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A FEASIBILITY STUDY USING SCENARIO METHODOLOGIES ON FUTURE UNMANNED AERIAL SYSTEM CAPABILITIES

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THESIS

A FEASIBILITY STUDY USING SCENARIO METHODOLOGIES ON FUTURE UNMANNED AERIAL SYSTEM CAPABILITIES

by

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December 2018

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This thesis demonstrates the feasibility of using computer-aided wargames (CAW) as a tool to help determine high-level system requirements for future reconnaissance-capable unmanned aerial vehicles (UAVs). This research uses a model-based systems engineering (MBSE) approach to establish high-level capability requirements and concepts of operations for the future fleet. Unmanned aerial vehicle design factors in this study include mission altitude, sortie size, and time between launches. Measures of effectiveness (MOEs) delineate which of these factors, or factor combinations, best enhances enemy high-value unit (HVU) detection while minimizing UAV losses in theater. The thesis utilizes Joint Theater Level Simulator-Global Operations (JTLS-GO) as the modeling environment and applies regression tools and visualization techniques to communicate model outcomes. While all three design factors affect the MOEs, results from the model suggest that UAV altitude has the most prominent impact on the MOEs. High altitudes decrease HVU detections but also lower UAV attrition, illustrating potential trade-offs that can be applied to an operational context. The interaction of the number of UAVs with this altitude points to a concept of operations. Swarms of low-altitude UAVs tend to have greater success with detecting HVUs while keeping a relatively low percentage of losses.

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A FEASIBILITY STUDY USING SCENARIO METHODOLOGIES ON FUTURE UNMANNED AERIAL SYSTEM CAPABILITIES

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Submitted in partial fulfillment of the
requirements for the degree of

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ABSTRACT

This thesis demonstrates the feasibility of using computer-aided wargames (CAW) as a tool to help determine high-level system requirements for future reconnaissance-capable unmanned aerial vehicles (UAVs). This research uses a model-based systems engineering (MBSE) approach to establish high-level capability requirements and concepts of operations for the future fleet. Unmanned aerial vehicle design factors in this study include mission altitude, sortie size, and time between launches. Measures of effectiveness (MOEs) delineate which of these factors, or factor combinations, best enhances enemy high-value unit (HVU) detection while minimizing UAV losses in theater. The thesis utilizes Joint Theater Level Simulator-Global Operations (JTLS-GO) as the modeling environment and applies regression tools and visualization techniques to communicate model outcomes. While all three design factors affect the MOEs, results from the model suggest that UAV altitude has the most prominent impact on the MOEs. High altitudes decrease HVU detections but also lower UAV attrition, illustrating potential trade-offs that can be applied to an operational context. The interaction of the number of UAVs with this altitude points to a concept of operations. Swarms of low-altitude UAVs tend to have greater success with detecting HVUs while keeping a relatively low percentage of losses.

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LIST OF ACRONYMS AND ABBREVIATIONS

ATC	aircraft target class
BAMS	broad-area maritime surveillance
CAE	computer-aided exercise
CCD	central-composite design
CEP	combat events program
CG18	Cobra Gold 2018
CIA	Central Intelligence Agency
CNO	Chief of Naval Operations
COCOM	combatant commander
CONOP	concept of operation
COP	common operating picture
CPX	command-post exercise
DAU	Defense Acquisition University
DoD	Department of Defense
DOE	design of experiments
FLIR	forward-looking infrared
FTX	field training exercise
HALE	high-altitude long endurance
HUP	high-resolution unit prototypes
HVU	high-value unit
INCOSE	International Council on Systems Engineering
IR	infrared
ISR	intelligence, surveillance and reconnaissance
ISR&T	intelligence, surveillance and tracking
J7	Joint Force Development
JTLS-GO	Joint Theater Level Simulation
JWC NATO	Joint Warfighting Center, North Atlantic Treaty Organization
LCS	Littoral Combat Ship
MANA	Map Aware Non-uniform Automata
MBSE	model-based systems engineering
MNF	multi-national force
MOE	measure of effectiveness
MOP	measure of performance

N9	Navy Warfare Systems Directorate
NPS	Naval Postgraduate School
OIF	Operation Iraqi Freedom
PACOM	Pacific Command
P_d	probability of detection
P_h	probability of hit
P_k	probability of kill
R&A	Rolands and Associates
R&D	research and development
SEED	Simulation Experiments and Efficient Designs
SUP	ship-unit prototypes
TUP	tactical-unit prototypes
TW	targetable weapons
UAS	unmanned aerial system
UAV	unmanned aerial vehicle
VTUAV	vertical-takeoff and landing tactical unmanned aerial vehicle
WHIP	web-hosted interface program

EXECUTIVE SUMMARY

Owens (2012) states that the art of force planning entails both strategic and structural considerations: the former deals with "war plans…employment and deployment" of military assets, while the latter pertains to the "currency of domestic politics," such as budgetary constraints or mission areas (1). As a result, decision makers entrusted with building tomorrow's fleet must maintain a keen understanding of domestic national strategy and military deficiencies, while also considering potential adversaries' strategy and capabilities. Fiscal constraints in the form of budgets further complicate this calculus, as a mismatch in strategic assumptions or force composition can be costly both financially and politically.

In order to manage risks inherent in force planning, the United States leverages technology as a "hedging tool," whereby current capabilities are reconciled with contemporary missions while anticipating how evolving technologies can rectify any existing shortfalls between the two (Owens 2012, 2). While this was a largely successful strategy in the years following the Soviet Union's collapse, the rise of military peer and near-peer adversaries, predominantly in China and Russia, make this option less tenable. Due to the rapid evolution of global military capabilities and the increasing lethality of potential adversaries' weapon systems, force planners need a tool that provides insight in how adopting emergent technologies can potentially supplement both strategic and structural considerations. This thesis studies the feasibility of using a computer-aided wargame (CAW) in conjunction with a model-based systems engineering (MBSE) approach to examine high-level system requirements and potential concepts of operation (CONOPs) for future reconnaissance-capable unmanned aerial vehicles (UAVs).

This research was conducted at the request of Navy Warfare Systems Directorate (N9) to determine the capability requirements and impacts of desired unmanned aerial vehicle (UAV) technologies in a future fleet construct. The thesis utilizes Joint Theater Level Simulator-Global Operations, or JTLS-GO, as the modeling environment, with the computer-aided exercise Cobra Gold 2018 (CG18) serving as the specific scenario. Testing variations of several UAV-specific design factors, such as sortie size, flight altitude, or

launch times, helps determine which factors or combinations of factors increase enemy high-value unit (HVU) detections and decrease UAV attrition to enemy anti-air weapons within the scenario.

A design of experiments, or DOE, provides a structured framework to identify which design factors have the greatest impact on the MOEs. This thesis uses a central-composite design (CCD) for experimentation. Each design factor encompasses three levels, resulting in 27 unique design points for data analysis; replicating each design point for 30 iterations reduces data variability. Regression tools and visualization techniques available in JMP statistical analysis software transforms raw data measuring HVU detection and UAV attrition into concise infographics that communicate model outcomes.

Figures 1 and 2 illustrate partition trees resultant from the experiment. As data-mining tools, partition trees help show which combinations of factors result in the best and worst outcomes within the model. The first partition tree shows that the highest UAV survivability is achieved by flying a large sortie at high altitudes. Conversely, employing a small sortie size at low altitude without staggering launch times results in the highest percent attrition. Generally, these results align with intuition. Flying at higher altitudes can exploit range limitations inherent in anti-aircraft weapons and take advantage of range-dependent signal losses inherent in radar systems. Moreover, employing a large number of UAVs can overwhelm the capabilities of an anti-air weapon system, resulting in a greater percentage of aircraft leaking by the weapon.

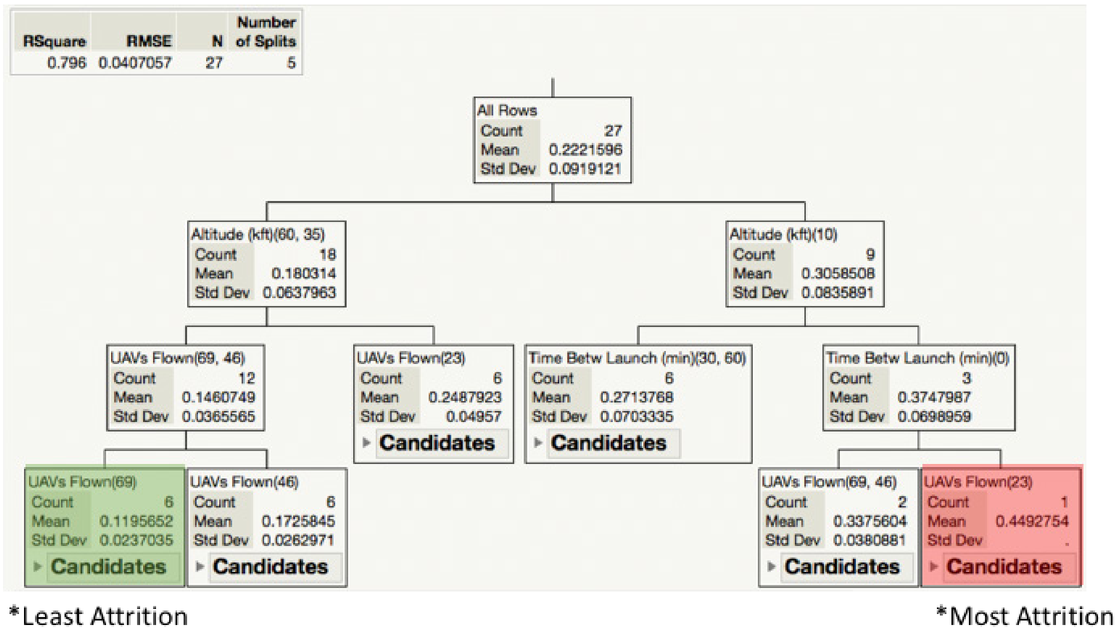

Figure 1. Partition Tree Illustrating Design Factor Impact on UAV Attrition

Figure 2 shows the how the UAV design factors impact HVU detections within the game. Flying at higher altitudes adversely affects HVU detections, while employing a large sortie size at low altitude results increases the number of enemy units discovered. These results are also logical in a real-world context. Flying at higher altitudes results in drastically lower HVU detections, suggesting the sensor is resolution-limited in the model. However, if flying at lower altitudes coinciding with the sensor's capabilities, employing more UAVs results in the greatest number of enemy HVUs detected since sensor coverage is maximized.

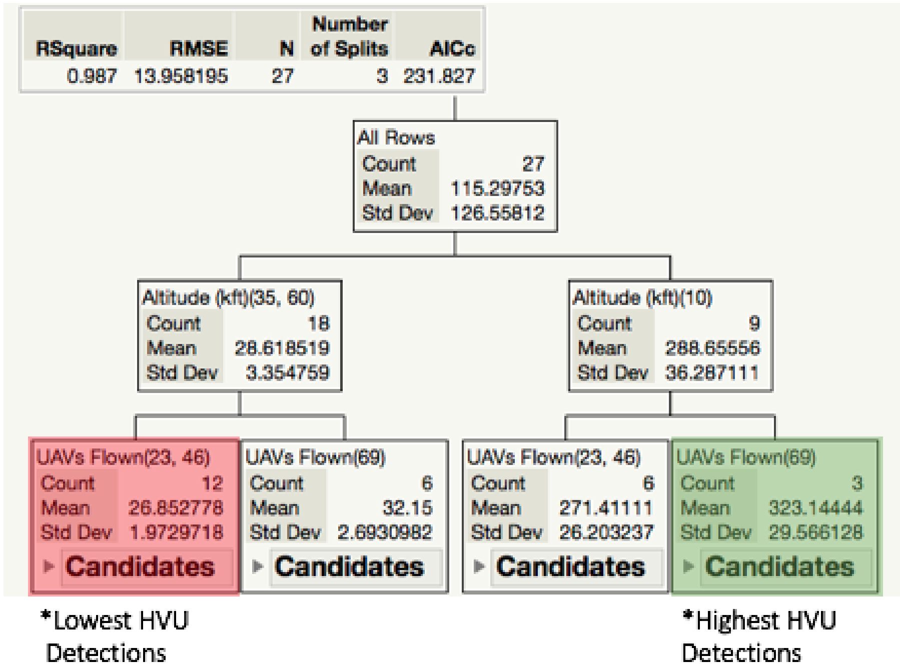

Figure 2. Partition Tree Illustrating Design Factor Impact on HVU Detection

Overall, the results from the model correlate to what would be expected operationally, validating the feasibility of using a CAW as a force planning tool. Moreover, the model communicates trends that can help decision makers determine which functional capabilities have the greatest impact in mission accomplishment, while consequently illustrating potential trade spaces. For example, if minimizing attrition were a critical performance metric, a high-altitude reconnaissance UAV may be an appropriate solution; consequently, additional research in enhancing sensor resolution would maximize its usefulness and prove beneficial.

Reference

Owens, Mackubin T. 2012. "Force Planning: The Crossroads of Strategy and the Political Process." Newport, RI: The United States Naval War College, October.

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I. INTRODUCTION

A. PURPOSE

This research is being conducted at the request of Navy Warfare Systems Directorate (N9) to determine the capability requirements and impacts of desired unmanned aerial vehicle (UAV) technologies in a future fleet construct. Results in gathered intelligence or aircraft casualties give insight to decision makers in determining the feasibility of future technologies and the benefits that they could offer to the fleet; moreover, this study explores how Navy leaders might implement these prospective technologies in future fleet architectures.

B. BACKGROUND

The collapse of the Soviet Union in 1991 gave the United States and its allies uncontested military advantages in multiple domains, be it ground, air or naval forces. However, over much of the past decade, this monopoly slowly disappeared. Although this erosion of U.S. dominance occurred across all domains, it was particularly exacerbated in the Navy due to the operational demand placed on the service (Harris 2018). Consequently, a more critical analysis of the future military in terms of quantity, capability and budget is necessary as domestic budget constraints converge with the reemergence of peer and near-peer competitors.

In his February 2018 statement before the House Armed Services Committee, former United States Pacific Command (U.S. PACOM) Commander Admiral Harry Harris (2018) warned of "peer competitors like China and Russia…closing the technological gap" and called for Navy "systems of increased lethality that go faster and further, are networked, are more survivable and affordable" as well as "critical capabilities to include UAVs for increased intelligence, surveillance and reconnaissance" (33). Admiral Harris' proposal echoes the future fleet capabilities that Chief of Naval Operations (CNO) Admiral John Richardson envisions. In his 2017 white paper, "The Future Navy," Admiral Richardson (2017) states there is "no question that unmanned systems must also be an integral part of the future fleet" (6). Both Admiral Richardson and Admiral Harris conclude that unmanned assets combine cost effectiveness, lethality and endurance, critical traits in the battlefield that would allow the United States to maintain superiority over a peer threat. However, there is uncertainty in the impact of integrating new unmanned system capabilities in the current force's operations, as well as the value such systems bring.

Unmanned capabilities can potentially have a significant impact on data collection and battlespace awareness in contested or hostile environments. With the increasing lethality of surface-to-air and air-to-air threats, mission accomplishment in such hostile environments can result in unacceptably high risk and attrition to both man and machine. An unmanned asset can mitigate this risk (Berner 2004). As indicated in the *Alternative Future Fleet Platform Architecture Study* circa October 2016, the Navy's future architecture includes a "[d]istributed [f]leet [l]ethality concept" accomplished in part by "unmanned vehicles…relying on [intelligence, surveillance, reconnaissance and tracking] ISR&T capability and capacity to execute the required kill chains" against a threat (8). Such a construct would address both the current CNO's vision and former PACOM's desire for an unmanned, lethal fleet component.

As the Navy's focus pivots to unmanned assets, key decision makers need the ability to extract and test future capability requirements and concepts of operations (CONOPs) for proposed and scheduled UAV assets. These considerations, however, must account for the emerging capability advances and CONOPs of the United States' adversaries, further stressing the domestic timeline from proposal to fleet integration. Adding a finite research and development (R&D) budget for future technologies further confounds the problem of strategic force planning. Given these considerations, the ability to vet, test, and evaluate potential impacts of future technologies is beneficial for stakeholders.

C. SCOPE AND METHODOLOGY

The scope of this thesis, part of the broader Navy Warfare Systems Directorate (N9) research, focuses on modeling futuristic unmanned aerial systems (UAS) capabilities in order to satisfy theater level requirements. Specifically, the models contained in this thesis represent various instantiations similar to the Navy's evolving broad area maritime surveillance (BAMS) UAV program. According to the Department of Defense (DoD) publication *Unmanned Systems Roadmap 2007–2032* (2007), BAMS is "a Navy fleet asset for operational and tactical users…[which provides] a variety of intelligence activities and nodes. In a secondary role, it will also be used alone or in conjunction with other assets to respond to theater level, operational, or national strategic tasking" (75). Unlike manned reconnaissance aircraft currently in use, unmanned BAMS assets provide the Navy a means of long-endurance, continuous surveillance of a threat area or area of interest with the added benefit of diminishing human loss of life. In turn, this asset offers commanders more continuity in understanding a given operating area.

This thesis applies a model-based systems engineering (MBSE) approach in conjunction with computer experimentation and customized designs of experiments (DOE). The general simulation environment is contained within the Joint Theater Level Simulation-Global Operation (JTLS-GO) program. Specifically, this thesis is tailored around Cobra Gold 2018 (CG18); therefore, while the results and conclusions of this work are relevant to CG18 and observations therein, the findings extend to similar theater-level exercises. Cobra Gold is an annual exercise held in Thailand under the direction of the PACOM Warfighting Center (PWC) and entails two components: a field training exercise (FTX) and a computer-based command post exercise (CPX). The CPX is the basis for the computer-aided exercise (CAE) and provides a common model and test environment to enhance stakeholder understanding. Experimentation and simulation analysis are major elements of the methodology to complete the study. Accomplishing this research requires a multi-step process. Step one is to extract data from the unaltered CG18 CPX to identify performance gaps that decision makers can potentially fill with UAVs. After identifying these shortcomings, the next step is to brainstorm the integration of future UAS technologies into the scenario. Subsequently, user defined outcomes establish UAS operational requirements in the simulation. Defining these operational requirements encompasses:

- mission definition
- performance parameters

- operational deployment
- utilization requirements
- effectiveness factors

Defining operational requirements allows modeling of UAV assets and subsequent injection into the CAE. User-established measures of effectiveness (MOEs) and measures of performance (MOPs) can determine if any significant differences exist between the original CPX and the modified CAE. These MOPs and MOEs encompass units lost (both existing manned and injected unmanned units), total detection events, detection time, and the number of decisions made. Using a design of experiments based on these measures determines quantitatively how UAV implementation in a future fleet construct affects the CAE outcome. Various instantiations explore how changes in launch time, mission altitude, and quantity of UAVs employed affect the scenario. Lastly, analysis of new capability gaps determines the operational tradeoffs associated with implementation of future capabilities. Chapter III articulates the methodology this thesis uses in greater detail.

D. PROBLEM STATEMENT

Current Navy intelligence, surveillance and reconnaissance (ISR) aircraft provide inadequate on-station time, resulting in an inability to maintain continuous surveillance along contested coastlines and littorals. Additionally, current assets are overly vulnerable to enemy weapon systems, putting crew and equipment at risk.

E. RESEARCH QUESTIONS

1. What insights can an automated computer-aided wargame provide to force planners to help shape future fleet capabilities?
2. What is the effect of adding future unmanned aerial assets on a combined task force's ability to maintain maritime domain awareness along contested coastlines and littorals?

3. What capabilities do future unmanned aerial systems require to be value-added to existing reconnaissance methods in a joint maritime force?

F. THESIS ORGANIZATION

In order to answer these questions, this thesis began by providing general background and significance of this research. Next, Chapter II reviews pertinent literature detailing current and proposed fleet reconnaissance capabilities, as well as previous efforts using UAVs in simulated and real-world environments. Chapter III describes the modeling scenarios' theoretical framework and methodology, the design factors for the injected UAV assets within the CAE, and segues to the experimental setup for this thesis. Chapter IV of this thesis focuses on data analysis and subsequent results from the experiment. Chapter V concludes this thesis with summary, recommendations, and potential areas for future studies.

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II. LITERATURE REVIEW

This chapter gives an overview of past and current manned Navy ISR assets that unmanned aerial systems augment or replace. A discussion of future fleet UAS capabilities illustrates how unmanned assets can satisfy mission requirements in the ISR domain. Lastly, it provides background information from other work using computer simulations to analyze UAV capabilities.

A. PAST AND CURRENT MANNED RECONNAISSANCE ASSETS

The two most recent Navy aircraft used for manned reconnaissance are Lockheed’s P-3 Orion and Boeing’s P-8 Poseidon. The latest iteration of the Orion, the P-3C, was introduced to the fleet in 1969, with production lasting until 1990 (Federation of American Scientists 1999). During the aircraft’s half-century service life, the U.S. used P-3s for wartime patrols in Vietnam, Iraq, and Afghanistan. With the exception of a 16-plane EP-3 squadron in Whidbey Island, Boeing’s P-8 Poseidon largely phased out the P-3 platform. Comparing the P-3 against the P-8, shown in Figure 1 and Figure 2 respectively, clearly illustrates the design evolution.

Figure 1. Boeing P-3C Orion. Source: Naval Air Systems Command (2018).

Figure 2. Lockheed P-8 Poseidon. Source: Federation of American Scientists (1999).

While the P-3 is a turbo-prop aircraft by design, the P-8 utilizes a pair of turbofan engines; combined with the greater volume of the 737-based fuselage, the Poseidon results in an aircraft that delivers "extended global reach, greater payload capacity, [and] higher operating altitude" compared to its predecessor (Naval Air Systems Command 2018, 3). Quantitatively, this translates to a range of 1,200 nautical miles and four hours of on-station time compared to the Orion's range of 2,380 nautical miles and three hours of on-station time (Naval Air Systems Command 2018).

Although the newer P-8 enhances mission accomplishment, both patrol aircraft share several limitations common to traditional manned aircraft. First and foremost are the personnel requirements to support a mission: the P-3 typically flies with a crew of 11, while the P-8 reduces that number to nine (Naval Air Systems Command 2018). Considerations relative to the manning requirement, such as requisite personnel and crew rest, in conjunction with aircraft maintenance requirements, constrains mission capacity and limits availability. Additionally, both airframes are engineered to accommodate and sustain the human operators within, increasing size and weight requirements, both of which impact on-station time. Lastly, using a human crew leaves personnel susceptible to enemy anti-air defenses. As history shows, the potential loss or endangerment of human life, particularly in reconnaissance missions, can have significant impacts on tactical, strategic and political levels.

The two most pertinent examples of this are the Hainan Island incident, circa 2001, and the U-2 incident, circa 1960. In the case of the former, a Chinese J-8 clipped and damaged an EP-3 Aeries II, destroying the fighter and forcing an emergency landing for the reconnaissance aircraft. As a result, the Chinese government gained possession of the damaged U.S. aircraft and much of the sensitive materials within, including cryptographic keys, manuals on exploiting signal intelligence and personal data on dozens of National Security Agency (NSA) employees (Zetter 2017). While the political ramifications of this particular incident were fairly minimal, that is not always the case when a manned reconnaissance asset is lost on mission. In 1960, a U-2 spy plane flown by Central Intelligence Agency (CIA) pilot Gary Powers was shot down while on patrol in the former Soviet Union, resulting in a two-year imprisonment for the pilot. Politically, the U-2 incident increased international tensions between the United States and Soviet Union and embarrassed the United States internationally (Wright 1960). These two case studies illustrate the significant political and military ramifications resulting from the loss of manned reconnaissance aircraft. Not only do policy makers contend with loss of national assets and the ramifications therein, consideration must be made for the return of the pilot and crew. As such, minimizing risk to the human element in intelligence-gathering missions warrants exploration.

B. PAST AND CURRENT UNMANNED RECONNAISSANCE ASSETS

Just over a decade passed after the Wright brothers' achievement in powered flight before Englishman Archibald Montgomery Low developed the first unmanned, remote-controlled aircraft system in 1916 (Kamienski and Piehler 2013). The idea of removing the pilot from the cockpit continued to evolve over several decades, initially as prototypical guided weapons in lieu of unmanned aircraft. As U.S. involvement in Indochina continued during the 1960s, the CONOPs for unmanned aircraft would see an inflection point; by the end of the Vietnam War, the military leveraged drones in "up to 40 reconnaissance flights per month" with 3,435 missions flown in totality (Kamienski and Piehler 2013, 2).

The next significant uptick for UAV usage in theater occurred in the Persian Gulf War, circa 1990–91, during which coalition forces used RQ-2 Pioneers, shown in Figure 3, to fly "almost 1,700 hours in… 500 reconnaissance sorties" (Kamienski and Piehler 2013, 2). The implementation of unmanned aircraft during the first Gulf War, and in smaller geopolitical conflicts in Somalia, Bosnia and Kosovo during the late 20th century, captured U.S. interest in unmanned systems. According to Kamienski and Piehler (2013), the success of UAVs spurred U.S. investment for research and development of unmanned systems and prompted additional drone deployments post-9/11. During Operation Iraqi Freedom (OIF), the United States military again deployed the RQ-2 Pioneer extensively, collating another 2,700 flight hours for the aircraft in theater (Koch 2004). For the Navy, RQ-2 Pioneers were employed from *Iowa*-class battleships to provide real-time targeting for the ships' organic 16-inch guns. Anecdotally, in this role the Pioneer achieved what is considered the first historic example of human troops surrendering to a machine. Launched from the USS *Wisconsin* (BB 64) and flying at low altitude, Iraqi forces, correlating that the "obnoxious sound of the [Pioneer's] two-cycle engine" quickly resulted in several tons of naval gunfire raining down at their precise position, took to "handkerchiefs and bedsheets" to signal surrender (United States Navy Fact File 2013, 3).

Figure 3. RQ-2 Pioneer. Source: United States Navy Fact File (2013).

After more than two decades of service, the Navy retired the RQ-2 in favor of the vertical takeoff and landing tactical UAV (VTUAV) MQ-8 Fire Scout, shown in Figure 4.

Initially fielded in 2009, the Fire Scout has successfully deployed from amphibious transports, frigates, littoral combat ships (LCS), as well as flew missions in Afghanistan (Heiss 2012). Unlike previous UAVs employed by the Navy, the Fire Scout is designed to operate autonomously during both launch and recovery (Northrup Grumman 2017).

Figure 4. MQ-8 Fire Scout VTUAV. Source: Northrup Grumman (2017).

Though still a relatively new platform, the Fire Scout provides the Navy greater flexibility in missions previously attributed to manned helicopters such as the MH-60. According to his 2012 Naval Postgraduate School (NPS) thesis, Commander Kevin Heiss asserts that the MQ-8 offers up to eight hours of endurance and greater stealth compared to the MH-60R (Heiss 2012). Moreover, the smaller size and simplicity resulting from the elimination of "crew support, hydraulics, instruments, [and] fire suppression" systems intrinsic in manned aircraft results in a platform that uses "3.7 times less fuel and 14.5 times less maintenance man-hours," while also offering up to 80% cost savings per airframe compared to the MH-60 (Heiss 2012, 13).

C. FUTURE FLEET UNMANNED AERIAL ASSETS

While the MQ-8 provides more flexibility and lower expected acquisition costs, it is primarily designed to support similar missions conducted by manned helicopters. As a consequently, the Navy has a current capability gap in performing persistent, high-altitude reconnaissance via unmanned aerial assets. According to the *Unmanned Systems Roadmap 2007–2032* (2007), this mission area garners significant interest across all military branches. Table 1 shows combatant commander (COCOM) preferences for UAVs gravitate heavily toward reconnaissance and precision targeting capabilities regardless of airframe size.

Table 1. COCOM UAS Needs Prioritized by Class.
Source: Department of Defense (2007).

Mission Area	Small	Tactical	Theater	Combat
Reconnaissance	1	1	1	1
Precision Target Location and Designation	2	2	2	2
Signals Intelligence	7	3	3	4
Battle Management	3	4	5	6
Communications/Data Relay	8	6	4	7
CBRNE Reconnaissance	5	5	9	8
Combat Search and Rescue	4	7	8	9
Weaponization/Strike	16	8	7	3
Electronic Warfare	12	11	6	5
Mine Detection/Countermeasures	6	9	12	11
Counter CCD	10	10	11	12
Information Warfare	13	12	13	10
Digital Mapping	15	14	10	14
Covert Sensor Insertion	11	15	15	13
Decoy/Pathfinder	9	13	18	16
SOF Team Resupply	14	16	14	15
GPS Pseudolite	18	17	17	17
Littoral Undersea Warfare	17	18	16	18

Much like the COCOMs, the Navy exhibits significant interest in using UAVs for reconnaissance. As a result, they are adapting a variant of Northrop Grumman's RQ-4 Global Hawk for use in broad-area maritime surveillance, or BAMS. While the United States Air Force currently fields the Global Hawk, the Navy variant exhibits modifications to enhance operability in a maritime environment, including changes to airframe strength (for wind gusts, bird strikes and the like) as well as to the de-icing system necessary to support high-altitude missions. Expected in the fleet around 2021, the MQ-4C Triton will satisfy the Navy's desire to maintain a "persistent, around-the-clock surveillance" asset operating at a far higher altitude than either the Fire Scout or Poseidon (Pomerlau 2018, 2), and is considered a “key element in the Navy’s recapitalization of airborne…ISR capabilities” per the Naval Aviation Enterprise (2016, 28).

In addition to the Triton’s primary mission of providing 24/7 coverage of an area, this high-altitude asset provides several distinct secondary advantages. First, the disclosed operating altitude between 55,000 and 60,000 feet places the aircraft above the typical flight altitudes of commercial jet routes, as shown in Figure 5, alleviating airspace management conflicts.

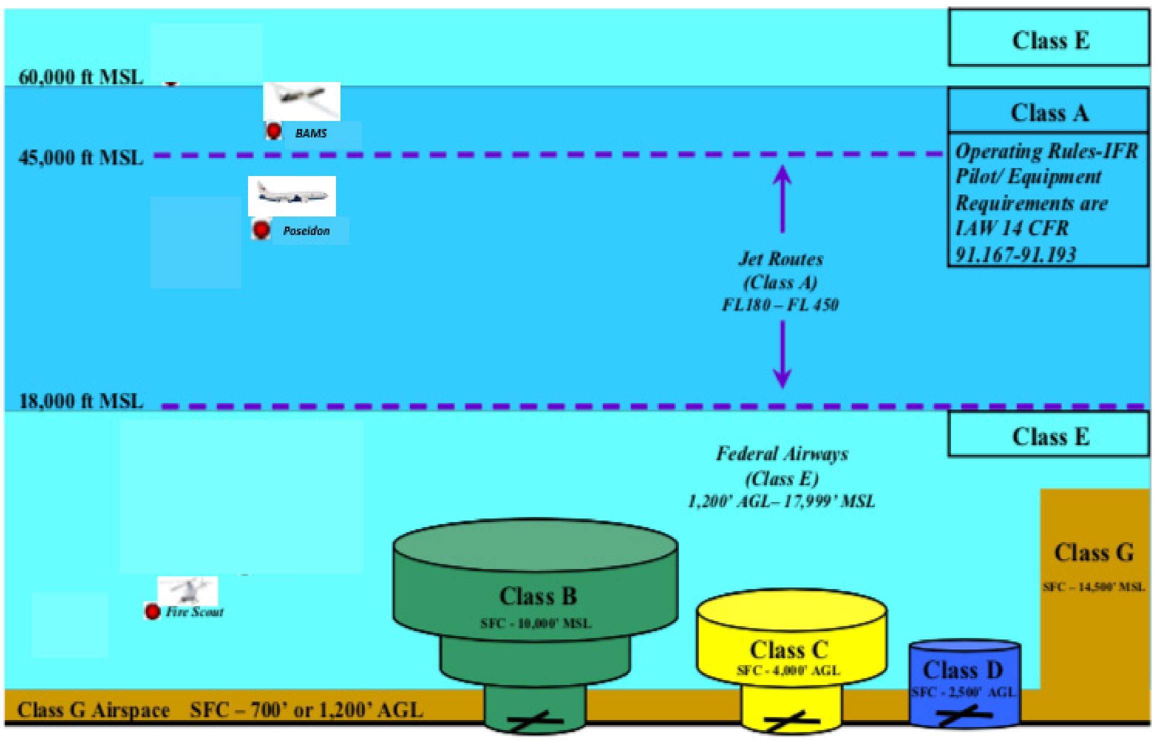

Figure 5. Operating Altitudes for Select Navy Aircraft. Adapted from: Department of Defense (2007).

Second, much like the U-2 spy plane, the high altitude of the Triton leaves the aircraft less susceptible to many conventional, ground-based weapons (Berner 2004). Finally, supplementing existing Navy reconnaissance platforms with the MQ-4 provides a means to satisfy multiple warfare areas simultaneously. According to Persistent Maritime Unmanned Aircraft Systems Program Office (PMA-262) program manager Captain Dan

Mackin, a sortie of four Tritons provides 24/7 coverage of a given target, allowing P-8s in theater to conduct their "primary mission [of] anti-submarine" warfare (Pomerlau 2018, 11).

While neither the MQ-4 nor MQ-8 are direct replacements for the P-8, the intermediate goal is to design a complementary system of systems leveraging both unmanned and manned aircraft. According to *Naval Aviation Vision 2016–2025* (2016), the "Navy's unmanned family of systems recapitalize[s] the airborne capabilities provided by the [EP-3E]" and "compliment[s] the P-8…on maritime patrol" (70). Figure 6 illustrates this concept.

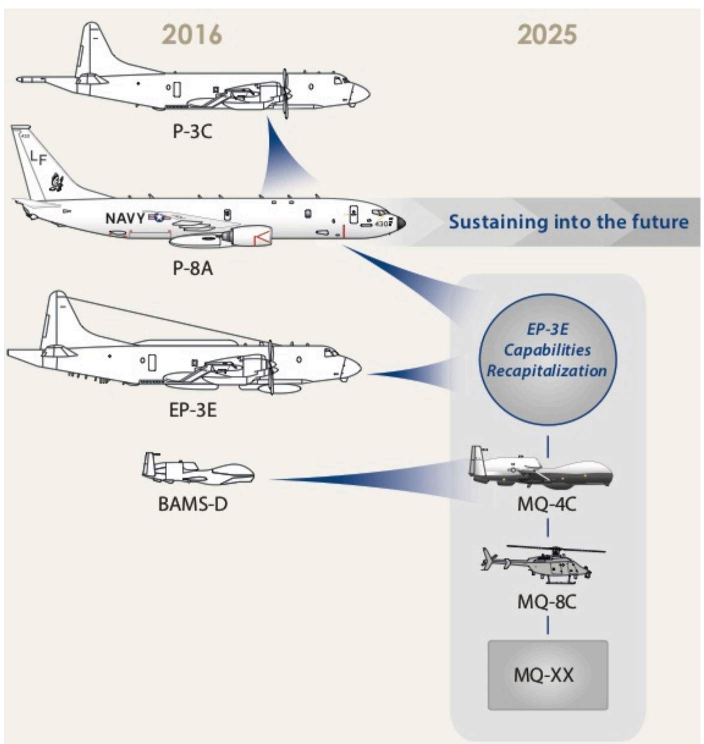

Figure 6. Navy Patrol Aircraft Roadmap. Source: Naval Aviation Enterprise (2016).

Although the notion of pairing manned and unmanned assets is hardly new, the figure qualitatively illustrates the evolving CONOPs for unmanned systems. Moreover, replacing an existing manned platform with multiple unmanned systems has ramifications in funding that potentially illustrate the future fleet's planned composition. According to Stephen Trimble (2011), budgeting for unmanned assets meant removing funds for EP-3 revitalization as well as for the manned EP-3 replacement program, dubbed the EP-X. Specifically, Trimble (2011) points out that out of an $8.6 billion budget set aside for ISR development, $1.1 billion went toward developing the Fire Scout; $3.9 billion was allocated to Northrup's BAM program; $2.5 billion was earmarked for an "unmanned carrier-launched airborne surveillance aircraft;" while the remaining $1.1 billion would be used for developing a "medium-range unmanned aircraft system," leaving "no room for extending the service life of the EP-3" beyond 2020 (4). Thus, in Trimble's estimation, the Navy exhibits less interest in continuing development of manned reconnaissance aircraft, and is gravitating more towards unmanned systems to fill reconnaissance roles.

D. PRIOR UAV COMPUTER MODEL THESES

Several prior NPS theses use computer-based models to explore functionality and parametric requirements for UAVs. The most recent study of interest is from Mohamed A. Alobaidli's 2017 NPS thesis, wherein he analyzes the use of UAVs for detection missions in support of Decisive Storm operations. Using the Map Aware Non-uniform Automata (MANA) agent-based simulation tool, Alobaidli (2017) investigates how vehicle performance and payload components of the UAS, including altitude, endurance, detection range, sensor slew rate, aperture size, and refueling time, affect enemy detection. Injecting permutations of these parameters in a simulated environment, Alobaidli's (2017) model shows that leveraging UAVs for reconnaissance operations has a positive impact on quantity of enemy forces identified; however, satisfying the operational requirements defined in his model would require "substantial financial investment and surplus flight performance and sensor capabilities" (60).

Captain Mark Raffetto conducted a similar study in 2004. Also using MANA as the simulation environment, his work explores how UAVs can contribute to intelligence, surveillance, and reconnaissance for Marine Corps expeditionary operations. Specifically, he investigates how UAV routing, sortie size, sweep width, employment, and classification ability interrelate for successful classification of enemy forces. With his particular model, Raffetto (2004) concludes that sweep width (or sensor field-of-view) has a significant impact on the quantity of enemy classifications compared to the other factors. Considering field-of-view as an altitude-dependent variable, this finding is of particular interest when analyzing the CONOPs for a future reconnaissance aircraft.

Continuing the areas of study of the two aforementioned theses, this work analyzes correlations between altitude and detection events, as well as potential relationships between sortie size and UAV survivability. However, unlike previous works, the model environment used in this thesis investigates how these characteristics affect mission outcomes in a joint, theater-level maritime environment. In turn, this provides insight in desirable high-level system requirements and helps shape CONOPs for future unmanned systems.

E. LIMITATIONS OF MANA

As with any model-based simulation software, it is prudent to understand the limitations of MANA. While a powerful tool with a minimal learning curve and set-up time, the simplicity and user-friendliness come at the cost of preconceived boundaries inherent in the software itself. Geographically, though the modeling environment is not constrained with respect to playboard size, the computational demands of an agent-based model makes it difficult to scale a scenario up to large force sizes (Fournier, Straver, and Vincent 2006). Moreover, grid-square definition directly impacts the time-steps and agent speeds used in the model in order to preclude "agents from moving through walls or other impassable terrain features"; in turn, this can result in a "very large number" of time steps necessary for fast-moving agents (Fournier, Straver, and Vincent 2006, 4).

Additionally, Fournier, Straver, and Vincent (2006) point out several shortcomings in how MANA models sensors. First and foremost, each agent in MANA is only allocated a limited set of very simple sensors, each of which applies to every target agent, regardless of type. Secondly, detection in MANA does not account for the size of the observed target, the posture relative to the sensor, nor the contrast of the target in relation to the surrounding environment, instead strictly relying on the relative range of the target to the sensor to trigger a detection event.

Using JTLS-GO as the simulation environment alleviates or eliminates many of these restrictions. However, there are inherent trade-offs with using a theater-level simulation that warrant consideration. Whereas MANA touts an easy-to-understand user interface and small learning curve, JTLS-GO is comparatively complex due to the scope of what the software attempts to model. While MANA is typically used to analyze small-scale, tactical engagements, JTLS-GO focuses primarily on simulating large-scale, theater-level exercises. As a result, JTLS-GO does not offer the same granularity for individual agents as MANA; however, since it is used to replicate theater-level command and control, it is possible to script a single wargame scenario to create multiple areas of study. Moreover, in lieu of collating sensors and the like as seen in MANA, JTLS-GO allows the user to assign units individual sensor packages, each programmed within the JTLS-GO database with discrete properties. This database structure also allows users to account for object size by explicitly entering detection, hit and kill probabilities for a particular agent. However, as with any model, JTLS-GO has its own unique shortcomings. Chapter III expounds on the merits and limitations of JTLS-GO as a model environment.

F. CHAPTER SUMMARY

This chapter provided the reader a brief history of past and current manned reconnaissance aircraft used by the Navy. It then discussed the evolution of unmanned aircraft to supplement or fulfill ISR missions. Finally, it provided an overview on how this thesis compliments former studies as well as the how unique aspects of this study enhance the existing body of knowledge.

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III. FRAMEWORK AND METHODOLOGY

This chapter begins with a definition and description of model-based systems engineering (MBSE). Next, it describes JTLS-GO in greater detail, explains the suitability of the model for this study, and reveals how the structure and inherent design of JTLS-GO alleviates some shortcomings of MANA. A description of the model scenario follows, transitioning into a discussion on injecting and measuring impacts of future UAV capabilities within the scenario. Lastly, this chapter concludes with an overview on how experimentation, design of experiments, data collection, and data analysis can provide insight to develop requirements for future UAVs.

A. A MODEL-BASED SYSTEMS ENGINEERING APPROACH

This study uses a model-based system engineering approach. According to the International Council on Systems Engineering (INCOSE), MBSE is "the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases" (Systems Engineering Book of Knowledge 2017, glossary). Specifically, this thesis focuses on theater-level concept exploration, establishing CONOPs as well as general high-level requirements. The red, dashed outline on the left-hand side of the "Vee" diagram in Figure 7 illustrates these activities in the systems engineering process.

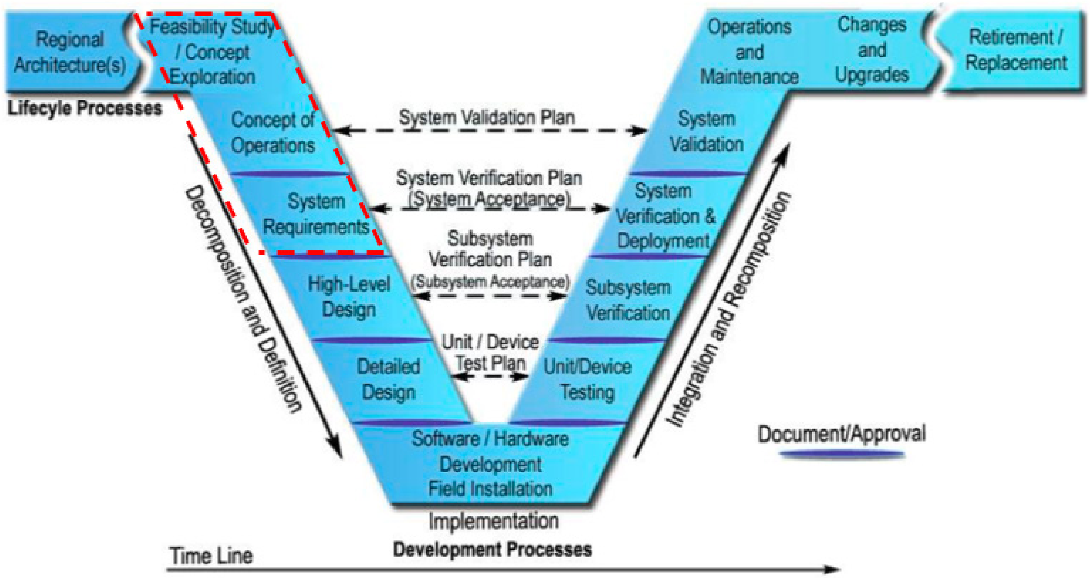


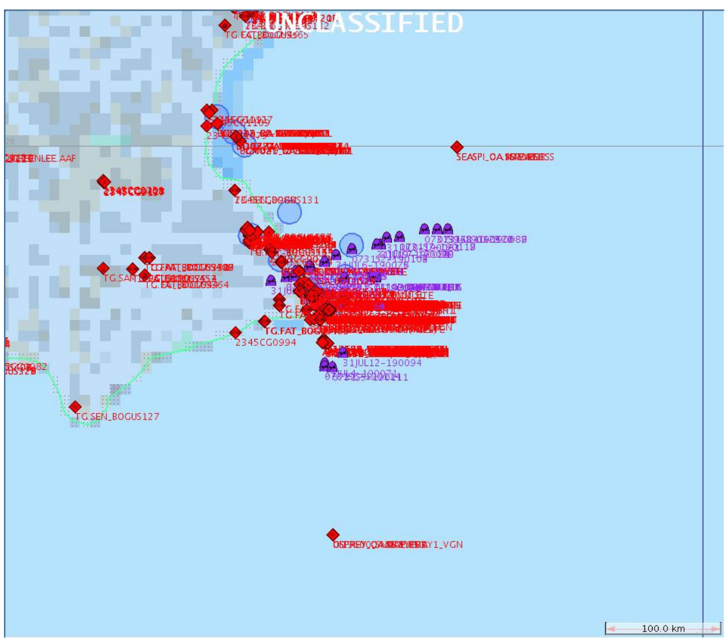
Figure 7. “Vee” Diagram. Adapted from Federal Highway Administration (n.d.).

B. JTLS-GO MODEL ENVIRONMENT

The modeling environment for this study is the Joint Theater Level Simulation-Global Operation (JTLS-GO). Rolands and Associates (R&A) developed JTLS-GO in 1983 and continues to refine the simulation model’s theater-level air, ground, and naval operations. Continuous updates ensure users gain contemporary insight about joint and coalition operations. JTLS-GO offers a number of inherent advantages for this study. First, it is a theater-level simulation specifically designed to evaluate alternative military strategies (Rolands and Associates, 2017b, 2-1). In addition, it is doctrine-neutral with user-defined database parameters for unit size and combat systems suites (Rolands and Associates 2018b). These features are helpful in establishing initial CONOPs and requirements for future systems, as it provides the user means to adjust the model as development progresses and the system is evaluated. Moreover, database refinement allows refinement of the model to satisfy different classification levels and audiences. Lastly, the fact that many DoD organizations (Joint Warfighting Center, North Atlantic Treaty Organization [JWC NATO]; the Army War College; U.S. Readiness Command; Joint Staff Joint Warfighting Directorate [J7]; and PACOM Warfighting Center [PWC]) have adopted the JTLS-GO as a model of choice lends credibility to the model's validity (Rolands and Associates, 2018c).

1. Gameplay

The simulation engine behind JTLS-GO is the combat events program, or CEP, which "determines all actions and interactions" between air, land, and naval factions, as well as "maintains and reports…the [simulated] warfare environment" (Rolands and Associates 2017a, 2-8). Users input game orders via a web-hosted interface program (WHIP). JTLS-GO utilizes two types of WHIP, one for game players and another for game controllers. Player-WHIPs allow manipulation of missions, unit tasks, and unit movement. Control-WHIPs allow creation or degradation of units and aspects of game control such as game speed. The WHIP also presents a common operating picture (COP) to the users as well as an interface in which to inject game orders. Figure 8 illustrates the WHIP interface.



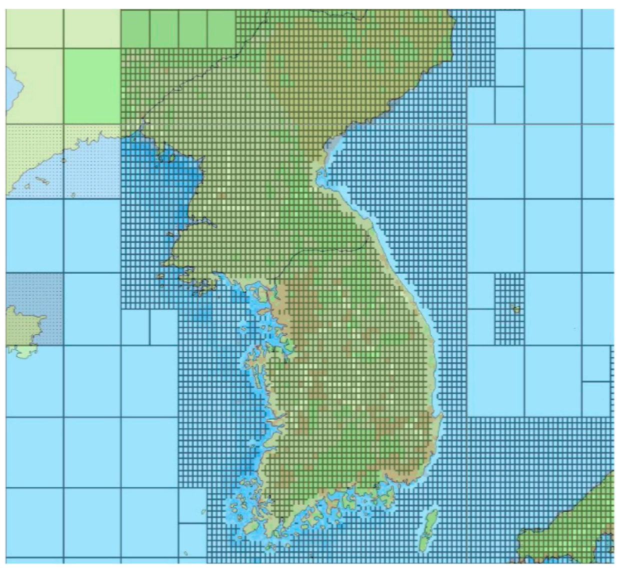
Screenshot from JTLS-GO exercise CG18. Red icons represent opposition forces. Purple icons represent U.S. units. Blue circles show search areas.

Figure 8. JTLS-GO WHIP Interface

The WHIP automatically routes orders from the player to the CEP. Once processed, the player observes changes in the COP in the form of graphics updates, or gains situational awareness via formatted messages populated in the message browser. Holistic insight for a game is accessible via a Control-WHIP, which also provides certain users direct manipulation in game speed, unit creation and unit placement.

2. Geography

JTLS-GO versions starting with release 5.0.0.0 exhibit a multi-level grid terrain in lieu of a hex-based terrain used in previous releases; these grids contain geographical data including terrain type and elevation. Grid squares vary in size from five-minute grids to one-degree grids, contingent on the terrain resolution desired; Figure 9 illustrates this.



Representation of 5-minute, 30-minute, and 1-degree grid squares.

Figure 9. JTLS-GO Layered Terrain Grid. Source: Rolands and Associates (2017b).

The scalable resolution inherent in JTLS-GO enhances this study's accuracy in two primary ways. First, geographical data automatically inhibits altitude-limited aircraft from entering certain areas of the map. Additionally, this data ensures that anti-air threats such as surface-to-air missiles or ground radar maintain a line-of-sight for a given air target prior to engagement (Rolands and Associates 2017a, 3-4). As with many aspects of the program, this geographical data is alterable via the database.

3. Unit Prototypes

JTLS-GO models military units and targets using a "'prototype' concept," wherein a single entity known as a unit prototype stores "common data for a large number of entities" (Rolands and Associates 2017b, 4-3). This simplifies data entry when building a scenario, reduces overall database size, and increases game reliability (Rolands and Associates 2017b).

According to the *JTLS-GO Analyst Guide* (2017b), the simulation presents three categories that segregate units: ship unit prototypes (SUP), high-resolution unit prototypes (HUP), and tactical-unit prototypes (TUP) (Rolands and Associates 2017a, 3-73). The SUP stores data for naval units, while the TUP holds data for all other unit types. The SUP and TUP information include object class (i.e., Los Angles-class submarine or commercial jet), speed, supply capacity, and sensor suites (Rolands and Associates 2017a, 3-73). The pre-programmed relationship between these parameters constrains how units in the model interact. For instance, an aircraft can only land on a naval unit during game play if the ship has a supporting SUP type (SUP TYPE CARRIER, for example). The aircraft, meanwhile, requires a naval qualification flag toggled to "yes." This structure within JTLS-GO limits illogical or flawed unit behaviors that could potentially invalidate or confound data that the model produces.

JTLS-GO configures airbases and squadrons as ground units, while the Aircraft Target Class (ATC) database collates groups of aircraft belonging to the squadron. The Aircraft Class Characteristics index further defines individual aircraft types within the ATC database. For example, high-altitude reconnaissance aircraft, such as the MQ-4, RQ-4, or U-2, belong to the same "High-Alt-Recce" ATC database, but operational parameters are uniquely defined under each aircraft's discrete index. These parameters include characteristics such as range, fuel, runway length requirements for takeoff and landing, cruise altitude, maximum altitude, probability of detection and weapons or sensors load-out.

A total of 20 discrete altitude zones, ranging from zero to 100,000 feet, define the operating altitudes available for aircraft within the model. Table 2 illustrates this.

Table 2. JTLS-GO Altitude Zones. Source: Rolands and Associates (2018a).

Zone	Zone Name	Highest Altitude in the Zone (Feet)
1	0-33FT	33.0000
2	34-50FT	50.0000
3	51-150FT	150.0000
4	151-200FT	200.0000
5	201-300FT	300.0000
6	301-1000FT	1000.0000
7	1001-2000FT	2000.0000
8	2001-5000FT	5000.0000
9	5001-7000FT	7000.0000
10	7001-10000FT	10000.0000
11	10001-13000FT	13000.0000
12	13001-15000FT	15000.0000
13	15001-20000FT	20000.0000
14	20001-25000FT	25000.0000
15	25001-35000FT	35000.0000
16	35001-45000FT	45000.0000
17	45001-55000FT	55000.0000
18	55001-65000FT	65000.0000
19	65001-80000FT	80000.0000
20	80001-100000FT	100000.0000

While these zones do not affect probability of detection (P_d) of an aircraft by a ground sensor, altitude data does impact aircraft movement, surface-to-air weapon lethality, range (for both aircraft and anti-air weapons), sensor performance, probability of hit (P_h) and probability of kill (P_k) (Rolands and Associates 2017a). Thus, experimenting with different altitude ranges or zones provides insight in UAV and enemy weapon systems behavior within the model.

Similar to how it models aircraft, JTLS-GO defines sensor and weapon traits in unique indexes. For sensors, pertinent parameters include sensor range, detection radius, maximum altitude for detection and recognition, probability of detection, target size discrimination, nighttime degradation and weather degradation. Air Defense Characteristics indexes define weapon systems, while Targetable Weapons (TW) indexes define the weapon itself. For instance, Air Defense Characteristic index 67 demarcates a Nike missile battery, while index 987 details the Nike missile parameters. The Air Defense Characteristics index includes parameters for engagement capability (simultaneous engagements, shots per engagement, shots before reload, reload time, and the like); degradation due to weather, day, or night factors; probability of detection when firing; maximum range and altitude; and probability of engagement against a given target. Likewise, the TW index defines weapon range and speed, radius of effect, circular error probable, guidance type(s) employed, altitude constraints, and weather, day, or night degradation.

4. Unit Detection and Attrition

JTLS-GO is discrete, meaning state changes or game events occur at specified times or specified time steps (Rolands and Associates 2017b). For example, intelligence reports over a given area are not available to the player "until a [discrete]… time has passed" (Rolands and Associates 2017a, 3-69). Likewise, detection is a discrete-time stochastic event "based on the probability of detection for units and targets" in a given area, or "specifically called out" by a player (Rolands and Associates 2017a, 3-69). According to Avery M. Law (2015), a stochastic process is a "collection of… random variables [known as the state space] ordered over time, which are all defined on a common sample place" (226). Comparing quantified database parameters (probability of detection, target size discrimination, nighttime degradation and the like) that compose each unique sensor to the CEP-generated state spaces drives detection events. For example, the CEP randomly draws a uniformly distributed number between 0.0 and 1.0 and compares it to a given sensor's database-defined parameters to determine if the sensor detects a unit (Rolands and Associates 2017b).

JTLS-GO uses Lanchestrian attrition models to compute unit casualties (Rolands and Associates 2017a, 3-31). According to Law (2015) Lanchestrian attrition, also known as an aimed-fire model, describes “a situation whereby a shooter is directly aiming at an enemy. If the enemy is destroyed, the shooter moves his fire to a new target” (710). Consequently, the firepower of a shooter becomes more concentrated as targets are neutralized. Equations 1 and 2 illustrate this concept mathematically.

$$\frac{dB}{dt} = -aR(t) \tag{1}$$

$$\frac{dR}{dt} = -bB(t) \tag{2}$$

B(t) delineates the force strength of one side, while *R(t)* signifies the strength of the opponent; *a* and *b* are attrition coefficients determined by database entries for lethality, P_h, P_k. In *Simulation Modeling and Analysis, 5th Edition,* Law (2015) describes this mathematical model as aimed-force combat, wherein a shooter (i.e., a surface-to-air missile battery) fires directly at an enemy (i.e., a UAV overhead). Should it destroy enemy, the missile battery re-targets and engages another threat, if applicable. Factors that influence unit attrition in JTLS-GO include lethality of the firing weapon, survivability of the victim, combat system range and firepower, distance between the threat and target, and the like. The sundry databases within the model quantify these parameters for each unit.

5. Model Limitations

As with any model, JTLS-GO has limitations. First, all scenarios within this thesis utilize unadulterated, unclassified databases. Therefore, some parameters, particularly concerning weapon lethality and aircraft capabilities, may deviate from real-world values. However, reviewing pertinent databases within the model and cross-referencing those values with open-source information suggests an acceptable level of realism for this study. The second inherent limitation is the representation of units. Since JTLS-GO is a theater-level simulator, it manipulates entities as units rather than as singular components. In the scope of this research, this means the database does not discretely define fine-resolution individual parameters (radar cross-section or target size, for instance) but rather collates these parameters to overall detection and hit probabilities. Nonetheless, since this study focuses on concept development and high-level requirements instead of proposing a detailed design, this limitation has minimal influence on the data or methodology.

C. SCENARIO DESCRIPTIONS

The events of Cobra Gold 2018 (CG18) frames the experimentation environment. Cobra Gold is a multinational exercise held annually in Thailand under the direction of the PACOM Warfighting Center (PWC). It entails two components: a field training exercise (FTX) and a computer-based command post exercise (CPX). The CPX uses JTLS-GO as the training environment in which military units from the United States, Japan, South Korea, Singapore, Malaysia, and Indonesia interact. The exercise simulates joint operation of navy, marine, army, and air forces from these nations. Injecting future UAV capabilities in different instantiations of CG18 allows comparative analysis between current and future military capabilities within the same exercise environment.

1. Baseline Scenario: Cobra Gold 2018

This scenario takes place in Pacifica, a fictional land mass southeast of Japan consisting of six sovereign countries: Sonora, Mojave, Kuhistan, Arcadia, Isla Del Sol, and Tierra Del Oro. Figure 10 depicts Pacifica.

Screenshot from JTLS-GO exercise CG18.

Figure 10. Pacifica

Regional destabilization occurs when Sonora invades land-locked Mojave, prompting response from a United Nations-sanctioned multi-national force (MNF). The goal of the MNF is to expel Sonoran invaders, enforce an embargo against Sonora, maintain sea control in international waters off the Sonoran coast, and provide humanitarian assistance to the displaced Mojave refugees.

Using CG18 as the baseline experimental environment to study future capabilities provides several advantages. First, there is ample area for UAV reconnaissance along the several hundred miles of Sonoran coastline, and complimenting the goals defined in the exercise. Next, Sonora's ground-based weapons systems, particularly surface-to-air missile (SAM) sites, are sufficient in quantity, quality and lethality to pose viable threats to manned and unmanned aircraft within the operating area. Additionally, an active Sonoran navy with anti-air capabilities endangers aircraft flying the littorals, thus providing a metric to gage UAV susceptibility in a contested maritime environment.

2. Test Vignettes

Test vignettes for this study occur during a 12-hour window of game play during which UAVs are injected into the CG18 scenario. Variations in UAV employment make up the factors for the design of experiments (DOE); the subsequent section discusses the variations more comprehensively.

The vignettes involve UAVs flying reconnaissance missions along the Sonoran coast and surrounding waters in user-created directed search areas (DSAs). JTLS-GO uses DSAs to define intelligence collection areas within the game. The DSA intelligence messages communicate the information collated in these areas and are displayed via the message browser; information in these messages includes detection of enemy aircraft, naval vessels, combat systems, emitters, and SAM sites.

D. PREPARING JTLS-GO VIGNETTES

This section provides an overview in preparing the test vignettes within JTLS-GO. Vignette preparation is a four-step process. Foreknowledge of enemy land- and sea-based threats drives DSA creation. Next, modeling and injecting UAVs into the simulation environment provides assets players can use to explore the DSAs. Finally, assigning reconnaissance missions to the UAVs initiates data collection.

1. DSA Creation

The player creates and defines DSAs within a player-WHIP. This study relies on information gathered from 22 DSAs: 12 on the coastline and 10 above naval vessels of interest. The user gains complete situational awareness of the battlespace via the COP presented in the control-WHIP, or limited situational awareness from the partial information presented in a given player-WHIP. Using the control-WHIP helps identify potential areas of interest in which to assign DSAs and is the method of choice for this study.

2. UAV Model

UAVs for this model are based on the MQ-4C Triton existing in the JTLS-GO database. As mentioned previously, the database explicitly states pertinent information such as range, runway requirements, and operating altitude. Comparing the parameters associated with the UAV modeled in JTLS-GO with unclassified data from the Unmanned Systems Roadmap and other open-source information reveals a reasonably accurate representation of expectations for a high-altitude, theater-sized UAV.

3. UAV Injection

Creating and injecting UAVs happens in the Control-WHIP. Options available to the user include name, unit prototype, naval qualification, squadron size, and home base. Injecting four squadrons with 18 aircraft each provides ample resources for experimentation. Lastly, changing the unit arrival time in the Control-WHIP from the default value of 99 days to the desired game time places the UAVs in the scenario for mission assignment. JTLS-GO acknowledges creation and placement via the message browser.

4. Mission Assignment

Assigning missions to UAVs is done using a Player-WHIP. JTLS-GO offers five primary types of air mission: offensive air operations, defensive air operations, support missions, logistics operations, and search and rescue missions. These mission types determine aircraft load out and ROE. Assigning the UAVs used in this study to reconnaissance (or recce) missions outfits them with visual, infrared (IR) and forward looking infrared (FLIR) sensors for realistic detection capability against enemy assets.

E. EXPERIMENTATION

Experimentation seeks to investigate and determine the "effects of input variables (factors) on an output variable (response) at the same time" (Minitab, Inc. 2017). Holistically, this process requires several steps. First, defining measures of effectiveness, or MOEs, provides a metric by which to gage the impact of UAVs within the simulation. These MOEs correspond to the output variables. Next, postulating and establishing factors thought to affect the MOEs is necessary. For this study, operational and performance parameters of the UAV (i.e., altitude or time between launches) compose the input variables, or factors. Changing factor values results in changes in the scenario response, which is then gaged against the MOEs. Subsequent sections define these input variables and MOEs more explicitly.

1. Measures of Effectiveness

Defense Acquisition University (n.d.) defines a measure of effectiveness as "data used to measure…mission accomplishment…that comes from using the system in its expected environment" (2236). According to DAU (n.d.), this environment entails "sensors, command and control, and platforms…needed to accomplish an end-to-end mission in combat" (2236). John M. Green (2001) further refines this definition by contextualizing MOEs as "quantifiable benchmarks against which the system concept and implementation can be compared" (1).

This study uses two MOEs to answer the proposed research questions, both of which are measured over a twelve-hour period of game play. The first MOE focuses on the survivability of UAVs while flying reconnaissance missions over a contested maritime environment. While 100% survivability is desirable, it is untenable in the simulated environment. Therefore, this MOE determines what combination of UAV operating parameters yields the least attrition and informs the stakeholder what capabilities are necessary to minimize vulnerability of unmanned aerial assets in hostile environments.

The second MOE is the number of UAV detection events in a twelve-hour period. DSA intelligence messages quantify this MOE, with further refinement accomplished by parsing the messages for enemy high-value units (HVU) within the DSA. This communicates and enumerates the effect UAVs have in maintaining and enhancing maritime domain awareness in a contested environment.

2. Design Factors

Law (2015) describes experimental design factors as "input parameters and structural assumptions composing a model…[affecting] output performance measures called responses" (629). In the context of this study, design factors are the parameters that comprise the operating characteristics of the UAV, while game outcomes pertinent to the MOEs illustrate the response. Thus, injecting new UAVs into the CG18 exercise alters the observed simulation outcome. Figure 11 shows the graphical representation of this concept, whereby UAV design factors are modified in the CG18 exercise.

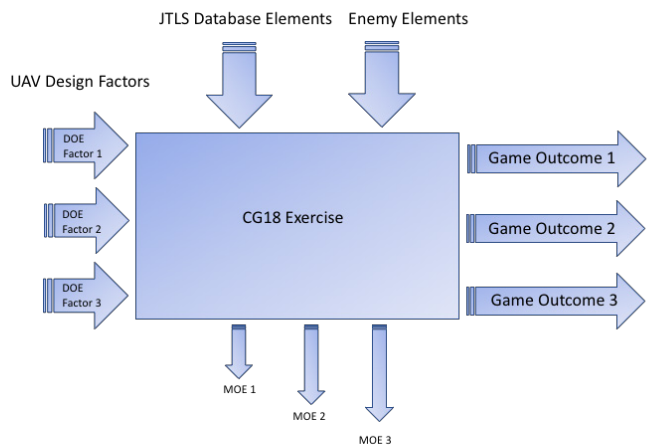


Figure 11. Designs of Experiment within Cobra Gold 2018

Each design factor is further segregated into discrete values, with unique combinations of factor values making up design points. For example, 1 UAV flying at 10,000 feet with an hour between launches would describe one design point. Thus, each design point represents a different, alternative UAV configuration within the game. Uncontrollable factors, such as unaltered database elements or the quantity and lethality of enemy units, are outside the scope of the study and thus remain consistent between each instantiation. Controllable factors are the basis for experimentation, and include UAV parameters that determine theater-level CONOPs; these parameters represent the independent variables of the experiment. Table 3 summarizes the design factors.

Table 3. Design of Experiment Factors and Ranges

Entity	DOE Factor	Min	Max	Units
UAV	Altitude	10	60	kft
UAV	Number Employed	1	3	UAVs
UAV	Time Between Sorties	0	60	min

Recalling that JTLS-GO uses discrete altitude zones in modeling weapon range and lethality, the design factor varying UAV altitude provides insight in an optimal flight altitude for detection and counter-detection. The minimum value represents the typical altitude of air missions in CG18, while the maximum altitude provides a realistic representation of the flight-altitude from a reconnaissance UAV.

Likewise, varying the quantity of targets (in this case, UAVs) against an adversary's weapon systems is expected to yield a noticeable trend since JTLS-GO uses Lanchestrian attrition. Since the Navy anticipates a four-UAV sortie will provide continuous ISR coverage of an area over a 24-hour period (Pomerlau 2018), this thesis assumed that a two-UAV sortie would be optimal for the 12-hour period on which each vignette is based. Thus, using between one and three UAVs in the modified scenarios provides two additional design points to test this hypothesis.

Finally, staggering UAV sortie time should result in a discernable variation in UAV survivability since database parameters for air defense weapons specify time between shots and simultaneous engagement capability. This design factor tests the effects of a swarm of UAVs saturating an enemy air defense system providing decision makers awareness in an optimal employment strategy for UAVs in contested environments. This thesis uses one hour as the upper boundary to ensure the last sortie has adequate transit time to reach the assigned DSA.

3. Experimental Design

After establishing design factors and measures of effectiveness, the next step is setting up a design of experiment to quantify relationships between these factors and

MOEs. Designs of experiment (DOEs) provide two primary benefits. First, DOE allow isolation of interactions within the model. Second, DOE help refine requisite UAV capabilities by identifying design factors that have the greatest impact on MOEs.

Experimentation for this study uses a central-composite design (CCD), which entails unique analysis of each design in relation to every other design factor. The number of UAVs in the modified scenario ranges between 23 and 69 UAVs, resulting in three levels. Time between launches varies from zero minutes (all UAVs launched simultaneously), a half-hour, or one-hour, resulting in three additional levels. Since each altitude chosen for experimentation represents a different altitude zone within JTLS-GO, covering the extrema (the minimum and maximum altitudes at 10,000 feet and 60,000 feet, respectively) and a midpoint necessitates three additional levels, resulting in 27 unique design points. Table 4 illustrates design levels derived from the aforementioned design factors.

Table 4. Design Factor Levels

Total Number Employed	Time (min)	Altitude (kft)
23	0	10
46	30	35
69	60	60

4. Factor Screening

Law (2015) describes factor screening as a means of determining "which factors have the greatest effect on a response… [with] the least amount of simulating" (630). This thesis uses a 2^k-factorial design for initial data analysis and progresses to a CCD for final analysis. The former employs only the extrema, or maximum and minimum values for each design factor, resulting in eight unique design points. The latter includes midpoints as delineated in the previous section, bringing the total number of design points to 27. Conversely, a full-factorial design maintaining continuity in all the design factors (i.e., 60 discrete values for time, each representing one-minute intervals and including all 10 pertinent altitude zones between 10,000 feet and 60,000 feet) would result in 1,800 unique design points. While this granularity might provide the highest resolution on how the design factors impact the game, the requisite time and computing power would negate any potential benefit.

Thus, limiting or screening these factors provides adequate insight on the impact each factor has in the simulation outcome. In other words, it illustrates quantitative and qualitative trends that communicate whether the individual design factors warrant further investigation before progressing to a more inclusive design and time-intensive simulation.

5. Central-Composite Design

Once factor screening is complete, using a central-composite design for analysis further refines the model and gives greater understanding of the data output. To accomplish this, CCD provides estimates of the constant term, coefficients and non-negligible cross-product terms within the model (Box, Hunter, and Hunter 2005). Since the factor screening experimentation shows all of the UAV design factors have an impact on the game outcome, using a CCD including 19 additional axial points along with a center point is appropriate to further analyze model behavior. This results in a total of 27 design points to test within the model.

6. Number of Replications

Each design point undergoes several replications in order to reduce data variability and account for random errors inherent within the experiment (Alobaidli 2017). This study maintains a 95% confidence interval for the data means and uses 30 replications per design point for the central composite experimentation. The resulting interval length, *w,* is calculated using Equation 3:

$$w = \frac{2Z_{\alpha/2}\sigma}{\sqrt{n}} \tag{3}$$

where $\alpha = 0.05$, $Z_{\alpha/2}$ corresponds to a value of 1.959 based on the confidence interval, σ is the sample standard deviation, and n is the sample size. Initial data analysis from 10 replications shows the standard deviations for HVU detections and UAV attrition as

105.5 and 4.02, respectively. Thus, 30 replications is expected to yield an interval length of approximately 76 HVU detections and around 3 UAV losses; these margins of error provide adequate precision for this study.

F. DATA COLLECTION

For data collection, this thesis uses three software applications designed by NPS SEED Center Research Associate Steve Upton. The user configures game replications with the first component, JTLSfarmer. Once complete, JTLSfarmer calls the next application, JTLSrunner, which automatically copies and runs multiple iterations of a modified game. For the scope of this thesis, the modified game encompasses the injection of UAVs in the CG18 scenario; it does not alter any units pre-existing within the game. Finally, JTLSminer parses data from the modified scenario by searching all the messages generated during the game and extracting those deemed important for discriminating MOEs. As previously discussed, this data includes DSA intelligence messages and aircraft loss reports generated during gameplay. Lastly, quantifying metrics within these messages communicates the impact of injected UAVs within the CG18 scenario. Figure 12 graphically illustrates this workflow.

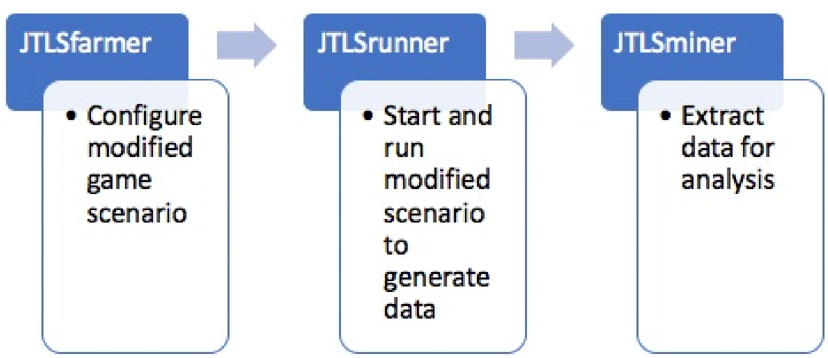


Figure 12. Data Collection Workflow

G. DATA ANALYSIS

JTLSminer extracts raw data from each game iteration, while JMP statistical analysis software provides quantitative and qualitative analysis of the raw data in order to help answer the research questions. This thesis uses regression analysis, visualizations and experiment-driven optimization to quantify and qualify the results of the modified scenarios. The following subsections discuss these tools and their use more explicitly.

1. Regression

Regression models communicate several pieces of pertinent information. Qualitatively, a regression plot reveals how well individual design points fit the modeled regression line, thus communicating the general fit of a data set to the regression model. Moreover, regression plots depict the relation of a singular design point to the overall mean response. Quantitatively, the R-squared (R^2) value communicates how well the data fits the regression model; in other words, it is a numerical representation delineating the variability of a data set within the model. The probability value, or p-value, shows the significance of the holistic model in affecting the model's response. Taken together, the regression plot provides a visual and numeric assessment of model fit and data variation.

Regression plots are a means to correlate response variables, plotted along the ordinate, with a set of independent variables along the abscissa (SAS Institute, Inc. n.d.). For this thesis, the response variables are HVU detections and percentage of UAV losses, which relate to the previously discussed MOEs, while the independent variables correspond to the aforementioned design factors: quantity of UAVs flown, altitude, and time between launches.

2. Main Effects Plots

Main effects plots explain how strongly individual design factors affect the response variable. Steeper slopes are indicative of a stronger interaction or effect on the response variable. Typically, positive slopes delineate that increasing a given parameter increases the associated response metric. Conversely, a negative slope means that increasing the parameter decreases the response metric, while a zero or near-zero slope indicates that the parameter has marginal effects on the metric. Figure 13 shows an example main effects plot.

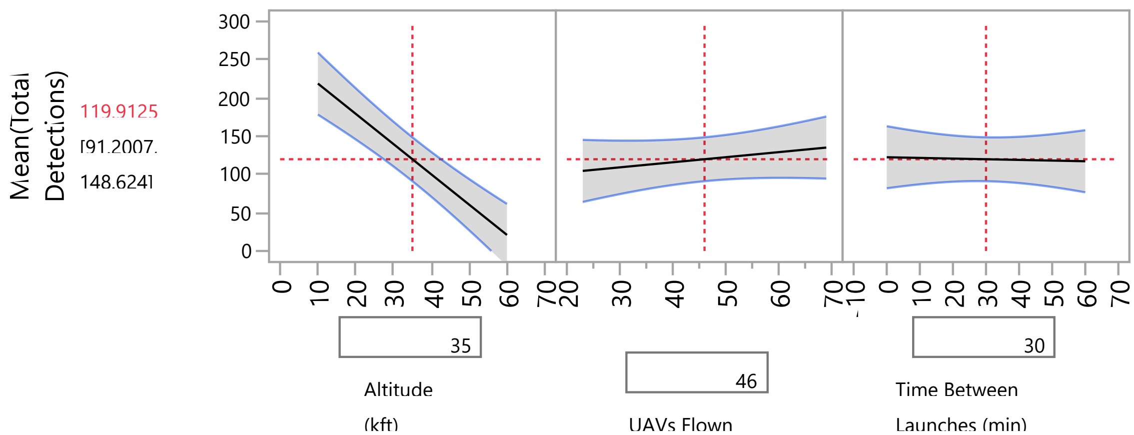


Figure 13. Example Main Effects Plot: HVU Detection

3. Interaction Plots

Interaction plots communicate possible interaction effects between the design factors. Similar to main effects plots, the slope on an interaction plot qualitatively denotes the strength of the interaction, while parallel lines correlate to minimal interaction. Figure 14 shows an example of an interaction plot.

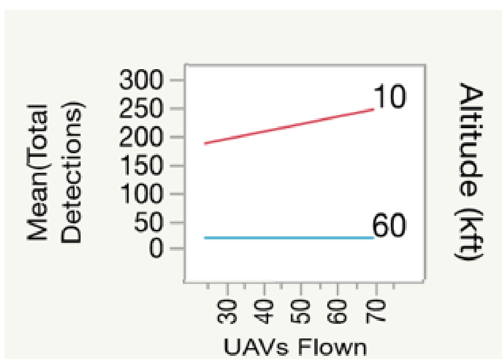


Figure 14. Example Interaction Plot: Altitude and UAV Quantity on HVU Detection

4. Partition Trees

As data-mining tools, partition trees compliment the information provided from a regression model (SAS Institute, Inc. 2018). A cutting value within JMP determines the data splits that result in the highest resultant R^2 value. As a result, each partition or split of the tree illustrates the most significant factor affecting the metric at that split. This provides a rudimentary decision tree, showing stakeholders which parameter or combinations of parameters result in good or undesirable outcomes. Figure 15 shows an example of a partition tree.

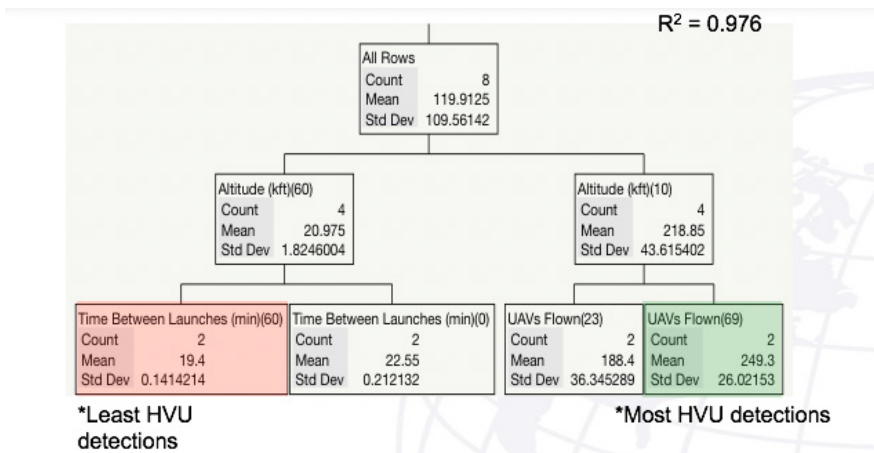


Figure 15. Example Partition Tree

H. CHAPTER SUMMARY

This chapter provides the reader a brief overview of the model-based systems engineering methodology. It then discusses JTLS-GO as the modeling environment, to include its history, structure, strengths and limitations for use in this thesis. The chapter then provides descriptions of the modeling scenario within CG18, as well as the test vignettes this thesis uses to test future UAV capabilities. Next, this chapter informs the reader how to prepare JTLS-GO for testing and simulation. Lastly, the chapter concludes with a brief discussion on designs of experiment, design factors, and data collection and analysis that comprise Chapter IV.

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IV. RESULTS AND DATA ANALYSIS

This chapter contains results from the computer-aided experimentation that address this thesis's research questions. The discussion starts with analysis of the 2^k screening results and examines the impact the chosen design factors have on the MOEs. Next, this chapter transitions to the results from the central-composite design, providing more thorough analysis of the two MOEs that comprise this work. Lastly, this chapter concludes with examination of potential correlations between the two MOEs, illustrating potential trade-offs inherent in system design.

A. RESULTS FROM 2^K-FACTOR SCREENING

The purpose of screening is to develop a preliminary understanding if, or how, the design factors influence the exercise outcome and potentially impact the MOEs. Table 5 shows the eight design points and associated design factors used for the screening experimentation.

Table 5. Design Points Used for Factor Screening

Design Point	Altitude (kft)	UAVs Flown	Time Between Sorties (min)
1	10	23	0
2	10	23	60
3	10	69	0
4	10	69	60
5	60	23	0
6	60	23	60
7	60	69	0
8	60	69	60

Starting data analysis with these eight design points provides a number of benefits for this study. First, limiting the scope of experimentation to eight unique design points with ten replications per point reduces the requisite time for data collection. In effect, this provides initial insight and rudimentary trends that qualify and quantify the impact that the three design factors (altitude, number of UAVs flown, and time between sorties) have on the scenario outcome, while reducing the necessary time investment to gather these trends. Next, correlating the design factors to the pre-established MOEs is also a benefit of experimental screening. This, in turn, validates the usefulness of the MOEs and determines if the appropriate requirements are established for the conceptual system prior to engaging in more intensive experimentation.

1. MOE 1: UAV Attrition

The regression model provides a visual assessment of model fit and data variation. Figure 16 shows the regression model for the first MOE and identifies several pertinent trends therein. First, the coefficient of determination, or R^2 value, quantifies how closely data fits a regression line. In this case, an R^2 value of 0.96 suggests that a high percentage of the response variable (percentage of UAVs lost to enemy defenses in this instance) can be predicted or explained by the model; in other words, 96% of the response variability falls around the projected mean (Minitab, Inc. 2013). This result communicates that the chosen design factors are useful for explaining the validity of the MOE.

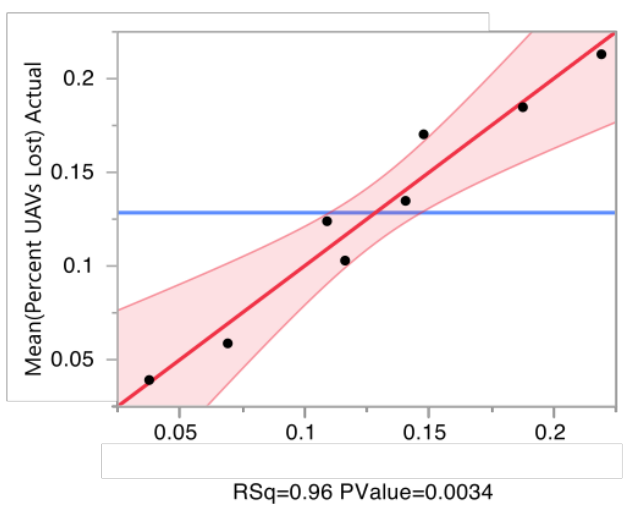
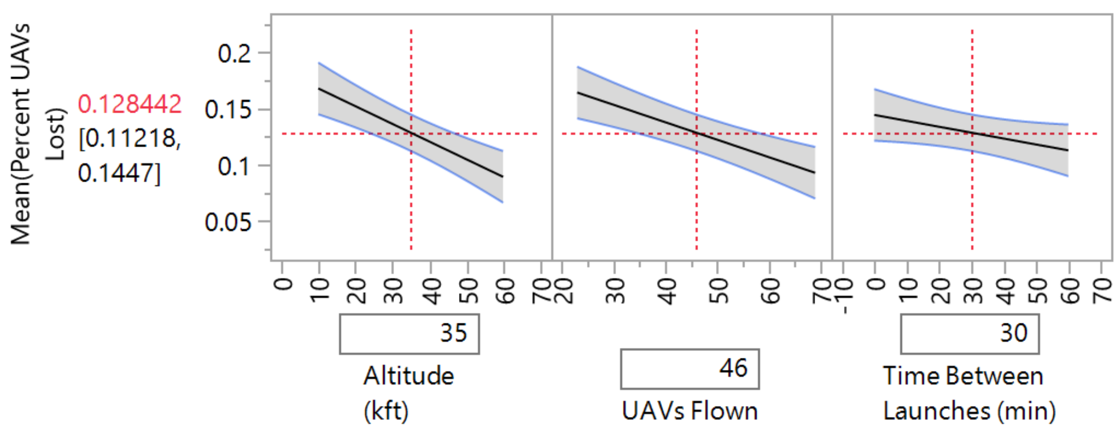


Figure 16. Actual versus Predicted Plot: UAV Attrition

The graph also illustrates the qualitative goodness-of-fit of the regression model. Each black dot represents a unique design point; the eight dots encompass the eight design points used for experimental screening. The bold red line between the abscissa and ordinate is the linear regression line, the pink swaths surrounding the regression line indicate the confidence curves, and the central blue line is the average percent attrition between the eight design points. The closer the eight design points are to the regression line, the better the model's fit. Moreover, since the confidence curves intersect at the mean of the response, the results can be considered as statistically significant, meriting further research.

The main effects plots illustrate and quantify the impact that each individual design point has on the mean percentage of UAVs lost to enemy fire. In context of a screening experiment, the main effects plot helps determine if a given design factor warrants more intensive examination. Figure 17 shows the main effects plot and associated parameter estimates for MOE 1.



Term	Estimate	Std Error	t Ratio		Prob>|t|
Altitude (kft)	-0.00157	0.000234	-6.71		0.0026*
UAVs Flown	-0.00155	0.000255	-6.09		0.0037*
Time Between Launches (min)	-0.000525	0.000195	-2.69		0.0546

Figure 17. Main Effects Plot: UAV Attrition

This figure exhibits several trends useful in analyzing potential impacts the individual design factors have in the mean percentage of UAVs lost. First, the three graphs all exhibit a non-zero slope, suggesting that altitude, quantity of UAVs flown, and time between launches all have an impact on the percentage of UAVs lost from enemy fire. The two-tailed t-test values further qualify this trend. These values, seen under the "Prob>|t|" column, correlate to the p-value and evaluate how well the sample data supports the null hypothesis that the individual design factors have no effect on UAV attrition (Minitab, Inc. 2014). The low p-values rejects the null hypothesis and suggests that changes in UAV attrition are attributable to changes in the design factors: altitude and the number of UAVs flown are primary factors determining UAV losses. Increasing time between sorties from zero minutes to 60 minutes also has a meaningful effect on UAV attrition, but is not as strong a factor as the other two.

2. MOE 2: High-Value Unit Detections

Figure 18 shows the regression model for the second MOE. As with UAV attrition, this model exhibits good fit ($R^2 = 0.98$) and is statistically significant based on the low p-value of 0.0087. Additionally, it shows that the design factors have meaningful impact on MOE 2. Similar to the previous model, the regression model for HVU detection relies on eight design points; however, the astute reader will notice only six points are explicitly illustrated on the graph. This suggests that a factor or combination of factors is predominantly driving the lower detection means seen in the bottom left corner of the graph. Testing this hypothesis is accomplished using main effects plots and interaction plots; the subsequent sections discuss the application of these techniques more precisely.

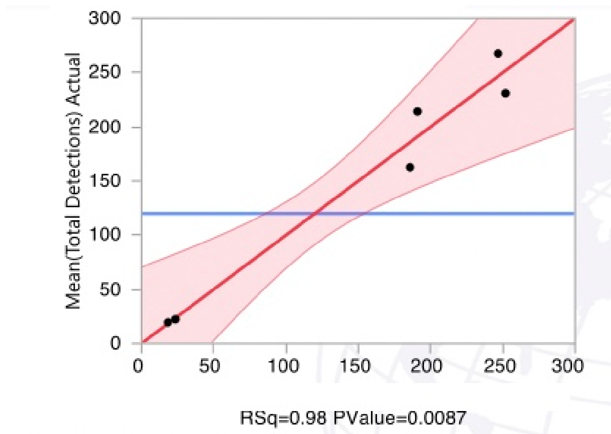
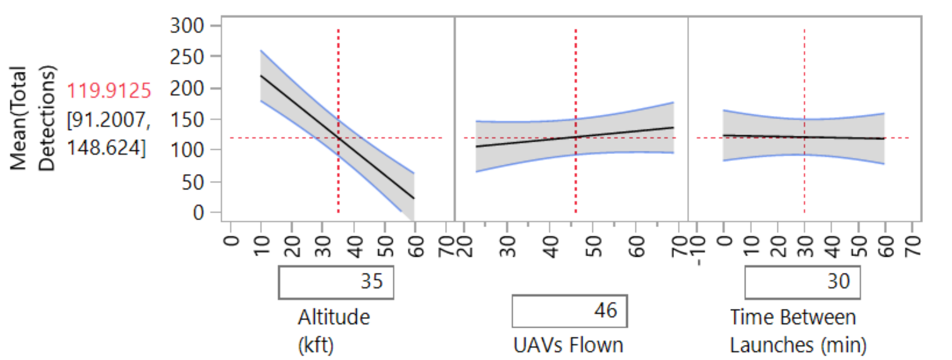


Figure 18. Actual versus Predicted Plot: HVU Detection

The main effects plots show that altitude is the driving factor determining the quantity of enemy HVUs detected; this is seen in both the graph and the accompanying probability-value of 0.0016. Conversely, time between launches has almost no impact, as seen by the near-zero slope and quantified by the large t-value. The quantity of UAVs flown has some effect in mean HVU detection, though it is not as prominent a factor as altitude. Figure 19 shows the main effects plot delineating how altitude, UAV quantity, and sortie size affect enemy HVU detection.



Term	Estimate	Std Error	t Ratio		Prob>|t|
Altitude (kft)	-3.95	0.361	-10.9		0.0016*
UAVs Flown	0.662	0.392	1.69		0.189
(Altitude (kft)-35)*(UAVs Flown-46)	-0.0264	0.0156	-1.69		0.190
Time Between Launches (min)	-0.0870	0.30073	-0.29		0.791

Figure 19. Main Effects Plot: HVU Detection

Unlike UAV attrition, HVU detection exhibits interaction effects as well, primarily between altitude and the quantity of UAVs flown. Figure 20 illustrates the interaction effect.

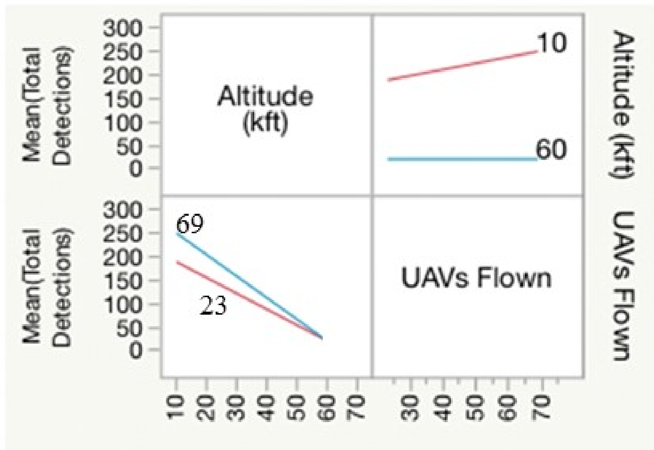


Figure 20. Interaction Effects between Altitude and UAV Quantity

The upper-right and lower-left quadrants of the graph illustrate the same trend; however, it is more clearly delineated in the top-right. Similar to the main effects plot, the slope of the lines correlate to the strength of the interaction effect. Thus, the graph communicates two valuable conclusions. First, the flat-line at 60,000 feet suggests that sensor resolution is severely limited at high-altitude; in other words, flying more UAVs does little in increasing HVU detections since the sensor resolution is insufficient within the game environment. Conversely, adding more reconnaissance UAVs at lower altitude results in a positive trend vis-à-vis HVU detection.

3. Experimental Screening Conclusions

The initial screening experiment provides two primary conclusions. First and foremost, the results show that all three design factors are significant enough in influencing the MOEs to warrant subsequent exploration. While altitude, quantity, and time between launches have a more prominent effect on MOE 1, the trends and interaction effects between these factors merit additional analysis for MOE 2.

Second, the results, though drawing from a relatively small sample size, exhibit behaviors that match expectations, indicating that the system is modeled in a reasonable manner. For instance, flying a UAV in contested areas at higher altitude decreases vulnerability, presenting the enemy air defenses a comparatively smaller target compared to a UAV flying at lower altitudes. The trends from the main effects plots and prediction illustrate this. Likewise, intuition suggests that flying at lower altitudes would result in a greater number of HVU detections, while high altitude flight results in decreased detection due to insufficient sensor resolution; the initial trends from the screening experiment supports this theory.

B. RESULTS FROM THE CENTRAL-COMPOSITE DESIGN

The data and results from the screening experiment show that all three of the selected design factors affect the model and warrant further investigation. A central-composite design forms the basis for the higher-resolution DOE, implementing an additional 19 design points to the 2^k-screening experiment. This more comprehensive DOE provides greater insight in how each design factor, or combinations of factors, affect the model outcome. Table 6 shows the design points for the CCD.

Table 6. Design Points for Central-Composite Design

Design Point	Altitude (kft)	UAVs Flown	Time Between Sorties (min)
1	10	23	0
2	10	23	30
3	10	23	60
4	10	46	0
5	10	46	30
6	10	46	60
7	10	69	0
8	10	69	30
9	10	69	60
10	35	23	0
11	35	23	30
12	35	23	60
13	35	46	0
14	35	46	30
15	35	46	60
16	35	69	0
17	35	69	30
18	35	69	60
19	60	23	0
20	60	23	30
21	60	23	60
22	60	46	0
23	60	46	30
24	60	46	60
25	60	69	0
26	60	69	30
27	60	69	60

1. MOE 1: UAV Attrition

Figure 21 shows the regression model delineating mean percentage of UAV losses across the 27 design points. The model exhibits decent fit, with 76% of the data variability falling around the projected mean and mostly within the 95% confidence bands. The subsequent section explains the effects of the individual design factors on the model.

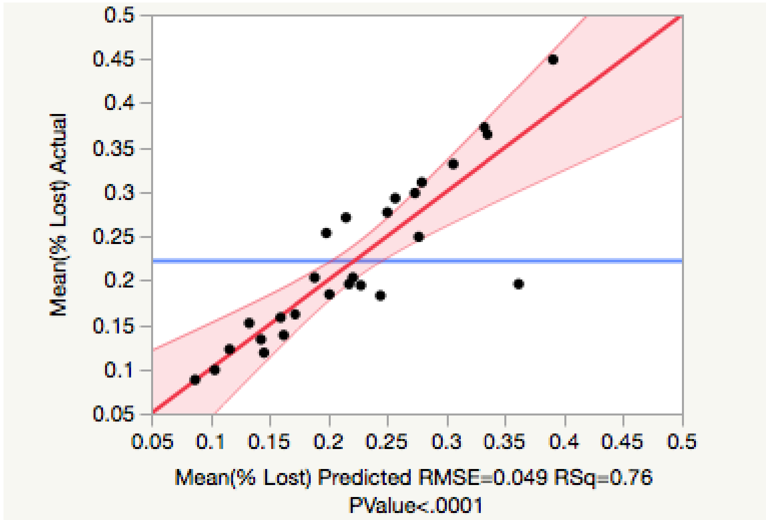
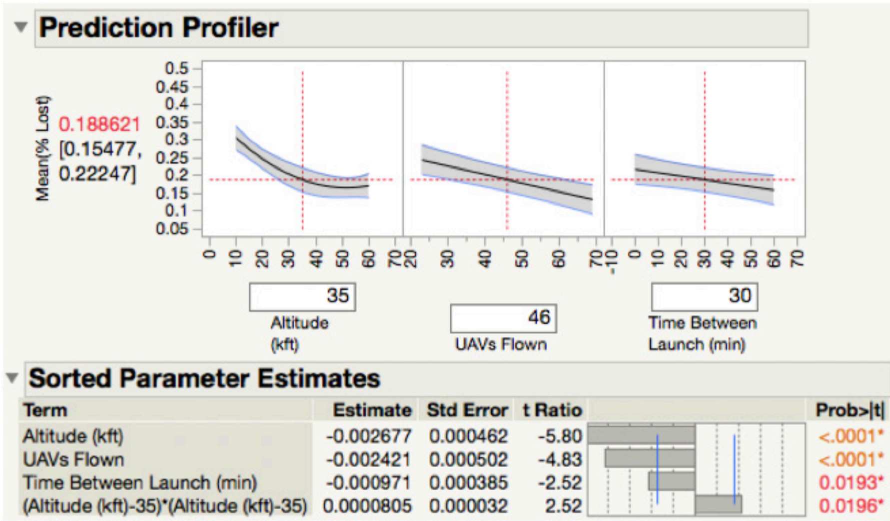


Figure 21. Regression Model for UAV Attrition

a. *Prediction Profiler and Parameter Estimates for MOE 1*

The prediction profiler graphically illustrates the effects that altitude, quantity of UAVs flown, and time between launches have on the mean percentage of UAVs lost, while the sorted parameter estimates quantify the statistical and practical impact of the three factors within the model via the estimate and t-ratio columns. The estimate column provides an approximate percentage change in UAV losses that results from altering one of the three design factors, while the t-ratio communicates statistical significance for a given factor. According to Law (2015) and Ross (2010), a larger t-value indicates stronger evidence to reject the null hypothesis. In the scope of this thesis, the null hypothesis postulates that all means are the same, suggesting that none of the three design factors influence the MOE. Figure 22 shows both the profiler and parameter estimates for MOE 1.



Term	Estimate	Std Error	t Ratio	Prob>|t|
Altitude (kft)	-0.002677	0.000462	-5.80	<.0001*
UAVs Flown	-0.002421	0.000502	-4.83	<.0001*
Time Between Launch (min)	-0.000971	0.000385	-2.52	0.0193*
(Altitude (kft)-35)*(Altitude (kft)-35)	0.0000805	0.000032	2.52	0.0196*

Figure 22. Prediction Profiler and Parameter Estimates for UAV Attrition

The left-most graph in the prediction profiler illustrates how increasing altitude decreases the mean percentage of UAVs lost to enemy fire, while the associated t-ratio shows this correlation is statistically significant. This result makes sense: higher altitudes can not only exploit range limitations of anti-aircraft weaponry, but also take advantage of the fact that radar systems suffer from range-dependent signal loss (Macfadzean 1992). Moreover, the curvature in the trend line suggests that altitude alone will not make the aircraft impervious to enemy artillery; however, it can reduce susceptibility by limiting the possible anti-air assets that the enemy could effectively employ.

Similar to increasing altitude, flying more UAVs in a hostile region has a positive effect on lowering attrition. This result also matches intuition since an increase in UAV quantity can overwhelm certain characteristics intrinsic in a fire control system, such as slew rate or firing rate.

The final main effect to analyze is the impact of launch time on UAV losses. Similar to the other two factors, time between launches also has a desirable effect on lowering UAV casualties; however, it is not as strong an influence as the others. While this seems contradictory to the previous trend, several factors may explain the results. One possibility is that the model inherently considers ADA avoidance between sorties. In other words, staggering launches provides an opportunity for future flights to circumvent areas of higher attrition en route to their respective DSA. Operationally, this would be realistic, as mission planners would reorient decisions based on battlefield observations.

Since there are no major interaction effects within the three design factors driving the percentage of UAV losses, another possible explanation is that there is an unresolved influence that specifically affects time between launches. For the scope of this thesis, UAV routing was not explicitly defined by the author. Thus, the model defaults to using fuel efficiency and time to dictate flight paths to the various DSAs. For example, the first sortie may be flying to a more volatile DSA than the second sortie, which launches at some discrete time interval (in this case, either 30 or 60 minutes). As a result, the second sortie experiences lower casualties, seemingly attributable to the temporal difference. Further research experimenting with UAV routes in situ could potentially reveal the actuality of this confounding effect.

b. Partition Tree for Attrition

The partition tree in Figure 23 more concisely illustrates trends based on attrition from the parameter estimates. The topmost node represents the 27 design points in their entirety, with the first split occurring at the most significant factor, UAV altitude. This split conveys a higher loss-rate percentage flying at 10,000 feet versus 35,000 feet or 60,000 feet; nine UAVs flying at 10,000 feet suffer nearly twice the attrition compared to 18 UAVs flying at 35,000 and 60,000 feet. Thus, if the primary concern of a stakeholder is minimizing attrition, the model suggests that flying at higher altitudes is a viable design option to achieve that goal.

The next split shows that the quantity of UAVs flown has the next-greatest influence on UAV survivability. In this instance, enemy forces in the model are less likely to attrite UAVs in larger sortie sizes. Conversely, at lower altitudes, staggering time between launches has the most impact on UAV survivability: launching every reconnaissance asset without delay maximizes low-altitude attrition.

The final split delineates the factor combinations within the model that provide the best survivability and conversely, the highest attrition. This partition shows that the lowest percentage of UAV losses are obtained when flying a large number of aircraft at high altitude; consequently, flying fewer UAVs at low altitude increases the loss rate within the model.

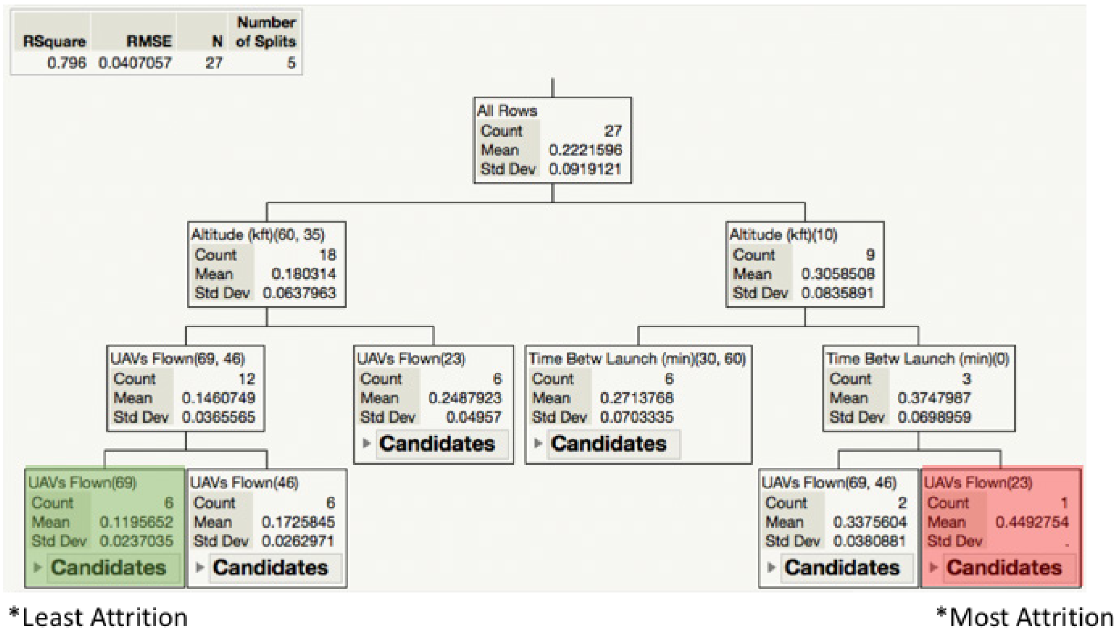


Figure 23. Partition Tree for MOE 1

2. MOE 2: High-Value Unit Detections

Figure 24 illustrates the regression model for MOE 2. The model shows a high R^2 of 0.99, suggesting that the model explains almost all of the data variability. However, rudimentary observation into the data dispersion reveals that mean detections as a whole fall into two groups: detections from an altitude of 10,000 feet in the upper right, and equally low detections from flights at 35,000 feet or 60,000 feet grouped in the lower left.

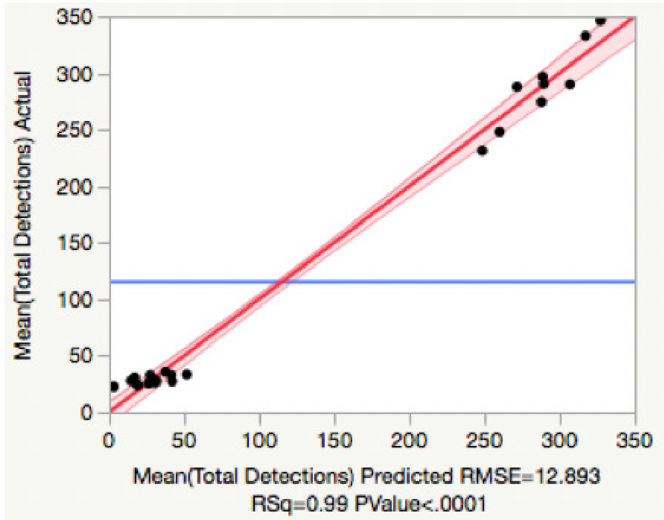


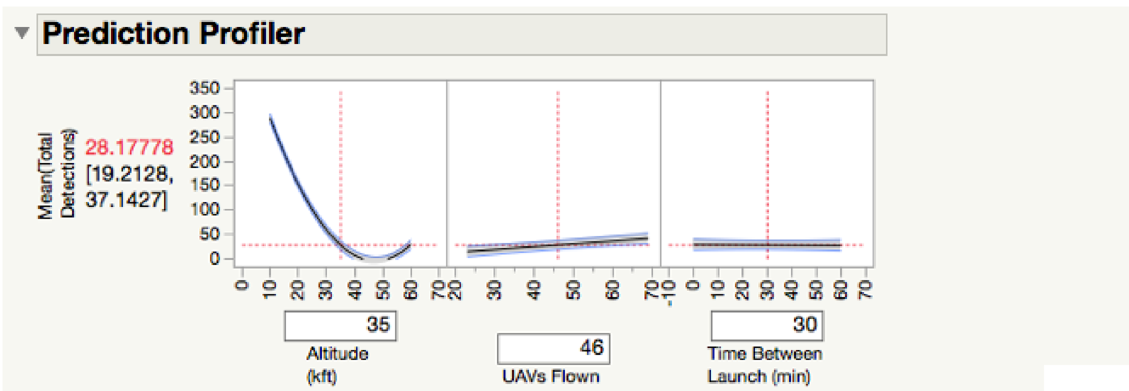
Figure 24. Regression Model for HVU Detection

a. Prediction Profiler and Parameter Estimates for MOE 2

Figure 25 illustrates the main effects plots for altitude, number of UAVs launched, and sortie times in driving MOE 2. From the left-most graph, it is apparent that detections flying at 10,000 feet results in significantly more HVU detections, while 35,000 feet or 60,000 feet flight altitudes have equally poor performance in resolving HVUs. The t-ratio quantifies the influence of altitude as a singular factor in resolving HVUs and shows this particular design factor to be the predominant influence for MOE 2. While the trend line shows a hockey-stick effect with an inflection point around 45,000 feet, this is not necessarily accurate and is likely an artifact resultant from limited repetitions across three design points. Further research in increasing repetitions and finer granularity in altitudes can provide a more thorough understanding of the model's behavior. However, the trend communicates meaningful data to stakeholders, as it illustrates the tradeoff within the model between high-altitude and HVU resolution. Within the context of the model, to be successful high-altitude UAVs require better sensor resolution; thus, decision makers can determine if the costs inherent in improving sensor performance are worth the benefits of high-altitude flight.

The next most significant design factor in influencing HVU detections is the quantity of UAVs allocated to each DSA. Again, the results of the model match expectations. Operationally, employing more sensors typically results in greater coverage, thus increasing the number of objects potentially detected. In this respect, the model can help decision makers in quantifying the necessary force composition (i.e., how many UAVs are needed) to meet mission requirements.

Unlike MOE 1, time between launches by itself has no meaningful impact in determining HVU detections as seen by the near-horizontal line and trivial t-value. Since detections are a binary event (it either occurs or does not occur), launch times should not have an impact once the UAV arrives at its DSA. However, there is a statistically significant interaction effect between launch time and the quantity of UAVs flown.



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Altitude (kft)	-5.191926	0.121559	-42.71	<.0001*
(Altitude (kft)-35)*(Altitude (kft)-35)	0.2090874	0.008422	24.83	<.0001*
UAVs Flown	0.5847826	0.132129	4.43	0.0003*
(Altitude (kft)-35)*(UAVs Flown-46)	-0.026217	0.006473	-4.05	0.0006*
(UAVs Flown-46)*(Time Between Launch (min)-30)	0.0156804	0.005394	2.91	0.0087*
Time Between Launch (min)	-0.023704	0.101299	-0.23	0.8174

Figure 25. Prediction Profiler and Parameter Estimates for HVU Detection

b. Interaction Effects

Figure 26 shows the interaction effects for MOE 2. The primary effects of interest occur between altitude and the quantity of UAVs flown, and time between launches and quantity of UAVs flown. The graph illustrates the interaction between altitude and UAV quantity in the middle row, leftmost graph and more clearly in the top row, center graph. The latter communicates that increasing the quantity of UAVs has different effects based on mission altitude. For example, at 60,000 feet, adding more UAVs does little to influence the MOE one way or the other. This is due to the fact that within the model, the sensor package is resolution-limited at high altitude; while the design factor changes the mission altitude for the UAVs, the sensor resolution remains constant throughout the experiment. Consequently, adding more sensors has no effect. Conversely, adding more UAVs at lower altitude has a desirable effect; greater sensor coverage leads to more mean detections since the sensor resolution in the model is adequate at 10,000 feet.

A second interaction occurs between the quantity of UAVs employed and the time between launches. The far-right graph in the middle row and the middle graph in the bottom row illustrate this interaction. As more UAVs are flown, staggering launches increases HVU detections, while staggering launch times with a minimal number of UAVs employed results in a slight decrease in HVU detections. This trend correlates with the quantity and launch time influences seen from MOE 1. As more UAVs are employed, staggering sorties increases survivability resulting in greater sensor coverage over the DSAs. Conversely, flying fewer UAVs with minimal time between launches results in higher attrition, negatively impacting HVU detections.

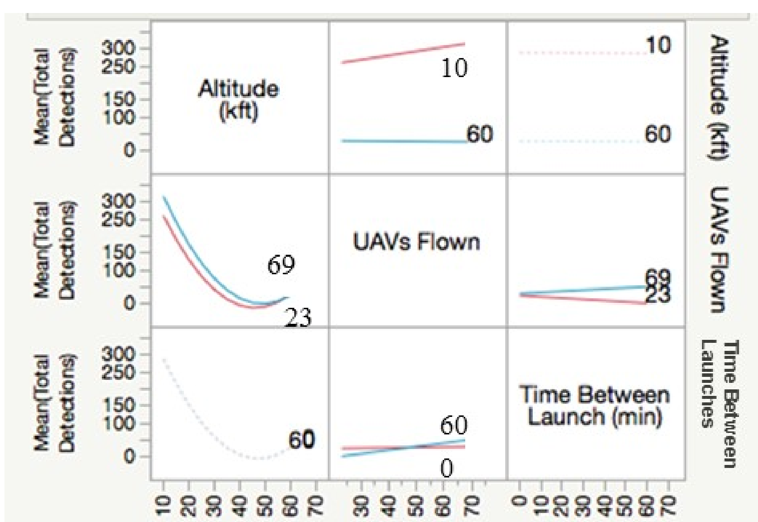


Figure 26. Interaction Effects for MOE 2

c. *Partition Tree on HVU Detection*

Figure 27 shows the partition tree for MOE 2, delineating the sets of design factors that most heavily influence HVU detection. The first split graphically illustrates the trend from the regression model; namely, low-altitude flight at 10,000 feet results in significantly more detections compared to either a 35,000-foot flight altitude or 60,000-foot flight altitude. The quantity of UAVs employed has the next most significant impact on HVU detections in the model. The results of this split make sense operationally. While sensor resolution is inhibited at 35,000 feet and 60,000 feet, adding more UAVs gives a slight advantage in detecting HVUs. The split on the right side of the tree mirrors this trend; in order to maximize HVU detections within the game, low altitudes combined with the maximum quantity of sensors employed results in the most detections.

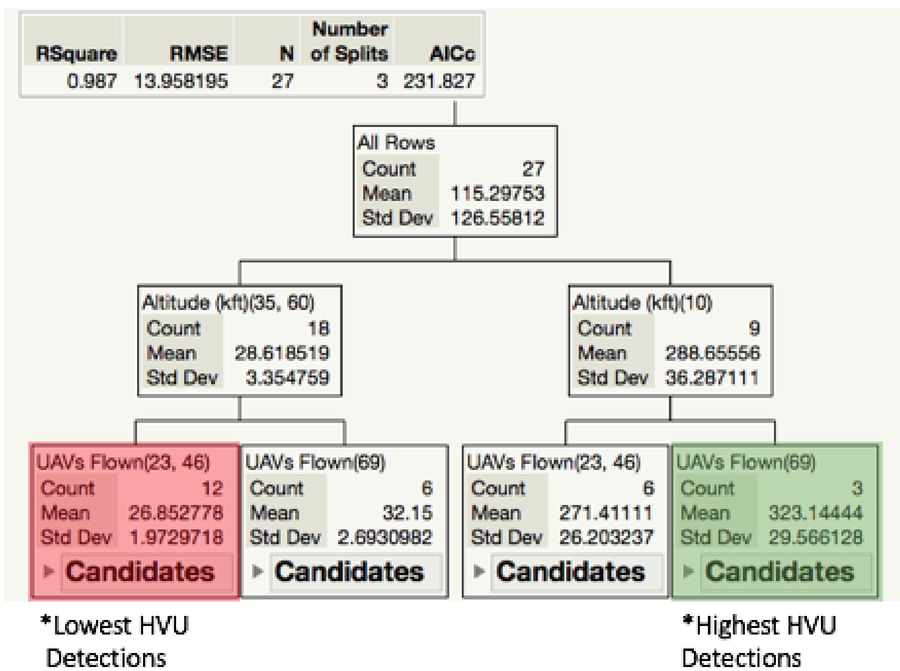


Figure 27. Partition Tree for MOE 2

C. MOE CORRELATION

Figure 28 illustrates the correlation between mean HVU detections versus mean UAV attrition across the 27 design points. Analyzing this relationship provides a concise visualization on the potential trade space between HVU detections and attrition within the model. The three colors (red, green, and blue) represent the experimental altitudes at 60,000 feet, 35,000 feet, and 10,000 feet respectively. The size of each of the points correspond to the number of UAVs flown. The largest points indicate 69 UAVs flown, while the smallest point indicates a design point with 23 UAVs flown. The abscissa represents the percentage of UAV losses; in this case, less is better. The ordinate shows HVU detections, wherein the higher points along the y-axis are desirable.

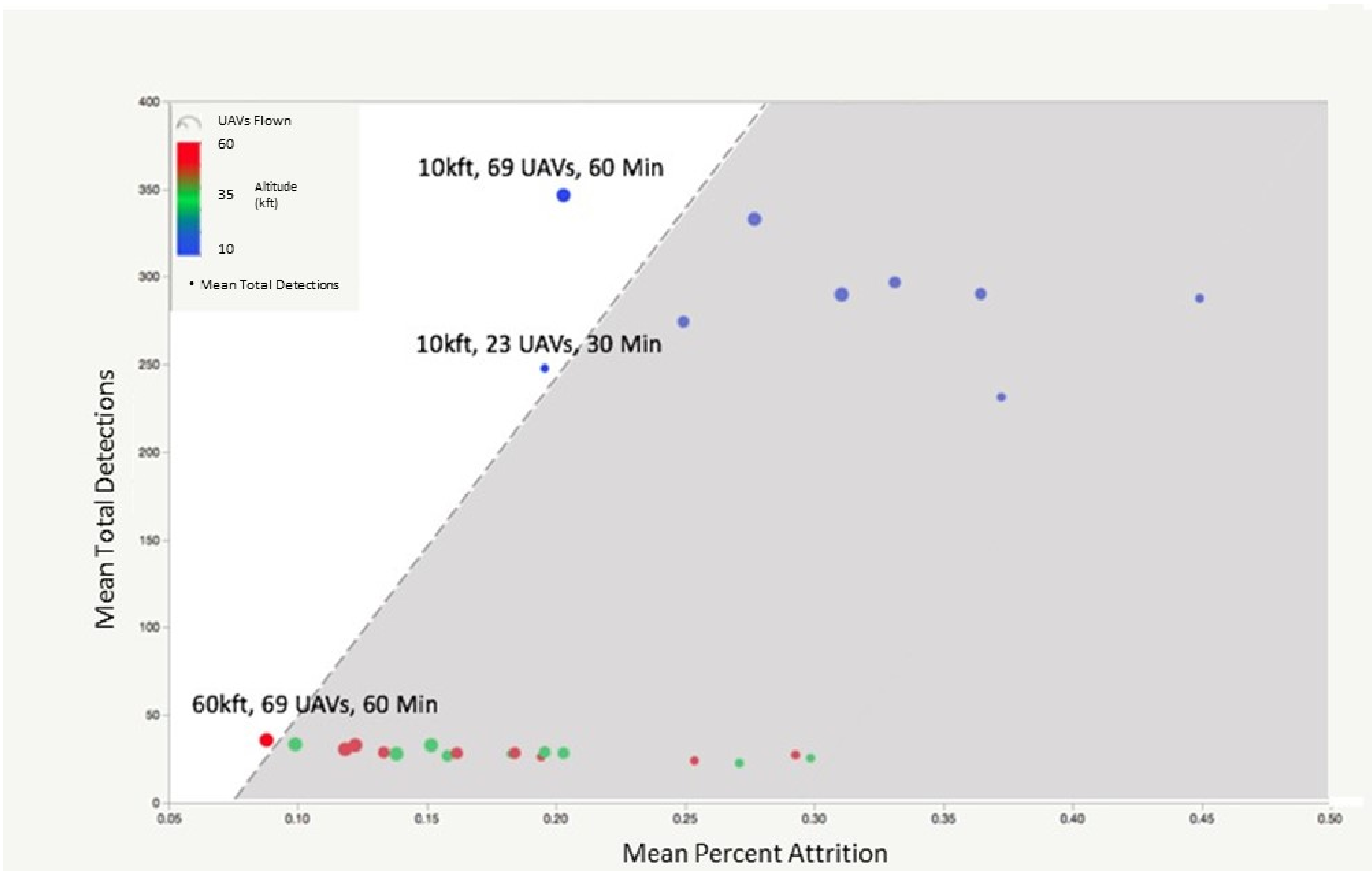


Figure 28. Mean HVU Detections versus Mean Attrition

The three labelled design points within the graph indicate a combination of design factors that dominate others and delineate a rudimentary Pareto frontier for the data. In the context of this thesis, a higher percentage of casualties with less HVU detections relative to other design points are characteristics of a dominated point. A Pareto frontier encompasses the set of design factors that are Pareto-efficient, wherein it is impossible to increase performance in one metric without making another metric worse. The linear boundary and shaded region demarcate the non-dominated points versus the dominated points; while the data for this thesis results in an explicit dividing line, this is not typical. Due to the relatively low number of replications and limited number of design points inherent in this thesis, this should not be interpreted as a de facto tradeoff curve; nevertheless, it gives decision makers an idea of potential compromises between increasing detections and higher UAV attrition.

Overall, the graph exhibits several trends that match operational expectations as well as anticipated model behavior. Generally, flying a greater number of UAVs results in higher raw attrition, but a lower loss percentage in the model. Since air defense weapons in JTLS exhibit explicitly defined firing rates, this result makes sense; a swarm of UAVs at a given time can oversaturate the weapon system, resulting in a higher percentage of aircraft leaking by the ADA sites. The second significant trend the MOE correlation shows is the effect that altitude has in sensor performance within the model.

While flying at higher altitudes lowers UAV attrition, it also adversely impacts the number of Sonoran HVUs detected. In the context of the model, such a result suggests that sensor performance needs to be improved in order to maximize the benefits from high-altitude missions. The final key trend the data communicates is the impact that additional UAVs have in increasing HVU detection. In a real-world environment, employing more sensors results in greater coverage of a given area, and thus can potentially increase the quantity of enemy unit detections. The model results show this: so long as sensor performance is adequate, employing a greater number of UAVs positively impacts the number of Sonoran HVUs reported.

D. CHAPTER SUMMARY

This chapter provides the qualitative and quantitative results from the designs of experiment detailed in Chapter III. This chapter starts with an overview of the screening experiment, showing how the results from experimentation with a limited number of eight design points warrants further study. The discussion then transitions to the central-composite design used in this thesis. This experiment utilizes 19 additional design points to further explore how the three design factors qualitatively and quantitatively influence the two MOEs. Moreover, it provides operational context for the results and explains how the outcomes from the various design points generally match real-world expectations. While the data and subsequent analysis in this chapter are from a limited number of repetitions and cover a fairly small number of design points, the trends and outputs nonetheless provide rudimentary insights in tradeoffs inherent in the model. Chapter V expands on potential areas for future research that can bolster the usefulness of these results, as well as recommendations for stakeholders interested in using JTLS to model future UAV capabilities.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This thesis shows how using a computer-aided wargame as a modeling and experimentation environment can provide decision makers insight regarding potential impacts and limitations of proposed future-fleet capabilities. Using a model-based systems engineering approach, this work outlines the establishment of theater-level concepts of operation and high-level requirements pertinent for unmanned aerial vehicle employment in a contested environment. Next, determining meaningful measures of effectiveness provide a way to quantify the impact that UAV employment has in various wargame scenarios. Using appropriate statistical and metamodeling techniques, this thesis offers rudimentary relationships between UAV design factors and the measures of interest, communicating to stakeholders the combinations of factor values that provide the most desirable and least beneficial outcomes within the model. Holistically, this research demonstrates how applying an MBSE methodology in conjunction with computer-aided wargaming and experimentation can enhance understanding in high-level system requirements and tradeoffs, providing decision makers an additional tool to determine future fleet capabilities. The remainder of this chapter includes a synopsis of the first four chapters, a discussion of the results in an operational context, and explains the applicability of the methodology for future work.

A. RESULTS SUMMARY

In the context of this thesis, implementing UAVs for intelligence, surveillance and reconnaissance had a positive effect on discovering enemy HVUs, regardless of sortie size; however, increasing sortie size increases HVU detections. Moreover, larger sorties suffer a lower percent-attrition rate in the scenario. In this regard, the model suggests to force planners that acquiring a large number of ISR-capable UAVs can satisfice reconnaissance missions and minimize loss rate.

Additionally, flying at low altitudes positively impacts HVU detections, but adversely influences UAV survivability, illustrating a potential trade-space within the model. Generally, staggering launch times for large sorties decreases percent attrition while increasing HVU detections.

Overall, the trends resultant from this research suggest larger sortie sizes and staggering launches benefits both HVU detections and survivability from enemy defenses. Contingent on mission requirements, using high-altitude UAVs can decrease aircraft attrition, while implementing low-altitude UAVs increases both attrition and HVU detections.

B. CONCLUSIONS AND RECOMMENDATIONS

This section describes how the results of the model correlate to the prescribed thesis research questions proposed in Chapter I. The first research question aims to determine some potential insights automated wargaming can provide to force planners. The second research question postulates on the potential effects that modeled UAVs with envisioned capabilities have in enhancing theater-level maritime domain awareness, in terms of HVU detection during the operational period. The final research question addresses what capability requirements are necessary to bring operational value for a reconnaissance asset, again using HVU detection as an MOE while also considering UAV susceptibility to enemy air defenses. The answers to these questions illustrate the potential tradeoffs and operational implications of various UAV instantiations within the scenario.

1. What insights can an automated computer-aided wargame provide to force planners to help shape future fleet capabilities?

The results from the model correlate to what would be expected operationally, validating the feasibility of using a CAW as a force planning tool. Moreover, the model communicates trends that can help decision makers determine which functional capabilities have the greatest impact in mission accomplishment, while consequently illustrating potential trade spaces. For example, if minimizing attrition were a critical performance metric, the model suggests that a high-altitude reconnaissance UAV may be an appropriate solution; however, high-altitude flights are sensor resolution-limited within the model, conveying a potential trade-off.

Overall, adopting an MBSE methodology in conjunction with an automated CAW can provide decision makers at N9 a viable tool to gage operational impacts and experiment with various CONOPs for planned future fleet assets. The complete decision support system for N9 enables repeatable, credible, and defensible analyses for decision makers. Based on the results of this study, N9 should continue researching automated CAWs as a useful force planning tool.

2. What is the effect of adding future unmanned aerial assets on a combined task force's ability to maintain maritime domain awareness along contested coastlines and littorals?

In the baseline Cobra Gold exercise, no reconnaissance assets (manned or unmanned) were allocated to patrol the Sonoran littorals. As a result, adding any number of UAVs in an ISR role proves beneficial in building situational awareness. Within the model, HVU detection is primarily contingent on two factors: the mission altitude and the number of UAVs employed. In general, flying more UAVs at lower altitudes maximize HVU detection. The absence of aerial reconnaissance in the littorals was in many ways a function of limited resources during Cobra Gold. Based on the results of the model, force developers should consider a contingent of UAVs to satisfy ISR mission requirements.

3. What capabilities do future unmanned aerial systems require to be value-added to existing reconnaissance methods in a joint maritime force?

Although the inefficacy of high-altitude UAVs in detecting enemy units is an artifact of this specific model, such results nevertheless communicate pertinent information. For example, in a real-world context such a trend conveys to stakeholders which functional areas for a planned high-altitude UAV require additional engineering or are perhaps technologically immature. In this case, a capability gap exists in the modeled sensor's target discrimination abilities at higher elevations; therefore, making high-altitude ISR missions tenable requires improving sensor performance or considering an entirely different sensor package.

While sortie size and altitude are primary drivers in determining HVU detections, time between launches also affects enemy detections; however, the effect of launch time is contingent on the sortie size. As a greater number of UAVs deploy, truncating time between launches increases HVU detections. Conversely, staggering times with a minimal number of UAVs results in a slight decrease in HVU detections. In an operational context, the relationship between the quantity of UAVs and launch times suggest that small swarms of UAVs are more effective in an ISR role when launched near-simultaneously. Therefore, if it is economically infeasible to procure a vast squadron of reconnaissance UAVs, engineering the capability for faster launch times would maximize HVU detections. From a real-world design perspective, this may necessitate vertical-takeoff functionality to support near-simultaneous launch times.

Generally, the data also shows that increasing altitude decreases UAV susceptibility to modeled enemy air defenses; however, while altitude is inversely proportional to attrition, UAV casualties never trend to zero, suggesting that a modicum of air-defense system efficacy remains regardless. Consequently, the model implies that high-altitude flight is not a panacea; there are inherent risks flying over enemy littorals that elevation alone does not entirely mitigate. This result further illustrates potential trade spaces; namely, it allows decision makers to explore whether the reduction in UAV losses at high elevation outweigh the costs associated with engineering and building a high-altitude capable UAV, especially if the sensor package for such an asset was particularly expensive. Conversely, further analysis may suggest that increased susceptibility and lower costs may prove most economical while still satisficing HVU detections.

With respect to sortie size, the model shows that increasing the quantity of UAVs increases raw attrition, but decreases the overall percentage of UAVs lost to enemy air defenses. From a force planning perspective, this communicates that a large squadron of UAVs may prove beneficial if operating in an environment with a significant quantity of capable enemy air defenses.

While flying large swarms of UAVs is favorable to both increasing HVU detections and minimizing attrition, this capability would require decision makers to determine whether the benefits of increasing HVU detections and lower percent attrition outweigh the costs of adding these additional UAV assets.

Overall, based on the output of the model, if force developers desire to implement high-altitude UAVs for reconnaissance, further experimentation with various sensor packages within the model may illustrate a more optimal choice to enhance HVU detection. Conversely, if lower-altitude missions satisfy operational requirements, large contingents of UAVs increase HVU detections. As a system, force planners need to establish monetary costs associated with sizeable UAV squadrons, as well as explore logistics and maintenance impacts, manpower requirements, and other resource tradeoffs associated with employing and sustaining a large UAV squadron.

C. FUTURE RESEARCH

There are two prominent questions fundamental in force planning: how much is enough, and what capabilities are requisite for mission accomplishment (Owens 2012); the results of this thesis help decision makers answer these questions. While the methodology, data and trends from this model provide useful insight in operational capabilities and functional requirements of ISR-capable UAVs, there are areas of refinement that can potentially maximize the usefulness and usability of JTLS-GO as a tool to study future fleet capabilities.

Since this thesis is a first-effort in utilizing JTLS-GO as a model to test future fleet capabilities, there are several areas where future study may prove beneficial. First, time constraints necessitated only 30 replications for each design point in this thesis; running more replications of each design point will reduce variability in the estimates of the means and will provide higher confidence that the trends are a result of something other than stochastic noise. Moreover, adding additional design points, particularly in altitude ranges between 10,000 feet to 35,000 feet, can help better illustrate the behavior of the model and potentially delineate a more definite inflection point in HVU detections. Similarly, additional research with the model may uncover which enemy ADA assets are successfully engaging UAVs flying at 60,000 feet. This can prove beneficial in refining necessary UAV capabilities and design factors that decrease attrition in the game. Moreover, modifying the experiment to entail user-defined UAV routes can help eliminate potential confounding effects with respect to time between launches and UAV losses.

Another area for future work is applying the methodology in this thesis to other JTLS-GO wargames, as well as other computer-assisted exercises and wargames. Since R&A maintains such a diverse client base, using other scenarios as the modeling environment can further refine requisite UAV capabilities to support ISR missions. Moreover, the extensive databases and units modeled in JTLS is conducive to creating other vignettes to test different future capabilities and warfare areas beyond the ISR-realm. Some example scenarios for additional exploration include:

- integrating a UAV in a hunter-killer role, wherein the aircraft detects an HVU and relays the information to a ship or other strike-capable asset for neutralization;
- leveraging electronic countermeasures or electronic warfare to enhance survivability of the UAV itself or other coalition assets in theater;
- combining UAVs with unmanned systems in other domains (i.e., unmanned underwater vehicles) to track and target enemy assets;
- exploring performance impacts in adverse weather or nighttime environments; and
- refining modeled sensor packages for high-altitude, long endurance (HALE) missions.

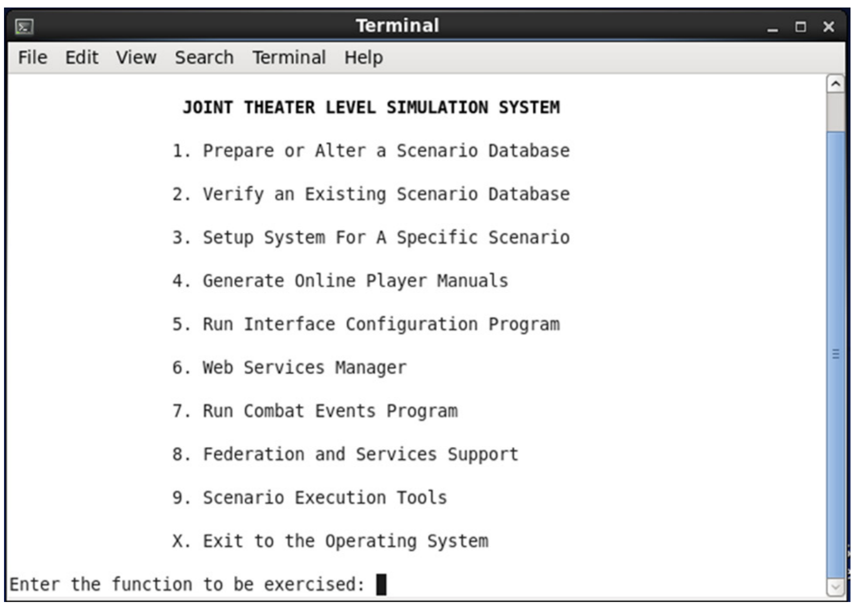
APPENDIX A. JTLS-GO SET-UP

This appendix describes how to set up and start JTLS-GO, create and implement UAV prototypes for use in the modified game scenarios, and splice orders for game automation. All images herein are screenshots from JTLS-GO taken by the author.

A. STARTING JTLS-GO

1. Open a terminal window.

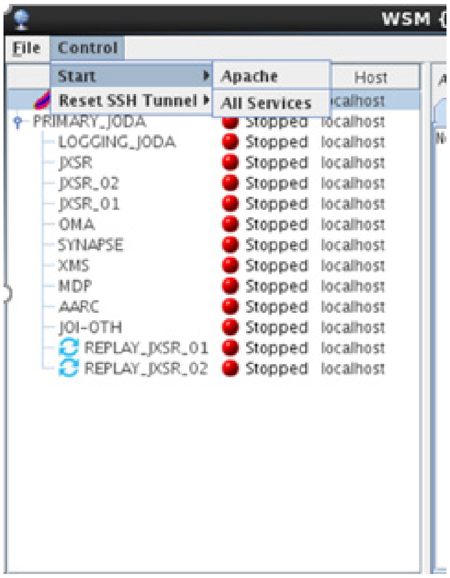
2. Type “jtlsmenu” and hit <ENTER>. A 10-option menu will appear.



3. Type “6” in the terminal window and hit <ENTER> to start the JTLS-GO Web Services Manager (WSM).

4. At the WSM window, enter desired scenario name (i.e., CG18) and hit <ENTER>.

5. In the WSM, click “Control” in the menu bar and start all services.



6. Ensure status indicators for JODA, OMA, and XMS all toggle green. Close the WSM and return to the terminal window.

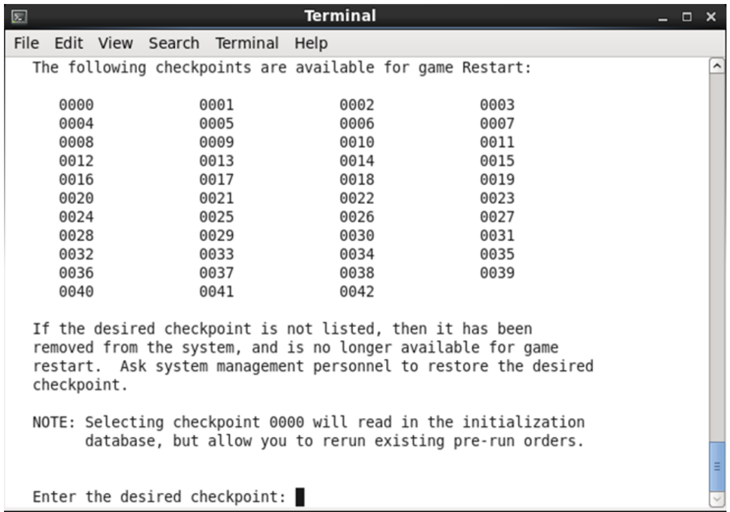
7. Type "7" in the terminal window and hit <ENTER>. This will run the JTLS-GO Combat Events Program (CEP).

8. At the CEP window, enter desired scenario name and hit <ENTER>. This must be the same scenario as entered in Step 4.

9. If the terminal window returns with message that scenario is locked, type "unlock [scenario name]" and hit <ENTER> to unlock the scenario. Repeat Step 8.

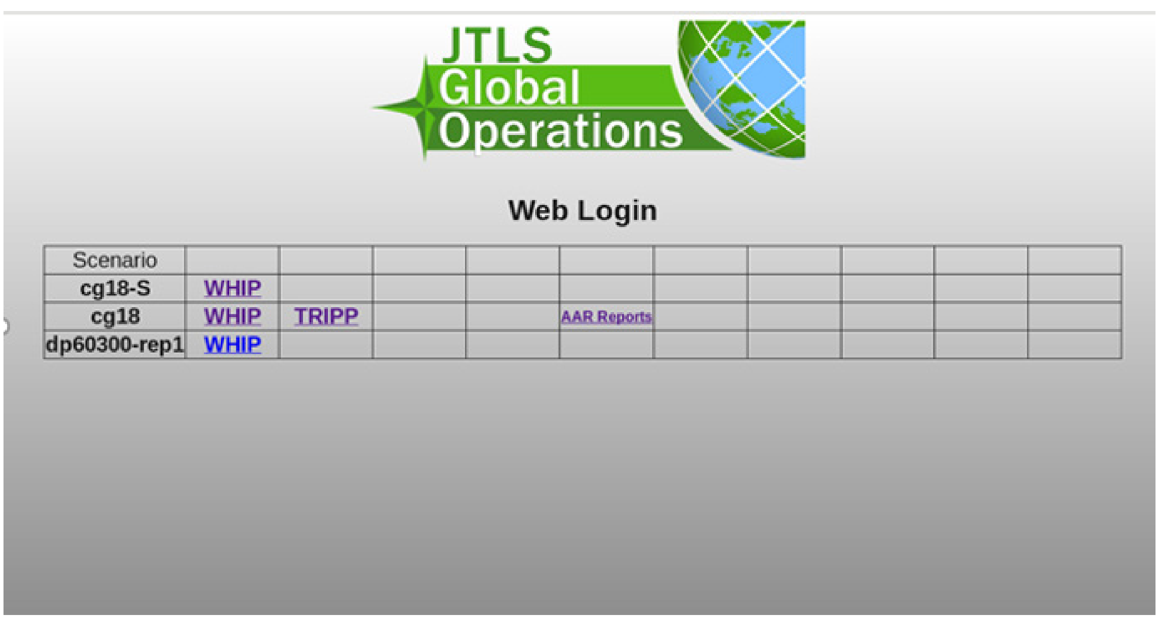
10. When prompted for "Start of Restart," type "R" and hit <ENTER>.

11. When prompted, type the desired start checkpoint from those listed and hit <ENTER>.



12. When prompted to push pre-run orders, type “Y” and hit <ENTER>. At this point, the CEP will unpack all the pertinent data for the desired game scenario.

13. When CEP completes the download to the JODA, open a web browser. In the address bar, type “localhost:8080” and hit <ENTER>. This opens the JTLS-GO web login.

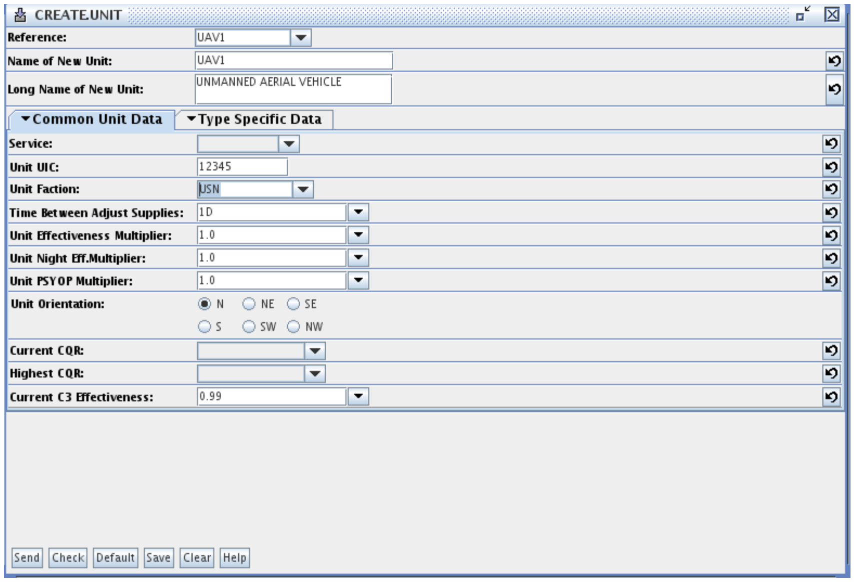


14. Open a Control-WHIP and a United States WHIP for the desired scenario. Click "Login."

B. CREATING UAV PROTOTYPES USING THE CONTROL-WHIP

1. Open a Control-WHIP.

2. Click Orders→Units→ Create New Units in the menu bar. A "Create.Unit" window appears.



3. In the Common Unit Data tab, enter the pertinent information for all data fields and drop-down menus.

a. Select "Navy" for Service and "USN" for unit faction.

b. Enter a five-digit UIC.

c. Select "Average-Medium" for Current CQR and Highest CQR.

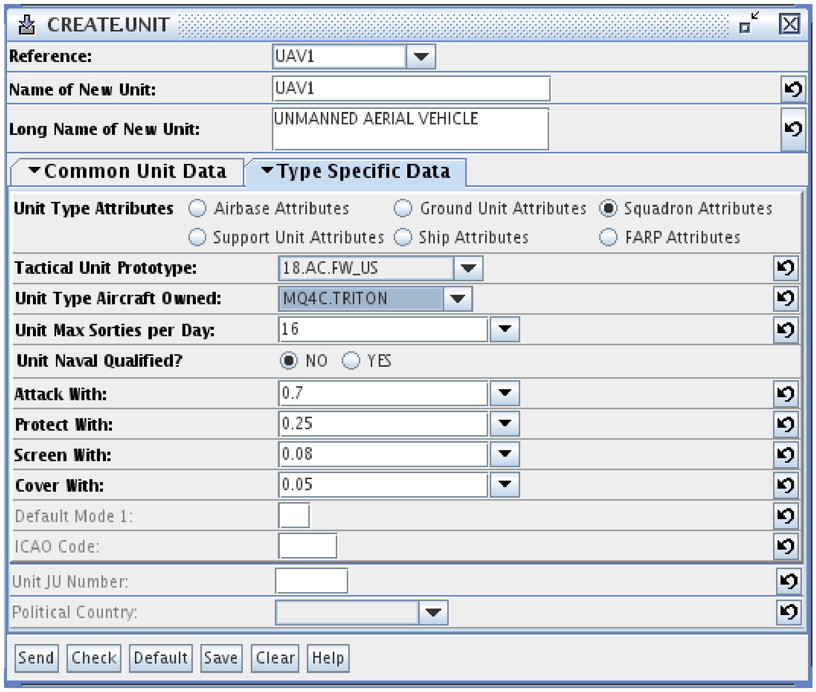
4. In the Type Specific Data tab, enter the following information in the requested data fields:

a. Under "Tactical Unit Prototype," select "18.AC.FW_US." This TUP contains 18 fixed-winged aircraft under control of the U.S.-player-WHIP.

b. Under "Unit Type Aircraft Owned," select "MQ4C.Triton" from the drop-down menu.

c. Enter the maximum sorties per day for the squadron.

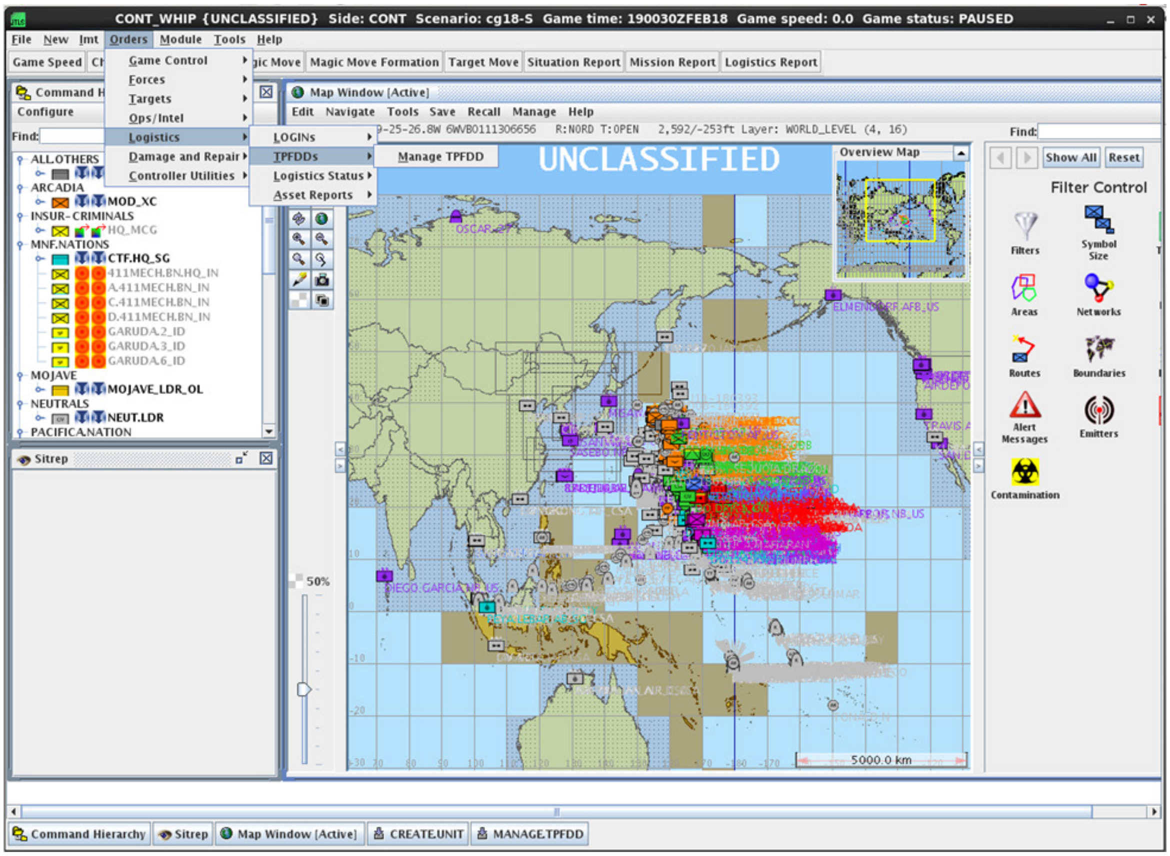
d. Toggle the "Unit Naval Qualified" radio-button to "yes." This allows the aircraft to launch and land on Navy aircraft carriers in the game.



5. When all the information is entered for the unit and type data, click "Send" in the bottom left corner to route the order to the CEP.

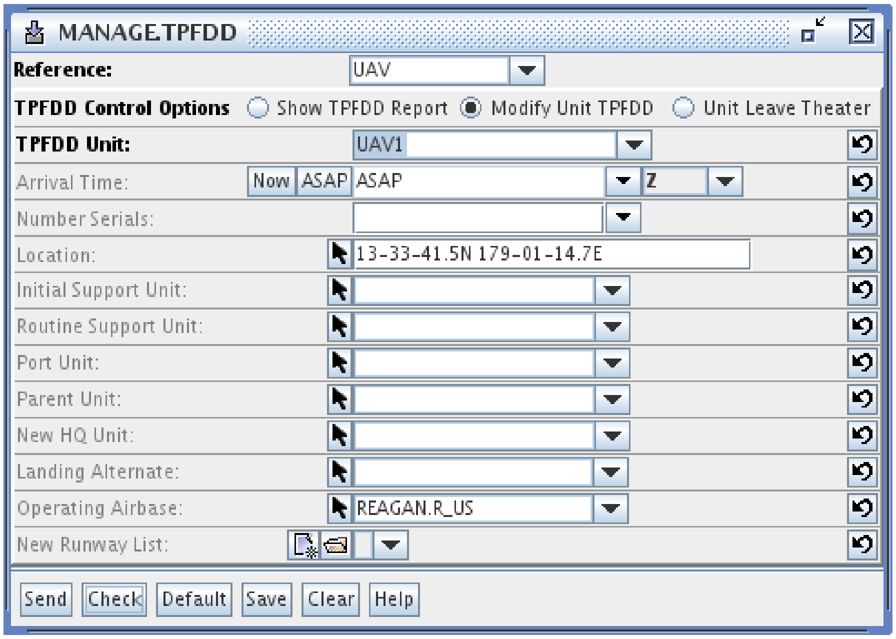
6. In the Message Browser, a "New Unit Report" will generate, verifying creation of the UAV squadron.

7. The default arrival time for a new unit is set to 99-game days. To change this, click Orders→ Logistics→TPFDDs→ Manage TPFDD in the menu bar. The "Manage.TPFDD" dialogue box will open.



8. Click the “Modify Unit TPFDD” radio button.

9. Under “TPFDD Unit,” type the unit name for the created prototype. This unit name should match that entered in the “Create.Unit” dialogue box.



10. Select “ASAP” for arrival time.

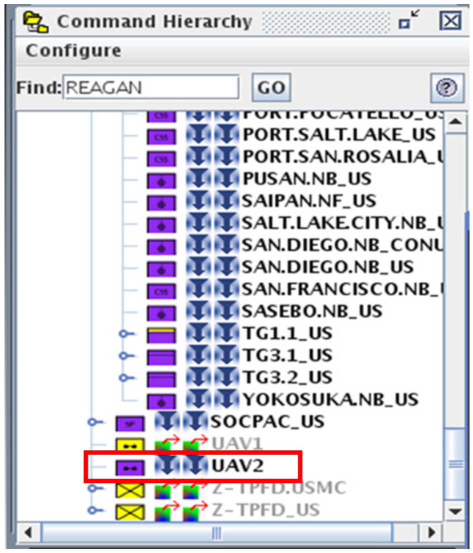
11. Under “Location” select “USS Ronald Reagan” from the Command Hierarchy window. The latitude and longitude for the unit will auto-populate.

12. Under “Operating Airbase” select “Ronald Reagan” from the Command Hierarchy window.

13. Click “Send” in the bottom-left corner to route the TPFDD to the CEP.

14. In the Message Browser, verify a “TPFDD Report” is generated.

15. In the Command Hierarchy window, verify the unit turns purple, signifying the unit is ready for orders from the U.S. player-WHIP.

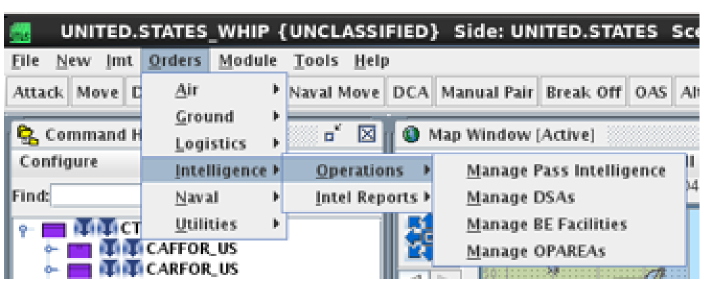


16. Click the “Game Speed” button and set the game speed to “10” for a few seconds. In order to process orders, the game needs conduct at least one time step. Once this is complete, set the game speed back to “0.0.”

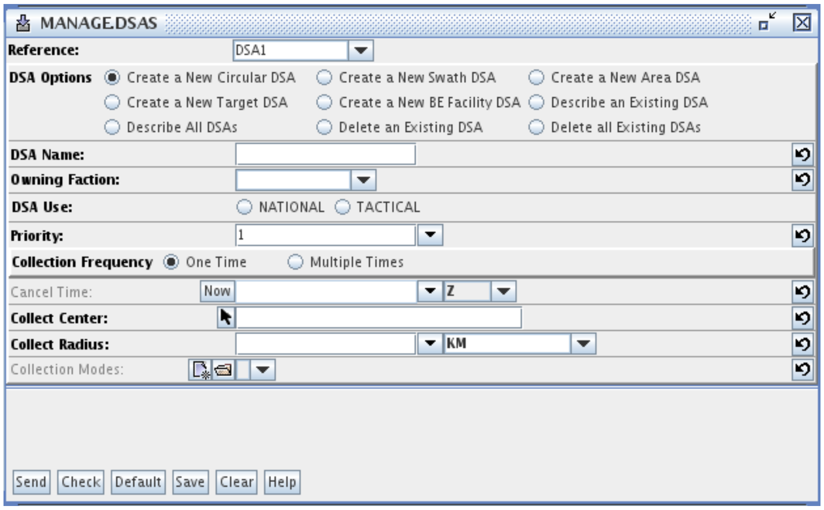
C. GENERATING ORDERS FOR UAV ISR MISSIONS USING THE U.S. WHIP

1. Open the U.S. Player-WHIP.

2. In the menu bar, click Orders→Intelligence→ Operations→ Manage DSAs to create DSAs.



3. Under “DSA Options,” toggle the “Create a New Circular DSA” radio-button.



4. Enter a DSA name and select U.S. for owning faction. Toggle the “DSA Use” radio-button to “National.”

5. In the “Collect Center” option, click the black arrow. Transition to the game map to select DSA collection areas. The text box will populate a latitude and longitude corresponding to the DSA.

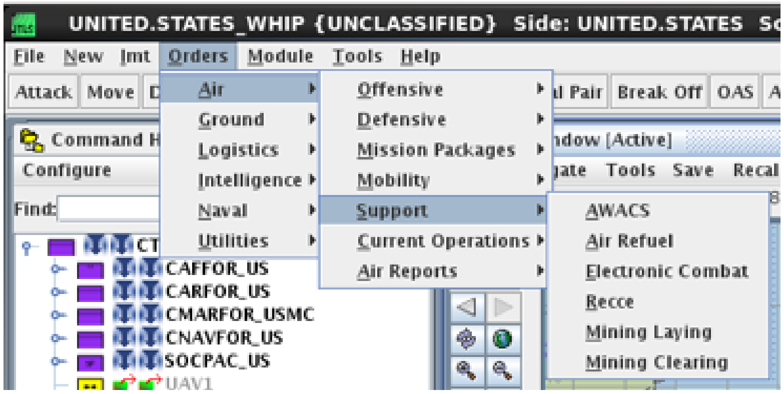
6. Change collection frequency to “Multiple times” and set the frequency to hourly. This dictates when DSA intelligence messages will populate the message browser.

7. Set the collection radius to 10 kilometers.

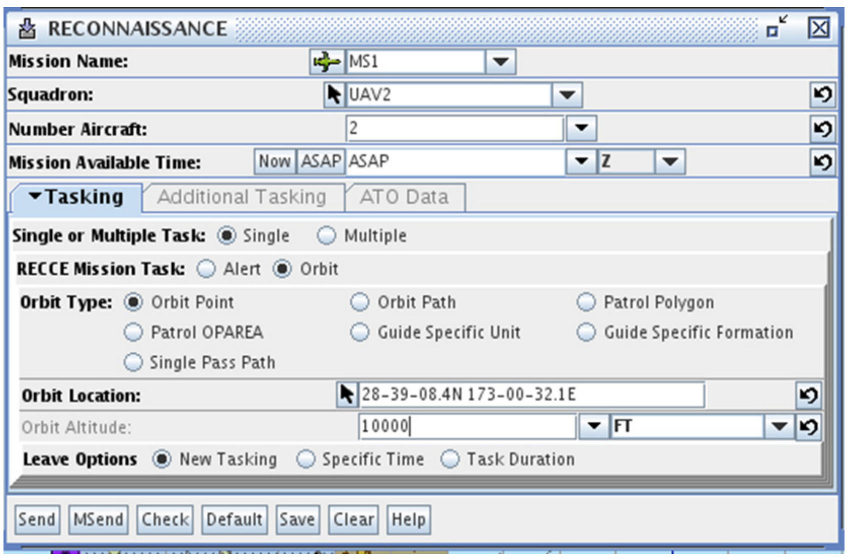
8. Click “Send” to complete DSA creation.

9. Repeat steps 2–8 until the desired number of DSAs are created.

10. In the menu bar, select Orders→Air→ Support→ Recce to create ISR missions.



11. In the “Reconnaissance” window, assign a mission name and squadron.



12. Set “Number Aircraft” to “1.”

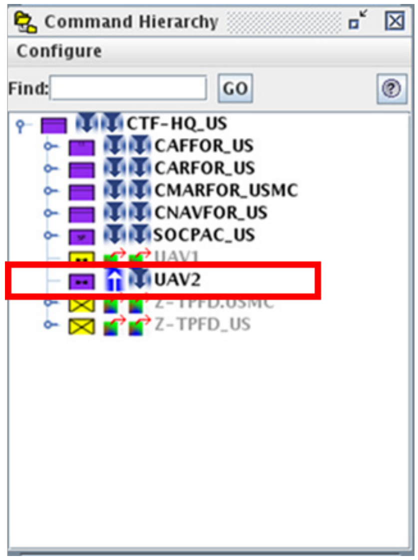
13. Select the “Orbit” radio button.

14. In “Orbit Location,” click the center of a DSA created in step 5. The latitude and longitude will automatically populate the text box.

15. Assign an Orbit Altitude. This thesis used altitudes of 10,000 feet, 35,000 feet and 60,000 feet for experimentation.

16. Click “Send” to route the order to the CEP.

17. In the Command Hierarchy window, the tasked UAV squadron will show an upward pointing arrow.



18. Repeat steps 10–16 until all aircraft are assigned as desired.

D. EXTRACTING AND SPLICING ORDERS

1. Open a file browser and find the “Game” folder. Open the folder.

2. Find the working scenario and open the .ci0 file. This file contains all the orders processed by the CEP in the scenario.

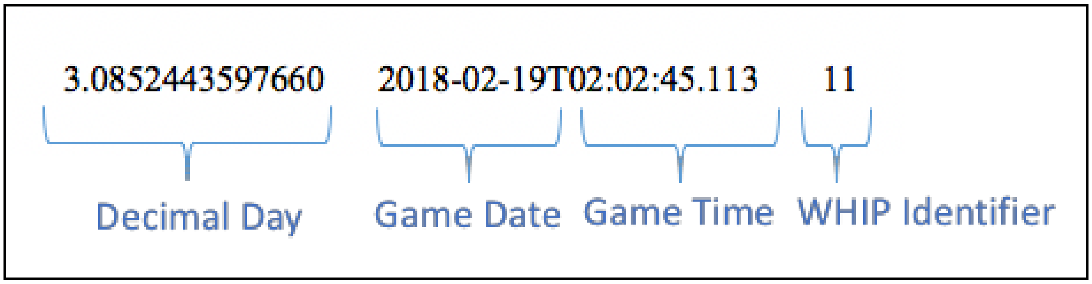
3. Find the appropriate UUV/UAV orders. These orders will be at the bottom of the ci0 file.

4. Copy the appropriate UUV/UAV orders.

5. Open the .ci0 file for desired start checkpoint.

6. Paste the UUV/UAV orders to the end of the ci0 file.

7. If necessary, alter the decimal-day to reflect the desired start time for unit creation or mission assignment. This information is in the header preceding every order.



a. To convert game hours to decimal days, divide the hour reported in the game time by 24.

b. To convert minutes to decimal days, divide the minutes reported in the game time by 1440.

c. To convert seconds to decimal days, divide the seconds reported in the game time by 86400.

d. Adding the results of a-c will yield the 13-digit decimal value in the decimal day.

8. When complete, save the modified ci0 file. These orders will automatically process when JTLSrunner is started.

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APPENDIX B. TABLE OF DESIGN POINTS

Design Point	Altitude (kft)	UAVs Flown	Time Between Launches (min)
dp10100	10	23	0
dp10130	10	23	30
dp10160	10	23	60
dp10200	10	46	0
dp10230	10	46	30
dp10260	10	46	60
dp10300	10	69	0
dp10330	10	69	30
dp10360	10	69	60
dp35100	35	23	0
dp35130	35	23	30
dp35160	35	23	60
dp35200	35	46	0
dp35230	35	46	30
dp35260	35	46	60
dp35300	35	69	0
dp35330	35	69	30
dp35360	35	69	60
dp60100	60	23	0
dp60130	60	23	30
dp60160	60	23	60
dp60200	60	46	0
dp60230	60	46	30
dp60260	60	46	60
dp60300	60	69	0
dp60330	60	69	30
dp60360	60	69	60

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