The allocation of automated test equipment capacity with variability in demand and processing rates

NAVAL POSTGRADUATE SCHOOL

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THESIS

THE ALLOCATION OF AUTOMATED TEST EQUIPMENT CAPACITY WITH VARIABILITY IN DEMAND AND PROCESSING RATES

by

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December 2010

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LIST OF ACRONYMS AND ABBREVIATIONS

AIMD	Aircraft Intermediate Maintenance Department/Detachment
A_o	Operational Availability
ATE	Automated Test Equipment
ATS	Automatic Test Systems
BCM	Beyond Capability of Maintenance
CASS	Consolidated Automated Support System
CB	Crystal Ball
CNI	Communication, Navigation, Identification CASS
CVW	Carrier Air Wing
D-Level	Depot Maintenance Level
DLR	Depot Level Repairable
DoD	Department of Defense
DON	Department of the Navy
EMT	Elapsed Maintenance Time
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
GP	Goal Programming
HPDTS	High Power Device Test Set
HYB	Hybrid CASS
I-Level	Intermediate Maintenance Level

JASMMM	Joint Aviation Supply, Material, and Maintenance Management
LRU	Line Replaceable Units
MCLP	Maximum Covering Location Programming
MLDT	Mean Logistics Down Time
MS	Management Science
MTBF	Mean Time Between Failure
MTOS	Mean Time on Station
MTTR	Mean Time To Repair (CASS)
NAMP	Naval Aviation Maintenance Program
NAVAIR	Naval Air Systems Command, Patuxent River, MD
NMCS	Non-Mission Capable Supply
O-Level	Organizational Maintenance Level
OR	Operations Research
OTPS	Operational Test Program Set
PMA	Program Manager Activity
PSE	Peculiar Support Equipment
RF	Radio Frequency CASS
RFHP	Radio Frequency and High Power Device Test Set CASS
RFI	Ready for Issue
RT	Reconfigurable Transportable CASS
SAR	Search and Rescue
SLF	Surge Load Factor
SRA	Shop Replaceable Assembly (circuit card)
SRU	Serviceable Repairable Unit
TAT	Turn-Around Time

TPM	Test Program Medium
TPS	Test Program Set
TYCOM	Type Commander
USMC	United States Marine Corps
USN	United States Navy
UUT	Unit Under Test
VAST	Versatile Avionics Shop Tester
WRA	Weapons Repairable Assembly

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I. INTRODUCTION

A. THE PROBLEM

The allocation of resources is a critical function to any organization. Understanding how many resources to be allocated and for what reason is critical in meeting customer demand in order to meet the required service level. The Consolidated Automated Support System (CASS) program office at Naval Air (NAVAIR) PMA 260 has the task of allocating five different CASS stations to 52 different United States Navy (USN) and United States Marine Corps (USMC) sites.

The program office receives calls from these sites periodically requesting more CASS stations in order to clear their backlog (queue) of parts. PMA 260s current method of CASS allocation has been effective but can be improved. One factor the current method does not explicitly consider is variability. If queues constantly build at sites, they contribute to long turn-around times (TAT), which "affect customer service level," also known as "operational availability" (A_o). The program office must be confident in their allocation in order to satisfy the A_o of each site.

B. FACTORS BEYOND THE CONTROL OF SITES

There are many inherent factors in the aviation community beyond the control of local repair sites which make support of aviation weapons systems difficult to manage. These factors are: (a) aircraft overfly hours, (b) actual failure rates exceed projected rates, (c) aircraft delivered prior to replacement parts, (d) readiness desired above that planned/designed, (e) TAT for repairs exceeds the plan, (f) configurations of aircraft and equipment frequently change, and (h) limited off-the-shelf buys (NALDA, 2003).

Aviation managers at each site face these issues, due to new political environments, such as changes in presidential administrations and Chief of Naval Operations, which were not originally planned for. At each site, control of external inherent factors (i.e., flight hours, configurations, number of replacement parts, etc.) is too limited to control variability. It is the responsibility of NAVAIR to support sites to meet requirements set within NAVAIR offices, even though changes in demand, high or low, occur (NAVAIRSYSCOM, 2002). PMA 260 cannot predict the future nor get a promise from another NAVAIR office to determine future demand to meet a service level consistently. PMA 260 can, on the other hand, support their sites by allocating resources based on possible increases in demand, and possible changes in the other factors mentioned above. To do this, they need to estimate variance for factors examined in this project (in some cases from sources outside PMA 260, and use this projects algorithms to choose CASS allocation which is robust to major sources of risk.

Additionally, the high variation in demand with current deployment schedules causes larger than predicted queues for CASS during some time periods, seriously affecting aircraft readiness. Allocating CASS based on real-time service rates is difficult and, concurrently, when demand is high, can be too costly. Currently, PMA 260 cannot allocate stations to meet every sites' peak periods. It strives to meet the long-run average of all sites combined with a surge load factor (SLF).

C. ADDITIONAL CONTRIBUTING FACTORS AFFECTING DOWNTIME

Other contributing factors affecting system downtime of weapons systems at the local level attributed to material management which CASS cannot improve: (a) improper material requested by the squadron, (b) lack of adequate technical research by maintenance and or supply, (c) improper trouble shooting practices, (d) delay in turn-in of removed material, (e) maintenance not returning not-mission-capable supply (NMCS) items to a ready-for-issue (RFI) condition expeditiously, (f) improper management and supervision practices, (g) lack of material planning for maintenance and supply personnel, (h) inadequate packaging/protection of repairable components, (i) improper utilization of existing resources, (j) improper application of established maintenance and supply practices, and (k) lack of coordination between maintenance and supply. These other factors do not play into this project's algorithm because adding additional CASS does not address the problems caused by these factors.

An improved CASS allocation as suggested in this project cannot by itself improve the entire fleet readiness or service level, but can address variability in demand and service times of CASS, to reduce backlogs during periods of peak demand, and provide a proper mix of each type of CASS. Additionally, the CASS network is part of a supply chain network, which is large and complex and could take months or years to adjust the entire network. This project focuses on understanding the current workload model formula, the history of it, why it should be adjusted to account for variability, and whether adding CASS stations will improve the queue length in order to meet a probable level of demand during a given time.

D. AN ALTERNATE SOLUTION PROPOSED BY THIS PROJECT

Controlling variability is a difficult task. Authors Wallace Hopp and Mark Spearman discuss variability and control in *Factory Physics* (Hopp & Spearman, 2000). Collecting data over time in order to forecast the service and demand to allocate CASS is a way to adapt to the variability, which, in turn, controls variability, or keeps it under control in order to meet the required customer service level. Understanding and capturing variability in service rates and demand (arrival rate) is important in order to have a maintenance capability to support the billions of dollars invested on the flight line. Once the variability is captured, the allocation of the CASS allocation decision can be made against any level of probable demand, not just the expected demand. For example, PMA 260 would be able to allocate stations to meet the demand of 80% of the time (rather than 50% of the time implied by allocating to average demand).

This projects goal is to allocate CASS using Integer Linear and Nonlinear Programming. Using this approach will give an integer value for the number of CASS to allocate based on a service level for a site and the distributions of each sites demand and service rate. The service rates of each site will vary due to several factors, including the time period of their turnover of experienced personnel. Such variance has an important impact on capacity, but may be the same for each site, because each site will go through the same turnover situation.

E. RESEARCH QUESTIONS

CASS is a critical logistics function to support the aircraft readiness of each site. The decision to add one more CASS station increases costs but can reduce TAT and spare repairable UUTs. The question in order to minimize total site cost is:

1. Primary Research Question

What is the best mix of CASS stations required at a site?

2. Secondary Research Questions

How does the current workload formula assign capacity and what are its key assumptions?

Can an alternative model be developed to account for demand and service rate variance?

II. LITERATURE REVIEW

In examining the literature pertinent to our research, it is necessary to first review a) the various levels of maintenance supported by Consolidated Automated Support System (CASS), b) the various types of units being repaired by CASS, and c) the various types of CASS benches. Following this review of the technology, we will review the central problem at hand, determining the correct number of benches and their allocation, and examine the current approach to solving this problem. Finally, since we are proposing an optimization approach coupled with a risk-based contingency analysis, we will review work on related problems which have used similar approaches.

A. MAINTENANCE LEVELS

The location of each CASS is important to Naval Aviation. The maintenance actions that are performed are dispersed through three levels of maintenance, each having its own degree of repair difficulty. Before beginning to define CASS and the way it works, it is necessary to understand the different levels of repair in Naval Aviation and how they affect the allocation of CASS. The Naval Aviation Maintenance Program (NAMP) defines three levels of maintenance as:

1. Depot Level Maintenance (D-Level)

This is the most in-depth, time-consuming, and costly maintenance level in Naval Aviation. This level of maintenance works on material requiring major rework or a complete rebuild of parts, assemblies, subassemblies, and end items, including manufacture, modification, testing, and reclamation of parts as required. D-level maintenance serves to support lower levels of maintenance by providing technical assistance and performing maintenance beyond the responsibility of O-level and I-level maintenance. D-level maintenance provides stocks of serviceable equipment by using more extensive facilities for repair than are available in lower-level maintenance activities. Items that are repaired or serviced here are called Depot Level Repairables, also commonly referred to as DLRs.

2. Intermediate Level Maintenance (I-Level)

This level of maintenance is referred to as Fleet Readiness Center (FRC), previously referred to as the Aviation Intermediate Maintenance Detachment (AIMD), attached to the Type Commander (TYCOM) of a specific aircraft platform. Its workforce consists of active duty aviation maintenance technicians, active duty ground maintenance officers, and civilian artisans with over 15 years of experience on the equipment which is repaired. Additionally, the artisans provide training and continuity to the facility, base, and operational capability of the squadrons. An I-level FRC is located on the same Naval Air Base/Station as the type/model/series aircraft it services. The I-level FRC performs (a) calibration, (b) repair or replacement of damaged or unserviceable parts, components, or assemblies; (c) the emergency manufacture of non-available parts. It also provides technical assistance to the squadrons. The D-level FRC is regionally located and performs in-depth overhaul, repair, and modification of aircraft, engines, and aeronautical components. Both levels of FRC are under the command of a Navy or Marine Corps O-6 in a respective region (i.e., Northwest, Southwest, East, etc.). A region can have up to eight I-level and one D-level FRCs, consisting of more than 20,000 active duty and civilian personnel.

3. Organizational Level Maintenance (O-Level)

These are squadrons of specific type/model/series aircraft. They are operationally deployable forces using assets and manpower in order to project naval power at sea and abroad. In order to maintain and sustain this war-fighting capability, the squadron must be able to maintain its own aircraft but with a little supply and equipment footprint. The maintenance performed at this level is trivial, but troubleshooting can be the time-consuming difficult task. The responsibility of the maintenance department for its assigned equipment consists of inspecting, servicing, lubricating, adjusting, and replacing parts, minor assemblies, and subassemblies (COMNAVAIRSYSCOM, 2008). If a part is broken or needs repair or a in-depth inspection, the O-level sends it to I- or D-level. This level of maintenance is commanded by a Navy or Marine Corps O-5 pilot or Naval flight officer and operates between 4 and 12 aircraft with 160 to 350 personnel.

B. AUTOMATIC TEST SYSTEM (ATS)

The Automated Test System (ATS) is a fully-integrated, computer-controlled suite of electronic test equipment and instrumentation hardware, software, documentation, and ancillary items designed to verify at any level of maintenance the functionality of a Unit Under Test[1] (UUT). The term UUT includes weapons replaceable assemblies and shop replaceable assemblies, described further in the next section (Belcher, 2009) The ATS combines three elements:

First, Automatic Test Equipment (ATE), which is an instrument or set of instruments to measure the reliability and figure out the faults and defects of various electronic and avionic parts which are currently used in the fleet. The ATE may be a single computer or several computers, depending on the size of its utility purpose. ATE software includes operating system software, test executive software, and instrument control software.

As for the ATE's operational rationale, they perform their jobs in line with the software by giving the input stimuli and by measuring the UUT output responses. These responses define a UUT's operational ready-for-issue (RFI) state or isolate a fault detection. Furthermore, ATE is used to meet I- and D-level maintenance requirements for electronic and avionic weapon systems and also tests their circuit boards.

Second, in order to connect the UUT to the ATE, a Test Program Set (TPS) is used. It is an interface set of hardware devices (with ancillary equipment) with test program software specific to a UUT with required documentation. The TPS software directs all test functions, including fault isolation and diagnostics, and can certify the condition of a UUT. The ancillary hardware consists of cables, probes, holding fixtures, and other peculiar instrumentation (Belcher, 2009). A set of UUTs has a unique TPS that has the electrical and mechanical tools and the test software to test those UUTs (Flynn, 2007).

Third, it gathers information in order to design test environment and TPS software for UUTs. This test environment includes a description of the ATS architecture,

[1] UUT: A component that is being tested on the CASS station.

programming, and test specification languages; compiler; and development tools. It also provides for capturing and using UUT design requirements and test strategy information in the generation and maintenance of TPS software (Belcher, 2009).

C. WRAs AND SRAs

ATSs are used throughout the Department of Defense (DoD) to perform both functional and diagnostic testing of different UUTs. UUTs include, but are not limited to, shop replaceable units (SRUs), line replaceable units (LRUs), shop replaceable assemblies (SRAs), weapons replaceable assemblies (WRAs), and other removable components from weapons platforms or support systems. For this project UUTs consist only of WRAs and SRAs.

D. TPS AND OTPS

A TPS, as mentioned earlier as part of the ATS, includes the software, hardware, and documentation needed to test, fault detect, and isolate, or perform any other evaluation of a specific UUT. An Operational Test Program Set (OTPS), on the other hand, is a logically-bundled group of TPSs (merging of one or more TPSs) that use the same set of hardware items, such as interface devices, cables, and mounting plates. An OTPS usually contains TPSs that test one or more WRAs and their SRAs (COMNAVAIRSYSCOM, 2009). OTPSs contain the following elements: Operational Test Program Hardware, Operational Test Program Medium, Operational Test Program Instruction, Master Test Program Set Index, Technical Manual, and User Logistic Support Summary. The TPS as part of the OTPS is used by Navy I- and D-level maintenance technicians to perform maintenance on selected UUTs. Each of the Test Programs (TPs) of an OTPS does reside on the test program medium (TPM). The TPM is structured in such a manner that it is possible to identify the individual test programs residing therein (e.g., a table of contents).

E. INTERFACE DEVICE (ID)

In order to understand the ATS run time and other variables that make up in the ATS, it is important to grasp the following: The interface device (ID) provides the necessary electrical, mechanical, hydraulic, pneumatic, radiated, and optical interfaces between the ATE and the UUT. An ID can consist of simply a panel ID that mates directly with the UUT and ATE interface, but can also include a cable set and test fixture as required by individual TPS requirements. All of the ID requirements of the individual TPSs of an OTPS merge into a common ID.

The ID is the necessary wiring and circuitry to interface the UUT to the ATE and to resolve any incompatibilities that exist between the ATE and the UUT in order to implement the test requirements. The cable set provides the means to route power, stimulus, measurement, and test point signals between the UUT, ID, and ATE to effect testing of the UUT and self-test of the panel ID. When required by a particular UUT, and in addition to the panel ID, a test fixture is provided as part of the TPS to provide an electrical and mechanical interface with the UUT. In such cases, the cable set interfaces the panel ID to the test fixture.

F. HISTORY OF AUTOMATIC TEST EQUIPMENT

Before the introduction of ATEs in the 1970s, the Navy used peculiar support equipment (PSE) to meet its testing requirements in avionics and electronics. Those PSEs were only supporting a single avionic system each, which resulted in a lot of complexity as the weapon systems proliferated and their relative sizes got much bigger after the 1970s (Meredith, 1990).

The DoN had its first ATE system in 1972 with Versatile Avionics Shop Tester (VAST). However, the problems began to increase with the advent of each new ATE system. Some of them required big spaces; others needed special operator training, and some others overheated during their operation periods. Moreover, each legacy ATE system required different installation and operation procedures and followed various supply chains to procure the necessary assemblies (Mena, 1994). All these problems made the Navy look meticulously for a single ATE system that was able to meet the requirements of nearly all the avionic and electronic components and is also able to operate all the existing TPSs to support both the I- and D-level maintenance needs. To better understand the complexity in testing needs, it is necessary to look at the numbers in 1990. More than 24 different ATEs and three hundred manual testers were used in 1990 to meet the test requirements of complex weapon systems (Meredith, 1990).

Seeing that the legacy test systems were pushing the maintenance costs up and only met the needs of their own specific components, DoN initiated programs to unify all test equipment during the late 1980s (Kelly, 2002). Finally, the Navy ordered the first new breed of ATE, CASS, in 1990 and introduced it to the fleet in 1994 to supplant all legacy ATE systems in order to solve testing, maintainability, and supportability problems. The last of the 553 mainframe CASS stations was delivered in December 2003. Currently, the Navy and Marine Corps use 713 of these stations for afloat and shore-based I- and D-level maintenance support. Some stations are used at various Navy depots, a National Oceanic and Atmospheric Administration depot, and around the world by more than 10 different countries (DoD, 2006).

Throughout its development, introduction, and operation, CASS was configured, designed, and developed with the sole aim of maximizing the utility of the new ATE system while eradicating the issues that the legacy ATE systems presented, such as overheating, space requirements, special operator training, and expensive TPS software (Mena, 1994). One of its biggest advantages was that it was designed to be easily adaptable to new technologies (Mulato, 1999).

"The CASS project was established in 1978 in response to the NAVAIR ATE Program Plan to provide a long-term solution to the many historical ATE problems and meet the challenge of emerging testing needs during its life cycle" (Meredith, 1990). CASS aesthetics, configurations, and design, were intended to meet the Navy's maintenance and testing needs through 2011. After that, e-CASS will replace CASS stations beginning in 2016.

1. Allocation of ATE

The allocation of ATE used a linear algebraic workload model called the ATE Workload Model. This model used averages for inherently random parameters, such as Elapsed Maintenance Time (EMT) and number of UUT inductions. The averages were used in an attempt to account for the repair queue of random surges in UUT inductions and variations in EMT by setting the CASS station utilization to some value less than one (Meredith, 1990). This was the Surge Load Factor (SLF) in the model in order to capture and integrate increased workload into the ATE network. If the SLF were one, it would not be capable of supporting a higher workload, in theory, and then there would be no allowance of additional workload if the average flight hours were increased unexpectedly. If the SLF were 50%, then there would be a planned 50% surge allowance of UUTs in order to handle additional demand, and then there would be two ATEs for the UUTs at the site. This would allow the site to account for any possible surge in demand.. If the flight hours increased, the UUTs that fell under that ATE would have to wait in a queue or be subject to Beyond Capability of Maintenance (BCM) action and be routed to another site. Problems arising from this Workload Model could be (a) having an underutilized network, (b) increasing costs if 100% were used, and (c) reducing worker efficiency below 100%, which could increase the TAT and cause a queuing problem.

G. CONSOLIDATED AUTOMATED SUPPORT SYSTEM (CASS)

CASS is defined by the Navy Training System Plan (NAVAIRSYSCOM, 2002) as “a computer-assisted, multi-functional automatic test equipment used to test various electronic components at Navy and Marine Corps Intermediate Maintenance Activities, Naval Weapons Stations, Naval Aviation Depots, and Naval Sea System Command support activities.”

Similarly, Meredith (Meredith, 1990) defines CASS as “a modular, reconfigurable, computer driven automatic test station capable of providing performance verification and diagnostic fault isolation for all complex electronic components.” According to his study, though CASS primarily targets I-level maintenance, it will also include D-level maintenance. So, while the official definition of CASS from Navy

Training System Plan focuses on the level of maintenance for various components, Meredith's definition of CASS explains its basic capabilities.

H. OBJECTIVE OF CASS

Officially, Navy Training System Plan (NAVAIRSYSCOM, 2002) defines the objective of CASS as "to consolidate electronic and avionics support into one standard ATE system." So, the most basic objective of the CASS was to provide common-ground ATE for the Navy and the Marine Corps. This commonality, then, was expected to eliminate various kinds of ATEs, which the literature defines as legacy systems, and it did so. The objectives of the CASS Project were two-fold: First, increase the throughput, which means to improve operational availability, readiness, and capability to meet sortie requirements. Second, have a standard ATE hardware, software, and support, which mean less ownership costs of diversified test equipment (Meredith, 1990).

A third objective might be providing commonality throughout the Navy and the Marine Corps, so that the I-level and D-level artisans and technicians can be the masters of the new ATE system, and they can address the needs of the fleets faster, better, and in a more accurate way. Moreover, eliminating these legacy systems would also decrease costs for the ATEs. Since CASS is common ATE now, and all kinds of parts, pieces, and assemblies are procured with their CASS-compatible TPSs, which will also be consistent with the next-phase ATE in the future, DoN has been reaping the harvest of this common ATE system by means of decreased costs.

I. FUNCTIONAL DESCRIPTION OF CASS

Navy Training Systems Plan (NAVAIRSYSCOM, 2002) describes a CASS station as "a five-rack integrated test system known as Hybrid Tester." The mounting of particular racks to the Hybrid Tester enables CASS to test different kinds of components for different kinds of aircraft platforms. Also, CASS was designed to accommodate deviations in the workload and to use common TPSs in different configurations. As of 2010, there are five CASS configurations (see Figure 1):

1. Hybrid (HYB)

The CASS Hybrid station provides the core test capability for general-purpose electronics, computers, instruments, and flight controls.

2. Radio Frequency (RF) and Ancillary High Power Device Test Set (HPDTS)

The CASS RF station provides Hybrid station test capability plus Electronic Countermeasure, Electronic Counter-Countermeasure, Electronic Warfare, Support Measures, Fire Control Radar, Navigation Radar, Tracking Radar, Surveillance Radar, and Radar Altimeter support capability. The CASS High Power station provides RF station capability plus the capability to test high power RADAR systems, such as the APG-65 and APG-73.

3. Communication, Navigation, Identification (CNI)

The CASS CNI station provides RF station capability plus communication, navigation, interrogation, and spread spectrum system support capability.

4. Electro-Optical (EO3)

The CASS EO3 station provides Hybrid station test capability plus support capability for Forward Looking Infrared, Lasers/Designators, Laser Range Finders, and Visual Systems.

5. Reconfigurable Transportable (RTCASS)

The RTCASS provides a man-portable CASS configuration using computer off-the-shelf hardware and software to meet USMC V-22 (Osprey) and H-1 (Helicopter models) support requirements as well as to replace mainframe CASS stations at USMC fixed wing aircraft EA-6B (Prowler), F/A-18 (Hornet), and AV-8B (Harrier) support sites.

J. HOW MANY CASS STATIONS ARE REQUIRED?

The objective in assigning a number of CASS stations to sites is related to cost effectiveness. On the one hand, if the Navy assigns more stations than a site needs, then it incurs unnecessary capital costs. On the other hand, if the Navy assigns fewer than a site needs, then this can lead to higher turn-around times, transportation costs due to BCMs, lower aircraft readiness, more cannibalization, and longer maintenance delays, which together might undermine the effectiveness and overall readiness in the Navy. "Implementation of CASS at a site is ultimately a question of cost-effectiveness: How many CASS stations are enough" (Lynn, 1996)? This question has been a challenge for NAVAIR, and for the past decade they have been using a workload formula (described below) to determine the number of CASS stations for each site. The workload formula is essentially the same as the past ATE workload model. One of the objectives of this research is to evaluate the suitability of the workload formula, and to suggest improvements in the formula and its application.

1. Assigning CASS Stations to Maintenance Centers

There are a lot of studies, articles, and government reports about how many CASS stations to assign to each maintenance center and what kind of factors to take into account. While the NAVAIR CASS program office (PMA 260) is using a workload formula depending on some variables, assumptions, and constants, Lynn (1996) uses five measures of effectiveness to evaluate CASS requirements: full-mission-capable (FMC) and mission-capable (MC) rates, sortie-generation rate, cannibalization rate, and turn-around time. According to the study, adding more CASS stations, at some point, does not improve the performance of a maintenance center (Lynn, 1996). The goal of Lynn's study is to find out both the type and the number of CASS stations to assign to each site.

2. Current Situation at PMA-260

The Program Office, PMA 260, for CASS in NAVAIR is using a workload formula right now to allocate the CASS stations to the 52 USN/USMC sites. Below are the workload formula and its assumptions.

$$\text{Workload} = \frac{(\text{\# of aircraft}) \times (\text{monthly flight hours}) \times (\text{MTOS})}{(\text{CASS } A_o) \times (\text{monthly op. hours}) \times (\text{MTBUM})}$$

- # of aircraft: The number of specific type/model/series aircraft at a specific site.
- monthly flight hours: Average monthly flight hours for each aircraft.
- MTOS: End-to end run time and other times for WRA
- CASS A_o : Operational Availability of the CASS station in a given month is assumed to be 80%. This was the SLF of the ATE workload model.
- Site Monthly Operating Hours: Total available hours of a CASS station in a month:
    - SEA = 2 shifts x12 hrs x 30 days x .85 = 612 hrs
    - SHORE = 2 shifts x 8 hrs x 22 days x .85 = 299.2 (300) (15% allowance for other activities of total man-hours).
- MTBUM: Mean time between unscheduled maintenance for each UUT (Cervenak, 2010)

PMA 260 is using this workload formula and calculating the CASS and TPS/OTPS requirements for each UUT. Finally, they add up all those requirements and figure out the total specific type of CASS and TPS/OTPS requirement. The formula contains several constants, which are estimates for the values of random variables. For example, the MTOS for any UUT includes an additional 180 minutes to represent administrative and setup delays. But, the MTOS is a global random variable. The constants are not necessarily estimates of mean values: they are standards that have built-in allowances for excess time required, but there is not a probability associated with the estimate, which would allow a risk-based contingency analysis. Because of congestion effects (delays in busy periods), assuming a constant value, even if that constant is inflated, might lead to an under-allocation of workstations in periods of peak demand. This argument is also true for other constant assumptions. We contend that a better way to deal with the built-in variability in this process is to use tools which explicitly incorporate the impact of variability. Therefore, our optimization approach will incorporate estimates of queuing delays due to variability, and we will use a Monte Carlo simulation tool (Crystal Ball) to conduct post-hoc sensitivity analyses in order to build contingency plans.

The current workload is a basic linear algebraic model where number of aircraft times monthly flight hours (200 * 30 = 6000) is the total number of expected flight hours. This is divided by the MTBF of the UUT (6000 / 100 = 60), which has an output of the expected demand of the UUT in a given month while flying 30 hours per aircraft. The other part of the workload is MTOS divided by the A_o (SLF/utilization/expected down CASS station) times availability of man-hours to work (4 / (.8 * 300) = .0166). This UUT workload requirement is (60 * .016667 = 1.00) one CASS station. The formula says that, with each increase in flight hours, the demand of a CASS station will linearly increase as in Figure 1.

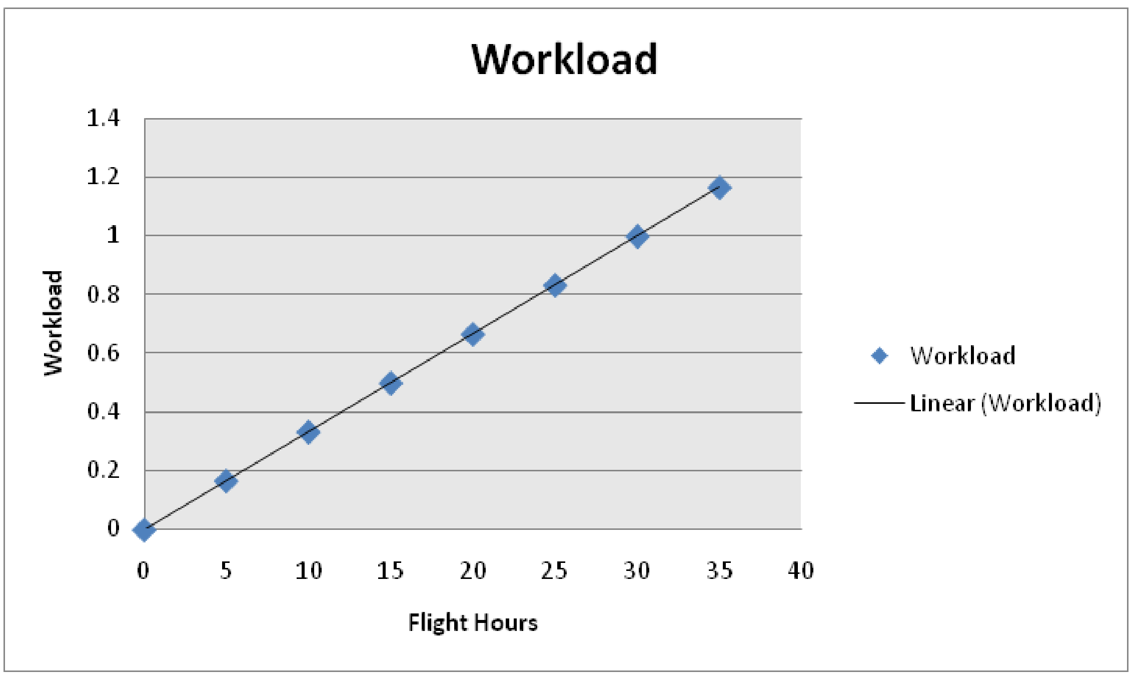

Figure 1. Workload linear relationship

The values in the example are approximations; an increase in flight hours will increase the expected number of failures. The workload output is a constant value affecting current and future months; thus the actual arrivals or demand will not be the same each month. If the average or the max (max peak hours) is calculated, the total will capture either 50 % or 100 % of the possible demand for a month for a UUT. This will affect the arrival rate into the I-levels for each type of CASS. This can cause an underutilized network of CASS stations or overutilized network of CASS and cause backlog of many UUTs.

K. RELATED PROBLEMS USING SIMILAR APPROACHES

Many public and private organizations are effectively using mathematical models of the sort we are proposing to solve their resource allocation problems (ReVelle & Eiselt, 2005). The managers in these organizations (emergency ambulance services, fire departments, forest services, military sites, banks, manufacturers, retailers, etc.) are looking for better methods to allocate their scarce resources and two of those methods are linear and nonlinear programs. However, these mathematical models also need constant values for the aforementioned assumptions. In order to decrease the effect of deterministic values for the processes, we are incorporating the spreadsheet simulation for our sensitivity analysis. Hence, we will see the effects of change in each assumption on the CASS requirement and provide a better model to the decision makers.

At the heart of our proposed optimization method is a linear and a nonlinear program. A good review of linear programming and its restrictions can be found in (Balakrishnan, Render, & Stair, 2007). In the linear mathematical programming, the objective function and the constraints are assumed to have linear relationship with the decision variables (Ragsdale, 2004). Although many of the problems we face in the real world are nonlinear, we can sometimes approximate these nonlinearities with linear, or piecewise-linear, elements, which are acceptable approximations of the more complex real-world problems (Jensen & Bard, 2003). But we cannot model all problems with linear approximations.

Below, we categorize and describe work related to our problem of determining the allocation of CASS stations to depot and intermediate maintenance sites.

A known problem which bears a superficial resemblance to ours is the maximal covering location problem (MCLP). Church and Revelle (1974) assert that MCLP tries to maximize the population to be served within a predetermined service distance or time given the number of facilities being constrained. According to Berman and Krass (2002), the MCLP is one of the best facility location models from theoretical and practical perspectives. The objective of the MCLP is to locate a number of facilities in order to maximize the total area of covered demand from customers or citizens, where they are accepted as covered if they are located within a specified distance from the closest facility location.

This is related to our CASS allocation problem if one considers the CASS stations as facilities to be located and part demand as a kind of consumer demand to be satisfied. However, the MCLP assumes coverage as binary. In other terms, a specific customer area is either covered or not covered by the location of a single facility, whereas we are concerned with the degree (or percentage) of coverage provided by some number ***n*** of workstations. Also, in the MCLP, the coverage depends on the specified distance, meaning that, if the facility is within the accepted distance, it is considered to have full coverage. But that assumption may be unrealistic, even in the MCLP problem (Berman & Krass, 2002), and in any event is not directly analogous to our CASS allocation problem.

Linear and integer programs differ from the goal programming (GP) in that they have single-objective functions. However, GPs have multiple-objective functions which most of the time conflict with each other. So, GP tries to satisfy each objective to a certain extent by ranking them in terms of their importance (Balakrishnan et al., 2007). Armstrong and Cook (1979) discuss some applications of GP to optimally allocate a number of search and rescue (SAR) aircraft to a fixed number of available bases. Their model also includes the type of SAR, along with the number of those available SAR aircraft. In fact, their model is similar to the resource allocation model.

Assigning the appropriate number of SAR aircraft to locations is a critical function to support economies and public safety. Armstrong and Cook (1979) use GP to derive the most effective level of service relative to various occurrences of air and marine emergencies. Their goal is to determine the appropriate mix of SAR aircraft allocation to bases and search areas. This programming technique is quite similar to the CASS allocation problem, which tries to determine both the type of CASS station and its location.

The SAR aircraft allocation model uses number of aircraft, man-hours, and hundreds and thousands of square miles of territory to be covered. These variables are similar to the CASS model in the following way: the number and type of CASS stations (number and type of aircraft), manpower to run the stations (man-hours), and number of aircraft squadrons to be served (area). This analogy supports the relevance to GP, which will validate the CASS model. When a UUT requires repair, the accessibility, availability, and capability of CASS stations are critical and essential to the mission capability of aircraft. Failure to meet demand with CASS availability could result in expensive depot-level repair and diminish squadron and aircraft readiness and reduce supply departments' stock due to the variability in transportation times and schedules.

The time phases mentioned in the model are: notification time, action time, transit time, search time, and rescue time. Notification, action, and rescue time can be assumed fixed. Transit time is a function of aircraft type and transit distance. Search time is a random variable. These time functions are critical to the SAR Aircraft model to determine area covered and speed of an aircraft relative to the amount of area that needs to be covered. The time variables may apply to CASS in the following ways:

- Notification Time – the clock time the failed UUT arrives in work center to be worked on; the time the stop watch begins to calculate total time in repair cycle.
- Action Time – time it takes a UUT to be set up on CASS work station; this is fixed with random variability but is the same for each UUT.
- Transit Time – time it takes for CASS to run system diagnostics. The times are different for each type of CASS and UUT.
- Search Time – time it takes for CASS to search for problems with the UUT and the quantity.
- Rescue Time – time it takes to repair the WRA software within the UUT. Search and rescue time is the other time counted in total TAT.

These time variables are critical to determine the appropriate capacity to meet demand. It is as essential to SAR to save lives in a timely manner to meet happy endings as it is to meet customer service/mission capability requirements.

However, Armstrong and Cook (1979) also discuss the problems with forecasting demand related to the model. To determine the number of aircraft required for applicable bases, demand should be forecasted. The nature of SAR operations is unknown since it is stochastic. That makes historical data the only route to making any reasonable forecast.

One of the studies about the multi-period set covering location model is the deployment of ambulances. Since the demand for the medical treatment is not constant throughout the time period (week, month, etc.), the best way to improve the system performance is to use a dynamic relocation model (Rajagopalan, Saydam, & Xiao, 2008). The objective of their study is to minimize the number of ambulances and determine their locations for each time period that a significant change occurs in the demand for ambulances while addressing the coverage requirement. Time permitting; our project will also look at the multi-period set covering location model for the dynamic redeployment of CASS stations each year. We are planning to update the model on a yearly basis, assuming that no significant change in the number of aircraft occurs throughout the year. Moreover, we also have to consider the Navy readiness level as one of our crucial constraints while redeploying the CASS stations on a yearly basis.

Finally, it is worth noting that one can use GP models in a different environment through adding some variations into the SAR model. For example, it is possible to use GP in the allocation of CASS stations to sites while achieving a predetermined service level, which is the Navy readiness level in our case.

The U.S. Coast Guard used optimization and simulation in a study called; “Operations Research Enhances Supply Chain Management at the U.S. Coast Guard Aircraft Repair and Supply Center.” This study was conducted by Purdue University and members of the U.S. Coast Guard during a period of five years (2001–2006), analyzing the substantial effects of implementing four separate operations research methodologies for efficient supply chain management to improve fleet readiness. The four projects focused on the improvement of the maintenance throughput and supply inventory of aircraft parts. The projects provided critical decision support for planning various repair and maintenance activities at their repair and supply centers (Everingham et. al., 2008).

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III. METHODOLOGY

A. STOCHASTIC RESOURCE ALLOCATION

The problem with allocating CASS is that it has a larger scope and higher degree of commonality between CASS stations, as compared to its predecessor ATE, which permits UUTs to be run on several different station configurations (Meredith, 1990). The ATE workload calculation was more accurate for that type of equipment because the demand and service times were not as variable for each UUT on each ATE. For systems that have known service parameters, low utilization and planned demand, we can easily determine the amount of equipment and material to buy and the number of employees to use while limiting the queue, backlog, and waiting line. If UUTs arrive one every five hours with a service rate of one every three hours, then there will be a minimal queue for getting the UUT back to the customer. With CASS, utilization is high during surge, and there are various service times and high variability in demand for each type of CASS because of commonality.

As an example of the CASS network: three UUTs arrive randomly within five hours, with a service time of three, four, and five hours respectively with an average service rate of ((3+4+5)/3) one UUT every four hours. If they arrive at the same time, we would start the shortest service time first in order to get the UUT back to the customer, but they arrive randomly and we do not know which one will arrive first. If the five-hour processing time UUT is first, it will use five hours of CASS. Within one hour, the three-hour processing time UUT arrives and will have to wait four hours in the queue until the first one is done, spending seven hours in the system. Then, after the second one arrives, the third UUT arrives two hours after the second UUT is done, leaving the CASS idle for two hours. The third UUT will spend its four hours on CASS and leave.

Using the scenario above in the current CASS workload model, we would not be accounting for the two hours the CASS is idle. Rather, the workload model plans for an 80% utilization to allow for this two-hour idle time to be captured. If during the month the idle time which was planned for is eaten up because of an increase in flying hours, there will be a large queue due to the scenario's first and second UUT arrival pattern.

In queuing theory, adding another machine will reduce the number in queue significantly. For the scenario provided above, the number in the waiting line was at worst one, but in the in the long run, assuming Exponential service times and Poisson arrival rates, a standard M/M/s queuing formula (Jacobs, Chase, & Aquilano, 2009) would predict that there will be 4.8165 UUTs waiting for service on average. Using the same formula, if one more CASS station is added, the waiting line on average would be 0.1873. The cost of adding an additional CASS station is $1,000,000, but the cost of having nearly five UUTs in the queue is $2,000,000. Hence, in this example, adding one CASS will have a total savings of $1,000,000.

The current PMA 260 workload formula, as mentioned in Chapter II, takes a UUT's MTBF (demand) and MTOS (service time) to calculate the demand for that UUT in a period. Figure 1 represents how the workload formula allocates CASS without considering any variability, which later will be explained. The workload takes the demand of, say, UUT 1 and takes a percentage of CASS utilization without regard for any other UUT that may arrive before or after it. For example, a UUT with a workload output of 0.1 is expected to use 10% of a station per time period. The problem with this is, the CASS does not reserve a 10% spot for that UUT at any given time; CASS may be serving another UUT at the time that UUT 1 is waiting. This causes backlogs/queues of UUTs, and there is no control of variability. The site may have to do a Beyond Capability Maintenance (BCM) action of the UUT due to backlog, calling it lack of equipment, tools, or facilities (BCM-2) or administrative necessity (BCM-8).

We provide this example because it is similar to the PMA 260 problem with allocating its CASS resources throughout all sites. The one thing PMA 260 cannot control is the management style of each site, mentioned above. All sites must be treated equally, so determining an algorithm which meets a steady state across all sites will enable PMA 260 to have a site look at their managing practices instead of holding PMA 260 responsible for queues. Sites which perform better with fewer CASS than sites with more CASS and similar demand inform PMA 260 that those sites have their variability under control through training, hours worked, number of shifts, and maintenance and care of their CASS.

B. THE CURRENT WORKLOAD MODEL

1. Factors That Affect These Assumptions

The current workload calculates the average expected demand by summing all UUTs' workload under a CASS station configuration. It does not accurately capture the surge in demand for different periods (return from deployments or large flight-hour months), nor does it accurately account for the length of the queue at each CASS station configuration. Instead, it allocates slack capacity by using a surge load factor (SLF) of 80% in the denominator, which allocates more CASS stations in an attempt to reduce queues and serve the peak demand. This SLF of 80% is essentially a buffering factor, and it does manage variability better than merely assigning benches based on average demand. Moreover, the SLF can be considered a CASS sparing factor to allocate one more CASS to every four assigned. Our models use queuing theory application to better estimate the impact of variability, and improve the allocation of CASS stations to meet that variability in demand.

C. THE NEW MODELS

We apply queuing theory concepts to our models with the following parameters:

1. Arrival Rate

The first parameter for queuing theory formula is the arrival rate. This is a measurement of jobs or UUTs per unit of time. To be consistent, the arrival rate is in the same units as the capacity, which is in hours (per hour). The arrival rate of a UUT entering the CASS work center is the number of UUTs per hour.

2. Service Rate

The sum of CASS station configurations make up a service capacity network. No CASS provides a constant service rate; thus, there must be a common measurement in order to determine the required number of CASS for capacity. The service times for each type of UUT vary, which we measure using the mean and standard deviation of all UUTs for the CASS configuration network. According to the current CIP (NAVAIRSYSCOM, 2002), when additional CASS stations are added, operators are added as well to fulfill total capacity. This calculation, to be consistent with arrival rate, is measured in number of UUTs per hour.

3. Queue Discipline

The queue discipline associated with the management of UUTs is difficult to model. At I-levels, the queue discipline is (1) Expeditious Repair (EXREP), (2) first come, first served (FCFS), then (3) shortest processing times. The best way to model this is through discrete-event simulation. For parsimony, the models in this project focus only on FCFS.

D. CONSTRUCTION OF LINEAR AND NONLINEAR INTEGER PROGRAM FOR CASS IMPLEMENTATION PLAN

We are looking at four notional USN sites for the CASS allocation problem. These sites are assumed to be having F-18 type model series. We are using integer linear and nonlinear programming to solve the resource allocation problem. Although demand and utilization constraints are linear, readiness constraints are nonlinear and therefore make the model nonlinear. We will explain the construction of those models step by step and show how we came down to the nonlinear integer programming. Below are the linear and nonlinear models that we set up.

1. Linear program with only demand constraints at 50% (expected demand)
2. Linear program with demand constraints at 95% (peak demand), utilization constraints at 90% (limit congestion)
3. Linear program with demand constraints at 95%, utilization constraints at 80%
4. Nonlinear program with demand constraints at 95%, utilization constraints at 80%, and readiness constraints (minimum availability) at 70%.

1. Notation

i = site, or installation (notional sites 1 through 4)

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

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

X_{ij} = number of CASS benches of type j to install at site i

d_{ik} = demand by WRA type k at site i

r_i= Dictated readiness level at site i

u_i=utilization of CASS type j at site i

C_j=unit cost of each type of CASS

Z=Available CASS hours per month

Q_{ij}=Dictated queue time of CASS type j at site i

2. Initial Pass Assumptions:

- Single-year horizon (not multi-period)
- Aircraft at each installation i are stationed at the installation for the whole year
- Every WRA type k demands service from exactly one type workbench, type j
- A_o improves with the increase in the number of CASS stations of specific j type.
- Spare repairable UUT fill rate is included in the readiness calculation.

E. LINEAR PROGRAM WITH ONLY DEMAND CONSTRAINTS AT 50%

Below are the formulations of our first linear program model, including only the demand constraints and the explanation of how we find the total demand by WRA type.

1. Linear Integer Program

$$\text{Min} \sum_{i,j} X_{ij} * C_j \qquad (1)$$

Subject to:

$$X_{i1} + (X_{i2} - d_{i2}) + 0.60 * [(X_{i3} - d_{i3}) + (X_{i5} - d_{i5})] + (X_{i4} - d_{i4}) \geq \frac{d_{i1}}{Z}, \text{ i=1 through 4} \qquad (2)$$

$$X_{i2} + 0.40 * [(X_{i3} - d_{i3}) + (X_{i5} - d_{i5})] \geq \frac{d_{i2}}{Z}, \text{ i=1 through 4} \qquad (3)$$

$$X_{i3} \geq \frac{d_{i3}}{Z}, \text{ i=1 through 4} \qquad (4)$$

$$X_{i4} \geq \frac{d_{i4}}{Z}, \text{ i=1 through 4} \qquad (5)$$

$$X_{i5} \geq \frac{d_{i5}}{Z}, \text{ i=1 through 4} \qquad (6)$$

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

2. Demand Constraints:

Demand by each WRA type k at site i (d_{ik}) is calculated using the expected number of failure formula.

Number of failures= $k \cdot \lambda \cdot t$

Where;

k=number of total components requiring same CASS

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

t=monthly flight hours

Then, we multiply the total number of failures by MTOS, which includes the 1.3 and 2 runs for the SRA and WRA, respectively. However, this demand is the mean and does not take into account the surge in demand (peak demand) during special events like extra monthly flight hours due to an unplanned mission or exercise, etc. To account for that, we are using an MS Excel Poisson_inverse macro (created using the Visual Basic for Applications) function by which we can find the 70%, 80%, or 90% of the surge in demand along with the 50% mean demand. So, our demand formula is able to capture the surge in demand, which means allocating more CASS stations.

For the demand constraints, there is one more trade-off, which leads us to the idea of sharing. That is, as we noted in the literature review, hybrid CASS is the core test station. The other four CASS stations can all provide the core test capabilities as well as their specific capabilities. So, total demand for the hybrid CASS station can be satisfied by any CASS type. The same idea also holds for the RF CASS. However, the demand for the RF CASS can be satisfied by RF CASS, CNI CASS, and RFHP CASS stations.

(2) Hybrid CASS capacity plus the 60% of CNI and RFHP CASS excess capacities and 100% EO3 and RF CASS excess capacities at sites-A/B/C/D must be greater than or equal to the hybrid CASS station demand.

(3) RF CASS capacity plus 40% of CNI and RFHP CASS excess capacities at sites-A/B/C/D must be greater than or equal to the RF CASS station demand.

(4) CNI CASS capacity at sites-A/B/C/D must be greater than or equal to the CNI CASS demand.

(5) EO3 CASS capacity at sites-A/B/C/D must be greater than or equal to the EO3 CASS demand.

(6) RFHP CASS capacity at sites-A/B/C/D must be greater than or equal to the RFHP CASS demand.

F. LINEAR PROGRAM MODEL WITH DEMAND CONSTRAINTS AT 95%, UTILIZATION CONSTRAINTS AT 90%

In our second LP model, we include the utilization constraints along with the demand at 95%. Below are the formulation of the model and the explanation of the utilization constraint.

1. Utilization Constraints

Utilization should not be ignored while allocating the scarce resources because the processes may create bottlenecks in the system if the utilization rates are high. The bottlenecks in the system may in turn create queues, which finally undermine the readiness levels in each site. So, we include an average utilization constraint for each site and say that it should be less than or equal to 90%. Our utilization formula is:

$$\text{Average Utilization} = \frac{\text{Total demand for CASS at each site}}{\text{Total available CASS hours at each site}}$$

The following constraints 7, 8, 9, and 10 are average CASS utilization constraints at sites A/B/C/D, respectively.

$$\frac{\sum d_{1k}}{\left(\sum X_{1j}\right)*Z} \leq 90\%, \text{ k and j=1 through 5} \tag{7}$$

$$\frac{\sum d_{2k}}{\left(\sum X_{2j}\right)*Z} \leq 90\%, \text{ k and j=1 through 5} \tag{8}$$

$$\frac{\sum d_{3k}}{\left(\sum X_{3j}\right)*Z} \leq 90\%, \text{ k and j=1 through 5} \tag{9}$$

$$\frac{\sum d_{4k}}{\left(\sum X_{4j}\right)*Z} \leq 90\%, \text{ k and j=1 through 5} \tag{10}$$

(7) Average CASS utilization at site-A must be less than or equal to 90%.

(8) Average CASS utilization at site-B must be less than or equal to 90%.

(9) Average CASS utilization at site-C must be less than or equal to 90%.

(10) Average CASS utilization at site-D must be less than or equal to 90%.

G. LINEAR PROGRAM MODEL WITH DEMAND CONSTRAINTS AT 95%, UTILIZATION CONSTRAINTS AT 80%

In our third model, we change the utilization constraint from 90% to 80% while keeping the demand constraint constant at 95% and try to figure out the effects of the utilization rate on the resource allocation process. In fact, the third model is the same as the second model except for the utilization rate.

H. NONLINEAR PROGRAM WITH DEMAND CONSTRAINTS AT 95%, UTILIZATION CONSTRAINTS AT 80%, READINESS CONSTRAINTS AT 70%, AND CONGESTION CONSTRAINTS AT 15 HOURS

In our nonlinear model, we introduce the readiness constraint to our model, and that converts our linear model to a nonlinear one. Below are the explanations of the readiness constraint and the way we incorporated it into our model.

1. Readiness Constraints

In our CASS allocation problem we had to use a nonlinear program after we incorporated site readiness into our model. The readiness constraint is not linear because it is a function of a stochastic turn-around time which incorporates a backlog/queuing delay. Because of this queuing delay, we face nonlinear decrease in the turn-around time when the number of CASS stations increase.

Readiness and operational availability are same ideas in this case where we are only examining one system (CASS) since readiness is about a site or command while operational availability is about a specific weapon system.

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

MCT=Mean Corrective Time

MPT=Mean Preventive Time

ALDT=Administrative and Logistics Delay Time

ALDT comprises of delays resulting from spare repairable UUTs, support equipment, personnel, facilities, and transportation. Furthermore; readiness is a nonlinear constraint since the ALDT decreases (not linearly) with the increase in the number of CASS stations. The idea in the model about ALDT is that, adding more CASS stations decreases only CASS-related queue time and not the MCT and MPT since they are independent of the number of CASS stations. That is, if you have an induction, there is no way of avoiding the MCT and MPT. Furthermore, the spare UUT parts also play big roles in the aircraft readiness levels since it is not viable to assume 100% fill rate for the spares (Jones, 2006). To account for that, we assume the following RFI (ready for issue) spare repairable UUT levels. The RFI levels we assume are based on the authors' professional experience rather than any systematic data gathering and we acknowledge that the true RFI rates might be completely different. Our purpose here is to make a proof of concept while using RFI estimates that have at least face validity: Detailed analysis of RFI rates is not within the scope of our study.

	HYB	RF	CNI	EO3	RFHP
Site-A	0.90	0.90	0.80	0.85	0.90
Site-B	0.85	0.90	0.80	0.85	0.90
Site-C	0.80	0.85	0.80	0.80	0.85
Site-D	0.85	0.85	0.80	0.85	0.80

Table 1. Spare part factor for UUTs

The probability of 0.90 for HYB components at site-A means 90% of the time site-A has the hybrid components ready for issue (RFI) in its inventory, and that increases the overall readiness level. However, 10% of the time site-A does not have those HYB components and, therefore, has to incur the off-base fill time.

$$A_o \geq r_i, \text{ where } r_i \text{ is 70\%, and i=1 through 4} \qquad (11)$$

(11) Readiness at sites-A/B/C/D must be greater than or equal to 70%

2. Congestion Constraints

Since we do not know the type of distribution (exponential, Poisson, etc.) for arrivals and service time, we are using a waiting time approximation, which the literature (Jacobs, Chase, & Aquilano, 2009) gives for G/G/s queues. The theory is for the waiting and service processes that have no specific distribution type. The "G" refers to general distribution for arrival and service rate while the "s" refers to the number of servers. Below is the formula for the G/G/s queuing theory (Jacobs, Chase, & Aquilano, 2009).

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

L_q= Expected length of the waiting line

ρ= Utilization of the servers = $\frac{\lambda}{s\mu} = \frac{\text{Demand/Arrival}}{\text{Capacity}}$

λ= customer arrival rate = $\frac{1}{\bar{X}_a}$

$\bar{X}_a$ = Mean interarrival time

μ= Customer service rate = $\frac{1}{\bar{X}_s}$

$\bar{X}_s$ = Mean service time

C_a = Coefficient of variation of interarrival time = $\frac{S_a}{\bar{X}_a}$

S_a = Standard deviation of the interarrival time sample

C_s = Coefficient of variation of service time = $\frac{S_s}{\bar{X}_s}$

S_s = Standard deviation of the service time sample

Using Little's law, we can calculate the expected time waiting in line (W_q).

W_q = Expected time waiting in line = $\frac{L_q}{\lambda}$

Finally, we multiply the W_q with the expected number of failures, which we calculate using the expected number of failures formula $k \cdot \lambda \cdot t$. This gives us the total W_q that is dependent on the number of servers (CASS stations in our case). Basically, the total W_q for a UUT decreases as the number of that specific CASS station increases.

$$(k \cdot \lambda \cdot t) \cdot W_q \leq Q_{ij} \text{ , where } Q_{ij} \text{ is 15 hours, i=1 through 4, j=1 through 5} \quad (12)$$

(12) Total queue time for CASS type j at sites-A/B/C/D must be less than or equal to 15 hours.

3. Integer and Non-negativity Constraints

Since rounding the decision variables up or down creates confusion for the decision makers, we are using integer non-linear programming in our model. However, sensitivity analyses available from integer, nonlinear reports through the Frontline Solver are limited. Therefore, we are using Oracle's spreadsheet simulation with Crystal Ball add-in in order to get a sensitivity report and make post-hoc analysis.

(13) All decision variables must be integers.

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

4. Unit Cost of Each Type of CASS

There is no current data about the cost of each type of CASS since the acquisition of CASS stations was finalized in 2006; however, we can use the historical data and convert those costs to FY 2010 dollars using the inflation indices. Table 2 shows the unit cost of each CASS station in 1995 and the inflation index to convert those to FY 2010 dollars.

Type of CASS	Average unit cost FY95	Inflation index [2]	Average unit cost FY10
Hybrid	$ 1,000,000	1.2897	$ 1,289,700
RF	$ 1,500,000	1.2897	$ 1,934,550
EO	$ 4,500,000	1.2897	$ 5,803,650
CNI	$ 1,700,000	1.2897	$ 2,192,490
RFHP	N/A	1.2897	$ 3,500,000 [3]

Table 2. Cost per CASS

[2] Inflation index is calculated using the inflation calculator of the Naval Center for Cost Analysis, and the index is Other Procurement Navy (OPN).

[3] RFHP unit cost is estimated to be about 3.5 million dollars.

I. SENSITIVITY ANALYSIS: CONSTRUCTION OF CRYSTAL BALL ON THE NON-LP

Since our model is a nonlinear integer program, we can't use the MS Excel's built-in sensitivity analysis for the solver. Setting up a simulation on the nonlinear program allows a decision maker to test optimality and compare costs with the desired estimated number in the queue. Mathematical programs use only constant values, and in that sense, the solutions prescribed by the mathematical programs which account for variability are only approximations. Testing the quality of the solution recommended through the mathematical program by applying statistical distributions to variables and applying them to a range of decision variables will allow the decision maker to see the differences in the output from the number of CASS assigned. A careful examination of this post-hoc sensitivity analysis may indicate to a decision maker that he should allocate one more, or one fewer CASS stations at a site in relation to the solution prescribed by the mathematical program.

Defined Assumption	
Number of CASS	Discrete Uniform
Poisson Demand	Constant
Number of Aircraft	Constant
Flight Hours	Constant
Forecasted Values	
1	Time in queue (Wq)
2	A_o
3	Additional may be applied

Table 3. Non-LP Crystal Ball defined values

Running the simulation a large number of times gives us the output to judge the non-linear program optimality and determine how many CASS to allocate to a site.

J. MONTE CARLO SIMULATION USING CRYSTAL BALL

We are using the Monte Carlo simulation via an Excel's add-in Crystal Ball simulation as another method for sensitivity analysis. This idea allows us to capture the possibility of high and low demand during a period. That is, we can figure out the best-case and the worst-case scenarios using the stochastic values instead of deterministic ones. We can also determine the total number of CASS stations, depending on what percentage of the surge in demand to be covered.

1. Construction of a Crystal Ball Simulation

We developed a notional sight in MS Excel to compare the current workload model output with Poisson distribution demand and Binomial Distributed to account for the expected number of down CASS stations. The second model shows how variability in demand and distributed. The Poisson distribution is a good modeling choice for demand processes where demands occur one by one and do not exhibit cyclic fluctuations. It is completely specified by one parameter, the mean, and is therefore convenient when one lacks information concerning variability of demand (Hopp & Spearman, 2000). Since demand is not arriving at the same rate every month, there will be high months and low months; the Poisson distribution provides a probability of a number of parts arriving per month. The run of the simulation will collect the high demand and low demand, which will provide a significant range of capacity to meet demand.

Setting up the notional site model, we took F/A-18 TPSs that are required at an F/A-18 site and chose the UUTs from the PMA-260 master database, which matched each TPS to get a total of UUTs for a site. The master UUT database provides all the required data in order to complete the simulation.

The data elements taken from the master UUT report are MTBF, ETE run time, the UUT CASS configuration, and number of runs required. There was one additional time not included in the UUT master, the "other time" of 180 minutes, which is included in the current workload model to calculate total MTOS. The 180 minutes is extra time required for a UUT to be run on a CASS bench. This time includes: setup time (plugging the UUT into the TPS and all the associated hardware), part-approval time (time for Production Control Supervisor to approve the part), waiting for parts (time to run and pick up parts), remove and replace time (time for part replacement), and identification test (self-test time). These other times are assumed to be consumed on a CASS station because, if a part is available, then it will be more efficient to keep the UUT hooked up to avoid double set up time. Moreover, the removing and replacing of a part in a UUT is assumed to be minuscule in relation to set up time. This time must be assumed to be part of the total CASS capacity to be fair to all sites.

The Crystal Ball setup has the following assumptions assigned:

	CURRENT WORKLOAD MODEL (A)	POISSON ARRIVAL, BINOMIAL 10% DOWN (B)	POISSON ARRIVAL, BINOMIAL 20% DOWN (C)	POISSON ARRIVAL, BINOMIAL 30% DOWN (D)
INPUT PARAMETERS				
# OF AIRCRAFT	CONSTANT	CUSTOM	CUSTOM	CUSTOM
MONTHLY FLIGHT HOURS	CONSTANT	NORMAL	NORMAL	NORMAL
CASS OPERATIONAL AVAILABILITY (SLF)	CONSTANT	*NOT INCLUDED*	*NOT INCLUDED*	*NOT INCLUDED*
# OF CASS DOWN PROBABILITY	*NOT INCLUDED*	BINOMIAL	BINOMIAL	BINOMIAL
VARIABLES				
# OF RUNS	CONSTANT	CUSTOM	CUSTOM	CUSTOM
OTHER TIME (180 MIN)	CONSTANT	NORMAL (EACH UUT)	NORMAL (EACH UUT)	NORMAL (EACH UUT)
OUTPUT PARAMETERS				
DEMAND FORMULA FOR EACH UUT	$\frac{kto}{scm}$	$p(k\lambda to)$	$p(k\lambda to)$	$p(k\lambda to)$
NUMBER OF CASS	NOT APPLICABLE	$\frac{\sum p(k\lambda to)}{c}$	$\frac{\sum p(k\lambda to)}{c}$	$\frac{\sum p(k\lambda to)}{c}$
BINOMIAL NUMBER OF DOWN CASS $bin(p,N)$	*NOT INCLUDED*	$bin(.10,\frac{\sum p(k\lambda to)}{c})$	$bin(.20,\frac{\sum p(k\lambda to)}{c})$	$bin(.10,\frac{\sum p(k\lambda to)}{c})$
TOTAL # OF CASS	$\sum\frac{kto}{scm}$	# OF CASS + DOWN CASS	# OF CASS + DOWN CASS	# OF CASS + DOWN CASS
DEFINED VARIABLES	k = # OF A/C t = FLIGHT HOURS PER AIRCRAFT o = MEAN TIME ON CASS STATION s = SURGE LOAD FACTOR c = CASS AVAILABLE HOURS m = MTBF λ = 1/MTBF $p()$ = POISSON DISTRIBUTION bin = BINOMIAL DISTRIBUTION			

Table 4. Crystal Ball setup and defined values

2. Input Parameters

These assumed distributions are for this model and are drawn from data provided from PMA 260. The number of aircraft is a custom distribution to explain the number at a site at a time in Table 5. This distribution is a probability of having a number of carrier air wings (CVW) at a site; each CVW that is not home takes 44 F/A-18s.

Number of Aircraft	Number of CVWs at site	Probability
269	5	15%
225	4	35%
181	3	25%
137	2	10%
93	1	10%

Table 5. Crystal Ball number of aircraft defined assumptions

Monthly flight hours change per aircraft continuously, so distributing them normally with a standard deviation of four is our assumption for this model.

CASS A_o is essentially an SLF for models A. This SLF acts as a utilization buffer to allow 20% more demand to be used on CASS to make it 100% utilized when peak demand hits. Moreover, it is a probability factor that assumes there are only 80% of the machines up at a time. If the latter is the assumption, then the CASS stations (system) will not be able to capture higher demand periods if it is also assumed one of five will be down, essentially putting the other four CASS stations at 100% utilization for average flight hours and max aircraft. For models B, C and D the SLF is set at 100%. To account for failures of CASS stations for each configuration to include the down CASS stations, instead of using the SLF, we assigned a binomial distribution to the probability of failure to determine the number of CASS that will be down. Moreover, by not assigning the SLF, this model will not only protect against down CASS, it will provide maximum utilization when the CASS are down.

Adding the binomial distribution to the required number of CASS to meet demand at 100% utilization gives the probability of having x number of that type of configuration of CASS down. We add the failed CASS stations to the number of CASS to meet demand to ensure we account for down CASS station(s).

CASS hours in a month are constant 300 hours for all models. This is the available worker hours in a month to operate CASS.

3. Variables

To calculate the processing times, the actual parameters are determined by the software development and are provided by PMA 260 to determine each UUT's end-to-end (ETE) run time. There is not a distribution on the ETE run times because they are set values at which the software runs in order to find a fault in the UUT. The number of times a UUT will be run on a CASS are provided by PMA 260. The ID, SRA, and WRA are run two times. This model distributes the probabilities of the number of runs due to the possibility of not finding a duplicate discrepancy which will run only once. The processing time on the CASS is multiplied by the number of ETE runs to get total processing time of a single UUT.

UUT	# of Runs	Probability	# of Runs	Probability
WRA	2	80%	1	20%
SRA	2	60%	1	40%
ID	2	50%	1	50%

Table 6. Crystal Ball number of runs defined assumptions

Processing times include a variable called other times consisting of setup time, ordering parts, administration, and miscellaneous times. The total of this time is distributed normally with a standard deviation 20% of the mean. The reason for this distribution is that experience of personnel, training, part runs, and speed of part approvals varies from site to site.

Total processing times includes the total of the ETE run time plus the other times. Once the processing times are totaled and determined, that number is multiplied by the expected number of failures ($k \lambda t$). This value will give total processing time required during a given time period based on t.

To determine the number of CASS, UUT processing times are added together for each type of CASS then divided by CASS available hours.

4. Demand and Capacity

Each UUT's demand is defined using the formulas in Table 4 (CB setup). The demand from each UUT is added for each type model using the formulas in Table 4. This gives the required amount of time demanded of CASS during the month. Expected demand for Models B, C and D uses the Poisson distribution for each UUT.

The capacity for Model A is the sum of all UUTs' workload calculations by the type of CASS station configuration the UUT uses. The capacity of Models B, C and D is the sum of all the demand of each UUT by the type of CASS station configuration divided by the number of CASS hours available in the month.

IV. RESULTS AND ANALYSIS

A. MODEL RESULTS

In this chapter, we are going to present the results for the linear and nonlinear models along with the Crystal Ball simulation results. Then, we are going to present results of sensitivity analyses using both the simulation and the optimization tools.

1. LP: Model 1

The results for the first linear program are presented below. This model covers the demand at 50%, which is the average demand. The LP model is assigning more CASS stations to site-A because it has more aircraft and more UUTs than any other site has. However, the results of this model are the best-case scenario. That is, it assumes no surge in demand, which is not realistic.

	Hybrid	**RF**	**CNI**	**EO3**	**RFHP**	**Total**
Site-A	11	9	1	4	2	27
Site-B	6	5	1	1	1	14
Site-C	3	3	1	2	1	10
Site-D	1	3	1	2	1	8
Total	21	20	4	9	5	59

Table 7. LP: Model 1 output

2. LP: Model 2

The results for the second linear program model are presented below. This model covers the demand at 95% (peak demand) and constrains the utilization of CASS stations at 90%. When compared with the previous LP model, this one is more realistic since it takes into account the utilization factor. It can be easily observed that this model is assigning more CASS stations than the previous model does in view of the fact that

CASS stations cannot be utilized above a threshold because of unexpected events. However, the number of CNI CASS stations does not change because of their low demand.

	Hybrid	RF	CNI	EO3	RFHP	Total
Site-A	11	9	1	4	2	27
Site-B	6	6	1	1	1	15
Site-C	3	4	1	2	1	11
Site-D	2	3	1	2	1	9
Total	22	22	4	9	5	62

Table 8. LP: Model 2 output

3. LP: Model 3

The results for the third linear program model are presented below. This model covers the demand at 95% (peak demand) and constrains the utilization of CASS stations at 80%. The second LP model and this one are the same models except for the utilization levels they are using. Model 3 provides better coverage against higher demand peaks (95% v. 90%), and reduces the chance of delays due to congestion (80% utilization limit vice 90%). Whether this additional coverage would be worth the cost of the additional two work benches would be a point for further analysis and discussion. Our reason for incorporating both models is to demonstrate the flexibility of the tool to provide varying levels of protection against variability and queuing delays. As we discussed earlier, the model assigns a total of four CNI CASS stations because of their low demand.

	Hybrid	RF	CNI	EO3	RFHP	Total
Site-A	14	9	1	4	2	30
Site-B	7	6	1	1	1	16
Site-C	4	4	1	2	1	12
Site-D	2	3	1	2	1	9
Total	27	22	4	9	5	67

Table 9. LP: Model 3 output

4. NonLP: Model 4

The results for the nonlinear program model are presented below. This model covers demand at 95% (peak demand), constrains the site readiness level at 70%, constrains the CASS utilization rate at 80%, and constrains the total queue time at 15 hours. The difference between the LP models and the NonLP models is that the latter has readiness and congestion constraints, which make the resource allocation more realistic, and provides better protection against the impacts of variability and queuing delays. Beyond the protection provided by the utilization rate constraints, the readiness constraints incorporate availability as a factor into the model, and allow decision makers to set a minimum availability level as a constraint. Multiple parameters determine availability in this model, (e.g., fill rates for spare repairable UUTs inventories). These parameters can be made the target of what-if analyses, to examine the impact of various performance improvement suggestions (e.g., increasing spare repairable UUT allowances). Furthermore, this model may be used when a readiness or congestion level is set by higher authority.

	Hybrid	RF	CNI	EO3	RFHP	Total
Site-A	15	11	1	4	2	33
Site-B	8	7	1	1	1	18
Site-C	4	4	2	2	1	13
Site-D	3	4	1	2	1	11
Total	30	26	5	9	5	75

Table 10. NonLP: Model 4 output

5. Output Analysis

We can say that the lower boundary for the number of CASS stations is Model-1, while the upper boundary is Model-4. This makes sense since we used average demand with no other constraints in Model-1, whereas we used peak demand (95%) with 80% utilization, 70% readiness level, and 15-hour congestion level in Model-4. Model-1 assigns 59 CASS stations, and those cover only the average demand. However, there are other factors to take into account while allocating the resources. When we included those factors in our model, it finally assigns 75 CASS stations. Those cover the peak demand and ensure the minimum waiting time for the UUTs that are waiting for service on the CASS station. Moreover, Model-4 also ensures a certain level of readiness by incorporating variability.

6. Summary of Models' Output

Table 11 shows the total number of CASS stations that are assigned to each site using the Models 1 through 4.

	Model-1	Model-2	Model-3	Model-4
Site-A	27	27	30	33
Site-B	14	15	16	18
Site-C	10	11	12	13
Site-D	8	9	9	11
Total	59	62	67	75
Cost (millions)	$144.24	$149.40	$155.84	$169.69

Table 11. LP and NonLP Models' total output comparison with cost

Table 11 shows the total number of CASS stations that are allocated using the Models 1 through 4. Thus, we can conclude that readiness and utilization constraints increase the number of CASS stations that are allocated to each site. This increase in the allocation results in an increase in the readiness level, which is dictated by the USN. In Model 4, it is always better to use the readiness as a constraint to figure out the inefficiencies, if any, in spare repairable UUT stock level, queue time, or MLDT, presented below in the use of Goal Seek in MS Excel. When we examine the number of CASS stations assigned by Model-1, we can say that the readiness level is less than 50%. Those readiness levels are unacceptable for a Naval Air fleet.

B. POST HOC ANALYSIS OF READINESS IMPROVEMENT

Readiness of a site is derived from the operational availability of a single aircraft at each site. So, it is worthwhile to look at the A_o formula.

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

We cannot improve the MCT and MPT by increasing the number of CASS stations since they are related to the structure of the maintenance logistics system and should be handled accordingly. But, it is possible to decrease the total queue time in the

ALDT and improve the A_o and readiness levels by assigning more CASS stations. But it is not possible or cost efficient to improve readiness more after a certain point by assigning more CASS stations. So, if the commands or fleets want to improve their readiness level toward 80% or more, they have to find ways to decrease the ALDT, MCT, and MPT accordingly. In order to answer such a question with our model, we used the Goal-Seek function of Excel. As an example, we tried to improve the readiness level of site-A to 80% while keeping the number of CASS stations constant. Below is the current ALDT and A_o of sites.

	Site-A	**Site-B**	**Site-C**	**Site-D**
ALDT	75 hours	75 hours	75 hours	75 hours
Flight Hours	20 hours	20 hours	20 hours	20 hours
A_o	0.715	0.740	0.722	0.749

Table 12. Current ALDT

1. Goal Seek

Table 13 shows the required ALDT to improve the readiness levels at sites from their current values to 80% without increasing the number of CASS stations.

	Site-A	**Site-B**	**Site-C**	**Site-D**
ALDT	14.41 hours	31.92 hours	19.54 hours	38.49 hours
A_o	0.80	0.80	0.80	0.80

Table 13. Goal Seek improvement of ALDT

For Site-A, we have to find ways to improve our ALDT from 75 hours to 14.41 hours. Similarly, ALDT should be improved from 75 hours to 31.92 hours, from 75 hours to 19.54 hours, from 75 hours to 38.49 hours for Site-B, Site-C, and Site-D, respectively.

However, finding ways to improve those ALDT is beyond the scope of this project. Those improvements are more related to a study about the application of lean six sigma or any process improvements to the Naval Air fleets.

2. Goal Seek

	Site-A	**Site-B**	**Site-C**	**Site-D**
Flight Hours	11.96 hours	13.63 hours	12.96 hours	14.40 hours
A_o	0.80	0.80	0.80	0.80

Table 14. Goal Seek flight hours

For Site-A, we have to decrease the flight hours from 20 hours to 11.96 hours. Similarly, we have to decrease the flight hours from 20 hours to 13.63 hours, from 20 hours to 12.96 hours, and from 20 hours to 14.40 hours for Site-B, Site-C, and Site-D respectively. Using goal seek function, the decision makers can find all the inefficiencies and look for way to improve those inefficiencies in order to reach their target readiness level.

3. Analysis of Flight Hours (Demand)

When demand, such as a change in operational tempo, is high and there are CASS planned for less demand, then the expected Lq and Wq will be high, which decreases readiness. Figure 2 tests the optimal mix of CASS stations when demand is at 20 flight hours and how the A_o is affected when operational tempo is increased at site A. When the operational tempo increases to 23 flight hours per aircraft per month the number of CASS is no longer feasible to meet the readiness threshold due to the increase of time in the queue. The solver must be run again on Model 4 when there is a change in flight hours to find the new optimal feasible solution. Figure 3 shows how an increase of one selected CASS (RF) improves readiness above 22 flight hours. Moreover, to achieve more readiness, different CASS, such as HYB, CNI, EO3, and RFHP, can be assigned to find the optimal mix, which the solver add-in will find, due to the sharing of CASS. Or working hours, although not recommended, can be increased or another shift can be added to increase CASS available working hours, thus increasing throughput.

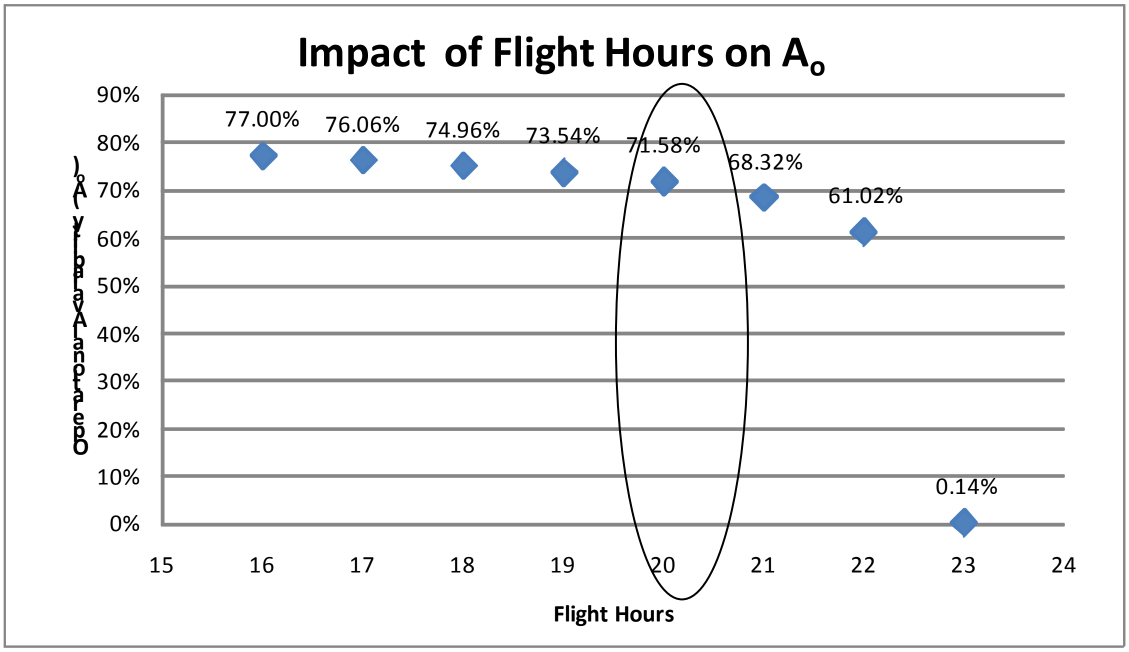

Figure 2. A_o impact chart

When one more RF CASS is assigned to site A the mix of CASS stations will be able to sustain the A_o when flight hours increase up to 24 flight hours per aircraft per month. If the goal is to achieve greater than 70% readiness with 24 flight hours or more, the mix of CASS stations must be reassigned using the solver to get an optimal feasible solution.

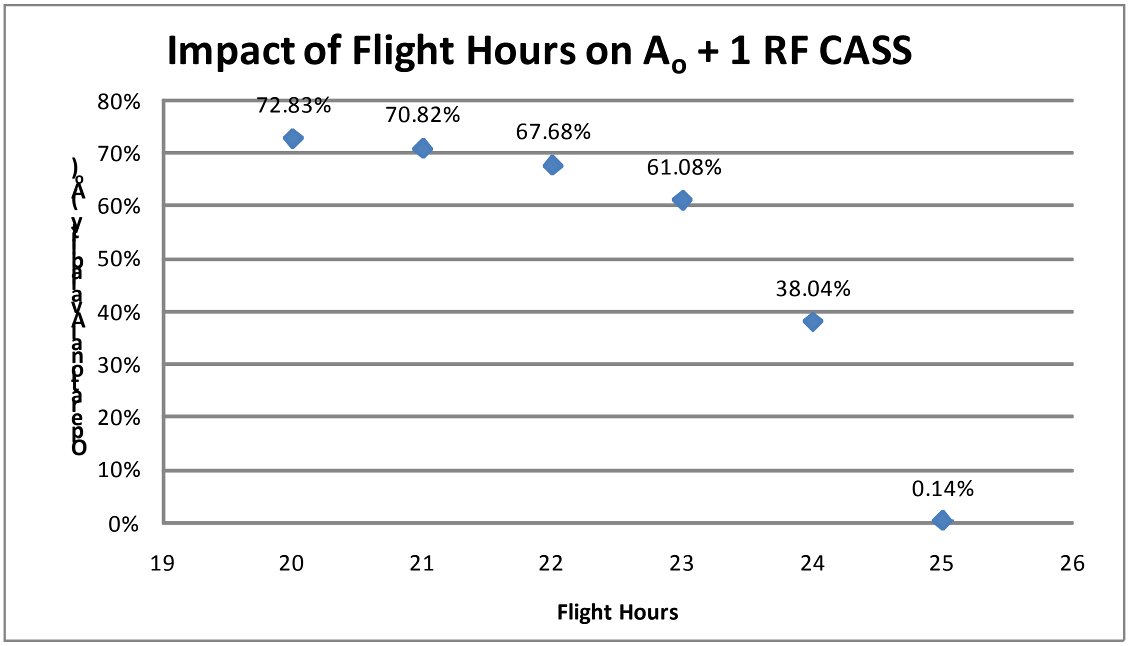

Figure 3. A_o impact chart + 1 RF CASS

C. POST-HOC SENSITIVITY ANALYSIS OF NONLP SOLUTION

Running Crystal Ball on the NonLP results shows how a proper mix of CASS stations is important to achieve minimal cost and meet the readiness threshold. Additionally, it shows how increasing the number of CASS stations can improve readiness and reduce the queue with additional costs. The simulation changes the number of each type of CASS station under the discrete uniform distribution. The number of CASS changes which provides different mix of CASS on each simulation step. The figures show the average Wq and average A_o for different mixes of the same number of CASS stations. Any of the input variables, such as aircraft, flight hours, and service times, can be changed or distributed, but was not modeled here. The circles around the graphs are the optimal results from Model-4.

1. Total Number of CASS

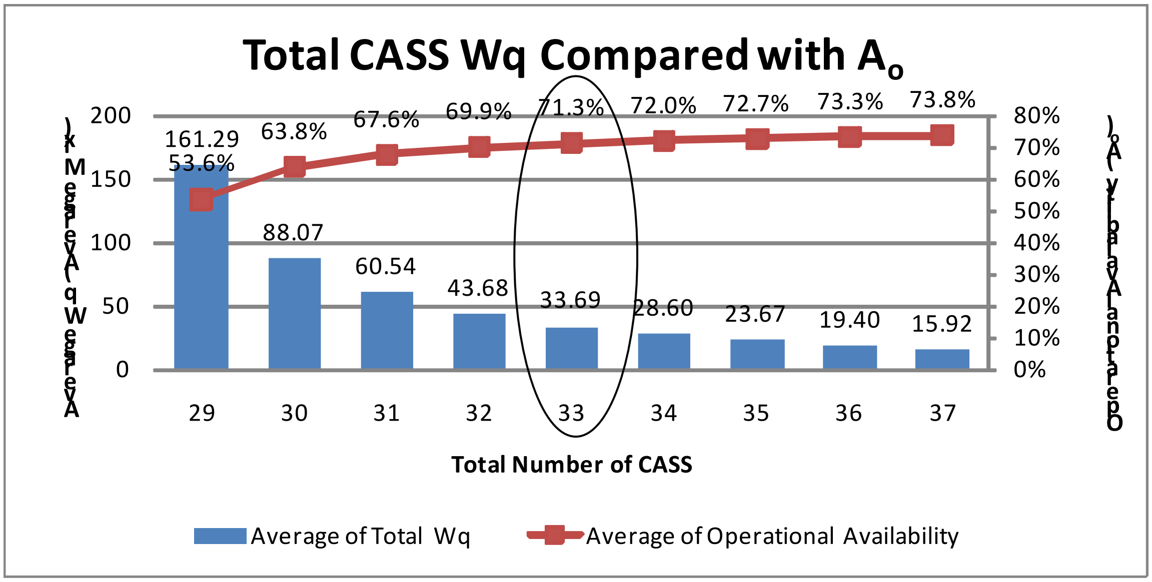

Figure 4. Total CASS and Wq

Figure 4 shows the comparison of how the total number of all CASS stations affects the Wq and A_o. When the total number of CASS stations is at 29, the average Wq is 161.29 hours with an average A_o of 53.6%, thus not meeting the readiness threshold of 70%. To meet the readiness threshold the total number of CASS should be at least 33 where average Wq is 33.69 hours and average A_o is 71.3%. Solver will find the optimal mix of each type of CASS station when the total is at 33, we already know that 33 is optimal, shown in Table 10.

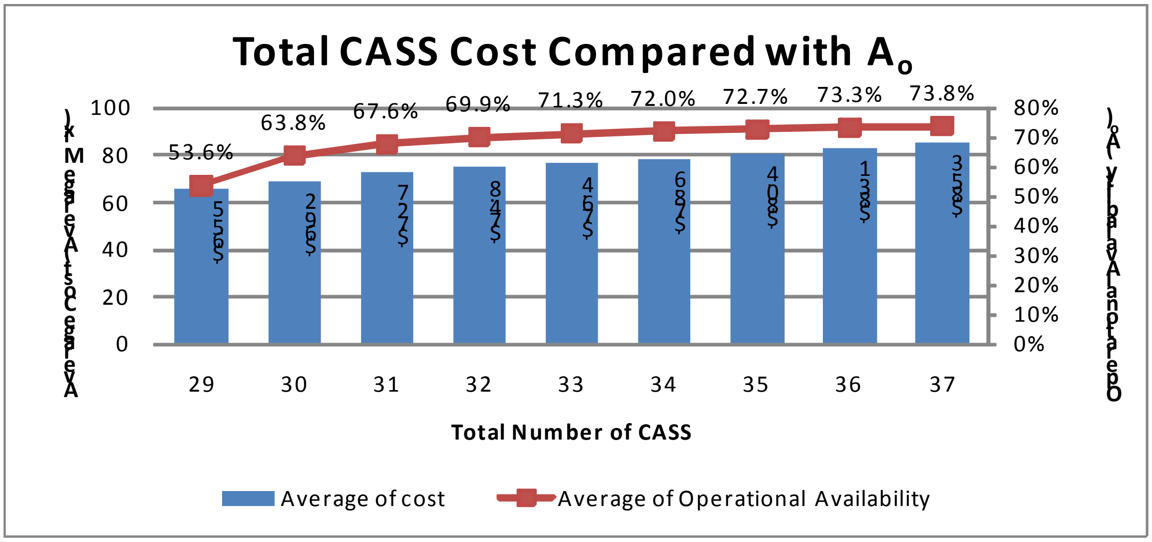

Figure 5. Total CASS and cost

Figure 5 shows how much it costs to have the number of total CASS stations at a given readiness level. To achieve 53.6% readiness it costs \$65.5 million and to achieve 71.3% is costs \$76.4 million. To achieve more readiness, it will cost more with minimal improvements in readiness. It is better to allocate the money to other factors, such as spare repairable UUTs, logistics, or training to increase readiness.

2. Hybrid

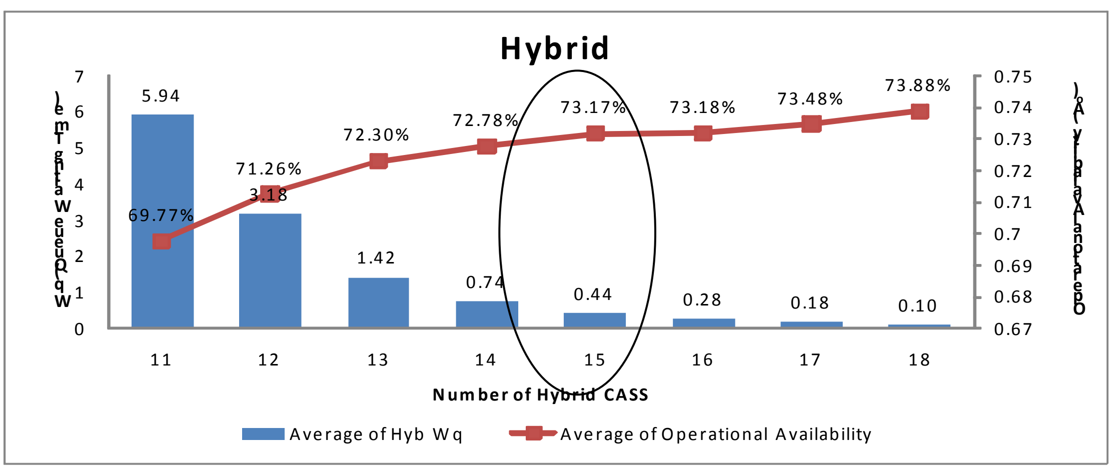

Figure 6. Crystal Ball NonLP Wq and A_o graph of Hybrid CASS

Figure 6 shows the comparison of how Hybrid CASS stations affect the Wq and A_o. When Hybrid CASS stations is at 11, the average Wq is 5.94 hours with an average A_o of 69.7%, thus not meeting the readiness threshold of 70%. To meet the readiness threshold there should be at least 15 Hybrid CASS where average Wq is .44 hours and average A_o is 73.1%. It is not cost beneficial to buy more Hybrid CASS stations unless the operational tempo is expected to increase.

3. RF

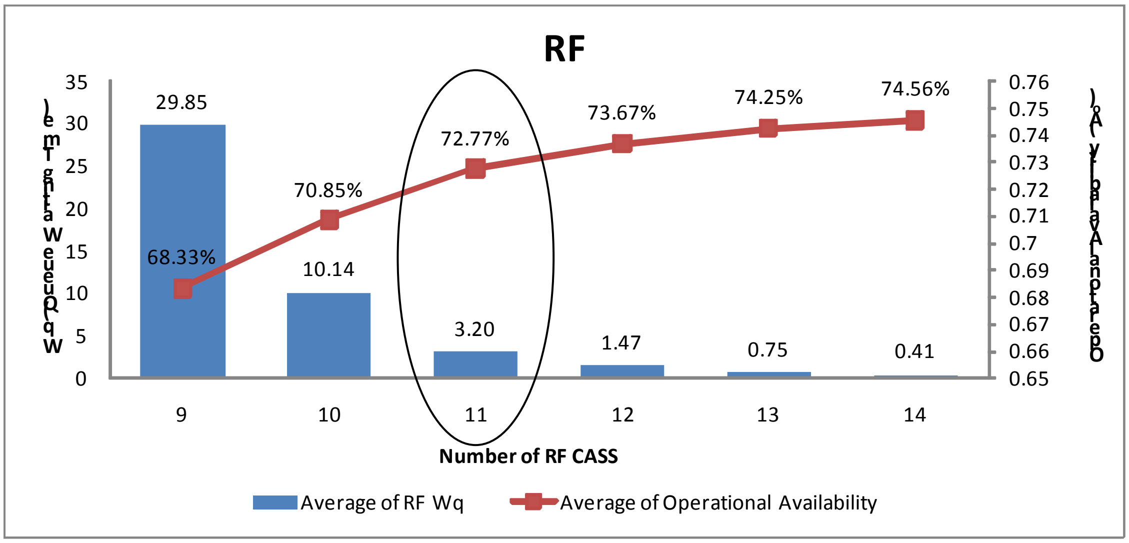

Figure 7. Crystal Ball NonLP Wq and A_o graph of RF CASS

Figure 7 shows the comparison of how RF CASS stations affect the Wq and A_o. When RF CASS stations is at 9, the average Wq is 29.85 hours with an average A_o of 68.3%, thus not meeting the readiness threshold of 70%. To meet the readiness threshold there should be at least 11 RF CASS where average Wq is 3.20 hours and average A_o is 72.7%. It is not cost beneficial to buy more RF CASS stations unless the operational tempo is expected to increase.

4. CNI

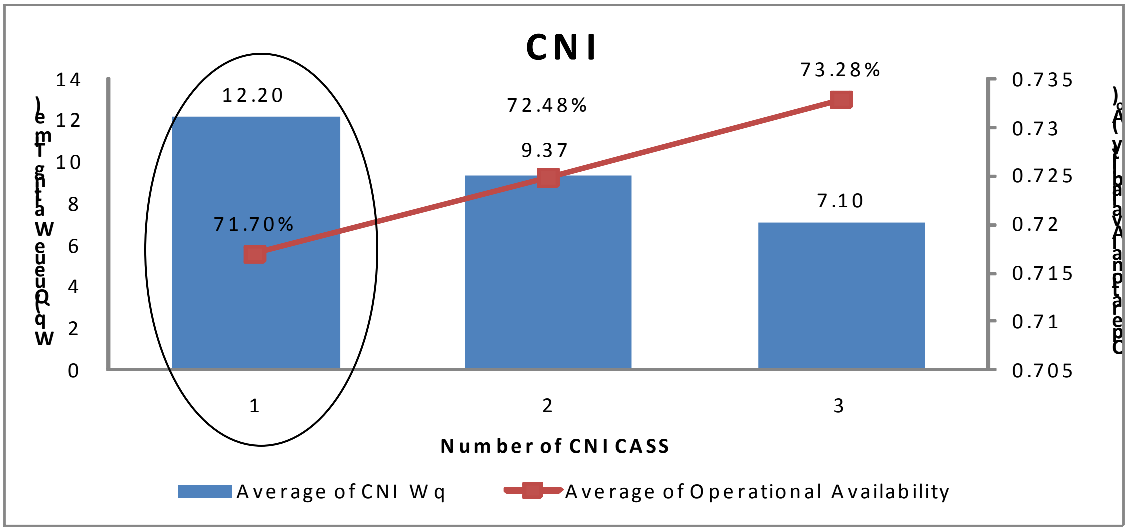

Figure 8. Crystal Ball NonLP Wq and A_o graph of CNI CASS

Figure 8 shows the comparison of how CNI CASS stations affect the Wq and A_o. When CNI CASS stations is at 3, the average Wq is 7.10 hours with an average A_o of 73.28%, thus meeting the readiness threshold of 70%. To avoid spending additional money and meet the readiness threshold there should be at least 1 CNI CASS where average Wq is 12.20 hours and average A_o is 71.7%. It is not cost beneficial to buy more RF CASS stations unless the operational tempo is expected to increase.

5. EO3

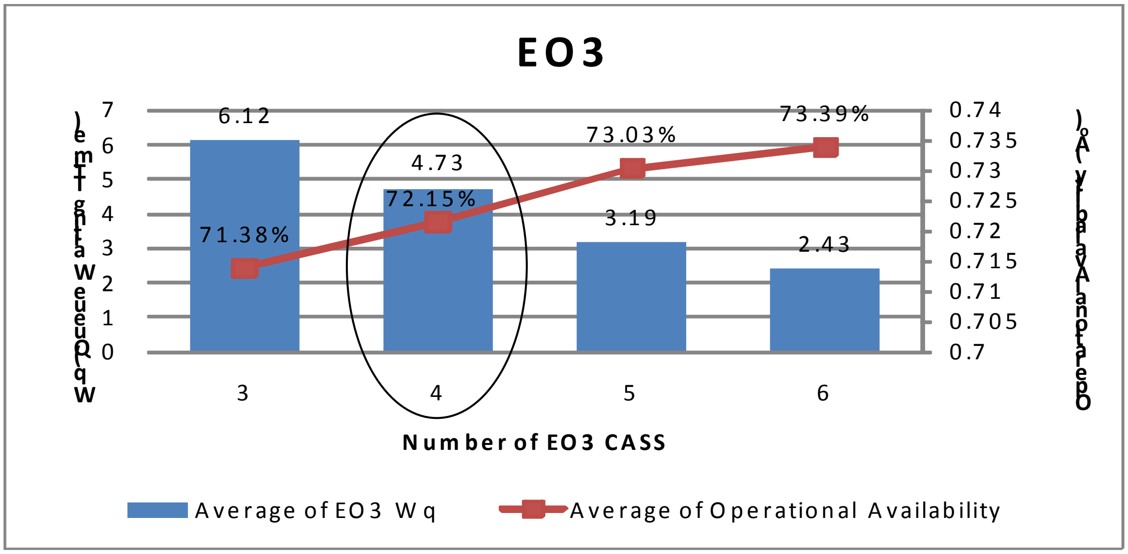

Figure 9. Crystal Ball NonLP Wq and A_o graph of EO3 CASS

Figure 9 shows the comparison of how EO3 CASS stations affect the Wq and A_o. When EO3 CASS stations is at 3, the average Wq is 6.12 hours with an average A_o of 71.38%, thus meeting the readiness threshold of 70%. To meet the readiness level, 4 EO3 CASS stations, where average Wq is 4.73 hours and average A_o is 72.15%, are sufficient enough to support the entire CASS system, which Hybrid UUTs can use EO3 capacity when there is excess capacity. It is not cost beneficial to buy more EO3 CASS stations unless the operational is tempo is expected to increase.

6. RFHP

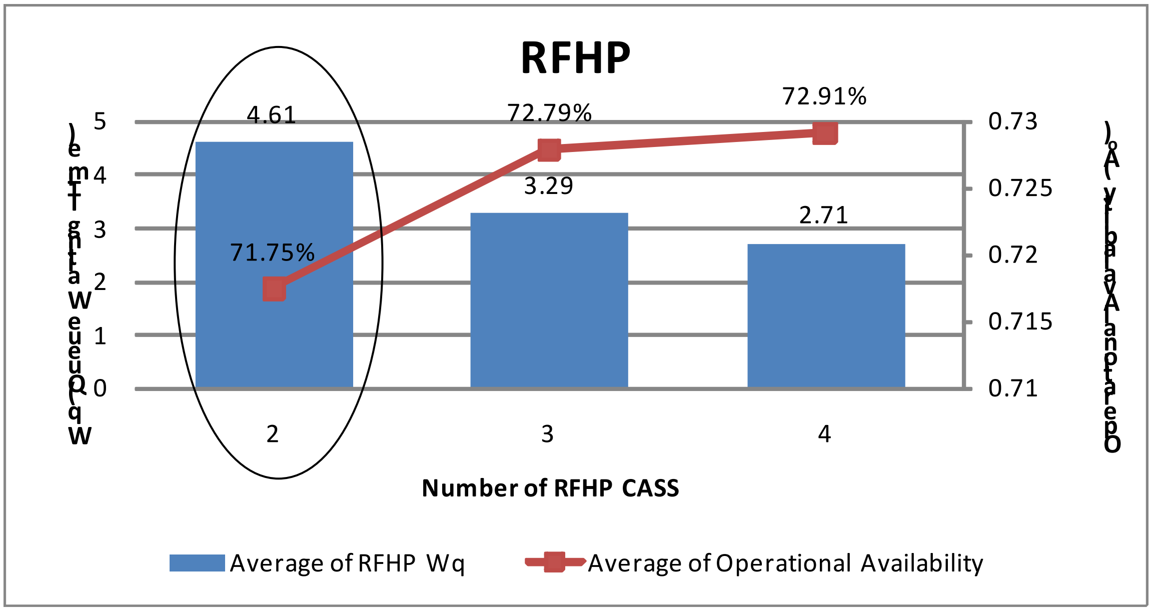

Figure 10. Crystal Ball NonLP Wq and A_o graph of RFHP CASS

Figure 10 shows the comparison of how RFHP CASS stations affect the Wq and A_o. When RFHP CASS stations is at 4, the average Wq is 2.71 hours with an average A_o of 72.91%, thus meeting the readiness threshold of 70%. To meet the readiness level, 2 RFHP CASS, where average Wq is 4.61 hours and average A_o is 71.75%, is sufficient enough to support the entire CASS system, which Hybrid and RF CASS UUTs can use RFHP capacity when there is excess. It is not cost beneficial to buy more RFHP CASS stations unless the operational is tempo is expected to increase.

D. POST HOC ANALYSIS OF CASS EXPECTED DOWN

We used Monte Carlo Simulation along with Crystal Ball to compare the workload model and determine the number of CASS stations that will be down associated with the number of CASS required to meet demand. We use the binomial distribution in order to find the number of down benches according to a failure probability. We use the required number of each type of CASS station to meet demand and determine the number of down CASS benches. We use 10%, 20%, and 30% as our probability of CASS being down. The comparison of the SLF at 80% in the workload model and the binomial distribution will either prove that SLF is good to use or binomial distribution is better. Additionally, the model assumes a Poisson distribution arrival of UUTs during a month, making the demand more variable.

While the level of demand varies, the capacity (number of each type of CASS) must adapt in order to meet the demand. Comparing the models, each figure shows the level of coverage at 50%, 70%, 80%, and 90%. This is the demand percentage of the total number of CASS required over the simulation. As a result, picking the number of CASS stations at 90% coverage, there will be enough CASS stations 90% of the time. The workload model contains no variability in demand or the expected number of down CASS stations, but does include the 80% SLF, which is why it is a constant number in all figures.

1. Total Number of CASS Comparison

	Model A	**Model B**	**Model C**	**Model D**
Min	38	10	11	10
50%	38	26	28	30
70%	38	29	32	34
80%	38	31	34	37
90%	38	33	36	40
Max	38	45	47	54

Table 15. Total number of CASS

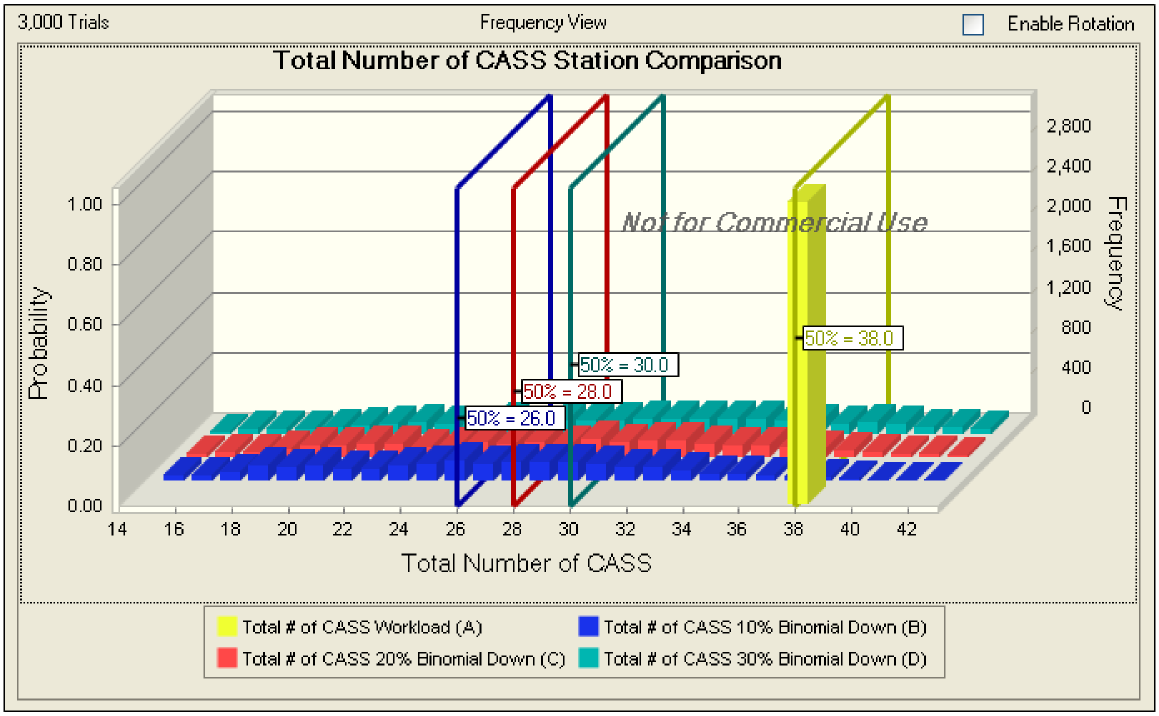

Figure 11. Total CASS comparison at 50%

Figure 11 is the total number of CASS stations comparison of the workload formula and the binomial distributions, which add CASS expected number of down stations to the required number of CASS stations at 100% utilization in order to meet demand, even when CASS stations are down. This figure shows the workload model at 38 total CASS stations as a constant value. Model B (total # of CASS 10% Binomial Down) shows 28 are required 50% of the time, which means, if this number of CASS were assigned, we would meet demand 50% of the time with regards to surge and an increase in UUT arrivals. Model C (total # of CASS 20% Binomial Down) requires 28 CASS stations 50% of the time and Model D (total # of CASS 30% Binomial Down) requires 30 CASS stations 50% of the time. The difference in each, while each has the same demand, is based on the probability of having x number down.

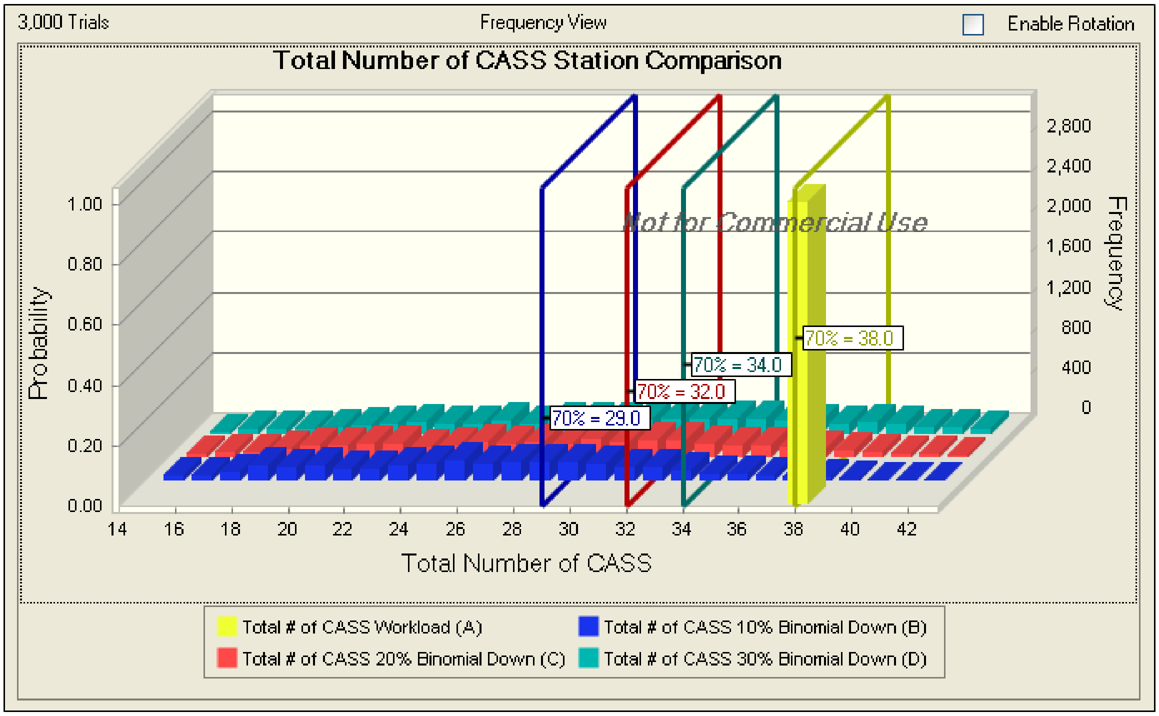

Figure 12. Total CASS comparison at 70%

Figure 12 is the total number of CASS station comparison of the workload formula and the binomial distributions, which add CASS expected number of down stations to the required number of CASS stations at 100% utilization in order to meet demand, even when CASS stations are down. This figure shows the workload model at 38 total CASS stations as a constant value. Model B shows 29 are required 70% of the time, which means, if this number of CASS were assigned, we would meet demand 70% of the time with regards to surge and an increase in UUT arrivals as well as having 10% down CASS stations. Model C requires 32 CASS stations 70% of the time and Model D requires 34 CASS stations 70% of the time. The difference in each, while each has the same demand, is based on the probability of having x number down.

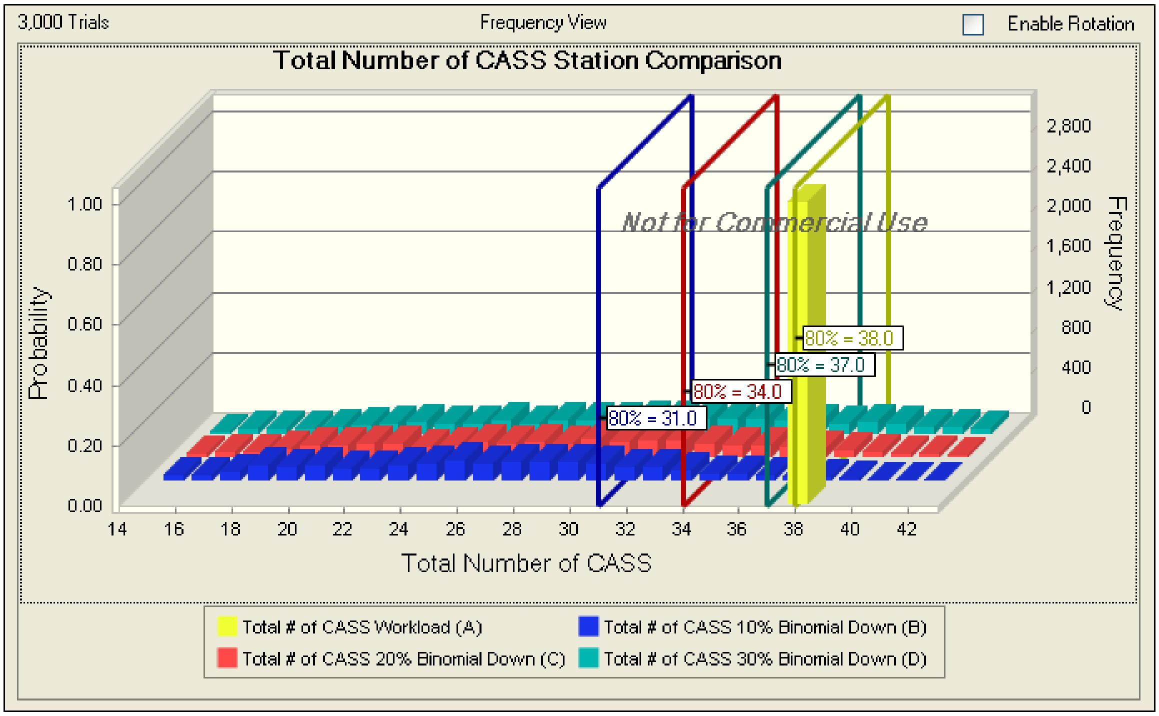

Figure 13. Total CASS comparison at 80%

Figure 13 is the total number of CASS stations comparison of the workload formula and the binomial distributions, which add CASS expected number of down stations to the required number of CASS stations at 100% utilization in order to meet demand, even when CASS stations are down. This figure shows the workload model at 38 total CASS stations as a constant value. Model B shows 31 are required 80% of the time, which means, if this number of CASS were assigned, we would meet demand 80% of the time with regards to surge and an increase in UUT arrivals as well as having 10% down CASS stations. Model C requires 34 CASS stations 80% of the time and Model D requires 37 CASS stations 80% of the time. Model D is one CASS station short of meeting the CASS workload model while having 20% of the CASS stations down. This shows by using the binomial distribution with 80% demand coverage and expecting 30% of the CASS stations down, we will be less than the workload formula. This is due to variability. Variability in service times and arrives are not constant, such that, we can pick demand level to meet which is enough to satisfy service levels. If we want to meet demand at 90% of the time if will increase the number of CASS, as in Figure 14.

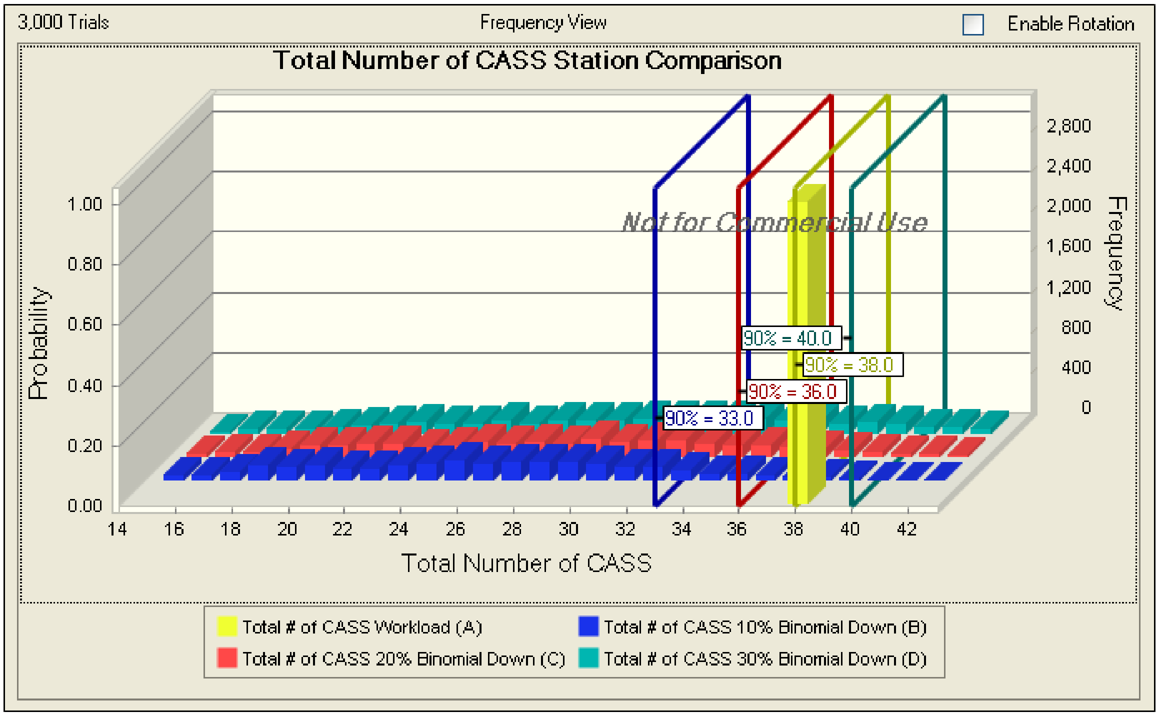

Figure 14. Total CASS comparison at 90%

Figure 14 is the total number of CASS stations comparison of the workload formula and the binomial distributions, which add CASS expected number of down stations to the required number of CASS stations at 100% utilization in order to meet demand, even when CASS stations are down. This figure shows the workload model at 38 total CASS stations as a constant value. Model B shows 33 are required 90% of the time, which means, if this number of CASS stations were assigned, we would meet demand 90% of the time with regards to surge and an increase in UUT arrivals as well as having 10% down CASS stations. Model C requires 36 CASS stations 90% of the time and Model D requires 40 CASS stations 90% of the time. Model D has two more CASS station than the workload model while having 30% of the CASS down. This shows by using the binomial distribution with 90% demand coverage and expecting 30% of the CASS stations down, we will nearly cover demand at the peak or highest operational tempo. This is due to variability. Variability in service times and arrives are not constant, such that, we can pick demand level to meet which is enough to satisfy service levels. But if we want to meet demand 100% of the time it will add 12 more CASS to

Model B, 11 more CASS to Model C, and 14 more CASS to Model D, as in Table 15. This is due to max arrivals and slow service times and the largest probability of having max number of CASS stations down. We can also conclude the workload model covers approximately between 80% and 90% of the demand.

2. Expected Number of CASS Stations Down

Having examined the total number of CASS stations which included the expected number of CASS stations that are down, now we look at the number of down CASS stations. Again the number of CASS stations that are down is based on the binomial distribution which assigns x number of CASS from a failure probability.

	Model A	**Model B**	**Model C**	**Model D**
Min	6	0	0	0
50%	6	2	4	7
70%	6	3	6	8
80%	6	4	6	9
90%	6	4	8	11
Max	6	10	13	18

Table 16. Expected number of down CASS stations

Table 16 shows the comparison of each model's average number of down CASS stations determined throughout the simulation. Model A, the workload model, has no variability so the number of CASS stations down remains constant because that is the determined number of CASS assigned from the 80% SLF. Model B (total # of CASS 10% Binomial Down) is less than the others because it only assumes 10% are down. Model C (total # of CASS 20% Binomial Down)is more than Model B and less than Model D (total # of CASS 30% Binomial Down) and Model D is the greatest number of CASS down due to having an expected number of 30% down. The figures show the 50%, 70%, 80%, and 90% of the simulation that that number of down CASS stations was required to satisfy the capacity number of CASS stations.

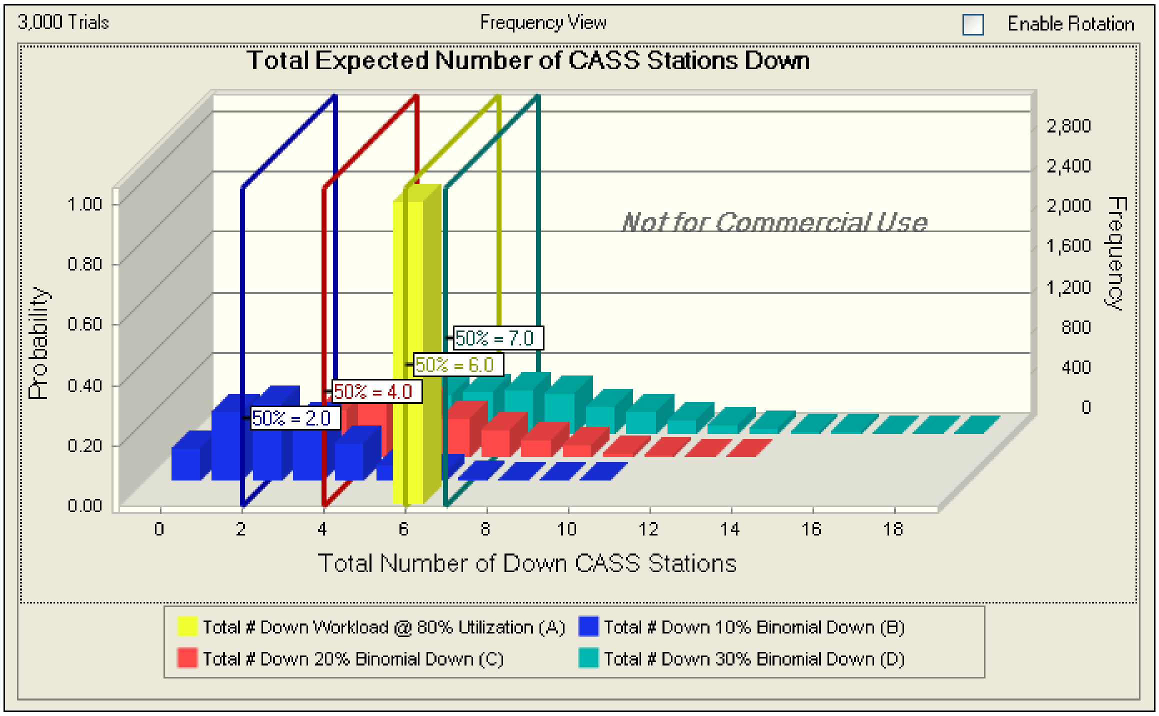

Figure 15. Total number of down CASS stations comparison at 50%

Figure 15 is the total number of down CASS stations comparison of the workload formula's SLF and the binomial distributions, which are added to the CASS station capacity in meeting demand at 100% utilization. This figure shows the workload model is expected to have 6 down CASS stations as a constant value. Model B shows 2 down CASS stations 50% of the time, which means, if this number of down CASS stations were assigned, we would meet demand 50% of the time with regards to surge and an increase in UUT. Model C shows 4 down CASS stations 50% of the time and Model D has 7 CASS stations 50% of the time. Model D has one more down CASS station than the workload model with 30% down CASS.

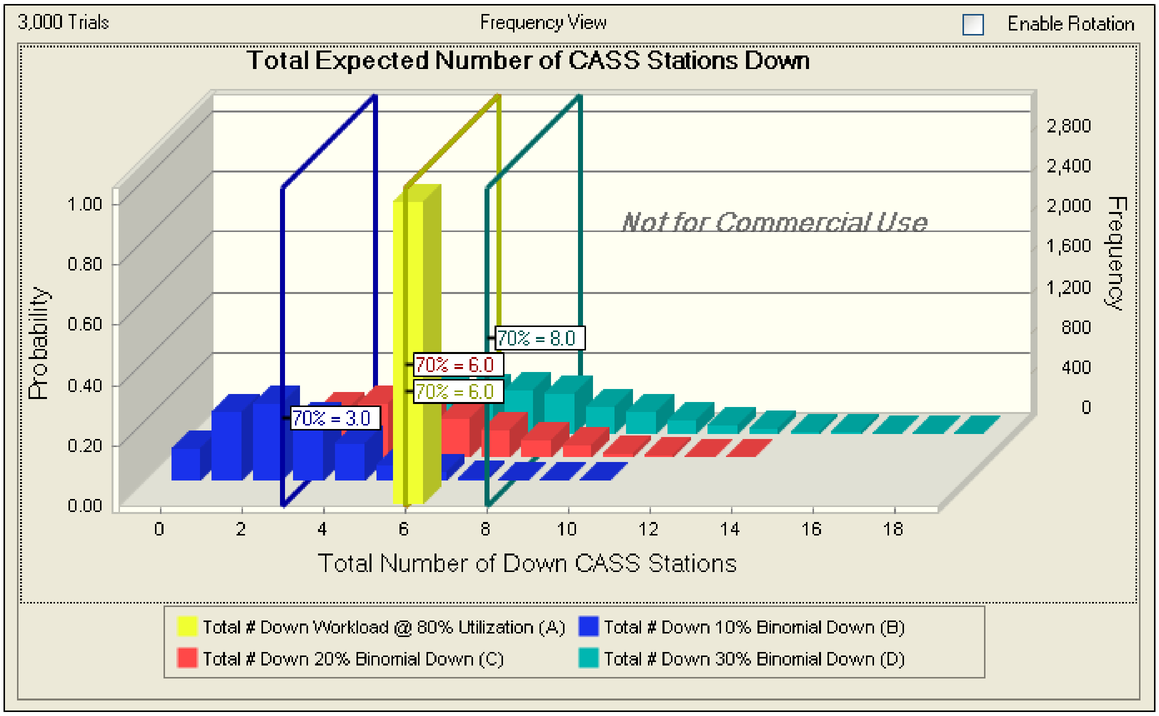

Figure 16. Total number of down CASS stations comparison at 70%

Figure 16 is the total number of down CASS stations comparison of the workload formula's SLF and the binomial distributions, which are added to the CASS station capacity in meeting demand at 100% utilization. This figure shows the workload model is expected to have 6 down CASS stations as a constant value. Model B shows 3 down CASS stations 70% of the time, which means, if this number of down CASS stations were assigned, we would meet demand 70% of the time with regards to surge and an increase in UUT. Model C shows 6 down CASS stations 70% of the time and Model D has 8 CASS stations 70% of the time. Model D has two more down CASS station than the workload model with 30% down CASS.

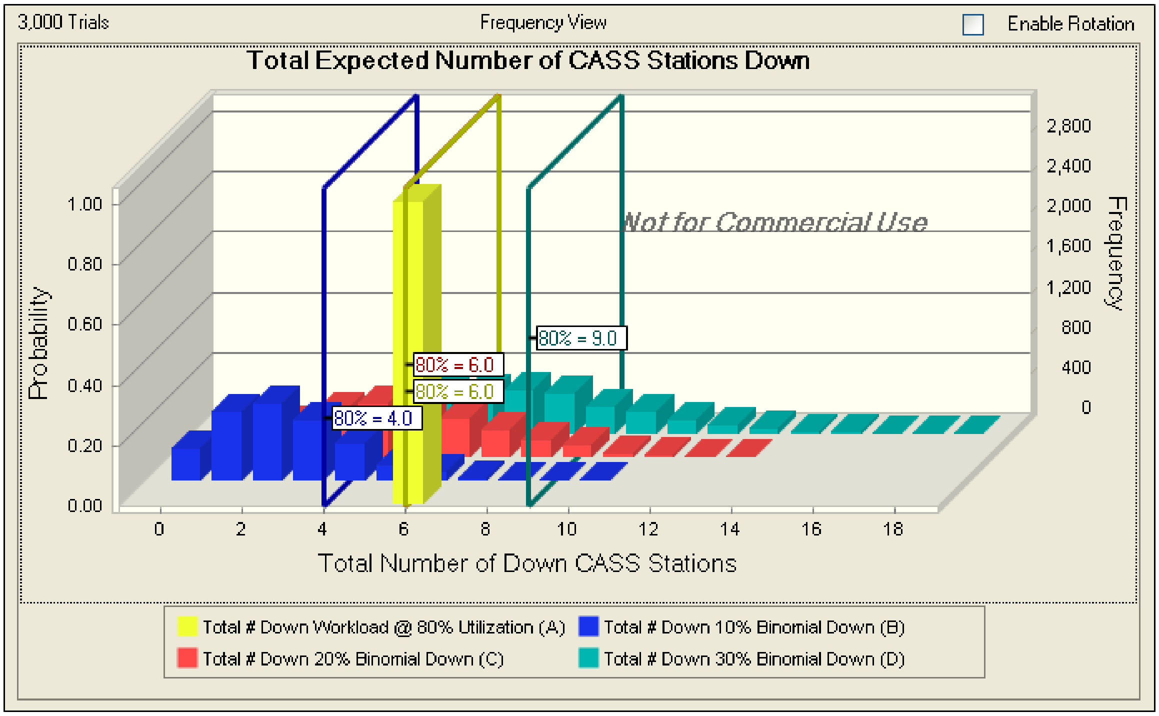

Figure 17. Total number of down CASS stations comparison at 80%

Figure 17 is the total number of down CASS stations comparison of the workload formula's SLF and the binomial distributions, which are added to the CASS station capacity in meeting demand at 100% utilization. This figure shows the workload model is expected to have 6 down CASS stations as a constant value. Model B shows 4 down CASS stations 80% of the time, which means, if this number of down CASS stations were assigned, we would meet demand 80% of the time with regards to surge and an increase in UUT. Model C shows 6 down CASS stations 80% of the time and Model D has 9 CASS stations 80% of the time.

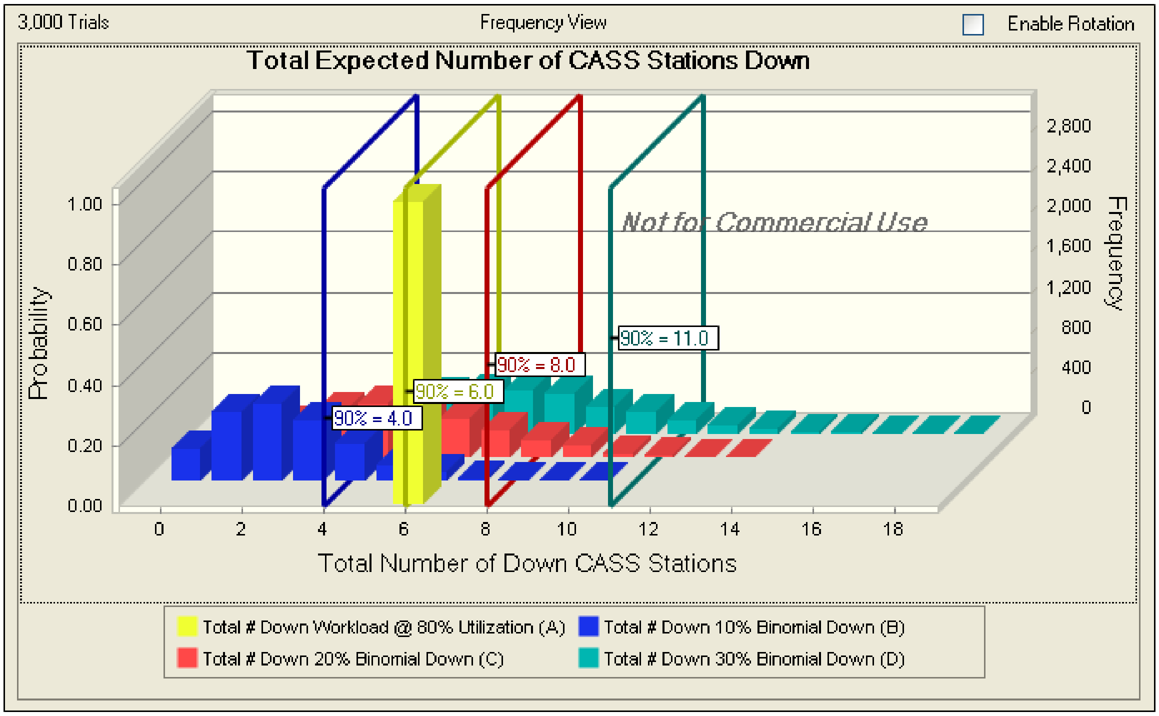

Figure 18. Total number of down CASS stations comparison at 90%

Figure 18 is the total number of down CASS stations comparison of the workload formula's SLF and the binomial distributions, which are added to the CASS station capacity in meeting demand at 100% utilization. This figure shows the workload model is expected to have 6 down CASS stations as a constant value. Model B shows 4 down CASS stations 90% of the time, which means, if this number of down CASS stations were assigned, we would meet demand 90% of the time with regards to surge and an increase in UUT. Model C shows 8 down CASS stations 90% of the time and Model D has 11 CASS stations 90% of the time.

We believe the optimal results for this test case (not accounting for cost) lie somewhere between 31 and 35, depending on the protection level of demand coverage and determining the expected number of down CASS from the SLF or Binomial reliability factors. We suggest covering between 90% and 95% of the demand with model 4 at 80% SLF or model D with Binomial expected number down. But of course, the specific levels of coverage need to be examined in the context of costs, and other factors (limited CASS station availability) not examined in this thesis.

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V. RECOMMENDATIONS

A. CONCLUSION

Allocating the optimal number of CASS to ensure UUTs are serviced in minimal time is critical in sustaining the fleet readiness level. Sustaining a demand at 50% is not adequate to cover some periods of surges in demand. A site may have to cover double the amount of demand for four months or more when all squadrons (aircraft) are at the site or an increase in operational tempo (flight hours). Meanwhile, each aircraft carrier has 19 CASS that are not utilized when aircraft are at their home base, which increases the demand at sites when the aircraft are at their home base. If the sites do not have the capacity to meet demand, then there will not be weapons systems available to meet aircraft readiness due to queues at the CASS work center or UUTs being repaired (BCM) off-site. Moving capacity of CASS stations is not cost- or time-efficient; this project proposes a site should plan on covering 90% of the estimated demand.

NAVAIR program office PMA 260 has been using a workload formula to allocate the CASS stations to the U.S. Navy sites. The workload formula functions correctly as designed, but it has limitations. First, the input parameters such as MTOS, CASS monthly available hours, and the MTBF are treated as constant values. Second, the formula does not capture the surge in demand which may result from either the increase in the number of aircraft or the increase in the monthly flight hours. Third, the formula's aim is to satisfy the workload, without an explicit consideration of the implications of workload on readiness.

To address these limitations and propose a better and easier process to allocate the CASS stations, we used modeling and simulation tools from the fields of Management Science and Operations Research. First, we tried to address the readiness issue using a nonlinear programming model and tried to achieve a readiness level of 70%. Moreover, we made the linear and nonlinear models to account for the utilization constraints as well. Second, we incorporated the sharing idea for the CASS stations into our models since the hybrid CASS is the core test station and all others can satisfy its demand. Third, we addressed the issue of constant parameters by using a simulation model. We defined several distribution types for the changing variables and calculated that accounting for variability in those processes significantly changes the total number of CASS stations that should be allocated to the sites. Finally, our models are dependent on MS Excel's features and several add-ins. So, they are accessible and can be used virtually everywhere.

B. IMPORTANCE OF VARIABILITY

When we get the results from the Crystal Ball simulation for both the static workload formula and the variable workload formula, we see that adding variability to several processes may significantly change the number of CASS stations. It is the responsibility of the decision makers and the PMA 260 staff to decide what percent of the demand to satisfy, but our analysis gives them a tool to better predict what percentage of demand will be satisfied by the planned capacity allocation.

Aside from increasing capacity, other elements for managing variability, such as scheduling, number of shifts (CASS available hours), manpower allocation, CASS failure rate (reliability), number of servers (CASS), training, inventory of UUTs, and MLDT, all exist in the repair process and have an enormous effect on site readiness. This project only focused on allocating the number of CASS, while the other important elements can be topics of other projects since they are out of the scope of this project.

Eliminating variability and creating better-defined processes prevents inefficiencies and can result in large savings. Keeping inventories for the failed parts might be a good example. Depending on the level of CASS workbench utilization, having ready for issue (RFI) parts for the failed UUTs may decrease the number of CASS stations notably. However, that is also a cost-benefit analysis and out of the scope of this project. Another important factor to meet the readiness constraint is to manage the CASS-independent TAT. That study would also be a cost-benefit analysis and further inform capacity planning for CASS. Furthermore, applying the lean six sigma theories to eliminate or to minimize the CASS-independent TAT may have positive effects. Thus, decision makers would have the optimum CASS-independent TAT and focus on the resource allocation problem to meet the readiness factor.

The management of UUTs consists of a large network of logistics, including vendors, item managers, depots, and maintenance facilities, which are all part of the supply chain network. Management Science and Operations Research (MS/OR) tools, such as optimization and simulation, are used to look at each process in order to reduce cycle time and work in process so that throughput is increased. This thesis has demonstrated the value of MS/OR methodologies to improve the supply chain of UUTs. We developed a decision support tool to assist PMA 260 in making these CASS allocation decisions. Moreover, the most significant contributions are the proof of concept that variable and peak demand can be incorporated into capacity planning (beyond planning for average demand) and linking predicted congestion to operational availability of aircraft (readiness).

There are a couple of ways the Navy can fix this: increase the repair capability, get more parts, or improve the reliability of the parts. Each of these requires an investment of scarce dollars, so guidance is needed as to which investment would be most effective. There are only so many parts to add; otherwise they will just become part of the vicious cycle and will be in the backlog (queue), but aircraft will still fly. The tradeoffs are difficult, but we believe our thesis can help PMA260 decision makers assess them.

C. FURTHER RESEARCH

The linear and nonlinear programming models, along with the simulation model, can be effectively used to solve resource allocation problems. Though we address variability by selecting particular thresholds (not the expected or average value) of demand and readiness to meet, the models remain deterministic, and are sensitive to the selection of input parameters. In our models, we had to make several assumptions, such as CASS-independent TAT and spare repairable UUT factors. We have conducted limited sensitivity analysis on these parameters, but more remains to be done before either our linear or non-linear models could be implemented in practice. Fortunately, researchers in the future can study those assumptions and get accurate data for those input parameters. On the other hand, Monte Carlo simulation model is a stochastic decision tool and works with random numbers. We have made only limited use of this tool, and more remains to be done. In particular, before any widespread implementation of our approach, we recommend validate the recommendations of our optimization models in a limited setting (e.g., one AIMD) through a detailed simulation model. The time frame of our own thesis did not allow us to complete such a detailed simulation model. Future researchers can use the discrete simulation model we have begun (not reported here) to further validate and improve results from the optimization model.

Finally a key assumption we make in our analysis is the spare repairable UUT fill rate. The model results are sensitive to this parameter, but its validation was beyond the scope of this study due to time constraints. Future researchers may also study the level of spare repairable UUTs to meet the aircraft readiness restriction and can provide better tools for the decision makers with cost-benefit analyses.

D. RECOMMENDATIONS

NAVAIR PMA 260 is about to introduce the e-CASS to the sites in the near future. So, it is important to keep in mind the effect of variability during the resource allocation process. We highly recommend PMA 260 use the peak demand at a predetermined level (i.e., 95%) and the readiness constraint while allocating the e-CASS stations to the U.S. Navy sites. Our research is a proof-of-concept that this can be done. Our approach should be extended to assist in the multi-year capacity planning effort to field e-CASS, and retire or refit older technology. Furthermore, it would also make sense to coordinate the spare repairable UUTs level with the responsible NAVAIR and NAVSUP office while trying to satisfy the readiness constraint.

BIBLIOGRAPHY

Armstrong, R. D., & Cook, W. D. (1979). Goal programming models for assigning search and rescue aircraft to bases. *Operational Research Society* , 555–561.

Balakrishnan, N., Render, B., & Stair, R. M. (2007). *Managerial Decision Modeling with Spreadsheets 2nd Edition.* Upper Saddle River, New Jersey: Pearson Education Inc.

Belcher, C. M. (2008, July 3). The future of automated test equipment is Called eCASS. (T. Waterline, Interviewer).

Belcher, M. (2009). *DoD ATS Selection Process Guide.* Patuxent River, MD: PMA-260.

Berman, O., & Krass, D. (2002). The generalized maximal covering location problem. *Computers & Operations Research* , 563.

Cervenak, B. (2010, April). *CASS Implementation Plan.* (B. Cervenak, Performer) NPS, Monterey, CA, USA.

Church, R., & ReVelle, C. (1974). The Maximal Covering Location Problem. *The Papers of Regional Science Association 32* , 103.

COMNAVAIRSYSCOM. (2008, February). Naval Aviation Manitenance Program. *Naval Air Systems Command Instructions* . Patuxent River, Maryland: COMNAVAIRSYSCOM.

COMNAVAIRSYSCOM. (2008, February). Naval Aviation Manitenance Program. *Naval Air Systems Command Instructions* . Patuxent River, Maryland: COMNAVAIRSYSCOM.

COMNAVAIRSYSCOM PMA260. (2005). *NAVY ATE and TPS ACQUISITION HANDBOOK.* Department of Navy. Department of Navy.

COMNAVAIRSYSCOM. (2009). *The CASS Family OTPS Sustainment Process.* NAVAIR PMA260.

Core, R. (2010, April 4). Lockheed Martin Gets $83 Million Contract For Navy Aircraft Test Equipment. (G. Fein, Interviewer).

DoD. (2006). *DoD Automatic Test Systems Program Plan.* Department of Defense.

Espejo, L. G., Galvao, R. D., & Boffey, B. (2003). Dual-based heuristics for a hierarchical covering location problem. *Computers & Operations Research* , 166.

Everingham, K., Polaski, G., Riedlin, F., Shirk, M., Deshpande, V., & Iyer, A. V. (2008). Operations Research Enhances Supply Chain Management at the US Coast Guard Aircraft Repair and Supply Center. *informs* , 61–75.

Flynn, M. J., Sarkani, S., & Mazzuchi, T. A. (2009). Regression Analysis of Automatic Measurement Systems. *IEEE Transactions On Instrumentation And Measurement , 58* (10), 3373–3379.

Flynn, M. (2007). Statistical Measurement Analysis Of Automated Test Systems. *IEEE Autotestcon* , 28–33.

Fried, J. S., & Haight, R. G. (2007). Deploying Wildland Fire Supression Resources with a Scenario-Based Standard Response Model. *INFOR 45* , 31.

Greenberg, H. (1971). *Integer Programming.* (R. Bellman, Ed.) Monterey, CA: Academic Press.

Hopp, W. J., & Spearman, M. L. (2000). *Factory Physics.* New York City: McGraw Hill.

Hosios, A. J., Laszlo, C. A., & Levine, M. D. (1978). A Model to Support Radiographic Equipment Allocation Decisions. *Journal of Operational Research Society* , 213.

Jacobs, F. R., Chase, R. B., & Aquilano, N. J. (2009). *Operations & Supply Management* (12th Edition ed.). New York: McGraw-Hill Companies, Inc.

Jensen, P. A., & Bard, J. F. (2003). *Operations Research: Models and Methods.* Hoboken, NJ: John Wiley & Sons, Inc.

Jones, J. V. (2006). *Integrated Logistics Support Handbook.* New York: McGraw Hill.

Kelly, A. (2002). *Comparative Analysis of Intermediate Level Maintenance Repair Process.* Naval Postgraduate School. Monterey: Naval Postgrauate School.

Kilian, G. F. (1995). *An Evaluation Of The Human Resource Development Process Supporting CASS.* Naval Postgraduate School . Monterey: Naval Postgraduate School.

Luenberger, D. G. (1984). *Linear and Nonlinear Programming* (2nd Edition ed.). Stanford, CA: Addison-Wesley Publishing Company.

Lynn, L. A. (1996). *CASS Requirements for a Regional Maintenance Center.* Center for Naval Analyses. Alexandria: The CNA Corporation.

Maples, D., Haftel, L., & Ruzicka, C. (2000). New Support Perspectives and Contracting Methodologies For the Consolidated Automated Support System (CASS). *IEEE* , 142–146.

Mena, A. C. (1994). CASS: Design for Supportability. *IEEE Autotestcon Systems Readiness Technology conference* , 1–5.

Meredith, M. S. (1990). *The Consolidated Automated Support System: A Comparative Evolution.* Naval Postgraduate School. Monterey: Naval Postgraduate School.

Moore, G. C., & ReVelle, C. S. (1982). The hierarchical service location problem. *Management Science* , 775.

Mulato, J. (1999). CASS Evolution To A Cost-Based Open-System Architecture. *IEEE Autotestcon Systems Readiness Technology Conference* , 545–547.

NALDA. (2003). *Introduction to the JASMMM Course.* page 1–1.

NAVAIR. (unk). *NAVAIR Consolidated Automated Support System.* Patuxent River: NAVAIR.

NAVAIRSYSCOM. (2002). *Navy Training System Plan: AN/USM-636(V) CASS.* Naval Air Systems Command.

Office Of The Inspector General. (1994). *Milestone Review Process For The Consolidated Automated Support System.* Arlington: Department of Defense.

OPNAVINST. (2003). *OPNAV Instruction 3000.12A.* Washington DC: DoN.

Oracle. (2008, January 1). Crystal Ball's Solution for Financial Forecasting and Analysis. Redwood Shores.

Oracle. (2008). Crystal Ball's Solutions for Finacial Forecasting and Analysis. Redwood Shores, CA.

Ragsdale, C. T. (2004). *Spreadsheet Modeling & Decision Analysis* (4th Edition ed.). Mason, OH: South-Western, Thomson Learning.

Rajagopalan, H. K., Saydam, C., & Xiao, J. (2008). A multiperiod set civering location model for dynamic redeployment of ambulances. *Computers & Operations Research* , 814.

Retterer, B. L., Richardson, S. C., Savage, H. S., Devers, W. C., Balaban, H. S., Bailey, E. K., et al. (1996). *The Capability of the Consolidated Automated support System (CASS) to meet Expanded Test Requirements.* Alexandria: Institute For Defense Analyses.

ReVelle, C. S., & Eiselt, H. A. (2005). Location Analysis: A synthesis and survey. *European Journal of Operational Research* , 1.

Ross, B. (2008, July 3). The Future of Automated Test Equipment is Called eCASS. (T. Waterline, Interviewer)

Ross, W. A. (2004). The New DoD Automatic Test systems Executive Organization. *IEEE Autotestcon* , 2-8.

Simmons, D. M. (1975). *Nonlinear Programming For Operations Research.* Englewood Cliffs, NJ, USA: Prentice Hall Inc.

Waterline, T. (2008, July 3). *www.dcmilitary.com*. Retrieved June 14, 2010, from http://www.dcmilitary.com/stories/070308/waterline_28142.shtml

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