SIMULATION MODELING AND ANALYSIS OF DEPLOYED F-16 OPERATIONS AND LOGISTICS SUPPORT

THESIS

Gregory D. Potts, 2nd Lieutenant, USAF

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AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

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Gregory D. Potts II, BS

2nd Lieutenant, USAF

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Gregory D. Potts II, BS

2nd Lieutenant, USAF

Committee Membership:

Dr. J. O. Miller
Chair

Dr. Paul L. Hartman
Member

AFIT-ENS-MS-17-M-154

Abstract

The purpose of this thesis is to reinforce and build upon past efforts identifying and demonstrating the need to better represent logistic capabilities and constraints within the realm of wargaming, war planning, and other analyses requiring the modeling of Air Force combat operations. We develop a framework for the porting of relevant logistic information and requirements from a reliable data source (LCOM- ATK) into a discrete event simulation environment (Simio), providing a simulation model for enhanced and robust analyses. The simulation we create explicitly reflects (for a selected subset of Work Unit Codes) the maintenance manpower, resources, and parts required to sustain the flying operations of a deployed unit of F-16 aircraft. This research considers two distinct scenarios with varied operational tempos over the phases of a 180 day deployment. We show that logistics can be incorporated in analyses and does have an impact on metrics and outcomes.

To my loving family and friends

Acknowledgments

I would like to express my heartfelt gratitude to my faculty advisor, Dr. J. O. Miller, for his significant guidance, sincere wisdom, and patience offered towards my success in completing this work. I would also like to thank Dr. Paul L. Hartman for his mentorship, insight, and operationally focused perspectives.

Gregory D. Potts II

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F-16 OPERATIONS AND MAINTENANCE IN RESOURCE CONSTRAINED ENVIROMENTS

I. Introduction

This thesis provides insight into the operations of F-16 aircraft in a deployed location to include explicit modeling of selected portions of the supply and maintenance support. The aim of this research is to utilize simulation software to analyze such a system with the goal of providing insight on how the operations of a deployed unit of F-16 aircraft are affected when accounting for required support as defined by multiple Unit Task Codes (UTC's). These UTC's serve as requirements for deploying forces according to predefined regulations that list what resources and how many are needed to support defined operational capabilities. The maintenance community and the Logistics Composite Model (LCOM) used in this research use Work Unit Codes (WUCs) in place of UTCs in defining maintenance manpower and parts required for specific scheduled and unscheduled maintenance tasks. For the sake of this analysis we only consider the unscheduled maintenance. Both UTCs and WUCS inherently bring to light the idea that these resources are countable and not infinite, meaning that there should be limits or constraints to their usage. By reflecting such constraints, our research shows that they should and can be explicitly represented in models for current and future analyses because they do have a significant impact.

Problem Statement

In many simulation driven studies, assumptions are made in developing models that make them easier to comprehend, compute, and analyze. This allows for increased tractability in simulations by allowing for the abstraction or neglect of pieces of reality that are deemed less critical or necessary for the validity of a model. Studies and recommendations that are produced from such models have been and continue to be useful in providing decision makers at all levels with tools that provide better results than those that can be obtained by common sense. We develop a simulation of a system with results close enough to reality to provide useful insight to decision makers, without sacrificing details or totally disregarding processes and/or resources within the system. This thesis effort is focused on laying ground work on developing an approach along with a simulation tool to help better understand and answer questions about how the factors of logistics and maintenance affects deployed operations to ultimately bolster analyses instead of the common practice of simply ignoring these constraints.

Research Focus

This research responds to a perceived lack of complete information provided to decision makers regarding mission capability of deployed forces. To capture the potential impact of logistics and maintenance on the mission capability of a deployed aircraft unit, we provide a framework for enhanced analyses that are capable of incorporating such insight. A key piece of our effort involves porting information from existing models such as LCOM into more flexible tools providing greater analysis capabilities. We define this flexibility as the ability to conduct higher fidelity analyses that allow us to look into metrics and measures as well as second and third order effects of these features that we previously could not.

Research Approach

We simulate the flying operations of a deployed unit of F-16 aircraft according to specific WUCs and focus our research on adequately modeling maintenance manpower and supplies to support these operations by bolstering the realism in this type of analysis. We begin with a well-defined deployment scenario with a large amount of data ported from LCOM that we filter and aggregate into manageable input for analysis within our model. A baseline simulation that includes logistics constraints and capabilities demonstrates our approach which is then compared with a similar alternative scenario with increased operational tempo over the phases of a 180 day deployment. In both scenarios, we look into the mission capability of the F-16 unit with respect to constraints and capabilities due to logistics.

Assumptions/Limitations

The UTCs that we base our analysis on contain a large amount of data concerning all of the resources needed in deploying flying assets. We carefully filter and aggregate this data for use in our analyses. In addition to the UTC data, we pull manpower and supply resources required for unscheduled maintenance tasks by WUC from a large LCOM data file. Our research focuses only on selected unscheduled maintenance tasks involving the aircraft propulsion systems.

Research Scope

The scope of this research is to develop an approach for incorporating maintenance manpower and supply data from multiple sources into a discrete event simulation model of sortie operations, and analyze the impact of constrained logistics for the aforementioned set of modeled scenarios. We show that there is a significant impact on situational outcomes when incorporating the constraints and capabilities due to logistics as opposed to disregarding them. Our definition of logistics constraints and capabilities includes the accurate representation of manpower and supply resources along with additional considerations for operating in a hostile environment. For our research we do not include any specific constraints due to a hostile environment such as casualties or destruction of resources. This is because we lack the pertinent data sources for these specific constraints that would mitigate the inclusion of false data into our analysis, however, such constraints could be added for future research.

Thesis Outline

The remainder of this paper is organized as follows. Chapter 2 provides background on the general concept of logistics constraints and capabilities and reviews pertinent material in the realm of our examination of the problem. Chapter 3 presents the methodologies applied in this research. Chapter 4 presents the results and analysis of our simulations, as well as analysis on the outputs from the simulations. Chapter 5 summarizes the contributions of this research and proposes directions for further studies.

II. Literature Review

Chapter Overview

We begin this chapter by introducing and discussing the topic of constrained and contested logistics along with the relevancy of constrained and contested logistics with regards to operational and current events within the United States Air Force. Then, we provide background in the general areas of combat modelling and wargaming, considering the lack of logistics and maintenance analysis within them. Following that, we discuss the general area of logistics and maintenance modeling to include summaries of previous studies in these fields. We lastly discuss Air and Space Expeditionary Force (AEF) planning and requirements and connect this back to our research approach.

Logistics in Constrained and Contested Environments

There is a growing and increased interested in looking into logistics and maintenance manpower support in deployed environments, which can be seen in the growing popularity of and inquiry into the topic. According to the most recent release of the Joint Concept For Logistics published by the Chairman of the Joint Chiefs of Staff, a known challenge in dealing with the future of military logistics is the increased demand for logistics requirements with constrained resources in "potentially contested environments" [1]. There are currently discussions on how to deal with this challenge, ranging from the concept of Globally Integrated Logistics, to reconciling competing demands for limited logistics resources based on strategic priorities [1]. Air Force General Paul J. Selva [1] also speaks on the necessity of an improved ability to include logistics consideration in operations and contingency planning. But the risks associated with addressing the challenge deal with having to heavily rely on advanced communication networks that cannot be completely protected or controlled by the U.S. military.

Relevant to the Air Force

As stated before, the increased amount of time that the topic of constrained or contested logistics shows up in current Air Force headlines makes the case for paying more attention to logistics and maintenance. For example, the Pacific Air Forces Major Command (PACOM) is currently interested in being able to rapidly assess the logistics support requirements necessary for dispersed operations for various numbers and mix of aircraft [2].

Another relevant application of this topic to the USAF can be seen in the critiques of current combat logistics from General Selva. He asserts that there is a logical misstep in Air Force planning that has historically and continues to ignore the “enablers” of the battlefield [3]. The enablers in question are the support units that provide the logistics, transportation, and medical personnel who are so often cut and disregarded during times of strict budget consideration. According to General Selva [3], the logistics infrastructure becomes an easy target when services attempt to increase combat power while drawing down in other areas because it is too often assumed that more fire power equates to better combat performance. But the perceived increase in combat power by doing this is left with an empty tail end of the aforementioned enablers which will ultimately render deployed combat power useless.

This boasts the importance of logistics in an operational context. Senior leaders are recognizing that combat power is not sustainable without substantial consideration of logistics but also know that the Air Force, as well as other services are “not quite there yet” [3]. Just recently, the Pentagon launched an $18 Billion innovation initiative that aimed to modernize the military but the propensity for the initiative to turn into one that calls for the procurement of more “shiny objects” needs to be parried by the consideration of logistics.

Little to No Consideration of Logistics

In this section, we look separately at the lack of logistics in combat modeling and wargaming.

Combat Modeling

At the very basic level, a model is a mathematical or otherwise logically rigorous representation of a system or a system's behavior.

> It may or may not be computerized and it may or may not be structured as a game. It may or may not attempt to represent the internal functioning of the real system. It may be abstract only, or it may be implemented as a computer program, a nomogram, pencil-and-paper procedures, or in a variety of other ways. [4]

The concept of Combat Modeling has a very long history of utilization by the United States military with the goal of exploring the potential impact, efficiency, and effectiveness of strategies, doctrine, and situational courses of action. Such a concept is beneficial because the ability to feasibly analyze the behavior of a complicated system without actually operating it saves large amounts of time and resources, which allows for the Department of Defense to analyze its military systems [5]. The systems modeled are military forces that are engaged in combat, composed of entities that represent anything from aircraft to soldiers, as well as supporting units, and command hierarchies.

The desired result from using combat models is the response of systems when various conditions are imposed on the controllable aspects of said systems and on the combat environment. The results are not perfect; for a model's representation of a real system has to invariably omit aspects and details deemed insignificant to decrease complication and support overall model tractability [5]. But the omitted details cause a cascading effect on a system's behavior thus leading to abstraction from reality.

When it comes to logistics, it is notoriously considered one of the insignificant details, and as previously stated, its omission inevitably leads to effects down the line in regards to a system's representation of reality. According to Robert Haffa, a renowned military and defense industry analyst, there is a definite failure in evaluating logistics operations which leads to overestimations of effectiveness and possible inaccuracy of analysis [6].

Wargaming

The art of Wargaming has a long history, dating back thousands of years in ancient China. The genesis of wargames is credited to Sun Tzu who created a basic strategy game called Wei Hai in which one player tries to outmaneuver another, based on real world combat at the time [7]. As time passed, other wargame type abstractions of actual combat were created. A notable next evolution of wargames came in 1664 in the form of a game called the Koenigspiel, which involved more pieces than those used in Sun Tzu's game and involved a larger board. The Koenigspiel utilized the same principles and rules as Wei Pei and as time progressed, games derived from both of these became more complex. Individual pieces grew to represent collections of individuals and eventually larger entities interacting over various types of terrain [7].

Fast forwarding to modern times, board based wargames were still in popular use up to the 1980’s [8]. During this time in wargaming history, there were peak amounts of wargame literature published but drawbacks of board based war games were becoming more evident as computer based wargames began to take over. The revolutionary computer based war games relieved users of the need to master many tedious metrics and mechanics that present themselves in the board based wargames [8].

From here, wargames have been developed into what we know of them today. No matter how archaic, the concepts utilized in creating and playing these aforementioned wargames are timeless, relevant, and useful in military application. As opposed to playing and participating in wargames for leisure, military users gained the ability to develop and apply strategies for maximum effectiveness on the real world battlefield.

Within the military, wargaming is conducted under Title 10 wargames. These represent a type of wargame that is defined as a “series of major service sponsored games that address future concepts and capabilities in the context of Title 10 responsibilities to organize, train, and equip its forces to carry out its roles and functions as a component of the national instrument of power” [9]. The USAF began title 10 wargaming in 1995 and within its series of the gaming, there are two games called Unified Engagement (UE) and Future Capabilities Games [9]. UE is focused to address military challenges and concept exploration and the Future Capabilities Game is focused to address future concepts and force structure alternatives [9].

When it comes to the idea of logistics, there is a stark absence of focus given to it in wargames. According to LaPlante et al. [10], logistics analyses are often conducted without the participation of warfighters, or would be wargamers, and wargames tend to avoid focusing on how impactful logistics support is concerning campaign planning and wargame outcome. Once again referencing Robert Haffa this failure in evaluating logistics operations leads to overestimations of effectiveness and analysis inaccuracy [6]. In 2003, Air Force Captain Daniel Krievs conducted research on this topic and developed a methodology concerning how to gather insights from Agile Combat Support metrics and demonstrated that logistics are a critical piece that can and should be incorporated into wargames, simulating a fleet of blue force aircraft and the supplies needed to keep them operational [11]. He statistically analyzed sortie missions to evaluate their effectiveness while faced with logistics constraints and created a meta-model that could be used during wargames as a solution to incorporating logistics.

Past Efforts in Logistics and Maintenance Modelling

There have been an increasing amount of academic efforts presented that consider the modeling and consideration of modeling logistics and maintenance. Two specific studies of this type are those done by previous AFIT students, Carl Parson and 2nd Lieutenant Kevin Cardenas.

B-1B Modeling with Logistics and Maintenance

Carl Parson studied and analyzed the operations of B-1B aircraft with a focus on how supply impacts mission capability (MC) [12]. The MC metric is comprised of two sub metrics: Total Non-Mission Capable due to Supply (TNMCS) and Total Non-

Mission Capable due to Maintenance (TNMCM). According to data from July 2008 to June 2009, the monthly TNMCS rates for the B-1 aircraft averaged 13.7% with a standard deviation of 3.3% with a target rate of 8%. Parson focused his analysis on the Air Force supply chain and developed a discrete event simulation to model portions of the supply chain that supported spares activity for maintenance actions at a single airbase to provide better understanding of how the system operates under certain conditions [12].

Parson's research used Arena Simulation Software to model sixteen B-1 aircraft over a five year timeframe. Each bomber cycled through his model based on Code 3 landings, which represented unscheduled failures [12]. The failures were then repaired with supplies accessed from different locations and the aircraft returned to MC status as soon as it had all of the parts it needed to be fixed installed. This cycle can be seen in Figure 1.

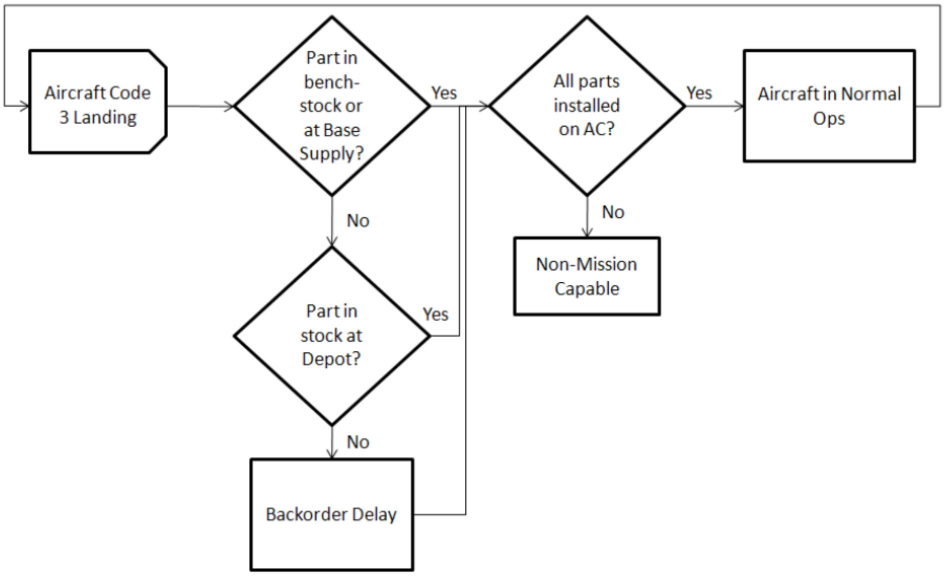


Figure 1. Parson's Model Supply Flow [12]

Parson collected pertinent data on how long each aircraft with a Code 3 landing was not MC while awaiting parts, which included processing and service delay times within the system. Parson’s work provided a basic frame work for future supply focused analysis and ultimately showed that there were indeed lessons to be learned and information to be gathered concerning the substantial impact of supply and logistics on Air Force metrics of focus [12].

LCOM ATK Logistic Simulation

Second Lieutenant Kevin Cardenas researched the “superseding necessity for logistics” in Air Force wargaming [13]. His research further illustrated the necessity for logistics to be more thoroughly considered in wargames to more accurately capture the capability and constraints that logistics provide to conflict operations. He analyzed and provided insight on a scenario representing the “Pivot to the Pacific” campaign as requested by AFMC/A4 and provided a proof of concept that a stand-alone logistics simulation can effectively capture a more accurate and realistic representation of logistics supply during an active war that lasts longer than a traditional wargame’s 7 to 10 day time period [13].

He used the Logistics Composite Model Analysis Toolkit (LCOM ATK) which is a detailed simulation model that identifies the effect of logistics resources (primarily maintenance personnel, equipment, facilities, and spare parts) on sortie generation [14]. It provides the capability to merge logistics models with maintenance, personnel, and equipment requirements and has been used within the military analyst community for many years.

Cardenas took a design of experiments approach to analyze the effects on a number of responses due to various levels of aircraft, manpower and spare parts as input factors in his LCOM ATK models. This was a follow on to Daniel Krievs' thesis work that used explicit logistic constraints and tracked all relevant data concerning its consideration [11]. Although Cardenas did not track supplies within his simulation , he was able to show that with increased operations tempo, there were statistically significant increases in the percent of time flying sorties, percent unscheduled maintenance, the amount of flying hours and sorties per aircraft, and the number of man hours required to maintain the modeled aircraft squadron [13]. Cardenas' findings resulted in further proof that there needs to be a larger focus on agile combat support in combat modeling and simulation.

AEF Planning and Requirements

The Air Expeditionary Force (AEF) is a concept utilized since 2000, created as a response to increasing numbers of contingencies that called for worldwide deployments. It was meant to enhance overall force readiness and reduce operations tempo in order to provide more predictability in regards to deployments and warfighting [15]. This concept allows for the Air Force to present its forces in a consistent way that was conducive to conducting many military operations. The Air Force's initial definition of the AEF plan was

> to link geographically separated Air Force operational wings, groups and squadrons, active, Reserve and Guard into 10 notional AEFs, each with a cross-section of Air Force weapon systems to include fighters, bombers, support aircraft, and tactical airlift, with integrated command and control, trained as a unit to respond rapidly and decisively to potential crises anywhere in the world or to fill in rotational assignments [16].

Before its implementation, the Air Force was sized for major theater war but was too often tasked to perform small scale operations and contingencies [15]. Units were selected on an ad hoc basis and each implementation of a unit for a wartime purpose was unique. This led to shortfalls in capabilities for many career fields due to the mismatch between the Air Force's configuration and missions it was tasked to do. The shortfalls caused excessive operations tempos for some people but with the AEF, the Air Force was able to better manage its resources to spread the workload and deployment burden across the force which ultimately resulted in more predictability in deployments.

Some key characteristics of the AEF concept can be summarized by F. Whitten Peters, the acting Secretary of the Air Force at the genesis of the AEF, who stated that

> - AEF's will be on call to handle contingency operations for a 90 day period every 15 months. On average, two AEFs will be on call at any onetime[16]
>
> - AEF's will train as it will fight, with its active, Reserve, and Guard units all training together using integrated command and control provided by a lead wing plus command elements from constituent units. Importantly, AEF units will train for deployment together in exercises like Red Flag [16]
>
> -Third, each AEF will be specifically tailored to a particular contingency in support of our warfighting CINCs, enabling our air forces to be lighter, leaner, and more lethal than ever before [16]

As a part of the AEF concept, commanders with forces to be deployed receive UTCs that serve as requirements for deploying forces according to predefined regulations that state what resources and how many to support defined operations capabilities are needed. We use these UTCs as a primary data source for maintenance manpower and supply resources that serve as inputs to our simulation.

Summary

This literature review discusses constrained and contested logistics, how relevant it is to the USAF, gives background in the areas of combat modeling ,wargaming, and logistics and maintenance modeling, and discusses AEF planning and requirements. We highlight the need to better represent supplies and maintenance in combat modeling and analysis. The next chapter of this thesis describes our methodology for achieving this.

III. Methodology

Chapter Overview

The purpose of this chapter is to outline our approach in conducting the analysis of mission capability with respect to constraints and capabilities due to logistics. We first describe the tool we use to perform our research and address the problem statement. Then we describe the model we created, as well as the assumptions made to increase the tractability of the analysis. Next we explain the sources of our data and how the data is specifically utilized. Lastly, we discuss the metrics created and measurements taken to assess the model, followed by a discussion on how we utilized experiments to bolster the significance of our findings as well as the way we verified and validated the model.

Simio Simulation Modeling Environment

The tool we use to conduct our research is Simio Discrete Simulation software created by Simio LLC, which is a unique multi-paradigm modeling tool that combines the simplicity of objects with the flexibility of processes to provide a rapid modeling capability without requiring programming [17]. The software is a fully object oriented 3D modeling environment that allows for users to construct models in either 3D or 2D physical layouts and utilize the benefits of simulation based analyses to address a variety of issues in several disciplines including but not limited to healthcare, manufacturing, service, military, and supply chain systems, all without the necessity of manual programming [18]. The use of the software assists in determining attractive configurations and alternatives to provide sufficient justification to convince managers and decision makers to adopt improvements.

The application of Simio in real world decision making is critical in its ability to model systems that are too expensive and risky to do live tests on. Its uniquely programed design allows for large and complex systems that are subject to variability and incomplete data, to be tested according to countless variations on plans and policies and to have data produced concerning such alternatives within its experimentation capability [19]. This allows for users to get a glimpse into the future of relevant projects with insight to questions such as what can happen and what will happen.

Considering the analytic application side of Simio, it can be used to exploit information to identify patterns, create possible change scenarios, make predictions about the future, and prescribe actions based on predicted results [19]. We chose to utilize and implement this software in our research for these reasons and capabilities.

Model Overview

As stated before, we began our model with a well-defined deployment scenario, largely based on data that we filtered and aggregated into manageable input for use within our model. We model maintenance manpower, supplies, and tasks performed to support the operations as generated model entities fly sorties throughout three phases of a deployment. A visualization of the model as it appears in the Simio Modeling Environment can be seen in Figure 2.

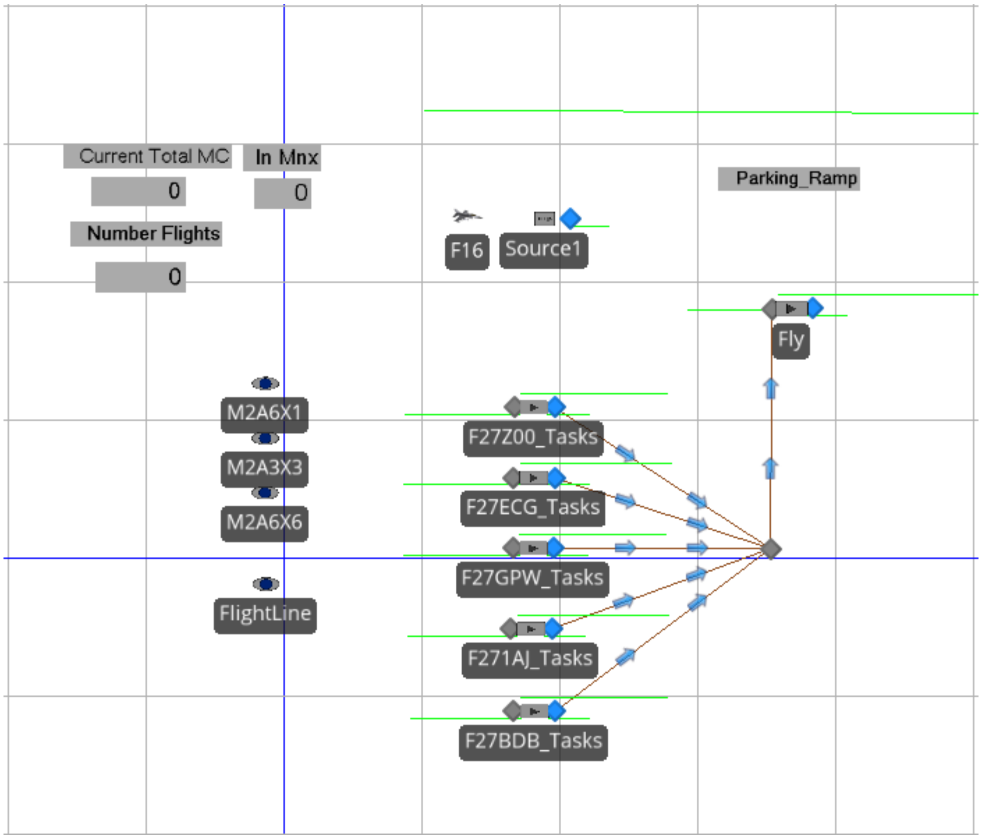


Figure 2. Overview of Simio Model

Our model is composed of 12 F-16s that all arrive into the system at Source 1, at a rate of 1 per hour starting at time 0 on the first day of the simulation. Once in the system, the aircraft obey flight logic that dictates a flying schedule that starts at 0600 and ends at 1800 every day in the simulation. The intervals between aircraft takeoff vary based on the deployment phase, which is described in following sections as the Surge Phase, Sustained Surge Phase, and Warfare Sustained Surge phase. In between the takeoff intervals, the aircraft queue individually in preparation for flying and launch from the Parking Ramp station one at a time. The aircraft are assigned random flight times based on a Uniform distribution between 3.25 and 3.75 hours and are limited to a maximum of 10 flights per week, defined as every 7 days from the beginning of the simulation. If an aircraft reaches its 10 flight limit, it is grounded operationally until the start of the next week.

Once the aircraft complete a sortie, it returns to the parking ramp until they are called upon to fly another sortie. Once selected to fly, they enter the model logic that determines if they need maintenance and repair according to flight hours being compared to uniquely designed failure clocks. These failure clocks are derived from LCOM ATK data provided by our stakeholders and represent the mean time between failures (MTBF) at which an aircraft flew long enough to trigger one of five Work Unit Codes (WUCs) to be performed. The failure clocks in our simulation take the MTBF from LCOM ATK for each WUC and use them as an input to an exponential distribution to determine the hours required for this to happen. These tasks are coded: 27Z00- Turbofan Engine, 27ECG- Seal Divergent, 27GPW- Cable Electrical (W-1), 271AJ- Indicator Oil Pressure, and 27BDB- Blade Stage 1 (Bleeding). The MTBF values for these WUCs can be seen in Table 1.

Table 1. LCOM MTBF Values

	LCOM MTBF
WUC27Z00	168.2 Hours
WUC27ECG	307.1 Hours
WUC271AJ	329.3 Hours
WUC27GPW	329.3 Hours
WUC27BDB	336.7 Hours

Each of these WUCs involves separate processes in repairing a system, subsystem, or part of the F-16 propulsion system that requires maintenance. LCOM uses the WUCs to identify task networks and associated parts. In a UTC, parts are identified using National Stock Numbers (NSNs). Unfortunately, no data dictionaries exist that match WUCs with NSNs. Because of the fact that we directly incorporate LCOM task networks into our simulation, we use the WUC designation for parts. The WUCs listed in Table 1 were selected because they had the shortest MTBFs for the propulsion system, allowing us to incorporate them into our model framework manually. This logic flow can be seen in Figure 3.

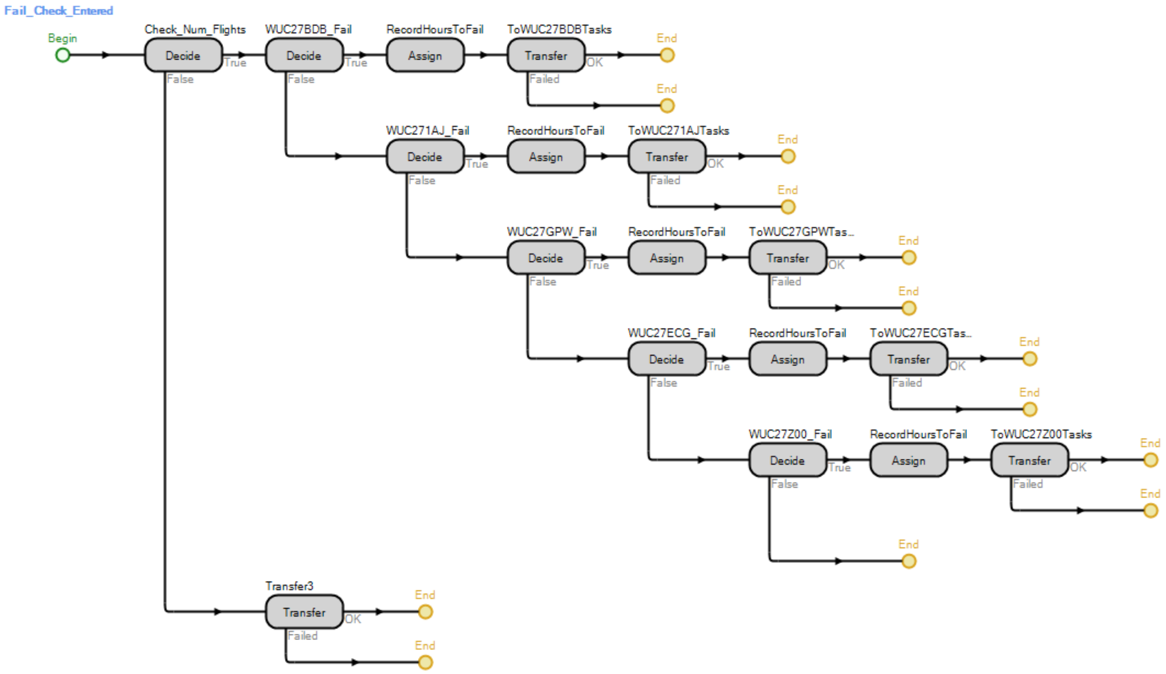
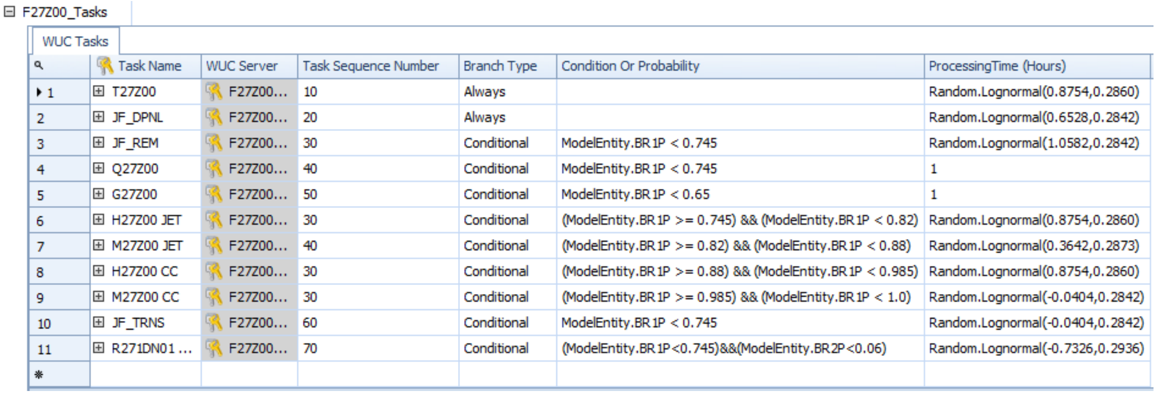


Figure 3. Aircraft Maintenance Checking Logic

The logic is set up to first determine if an aircraft has exceeded its weekly flight limit and then decide if and where a first failure occurred, starting from the WUC with the longest MTBF. Then it assigns relevant tracking statistics for analysis, and transfers the aircraft into the appropriate maintenance station. After an aircraft completes repairs for a WUC, the aircraft returns to the system to continue flying its scheduled sorties until the next failure clock is triggered.

There are five maintenance task stations in the model associated with a WUC failure that the aircraft are routed to when a repair is deemed necessary. The task stations are: F27Z00_Tasks, F27ECG_Tasks, F27GPW_Tasks, F271AJ_Tasks, and F27BDB_Tasks.

Each of these tasks have unique task sequences derived from LCOM ATK data and have different resource (manpower and parts) requirements along with individual processing times based on deterministic or random times generated from a Lognormal distribution. We use this distribution because it is utilized in LCOM and it is logical for use regarding such processes. The task sequences include probabilistic and conditional routing. It should be noted that the F27Z00 tasks are only represented by the initial set of general tasks derived from LCOM for the turbofan engine. Once an aircraft has completed all of the required tasks, the flying hours for the repaired WUC is reset to zero and the associated failure clock draws a new random time until the next failure. To further demonstrate the task sequences within the model, the Simio input for the F27Z00 tasks can be seen in Figure 4.



	Task Name	WUC Server	Task Sequence Number	Branch Type	Condition Or Probability	ProcessingTime (Hours)
1	T27Z00	F27Z00...	10	Always		Random.Lognormal(0.8754,0.2860)
2	JF_DPNL	F27Z00...	20	Always		Random.Lognormal(0.6528,0.2842)
3	JF_REM	F27Z00...	30	Conditional	ModelEntity.BR1P < 0.745	Random.Lognormal(1.0582,0.2842)
4	Q27Z00	F27Z00...	40	Conditional	ModelEntity.BR1P < 0.745	1
5	G27Z00	F27Z00...	50	Conditional	ModelEntity.BR1P < 0.65	1
6	H27Z00 JET	F27Z00...	30	Conditional	(ModelEntity.BR1P >= 0.745) && (ModelEntity.BR1P < 0.82)	Random.Lognormal(0.8754,0.2860)
7	M27Z00 JET	F27Z00...	40	Conditional	(ModelEntity.BR1P >= 0.82) && (ModelEntity.BR1P < 0.88)	Random.Lognormal(0.3642,0.2873)
8	H27Z00 CC	F27Z00...	30	Conditional	(ModelEntity.BR1P >= 0.88) && (ModelEntity.BR1P < 0.985)	Random.Lognormal(0.8754,0.2860)
9	M27Z00 CC	F27Z00...	30	Conditional	(ModelEntity.BR1P >= 0.985) && (ModelEntity.BR1P < 1.0)	Random.Lognormal(-0.0404,0.2842)
10	JF_TRNS	F27Z00...	60	Conditional	ModelEntity.BR1P < 0.745	Random.Lognormal(-0.0404,0.2842)
11	R271DN01 ...	F27Z00...	70	Conditional	(ModelEntity.BR1P<0.745)&&(ModelEntity.BR2P<0.06)	Random.Lognormal(-0.7326,0.2936)
*						

Figure 4. Simio F27Z00 Task Sequence

Figure 4 shows how the tasks to be performed are ordered and what conditions must be met for them to occur. The ModelEntity.BR1P and ModelEntity.BR2P are model generated probabilities derived from Uniform(0,1) distribution that are assigned to an individual aircraft every time they enter the task networks that deal with the functionality of the turbofan engine to represent damage states of the aircraft as well as the parts that failed.

In regards to an aircraft going through the task sequences depicted in Figure 4, it always starts at task T27Z00, with a sequence number of 10. This task is always performed when an aircraft enters the sequence, based on its Branch Type. The Branch Type of a task shows if it is always be performed or if conditions have to be met for it to be performed. The time it takes for this task to be performed when it is performed can be seen in the Processing Time column depicted in Figure 4. The model then checks for tasks with an equivalent sequence number or the task with a subsequently high value sequence number to move on to. In the case of our model, the aircraft next goes through task JF_DPNL with a sequence number of 20 that is performed every time as well. For the next task, JF_REM with a sequence number of 30, the model checks the value of the ModelEntity.BR1P variable against the task's conditional < 0.745 requirement. If this condition is satisfied, then the task is performed. If not, the task is skipped entirely. The next task, H27Z00 JET, has an equivalent sequence number so it is performed next. This task has a dual conditional requirement that the value for ModelEntity.BR1P must be greater than or equal to 0.745 and that the value for ModelEntity.BR2P must be less than 0.82 for this task to be performed. The same logic applies to the H27Z00 CC and M27Z00 CC tasks, which both have sequence numbers of 30 and follow the previously described tasks. At this point, there no longer any tasks with an equivalent sequence number so task Q27Z00 (sequence number 40) is selected next. The performance of this task hedges on the same ModelEntity.BR1P and ModelEntity.BR2P factors as described above then the model then moves on to evaluating task M27Z00 JET with its equivalent sequence number. Next, the model selects the G27Z00 (sequence number 50). The remaining tasks in this specific grouping follow all previously discussed logic while abiding to their listed sequence numbers. Once the last task is completed, this WUC on the aircraft is considered to be repaired.

The manpower resources required in the model (M2A6X1, M2A3X3, M2A6X6) and the material resources (P27Z00, P27GPW) are set with initial capacities of 3 and serve as representations of the assets required to perform certain maintenance tasks as defined in the model's process logic. Since we are only modeling a few specific unscheduled maintenance tasks and no scheduled maintenance, utilization statistics for most of these resources are not useful to our analysis. As for the material resources, when an aircraft enters the F27Z00 or the F27GPW task networks, the P27Z00 and P27GPW materials are required at certain steps within their respective networks. The P27GPW material resource will always be consumed by an aircraft but it will always regenerate once it's utilized, representative of the part being taken off of the aircraft, replaced by a spare, and successfully refurbished every time. The P27Z00 material resource is representative of an engine and is both consumed and regenerated based on the damage state condition, ModelEntity.BR1P. It must be noted that we altered the previously mentioned LCOM provided ModelEntity.BR1P condition from a value of 0.745 to 0.65 to induce a need for more engines within the model. The act of consuming the part means that the part currently on the engine is no longer operational so it must be removed. There is a chance that the 3 initial P27Z00 parts will be consumed but not regenerated based on the randomness of the ModelEntity.BR1P criteria, so we also model logic for the deployed maintenance shop ordering additional P27Z00 parts from an offsite maintenance depot. If an aircraft consumes the part but there isn't one available to be placed back on the aircraft, the deployed maintenance shop will order one part that arrives in 6 days. Lastly, there is an additional FlightLine resource that represents the airfield schedule and availability to assist in ensuring a realistic flight schedule, allowing flights to take off only between the hours of 0600 and 1800.

Model Assumptions

Due to tradeoffs in computational necessity versus accuracy, we had to make assumptions about the F-16s and their parts that can break in the model. We assume that the aircraft always take off with a maximum amount of fuel and any aerial refueling deemed necessary is considered to take place during the modeled flying time without explicit representation. We also assume that refueling in preparation for an upcoming sortie occurs during a time delay that happens before actual takeoff.

The next assumption concerns the flight hours and the amount of hours for each part. When an aircraft enters the system, it arrives with a random amount of flying hours on all of its parts as well as random failure clock trigger values based on a seeded exponential distribution with the respective failure clock's mean time until failure as the input. This is done to reflect the idea that aircraft would not arrive at a deployed location in pristine condition with no flying hours on any parts and everything functioning perfectly.

The last assumption is that only one WUC will be flagged as failing when an aircraft enters the model logic. It is a reasonable assumption because of the fact that it is not normal for aircraft to be completely stripped and checked for all possible malfunctions when they enter maintenance for other specific issues.

Data Sources and Model Inputs

We focus on simulating the operations of a deployed F-16 unit according to verified and validated data from LCOM ATK. We utilized data from an LCOM ATK database for F-16's, sent by Philip R. Torres, Jr [20] to define the tasks necessary for maintenance repair, the sequences of those tasks, and what resources the tasks required. We modeled our sortie rates using data from this F-16 database as well as following patterns from the Joint Strike Fighter (JSF) Key Performance Parameter database used by Krievs [11] and Cardenas [13].

We followed Krievs [11] and Cardenas [13] to define the model's deployment phase cycle. This phase cycle has three phase shifts from Surge, to Sustained Surge, to Warfare Sustained Surge. These phases dictated the sortie rates for the aircraft between 0600 and 1800 daily. The Surge phase has one aircraft set to fly every 40 minutes for 7 days. Then the Sustained Surge dictates the aircraft fly every 60 minutes for 23 days. The last Warfare Sustained Surge schedules sorties every two hours for 150 days. The lengths of these phases are modified as part of our analysis.

Model Metrics and Measurements

In order to provide insight on the effects of constrained logistics on a deployed force with our simulation, we created and kept track of the following metrics: the number of individual WUC failures, the number of aircraft in maintenance at any point, the amount of time that the aircraft are not mission capable due to maintenance needs, the number of engines ordered from the maintenance depot, sortie lengths, the total flight hours achieved in the simulation run, the number of spare engines in maintenance at any time, the sortie schedule effectiveness, the number of sorties flown per day, the time aircraft take to be repaired, the number of failures per day, and the amount of fuel consumed by the aircraft.

Experiments

We utilize the experiment capability within Simio to vary key aspects of the model in order to determine their impact and significance in comparison to the base model. The things we vary are the lengths of the phases in the deployment cycle in order to gain insight into how ops tempos affect the overall model performance when their durations are extended and changed.

The base model, the “Surge Scenario”, is based on previous research efforts as well as information from the Long Duration Logistics Warfare Workshop. It has the Surge, Sustained Surge, and Warfare Sustained Surge phases with lengths of 7 days, 23 days, and 150 days respectively. The sortie rates in this baseline model between the phases are one flight every 40 minutes, 60 minutes, and 120 minutes. In the second scenario, the “Extended Surge Scenario”, we extend the Surge and Sustained Surge phases out to 30 days per phase with a Warfare Sustained Surge phase length of 120 days. This was done in order to capture any statistical differences between the scenarios that demonstrate the impact of constrained logistics on war fighting effectiveness.

Verification and Validation

As the popularity of utilizing simulation models to make decisions and solve problems is increasing, the general concept of Verification and Validation (V&V) is a maxim critical to the fidelity of any information, research, and analyses delivered to any interested entity.

In terms of our research, the process of Verification is intended to check if the simulation model was built correctly according to all of the data that we had to work with. We checked this by monitoring many elements of the model that dealt with its functionality, ranging from how many planes were flying at any point to how often the system would be starved for resource by varying individual values and probabilities within the model logic. These elements were monitored in terms of both real time and model termination and would be checked against what would be expected to happen. For example, an experimental increase in the probability of a specific part being replaced within an individual WUC should cause more aircraft than normal to fail in this fashion, therefore causing longer service times within the specified task network and shorter flight hours on a part until the next failure. An example of a specific element that was critical to our validation effort were the statistics dealing with flight hours on each part until failure. This element would be analyzed at the end of a model run by checking the values and ensuring that with changes to varied parameters, these statistics would change predictably in regards to our knowledge of the system. We did not expect an exact match to the LCOM database mean input values for each part because of the interactions in the simulation. The results shown in Table 2 show a reasonable range of values for each WUC.

Table 2. Flight Hours until Failure Element for Verification

	Baseline Scenario				
	F27BDB Average TTF	F271AJ Average TTF	F27GPW Average TTF	F27ECG Average TTF	F27Z00 Average TTF
LCOM Mean	336.7	329.3	329.3	307.1	168.2
Mean	278.65	298.08	280.03	271.52	141.58
95% HW	20.25	36.46	29.06	25.08	7.26
Min	198.38	208.95	142.37	173.95	108.91
Max	366.46	579.75	450.06	389.10	185.34

	Extended Surge Scenario				
	F27BDB Average TTF	F271AJ Average TTF	F27GPW Average TTF	F27ECG Average TTF	F27Z00 Average TTF
LCOM Mean	336.7	329.3	329.3	307.1	168.2
Mean	275.80	292.35	274.40	259.33	142.99
95% HW	17.96	33.52	26.38	19.96	7.75
Min	213.49	209.09	172.23	173.83	106.64
Max	360.52	549.83	421.48	352.30	174.36

The process of Validation is intended to check the accuracy of a model's representation to a real world system, ultimately determining how reasonable any output values are. This was done by having the model setup, inputs, and results reviewed and approved by a qualified deployed operations subject matter expert.

Summary

In creating our model and approach to conducting the analysis of key statistics with respect to constrained logistics, we develop a robust model that is able to utilize output from an independent high fidelity model in a discrete simulation. Although, some of the aspects of our model as well as our choices for what we look into are built on previous research efforts, our model along with the previously discussed methodology not only gives general insight into how a deployed unit of similar characteristics to the one we simulated will generally perform under the same circumstances when considering certain system performance measures, but provides a foundation for future work on integrating more detailed real world data as well as more data from other model sources into such a simulation model as ours, in order to gain even more insight on the impact of constrained logistics.

IV. Analysis and Results

Chapter Overview

In this analysis section, we assert the significance of our model in representing maintenance manpower, supplies, and tasks performed to support the simulated operations and capturing the impact of logistics and maintenance on the overall mission capability of a deployed force. We do so by presenting metrics that we pull from the model as well as examining key measures of effectiveness (MOEs) that we generated in SIMIO based on our gathered metrics for the simulated deployment in order to gather a broader insight to the model and overall effect of logistical limitations and varied phase lengths on force readiness, as explained in Chapter 3. We discuss the reasoning and significance behind each MOE as well as explain each of their formulations and results in the following section. We then summarize these results in terms of their application to the original problem statement that motivated our research.

Results of Simulation Scenarios

Twenty-five experiment replications were conducted with no simulation warm-up period and relevant MOEs were calculated and generated. The MOEs that were generated were: Schedule Effectiveness, Average Daily Sorties, Time to Repair (TTR) for the WUCs, Average Daily Failures, and Fuel Usage. These MOEs are displayed in later Tables and Figures along with their appropriate discussions. The other metrics that were tracked and recorded, previously listed in Chapter 3 of this thesis, were the number of individual WUC failures, the force wide number of aircraft in maintenance at any point (Non-Mission Capable Rate), the amount of time that the aircraft are not mission capable

(Non-Mission Capable Hours), the number of engines ordered from the maintenance depot (Depot Ping), the total flight hours achieved in the simulation run (Overall Flying Hours), and the number of spare engines in maintenance at any time (Spare Stock). Table 3 shows the recorded values for these other metrics.

Table 3. Model Metrics

	Metric	Mean	95% HW
Baseline Scenario	**F27BDB Fail Count**	19.20	1.57
	F271AJ Fail Count	18.92	1.62
	F27GPW Fail Count	19.48	1.51
	F27ECG Fail Count	19.56	1.14
	F27Z00 Fail Count	33.56	2.12
	Force Non-Mission Capable Rate	2.3%	0.26%
	Non-Mission Capable Hours/ Fighter	98.54	11.45
	Depot Ping	1.12	0.75
	Overall Flying Hours	4428.58	27.08
	Spare Stock	1.64	0.22

	Metric	Mean	95% HW
Extended Surge Scenario	**F27BDB Fail Count**	21.72	1.77
	F271AJ Fail Count	21.20	19.95
	F27GPW Fail Count	22.12	1.68
	F27ECG Fail Count	22.44	1.11
	F27Z00 Fail Count	39.24	2.25
	Force Non-Mission Capable Rate	2.7%	0.19%
	Non-Mission Capable Hours/ FIghter	118.51	8.08
	Depot Ping	2.64	0.73
	Overall Flying Hours	5286.94	93.33
	Spare Stock	1.55	0.16

It should be noted that the Non-Mission Capable Rate metric has appropriately low values because of the fact that we are only modeling failures associated with a small piece of the aircraft propulsion systems. Given more components modeled and adding constraints would result in higher rates. The Non-Mission Capable Hours metric also has a reasonable value because of the aforementioned reasoning.

Schedule Effectiveness

The Schedule Effectiveness MOE is based on requirements listed under Air Force Instruction 21-165 that delineates definitions, requirements, and exceptions in processing Flying Schedule Effectiveness [21]. We use it as a measurement that reflects the total amount of sorties flown during a phase in relation to the total amount of sorties expected to be flown given perfect conditions. The amount of sorties flown is divided by the number of sorties anticipated, resulting in a percentage that shows how effective the flying schedule is at generating sorties given the variables and conditions we simulate. Its formulation is

$$Schedule\ Effectiveness = Sorties_{flown}/Sorties_{anticipated}$$

Where:

$Sorties_{flown}$ = The number of sorties actually flown within a given time period
$Sorties_{anticipated}$ = The maximum number of sorties expected to be flown within a given time period

For our analysis, the daily sorties anticipated are 18 for the Surge phase, 12 for the Sustained Surge phase, and 6 for the Warfare Sustained Surge phase based on our daily flight schedule. This MOE is important in relation to a unit's effectiveness during a deployment because it provides clear snapshot of how operations are being conducted. It was applied to each of the three deployment phases. The resulting statistics for Schedule Effectiveness can be seen in Table 4.

Table 4. Schedule Effectiveness Statistics

	Baseline Scenario			
	Schedule Effectiveness: Surge Phase (7 days)	Schedule Effectiveness: Sustained Surge Phase (23 days)	Schedule Effectiveness: Warfare Sustained Surge Phase (150 days)	Schedule Effectiveness: Overall
Mean	81.08%	95.54%	99.93%	97.18%
95% HW	4.11%	2.02%	0.10%	0.60%
Min	61.11%	85.14%	99.00%	93.32%
Max	100%	100%	100%	99.54%
	Extended Surge Scenario			
	Schedule Effectiveness: Surge Phase (30 days)	**Schedule Effectiveness: Sustained Surge Phase (30 days)**	**Schedule Effectiveness: Warfare Sustained Surge Phase (120 days)**	**Schedule Effectiveness: Overall**
Mean	84.80%	92.47%	99.93%	93.23%
95% HW	4.04%	4.14%	0.13%	1.63%
Min	71.11%	72.50%	98.89%	85.86%
Max	100%	100%	100%	100.00%

Table 4 shows mostly anticipated and sensible results. But, as the length of the Surge phase increases from 7 days to 30 days, the amount of sorties fulfilled increases slightly. We initially expected a decrease in the Schedule Effectiveness between the scenarios because of the extended length of high tempo operations with the Extended Surge scenario. This may be due to the stochastic nature of the model as well as the fact that there could be underlying effects of system initialization on both scenarios. Because the Baseline scenario is significantly shorter than the Extended Surge scenario, these effects may be more pronounced. We hypothesize that the lower Schedule Effectiveness is a result of our random initialization of flying hours on each WUC for each fighter as they enter the simulation system. When looking at the experiment results and each of the 25 replications, the best case scenario yields perfect schedule effectiveness for the Surge phases in both scenarios. In the worst case, the baseline scenario reports a Surge phase schedule effectiveness of 61.11% while the Extended Surge scenario reports a Surge phase schedule effectiveness of 71.11%. The Simio simulation software has the capability of graphically relaying experiment results and data in the form of SIMIO Measure of Risk and Error (SMORE) plots and we utilize this capability to verify if there is a statistical difference between the Baseline and Extended Surge Scenarios. The SMORE plot shown in Figure 5 depicts the spread of the data in the form of maximum and minimum observations; mean and 95% confidence intervals; and median with upper (75%) and lower (25%) percentile confidence intervals.

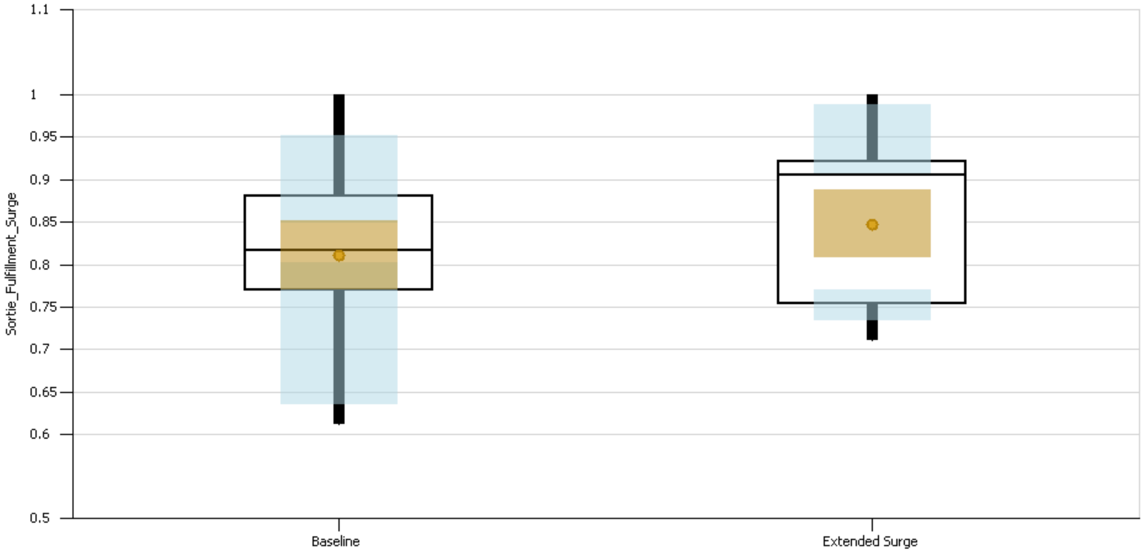


Figure 5. SMORE Plot for Surge Phase Schedule Effectiveness

Because of the fact that the confidence intervals between the scenarios overlap in Figure 5, we do not have enough evidence to conclude that the differences between them are statistically significant. But enlisting the explanatory power of a Paired t-Test in Microsoft Excel on this data also shows us that there the differences are not statistically significantly, despite a small p-value. This t-Test as well as the following tests in this analysis are all conducted at a 95% level of significance with a hypothesized data difference of zero between the two means. The t-Tests results of this data are included in Appendix A. Also of interest from Figure 5, note how the data for the baseline Surge scenario of 7 days, where we started with randomly assigned hours on all WUCs, looks roughly normally distributed with nearly equal mean and median along with a nearly symmetric spread. With the Extended Surge scenario and its additional 23 days, note the skewed distribution with the median and spread of the data toward higher values. This skew to the right is a result of more WUCs experiencing their first failure and having flying hours reset to zero for subsequent failures.

Considering the Sustained Surge phase, its length is increased from 23 days to 30 days between the scenarios. A drop in schedule effectiveness for this phase is observed and can be attributed to the longer phase length in the Extended Surge scenario. With more days of flying at the set operations tempo for the phase, the entire system incurs more failures that impact sortie fulfillment. The best case within the experiment for the scenarios also shows perfect schedule effectiveness. In the baseline scenario, the worst performance yields a schedule effectiveness of 85.14% and the Extended Surge scenario yields a worst case of 72.50% schedule effectiveness. The SMORE plots generated for this data can be seen in Figure 6.

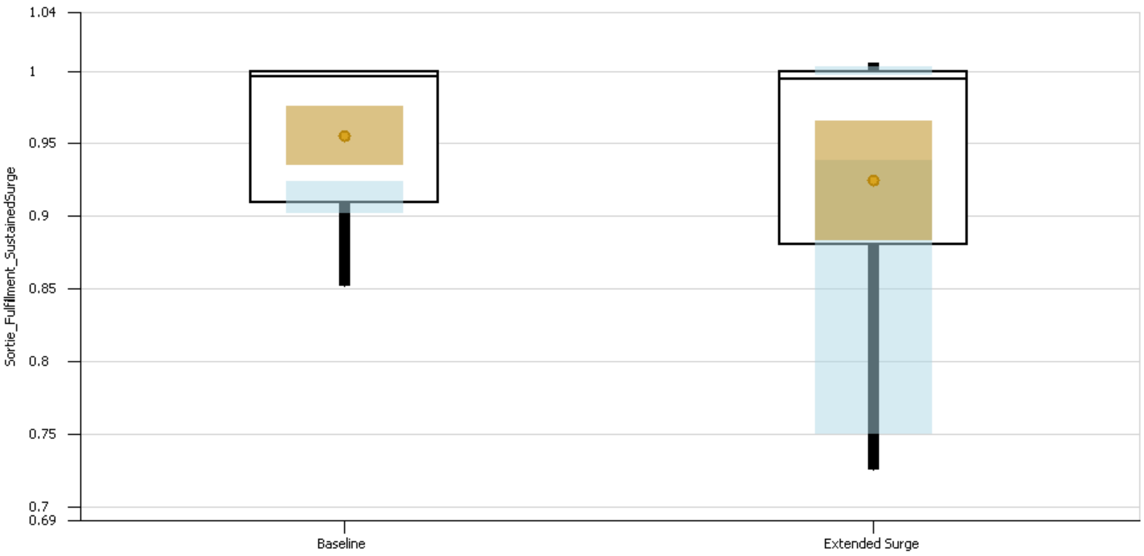


Figure 6. SMORE Plot for Sustained Surge Phase Schedule Effectiveness

Figure 6 shows that the confidence intervals of the data overlap therefore causing us to utilize another Paired t-Test. Although the t-Test found in Appendix A yields a small p-value, it confirms a lack of statistically significant differences between the scenarios based on our level of significance. For both the Baseline and Extended Surge scenarios in Figure 6, we see a median very close to one, with the data skewed toward smaller values for the Extended Surge scenario to include a minimum value of 72.5% versus a minimum value of 85% for the Baseline. Along with this, we also note a drop of about 4% in the mean Schedule Effectiveness for the Extended Surge scenario, indicating a practically significant decrease in Schedule Effectiveness for the Extended Surge.

The Warfare Sustained Surge phase for both scenarios shows nearly no change in schedule effectiveness. The Warfare Sustained Surge phase drops from 150 days to 120 days with the Extended Surge scenario. So, there is less time available for operations which could result in less flying hours and ultimately fewer failures. But, the operations tempo is so comparatively low during this phase that the system is almost always able to fulfill all scheduled sorties. Essentially, with a low operations tempo of six flights per day, the hours on the aircraft and their parts are accumulated at a slower pace and the maintenance shop is able to utilize its manpower, materials, and parts make repairs in a timely manner that does not strain the system for mission capable aircraft. The best case schedule effectiveness for the baseline and Extended Surge scenarios Warfare Sustained Surge phase is 100% . At their worst values, the schedule effectiveness for the baseline and Extended surge scenarios are 99% and 98.99% respectively. The SMORE plots generated for this data can be seen in Figure 7.

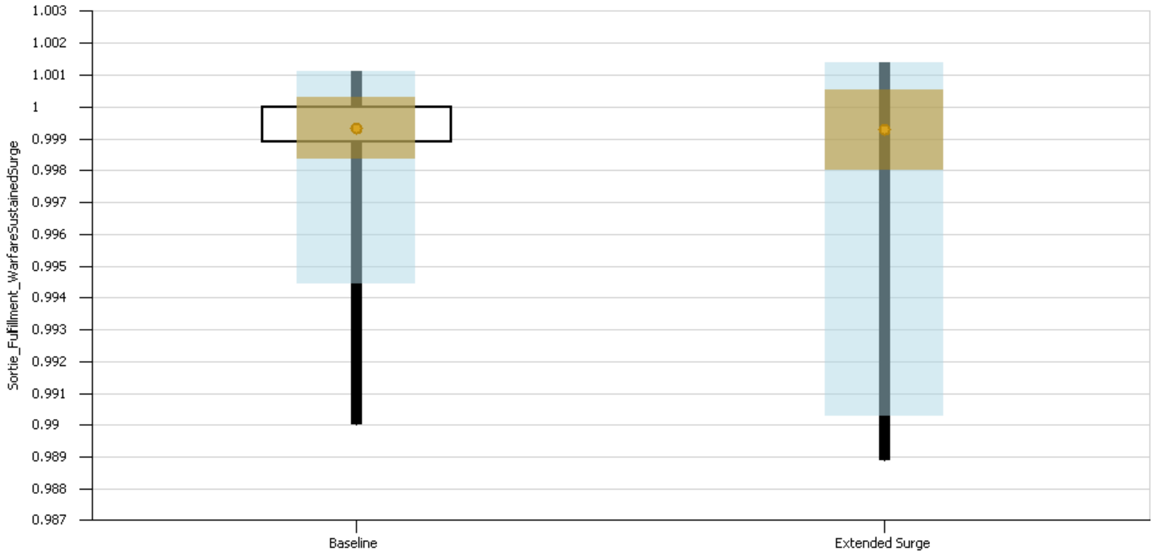


Figure 7. SMORE Plot for Warfare Sustained Surge Phase Schedule Effectiveness

Similar to the previous results, there is not a statistically significant difference between the scenarios cannot be determined with the SMORE plot shown in Figure 7. So, the Paired t-Test found in Appendix A was used to confirm that there is no statistical difference in the data. However, we once again note the data for the Extended Surge scenario is skewed toward longer values, indicating some decrease in Schedule Effectiveness for the Extended Surge.

We last look at the Schedule Effectiveness for each scenario overall. This data reports seemingly different results based on visual data inspection and the SMORE plots shown in Figure 8 with non-overlapping mean confidence intervals. In their best cases, the Baseline scenario maintained an overall effectiveness of 99.54% across all of the phases while the Extended Surge scenario reported at least one instance of perfect Schedule Effectiveness in a model run. In their worst cases, the Baseline scenario reports a Schedule Effectiveness of 93.32% while the Extended Surge scenario reports a Schedule Effectiveness of 85.86%.

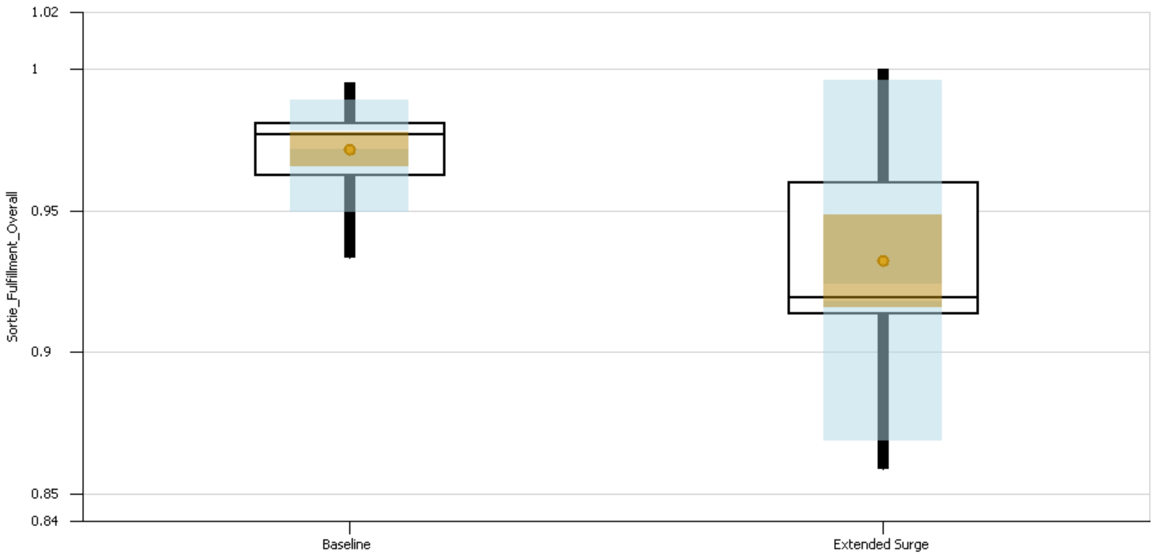
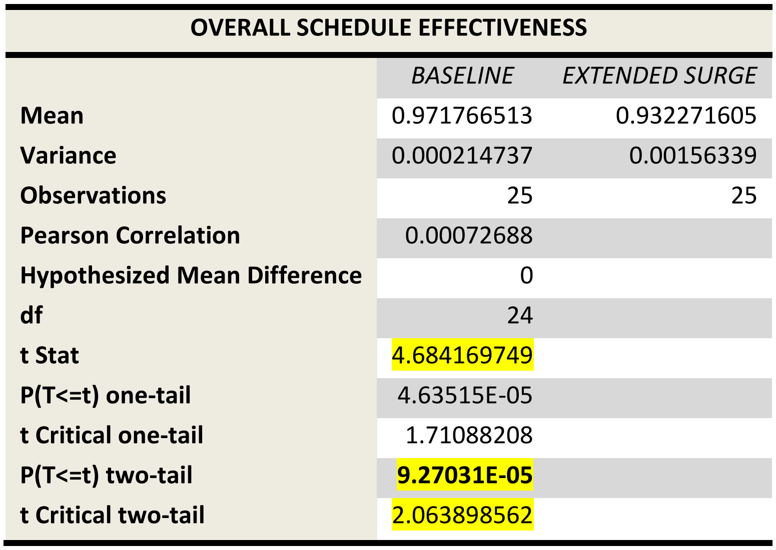


Figure 8. SMORE Plot for Overall Schedule Effectiveness

We also conduct another paired t-Test that yields significant results for Overall Schedule Effectiveness as seen in Appendix ATable 5. These results indicate that there is a statistically significant difference between the Baseline scenario and the Extended

Surge scenario where we altered the lengths of the sortie generation phases and reflected a small representation of constrained logistics.

Table 5. Paired t-Test for Overall Schedule Effectiveness



OVERALL SCHEDULE EFFECTIVENESS		
	BASELINE	*EXTENDED SURGE*
Mean	0.971766513	0.932271605
Variance	0.000214737	0.00156339
Observations	25	25
Pearson Correlation	0.00072688	
Hypothesized Mean Difference	0	
df	24	
t Stat	4.684169749	
P(T<=t) one-tail	4.63515E-05	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	**9.27031E-05**	
t Critical two-tail	2.063898562	

Average Daily Sorties

Correlated with the Schedule Effectiveness MOE is the Daily Sorties MOE, which represents the average number of sorties flown each day. The data that was used to compute this MOE was tracked and calculated using State Statistics within the Simio software. This MOE also lends to transparency in the model to verify how the unit is performing during the course of the deployment. The resulting statistics for Daily Sorties can be seen in Table 6 for each phase. Based on our daily flight schedule there are 18 sorties scheduled each day for the Surge phase, 12 for the Sustained Surge phase, and 6 for the Warfare Sustained Surge phase.

Table 6. Daily Sorties Statistics

	Baseline Scenario			
	Average Daily Sorties: Surge Phase (7 days)	Average Daily Sorties: Sustained Surge Phase (23 days)	Average Daily Sorties: Warfare Sustained Surge Phase (150 days)	Average Daily Sorties: Overall
Mean	14.59	11.46	6.00	7.03
95% HW	0.74	0.24	0.01	0.04
Min	11.00	10.22	5.94	6.75
Max	18.00	12.00	6.01	7.20
	Extended Surge Scenario			
	Average Daily Sorties: Surge Phase (30 days)	Average Daily Sorties: Sustained Surge Phase (30 days)	Average Daily Sorties: Warfare Sustained Surge Phase (120 days)	Average Daily Sorties: Overall
Mean	15.26	11.10	6.00	8.39
95% HW	0.73	0.50	0.01	0.15
Min	12.80	8.70	5.93	7.73
Max	18.00	12.07	6.01	9.00

Looking at the resulting data, an interesting effect can be seen on the average amount of sorties flown daily in the Surge phase for both scenarios. By increasing the number of days in the Surge phase, there is a resulting increase in the average number of sorties flown per day. This was an unexpected outcome and counter intuitive due to the fact that we anticipate less sorties being flown because of the increased wear and tear on the aircraft. With the increased operations tempo, there should be more failures but this result from our experiment may be attributed to the stochastic nature of the model or discrepancies due to system start-up bias as mentioned before. We hypothesize that the lower amount of daily sorties is a result of the same random initialization of flying hours on each WUC for each fighter. SMORE plots are shown in Figure 9.

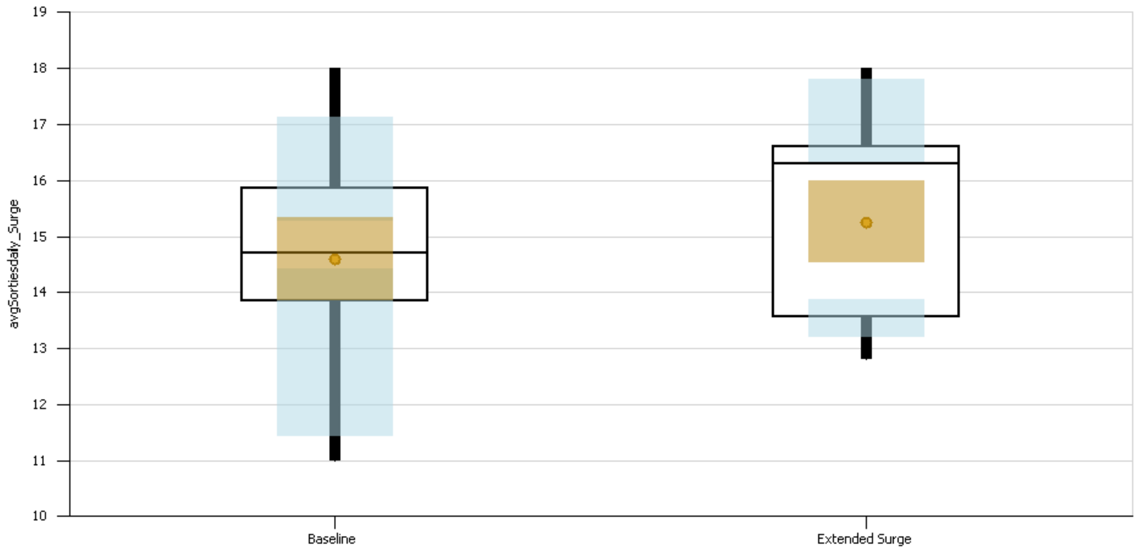


Figure 9. SMORE Plot for Surge Phase Differences

The interpretation of these results in Figure 9 reveals that the confidence intervals for the data representing both scenarios overlap. So we cannot justify the conclusion that there is a statistically significant difference between them. As a result, we conduct the Paired t-Tests found in Appendix B which leads us to conclude that the experiment results do not have a statistically significant difference. We see the same pattern in Figure 9 between the two scenarios as we saw in Figure 5.

As for the subsequent deployment phases, the results show a logical decrease in the MOE for the Sustained Surge phase between the scenarios and a seemingly no difference between the scenarios for the Warfare Sustained Surge phase due to the relative length and operations tempo of the phase. Our efforts in conducting a full analysis lead us to examining and testing if there were statistically significant differences between the scenarios for these phases as well. Visual inspection of the confidence intervals using the Simio SMORE plots as well as the same Paired t-Tests in Appendix B lead us to conclude that there is not a statistical difference.

Lastly, we looked at the number of sorties flown daily for each scenario overall. Visual inspection of the data clearly shows more sorties flown per day in the Extended Surge scenario. The SMORE plot shown in Figure 10 shows a statistical difference between the scenarios with non-overlapping confidence intervals. This indicates that there is a statistically significant increase in the average number of sorties flown in the Extended Surge scenario over the Baseline scenario.

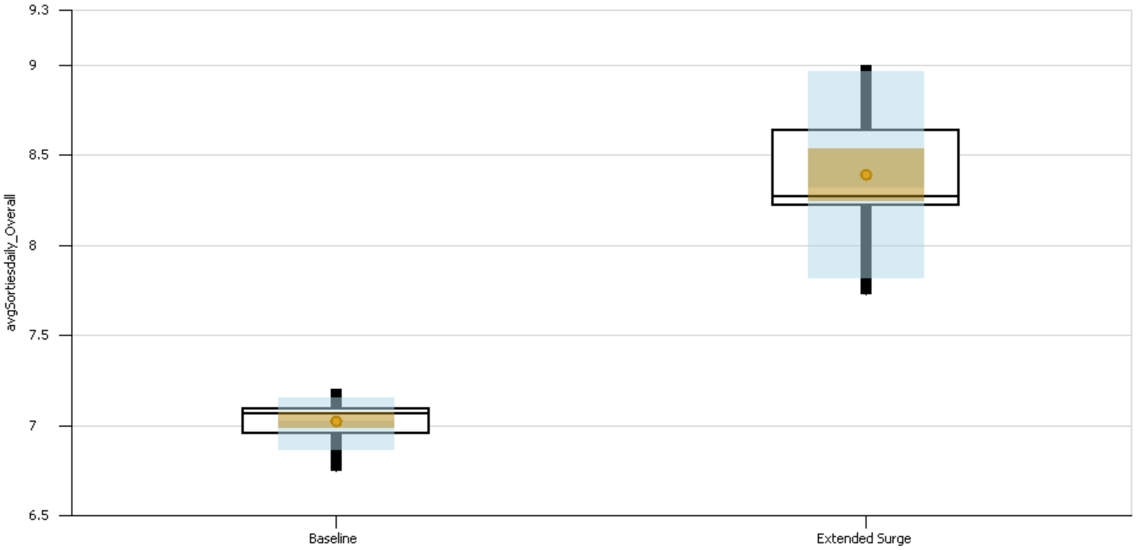


Figure 10. SMORE Plot for Overall Daily Sorties

Time To Repair

The Time to Repair (TTR) MOE represents the average amount of time it takes for an aircraft to be repaired in regards to a specifically broken WUC. The MOE was tracked using Tally Statistics within the Simio software. This MOE shows how the repair processes that utilize different parts and manpower entities are operating with respect to expected performance in a deployed or high impact environment. The resulting statistics for TTR for each of the modeled WUCs can be seen in Table 7 and Table 8. These TTR values are based on the task networks and tasks derived from LCOM.

Table 7. WUC Average TTR Statistics

	Baseline Scenario				
	F27BDB TTR Average	F271AJ TTR Average	F27GPW TTR Average	F27ECG TTR Average	F27Z00 TTR Average
Mean	2.59	1.26	14.76	6.61	20.29
95% HW	0.28	0.15	0.99	0.70	2.54
Min	1.92	0.74	11.65	3.13	15.31
Max	4.47	2.27	20.69	9.71	44.21
	Extended Surge Scenario				
	F27BDB TTR Average	F271AJ TTR Average	F27GPW TTR Average	F27ECG TTR Average	F27Z00 TTR Average
Mean	2.56	1.16	14.49	6.19	22.40
95% HW	0.25	0.11	0.92	0.64	1.92
Min	1.90	0.79	11.89	3.59	15.98
Max	4.24	1.77	21.29	10.22	30.56

Based on visual inspection as well as analysis in Microsoft Excel, the Table 5 results are not different between scenarios at our 95% level of statistical significance. In the case of our model, the only change between the scenarios is the length of the phases. Because of this, the repair processes within the simulation remain unaffected. So the differences that are seen above can be attributed to the stochastic nature of the model. The Paired t-Tests conducted on this data also support our conclusion of no statistical difference and can be found in in Appendix C.

This MOE is still relevant and valuable in terms of the framework we create for future analysis of this type. Given more data and constraints concerning the number of resources and the utilization of the logistical support aspects in the system, this MOE can effectively capture within the simulation how changes to repair processes impact the time it takes for WUCs to be repaired. This is a critical piece to decision makers looking into the limits and upper bounds of their capabilities given different scenarios and real world deployment outcomes.

Table 8. WUC Maximum TTR Statistics

	Baseline Scenario				
	F27BDB Maximum TTR	**F271AJ Maximum TTR**	**F27GPW Maximum TTR**	**F27ECG Maximum TTR**	**F27Z00 Maximum TTR**
Mean	6.79	6.19	25.86	17.80	73.62
95% HW	2.41	2.14	2.94	1.27	32.07
Min	2.65	0.97	18.88	13.63	23.47
Max	19.48	15.01	42.81	23.44	355.00
	Extended Surge Scenario				
	F27BDB Maximum TTR	**F271AJ Maximum TTR**	**F27GPW Maximum TTR**	**F27ECG Maximum TTR**	**F27Z00 Maximum TTR**
Mean	6.83	4.59	25.89	17.91	113.78
95% HW	2.40	1.58	2.94	1.22	21.89
Min	2.67	2.14	17.53	14.24	23.10
Max	19.48	14.74	42.81	23.44	157.37

Table 8 also shares conceptually similar results to those shown in Table 7. For, these numbers reveal the same lack of significant change in value between the scenarios for the aforementioned reasons. But, this MOE is also very important because it grants transparency to a decision maker on policy and strategy when dealing with the possibilities of long and potentially straining repair times for each of the WUCs considered for analysis. Essentially, knowing the longest a repair process could take can add another layer of reliability to an adequately informed decision making process.

Daily Failures

The Daily Failures MOE represents the average number of aircraft that fail per day. It was generated by utilizing the aforementioned Tally Statistics. As another MOE that provides critical information to decision makers, the average number of daily failures grants the ability to see how different operations tempos affect the maintainability of the aircraft. The resulting statistics for Daily Failures for each phase can be seen in Table 9.

Table 9. Daily Failures Statistics

	Baseline Scenario			
	Average Daily Failures: Surge Phase (7 days)	**Average Daily Failures: Sustained Surge Phase (23 days)**	**Average Daily Failures: Warfare Sustained Surge Phase (150 days)**	**Average Daily Failures: Overall**
Mean	4.94	0.78	0.39	0.61
95% HW	0.21	0.08	0.02	0.02
Min	4.14	0.48	0.31	0.53
Max	6.00	1.09	0.53	0.67

	Extended Surge Scenario			
	Average Daily Failures: Surge Phase (30 days)	**Average Daily Failures: Sustained Surge Phase (30 days)**	**Average Daily Failures: Warfare Sustained Surge Phase (120 days)**	**Average Daily Failures: Overall**
Mean	1.93	0.68	0.40	0.70
95% HW	0.07	0.06	0.02	0.02
Min	1.60	0.43	0.30	0.59
Max	2.23	1.07	0.49	0.79

These results show that as the lengths of the Surge and Sustained Surge phases increase going between the scenarios, there is a decrease in the average number of daily failures. There is an increase between the scenarios for the Warfare Sustained Surge phase. Regarding the Surge phase, we see that on visual inspection, the data appears to be different depending on the scenario. So, we look at the SMORE plot as seen in Figure 11 that shows a lack of overlap between the data confidence intervals which leads us to conclude that there is a statistically significant difference between the scenarios during the Surge phase. Initiating our model with random hours on each WUC for each fighter again comes to mind when considering the decrease in this MOE during this phase.

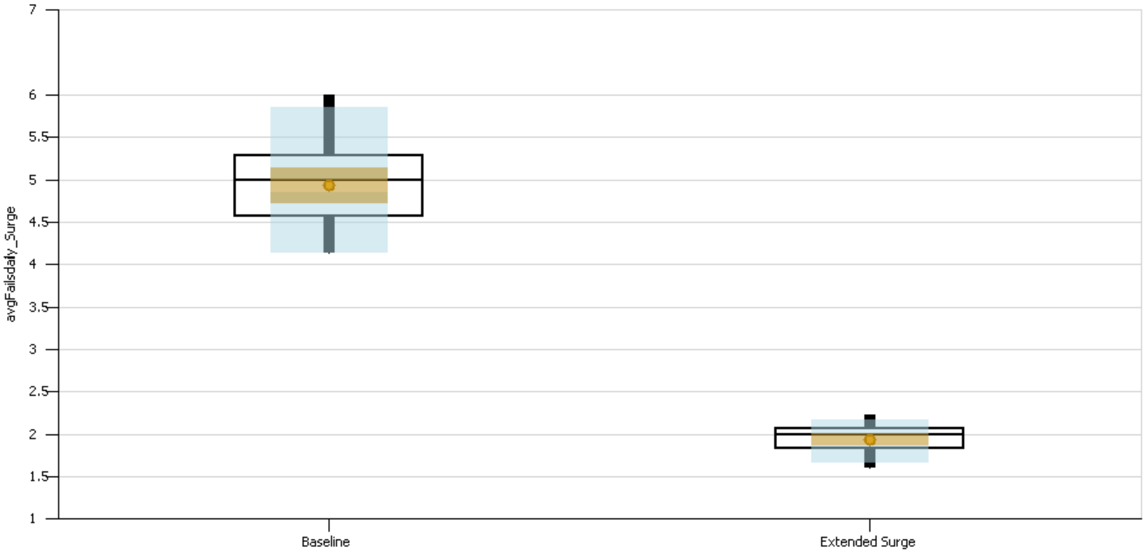


Figure 11. SMORE Plots for Surge Phase Daily Failures

Because of the visually small magnitude of the differences in the data seen in Sustained Surge and Warfare Sustained Surge phases, we look at their respective SMORE plots as well conduct the Paired t-Tests found in Appendix D and conclude that there is no statistically significant difference. Considering the data for the overall system, there is a logical increase in this MOE's value. Figure 12 depicts the SMORE plot spread of this data which shows no overlap between confidence intervals regarding the scenarios and the accompanying Paired t-Test in Appendix D tells us that there is a statistically significant difference in the data. However, practically speaking this difference is not significant due to the fact that all values are less than one fighter.

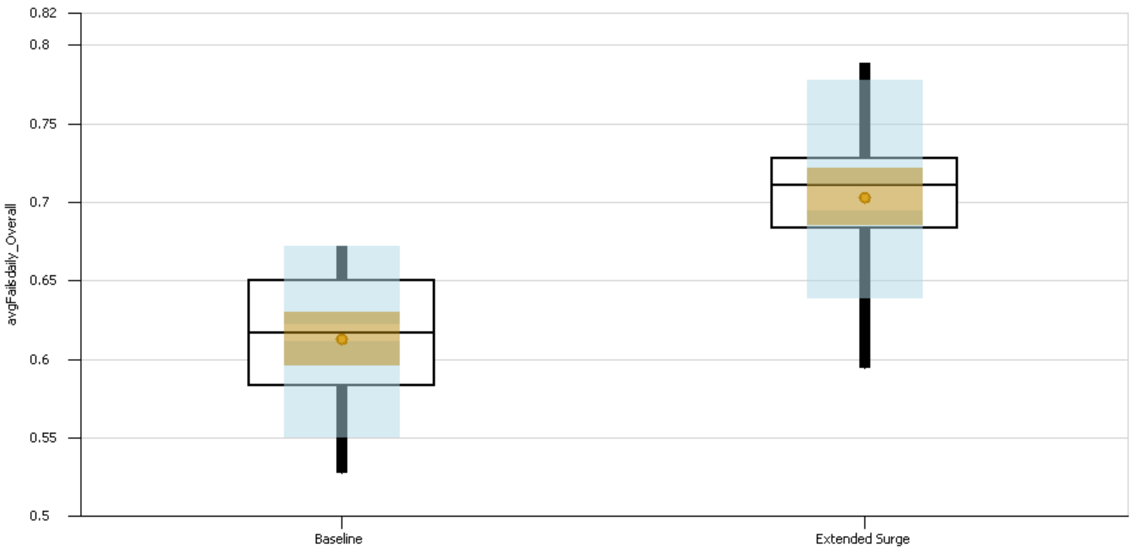


Figure 12. SMORE Plot for Overall Daily Failures

Fuel Usage

Fuel usage per sortie informs us on the average amount of fuel used per sortie, throughout the entire simulation. It provides another metric that is significant to mission planning and analysis for decision makers. The resulting statistics for Fuel usage per phase can be seen in Table 8.

Table 8. Fuel Usage Statistics

	Baseline Scenario
	Fuel Usage
Mean	20283.68
95% HW	9.30
Min	20245.53
Max	20319.25

	Extended Surge Scenario
	Fuel Usage
Mean	20285.91
95% HW	10.59
Min	20236.07
Max	20322.07

To inspect the differences between the scenarios, we look at the Simio SMORE plots once again with the goal of seeing how the data is distributed as seen in Figure 13.

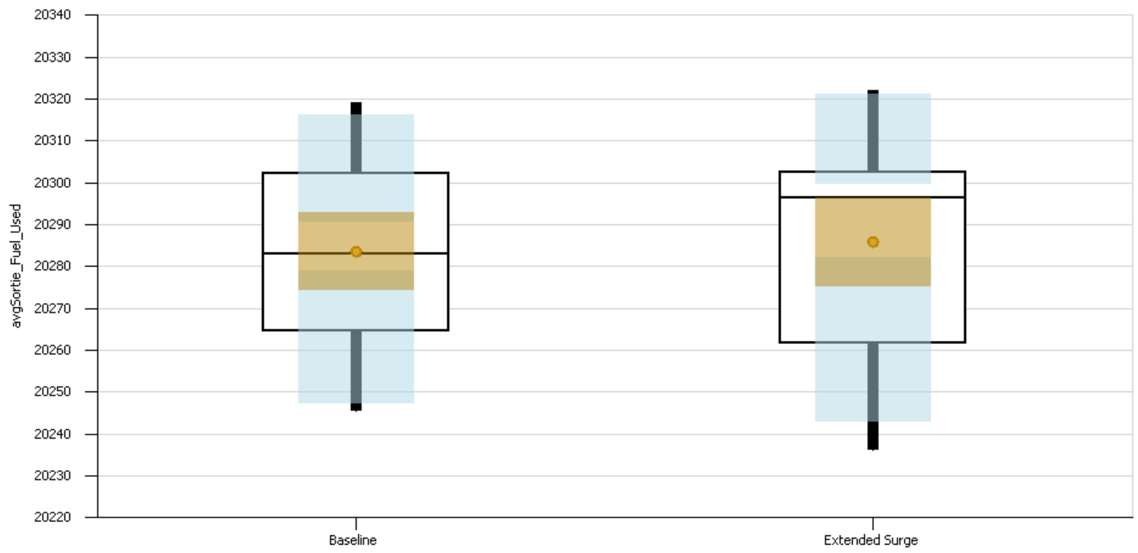


Figure 13. SMORE Plot for Fuel Usage

With no visual separation between the confidence intervals of the scenarios, we once again rely on the results of the Paired t-Test found in Appendix E to verify there is not a statistically significant difference between the scenarios. This MOE is critical to transparency in analysis because of the fact that given changes in the scenarios and how the aircraft operate, the ability to see circumstantially generated ramifications on operational capabilities. It can also be used in the future to look deeper into how the system operates and changes by paving the way for the addition of many more details to include second order effects due to this piece.

Summary

Our analysis and results provided us with mostly expected outcomes that make sense based on how we understand the system and how it operates. Although we did run into some unexpected results such as the decrease in Average Daily Sorties flown during the Surge Phases of each scenario, we are able to deduce the reasons for such occuranes.

Overall, this provides us with a high level of confidence in our results. As stated before, our research serves as a framework for this type of aggregated analysis that successfully takes into account data and information from external sources to ultimately simulate a system that is affected by constrained logistics. These results show that it is computationally feasible and necessary to have a developed approach for incorporating maintenance manpower and supply data from multiple sources into a discrete event simulation model of sortie operations. Real world conclusions should not be drawn from the research we performed as it stands, but the future of this effort will allow for better, more informed decisions to be made. The effect of constrained logistics on our modeled scenarios shows that there is a significant impact on situational outcomes. The metrics we look at and the MOEs we use to reinforce this point adequately provide an overview of the capabilities that a decision maker would have in regards to operational planning and wargaming as an aid for better informed decisions to be made.

V. Conclusions and Recommendations

Chapter Overview

In this ending section of this thesis, we present the conclusions of our research and what we found by conducting our simulation study, we assert the significance of our research and how it contributes to addressing the issue of accepting abstraction and neglecting of pieces of reality that are deemed unnecessary for the validity of military simulation models, and we finally offer recommendations for future research regarding the topic of the consideration of logistics to includes its constraints and capabilities.

Conclusions of Research

This thesis and our research was conducted with the goal of shedding light upon the existential issue of the impact of constrained logistics on wargaming and analysis and creating the framework for a way to utilize discreet event simulation to analyze how a system of deployed aircraft in a potentially logistically contested location will perform when taking into account the data generated from data and information that is non-native to the simulation environment. We successfully demonstrate that incorporating constrained logistics does play an integral role in effecting model outcomes and that we can port information from existing models such as LCOM into more flexible tools for greater analytic capability.

Recommendations for Future Research

An area of future research that is recommended to further the efforts presented in this thesis has to do with the incorporation of more data into such a model. As previously stated in Chapter 3 of this thesis, we focus our modeling and research on data about the maintenance manpower, supplies, and tasks that are performed to support the operations of a simulated deployment scenario. But, we select data to utilize in our research based on our ability to truncate, aggregate, and incorporate into our model. Based on the intricate experience of manipulating the data in the aforementioned ways by hand, we recommend the use of a macro or programming code to sort and incorporate the data into our model automatically. One could save themselves time and effort in utilizing automation to feed data into the model which can be beneficial to the overall analysis. Within computational limits, the access to more data means that the real world equivalent to a modeled system will be better represented.

Aside from the simple addition of more data, an automated way to parse and include the task networks from LCOM into a model would be an excellent area for further research. Looking into the task networks as they stand within an LCOM database, the tasks are intertwined and very convoluted. As a consequence, the inclusion of entire task networks that we do not represent and that could have significant impacts on simulation outcomes requires a large investment of time and examination. With an automated way of doing this, the same previously stated result of better real world simulation representation would be achieved.

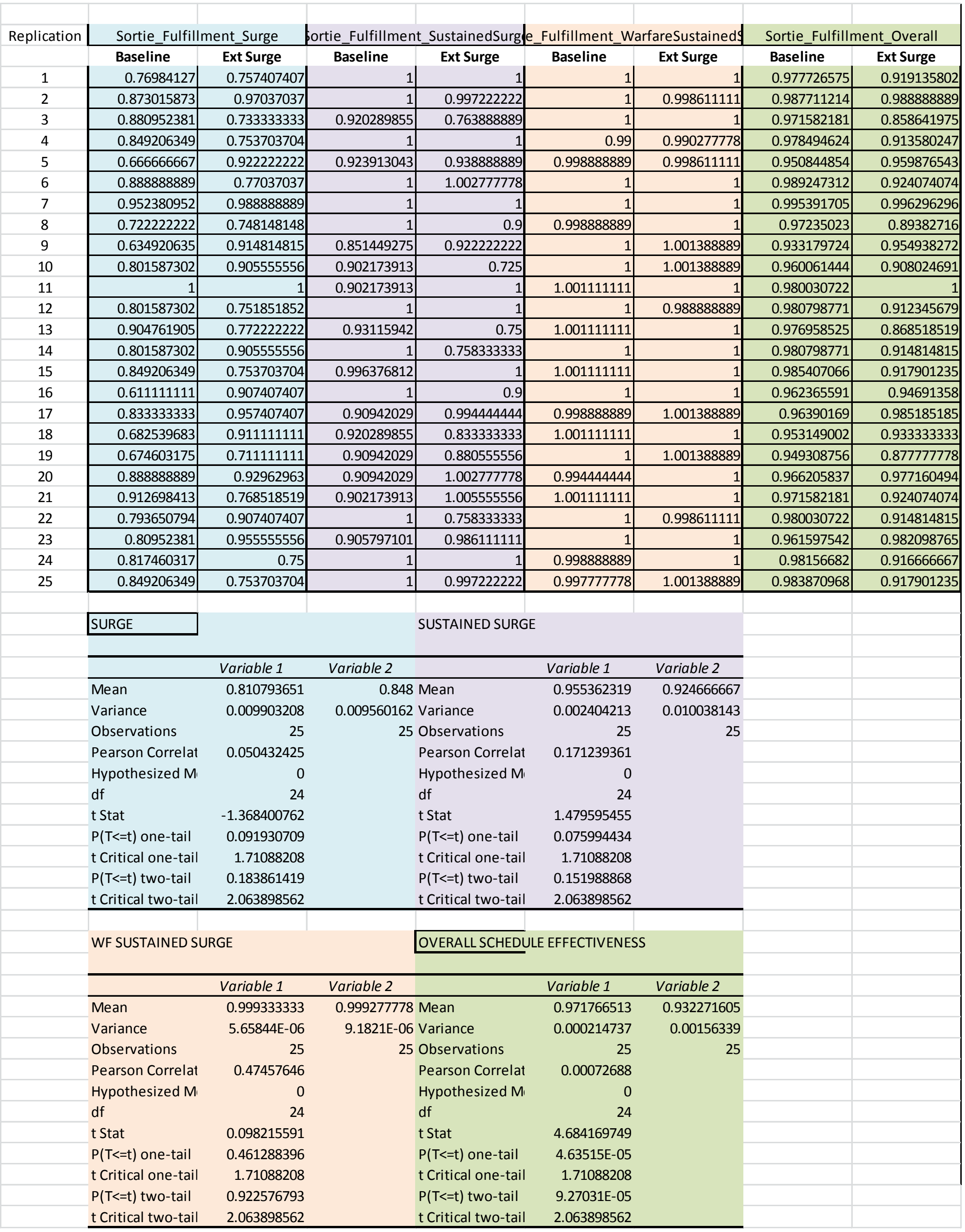
Lastly, we see the creation of a data dictionary that allows the incorporation of UTCs into our model framework as a critical area of future research. Such a data dictionary would allow WUCs to be matched with National Stock Numbers (NSN) that are used by UTCs. As a simple explanation that relates to this research, UTCs along with the NSNs describe what parts and resources are moving into a deployed location. The WUCs describe which of those parts and resources are needed and in what manner. As it stands, there is lies disconnect between these two concepts. If there were a bridge between them such as a data dictionary to match the parts and resources coming in with those necessary for maintenance, exceptional insight could be gained.

Summary

This thesis studies and simulates the operations of a flying unit of F-16 aircraft that are deployed to include the explicit modeling of selected portions of supply and maintenance support aspects. We accomplish our goal of further providing conceptually verified proof that integrating logistics into analytical efforts will yield the conclusion that there is more information to be discovered and relayed to decision makers. Essentially, the consideration of the constraints and capabilities due to logistics can and should be represented in models for current and future analyses because they do have a significant impact on analytic outcomes. By simulating the constraints and capabilities due to logistics, we provide proof of concept for including them into our model which gives insight to the ramifications of war time, wargaming, and war planning decisions for all interested parties. Incorporating logistics in simulation models provides a more complete view of a military scenario and will be the crucial addition to analysis that bolsters the United States Air Force in maintaining its dominance in air, space, and cyberspace.

Appendix

Appendix A. Paired t-Test Results for Schedule Effectiveness

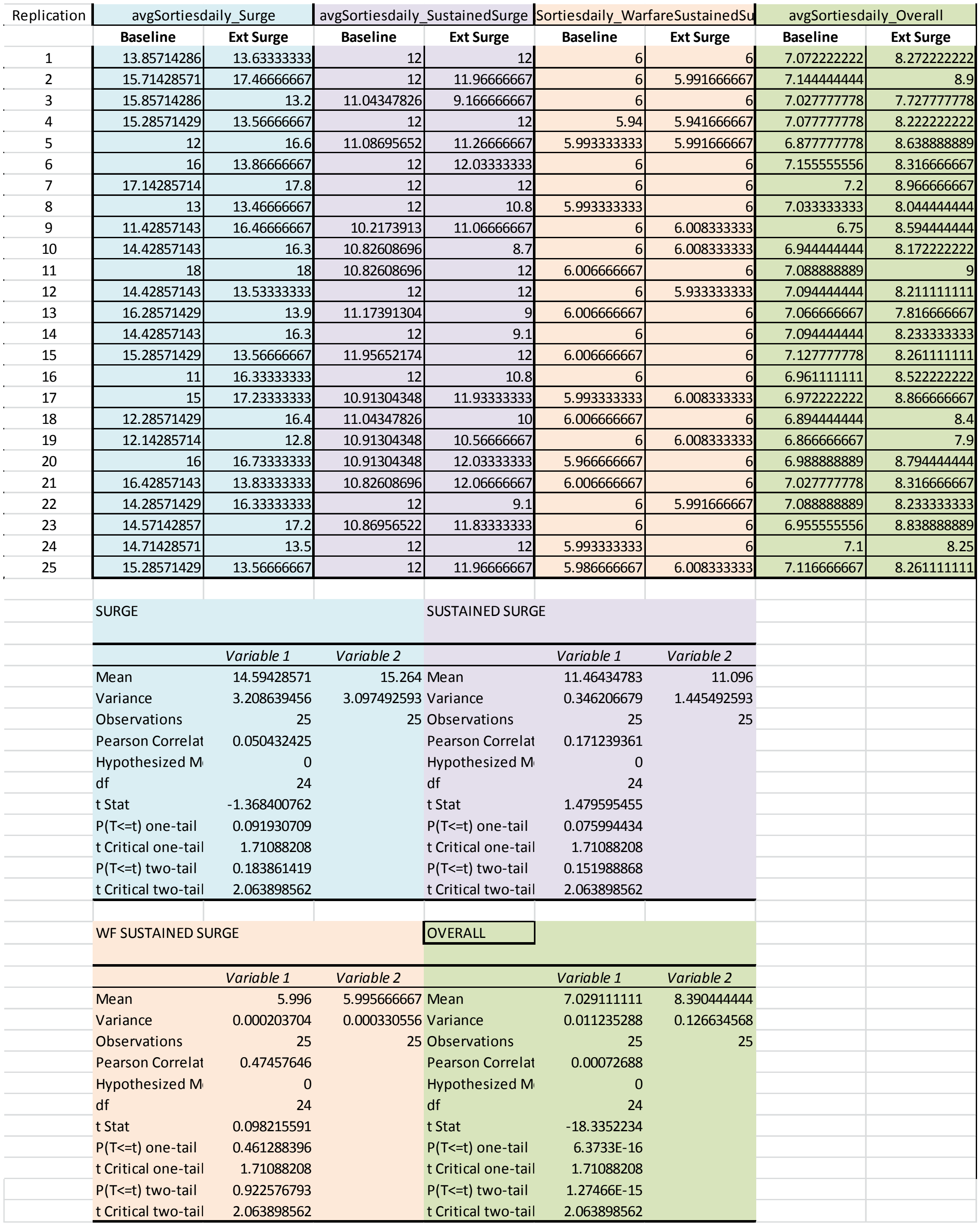


Replication	Sortie_Fulfillment_Surge		ortie_Fulfillment_SustainedSurg		e_Fulfillment_WarfareSustained		Sortie_Fulfillment_Overall	
	Baseline	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**
1	0.76984127	0.757407407	1	1	1	1	0.977726575	0.919135802
2	0.873015873	0.97037037	1	0.997222222	1	0.998611111	0.987711214	0.988888889
3	0.880952381	0.733333333	0.920289855	0.763888889	1	1	0.971582181	0.858641975
4	0.849206349	0.753703704	1	1	0.99	0.990277778	0.978494624	0.913580247
5	0.666666667	0.922222222	0.923913043	0.938888889	0.998888889	0.998611111	0.950844854	0.959876543
6	0.888888889	0.77037037	1	1.002777778	1	1	0.989247312	0.924074074
7	0.952380952	0.988888889	1	1	1	1	0.995391705	0.996296296
8	0.722222222	0.748148148	1	0.9	0.998888889	1	0.97235023	0.89382716
9	0.634920635	0.914814815	0.851449275	0.922222222	1	1.001388889	0.933179724	0.954938272
10	0.801587302	0.905555556	0.902173913	0.725	1	1.001388889	0.960061444	0.908024691
11	1	1	0.902173913	1	1.001111111	1	0.980030722	1
12	0.801587302	0.751851852	1	1	1	0.988888889	0.980798771	0.912345679
13	0.904761905	0.772222222	0.93115942	0.75	1.001111111	1	0.976958525	0.868518519
14	0.801587302	0.905555556	1	0.758333333	1	1	0.980798771	0.914814815
15	0.849206349	0.753703704	0.996376812	1	1.001111111	1	0.985407066	0.917901235
16	0.611111111	0.907407407	1	0.9	1	1	0.962365591	0.94691358
17	0.833333333	0.957407407	0.90942029	0.994444444	0.998888889	1.001388889	0.96390169	0.985185185
18	0.682539683	0.911111111	0.920289855	0.833333333	1.001111111	1	0.953149002	0.933333333
19	0.674603175	0.711111111	0.90942029	0.880555556	1	1.001388889	0.949308756	0.877777778
20	0.888888889	0.92962963	0.90942029	1.002777778	0.994444444	1	0.966205837	0.977160494
21	0.912698413	0.768518519	0.902173913	1.005555556	1.001111111	1	0.971582181	0.924074074
22	0.793650794	0.907407407	1	0.758333333	1	0.998611111	0.980030722	0.914814815
23	0.80952381	0.955555556	0.905797101	0.986111111	1	1	0.961597542	0.982098765
24	0.817460317	0.75	1	1	0.998888889	1	0.98156682	0.916666667
25	0.849206349	0.753703704	1	0.997222222	0.997777778	1.001388889	0.983870968	0.917901235

SURGE			SUSTAINED SURGE		
	Variable 1	*Variable 2*		*Variable 1*	*Variable 2*
Mean	0.810793651	0.848	Mean	0.955362319	0.924666667
Variance	0.009903208	0.009560162	Variance	0.002404213	0.010038143
Observations	25	25	Observations	25	25
Pearson Correlat	0.050432425		Pearson Correlat	0.171239361	
Hypothesized M	0		Hypothesized M	0	
df	24		df	24	
t Stat	-1.368400762		t Stat	1.479595455	
P(T<=t) one-tail	0.091930709		P(T<=t) one-tail	0.075994434	
t Critical one-tail	1.71088208		t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.183861419		P(T<=t) two-tail	0.151988868	
t Critical two-tail	2.063898562		t Critical two-tail	2.063898562	

WF SUSTAINED SURGE			OVERALL SCHEDULE EFFECTIVENESS		
	Variable 1	*Variable 2*		*Variable 1*	*Variable 2*
Mean	0.999333333	0.999277778	Mean	0.971766513	0.932271605
Variance	5.65844E-06	9.1821E-06	Variance	0.000214737	0.00156339
Observations	25	25	Observations	25	25
Pearson Correlat	0.47457646		Pearson Correlat	0.00072688	
Hypothesized M	0		Hypothesized M	0	
df	24		df	24	
t Stat	0.098215591		t Stat	4.684169749	
P(T<=t) one-tail	0.461288396		P(T<=t) one-tail	4.63515E-05	
t Critical one-tail	1.71088208		t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.922576793		P(T<=t) two-tail	9.27031E-05	
t Critical two-tail	2.063898562		t Critical two-tail	2.063898562	

Appendix B. Paired t-Tests for Daily Sorties



Replication	avgSortiesdaily_Surge		avgSortiesdaily_SustainedSurge		Sortiesdaily_WarfareSustainedSu		avgSortiesdaily_Overall	
	Baseline	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**
1	13.85714286	13.63333333	12	12	6	6	7.072222222	8.272222222
2	15.71428571	17.46666667	12	11.96666667	6	5.991666667	7.144444444	8.9
3	15.85714286	13.2	11.04347826	9.166666667	6	6	7.027777778	7.727777778
4	15.28571429	13.56666667	12	12	5.94	5.941666667	7.077777778	8.222222222
5	12	16.6	11.08695652	11.26666667	5.993333333	5.991666667	6.877777778	8.638888889
6	16	13.86666667	12	12.03333333	6	6	7.155555556	8.316666667
7	17.14285714	17.8	12	12	6	6	7.2	8.966666667
8	13	13.46666667	12	10.8	5.993333333	6	7.033333333	8.044444444
9	11.42857143	16.46666667	10.2173913	11.06666667	6	6.008333333	6.75	8.594444444
10	14.42857143	16.3	10.82608696	8.7	6	6.008333333	6.944444444	8.172222222
11	18	18	10.82608696	12	6.006666667	6	7.088888889	9
12	14.42857143	13.53333333	12	12	6	5.933333333	7.094444444	8.211111111
13	16.28571429	13.9	11.17391304	9	6.006666667	6	7.066666667	7.816666667
14	14.42857143	16.3	12	9.1	6	6	7.094444444	8.233333333
15	15.28571429	13.56666667	11.95652174	12	6.006666667	6	7.127777778	8.261111111
16	11	16.33333333	12	10.8	6	6	6.961111111	8.522222222
17	15	17.23333333	10.91304348	11.93333333	5.993333333	6.008333333	6.972222222	8.866666667
18	12.28571429	16.4	11.04347826	10	6.006666667	6	6.894444444	8.4
19	12.14285714	12.8	10.91304348	10.56666667	6	6.008333333	6.866666667	7.9
20	16	16.73333333	10.91304348	12.03333333	5.966666667	6	6.988888889	8.794444444
21	16.42857143	13.83333333	10.82608696	12.06666667	6.006666667	6	7.027777778	8.316666667
22	14.28571429	16.33333333	12	9.1	6	5.991666667	7.088888889	8.233333333
23	14.57142857	17.2	10.86956522	11.83333333	6	6	6.955555556	8.838888889
24	14.71428571	13.5	12	12	5.993333333	6	7.1	8.25
25	15.28571429	13.56666667	12	11.96666667	5.986666667	6.008333333	7.116666667	8.261111111

SURGE

	Variable 1	*Variable 2*
Mean	14.59428571	15.264
Variance	3.208639456	3.097492593
Observations	25	25
Pearson Correlat	0.050432425	
Hypothesized M	0	
df	24	
t Stat	-1.368400762	
P(T<=t) one-tail	0.091930709	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.183861419	
t Critical two-tail	2.063898562	

SUSTAINED SURGE

	Variable 1	*Variable 2*
Mean	11.46434783	11.096
Variance	0.346206679	1.445492593
Observations	25	25
Pearson Correlat	0.171239361	
Hypothesized M	0	
df	24	
t Stat	1.479595455	
P(T<=t) one-tail	0.075994434	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.151988868	
t Critical two-tail	2.063898562	

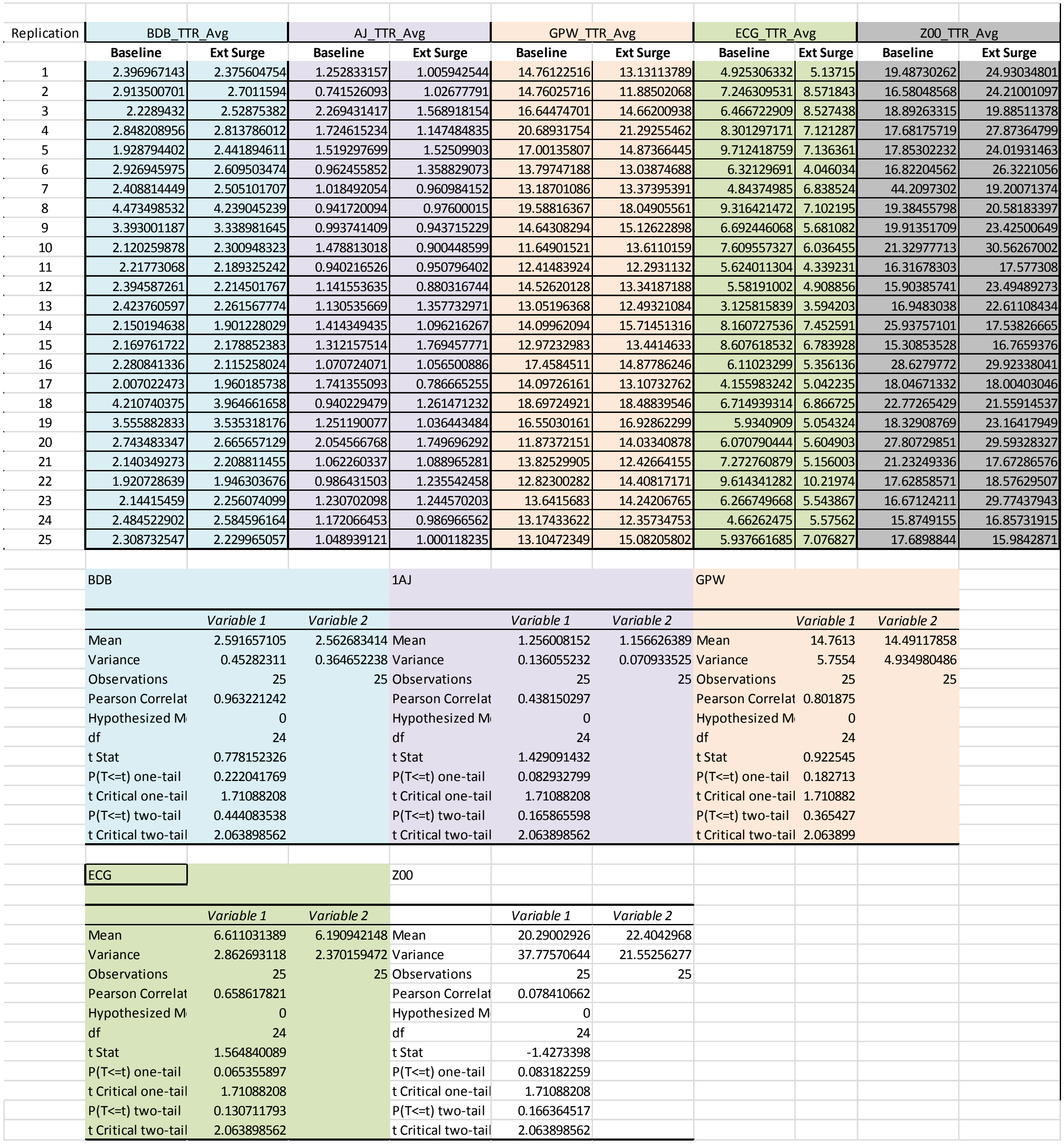
WF SUSTAINED SURGE

	Variable 1	*Variable 2*
Mean	5.996	5.995666667
Variance	0.000203704	0.000330556
Observations	25	25
Pearson Correlat	0.47457646	
Hypothesized M	0	
df	24	
t Stat	0.098215591	
P(T<=t) one-tail	0.461288396	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.922576793	
t Critical two-tail	2.063898562	

OVERALL

	Variable 1	*Variable 2*
Mean	7.029111111	8.390444444
Variance	0.011235288	0.126634568
Observations	25	25
Pearson Correlat	0.00072688	
Hypothesized M	0	
df	24	
t Stat	-18.3352234	
P(T<=t) one-tail	6.3733E-16	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	1.27466E-15	
t Critical two-tail	2.063898562	

Appendix C. Paired t-Tests for TTR



Replication	BDB_TTR_Avg		AJ_TTR_Avg		GPW_TTR_Avg		ECG_TTR_Avg		Z00_TTR_Avg	
	Baseline	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**
1	2.396967143	2.375604754	1.252833157	1.005942544	14.76122516	13.13113789	4.925306332	5.13715	19.48730262	24.93034801
2	2.913500701	2.7011594	0.741526093	1.02677791	14.76025716	11.88502068	7.246309531	8.571843	16.58048568	24.21001097
3	2.2289432	2.52875382	2.269431417	1.568918154	16.64474701	14.66200938	6.466722909	8.527438	18.89263315	19.88511378
4	2.848208956	2.813786012	1.724615234	1.147484835	20.68931754	21.29255462	8.301297171	7.121287	17.68175719	27.87364799
5	1.928794402	2.441894611	1.519297699	1.52509903	17.00135807	14.87366445	9.712418759	7.136361	17.85302232	24.01931463
6	2.926945975	2.609503474	0.962455852	1.358829073	13.79747188	13.03874688	6.32129691	4.046034	16.82204562	26.3221056
7	2.408814449	2.505101707	1.018492054	0.960984152	13.18701086	13.37395391	4.84374985	6.838524	44.2097302	19.20071374
8	4.473498532	4.239045239	0.941720094	0.97600015	19.58816367	18.04905561	9.316421472	7.102195	19.38455798	20.58183397
9	3.393001187	3.338981645	0.993741409	0.943715229	14.64308294	15.12622898	6.692446068	5.681082	19.91351709	23.42500649
10	2.120259878	2.300948323	1.478813018	0.900448599	11.64901521	13.6110159	7.609557327	6.036455	21.32977713	30.56267002
11	2.21773068	2.189325242	0.940216526	0.950796402	12.41483924	12.2931132	5.624011304	4.339231	16.31678303	17.577308
12	2.394587261	2.214501767	1.141553635	0.880316744	14.52620128	13.34187188	5.58191002	4.908856	15.90385741	23.49489273
13	2.423760597	2.261567774	1.130535669	1.357732971	13.05196368	12.49321084	3.125815839	3.594203	16.9483038	22.61108434
14	2.150194638	1.901228029	1.414349435	1.096216267	14.09962094	15.71451316	8.160727536	7.452591	25.93757101	17.53826665
15	2.169761722	2.178852383	1.312157514	1.769457771	12.97232983	13.4414633	8.607618532	6.783928	15.30853528	16.7659376
16	2.280841336	2.115258024	1.070724071	1.056500886	17.4584511	14.87786246	6.11023299	5.356136	28.6279772	29.92338041
17	2.007022473	1.960185738	1.741355093	0.786665255	14.09726161	13.10732762	4.155983242	5.042235	18.04671332	18.00403046
18	4.210740375	3.964661658	0.940229479	1.261471232	18.69724921	18.48839546	6.714939314	6.866725	22.77265429	21.55914537
19	3.555882833	3.535318176	1.251190077	1.036443484	16.55030161	16.92862299	5.9340909	5.054324	18.32908769	23.16417949
20	2.743483347	2.665657129	2.054566768	1.749696292	11.87372151	14.03340878	6.070790444	5.604903	27.80729851	29.59328327
21	2.140349273	2.208811455	1.062260337	1.088965281	13.82529905	12.42664155	7.272760879	5.156003	21.23249336	17.67286576
22	1.920728639	1.946303676	0.986431503	1.235542458	12.82300282	14.40817171	9.614341282	10.21974	17.62858571	18.57629507
23	2.14415459	2.256074099	1.230702098	1.244570203	13.6415683	14.24206765	6.266749668	5.543867	16.67124211	29.77437943
24	2.484522902	2.584596164	1.172066453	0.986966562	13.17433622	12.35734753	4.66262475	5.57562	15.8749155	16.85731915
25	2.308732547	2.229965057	1.048939121	1.000118235	13.10472349	15.08205802	5.937661685	7.076827	17.6898844	15.9842871

BDB

	Variable 1	*Variable 2*
Mean	2.591657105	2.562683414
Variance	0.45282311	0.364652238
Observations	25	25
Pearson Correlat	0.963221242	
Hypothesized M	0	
df	24	
t Stat	0.778152326	
P(T<=t) one-tail	0.222041769	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.444083538	
t Critical two-tail	2.063898562	

1AJ

	Variable 1	*Variable 2*
Mean	1.256008152	1.156626389
Variance	0.136055232	0.070933525
Observations	25	25
Pearson Correlat	0.438150297	
Hypothesized M	0	
df	24	
t Stat	1.429091432	
P(T<=t) one-tail	0.082932799	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.165865598	
t Critical two-tail	2.063898562	

GPW

	Variable 1	*Variable 2*
Mean	14.7613	14.49117858
Variance	5.7554	4.934980486
Observations	25	25
Pearson Correlat	0.801875	
Hypothesized M	0	
df	24	
t Stat	0.922545	
P(T<=t) one-tail	0.182713	
t Critical one-tail	1.710882	
P(T<=t) two-tail	0.365427	
t Critical two-tail	2.063899	

ECG

	Variable 1	*Variable 2*
Mean	6.611031389	6.190942148
Variance	2.862693118	2.370159472
Observations	25	25
Pearson Correlat	0.658617821	
Hypothesized M	0	
df	24	
t Stat	1.564840089	
P(T<=t) one-tail	0.065355897	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.130711793	
t Critical two-tail	2.063898562	

Z00

	Variable 1	*Variable 2*
Mean	20.29002926	22.4042968
Variance	37.77570644	21.55256277
Observations	25	25
Pearson Correlat	0.078410662	
Hypothesized M	0	
df	24	
t Stat	-1.4273398	
P(T<=t) one-tail	0.083182259	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.166364517	
t Critical two-tail	2.063898562	

Replication	BDB_TTR_Max		AJ_TTR_Max		GPW_TTR_Max		ECG_TTR_Max		Z00_TTR_Max	
	Baseline	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**
1	3.983971	3.983970893	3.536055633	2.156879066	25.79702131	25.79702131	14.32442801	16.16688728	41.51400831	147.1154863
2	5.920476	5.920476194	0.965408533	2.619554067	21.73754481	21.73754481	17.94282609	17.94282609	25.15373363	147.1448703
3	3.344405	4.223797821	14.7380358	14.7380358	28.04291853	28.04291853	23.20397072	23.20397072	41.53904969	110.5395132
4	17.29018	17.29018381	15.01475111	3.201311716	41.95724282	41.95724282	19.55470644	19.55470644	29.82114429	146.8623895
5	3.615101	4.238737656	14.52325277	14.52325277	24.89997102	24.89997102	20.44556306	20.44556306	29.72766012	146.9222214
6	4.654592	5.093415387	2.923385681	3.897530247	21.57641511	22.21577109	16.23487944	14.25459934	23.68680563	157.37282
7	3.23565	5.000036356	3.114521508	2.55077088	24.69566918	24.69566918	13.63353773	14.25333505	355	156.5404605
8	19.48027	19.48026982	3.681395467	3.681395467	42.81220758	42.81220758	21.56085131	21.56085131	27.56176396	145
9	17.07252	17.07251754	2.568917358	2.877651384	22.05225164	22.05225164	23.4405105	23.4405105	42.76464744	146.8430008
10	3.50405	3.643983422	13.46768292	3.181285866	21.16630862	21.16630862	19.31092219	19.31092219	147.5584734	146.989238
11	3.878851	3.87885065	2.269754141	2.77011996	18.87763409	20.70973518	14.36540808	15.9266505	23.55081403	146.7339753
12	4.196086	4.196086373	3.383147969	3.47570125	23.16106709	23.16106709	14.29606885	14.39540045	26.05561587	146.5547068
13	3.815146	3.971076467	2.602554297	2.761281814	20.94333696	20.57547288	13.89234244	14.23777025	23.47040492	128.8347127
14	3.786212	2.668644695	14.22674116	4.28422935	24.91712906	24.91712906	21.92615883	21.92615883	147.1305497	26.20971124
15	3.022523	3.329683651	3.262653327	4.334375245	20.96363528	20.96363528	16.96307155	16.96307155	26.15930591	52.47497327
16	5.125631	3.463568977	2.810207074	3.147467791	37.33103408	37.33103408	20.7917298	20.7917298	147.0840506	147.4572649
17	2.651963	2.84792742	13.46041794	2.470475287	25.31209339	25.31209339	14.35751751	16.25785578	27.47569338	27.47569338
18	18.80565	18.80565161	2.839613365	3.387342089	41.70026121	41.70026121	19.4753648	19.4753648	146.8638596	147.0635815
19	17.77519	17.77518873	3.300384804	3.300384804	25.16287716	25.16287716	16.06962306	16.06962306	66.63092577	157.2090742
20	5.610109	5.610108915	14.2968747	14.65617544	18.88957353	17.53320639	17.72467096	17.72467096	156.8620451	147.855352
21	4.739042	3.910516366	3.191963494	4.066415659	22.5885488	22.5885488	16.18471866	14.38202904	146.6836794	23.09705009
22	2.808235	2.726320546	2.900956718	3.71949442	24.81081585	24.81081585	19.89642217	19.89642217	38.19989599	38.19989599
23	3.394888	3.642075523	3.636668651	3.292809358	24.15461583	24.15461583	14.89071574	14.89071574	42.99982595	147.0878406
24	3.785136	3.785135617	4.105489863	3.479559744	20.21950266	20.21950266	15.46298985	15.46298985	29.05355028	29.05355028
25	4.225396	4.225396068	3.81609439	2.139450717	22.78596709	22.78596709	19.09788304	19.09788304	27.86575432	27.86575432

BDB

	Variable 1	*Variable 2*
Mean	6.788850956	6.83134482
Variance	34.01663617	33.75688862
Observati	25	25
Pearson C	0.994249734	
Hypothesi	0	
df	24	
t Stat	-0.340131344	
P(T<=t) on	0.36835831	
t Critical o	1.71088208	
P(T<=t) tw	0.736716619	
t Critical tw	2.063898562	

1AJ

	Variable 1	*Variable 2*
Mean	6.185477147	4.588518007
Variance	26.76610158	14.69931897
Observations	25	25
Pearson Correlat	0.610435631	
Hypothesized M	0	
df	24	
t Stat	1.922571994	
P(T<=t) one-tail	0.033240067	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.066480133	
t Critical two-tail	2.063898562	

GPW

	Variable 1	*Variable 2*
Mean	25.86222571	25.89211474
Variance	50.76420245	50.64664982
Observations	25	25
Pearson Correlat	0.997651278	
Hypothesized M	0	
df	24	
t Stat	-0.306169494	
P(T<=t) one-tail	0.381057916	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.762115831	
t Critical two-tail	2.063898562	

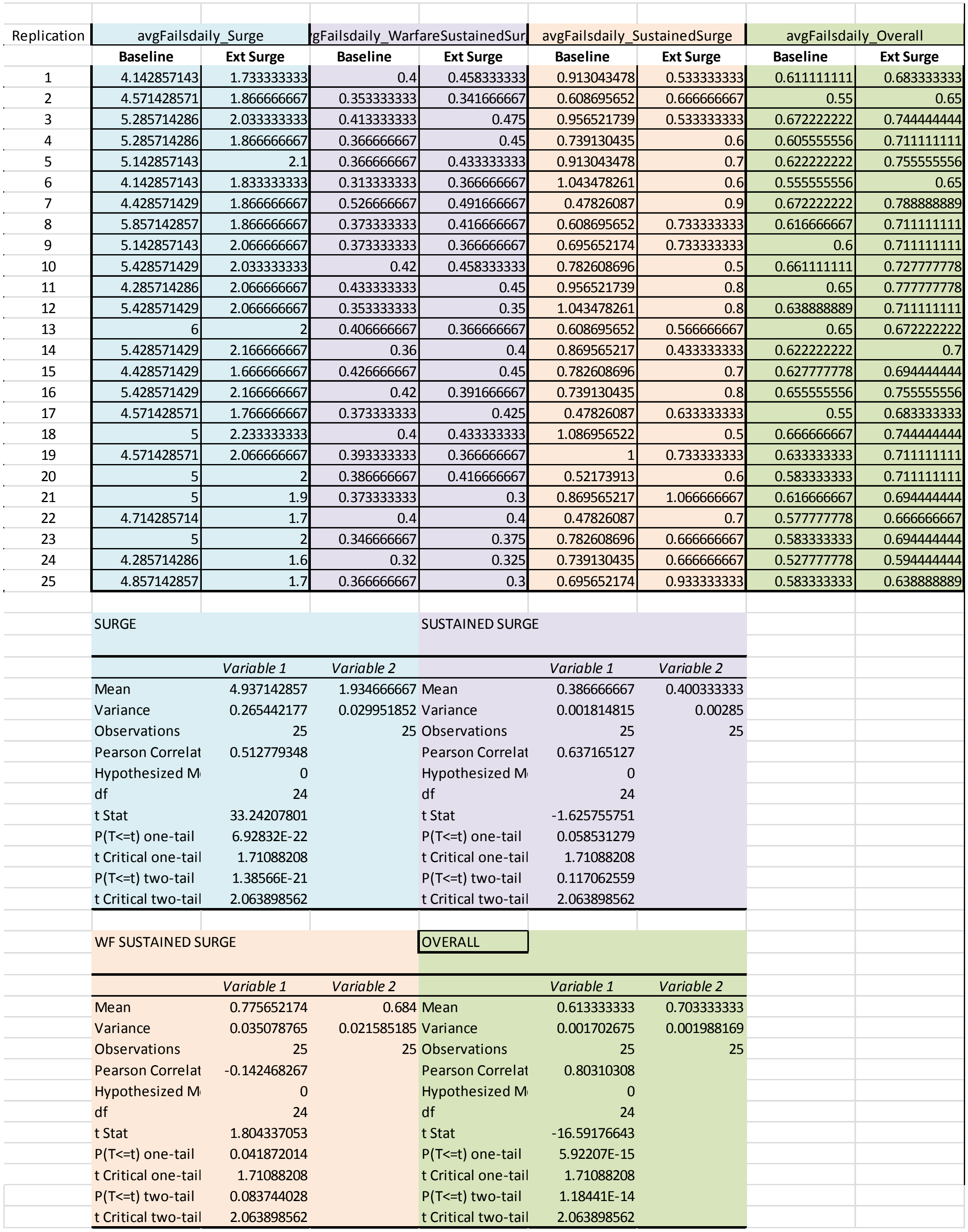
ECG

	Variable 1	*Variable 2*
Mean	17.80187523	17.90530031
Variance	9.405144856	8.72587059
Observati	25	25
Pearson C	0.961928329	
Hypothesi	0	
df	24	
t Stat	-0.616972488	
P(T<=t) on	0.271531101	
t Critical o	1.71088208	
P(T<=t) tw	0.543062201	
t Critical tw	2.063898562	

Z00

	Variable 1	*Variable 2*
Mean	73.61653029	113.7801255
Variance	6036.74516	2811.815053
Observations	25	25
Pearson Correlat	0.111647128	
Hypothesized M	0	
df	24	
t Stat	-2.255301055	
P(T<=t) one-tail	0.016753928	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.033507856	
t Critical two-tail	2.063898562	

Appendix D. Paired t-Tests for Daily Failures



Replication	avgFailsdaily_Surge		gFailsdaily_WarfareSustainedSur		avgFailsdaily_SustainedSurge		avgFailsdaily_Overall	
	Baseline	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**	**Baseline**	**Ext Surge**
1	4.142857143	1.733333333	0.4	0.458333333	0.913043478	0.533333333	0.611111111	0.683333333
2	4.571428571	1.866666667	0.353333333	0.341666667	0.608695652	0.666666667	0.55	0.65
3	5.285714286	2.033333333	0.413333333	0.475	0.956521739	0.533333333	0.672222222	0.744444444
4	5.285714286	1.866666667	0.366666667	0.45	0.739130435	0.6	0.605555556	0.711111111
5	5.142857143	2.1	0.366666667	0.433333333	0.913043478	0.7	0.622222222	0.755555556
6	4.142857143	1.833333333	0.313333333	0.366666667	1.043478261	0.6	0.555555556	0.65
7	4.428571429	1.866666667	0.526666667	0.491666667	0.47826087	0.9	0.672222222	0.788888889
8	5.857142857	1.866666667	0.373333333	0.416666667	0.608695652	0.733333333	0.616666667	0.711111111
9	5.142857143	2.066666667	0.373333333	0.366666667	0.695652174	0.733333333	0.6	0.711111111
10	5.428571429	2.033333333	0.42	0.458333333	0.782608696	0.5	0.661111111	0.727777778
11	4.285714286	2.066666667	0.433333333	0.45	0.956521739	0.8	0.65	0.777777778
12	5.428571429	2.066666667	0.353333333	0.35	1.043478261	0.8	0.638888889	0.711111111
13	6	2	0.406666667	0.366666667	0.608695652	0.566666667	0.65	0.672222222
14	5.428571429	2.166666667	0.36	0.4	0.869565217	0.433333333	0.622222222	0.7
15	4.428571429	1.666666667	0.426666667	0.45	0.782608696	0.7	0.627777778	0.694444444
16	5.428571429	2.166666667	0.42	0.391666667	0.739130435	0.8	0.655555556	0.755555556
17	4.571428571	1.766666667	0.373333333	0.425	0.47826087	0.633333333	0.55	0.683333333
18	5	2.233333333	0.4	0.433333333	1.086956522	0.5	0.666666667	0.744444444
19	4.571428571	2.066666667	0.393333333	0.366666667	1	0.733333333	0.633333333	0.711111111
20	5	2	0.386666667	0.416666667	0.52173913	0.6	0.583333333	0.711111111
21	5	1.9	0.373333333	0.3	0.869565217	1.066666667	0.616666667	0.694444444
22	4.714285714	1.7	0.4	0.4	0.47826087	0.7	0.577777778	0.666666667
23	5	2	0.346666667	0.375	0.782608696	0.666666667	0.583333333	0.694444444
24	4.285714286	1.6	0.32	0.325	0.739130435	0.666666667	0.527777778	0.594444444
25	4.857142857	1.7	0.366666667	0.3	0.695652174	0.933333333	0.583333333	0.638888889

SURGE

	Variable 1	*Variable 2*
Mean	4.937142857	1.934666667
Variance	0.265442177	0.029951852
Observations	25	25
Pearson Correlat	0.512779348	
Hypothesized M	0	
df	24	
t Stat	33.24207801	
P(T<=t) one-tail	6.92832E-22	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	1.38566E-21	
t Critical two-tail	2.063898562	

SUSTAINED SURGE

	Variable 1	*Variable 2*
Mean	0.386666667	0.400333333
Variance	0.001814815	0.00285
Observations	25	25
Pearson Correlat	0.637165127	
Hypothesized M	0	
df	24	
t Stat	-1.625755751	
P(T<=t) one-tail	0.058531279	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.117062559	
t Critical two-tail	2.063898562	

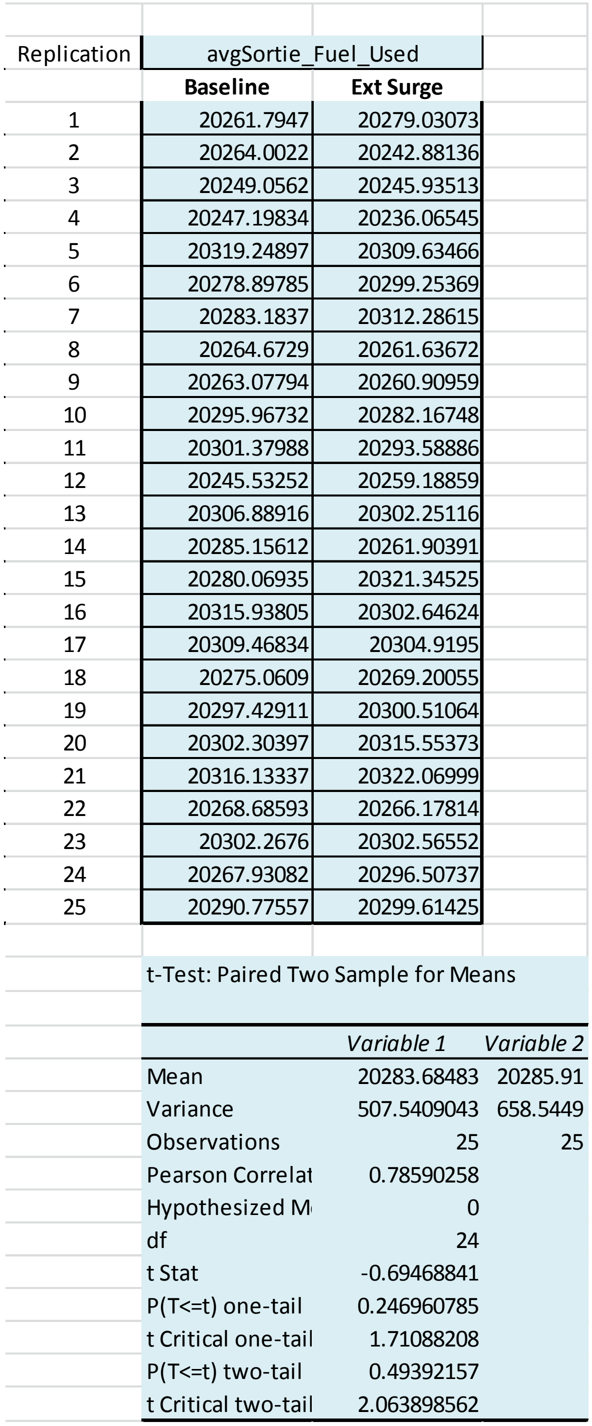
WF SUSTAINED SURGE

	Variable 1	*Variable 2*
Mean	0.775652174	0.684
Variance	0.035078765	0.021585185
Observations	25	25
Pearson Correlat	-0.142468267	
Hypothesized M	0	
df	24	
t Stat	1.804337053	
P(T<=t) one-tail	0.041872014	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.083744028	
t Critical two-tail	2.063898562	

OVERALL

	Variable 1	*Variable 2*
Mean	0.613333333	0.703333333
Variance	0.001702675	0.001988169
Observations	25	25
Pearson Correlat	0.80310308	
Hypothesized M	0	
df	24	
t Stat	-16.59176643	
P(T<=t) one-tail	5.92207E-15	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	1.18441E-14	
t Critical two-tail	2.063898562	

Appendix E. Paired t-Test for Fuel usage



Replication	avgSortie_Fuel_Used	
	Baseline	**Ext Surge**
1	20261.7947	20279.03073
2	20264.0022	20242.88136
3	20249.0562	20245.93513
4	20247.19834	20236.06545
5	20319.24897	20309.63466
6	20278.89785	20299.25369
7	20283.1837	20312.28615
8	20264.6729	20261.63672
9	20263.07794	20260.90959
10	20295.96732	20282.16748
11	20301.37988	20293.58886
12	20245.53252	20259.18859
13	20306.88916	20302.25116
14	20285.15612	20261.90391
15	20280.06935	20321.34525
16	20315.93805	20302.64624
17	20309.46834	20304.9195
18	20275.0609	20269.20055
19	20297.42911	20300.51064
20	20302.30397	20315.55373
21	20316.13337	20322.06999
22	20268.68593	20266.17814
23	20302.2676	20302.56552
24	20267.93082	20296.50737
25	20290.77557	20299.61425

t-Test: Paired Two Sample for Means

	Variable 1	*Variable 2*
Mean	20283.68483	20285.91
Variance	507.5409043	658.5449
Observations	25	25
Pearson Correlat	0.78590258	
Hypothesized M	0	
df	24	
t Stat	-0.69468841	
P(T<=t) one-tail	0.246960785	
t Critical one-tail	1.71088208	
P(T<=t) two-tail	0.49392157	
t Critical two-tail	2.063898562	

Appendix F. Summary Chart

SIMULATION MODELING AND ANALYSIS OF DEPLOYED F-16 OPERATIONS AND LOGISTICS SUPPORT

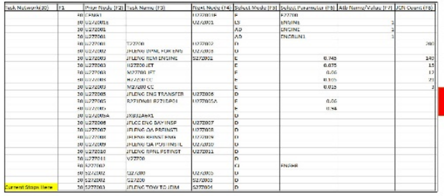
INTRODUCTION

The purpose of this thesis is to reinforce and build upon past efforts identifying and demonstrating the need to better represent logistic capabilities and constraints within the realm of wargaming, war planning, and other analyses requiring the modeling of Air Force combat operations. We develop a framework for the porting of relevant logistic information and requirements from a reliable data source (LCOM- ATK) into a discrete event simulation environment (SIMIO), providing a simulation model for enhanced and robust analyses. The simulation we create explicitly reflects (for a selected subset of Work Unit Codes) the maintenance manpower, resources, and parts required to sustain the flying operations of a deployed unit of F-16 aircraft. This research considers two distinct scenarios with varied operational tempos over the phases of a 180 day deployment. We show that logistics can be incorporated in analyses and does have an impact on metrics and outcomes.

PROBLEM STATEMENT

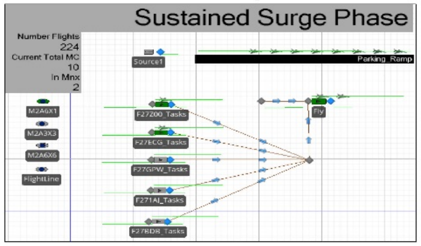
This research responds to a perceived lack of complete information provided to decision makers regarding mission capability of deployed forces. Our effort focuses on exploring a flexible and easy to use simulation approach to help better understand and answer questions about how logistics and maintenance impacts deployed operations.

LCOM 30 Cards (WUC Task Networks)

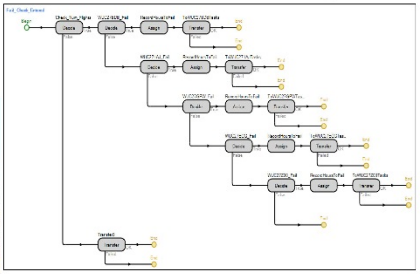


2d Lt Gregory D. Potts II
Advisor: Dr. J. O. Miller
Reader: Dr. Paul L. Hartman
Department of Operational Sciences (ENS)
Air Force Institute of Technology

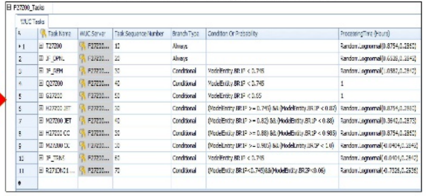
Simulation Model Top View



Model Maintenance Check Process Logic



Task Network integrated into SIMIO



METHODOLOGY

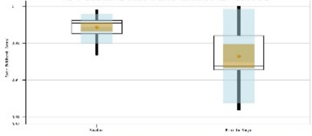
- Development of a discrete-event simulation framework that can take data from one high fidelity data source, Logistics Composite Model Analysis Toolkit (LCOM-ATK), and port it into a more flexible simulation tool, SIMIO with enhanced analysis tools
- Simulate a well-defined deployment scenario based on LCOM-ATK data
  - Model maintenance manpower, supplies, and tasks performed to support flying operations (12 hours/day) throughout three phases of a 180 day deployment
- Creation of a baseline simulation that includes logistics constraints and capabilities for comparison of Measures of Effectiveness (MOEs) regarding mission capability with an alternative Extended Surge scenario with increased operational tempo over the deployment phases

	Surge Phase	Sustained Surge Phase	Warfare Sustained Surge Phase
Baseline	7 Days	23 Days	150 Days
Extended Surge Scenario	30 Days	30 Days	120 Days

	Surge Phase	Sustained Surge Phase	Warfare Sustained Surge Phase
Sortie Interval	40 mins	60 mins	120 mins
Sorties per Day	18	12	6

RESULTS

SIMIO Measure of Risk and Error (SMORE) Plot
Overall Schedule Effectiveness



	Baseline Scenario			
	Schedule Effectiveness: Surge Phase (7 days)	Schedule Effectiveness: Sustained Surge Phase (23 days)	Schedule Effectiveness: Warfare Sustained Surge Phase (150 days)	Schedule Effectiveness: Overall
Mean	91.06%	95.34%	99.99%	97.18%
95% HW	4.11%	2.02%	0.10%	0.00%
Min	61.11%	85.14%	99.00%	93.92%
Max	100%	100%	100%	99.54%

	Extended Surge Scenario			
	Schedule Effectiveness: Surge Phase (30 days)	Schedule Effectiveness: Sustained Surge Phase (30 days)	Schedule Effectiveness: Warfare Sustained Surge Phase (120 days)	Schedule Effectiveness: Overall
Mean	84.80%	92.47%	99.90%	93.23%
95% HW	4.04%	4.14%	0.13%	1.03%
Min	71.11%	77.40%	98.85%	87.96%
Max	100%	100%	100%	100.00%

DEPARTMENT OF OPERATIONAL SCIENCES

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14. ABSTRACT

The purpose of this thesis is to reinforce and build upon past efforts identifying and demonstrating the need to better represent logistic capabilities and constraints within the realm of wargaming, war planning, and other analyses requiring the modeling of Air Force combat operations. We develop a framework for the porting of relevant logistic information and requirements from a reliable data source (LCOM- ATK) into a discrete event simulation environment (SIMIO), providing a simulation model for enhanced and robust analyses. The simulation we create explicitly reflects (for a selected subset of Work Unit Codes) the maintenance manpower, resources, and parts required to sustain the flying operations of a deployed unit of F-16 aircraft. This research considers two distinct scenarios with varied operational tempos over the phases of a 180 day deployment. We show that logistics can be incorporated in analyses and does have an impact on metrics and outcomes.

15. SUBJECT TERMS
Simulation, wargames, Logistics, Deployed, long duration, LCOM, SIMIO

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