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THESIS

ANALYSIS OF THE USE OF UNMANNED COMBAT AERIAL VEHICLES IN CONJUNCTION WITH MANNED AIRCRAFT TO COUNTER ACTIVE TERRORISTS IN ROUGH TERRAIN

by

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June 2015

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ANALYSIS OF THE USE OF UNMANNED COMBAT AERIAL VEHICLES IN CONJUNCTION WITH MANNED AIRCRAFT TO COUNTER ACTIVE TERRORISTS IN ROUGH TERRAIN

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Turkey has been battling with terrorist groups since the 1980s. In total, more than 35,000 Turkish people have been killed by terrorists. The majority of the terrorist activities take place near the Turkish-Iraqi border, which is characterized by rough terrain. Problems, such as lengthy distances, often prevent aircraft from reaching the area before the terrorists achieve their objectives. Limited fuel capacity and challenging geographical conditions are other issues that must be overcome. Because of their technical capabilities and longer flight times, Unmanned Combat Aerial Vehicles (UCAVs) may enhance Turkey's ability to counter active terrorists in that region. In this research, Map Aware Non-uniform Automata (MANA) is used to model different counterterrorism scenarios taking place along the Turkish-Iraqi border. We examine the potential effectiveness of using UCAVs in conjunction with manned aircraft to detect and eliminate terrorists trying to cross the border and attack Turkish military assets. For this purpose, we analyze the data from 102,800 simulated air-to-ground attacks using data analysis techniques, such as comparison and regression analysis. The analysis shows that UCAVs, with their additional sensors on the border and being able to rapidly attack identified targets, are very efficient in quickly countering terrorists and preventing them from attacking military forces.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABSM	Agent-Based Modeling and Simulation
AFB	Air Force Base
AGM	Air-to-Ground Missile
ASMD	Anti-Ship Missile Defense
ASW	Anti-Submarine Warfare
CAS	Close Air Support
CSV	Comma-Separated Value
DOD	Department of Defense
DOE	Design of Experiment
DP	Design Point
DTA	Defense Technology Agency
ESRI	Environmental System Research Institute
EW	Electronic Warfare
GBU	Guided Bomb Unit
GIS	Geographic Information System
GPS	Global Positioning System
GUI	Graphical User Interface
ISI	Islamic State of Iraq
ISIL	Islamic State of Iraq and the Levant
ISIS	Islamic State of Iraq and Syria-Sham
ISR	Intelligence, Surveillance, and Reconnaissance
JDAM	Joint Direct Attack Munition
LOS	Line-of-Sight
MALE	Medium-Altitude Long-Endurance
MANA	Map Aware Non-Uniform Automata
MANA-V	Map Aware Non-Uniform Automata-Vector
NBC	Nuclear, Biological, Chemical
NCW	Network-Centric Warfare
NOLH	Nearly Orthogonal Latin Hypercube
NSFS	Naval Surface Fire Support

OECD	Organization for Economic Co-operation and Development
OTH-T	Over-the-Horizon Targeting
PKK	Kurdish Workers’ Party
RSS	Residual Sum of Squares
SA	Situational Awareness
SIGINT	Signal Intelligence
SOF	Special Operation Force
TAI	Turkish Aerospace Industry
UA	Unmanned Aircraft
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicles
UCAV	Unmanned Combat Aerial Vehicle
XML	Extensible Markup Language

THESIS DISCLAIMER

The reader is cautioned that the computer programs presented in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logical errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

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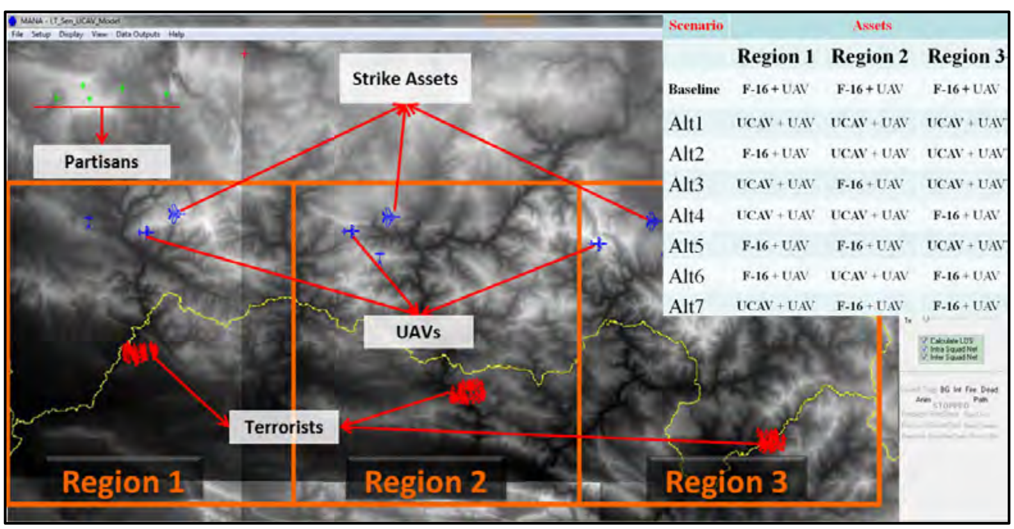
EXECUTIVE SUMMARY

Terrorism has become a significant problem and threatens many countries. Turkey has been dealing with active terrorist groups since the 1980s. In total, excluding those unrecorded, more than 35,000 Turkish people have been killed by terrorists. The Turkish-Iraqi border, which is the focus of this thesis, is characterized by rough geographical conditions, deep valleys, and steep mountains. The challenging terrain of the Turkish-Iraqi border allows terrorist groups to make surprise attacks on military and police facilities along the border and then disappear. The dominant terrorist group in the region has been the Kurdish Workers' Party (PKK).

This thesis focuses on the methods that the Turkish Air Force uses to detect and eliminate terrorists. Only the Turkish-Iraqi border is taken into consideration (rather than the whole southeastern border of Turkey). The Turkish Air Force has used the methods described below to kill terrorists or prevent them from attacking military stations, government agencies, and military and police lodgings along the Turkish-Iraqi border. After obtaining information and assessing it carefully, the Air Force immediately sends manned aircraft to the region to conduct attack missions. Problems, such as lengthy distances, often prevent aircraft from reaching the area before the terrorists achieve their objectives. Limited fuel capacity and challenging geographical conditions are other issues that must be overcome.

The majority of the problems that Turkey has to overcome are related to limited time and challenging terrain. Using unmanned combat aerial vehicles (UCAVs) in southeastern Turkey may help solve some of the problems. UCAVs are weaponized unmanned aerial vehicles that can be used for air-to-ground attack missions against active terrorists. This thesis analyzes the use of unmanned combat aerial vehicles in conjunction with manned aircraft against active terrorists in rough terrain. For this purpose, we modeled the entire Turkish-Iraqi border in Map Aware Non-Uniform Automata (MANA), an agent-based, time-stepped, stochastic mission-level model. We examine the influence of UCAVs against active terrorists by looking at the number of terrorists killed, the time required to kill terrorists, and the probability that the terrorists reach their objective. We also vary the parameters of F-16s, unmanned aerial vehicles (UAVs), and UCAVs, such as sensor detection ranges, hit probabilities, speed, and reaction times, to explore the most effective parameters for mission success.

We built our scenarios by taking historical incidents as a reference. We are trying to figure out how effective UCAVs might be in that area as an alternative to F-16s. For this purpose, we constructed eight different air-to-ground attack plans comprising combinations of F-16s, UAVs, and UCAVs. We are going to call them different scenarios throughout the thesis since each of them needs to be run separately in MANA, one baseline and seven alternate scenarios. Our scenarios include three air-to-ground strike assets, three UAVs for intelligence, surveillance, and reconnaissance (ISR) missions, and three terrorist groups that attempt to cross the border and make their way to attack three blue battalions. The scenarios also have partisans, who are the supporters of terrorists in the cities, and a dummy agent, who is used to terminate the runs. The battle area is separated into three regions, and each air-to-ground strike asset, UAV, and terrorist group is assigned to a specific region. If a UAV detects and classifies any terrorist activity along the border, it immediately reports it to the strike assets that are responsible for that specific region. Each UAV and strike asset conducts operations in a dedicated region, and they do not have any activity in other regions. The following figure depicts the general overlay of the scenarios.



There are three regions along the border. The combination of the air assets by scenario is shown on the upper right table. UAVs are used in all scenarios.

We explore the effects of 28 different factors in this thesis. Among these 28 factors, 20 are controllable factors and eight are uncontrollable factors. Controllable factors include the parameters of F-16s, UCAVs, and UAVs. Uncontrollable factors include the parameters of terrorists and partisans. We used a nearly orthogonal Latin hypercube (NOLH) design, which provides an efficient design while covering a broad section of input space with 257 design points. The NOLH design also guarantees that the factors are not confounded. We ran 50 replications for each design point and each scenario, and came up with a final data set based on 102,800 air-to-ground attack missions. Afterwards, the data was analyzed using data analysis techniques, such as comparison, partition trees, and regression analysis. The following list summarizes the results of our analysis.

- The analysis shows that UCAVs, with their additional sensors on the border and being able to rapidly attack identified targets, are very efficient in quickly countering terrorists and preventing them from attacking military forces.
- In general, F-16s, with more powerful weapons, are better at inflicting red casualties, but UCAVs kill more quickly and are better at preventing the terrorists from attacking blue.
- More specifically, the scenarios where we use two F-16s and one UCAV are more advantageous for killing terrorists than the scenarios with one F-16 and two UCAVs. On the other hand, the scenarios with two UCAVs are preferable in terms of the time to complete the mission and preventing terrorists from reaching their goal.
- The most common conclusion about the factors is that weapons-related variables have a strong influence on the number of terrorists killed while sensor-related factors are the most effective on the time to counter the terrorists and minimizing the probability that terrorists attack blue.
- The weapon range of an F-16 and a UCAV are the two most influential factors on the number of terrorists killed. The sensor classification range of the UAVs have a strong effect on the number of terrorists killed, the time to complete the mission, and the probability that the terrorists attack reach their goal.
- The hit probability of an F-16 and a UCAV are two of the most significant factors in all of the regression model fits.
- The range at which the terrorists classify blue is a significant factor for the time to complete the mission.
- Finally, the ranges at which the terrorists and the partisans detect blue have a significant influence on the probability that the terrorists attack blue.

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I. INTRODUCTION

"Peace at home, peace in the world."

– Mustafa Kemal Ataturk

Terrorism has become a significant problem and threatens many countries. Many countries spend significant amounts of money to protect their citizens from terrorist activities. The government of the United States spent more than half a trillion dollars to protect against and respond to terrorist activities between September 11, 2001, and 2012 [1]. Turkey has been dealing with active terrorist groups even longer, since the 1980s [2]. In total, excluding those unrecorded, more than 35,000 Turkish people have been killed by terrorists [3]. This chapter provides information about Turkey's geographical characteristics and challenges surrounding its southeastern border. It also describes major terrorist organizations that threaten Turkish citizens and conventional forces in that area and provides examples of the most bloody terrorist attacks in Turkey's history. This chapter also provides an explanation about current counterterrorism methods and problems that the Turkish Air Force encounters and describes potential solutions for these problems.

A. MOTIVATION

1. Geography of Turkey and Challenges

The lands of Turkey are located where Asia meets Europe. The land boundaries of Turkey stretch 2,949 kilometers, and coastlines stretch 8,333 kilometers. The country shares its borders with the European countries Bulgaria and Greece and the Asian countries Georgia, Armenia, Azerbaijan, Iran, Iraq, and Syria (Figure 1) [4]. Because Turkey holds lands that border both southeastern Europe and southwestern Asia, it has been a crossroads country between the two continents. Because of the strategic significance of Turkey's location, legal travelers as well as terrorist groups use it for passage and refuge. A majority of anti-Turkey terrorist activities take place in southeastern Turkey. Terrorist groups are taking advantage of political and economic instability and regime changes in neighboring countries. Since the beginning of Syria's civil war, around 450,000 Syrian refugees have crossed the Turkish-Syrian border and started to live in camps thanks to Turkey's open-door policy [5]. The Turkish-Iraqi border, which is the focus of this thesis, is characterized by rough geographical conditions, deep valleys, and steep mountains. The challenging terrain of the Turkish-Iraqi border allows terrorist groups to make surprise attacks on military and police facilities along the border and then disappear.

Turkey has also been used as a corridor by terrorist groups for smuggling. One of the most important money sources of terrorist groups is drug smuggling [6]. Terrorists choose Turkey as the first course to transport illegal materials from African and Asian countries into Europe. Due to its rugged terrain, terrorist groups opt to use the Turkish-Iraqi border as a passage for illicit activities. It is difficult for Turkish conventional forces to prevent those terrorist groups from committing crimes in that area because of the rough terrain.

Figure 1. Location of Turkey and its neighbors. Image from Worldatlas.com.

2. Terrorist Organizations in Turkey

Turkey has been battling terrorist groups for a long time. According to the 2014 Global Terrorism Index published by Institute of Economics and Peace, Turkey is one of the countries from the Organisation for Economic Co-operation and Development (OECD) that experienced the highest number of deaths as a result of terrorist attacks [7]. Some of the most effective terrorist organizations that threaten Turkey's southeastern borders are the following.

a. PKK

The dominant terrorist group in the region has been the Kurdish Workers' Party (PKK). The PKK was founded by Abdullah Ocalan on November 27, 1978. Their main objective is to establish an independent Kurdish state within Turkey's borders through communist revolution and armed struggle [8]. Although the PKK's leader Abdullah Ocalan was captured in 1999 and sentenced to life imprisonment after trial, the PKK never ended its terrorist activities in Turkey and northern Iraq. After they lost their leader, the PKK started to claim that it changed its strategy to peaceful ways. In order to prove itself as a legitimate political organization to international countries, the PKK changed its name to Kurdistan Freedom and Democracy Congress (KADEK) in April 2002. In 2003, the terrorist organization changed its name again to Kurdistan Peoples' Congress (KONGRA-GEL). Despite two name changes and a declaration of policy change, the leading members of the PKK did not change. The organization is still led by Abdullah Ocalan, who gives directions from prison transmitted to the other members of the organization by his lawyers. Also, other leading figures such as Zubeyir Aydar, Murat Karayilan, and Cemil Bayik have kept their leading roles in the PKK [8]. They have also continued terrorist activities in Turkey. The PKK has also been on the U.S. Department of State's foreign terrorist organizations list since 1997 [9]. In 2010, Europol, a European Union Law Enforcement Agency, described the PKK as an ethno-nationalist and separatist terrorist group seeking international recognition and political self-determination [10]. According to Turkey's Ministry of Foreign Affairs, legal and illegal sources of PKK revenue can be listed as follows:

- Extortion
- Revenue from the “special nights” organized by affiliates
- Sales of publications
- Revenue from commercial establishments belonging to/affiliated with the organization
- Money collected through drug trafficking, arms smuggling, and human trafficking [11].

b. ISIS

Another terrorist organization called the Islamic State of Iraq and Syria-Sham (ISIS), or Islamic State of Iraq and the Levant (ISIL), recently started conducting terrorist activities along the Turkish-Iraqi and Turkish-Syrian borders. ISIS was preceded by another terrorist group known as the Islamic State of Iraq (ISI), which was formed in 2006. ISI was comprised of different rebel groups, most significantly Al-Qaeda. The terrorist organization known as ISIS was established in April 2013 and became one of the main terrorist organizations battling against conventional government forces in Iraq and Syria [12]. ISIS’s primary objective has been to establish an Islamic state ruled by shariah law [13]. The United States and many of its allies have been fighting ISIS for a couple of years, but in February 2015, President Obama formally asked Congress for approval of military force against ISIS [14]. In the last three years, ISIS has evolved from a classic terrorist organization into a complicated, well organized group [12]. In a short period of time, ISIS has replaced the PKK as the most deadly terrorist group in Turkey. Over the last couple of years, ISIS has been responsible for a quarter of all the deaths from terrorist attacks in Turkey [7]. As ISIS continuously increases its power, it becomes a more significant threat to Turkey’s borders.

The known primary funding sources of ISIS are as follows:

- Extortion
- Collection of taxes and fees in areas under its control
- Selling oil from fields it controls
- Looting the homes of people who flee under threat of the militants [13].

c. Al-Qaeda

The main objective of Al-Qaeda is to take down the current governments in Muslim countries and establish a new Islamic regime. Al-Qaeda calls existing Muslim countries “puppets of the West” [16]. Al-Qaeda has been active in many countries as well as along Turkey’s southeastern border. Al-Qaeda usually appears with its suicide attacks and bombings. The main sources of money for this terrorist group are donations and fees gathered from its sympathizers [15].

3. Major Terrorist Incidents in the Region

Officially, there have been, more than 35,000 Turkish people recorded as killed by terrorists since the 1980s [3]. Some of the terrorist attacks have occurred in big cities, but most of them have been carried out in rural areas, especially in southeastern Turkey. There are hundreds of terrorist attacks committed by PKK, ISIS, Al-Qaeda, and others terrorist organizations in Turkey. Below are listed some of the most violent terrorist incidents, defined as incidents in which more than 20 people died.

> **June 20, 1987:** Massacre launched in Pinarcik village of Omerli district in Mardin. Sixteen children, six women, eight men; in total 30 people were killed by the PKK [16].
>
> **November 26, 1989:** In Iki Yaka village of Yuksekova district in Diyarbakir, 21 people were killed, and nine citizens were kidnapped by the PKK [16].
>
> **June 11, 1990:** The PKK raided Cevrimli Village of Sirnak and killed 27 people. A conflict occurred between PKK terrorists and the village guards, and in the end four guards lost their lives [16].
>
> **October 1, 1992:** PKK terrorists raided Cevizdali village of Bitlis and killed 30 people. There were women and children among them, and 25 were wounded. Terrorists set the village on fire and kidnapped 13 village guards [16].
>
> **July 6, 1993:** The PKK made an armed raid on Basbaglar village of Kemaliye district in Erzincan and killed 28 people, among whom there were women, and wounded three people. After setting 57 houses on fire, the terrorists fled away [16].

July 19, 1993: The PKK attacked Vanizer village of Bahcesaray district in the city of Van and killed 26 people, 22 of them were women [16].

August 4, 1993: PKK terrorists stopped two minibuses traveling between Kavakbasi and Yenidogan villages of Mutki district in Bitlis and shot 28 people. In this attack 15 people were killed and 13 people were wounded [16].

October 5, 1993: A series of attacks by the PKK in several arable fields and villages of Batman, Siirt, and Hakkari caused the deaths of 35 people (most of them women and children). Also, 10 people were on the victims list as wounded, and 22 houses were sabotaged [16].

October 25, 1993: PKK terrorists raided Erzurum's Cat district in Yavi region and took citizens from their homes and gathered them together in a coffee shop. They propagandized their declarations, and then killed them with automatic weapons. During the attack, 35 people died, and nearly 50 were wounded. The terrorists then set the houses on fire and escaped [16].

November 15, 2003: Thirty people were killed and 146 wounded when car bombs shattered two synagogues in Istanbul. Authorities identified two men from southeast Turkey as the suicide bombers, saying the attacks bore the hallmarks of the al Qaeda network [17].

May 11, 2013: Reyhanli, a Turkish town on the border with Syria, was attacked by Al-Qaeda with twin car bombs, leaving behind an official toll of 52 deaths and 146 injuries [18].

B. CURRENT COUNTERTERRORISM METHODS AND PROBLEMS

1. Methods

This thesis focuses on the methods that the Turkish Air Force uses to detect and eliminate terrorists. It does not look at other methods applied by Turkish Army assets or police forces. Only the Turkish-Iraqi border is taken into consideration (rather than the whole southeastern border of Turkey). The Turkish Air Force has used the methods described below to kill terrorists or prevent them from attacking military stations, government agencies, and military and police lodgings along the Turkish-Iraqi border.

The Turkish Armed Forces have a couple of resources that provide intelligence to the Turkish Air Force in southeastern Turkey. Unmanned aerial vehicles (UAVs) provide the most valuable information. UAVs facilitate intelligence, surveillance, and reconnaissance (ISR) missions over the border and provide information about terrorist activities and locations. Besides UAVs, intelligence may be provided by another source, such as Special Operations Forces (SOF), other military patrols, or police forces. Sometimes, villagers provide significant information about terrorist activities in the region as well.

After obtaining information and assessing it carefully, the Air Force immediately sends manned aircraft to the region to conduct attack missions. Commonly used Air Force bases are Diyarbakir Air Force Base (AFB), located in Diyarbakir city, and Erhac Air Force Base, located in Malatya city. In this thesis, we assume that only F-16s, deployed in Diyarbakir AFB are available for this kind of operation. After F-16s take off, they deploy to the area and, if they acquire a target, drop their air to ground weapons on terrorist militants. F-16s can locate and attack terrorists by using their onboard sensors or by using a UAV's sensors. However, the preferred method is to locate the terrorist group with onboard sensors based on coordinates provided by UAVs and then drop a bomb and support it with onboard sensors. After releasing their bombs, F-16s may continue flying over the area for battle damage assessment or leave the area and return to base and rely on UAVs to make the assessment.

2. Problems

The Turkish Air Force has been encountering many problems with the current counterterrorism methods in southeastern Turkey. Diyarbakir AFB is the closest Air Force base to the Turkish-Iraqi border that accommodates strike aircraft. The distance between Diyarbakir AFB and the most western part of the Turkish-Iraqi border is approximately 115 nautical miles away, which takes at least 25 minutes to travel for an F-16. The distance between Diyarbakir AFB and the most eastern part of the Turkish-Iraqi border is approximately 220 nautical miles away, which takes at least 45 minutes to travel for an F-16. We also need to add 5 to 15 minutes to the travel time for scramble response delays. Due to this inevitable delay, sometimes aircraft cannot reach the area in time, and as a result, they cannot prevent terrorists from attacking military facilities along the border.

Terrorist groups, such as the PKK, ISIS, and Al-Qaeda, which operate at the Turkish-Iraqi border, have supporters in urban areas. Sometimes, terrorist supporters who live in the cities where air force bases are located inform terrorists about aircraft activities at the air force base. As a result, terrorists sometimes know that aircraft are coming with fully loaded air-to-ground weapons and hide inside caves or deep valleys before the fighter aircraft reach the area. UAVs can also lose contact with terrorists and strike aircraft may find it difficult to locate and drop their air-to-ground weapons.

Another problem the Turkish Air Force struggles with is bad weather conditions. The weather at the border area may be clear, but if weather conditions are bad in the city where the AFB is located, the strike package cannot take off and deploy to the area.

The challenging terrain of the border is another problem for strike aircraft. The topography of the Turkish-Iraqi border is rough, which provides terrorists a strong advantage. Also, terrorists are well adapted to the area because they have been operating in the region for decades. Deep valleys and caves inside the mountains are perfect places for terrorists to hide and be protected. Therefore, it is difficult for strike aircraft to conduct attack missions in such terrain. Figure 2 and Figure 3 give examples of the rough terrain and terrorist caves near the Turkish-Iraqi border.

Another significant problem is that manned aircraft have a limited fuel capacity relative to unmanned aircraft. The operational range of an F-16 with standard air-to-ground weapons loaded is 1,740 nautical miles, which means it cannot fly over the area too long without air-to-air refueling [19]. Air-to-air refueling also requires significant time, depending on the location of tanker aircraft. F-16s may need to return to base without dropping their weapons if they cannot find an opportunity to attack terrorists within a limited time interval.

Figure 2. An example of mountains near the Turkish-Iraqi border. Turkish military forces are conducting an operation against the PKK. Image from etkihaber.com.

Figure 3. Turkish military forces found terrorist caves in Turkish-Iraqi border. Image from aktifhaber.com.

C. SCOPE OF THE THESIS

The majority of the problems that Turkey has to overcome are related to limited time and challenging terrain. Using unmanned combat aerial vehicles (UCAVs) in southeastern Turkey may help solve some of the problems. UCAVs are weaponized UAVs that can be used for air-to-ground attack missions against active terrorists. More detailed information about UAVs and UCAVs is given in Chapter II.

This thesis analyzes the use of UCAVs in conjunction with manned aircraft against active terrorists in rough terrain. Replacing manned aircraft and/or F-16s with UCAVs may help secure the Turkish-Iraqi border more effectively. Because UCAVs can fly for more than 24 hours, they can apply unlimited pressure on terrorist groups and attack them right after detecting and classifying them. Using UCAVs in some regions of the border and F-16s in other regions might also increase effectiveness. For this purpose, we modeled the entire Turkish-Iraqi border in Map Aware Non-Uniform Automata (MANA), an agent-based, time-stepped, stochastic mission-level model. More detailed information about MANA appears in Chapter II. We examine the influence of UCAVs against active terrorists by looking at the number of terrorists killed, the time required to kill terrorists, and the probability that the terrorists reach their objective. We also vary the parameters of F-16s, UAVs, and UCAVs, such as sensor detection ranges, hit probabilities, speed, and reaction times to explore the most effective parameters for mission success.

Turkey began developing its own unmanned aerial vehicle, called ANKA, in the 2000s to reduce its reliance on foreign industry. ANKA is being developed by Turkish Aerospace Industries (TAI). It will be delivered to the Turkish military forces during the period 2016 to 2018 [20]. It is in the advanced medium-altitude long-endurance (MALE) class of unmanned aerial systems. ANKA can perform day and night and in all weather conditions for more than 24 hours continuously [21]. It will have both armed and unarmed versions. Figure 4 depicts unarmed versions of ANKA, which will be used for ISR missions. In our MANA model, we use ANKA’s performance characteristics to simulate those of the UCAVs.

Figure 4. ANKA during a test flight. Image from tai.com.tr.

D. RESEARCH QUESTIONS

This research is guided by the following questions:

1. How might UCAVs enhance Turkey's ability to secure its border characterized by rough geographical conditions?
2. What combination of UCAVs and UAVs provides the same or better effectiveness as the combination of manned aircraft and UAVs currently in use?
3. Is there a combination of manned aircraft, UCAVs, and UAVs that provides the same or better effectiveness than the manned aircraft and UAVs in use?
4. What are the advantages and disadvantages of using UCAVs and UAVs only, manned aircrafts and UAVs only, or UCAVs, manned aircraft, and UAVs?

E. THESIS FLOW

Chapter II contains the background and provides useful information about vehicles, tools, techniques, and concepts. We provide definitions and benefits of UAVs and UCAVs, discuss agent-based simulation and modeling, and provide information about the Map-Aware Non-Uniform Automata (MANA) software to prepare the reader for the following chapters. Chapter III covers the development of the model and different scenarios that are used in this thesis. A detailed description of the agents in the model is explained in this chapter as well. Chapter IV explains design of experiment techniques and simulation runs. First, it describes the factors and levels that we vary in this thesis. Then, it explains the nearly orthogonal Latin hypercube (NOLH) design that was used to efficiently explore the experiment space. Last, it covers tools and techniques that we used to run our combat simulation. Chapter V concludes the thesis. It focuses on the analysis of the output. After describing the analysis tools used, it covers different analysis techniques and the results. Finally, it provides the findings and gives recommendations for further research.

II. BACKGROUND AND LITERATURE REVIEW

“The future is in the skies.”

– Mustafa Kemal Ataturk

This chapter provides a review of the tools, systems, and concepts that we use in this thesis. First, we provide definitions and background about UAVs, with an emphasis on UCAVs. Second, we provide definitions and a discussion of the benefits of agent-based modeling and simulation (ABMS). We also provide some information about Map Aware Non-Uniform Automata (MANA), which is the modeling tool used in this thesis. Last, we provide some examples of related studies on UAVs and UCAVs for border security and air-to-ground attack missions.

A. UNMANNED VEHICLES

1. Definitions of UAV/ UCAV and Background

Before defining UAVs or UCAVs, we need to define an unmanned aircraft system (UAS). The DOD defines a UAS as “that system whose components include the necessary equipment, network, and personnel to control an unmanned aircraft” [22]. In other words, an unmanned aircraft system includes an unmanned aerial vehicle, human element (operator, technician), payload (sensors, weapons), and data link, among other components. Figure 5 shows the major components of a UAS [23]. A UAV is only one component of an unmanned aircraft system (UAS). According to the DOD UAS roadmap, a UAV is “a powered, aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely” [24]. In other words, a UAV is an aircraft without a pilot in it.

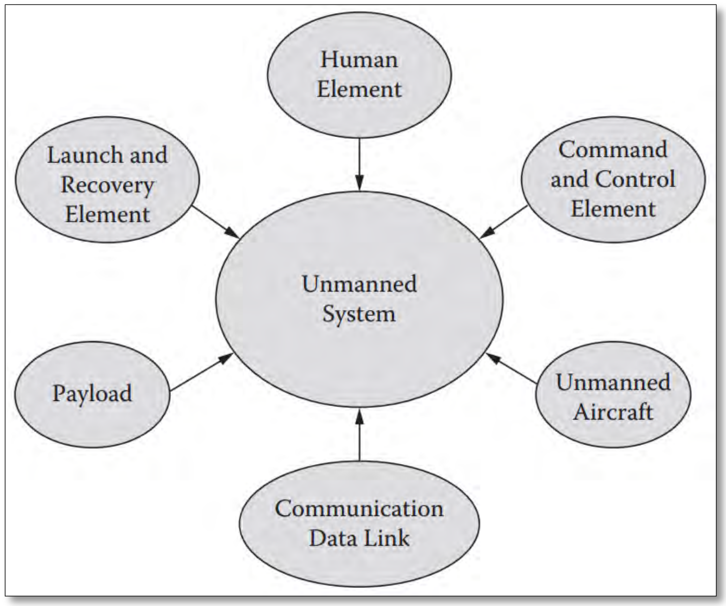

Figure 5. Elements of an unmanned aircraft system (UAS). Image from [23].

UAVs were first introduced during WWI and were also used in Vietnam, but interest in them increased dramatically during the Balkan Peninsula conflict and Operation Desert Storm [25]. Interest in UAVs has continued to increase because of their great contribution to mission success during these conflicts. UAVs are critical components of ISR missions as stated in the DOD UAS roadmap.

> In today's military, unmanned systems are highly desired by combatant commanders for their versatility and persistence. By performing tasks such as surveillance; signals intelligence (SIGINT); precision target designation; mine detection; and chemical, biological, radiological, nuclear (CBRN) reconnaissance, unmanned systems have made key contributions to the Global War on Terror. [26]

UAVs can be separated into two distinct groups: remotely piloted UAVs and autonomous UAVs [27]. Remotely operated UAVs require someone to control the aircraft from a distance whereas autonomous UAVs do not require a human operator. The primary way of operating UAVs is still man-in-the-loop control rather than fully autonomous control. Militaries use UAVs in autonomous mode only for non-critical missions [28]. This is because of the fact that a human is still more reliable than a computer program for most of the decision-making process.

The primary application of UAVs has been in ISR, but in the last several years, governments and militaries have started to arm their UAVs. A weaponized version of a UAV, called the UCAV, can be used for air-to-ground or air-to-air attack missions. UCAVs, similar to manned aircraft, can be armed with a variety of weapons, such as missiles (AGM 114 Hellfire), laser-guided weapons (GBU-12 Paveway II), and GPS-guided weapons (GBU-38 JDAM). They can be used to attack high-value, fixed-ground targets as well as moving ground and air targets in military operations.

According to the U.S. DOD, UAV missions may include but are not limited to:

- RSTA missions
- Surveillance for search and rescue
- Deception operations
- Maritime operations such as naval surface fire support (NSFS), over-the-horizon targeting (OTH-T), ship classification, anti-ship missile defense (ASMD), antisubmarine warfare (ASW)
- Electronic warfare (EW) and directed energy sensor reconnaissance
- Nuclear, biological, and chemical (NBC) reconnaissance
- Special and psychological operations
- Meteorology missions
- Route and landing zone reconnaissance support
- Adjustment of indirect fires and close air support (CAS)
- Rear area security support
- BDA
- Radio and data relay [29]

Many of the missions listed above can be achieved by manned aircraft as well, but some of the missions, such as nuclear, biological, and chemical reconnaissance, are too risky for a human. Therefore, UAVs are critical components for militaries.

2. Benefits of Unmanned Aircraft

Nowadays, governments and militaries are discussing what combination of piloted aircraft, UAVs, and UCAVs are best for ISR and attack missions. According to the DOD UAS roadmap, "Unmanned systems have proven they can enhance situational awareness, reduce human workload, improve mission performance, and minimize overall risk to both civilian and military personnel, and all at a reduced cost" [30]. In other words, UAVs have become desirable components for military operations as well as civilian affairs because of their proven benefits.

Moreover, military services can purchase and operate UAVs for less money than they pay for manned aircraft [31]. Including ground control stations, the procurement cost of a UAV is 40 to 80% of a manned aircraft cost and operation—in addition, the maintenance cost of a UAV is 20% of a manned aircraft cost [32]. According to the DOD, "transportation and logistics requirements to deploy the UAV systems are usually smaller than other airborne intelligence collection resources." Also, "extensive special training is not required to use much of the information provided by UAVs." [33] This is because UAVs are relatively smaller and less complex systems than manned aircraft.

Among all benefits listed in the DOD's UAS roadmap, the primary benefit of UAVs is their ability to decrease or prevent the loss of personnel life. Even when the environmental conditions do not allow using manned aircraft, UAVs can still provide effective military options. For example, it may be too risky to assign a manned aircraft to an NBC reconnaissance mission, but a UAV may still be an option for this mission. Because we do not need to worry about a pilot's life, we can assign UAVs to the most dangerous missions.

UAVs and UCAVs allow military forces to conduct surveillance and attack missions against highly defended targets. Because UAVs do not require a pilot in the cockpit, they can withstand extreme conditions that their piloted counterparts cannot, such as high acceleration forces (g) and long flight times. In general, removing the pilot from the aircraft provides the ability to design innovative concepts and to use them in all environmental conditions.

B. AGENT-BASED MODELING SIMULATION

Significant developments in computer technology and the high operating costs of real systems have given rise to the use of simulation programs in military services [34].

There are a variety of military applications, such as training methods, attack/defense mission rehearsals, system effectiveness, new concepts of operations, and military tactics and techniques that can be explored or analyzed by modeling in a computer environment. Furthermore, due to the lower cost of computer simulation over real system use, military services can simulate large-scale military operations over and over again without spending more money. Simulation programs can also be used to bound complex problems, eliminate irrelevant options, and determine the areas where actual tools should be used or field experiments are needed.

Agent-based modeling and simulation (ABMS) is one of the modeling and simulation techniques that allow users to represent real-world problems within a computer program. Sanchez and Lucas describe agent-based simulations as "models where multiple entities sense and stochastically respond to conditions in their local environments, mimicking complex large-scale system behavior" [35]. Agent-based modeling allows military agencies to simulate complicated and variable interactions of opposing military organizations in a battlespace. In agent-based modeling, autonomous agents such as aircraft, tanks, helicopters, ships, unmanned vehicles or humans, execute programmable stochastic behavioral and decision-making rules. As a result of individual agent behaviors and interactions between different agents an overall simulation result arises as a sophisticated global model. Castiglione lists ABMS's properties as follows:

1. Agents have internal states which can be represented by discrete or continuous variables.
2. Agents may change their states after interacting with another agent or a state change may cause a change in behavior.
3. Every agent may interact with another agent locally or globally.
4. Rules, which range from simple logic to complex algorithms, drive agents' behaviors.
5. The system evolves over the time and both time and space can be discrete or continuous [36].

Agent-based modeling is a suitable and beneficial tool to be used in military applications. In his paper, Bonabeau states the benefits of ABMS techniques.

1. ABMS captures emergent events which stem from interactions of individual entities.
2. In many cases, ABMS is most inherent for explaining and simulating a system formed by ‘‘behavioral’’ entities.
3. ABMS is flexible along multiple dimensions. It is easy to modify (add or delete agents) an agent-based model [37].

ABMS can be executed through many different programs, such as Microsoft Excel, Java, C++, MATLAB, and R. In this thesis, we use an ABMS platform called Map Aware Non-Uniform Automata (MANA) to explore the research questions. MANA is one of the most user friendly modeling tools, and for that reason, it has been widely used by NPS faculty and students [38].

C. MANA

This section draws from the MANA user manual versions 4 and 5. For more detailed information about the descriptions and features of the modeling tool, the reader should look to the MANA manual.

MANA is an agent-based, time-stepped, stochastic, mission-level simulation environment. It was developed by New Zealand’s Defense Technology Agency (DTA) and is used in a wide range of national and international scientific defense studies. The development of MANA has been ongoing since its first introduction in 2000. After DTA started to increase the sophistication of its agent-based models in the early 2000s, it has continually improved MANA by adding new features. DTA introduced the most recent version of MANA, MANA-V, in 2009. We use MANA-V as a modeling tool in this thesis. Different than early versions, MANA-V uses a vector-based approach for agent movement rather than a grid-based movement scheme. This feature of MANA-V provides a number of advantages, such as larger battlefields and greater flexibility for developing new model features. Moreover, MANA-V provides easier interpretation of scenarios because it uses international system (SI) units for ranges. Figure 6 illustrates the two different movement schemes used in previous versions and in MANA-V [39].

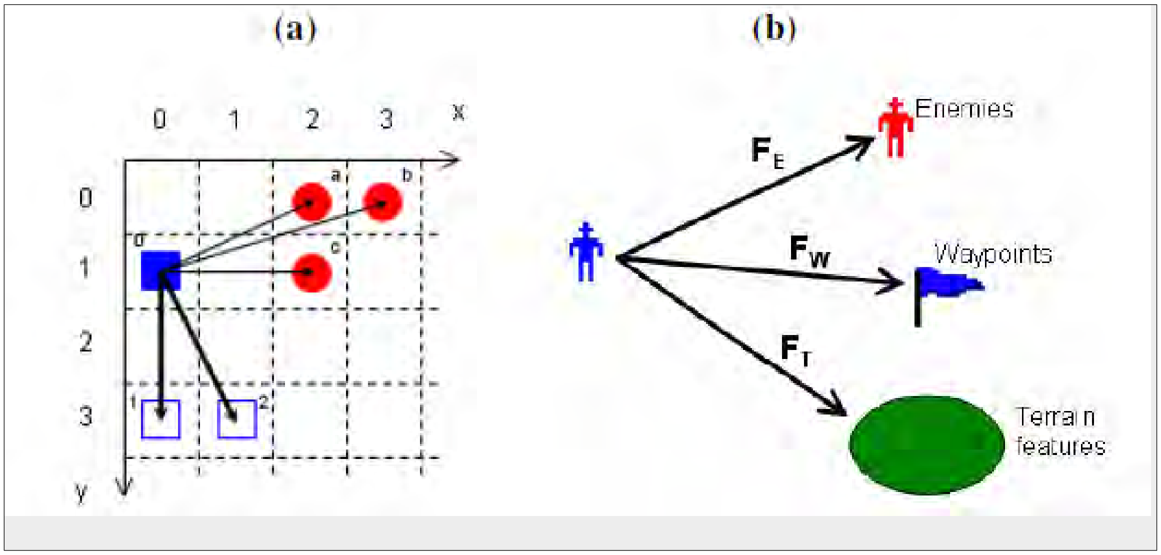

Figure 6. Two distinct movement schemes used in MANA: (a) grid-based approach used in MANA 2, 3, and 4; (b) vector-based approach used in MANA-V. Image from MANA manual.

Primary elements of the MANA model are squads. In MANA, a squad is a collection of initially homogeneous agents and can be a single agent or a group of agents. Each squad can be defined as friend, enemy, or neutral. This affects the squad's behaviors when interacting with other squads. Autonomous agents in MANA are

- **Map-Aware:** Agents are aware of their environment through their organic sensing capability or through communication with other agents.
- **Non-uniform**: Each major agent type has its own unique set of properties.
- **Automata**: Agents react independently to various scenarios based on the information they have about their environment [39].

Each agent in MANA has personality characteristics that can drive it toward or away from other agents or objects in their environment. These personality settings can be changed depending on user-defined trigger states that switch the personality when (or if) certain events occur (e.g., an agent being shot at). A state is a collection of parameter values, such as personality weightings, sensor and weapon ranges, concealment percentages, and speed [39].

Movement of the agents is limited to the size of the battlefield. Direction and speed of the movement is determined by vector-based algorithms that consist of personality weightings and penalty calculations defined by the user. Terrain, elevation, and background maps can be loaded into the model. These maps are basically Windows bitmaps that the user can modify using the built in MANA map editor or using some software such as Microsoft Paint or Adobe Photoshop. The terrain map affects agents' "Going," "Cover," and "Concealment." "Going" refers to how the terrain affects an agent's speed. "Cover" defines the level of protection of an agent against enemy attacks. "Concealment" refers to the level of invisibility of an agent in the terrain. "Going," "Cover," and "Concealment" parameters are determined by the colors which form the whole terrain map. The elevation map is gray-scale map ranging from black to white, and it is used for line-of-sight (LOS) calculations. The elevation map provides a realistic implementation of the battlefield. For example, an agent on one side of a hill cannot see or shoot at an agent on the other side of the hill. The background map does not affect agents. It can be stored to enhance a scenario's appearance to the user [39].

An agent can detect and classify another agent within a range defined by the developer by using its own sensor (or sensors). The simple mode of the sensor operates as cookie-cutter sensor while in the advanced mode a user can define different sensor characteristics for different ranges. For example, it is more likely to detect nearby agents than farther agents. No matter if the simple mode or the advanced mode is used, detection requires a LOS between two agents. Similar to sensors, an agent can have weapons in the form of a kinetic energy weapon and/or a high explosive weapon. Agents can use those weapons against enemy agents. MANA uses a user-defined range probability table to determine the degree of effect of a weapon [39].

In MANA, agents can communicate with other agents in the same squad or with agents in different squads. Communication ranges, latency, reliability, and capacity of the transmission, and the type of information that is intended to be passed, is determined by the user. Communications between squads can be visualized in a situational awareness (SA) map. There are two types of SA maps, squad SA maps and inorganic squad SA maps. Any enemy detection made by one agent in the squad is put onto the squad's SA map so that other agents in the same squad can access the information. Similar to the squad SA map, the inorganic squad SA map shows detections made by an agent from a different squad that been communicated to the squad [39].

In terms of agent-based models, MANA has a number of advantages. Those advantages are listed in the MANA manual as follows.

- It is user friendly and has an easily navigable user interface. Scenarios can be quickly edited "on the fly" during development, allowing different ideas to be quickly explored. In this regard, MANA can be thought of as a "sketch pad" for trying new military tactics.

- MANA is supplied as a pre-compiled executable, so it runs relatively fast compared with other agent-based models built on interpreted languages.

- The model has a built-in data farming capability which allows rapid exploration of parameter spaces.

- MANA can model communications links between agents for information sharing. Hence, aspects of network-centric warfare (NCW) can be studied.

- To model terrain features, MANA uses colored bitmaps. This has the advantage that terrain features can be quickly altered using a simple image editor (for example, MS Paint), while a scenario is in development.

- MANA has a large number of trigger states that agents can go into based upon various events occurring on the battlefield. This increases the richness of behaviors and insights that can be obtained from scenarios [39].

D. LITERATURE REVIEW

UAVs and UCAVs have been improving every day, and they are now regarded as a main element of modern warfare. Because of their undebatable contribution to battles, especially in asymmetric warfare environments, new and improved versions of UAVs and UCAVs are being produced by many different countries [40]. A significant number of studies that address UCAVs and border security issues depict the importance of the matter. We reviewed some of these studies below.

In his thesis, Bessemer [41] points out the United States Air Force's demand for UCAVs and seeks a quick fix to satisfy this demand until fully capable unmanned vehicles are produced [41]. He argues that the most effective way to decrease risk-of-life and budget costs is to introduce an F-16 unmanned aerial system (UAS) aircraft for combat. He illustrates "how an effective F-16 UAS can synchronize recourses to properly complete UCAV development while instantly reducing risk of life" [41]. His overall assessment is that the F-16 UAS is a good solution for American air supremacy.

In his study, Kumar [42] expresses that major improvements in UAVs have been in the role of tactical reconnaissance [42]. He demonstrates that UAVs are perfect tools to fill the information gap on the battlefield. If militaries employ UAVs in an efficient manner, the inherent characteristics of UAVs make them capable of complementing manned aircraft in the role of tactical reconnaissance [42]. Although militaries started to use UAVs instead of manned aircraft for some missions, they always seek more efficient designs and employment methods for UAVs, as Kumar pointed out.

In his thesis, Beales [43] reviews the U.S. government's decision to end F-22 production and switch to UCAV procurement. He states that it is very obvious that UCAVs are cheaper and more persistent, but on the other hand, terminating F-22 production decreases the USAF's ability to defend the homeland against some potential threats [43]. As a result, he suggests a concentration toward UCAVs in future procurement while improving versatility and availability.

In his thesis, Gill [44] constructs a simulation model of a strike scenario that focuses on the coordination of the Navy Unmanned Combat Air System (NUCAS), F/A 18 Super Hornet, and the F-35C Lightning II. By using design of experiment techniques and making 12,000 simulation runs, he evaluates the results in order to determine the number of aircraft needed for mission success and the factors that are required to reduce friendly aircraft losses [44]. He determines that a four NUCAS division is advantageous and a stealth requirement is crucial in future aircraft development.

In his thesis, Sulewski points out that "the future force will rely heavily on UAVs to provide eyes on the battlefield" [45]. He analyzes the effect of the numbers and capabilities of armed and unarmed UAVs in the U.S. Army's future combat battalions. For this purpose, Sulewski builds a simulation model in MANA and makes 46,440 computational experiments. He finds that UAVs significantly enhance the performance and armed UAVs (UCAVs) are critical in the opening phase of the battle.

In his study, Hume examines “the issue of weaponized UAV integration into the battlespace from the standpoint of doctrine, operational concept, and roles and missions” [46]. Hume makes some recommendations about how best to employ weaponized UAVs in the future. He recommends giving weaponized UAV missions to the U.S. Air Force, to create a joint acquisition strategy, to establish joint standards for unmanned aircraft (UA) employment, and to improve command and control systems of weaponized UAs.

In her thesis, Ozcan analyzes the effectiveness of the UAVs in helping secure the Turkish-Iraqi border characterized by rough terrain and active terrorists [47]. She modeled the Turkish-Iraqi border in MANA and examined the potential impact of UAVs on detecting and classifying terrorists trying to pass the border and attack the blue forces. The results from the 103,200 runs showed that UAVs are very efficient in the detection and the classification of terrorists in this region. She also points out that the most significant factors of UAVs are the detection and the classification performance.

All of the studies and theses that we summarized discuss different perspectives on the use of UCAVs. Some of them, such as [46], point out the strategic importance of UCAVs, whereas others, such as [45] and [42], discuss tactical level contributions. Moreover, some researchers, such as [44], examined the results of using UCAVs and manned aircraft together in a battlefield, while others, such as [43], discuss using only UCAVs alone. Building on the literature, this thesis examines the importance of using UCAVs in conjunction with manned aircraft in areas of rough terrain.

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III. MODEL AND SCENARIO DESCRIPTION

In this chapter, we explain the model development process and describe the scenarios we constructed to examine UCAV effectiveness. First, we discuss how we designed the battlefield and constructed the maps we needed for the model. Next, we describe our baseline scenario and seven alternative scenarios in detail. Finally, we explain the agents in the model.

A. MODEL DEVELOPMENT

Map Aware Non-Uniform Automata Vector (MANA-V) was used as a modeling tool in this thesis. It took approximately two months to complete the model and make it ready to run. This two-month period included learning MANA, by reading the manual, and reviewing old models; constructing maps, elevation, background, and terrain maps; building the basic scenario; and finally, building alternative scenarios.

1. Battlefield

For this thesis, the 384 km Turkish-Iraqi border was modeled as a battlefield in MANA. 384 km is the real length of the Turkish-Iraqi border; as far as air distance is concerned, it is approximately 222 km. This served as the length of the battlefield. 108 km was chosen as the width of the battlefield to include blue battalions on the north of the border and to adjust the map ratio. Therefore, a 222 km × 108 km terrain was considered the area of interest. The battlefield was bounded by the Turkish-Iranian border on the east and the Turkish-Syrian border on the west. We separated the battlefield into three independent operational regions. Each agent operates in a dedicated region and does not involve any activity in other regions. We display those regions on the map in the scenario description section later in this chapter.

2. Map Construction

As explained in Chapter II, MANA needs elevation and terrain map input if the user wants topography to affect the agents. Also, MANA accommodates a background map to improve visualization of the scenario. In this thesis, all three types of maps were used because together they constructed a realistic mission-level model, which included humans moving on the ground, stationary ground assets, and aerial vehicles.

a. Elevation and Background Maps

The elevation map in gray-scale helps formulate line-of-sight (LOS) calculations. After selecting the area of interest, an elevation map was constructed using a variety of sources and software. Environmental Systems Research Institute (ESRI), the international developer of the geographic information system (GIS), was used to obtain raw elevation data for the Turkish-Iraqi border. We used ArcGIS software online to create, display, and analyze geospatial data developed by ESRI. Elevation data was stored as a keyhole markup language zipped (kmz) extension file that could be used by Google Earth. After opening the downloaded data in Google Earth, we saved a picture of the area of interest in a picture format. Finally, Microsoft Paint helped us adjust the size and resolution, and store the final version in bitmap (bmp) format, which is an acceptable format for MANA (see Figure 7). In this study, real world elevation was defined between 650 and 3200 meters above sea level for the lowest and highest points, respectively. We also used the elevation map as a background map in the model by adding the Turkish-Iraqi border on the elevation map as a line. The background map does not affect agents. It simply enhances a scenario's appearance to the user.

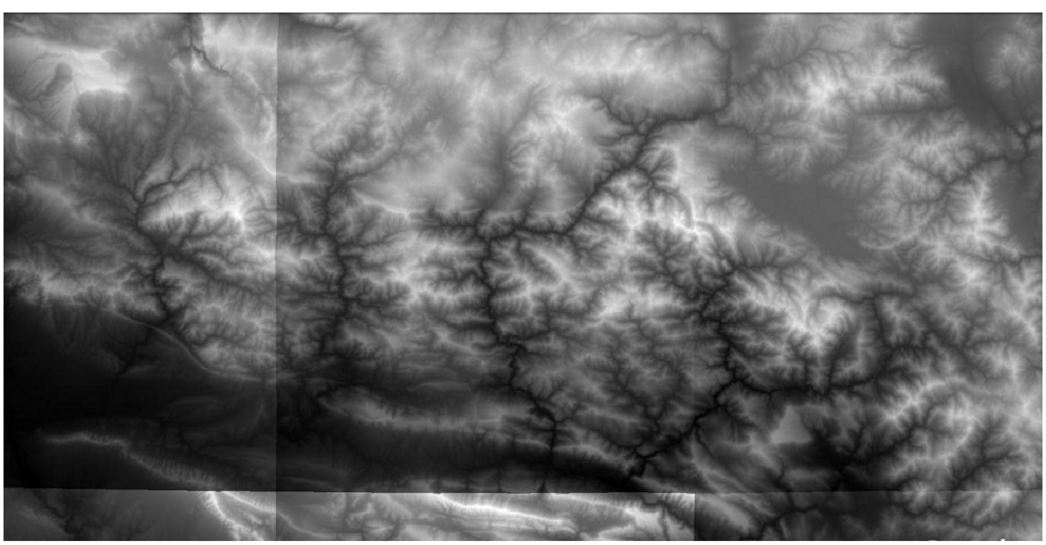
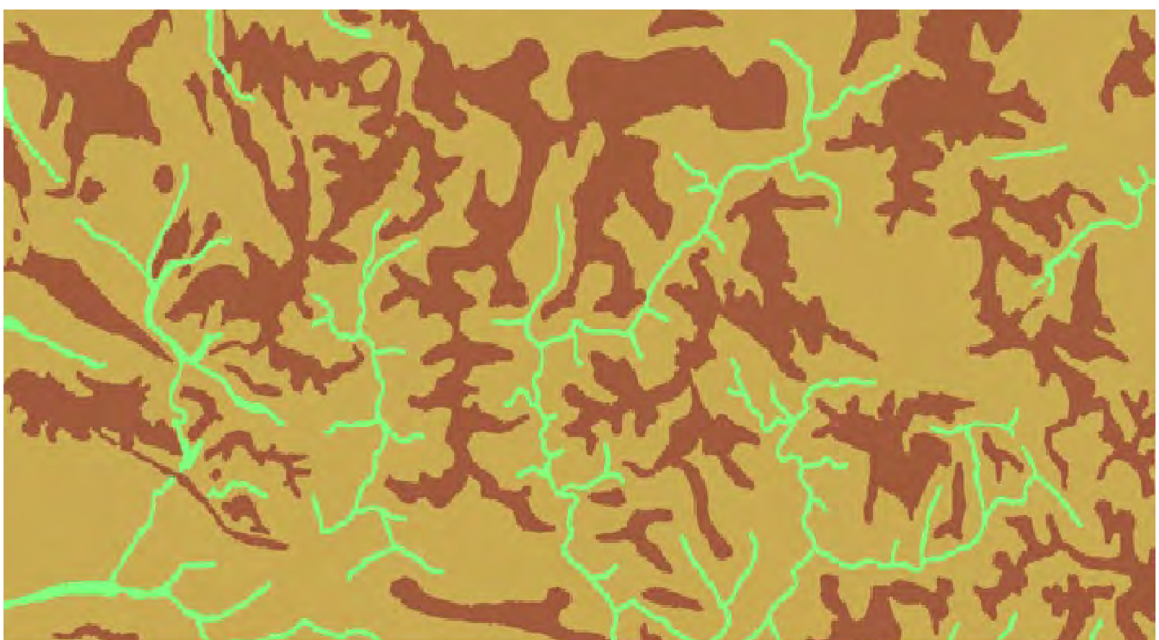


Figure 7. Elevation map used in the model.

b. Terrain Map

The gray-scale elevation map was referenced to construct an accurate terrain map. The lightest parts of the elevation map are the tops of the mountains while the darkest parts are valleys. We used Microsoft Visual Studio to construct the terrain map. This process took more than a week because Visual Studio separates the elevation map into its pixels and the user needs to cross-reference the colors of every pixel with the elevation map. Using more improved software, such as Photoshop, is highly recommended for terrain map construction in order to save days or even weeks.

The terrain map comprises three different colors, which represent three different terrain characteristics for mountains, off-road, and valleys. Each color on the terrain map, or in other words each terrain type, has a certain “Going,” “Cover,” and “Concealment” value ranging from 0.0 to 1.0. A value of 0.0 means “No” “Going,” “Cover” or “Concealment,” while a value of 1.0 means “Full” “Going,” “Cover” or “Concealment.” Terrain types and parameters are depicted in Figure 8.



	Going	Cover	Concealment	Red	Green	Blue	Color
Mountain	0.1	0.4	0.6	160	90	60	
OffRoad	0.6	0.4	0.8	200	170	82	
Valley	0.5	0.8	0.9	128	255	128	

Figure 8. Terrain types and parameters.

3. Model Time Step

MANA is a time-stepped model, (i.e., all events occur in discrete intervals). In time-stepped models, each time the main script is executed, the simulation time is incremented by the simulation time step. In other words, the computer makes all the required calculations for every time step, and the next calculation occurs in the next time step. Using large time steps results in fast but inaccurate simulations because the user may miss some important events. On the other hand, small time steps lead to more precise simulations, but will take more time. If the model is too complex, the run time will be even more because the computer will have to make more calculations every time step. In our model, the time step was set to one second to catch most every detail during simulation runs. The time step of the model was set to one second, which meant that each time step corresponded to one second in real time.

B. SCENARIOS

We built our scenarios by taking historical incidents as a reference. Terrorist groups have conducted bloody attacks against Turkish military assets, police forces, and civilians along the Turkish-Iraqi border in the past causing many deaths. We gave some examples of these attacks in Chapter I. Sometimes terrorist groups attacked with only a couple of terrorists and sometimes made simultaneous coordinated attacks in different locations with many different groups. One of these examples occurred on September 11, 2011 in Semdinli province of southeastern Turkey. A total of 130 PKK terrorists attacked Semdinli’s District Police Headquarters, District Gendarmerie command, 3rd Tactical Mountaineer Gendarmerie Brigade, and police checkpoint simultaneously with machine guns and rocket launchers [48]. Three people were killed, and seven were injured in this attack. Turkish military and police forces immediately responded to the attacks; seven terrorists were killed, and the rest ran away towards northern Iraq.

Our scenario is based on this incident. By experiencing this horrible terrorist attack, we were reminded that preventing terrorist groups from crossing the border is crucial. Otherwise, a skirmish between our soldiers and terrorists and resulting deaths are inevitable. We are trying to figure out how effective UCAVs might be in that area as an alternative to F-16s. For this purpose, we constructed eight different air-to-ground attack plans comprising different combinations of F-16s, UAVs, and UCAVs. We call them different scenarios throughout the thesis since each of them needs to be run separately in MANA, one baseline and seven alternative scenarios.

1. Baseline Scenario

The baseline scenario was constructed based on the skirmish explained above. This scenario represents current counterterrorism methods of the Turkish Air Force. Our baseline scenario includes three F-16s as strike assets, three UAVs for ISR missions, and three terrorist groups that attempt to cross the border and make their way to attack three blue battalions. The baseline scenario also has partisans, who are the supporters of terrorists in the cities, and a dummy agent, who is used to terminate the runs after a terrorist reaches their objective. As mentioned previously, the battle area is separated into three regions and each F-16, UAV, and terrorist group are assigned to a specific region. Figure 9 depicts the general overlay of the baseline scenario and its three regions. In this scenario, if a UAV detects and classifies any terrorist activity along the border, it immediately reports it to the F-16 that is responsible for that specific region. Each UAV and F-16 conduct operations in a dedicated region, and they do not have any activity in other regions.

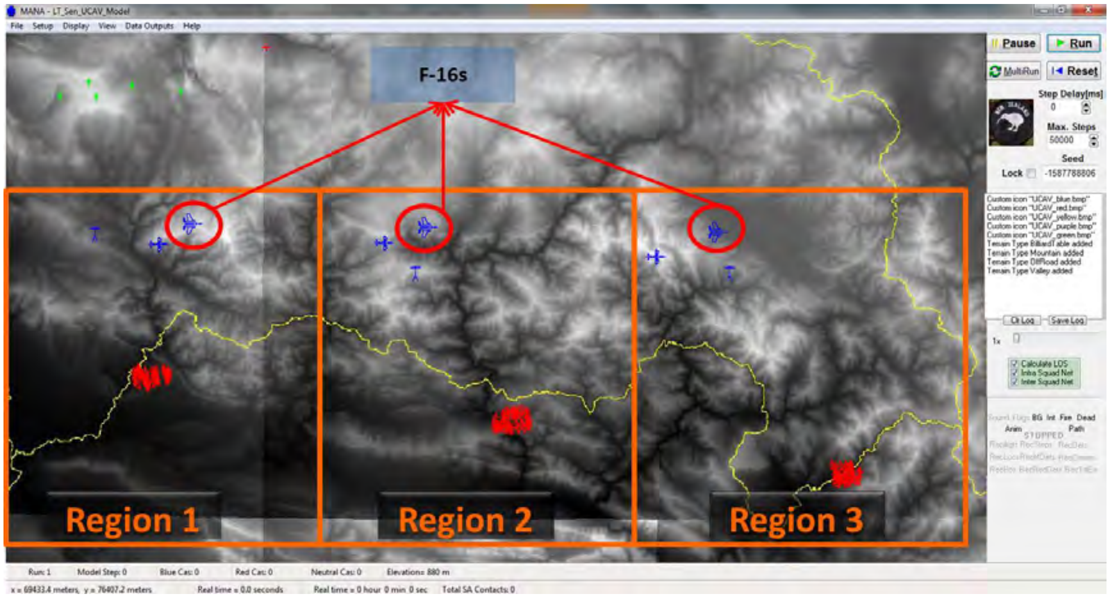


Figure 9. Baseline scenario.

2. Alternative Scenario 1

In this alternative scenario (see Figure 10), we replace all F-16s with UCAVs. UAVs still conduct ISR missions in their regions. Similar to baseline scenario, in alternative scenario 1, each UCAV is responsible for one specific region. The biggest difference between the baseline scenario and alternative scenario 1 is that in alternative scenario 1 we double our detection sensors with the addition of UCAVs. UCAVs also search for terrorist activities along the border in conjunction with UAVs, and if they find a terrorist group, they can quickly conduct an attack mission against them.

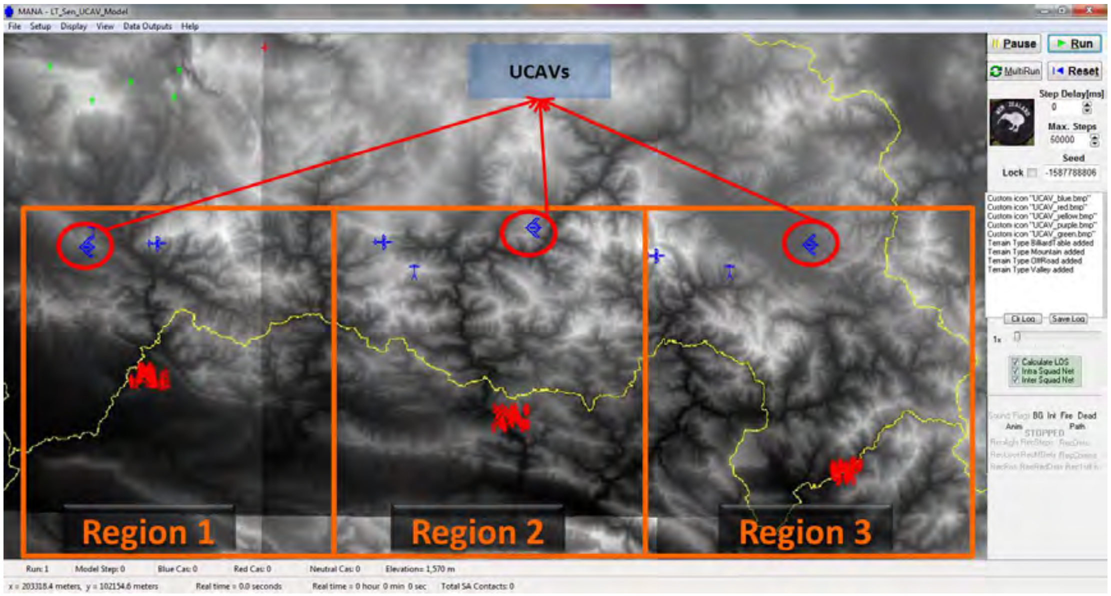


Figure 10. Alternative scenario 1.

3. Alternative Scenarios 2, 3, and 4

In alternative scenarios 2, 3, and 4, we use one F-16 and two UCAVs as air-to-ground strike assets. We assign those assets to different regions in each scenario. In alternative scenario 2, the F-16 is responsible for region 1 and UCAVs are responsible for regions 2 and 3. In alternative scenarios 3 and 4, the F-16 is assigned to regions 2 and 3, respectively. We keep UAVs active in these scenarios, like we do in our other alternative scenarios. Therefore, two of the three regions have two detection sensors (the sensors on the UAVs and UCAVs) while one of the regions has only one sensor, the UAV’s sensor. As a result, we expect the reaction time to be smaller in the single-sensor regions than the reaction time in the double-sensor region. Figure 11 shows alternative scenario 3 as an example of one of the F-16 and two UCAVs scenarios.

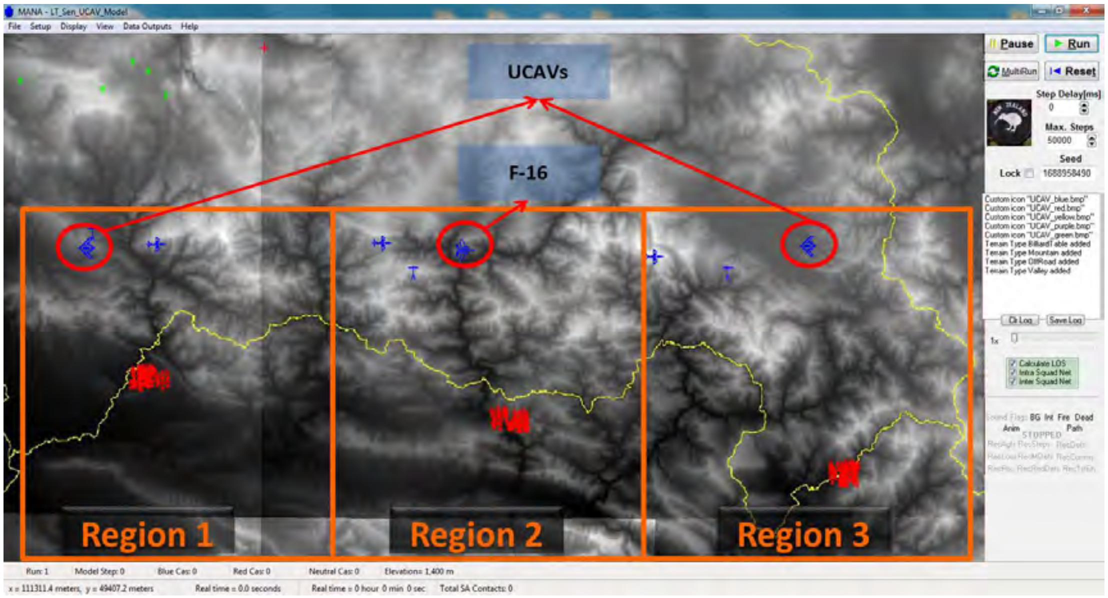


Figure 11. Alternative scenario 3.

4. Alternative Scenarios 5, 6, and 7

In alternative scenarios 5, 6, and 7, we use two F-16s and one UCAV as air-to-ground strike assets. We assign those assets to different regions in each scenario. In alternative scenario 5, F-16s are responsible for regions 1 and 2, whereas a UCAV is responsible for region 3. In alternative scenarios 6 and 7, the lone UCAV is assigned to regions 2 and 1, respectively. We keep UAVs active in these scenarios just as we did for the other alternative scenarios. Therefore, one of the regions among three have two detection sensors (UAVs and UCAVs) while the other two regions have only one sensor, the UAV's sensor. As a result, we expect the reaction time to be larger in single-sensor regions than the reaction time in double-sensor region. Figure 12 shows alternative scenario 7 as an example of a two F-16s and one UCAV scenario.

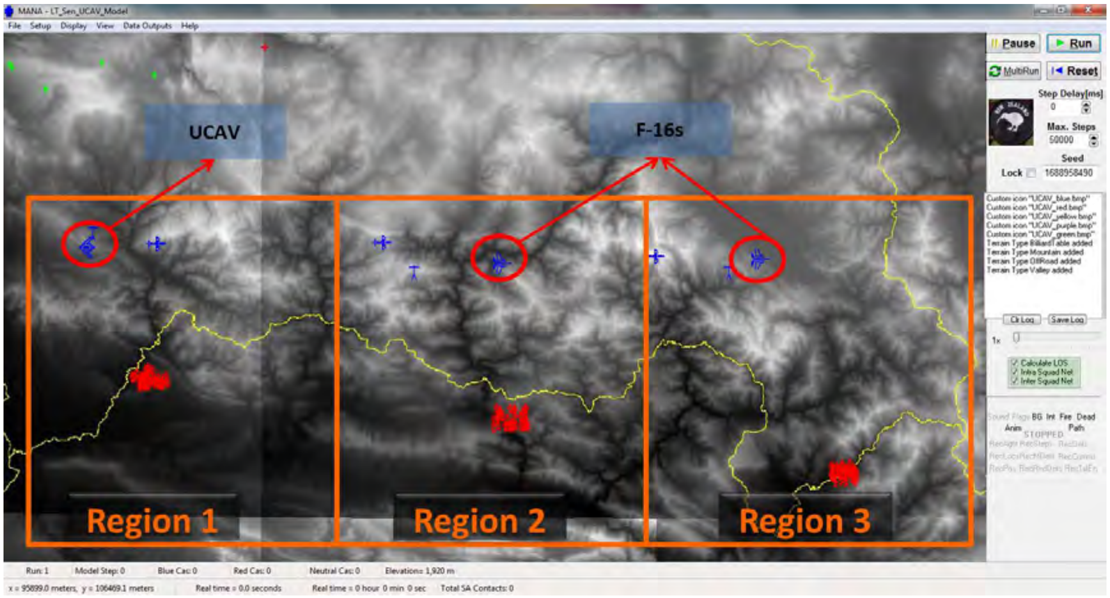


Figure 12. Alternative scenario 7.

C. MANA USER INTERFACE

After defining the battlefield, constructing necessary maps, and building the basic scenario, the user can edit agent properties using MANA's graphical user interface (GUI). The "edit squad properties" tab under the "setup" menu provides access to squad properties. The user can change various properties of a squad by selecting tabs under the "edit squad properties" window. These tabs include general, map, personalities, tangibles, sensors, weapons, intra-squad SA, inter-squad SA, and advanced. The tabs in the "edit squad properties" window are shown in Figure 13. Before explaining these tabs, we explain the trigger states first. The MANA manual defines *trigger states* as follows.

> For a simple MANA scenario, personality weightings and other agent characteristics are first defined for each squad's Default state. This may be all that is required for a simple scenario. Once a scenario starts running MANA has the flexibility to allow agents to trigger into other states apart from the Default state depending on different events occurring on the battlefield. This adds a new level of richness to the types of agent behavior which might emerge in a scenario. [39]

The "general" tab is the place where general squad data is defined. The user can change a squad's name, number of agents, and initial fuel capacity by using this tab. The user can also activate or deactivate a squad from here for a specific replication of the simulation. The “general” tab also allows the user to save, delete, or load a squad. The “map” tab is the place where the user defines the home and waypoints of a squad. The information in both general and map tabs does not vary as a function of trigger states.

The “personality” tab allows the user to define a set of personality weightings for a squad of agents using slider bars, as illustrated in Figure 13. The slider bars on the panel are for adjusting agent propensities. A positive value means an agent has a positive propensity towards the associated object while a negative value indicates a negative propensity. The higher the weighting value is, the greater the attraction. For example, in Figure 13 there is a positive movement weighting of 100 toward enemy agents. There are three sources from which the information originates. The information that agents collect directly using their own sensors corresponds to the “agent SA” section. The shared squad information corresponds to the “squad SA” section. Inorganic SA refers to the information that has been obtained from other squads via communications links. Different trigger states can have different settings.

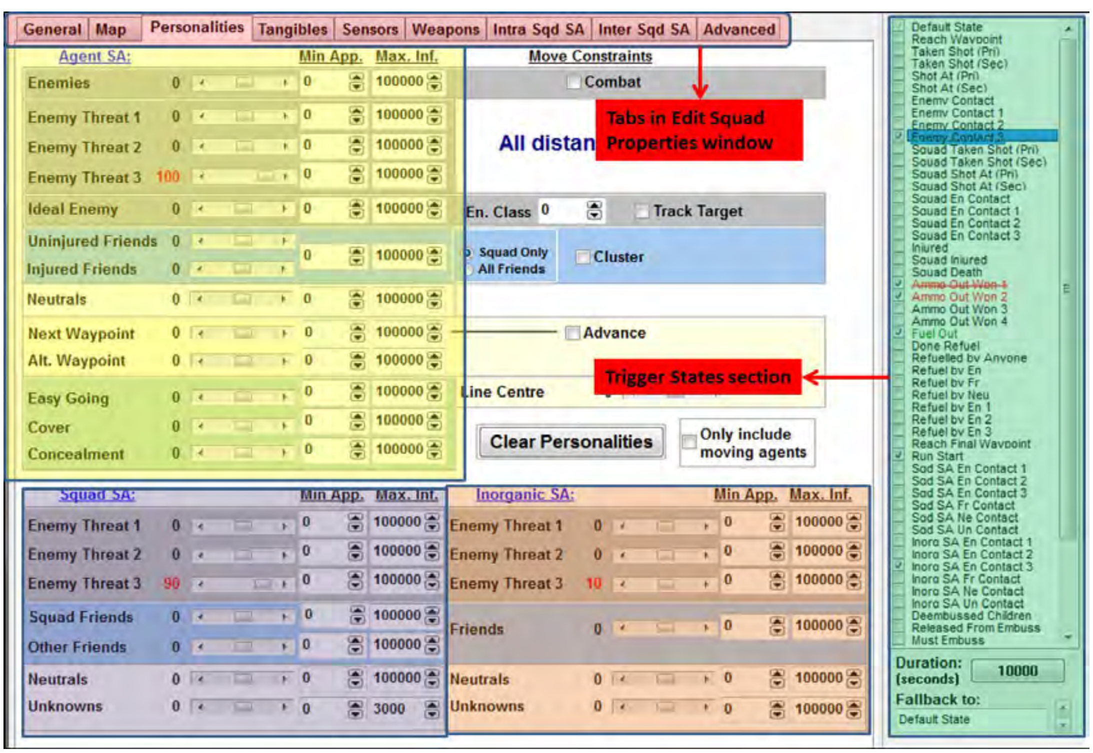


Figure 13. Personality settings panel.

The “tangibles” tab allows the user to adjust an agent’s speed, icon type and color, allegiance, threat level, and class. The user can also define the number of shots required to kill an agent and armor thickness using the “tangibles” tab. For more detailed information, please refer to the MANA manual [39]. The “tangibles” tab in the “edit squad properties” window is shown in Figure 14.

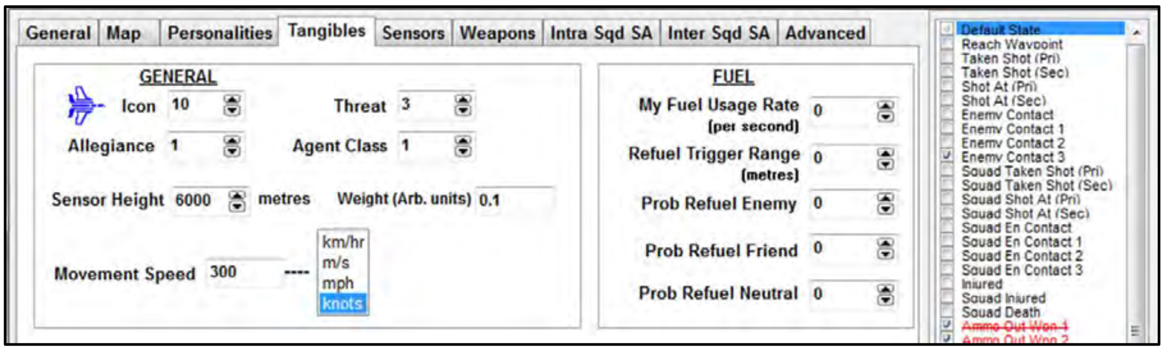


Figure 14. Tangibles panel.

The “sensors” panel, shown in Figure 15, allows the user to define up to six different sensors for an agent. The user can select any sensor, and change its name and use it in simple or advanced mode. The range tables allow the user to adjust the detection and classification ranges of a sensor. The user also defines an average time between detections and a classification probability for a sensor in this panel. The user can define a single range, time, and probability value or range tables to define the change in sensing capability as a function of the distance. The target classes section allows the user to specify target classes for this sensor. Sensor characteristics can vary depending on the agent’s trigger state.

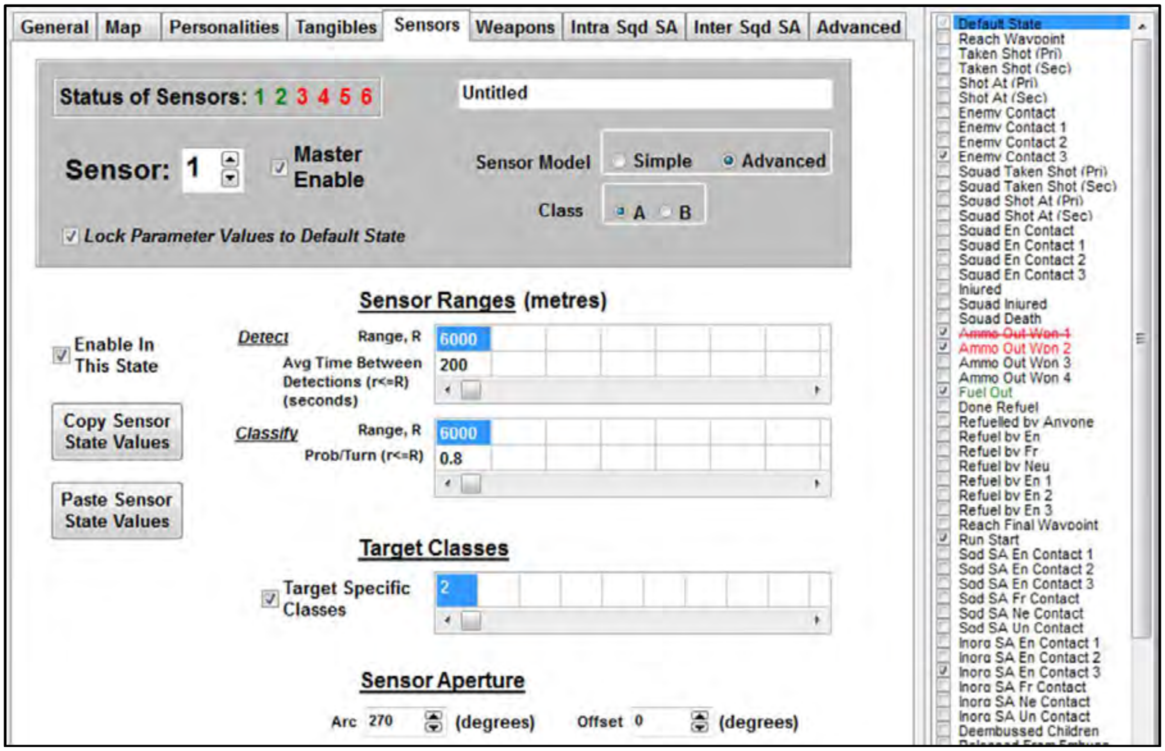


Figure 15. Sensors panel.

The “weapons” tab consists of information about an agent’s weapons. Similar to sensors, the user can define up to six different weapons for each agent. Each weapon’s characteristics can be set up differently using this panel. The user can define a weapon’s class, model, and fire mode as well as the number of ammunition an agent has. Similar to the “sensors” panel, there is a range-probability table for each weapon to define the probability of hitting a target at a corresponding distance. In another table, the user specifies target and non-target classes. Weapon characteristics can vary depending on the agent’s trigger state. The user can also enable or disable a weapon from this panel. The “weapons” tab in the “edit squad properties” window is shown in Figure 16. For other sections that we did not explain here, please refer to the MANA manual [39].

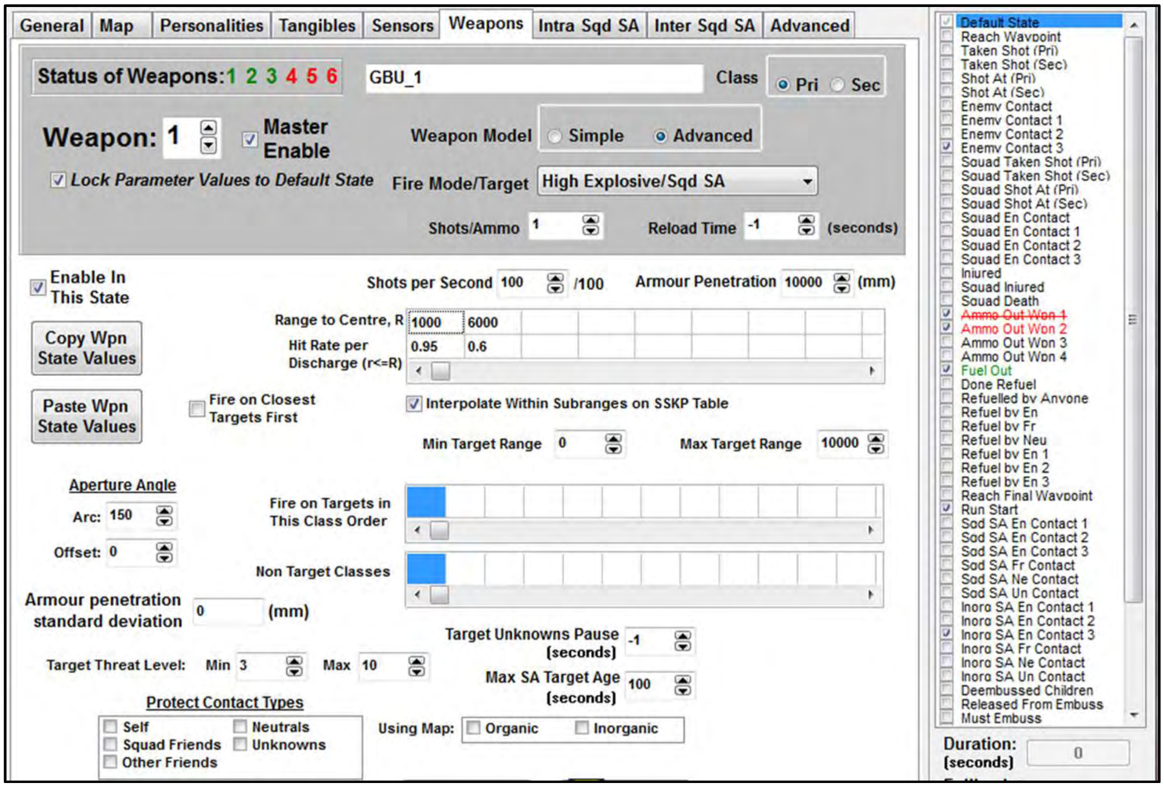


Figure 16. Weapons panel.

The “intra-squad” and the “inter-squad SA” tabs refer to how the information is shared within the squad and between the squads, respectively. By using the “intra-squad SA” tab, the user defines communication delays between the agents within a squad as well as the squad contact persistence. The “inter-squad” tab, depicted in Figure 17, allows the user to define a communication link between any two squads. The user can change the maximum communication range, latency, maximum capacity, and reliability of communication for each agent or squad using this panel. The allegiance, location, velocity, and movement direction of an agent can be transferred through these links.

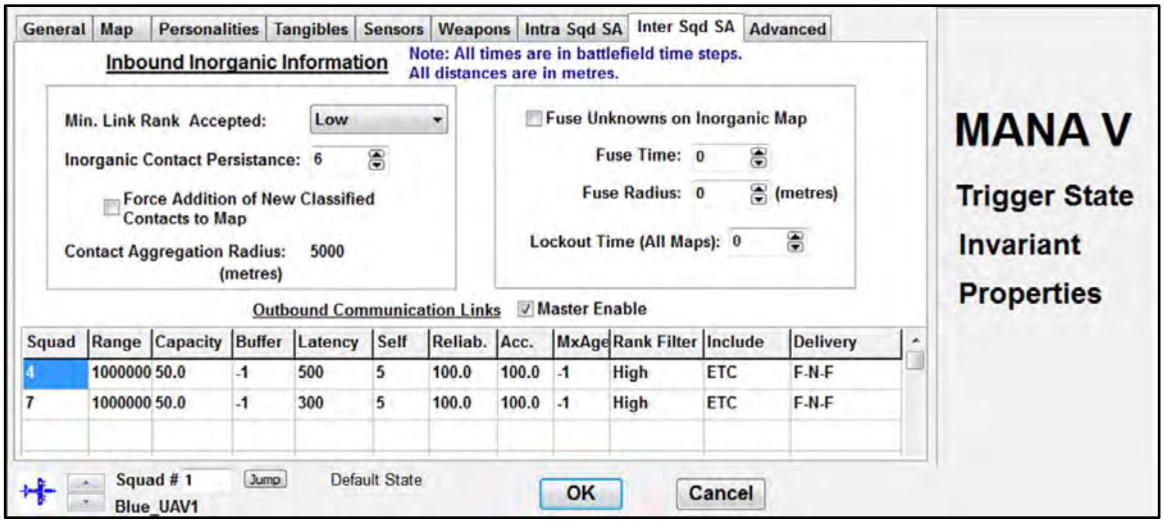


Figure 17. Inter-squad SA panel.

Finally, the “advanced” tab provides the user more sophisticated information such as the random patrol tendency of an agent, formation type of a squad, and the search algorithm type of an agent.

D. AGENT DESCRIPTIONS

The primary element of the MANA model is the squad. A squad can be either a single agent or a group of agents. When we define each squad’s allegiance in MANA, it affects a squad’s behavior when it interacts with other squads. Table 1 displays the 17 squads used in this model.

Allegiance determines which side of the battle an agent will fight on. There are three options for an agent’s allegiance: enemy, friend, or neutral. Neutral can be used to represent civilians or noncombatants in a scenario. Agent threat levels and agent class are used to delineate between enemy types in a scenario. For example, the user can differentiate between heavy-armored vehicles or light infantry by defining heavy-armored vehicles as threat-level three and light infantry as threat-level two.

Table 1. Allegiance, threat level, and class of squads.

Squad No	Squad Name	Allegiance	Threat Level	Class
1	Blue_UAV1	1	3	1
2	Blue_UAV2	1	3	1
3	Blue_UAV3	1	3	1
4	F-16_1	1	3	1
5	F-16_2	1	3	1
6	F-16_3	1	3	1
7	UCAV1	1	3	1
8	UCAV2	1	3	1
9	UCAV3	1	3	1
10	Blue_Bat_1	1	3	1
11	Blue_Bat_2	1	3	1
12	Blue_Bat_3	1	3	1
13	Red_Team1	2	3	2
14	Red_Team2	2	3	2
15	Red_Team3	2	3	2
16	Partisan	2	0	0
17	Dummy Agent	2	3	99

Figure 18 depicts the starting positions of the agents on the battlefield. The yellow line represents the Turkish-Iraqi border. Three terrorist groups are located south of the border while UAVs and UCAVs are located to the north. F-16s are waiting to be called at the top left corner, where the symbolic air force base is located. Terrorist partisans are located around the air force base, so they can provide the terrorists with information on aircraft activity.

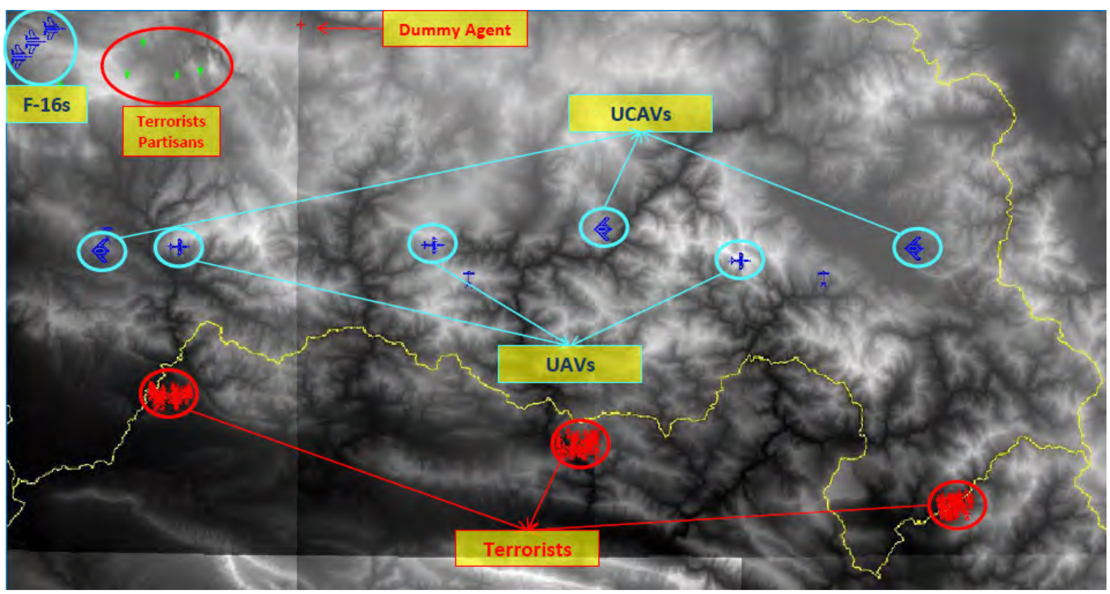


Figure 18. Overview of the battlefield with all agents included.

1. Blue UAVs

Blue UAVs are assigned to intelligence surveillance and reconnaissance missions in a designated region along the Turkish-Iraqi border. Simulated UAVs in this thesis are medium-altitude, long-endurance UAVs capable of flying over 24 hours. Blue UAVs follow predetermined waypoints after the simulation starts. They are basically programmed to fly back and forth along the border section to which they are assigned in a "default" state. Using their onboard sensors, the UAVs try to detect and classify terrorists if they exist. Once they detect any activity along the border, they focus on this location and try to classify the detected activity. If the UAVs confirm a terrorist presence, they go into an "enemy contact" state and report it to the weaponized units through communication links after a user input delay. This time-delay accounts for the time spent during conversation and the reaction time. This process is summarized in Table 2.

Table 2. State process of blue UAV squads in MANA.

State	Positive propensity	Negative propensity	Speed	Duration (sec)	Fallback state	Communication link
Run start	Next waypoint Unknowns	-	0	1	Default	F-16 squads UCAV squads
Default	Next waypoint Unknowns	-	90 knots	-	-	
Enemy contact 3	Enemy threat 3 Unknowns	-	90 knots	5000	Default	

2. F-16s

There are three F-16s located at the Air Force base. They are configured with air-to-ground weapons as well as with sensors. F-16s do not act until they receive a scramble order as a result of a terrorist detection by a UAV. A scramble response time of 5 to 15 minutes for F-16 squads accounts for the communication latency between them and the UAVs. After UAVs detect terrorist activity, F-16s go into an "inorganic SA enemy contact" state and fly directly to the region. Afterward, using their onboard sensors, they detect and classify the terrorist group, based on the UAV report, which means they are in an "enemy contact" state and conduct an air-to-ground attacks.

Each F-16 can carry two weapons. After launching the first bomb, they go into an "ammo out weapon 1" state in which a five-minute delay accounts for a repositioning time for the F-16s. F-16s have two sensors, one for terrorists and the other for dummy agents. They also have three weapons, two of which will be used against terrorists and one against dummy agents.

Effective ranges of F-16 sensors and weapons in the simulation are greater than their real-world values. The reason for this is the following. Real-world terrorist formations are normally very small compared to the battlefield, and during an attack, they typically scatter in a 2 to 3 km area. But if we modeled our scenario this way, we would see an entire terrorist group as a dot on the battlefield. Therefore, we dispersed them 10 to 15 km to see actions and make modifications to the model more easily. Finally, we increased detection, classification, and weapon ranges proportionally as well in order to get a realistic result.

After dropping two bombs, F-16s go into the "ammo out weapon 2" state, return to a designated area where a dummy agent is located, and kill the dummy agent to halt the scenario run. The scenario terminates when the dummy agent takes three hits. If F-16s run out of fuel before they drop their second weapon, they suspend their missions for 25 minutes, which corresponds with the time spent during air-to-air refueling. This process is summarized in Table 3.

Table 3. State process of F-16 squads in MANA.

State	Positive propensity	Negative propensity	Speed	Duration (sec)	Fallback state	Communication link
Run start	Next waypoint	-	0 knots	99999	Default	UAV squads
Default	Enemy threat 3	-	300 knots	-	-	
Enemy contact 3	Enemy threat 3	-	300 knots	10000	Default	
Inorganic SA Enemy contact 3	Enemy threat 3	-	150 knots	99999	Spare 1	
Spare 1	Enemy threat 3	-	300 knots	99999	Default	
Ammo out weapon 1	Enemy threat 3	-	300 knots	300	Spare 1	
Fuel out	Enemy threat 3	-	0 knots	1500	Spare 2	
Spare 2	Enemy threat 3	-	0 knots	1	Default	
Ammo out weapon 2	Next waypoint	-	2000 knots	99999	Default	

3. UCAVs

There are three UCAVs assigned to a specific portion of the border. Similar to UAVs, UCAVs start searching for terrorists along the border in their "default" state. However, different than the UAVs, they can carry two air-to-ground weapons, like the F-16s. When they detect and classify terrorists, they go into an "enemy contact" state. Thereafter, they drop their first weapons and go into the "ammo out weapon 1" state in which a five-minute delay accounts for a repositioning time for the UCAVs. After dropping their second bombs, they go into the "ammo out weapon 2" state and fly to a designated area where a dummy agent is located. UCAVs can also communicate with UAVs. If UAVs detect terrorist activity first, they report it to the UCAVs who then come and launch their air-to-ground weapons.

Sensor and weapon settings of UCAV squads are similar to those of F-16s, but the ranges are shorter. UCAVs have two sensors, one for terrorists and the other for dummy agents. They also have three weapons, two of which are used against terrorists and one against dummy agents. Similar to F-16 squads, we re-scaled the sensor and weapon ranges of UCAV squads in order to get a realistic result. This process is summarized in Table 4.

Table 4. State process of UCAV squads in MANA.

State	Positive propensity	Negative propensity	Speed	Duration (sec)	Fallback state	Communication link
Run start	Next waypoint Unknowns	-	100 knots	1	Default	UAV squads
Default	Next waypoint Unknowns	-	100 knots	-	-	
Enemy contact 3	Enemy threat 3 Unknowns	-	90 knots	5000	Default	
Inorganic SA Enemy contact 3	Enemy threat 3	-	100 knots	99999	Spare 1	
Spare 1	Enemy threat 3	-	90 knots	99999	Default	
Ammo out weapon 1	Enemy threat 3	-	90 knots	300	Spare 1	
Fuel out	Enemy threat 3	-	0 knots	1500	Spare 2	
Ammo out weapon 2	Alt waypoint	-	2000 knots	99999	Default	

4. Blue Battalions

Blue battalions in this model are symbolic agents, so they do not have any active mission. There are three blue battalion agents that provide visual information about the final waypoints of terrorists. Terrorists try to reach blue battalions and attack simulated military facilities.

5. Red Teams

There are three terrorist groups in the model. Each terrorist group consists of 40 terrorists whose main objective is to cross the border, reach military facilities, and attack them. These groups are initially located south of the Turkish-Iraqi border and start to proceed to the north when the runs begin. We adjust personality settings of terrorist groups so that they stick together while they are proceeding. As we mentioned before, each trigger state can have different settings. In the "default" state, terrorists move towards their next waypoint with a 70% propensity while they conceal at a value of 40%. When any of the terrorists inside the group detects a blue agent, it goes into an "enemy contact" state and informs other agents in the group. As a result, all agents in this specific group go into a "squad enemy contact" state and implement this state's personality settings. In an "enemy contact" or "squad enemy contact" state, terrorists increase their concealments to prevent blue agents from detecting them. In order to increase their concealment, terrorists tend to use the terrain types that provide more concealment, such as moving toward "green" regions on the terrain map, which represents deep valleys. Therefore, they start to separate from each other a little bit.

Another trigger state that terrorists can get into is an "inorganic SA enemy contact" state. Terrorists go into this state after partisan agents detect aircraft activity and deliver this information to terrorists with some delay. Terrorists increase their concealment in an "inorganic SA enemy contact" state as well. A "squad shot at (sec)" state means that F-16s or UCAVs have dropped their second weapons on the terrorists. In this state terrorists turn back, and run away toward the mountains and hide inside the caves.

Terrorists can detect and classify enemy agents within a defined range. The elevation map affects detection and classification capabilities of terrorists. Terrorists have weapons that can fire within a certain range. They will use this weapon against imaginary blue soldiers inside the blue battalions. Because there are no blue soldiers in the model, the number of terrorists who have reached the blue battalions before the simulation ends is determined by the number of blue soldiers killed. This process is summarized in Table 5.

Table 5. State process of red team squads in MANA.

State	Positive propensity	Negative propensity	Speed	Duration (sec)	Fallback state	Communication link
Run start	Next waypoint	-	50 km/h	100	Default	Partisan squad
Default	Next waypoint Concealment	Uninjured Friends Injured Friends	3 km/h	-	-	
Enemy contact 3	Next waypoint Concealment Cover	-	2 km/h	1500	Default	
Inorganic SA Enemy contact 3	Next waypoint Concealment Cover	-	2 km/h	3000	Default	
Squad Enemy contact 3	Next waypoint Concealment Cover	-	2 km/h	1500	Default	
Squad shot at (sec)	Alt waypoint Concealment	-	5 km/h	99999	Default	

6. Partisans

Partisans are the civil supporters of terrorist groups who live in the cities where the AFB is located. When they see aircraft activity inside the AFB, they inform terrorists about this, so terrorists can hide or take some precautions. Partisans communicate with terrorist groups through communication links which are set using the "inter-squad SA" tab in MANA.

7. Dummy Agent

Dummy agents are only used to terminate each run. Each strike asset, either an F-16 or a UCAV depending on the scenario, carries a weapon that can be employed against dummy agents. After finishing their missions, F-16s and UCAVs fly to the dummy agent's coordinate and drop their special weapons. A dummy agent is killed after it takes three shots, thereby terminating the scenario (i.e., all three terrorist groups have been attacked and stopped).

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IV. EXPERIMENTAL DESIGN

Design-of-experiment (DOE) techniques allow the user to vary the input parameters in an efficient manner and to generate multiple variations of a model [49]. The user can explore the effects of the factors used in the model as well as the interactions between the factors by using DOE techniques. DOE is a critical part of the modeling and simulation analysis process. In this chapter, we explain the factors used to construct the experimental design of our study. Next, we explain the nearly orthogonal Latin hypercube (NOLH) design that is used in this thesis. Last, we mention the model running process.

A. FACTORS OF INTEREST

There are numerous factors that affect the outcome of a military operation in the real world. We can divide these factors into two groups: controllable and uncontrollable. Controllable factors, also known as decision variables, are those that the user can manipulate in the real world during the system development or the employment phase. For instance, aircraft speed, sensor detection range, or aircraft altitude are controllable factors. Uncontrollable factors are those that the user cannot manipulate in the real world. Enemy characteristics, such as number of terrorists and enemy weapon capabilities, or environmental characteristics, such as wind speed, can be considered uncontrollable factors. It is impossible to take into account every factor in a simulation environment. Therefore, we varied the 28 factors that we believe will influence the outcome the most. Among these 28 factors, 20 are controllable factors and eight are uncontrollable factors.

1. Controllable Factors

In this thesis, controllable factors include the parameters of F-16s, UCAVs, and UAVs. We varied the sensor, weapon, and time-related parameters of F-16s, UCAVs, and UAVs within some ranges to explore the effects on the outcome. The factor names are the same as those produced in the MANA output. Table 6 provides a general explanation of controllable factors and their ranges. The following sections explain the factors and the reasons of selecting minimum and maximum values associated to those factors in detail. Because we use the same factors for F-16s, UCAVs, and UAVs, we explain the factor and the differences among the platforms for that factor in the same section.

Table 6. Controllable factors, brief explanations, minimum and maximum ranges, and units of the factors used in the model.

Agents	Factors	Explanation	Min	Max	Unit
F-16	F16SnrClsRng	Sensor classification range in the default state	4000	8000	meter
	F16SnrDetToClassRatio	Sensor detection to classification range ratio in the default state	1	2	
	F16ClsProb	Classification probability in the default state	0.6	0.9	
	F16TimeBetwDet	Average time between detections in the default state	100	800	second
	F16WpnRng	Maximum effective weapon range	4000	8000	meter
	F16HitProb	Weapon hit probability at maximum weapon range	0.4	0.8	
	F16ScrTime	Scramble response time	420	900	second
UCAV	UCAVSnrClsRng	Sensor classification range in the default state	6000	8000	meter
	UCAVSnrDetToClassRatio	Sensor detection to classification range ratio in the default state	1	2	
	UCAVClsProb	Classification probability in the default state	0.1	0.7	
	UCAVTimeBetwDet	Average time between detections in the default state	400	1000	second
	UCAVWpnRng	Maximum effective weapon range	3000	5000	meter
	UCAVHitProb	Weapon hit rate at maximum weapon range	0.5	0.8	
	UCAVScrTime	Communication delay with UAV	100	600	second
	UCAVSpd	Velocity in the default state	90	200	kts
UAV	UAVSnrClsRng	Sensor classification range in the default state	4000	8000	meter
	UAVSnrDetToClassRatio	Sensor detection to classification range ratio in the default state	1	2	
	UAVClsProb	Classification probability in the default state	0.07	0.5	
	UAVTimeBetwDet	Average time between detections in the default state	700	1300	second
	UAVSpd	Velocity in the default state	80	110	kts

a. Sensor Classification Range

The sensor classification range (SnrClsRng) applies for F-16, UCAV, and UAV squads. Sensor classification range is the distance at which an F-16, UCAV, and UAV can classify other squads.

For F-16s, this value varies from 4000 to 8000 meters. Classification range of an F-16 is greater than its real-world value because, in the real world, terrorists are normally very small compared to the battlefield. During an attack, they normally scatter in a 2 to 3 km area, but if we modeled our scenario this way, we would see one terrorist group as a dot on the battlefield. Therefore, we dispersed them 10 to 15 km to see actions and make modifications on the model. Finally, we increased the classification range proportionally in order to get a realistic result. The same rule applies for UCAV and UAV squads as well.

For UCAVs, this value varies from 6000 to 8000 meters, which is greater than those for F-16s. This difference is because of two reasons. First, the UCAV that we use in our model will have more sophisticated sensors. Second, based on our experience and previous operations, it is more difficult for a pilot to classify terrorists while flying the jet than for a remote operator of a UCAV. Therefore, we give the advantage to the UCAV for classifying the terrorists.

For UAVs, this value varies from 4000 to 8000 meters, which is the same of those for F-16s. This is because UAVs that we simulate in this thesis are old compared to the UCAVs.

b. Sensor Detection to Classification Range Ratio

The sensor detection to classification range ratio (SnrDetToClassRatio) applies for F-16, UCAV, and UAV squads. This ratio is the value obtained by dividing the sensor detection range by a factor to get the sensor classification range.

The sensor detection range must be less than or equal to the sensor classification range because a sensor cannot classify a threat without first detecting it. Therefore, we vary the sensor detection to classification ratio from 1 to 2 for F-16s, UCAVs, and UAVs. We multiply this number with the classification range to determine the detection range that MANA will use for calculations. By utilizing this feature, we prevent MANA from producing a detection range that is smaller than a classification range.

c. Classification Probability

The sensor classification probability (ClsProb) applies for F-16, UCAV, and UAV squads. The sensor classification probability refers to how likely is it for an F-16, UCAV, and UAV to classify a terrorist. For this research, we ignored false-positive classification probabilities, which is when an agent wrongly classifies another agent as a terrorist. The classification probability depends on several factors in the real world, such as sensor capabilities, pilot capabilities, weather, and terrain.

Based on personal experiences and previous operations, we vary the classification probability of an F-16 from 0.6 to 0.9. This range seems higher than the real world values. The reason for that is the following. F-16 squads first interact with terrorist groups after UAVs detect and classify them. Therefore, F-16s deploy to the area with the location information of the terrorist groups and start searching for terrorists based on this information. As a result, it is more likely for an F-16 to classify a terrorist group than other units in the model.

We vary the classification probability from 0.1 to 0.7 and from 0.07 to 0.5 for UCAVs and UAVs, respectively. The difference between the UCAV and the UAV classification probability is because UCAVs have more sophisticated sensors than UAVs in our model.

d. Average Time Between Detection

The average time between detection (TimeBetwDet) applies for F-16, UCAV, and UAV squads. The average time between detections factor corresponds to the detection capability of an F-16, UCAV, and UAV. Different than the classification probability, MANA does not provide an option to explicitly define detection probability to the user. In MANA, the per time-step detection probability is set given the average time between detection—as one gets with a geometric random variable.

For F-16s, we vary the average time between detections from 100 to 800 seconds, whereas we use 400 to 1000 and 700 to 1300 seconds for UCAVs and UAVs, respectively. The average time between detections is smaller for F-16s than those for UCAVs and UAVs because F-16s start to search for the terrorists with a location knowledge provided by UAVs. However, UCAVs and UAVs do not have any preliminary knowledge about the location of the terrorists. The reason that a UACV's average time between detections is smaller than those of a UAV is UCAVs have more advanced onboard sensors in the model.

e. Maximum Effective Weapon Range

The maximum effective weapon range (WpnRng) applies for F-16 and UCAV squads. The weapon range is the maximum effective range at which an air-to-ground weapon of an F-16 and UCAV can kill a terrorist. MANA has two modes for weapon settings, simple and advanced. We used the advanced mode in which weapon effectiveness is determined by a probability-range table. We defined two ranges and probabilities corresponding to these ranges in a table, one for minimum and the other for maximum range. In our model, we only vary the maximum weapon range for the weapons that an F-16 and a UCAV can carry. MANA interpolates the ranges and the probabilities between the minimum and maximum values.

Similar to the sensor ranges, weapon range is also greater than real world values because we increased it proportionally to the terrorist dispersion on the battlefield. We vary maximum effective weapon range of an F-16 from 4000 to 8000 meters. We reduce this range to 3000 to 5000 meters for UCAVs because the UCAVs that we simulate in the model carry smaller weapons than those of the F-16s. Based on personal experience and previous operations, we decided that these ranges are appropriate for our model’s scale.

f. Weapon Hit Probability

The weapon hit probability (HitProb) applies for F-16 and UCAV squads. The weapon hit probability is the probability that an air-to-ground weapon of an F-16 and UCAV hits the target. Similar to the weapon range factor, we only vary the weapon hit probability at the maximum weapon range and MANA interpolates the values between minimum and maximum. This probability depends on several factors, such as sensor capabilities, weather, target mobility, pilot capability, and terrain.

We vary this value from 0.4 to 0.8 and from 0.5 to 0.8 for F-16s and UCAVs, respectively. We give UCAVs a small advantage because they have more advanced onboard sensors and more precise weapons than F-16s in the model.

g. Scramble Response Time

The scramble response time (ScrTime) applies for F-16 and UCAV squads. The scramble response has different meanings in the model. For an F-16, it is the time in which an F-16 takes off after receiving a scramble order. In our model, we utilize this time by defining communication latency between the F-16 and the UAV. After a UAV classifies a terrorist group, it reports this group to the F-16 with some delay, which corresponds to the scramble response time of F-16. We vary this value from 420 to 900 seconds for an F-16.

For a UCAV, the scramble response time is the time in which a UAV can pass the information of terrorist locations to a UCAV. Different than the F-16s, UCAVs start searching for terrorists along the border like UAVs. If a UAV detects a terrorist activity first, it reports it to the UCAV. For this case, we use the scramble response time factor to represent a communication delay between the UAV and the UCAV through the communication latency in MANA. We vary this value from 100 to 600 seconds for a UCAV. It is smaller than those for the F-16 because this factor represents both the communication delay and the reaction time for an F-16 while it refers only to the communication delay for a UCAV.

h. Speed

The speed factor applies for UAV and UCAV squads. The speed is the velocity of a UAV and a UCAV during the search. We vary this value from 90 to 200 knots for a UCAV, while we vary it from 80 to 110 knots for a UAV. Again, the increased speed is because UCAVs are newer systems than UAVs.

2. Uncontrollable Factors

Uncontrollable factors include the parameters of terrorists and partisans. We varied sensor and time-related parameters of terrorists and partisans within some ranges to explore the effects on the outcome. The factor names are the same as those produced in MANA output. Table 7 provides a general explanation of the uncontrollable factors and their ranges. The following sections explain the factors and the reasons of selecting the minimum and maximum values associated to those factors in detail. Similar to previous section, we explain the factor and the differences among the platforms for that factor in the same section.

Table 7. Uncontrollable factors, brief explanations, minimum and maximum ranges, and units of the factors used in the model.

Agents	Factors	Explanation	Min	Max	Unit
Terrorist	TerroristClsRng	Sensor classification range in the default state	700	1300	meter
	TerroristDetToClassRatio	Sensor detection to classification range ratio in the default state	1	2	
	TerroristClsProb	Classification probability in the default state	0.3	0.7	
	TerroristTimeBetwDet	Average time between detections in the default state	300	700	second
Partisan	PartClsRng	Sensor classification range	1500	2500	meter
	PartDetToClassRatio	Sensor detection to classification range ratio in the default state	1	2	
	PartNumber	Number of agents	5	10	
	PartComDelay	Communication delay with terrorists	500	900	second

a. Sensor Classification Range

The sensor classification range (SnrClsRng) applies for terrorist and partisan squads. Sensor classification range is the distance at which a terrorist and a partisan can classify other squads.

This value varies from 700 to 1300 meters for a terrorist while it varies from 1500 to 2500 meters for a partisan. We define this value larger for partisans because partisans live in the cities and terrorists are traveling on a rough terrain, which decreases the line-of-sight of a terrorist.

b. Sensor Detection to Classification Range Ratio

The sensor detection to classification range ratio (SnrDetToClassRatio) applies for terrorist and partisan squads. This ratio is the value obtained by dividing the sensor detection range by a factor to get the sensor classification range.

The sensor detection range must be less than or equal to the sensor classification range because a sensor cannot classify a threat without detecting it. Therefore, we vary the sensor detection to classification ratio from 1 to 2 for terrorists and partisans. We multiply this number with the classification range to determine the detection range that MANA uses for calculations. By utilizing this feature, we prevent MANA from producing a detection range that is smaller than a classification range.

c. Sensor Classification Probability

The sensor classification probability (TerroristClsProb) applies for terrorist squads. The sensor classification probability refers to how likely it is for a terrorist to classify a blue agent. We ignored false-positive classification probability, which means a terrorist agent classifies a blue agent as terrorist (or neutral) but it is actually not a terrorist. We vary the classification probability of a terrorist from 0.3 to 0.7.

d. Average Time Between Detection

The average time between detection (TerroristTimeBetwDet) applies for terrorist squads. The average time between detections factor corresponds to the detection capability of a terrorist. As we explained under the average time between detection section of controllable factors, we use this factor to obtain more realistic results in terms of detection time. We vary this value from 300 to 700 seconds for a terrorist.

e. Number of Partisan Agents

The number of partisan agents (PartNumber) is the count of partisans living in the cities. We vary this value from 5 to 10.

f. Partisan Communication Delay

The partisan communication delay (PartComDelay) is the time in which a partisan can pass information on aircraft activity to a terrorist squad. We use the partisan communication delay factor to represent the communication delay between the partisans and the terrorists through the communication latency capability in MANA. We vary this value from 500 to 900 seconds.

B. NEARLY ORTHOGONAL LATIN HYPERCUBE DESIGNS

We explore the effects of 28 different factors in this thesis. These are sensor, weapon, and time-related factors of the agents. Some of these factors have a wide range between their maximum and minimum levels. It is impossible to run our model for each possible combination of the factor levels because we would have to run many billions of combinations, depending on the number of decimals of each factor. It would take too long to complete our simulation, even using a supercomputer. As a result, we need to use an advanced design of experiment technique to reduce the computation time, but at the same time cover a broad section of the input space. For this purpose, we used a nearly orthogonal Latin hypercube (NOLH) design. The NOLH design was developed by Lieutenant Colonel Thomas M. Cioppa during his doctoral studies at the Naval Postgraduate School (NPS), Monterey, CA [50]. The NOLH design "combines orthogonal Latin hypercube and uniform designs to create designs having near orthogonality and excellent space-filling properties." [50]

We used an Excel spreadsheet developed by Professor Susan Sanchez at the NPS Simulation Experiments and Efficient Designs (SEED) Center [51] to generate a NOLH design for this thesis. The user specifies factor names, and maximum and minimum values of factor levels as inputs. The spreadsheet provides a NOLH design in the units of the problem. This worksheet allows the user to select between different designs depending on the number of factors, with a minimum of seven and maximum of 29 factors. For other numbers of factors, NOLHs can be generated using the mixed-integer programming algorithm of Hernandez [52]. We used the spreadsheet for up to 29 factors in this thesis. Figure 19 illustrates a partial screenshot of the NOLH design for the 28 factors varied in this thesis.

factor name	F16SnrDetToClassRatio	F16SnrClsRng	F16TimeBetwDet	F16ClsProb	F16HitProb	F16WpnRng	F16ScrTime	UCAVSnrDetToClassRatio	UCAVSnrClsRng	UCAVTimeBetwDet	UCAVClsProb	UCAVHitProb	UCAVWpnRng	UCAVSpd	UCAVScrTime	UAVSnrDetToClassRatio	UAVSnrClsRng	UAVTimeBetwDet	UAVClsProb	UAVSpd	TerroristDetToClassRatio
low level	1	4000	100	0.6	0.4	4000	420	1	6000	400	0.1	0.5	3000	90	100	1	4000	700	0.07	80	1
high level	2	8000	800	0.9	0.8	8000	900	2	8000	1000	0.7	0.8	5000	200	600	2	8000	1300	0.5	110	2
decimals	1	0	0	2	2	0	0	1	0	0	2	2	0	0	0	1	0	0	2	0	1
	1.4	7531	516	0.78	0.65	7594	900	1.9	6375	440	0.24	0.62	3125	110	270	1.4	5781	735	0.09	85	1.3
	1.1	5594	688	0.89	0.69	6125	887	1.8	7086	766	0.48	0.72	5000	188	356	1	4250	782	0.07	91	1.6
	1.2	6375	182	0.77	0.78	7250	872	1.9	7289	618	0.22	0.57	3258	106	569	1.8	6266	1258	0.43	87	1.1
	1.4	4641	379	0.79	0.69	6984	842	1.9	6305	728	0.66	0.73	4930	195	422	1.6	7156	1300	0.4	80	1.1
	1.4	6234	529	0.72	0.77	7172	782	1.7	6133	890	0.15	0.52	3641	99	352	1.2	4594	768	0.19	108	1.7
	1.4	5469	770	0.65	0.75	7625	773	2	7445	674	0.6	0.73	4680	168	557	1.4	5531	965	0.23	107	1.9
	1	6453	409	0.64	0.61	6078	788	1.6	7344	752	0.1	0.58	3617	125	172	1.9	7656	1096	0.49	104	1.5
	1.4	4172	357	0.72	0.77	6969	756	1.7	6969	442	0.38	0.66	4617	162	313	1.9	6922	1199	0.33	100	1.8
	1.1	6063	751	0.79	0.55	7141	774	2	6352	630	0.67	0.57	3914	137	192	1.7	5625	878	0.22	99	1.2
	1.5	4297	704	0.82	0.42	6438	692	1.6	7914	850	0.34	0.71	4516	194	166	1.6	5766	766	0.18	105	1.5
	1.1	7719	439	0.89	0.58	6016	889	1.6	7805	571	0.49	0.56	3422	134	424	1.1	7078	1012	0.3	106	1.4
	1.1	4547	152	0.82	0.55	6672	789	1.6	6984	993	0.36	0.65	4961	160	459	1.4	6391	1180	0.43	98	1.3
	1.3	7844	540	0.62	0.56	7188	729	1.7	6742	963	0.56	0.56	3086	142	506	1.7	5031	747	0.16	93	1.7
	1	5078	603	0.64	0.46	7203	894	1.5	7430	508	0.31	0.73	4344	163	401	1.9	5688	906	0.2	93	1.5
	1.3	6516	127	0.75	0.45	6109	786	1.6	7477	984	0.44	0.58	3094	106	155	1.3	7359	1274	0.3	84	1.8
	1.4	5125	289	0.62	0.56	6891	870	1.9	6211	702	0.11	0.66	4547	154	188	1.4	6828	1138	0.31	94	1.8

Figure 19. Partial screenshot of NOLH design spreadsheet for 29 factor design, after [51].

Sanchez's spreadsheet provides 257 different combinations of factor values, using the ranges of the factor levels. In other words, it selects 257 different design points (DP) among the entire set of input combinations, which provides an efficient design while covering a broad section of input space. This property of NOLH designs is called the space-filling property. We can visualize the space-filling property of our NOLH designs by using a scatterplot matrix. Figure 20 depicts a partial screenshot of the scatterplot matrix for the factors used in our model. The entire scatterplot matrix for all factors is included in Appendix A. The diagonal of the scatterplot shows the factor names while the ranges are shown on left side. The figure shows that each pair of factors is sampled throughout the possible region.

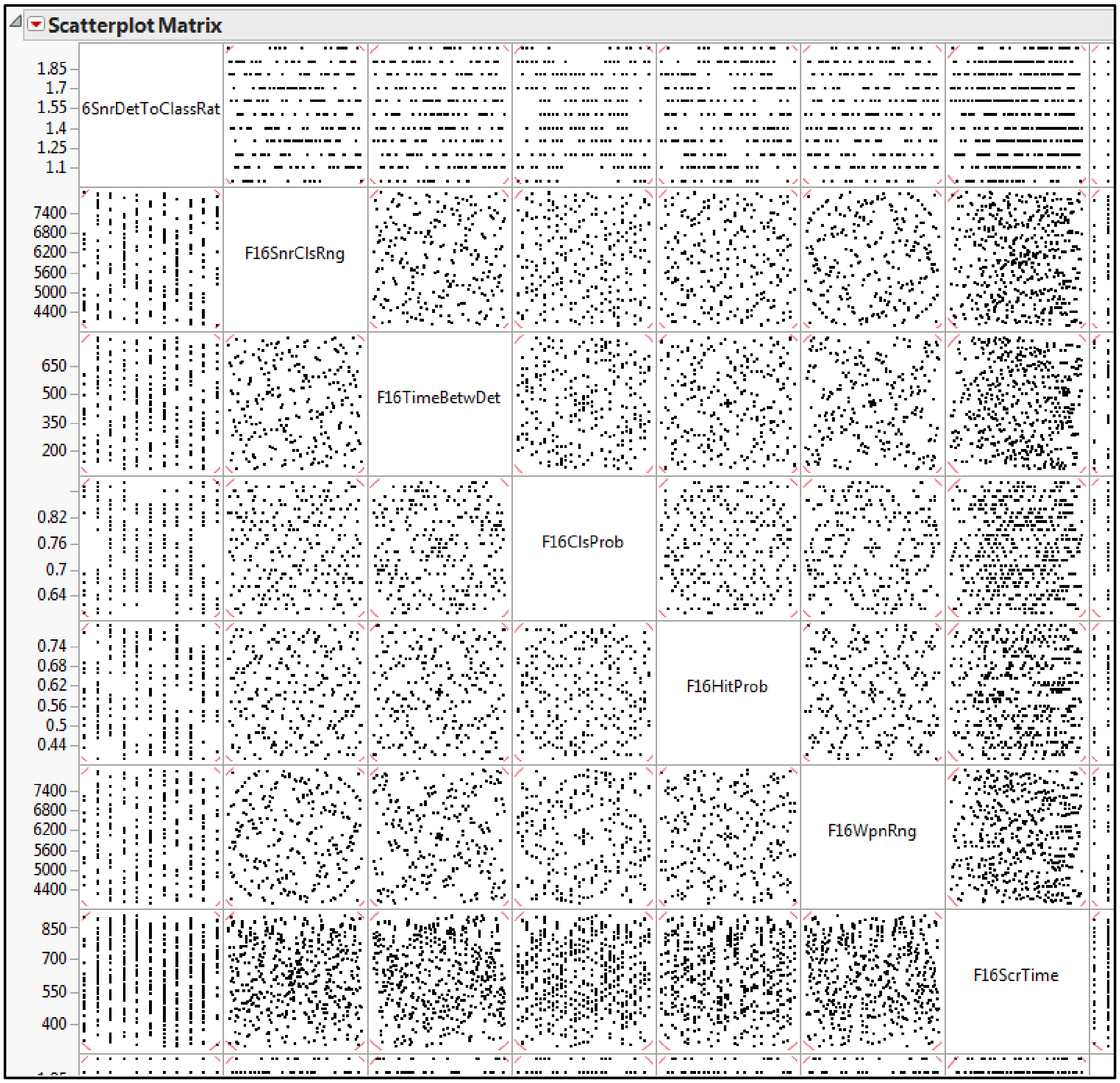


Figure 20. Partial screenshot of the scatterplot matrix for the factors.

Another property of our NOLH designs is near-orthogonality. Near-orthogonality guarantees the factors are not confounded. Orthogonality of a design can be examined through a color map of correlations, as shown in Figure 21. A red color refers to a strong positive correlation, while blue implies a strong negative correlation between the factors. The grayer the diagram is, the nearer to orthogonality. The diagonal line in the diagram shows the correlation of a factor by itself. The correlations between all $\binom{28}{2} = 378$ pairs of factors are close to zero.

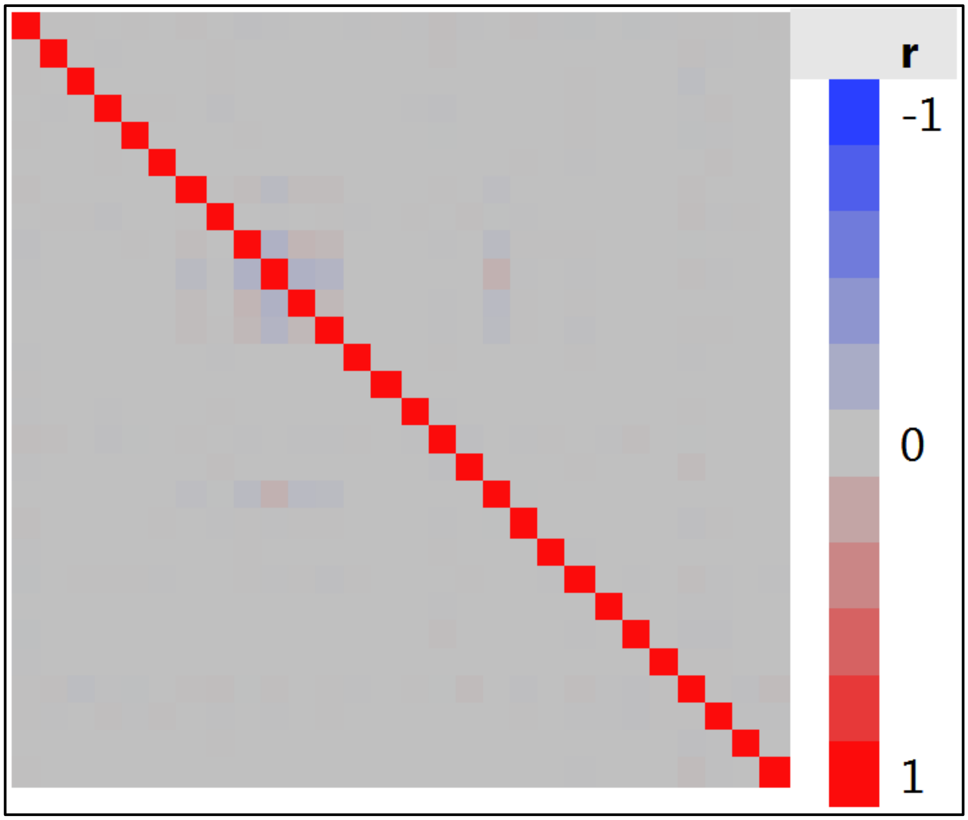


Figure 21. Color map on correlations for the factors used in design.

C. MODEL RUNNING PROCESS

Sanchez’s spreadsheet provides 257 different combinations of factor values, in other words design points (DPs), using the ranges of factor levels. As a result, we obtained a DOE file. We entered the base case MANA scenario, in eXtensible Markup Language (XML) format, and the DOE file, in comma-separated value (CSV) format into a software program called XStudy, written by SEED Center research associate Steve Upton [51]. XStudy enables the user to map each column in the design file to a specific parameter element in MANA, using XPaths. An XPath is a reference to a specific location in an xml file. We also entered other details about the study design, such as the version of MANA and the number of replications per design point, into this tool, yielding a single “study.xml” file.

This study file is used by another program called oldmcdata, also written by Steve Upton, which programmatically modifies the MANA XML file, producing a separate

XML scenario file for each design point [51]. We used an open source software package called Condor, available from the University of Wisconsin (http://www.cs.wisc.edu/condor), to distribute and manage the MANA jobs in parallel across a set of available processors. The oldmcdata software creates the set of submit.dat files needed by condor, one for each design point job. A job consists of a set of replications for one design point excursion.

Upon completion of the runs, oldmcdata includes a data post-processor that combines the MANA summary file output from the individual design point excursions into one CSV file, ready for use with any data analysis software package. This output file contains input factor settings from the DOE, the random number seed, and outputs for each replication. The SEED Center high performance computing cluster configuration used for these runs was composed of 128 Windows processors, with 2 to 4 GB RAM per processor.

Our model is a time-stepped, agent-based, stochastic model. Because it is a stochastic process, we need to make a number of replications for each design point to capture the desired precision of the results and see a range of outcomes. We determined the desired number of replications per DP by using equation (1).

$$n = \left(\frac{\sigma(Z_\alpha + Z_\beta)}{(\mu_0 - \mu')} \right)^2 \tag{1}$$

In our calculations, we use a α value of 0.05 and a β value 0.10. α and β are also called the type I and type II error probability, respectively. We also want to capture a practical difference of three terrorists killed. σ is the standard deviation obtained from the initial 100 replications of the baseline scenario. After plugging in all required information, we come out with approximately 50 replications per DP. Figure 22 illustrates the number of replications required as a function of the desired practical difference.

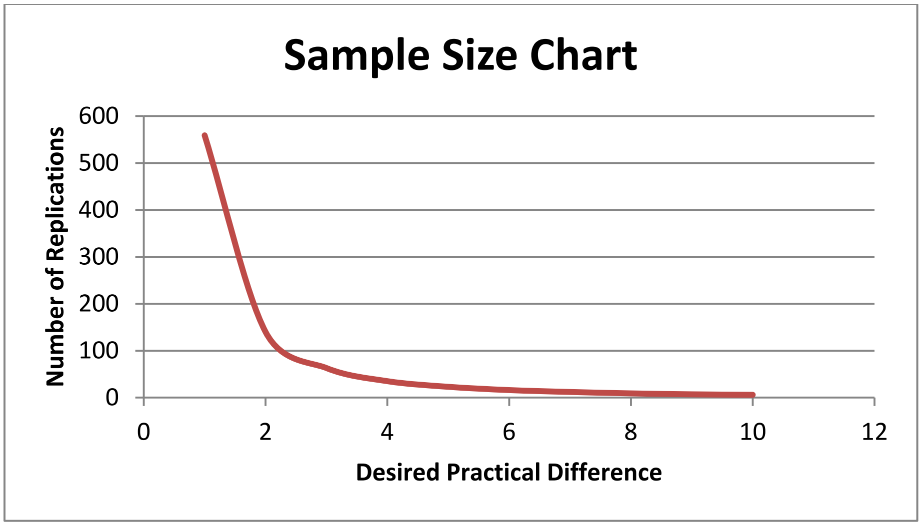


Figure 22. Number of replications required as a function of desired practical difference.

After multiplying the number of replications required per DP (50) by the number of DP (257), we get 12,850 runs per scenario. Finally, we multiplied this number by number of scenarios (8), and we end up with a total of 102,800 simulated engagements. These runs would have taken over 600 days to complete if we used a single processor computer. However, we used a 128-processor cluster, which took approximately 15 days to complete all of the runs. After 15 days, we received the output in a CSV file format, which included a total of 102,800 rows of data to be analyzed.

V. DATA ANALYSIS

In this chapter, we define the measures of effectiveness (MOEs) and the analysis tool that we used in this thesis. After providing general summary statistics for our MOEs, we compare scenarios in detail using different comparison techniques. Afterward, we fit regression models to identify influential factors.

A. MEASURES OF EFFECTIVENESS

The U.S. DOD defines a measure of effectiveness (MOE) as "a criterion used to assess changes in system behavior, capability, or operational environment that is tied to measuring the attainment of an end state, achievement of an objective, or creation of an effect." [22] The purpose of this thesis is to analyze the effectiveness of the use of UCAVs against active terrorists in rough terrain. We also want to explore the effectiveness of using F-16s and UCAVs together. Therefore, we have three different MOEs in this thesis to answer the research questions and gain operational insights.

First, we measure the total number of terrorists killed (MOE 1), in other words, the number of red casualties at the end of each run. As we explained in Chapter III, there are 120 terrorists separated into three groups. Each air-to-ground strike asset engages one of the terrorist groups and kills a portion of this group. MOE 1 is necessary but not sufficient to understand the effectiveness of UCAVs because UCAVs can carry smaller air-to-ground weapons compared to F-16s. We need to define another MOE to better explore the effectiveness of the UCAVs.

Second, we measure the time to complete the mission (MOE 2), i.e., counter the terrorists. The time is a very important MOE because, as we mentioned in early chapters, terrorists are well adapted to rough terrain, so they can travel long distances in relatively short time periods. Even if they cannot reach their final destinations, they can pass through villages or other military facilities where they can conduct attacks and kill many people.

Third, we measure the probability that the terrorists (red) reach their goal (MOE 3). That is, the probability that at least one of the terrorist groups attacks a blue battalion.

In some of the runs, blue forces cannot detect or classify one, two, or all of the terrorist groups, which means that the undetected terrorist groups attack a blue battalion. If any of the blue battalions are attacked, it means a mission failure for blue and a mission success for red. Therefore, we created a column named red reached goal. If any of the terrorist squads remain undetected until the end of a run of a maximum 90,000 time steps, we enter a “1” in the corresponding cell for that column. Otherwise, we give a value of “0.” This column provides an estimated probability for each design point in each scenario when we average the values over the replications.

B. ANALYSIS TOOL

The only analysis tool that we use in this thesis is JMP, which was first launched in 1989 by SAS Company and is available for purchase at http://www.jmp.com [53]. JMP software helps the user interactively visualize and analyze the data. It makes importing and processing the data easy as well as performs the appropriate analysis techniques. JMP also has drag-and-drop interface and dynamically linked graphs, which allows users to discover more from their data.

The user can apply various statistical techniques such as, linear and nonlinear regression, model comparisons, partition trees, Gaussian processing, and time series. In this thesis, we used JMP software 11.2.0 to analyze our simulation output.

C. INITIAL DATA ANALYSIS BY SCENARIOS

In this section, we provide the general results obtained from the histograms, summary statistics, and box plots for the MOEs across our eight scenarios. The detailed figures for the distributions of each MOE, including histograms and summary statistics, are provided in Appendix B. In this section, we provide only a table that summarizes all of the results (see Table 8). The highest and the lowest values for each MOE are highlighted in Table 8.

We also provide box plots for the MOEs categorized by scenarios. Boxplots show the distribution of the data in one dimension and are appropriate tools for comparing the distributions of continuous variables between categorical groups. As we can see from

Figure 23, in a box plot, the median is bounded by the 25% and 75% percentiles. The most outlying observations are defined as outliers or extreme outliers. JMP discriminates between the data and the outliers, but not the extreme outliers.

Table 8. The mean and standard deviation of three MOEs for eight different scenarios.

	MOE1		MOE2		MOE3	
Scenario	**Mean**	**Std.Dev.**	**Mean(sec)**	**Std.Dev.(sec)**	**Mean**	**Std.Dev.**
Baseline	35.61	11.67	58,757	23,937	0.18	0.30
Alt1	30.68	8.00	53,051	23,132	0.09	0.22
Alt2	32.31	8.17	54,580	23,201	0.24	0.24
Alt3	30.95	8.85	58,505	24,032	0.18	0.31
Alt4	31.90	8.26	53,855	22,549	0.09	0.21
Alt5	32.77	8.74	63,290	22,202	0.21	0.31
Alt6	33.84	9.27	56,616	22,141	0.13	0.26
Alt7	32.17	9.64	61,178	24,234	0.22	0.33

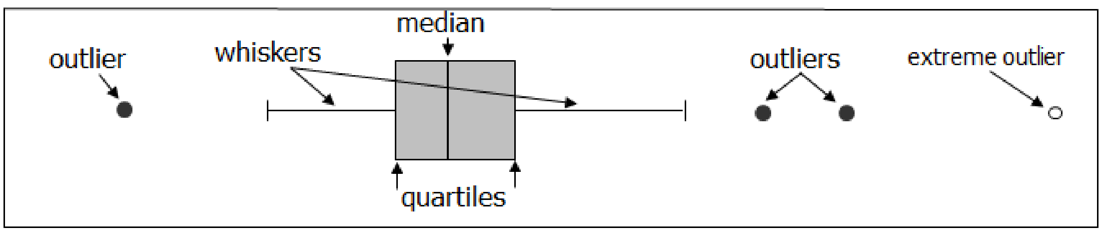


Figure 23. Key for reading the boxplots [54].

We will make general comparisons and provide general insights in this section, but the detailed statistical comparisons are provided in the further sections.

1. MOE (1): The Number of Terrorists Killed

According to the summary statistics in Table 8 and the box plots on the left side of Figure 24, the number of terrorists killed is the highest in the baseline scenario. Recall that in the baseline scenario we allocate three F-16s to the three regions on the Turkish-Iraqi border. The alternative scenarios 5, 6, and 7 have two F-16s, while alternative scenarios 2, 3, and 4 have only one F-16, and alternative scenario 1 does not have any F-16s. The F-16s can carry more effective weapons than the UCAVs in our model. Therefore, the baseline and the alternative scenarios 5, 6, and 7 have a larger mean number of terrorists killed compared to the others. The alternative scenario 1 has the smallest mean number of red casualties. When we look at the box plots for the mean number of red casualties in Figure 24, we see small differences between all of the scenarios, but we cannot discriminate them correctly because the means are very close to each other and the variations are large. In other words, there may be statistical differences between the scenarios but we cannot easily see them by only looking at the box plots. Note: the variation is high because each scenario is examined at 257 different design points.

These results are not surprising because we always use three air-to-ground strike assets in each run. Therefore, we expect more casualties when we use more powerful weapons. However, these results show that using even three UCAVs rather than three F-16s does not yield extremely small red casualties. Moreover, the baseline scenario has only three more red casualties than Alt2, in which one F-16 and two UCAVs are used. Looking at other MOEs provides the decision-maker better insight.

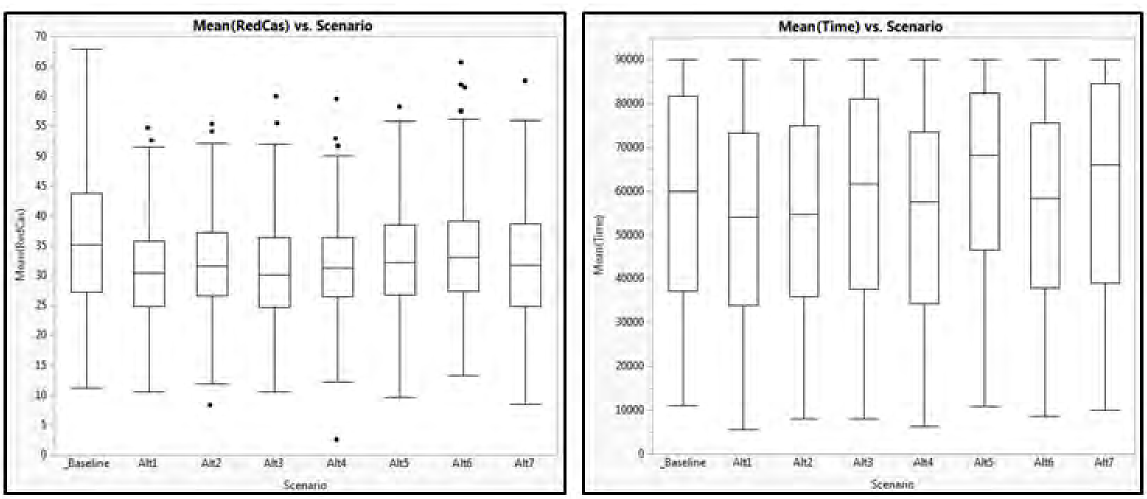


Figure 24. Boxplot for mean number of terrorists killed (left) and mean time spent to complete the mission (right) by scenario.

2. MOE (2): The Time to Complete the Run

According to Table 8, alternative scenario 1, in which three UCAVs are allocated to the three regions, has the lowest mean time to counter all three terrorist groups. In other words, if we use three UCAVs along the Turkish-Iraqi border rather than three F-16s, we prevent the terrorist groups from attacking blue assets in a shorter time. Moreover, the scenarios in which we use two UCAVs, alternative scenarios 2, 3, and 4, have shorter mean times than the ones in which we use one UCAV, alternative scenarios 5, 6, and 7. Alternative scenarios 6 and 3 are exceptions for this generalization. However, similar to MOE 1, as shown in the box plots on the right side of Figure 24, the variations are large also for MOE 2. Therefore, we cannot say that differences between the means are statistically significant by only looking at the summary statistics and the box plots.

3. MOE (3): The Probability that the Red Reaches its Goal

Similar to the time MOE, alternative scenarios that consist of two UCAVs and one F-16 have a smaller probability that the terrorists reach their goal than the ones that have one UCAV and two F-16s. According to the summary statistics in Table 8, alternative scenario 1, which has three UCAVs, has the smallest probability for red reaching the goal. Similar to MOE 2, alternative scenarios 3 and 6 are exceptions for that generalization. The baseline scenario has a higher probability than the two and three UCAV scenarios, with the exception of alternative scenario 3.

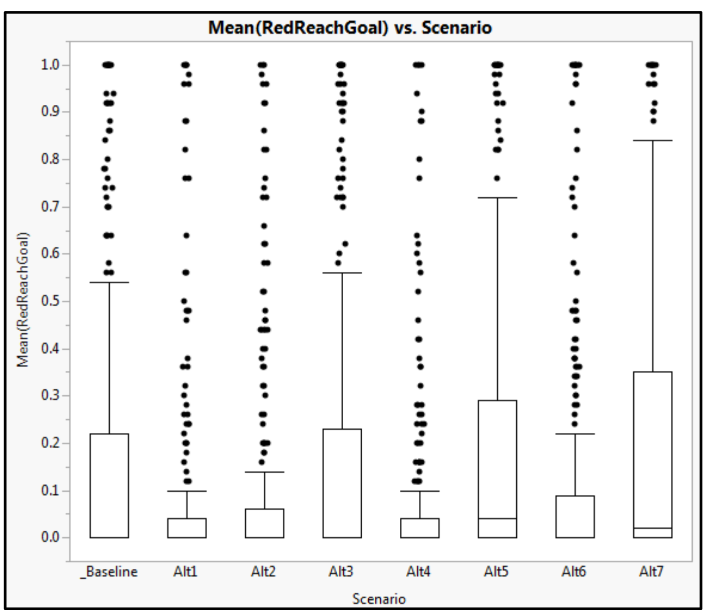


Figure 25. Boxplot for mean probability of red reaching goal, by scenario.

We can see the differences between the means and the variations from the box plots provided in Figure 25. In contrast to MOEs 1 and 2, MOE 3 has larger differences between the variances. Alternative scenarios 1, 2, 4, and 6 (i.e., using more UCAVs) seem more preferable according to the box plots.

The summary statistics and the box plots provide general information about the data. However, we need to apply different comparison techniques in order to figure out statistical differences in detail between the scenarios. Therefore, we perform t-test comparisons of the means for each MOE and scenario in the following section.

D. DETAILED T-TEST COMPARISONS FOR THE MEANS OF THE MOES

A t-test is one of the hypothesis-testing techniques that we can use. The information in this section comes from T. W. Lucas's statistics class notes. A hypothesis is "a statement or claim about a population or populations, often concerning the parameters." [55] In hypothesis-testing, there are two hypotheses of interest: the null hypothesis (H_0) and the alternative hypothesis (H_a). The null hypothesis is "the claim that is initially assumed to be true" [55], and the alternative hypothesis is "an assertion that is contrary to the null hypothesis. Possible conclusions from hypothesis-testing analysis are *reject* H_0 or *fail to reject* H_0." [55]. Equations (2) and (3) illustrate the null and the alternative hypothesis testing, respectively, where μ_1 and μ_2 are the means of two populations.

$$H_0 : \mu_1 - \mu_2 = 0 \tag{2}$$

$$H_a : \mu_1 - \mu_2 \neq 0 \tag{3}$$

First, we calculate a test statistic using a specific significance level (α). If the test statistic falls in the rejection region, we reject the null hypothesis; otherwise, we say that there is not enough evidence to reject, or in other words, we fail to reject the null hypothesis. A test statistic (see Equation [4]) is "a function of the sample data on which the decision is to be based." [55] A rejection region is "the set of all statistics values for which H_0 will be rejected" and a significance level is "the probability that we will wrongly reject H_0." [55]

$$Test\ statistic\ value: t = \frac{\overline{x} - \overline{y}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \qquad \begin{pmatrix} \overline{x}, \overline{y} = sample\ means \\ s_1, s_2 = sample\ std.\ deviations \\ n_1, n_2 = number\ of\ observations \end{pmatrix} \tag{4}$$

Another way to decide whether to reject or fail to reject the null hypothesis is to look at the p-values. A p-value is "the probability, if H_0 were true, of obtaining a test statistics value as extreme or more extreme than what is observed." [55] We reject H_0 if the p-value is less than the significance level (α). Figure 26 depicts the rejection regions and the interpretation of a p-value.

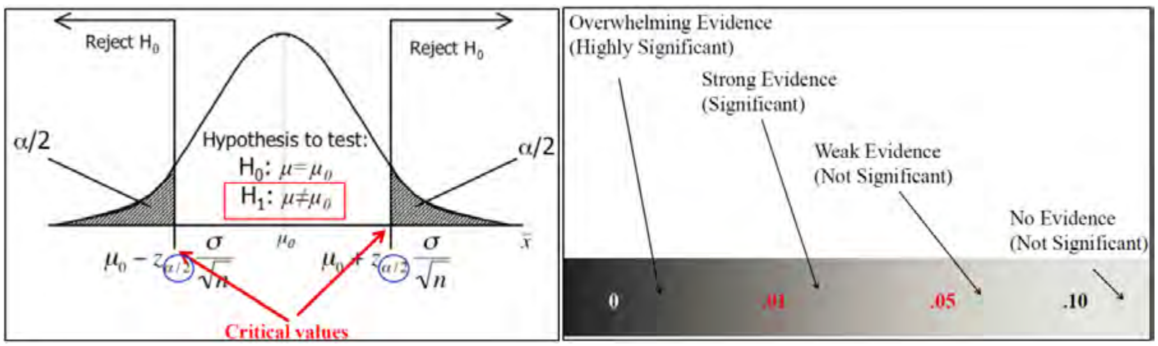
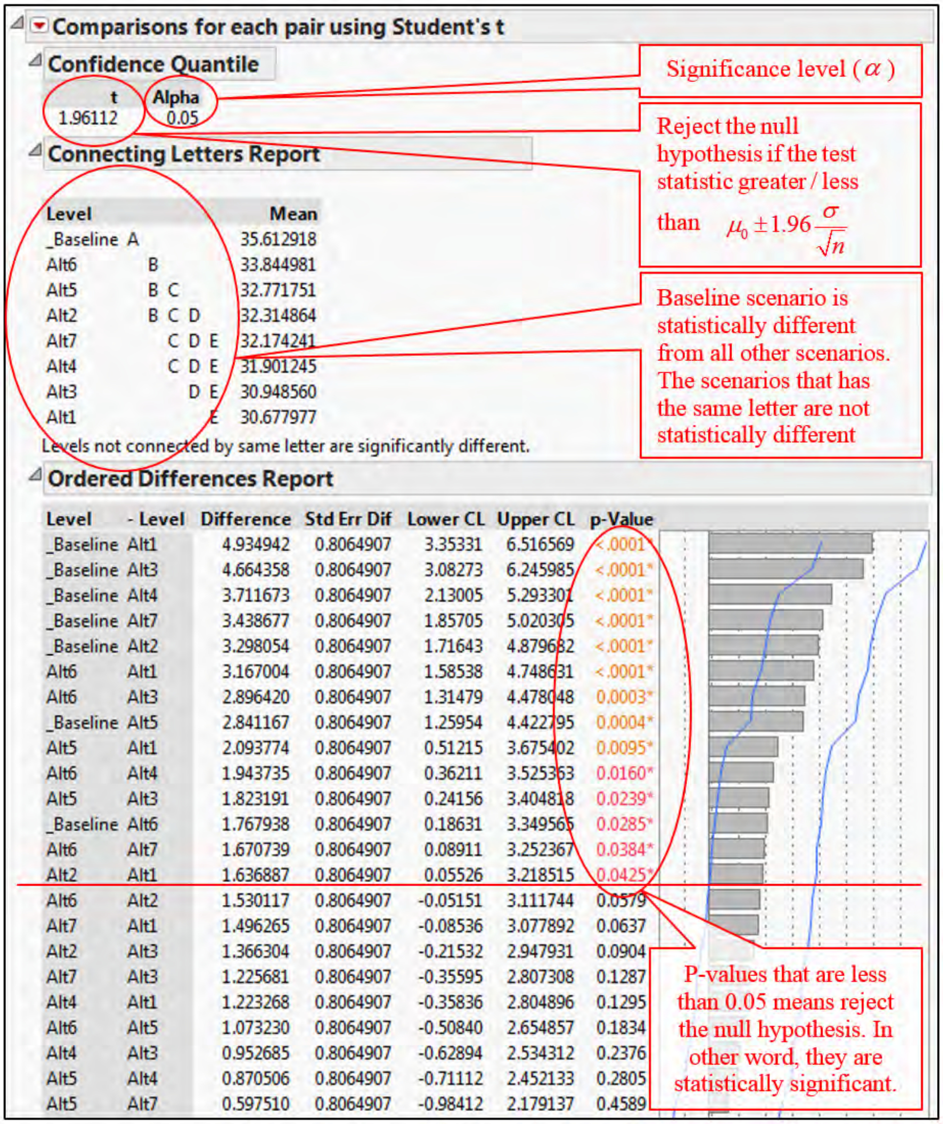


Figure 26. Rejection regions (left) and interpretation of *p-value* (right) [55].

We use JMP to test the hypotheses for the means of the MOEs. Our null hypothesis is that the sample mean of a scenario for our MOEs is equal to the sample mean of the other scenarios. In other words, there is no statistical difference between the scenarios in terms of the means of the MOEs. Our alternative hypothesis is that the scenarios are statistically different. We always use the significance level (α) of 0.05 for all calculations in this thesis, which means if the *p-value* is less than 0.05, we reject the null hypothesis. Thus, the two compared scenarios are statistically different. Otherwise, we fail to reject the null hypothesis, which means that the compared scenarios are not statistically different. The following sections make a t-test comparison of the scenarios in terms of our three MOEs.

1. MOE (1): The Number of Terrorists Killed

The mean number of terrorists killed is very close in all of the scenarios, but there are both practical and statistical differences between some of the scenarios. A ractical significance means that the result is important to the decision-maker. For instance, for an air-to-ground operation like we simulate in this thesis, the decision-maker can say that killing one more terrorist is important, which means the practical difference is one. If killing 10 more terrorists makes a difference for the decision-maker, then the practical difference is 10. However, “no matter how small the effect, if we take a big enough sample, we can make it statistically significantly different.” [55]



Comparisons for each pair using Student's t

Confidence Quantile

t	Alpha
1.96112	0.05

Connecting Letters Report

Level						Mean
_Baseline	A					35.612918
Alt6		B				33.844981
Alt5		B	C			32.771751
Alt2		B	C	D		32.314864
Alt7			C	D	E	32.174241
Alt4			C	D	E	31.901245
Alt3				D	E	30.948560
Alt1					E	30.677977

Levels not connected by same letter are significantly different.

Ordered Differences Report

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
_Baseline	Alt1	4.934942	0.8064907	3.35331	6.516569	<.0001*
_Baseline	Alt3	4.664358	0.8064907	3.08273	6.245985	<.0001*
_Baseline	Alt4	3.711673	0.8064907	2.13005	5.293301	<.0001*
_Baseline	Alt7	3.438677	0.8064907	1.85705	5.020305	<.0001*
_Baseline	Alt2	3.298054	0.8064907	1.71643	4.879682	<.0001*
Alt6	Alt1	3.167004	0.8064907	1.58538	4.748631	<.0001*
Alt6	Alt3	2.896420	0.8064907	1.31479	4.478048	0.0003*
_Baseline	Alt5	2.841167	0.8064907	1.25954	4.422795	0.0004*
Alt5	Alt1	2.093774	0.8064907	0.51215	3.675402	0.0095*
Alt6	Alt4	1.943735	0.8064907	0.36211	3.525363	0.0160*
Alt5	Alt3	1.823191	0.8064907	0.24156	3.404818	0.0239*
_Baseline	Alt6	1.767938	0.8064907	0.18631	3.349565	0.0285*
Alt6	Alt7	1.670739	0.8064907	0.08911	3.252367	0.0384*
Alt2	Alt1	1.636887	0.8064907	0.05526	3.218515	0.0425*
Alt6	Alt2	1.530117	0.8064907	-0.05151	3.111744	0.0579
Alt7	Alt1	1.496265	0.8064907	-0.08536	3.077892	0.0637
Alt2	Alt3	1.366304	0.8064907	-0.21532	2.947931	0.0904
Alt7	Alt3	1.225681	0.8064907	-0.35595	2.807308	0.1287
Alt4	Alt1	1.223268	0.8064907	-0.35836	2.804896	0.1295
Alt6	Alt5	1.073230	0.8064907	-0.50840	2.654857	0.1834
Alt4	Alt3	0.952685	0.8064907	-0.62894	2.534312	0.2376
Alt5	Alt4	0.870506	0.8064907	-0.71112	2.452133	0.2805
Alt5	Alt7	0.597510	0.8064907	-0.98412	2.179137	0.4589

Figure 27. T-test for comparison of mean number of terrorists killed.

Figure 27 shows the t-test comparison between the scenarios for a significance level of 0.05 in terms of the mean number of terrorists killed, or red casualties. The connecting letters report section from Figure 27 illustrates the means and the general comparison between the scenarios. If the compared levels (scenarios) have different letters, it means that they are statistically different in terms of the mean number of terrorists killed. Based on that section of the graph, the baseline scenario is different from all other scenarios. In addition, the baseline scenario has the highest mean for red casualties while the alternative scenario 1 has the smallest. That is, three F-16s results in the most terrorists killed, while 3 three UCAVs results in the fewest.

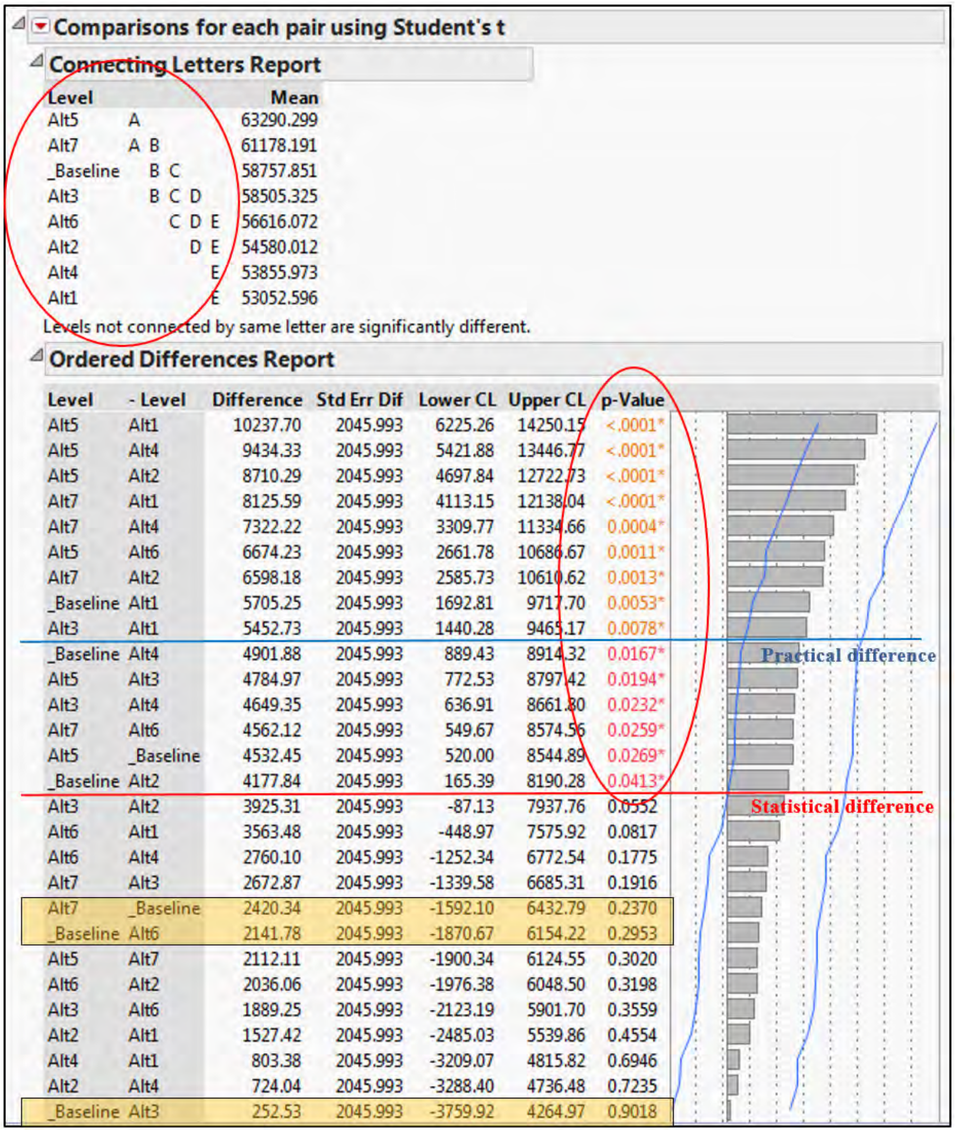
The ordered differences report section provides more detailed information, such as the p-values for tests on all mean comparisons. Circled p-values are less than the significance level of 0.05, which means the corresponding scenario pairs on the left are statistically different. In other word, the scenario pairs above the horizontal red line are statistically significantly different.

As far as a practical difference is concerned, which will be determined by the decision-maker, we can say the following. If we assume that killing four more terrorists is important for the decision-maker, then we can say that the baseline scenario is practically different form alternative scenarios 1 and 3. A more detailed comparison report for MOE 1 is provided in Appendix C.

2. MOE (2): The Time to Complete the Run

The time to complete a run is also an important MOE. Terrorists are adapted to the rough terrain in Turkish-Iraqi border, and they can travel relatively long distances in a short period of time. They can attack every village or military facility that they pass through during this time period even if they cannot reach their final destination. Therefore, we want to prevent them from proceeding in the shortest possible time.

Figure 28 provides information about t-test comparison of the scenarios in terms of the time to counter the terrorists for the α level of 0.05. The connecting letters section points out that there are statistical differences between some of the scenarios, such as alternative scenarios 5 and 7 and the baseline scenario, or between the baseline scenario and alternative scenarios 1, 2, 4, and 6. The scenario pairs above the horizontal red line are statistically different because the corresponding *p-values* are less than 0.05. Those that are above the horizontal blue line are considered practically different, assuming 5,000 seconds (approximately 1.5 hours) makes an important difference for the decision-maker. On the other hand, the baseline scenario and the alternative scenarios 3, 6, and 7 are the same in terms of the mean time to complete the run. The main takeaway is that more UCAVs reduces the time to counter the terrorists. A more detailed comparison report is provided in Appendix D.



Comparisons for each pair using Student's t

Connecting Letters Report

Level		Mean
Alt5	A	63290.299
Alt7	A B	61178.191
_Baseline	B C	58757.851
Alt3	B C D	58505.325
Alt6	C D E	56616.072
Alt2	D E	54580.012
Alt4	E	53855.973
Alt1	E	53052.596

Levels not connected by same letter are significantly different.

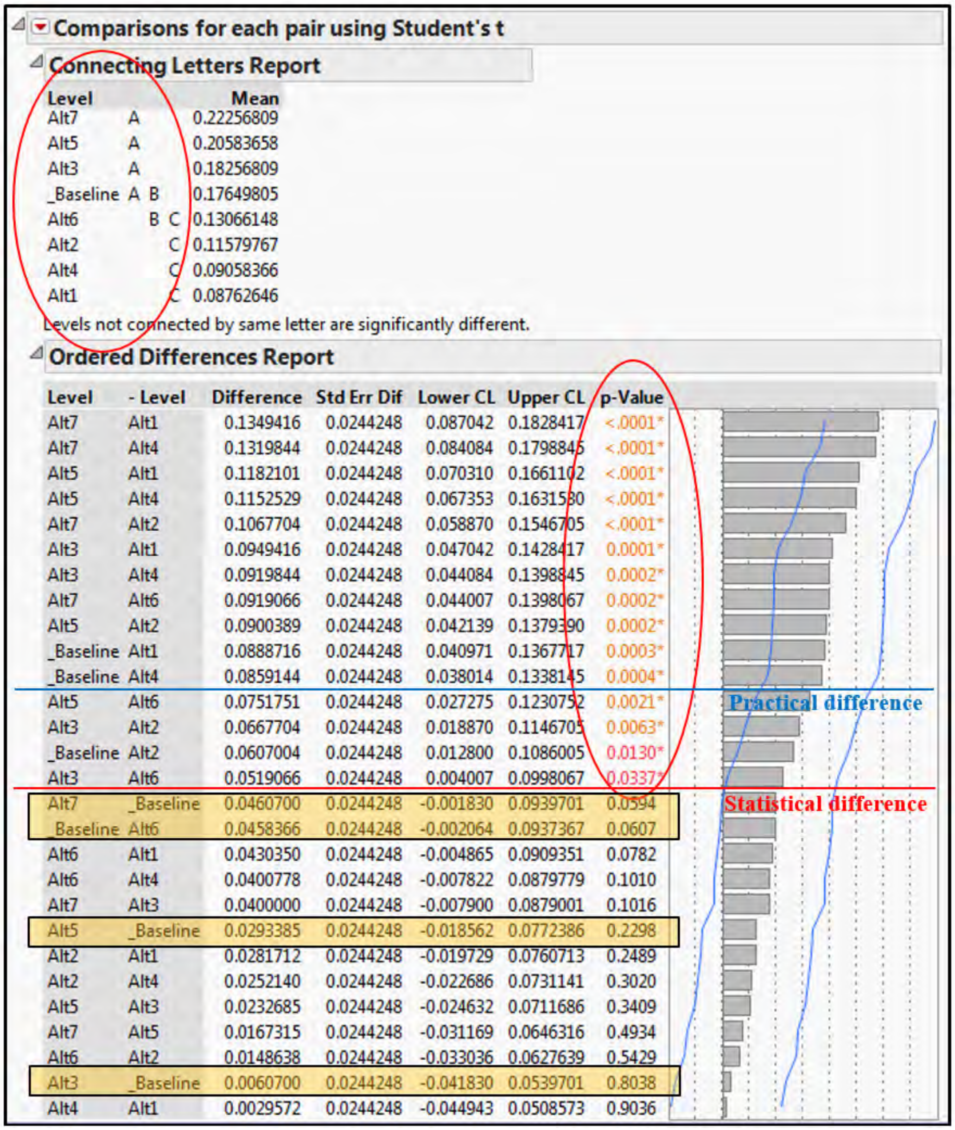
Ordered Differences Report

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
Alt5	Alt1	10237.70	2045.993	6225.26	14250.15	<.0001*
Alt5	Alt4	9434.33	2045.993	5421.88	13446.77	<.0001*
Alt5	Alt2	8710.29	2045.993	4697.84	12722.73	<.0001*
Alt7	Alt1	8125.59	2045.993	4113.15	12138.04	<.0001*
Alt7	Alt4	7322.22	2045.993	3309.77	11334.66	0.0004*
Alt5	Alt6	6674.23	2045.993	2661.78	10686.67	0.0011*
Alt7	Alt2	6598.18	2045.993	2585.73	10610.62	0.0013*
_Baseline	Alt1	5705.25	2045.993	1692.81	9717.70	0.0053*
Alt3	Alt1	5452.73	2045.993	1440.28	9465.17	0.0078*
_Baseline	Alt4	4901.88	2045.993	889.43	8914.32	0.0167*
Alt5	Alt3	4784.97	2045.993	772.53	8797.42	0.0194*
Alt3	Alt4	4649.35	2045.993	636.91	8661.80	0.0232*
Alt7	Alt6	4562.12	2045.993	549.67	8574.56	0.0259*
Alt5	_Baseline	4532.45	2045.993	520.00	8544.89	0.0269*
_Baseline	Alt2	4177.84	2045.993	165.39	8190.28	0.0413*
Alt3	Alt2	3925.31	2045.993	-87.13	7937.76	0.0552
Alt6	Alt1	3563.48	2045.993	-448.97	7575.92	0.0817
Alt6	Alt4	2760.10	2045.993	-1252.34	6772.54	0.1775
Alt7	Alt3	2672.87	2045.993	-1339.58	6685.31	0.1916
Alt7	_Baseline	2420.34	2045.993	-1592.10	6432.79	0.2370
_Baseline	Alt6	2141.78	2045.993	-1870.67	6154.22	0.2953
Alt5	Alt7	2112.11	2045.993	-1900.34	6124.55	0.3020
Alt6	Alt2	2036.06	2045.993	-1976.38	6048.50	0.3198
Alt3	Alt6	1889.25	2045.993	-2123.19	5901.70	0.3559
Alt2	Alt1	1527.42	2045.993	-2485.03	5539.86	0.4554
Alt4	Alt1	803.38	2045.993	-3209.07	4815.82	0.6946
Alt2	Alt4	724.04	2045.993	-3288.40	4736.48	0.7235
_Baseline	Alt3	252.53	2045.993	-3759.92	4264.97	0.9018

Figure 28. T-test for comparison of mean time to complete run.

3. MOE (3): The Probability that the Red Reaches Its Goal

Figure 29 provides the information about the t-test comparison for the scenarios in terms of the mean probability that terrorists reach their goal. The main goal of the terrorists is to attack blue battalions, so we want this probability to be as small as possible.



Comparisons for each pair using Student's t

Connecting Letters Report

Level				Mean
Alt7	A			0.22256809
Alt5	A			0.20583658
Alt3	A			0.18256809
_Baseline	A	B		0.17649805
Alt6		B	C	0.13066148
Alt2			C	0.11579767
Alt4			C	0.09058366
Alt1			C	0.08762646

Levels not connected by same letter are significantly different.

Ordered Differences Report

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
Alt7	Alt1	0.1349416	0.0244248	0.087042	0.1828417	<.0001*
Alt7	Alt4	0.1319844	0.0244248	0.084084	0.1798845	<.0001*
Alt5	Alt1	0.1182101	0.0244248	0.070310	0.1661102	<.0001*
Alt5	Alt4	0.1152529	0.0244248	0.067353	0.1631530	<.0001*
Alt7	Alt2	0.1067704	0.0244248	0.058870	0.1546705	<.0001*
Alt3	Alt1	0.0949416	0.0244248	0.047042	0.1428417	0.0001*
Alt3	Alt4	0.0919844	0.0244248	0.044084	0.1398845	0.0002*
Alt7	Alt6	0.0919066	0.0244248	0.044007	0.1398067	0.0002*
Alt5	Alt2	0.0900389	0.0244248	0.042139	0.1379390	0.0002*
_Baseline	Alt1	0.0888716	0.0244248	0.040971	0.1367717	0.0003*
_Baseline	Alt4	0.0859144	0.0244248	0.038014	0.1338145	0.0004*
Alt5	Alt6	0.0751751	0.0244248	0.027275	0.1230752	0.0021*
Alt3	Alt2	0.0667704	0.0244248	0.018870	0.1146705	0.0063*
_Baseline	Alt2	0.0607004	0.0244248	0.012800	0.1086005	0.0130*
Alt3	Alt6	0.0519066	0.0244248	0.004007	0.0998067	0.0337*
Alt7	_Baseline	0.0460700	0.0244248	-0.001830	0.0939701	0.0594
_Baseline	Alt6	0.0458366	0.0244248	-0.002064	0.0937367	0.0607
Alt6	Alt1	0.0430350	0.0244248	-0.004865	0.0909351	0.0782
Alt6	Alt4	0.0400778	0.0244248	-0.007822	0.0879779	0.1010
Alt7	Alt3	0.0400000	0.0244248	-0.007900	0.0879001	0.1016
Alt5	_Baseline	0.0293385	0.0244248	-0.018562	0.0772386	0.2298
Alt2	Alt1	0.0281712	0.0244248	-0.019729	0.0760713	0.2489
Alt2	Alt4	0.0252140	0.0244248	-0.022686	0.0731141	0.3020
Alt5	Alt3	0.0232685	0.0244248	-0.024632	0.0711686	0.3409
Alt7	Alt5	0.0167315	0.0244248	-0.031169	0.0646316	0.4934
Alt6	Alt2	0.0148638	0.0244248	-0.033036	0.0627639	0.5429
Alt3	_Baseline	0.0060700	0.0244248	-0.041830	0.0539701	0.8038
Alt4	Alt1	0.0029572	0.0244248	-0.044943	0.0508573	0.9036

Figure 29. T-test for comparison of mean probability that red reaches goal.

According to the Figure 29, the paired scenarios that have a *p-value* less than 0.05 are statistically different. The baseline scenario and alternative scenarios 1, 2, and 4 are statistically different, while the baseline scenario and alternative scenarios 1 and 4 are practically different as well, if the decision-maker takes the threshold probability as 0.08.

On the other hand, we can say form Figure 29 that the baseline scenario and alternative scenarios 3, 5, 6, and 7 are the same in terms of the probability that the red reaches the goal. The main takeaway here is that using more UCAVs reduces the probability that the terrorists reach their goal. This follows from having more sensors along the border and a quicker response time. It is important to note that we assume that a terrorist group withdraws after suffering casualties. A more detailed comparison report is provided in Appendix E.

4. Insights from the Scenario Comparisons

We define three different MOEs in order to look at the problem from different perspectives and provide comprehensive insight to the decision-maker. From the result of the initial data analysis and the scenario comparisons, we can say that the advantages and disadvantages of the scenarios differ depending on the MOEs. The decision-maker should decide whether he/she wants to get more red casualties, or eliminate the terrorists as quickly as possible, or decrease the probability of being attacked by the terrorists.

In general, F-16s are better at causing more red casualties, but UCAVs kill quicker and are better at preventing terrorists from attacking blue. The reason for this is that F-16s have more powerful weapons, but UCAVs have more sophisticated sensors (and are near the border) so they can detect, classify, and attack terrorists in a relatively shorter time. More specifically, the scenarios where we use two F-16s and one UCAV are more advantageous for killing red than the scenarios with one F-16 and two UCAVs. On the other hand, the scenarios with two UCAVs are preferable in terms of MOEs 2 and 3.

We recommend the decision-maker to use at least two UCAVs in that area rather than using three F-16s. We think that decreasing the probability of red's attacking blue is more important than the number of red casualties. We also want to assign one of the UCAVs to the region two because statistical results show that using UCAVs in region two increases the performance in terms of MOE 2 and 3. In other words, using F-16s in region two decreases the performance in terms of MOE 2 and 3. This may be because of the terrain effects in region 2, but we need to make further investigations to understand the actual reason, which is beyond the scope of this thesis.

In sum, using three UCAVs or a combination of two UCAVs and one F-16 seems preferable for a decision-maker. Now, we want to know what kind of characteristics the F-16s and the UCAVs should have in order to obtain better results. For this purpose, we perform regression analyses to find significant factors that have an influence on the response.

E. LINEAR REGRESSION ANALYSIS

A regression analysis is used to figure out the effects of, and the relationship between, the input factors and the response variables. A regression fits a mathematical model and tries to minimize the square distances to the observed data. The general mathematical equation for the linear regression is shown in Equation (5) [56].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{p-1} X_{p-1} + \varepsilon \tag{5}$$

In Equation (5), $\beta_i, i = 0,1,2,...,\mathrm{p}-1$ are unknown parameters and β_0 is called the intercept term. Y is called the response and $X_i,...,\mathrm{X}_{\mathrm{p}-1}$ are the predictors. ε is an error term, often assumed to be normal [56].

In the following section, we examine the significantly influential input factors, including two-way interactions and nonlinear effects, on the mean number of terrorists killed (MOE 1), the time to complete the run (MOE 2), and the probability that red reaches the goal (MOE 3). However, we only explain the models for the mean number of red casualties in detail supported with graphs and tables. The results for other MOEs are summarized, and the detailed results are provided in Appendix F.

Two approaches were considered to fit regression models to the factors we varied. The first approach was to fit the model, grouped by both scenario and the design point. In this first approach, we obtained very low R^2 values indicating a poor model fit. The second approach was to fit the model, collapsing across the scenarios for every design point. The second approach gave us higher R^2 values indicating better model fits with fewer degrees of freedom. Moreover, the most influential variables and the order of importance of these variables were exactly the same for both approaches. In addition, with fewer rows of data, the graphs are easier to interpret. Thus, we preferred to use the second approach that uses the summary data file with 257 rows of data.

1. Main Effects Model

In our thesis, we use stepwise regression in JMP to fit the mean number of terrorists killed using only the input factors as the candidate influential terms in the model, also called a main effects model. Main effects models are easy to understand and interpret because there are no quadratic terms or interactions in the model. Figure 30 illustrates the statistical results of the basic model.

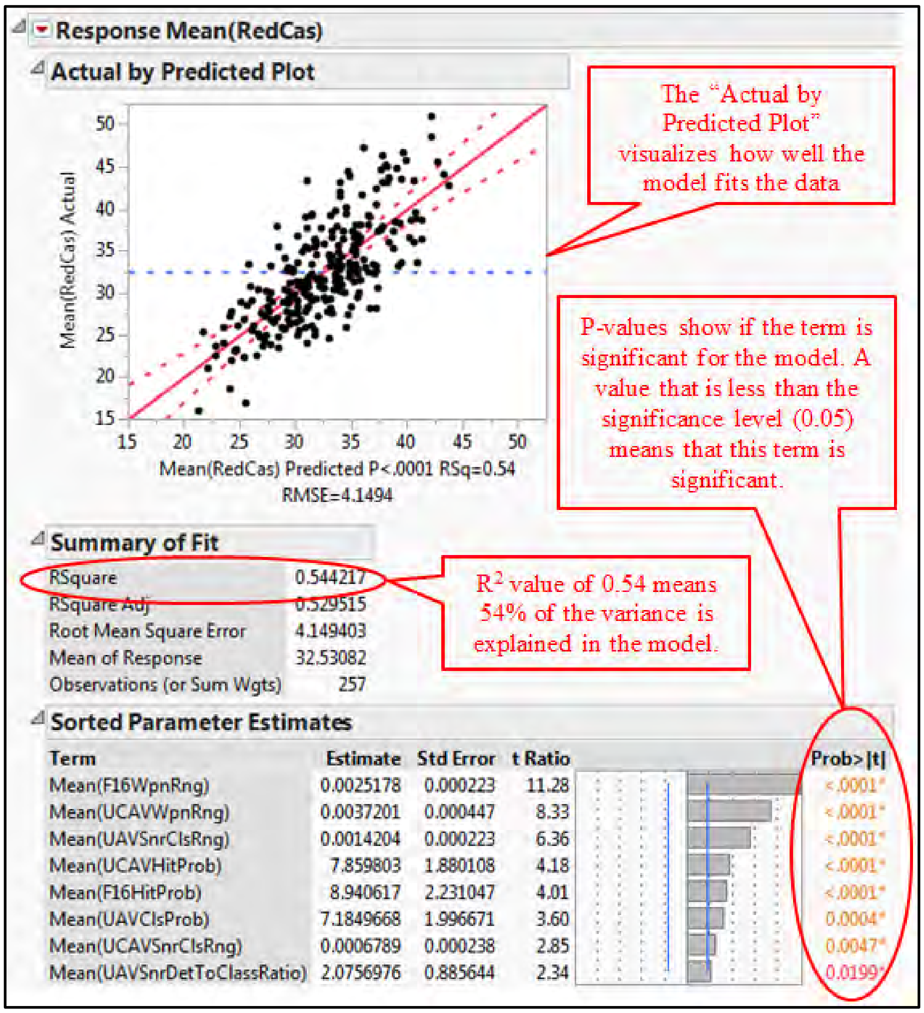


Figure 30. Results for main effects model for mean number of terrorists killed.

The "Summary of Fit" table in Figure 30 provides information about how much the variance is explained by the regression model, which is represented by RSquare (R^2). The "Actual by Predicted Plot" visualizes how well the model fits the data. The "Sorted

Parameter Estimates" table provides information about the factors and the model. The factors used in the model are listed under the "Term" column. These terms correspond to X_i in equation (5). The "Estimate" column includes the multipliers of X_i, which correspond to β_i in equation (5) whereas the "Std.Error" column shows the uncertainties. The "t Ratio" and the "Prob>|t|" columns show if the terms are necessary for the model and how much influence they have. If the "Prob>|t|" value or *p-value* is greater than the selected significance level of the model, which is 0.05 in this thesis, then this term is significant. An example of the interpretation of the model is the following. A one unit increase in F-16's hit probability (F16HitProb) causes 8.94 unit increases in the mean number of terrorists killed.

According to the results, there are eight input factors that have a significant effect on the mean number of terrorists killed for a significance level of 0.05. The most significant terms in the model are the weapon range and the hit probability of the F-16s and the UCAVs, and the sensor classification range of the UAVs and the UCAVs. The detection range of the UAVs also appears to be significant in the model.

The R^2 value is 0.54, which means 54% of the variance is explained in the model. Determining a good value of R^2 depends on the area of application. For example, "in the biological and social sciences, variables tend to be more weakly correlated and there is a lot of noise. We would expect lower values of R^2 in these areas. Some experience with the particular area is necessary to judge the R^2 well." [57] In reality, there are a lot of uncontrollable factors in air-to-ground operations, such as weather, terrain, temperature, moisture, and system malfunctions, etc. Therefore, it is impossible to predict the future perfectly for this kind of operations. In order to make our model as realistic as possible, we adjusted the range of the factors in a way that we can include those noise factors in the model. Moreover, we modeled the entire Turkish-Iraqi border, which is very large compared to the agents on the ground or in the air. Therefore, there is a lot of variation in detection and classification of terrorists during the simulation because of the LOS calculations (e.g., a small move of an agent can make it invisible to the sensors). As a result, lower values of R^2 are expected in our model.

R^2 is not the only factor for deciding whether a model is good or bad. We also need to check some assumptions using the regression diagnostics, because the estimation and inference from the regression model depends on these assumptions [57]. Those assumptions are:

1. The error term ε has mean of zero.
2. The error term ε has constant variance.
3. The errors are normally distributed.
4. The errors are uncorrelated.
5. The relationship between the response and the regression variables is correct.
6. The regression variables are independent. [58]

These assumptions can be checked graphically or analytically. Assumptions 1 through 4 are related to the residuals. Figure 31 shows the information about the residuals for the main effects model.

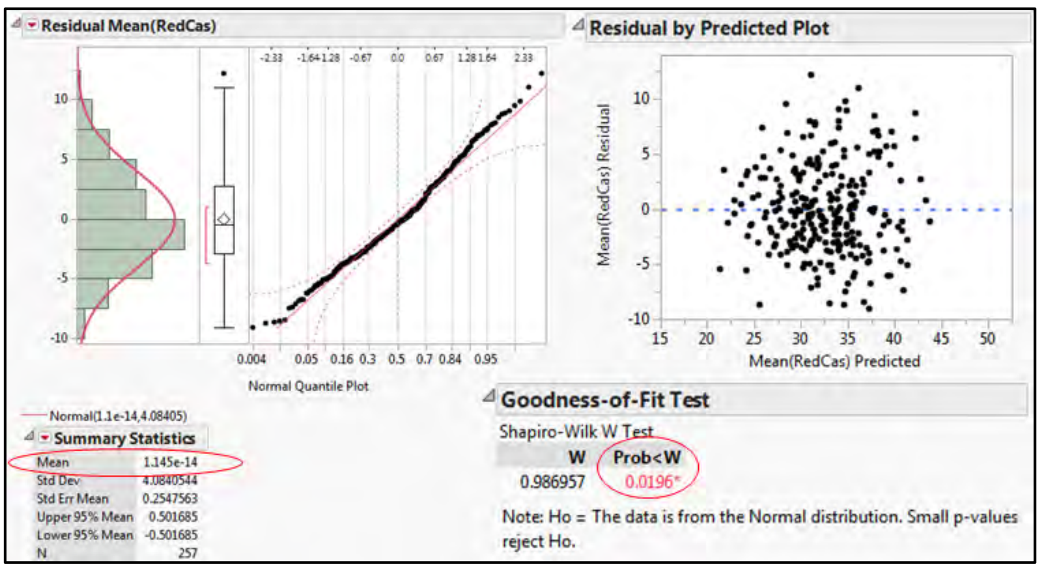


Figure 31. Useful statistics and plots for residuals of main effects model.

The error term has the mean of 1.145×10^{-14}, which is very close to zero. Constant variance assumption can be checked from "Residuals by Predicted Plot." We want all of the data to spread out equally around the dotted blue line in the graph. The residual by predicted plot is not perfect in our model. The normality of the error terms can be checked visually by looking at the "Normal Quantile Plot" or analytically by conducting Shapiro-Wilk test. The normal quantile plot seems good except on the edges, but we do not pass the Shapiro-Wilk test because the p-value is less than 0.05. Therefore, we perform a Box-Cox transformation on the response variable to fix the constant variance and satisfy the normality assumption for the residuals. The Box-Cox transformation suggests a lambda value of 0.2, which we can also see from the graph in Figure 32.

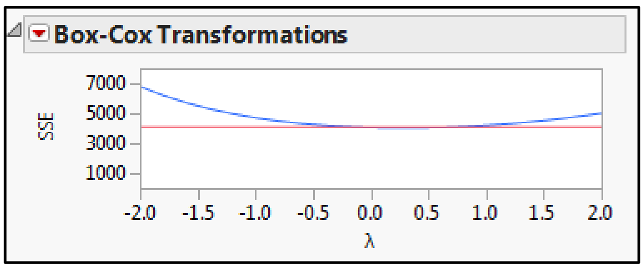


Figure 32. Graphical illustration of the Box-Cox transformation in the JMP.

After a Box-Cox transformation, we fit a new model using the new response variable with the power transformation. The influential factors on the response variable remain the same with previous model, and the R^2 value increases from 0.54 to 0.55 (see Figure 35). As shown in Figure 33, the residual by predicted plot seems better than the previous plot, which shows that the error terms has constant variance. Moreover, the normal quantile plot is good, and we also pass the Shapiro-Wilk test because our *p-value* is greater than the significance level of 0.05, indicating the normality assumption is also met. In addition, the error term has a mean value that is even closer to zero than the one in the previous model.

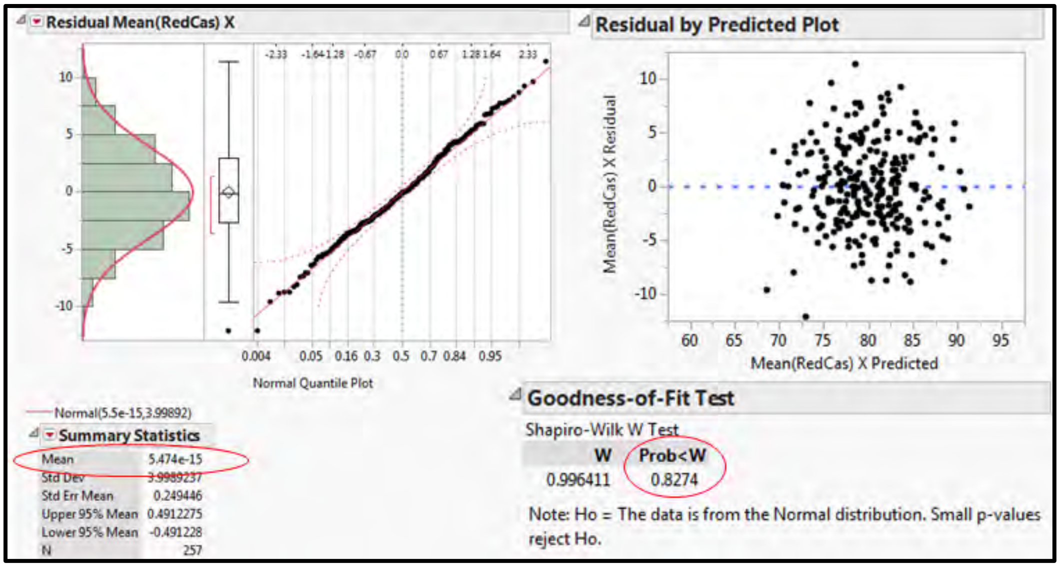


Figure 33. Statistics and plots for residuals after Box-Cox transformation on response variable.

After the first three assumptions are met, we check whether the errors are uncorrelated. This assumption can be checked visually by looking at the residual by predicted plot. We would like to see no evident sequence of points [58], which is the case for the plot in Figure 33. We can check the assumptions 5 and 6 from the scatter plot visually [58]. The scatter plot that we provide in Appendix A satisfies these assumptions. In addition, we want to see whether there is any influential point by looking at the Cook's distance values. Figure 34 shows that all of the Cook's distance values are less than one, indicating no influential values.

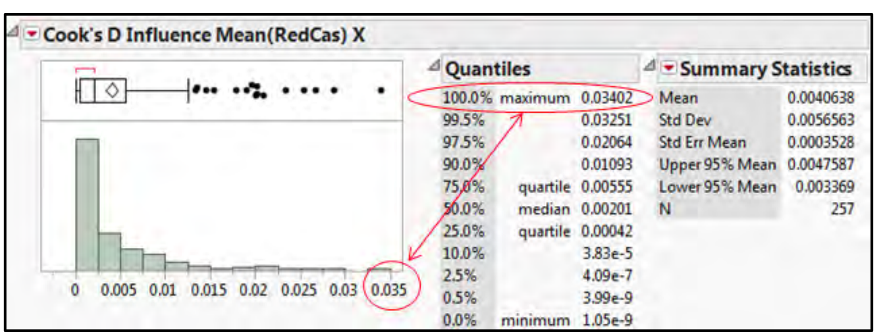
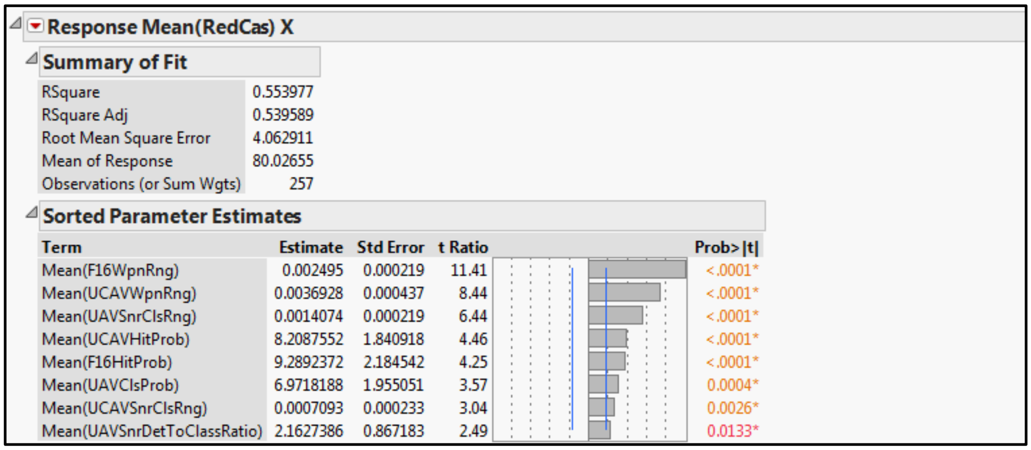


Figure 34. Cook's distance values indicate that there are no influential points.

The final main effects model is provided in Figure 35. Notice that the new model has the same influential factors on the response variable with slightly different t-ratios and p-values. The R^2 value is also greater than the first model.


Response Mean(RedCas) X

Summary of Fit

RSquare	0.553977
RSquare Adj	0.539589
Root Mean Square Error	4.062911
Mean of Response	80.02655
Observations (or Sum Wgts)	257

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mean(F16WpnRng)	0.002495	0.000219	11.41	<.0001*
Mean(UCAVWpnRng)	0.0036928	0.000437	8.44	<.0001*
Mean(UAVSnrClsRng)	0.0014074	0.000219	6.44	<.0001*
Mean(UCAVHitProb)	8.2087552	1.840918	4.46	<.0001*
Mean(F16HitProb)	9.2892372	2.184542	4.25	<.0001*
Mean(UAVClsProb)	6.9718188	1.955051	3.57	0.0004*
Mean(UCAVSnrClsRng)	0.0007093	0.000233	3.04	0.0026*
Mean(UAVSnrDetToClassRatio)	2.1627386	0.867183	2.49	0.0133*

Figure 35. Results for main affects model after Box-Cox transformation.

2. Main Effects Model for MOE 2 and MOE 3

We also fit the time (MOE 2) and the probability that red reaches the goal (MOE 3) using only the main effects. We use linear regression for MOE 2, but logistic regression for MOE 3 since the response is binary. The summary statistics, parameter estimates, and the receiver operating characteristics (ROC) curve for logistic regression are provided in Appendix F.

The results of the linear regression for MOE 2 shows that the most significant factors in the model are the sensor classification range, the time between detections, the sensor classification probability of the UAVs, and the time between detections of the UCAVs. As the sensor capabilities of the UAVs and the UCAVs increases, the time decreases. Different than with MOE 1, use of the F-16s does not have any influence on the time to complete the run. That is, the sensors of the systems on the border (i.e., UAVs and UCAVs) are the most important variables in quickly detecting, classifying, and countering the terrorists.

The results of the logistic regression for MOE 3 show that the most influential factors are the UAV-related factors, such as UAV sensor classification range and probability. However, the UCAV and the F-16-related factors also have a strong effect on the response as well as the terrorist-related factors.

3. Insights from the Main Effects Model

The main effects models show that all of the air assets that we use in the model have a strong influence on MOE 1 and MOE 3 in some way. However, the F-16 does not have a significant influence on the time (MOE 2). The most influential factors are related to the weapons and the sensor capabilities of the air assets. Other factors, such as speed and scramble time, appear to be insignificant for MOE 1. Moreover, there are no uncontrollable factors that affect the response in the main effects model for MOE 1 and MOE 2. In addition, we do not see any direct sensor-related factors of the F-16s in the model for MOE 1 and MOE 2, but hit probability can be considered as sensor related in reality (e.g., as sensor capability increases, the hit probability also increases). As a result, the decision-makers should focus on increasing the sensor capabilities of the UAVs and the UCAVs. They also should use more powerful weapons for the operations in that area.

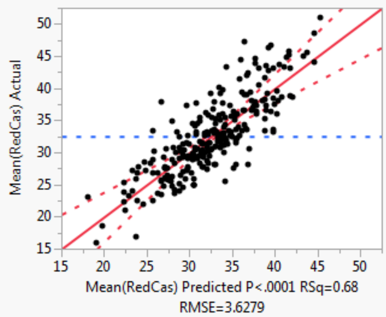
4. Second Order Model

In addition to the main effects model, we also consider the effects of the interactions between the main input factors as well as the quadratic terms. Using stepwise regression in JMP, we started to construct our model by adding the quadratic terms and the interactions. In order to keep the model as simple as possible, we excluded the terms that make no sense for the model and the terms that have very small influence on the R^2 value. In addition, if a main effect is included in a quadratic or interaction term, we keep this factor in the model to achieve the model hierarchy even if it does not have a significant effect for the model. The summary statistics, actual by predicted plot, and sorted parameter estimates for the second order model is depicted in Figure 36.

The second order model has an R^2 value of 0.68, which means the significant terms explain roughly 68% of the variability in the mean number of red causalities.

Response Mean(RedCas)

Actual by Predicted Plot



Summary of Fit

RSquare	0.682498
RSquare Adj	0.640351
Root Mean Square Error	3.627871
Mean of Response	32.53082
Observations (or Sum Wgts)	257

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mean(F16WpnRng)	0.0025138	0.000195	12.88	<.0001*
Mean(UCAVWpnRng)	0.0037296	0.000391	9.55	<.0001*
Mean(UAVSnrClsRng)	0.0014115	0.000195	7.23	<.0001*
Mean(UCAVHitProb)	7.8149277	1.643857	4.75	<.0001*
Mean(F16HitProb)	8.9176805	1.950685	4.57	<.0001*
Mean(UAVClsProb)	7.2263771	1.745813	4.14	<.0001*
(Mean(UCAVSnrClsRng)-6125.06)*(Mean(UCAVSpd)-145.004)	-2.581e-5	6.238e-6	-4.14	<.0001*
(Mean(F16WpnRng)-6000.06)*(Mean(UAVClsProb)-0.27627)	0.0080081	0.00198	4.04	<.0001*
(Mean(UCAVWpnRng)-4000.03)*(Mean(UAVTimeBetwDet)-1175.02)	6.6432e-6	1.8e-6	3.69	0.0003*
(Mean(UCAVSnrClsRng)-6125.06)*(Mean(TerroristTimeBetwDet)-500.031)	6.8652e-6	1.93e-6	3.56	0.0005*
(Mean(UCAVTimeBetwDet)-1137.52)*(Mean(UCAVScrTime)-350.008)	-2.384e-5	7.078e-6	-3.37	0.0009*
Mean(UCAVSnrClsRng)	0.0006803	0.000208	3.27	0.0013*
(Mean(F16TimeBetwDet)-450.008)*(Mean(PartComDelay)-700.031)	-0.000039	1.286e-5	-3.03	0.0027*
(Mean(UCAVSpd)-145.004)*(Mean(UAVSnrDetToClassRatio)-1.50039)	-0.074147	0.025721	-2.88	0.0043*
(Mean(UCAVWpnRng)-4000.03)*(Mean(TerroristClsProb)-0.50016)	0.0100046	0.003572	2.80	0.0055*
(Mean(F16HitProb)-0.60016)*(Mean(UCAVHitProb)-0.56254)	-38.20492	13.69923	-2.79	0.0057*
Mean(UAVSnrDetToClassRatio)	2.095392	0.774594	2.71	0.0073*
(Mean(UCAVSnrDetToClassRatio)-1.50039)*(Mean(PartComDelay)-700.031)	0.0252265	0.009404	2.68	0.0078*
Mean(TerroristClsRng)	-0.003386	0.001301	-2.60	0.0099*
(Mean(F16TimeBetwDet)-450.008)*(Mean(UAVSnrClsRng)-6000.06)	-3.166e-6	1.353e-6	-2.34	0.0202*
Mean(UAVTimeBetwDet)	-0.00192	0.000822	-2.34	0.0204*
(Mean(UCAVHitProb)-0.56254)*(Mean(UAVTimeBetwDet)-1175.02)	0.0119253	0.005849	2.04	0.0426*
Mean(UCAVTimeBetwDet)	-0.001654	0.000822	-2.01	0.0454*
Mean(UCAVSnrDetToClassRatio)	1.3933245	0.774377	1.80	0.0733
Mean(PartComDelay)	0.002622	0.001952	1.34	0.1806
Mean(TerroristClsProb)	-2.201913	1.950694	-1.13	0.2602
Mean(UCAVSpd)	-0.004289	0.007096	-0.60	0.5461
Mean(F16TimeBetwDet)	-0.00065	0.001116	-0.58	0.5605
Mean(UCAVScrTime)	0.0002856	0.001562	0.18	0.8551
Mean(TerroristTimeBetwDet)	-7.979e-5	0.001953	-0.04	0.9674

Figure 36. Results for main effects model for mean number of terrorists killed.

Notice that the primary factors that exist in the main effects model also appear to be the most significant factors in the second order model. Besides those factors, the time between detection for the UAV and the UCAV are significant in the new model. Moreover, terrorist classification range also has a significant influence on the number of terrorists killed. Specifically, as their classification range increases, so does their survivability. There is no quadratic term in the second order model, but some interactions between the controllable factors or the controllable and uncontrollable factors are in the model.

5. Second Order Model for MOE 2

We also fit the time to complete the run using the main effects and the second order terms. The summary statistics and the parameter estimates are provided in Appendix F.

Similar to the main effects model, the results of the second order model for the MOE 2 show that the most significant factors in the model are the sensor classification range, the time between detections, the sensor classification probability of the UAVs and the time between detections of the UCAVs. As the sensor capabilities of the UAVs and the UCAVs increases, the time decreases. Different then the main effects model, use of the F-16s also has an influence on the response. The interaction between the F-16's time between detections and the sensor classification range of partisans are in the model.

6. Insights from the Second Order Model

Similar to the main effects models, in the second order models the most significant factors are related to the weapon and the sensor capabilities of the air assets. Different from the main effects models, the second order models contain also factors related to the red agents, such as sensor capabilities of terrorists. Also, other uncontrollable factors, such as communication capability of terrorists and partisans, are in the model. Therefore, preventing terrorists from communicating with civil supporters in the cities may increase the number of red casualties. UCAV speed, which does not exist in the main effects model, is also influential on the response. According to the results, the UCAVs should fly slower to increase the number of red casualties.

F. REGRESSION TREE ANALYSIS

Regression trees, also known as partition trees, are another way to analyze the data and explore the influences of the factors on the response variable. The partition tree is easy to understand and interpret because of its tree structure. The recursive partitioning regression algorithm is the following.

First, we partition a predictor by selecting a point within the range of this predictor to decide from where to split. Second, we calculate the mean of the response variable in that partition. We apply the same procedure for each partition. Then, we fit a model for each partition and choose the one that minimizes the residual sum of squares (RSS). Finally, we continue subpartitioning the partitions in a recursive manner [56]. The overall model after each split is shown in a tree structure.

We perform a partition tree analysis for the mean number of terrorists killed using JMP. Figure 37 illustrates the first six splits of the tree model. We read a partition tree from top to bottom. Each box contains the name of the factor and the value for optimal split. The mean and the standard deviation of the number of terrorists killed are also included in each box as well as the number of observations for that partition.

The results of the partition tree analysis support the linear regression results since the most significant factors are the same for both. The F-16 weapon range of 6047 meters is the first split in the tree. The second and the third splits are the UCAV weapon range of 4180 and the UAV sensor classification range of 6547, respectively. Notice that these factors are also the most significant factors in both the main effects and the second order linear regression model. We prefer the branches on the right because we want to have higher red casualties. The red circle shows the most preferable configuration for first six splits where F-16s have a weapon range greater than 6047 meters and the UCAVs have a weapon range greater than 4180 meters. Note: recall that our weapon ranges are inflated since we spread our terrorists more than they would in the real world.

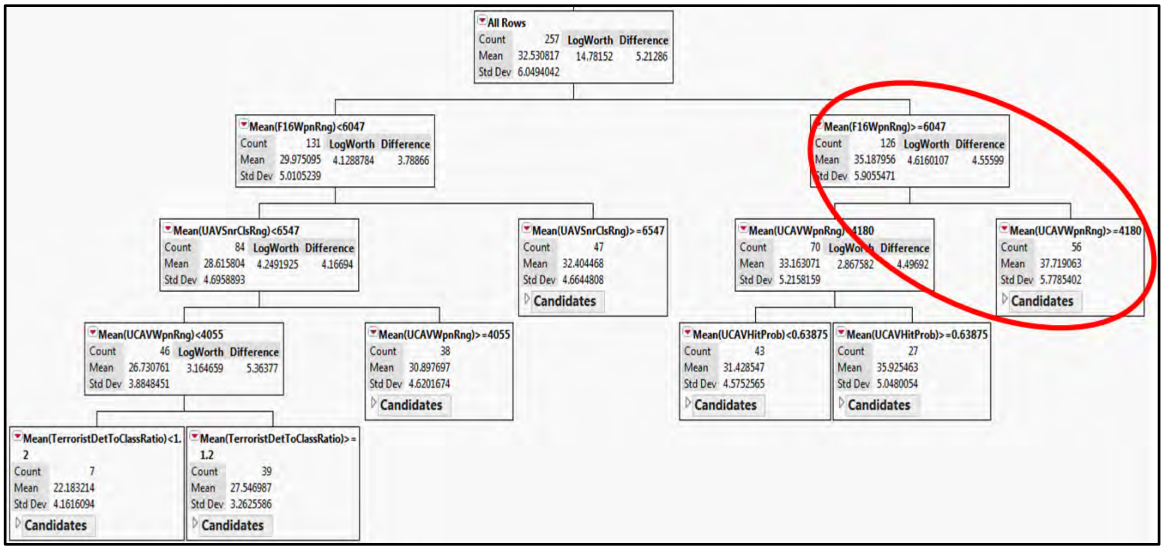


Figure 37. First six splits of partition tree model for number of terrorists killed.

Although the R^2 value increases as we continue splitting, we stop on the 20th split and get an R^2 value of 0.62. We provide the tree model for the first 15 splits in Appendix G. Figure 38 displays the improvement of R^2 value with number of splits and the contributions of the factors to the explanatory power of the tree model.

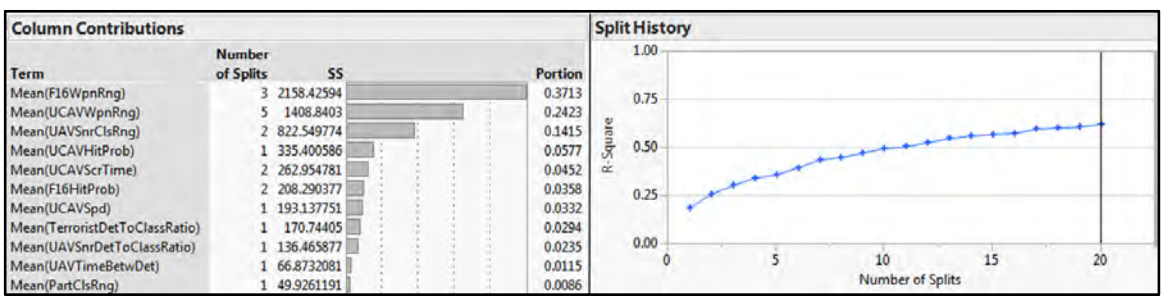


Figure 38. Improvement of R^2 value with number of splits (right) and contributions of factors to explanatory power of tree model (left).

The partition tree results show a strong correlation with the main effects and the second order linear regression results. The sensor- and weapon-related factors are mostly influential factors. As we continue splitting, other terms related to the blue or red forces are added to the tree with a small effect. Overall, having more powerful weapons and more sophisticated sensors increases the number of red casualties.

VI. CONCLUSION

A. OVERVIEW

We analyze the effectiveness of the use of UCAVs in conjunction with the manned aircraft to counter active terrorists in rough terrain in this thesis. We try to figure out whether replacing or combining the manned aircraft with UCAVs is effective for air-to-ground operations in a rough terrain. For this purpose, we build a simulation model and run 102,800 simulated air-to-ground attacks comprising eight different scenarios of manned aircraft and UAV combinations. The results are based on our assumption that three air-to-ground strike assets will always be used. Therefore, it is impossible to cover every aspect of these kinds of operations, but we provide significant insights to the decision-maker. After performing data analysis techniques on the output, we explore useful results for the effectiveness of UCAVs as well as the significant factors that have a strong influence on the outcome.

B. RESEARCH QUESTIONS

The results of this research provide answers to the following research questions.

(1) How might UCAVs enhance Turkey's ability to secure its border characterized by rough geographical conditions?

In general, the results of this research show that using the UCAVs enhances Turkey's ability to secure the southeastern border. The scenario comparisons point out that the scenarios in which we use more UCAVs, are statistically different in favor of UCAVs in terms of the time to complete the mission and the probability that the terrorists reach their goal. The scenarios where we use more F-16s are preferable in terms of the number of terrorists killed. However, some of the scenarios that have two UCAVs and one F-16 (Alternatives 2 and 4) have slightly less mean red casualties than the baseline. Therefore, the UCAVs may kill fewer terrorist compared to the current methods, but we prevent them from attacking the blue more quickly and with higher probability.

(2) What combination of UCAVs and UAVs provides the same or better effectiveness than the combination of manned aircraft and UAVs currently in use?

The only scenario that we use UCAV and UAV combination only is alternative scenario 1, in which we allocate three UCAVs to the Turkish-Iraqi border. When the response variable is the number of terrorists killed, the alternative scenario 1 has the lowest mean. However, when the response variable is the time to stop terrorists or the probability of terrorists' attacking the blue assets, alternative scenario 1 is preferred over the baseline. We think that preventing terrorists from attacking the blue forces is more important than killing more terrorists, so we say that using three UCAVs and three UAVs provides better effectiveness than the currently used baseline.

(3) Is there a combination of manned aircraft, UCAVs, and UAVs that provides the same or better effectiveness than the manned aircraft and UAVs in use?

The scenario comparisons and the statistics show that using more F-16s than UCAVs yields more casualties but a higher probability of the terrorists' attacking blue. The preferred combination of the F-16s and the UCAVs depends on the decision-maker's measure of effectiveness selection. Assuming that the decision-maker always wants to keep the blue forces safe, alternative scenarios 2 and 4 appear to have better effectiveness than the manned aircraft and UAVs in use.

(4) What are the advantages and disadvantages of using UCAVs and UAVs only, manned aircraft and UAVs only, or UCAVs, manned aircraft, and UAVs?

The first advantage of using UCAVs and UAVs only (Alternative 1) is that we stop the terrorists in shortest time and with the highest probability. Therefore, we keep the terrorists away from the villages and the military facilities, resulting less blue casualties. Parallel to the time, the probability that terrorist attack blue forces also decreases. In addition, reducing the risk of the pilot's life or decreasing the cost can be considered as other advantages but these areas are beyond the scope of this thesis. The disadvantage of this configuration is having less red casualties.

The advantage of using manned aircraft and UAVs only is having more red casualties. On the other hand, this combination yields more time and the likelihood of being attacked by the terrorists.

The manned aircraft, UCAVs, and UAVs combination is advantageous in terms of resulting in relatively more red casualties in general than the UAVs and UCAVs combination. However, it is disadvantageous in terms of giving terrorists more chance to attack blue.

C. OTHER FINDINGS

- The most common conclusion about the factors is that weapon-related factors have a strong influence on the number of terrorists killed while the sensor-related factors are the most effective factors on the time of completion and the probability that terrorists attack blue.
- The weapon range of an F-16 and a UCAV are the two most influential factors on the number of terrorists killed. The main effects model, the second order model, and the first two splits of the partition tree analysis yields the F-16 and the UCAV weapon ranges as the most significant factors. Therefore, we should improve current air-to-ground weapons if we want to get higher red casualties.
- The sensor classification range of the UAVs have a strong effect on the number of terrorists killed, the time to complete the runs, and the probability that the terrorists attack the blue. When we increase the classification range, the number of terrorists killed also increases while the time and the probability of being attacked by red decreases. Mounting more sophisticated sensors on the UAVs should be considered to increase their effectiveness.
- The hit probabilities of an F-16 and of a UCAV are also two of the most significant factors in all regression model fits. As the hit probabilities of these assets increases, the number of red casualties increases. Hit probability is mostly related to the sensors in real world. Thus, increasing the sensor capabilities also increases the probability of hit. However, this relationship was not considered in this thesis.
- According to the main effects and the second order models, the UAV sensor classification probability also has a strong positive influence on the number of terrorists killed and a strong negative influence on the time to complete the run.
- Another important factor that increases the number of terrorists killed is the sensor classification range of the UCAVs. Both the main effects and the second order regression analysis yield this result. Similar to the UAVs, the UCAVs should be also configured with advanced sensors that can see farther.

- The factors related to the F-16s do not exist in the model for the time to completion except in an interaction with the classification of the partisan agents. The sensor-related factors of the UAVs and the UCAVs are the ones that have a significant influence on the time to completion. We should focus on the UAVs to find and kill terrorists in a shorter time.
- The sensor-related factors of the UAVs and the UCAVs, and the weapon-related factors of the UCAVs, are the most influential variables on the probability of terrorists' attacking blue. Similar to the time to completion, we need advanced unmanned vehicles more than the manned aircraft to decrease the probability of being attacked.
- The classification range of the terrorists appears to be a significant factor in the second order model fit on the time to complete the run. Flying ata higher altitude and/or having more silent aircraft can be considered to reduce this effect.
- Finally, the detection ranges of the terrorists and the partisans have a significant influence on the probability that terrorists attack blue. Thus, preventing partisans from communicating with terrorists can be considered.

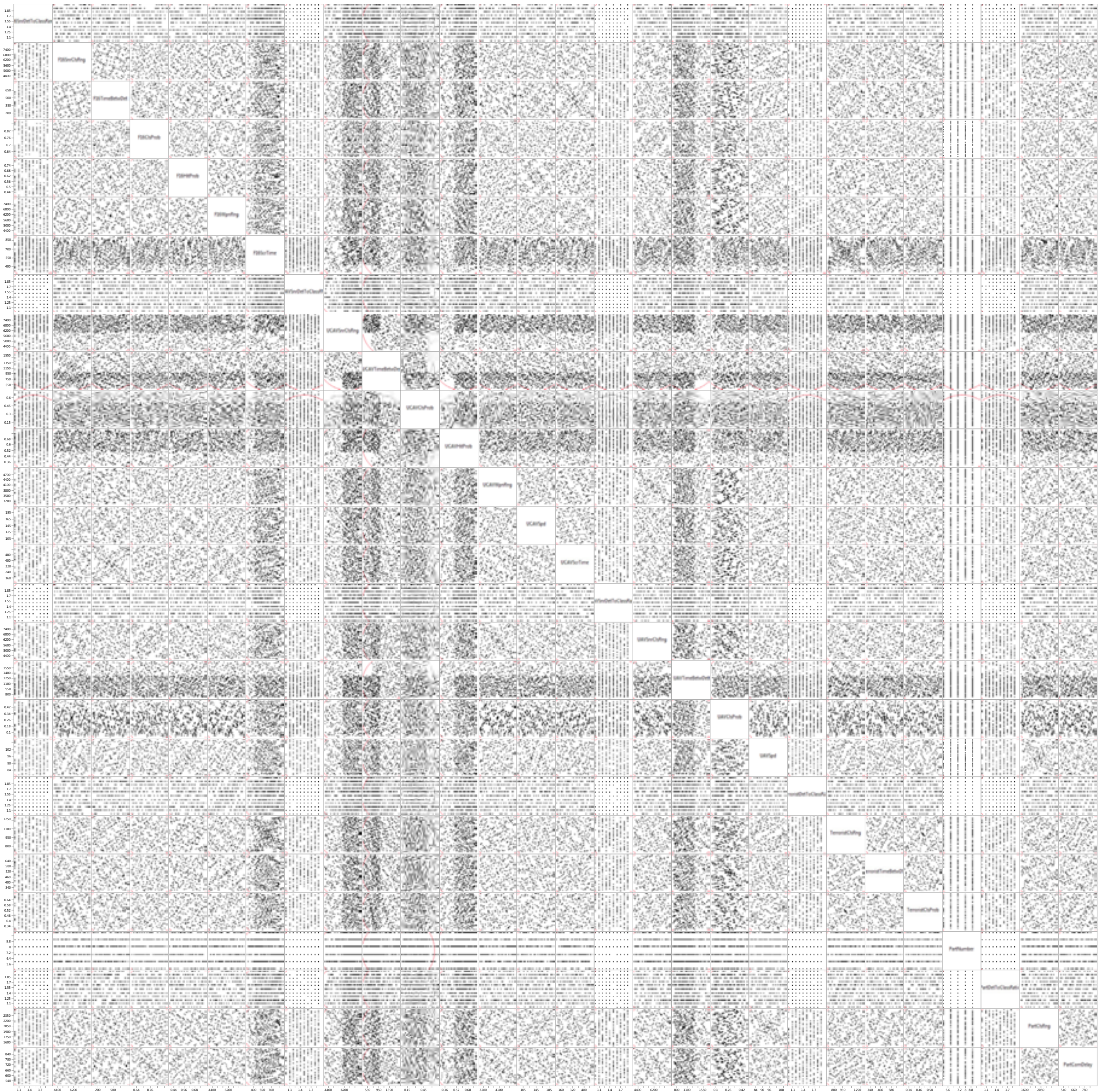
D. FUTURE RESEARCH

This model is well suited for several excursions that were not done for lack of time. The followings are examples of the many potential scenarios, which could be covered.

- One aspect that could be modeled is the impact of the civilians and the friendly forces in an urban area.
- The effect of false-positive detections should be looked at.
- Another excursion that could be modeled is dedicated UCAV sorties without the UAVs and the manned aircraft to ascertain a nearly optimal number of UCAVs required for securing the entire border.
- Based on the restrictive rules of engagement, this research did not explore an offensive scenario. Therefore, modeling an offensive air-to-ground attack scenario might better inform a decision-maker if conditions were to escalate.

APPENDIX A. SCATTERPLOT MATRIX FOR ALL FACTORS

The scatterplot matrix for all factors, including controllable and uncontrollable factor shows the space-filling property of our nearly orthogonal Latin hypercube design (NOLH).



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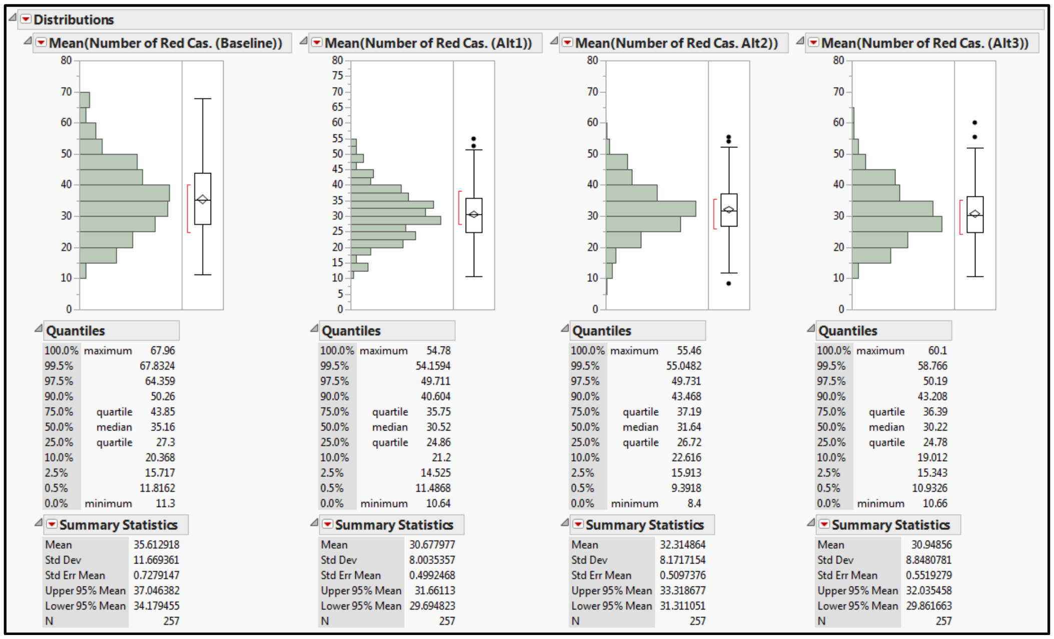
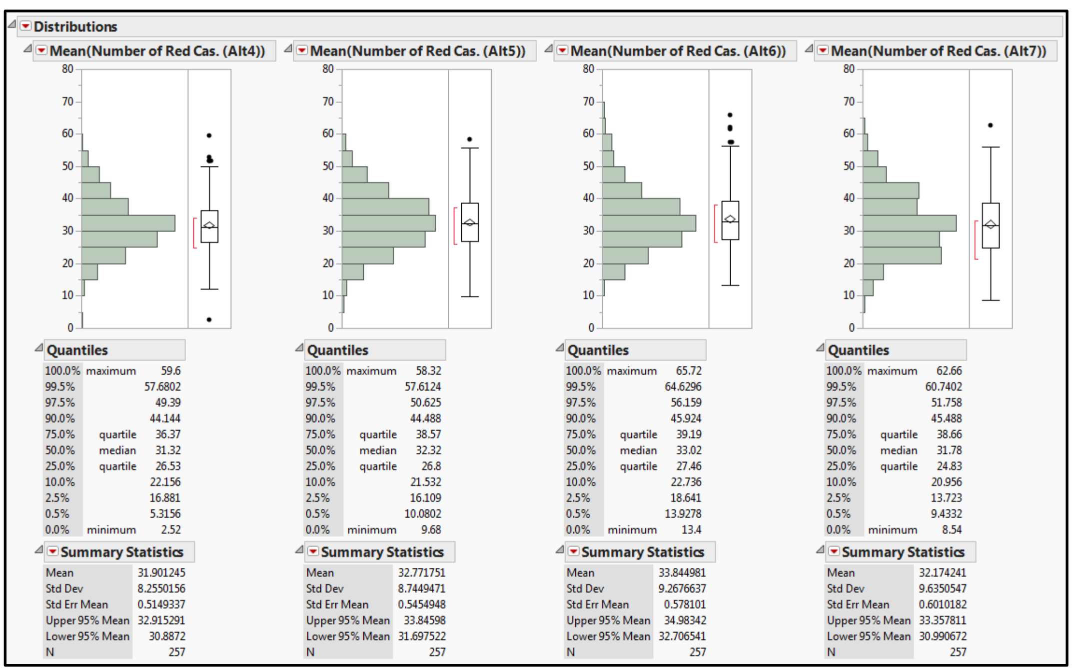
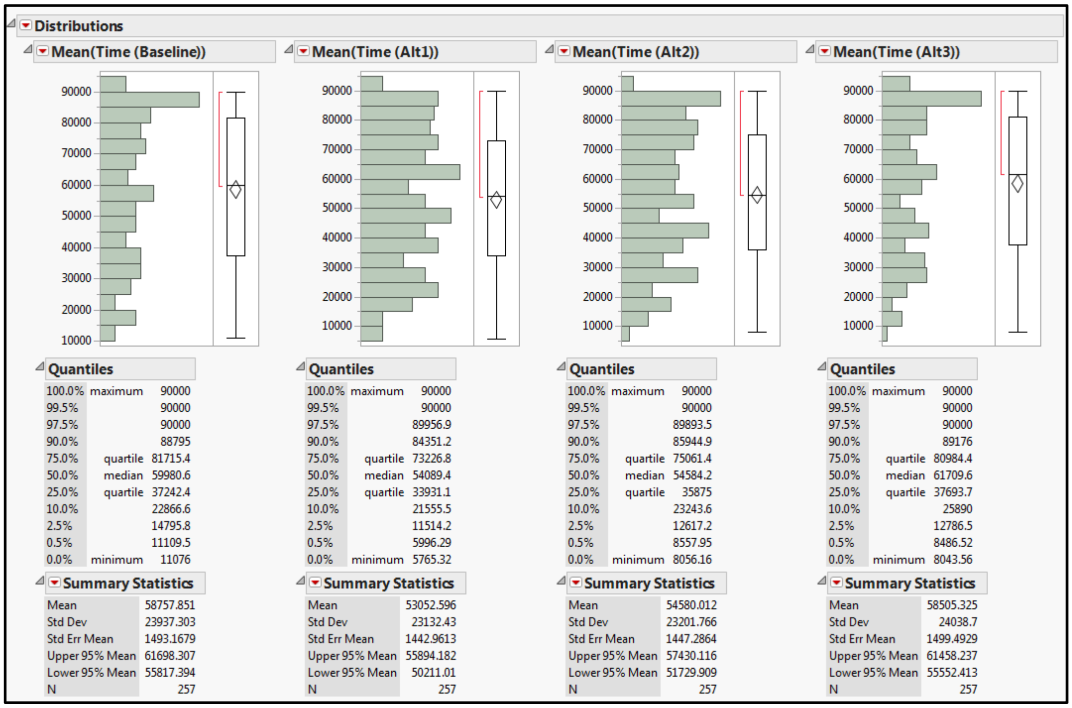
APPENDIX B. HISTOGRAMS AND SUMMARY STATISTICS

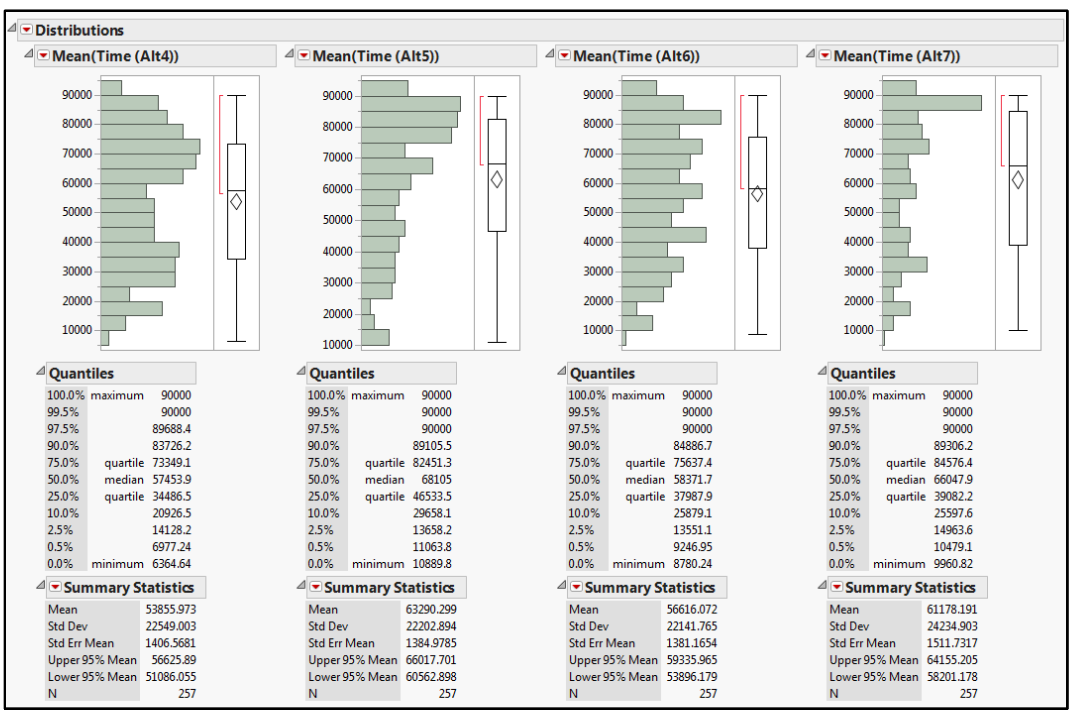
The following two figures show the distribution of the number of terrorists killed (MOE) for all of the scenarios.



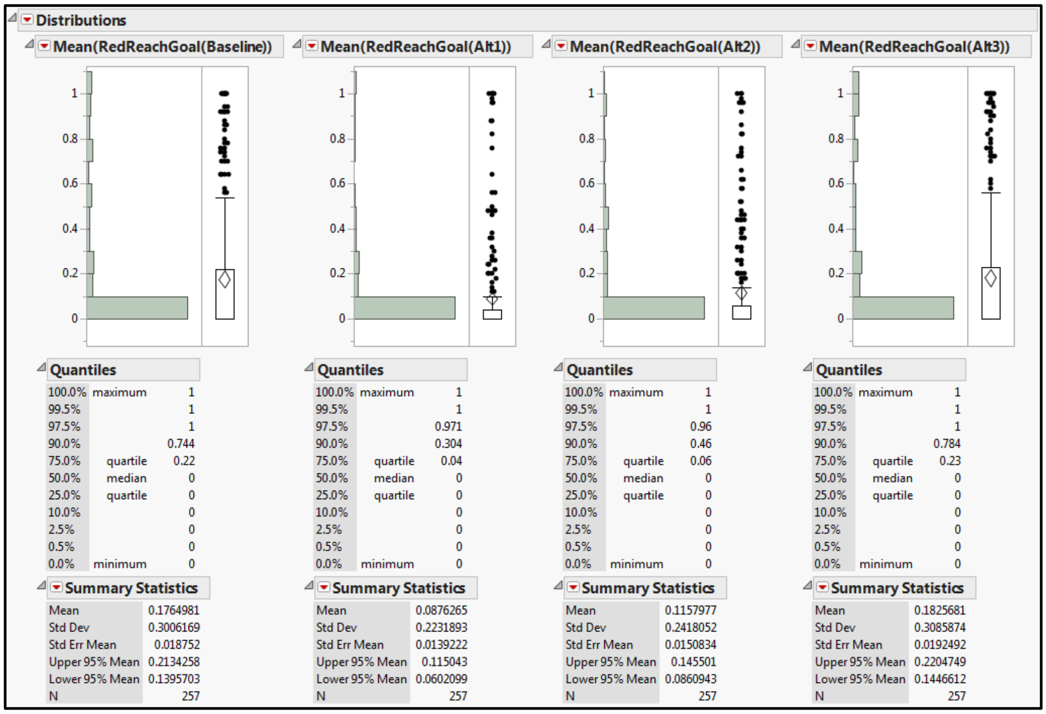


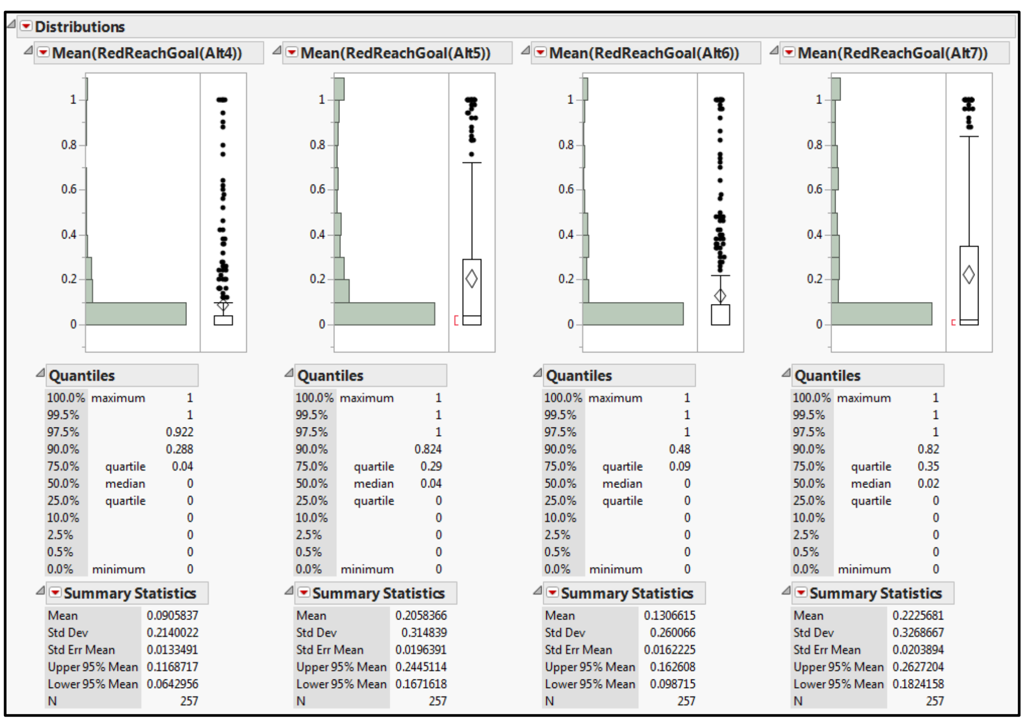
The following two figures show the distribution of the time to complete the runs (MOE 2) for all of the scenarios.





The following two figures show the distribution of the probability that the red reaches the goal (MOE 3) for all of the scenarios.





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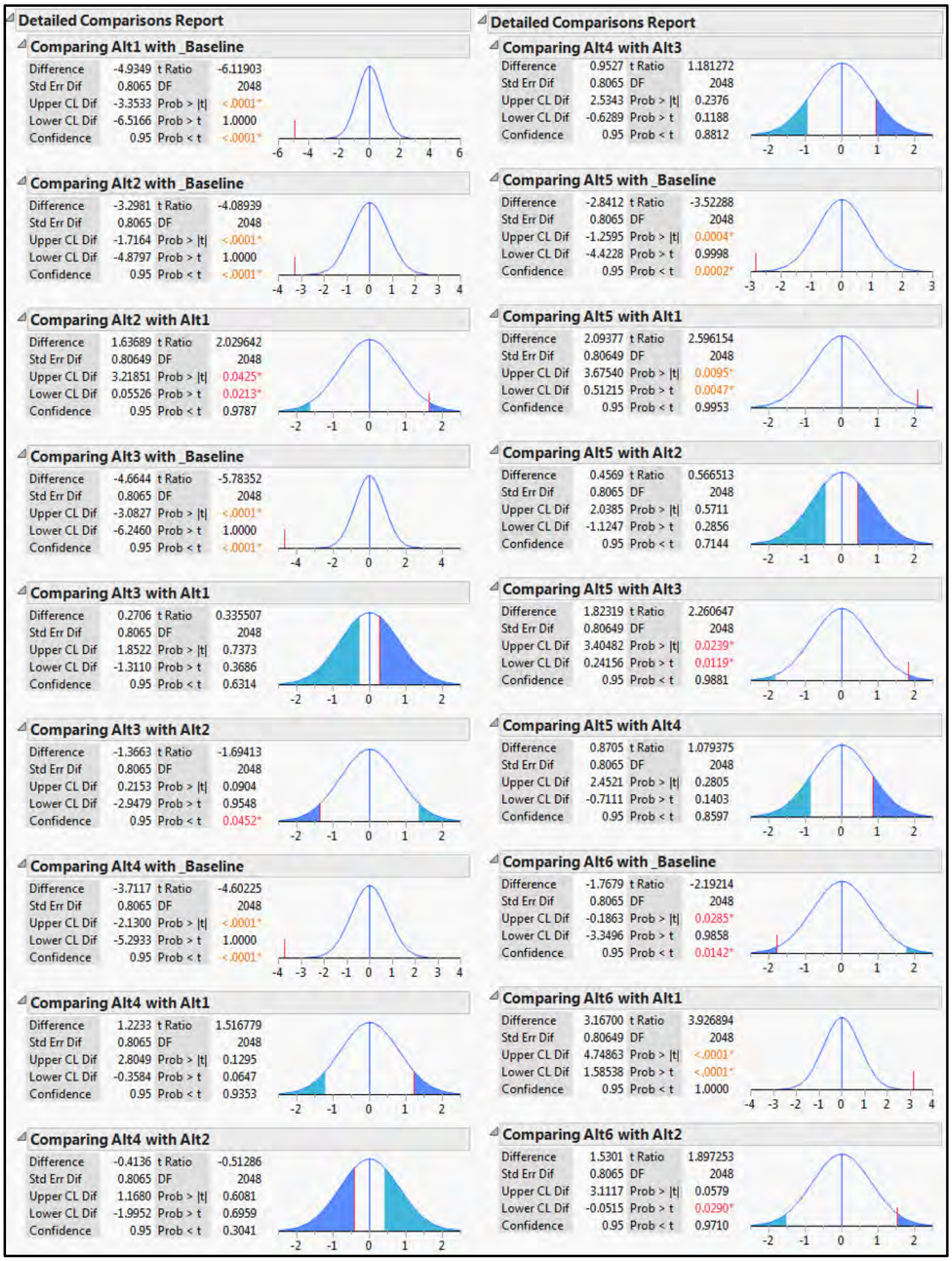
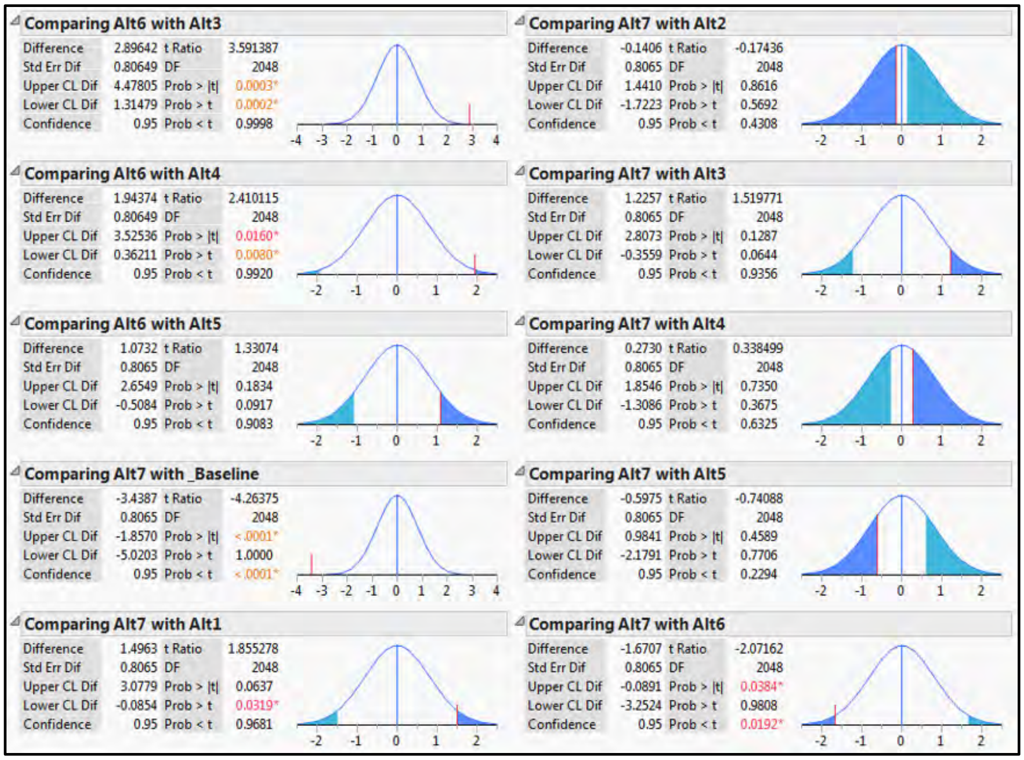
APPENDIX C. DETAILED COMPARISON REPORT FOR MOE 1

The following figures provide the paired t-test comparisons of the scenarios in terms of the number of red casualties.





Comparing Alt6 with Alt3

Difference	2.89642	t Ratio	3.591387
Std Err Dif	0.80649	DF	2048
Upper CL Dif	4.47805	Prob > |t|	0.0003*
Lower CL Dif	1.31479	Prob > t	0.0002*
Confidence	0.95	Prob < t	0.9998

Comparing Alt6 with Alt4

Difference	1.94374	t Ratio	2.410115
Std Err Dif	0.80649	DF	2048
Upper CL Dif	3.52536	Prob > |t|	0.0160*
Lower CL Dif	0.36211	Prob > t	0.0080*
Confidence	0.95	Prob < t	0.9920

Comparing Alt6 with Alt5

Difference	1.0732	t Ratio	1.33074
Std Err Dif	0.8065	DF	2048
Upper CL Dif	2.6549	Prob > |t|	0.1834
Lower CL Dif	-0.5084	Prob > t	0.0917
Confidence	0.95	Prob < t	0.9083

Comparing Alt7 with _Baseline

Difference	-3.4387	t Ratio	-4.26375
Std Err Dif	0.8065	DF	2048
Upper CL Dif	-1.8570	Prob > |t|	<.0001*
Lower CL Dif	-5.0203	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*

Comparing Alt7 with Alt1

Difference	1.4963	t Ratio	1.855278
Std Err Dif	0.8065	DF	2048
Upper CL Dif	3.0779	Prob > |t|	0.0637
Lower CL Dif	-0.0854	Prob > t	0.0319*
Confidence	0.95	Prob < t	0.9681

Comparing Alt7 with Alt2

Difference	-0.1406	t Ratio	-0.17436
Std Err Dif	0.8065	DF	2048
Upper CL Dif	1.4410	Prob > |t|	0.8616
Lower CL Dif	-1.7223	Prob > t	0.5692
Confidence	0.95	Prob < t	0.4308

Comparing Alt7 with Alt3

Difference	1.2257	t Ratio	1.519771
Std Err Dif	0.8065	DF	2048
Upper CL Dif	2.8073	Prob > |t|	0.1287
Lower CL Dif	-0.3559	Prob > t	0.0644
Confidence	0.95	Prob < t	0.9356

Comparing Alt7 with Alt4

Difference	0.2730	t Ratio	0.338499
Std Err Dif	0.8065	DF	2048
Upper CL Dif	1.8546	Prob > |t|	0.7350
Lower CL Dif	-1.3086	Prob > t	0.3675
Confidence	0.95	Prob < t	0.6325

Comparing Alt7 with Alt5

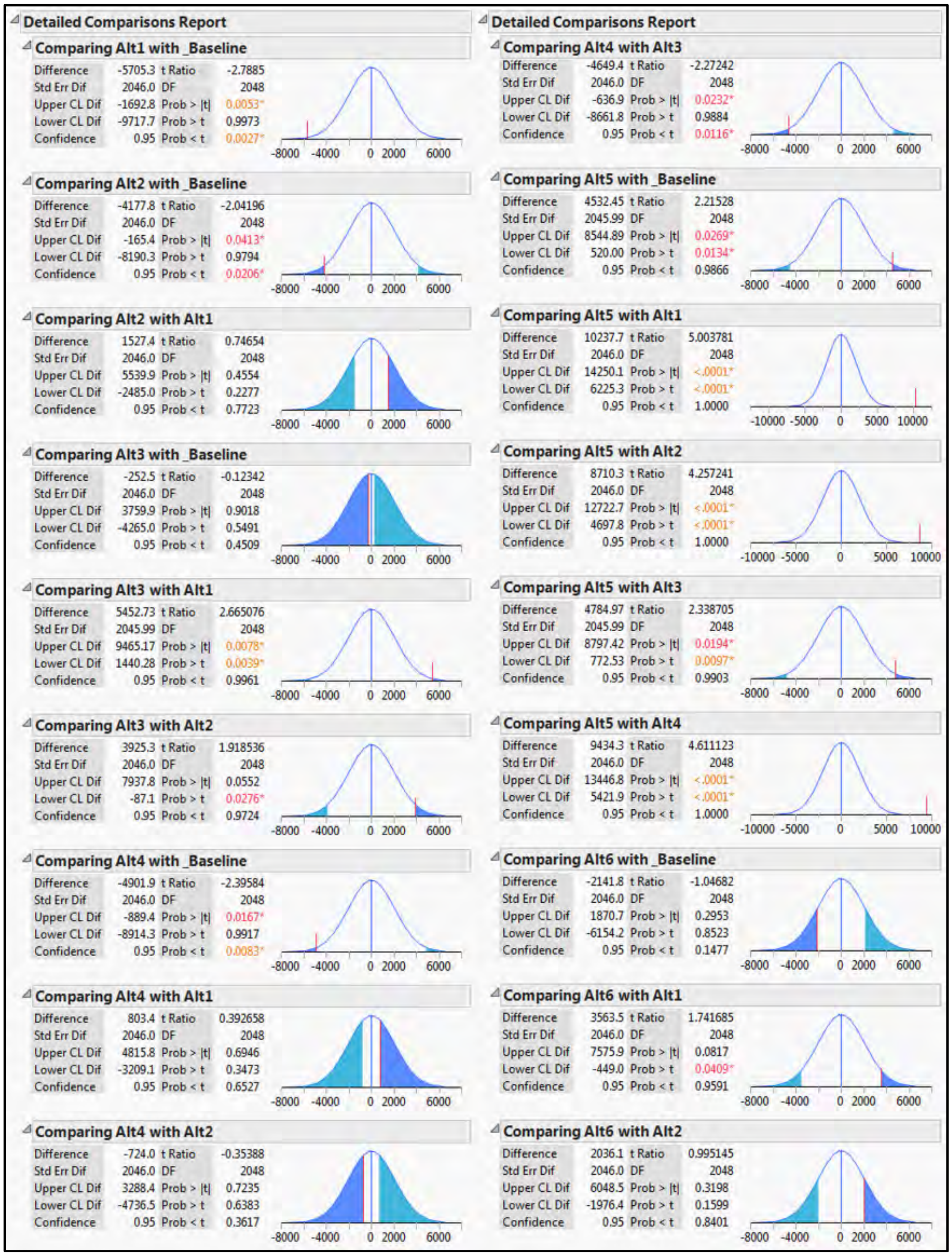
Difference	-0.5975	t Ratio	-0.74088
Std Err Dif	0.8065	DF	2048
Upper CL Dif	0.9841	Prob > |t|	0.4589
Lower CL Dif	-2.1791	Prob > t	0.7706
Confidence	0.95	Prob < t	0.2294

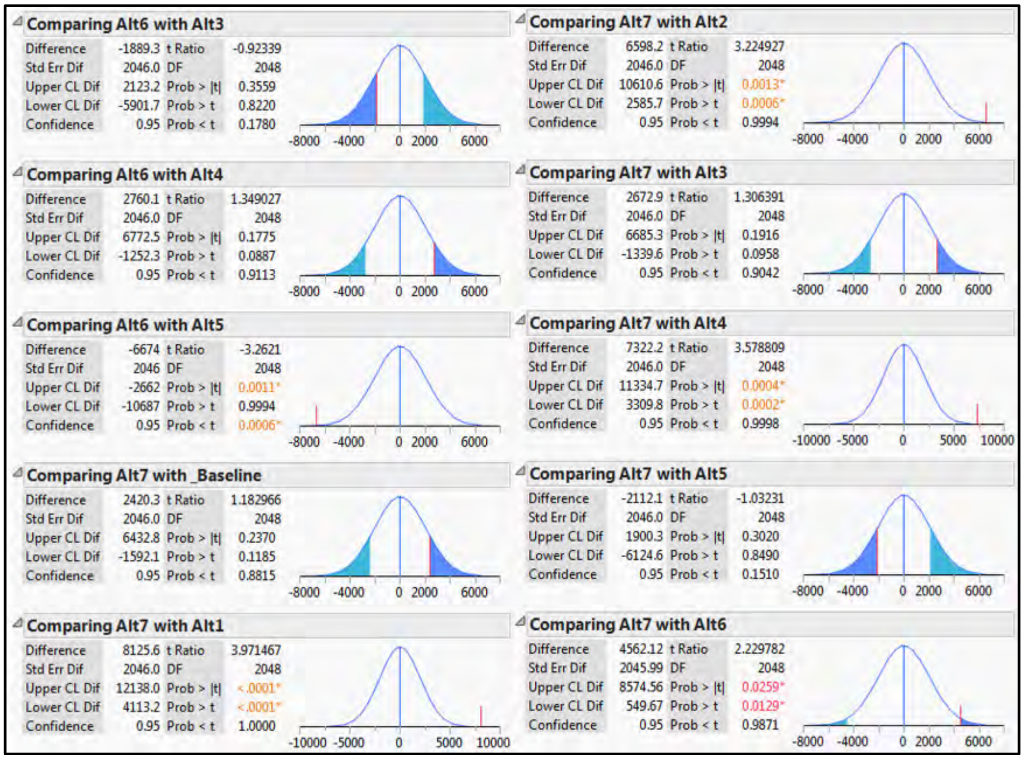
Comparing Alt7 with Alt6

Difference	-1.6707	t Ratio	-2.07162
Std Err Dif	0.8065	DF	2048
Upper CL Dif	-0.0891	Prob > |t|	0.0384*
Lower CL Dif	-3.2524	Prob > t	0.9808
Confidence	0.95	Prob < t	0.0192*

APPENDIX D. DETAILED COMPARISON REPORT FOR MOE 2

The following figures provide the paired t-test comparisons of the scenarios in terms of the time to complete the run.

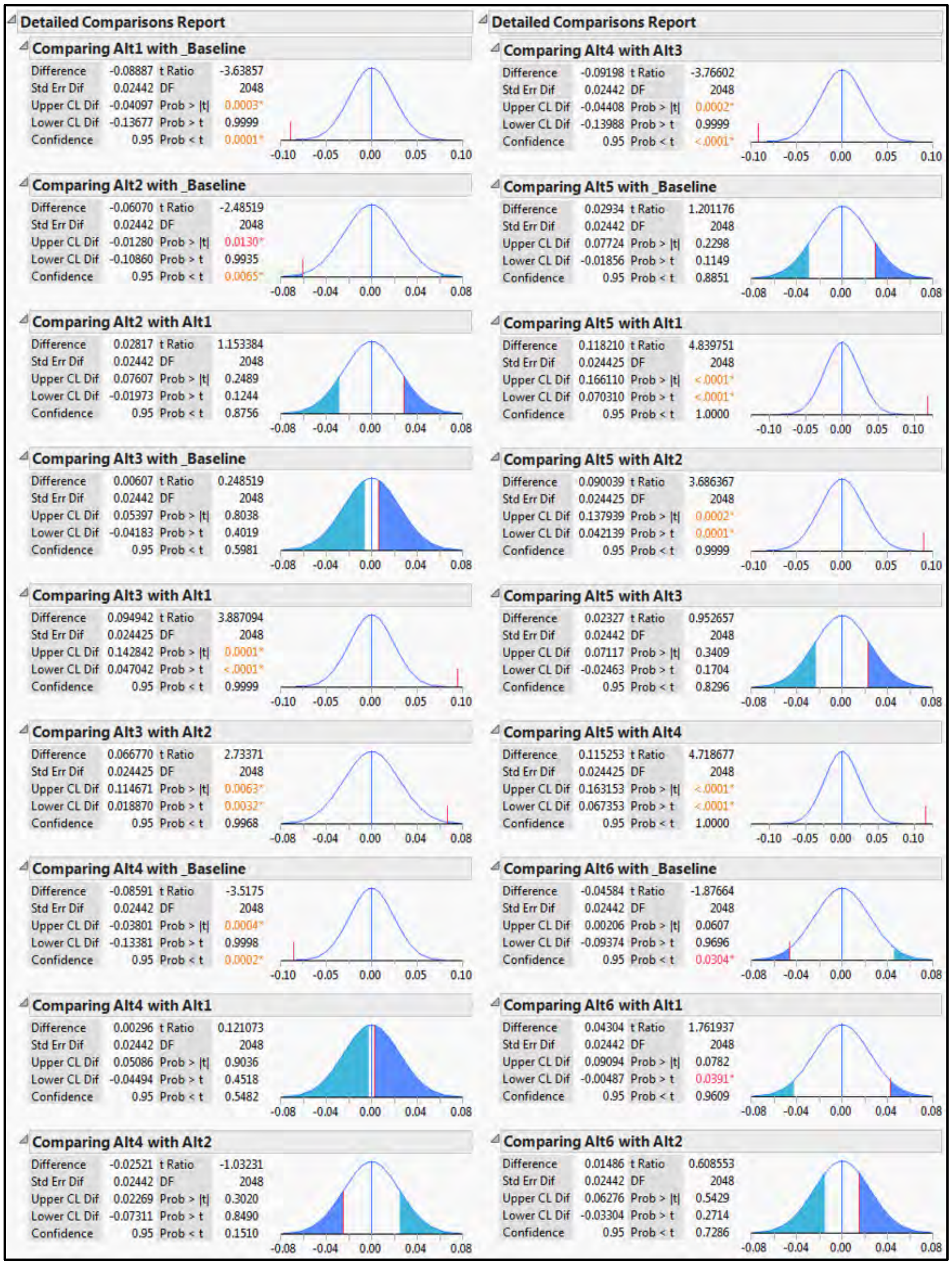


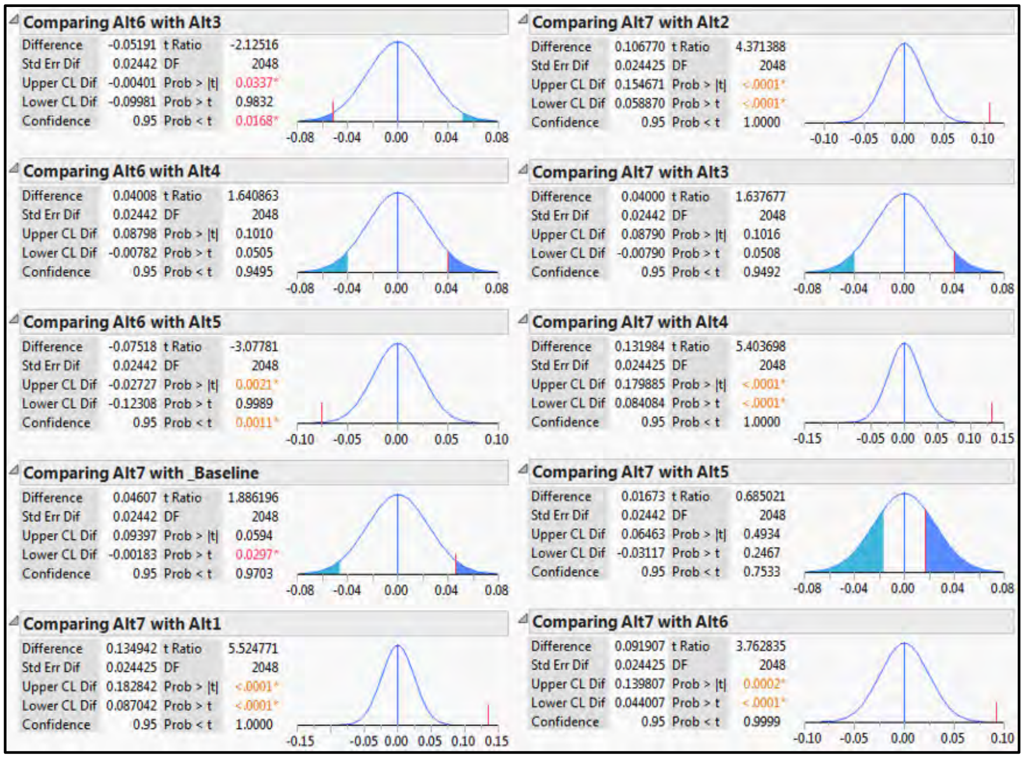


Comparing Alt6 with Alt3
Difference -1889.3 t Ratio -0.92339
Std Err Dif 2046.0 DF 2048
Upper CL Dif 2123.2 Prob > |t| 0.3559
Lower CL Dif -5901.7 Prob > t 0.8220
Confidence 0.95 Prob < t 0.1780
-8000 -4000 0 2000 6000
Comparing Alt7 with Alt2
Difference 6598.2 t Ratio 3.224927
Std Err Dif 2046.0 DF 2048
Upper CL Dif 10610.6 Prob > |t| 0.0013*
Lower CL Dif 2585.7 Prob > t 0.0006*
Confidence 0.95 Prob < t 0.9994
-8000 -4000 0 2000 6000
Comparing Alt6 with Alt4
Difference 2760.1 t Ratio 1.349027
Std Err Dif 2046.0 DF 2048
Upper CL Dif 6772.5 Prob > |t| 0.1775
Lower CL Dif -1252.3 Prob > t 0.0887
Confidence 0.95 Prob < t 0.9113
-8000 -4000 0 2000 6000
Comparing Alt7 with Alt3
Difference 2672.9 t Ratio 1.306391
Std Err Dif 2046.0 DF 2048
Upper CL Dif 6685.3 Prob > |t| 0.1916
Lower CL Dif -1339.6 Prob > t 0.0958
Confidence 0.95 Prob < t 0.9042
-8000 -4000 0 2000 6000
Comparing Alt6 with Alt5
Difference -6674 t Ratio -3.2621
Std Err Dif 2046 DF 2048
Upper CL Dif -2662 Prob > |t| 0.0011*
Lower CL Dif -10687 Prob > t 0.9994
Confidence 0.95 Prob < t 0.0006*
-8000 -4000 0 2000 6000
Comparing Alt7 with Alt4
Difference 7322.2 t Ratio 3.578809
Std Err Dif 2046.0 DF 2048
Upper CL Dif 11334.7 Prob > |t| 0.0004*
Lower CL Dif 3309.8 Prob > t 0.0002*
Confidence 0.95 Prob < t 0.9998
-10000 -5000 0 5000 10000
Comparing Alt7 with _Baseline
Difference 2420.3 t Ratio 1.182966
Std Err Dif 2046.0 DF 2048
Upper CL Dif 6432.8 Prob > |t| 0.2370
Lower CL Dif -1592.1 Prob > t 0.1185
Confidence 0.95 Prob < t 0.8815
-8000 -4000 0 2000 6000
Comparing Alt7 with Alt5
Difference -2112.1 t Ratio -1.03231
Std Err Dif 2046.0 DF 2048
Upper CL Dif 1900.3 Prob > |t| 0.3020
Lower CL Dif -6124.6 Prob > t 0.8490
Confidence 0.95 Prob < t 0.1510
-8000 -4000 0 2000 6000
Comparing Alt7 with Alt1
Difference 8125.6 t Ratio 3.971467
Std Err Dif 2046.0 DF 2048
Upper CL Dif 12138.0 Prob > |t| <.0001*
Lower CL Dif 4113.2 Prob > t <.0001*
Confidence 0.95 Prob < t 1.0000
-10000 -5000 0 5000 10000
Comparing Alt7 with Alt6
Difference 4562.12 t Ratio 2.229782
Std Err Dif 2045.99 DF 2048
Upper CL Dif 8574.56 Prob > |t| 0.0259*
Lower CL Dif 549.67 Prob > t 0.0129*
Confidence 0.95 Prob < t 0.9871
-8000 -4000 0 2000 6000

APPENDIX E. DETAILED COMPARISON REPORT FOR MOE 3

The following figures provide the paired t-test comparisons of the scenarios in terms of the probability that red reaches the goal.





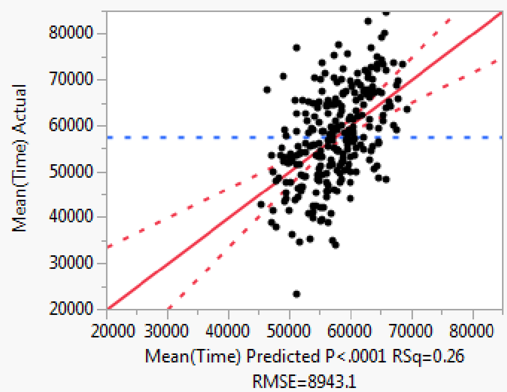
Comparing Alt6 with Alt3
Difference -0.05191 t Ratio -2.12516
Std Err Dif 0.02442 DF 2048
Upper CL Dif -0.00401 Prob > |t| 0.0337*
Lower CL Dif -0.09981 Prob > t 0.9832
Confidence 0.95 Prob < t 0.0168*
-0.08 -0.04 0.00 0.04 0.08
Comparing Alt6 with Alt4
Difference 0.04008 t Ratio 1.640863
Std Err Dif 0.02442 DF 2048
Upper CL Dif 0.08798 Prob > |t| 0.1010
Lower CL Dif -0.00782 Prob > t 0.0505
Confidence 0.95 Prob < t 0.9495
-0.08 -0.04 0.00 0.04 0.08
Comparing Alt6 with Alt5
Difference -0.07518 t Ratio -3.07781
Std Err Dif 0.02442 DF 2048
Upper CL Dif -0.02727 Prob > |t| 0.0021*
Lower CL Dif -0.12308 Prob > t 0.9989
Confidence 0.95 Prob < t 0.0011*
-0.10 -0.05 0.00 0.05 0.10
Comparing Alt7 with _Baseline
Difference 0.04607 t Ratio 1.886196
Std Err Dif 0.02442 DF 2048
Upper CL Dif 0.09397 Prob > |t| 0.0594
Lower CL Dif -0.00183 Prob > t 0.0297*
Confidence 0.95 Prob < t 0.9703
-0.08 -0.04 0.00 0.04 0.08
Comparing Alt7 with Alt1
Difference 0.134942 t Ratio 5.524771
Std Err Dif 0.024425 DF 2048
Upper CL Dif 0.182842 Prob > |t| <.0001*
Lower CL Dif 0.087042 Prob > t <.0001*
Confidence 0.95 Prob < t 1.0000
-0.15 -0.05 0.00 0.05 0.10 0.15
Comparing Alt7 with Alt2
Difference 0.106770 t Ratio 4.371388
Std Err Dif 0.024425 DF 2048
Upper CL Dif 0.154671 Prob > |t| <.0001*
Lower CL Dif 0.058870 Prob > t <.0001*
Confidence 0.95 Prob < t 1.0000
-0.10 -0.05 0.00 0.05 0.10
Comparing Alt7 with Alt3
Difference 0.04000 t Ratio 1.637677
Std Err Dif 0.02442 DF 2048
Upper CL Dif 0.08790 Prob > |t| 0.1016
Lower CL Dif -0.00790 Prob > t 0.0508
Confidence 0.95 Prob < t 0.9492
-0.08 -0.04 0.00 0.04 0.08
Comparing Alt7 with Alt4
Difference 0.131984 t Ratio 5.403698
Std Err Dif 0.024425 DF 2048
Upper CL Dif 0.179885 Prob > |t| <.0001*
Lower CL Dif 0.084084 Prob > t <.0001*
Confidence 0.95 Prob < t 1.0000
-0.15 -0.05 0.00 0.05 0.10 0.15
Comparing Alt7 with Alt5
Difference 0.01673 t Ratio 0.685021
Std Err Dif 0.02442 DF 2048
Upper CL Dif 0.06463 Prob > |t| 0.4934
Lower CL Dif -0.03117 Prob > t 0.2467
Confidence 0.95 Prob < t 0.7533
-0.08 -0.04 0.00 0.04 0.08
Comparing Alt7 with Alt6
Difference 0.091907 t Ratio 3.762835
Std Err Dif 0.024425 DF 2048
Upper CL Dif 0.139807 Prob > |t| 0.0002*
Lower CL Dif 0.044007 Prob > t <.0001*
Confidence 0.95 Prob < t 0.9999
-0.10 -0.05 0.00 0.05 0.10

APPENDIX F. THE REGRESSION MODELS FOR MOE 2 AND MOE 3

The following figure depicts the main effects linear regression model fit on the time to complete the run (MOE 2).

Response Mean(Time)

Actual by Predicted Plot



Summary of Fit

RSquare	0.255266
RSquare Adj	0.24043
Root Mean Square Error	8943.051
Mean of Response	57479.54
Observations (or Sum Wgts)	257

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mean(UAVSnrClsRng)	-3.150734	0.481308	-6.55	<.0001*
Mean(UAVTimeBetwDet)	9.1757822	2.02632	4.53	<.0001*
Mean(UAVClsProb)	-14043.33	4303.234	-3.26	0.0013*
Mean(UAVSnrDetToClassRatio)	-5081.149	1908.408	-2.66	0.0083*
Mean(UCAVTimeBetwDet)	4.7989412	2.026308	2.37	0.0186*

The following figure depicts the main effects logistic regression model fit on the probability that red reaches the goal (MOE 3).

Nominal Logistic Fit for RedReachGoal

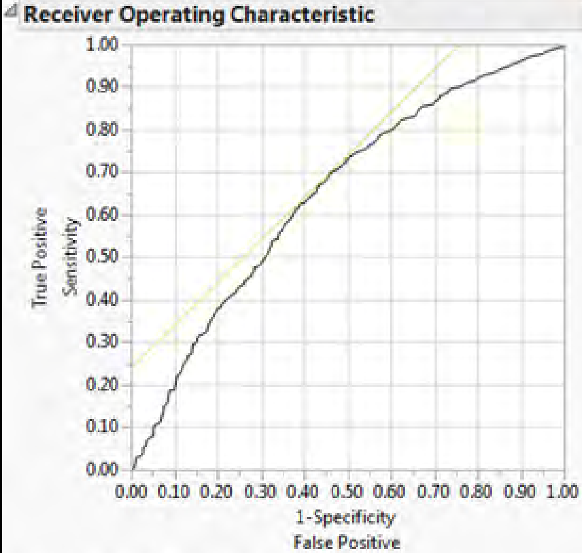
Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	1860.065	21	3720.13	<.0001*
Full	41864.101			
Reduced	43724.166			

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	-0.3397817	0.20677	2.70	0.1003
F16SnrClsRng	3.11741e-5	7.688e-6	16.44	<.0001*
F16TimeBetwDet	-0.0002004	0.0000438	20.93	<.0001*
F16ClsProb	0.3481061	0.1020107	11.64	0.0006*
F16WpnRng	-5.0174e-5	7.6422e-6	43.10	<.0001*
UCAVSnrDetToClassRatio	0.15402064	0.0303916	25.68	<.0001*
UCAVSnrClsRng	-2.6319e-5	7.8215e-6	11.32	0.0008*
UCAVTimeBetwDet	0.00010039	0.0000284	12.49	0.0004*
UCAVClsProb	-0.3278716	0.0633011	26.83	<.0001*
UCAVWpnRng	-0.0001292	1.5313e-5	71.22	<.0001*
UCAVSpd	-0.0009017	0.0002786	10.47	0.0012*
UAVSnrDetToClassRatio	0.39700852	0.0303812	170.76	<.0001*
UAVSnrClsRng	0.00030344	7.8344e-6	1500.1	<.0001*
UAVTimeBetwDet	-0.0009587	3.1583e-5	921.49	<.0001*
UAVClsProb	1.72127348	0.0689618	622.99	<.0001*
TerroristDetToClassRatio	0.23725455	0.0303494	61.11	<.0001*
TerroristClsRng	-0.0001743	5.1034e-5	11.66	0.0006*
TerroristTimeBetwDet	0.0003616	0.0000767	22.22	<.0001*
TerroristClsProb	0.27859353	0.0764122	13.29	0.0003*
PartNumber	0.03115441	0.005932	27.58	<.0001*
PartDetToClassRatio	0.29842842	0.0305079	95.69	<.0001*
PartComDelay	-0.0004041	7.6444e-5	27.95	<.0001*

Receiver Operating Characteristic



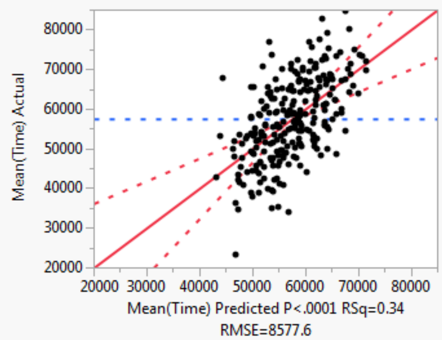
Using RedReachGoal='0' to be the positive level

AUC
0.65130

The following figure depicts the second order linear regression model fit on the time to complete the run (MOE 2).

Response Mean(Time)

Actual by Predicted Plot



Summary of Fit

RSquare	0.336719
RSquare Adj	0.301234
Root Mean Square Error	8577.636
Mean of Response	57479.54
Observations (or Sum Wgts)	257

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mean(UAVSnrClsRng)	-3.148172	0.461645	-6.82	<.0001*
Mean(UAVTimeBetwDet)	9.1750078	1.943533	4.72	<.0001*
Mean(UAVClsProb)	-14088.16	4127.46	-3.41	0.0008*
(Mean(F16TimeBetwDet)-450.008)*(Mean(PartClsRng)-2000.02)	-0.029845	0.00896	-3.33	0.0010*
Mean(UAVSnrDetToClassRatio)	-5123.473	1830.76	-2.80	0.0055*
(Mean(UCAVWpnRng)-4000.03)*(Mean(TerroristClsRng)-1000.02)	-0.013571	0.005235	-2.59	0.0101*
(Mean(UCAVSnrClsRng)-6125.06)*(Mean(UAVSnrDetToClassRatio)-1.50039)	4.5104047	1.819877	2.48	0.0139*
Mean(UCAVTimeBetwDet)	4.8051381	1.943537	2.47	0.0141*
Mean(F16TimeBetwDet)	4.4859	2.637553	1.70	0.0903
Mean(TerroristClsRng)	4.4156493	3.077131	1.43	0.1526
Mean(UCAVWpnRng)	1.269342	0.923206	1.37	0.1704
Mean(PartClsRng)	-1.695915	1.846362	-0.92	0.3593
Mean(UCAVSnrClsRng)	-0.417597	0.492397	-0.85	0.3972

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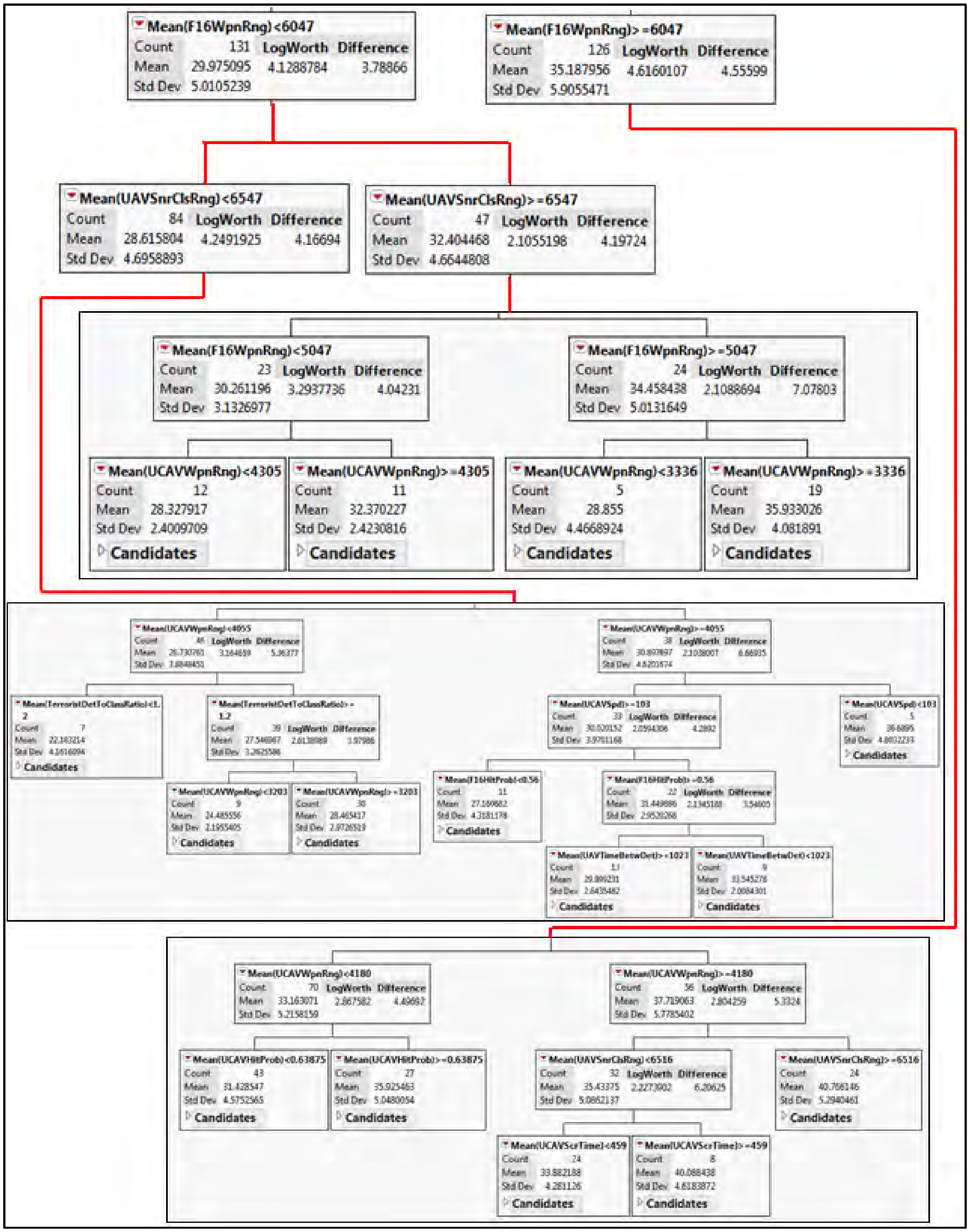
APPENDIX G. FIFTEEN SPLITS OF THE PARTITION TREE FOR THE MEAN NUMBER OF TERRORISTS KILLED



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