS Stations at examined FRC							
		Work Center					
		63E	63X	64C	64D	650	Total
Type of CASS Station	**HYB**	0	0	1	0	3	4
	RF	3	1	1	0	9	14
	CNI	0	0	1	0	0	1
	EO3	0	0	0	5	0	5
	RFHP	5	0	0	0	0	5

Table 2.   Distribution of CASS Stations at Examined FRC

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Only the MAFs issued to the five work centers were examined, since those are the only work centers that have CASS stations. We assumed that if a MAF was written for one of the five work centers, and that UUT had a part number listed on the master UUT list, then that UUT was tested and repaired using that specific CASS station, as designated by the master UUT list. As previously discussed, some CASS stations have the capability to perform multiple functions. For some UUTs in some work centers, a technician has the ability to decide which station to use. For example, if a technician in work center 64C has a part that the master UUT lists as "HYB," the technician has the option of testing the part on any one of the three types of test stations in that work center.

(2) HYB CASS station capacity in addition to the 60% of the CNI and RFHP CASS station excess capacities and 100% of the EO3 and RF CASS station excess capacities must be greater than or equal to the HYB CASS station demand (Akturk & Beckham, 2010).

(3) RF CASS station capacity in addition to 40% of CNI and RFHP CASS station capacities must be greater than or equal to the RF CASS station demand (Akturk & Beckham, 2010).

(4) CNI CASS station capacity must be greater than or equal to the CNI CASS station demand (Akturk & Beckham, 2010).

(5) EO3 CASS station capacity must be greater than or equal to the EO3 CASS station demand (Akturk & Beckham, 2010).

(6) RFHP CASS station capacity must be greater than or equal to the RFHP CASS station demand (Akturk & Beckham, 2010).

Numbers of MAFs in a given month will be summed and averaged according to CASS station type. Those numbers will provide the inputs for the demand numbers instead of the calculated failure number that Akturk and Beckham used.

5.   **Unit Cost of Each Individual CASS Station**

Akturk and Beckham (2010) identified that no current cost data for the CASS benches is available since the CASS program acquisition was finalized in 2006. In their

model, they utilized an inflation factor index to estimate the CASS station costs in FY10. We applied the same formula to estimate costs for FY14 dollars.

Type of CASS Station	Average unit cost FY95	Estimated unit cost FY10	Inflation factor index[1]	Average unit cost FY14
HYB	$1,000,000.00	N/A	1.39188192	$1,391,881.92
RF	$1,500,000.00	N/A	1.39188192	$2,087,822.88
EO	$4,500,000.00	N/A	1.39188192	$6,263,468.64
CNI	$1,700,000.00	N/A	1.39188192	$2,366,199.26
RFHP	N/A	$3,500,000.00	1.080308706	$3,781,080.47

[1] Inflation index was calculated using the Joint Inflation Calculator (JIC) prepared by the Naval Center for Cost Analysis, and the index is Other Procurement Navy (OPN).

[2] RFHP unit cost for FY10 was estimated in the Akturk and Beckham project (from Akturk & Beckham, 2010).

Table 3.   Cost per CASS Station

6.   Utilization Constraints

Utilization in this model is a primary metric. CASS stations are assets that hold a monetary value to the Navy. Naval aviation managers need to know utilization rates on CASS stations to ensure sufficient allocation. If CASS station utilization is low, idle stations will ensue. On the other hand, high CASS station utilization rates may cause congestion. In this model, we will use the Akturk and Beckham formula for calculating utilization.

$$\text{Average Utilization} = \frac{\text{Total demand for CASS}}{\text{Total available CASS hours}} \quad (\text{Akturk \& Beckham, 2010})$$

To ensure the utilizations rates are kept low enough to prevent bottlenecks, the average CASS station utilization will be constrained.

$$\frac{\sum d_j}{(\sum X_i) * Z} \leq 80\%, \text{ j and i} = 1 \text{ through } 5 \tag{7}$$

(7) Average CASS station utilization must be less than or equal to 80%.

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7. Readiness Constraints

The general calculations used to calculate readiness in the Akturk and Beckham research project will be utilized in this model. However, since we will use demand data, we have the ability to apply those numbers instead of the failure calculation. Our arrival rates will consist of the number of MAFs recorded in a month divided by total hours.

$$\text{Arrival rate} = \frac{\text{Number of UUT MAFs for a given CASS station}}{\text{Total Time}}$$

Service rate calculation will remain the same as the Akturk and Beckham model. MCT is another calculation where we will utilize the number of MAFs recorded in a given month. Finally, the number of failure actions will be calculated using the number of failures in a month as recorded by the amount of MAFs written against a particular CASS station. These changes in the calculations will represent a more realistic total waiting time for UUTs. This will give us better insight to the effects of aircraft down time and therefore aircraft readiness.

As per the NAMP, overall aircraft readiness shall not fall below 73% (COMNAVAIRFOR, 2013).

$$A_o \geq r, \text{ where r is 73\%} \tag{8}$$

(8) Readiness must be greater than or equal to 73%.

As part of our research, the current CASS station configuration of the studied FRC will be inputted into the model to examine utilization and readiness rates based on current MAF input. A general assumption is that the higher number of CASS stations, the higher aircraft readiness (Akturk & Beckham, 2010). As such, the readiness of the FRC should be higher based on this assumption. An additional constraint will be applied to a second run of the model in which the A_o of the optimal solution must be greater than or equal to the FRC A_o.

$$\text{Optimal r} \geq \text{FRC r} \tag{9}$$

(9) Optimal readiness must be greater than or equal to FRC readiness as calculated by the model.

8. Integer and Non-negativity Constraints

CASS stations require delivery in whole units. To prevent the model from returning CASS stations that are not whole units, the integer constraint will be applied in the model.

(10) All decision variables must be integers.

(11) All decision variables must be greater than or equal to zero (Non-negativity constraint).

D. EXECUTION OF THE MODEL

After the completion of the model, the average monthly demand data will be inputted into the model as failed UUTs. The model will be run once using the solver add-in feature embedded in Microsoft Excel, where readiness must be greater than or equal to 73%. Total cost of the allocated benches will be compared to the cost of the current allocation at the FRC. With an optimal allocation of CASS stations, we will input each month's data into the model as failures. For each month, we will record both the utilization and the readiness for the optimal solution and the FRC site.

Next, the model will be run a second time using the solver add-in. This time the readiness constraint will be changed to reflect such that the optimal readiness must be greater than or equal to the FRC readiness. Total cost for the optimization of this configuration of CASS stations will be recorded. As before, each month of available MAF data will be inputted as failure data and we will record the calculated utilization and readiness for each month.

Finally, we plan to manipulate the optimal CASS station allocation in a heuristic fashion, using the following logic: In the event, the optimal CASS station allocation cannot sufficiently account for the actual given demand in a month (that is, in the event that a constraint is violated), we will examine the given impact of adding or subtracting a single CASS station. In this analysis, we will compare the total cost of the CASS stations.

Our intent in this post-hoc analysis is to examine the benefit of a small amount of flexibility (obtained, for example, by bringing in an additional bench when demand is high).

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IV. RESULTS AND ANALYSIS

This chapter will provide the results of applying the models described in the last chapter to our field dataset, and a post-hoc analysis of those results. This project performed three specific runs of the modified model presented in the Akturk and Beckham project.

Akturk and Beckham's project calculated demand from notional data based on a series of assumptions, but this project uses field data for demand; therefore it is necessary to describe how the demand data for this project was obtained.

A. DEMAND RESULTS

In each work center, we isolated CASS station demand by specific MAFs. The MAFs were identified by part number as listed in the master UUT database. The number of MAFs for each work center was combined to represent a total for each station in one month. A plot of demand as demonstrated by the number of MAFs is shown in Figure 1.
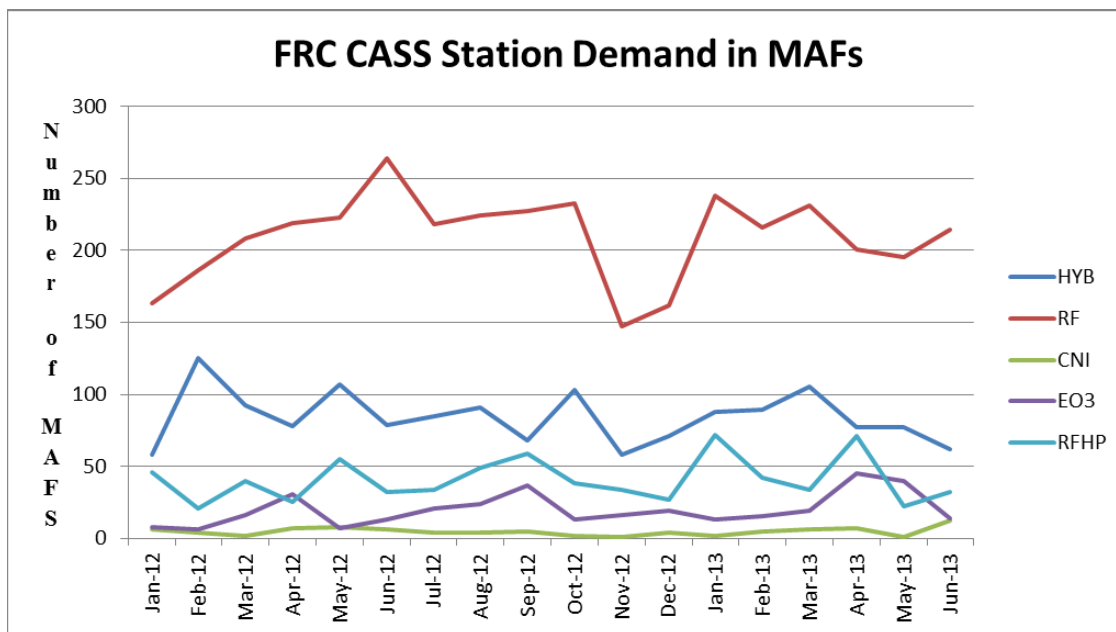

Figure 1.   FRC CASS Station Demand in Number of MAFs

After summing the MAFs for each of the 18 months of available data, an average was calculated for each CASS station. Table 4 lists the average demand for the period provided.

CASS Station	HYB	RF	CNI	EO3	RFHP
MAF Avg	85	210	5	20	41

Table 4.   Demand Average per CASS Station

B.   OPTIMIZED MODEL

1.   Model Results

In the first model run, we applied only average demand to the model. The data solver add-in tool in Microsoft Excel was used to calculate to determine the best allocation of CASS stations given the constraints. The results along with the examined FRC's current allocation are listed in Table 5.

CASS Station	HYB	RF	CNI	EO3	RFHP	Cost
Optimized Allocation	1	3	1	1	1	$20.066M
Current Allocation	4	14	1	5	5	$87.386M

Table 5.   Optimized and Current Allocations of CASS Stations

Once we had the model with the optimized allocation, we applied each month's data to the model and recorded the results for A_o and utilization. That is, rather than using A_o and utilization as constraints as we did in obtaining the optimal solution, we use the model to predict A_o and utilization, as we vary the data from the average. The results for CY 2012 are shown in Table 6. Table 7 shows the results of A_o and utilization rates for CY 2013.

2012 CASS station A_o and utilization rates Actual (A) versus Optimal (O)							
Optimal Quantity		**1** **HYB**	**3** **RF**	**1** **CNI**	**1** **EO3**	**1** **RFHP**	**A_o**
JAN	O	27.2%	71.4%	61.1%	61.1%	61.1%	85.2%
	A	3.5%	15.5%	14.8%	14.8%	14.8%	85.4%
FEB	O	60.1%	78.0%	73.7%	73.7%	73.7%	84.6%
	A	7.7%	17.5%	17.8%	17.8%	17.8%	85.2%
MAR	O	58.4%	89.5%	78.5%	78.5%	78.5%	84.0%
	A	5.8%	19.7%	19.0%	19.0%	19.0%	85.1%
APR	O	62.3%	93.0%	81.6%	81.6%	81.6%	83.5%
	A	5.0%	20.7%	19.7%	19.7%	19.7%	85.0%
MAY	O	74.4%	99.5%	86.2%	86.2%	86.2%	71.2%
	A	6.8%	21.3%	20.8%	20.8%	20.8%	84.9%
JUN	O	75.5%	**113.1%**	86.5%	86.5%	86.5%	-
	A	5.2%	25.0%	20.9%	20.9%	20.9%	84.9%
JUL	O	60.6%	93.3%	80.4%	80.4%	80.4%	83.6%
	A	5.4%	20.7%	19.4%	19.4%	19.4%	85.0%
AUG	O	75.9%	98.2%	87.0%	87.0%	87.0%	80.4%
	A	5.9%	21.3%	21.0%	21.0%	21.0%	84.9%
SEP	O	77.5%	**101.4%**	89.7%	89.7%	89.7%	-
	A	4.5%	21.7%	21.7%	21.7%	21.7%	84.8%
OCT	O	75.1%	**100.0%**	84.8%	84.8%	84.8%	-
	A	6.6%	22.1%	20.5%	20.5%	20.5%	84.9%
NOV	O	25.5%	62.6%	56.8%	56.8%	56.8%	85.4%
	A	3.5%	13.9%	13.7%	13.7%	13.7%	85.5%
DEC	O	34.2%	68.6%	63.1%	63.1%	63.1%	85.1%
	A	4.4%	15.3%	15.2%	15.2%	15.2%	85.4%

Table 6.　　2012 CASS Station A_o and Utilization Rates

2013 CASS station A_o and utilization rates Actual (A) versus Optimal (O)						
Optimal Quantity		**1** HYB	**3** RF	**1** CNI	**1** EO3	**1** RFHP	A_o
JAN	O	78.6%	**107.9%**	89.6%	89.6%	89.6%	-
	A	5.7%	22.8%	21.6%	21.6%	21.6%	84.8%
FEB	O	60.4%	93.8%	80.5%	80.5%	80.5%	83.5%
	A	5.7%	20.5%	19.4%	19.4%	19.4%	85.0%
MAR	O	81.8%	99.3%	87.1%	87.1%	87.1%	75.2%
	A	6.8%	21.9%	21.0%	21.0%	21.0%	84.9%
APR	O	82.5%	91.9%	91.6%	91.6%	91.6%	82.0%
	A	5.1%	19.3%	22.1%	22.1%	22.1%	84.8%
MAY	O	54.4%	81.5%	77.2%	77.2%	77.2%	84.4%
	A	4.9%	18.4%	18.6%	18.6%	18.6%	85.1%
JUN	O	40.8%	92.8%	73.9%	73.9%	73.9%	84.1%
	A	3.9%	20.3%	17.8%	17.8%	17.8%	85.1%

Table 7.   2013 CASS Station A_o and Utilization Rates

In examining A_o, the current A_o was always greater than the optimized A_o. As previously mentioned, a higher number of CASS stations will cause A_o to be higher due because there will be less waiting for needed parts. This reduces both the length of the queue and the waiting time in the queue. In six of the months analyzed, A_o in the optimal solution is substantially lower than A_o in the actual solution; in four of the months A_o cannot be captured for the optimal solution (this is represented by dashes in the table) because a least once bench-type has a utilization over 100%—hence there is no steady state average for A_o in that month. This is represented in Figure 2.
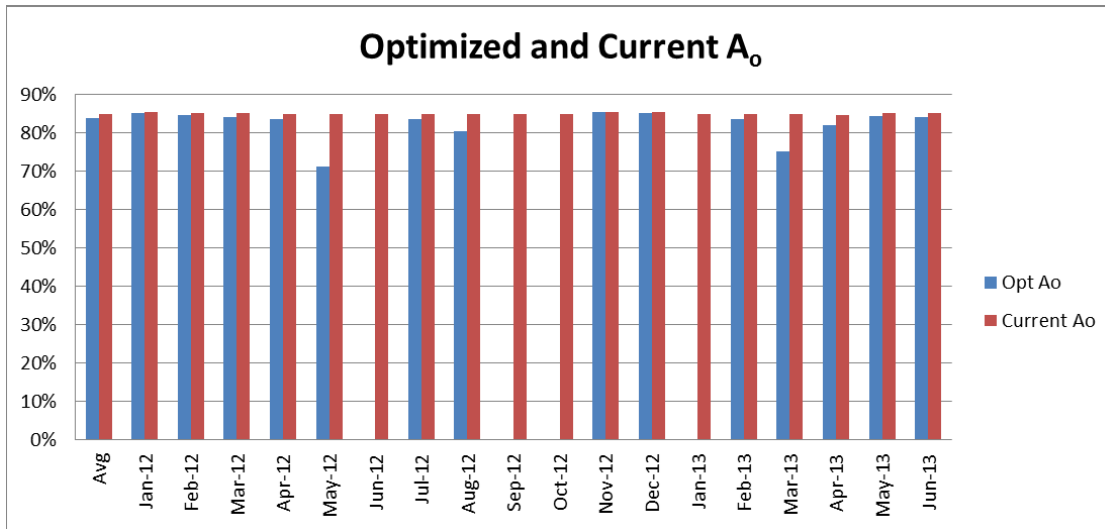
Figure 2.   Overall A_o for Optimized and Current Allocations

2.   Model Analysis

The discrepancy in the six months where A_o for the optimal solution is undefined, or is substantially lower than current A_o occurs because the RF CASS station's utilization is either close to or above 100%. In months where bench utilization exceeds 100%, the wait for parts to use the bench will continue to grow across that month—there will be no steady state average wait that month, and hence, no steady-state average A_o. In months where bench utilization is close to 100%, the non-linear impact of queuing congestion means that the wait for parts will become very long, significantly degrading A_o. (Effectively, A_o will decline across the month, until capacity can catch up with demand in the next month.) This is depicted in Figure 3.
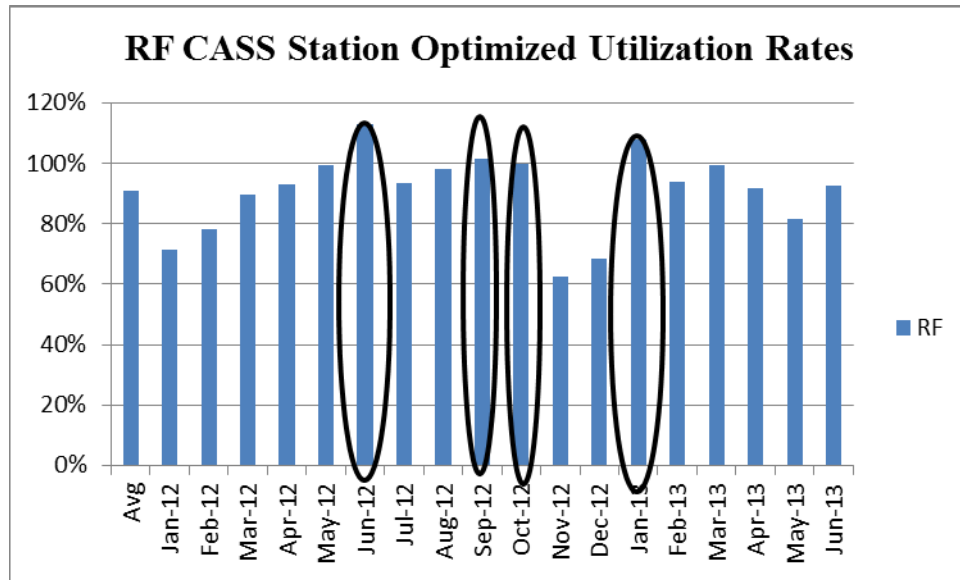
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Figure 3.   RF CASS Station Optimized Utilization Rates

The remaining CASS stations' utilization remained low enough to prevent an excessive queue from forming at those benches. It is important to note that these higher utilization rates occurred after inputting demand for each individual month. In peak months, additional RF CASS station capacity us needed to ensure that the monthly demand can be satisfied.

C.   RF CASS STATION ADJUSTMENT–POST HOC ANALYSIS

The optimization model attempts to prevent the kind of peak overload we observe in our month-to-month data by constraining utilization percentage from above, and A_o percentage from below. However, the data used for the optimization model was based on averages, assumed implicitly to follow Markovian distributions (Poisson arrivals, Exponential repair times). When the solution of the optimal model is tested against the actual month-to-month variability in the data, capacity is insufficient to handle demand in six out of eighteen months. However, in obtaining these results, it became apparent that a small addition to capacity of a single bench type might ameliorate the problem.

1. Model Results

In this analysis, we attempted to ensure that demand could be satisfied during the entire evaluated period. This goal was accomplished by adding a single RF CASS station to the optimized model results; bringing the total RF CASS stations from 3 to 4. Once that was done, we inputted demand data from each month and examined both utilization and A_o rates. The resultant utilization rates for the RF CASS stations are listed in Figure 4. The outcome of utilization rates for all the CASS stations by adding one additional RF CASS station is shown in Figure 5.
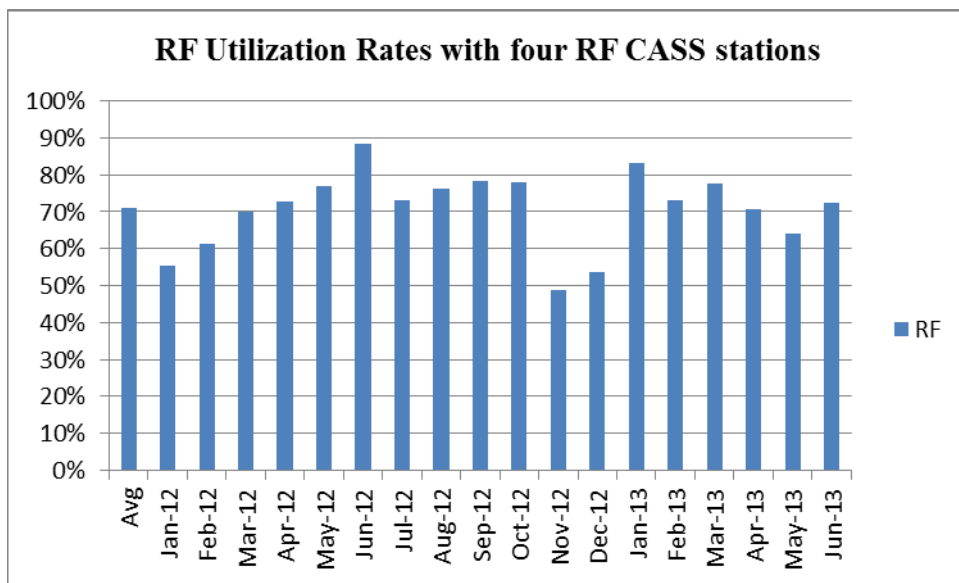

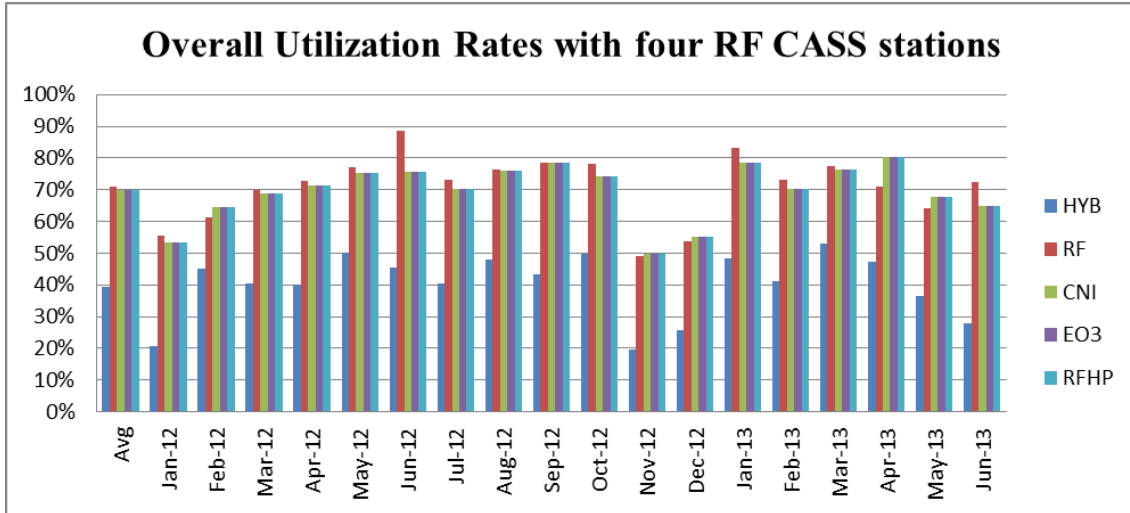Figure 4.   RF Utilization Rates with Four RF CASS Stations

Figure 5.   Overall Utilization Rates with Four RF CASS Stations

2.   Model Analysis

Utilization rates for the RF CASS stations decreased substantially. However, the utilization rates for the other remaining CASS stations also decreased. This outcome is explained by the sharing capability of the CASS stations.

	HYB	RF	CNI	EO3	RFHP	A_o
3 RF CASS	58.3%	91.1%	79.9%	79.9%	79.9%	83.9%
4 RF CASS	39.4%	71.0%	69.9%	69.9%	69.9%	84.6%

Table 8.   Utilization and A_o Difference for Average Demand with Increase of One RF CASS station

Demand for the RF CASS station is greater than demand in any of the other four CASS stations. In the optimized solution, the other CASS stations that can serve RF demand make up for the excess RF demand. Adding one more RF CASS station reduces utilization across all the other CASS stations. The cost of the additional RF CASS station increases the total cost to $22.154M. Compared to the current allocation cost of $87.386M, the adjusted optimized cost still reflects a savings of $65.232M. Additionally, under this configuration the current average A_o is greater than the model average A_o by only 0.39%.

The ability to add just one RF CASS station ensures demand for the entire 18-month period is satisfied. However, the decrease in utilization means that CASS stations remain idle for a greater amount of time. Ideally, the ability to move a CASS station ahead of a forecasted peak demand provides the Navy with the maximum utilization rate without a significant decrease in A_o.

D.   OPTIMIZED A_O EQUALS CURRENT A_O MODEL

In the previous model, current A_o remained greater than the optimized A_o (though only slightly). In this last analysis, we examine the cost of constraining A_o on a month-to-month basis, so that operational readiness should not suffer as a result of this model. Under that context, this model will examine the results if the optimized model A_o must equal current A_o.

1.   Model Results

The major difference in this model is that the model is constrained to find a solution while maintaining an A_o greater than or equal to the current A_o. This new solution was obtained by using average monthly data to solve the model, and adding the constraint that A_o could never fall below the A_o that would be obtained with the actual solution. The number of CASS stations increased under this constraint, as shown in Table 9.

CASS Station	HYB	RF	CNI	EO3	RFHP	Cost
Optimized Allocation	9	8	5	2	3	$64.931M
Current Allocation	4	14	1	5	5	$87.386M

Table 9.   CASS Station Allocation where Optimized A_o Equals Current A_o

The increased number of CASS stations changes utilization rates. In this result, many of the stations have an increased amount of time where the stations remain idle. This is shown in Figure 6.
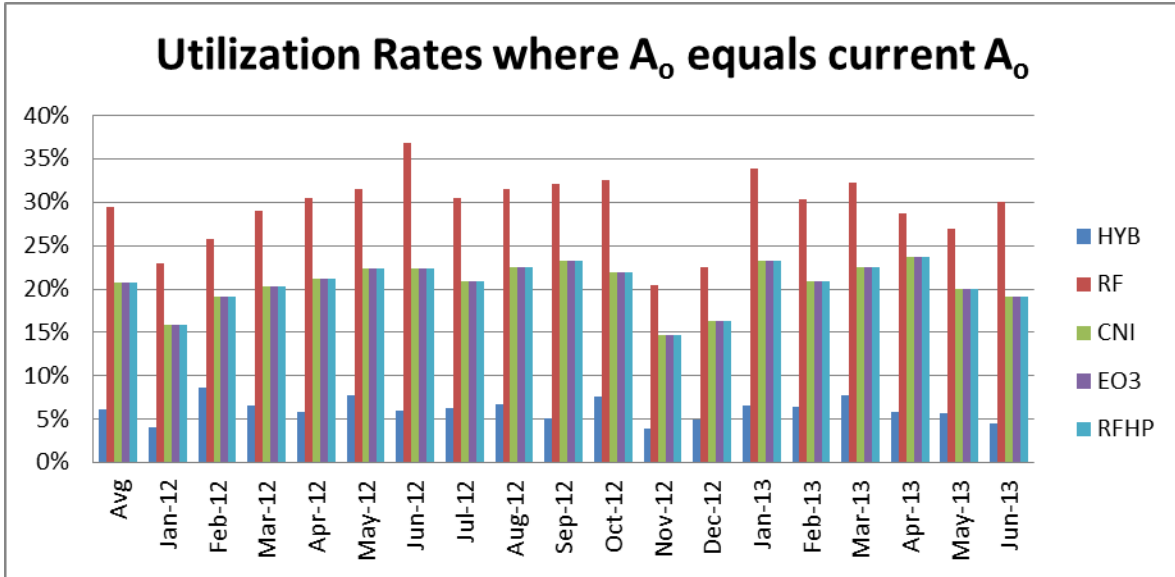
Figure 6.   Utilization Rates where A_o Equals Current A_o

2.   Model Analysis

Ultimately, this model demonstrates the costs of changing A_o from 84.6% to 85.0%. This change represents an additional 2.8 hours of ready for tasking (up time) time for each aircraft per month. With this change, the FRC examined has to incur an additional cost of $42.777m in CASS stations. As CASS stations continue to increase, the return diminishes in waiting time for the UUT. As a result, the gain achieved in A_o is reduced as CASS stations are added.

The CNO Guidance requires aircraft readiness of 73% (COMNAVAIRFOR, 2013). Naval leaders need to assess if the additional costs are worth the change in A_o, especially since the calculated A_o from the optimized solution is already 84.6%.

E.   LIMITATIONS

In this project, there exist several limitations that are worth noting. First, CASS stations are divided amongst five separate work centers. This project assumes that the CASS stations are located under one work center, or equivalently, that work bench capacity can be shared freely between work centers. As such, the model can maximize on the ability of some of the CASS stations to perform different types of testing. Under the

current configuration at the FRC, the ability to share demand across all the CASS stations allocated to the command is limited.

CASS stations are just one component required to repair UUTs. In order to repair a UUT, there needs to be an available CASS station, a TPS and a technician qualified to work on that specific UUT. Technicians are trained in a formal school to repair UUTs. Upon completion of school, the technician is awarded a specific Navy Enlisted Classification (NEC) that forms the basis of the certification required to repair a given UUT. The NEC will determine which work center a technician is assigned to once the technician arrives at the FRC. A technician trained and assigned to work center 63E cannot repair a UUT in work center 64D. CASS stations may remain idle due to the lack of a qualified technician.

As previously stated, a TPS is also required to repair a UUT. TPS availability was not studied during this project. However, this remains a factor in determining overall capability to repair UUTs. CASS stations may remain idle due to a lack of available or operational TPSs.

The concept of moving CASS stations in anticipation of a change in forecasted demand was discussed. In the context of this research, moving CASS stations ahead of demand changes improves overall utilization of the CASS stations and minimizes cost realized in holding excess assets. However, moving CASS stations bear additional operating costs; such as installation, removal, and transportation costs. Additionally, there is an assumed risk to removing, transporting and installing CASS stations. This project did not focus on the costs moving CASS stations or the involved risks.

Availability of data limited the scope of this research. In conducting the research, UUT service time was applied from the Akturk and Beckham research. For a better output of the model, service time should have been a mean of the actual service time for a given month. This would have provided a more accurate indication of the utilization rates currently observed at the FRC. In the data we received, service time was not recorded.

Finally, this project examined a time in a unit of months. Time is actually continuous, of course. In the four months where demand was not satisfied in the

optimized allocation, the excess demand could have been satisfied in a following month when overall utilization was lower. The argument could be made that the finding that monthly A_o was significantly degraded is artifactual: over a longer time period (a quarter, or a year) the average A_o obtained by the optimal solution would be satisfactory. On the other hand, the fleet operates on a continuous basis. The results show that demand for CASS stations in some periods is significantly different from demand in other periods. The fact that 'on average' there is going to be enough capacity to meet quarterly demand may be of little comfort to an operations officer who has to meet monthly (or daily) targets.

V. RECOMMENDATIONS

A. CONCLUSION

In the past, the DON fiscal budget may have been robust enough for the Navy to purchase assets for the worst case scenario. The Navy purchased and allocated assets based on the ability to support a peak demand contingency. In today's fiscally constrained environment, that goal may be unattainable. As fiscal budget cuts continue, naval leaders need a better understanding of how actual demand and variability in that demand affects the allocation of assets.

An allocation plan built to satisfy a constant level of peak demand only results in an underutilized system. Demand analysis allows a better understanding in the allocation of scarce resources. As demonstrated in the model, the optimized configuration satisfied demand for an entire 18-month period except for four months. An addition of just one RF CASS station satisfies demand for those four months where RF CASS station capacity was exceeded. Managers have to decide if the benefits of meeting demand in a given month are worth the cost of moving a CASS station, or the cost of permanently adding a bench that may only be needed six months out of 18.

In the current operational environment, the number of aircraft, the number of UUTs and the number of flight hours are relatively known figures. Naval planners have training and deployment cycles planned in advance. Peaks and troughs in demand cycles can be predicted with relative reliability. The capability exists to forecast this demand and apply that forecast to a non-linear model to determine if a change in the CASS station allocation is required. Also, in the event of an increased demand and managers decide not to move CASS stations; managers have better idea of the potential risks of not meeting that demand or can redirect that demand to a moored aircraft carrier if desired.

The composition of aircraft in the Navy's inventory has changed significantly since the purchase and development of the current CASS stations. Technological advances in aviation components have increased the MTBF of these components since the initial purchase of CASS stations. Advances in maintenance practices have also

improved the MTBF and other factors such as reduced service time. Changes in these factors greatly affect utilization rates. Management needs to be aware of these improvements in order to make the most accurate decisions.

Operational readiness is a scrutinized metric in naval aviation. Operational readiness ensures that the DON has the available assets to carry out its assigned mission. However, this model demonstrates that as A_o increases, the return on the capital investment diminishes. The optimized A_o was less than the actual A_o of the FRC as calculated by the model. When the model was forced to produce an A_o that equaled the examined FRC calculated A_o, a significantly greater number of CASS stations had to be added. Although the optimized result in the equal A_o configuration was still less than the amount of CASS Stations currently in place at the examined FRC, costs rose substantially. The large increase of CASS stations required

B.   RECOMMENDATIONS

The CASS station is near the end of its life cycle. The replacement ATE is the eCASS system. The eCASS system will combine the capabilities of the five CASS stations into one ATE. As eCASS stations deploy to the fleet, this project exposes some ideas to the allocation and use of the eCASS stations.

First, it is recommended that eCASS is allocated using a non-linear mathematical model based on actual demand. Using the CASS station as an example in the project, millions of dollars are saved using a non-linear mathematical model instead of the algebraic method currently in use. Additionally, as spaces in the FRC are converted to accommodate eCASS, it is recommended that spare eCASS "slots" are built. In the event that demand signals show a future increase failure rate beyond the capacity of the current eCASS stations on-hand, additional eCASS stations can easily be installed to account for the additional demand.

As eCASS stations are incorporated into FRCs and AIMDs, a centralized work center needs to be incorporated instead of the five work centers currently in place. In this project, the sharing ability of the CASS stations provides a more efficient method of repairing UUTs. In eCASS, all of the testing capabilities will be shared in one unit. A

centralized work center means lower costs in the form of eCASS stations, personnel, training and TPS equipment. Other barriers may exist that preclude incorporation of a centralized eCASS work center; it is recommended that a thorough examination occur prior the incorporation of eCASS.

Finally, collection of data needs improvement. Advances and applications in the theories of Operational Research and Lean management require accurate, relevant, and readily obtainable data. Much of this data is available; however it resides in multiple databases that do not interface with each other. Standardization of data under the fewest databases possible needs to be a priority in the continual process improvement of the Navy.

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