



**QUANTIFYING AND EVALUATING THE RESILIENCE OF OPTIMIZED
SPACE CONSTELLATIONS FOR FIRE DETECTION**

THESIS

Joseph J. Cuhran

Mathew K. Jenkins

Michael J. Walters

AFIT-ENV-MS-17-J-057

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government. This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

AFIT-ENV-MS-17-J-057

QUANTIFYING AND EVALUATING THE RESILIENCE OF OPTIMIZED SPACE
CONSTELLATIONS FOR FIRE DETECTION

THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the
Degree of Master of Science in Systems Engineering

Joseph J. Cuhran, BS

Matthew K. Jenkins, BS

Michael J. Walters, BS

June 2017

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

AFIT-ENV-MS-17-J-057

QUANTIFYING AND EVALUATING THE RESILIENCE OF OPTIMIZED SPACE
CONSTELLATIONS FOR FIRE DETECTION

Matthew K. Jenkins, BS

Joseph Cuhran, BS

Michael J. Walters, BS

Committee Membership:

John M. Colombi, Ph.D.
Chair

Mr. David Meyer
Member

Thomas C. Ford, Ph.D.
Member

Abstract

With greater emphasis on space operations (both offensive and defensive), greater numbers of spacecraft and space debris in various congested orbits, and greater reliance on space capabilities (communications, navigation and surveillance), resilience has become a priority across the space community. However, there is surprisingly limited extant research and analysis on methods for quantifying the resilience of neither a single satellite, nor an entire constellation. This thesis seeks to address this gap in knowledge and applies versions of a resilience equation on large solution sets of satellite constellations optimized for the fire detection mission. The resilience calculation is composed of the following probabilistic components: avoidance, robustness, recovery, and reconstitution. Research explores how to calculate these components and shows their relationship to total resilience of the constellation, and the relationships to numbers of satellites, numbers of orbital planes and overall acquisition cost. A new method for calculating resilience is proposed which is based solely on performance from simulated data and uses only the components of robustness and recovery. This thesis fills a missing body of knowledge on how to incorporate a quantitative measure of resiliency, together with optimization and simulated mission performance, while conducting space constellation design trades.

Acknowledgments

We would like to express our sincere appreciation for our faculty advisor, Dr. John Colombi, for his guidance, patience, and support throughout the course of this thesis effort. The flexibility to work with such a unique group and coursework format was certainly appreciated. We would also like to thank our supporting organization, the National Air and Space Intelligence Center, for the opportunity to complete our program through the use of the NASIC Scholarship Program.

Joseph J. Cuhran, Matthew K. Jenkins, and Michael J. Walters

Table of Contents

	Page
Abstract	iv
Table of Contents	vi
List of Figures	viii
List of Tables	xii
I. Introduction	13
Background.....	13
Problem Statement.....	14
Research Objective/Questions/Hypothesis.....	14
Research Focus	15
Methodology.....	16
Assumptions/Limitations.....	17
Implications	18
II. Literature Review	19
Defining Resilience	19
Quantifying Resilience	21
O/FUEGO Background	26
Avoidance of Space Debris	29
III. Methodology	31
Method 1 Methodology	31
Method 2 Methodology	50
IV. Analysis	57
Method 1 Analysis.....	58
Method 2 Analysis.....	72

Summary.....	100
V. Conclusions and Recommendations.....	101
Introduction of Research	101
Summary of Research Gap, Research Questions and Answers	102
Study Limitations	103
Recommendations for Action.....	104
Recommendations for Future Research.....	105
Significance of Research	106
References	116

List of Figures

	Page
Figure 1. Optimization Model.....	28
Figure 2. Relative Velocity vs. Orbit Altitude.....	36
Figure 3. Probability of Collision vs. Satellite Cross-Section Area	37
Figure 4. Probability of Collision vs. Varying Mission Life	38
Figure 5. Spatial Density of Debris vs. Altitude (Pisacane, 2008)	38
Figure 6. Approximate Spatial Density vs. Orbit Altitude	39
Figure 7. Probability of Collision vs. Altitude for Small Satellites	40
Figure 8. Probability of Collision vs. Altitude for Large Satellites	41
Figure 9. Probability of Avoidance vs. Altitude for Small Satellites	42
Figure 10. Probability of Avoidance vs. Altitude for Large Satellites	42
Figure 11. Identifying the Satellite That Would be Removed	45
Figure 12. Removing the Satellite From the Orbit Plane.....	46
Figure 13. Calculating Value Each Remaining Satellite Would Shift.....	47
Figure 14. Evenly Spaced Satellites In Orbit After Shifting	47
Figure 15. Gap Duration Report For Lowest 20% of Access Events	53
Figure 16. Gap Duration Report For Highest 24% of Access Events	53
Figure 17. Total Constellation Cost vs. Resilience for Method 1 Optimized Trial Solutions.....	63
Figure 18. Avoidance vs. Resilience for Method 1 Optimized Trial Solutions.....	64
Figure 19. Robustness vs. Resilience for Method 1 Optimized Trial Solutions.....	65
Figure 20. Recovery vs. Resilience for Method 1 Optimized Trial Solutions.....	65

Figure 21. Reconstitution vs. Resilience for Method 1 Optimized Trial Solutions.....	66
Figure 22. Total Number of Satellites vs. Resilience for Method 1 Optimized Trial Solutions.....	68
Figure 23. Total Number of Orbital Planes vs. Resilience for Method 1 Optimized Trial Solutions.....	68
Figure 24. Total Constellation Cost vs. Resilience for Method 2 Optimized Trial Solutions.....	75
Figure 25. Avoidance vs. Resilience for Method 2 Optimized Trial Solutions.....	76
Figure 26. Robustness vs. Resilience for Method 2 Optimized Trial Solutions.....	76
Figure 27. Recovery Metric vs. Resilience for Method 2 Optimized Trial Solutions	77
Figure 28. Reconstitution Metric vs. Resilience for Method 2 Optimized Trial Solutions	77
Figure 29. Total Number of Satellites in the Constellation vs. Resilience for	79
Figure 30. Total Number of Orbital Planes vs. Resilience for Method 2 Optimized Trial Solutions.....	79
Figure 31. Total Cost vs. Resilience for the Final Populations of all 13 Method 2 Trials	81
Figure 32. Total Cost vs. Resilience for Method 2 Trial Filtered Population Solutions ..	82
Figure 33. Avoidance vs. Resilience for Method 2 Trial Filtered Population Solutions..	83
Figure 34. Robustness vs. Resilience for Method 2 Trial Filtered Population Solutions.	84
Figure 35. Recovery vs. Resilience for Method 2 Trial Filtered Population Solutions....	84
Figure 36. Reconstitution vs. Resilience for Method 2 Trial Filtered Population Solutions	85
Figure 37. Total Cost vs. Avoidance for Method 2 Trial Filtered Population Solutions..	86

Figure 38. Total Cost vs. Robustness for Method 2 Trial Filtered Population Solutions.	87
Figure 39. Total Cost vs. Recovery for Method 2 Trial Filtered Population Solutions....	87
Figure 40. Total Cost vs. Reconstitution for Method 2 Trial Filtered Population Solutions	88
Figure 41. Total Satellites vs. Resilience for Method 2 Trial Filtered Population Solutions	89
Figure 42. Number of Planes vs. Resilience for Method 2 Trial Filtered Population Solutions.....	89
Figure 43. Total Cost vs. New Resilience for Method 2 Trial Final Population Solutions	91
Figure 44. Robustness vs. New Resilience for Method 2 Trial Final Population Solutions	92
Figure 45. Recovery vs. New Resilience for Method 2 Trial Final Population Solutions	93
Figure 46. Total Satellites vs. New Resilience for Method 2 Trial Final Population Solutions.....	94
Figure 47. Total Planes vs New Resilience for Method 2 Trial Final Population Solutions	94
Figure 48. Total Cost vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience	95
Figure 49. Robustness vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience	96
Figure 50. Recovery vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience	97

Figure 51. Total Cost vs. Revisit Time after Recovery for Method 2 Trial Final

Population Solutions above 0.95 New Resilience.....	98
---	----

List of Tables

Table 1. Key Parameter Output from the DISCO GA for Method 1 Optimized Trial Solutions.....	60
Table 2. Resilience Components for each Method 1 Optimized Trial Solution	62
Table 3. Total Number Satellites and Planes with the Total Cost and Resilience for Method 1 Optimized Trial Solutions.....	67
Table 4. Maximum Revisit Time for the Method 1 30-minute Scenario.....	70
Table 5. Maximum Revisit Time for the Method 1 24-hour Scenario	71
Table 6. Key Parameter Output From DISCO GA for Method 2 Optimized Trial Solutions.....	73
Table 7. Resilience Components for Each Method 2 Optimized Trial Solution	74
Table 8. Total Number Satellites and Planes with the Total Cost and Resilience for	78
Table 9. Solutions of Greater than 0.95 New Resilience with a Cost Under.....	99
Table 10. Method 1 Trials 1-18 Output Parameters - Satellite Type 1	108
Table 11. Method 1 Trials 1-18 Output Parameters (continued) - Satellite Type 2	109
Table 12. Method 1 Trials 1-18 Output Parameters (continued) - Satellite Type 3	110
Table 13. Method 1 Trials 1-18 Output Parameters (continued) - Launch Vehicles.....	111
Table 14. Method 2 Trials 1-13 Output Parameters - Satellite Type 1	112
Table 15. Method 2 Trials 1-13 Output Parameters (continued) - Satellite Type 2	113
Table 16. Method 2 Trials 1-13 Output Parameters (continued) - Satellite Type 3	114
Table 17. Method 2 Trials 1-13 Output Parameters (continued) - Launch Vehicles.....	115

QUANTIFYING AND EVALUATING THE RESILIENCE OF OPTIMIZED SPACE CONSTELLATIONS FOR FIRE DETECTION

I. Introduction

Background

“The National Security Space Strategy (NSSS) charts a path for the next decade to maintain and enhance the advantages derived from space while confronting the challenges of an evolving space environment. The NSSS seeks to address a strategic space environment that is increasingly congested with increasing amounts of space debris; contested by a growing range of foreign counterspace capabilities; and competitive as more and more countries and companies operate in space. Resilience is one way to address this more challenging space environment. The strategy notes that strengthening the resilience of our architectures can deny the benefits of an attack on our space infrastructure, as well as enable our ability to operate in a degraded space environment (Department of Defense, 2011).”

Resilience in space systems design has been a topic of much discussion in recent Department of Defense policies and research. The topic is fairly new and has a wide diversity of accepted definitions. There is a desire to begin designing space systems to be more resilient in a time of increasing threats. Quantifying resilience in space systems, though, is an area of little research. The DoD defines resilience for space systems as being composed of avoidability, robustness, reconstitution, and recovery (Department of Defense, 2011). In order to best assess the level of resilience to which a space system is designed, it is necessary to characterize and quantify the various qualities that attribute to resilience. When considering an entire constellation of satellites, the components of resilience can vary depending on the combination of various orbital design parameters for the many different satellites that make up the constellation.

Problem Statement

While some have proposed metrics for quantifying resilience, there is a lack of real application across large number of varying satellite constellation designs.

Research Objective/Questions/Hypothesis

Hypothesis.

Resilience values will vary for each of the solutions generated by the optimizer based on different combinations of orbit design parameters.

Objective.

This thesis seeks to quantify resilience for an entire satellite constellation to assess which constellation design solution is the most resilient among a group of optimized design solutions. The quantification of resilience is based on the four components defined by the DoD and the attempts of Boeing to quantify these components for space systems. Criteria for each of the four components will be defined in terms of a constellation of satellites, rather than the common examination of a single satellite. The four components will then be used to evaluate the resilience of multiple spacecraft constellations generated using the Disaggregated Integral System Concept Optimization (DISCO) tool. The results of the analysis will show which of the optimal disaggregated constellation solutions is the most resilient.

Research Questions.

- How can resilience be quantified for entire spacecraft constellation designs?
- How can resilience be used to evaluate possible optimized constellation design choices to choose the most resilient and cost-effective option?

Research Focus

Effort will initially be placed on defining resilience. There are many definitions for resilience, so emphasis will be placed on aggregating the various definitions and comparing and contrasting them. The goal of this comparison will be to yield a single, quantifiable definition for resilience that is applicable for spacecraft systems.

Once a definition for resilience is established, it will be necessary to determine how to quantitatively apply it to satellite constellations. Each orbital design element for a single satellite could affect the resilience value of the entire satellite constellation. Therefore, research will be conducted to examine which parameters will have the greatest impact on resilience and how they should be included in quantitatively evaluating the constellation design. For example, the altitude in which a satellite orbits the earth will have effect on the probability of it encountering space debris.

After a firm understanding of resilience, satellite constellations, and the threat environment is developed, focus will be directed towards creating multiple models of optimized satellite constellations. To create these models, research will be conducted on the efforts of previous AFIT students who used MATLAB and STK to construct optimized satellite constellations. The goal of this research will be to use the pre-existing optimization algorithms to create satellite constellations for which a resilience value can be assessed. Additional coding will be necessary to analyze the different components of resilience and will require a strong understanding of the optimization suite of code in order to effectively evaluate the multiple solutions.

Methodology

The methodology used will mostly be experimental. Initially, research will be performed to arrive at an acceptable definition of resilience as it relates to the design of space systems. Additional research will be done to find what methods others have used to quantify resilience. Depending on the results of this research, it may be necessary to develop a customized solution for the application of resilience to an entire satellite constellation. The case study will use FUEGO, a fire detection satellite constellation, and the thesis work from AFIT graduate Dr. Robert Thompson. In Thompson's dissertation research, a constellation optimization algorithm, DISCO, was created to generate optimized disaggregated constellation designs based on minimum performance and maximum cost requirements (Thompson, 2015). DISCO utilizes a genetic algorithm which usually produces slightly different results in the combinations of orbital parameters and satellite/plane numbers due to the nature of algorithm. DISCO will be run multiple times to generate several different constellation solutions using MATLAB and STK. The results of the multiple DISCO runs will be compiled for further analysis. Each result will be examined according to the chosen criteria for calculating resilience. Additional coding will be required to iteratively evaluate each constellation design solution to arrive at an overall resilience value. The resilience results for each of the solutions will be compared to assess the validity of the calculation methodology. Additional analysis may be performed to assess how resilience could be increased for these optimized solutions by the addition of extra satellites in order to further exceed the required performance requirements and the relationship of this change with the total cost of the constellations.

Assumptions/Limitations

Since resilience is still a developing systems engineering "-ility," assumptions were made about the correct definition of this concept for the area of research in this paper. Since the DoD defines resilience as being comprised of the components avoidability, robustness, reconstitution, and recovery, these four areas were utilized during research and attempts were made to quantify their value in regards to an entire satellite constellation. A key component of the research was using the disaggregated constellation optimizer (DISCO) tool created by Thompson (Thompson, 2015). The tool utilizes MATLAB and STK to iteratively create satellite constellations based on input criteria. Due to the nature of the optimization algorithm, the simulation can take on the order of 24 hours to run. In order to create enough solutions for proper analysis, the criteria for the genetic algorithm was decreased to shorten the run time by using a generation size of 50, a population size of 30, and a stall limit of 30 generations. For the orbital parameter value limits for the three satellite types, the same bounds were used as defined by Thompson in the DISCO tool (Thompson, 2015). The satellite mission analyzed in this research is the FUEGO constellation for fire detection as was originally used by Thompson for his DISCO tool.

For analyzing the space environment and its potential effect on satellite constellations, focus was placed on assessing the probability of collision with orbital debris based on the orbit, size, and lifetime of the satellite. Since FUEGO's mission is for fire detection, the threat of ASAT weapons was assumed too low for consideration. Additionally, hazards posed by solar particle events and galactic cosmic rays were assumed to be low. When considering the probability of avoidance, the satellite type with the lowest probability of avoidance is chosen and this satellite type is used for the remaining resilience calculations. The satellites are also assumed to be incapable of actively avoiding collisions with debris.

The quantification of robustness and recovery are based on change of performance, either for percent coverage or revisit time. One satellite is removed from any of the planes of the chosen satellite type based on the largest degradation in performance. The research only focuses on the change after removing one satellite. The remaining satellites in the plane from which the satellite was removed are re-phased to have equidistant spacing. The phasing of the other planes are not changed. Reconstitution is considered as the fractional component of the cost to launch one replacement satellite on the cheapest available launch vehicle compared to the total cost to design, build, and launch the entire constellation. The smaller the fraction of cost to replace the satellite, the larger the value for the reconstitution, since it was assumed to have a higher probability of being replaced. Time or responsiveness to launch a replacement satellite is a key factor in considering reconstitution due to the direct effect on mission performance. Time was not considered in this research because of the difficulty in quantifying it in the calculation and the unknown circumstances for different missions.

Implications

The research in this paper will further develop the application of resilience in the design of satellite constellations. Little research has been performed to assess the resilience of entire satellite constellations. The efforts in this paper will not only develop the quantification of resilience in relation to an entire satellite constellation, but will also show how resilience is affected by different constellation design configurations. The assessments made from this research could be useful for future space system acquisition considerations in order to evaluate the most cost effective and resilient design proposals.

II. Literature Review

Defining Resilience

Resilience is defined several different ways. Understanding the different definitions will help to resolve and narrow the focus for resilience in space specific systems. Resilience may never have one set definition that covers every aspect or every system type. By defining what resilience encompasses specific to the system being designed, the designer can make judgements on how ‘resilient’ that system must be in order to adequately meet the mission requirements.

Some example definitions for resilience are “(1) Resilience is the ability of a system to absorb external stresses (Haimes, 2016). (2) Resilience is a system’s capability to create foresight, to recognize, anticipate, and to defend against the changing shape of risk before adverse consequences occur (Haimes, 2016). (3) Resilience refers to the inherent ability and adaptive responses of systems that enable them to avoid potential losses (Haimes, 2016). (4) Resilience is the result of a system (i) preventing adverse consequences, (ii) minimizing adverse consequences, and (iii) recovering quickly from adverse consequences (Haimes, 2016).” Most applicably, one definition for resilience is “Resilience...is defined as the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks (Aven, 2011).” This definition encompasses characteristics important to spacecraft or constellations of spacecraft. There are going to be disruptions and threats to a spacecraft due to the harsh conditions in which it needs to operate. It is important for the system or system of systems to be able to accept some of these disruptions to a limit but if pushed beyond the limit, have the capability to withstand that disruption without major consequences. This can be either redundant subsystems on-board the spacecraft to maintain mission capabilities or it may mean extra coverage from multiple satellites in the case

that one is unable to perform the mission so that a loss of service or overall capability from that constellation is not compromised. It may also mean rapid response capabilities for launching an additional satellite to fill the void. This would all be system dependent and can be addressed later when discussing the design and intent of a satellite constellation.

Resilience is often compared to or listed as a subset or parent of a variety of “ilities.” By inspecting some of the “ilities” that bear strong similarities to resilience, a better understanding or more formal definition can be realized. Richards et al. developed a formal definition for survivability with respect to the engineering system domain. They define survivability as the “ability of a given system to reduce the effect a disturbance has on its mission by either reducing the probability or magnitude of the disturbance or by being able maintain a minimum level of performance during or after the disturbance (Richards, 2007)”. This definition for survivability has many parallels to that which one would expect for resilience.

The researchers have further divided survivability into two types: passive and active. Passive survivability refers to a system’s ability to innately maintain performance during or after a disturbance. Methods for instilling passive stability include hardness, stealth, redundancy, and diversity (Richards, 2007). A potential difficulty for passive stability is that it would likely require advanced knowledge of a potential disturbance so that the system can be designed to counteract that disturbance. Unfortunately, many disturbances cannot be accurately predicted to occur over the course of a system’s lifecycle; leaving the system either unnecessarily over-designed or defenseless against a threat event.

Active survivability refers to a system’s ability to react to and mitigate a given disturbance. Methods of active survivability include regeneration, evolution, relocation, and retaliation (Richards, 2007). While still not guaranteeing success, instilling active survivability

in a system's design enables it to appropriately respond to and attempt to recover from a disturbance. Since this type of survivability is active, less knowledge is required beforehand of potential threats and the system will be more capable of responding on the fly.

Vulnerability and capability are more examples of 'ilities' commonly associated with resilience. Resilience is a state of the system composed of several vectors of substates which may include components such as vulnerability or capability (Haimes, 2016). The ability for a system to react to one specific failure more than another may not make it resilient as a whole but just to that one failure mode (Haimes, 2016). Imposing features on the system that can account for more than one failure mode or a larger, overarching set of failures creates a resilient system (Haimes, 2016). Recovery appears to be the key component when measuring resilience. Redundancy and robustness may also be vectors of resilience (Haimes, 2016). A system's resilience may be the set of outputs that result from a set of inputs to the system (Haimes, 2016).

Quantifying Resilience

Despite being a topic of much discussion, only a few attempts have been made to actually quantify resilience in spacecraft, with widely varying approaches. The research on quantification proved to be difficult since the methods being used were so different. This section summarizes the research process for arriving at the final methodology used in this paper for quantifying resilience.

One method that has been proposed is a complex mathematical process of continuous time Markov chains (Luo, Okamura, & Dohi, 2013). In this work, the authors propose there are two different states for a system: normal and change states. The two states are characterized by mathematical functions and several mathematical relationships are used to arrive at a final equation. Since the basis of this approach relied on examining time, it would be very difficult to

apply this methodology. Time is a large uncertainty for many of the instances in which resilience would be considered. In very specific cases where much testing has been performed on known systems, this method could be possible, but in the case of more random cases, it appears too specific to apply.

Another group examined resilience of the entire space architecture through a operational viewpoint (Zaerpoor, Ghashghai, Thai, & Kim, 2013). The authors created a tool suite to perform the analysis that captured the system architecture as a large system of communicating nodes starting with the source and going to the end destination. The tool attempted to find the ways to most affect the performance of the system for the cheapest cost, since the analysis was mainly concerned with adversarial threats and assumed the adversary would choose this approach. Overall, the methodology in this paper was unique and had some similarities to this research's goal of characterizing the resilience of a constellation of satellites. Each satellite in the constellation could be viewed as a node and depending on the different orbits of the satellites, the performance value of each one could vary and have more of an effect if removed from use. As for the underlying mathematics in the tool suite developed in the paper, it was not the proper fit for the analysis in this paper since it was focused on a communications mission where the data path was the key measure for mission performance.

Work has also been done to compare candidate architectures by quantifying their performance, resilience, and cost (Trussell, Bellagamba, Maguire, & Yung). The authors propose an analytical framework to find the best architecture that "provides the most capability and resilience consistent with cost that can be incurred (Trussell, Bellagamba, Maguire, & Yung)". The research begins by defending the use of disaggregation to help reduce costs, an emphasis in this paper by using Thompson's optimization code (Thompson, 2015). The paper continues by

quantifying resilience in terms of resources and plotting the capability of the architecture as one after another asset is lost. The authors also describe a method called "hostile action resilience (Trussell, Bellagamba, Maguire, & Yung)." This method incorporates assumptions of a supposed adversary and the number of possible threats that could negatively affect the architecture in question. The architecture design creates an excess of systems to produce an abundance of initial capability with some of the excess systems in special orbits that are less likely to encounter threats and would display clear warnings if another object was closing in on the system. The paper provides several interesting ideas, but focusing much on adversary threats, which is a large uncertainty in this educational environment. It does support the idea of disaggregation and the notion of measuring the capability of the entire architecture as individual elements are removed, which is a large part of the methodology used in this paper.

In research performed by Northrop Grumman, "an intuitive and measurable approach that avoids subjective measures" was explored (Edlund, 2013). The paper focuses on adversary threats since "these effects are the least understood and likely the most detrimental to DoD systems (Edlund, 2013)." Two methods of analysis are proposed: analytic modeling and deterministic methods. Analytic modeling is quickly disregarded due to a lack of intuitive and measurable function that result in subjective assessments (Edlund, 2013). The paper defends that subjective approaches are not the right approach for creating a unified understanding of the topic for the DoD community for the application to space architectures (Edlund, 2013). The deterministic method utilizes a system engineering discipline to focus on the space system breakpoints, i.e., the areas in which a threat system can successfully deny the system from performing it's required capability (Edlund, 2013). Some of the metrics used are: "the type of system, the cost of the system, and the reliability of the system (Edlund, 2013)." The paper also

describes how to apply this approach for characterizing threat systems to help identify threats of particular concern. It is possible to compare the characterizations of the system in question and possible adversary threats to determine the investment value, since it might not be wise to invest in an extremely expensive system that can be neutralized by a low cost, highly available threat. The paper presents the conclusion that the most pressing threat to space-based systems is the ground network since ground based threats are more readily available and low cost. Once the ground threat is considered, the paper proposes that the next focus should be placed on making the satellites as affordable as possible and to distribute the satellites in multiple orbits.

The Northrop Grumman research focused strongly on adversary threats, which again is a large uncertainty for academia. The paper criticized subjective quantification techniques and presented a method rooted in systems engineering and knowledge of threat system capabilities. The methodology utilized in the Northrop Grumman paper does not suit the research in this paper, but presented a very diverse viewpoint of quantifying resilience.

Boeing presents a simple, single equation to quantify resilience in the final reference discovered during preliminary research (Burch, 2013). Boeing takes the four measures of resilience defined by the U.S. DoD Fact Sheet (Department of Defense, 2011) and uses them to build an equation that encapsulates the overall resilience of the system. This equation is shown below in Equation 1.

$$R = R_{AV} + (1 - R_{AV})R_{RO} + (1 - R_{AV})(1 - R_{RO})R_{RV} + (1 - R_{AV})(1 - R_{RO})(1 - R_{RV})R_{RC} \quad (1)$$

Resilience

Robustness Metric:
Capability Retained

Recovery Metric:
Capability Recovered and Recovery Time

Reconstitution Metric:
Replacement metric based upon responsiveness

The first measure, avoidance, characterizes the probability that the system will avoid the threat being considered. The remaining measures then account for the current capability of the system. In the case of an imaging satellite, the capability would be the amount of coverage provided by the satellite or the maximum duration of imaging possible for each orbit. Once avoidance is considered or how likely the threat is to occur, the amount of capability that is retained after the threat occurs, robustness, is accounted for. The system suffers the threat, but it is possible the satellite can recover some of the lost capability over a period of time. The time could be short as in the next time it is over a ground site and a problem is identified and then later corrected during another pass. The recovery time could be longer as in the case of having to perform series of tests to determine the best method to restore some or all of the lost capability. Finally, whatever capability is not recovered over time can be restored through replacement that is encapsulated in the reconstitution measure. Reconstitution could be through the launch of a replacement satellite. The author notes that reconstitution is distinguished from recovery in that it is a much longer time period and recovery is usually contained within the system.

The paper continues to describe that each threat must have its own unique equation to calculate resilience (Burch, 2013). It addresses the DoD's concern with "a wide range of scenarios, conditions, and threats" by proposing two ways of culminating a group of resilience values calculated for multiple threats. Either the values can be combined into a multiple-threat resilience value or into a full-spectrum resilience value (Burch, 2013). The multi-threat resilience value shown in Equation 2, where R_1 represents the initial threat and R_n represents the total number of threats, accounts for the decrease of overall capability of the system due to an individual threat (Burch, 2013). The multi-threat scenario accounts for a coordinated attack of several threats occurring simultaneously (Edlund, 2013). As for the full-spectrum resilience

value shown in Equation 3, each threat, R_n , is considered individually along with the probability of the threat occurring, P_n (Burch, 2013).

$$R_s = R_1 - \sum_{n=2}^N (1 - R_n) \quad (2)$$

$$R_{FS} = 1 - \sum_{n=1}^N (1 - R_n)P_n \quad (3)$$

The approach by Boeing was the most intuitive method discovered that adhered to the principles of resilience proposed by the U.S. DoD. The equation provides a simple format to explore more interesting definitions of the individual measures encapsulated inside. There was a lot of flexibility in how to define these measures. As for considering multiple on-orbit threats, the initial goal was to focus on non-adversary threats. The main threat became collision with space debris since it would help create a disparity in the different solutions based on satellite size and orbit design.

O/FUEGO Background

The Fire Urgency Estimation from Geosynchronous Orbit (FUEGO) satellite constellation mission utilized a Walker constellation consisting of 12 satellites at an altitude of 700 km and an inclination of 47.5 degrees using pushbroom sensors (D. Escorial, 2003). The requirements for the system were derived from the European Space Agency (ESA) and necessitate two bands of latitude both north and south of the equator falling between ± 37 and 46 degrees (D. Escorial, 2003). Optimal revisit time is on the order of 25 minutes with a fire outbreak detection time of less than 15 minutes on average (D. Escorial, 2003). The minimum size of the detected fire is 50 m^2 which will be geolocated within 300m of the fire at nadir and 500 m off-nadir with a signal-to-noise ratio (SNR) less than 100 (D. Escorial, 2003). All of these

requirements are user driven and are aimed at minimizing the cost while also accomplishing the desired revisit rate. (D. Escorial, 2003)

The Optimized FUEGO (O/FUEGO) solution was developed using the DISCO methodology and is defined in the Thompson's dissertation where the FUEGO satellite constellation was optimized based on cost and subject to different parameters such as coverage, sensor performance, and launch vehicle capacity. The full derivation of the optimization of the disaggregated, multi-orbit solution is not the focus of this research, so only a brief overview of the process will be covered. For further background on the development of the optimization routine, please refer to Thompson's dissertation. An adaptation of this method and code will be discussed in the Methodology section of this thesis where the problem set is expanded to include the calculation of resilience. (Thompson, 2015)

The optimization model, seen in Figure 1, uses a genetic algorithm running in MATLAB to optimize the various orbital parameters of the constellation by minimizing the cost model while subjecting the algorithm to the launch vehicle lift capacity, sensor performance (SNR), and coverage. This information was used to calculate the orbits which were sent to System Toolkit (STK) where a scenario was generated. A report was produced by STK with information such as the coverage in order to verify the orbit solution. This information was fed iteratively back into the genetic algorithm which ran several times in order to find many locally optimal solutions. This algorithm was run several times in order to find a more globally optimal solution (Colombi, et al., 2012).

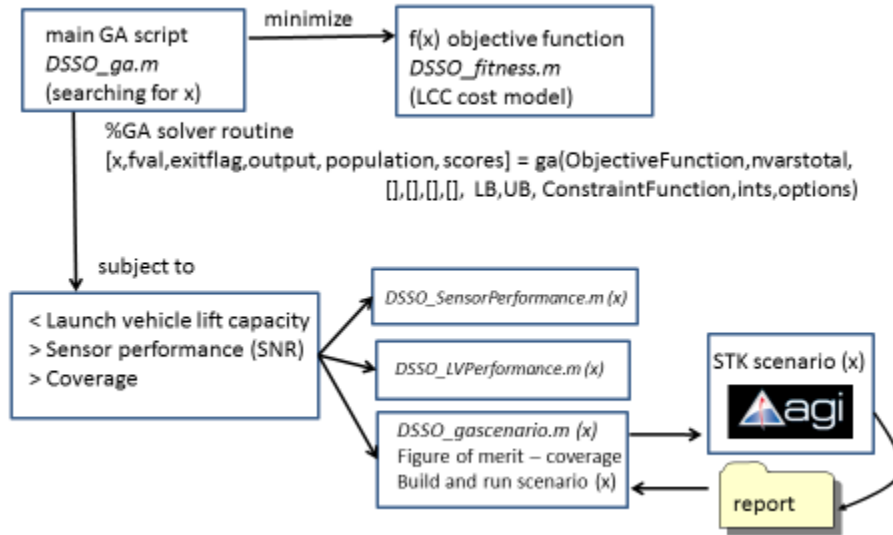


Figure 1. Optimization Model

The O/FUEGO constellation is a good example to use when researching resilience. Since so many different solutions are generated in order to optimize the constellation based on cost, the resilience of each of those constellations can be tested to determine if there is a correlation between the optimal (cheapest) solution and the resilience. Is it truly the best idea to use the cheapest constellation design if a slightly larger design option can be used to achieve higher resilience and potentially save money over time? The O/FUEGO constellation highlights the fact that small satellite designs are becoming a more prominent way of solving spacecraft mission problems. However, Thompson's algorithm also accounts for solutions of larger satellites as well which truly allows us to test whether fewer smaller satellites are more or less resilient than multiple orbits filled with several smaller satellites. While redundancy and additional capability can be built onto a larger satellite, smaller satellites may actually be a more resilient option. Small satellites are less susceptible to collision with space debris due to their smaller cross-sectional area. Additionally, since more small satellites can be launched on a

launch vehicle, the loss of one of many small satellites may be less detrimental to the constellation than the loss of one large satellite.

Avoidance of Space Debris

Potential spacecraft collisions with orbital debris is an important concern for those planning spacecraft missions. There are two types of orbital debris to be considered, man-made and natural, with man-made debris consisting of objects from spacecraft operations and natural debris including micrometeorites and asteroid particles (Wertz, Everett, & Puschell, 2011).

There have been many examples of spacecraft damage that can result from impacts with space debris throughout the history of space exploration. For example in 1996, a French spacecraft, *Cerise*, collided with a spent third stage from an Ariane rocket causing serious damage to the spacecraft (Pisacane, 2008). Additionally, throughout its mission history the space shuttle has had its windows, radiators, and other modules damaged by impacts from micro-meteoroid debris (Pisacane, 2008). The first collision between two satellites occurred in 2009 between an inactive Russian communications satellite, *Cosmos 2251*, and an active communications satellite, *Iridium 33*, owned by a US based corporation, Iridium Satellite LLC (Weeden, 2010). This collision added 2,000 pieces of debris 10 cm in diameter or larger and thousands more pieces of debris of smaller diameter (Weeden, 2010). The *Iridium 33* incident demonstrates not only the dangers of debris collisions but also shows that the problem is self-feeding; more debris increases the chances of collision and more collisions increase the quantity of space debris.

According to Wertz, Everett, and Puschell there are two main reasons for concern regarding space debris; spacecraft collisions with space debris are likely to occur at high velocity and it is impossible to detect and monitor small debris objects (10 cm LEO and 1 m for GEO).

For these reasons it is best to attempt to mitigate the occurrence of collision by identifying and selecting orbits with lower densities of orbital debris. To do this it is necessary to model the space debris environment. Pisacane notes two models for simulating the debris environment: NASA Orbit Debris Engineering Model (ORDEM) and the ESA Meteoroid and Space Debris Terrestrial Environmental Reference Model (MASTER). Given spacecraft orbital parameters, ORDEM provides tables and plots of the average speed and the average mass flux as a function of particle diameter for debris between 10 μm and 10 m between altitudes of 200 and 2000 km (Pisacane, 2008). Given information regarding an orbiting spacecraft, MASTER provides a meteoroid and debris model providing flux values for debris 1 μm and larger at altitudes beyond geostationary (Pisacane, 2008).

III. Methodology

The methodology of the research consisted of two different approaches based on how the optimized solutions were created and the manner in which the performance of the solutions was used to calculate the overall resilience. Method 1 was the initial approach that consisted of using Thompson's original DISCO code to produce optimized solutions based on the performance criteria of total percent coverage. When measuring changes in performance, the difference in total percent coverage is used. Method 2 changes the performance constraint of the optimizer to be the maximum revisit time. When measuring the changes in performance for this method, the percent change from the original revisit time is used. The following chapter explains the details of how these two approaches were used to generate the constellation solutions and how the overall resilience value was calculated.

Method 1 Methodology

The Method 1 approach utilized the original DISCO code for creating optimized solutions for the FUEGO constellation requirements. The code used the performance constraint of total percent coverage for determining whether a solution met the minimum performance requirement for a 30-minute scenario time. In order to calculate resilience, the following components were calculated: avoidance, robustness, recovery, and reconstitution. The following section describes how these components were calculated and applied for the Method 1 solution set.

Adapting Thompson's DISCO Code.

Thompson's code for the optimization of the FUEGO constellation was used. The code included larger pushbroom satellites, small pushbroom satellites, and small whiskbroom satellites. It also analyzed the space launch vehicle lift capacity, the SNR of the sensors on the

satellites, and the percent coverage that orbit can achieve, as well as a model to minimize the cost of everything, including the cost of the launch vehicles. Based on the constraints set forth in Boeing's equation for resilience, the parameters of the satellite constellations will be evaluated and compared in order to come up with a comprehensive view of the constellation sets. The idea behind evaluating all of the generated solutions is to understand if there is a trend between resilience and the 'optimal' lower cost options.

The genetic algorithm was run with 30 populations and 50 generations and with a stall limit of 30 generations; where the algorithm would stop generating solutions if the score of the solution was within a given tolerance of the previous best solution. If the score tolerance was never met, the algorithm would run to the full 50 generations. This provided a wide swath of solutions on which to test resilience. Then, 18 trials of the optimizer were run in order to find a 'globally' optimal solution as well as many local optima. The correlation between the resilience of each solution and cost was measured in order to understand if optimal solutions at the minimal cost were also the most resilient solutions.

Thompson's research included the launch vehicle lift capacity based on the total weight of the satellites needed to populate the various orbit solutions. This process was simplified to only consider the total lift capacity of the four different space launch vehicles, the Mintoaur IV, Falcon 9, Atlas V, and Delta IV heavy and the total mass of the required satellites. These different vehicles have different lift capacities. Based on the optimal cost, the total weight needed to be lifted into space, and the total number of planes, some combination of these launch vehicles was chosen to launch the satellites. The code does not account for partial satellites fitting onto individual space launch vehicles and was ultimately simplified to find a total lift capacity of the launch vehicle combination in order to lift the total calculated weight of satellites

populating the orbit. In order to calculate the reconstitution portion of the resilience equation, it was necessary to inspect unused lift capacity of the launch vehicles. Additional, redundant satellites could then be carried into orbit to enter a sleep mode in the case that one of the other satellites in the orbit fails. Since the scope of the research was constrained to the resilience of the optimized solutions and not the optimization itself, the existing capabilities of the optimizer were used. This also held true for the calculation of the cost model used to optimize solutions; although some costs have likely changed since Thompson's research, accounting for this fell outside of the scope of this research. Since the lift capacity for the launch vehicle requirement did not consider launch restrictions such as volume or number of whole satellites per vehicle, the metric of unused lift capacity was not used in order to measure reconstitution or for the idea of the additional spare satellites being launched.

A function was added that incorporates an adapted version of Boeing's equation for resilience. The function takes the resulting optimal trajectories and uses the information about the number of satellites in each orbit, the orbital parameters themselves, and the resulting changes in coverages by manipulating the orbit. If a satellite's functionality was eliminated, the coverage of the constellation would be effected and it was important to determine that resulting change in coverage. Calculations were made to assess the amount of coverage recuperated if the remaining satellites in a given orbit were repositioned around the orbit evenly. This resultant value feeds into the resilience equation.

Finally, there was one additional satellite in each orbit that could be brought out of its inert mode to begin actively contributing to the mission of the constellation. This was used to determine a value for reconstitution. All of these values will be logged by the function and then plotted in order to make the correlations between optimal solutions and their resulting resilience.

Applying the Resilience Equation.

In order to assess the resilience of a constellation design, it was necessary to adapt the four components of resilience that Boeing applied for a single satellite for the case of an entire constellation of satellites (Burch, 2013). Certain assumptions and simplifications were made in order to create a manageable method for characterizing the resilience of proposed constellation solutions. This section explains the approach used for each resilience measure. The following equation, taken from (Burch, 2013), shows the complete resilience equation and defines the variables for each measure.

$$R = R_{AV} + (1 - R_{AV})R_{RO} + (1 - R_{AV})(1 - R_{RO})R_{RV} + (1 - R_{AV})(1 - R_{RO})(1 - R_{RV})R_{RC} \quad (4)$$

Where,

R = *Resiliency*

R_{AV} = *Probability of Avoidance*

R_{RO} = *Robustness*

R_{RV} = *Recovery*

R_{RC} = *Reconstitution*

Avoidance.

To quantify the probability of avoidance, R_{AV} , focus was directed at the hazard posed by the space environment. For this it was important to determine the dangers of collisions with space debris. It was assumed that the satellites in a given constellation would be passive and not actively avoiding debris. Analysis was modeled after Wertz, Evererett, & Puschell who used the kinetic theory of gases to assess the probability of debris impacting a spacecraft (2011).

$$P_C = 1 - e^{(-SPD \cdot AC \cdot T \cdot VREL)} \quad (5)$$

Where,

SPD = spatial density of the debris (number/km³)

AC = cross-section area of the satellite (km²)

T = satellite mission life (sec)

$VREL$ = relative velocity between satellite and debris (km/sec²)

Wertz, Everett, & Puschell lists the average relative velocity between orbiting objects in LEO as being between 9 and 10 km/s and GEO as being between 0 and 2.5 km/s (2011). To approximate the $VREL$ term a constant value of 9.5 km/s was used for orbits up to and including an altitude of 1,500 km. To account for altitudes greater then LEO a linear function was used for orbits greater than 1,500 km up to 2,500 km. For orbits at an altitude greater the 2,500 km, $VREL$ was set to 1.25 km/s. Equation 6 shows the resultant functions used to calculate $VREL$ based on altitude.

$$VREL = \begin{cases} 9.5, & 0 \leq x \leq 1500 \\ (-0.00825)x + 21.875, & 1500 < x \leq 2500 \\ 1.25, & 2500 < x \end{cases} \quad (6)$$

Where,

x = orbit altitude (km)

Plotting $VREL$ as a function of altitude yields the plot shown in Figure 2.

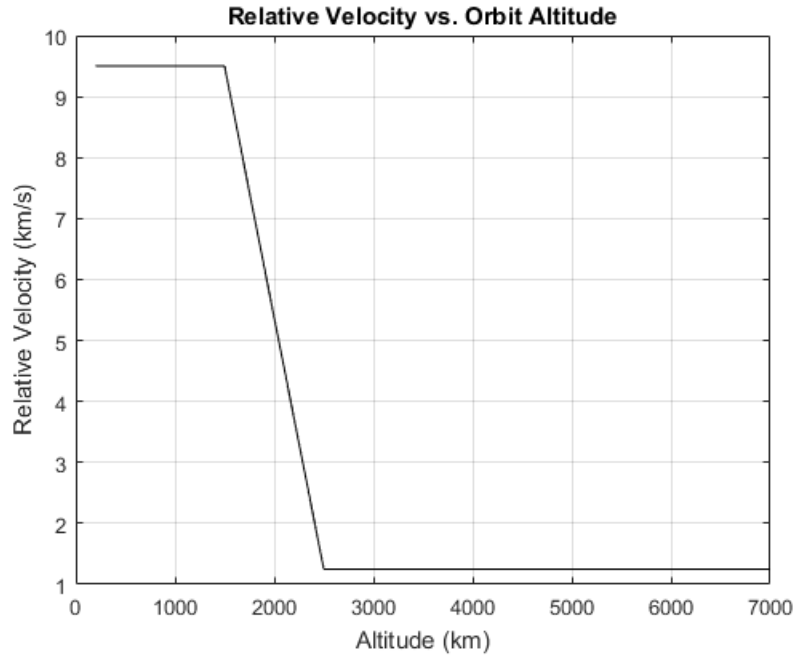


Figure 2. Relative Velocity vs. Orbit Altitude

The cross-section area of the satellite, AC , was approximated based on the size of the satellites. Small satellites were assumed to be the size of a 27U (3U x 3U x 3U cube) satellite. Assuming 1U is equal to 10 cm, this gave a cross-section area of 0.09 m^2 . The cross-section area for the large satellites, 2.87 m^2 , was estimated based on the sizing for the Ikonos-2 satellite which has a body size of $1.83 \text{ m} \times 1.57 \text{ m}$ (Ikonos-2, 2017). The Ikonos-2 spacecraft was selected because it is a commercial Earth imaging satellite which parallels the remote sensing mission of the FUEGO satellites (Ikonos-2, 2017). Figure 3 shows the probability of satellite collision vs. a varying satellite cross-section area with the other variables held constant (orbit altitude at 1,800 km and satellite life at 5 years). As would be expected, probability of collision with space debris increases with satellite cross-section area. The nonlinear relationship between AC and P_c shown in Equation 7 was found by fitting a 2nd order polynomial to the sample data. The R^2 value for this equation is 1.0.

$$P_c = -4.6199 \cdot AC^2 + 37.59 \cdot AC + 0.037 \quad (7)$$

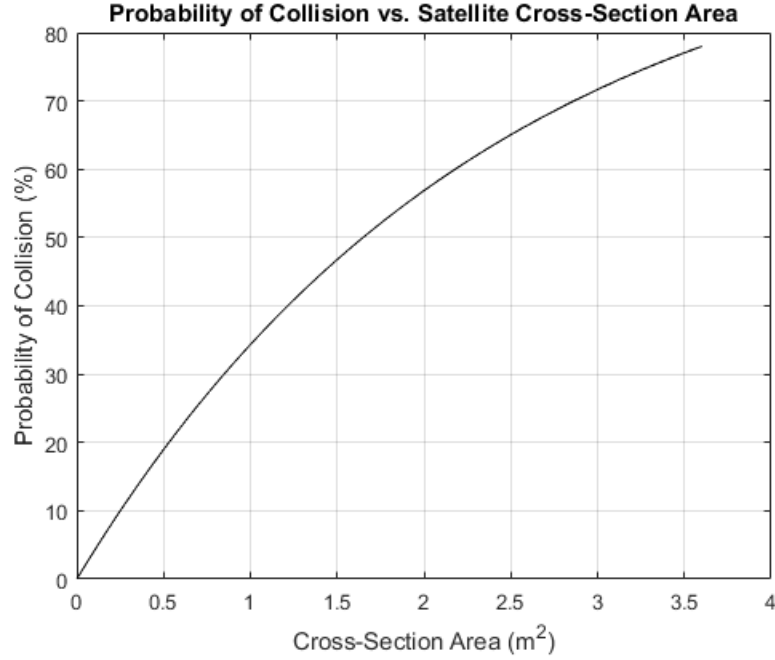


Figure 3. Probability of Collision vs. Satellite Cross-Section Area

The expected mission life of a given satellite, T , was set to 5 years based on FUEGO mission requirements. Figure 4 shows the relationship between T and P_c with all other variables held constant (orbit altitude equal to 1,800 km, small satellite size at 0.09 m²). As would be expected the behavior seen is very similar to that for satellite cross-section area. The relationship between T and P_c described by Equation 8 was found by fitting a 2nd order polynomial to the sample data. The R^2 value for this equation is 1.0.

$$P_c = -0.0028 \cdot T^2 + 0.7565 \cdot T + 0.0003 \quad (8)$$

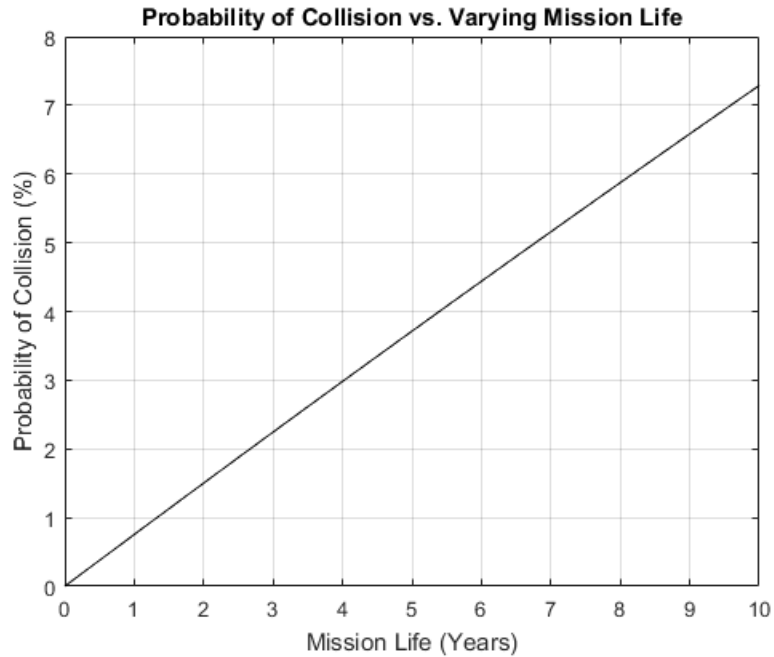


Figure 4. Probability of Collision vs. Varying Mission Life

Values for spatial density of debris and meteoroids with respect to altitude were modeled from the ESA MASTER plot shown in Figure 5. To maximize the probability of collision, the spatial density data for objects greater than 1 mm in diameter was emulated.

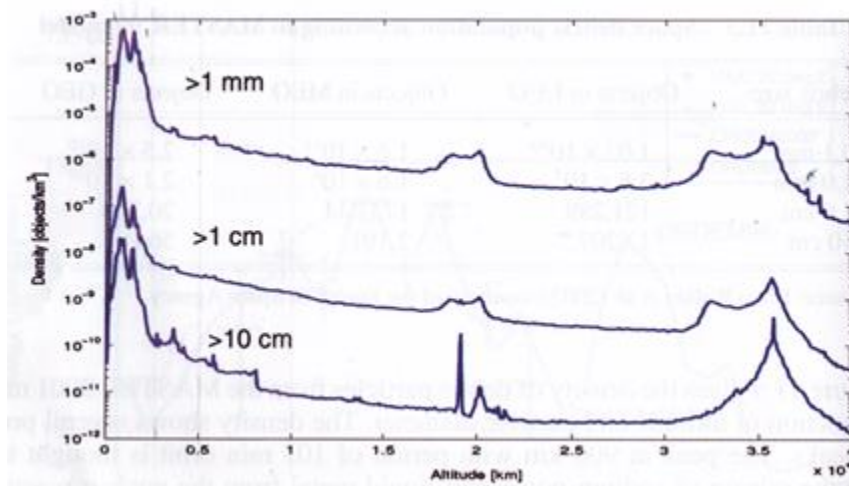


Figure 5. Spatial Density of Debris vs. Altitude (Pisacane, 2008)

This replication was performed in MATLAB by creating a series of piecewise linear and non-linear segments shown below in Equation 9. The bounds for these segments was approximated based on the data in Figure 5.

$$SPD = \begin{cases} x \cdot 1.1999E - 06, & 0 \leq x \leq 416.7 \\ (-x \cdot 1.08017E - 06) + 0.000950108, & 416.7 < x \leq 833.3 \\ (x \cdot 4.79962E - 07) - 0.000349952, & 833.3 < x \leq 1666.7 \\ (-x \cdot 5.28021E - 07) + 0.00133005, & 1666.7 < x \leq 2500 \\ -0.0000064921 \cdot \log(x) + 0.000060628, & 2500 < x \end{cases} \quad (9)$$

Where,

$$x = \text{orbit altitude (km)}$$

Plotting this data in MATLAB yields the results shown below in Figure 6.

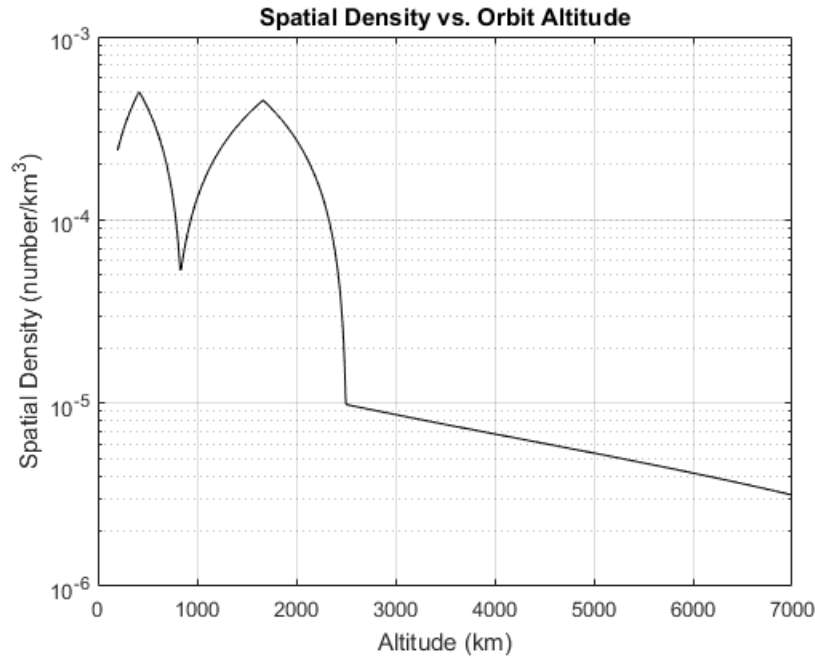


Figure 6. Approximate Spatial Density vs. Orbit Altitude

For the FUEGO constellations, both T and AC will be constant, for a given satellite type, and SPD and $VREL$ will vary based on orbit altitude. Therefore, P_c can be directly calculated based on both satellite type and orbit altitude. For the FUEGO constellation, small satellites are bounded between an orbit altitude range of 200 km – 7,000 km and large satellites are bounded

between 200km – 2,000 km. Figures 7 and 8 show varying P_c across the operational orbit altitude for both small and large satellites. For small satellites, the maximum P_c , 6.5%, is found at an altitude of 420 km. A second local maxima, P_c equal to 5.1%, is found at 1,665 km. For large satellites, these two maximum P_c values are found at the same two altitudes and are 88.2% and 80.9% for 420 km and 1,665 km respectively.

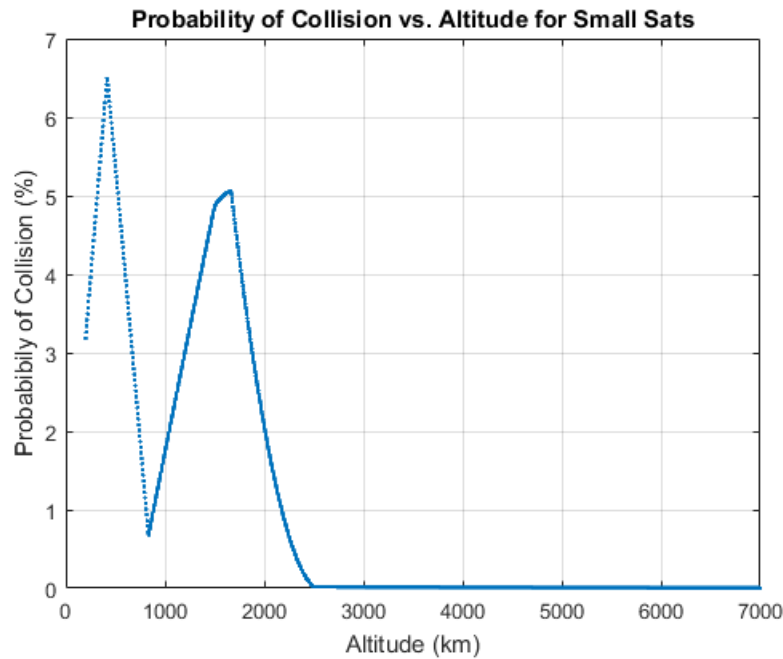


Figure 7. Probability of Collision vs. Altitude for Small Satellites

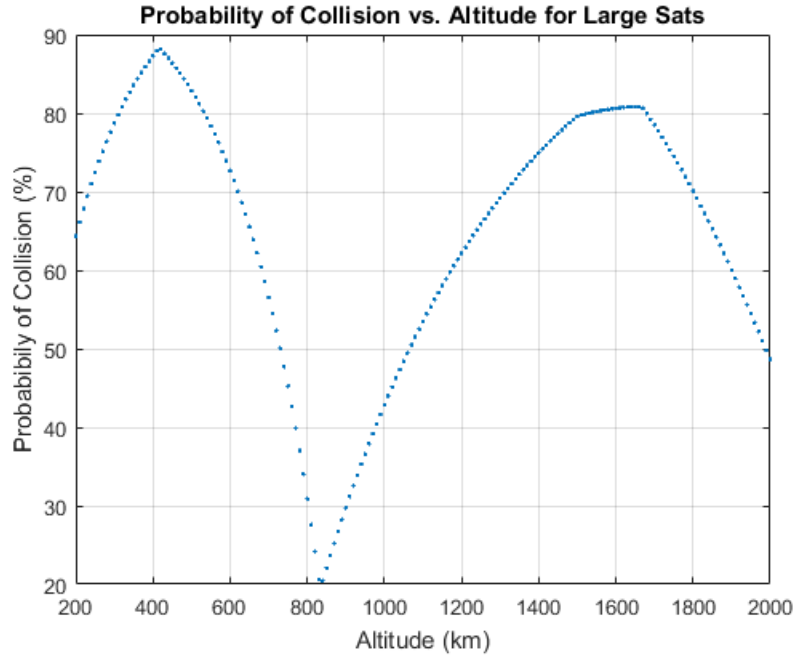


Figure 8. Probability of Collision vs. Altitude for Large Satellites

The threat to satellites posed by collision with space debris is not the only danger in the space environment. It was necessary to account for anti-satellite (ASAT) attacks and other space hazards. In an effort to account for ASAT hazards, solar particle events and galactic cosmic rays, as well as to artificially lower the value for R_{AV} , a value of 30% was removed from the avoidance component of resilience. Therefore the equation to calculate R_{AV} is shown by Equation 10. Resultant values for R_{AV} that are negative are set equal to zero.

$$R_{AV} = 1 - Pc - .3 \quad (10)$$

The probability of avoidance vs. orbit altitude for both small and large satellites is shown in Figures 9 and 10. As would be expected minimum values occur where the values of Pc were highest (420 km and 1,665 km). Additionally, maximum values for R_{AV} can be found at altitudes of 840 km and 2,500 km or higher.

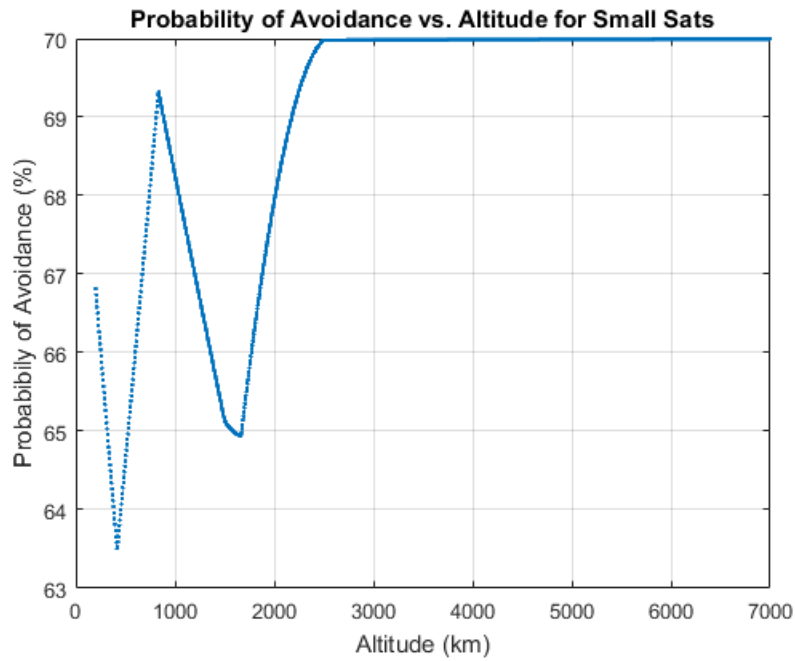


Figure 9. Probability of Avoidance vs. Altitude for Small Satellites

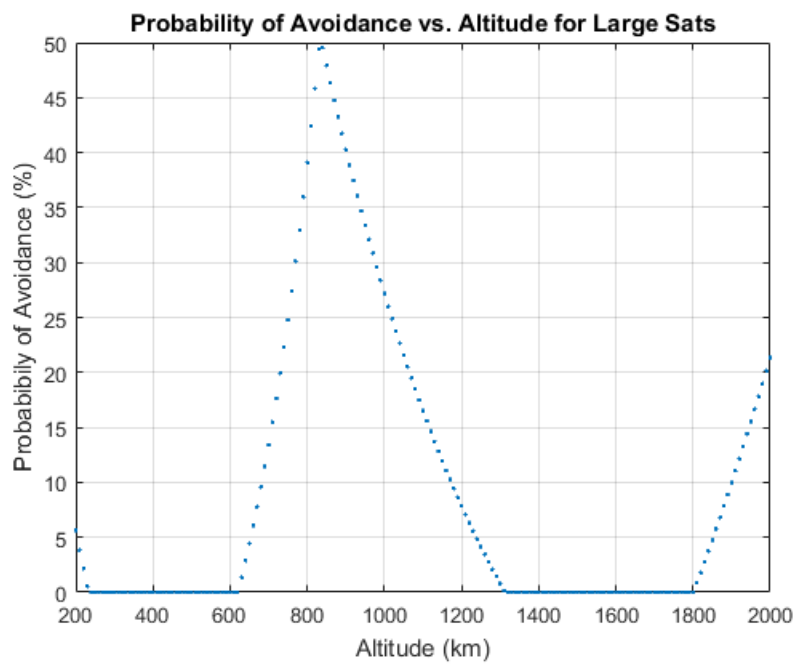


Figure 10. Probability of Avoidance vs. Altitude for Large Satellites

Robustness.

After avoidance is calculated, the next measure of resilience is robustness. For a single satellite, robustness would typically measure the level of resistance to a loss in performance, i.e. redundant components or high damage threshold. Applying robustness to a constellation becomes more complex. Therefore, robustness of a satellite constellation was calculated by measuring how much capability remained, compared to the original full constellation value, after the removal of one satellite from the constellation. The percent coverage of the new constellation would be calculated through running the simulation again and compared to the original coverage value. The number used for the robustness measure would then be the percent capability retained, or the new coverage percentage divided by the original coverage percentage. The value thus ranges from 0 to 1 where 1 would be no change in coverage and 0 would a total loss of coverage.

$$R_{RO} = \frac{\text{minimum}\{ \text{coverage percentage from removing any one satellite} \}}{\text{original coverage percentage}} \quad (11)$$

Where,

$$0 \leq R_{RO} \leq 1$$

The optimizer includes three types of systems: large satellite with pushbroom, small satellite with pushbroom, and small satellite with whiskbroom. It is possible that an optimized solution could be made of different satellite types where each type is in a different Walker constellation. In cases of more than one satellite type, the probability of avoidance is used and the satellite type which has the lowest probability of avoidance is chosen for the subsequent robustness calculation. The resilience code iterates to remove one satellite at a time and calculates the new total percent coverage. The satellite which produces the largest decrease in performance when removed is determined and removed.

Recovery.

Once the coverage performance of the constellation had been measured with one satellite being removed, the next component of resilience to consider is recovery. From a single satellite perspective, recovery would typically include how much percent coverage the satellite can regain after suffering a negative loss. Considering a satellite constellation, recovery was determined by measuring how much capability the constellation can regain from on-orbit adjustments after suffering the loss of the single satellite. The most cost-effective means of adjusting orbits is to perform in-plane maneuvers resulting in satellites shifting within their present plane and effectively changing their spacing. For example, instead of six satellites in a plane being equidistantly spaced 60 degrees apart, the now five satellite plane would have a spacing of 72 degrees. By altering the phasing of the satellites in the plane, the remaining satellites can help to cover the missing spot of the satellite that suffered the loss until a replacement can be launched or maneuvered from a different orbit to regain full coverage.

The resilience code chooses the plane from which the satellite that was removed in the previous robustness calculation. An example of the methodology for removing and re-phasing satellites in a single orbital plane is highlighted in the next few images which capture the STK output step-by-step. The focus of the methodology remained on re-phasing over a single orbital plane and did not address the phasing in relation with multiple planes, since this would be a major adjustment to the optimized solutions produced by the DISCO optimizer. First in Figure 11, the algorithm to identify which satellite to remove based on the resultant highest value of mission degradation due to removal has already been used. In the images, the other planes and satellites have been hidden so that it is easier to see the plane and satellite of interest. In this

case, the 2thType14 (the 4th small satellite with a pushbroom sensor in the first plane of that satellite type) will cause the most degradation to the mission.

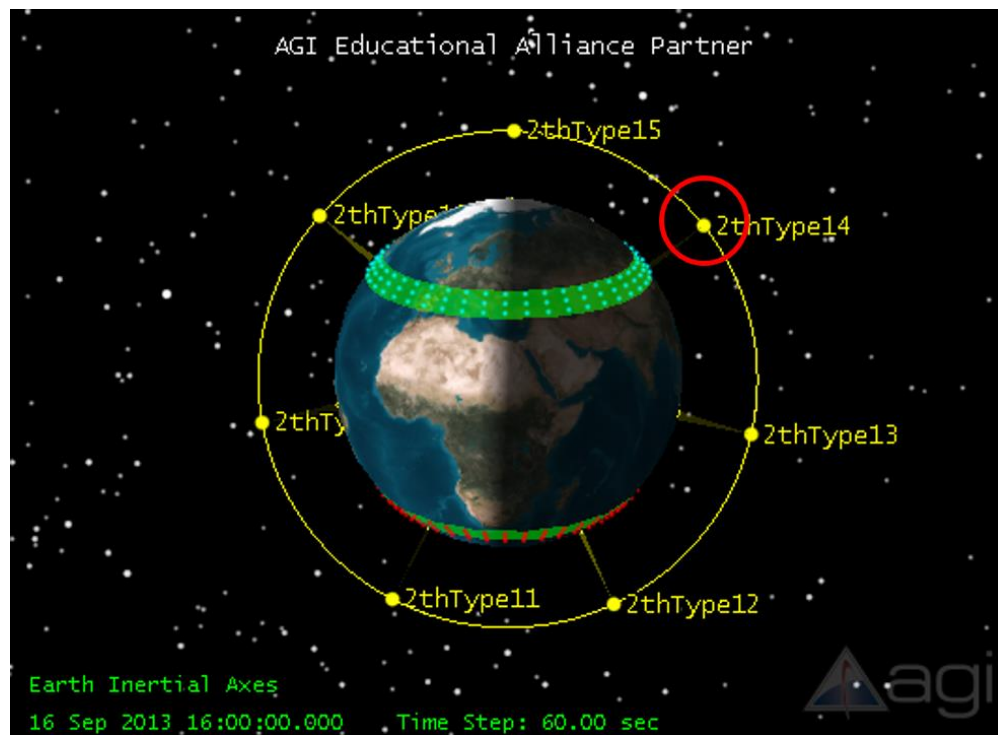


Figure 11. Identifying the Satellite That Would be Removed

Next, the MATLAB code sends a command to STK to remove that particular satellite and its properties from the STK generated solution which creates a gap in that particular orbit where 2thType14 used to be. At this time, the other satellites in that plane are unaffected by the removal of this satellite.

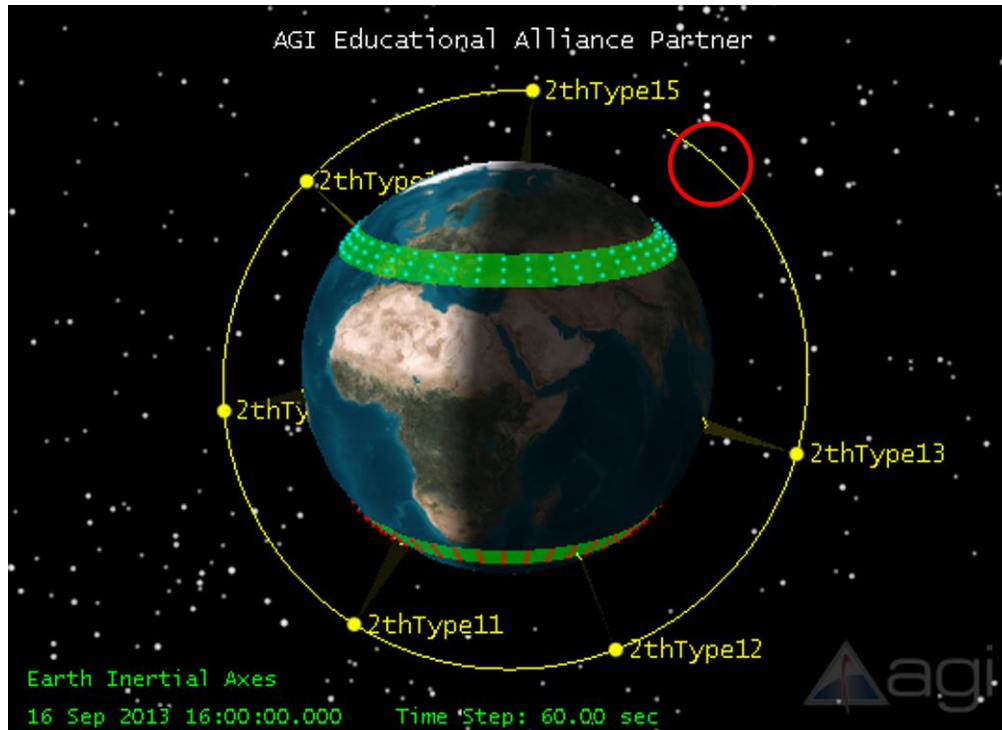


Figure 12. Removing the Satellite From the Orbit Plane

MATLAB code was created to redistribute the remaining satellites within the plane in which the satellite was removed. The original satellite spacing was first calculated by dividing 360 by the original number of satellites in the plane. The new spacing was then determined by dividing the 360 degree plane by the remaining satellites in the plane. The shift required for each remaining satellite until their spacing was even again was iteratively calculated by using these two numbers. The final satellite won't be shifted using this approach. The first satellite shifted in the test case was 2thType 15. The rotation is 42.85 degrees for that satellite. These shift values are then added to the mean anomaly value STK will use to populate the orbit. STK does not care what the shift amount is, just what the new properties of the object are. This was done using the STK connect commands used for many of the other processes.

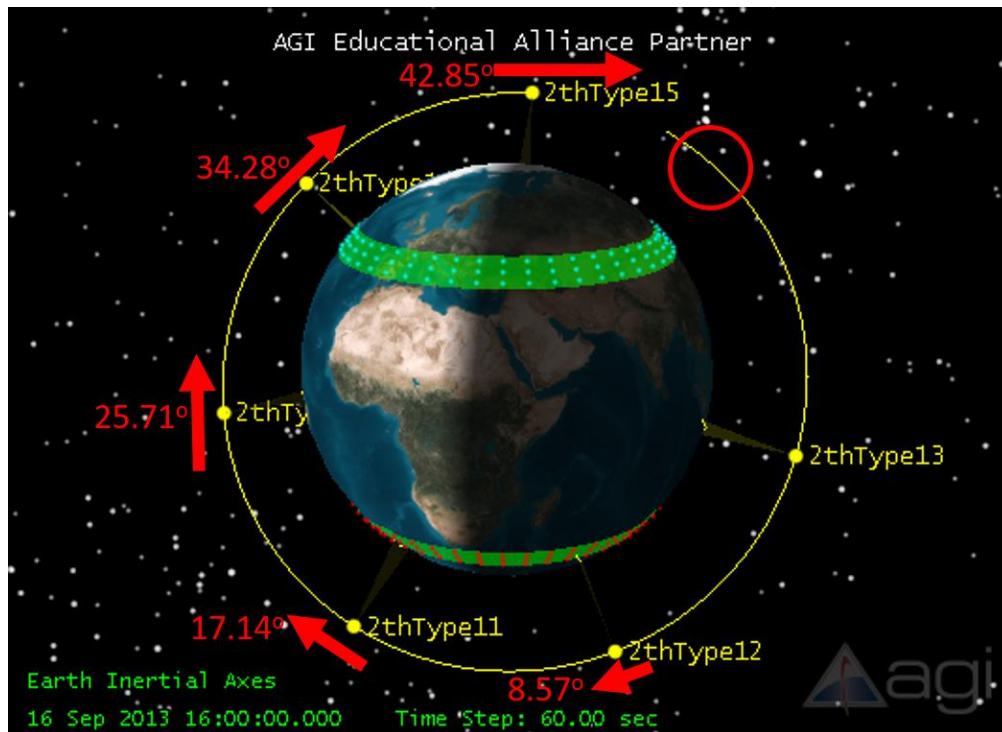


Figure 13. Calculating Value Each Remaining Satellite Would Shift

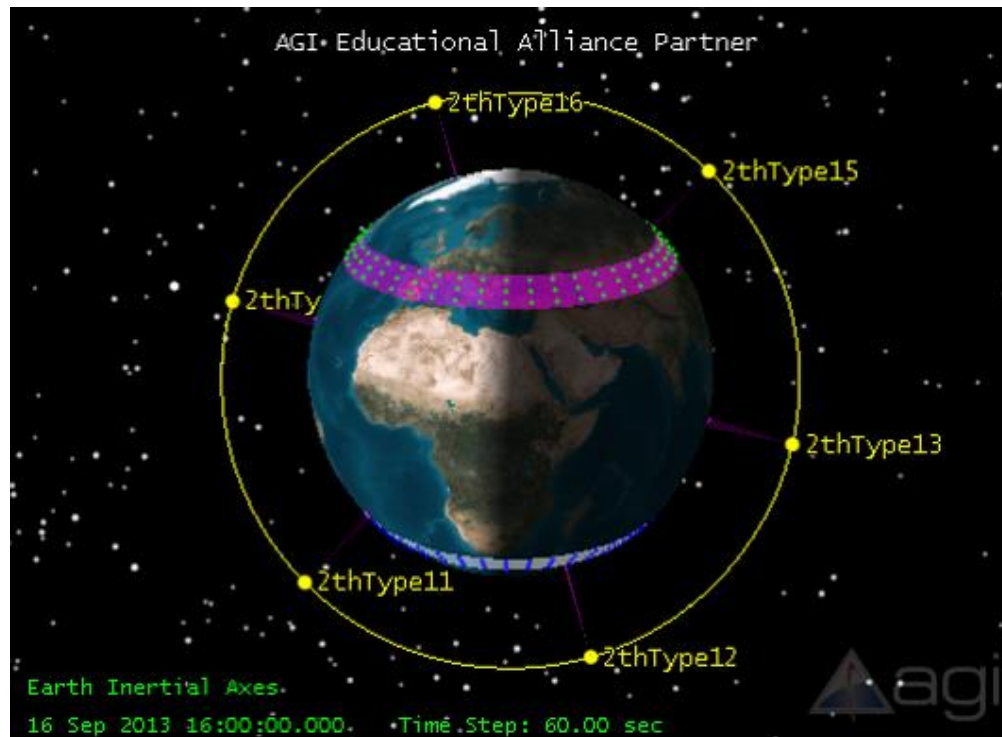


Figure 14. Evenly Spaced Satellites In Orbit After Shifting

The coverage calculator simulation was run again to calculate the new coverage value. The amount of performance recovered is how much of percent coverage that was lost was regained from performing the in-plane maneuvers. The value for recovery ranges from 0 to 1 where 1 would be a complete recovery of the coverage that was lost and 0 would be no change in the coverage from performing the maneuvers.

$$R_{RV} = \frac{(\% \text{ coverage after recovery}) - (\% \text{ coverage after loss})}{(\text{original } \% \text{ coverage}) - (\% \text{ coverage after loss})} \quad (12)$$

Where,

$$0 \leq R_{RV} \leq 1$$

Reconstitution.

The reconstitution measure is the final consideration for resilience as it can correct any losses in performance with the replenishment of resources, mainly launched replacement satellites. In the ideal case, a loss of an on-orbit satellite would be immediately responded to with the launch of a replacement satellite. The expense of space vehicle launches, lengthy schedules, and development time of spacecraft are just some of the prohibiting reasons why this ideal replacement case is not feasible. Especially in the case of large constellations, repetitive replenishment is necessary to maintain a minimum level of performance which restricts the availability of launch opportunities and resources.

This research's approach was to focus reconstitution on the total cost to build and launch a satellite of the same type that was lost relative to the total cost it took to develop, build, and launch the entire optimized constellation in the first place. If the constellation was initially relatively inexpensive, then the reconstitution would inherently be lower since it cost a larger fraction of the total cost to launch one extra satellite into orbit on a separate launch. The

approach did not take into consideration schedule delays, build time, or the possibility of piggybacking the satellite launch onto a unrelated launch with additional space; but instead used the cost to build a satellite and to deploy a launch vehicle of a certain type from the LCC in the FUEGO constellation optimization code. This approach simplified the reconstitution portion of the equation but a more complex analytic technique could be employed to achieve a more accurate representation of all of the components that go in to launching satellites into orbit.

Reconstitution is also a function of time since a replacement that is several months delayed might be considered a complete loss in the opinion of certain stakeholders. However, this approach ignored the gap in time from losing a satellite until the replacement was on orbit and operational. There are several unknowns associated with incorporating time, the responsiveness of a rapid launch timeline if a spare is not feasible, etc. This research's methodology does not account for this and makes the assumption that a new satellite could be built and launched within a timeline that stakeholders would deem acceptable and not affect the resilience metric of the equation.

In Thompson's optimization code, there were several assumptions made in regards to launch vehicles as well. Thompson's code approximates the number of launch vehicles required and their respective cost by taking the total weight of the satellites required for the optimal constellation and finding the most cost effective combination of launch vehicle types. There is no logic in the code that assigns a certain number of satellites to a specific launch vehicle with regard to the maximum capacity of the respective launch vehicle or with regard to how many planes or satellites are in that solution in general. It simply distributes the weight of all of the required spacecraft over the total available launch capacity of the optimized launch vehicle distribution. Using this logic, it could be possible that fractions of satellites would technically be

launched on every launch vehicle or that there could be only one satellite on every launch vehicle. Since this piece of the software was so integrated, it was decided to continue using the assumption and adapt the results for the research. The algorithm that calculates launch vehicle solutions for optimized constellations could be considered a section that needs future work. Reconstitution was very much the measure of resilience that had the most difficulty in creating an intuitive quantification.

When developing the reconstitution measure, it was essential to account for the cost of the satellite as well as the cost of the launch vehicle to replace the lost capability. It was then necessary to account for the total cost of the constellation in order to determine the percentage of the original constellation cost that launching a replacement would cost. The approach used for quantifying reconstitution can be seen in Equation 13. The measure is scaled to range from 0 to 1. More adjustments may be necessary for this measure once multiple simulations have been performed such as incorporating launch vehicle capacity in order to launch additional spare satellites in the first place.

$$R_{RC} = 1 - \frac{(Cost\ of\ Cheapest\ LV + Cost\ of\ Satellite\ Type\ to\ Replace)}{Total\ Cost\ To\ Develop\ and\ Launch\ Constellation} \quad (13)$$

Where,

$$0 \leq R_{RC} \leq 1$$

Method 2 Methodology

The Method 2 approach makes changes to the DISCO optimizer to generate solutions over a 24-hour scenario time with the performance constraint of maximum revisit rate. The solutions produced from these changes consistently achieved the minimum performance requirement of a 25-minute revisit rate for FUEGO. The same four components of resilience

were used that were part of the Method 1 analysis. With the data set changed, the methods for how the performance-based components of resilience -- robustness and recovery -- needed to change accordingly to represent any loss in revisit time. The methods to calculate avoidance and reconstitution were unchanged. The following section describes how Method 2 changed the approach used in Method 1 and how robustness and recovery were calculated.

Updates to Thompson's DISCO GA Scripts.

There were two major changes made to the DISCO suite of scripts. The first change was to make the STK scenario time for each simulation a 24-hour period, rather than the original 30 minutes. This allowed for more unique orbit relationships to be demonstrated than was being briefly sampled in the 30-minute scenarios. The second major change was replacing the performance constraint of percent coverage with the maximum revisit time. This change ensures that the solution can successfully hit every point in the two coverage bands under this time over the 24-hour scenario. In the original code, any percent coverage over 95 was scored favorably. This research added an additional constraint; the revisit time must be under 25 minutes in order for the solution to score favorably since this is the real requirement of the ESA FUEGO constellation. The revisit time was generated through the STK "Gap Duration" report which is described in the subsequent section.

Additional changes were made to the properties of the GA. A generation maximum of 50 and a population size of 30 were still used. The goal was to allow the solutions more chances to mutate over the 50 generations. The population size was decreased down to 30 from the original 50 to cut down any extra computing time associated with calculating 20 extra solutions for every generation. The stall limit was changed for 15 generation to 30 to ensure a minimum of 30 generations was completed before the program quit. Four of the 13 solutions that were

successfully ran did not have this last change and completed due to stalling out on the 16th generation producing large and inefficient results.

Changes to the Resilience Equation.

With a solution set that was valid over a 24-hour scenario and met the 25-minute revisit requirement of FUEGO, it was necessary to redevelop the performance related parameters of the resilience equation – robustness and recovery. There were several other changes that were required in the original code to calculate these new values.

Resilience Code Changes.

Since the solutions sets were optimized over a 24-hour scenario, it was now possible to change the resilience code scenario time to 24-hours and not get extraneous answers as was the case with the 30-minute percent coverage scenarios. The performance constraint of Percent Coverage was no longer being used. A new STK report named “Gap Duration” was used to report the percentage of events (events are considered time between accesses) that fall above or below a certain percent of the total number of events and the corresponding time (in seconds) for each percent level. Figure 15 and Figure 16 below show an example STK report of Gap Duration. Effectively, the report considers every access from any satellite sensor to every point in the coverage shapes and calculates the amount of time until the next sensor hits those points. The time between accesses is stored as events and the percentage breakdown of those points is reported in the Gap Duration report. Figure 15 shows the Gap Duration Report displaying the lowest 20% of access events. Figure 16 lists the highest 24% of access events from the Gap Duration Report.

Duration (sec)	% Over	% Under
4.35	100.00	0.00
12.43	99.00	1.00
20.64	97.99	2.01
27.70	96.99	3.01
30.07	95.99	4.01
33.04	94.98	5.02
37.08	93.98	6.02
42.60	92.98	7.02
45.36	91.97	8.03
48.58	90.97	9.03
49.99	89.97	10.03
51.53	88.96	11.04
53.27	87.96	12.04
55.70	86.96	13.04
58.43	85.95	14.05
62.80	84.95	15.05
65.06	83.95	16.05
68.36	82.94	17.06
69.25	81.94	18.06
70.64	80.94	19.06
71.48	79.93	20.07

Figure 15. Gap Duration Report For Lowest 20% of Access Events

686.43	23.91	76.09
699.79	22.91	77.09
712.74	21.91	78.09
722.01	20.90	79.10
729.62	19.90	80.10
735.77	18.90	81.10
745.13	17.89	82.11
749.88	16.89	83.11
756.47	15.89	84.11
760.94	14.88	85.12
771.12	13.88	86.12
784.46	12.88	87.12
795.99	11.87	88.13
807.60	10.87	89.13
824.60	9.87	90.13
836.28	8.86	91.14
859.27	7.86	92.14
947.75	6.86	93.14
1070.58	5.85	94.15
1168.33	4.85	95.15
1240.64	3.85	96.15
1312.04	2.84	97.16
1362.38	1.84	98.16
1488.00	0.84	99.16
1800.00	0.00	100.00

Figure 16. Gap Duration Report For Highest 24% of Access Events

From the Gap Duration Report, the last line of the report is the maximum amount of time between revisits for any point in the Coverage shape. This time is the maximum of the maximum for all points in the Coverage Bands. The “% Over” is zero and the “% Under” is 100 percent. The first column represents the seconds where this percentage level is valid. When the code produces these reports, it pulls out the time in the first column which represents the maximum revisit time. From the example Gap Duration report above, the maximum revisit time for the constellation was 1800 seconds, or 30 minutes. This is from a 30-minute scenario Method 1 solution that reached the limit of the scenario time before the next access for the worst gap in revisit time. This is an example of why it was necessary to shift to 24 hour scenarios with solutions that were optimized on the constraint of revisit time and not total percent coverage.

Robustness.

The robustness parameter was changed to reflect the switch from using percent coverage with the Method 1 data to revisit time for the Method 2 data. The overall methodology from the previous robustness parameter stayed the same. Robustness measures the change in performance after one of the satellites is removed. Instead of comparing the change in percent coverage, the new equation compares the change in maximum revisit time. The satellite that is removed is determined by calculating the new maximum revisit time after removing each satellite of the satellite type determined to have the lowest probability of avoidance. Equation 14 shows how the robustness parameter is calculated from these values. All times used are in seconds.

$$R_{RO} = 1 - \frac{[Max. Revisit After Removal] - [Original Max. Revisit Time]}{[Original Max. Revisit Time]} \quad (14)$$

Recovery.

The recovery parameter was also changed to reflect the switch from using percent coverage with the Method 1 data to revisit time for the Method 2 data. As was the case with

robustness, the methodology for calculating recovery stayed the same. Recovery measures the amount of performance that is regained after the one of the satellites is removed by re-phasing all of the satellites within the same plane of the removed satellite. Instead of calculating the amount of percent coverage that is recouped, the recovery parameter calculates the amount of revisit time that is gained by shifting the satellites. As was the case with the Method 1 data, planes of satellites with one remaining satellite are not shifted due to there being no real impact. Equation 15 shows how the recovery parameter is calculated from these values. All times used are in seconds.

$$R_{RV} = \frac{[Max. Revisit After Removal] - [Max. Revisit After Shift]}{[Max. Revisit After Removal] - [Original Max. Revisit Time]} \quad (15)$$

Revised Performance-Only Resilience Equation.

A modification to the Method 2 methodology was made to characterize the solutions strictly based on changes in performance. The methodology used during the Method 2 analysis produced resilience results that were expected for the metrics and constraints that were in place. It was difficult to quantify the avoidance and reconstitution components of resilience, therefore, focus was shifted to solely analyze the performance components of resilience - robustness and recovery. The two components rely specifically on measurable simulation data. These calculations continued to use the methodology of the avoidance component to determine which satellite type to remove to measure the change in performance, but did not factor in the calculated avoidance value like the previous analysis. Robustness is calculated in the same manner as described in the previous section as is the recovery parameter. Equations 16 and 17 show the equation used for calculating the performance-only resilience.

$$Resilience = 1 - (1 - R_{RO}) + R_{RV} (1 - R_{RO}) \quad (16)$$

$$Resilience = R_{RO} + R_{RV} - R_{RV}R_{RO} \quad (17)$$

Where,

$$R_{RO} = robustness$$

$$R_{RV} = recovery$$

From the equation, each solution starts at a resilience of 1.0 meaning it is perfectly resilient. If the satellite is completely robust, meaning that by removing any one satellite the maximum revisit time will not increase, the resilience will stay 1.0. In the case that the robustness is not 1.0, if the recovery of the constellation is 1, the revisit time will be fully recovered and resilience will also stay a perfect 1.0.

The revised resilience equation was used specifically on the final population of each of 13 Method 2 trials. The large number of results were filtered based on the original revisit time of the solution being less than the 25-minute requirement of FUEGO. The remaining solutions were examined for possible trending between total cost, resilience, number of satellites, etc.

IV. Analysis

The analysis section is broken into two major parts based on the solution set being analyzed and are named Method 1 and Method 2. Method 1 consisted of a solution set created using Thompson's original DISCO code which used the STK "Percent Coverage" report results as one of its constraints to score and rank solutions. The resilience calculation was initially created based on this percent coverage when measuring robustness and recovery. This metric was assumed to be measuring the percentage of the points in the Coverage shape that have been covered by a sensor in the time period measured. After some research into various STK report options, it was realized that the Percent Coverage report was calculating the total percent coverage of all of the points in the Coverage shape. Thompson's code tested the constellations over a scenario time of 30 minutes in order to obtain 95% or better total percent coverage of all of the Coverage points. This was a fair approximation for the solutions in order to ensure the mission requirements of FUEGO of a 25-minute revisit time for any point in the coverage bands. A sample set of the solutions was tested by creating "Gap Duration" reports in STK and it was discovered that several of solutions had points with gaps in their revisit time of 1800 seconds (30 minutes). This time is significant because it shows that at least some of the points on the Coverage shape were not being covered at all during the 30-minute scenario. These cases make sense given Thompson's constraint of 95% or better total percent coverage. The scenario time was extended for these solutions and it was determined that several of them exceeded reasonable durations for the revisit times. After this discovery, the DISCO GA code was altered to optimize solutions using the constraint of a revisit time less than 25 minutes. The altered code was run over a scenario time of 24 hours. These solutions are described in the Method 2 section below.

The appropriate changes were made to the resilience equation for measuring robustness and recovery as described in Chapter III.

The Method 2 section first begins to analyze the optimized trial solutions for the 13 completed trials. The following sections begin to analyze the entire population of the last generation of each trial. Each of the trial populations were composed of 30 solutions creating a new total of 390 solutions. The data is filtered based on the performance metric of meeting the 25-minute revisit time for FUEGO.

The final section takes a new approach for calculating resilience and applies it to the filtered population data. The new approach focuses solely on the robustness and recovery components. The new resilience value is compared to the total cost and the other variables of interest. Additional assessments are made based on the total cost versus performance.

Method 1 Analysis

Initial analysis was performed on solutions created from Thompson's original DISCO code. The code optimized the constellations using the performance constraint of the "Percent Coverage" Report in STK. Percent Coverage measures the cumulative total percent coverage of each point in the Coverage shape. Whenever any satellite's sensor hits one of the points in the scenario time, it satisfies that point in the Coverage shape and adds the appropriate fractional percent (calculated based on total number of points in the coverage shape) to the currently calculated total cumulative percent coverage. For example, if a satellite's sensor hits Points 1 and 2 of a Coverage shape composed of 100 points, that would mean 2% of the total coverage has been achieved for that time period. Once all points of the Coverage shape have been hit, the Percent Coverage reaches the maximum 100%. No other factors impact this metric, such as time of hitting the point or frequency of hits. To stay aligned with the parameters Thompson

optimized the GA script based on, the solutions based on Percent Coverage were still analyzed. The following section describes the results found after running the solutions through the resilience calculation based on percent coverage.

Method 1 Resilience Results.

The DISCO GA was set for a generation size of 50 and a population size of 30 with a stall limit of 30 generations when producing the Method 1 data. Using these GA options produced 18 successful trials. The computing time to run a single trial was approximately 16 hours for a trial that stalled out at 31 generations. A few of the trials did run close to the 50 generations and took close to 46 hours to complete. Table 1 below lists some of the generated parameters from the DISCO code for the 18 optimized trial solutions. The complete solution set can be found in Appendix A.

Table 1. Key Parameter Output from the DISCO GA for Method 1 Optimized Trial Solutions

Trial	Satellite Type 1					Satellite Type 2					Satellite Type 3				
	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)
1	-----	-----	-----	-----	-----	1	8	167	6635	93	-----	-----	-----	-----	-----
2	-----	-----	-----	-----	-----	6	5	323	4753	57	-----	-----	-----	-----	-----
3	-----	-----	-----	-----	-----	1	10	294	5983	24	5	3	234	966	42
4	-----	-----	-----	-----	-----	1	12	164	6054	83	-----	-----	-----	-----	-----
5	4	4	28	1924	92	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
6	-----	-----	-----	-----	-----	1	19	32	6942	81	-----	-----	-----	-----	-----
7	-----	-----	-----	-----	-----	5	7	174	6053	74	-----	-----	-----	-----	-----
8	-----	-----	-----	-----	-----	3	9	141	4613	21	-----	-----	-----	-----	-----
9	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	2	10	133	5246	71
10	-----	-----	-----	-----	-----	8	2	157	5336	29	-----	-----	-----	-----	-----
11	-----	-----	-----	-----	-----	1	10	294	5983	24	5	3	234	966	42
12	-----	-----	-----	-----	-----	3	10	274	5711	19	9	2	258	944	19
13	-----	-----	-----	-----	-----	1	11	356	6982	98	-----	-----	-----	-----	-----
14	-----	-----	-----	-----	-----	19	2	35	6359	86	-----	-----	-----	-----	-----
15	-----	-----	-----	-----	-----	14	1	187	6579	75	-----	-----	-----	-----	-----
16	-----	-----	-----	-----	-----	1	6	316	5791	84	16	1	214	3176	44
17	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	13	2	349	4680	92
18	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	3	9	283	4731	40

The 18 Method 1 optimized trial solutions were run through the resilience code to calculate the resilience value. From the methodology described in Chapter III, the satellite type with the lowest avoidance value is determined. The robustness value is calculated by finding the satellite in the constellation whose removal resulted in the largest increase in revisit time. The satellite is removed and the new maximum revisit time is used to calculate the robustness. Then, if possible, the remaining satellites in the orbital plane where the satellite is removed are re-phased to create equidistant spacing to make up for the loss of the satellite. The new maximum revisit time is calculated and used to determine the recovery value. The cost of the satellite type along with the cheapest available launch vehicle to put it in orbit are then compared to the total cost of the original constellation to calculate the reconstitution value. The resilience value is then calculated as described in Chapter III. Table 2 lists the values for the resilience components for each optimized trial solution along with the total cost of the constellation.

Table 2. Resilience Components for each Method 1 Optimized Trial Solution

Trial	Avoidance	Robustness	Recovery	Reconstitution	Resilience	Cost (\$M)
1	0.6994	0.5348	0.8031	0.4566	0.9850	0.0451
2	0.6990	0.9463	0.4461	0.9231	0.9993	0.3058
3	0.5579	0.8882	0.0000	0.9451	0.9973	0.6217
4	0.6993	0.7619	1.0000	0.9083	1.0000	0.3265
5	0.2856	0.9311	0.1098	0.9555	0.9980	2.9770
6	0.6994	0.9848	1.0000	0.9208	1.0000	0.3009
7	0.6993	0.9770	1.3632	0.9663	1.0001	0.8343
8	0.6990	0.9714	1.0000	0.9690	1.0000	0.9101
9	0.6991	0.8818	1.0000	0.9384	1.0000	0.5772
10	0.6991	0.8715	0.0000	0.8955	0.9960	0.2263
11	0.5579	0.8882	0.0000	0.9451	0.9973	0.6217
12	0.5702	1.0000	0.0000	0.0000	1.0000	1.7978
13	0.6994	0.7249	1.0000	0.5568	1.0000	0.0559
14	0.6993	1.0000	0.0000	0.0000	1.0000	0.4741
15	0.6994	0.7868	0.0000	0.9605	0.9975	0.7017
16	0.6985	0.9585	0.0000	0.9806	0.9998	2.3796
17	0.6990	0.9683	0.0000	0.9631	0.9996	1.1406
18	0.6990	0.8741	1.0000	0.9864	1.0000	2.6545

The calculated resilience components revealed some characteristic behaviors that are evident in most of the results of this analysis. The resilience values of all 18 trials are all greater than 0.98 with the majority being greater than 0.99. From a general observation, the resilience values make sense given the values for the equation components. The solutions with a resilience of 1 either have a robustness of 1 or a recovery of 1, meaning they were able to retain their original percent coverage for the scenario time. Figure 17 shows the relationship between total cost and resilience. The color bars on the right side of the figure and all subsequent figures in this research provide a color representation of the number of the solution being evaluated for those particular plots in order to compare with plots of other parameters on the same data set.

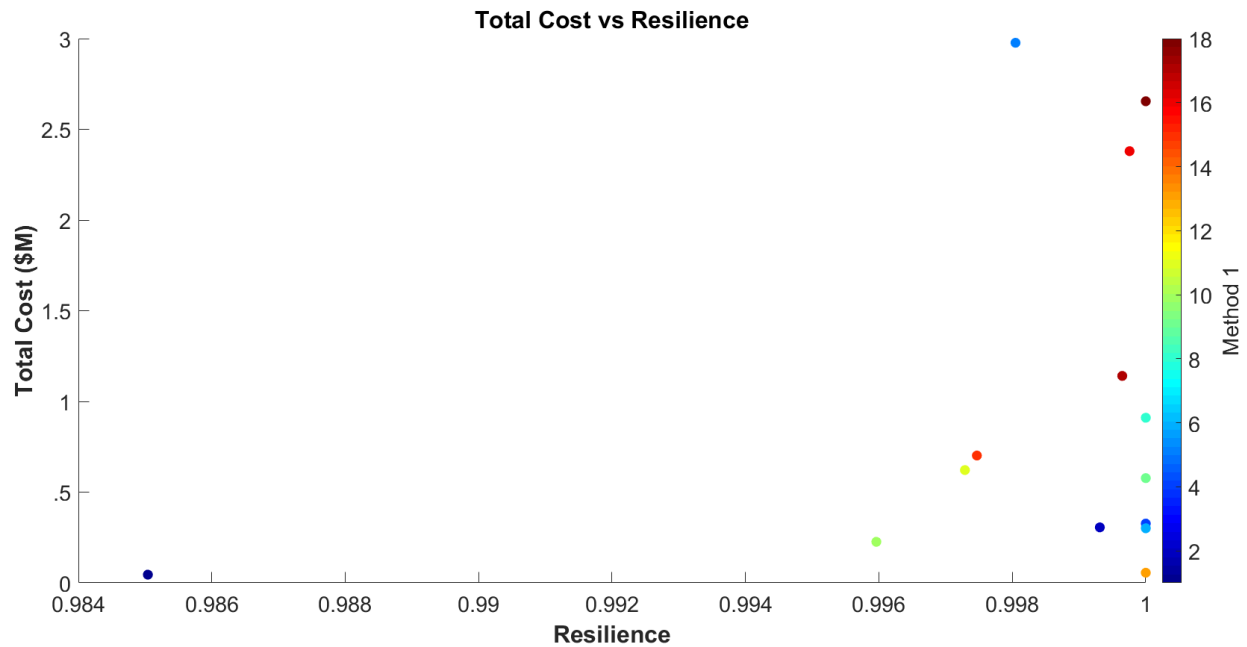


Figure 17. Total Constellation Cost vs. Resilience for Method 1 Optimized Trial Solutions

Examining the four components of resilience, there are some general observations that can be made for this data. Minimal time was spent analyzing the results of the Method 1 approach as it was determined that these results did not appropriately meet the mission requirements of FUEGO since the solutions were optimized using a simplified scenario. The evaluation of these solutions was critical in understanding how simplifying the revisit requirement can have larger effects over a longer duration scenario time. The Method 1 results were optimized for total coverage over a 30 minute scenario rather than truly measuring the maximum revisit time of the coverage bands over an extended (24 hour) period of time. Simplifying this constraint can have effects on the long-term resilience of the constellation. Figures 18 - 21 plot each of the four resilience components versus the resilience value. From the avoidance plot, a trend of values being around 0.7 can be seen. The common value is due to the 0.3 avoidance bias that is subtracted from every result to account for miscellaneous causes. The solutions have such low avoidance because they are small satellites and orbiting at high altitudes

corresponding to a very low probability of collision. This will be a common issue given the altitude range allowed by the DISCO GA code and the profile of altitude versus probability of collision.

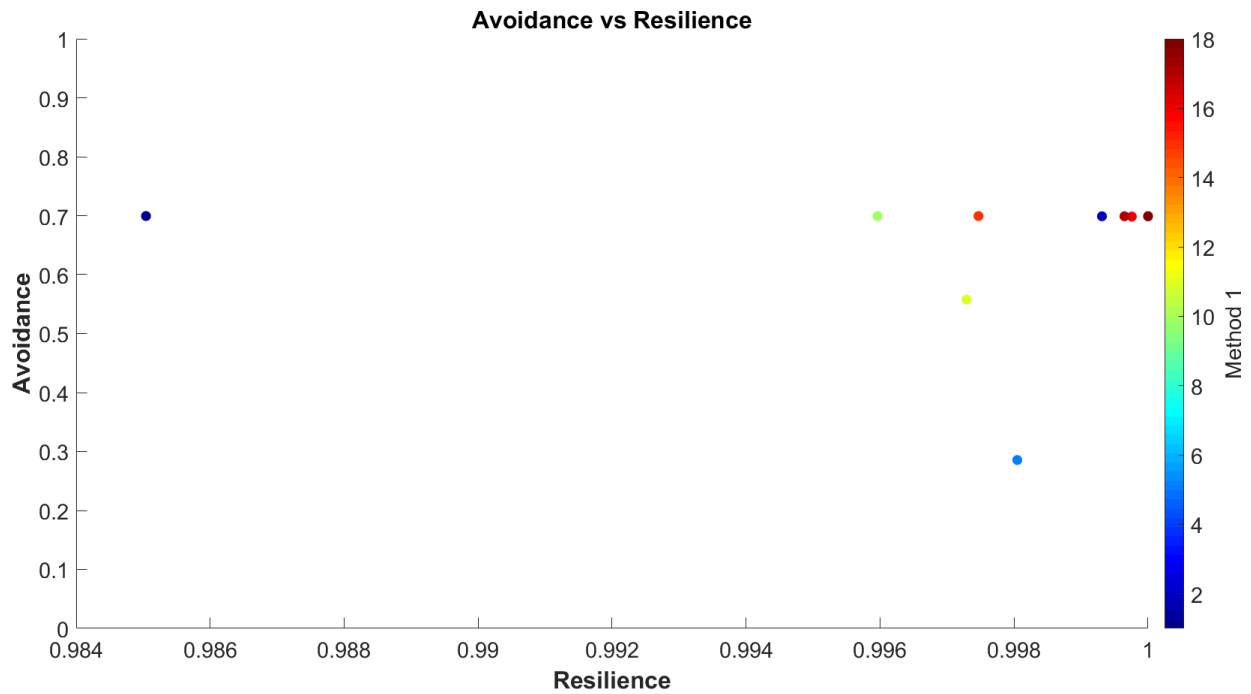


Figure 18. Avoidance vs. Resilience for Method 1 Optimized Trial Solutions

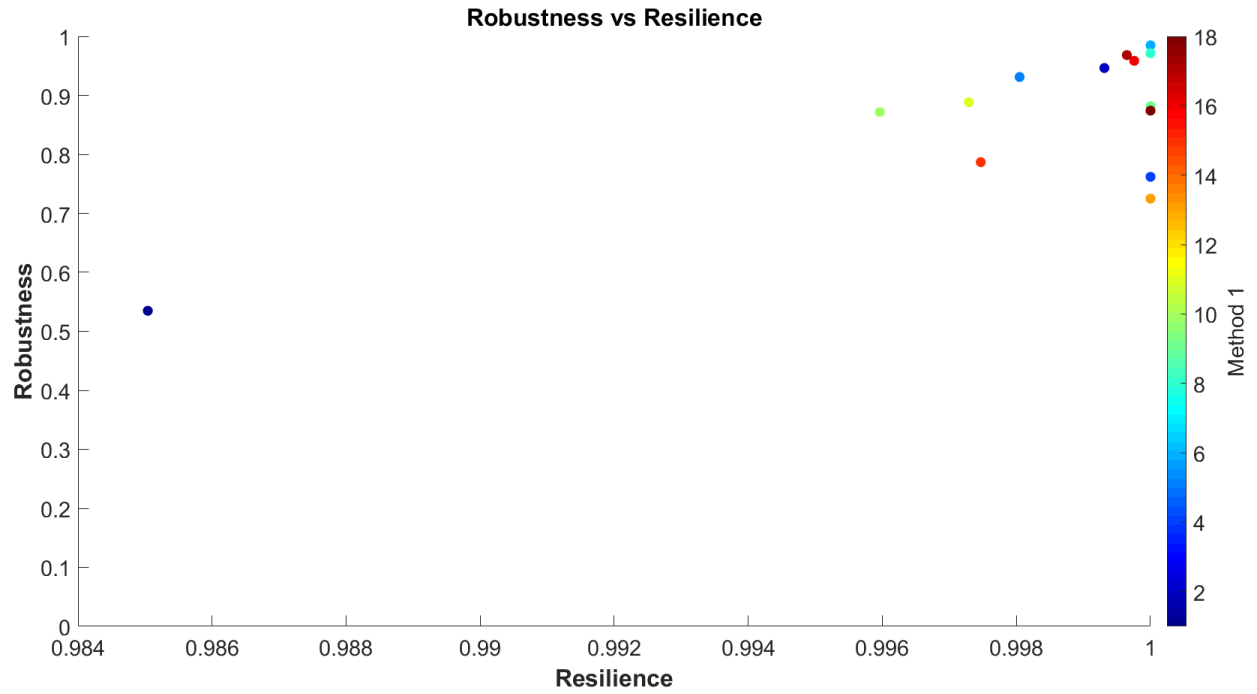


Figure 19. Robustness vs. Resilience for Method 1 Optimized Trial Solutions

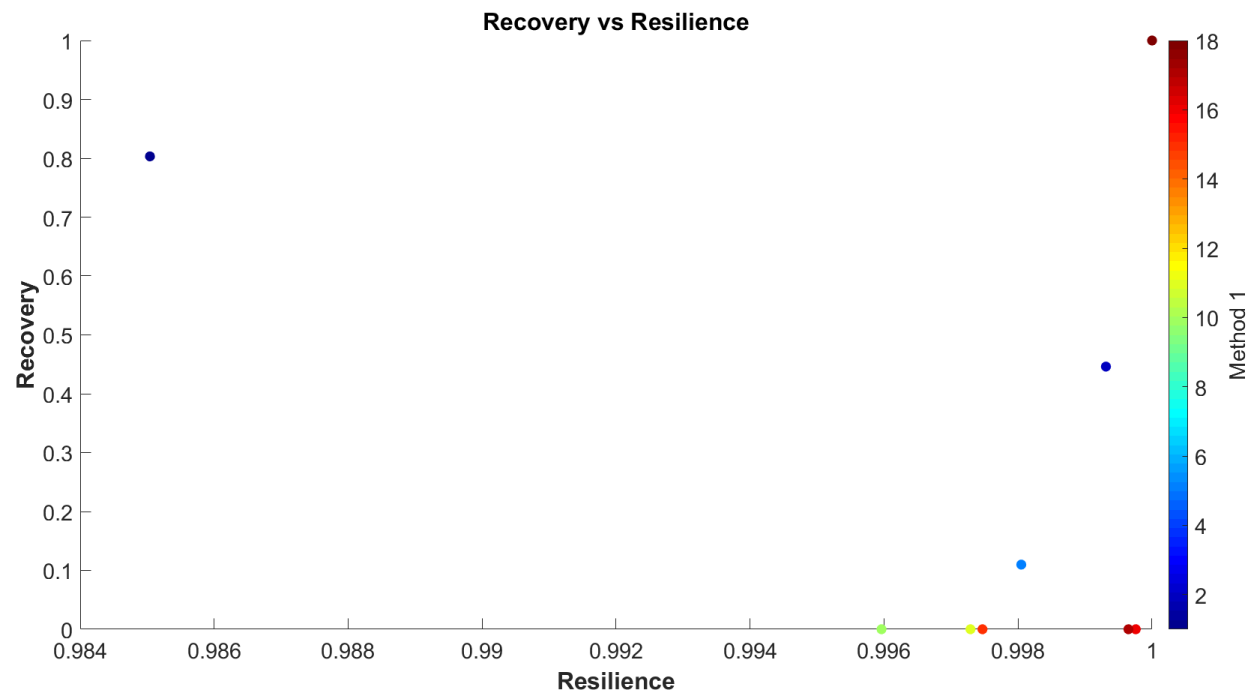


Figure 20. Recovery vs. Resilience for Method 1 Optimized Trial Solutions

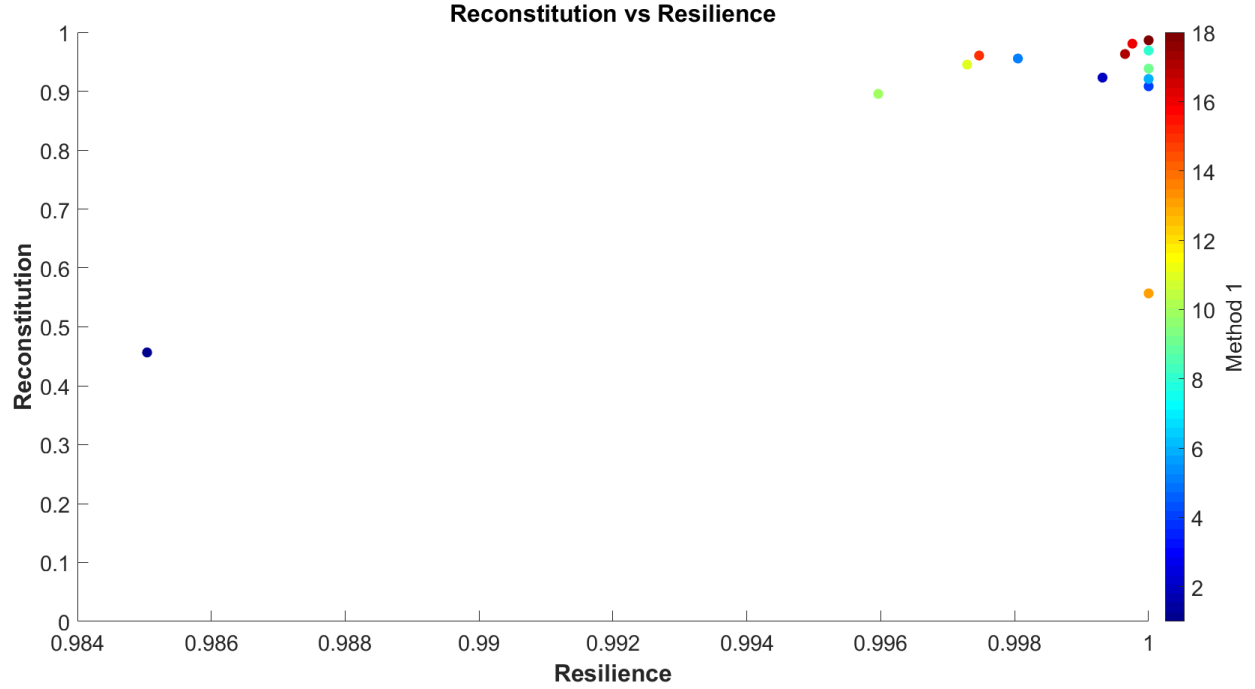


Figure 21. Reconstitution vs. Resilience for Method 1 Optimized Trial Solutions

In addition to the resilience components, the total number of satellites used for the constellation and the total number of orbital planes were evaluated. These values for the Method 1 optimized trial solutions are listed in Table 3 along with their resilience value and total cost. These parameters may be important criteria for judging competing solutions due to launch vehicle requirements consisting of such a large component of the overall cost. Figures 22 and 23 plot the total number of satellites and the total number of planes versus resilience.

Table 3. Total Number Satellites and Planes with the Total Cost and Resilience for Method 1 Optimized Trial Solutions

Trial	# of Satellites	# of Planes	Resilience	Cost (\$M)
1	8	1	0.9850	0.0451
2	30	6	0.9993	0.3058
3	25	6	0.9973	0.6217
4	12	1	1.0000	0.3265
5	16	4	0.9980	2.9770
6	19	1	1.0000	0.3009
7	35	5	1.0001	0.8343
8	27	3	1.0000	0.9101
9	20	2	1.0000	0.5772
10	16	8	0.9960	0.2263
11	25	6	0.9973	0.6217
12	48	12	1.0000	1.7978
13	11	1	1.0000	0.0559
14	38	19	1.0000	0.4741
15	14	14	0.9975	0.7017
16	22	17	0.9998	2.3796
17	26	13	0.9996	1.1406
18	27	3	1.0000	2.6545

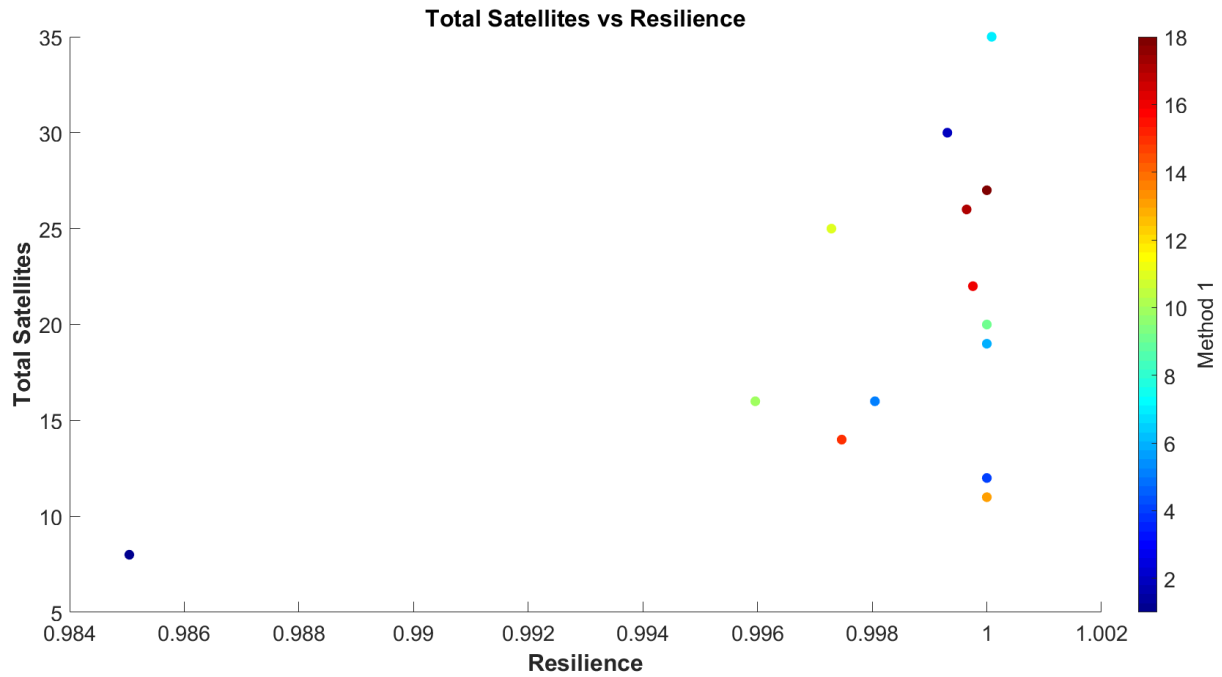


Figure 22. Total Number of Satellites vs. Resilience for Method 1 Optimized Trial Solutions

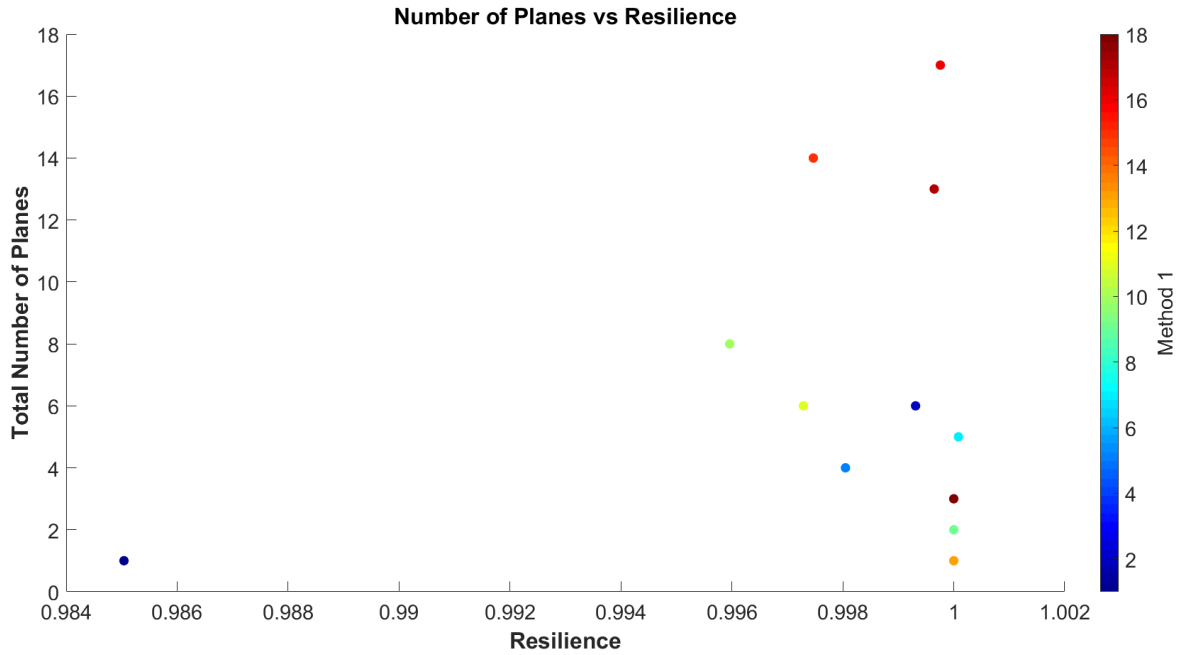


Figure 23. Total Number of Orbital Planes vs. Resilience for Method 1 Optimized Trial Solutions

Validity Check on Method 1 Solutions.

This section describes the performance results of the solutions produced through the Method 1 DISCO GA simulations. During simulation tests to check the validity of the Method 1 solutions, several of the solutions did not meet the revisit rate requirement of 25 minutes specified for the FEUGO mission. The simulations involved running the solution in STK for a 30-minute duration for all of the Method 1 solutions to find the maximum revisit rate for any one of the points in the Coverage shape. With a significant number of solutions reaching a maximum revisit time of 30 minutes, the entire scenario duration being tested, all of the solutions were ran again through STK simulations for a scenario time of 24 hours to find just how large the gaps in revisit times were.

Table 4 lists the maximum revisit time for any of the points in the two Coverage Bands for the 30-minute scenario time. These times were generated from the methodology described in Chapter III and represent the maximum of the maximum accesses for all points in the Coverage Bands. Of the 18 total solutions, 10 reached the maximum cut-off of the 30-minute scenario time for the maximum revisit time. Only eight of the solutions were under 30 minutes. Of those eight solutions, seven of the solutions were under the FUEGO requirement of 1500 seconds. The other constraints of the FUEGO requirement were still constrained properly allowing for accurate modeling and solutions regarding the sensor and altitude requirements.

Table 4. Maximum Revisit Time for the Method 1 30-minute Scenario

Trial Number	Original Maximum Revisit Time (s)
1	1800.0
2	1800.0
3	1800.0
4	1388.4
5	1800.0
6	986.6
7	1800.0
8	1425.5
9	1436.6
10	1800.0
11	1800.0
12	1010.3
13	1600.8
14	960.2
15	1800.0
16	1800.0
17	1800.0
18	1572.1

The solutions for Method 1 were ran through an STK scenario again, but for a scenario duration of 24 hours to determine the actual maximum revisit time without the 30-minute cut-off. Table 5 lists the maximum revisit time for any of the points in the two Coverage Bands for the 24-hour scenario time. As can be seen from the table, the solutions which maxed out at 30 minutes in the 30-minute scenario have continued to increase to unacceptable levels. Another good example is the data from Trial 14. During the 30-minute scenario, it had a maximum revisit time of 960 seconds, much under the required time of 1500 seconds (25 minutes). However, over the 24-hour scenario time, the maximum revisit time more than doubles to 2133 seconds, greatly over the minimum requirement.

Table 5. Maximum Revisit Time for the Method 1 24-hour Scenario

Trial Number	Original Maximum Revisit Time (s)
1	2368.1
2	2025.0
3	2238.0
4	1389.2
5	1949.0
6	987.4
7	2257.9
8	1425.5
9	1438.6
10	2233.0
11	2238.0
12	1018.2
13	1768.4
14	2133.4
15	4044.3
16	2619.7
17	3262.2
18	4399.2

The revisit rate results from the 30-minute and 24-hour scenarios prove that the solutions created from the original DISCO GA were not suitable for the FUEGO requirements given the use of the total percent coverage constraint. This discovery justified the alteration of the DISCO GA code to incorporate revisit time as the performance constraint instead of percent coverage and to consider the scenario over a 24-hour time period to better approximate how the coverage changes over several orbits. The solutions produced from this modified version of the DISCO GA are discussed in the following section.

Method 2 Analysis

Altering the DISCO GA code to incorporate revisit time as a performance constraint and to run the simulations over a scenario time of 24-hours resulted in a new method to produce optimized constellation solutions that met the 25-minute revisit requirement of FUEGO. This section describes the resilience results produced from analyzing this new set of data, called Method 2, as it was the second attempt at producing a valid solution set.

Method 2 Resilience Results.

As was the case with the Method 1 runs, the DISCO GA was set for a generation size of 50 and a population size of 30 with a stall limit of 30 generations when producing the Method 2 data. Using these GA options, produced 13 successful trials. The computing time to run a single trial was exceptionally longer than the Method 1 times. The run time was approximately 24 hours to stall out at generation 31, compared to 16 hours for Method 1 to reach the same point. This was due to STK calculating the coverage for a period of 24 hours versus 30 minutes for Method 1. Most of the trials were run on two 10-core machines and the run times could not be improved. The incredibly long run times limited the number of successfully run trials through the Method 2 optimizer to 13. Table 6 below lists some of the generated parameters from the DISCO code for the 18 optimized trial solutions. The complete set of solutions can be found in Appendix B.

Table 6. Key Parameter Output From DISCO GA for Method 2 Optimized Trial Solutions

Trial	Satellite Type 1					Satellite Type 2					Satellite Type 3				
	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)	# of Planes	# of Sats/Plane	RAAN Increment (deg)	Altitude (km)	Inclination (deg)
1	0	2	164	1222	64	14	4	306	4260	40	0	1	197	6836	67
2	0	2	160	364	52	0	9	101	763	81	6	3	102	1780	56
3	0	2	78	322	10	17	2	341	6312	95	15	0	9	6073	12
4	0	3	7	442	73	2	17	290	6911	96	1	0	9	233	87
5	0	0	167	921	74	2	5	266	4782	2	0	14	225	2230	28
6	3	4	152	1178	72	2	6	105	2573	84	0	11	248	1876	48
7	4	0	184	1613	66	2	7	160	2963	42	0	19	112	1849	87
8	1	0	22	375	37	15	3	34	873	43	0	9	3	796	98
9	1	0	129	621	23	10	2	321	2915	70	8	0	327	1080	72
10	0	3	276	1123	40	1	13	30	5275	90	7	0	100	3559	75
11	0	0	221	1653	59	2	9	254	5019	57	0	17	26	1515	84
12	0	2	277	1127	8	0	16	297	2749	33	4	6	103	3400	61
13	1	0	213	1392	38	0	4	253	3903	64	3	7	264	3210	66

The 13 Method 2 optimized trial solutions were run through the resilience code to calculate the resilience value. From the methodology described in Chapter III, the satellite type with the lowest avoidance value was determined. The robustness value was calculated by finding the satellite in the constellation whose removal resulted in the largest increase in revisit time. The satellite is removed and the new maximum revisit time is used to calculate the robustness. Then, if possible, the remaining satellites in the orbital plane where the satellite is removed are re-phased to create equidistant spacing to make up for the loss of the satellite. The new maximum revisit time was calculated and used to determine the recovery value. The cost of the satellite type along with the cheapest available launch vehicle to put it in orbit were then compared to the total cost of the original constellation to calculate the reconstitution value. The resilience value was then calculated as described in Chapter III. Table 7 lists the values for the resilience components for each optimized trial solution along with the total cost of the constellation.

Table 7. Resilience Components for Each Method 2 Optimized Trial Solution

Trial	Avoidance	Robustness	Recovery	Reconstitution	Resilience	Cost (\$M)
1	0.6989	0.9616	0.0000	0.9865	0.9998	6.4194
2	0.3716	0.2333	0.0000	0.9552	0.9784	20.0736
3	0.6993	0.5305	0.0000	0.9905	0.9987	2.9746
4	0.6994	0.8385	0.6499	0.9845	0.9997	3.3367
5	0.6990	0.1681	0.0000	0.9347	0.9837	6.6211
6	0.2594	1.0000	0.0000	0.0000	1.0000	7.1821
7	0.6985	-0.0013	0.8333	0.9466	0.9973	1.0378
8	0.6111	0.4684	0.0000	0.9898	0.9979	3.1540
9	0.6984	0.5964	0.0000	0.9635	0.9956	2.3539
10	0.6991	-0.0050	0.9166	0.9664	0.9992	0.8378
11	0.6991	0.0020	0.8753	0.8504	0.9944	0.1666
12	0.6986	0.4779	0.0012	0.9602	0.9937	1.2444
13	0.6985	0.0035	0.8314	0.9564	0.9978	7.5585

From the results, a similar pattern can be observed as from the Method 1 analysis where the resilience is incredibly high. Unlike the Method 1 data, there are less solutions with a resilience of 1. A resilience of 1 for the Method 2 data carries more significance since it is actually measuring the maximum revisit time for the constellation and not simply the total cumulative percent coverage. Figure 24 shows the relationship between total cost and resilience for the 13 Method 2 optimized trial solutions.

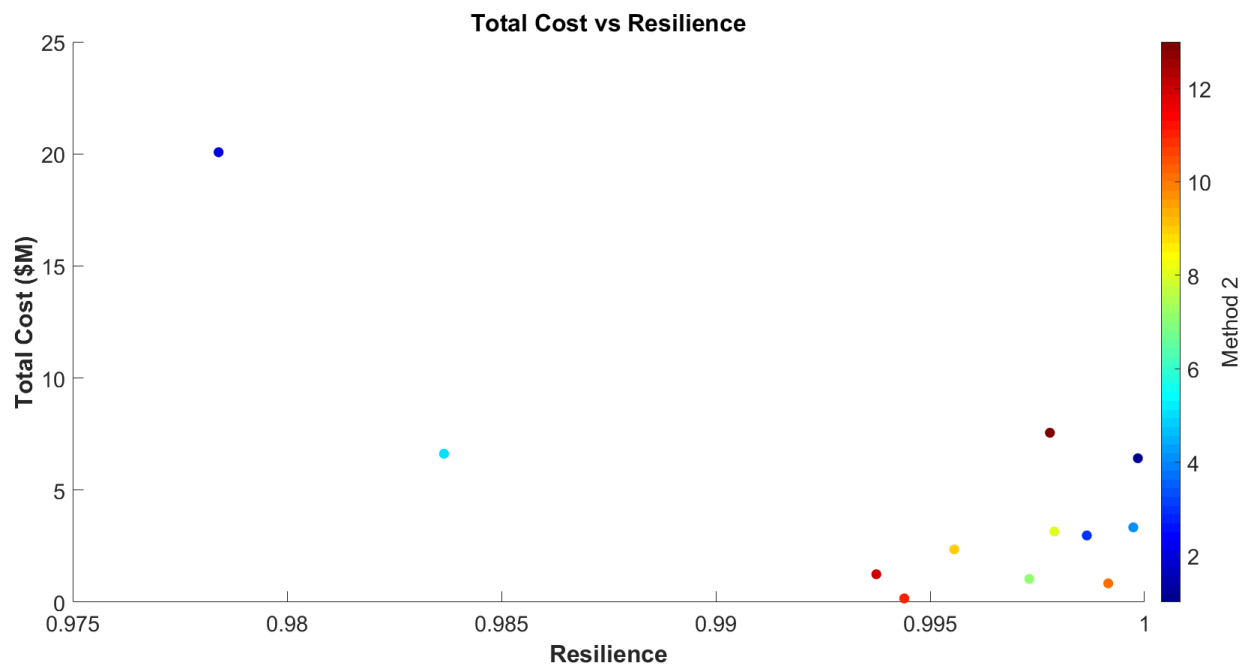


Figure 24. Total Constellation Cost vs. Resilience for Method 2 Optimized Trial Solutions

The four components of resilience were examined versus the total resilience. Figures 25-28 plot each of the four components versus the resilience of the solution. A majority of the solutions display the same avoidance pattern as seen in the Method 1 analysis of being approximately 0.7 due to the added 0.3 bias. The points that stray from this value are either large satellite solutions (Trial 2) or are small satellites at a lower altitude (Trial 6). The remaining components do not display much of a discernible trend given the number of data points available.

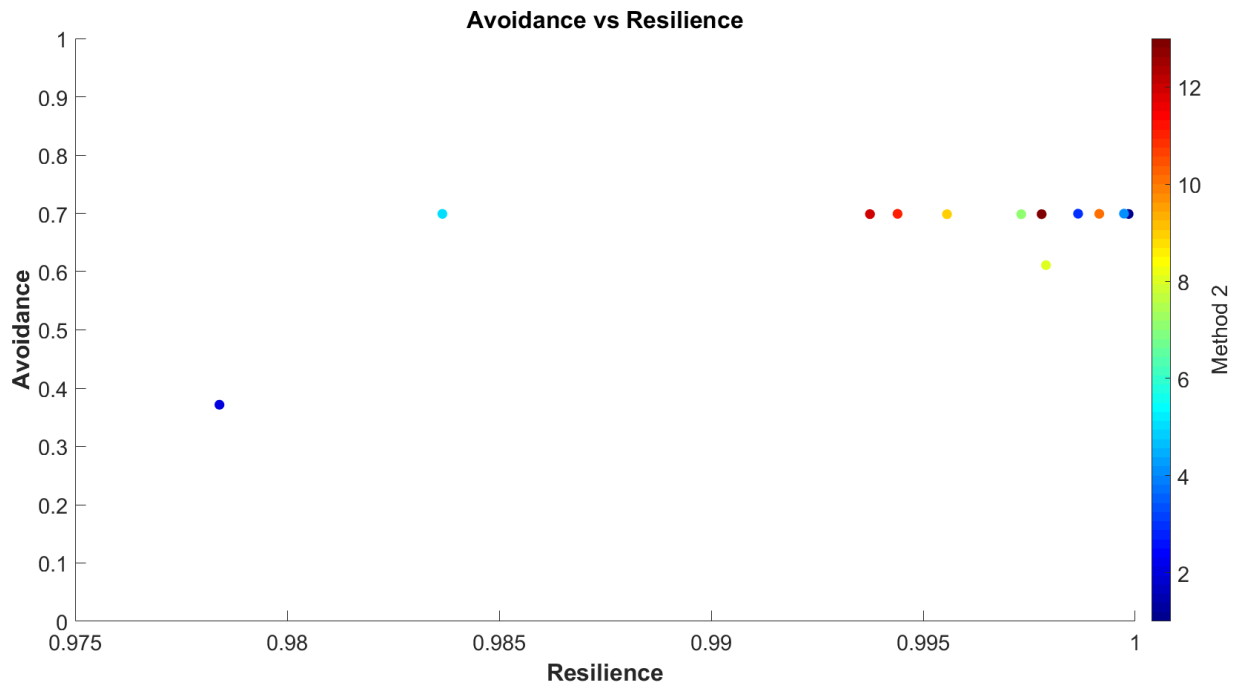


Figure 25. Avoidance vs. Resilience for Method 2 Optimized Trial Solutions

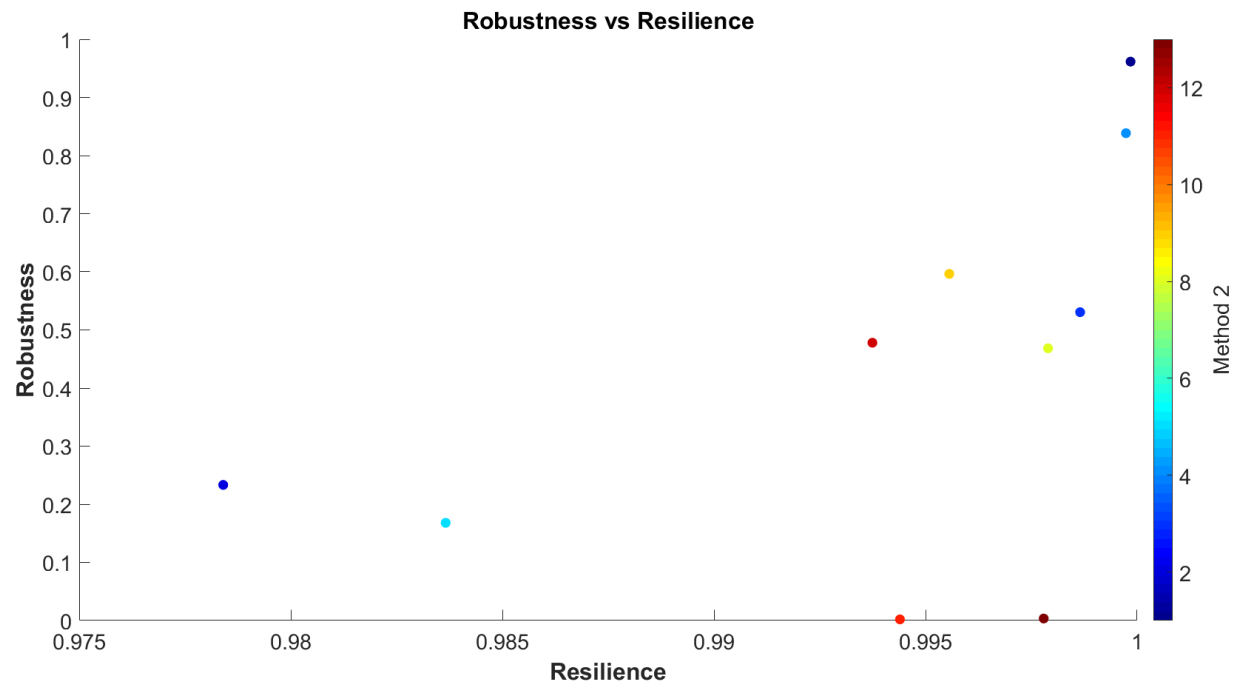


Figure 26. Robustness vs. Resilience for Method 2 Optimized Trial Solutions

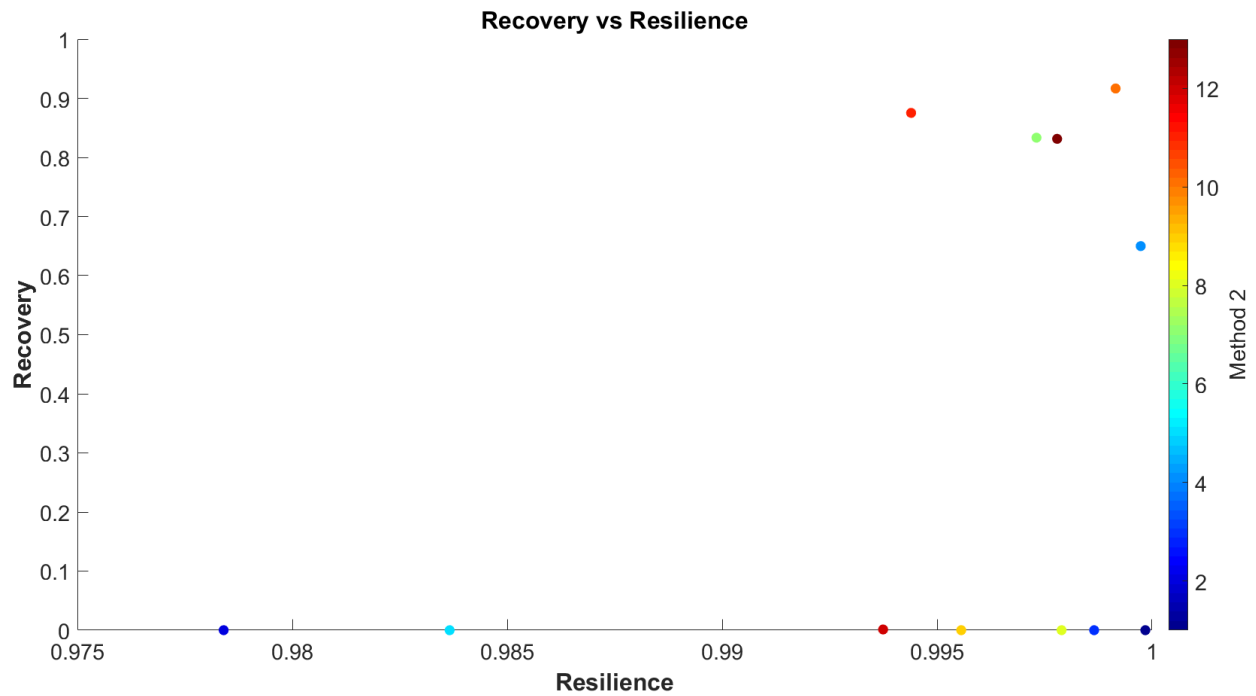


Figure 27. Recovery Metric vs. Resilience for Method 2 Optimized Trial Solutions

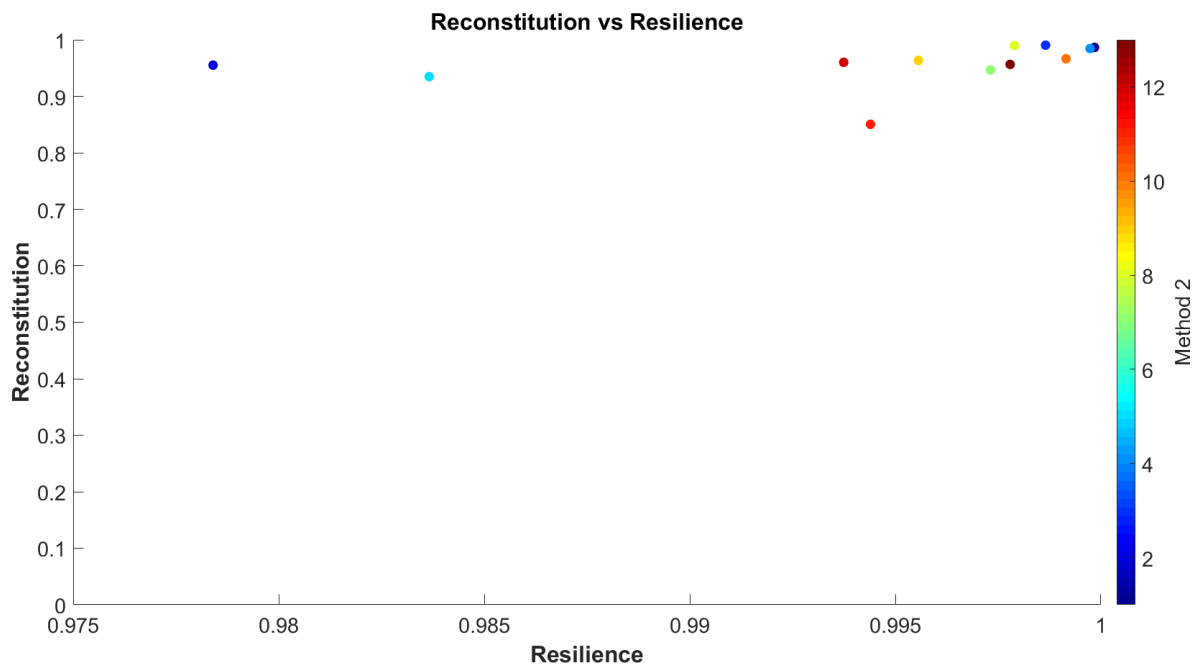


Figure 28. Reconstitution Metric vs. Resilience for Method 2 Optimized Trial Solutions

In addition to the resilience components, the total number of satellites used for the constellation and the total number of orbital planes were evaluated. These values for the Method 2 optimized trial solutions are listed in Table 8 along with their resilience value and total cost. As with Method 1, these parameters could be important criteria for judging competing solutions due to launch vehicle requirements being such a large component of the overall cost. Figures 29 and 30 plot the total number of satellites and the total number of planes versus resilience. Generally, the more satellites used in the solution, the higher the resilience value which makes logical sense. The number of planes does not display any relationship. The planes used do vary based on the number of satellites in each plane which play a significant factor in the overall constellation performance.

Table 8. Total Number Satellites and Planes with the Total Cost and Resilience for Method 2 Optimized Trial Solutions

Trial	# of Satellites	# of Planes	Resilience	Cost (\$M)
1	56	14	0.9998	6.4194
2	18	6	0.9784	20.0736
3	34	17	0.9987	2.9746
4	34	2	0.9997	3.3367
5	10	2	0.9837	6.6211
6	24	5	1.0000	7.1821
7	14	2	0.9973	1.0378
8	45	15	0.9979	3.1540
9	20	10	0.9956	2.3539
10	13	1	0.9992	0.8378
11	18	2	0.9944	0.1666
12	24	4	0.9937	1.2444
13	21	3	0.9978	7.5585

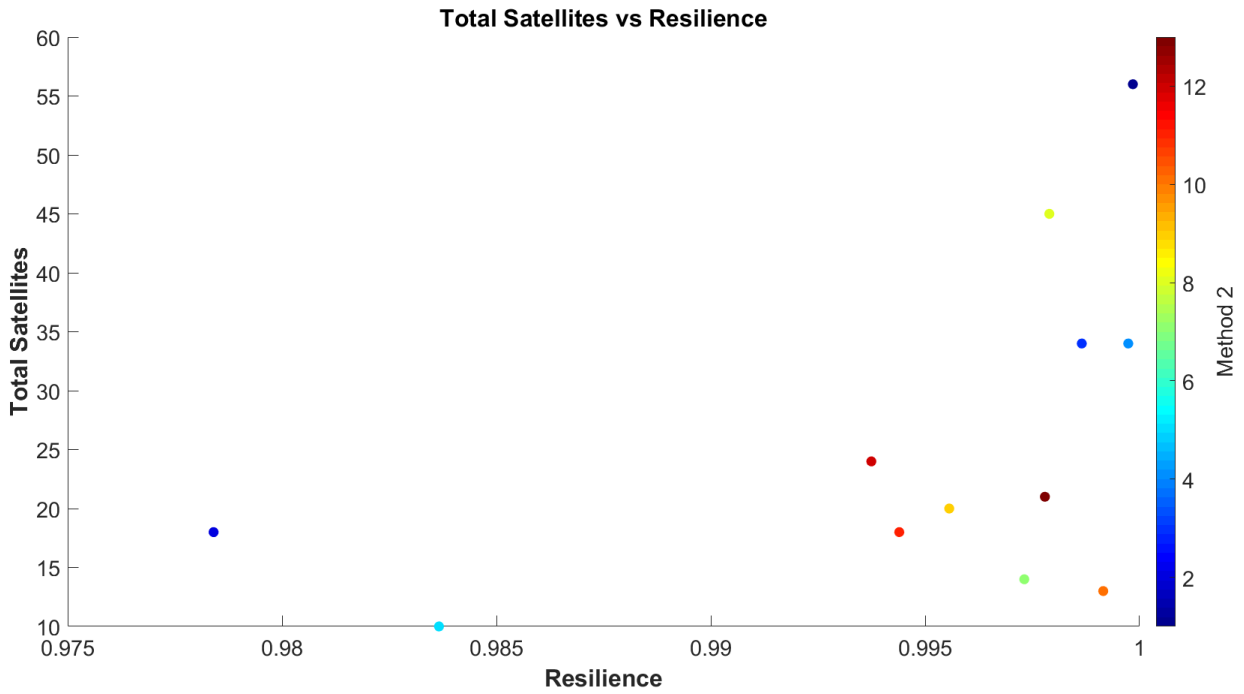


Figure 29. Total Number of Satellites in the Constellation vs. Resilience for Method 2 Optimized Trial Solutions

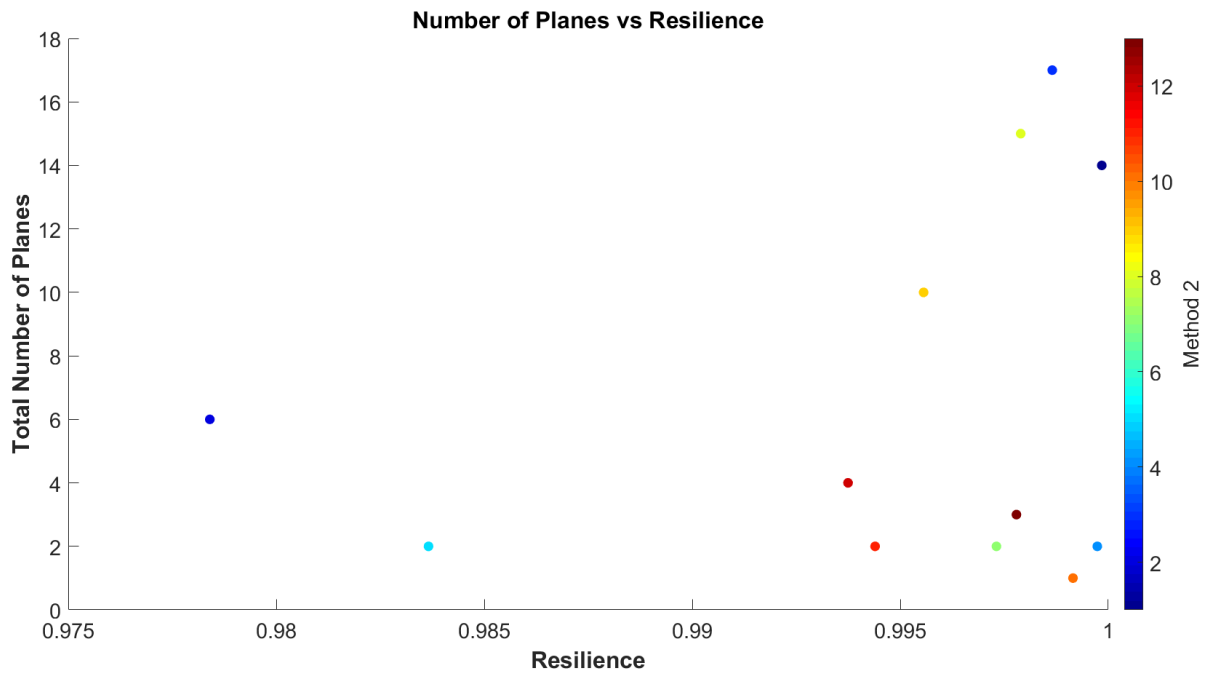


Figure 30. Total Number of Orbital Planes vs. Resilience for Method 2 Optimized Trial Solutions

Method 2 - Analyzing Trial's Final Populations.

Since the best solution from each of the 13 trials did not provide enough substantive data to make any conclusions, the entire last population of the final generation for each trial as data points was included; increasing from 13 data points to 390 points (13 trials times a population size of 30). A significant number of the solutions were immediately disregarded since they did not meet the minimum revisit requirement for FUEGO. The DISCO code incorporates constraints to ensure solutions meet the minimum specified requirements (performance, lift capacity, signal-to-noise, etc). However, these constraints serve to score the various solutions in the population to determine whether they are valid after they have already been included as a viable solution. Therefore, it will be common for solutions in the population to not meet the minimum constraint requirements, but these solutions would not be beneficial for the analysis of this research since they are not valid solutions for FUEGO. In order determine the performance of the solutions, each one was run through the resilience code to produce the resilience components. Figure 31 shows the relationship between total cost and resilience for all 390 solutions before filtering out the solutions that exceeded the minimum revisit requirement. The general grouping of lower cost, higher resilience solutions is an artifact of the optimizer forcing solutions towards lower cost and lower numbers of satellites.

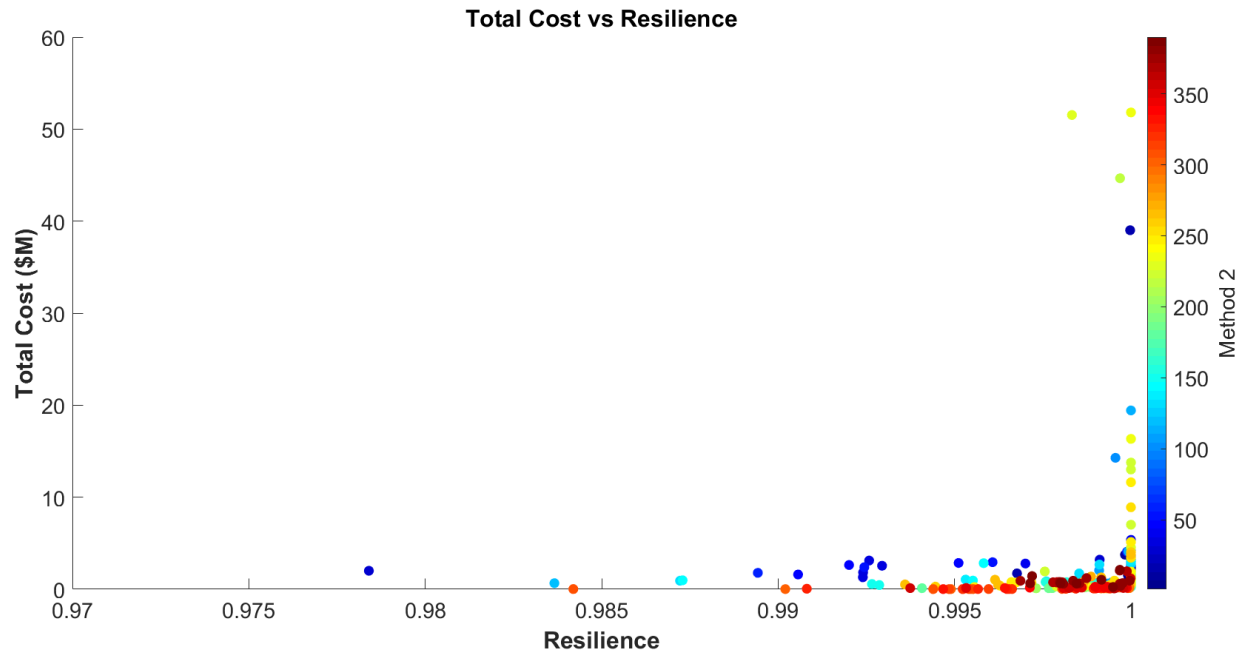


Figure 31. Total Cost vs. Resilience for the Final Populations of all 13 Method 2 Trials

In order to better evaluate the large amount of solutions, a filter to remove any solution that did not originally meet the 25-minute revisit requirement of FUEGO was applied. The GA can generate some unlikely solutions due to changing combinations of various orbit related parameters. For example, four solutions resulted in a zero quantity for each of the three satellite types. Using the 25-minute revisit metric removed 119 solutions. The remaining 271 solutions are described in the following section.

Method 2 - Filtered Trial's Final Populations Based on Revisit Time.

With extraneous solutions filtered out from the trial final populations, analysis on the components of resilience was conducted to discover any possible trending. Figure 32 shows the relationship between total cost and resilience for all of the filtered solutions. There appears to be a threshold of cost as seen from the line of data points along the bottom of the plot. At values very close to resilience equal to one, the cost starts to increase. This relationship is logical since

these constellations likely have more satellites than needed to meet the required revisit requirement. There is a significant portion of the solutions that are in between these two lines of low cost and high resilience as a compromise between the two parameters. The cost values for solutions varied greatly, even in the solution sets filtered on the original 25-minute revisit requirement. The cost ranged anywhere from several tens of thousands of dollars all the way up to \$25 billion. In general there were only a few extraneous solutions that reached such high costs and therefore the plots appear to depict several solutions with a cost of zero dollars but this is misleading since the costs are relatively low when compared to the exceptionally high cost solutions.

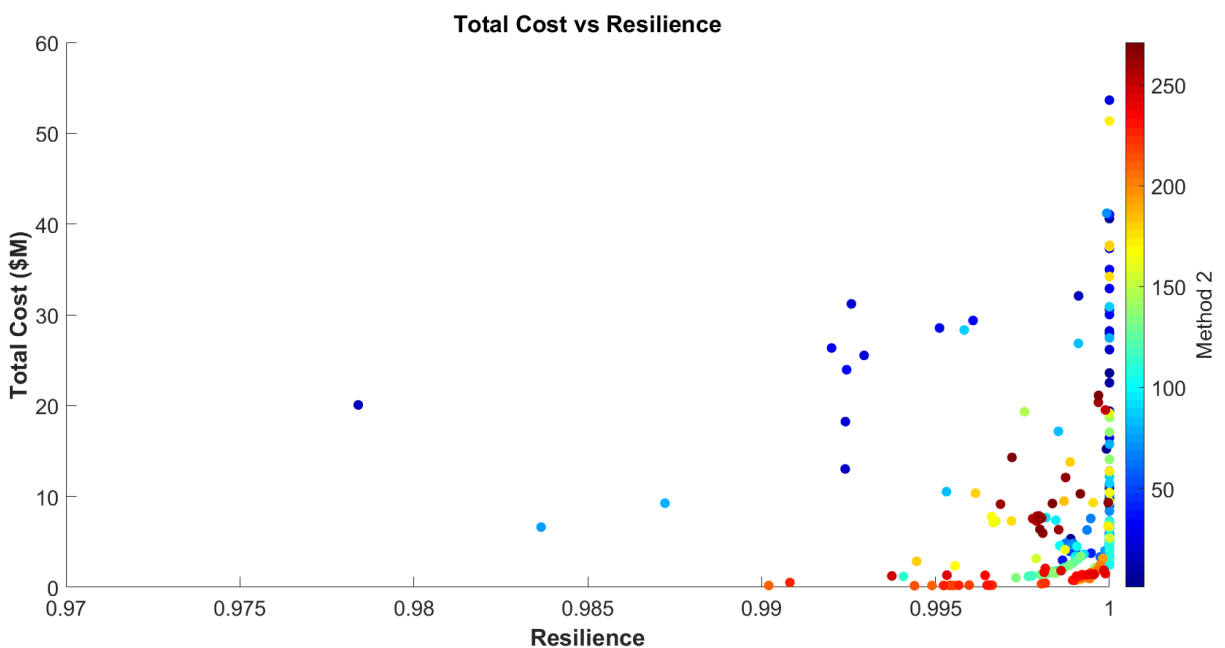


Figure 32. Total Cost vs. Resilience for Method 2 Trial Filtered Population Solutions

Each of the four components of resilience were examined to determine any possible relationships with the overall resilience. Figures 33-36 plot each of the four components of resilience versus the overall resilience of the solution for all of the filtered final population

solutions. The avoidance component again demonstrated the dependence on the 0.3 bias with a large portion of the solutions falling along the 0.7 line. There is a large number of solutions that near a resilience of 1 and have varying avoidance between 0 and 0.5.

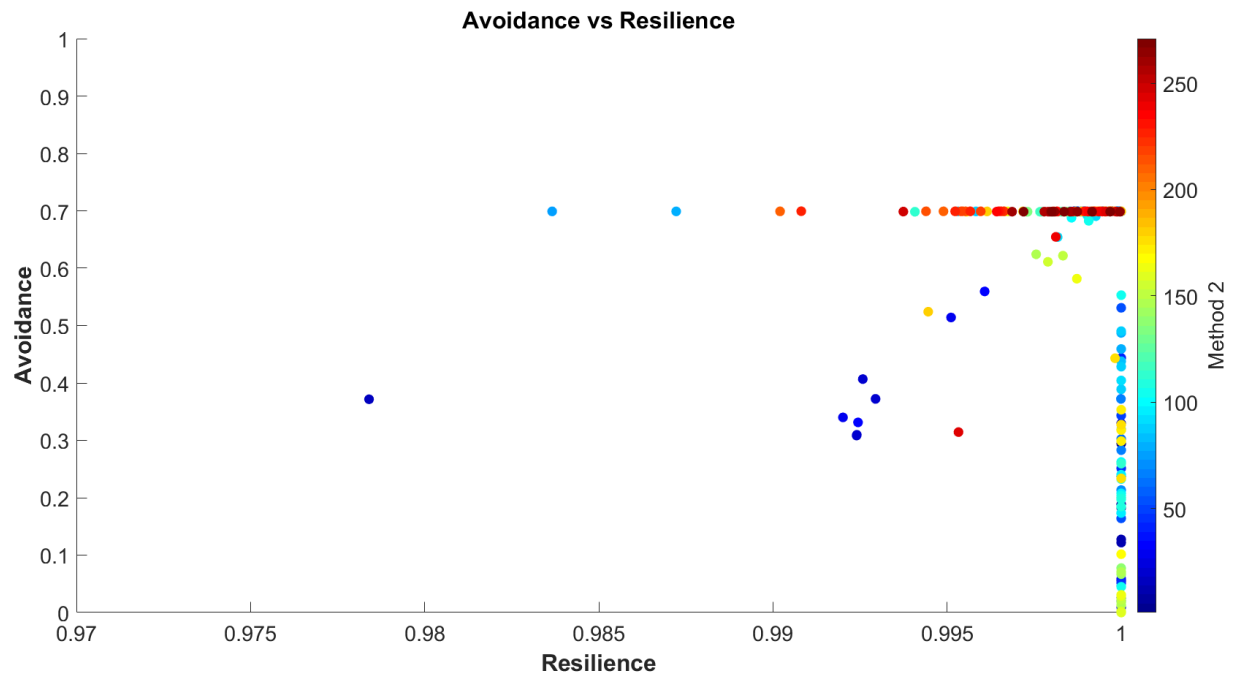


Figure 33. Avoidance vs. Resilience for Method 2 Trial Filtered Population Solutions

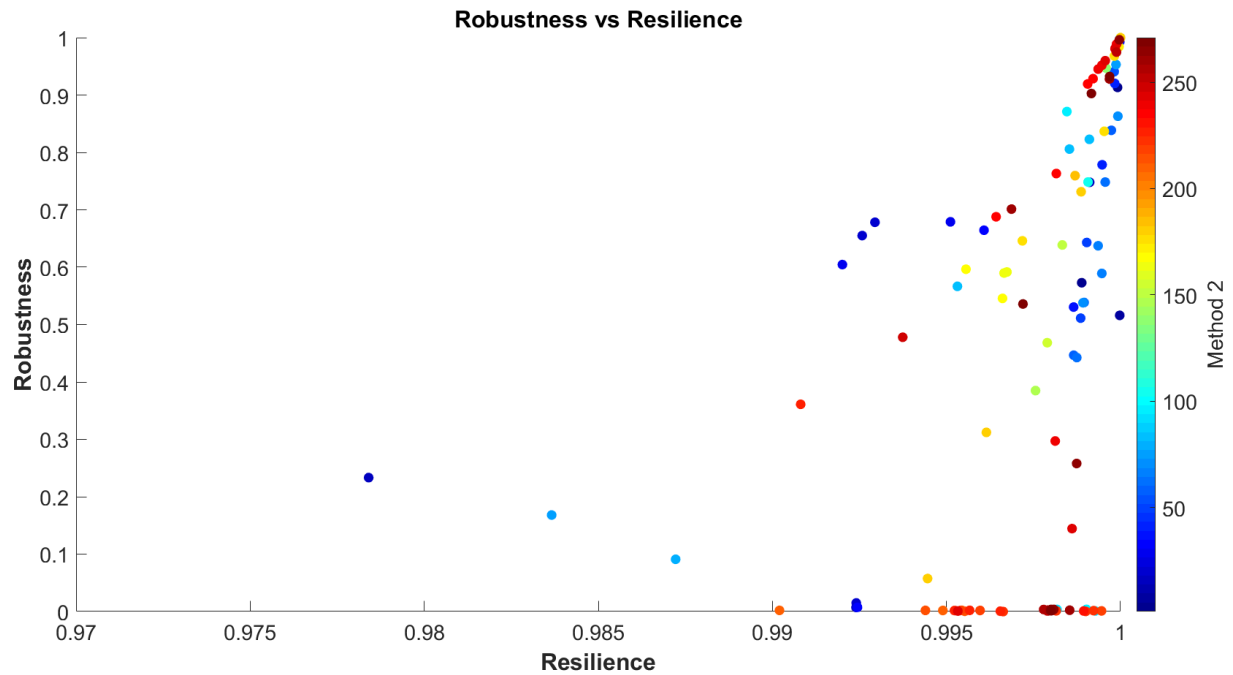


Figure 34. Robustness vs. Resilience for Method 2 Trial Filtered Population Solutions

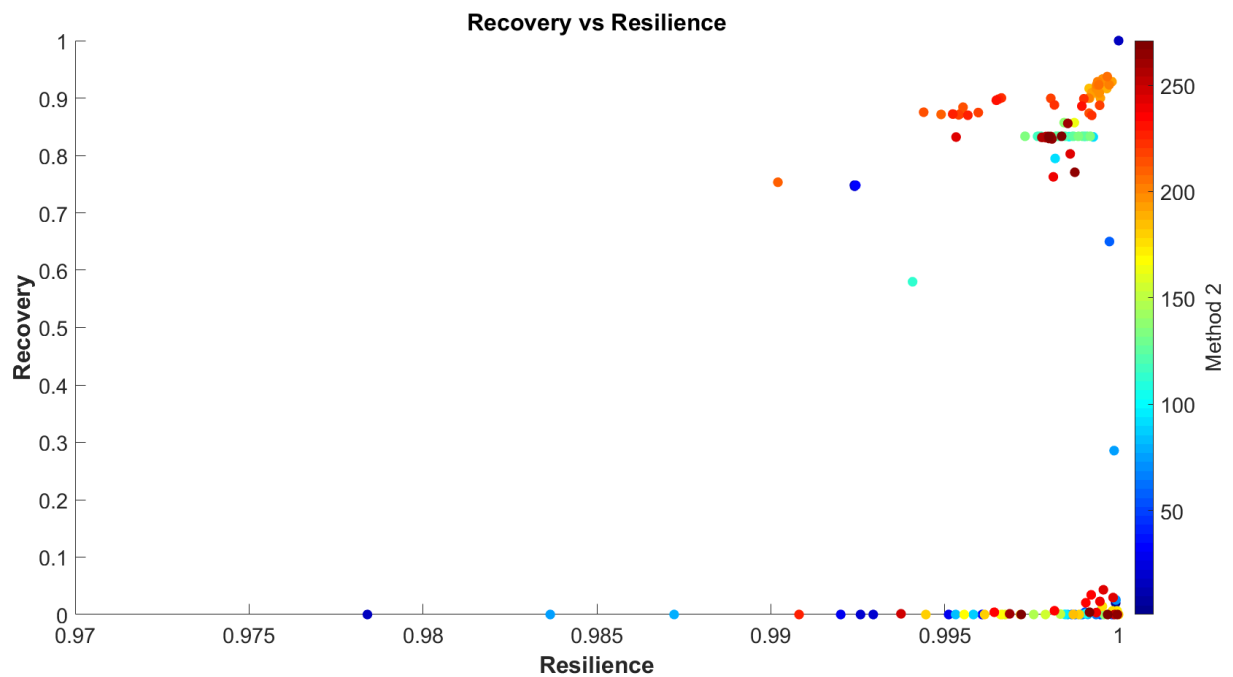


Figure 35. Recovery vs. Resilience for Method 2 Trial Filtered Population Solutions

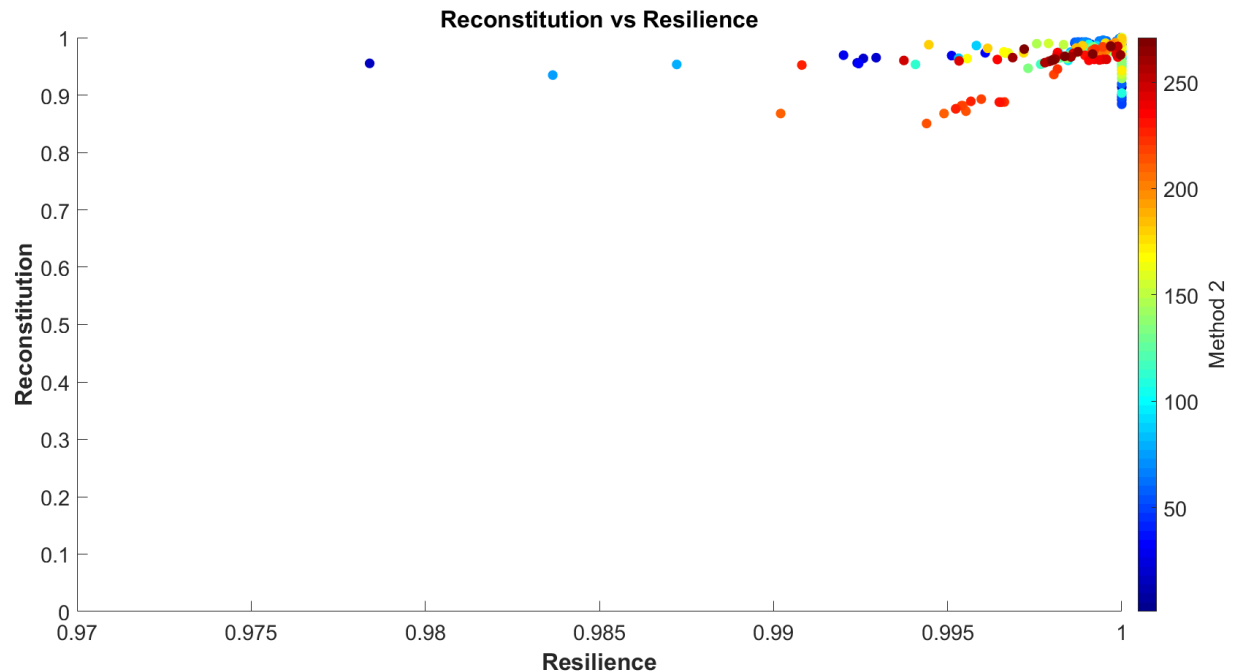


Figure 36. Reconstitution vs. Resilience for Method 2 Trial Filtered Population Solutions

Looking at robustness, a significant amount of solutions are near a value of 0 with varying resilience values. The rest of the data seems to follow a positive linear relationship as robustness increases the resilience value increases. For the recovery component, the data is separated in two large groups. One group is floating along a recovery of 0 with varying resilience. The rest of data is at very high values of recovery with the increasing recovery values appearing to relate to increasing resilience. Reconstitution values are all very high due to the fractional cost of launching single satellite compared to the overall constellation cost. A small group of the data can be seen to display a direct linear relationship between reconstitution and resilience. The majority of points are concentrated around a reconstitution and resilience values near 1.

Since the four components of resilience did not display a discernable trend when compared to the overall resilience of the constellation, the component data was then compared to

cost in order to identify any trends associated with spending more money. Figures 37-40 plot each of the components against cost. Again, there does not appear to be a discernable trend between the two values.

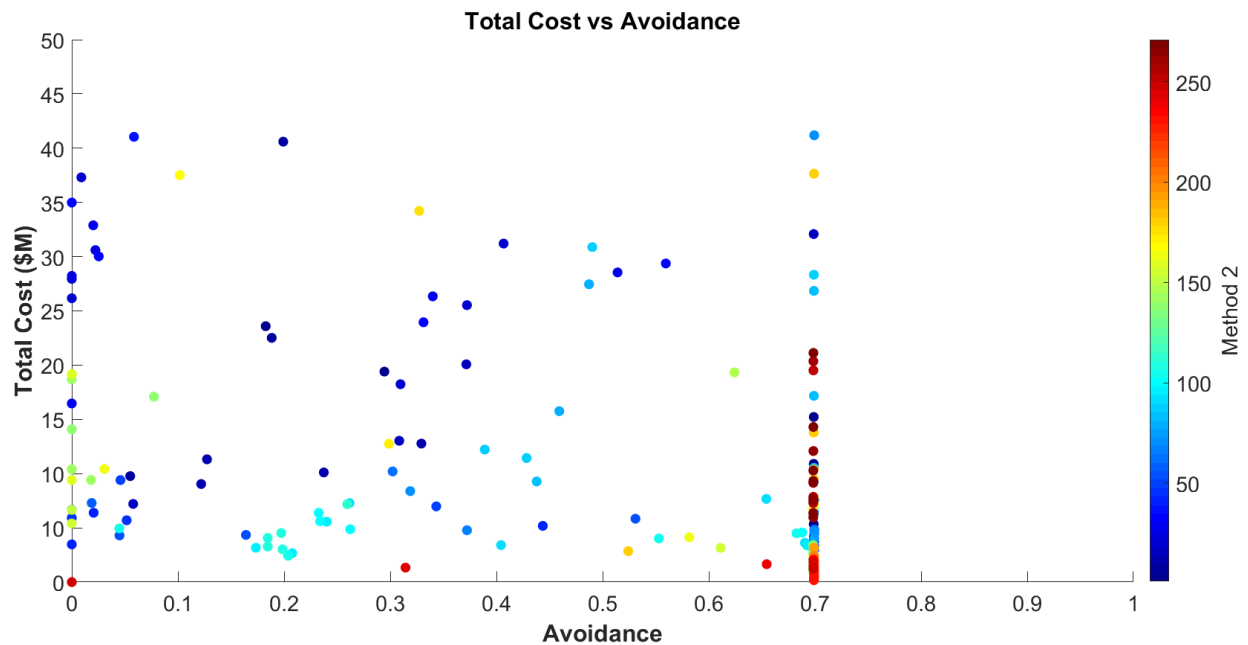


Figure 37. Total Cost vs. Avoidance for Method 2 Trial Filtered Population Solutions

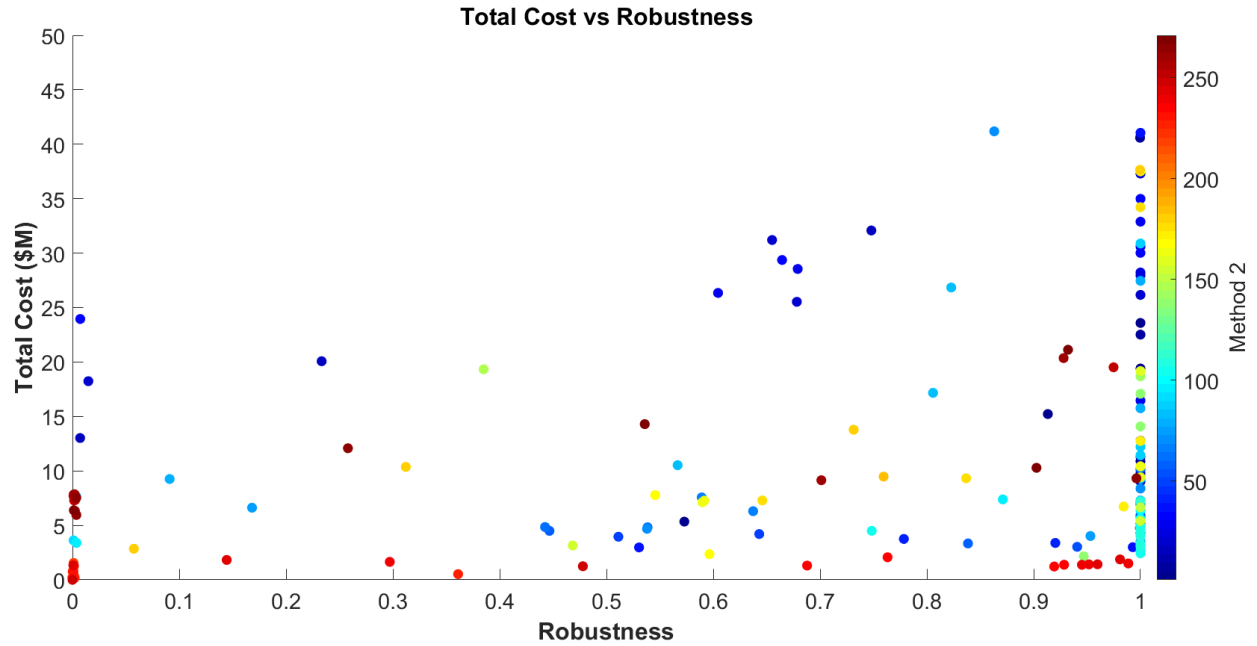


Figure 38. Total Cost vs. Robustness for Method 2 Trial Filtered Population Solutions

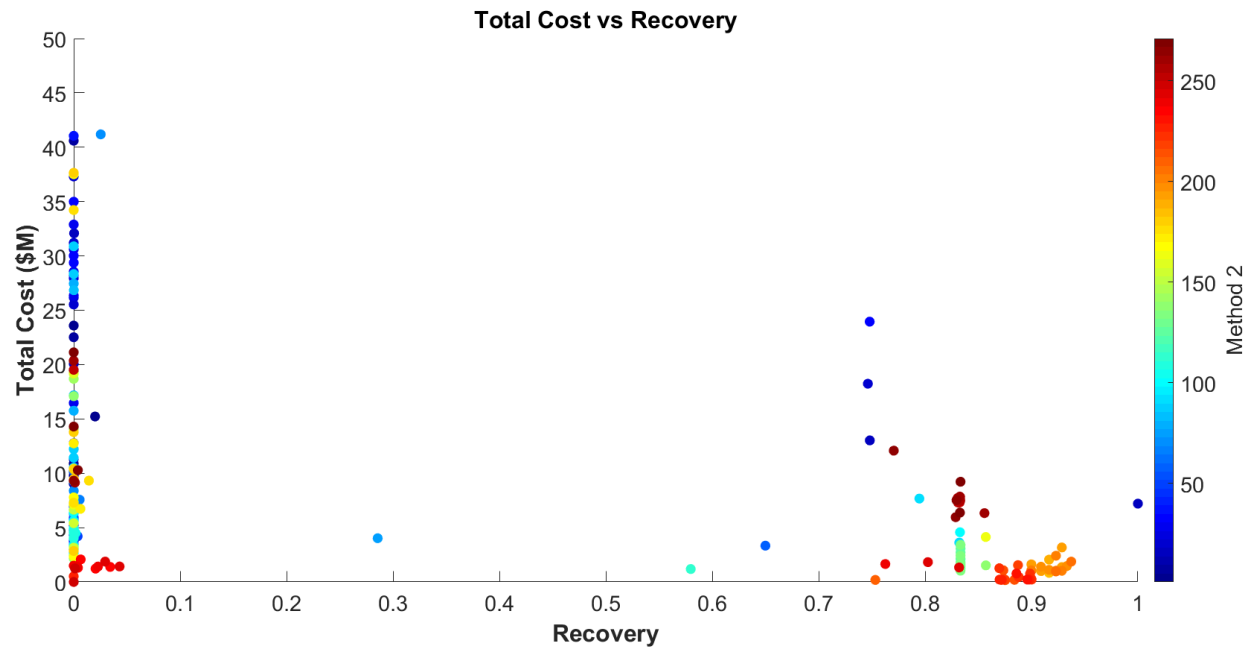


Figure 39. Total Cost vs. Recovery for Method 2 Trial Filtered Population Solutions

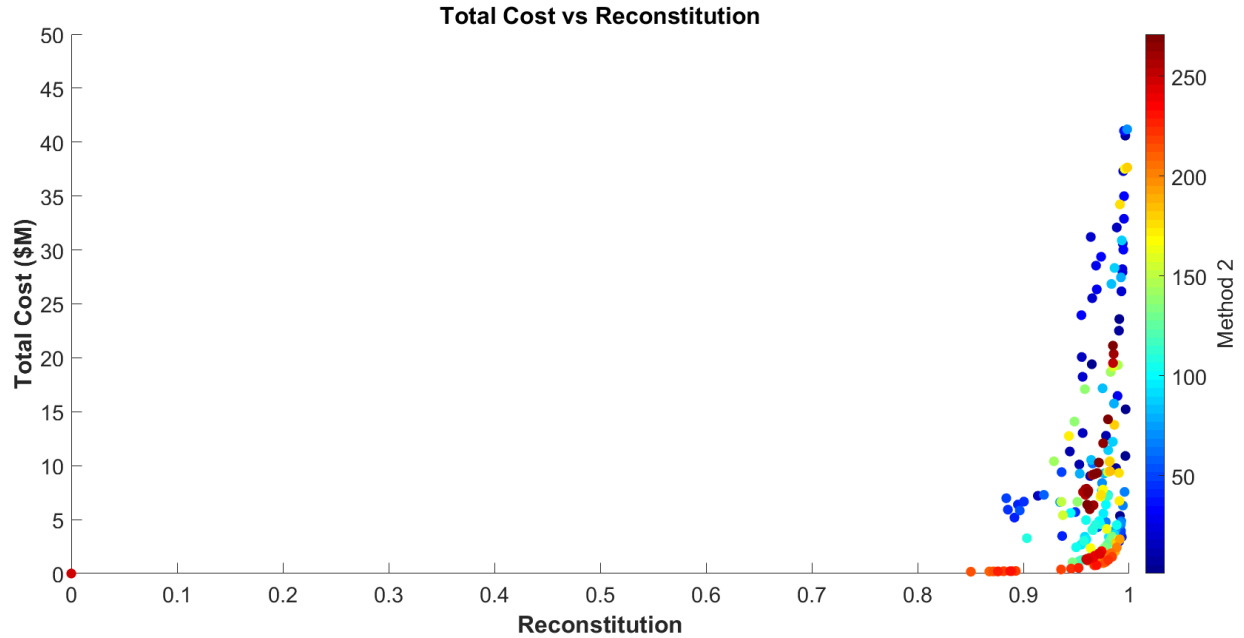


Figure 40. Total Cost vs. Reconstitution for Method 2 Trial Filtered Population Solutions

The total number satellites and total planes used in each of solutions were examined. Figure 41 shows the relationship between total satellites and resilience. Figure 42 shows the relationship between the number of orbital planes and resilience. The total number of satellites have a fairly defined line for the minimum number of satellites creating a line of points along the bottom of the data. Getting close to a resilience of 1 requires more satellites as demonstrated in the data with the density of points slowly diminishing as the total number goes up. There is a large cluster of solutions that fall in between these two boundaries that compromise between the two parameters. As for the number of planes, there is a loose relationship between total number of planes and resilience with increasing number of planes resulting in high resilience. However, many of the low plane solutions still have very high resilience. This plot does not factor in how many satellites are in each plane which is a significant factor.

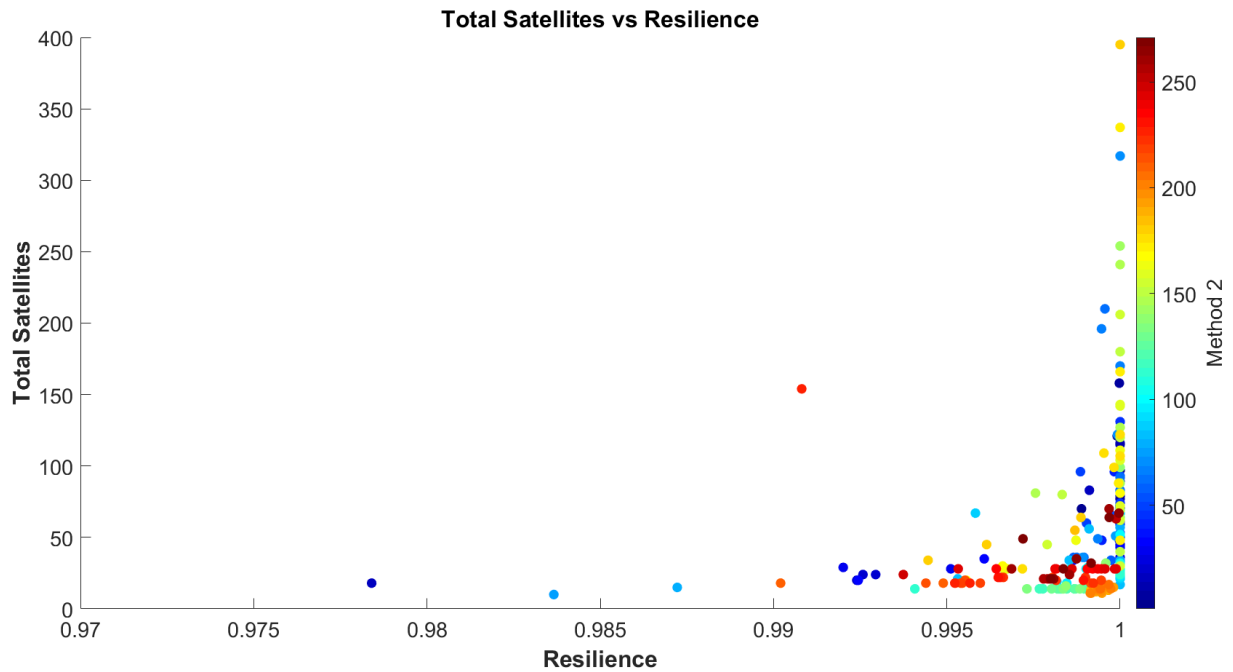


Figure 41. Total Satellites vs. Resilience for Method 2 Trial Filtered Population Solutions

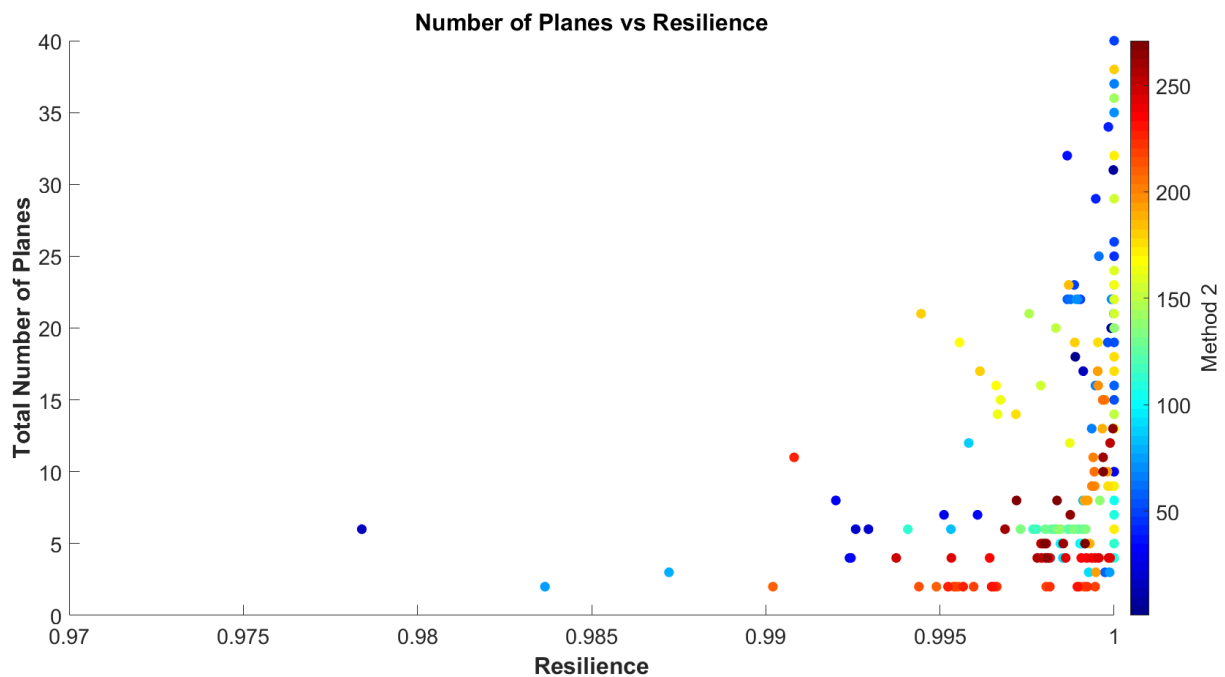


Figure 42. Number of Planes vs. Resilience for Method 2 Trial Filtered Population Solutions

After examining the filtered solutions from the final population of each Method 2 trial, a relationship between the components of resilience and total cost was developed. It is possible that the assumptions made when constructing the avoidance and reconstitution parameters may have skewed some of the data results. Therefore, a performance specific method for analyzing the resilience was developed and is explained in Chapter 3. The analysis of the results are discussed in the next section.

Performance-Only Resilience Analysis.

The method for calculating resilience did not yield a clear relationship between cost and resilience. Some of the reasons this method did not work as well as anticipated are explored in Chapter V. One of the biggest causes is suspected to be the avoidance and reconstitution components in the methodology of how each one is calculated for inclusion in the resilience equation. It was decided to focus solely on the performance components of resilience - robustness and recovery. The two components rely specifically on measurable simulation data. The methodology of the avoidance component to determine which satellite type to remove to measure the change in performance was used similarly to previous data sets. This component appears to accurately determine the most susceptible satellite type to have an issue resulting in performance loss. The performance-only resilience calculation was applied to the filtered population data that was used in the previous section since this data best meets the required revisit time of FUEGO. Figure 43 shows the relationship between the total cost and the new resilience value based on only performance.

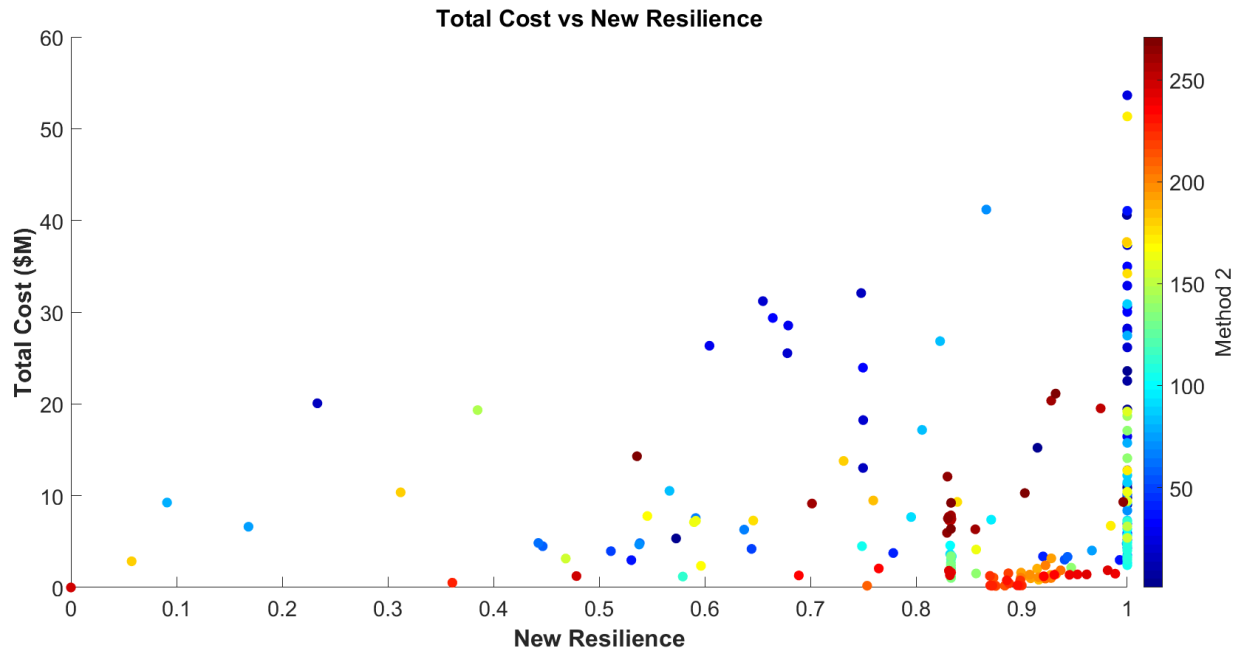


Figure 43. Total Cost vs. New Resilience for Method 2 Trial Final Population Solutions

The robustness and recovery values for the solutions were examined against the overall new resilience. Figure 44 shows the relationship of the robustness and new resilience of the solutions. There is a clear direct linear relationship between robustness and new resilience which is because of the importance of robustness in the new resilience calculation. There is a grouping of solution points that are around a value of 0 robustness. Some more explanation for this grouping can be seen in Figure 45 which shows the relationship between the recovery and new resilience of the solutions. The majority of points in the recovery plot are along the zero recovery value. There is a small group that has a direct linear relationship. This small group corresponds to the grouping seen in the robustness plot. This is due to the relationship between robustness and recovery and their relationship in the new resilience calculation. If a solution has a low robustness near zero, there is more room for the constellation to improve and recover more of original performance back. The linear trend in the recovery shows that for solutions that were

able to recover higher percentages of their original revisit time have increasingly higher overall new resilience.

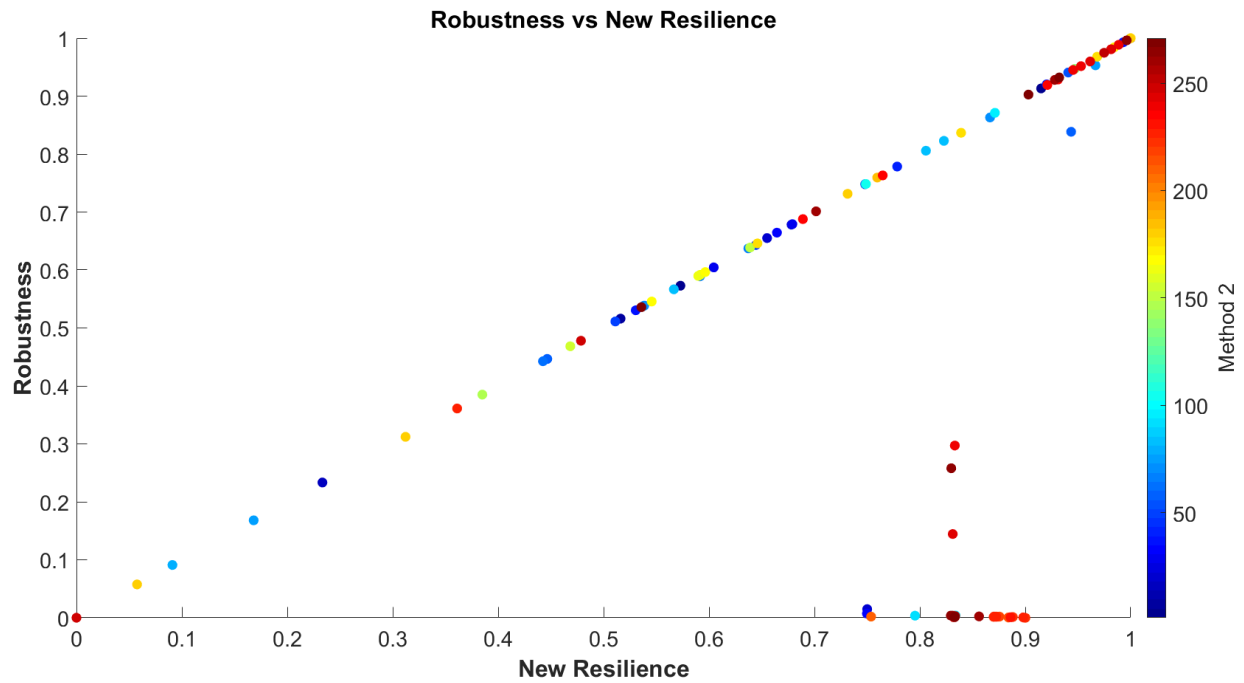


Figure 44. Robustness vs. New Resilience for Method 2 Trial Final Population Solutions

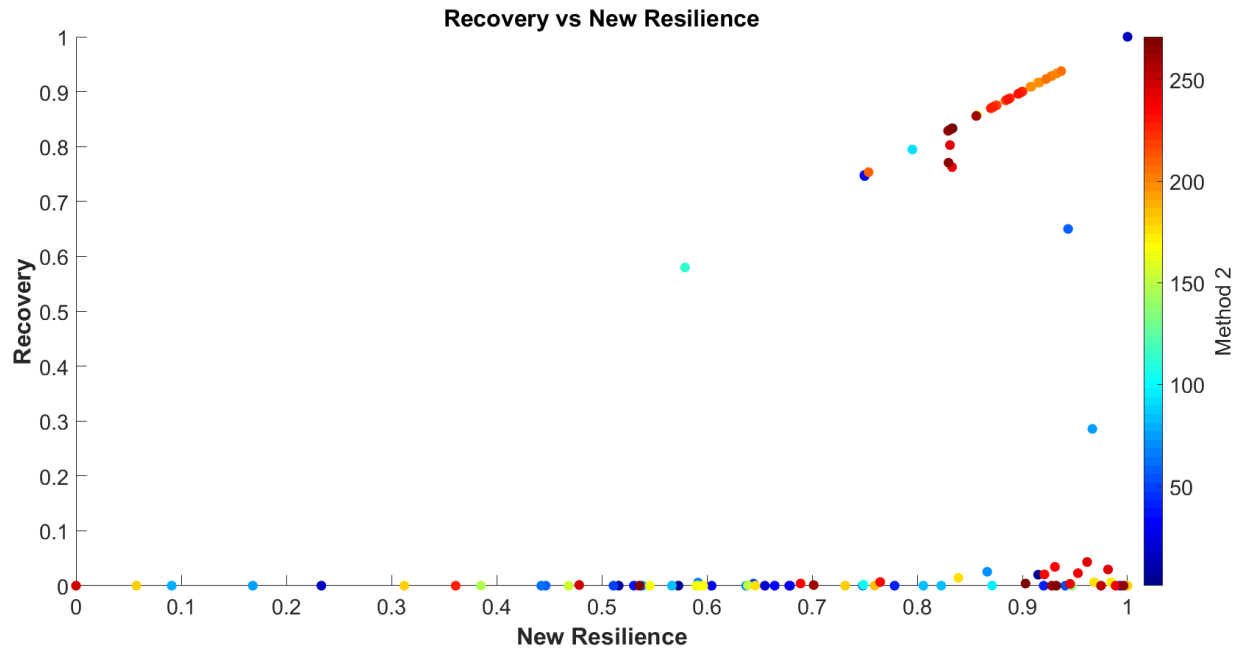


Figure 45. Recovery vs. New Resilience for Method 2 Trial Final Population Solutions

Looking at the total satellites and total number of planes used in solutions versus the new resilience produces a similar trend as was seen from the Method 2 resilience analysis. Figure 46 shows the relationship between total satellites and new resilience. The total number of satellites vary in new resilience floating between a range of total satellites. A large portion of the solutions are nearly a new resilience of 1 with the density increasing as the total number of satellites decreases. This relationship may be driven by the fact that the optimizer pushes the solutions toward a lower cost and so the majority of solutions will converge in that area. Figure 47 shows the relationship between total planes and new resilience. There is not a strong relationship between the number of planes and the new resilience. As has been mentioned in the previous sections, a significant factor for the number of planes is the number of satellites per plane for determining the revisit time. The number of planes is important to consider since it has a direct impact on the number of launch vehicles needed to launch the constellation.

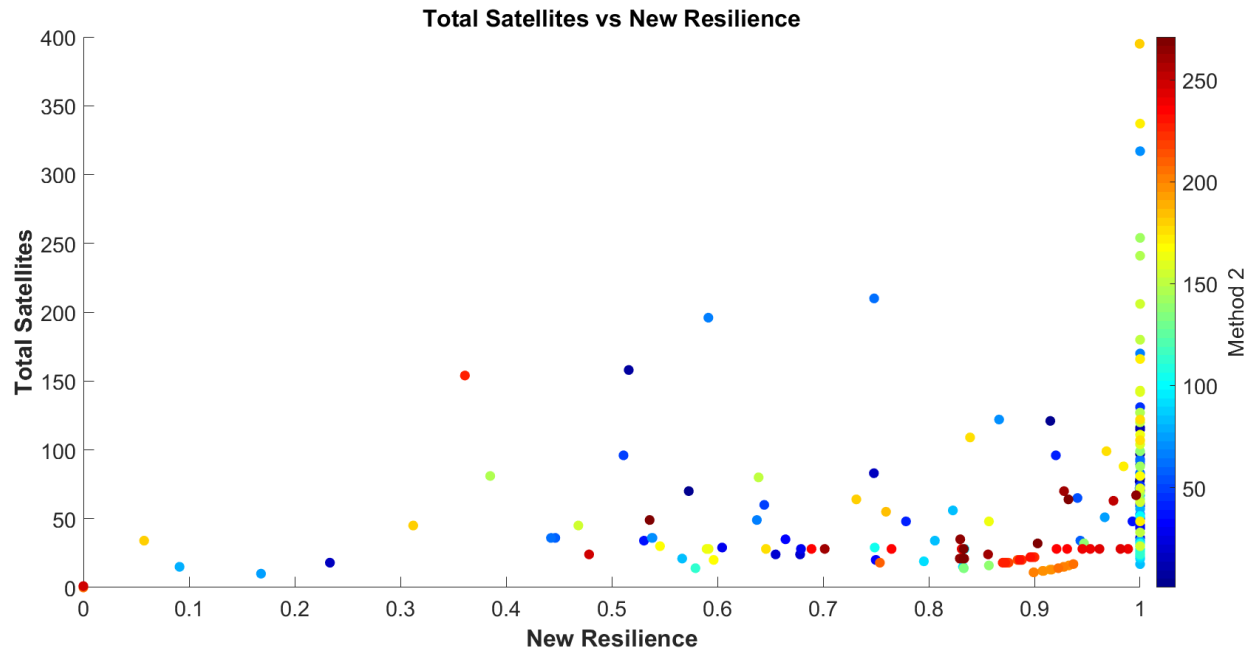


Figure 46. Total Satellites vs. New Resilience for Method 2 Trial Final Population Solutions

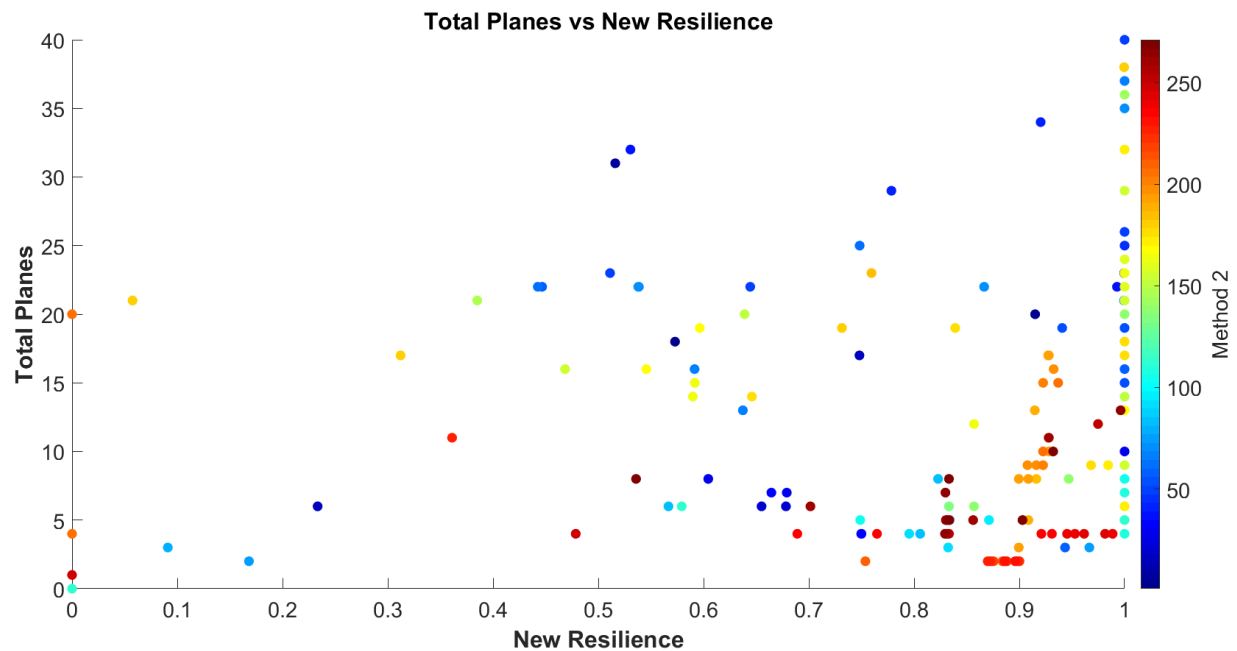


Figure 47. Total Planes vs New Resilience for Method 2 Trial Final Population Solutions

The solutions that had a new resilience of 0.95 or greater were selected analyzed in order to find any evident trends. Selecting this cut-off ensured that the solutions had a very high robustness and avoided the necessity of re-phasing the satellites after the loss of one of the satellites. This analysis is presented in the following section.

Performance-Only Resilience Analysis - 0.95 and Higher.

Solutions were limited to those that were above a new resilience value of 0.95. This resulted in 106 solutions and represented the most resilient solutions of the data set. Again, the relationship between total cost and new resilience was examined and shown in Figure 48. Nearly all of the solutions are greater than 0.995 resilience and nearly 1. The cost varies among the solutions with the density of points increasing as cost decreasing. This is a clear indicator of the optimizer attempting to find the lowest cost solutions.

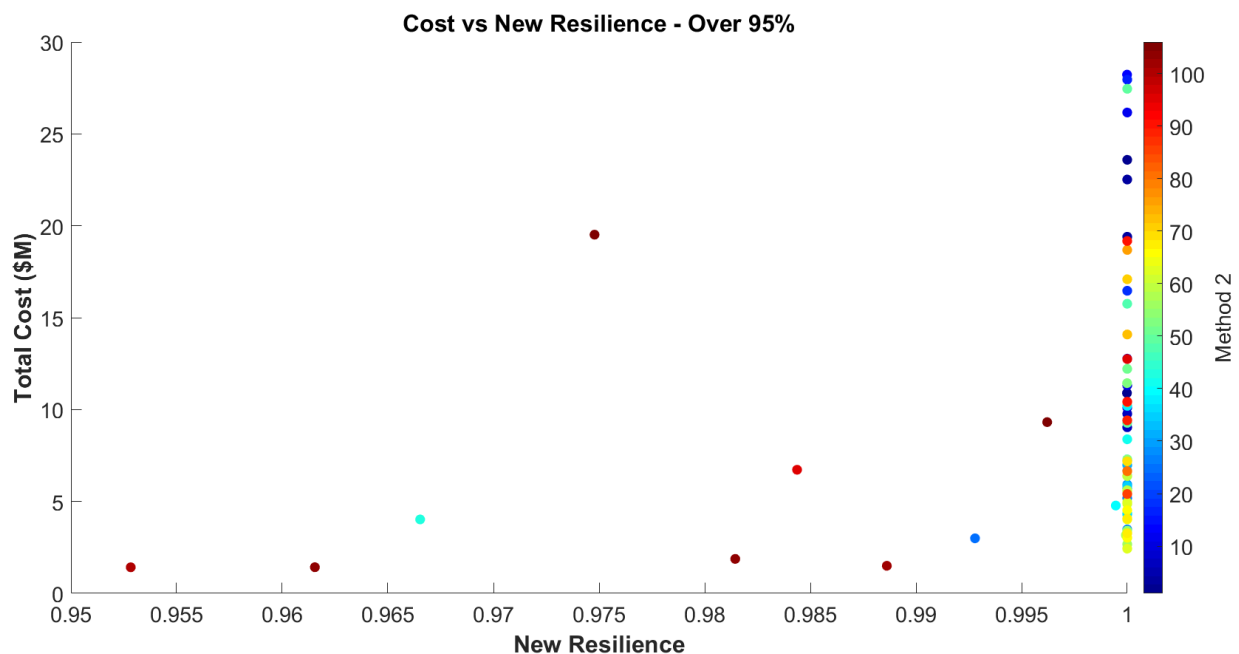


Figure 48. Total Cost vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience

Figure 49 shows the relationship between robustness and new resilience for the solutions greater than 0.95 resilience. The robustness values for the solutions now have a distinct, direct linear relationship where increasing resilience results in increasing robustness. Again, this relationship makes sense based on the equation used to calculate resilience since both of the components include the robustness value. All of the values for robustness are extremely high starting at a minimum value of 0.95. From this data, it the judgment could be made that the most resilient solutions based solely on performance are the solutions that possess extremely high robustness.

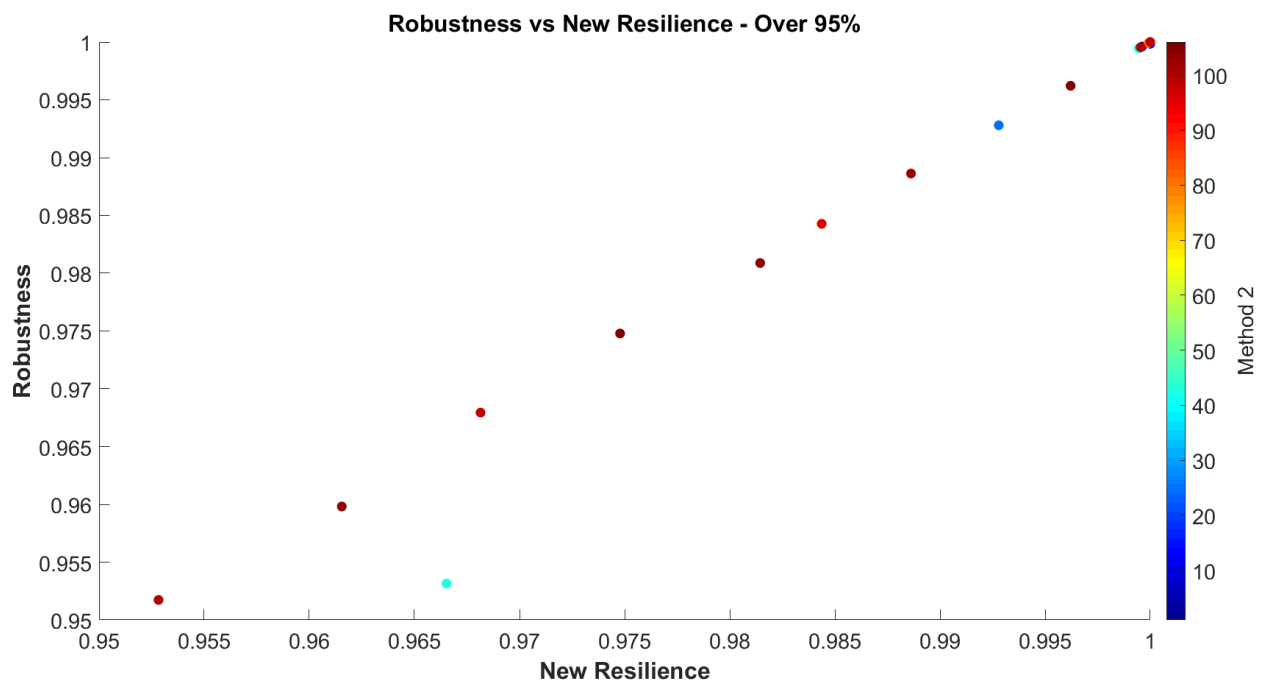


Figure 49. Robustness vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience

Figure 50 shows the relationship between recovery and new resilience for the limited data. Most of the solutions have a recovery value close to zero. This relationship makes sense given that robustness of the solutions in this limited data set are so high. There is not much performance that can be recovered after the loss since it was so small in the first place. As was

evident from the robustness plot above, the data suggests the most resilient constellation solutions based solely on performance are the solutions that retain the most capability after suffering a loss and do not require a large amount of recovery to regain the lost capability.

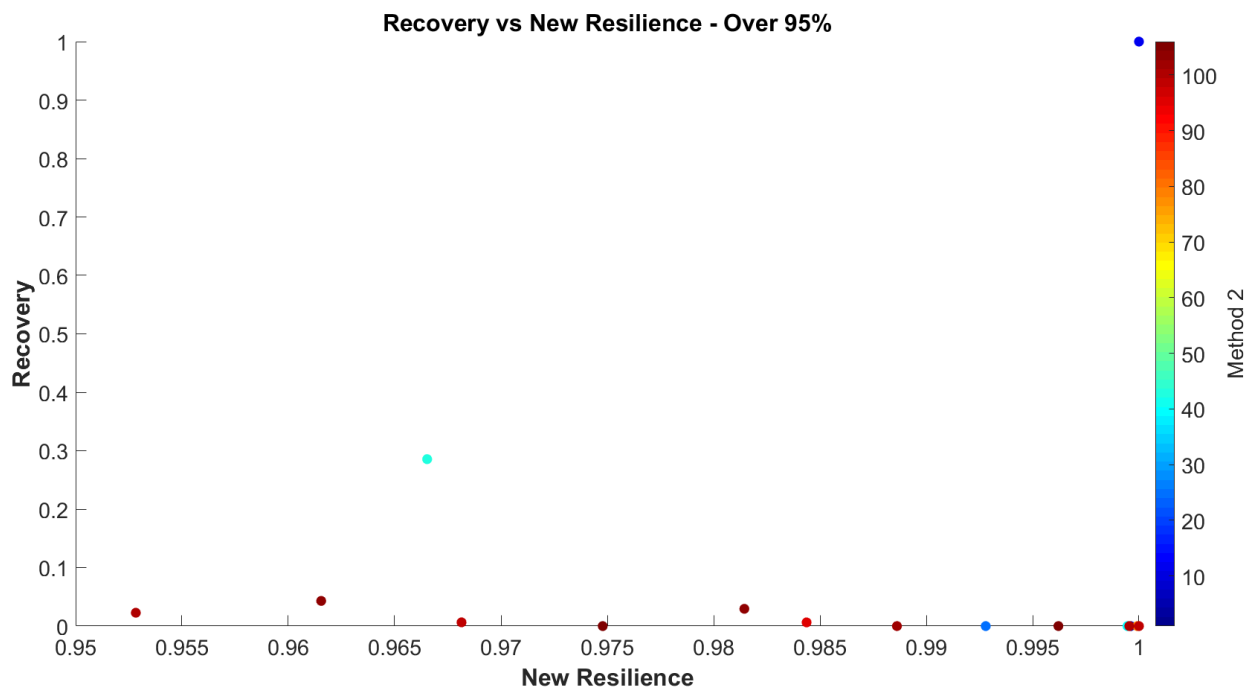


Figure 50. Recovery vs. New Resilience for Method 2 Trial Final Population Solutions above 0.95 New Resilience

The relationship between total cost and revisit time was examined to identify any visible trend between the amount of money spent and the level of performance for a constellation. Figure 51 shows the relationship between total cost and the revisit time after the constellation has recovered from the loss. There is a grouping of data points between 600 and 1500 seconds and between 0 and \$1.5B that display a slight inverse relationship between cost and revisit time. As the revisit time increases, the total cost slowly increases with the set of data between 600 and 800 seconds being more expensive the data close to 1500 seconds.

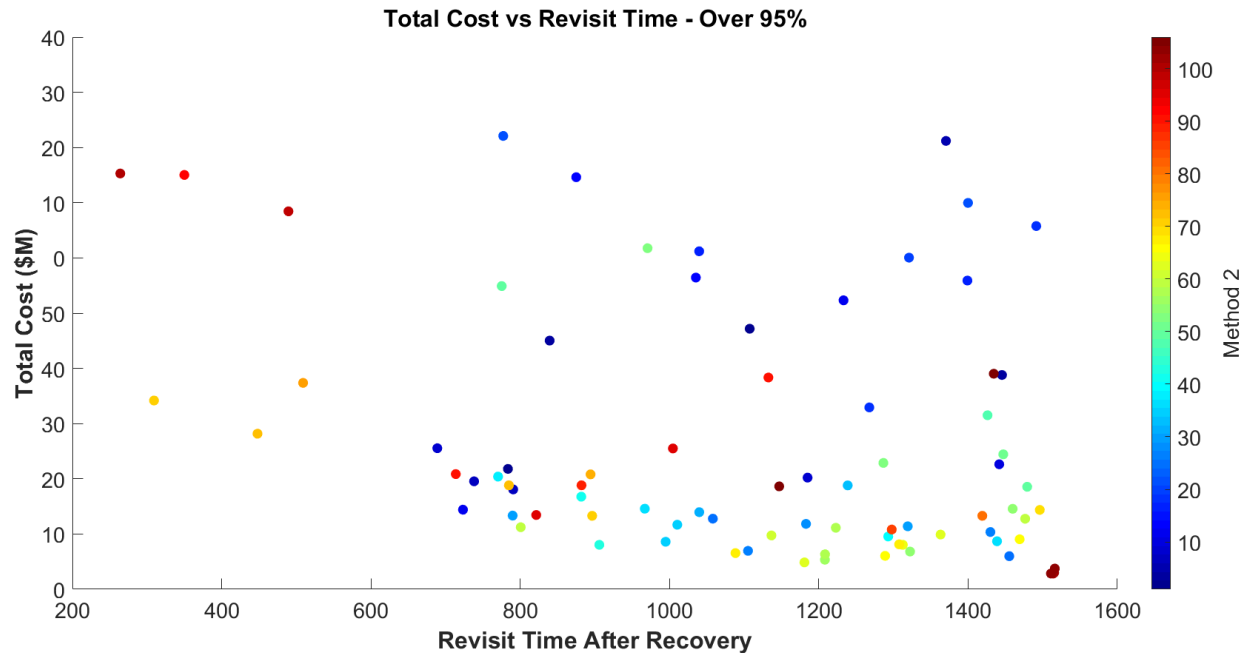


Figure 51. Total Cost vs. Revisit Time after Recovery for Method 2 Trial Final Population Solutions above 0.95 New Resilience

The last analysis performed was to examine the most competitive solutions based on the lowest cost. In order to look at about 10% of the solutions, a price boundary of 4.5 million dollars was created. The solutions that cost under this price are listed in Table 9, with solutions sorted cheapest to most expensive. There are four solutions that have a distinct price differential compared to the rest of the cheapest solutions. However, it can be seen that all four of these solutions are near the 25-minute revisit time before removing one of the satellites. After the removal, all four solutions experience an increase to over 25-minutes for revisit, but are only over this limit by at most 16 seconds. From those solutions down, the solutions begin to get exceptionally more expensive, but most of them have a significant increase in the performance of the revisit time to justify that cost. The trend displayed in the table supports the theory that as more money is spent, the performance should increase. There are some obvious exceptions to

this rule in the table where money was not used effectively and the revisit time was closer to the 25-minute minimum and did not justify the increased cost.

Table 9. Solutions of Greater than 0.95 New Resilience with a Cost Under 4.5 million dollars

Cost (\$mil)	# of Planes	# of Satellites	Robustness	Recovery	Resilience	Original Revisit Time (s)	Maximum Revisit After Removal (s)	Revisit Time After Recovery (s)
1.4178	4	28	0.9517	0.0228	0.9528	1445.9	1515.6	1514.1
1.4233	4	28	0.9598	0.0431	0.9615	1455.0	1513.5	1510.9
1.4995	4	28	0.9886	0.0000	0.9886	1498.2	1515.3	1515.3
1.8736	4	28	0.9809	0.0295	0.9814	1488.5	1517.0	1516.1
2.4310	5	27	1.0000	0.0000	1.0000	1180.7	1180.7	1180.7
2.6704	4	24	1.0000	0.0000	1.0000	1208.1	1208.1	1208.1
2.9958	22	48	0.9928	0.0000	0.9928	1444.8	1455.2	1455.2
3.0233	4	24	1.0000	0.0000	1.0000	1288.8	1288.8	1288.8
3.1688	5	30	0.9999	0.0000	0.9999	1208.2	1208.3	1208.3
3.2741	5	31	1.0000	0.0000	1.0000	1088.3	1088.3	1088.3
3.4116	5	22	1.0000	0.0000	1.0000	1322.2	1322.2	1322.2
3.4772	26	70	1.0000	0.0000	1.0000	1105.1	1105.1	1105.1
4.0227	3	51	0.9531	0.2856	0.9665	876.6	917.7	905.9
4.0232	7	32	1.0000	0.0000	1.0000	1312.6	1312.6	1312.6
4.0651	7	25	1.0000	0.0000	1.0000	1307.6	1307.6	1307.6
4.3009	15	83	1.0000	0.0000	1.0000	994.8	994.8	994.8
4.3477	18	51	1.0000	0.0000	1.0000	1438.7	1438.7	1438.7

It was determined that all the data and comparisons had been extracted from the solutions that were produced. Some of the expected behaviors were identified, but there are many improvements that need to be made to the methodology used in this analysis to more accurately characterize the resilience of a constellation of satellites. Chapter V provides more details regarding conclusions, issues, and recommendations for future work.

Summary

The research examined resilience on two different sets of data, each optimized according to different performance constraints. The set of solutions optimized based on revisit time proved to be more useful than the solutions that utilized total percent coverage. The small number of data points from the second method did not provide enough information to work with so the final population of each trial was used and allowed for more extensive analysis, albeit on possibly less optimal solutions. Using a new resilience equation based solely on performance calculated from robustness and recovery, produced new set of data where performance and cost could be evaluated together. The resilience value did still provide insight into how the constellation was affected from the satellite removal and the recovery shifting. Overall, the small subset of data which had a new resilience value of 0.95 and higher demonstrated the expected behavior in terms of cost being directly related to performance. As the performance was improved past the required minimum revisit time, the total cost began to increase. This analysis demonstrated the trade-off between total cost and performance. The cheapest solutions were those near the minimum revisit time. If the total cost was increased, more robust and resilient solutions that exceeded the minimum revisit time requirement could be found, since more satellites and/or planes were used compared to the cheapest solutions.

V. Conclusions and Recommendations

Introduction of Research

The research explored the quantification of resilience for an entire satellite constellation and sought to discover methods to evaluate the most resilient and low cost solutions from a variety of optimized solutions. The optimization solutions were leveraged from the research of Thompson and his DISCO genetic algorithm tool suite. The solutions are optimized based on meeting minimum performance requirements and minimum total cost. Changes were made to Thompson's original code to more appropriately model the mission requirements for the FUEGO mission. Solution sets for both of these methods were analyzed using a resilience equation composed of the following components: avoidance, robustness, recovery, and reconstitution. Two versions of the equation were used based on the methodology that created the data set. The first method utilized solutions that were created based on a total percent coverage performance requirement. The second method used a more accurate performance requirement of revisit time to constrain the solutions to those that meet the FUEGO mission requirements and the components of resilience based on performance were changed to account for this difference. After analyzing the solution set, it was determined that the methods for quantifying avoidance and reconstitution were ineffective for creating substantial differences in total resilience for the constellations based on changing orbital parameter combinations. A new version of the resilience equation was created that focused solely on the components that considered only the performance of the constellation - robustness and recovery.

Summary of Research Gap, Research Questions and Answers

- Hypothesis: “This paper attempts to prove that resilience values will vary for each of the different disaggregated constellation solutions generated by the optimizer based on the different combinations of orbit design characteristics.”

The research presented in this paper shows that for the methodologies chosen, the resilience components change and are representative of the level of optimization for the number of planes, number of satellites per plane, altitude, inclination, and spacing between planes for the constellation. The key performance metric, maximum revisit time, can be used to judge the various low-cost solutions and compare how resilient the solutions are in the case of losing the performance of a single satellite.

- Research Question 1: How can resilience be quantified for entire spacecraft constellation designs?

Two different methodologies were used to quantify resilience based on values calculated for avoidance, robustness, recovery, and reconstitution. The first incorporated all four of these components and utilized total percent coverage as the performance requirement. The second method incorporated maximum revisit rate as the performance constraint and examined the same four components of resilience. A modification was made to the second method that took a more performance-based approach and focused on the robustness and recovery components with some supplemental data from avoidance. The first method resulted in values for resilience on a scale of 0 to 1 that were all very close to 1, with 1 being a perfectly resilient solution. The second modified method created a slightly bigger disparity in the resilience values for the data set, but still had a concentrated amount near 1.

- Research Question 2: How can resilience be used to evaluate possible optimized constellation design choices in order to choose the most resilient and cost effective option?

The components of resilience that produced the most effective and useful criteria for analyzing a multitude of constellation design choices were robustness and recovery. The methodology implemented was simulation based and produced consistent and accurate results based on the change in performance for the constellations as they were tested for resilience. The original and new level of performance when compared with cost, provide an effective way to compare competing constellation designs. Tradeoffs between performance and cost are very evident and the choice can be made by the designer.

Study Limitations

The research performed had limitations in both the amount of research into the field and in the computer requirements to create the solutions needed to have a quality set of data to analyze. As described in Chapter II, there was an issue with developing a means to characterize the components of resilience for an entire constellation of satellites. As seen in the results, there is much room for improvement in evaluating the avoidance and reconstitution components. Lack of research into methods for quantifying the probabilities that characterize these two components limited the ability of the equation to properly represent them in the overall resilience value.

A significant hindrance to the research was due to issues in computing time. It was assumed that the best set of data would be achieved from running the DISCO code for many trials and using the optimized trial solutions as the sample set. Running the optimizer for Method 1 took around 16 hours and later for Method 2 took around 24 hours. Since the run times were so long, the GA parameters were not designed to be as stringent such that more trials could be completed. However, it was discovered that the quantity of optimized trial solutions did not

provide enough data for the analysis which required the use of the population of the last generation. Since the GA parameters were lowered, the quality of the solutions in these populations likely decreased significantly. This most likely had an adverse effect on both the consistency and accuracy of the data available to analyze which limited the ability to make assessments.

Recommendations for Action

Thompson's original DISCO suite of tools that produce results for the FUEGO mission requirements must be changed to incorporate revisit rate instead of total cumulative percent coverage. The code should be made to evaluate solutions over a scenario time greater than 30 minutes in order to ensure the mission requirements are satisfied over an extended period of time. It would also be beneficial to adapt the code to utilize a "headless" version of STK - the same STK software but without a visual display which improves the computing time of simulations and permits more intensive computational analysis. This will allow the optimizer to run faster since it will not be attempting to display graphics to a screen. The launch vehicle component of the code also needs to be re-assessed. The key metric which drives the number of launch vehicles is the required mass for launch and the launch capacity of the various vehicles. A constraint does exist to ensure the number of planes does not exceed the number of launch vehicles since this would be impossible. The launch vehicle optimization should be constrained more in order to account for the number of planes in the current solution. As the code is currently written, concurrently generating the constellation solution and the launch vehicle configuration does not seem to be the optimal way to handle the problem. For example, a solution consisting of three planes of three small satellites per plane could be achieved with three launch vehicles, but the optimizer could produce a solution of 15 launch vehicles. The number of

launch vehicles satisfies the lift capacity constraint so the solution is valid, but clearly not optimized. So long as the total weight of the satellites is less than the total launch vehicle capacity, the launch vehicle configuration is considered valid, regardless of how much more that capacity is. The launch vehicles can represent a very large portion of the total cost of a particular solution so it is important that this is properly coded otherwise the cost values of the solutions could be inadvertently inflated. The new code should include a more sophisticated means to optimize payload capacity for each launch vehicle and account for the number of satellites and required launch vehicle volume.

Recommendations for Future Research

Continued research into avoidance and reconstitution is necessary for the resilience equation to be successful in accurately characterizing constellation solutions. Most of the constellation solutions were at an altitude large enough that the calculated probability of collision was negligible. The avoidance component is an important piece of resilience and should play a major role in determining overall resilience, but the component had little variation across the solution sets. The reconstitution component needs to be further researched. The methodology used focused on characterizing the cost of the satellite compared to how much the entire constellation cost. In nearly all the solutions, this fraction is incredibly low. Time is also an important factor for evaluating reconstitution but a way to incorporate it in the calculation was not determined.

For the continued use of the DISCO GA, a generation size of 50 and a population size of 50 and setting the stall limit to 50 generations is recommended to ensure the solutions are optimized and the trial is not prematurely terminated due to the scores of the solutions. In order to complete more trials, the code for a smaller population size was altered and most of the trials

stalled out at the stall limit generation, although there was still room for improvement. Another recommendation is to assess the accuracy of the launch vehicle data produced by optimizer and implement the changes described in the section above. If the launch vehicles are not accurately calculated, the calculated total cost of the constellation could be much larger than in reality.

Significance of Research

The research provided analytic results for multiple variations of a method for calculating the resilience of various optimized constellation solutions. The resilience equation which incorporated the methodology of Method 2 revisit time optimization produced more accurate results for performance than the Method 1 methodology of total percent coverage. The modified form of the resilience equation based solely on performance provided slightly larger differentiation in resilience values to where the different solutions could be compared. The most important analysis that was produced was the robustness and recovery calculation in determining the change in performance for the constellation after removing a satellite and re-phasing the plane in which it was removed to compensate for the removal. After evaluating the revisit time for the constellations compared to the total cost along with the number of satellites and orbital planes, a decision can be made on what is the optimal trade-off between lowest cost or increased performance.

The goal of the research was to find a method for choosing the cost-effective, resilient constellation design from a multitude of optimized solutions. The research and analysis achieved this goal and made big steps in beginning to quantify and evaluate resilience as a design metric. Unfortunately, a direct relationship between cost and resiliency was not found. This lack of relationship could hold implications for the commercial and government space sector. It may not always be possible to instill resiliency by simply spending more money on a given mission.

Looking at the equation for resilience presented by Boeing suggests that each component of resilience is equally weighted. Therefore, mission planners may be able to instill a high level of resilience by focusing on one component. For example, if a satellite orbits in a safe sector of space resulting in negligible mission threats (high avoidance), the remaining components of the resilience equation (robustness, recovery, and reconstitution) become unnecessary. Likewise, if a satellite constellation is designed with an ease for reconstitution, whether or not a satellite can avoid threats, is robust, or can recover becomes insignificant. If optimizing based on cost, analysis should be performed for a given satellite mission to determine the cheapest component(s) of resilience that can be maximized.

Research into the current state of knowledge on resilience, showed that there were few methods being explored in order to calculate it. Research was taken a step further to apply one of the few existent ideas for quantifying resilience and adapted it to an entire satellite constellation. This research provides significant contributions to the body of knowledge of resilience and could be the basis for further research and improved analysis in the field.

Appendix A: Complete Solution Set for Method 1

Table 10. Method 1 Trials 1-18 Output Parameters - Satellite Type 1

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
2	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
3	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
4	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
5	4	4	323	28	1924	1.00E-06	92	359.36	283.29	315	0.28
6	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
7	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
8	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
9	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
10	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
11	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
12	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
13	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
14	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
15	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
16	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
17	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
18	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

Table 11. Method 1 Trials 1-18 Output Parameters (continued) - Satellite Type 2

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	1	8	30	167	6635	1.00E-06	93	29.09	344.43	70	0.04
2	6	5	217	323	4753	1.00E-06	57	95.49	230.87	297	0.03
3	1	10	135	294	5983	1.00E-06	24	2.31	247.43	171	0.03
4	1	12	341	164	6054	1.00E-06	83	156.47	315.04	137	0.07
5	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
6	1	19	124	32	6942	1.00E-06	81	327.12	6.85	334	0.03
7	5	7	315	174	6053	1.00E-06	74	332.49	55.88	242	0.06
8	3	9	280	141	4613	1.00E-06	21	279.12	147.70	267	0.05
9	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
10	8	2	304	157	5336	1.00E-06	29	54.33	356.48	91	0.03
11	1	10	135	294	5983	1.00E-06	24	2.31	247.43	171	0.03
12	3	10	56	274	5711	1.00E-06	19	1.50	358.65	167	0.03
13	1	11	171	356	6982	1.00E-06	98	264.41	225.57	163	0.04
14	19	2	353	35	6359	1.00E-06	86	357.73	280.75	116	0.03
15	14	1	75	187	6579	1.00E-06	75	327.72	93.28	142	0.06
16	1	6	21	316	5791	1.00E-06	84	206.83	265.29	318	0.10
17	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
18	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

Table 12. Method 1 Trials 1-18 Output Parameters (continued) - Satellite Type 3

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
2	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
3	5	3	202	234	966	1.00E-06	42	144.29	347.75	56	0.03
4	4	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
5	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
6	2	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
7	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
8	7	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
9	2	10	273	133	5246	1.00E-06	71	51.67	286.76	125	0.03
10	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
11	5	3	202	234	966	1.00E-06	42	144.29	347.75	56	0.03
12	9	2	37	258	944	1.00E-06	19	349.40	344.36	56	0.03
13	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
14	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
15	4	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
16	16	1	29	214	3176	1.00E-06	44	356.23	354.38	100	0.03
17	13	2	60	349	4680	1.00E-06	92	352.77	82.44	210	0.03
18	3	9	312	283	4731	1.00E-06	40	41.57	93.20	133	0.03

Table 13. Method 1 Trials 1-18 Output Parameters (continued) - Launch Vehicles

Trial	# of Minotaur	# of Falcon 9	# of Atlas V	# of Delta-4H
1	1	0	0	0
2	4	3	0	0
3	3	6	0	0
4	10	0	0	0
5	17	9	0	0
6	12	0	0	0
7	7	2	2	0
8	8	3	1	1
9	13	0	0	0
10	9	0	0	0
11	3	6	0	0
12	4	10	0	4
13	1	0	0	0
14	19	0	0	0
15	15	5	0	0
16	9	0	3	5
17	19	3	0	0
18	8	7	6	3

Appendix B: Complete Solution Set for Method 2

Table 14. Method 2 Trials 1-13 Output Parameters - Satellite Type 1

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
2	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
3	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
4	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
5	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
6	3	4	195	152	1178	1.00E-06	72	216.34	99.00	258	0.32
7	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
8	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
9	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
10	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
11	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
12	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
13	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

Table 15. Method 2 Trials 1-13 Output Parameters (continued) - Satellite Type 2

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	14	4	195	306	4260	1.00E-06	40	279.42	336.01	192	0.13
2	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
3	17	2	327	341	6312	1.00E-06	95	354.11	349.91	113	0.05
4	2	17	24	290	6911	1.00E-06	96	275.99	330.90	285	0.10
5	2	5	203	266	4782	1.00E-06	2	220.76	226.46	222	0.21
6	2	6	287	105	2573	1.00E-06	84	183.74	42.00	260	0.17
7	2	7	235	160	2963	1.00E-06	42	29.23	254.78	223	0.11
8	15	3	7	34	873	1.00E-06	43	0.00	0.00	20	0.08
9	10	2	310	321	2915	1.00E-06	70	155.68	102.86	127	0.13
10	1	13	165	30	5275	1.00E-06	90	28.67	13.45	325	0.05
11	2	9	128	254	5019	1.00E-06	57	265.80	132.91	179	0.04
12	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
13	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----

Table 16. Method 2 Trials 1-13 Output Parameters (continued) - Satellite Type 3

Trial	# of Planes	# of Sats/Plane	True Anomaly Phasing (deg)	RAAN Increment (deg)	Altitude (km)	Eccentricity	Inclination (deg)	RAAN (deg)	Argument of Perigee (deg)	Mean Anomaly (deg)	Lens Diameter (m)
1	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
2	6	3	111	102	1780	1.00E-06	56	61.62	259.52	258	0.08
3	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
4	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
5	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
6	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
7	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
8	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
9	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
10	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
11	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
12	4	6	263	103	3400	1.00E-06	61	144.40	265.04	92	0.03
13	3	7	73	264	3210	1.00E-06	66	21.47	284.91	243	0.06

Table 17. Method 2 Trials 1-13 Output Parameters (continued) - Launch Vehicles

Trial	# of Minotaur	# of Falcon 9	# of Atlas V	# of Delta-4H
1	16	6	8	3
2	12	5	9	4
3	19	10	4	5
4	19	1	8	2
5	15	2	1	6
6	16	5	6	6
7	3	8	0	0
8	20	10	6	3
9	16	2	3	0
10	16	7	0	0
11	5	0	0	0
12	2	5	0	1
13	9	1	1	1

References

- Aven, T. (2011). On Some Recent Definitions and Analysis Frameworks for Risk, Vulnerability, and Resilience. *Risk Analysis*, 515–522.
- Burch, R. (2013). A Method for Calculation of the Resilience of a Space System. *2013 IEEE Military Communications Conference*. San Diego, CA.
- Colombi, J., Miller, M. E., Schneider, M., McGrogan, J., Long, D. S., & Plaga, J. (2012). Predictive mental workload modeling: implications for system design. *Journal of Systems Engineering*, 15(4), 448-460.
- D. Escorial, I. T. (2003). *Acta Astronautica*. Retrieved from Science Direct.
- Department of Defense. (2011). *FACT SHEET: Resilience of Space Capabilities*.
- Edlund, G. (2013). *Military Space Resilience: Definition, Measurement and Application*. Northrop Grumman Aerospace Systems.
- Haimes, Y. Y. (2016). *Risk Modeling, Assessment, and Management*. Hoboken: John Wiley & Sons, Inc.
- Ikonos-2*. (2017, May 12). Retrieved from eoPortal:
<https://directory.eoportal.org/web/eoportal/satellite-missions/i/ikonos-2>
- Luo, C., Okamura, H., & Dohi, T. (2013). Characteristic Analysis of Quantitative Definition of Resiliency Measure. *2013 IEEE International Symposium on Software Reliability Engineering Workshops*, (pp. 11-12). Pasadena, CA.
- Pisacane, V. L. (2008). *The Space Environment and Its Effects on Space Systems*. Reston, Virginia: American Institute of Aeronautics and Astronautics, Inc.
- Richards, M. G. (2007). Defining Survivability for Engineering Systems. *CSE*, (pp. 1-12).
- Thompson, M. R. (2015). *A Methodology For The Optimization of Disaggregated Space System Conceptual Designs*.
- Trussell, T., Bellagamba, L., Maguire, S., & Yung, K. (n.d.). *Analytic Framework to Identify Resilient Space Architectures*.

Weeden, B. (2010, November 10). *2009 Iridium-Cosmos Collision Fact Sheet*. Retrieved from Secure World Foundation:
https://swfound.org/media/6575/swf_iridium_cosmos_collision_fact_sheet_updated_2012.pdf

Wertz, J. R., Everett, D. F., & Puschell, J. J. (2011). *Space Mission Engineering: The New SMAD*. Hawthorne, CA: Microcosm Press.

Zaerpoor, F., Ghashghai, E., Thai, D., & Kim, J. (2013). *Measuring and Enhancing Resilience of Space Architectures: An Operationally Based Method*. AEROSPACE.

REPORT DOCUMENTATION PAGE				Form Approved OMB No. 074-0188	
The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number. PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.					
1. REPORT DATE (DD-MM-YYYY) 15-06-2017		2. REPORT TYPE Master's Thesis		January 2016 – June 2017	
TITLE AND SUBTITLE Quantifying and Evaluating the Resilience of Optimized Space Constellations for Fire Detection				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Cuhran, Joseph J, Mr. GG-12 Jenkins, Matthew K, Mr. GG-13 Walters, Michael J, Mr. GG-13				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 WPAFB OH 45433-7765				8. PERFORMING ORGANIZATION REPORT NUMBER AFIT-ENV-MS-17-J-057	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Sponsor not disclosed				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT DISTRIBUTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.					
13. SUPPLEMENTARY NOTES This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.					
14. ABSTRACT With greater emphasis on space operations (both offensive and defensive), greater numbers of spacecraft and space debris in various congested orbits, and greater reliance on space capabilities (communications, navigation and surveillance), resilience has become a priority across the space community. However, there is surprisingly limited extant research and analysis on methods for quantifying the resilience of neither a single satellite, nor an entire constellation. This thesis seeks to address this gap in knowledge and applies versions of a resilience equation on large solution sets of satellite constellations optimized for the fire detection mission. The resilience calculation is composed of the following probabilistic components: avoidance, robustness, recovery, and reconstitution. Research explores how to calculate these components and shows their relationship to total resilience of the constellation, and the relationships to numbers of satellites, numbers of orbital planes and overall acquisition cost. A new method for calculating resilience is proposed which is based solely on performance from simulated data and uses only the components of robustness and recovery. This thesis fills a missing body of knowledge on how to incorporate a quantitative measure of resiliency, together with optimization and simulated mission performance, while conducting space constellation design trades.					
15. SUBJECT TERMS Resilience, resiliency, space constellation design, space simulation, optimal design					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Dr. John M. Colombi, AFIT/ENV
U	U	U	U	118	19b. TELEPHONE NUMBER (Include area code) (937) 255-3636, ext 3347 (john.colombi@afit.edu)

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18