ELECTRO-OPTIC SATELLITE CONSTELLATION DESIGN USING MULTI-OBJECTIVE GENETIC ALGORITHM

THESIS

Yasin Tamer, Captain, TURAF

AFIT-ENY-MS-20-D-071

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENY-MS-20-D-071

ELECTRO-OPTIC SATELLITE CONSTELLATION DESIGN USING MULTI-OBJECTIVE GENETIC ALGORITHM

THESIS

Presented to the Faculty

Department of Aeronautics and Astronautics

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 Space Systems

Yasin Tamer

Captain, TURAF

December 2020

AFIT-ENY-MS-20-D-071

ELECTRO-OPTIC SATELLITE CONSTELLATION DESIGN

USING MULTI-OBJECTIVE GENETIC ALGORITHM

Yasin Tamer

Captain, TURAF

Committee Membership:

Dr. A.S. Keys
Chair

Lt.Col. B.D. Little, PhD
Member

Lt.Col. A.M. Cox, PhD
Member

AFIT-ENY-MS-20-D-071

Abstract

Satellite constellation design is a complex, highly constrained, and multidisciplinary problem. Unless optimization tools are used, tradeoffs must be conducted at the subsystem level resulting in feasible, but not necessarily optimal, system designs. As satellite technology advances, new methods to optimize the system objectives are developed. This study is based on the development of a representative regional remote sensing constellation design. This thesis analyses the design process of an electro-optic satellite constellation with regional coverage considerations using system-level optimization tools. A multi objective genetic algorithm method is used to optimize the constellation design by utilizing MATLAB and STK integration. Cost, spatial resolution, and coverage are computed as objective functions. A single variable Space Telescope Cost Model is used to determine the system cost. The search parameters of the optimization method are the 6 classical orbital elements, Walker constellation parameters such as number of planes and number of satellites per plane, and the sensor diameter length as the driving variable for the cost model. The results from this model will provide a trade-space for the baseline satellite design based on the sensor's diameter length and cost, versus mission requirements. Resulting tradeoffs allow decision makers to have a broad perspective of constellation usage for remote sensing missions for their preferences.

Acknowledgments

I would like to express my sincere appreciation to my faculty advisor, Dr. Andrew Keys, for his guidance and support throughout the completion of this thesis effort. He always had time to work with me and the completion of this thesis was made possible in a short span of time of his advising period. I would also like to thank my former faculty advisor, Lt.Col. Jacob Freeman, for his support and leadership to design the scope of this thesis work at the beginning. I definitely learned a lot from them.

I would also like to express my thanks and appreciation to AFIT members who assisted me and interacted along the way from the beginning of my student time at AFIT to graduation. Among numerous many, special thanks to Registrar Office members, Ms. Annette Robb and Mr. Michael Paprocki from International Military Student Office and ENY4 17M class members.

Yasin Tamer

Table of Contents

Page

List of Figures

List of Tables

Page

ELECTRO-OPTIC SATELLITE CONSTELLATION DESIGN

USING MULTI-OBJECTIVE GENETIC ALGORITHM

Chapter 1

Introduction

Usage of near space for satellite applications is one of the greatest engineering achievements of the modern age. From communications to remote sensing, space technologies are used in numerous disciplines. Not only has it provided a better understanding of our solar system and universe, but it has also enabled changes in our lifestyle, including the huge breakthroughs from GPS applications. Beginning with the Sputnik launch in 1957, thousands of satellites have been successfully launched into Earth or interplanetary orbits, but since the Cold War, changes in the space industry demand space programs to produce faster, cheaper solutions. This new approach on spacecraft design aims to minimize the cost under performance constraints, rather than maximizing performance under technology constraints [1]. Figure 1-1 illustrates the change in spacecraft design problem [2]. The aerospace design practice has gone from an environment where performance is prioritized, and technology was the limiting factor to an environment where funding and budgets are prioritized, and performance is used as the limiting factor to control costs.

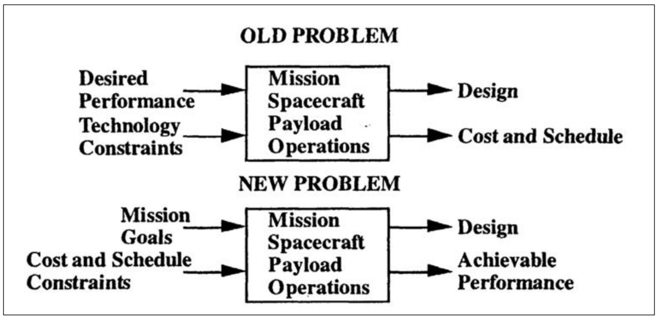

Figure 1-1: Change in Spacecraft Design Problem

Space programs of various countries are planning on smaller satellites with smaller constrained budgets for their future work. Specifically, space-based remote sensing systems will likewise consist of smaller, less expensive satellites. It is therefore necessary to consider methods of optimization that seek to maximize satellite performance under constrained budgets using cost estimation models to achieve desired objectives.

1.1 Motivation

Remote sensing satellites have been used in many areas, such as geographic and geologic mapping, environmental studies, disaster monitoring, city planning, forest fire monitoring and military purposes [3]. Although a single satellite or a combination of a few satellites are generally used for a specific mission or by the user organization, regional or global coverage require the use of many satellites in a constellation. An advantage of constellation usage is the robustness. Although the technology is developing rapidly, there is always a risk of failure at launch or in the orbital checkout phase. Constellation systems can tolerate the failure of a single satellite, or even a few satellites, and the mission objectives can be achieved with only minor degradation.

Low Earth orbits (LEO) yield a possible usage for remote sensing satellites as the optical systems cannot achieve the desired resolution objectives from higher orbits without larger, heavier sensors and more power. Even with placing a satellite into LEO, the optical payload of a satellite needs to be sized reasonably large due to the resolution requirements. However, recent technological developments in optics make it possible to produce smaller solutions for such missions. Although, the resolution is still limited by the size of diffraction. [4]. By using smaller and less expensive satellites, the same mission objectives can be met with a smaller budget. Considering the need for coverage, and given a fixed budget, these technological developments allow for a greater number of satellites that will then achieve increased coverage, persistent observations, redundancy and increased reliability.

As using a constellation of smaller satellites becomes more common for space programs, there have been studies on designing the systems. Constellation design consists of a complex combination of sub disciplines with various factors.

Figure 1-2 shows the major areas of the constellation design problem [5]. The design elements may be categorized as configuration & orbit design, spacecraft design, launch manifest, and cost through deployment. As the interdisciplinary subsystem variables couple the disciplines together; dependence of disciplines on each other makes the constellation design problem an iterative process.

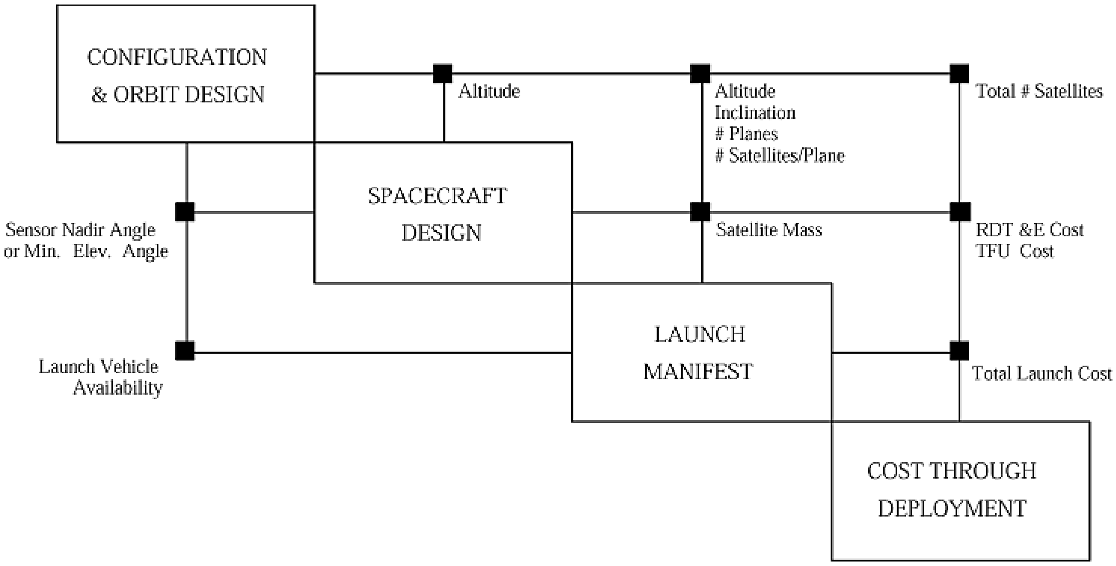

Figure 1-2: Satellite Constellation Design Problem

Therefore, design of a satellite constellation may be approached as a complex, highly constrained and multidisciplinary problem. These complexities could potentially influence designers to simply develop a feasible solution instead of the more complex optimal solution. Trade studies are generally conducted at the subsystem level instead of the system level. As a result, and unless optimization methods are used at the system level, design teams optimize solutions of the various subsystems, making tradeoffs among the subsystems; this yields optimal subsystems within a feasible system, but not an optimized overall system. Figure 1-3 illustrates trade issues on subsystems and how improvement of each subsystem affects the overall system [5].

Variable	Configuration and orbit design	Spacecraft design	Launch manifest
Altitude	↑	↓	↓
Inclination	↑	——	↓
Minimum elevation angle	↓	↑	——
Number of planes	↑	——	↓
Number of satellites per plane	↑	——	↓

Figure 1-3: Trade Issues for Satellite Constellation Designs

The complexities of satellite constellation design, combined with this sub-optimal system-level design, drove the designer to develop optimization algorithms to achieve optimal solutions. As a result, multidisciplinary design optimization (MDO) emerged as a field of aerospace research developed to fill the gap in system level optimality [5]. This approach improves the conceptual design process as it bridges the gap between disciplinary analysis and optimal design framework [6, 7]. When compared to the typical trade study process, MDO applications offer significant time savings for design teams and improved understanding for complex engineering problems. With computer-aided solutions of these problems, designers can analyze the interactions among different sub-disciplines and determine the best solution to the conceptual design problem [8].

Different MDO applications have been used on space programs, including individual satellite design, as well as constellation design. The most common methods of MDO are the gradient-based optimization methods. But for constellation optimization problems, where the focus is system level, these enumerative methods are not applicable [9]. Constellation designs include nonlinear problems with discrete variable sets and multiple objective functions; thus, dynamic programming or heuristic methods must be employed to provide feasible solutions for the constellation optimization problem.

Among the heuristic methods for constellation problems, the literature in this field highlights many proven genetic algorithms to work on this problem [10]. George applied a genetic algorithm to a sparse-coverage constellation design problem which surpassed Walker constellation design in performance with reference to maximum revisit time [11]. Multiple studies were conducted for constellation design with a focus on zonal [12, 13] and global [14, 15] coverage metrics.

Considering the requirements of the constellation problem, conflicting objectives occur at the system level, such that decision-makers must make trade-offs to obtain the most suitable solution. Further, multi-objective genetic algorithms (MOGA) are beneficial, as they can provide a non-deterministic set of solutions to evaluate the trade-offs [16]. In this study, a MOGA algorithm will be used.

1.2 Problem Statement and Solution Approach

The usage of space-based remote sensing systems is rapidly increasing. Development of optics technology makes it possible to design smaller and cheaper solutions. This thesis is a study on electro-optic satellite constellation design with regional coverage considerations. At present, remote-sensing satellite solutions consist of using large satellites to obtain high resolution, but current developments and near-term applications for small satellites (around 50 kg of mass) aim to produce comparable sub-meter resolution [17] as obtained through diffraction-limited instruments.

This research analyses the design of a constellation using small satellites with a given budget and mission requirements. We use methods of optimization that seek to maximize satellite performance under constrained budgets using cost estimation models. The research uses the Matlab MOGA tool and Analytical Graphics, Inc. (AGI) Systems Tool Kit (STK) to design and analyze a constellation model. The cost of individual satellites in the system will be estimated using a linearized conceptual method that is a function of the sensor diameter [18].

1.3 Research Objectives

The aim of this study is to design an electro-optic satellite constellation using optimization tools and cost model.

This study has two main objectives: (1) development of a robust constellation design; and (2) analysis of the candidate solutions to give decision makers an understanding of the trade space. The purpose of the design is to achieve a constellation that can meet the mission objectives, such as resolution and coverage, with a given budget constraint. Design tools consist of cost estimation, resolution functions, and the MOGA optimization; they must work together to provide robust design solutions. The design also gives a conceptual baseline design of the satellite model that will be used in the constellation. The results from this model will provide a trade-space for the primary optical instrument's aperture diameter, length, and cost, versus mission requirements.

As a result of the design simulations, the tradeoffs will give decision makers broad guidelines for the design and implementation of remote sensing constellations. With these analyses, it is aimed to achieve a solution that provides an achievable constellation for a given budget. The tradeoffs will show the cost, resolution and revisit time parameters of the constellation design, as well as the baseline conceptual design of the small satellite to use in the constellation.

1.4 Summary

With the developments on technology and space mission objectives of users, constellation usage is rapidly increasing. This leads the space programs to develop more effective design methods. As the constellation design problem has a highly complex nature, computer aided optimization methodologies develop rapidly.

This study is based on the necessity of a regional remote sensing constellation design. The research tools include MOGA and STK. This thesis is the extension of previous AFIT thesis works on constellation design optimization [16, 19]. Resulting tradeoffs allow decision makers to have a broad perspective of constellation usage for remote sensing missions for their preferences.

Chapter 2 presents the concepts of constellation design and literature review on optimization methods. Chapter 3 presents a detailed description of the methodology, objective functions, decision variables and the constraints. Chapter 4 gives the results of the research, and Chapter 5 presents the conclusions and the suggestions for future work.

Chapter 2: Literature Review

Background

This chapter presents a summary of topics relevant to constellation design and optimization methods. It covers the concepts related to constellation design and different constellation configurations. Advantages and disadvantages of various optimization methods are analyzed, which have been chosen to find a suitable method for this research. Finally, a description of previous and current work is given.

2.1 Concepts of Constellation Design

Even though it has only been a few decades since the dawn of the space age, humanity has developed multiple ways to utilize it. From the first launch to current operations, we have become more and more reliant on space applications in our daily lives. Although we are far from exploring the full potential of space, current technology already has significant effects on our modern lifestyle. The most common categories of space utilization can be listed in four general areas: communications, navigation, science and exploration, and remote sensing. Each mission type demands a different spacecraft design with a different engineering mindset. Similarly, certain types of orbits can be utilized for each mission type. Sellers et al. define an orbit as the path an object follows through space [20].

In astronautical engineering studies, spacecraft motion can be described by Keplerian orbits as “one in which gravity is the only force; the central body is spherically symmetric; the central body’s mass is much greater than that of the satellite; and the central body and satellite are the only two objects in the system.” [20]. The following sections describe different orbit types, classical orbital elements, and the perturbations related to astrodynamics and constellation types.

2.1.1 Orbit Types

Orbits can be listed in different categories based on their altitude or shape. Understanding different types of orbits is important for the scope of this study. The two main categories are: Earth orbiting (Earth orbits) and interplanetary orbits. Interplanetary orbits are used for travelling among planets. The focus of this study is on Earth orbits. There are three essential types of Earth orbits based on their altitude: Low-Earth Orbit (LEO), Medium-Earth Orbit (MEO), and High-Earth Orbit (HEO). Each of these orbital types is loosely defined by their respective distance from the surface of the Earth.

LEO orbits range between 180 and 2,000 km. Most scientific satellites, including the International Space Station (ISS), are located at this orbit. LEO is used for all remote sensing missions because it is closer to the Earth, and the distance between the spacecraft and the target location makes it possible for the optics payload to work.

MEO orbits range between 2,000 and 35,780 km. Theses orbits have a larger coverage area on Earth and are used for navigation and communications purposes, for larger regional coverage. However, with the current remote sensing technology, MEO is not desirable for imaging purposes. Therefore, a constellation with a number of satellites located at LEO should be used to provide larger coverage.

Lastly, HEO orbits have altitudes greater than 35,780 km. The orbit at 35,780 km is often called Geosynchronous orbit (GEO), as the angular velocity of the GEO orbit matches the angular velocity of the Earth's rotation, and the period of the orbit is one day. The significance of this orbit is that a spacecraft at GEO is oscillatory (geosynchronous orbit) or stationary (geostationary orbit) over a specific location at the Earth’s equator. Figure 2-1 illustrates these three types of orbits [21]. The lunar orbit in the figure is the orbit of Moon around the Earth at 384,000 km.

Figure 2-1: Orbit Types

2.1.2 Astrodynamics

Six parameters are needed in order to define the orbit of a spacecraft around the Earth. These parameters are often called classical orbital elements (COEs), or Keplerian elements. These elements include semi-major axis, eccentricity, inclination, right ascension of the ascension node, argument of perigee, and true anomaly.

The orbit’s shape and size are described by semi-major axis and eccentricity. Orbit size is measured by the semi-major axis, as it is half the distance of the major axis of the ellipse. This element also specifies the orbit’s period [22], which is measured from the center of the Earth. It is important to note that the altitude and the semi-major axis are different values. The shape of the orbit is determined by its eccentricity. Table 2-1 summarizes the relationship between an orbit’s shape, semi-major axis, and eccentricity [23].

Conic section	Semi-major Axis	Eccentricity
Circle	> 0 (radius)	= 0
Ellipse	> 0	0 < e < 1
Parabola	∞	= 1
Hyperbola	< 0	> 1

Table 2-1: Properties of Keplerian Orbits

After defining the size and shape of the orbit, the orientation of the orbital plane is explained, using three of the remaining elements. Inclination is the angle of the orbital plane from the reference plane, the equatorial plane, as shown in Figure 2-2 [24]. For orbits with 0 to 90 degrees of inclination, the orbit is called a prograde orbit. If the inclination is between 90 and 180 degrees, the orbit is called a retrograde orbit. Prograde orbits rotate in the same direction as the Earth’s rotation, whereas retrograde orbits rotate in the direction opposite to the Earth’s rotation.

The intersection of the orbital plane and the reference plane through the center of the Earth is called the line of nodes, as seen in the Figure 2-2. For a spacecraft in the Earth orbit, the point in the orbit where the spacecraft moves from south to north is called the ascending node, and the point where the spacecraft moves from north to south is called the descending node. In order to fully define the orbit, we need to specify the orientation of the line of nodes as well.

The element, right ascension of the ascension nodes, defines this orientation, as it is the angle measured eastward from the vernal equinox to the ascension node of the orbit. Vernal equinox is the vector of the direction, which shows the location of the Sun in the sky on the first day of spring. It is used as the reference point of inertial frame in space flight dynamics studies [23].

Another element that defines the alignment of the orbit shape in the orbital plane is the argument of perigee. It is the angle from the ascension node to the direction of the perigee of the orbit. Lastly, the element that describes the position of the spacecraft on the orbit is the true anomaly. It is measured from the direction of perigee to the direction of spacecraft travel in the orbit. An orbit can be fully described with all these elements, and the position of the spacecraft can be ascertained.

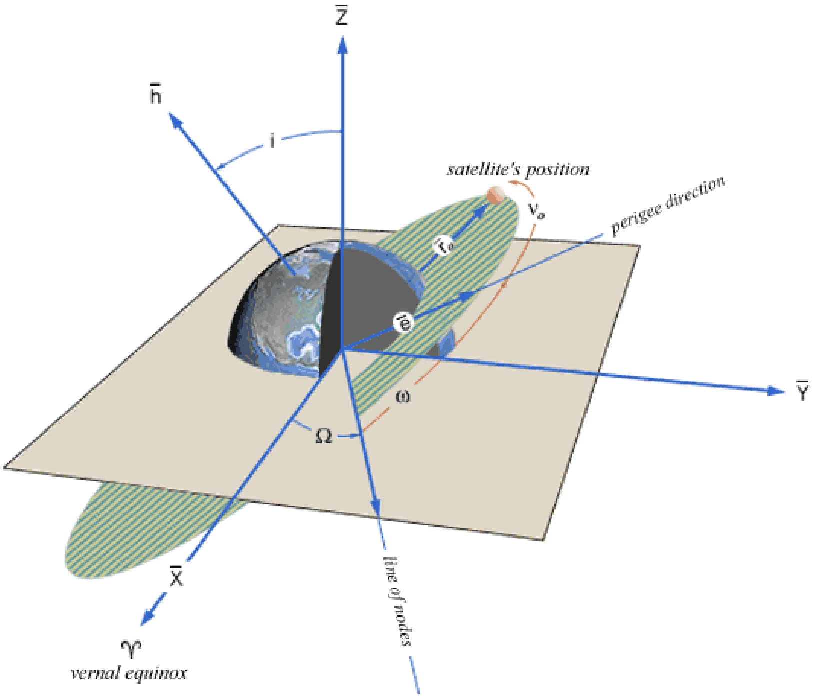

Figure 2-2: Classical Orbital Elements

The COE's defined above are accurate and fully describe the orbit of a spacecraft around the Earth under various assumptions. The first assumption is that gravity is the only force applied to the spacecraft. Another assumption is the ratio of Earth's and spacecraft's masses that the Earth's mass is much greater than that of the spacecraft. The last assumption is the mass of the spacecraft remains constant over time. These assumptions do not accurately reflect orbits in real world: but still, Keplerian orbits yield a reasonable estimation for orbital parameters and spacecraft motion. When a change occurs on the assumptions and COE's, the force acting on the spacecraft in the orbit will change as well. Any changes to the COE's, due to other forces, are called perturbations [20]. Different perturbations can occur for different orbit types, which will result in influences on constellation designs.

Affects, due to the Earth's atmosphere, can be observed at lower altitudes. Although free space is a vacuumed environment, some gas particles can exist at low altitudes. For low altitudes up to 600 km, the atmosphere still exists as a very thin layer. These particles and the thin air cause a drag force on the spacecraft. The atmospheric drag caused by the friction eventually leads the semi-major axis and eccentricity to decrease over time. This perturbation introduces complexities to the constellation design, due to the fact that atmospheric drag is very difficult to model because of the many factors affecting Earth's upper atmosphere and the spacecraft's altitude [20].

The second perturbation is the oblateness of the Earth. The shape of the planet is not a perfect sphere, which prevents the assumption of the Earth as a pure point mass. The gravitational pull is not centered at the Earth's center; therefore, it causes perturbation on the spacecraft. This perturbation can be called the J2 effect, where J2 is a constant describing the size of the bulge in the mathematical formulas used to model the oblateness of the Earth. Due to the perturbation that the gravitational pull does not come from the exact center of the Earth, a precession occurs for the orbit. Affected COE's of this precession are the right ascension of the ascension node and the argument perigee. The location of the ascending node changes in time. This change is called the nodal change rate. Similarly, the location of the perigee also changes. This change is called the perigee rotation rate. This perturbation is more obvious for lower altitudes and needs to be taken into account for the missions at LEO and MEO orbits.

Lastly, another perturbation is the solar radiation pressure. This is the force of sunlight acting on the surface of the spacecraft. Sunlight consists of protons travelling in the space. When it impacts on the surface, protons are absorbed by the spacecraft and cause transmission of energy to the surface. This force is not as significant as the perturbations caused by Earth's oblateness and the atmospheric drag, but it should be considered depending on the accuracy objective of the mission. In this research, perturbations are not taken into considerations, but this section presents the possible effects of perturbations on spacecraft, in order to have a better understanding of the advantages and disadvantages of orbit types.

2.1.3 Constellation Types

Constellations can increase the mission objectives such as Earth coverage by using multiple satellites. A constellation yields better performance for the missions that require coverage. As an example, constellations provide more frequent observations and communications capacity than a single satellite. For this study, a Walker constellation is used. This constellation type was developed by J.G. Walker at the British Royal Aircraft Establishment in order to find optimal global coverage [23]. His analysis concluded that a minimum of five satellites is required for continuous Earth coverage. Although Walker constellation is designed for global coverage, it is an accurate model for regional coverage for a geographic area between the poles and the Earth's equator. This constellation type consists of circular Earth orbits with the same semi-major axis lengths. Each orbit has the same inclination angle, and orbital planes are evenly separated with reference to the equatorial plane. Satellites on an orbital plane are evenly separated as well. The parameters to define a Walker constellation are the number of orbital planes, the number of satellites per plane, and inter-plane spacing. Some examples for Walker constellation with global coverage are GPS and Iridium constellations. GPS is a navigation constellation, and Iridium constellation is an example of communications mission. Figure 2-3 presents the concept of a Walker constellation [25].

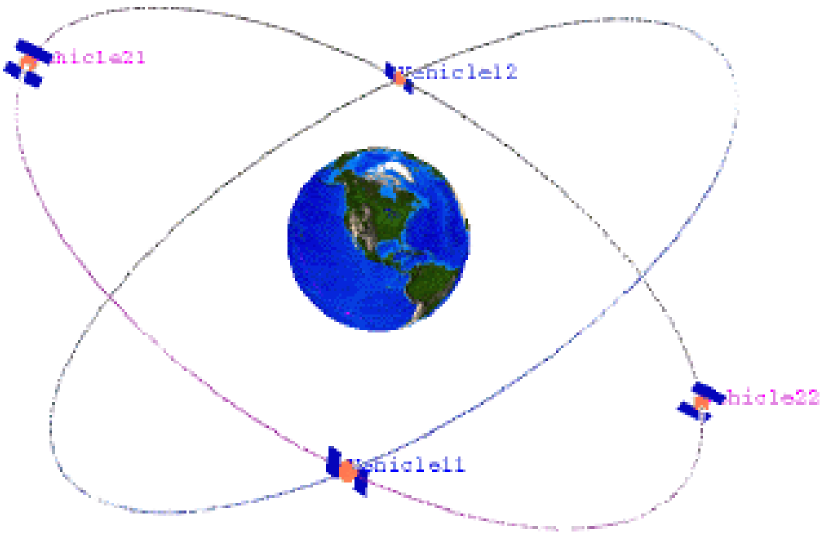

Figure 2-3: Walker Constellation

Non-Walker constellations may be more appropriate for missions with purposes different than global coverage. Such constellations are based on different geometries that utilize polar or equatorial coverage. Figure 2-4 shows examples of these geometries [23]. Option A yields a polar coverage using orbital planes with inclination of 90 degrees. To increase the coverage on equatorial areas, another orbit can be added to the constellation, as seen in Option B. Option C shows a geometry that consists of perpendicular non-polar orbital planes. Finally, Option D provides better equatorial coverage than Option A. For this study, Walker constellation was chosen. For a regional coverage purpose with a target location between polar and equatorial areas, Walker constellation is suitable based on coverage and revisit time considerations.

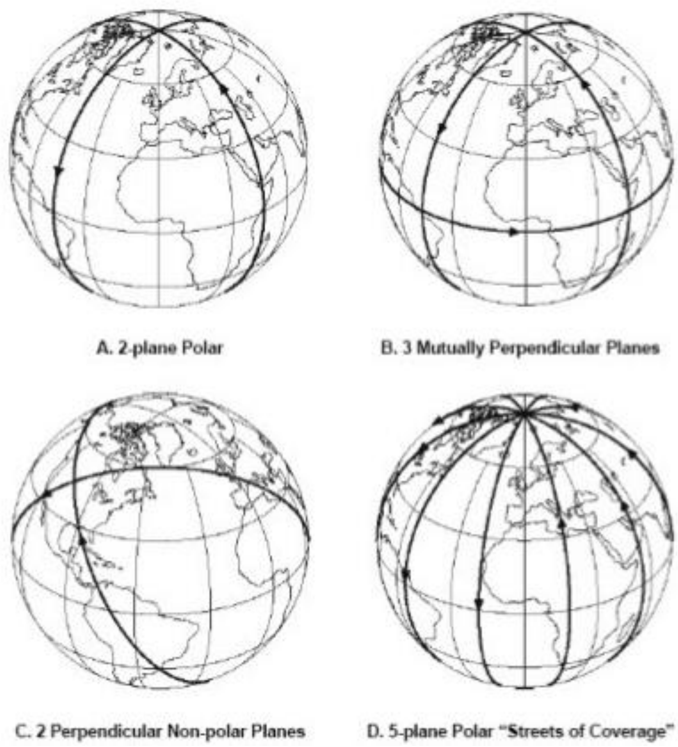

Figure 2-4: Examples of Non-Walker Circular Constellations

2.2 Electro-Optic Constellation Design

Constellation and/or a spacecraft design begins with identifying the needs of the target mission. This process involves identifying the mission, mission objectives and the constraints [20]. Identifying the mission type draws the perspective of the design space and the engineering mindset of the problem. The need of the design problem in this study is to have a constellation design that consists of satellites with optic payloads. Therefore, the mission type is remote-sensing. Mission objectives define the purpose of the mission. In this case, top-level objectives include a regional coverage over the target area on Earth's surface, revisit time, which is the time interval of having an image of a desired target location, and the resolution of the images we obtain from the satellites. As for constraints, the most important factor driving the design process is the budget. The following sections present the concepts design of a satellite in the constellation and the process of constellation design.

2.2.1 Satellite Design Problem

A constellation consists of the satellites in the system. These satellites may be of different designs, which are used together for the same mission, or only one design can be used. Having multiple satellite designs in the constellation is commonly called a distributed satellite system [8] or disaggregation system [19]. Global Positioning System (GPS) is an example of these systems. The scope of this study is to use a small satellite model in the constellation. One of the top-level objectives is to minimize the cost per satellite which concludes the constellation design optimization. Therefore, a baseline conceptual cost model will be used. The remaining parts of this section present the selected cost model for this study.

After the Cold War ended, space programs were compelled to change the design approaches for future projects [2]. With the new concept of cheaper and faster spacecraft design process and the technologic developments used in systems engineering, various satellite cost models have been developed.

2.2.1.1 Satellite Cost Models

Satellite cost models are parametric estimations that are developed based on the traditional weight-based parametric cost-estimating relationships (CERs) and the data from previous space projects [26]. They can be used for both Earth-orbiting or interplanetary missions. Satellite cost models are either multivariable or single variable cost estimation models. Some examples of such cost models that developed by previous design projects are discussed in following sections.

2.2.1.2 Multivariable Satellite Cost Models

Multivariable cost models are developed based on the traditional weight-based parametric cost-estimating relationships (CERs) and the data from previous space projects [26]. These models provide estimations of subsystems such as mass, power, and spacecraft cost. Furthermore, these models require detailed work on spacecraft systems engineering and design process of individual spacecraft.

Some examples of such models are Small Satellite Cost Model (SSCM) of the Aerospace Corporation, National Aeronautics and Space Administration (NASA) Instrument Cost Model (NICM), Unmanned Space Vehicle Cost Model (USCM), and Demonstration Satellite Cost Model of the National Reconnaissance Office [23, 27]. All of these models utilize design and cost parameters such as size, weight, power, pointing accuracy, delta-v, downlink rate, etc. As an illustration, Demonstration Satellite Cost Model's (DSCM) estimating table is shown in Table 2-2.

Subsystem	CER / SER Form
SE / PM	$[\text{Cost (FY06\$K)}] = 0.26\ [\text{Base (FY06\$K)}]^{1.03}$
I&T	$[\text{Cost (FY06\$K)}] = 33.0\ [\text{S/C Dry Weight (lb)}]^{0.66} * 1.32^{[\text{Contract Includes Payload Integration}]} * 1.40^{[\text{Optical Payload}]} * 1.70^{[\text{Propulsion}]}$
Structure	$[\text{Cost (FY06\$K)}] = 45.1\ [\text{Subsystem Weight (lb)}]^{0.77} * 1.34^{[\text{Solar Array Mechanics}]}$
Thermal	$[\text{Cost (FY06\$K)}] = 62.7\ [\text{Subsystem Weight (lb)}]^{0.70} * 1.63^{[\text{Optical Payload}]} + 144$
EPS	$[\text{Cost (FY06\$K)}] = 37.1\ [\text{Subsystem Weight (lb)}]^{0.89} * 1.44^{[\text{Nickel-Hydrogen Battery}]}$
ADCS	$[\text{Cost (FY06\$K)}] = 288\ [\text{Subsystem Weight (lb)}]^{0.59} * [\text{Number of Attitude Sensors}]^{0.23}$
Propulsion	$[\text{Cost (FY06\$K)}] = 398\ [\text{Propellant Weight (lb)}]^{0.22} * [\text{Number of Thrusters}]^{0.37}$
TTC&DH	$[\text{Cost (FY06\$K)}] = 15.5[\text{Subsystem Weight (lb)}]^{0.86} * [\text{Vehicle End of Life Power (W)}]^{0.41}$
Software	$[\text{Cost (FY06\$K)}] = 16.8[\text{TT\&C Subsystem Weight (lb)}]^{1.18}$
Launch Support	$[\text{Cost (FY06\$K)}] = 82.3[\text{Base (FY06\$K)}]^{0.22} * [\text{Number of Payloads}]^{0.51} * 1.60^{[\text{Hydrazine Propellant}]}$
Optical Payload	$[\text{Cost (FY06\$K)}] = 760\ [\text{Payload Weight (lb)}]^{0.69} * (\log[\text{Spectral Range (A)}])^{0.37} * 0.28^{[\text{Cryostat}]}$
RF Payload	$[\text{Cost (FY06\$K)}] = 119\ [\text{Payload Weight (lb)}]^{0.97} * [\text{Design Life (mo)}]^{0.28}$
Schedule	$[\text{Time to First Launch (mo)}] = 9.4\ [\text{S/C Dry Weight (lb)}]^{0.14} * [\text{Design Life (mo)}]^{0.19} * 1.13^{[\text{Optical Payload}]} - 5.6^{[\text{Option on Extant Contract}]}$

Table 2-2: DSCM Estimating Table

Since the focus of this study is the constellation design optimization as opposed to overall satellite cost optimization, these models are not utilized herein. Employing these models needs further study regarding the satellite model design to use in the constellation. This study requires the identification of parameters of a satellite model, which are the costs of the satellite and diameter length of the optics payload. Using these parameters, a constellation design model can be created regarding the mission objectives and constraints. A parametric cost model, which consists of these parameters, will be utilized in this study. Diameter length parameter will be the key factor that defines the payload requirements, as well as the cost per satellite.

2.2.1.3 Single Variable Constellation Cost Model

Multiple parameter models on space telescopes mainly use diameter and telescope mass, whereas a single parameter model uses either one of them. The parametric cost model methodology to be utilized in this study was developed by Stahl et al. at NASA Marshall Space Flight Center [4, 28]. This methodology is a current survey of the latest available data on space telescopes applying rigorous analytical techniques [28].

The benefit of using this method in this study is based on the diameter length, which is the required parameter for modeling the constellation design.

Stahl et al. stated in their study that the aperture diameter is the primary cost driver for space telescopes [28]. In this model, the optical payload subsystem of the spacecraft is defined as Optical Telescope Assembly (OTA). Using the single parameter model for diameter, the telescope cost estimation relationship (CER) is found using the Equation 2.1, where the aperture diameter unit is in meters and the cost is in million dollars.

$$OTA\ Cost \sim \$30\ M * Diameter^{1.4} \tag{2.1}$$

The fraction of the total spacecraft cost allocated to the OTA is approximately 10 to 15 percent. As the telescope diameter decreases, the cost will increase, due to the fact that larger aperture telescopes cost less per square meter than smaller aperture telescopes. The findings of this methodology indicated that the average cost fraction of the normalized OTA with respect to the total spacecraft cost is 12%. Figure 2-5 illustrates the typical cost breakdown of a space telescope satellite system presented by Stahl et al. in their work based on 15 space telescope projects.

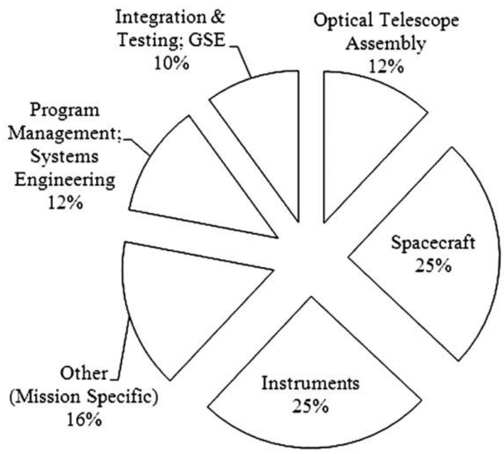

Figure 2-5: Typical Cost Breakdown for Space Telescopes

Table 2-3 illustrates the historical data of percentage of the OTA cost of the total cost as a function of the aperture diameter [28].

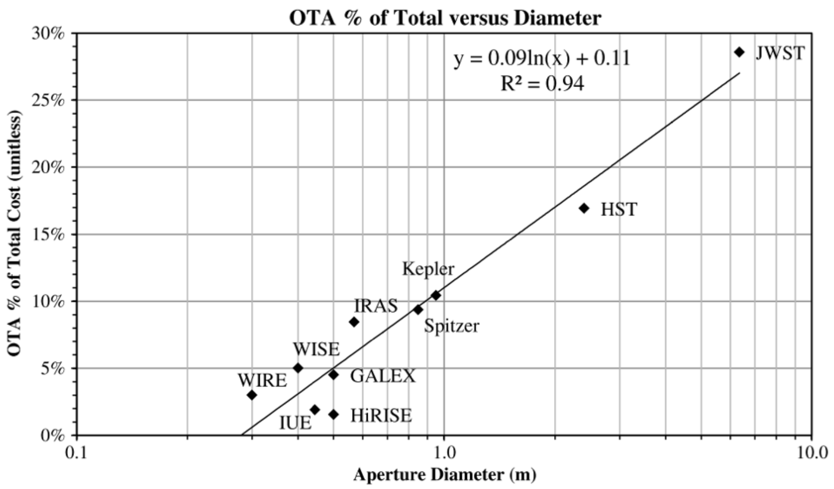

Table 2-3: Relationship Between OTA Cost and Total Cost.

To sum up, using the normalized relationship between OTA cost and total cost as 12%, we obtain the total cost equation of a satellite as shown in Equation 3.2, where the diameter is in meters and the total cost of a satellite is in million dollars.

$$Total\ Cost\ = \$250M\ *\ Diameter^{1.4} \qquad (2.2)$$

2.2.2 Constellation Design Process

A constellation design process is described with several steps in Wertz's work [23]. The first step of a constellation design process is to identify the orbit type to use.

This type is either Earth orbiting or interplanetary orbit. As described before, Earth orbits provide coverage on Earth's surface, whereas interplanetary orbits are used for travelling among planets. Since the focus of this study is to design a remote-sensing constellation system, Earth orbits will be used. The next step of the constellation design process to establish the mission requirements. This includes factors such as the limit on orbital altitude needed for coverage, given budget, and the limit of the number of satellites.

For remote-sensing missions, resolution requirements limit the orbit altitude to LEO orbits. Resolution and coverage requirements are in contradiction with each other on defining the orbital altitude. LEO orbit altitudes lower than 300 km result in reduced coverage, as well as shortening the lifetime of the satellite, due to the atmospheric drag. On the other hand, altitudes closer to 1000 km do not yield solutions for high-resolution requirements without the investment in extremely expensive and large observing instruments. Figure 2-6 shows the geometry of coverage. As the altitude (h) increases, the coverage area on Earth's surface increases as well.

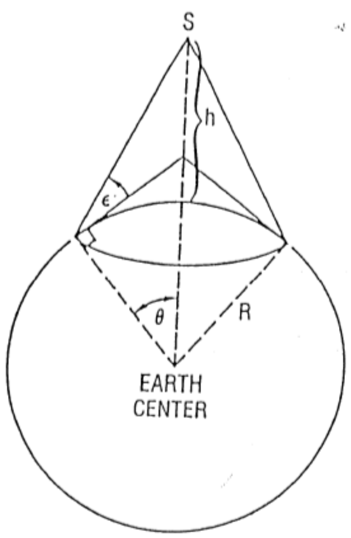

Figure 2-6: Single Satellite Coverage Geometry

Third step of the constellation design process is the evaluation of the orbit. After the orbit type and the altitude range are identified based on the mission requirements, this step addresses the usage of constellation versus single satellite. Using a single satellite provides a solution with less cost. On the other hand, the constellation can give better results in order to reach the mission requirements, such as coverage and revisit times. Furthermore, constellation usage is more reliable in the case of satellite or payload failures. The last step in this constellation design process is to analyze the overall mission cost. Although constellation usage, as discussed in the previous step, ensures the achievement of mission requirements, it may result in an excessive cost budget. After this process is studied, documentation and iteration conclude the process. During the process, trade studies and updates on mission requirements change the factor of the design process. Documentation ensures saving the records of the study, and the design can be re-evaluated through iteration.

2.3 STK-MATLAB Interface

The constellation design in this research consists of a model that uses MATLAB and STK tools. STK program allows for modelling the constellation design. By this model, payload and orbital parameters, as well as the target locations on Earth’s surface, are defined to test and analyze the design outcomes. All the commands to run the model in STK are embedded into the MATLAB scripts. Through this interface, the MATLAB MOGA algorithm can execute the model in STK, in order to optimize the constellation design. This study utilizes the scripts created in prior constellation optimization design thesis works of Lt. Diniz [16] and Lt. Abbate [19].

2.4 Optimization

According to Arora, “the design of a system can be formulated as problems of optimization in which a performance measure is optimized while all other requirements are satisfied” [29]. Regardless of complexity of the design problem, the form of a typical optimization is applicable to all problems. Optimization problem formulation process follows these steps;

Minimize a cost function:

$$f(x) = f(x_1, x_2, \dots, x_n) \tag{2.3}$$

Subject to *p* number of equality constraints:

$$h_j(x) = h_j(x_1, x_2, \dots, x_n) = 0;\ j = 1\ to\ p \tag{2.4}$$

and *m* number of inequality constraints:

$$g_i(x) = g_i(x_1, x_2, \dots, x_n) \leq 0; i = 1\ to\ m \tag{2.5}$$

The solution of the problem is vector that consists of the decision variables:

$$x = (x_1, x_2, \dots, x_n) \tag{2.6}$$

Many numerical methods are developed and applied to engineering design problems in various disciplines. An illustration of optimization categories is shown in Figure 2-7, as stated in Taylor’s work [7]. Further sections of this chapter present different optimization methods, which have been chosen as candidate methods for this research. For this study, a multi-objective genetic algorithm method is chosen among the methods which were examined in this research.

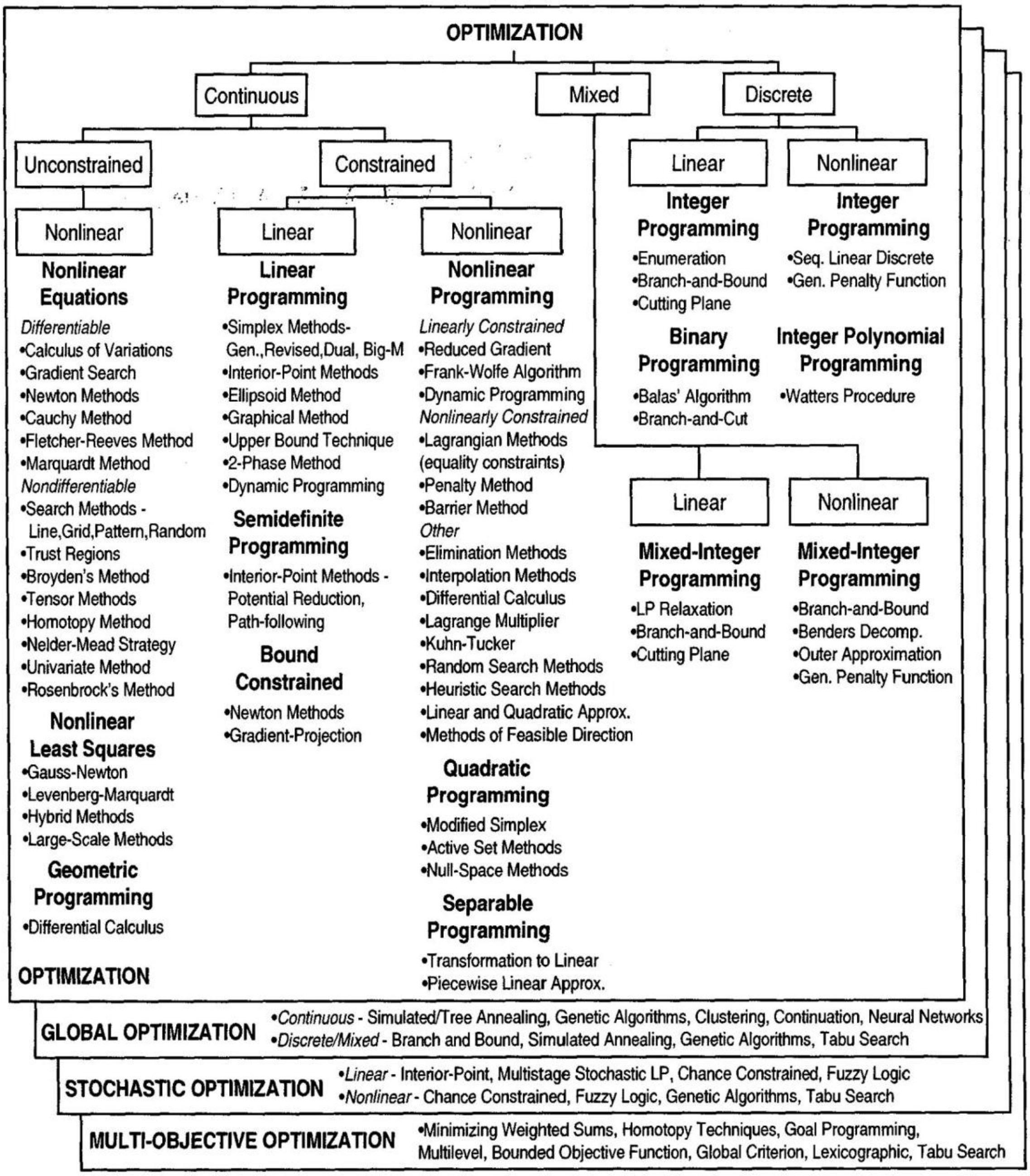

Figure 2-7: Optimization Categories

2.4.1 Multi-Disciplinary Design Optimization (MDO)

Multi-Disciplinary Design Optimization (MDO) may be described as “a methodology for the design of systems where the interaction between several disciplines must be considered, and where the designer is free to significantly affect the system performance in more than one discipline” [30]. MDO applications are widely used in aerospace system designs as well as other engineering areas. The change in the space industry for cheaper and smaller solutions, with the same mission objectives, drove design teams to use these methods. MDO methods can vary based on the system scale and structure to optimize. Some MDO methods, which have been used in previous engineering studies, are discussed in the following sections.

2.4.2 Numerical Methods

Most engineering problems are based on nonlinear objective functions and/or constraint sets. For the problems that have linear sets and consist of fewer than three decision variables, several methods apply such as graphical solution, simplex, branch and bound, and other linear mathematical methods [29]. Numerical methods are necessary to solve nonlinear problems with more than three decision variables. These methods are often referred to as classical optimization methods [31]. These methods work on the assumption that all functions of the problem are continuous and at least twice continuously differentiable. Numerical methods are based on the following iterative equation:

$$x_i^{(k+1)} = x_i^{(k)} + \Delta x_i^{(k)}; i = 1 \; to \; n; and \; k = 0,1,2 \ldots \quad (2.7)$$

The iterative research starts with the initial estimate of the decision variables, $x_i^{(0)}$. After selecting the starting points, optimum solutions can be found by using different methods to calculate the next step, the change in the design, $\Delta x_i^{(k)}$. Then, the design is updated, as in Equation 2.7, and iterated until reaching the stop criteria. These methods apply for both constrained and unconstrained problems.

Numerical methods are classified in three categories based on their step search strategies. The first type of numerical methods to list is derivative-based methods. Another description for this type is gradient-based methods. These methods use the gradients of the functions to search for next step in the algorithms (local minimum points). These methods require that the first-order derivatives must be calculated accurately. Another numerical method type is the direct search methods. For these methods, the functions of the problem still need to be continuous and differentiable, but their derivatives are either unavailable or untrustworthy. Rather than the gradients, values of the functions are used to calculate the design change. Lastly, derivative-free methods use the approximation of the derivatives in search steps. Values of the functions are used in various methods to approximate the derivatives.

Although these methods were successfully used in previous space studies, they aren't suitable for constellation design problems, as in this study [5]. The structure of the constellation design includes nonlinear functions and discrete sets. Such sets of constraints cannot be normalized to get continuous functions for use in gradient-based methods. Since numerical methods are not applicable for the constellation design problem of this study, a different approach must be used.

2.4.3 Dynamic Optimization

Dynamic programming is a suitable method to solve sequential problems. Such problems consist of multiple stages that can be conceived, as the sub-problems or the parts of the overall system design. Riddle states in her study that "dynamic programming has been found to be a very useful mathematical technique for a wide range of complex problems in several areas of decision making" [6]. A typical dynamic programming problem has an objective function for the system-level of problem formulation. Each sub-problem of the design is a sequence in the process. When the optimal solution is achieved for a sub-problem, the objective function is included in the system-level objection function, in order to achieve the global optimal solution set.

Another feature of this method can be explained as “Dynamic programming is related to the branch and bound method in the sense that it performs an intelligent enumeration of all the feasible points of a problem, but it does so in a different way. The idea is to work backwards from the last decisions to the earlier ones” [5]. On the other hand, the algorithm is not particularly efficient or useful for non-sequential problems involving a large number of discrete and continuous variables [6]. The design of a single satellite problem can be more suitable for this method, as each part in the system-level of the overall design is based on a different discipline. However, a constellation design problem doesn’t apply for this method - considering the fact that if dynamic programming is used, then each part in the design needs to be optimized using a gradient-based method. This method is not suitable for application to this study.

2.4.4 Collaborative Optimization

Another method for constellation design is the collaborative optimization (CO). Similar to dynamic programming, this comprehensive method handles the problem as a combination of parts. Each part of the system-level problem consists of different areas of constellation design - such as single satellite design, configuration and orbit design, and launch manifest [5]. However, the advantageous feature of this method is that each individual part is a subsystem, which can be optimized using a different approach. It provides the subsystems’ freedom to contribute to the system-level problem with using its own local decision variables and constraint sets. The literature review shows that CO has been successfully applied to many large-scale MDO problems related to aircraft and spacecraft design [5].

In their work, Budinanto and Olds used CO for a constellation design to solve a nonlinear problem with mixed-integer constraint sets using nongradient-based optimization techniques. The architecture of the method used in this study is shown in the Figure 2-8.

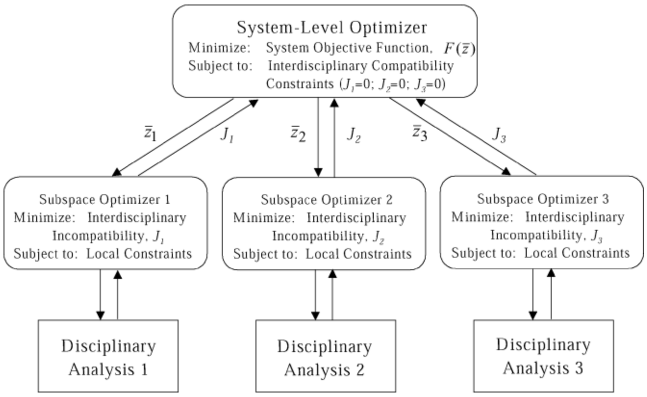

Figure 2-8: CO Architecture.

CO method is advantageous on large-scale design problems, as each part of the problem is dependent on its own decision variables and constraint sets. Moreover, each sub-problem of a CO method can use a different method such as gradient-based, dynamic, or genetic algorithms. On the other hand, the combined computational effort can be fairly intensive, because the subsystems are required to perform local optimization at each iteration [5]. For the problems that are not large-scale, other optimization methods may be more suitable with simpler function evaluations. The scope of this study does not include the design problem of single satellite or the launch manifest. A single-parameter space telescope cost model methodology is used to evaluate the conceptual design of single satellite. Therefore, only one method for the whole design is suitable. In the case of this research, it is not practical to use CO and divide the design problem into sub-problems. The constellation design problem may be solved in one multi objective genetic algorithm model.

2.4.5 Genetic Algorithms (GA)

Genetic algorithms (GA) are one of the nature-inspired search methods. Other methods of this type are stochastic programming, evolutionary algorithms, swarm intelligence and evolutionary computation. Understanding the structure of GAs is essential, as this type of method will be utilized in this study. Aurora states that these methods are also called as nature-inspired metaheuristics methods, as they make no assumptions regarding the optimization problem and can search very large spaces for candidate solutions [29]. These algorithms simulate biological evolution and the natural selection theory of Charles Darwin [32]. They can overcome the complexities of problem structures such as multiple objectives, mixed design variables, unreliable function gradients, and uncertainties of the model and environment. The basic idea of a GA is to generate a new set of designs (population) from the current set, such that the average fitness of the population is improved [29].

A summary of GA terms is shown below, as stated in Arora’s textbook, Introduction to Optimum Design [29]:

Population. The set of design points at the current iteration, representing a group of designs as potential solution points.

Population size. The number of designs in a population.

Generation. A calculation in the genetic algorithm, having a population of a size that is manipulated to find the best function value. This may consist of multiple iterations, which are defined by specific values of design variables.

Tolerance. The smallest change in value that is considered significant. A function tolerance refers to the smallest change in the cost function between generations, and a constraint tolerance refers to the greatest constraint violation that is acceptable.

Chromosome. A synonym in genetic algorithms for a design point. This design can be feasible or infeasible and contains values for all the design variables of the system.

Gene. A scalar, valued component of the design vector (the value of a particular design variable).

The main advantages of GAs compared with the numerical methods are: less computational time and achieving optimality without needing gradients [10]. GAs have an additional advantage of working on populations of points, which ease the search for several solutions in the case of multi-objective optimization [33]. Figure 2-9 illustrates the process of GA algorithm [34].

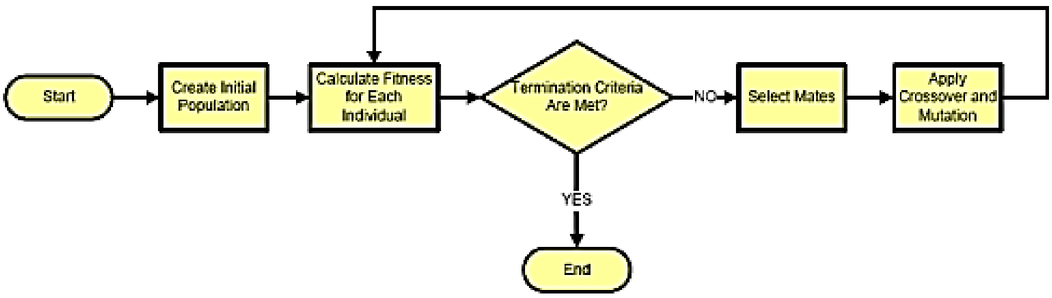

Figure 2-9: GA Flowchart

As with all optimization methods, a GA method consists of three main parts: the objective function, constraints, and decision variables. The objective function is called the fitness function in a GA formulation. In this study, there are multiple fitness functions. Decision variables are represented as genes in GAs. In her thesis, Lt. Diniz stated that the MATLAB multi-objective GA tool cannot process non-linear constraints [16]. Similarly, the model of this study will consist of two parts: fitness functions and genes.

2.4.6 Multi-Objective Genetic Algorithms (MOGA)

Multi-objective genetic algorithms (MOGA) are based on the GA algorithms. For design problems, multiple mission objectives can be asked by decision makers. These objectives often result in having multiple objective functions, which may initially be in contrast with each other. One way of formulating such objectives is to combine each objective function into one single function to be optimized. Various methods can be used to determine that combined single objective function, such as utility theory, weighted sum method, etc. [10]. However, the determination brings problems that the combined objective may not accurately represent decision-makers' choices. Even small changes in weighting the single objectives can result in different solutions.

MOGAs are commonly chosen methods, in order to converge single objective function by producing pareto optimal sets. Konak et al., described that "a pareto optimal set is a set of solutions that are non-dominated with respect to each other. While moving from one pareto solution to another, there is always a certain amount of sacrifice in one objective(s) to achieve a certain amount of gain in the other(s). Pareto optimal solution sets are often preferred to single solutions, because they can be practical when considering real-life problems, since the final solution of the decision-maker is always a trade-off." [10].

The search for achieving the pareto optimal set is called as Pareto optimality. Arora states that "A point x^* in the feasible design space S is pareto optimal if and only if there doesn't exist another point x in the set, S such that $f(x) \leq f(x^*)$ with at least one $f_i(x) < f_i(x^*)$" [29]. Figure 2-10 presents the pareto optimality with feasible (dominated) and non-dominated solutions (pareto front) [9].

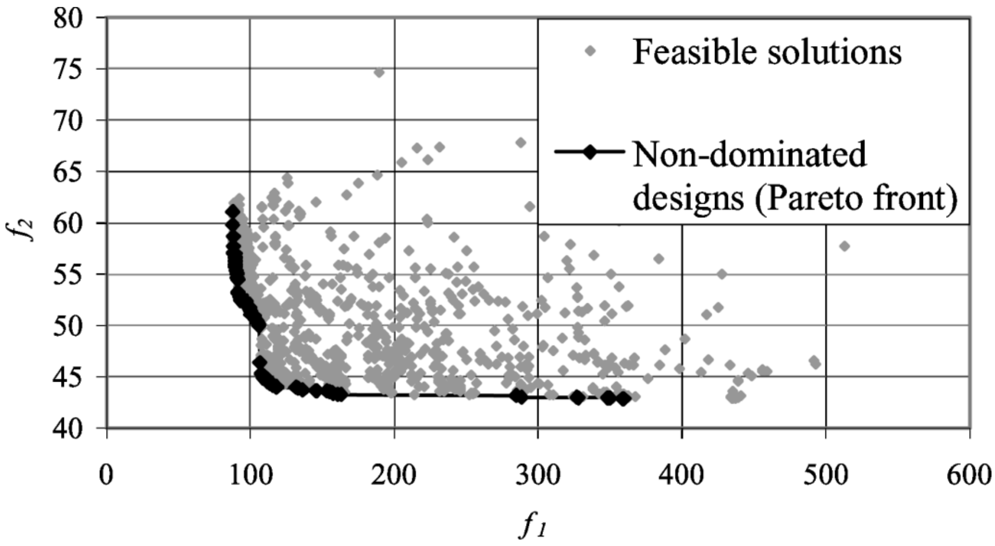

Figure 2-10: Pareto Optimality

For this study, tradeoffs can be achieved that draw the solutions for cost, revisit times, and resolution objectives using pareto optimality. The MATLAB MOGA tool will be used in order to achieve solutions with pareto fronts.

2.5 Optics

The last necessary piece of the constellation design problem is the influence the optical instrument as hosted on the satellites within the constellation has on the design problem. Understanding general concepts is beneficial, in order to model the problem with the required optical parameter and equations. The optical parameter to be included in the design model formulation is the diameter length of the optical payload. The cost model methodology is based on the diameter length. Resolution and coverage calculations can also be made using this parameter.

Single satellite coverage geometry is illustrated before in Figure 2-6. Optical resolution may be calculated in different methods. One method is to use Joh Irvine's National Imagery Interpretability Rating Scale (NIIRS) [35]. NIIRS consists of resolution levels scaled from 0 to 9. These scales are configured based on different mission types such as military reconnaissance or agricultural purposes. Another method is spatial resolution. In this method, the smallest object that the optics system can detect in detail is measured in meters. Figure 2-11 illustrates the spatial resolution concept [36]. High spatial resolution ranges between 0.4 to 4 meters, which is one of the objectives in this study.

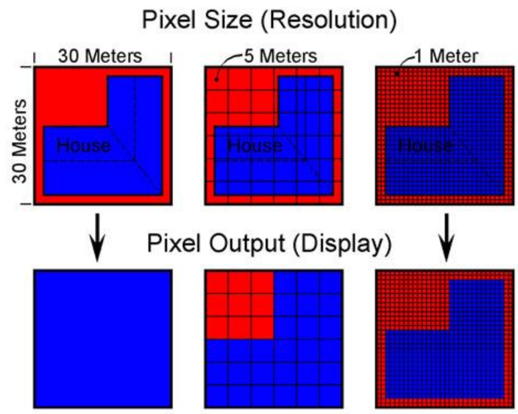

Figure 2-11: Spatial Resolution

Spatial resolution of an optics system is affected by various qualities such as lens design, pixel pitch or spacing, defocus, aberrations, etc. Whereas an optical system cannot get better resolution than the diffraction limit. This, in return, is dependent on the diameter of the optic and the wavelength being observed. Therefore, diameter length is selected in this study as the guiding metric for cost and constellation optimization.

The equations for determining the spatial resolution and the coverage are described in Chapter 3.

2.6 Previous and Current Work

Constellation design process is a key factor for space missions. Although each design has a unique structure based on mission, altitude, and spacecraft types, the main design process is similar for other missions. Therefore, previous studies in this field can be utilized by modifying and improving the design structure.

At the Air Force Institute of Technology (AFIT), Lt. Abbate developed a disaggregated constellation design. In her work, she used a GA method for a remote-sensing mission that was based on different types and sizes of imaging satellites. The model consisted of a single objective function that was to minimize the overall cost. The constraints consisted of percentage of coverage, desired NIIRS resolution level, and the revisit time. The decision variables for this study were Walker parameters, COEs, and sensor size.

Another study was conducted on GPS constellation design by Lt. Diniz using MATLAB's MOGA. Her objective functions were minimizing total cost and minimizing position dilution of precision (PDOP) function. The decision variables were Walker parameters, COEs, and transmit power. As stated in section 2.4.6, the model has consisted of only decision variables (genes) and the objective functions (fitness functions).

Results of both studies show successful usage of a GA or MATLAB's MOGA and STK tools with given objectives. The tool presented in this study analyzes the remote sensing constellation design of Lt. Abbate's work and MOGA algorithm of Lt. Diniz's work. The desired outcome of this study is to develop an electro-optic (remote sensing) constellation design using MOGA method, combining with both methodologies.

2.7 Summary

This thesis will use a MOGA to design an electro-optic constellation and analyze tradeoffs for system cost, resolution, and revisit time. Conceptual knowledge regarding astrodynamics, constellation types, and optics will provide an understanding of how the constellation design methodology works. Several optimization techniques are listed, which have been successfully used in previous space studies, in order to analyze the advantages and disadvantages of each method. MOGA method is found to be suitable for constellation design problems in which the decision-makers typically have multiple mission objectives. The next chapter will apply these concepts by explaining the model in detail.

Chapter 3: Methodology

The advancements in the space industry provides for the usage of constellation systems as the spacecraft designs get smaller. For remote sensing purposes, smaller satellites and optical payloads are being developed that satisfy the same mission objectives as accomplished by the larger, single satellite platform architectures of current systems. Therefore, the usage of constellations is considered in this research. The design tool presented in this thesis provides optimal batch Pareto fronts and illustrates the tradeoffs of the objective functions. This chapter outlines the methodology used to develop the constellation batch Pareto fronts.

3.1 Problem Statement

In this study an electro-optic remote sensing satellite constellation model is developed by utilizing MATLAB's MOGA and implementing STK features with a focus of regional coverage. The aim is to evaluate objective functions and analyze the tradeoffs between cost, resolution, and the revisit times of different solutions. By MOGA implementation, genetic algorithm optimization technique is used to maximize the performance of the constellation design that is mainly constrained by budget. The focus is to have solutions with fairly small sized diameter length of the optical instrument and therefore resulting smaller satellites that achieve high resolution and reasonable revisit times. The objective functions of the model are not constrained and the pareto fronts gives the optimal solutions of all the design space limited by the bounds.

This thesis aims to identify solutions to the satellite constellation parameters for objective function values. Boundaries include a constellation budget of less than 1 billion dollars, an optical instrument capable of imaging less than a meter resolution and less than ten hours between surface location revisit time. The results fitting to this design space will be evaluated in the following chapters. Different test cases were analyzed to determine an optimal constellation design.

3.1.1 Assumptions

The produced results of this study that are given in Pareto fronts depend on several assumptions. The resolution calculation is based on Rayleigh criterion formulas and altitude parameter values are used in each iteration as range values. The satellite sensor pointing type of the model used in this thesis is configured to be a fixed, nadir pointing instrument. In this case, the actual range distances from the sensor to targets that are slightly located apart from the centerline are neglected and satellite altitude values are calculated.

Calculations for the satellite communications (SATCOM) considerations, and the ground control network coverage, is not included in this study. It is assumed that efficient ground control systems and the SATCOM network will be selected, or created, in order to fully support the design system. A single satellite cost model is based on a conceptual design. Each subsystem of the satellite mission will be assumed to be ideally chosen. The cost model of the satellite design consists of a normalized cost calculation. Therefore, it is assumed that the preliminary satellite design budget will not exceed the given budget per satellite.

The costs of the single parameter cost model are in fiscal year 2010 dollars (FY2010$). The cost model is an approximation of the similar size telescopes and satellites of the historical designs. The assumptions and the determinations of the bounds on the parameters driving the satellite size based on the diameter length and the selection of the launch vehicles that would carry all of the satellites of the same orbital planes are based on this assumption.

3.1.2 Decision Variables (DV's)

The design vectors are generated by the MOGA on each iteration with a limitation specified by the lower and upper bounds. The decision variables can be categorized into three groups: Walker parameters, orbital parameters, and diameter length.

Walker parameters are used to create the constellation by using a number of satellites per plane, number of planes, and interplane spacing. Interplane spacing parameters vary based on the Walker constellation type. Three types of Walker constellations can be modeled in STK: Delta, Star and Custom [37]. Type Delta ensures the evenly spacing of the orbital planes as well as the spacing of satellites in adjacent planes. Type Star distributes the orbital planes on a span of 180 degrees whereas type Delta distributes on a span of 360 degrees. Type Custom is a configuration which allows for explicit inputs of the span. In this thesis, each set of models are generated twice for type Delta and type Custom. For type Delta models, interplane phasing increment is set to 1 in order to ensure the evenly spacing of satellites on adjacent orbital planes. For type Custom models, true anomaly increment, and right ascension of ascension node increment parameters are added to the decision variable sets on a span of 180 degrees. By creation of different constellation configurations for the model sets, the analysis seeks to determine whether the Walker type has a significant effect on the results and what is the optimal constellation design.

Orbital parameters define the alignment of the plane and the position of the satellite. The diameter length defines the size of the optical payload. This parameter, along with the constellation altitude, heavily influence the cost model and the objective functions.

The decision variables and lower and upper bounds of different sets of models created in this thesis are shown on Table 3-1. By the creation of different sets, effects of constellation types as well as orbit types and diameter sizes are aimed to be analyzed. The results and analysis of the changes among sets are discussed in proceeding chapters. First two sets analyze circular orbits with inclination bounds zero to ninety degrees, maximum angle of polar orbits. Optical instrument aperture diameter length bounds are kept between 0.5 and 1.5 meters. The first set is calculated once with Walker type Delta constellation with a smaller model size consisting of 200 scenarios. The rest of the sets are composed of 900 scenarios. In the second set, the model is simulated twice for different Walker constellations of type Delta and Custom. For the rest of the sets, diameter length bounds are kept between 0.3 and 1.5 meters. This change is made in order to evaluate smaller size diameters. For third set, inclination bounds are set between zero and a hundred degrees, defining the orbits to be sun synchronous in the cases where the inclination angle is more than ninety-six degrees. Again, this set is simulated for two Walker constellation types. Fourth set is defined to be sun synchronous in order to analyze the sun synchronous orbit configuration results especially. This set is simulated for different Walker constellation types as well. In this last set, the inclination decision variable is not used.

Sets/ Parameters	Number of Planes	Number of Satellites per Plane	Altitude	Diameter Length	Eccentricity	Inclination	RAAN	Argument of Perigee	True Anomaly	RAAN Increment	True Anomaly Increment
1	2 - 5	2 - 5	350 - 1000	0.5 – 1.5	0	0 – 90	0 – 180	0 – 180	0 – 180	- (Delta)	- (Delta)
2	2 - 5	2 - 5	350 - 1000	0.5 – 1.5	0	0 – 90	0 – 180	0 – 180	0 – 180	- (Delta)	- (Delta)
	2 - 5	2 - 5	350 - 1000	0.5 – 1.5	0	0 – 90	0 – 180	0 – 180	0 – 180	0 – 180	0 – 180
3	2 - 5	2 - 5	350 - 1000	0.3 – 1.5	0	0 – 100 (> 96 Sun Sync)	0 – 180	0 – 180	0 – 180	- (Delta)	- (Delta)
	2 - 5	2 - 5	350 - 1000	0.3 – 1.5	0	0 – 100 (> 96 Sun Sync)	0 – 180	0 – 180	0 – 180	0 – 180	0 – 180
4	2 - 5	2 - 5	350 - 1000	0.3 – 1.5	0	Sun Sync	0 – 180	0 – 180	0 – 180	- (Delta)	- (Delta)
	2 - 5	2 - 5	350 - 1000	0.3 – 1.5	0	Sun Sync	0 – 180	0 – 180	0 – 180	0 – 180	0 – 180

Table 3-1: Decision Variables for Different Sets

3.1.3 Objective Functions

The objective functions of this study are the cost, resolution, and revisit time. For the cost function, a space telescope cost model was used [4, 28]. This cost model uses the diameter length and provides a normalized cost for the conceptual satellite design. Resolution function consists of the Rayleigh Criterion spatial resolution calculation methods, which use the diameter length as well as the altitude. The objective is to have a high resolution, which is less than one meter.

The last objective function is the revisit time. This calculation uses the MATLAB scripts, which command the STK tool to calculate the maximum time interval of two satellites over a specific ground-based target.

The MOGA algorithm cannot tolerate nonlinear constraints. Therefore, the model will not be constrained but the constraints will be evaluated on the pareto front charts.

3.2 Objective Function Calculations

This section describes the equations or the scripts and STK features used in this thesis to calculate the objective functions evaluated with MOGA. For cost and resolution calculations, STK features and access report items are not used. These two objective function calculations include equations of the selected calculation methods. For the revisit tine calculations, general layout of the STK scenario and the implemented STK features will be discussed. For each objective function, equations or scripts are calculated as separated MATLAB function files. MOGA overall function is calculated in the main MATLAB file in which the objective function files are defined as the fitness functions.

3.2.1 Cost Calculations

The single variable space telescope cost model is used to calculate the procurement cost of a satellite in this thesis. This cost model is based primarily on the diameter length parameter. Equation 3.1 represents the calculation of the cost model.

$$Satellite\ Cost\ = \$250M\ *\ Diameter^{1.4} \tag{3.1}$$

Equation 3.2 represents the total cost calculating for the total number of satellites:

$$Total\ Cost\ = \$250M\ *\ Diameter^{1.4} *\ N_{satellite} *\ N_{plane} \tag{3.2}$$

Where

$$N_{satellite} = number\ of\ satellites\ in\ an\ orbital\ plane$$

$$N_{plane} = number\ of\ orbital\ planes$$

The last step to calculate the overall cost is to add the launch cost calculation. This calculation includes the selection of launch vehicles and calculating which vehicle to be used based on the vehicle capacity, number of satellites per plane and the cost to launch a satellite per lift.

Earlier in the assumptions section, it is stated that the cost model is an approximation using the historical data of the former missions. And the bounds on the parameters are defined in order to keep the design of the satellites in the design vector. The bounds drive the design of the model to utilize small size satellites with a reasonably small constellation for regional coverage considerations. Therefore, the diameter length upper bound is defined as 1.5 meter and the number of satellites per plane is bounded as 5, presuming that all satellites in an orbital plane of this model can be lifted by a single launch vehicle. Candidate launch vehicles are selected from Table 11-23 of Space Mission Engineering textbook [23]. Table 3-2 illustrates the candidate launch vehicles with their lift capacity and cost parameters.

Vehicle/ Parameter	**Minotaur IV**	**Taurus**	**Falcon 9**	**Long March 2C**	**Ariane 4G**	**Atlas 5**
Capacity per Lift (kg)	1650	1380	10450	3200	18000	20050
Cost per Satellite (Million $)	22	25.878	56.75	30.645	224.73	172

Table 3-2: Launch Vehicle Candidates

Using the data from Table 3-2, the launch cost and the overall cost equations are shown in Equation 3.3 and Equation 3.4.

$$Launch\ \ Cost\ = Cost\ per\ Satellite\ *\ Number\ of\ Satellites \quad (3.3)$$

$$Overal\ \ Cost\ = Total\ Cost + Launch\ Cost \quad (3.4)$$

3.2.2 Resolution Calculations

Based on the assumptions and parameters stated above, for the resolution calculation, spatial resolution method is used based on Rayleigh criterion. Equation 3.5 represents the resolution calculation. The calculation of resolution objective function contains diameter length and altitude parameters of MOGA as decision variables. In each iteration of the algorithm, the resolution is calculated using these parameters in the following equation:

$$Spatial\ Resolution\ = \frac{(1.22 * \lambda)}{diameter} * altitude \quad (3.5)$$

Where

$\lambda = visible\ light\ wavelength\ (assumed\ as\ 500\ nanometers)$

$diameter = sensor\ diameter\ length\ in\ meters$

$altitude = satellite\ altitude\ in\ meters$

3.2.3 Revisit Time Calculations

This section describes the STK scenario and the STK features and access reports used in this thesis in order to calculate the revisit time function.

Revisit time calculations is the part where the STK scripts are run and the scenario is generated. In each iteration of the algorithm new STK scenario is initialized with a 48 hours of scenario period. The visibility of the scenario is set to zero for computational purposes. Based on the parameters, a satellite model with a fixed sensor is generated. The sensor type is set to fixed with a 30 degrees of cone half angle. This definition creates sensors with nadir pointing. The orbit type is defined as a sun synchronous orbit using STK’s Orbit Wizard when the inclination angle is above 96 degrees. Then a Walker constellation is generated of a defined type. The targets are defined as the grids of an area target over a region. Figure 3-1 illustrates the area target and the grid points.

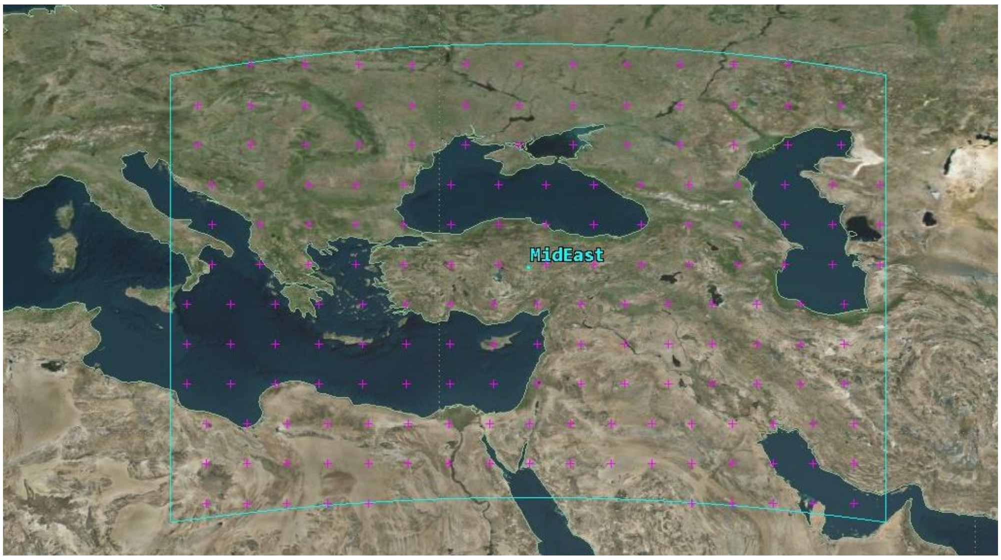

Figure 3-1: STK Area Target

In order to calculate the revisit time, a coverage definition object is created initially. The created area target and the sensors of all satellites in the constellation are defined as the assets of the coverage definition. A figure of merit (FOM) object is created to measure the coverage. The FOM type is set to revisit time. By this definition, the FOM calculates the maximum gap durations for each of the grid points on the area target including the intervals of all the sensors of the satellites in the constellation. Once the access report is generated by FOM calculation, the maximum gap duration is achieved. This obtained result is used as the maximum revisit time of any grid point of the area target. This value is the objective function used in the MOGA as the third fitness function.

3.3 Optimization Methodology

In this section, the structure of the MOGA method is described. In general, an initial population is generated by the MOGA and the algorithm then processes this population to result with the batch Pareto fronts. Before the algorithm starts, upper and lower bounds should be defined for the decision parameters. By the bounds, initial population is produced for each of the decision parameter of the algorithm. As the algorithm processes, a new set of parameters of the current generation is created to be the new generation. Creation of the new generations are made by this selection process. The algorithm ends with the latest generation when the stopping criteria is met. In this study, the stopping criteria is the total number of generations. By another definition, the algorithm creates candidate solution sets to evaluate by the number of generations times the number of populations. The MOGA gives the optimal solutions in the batch pareto fronts.

3.3.1 Population Size

The user defines the population size and the number of generations which also defines the number of candidate solutions and the number scenarios to run. The size of the initial population is critical as it provides the tradeoff between efficiency and effectiveness. If the population size is kept very small, an effective design space may not be created by the algorithm. On the other hand, if the population size is defined to be too large, the efficiency of the algorithm worsens as the determination of the optimal solutions may not be achieved when a reasonable computational time is regarded. Determination of the generation size falls under the same considerations. In this thesis, the population size is 30 and the number of generations is 30. By this design space, a total number of 900 scenarios and candidate solutions are evaluated in each model set. The first set of the model that will be presented in the following chapter remains only 200 scenarios with a population size of 10 and a number of generations of 20. The results of these sets make up the preliminary findings. One other aspect of keeping the initial set fairly small is to evaluate how the MOGA generates the pareto fronts and the number of optimal solutions depending on these numbers. The results are discussed in the following chapter.

3.3.2 Selection

The algorithm evaluates the objective value of each individual of the current population in order to create a new population. By this evaluation, useful range of values are created from the raw fitness scores of the individuals. Parents of the population are selected according to their fitness values. Likelihood of the selection of the parents are proportional to their scores in the selection process. As the children are produced from the parents, the “genes” of the parents are transferred.

3.3.3 Mutation and Crossover

The children creation process starts as the algorithm selects the parents from the population. Mutation and crossover are the defining operators of the selection process within the genetic algorithm process. The first function on creating the children is mutation. Mutated children are generated by the parents with randomly changes applied to the genes. The mutation function ensures the diversity of a population as the performance of the algorithm is developed to generate individuals with better fitness values. The other function used in the children creation is the crossover. By this function, a vector of genes from two parents are randomly chosen and assigned to a new offspring. Crossover yields for the algorithm to get the best genes from different individuals of a population and gather them with a better and superior offspring.

As the MOGA creates new genes of the populations, generation of integer values are not ensured. The genes, representing the parameters, are arbitrarily produced between the bounds as fractional values. In this thesis, parameters of number of satellites per plane and number of orbital planes are defined as integer values where other parameters are kept as fractional values. The MATLAB functions for mutation and crossover operators to ensure this alignment are produced by Diniz [16] and adopted for the parameters to define integer values for the scope of this study.

3.3.4 Stop Criteria

Three stopping determination conditions are utilized by the MOGA. The first condition is the generation number. By this criterion, the algorithm stops when the defined number of generations value is reached. Another condition is the spread change, where the algorithm stops as the change of the spread is less than the tolerance defined for the Pareto front. The third condition is the limit of time. This limit is infinity unless defined for a value by the user. Once the algorithm stops, termination reason is output on MATLAB command window. The stopping criterion used in this thesis is the generation number.

3.4 Refining Results

The results are refined as the solutions are generated by MOGA for each test case. The lower and upper bounds for the decision parameters need to be defined accurately for each different test case. 3D plotting functions of the MATLAB is utilized to generate the Pareto fronts and the solutions of the Pareto fronts are examined for their accuracy.

The distribution of the solutions is tested based on the population and generation sizes of the algorithm. As the preliminary findings are evaluated, the size of the algorithm and the bounds of the parameters are adjusted for a larger and better design space. In the cases where the type of the constellation is changed, or the type of the orbit is changed based on the inclination angle, relevant adjustments are made on parameters and scripts.

This method of refinement is intended to improve the design space for the MOGA and produce strong Pareto fronts for each test case.

3.5 Summary

This chapter outlined the decision parameters, test cases, calculation methods of the objective functions and equations used for these functions. Optimization process and the creation of model sets are discussed. Validation of the model based on the results and comparison with the current systems will be discussed in following chapters. The design solutions and analysis will be presented in Chapter 4.

Chapter 4: Results

The algorithm was run for several test cases. Each test set was run twice with different Walker constellation types. In the initial set, the scenario was run 200 tines where the remaining sets were run for 900 times. The results and the change of the design space are discussed. Throughout the sets, diameter length parameter bounds are changed to accommodate analysis of smaller telescope designs.

It is found out that the results of each test case are composed of sets including accurate designs as shown in the Pareto fronts. Therefore, no irrelevant points are found in the Pareto fronts and the findings are given in 3D Plots. The parameters of the solutions for each case are given in tables Table 4-1 through Table 4-7.

4.1 Results of the Simulation

The results of the simulation are categorized into 4 cases. These 4 case sets are separated based on the change of design space, bounds of parameters, and the orbital type. Three objective functions are calculated by MOGA as fitness functions and optimal solutions are presented in Pareto fronts. These objective functions are not constrained in the model. Therefore, all feasible solutions that reside in the design space are illustrated. For the focus of this study, desired performances of the solutions are in the design space bounded by parameter restrictions where the cost is less than a billion dollars, the resolution is less than 1 meter and revisit time duration is less than 10 hours. The solutions that the MOGA yielded corresponding to these criteria are highlighted in the tables for each case. In some of the cases, some feasible solutions that are slightly above this design space but providing good performance by common sense are also highlighted. The cost values of the results are presented in the tables and include the launch cost calculations whereas the Pareto fronts include the resulting cost values of the cost model. The tradeoffs and the analysis are presented in the following sections.

4.1.1 Case 1 Results

In the first case, the scenario size is 200 runs. The diameter length bounds are between 0.5 and 1.5 meters whereas the inclination is from 0 to 90 degrees.

This set is calculated once with a Walker Delta constellation. The results of this case are the preliminary findings of this thesis study. The purpose of this case is to analyze the effect of change on the design space by comparing the following cases. The bounds of parameters are conserved in the first and second cases whereas the scenario is changed from 200 to 900. Figure 4-1 illustrates the plotting of the Pareto front for case 1.

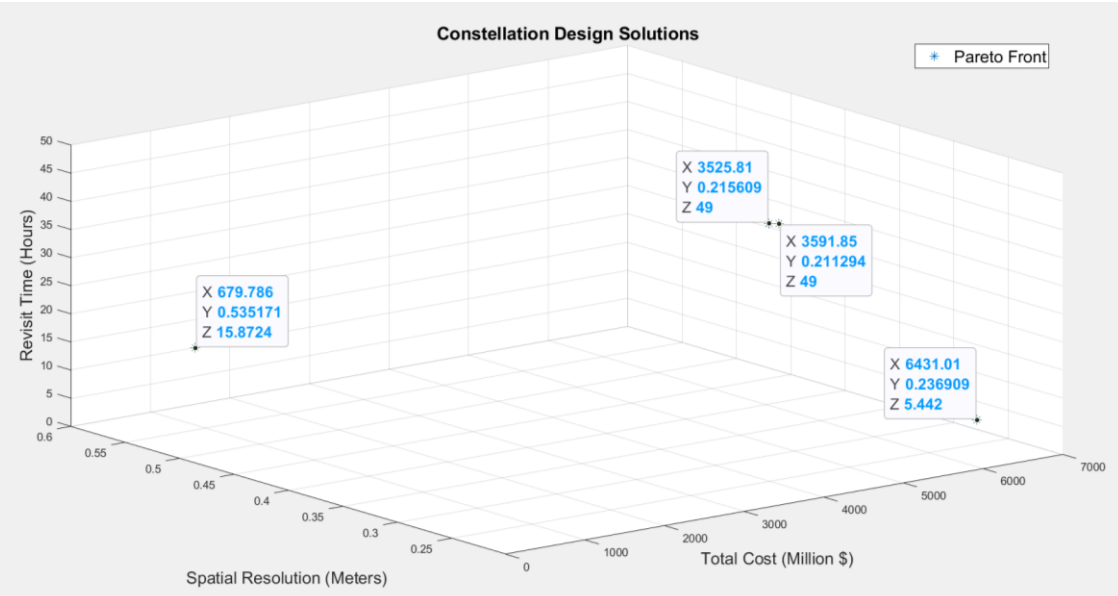

Figure 4-1: Set 1 Results

The fitness scores of the objective functions and key decision parameters for each optimal solution of the Pareto front are presented in the Table 4-1.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter Length
1	**811.8**	**0.53**	**15.87**	2	3	498.48	0.57
2	**3855.8**	**0.21**	**49**	3	4	393.92	1.14
3	**3789.8**	**0.22**	**49**	3	4	396.67	1.12
4	**811.8**	**0.24**	**5.44**	4	4	545.19	1.40

Table 4-1: Set 1 Fitness Scores and Parameters

Findings of the Case 1 illustrates that the number of optimal solutions in the design space is fairly small for smaller size models. The algorithm concluded with optimal solutions weighted on different selection of parameters. It is found out that the revisit time score becomes a fairly low performance when a low Altitude value is implemented. The first solution of this case is highlighted as it resides in the focus of the design space stated earlier.

4.1.2 Case 2 Results

For the second case, the same model set is implemented with a bigger size of 900 scenarios. The set is simulated twice for different Walker constellation types to analyze the effect of the change of constellation type and spacing of the satellites and orbital planes. Findings of the second set for Walker Delta constellation usage is illustrated in Figure 4-2.

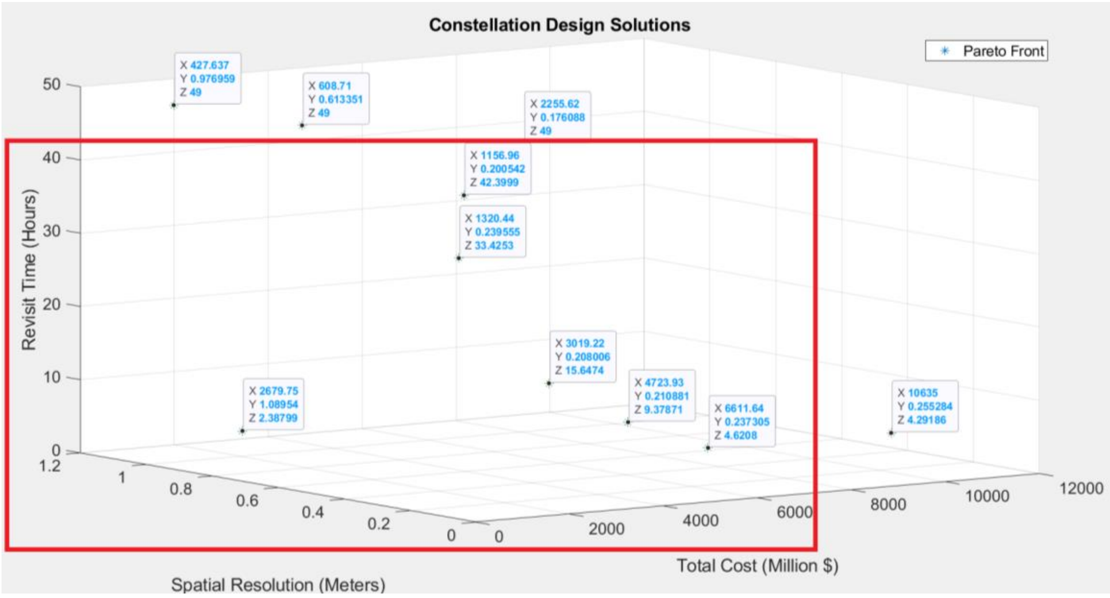

Figure 4-2: Set 2 Results for Walker Delta Constellation

The bigger design space resulted with a bigger number of solutions in the space. It is also found out that the weighting of the solutions is far from the desired space marked with the red selection. Values of the fitness functions and the key parameters of the solutions are presented in Table 4-2.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter Length
1	**1245**	**0.20**	**42.40**	2	2	364.8	1.11
2	**1408.4**	**0.24**	**33.43**	2	2	478.9	1.22
3	**3229.8**	**1.09**	**2.39**	5	5	975	0.55
4	**3217.2**	**0.21**	**15.65**	3	3	420.7	1.23
5	**4987.9**	**0.21**	**9.38**	3	4	478.1	1.38
6	**6963.6**	**0.24**	**4.62**	4	4	557	1.43

Table 4-2: Set 2 Fitness Scores and Parameters for Walker Delta Constellation

Compared with the findings of the first set, it is verified that the low altitude designs yield fairly poor revisit time values. One other significant finding of this model set is that the diameter length is the main driver for the resolution value whereas its effect is inversely proportional to the cost performance. Bigger telescopes can give better resolution performances, but the tradeoff should be made with the cost of the system.

The same set is simulated once more for Custom type Walker constellation in order to compare and analyze the effect of the change in the constellation. The solutions of the simulation are presented as the Pareto front in Figure 4-3.

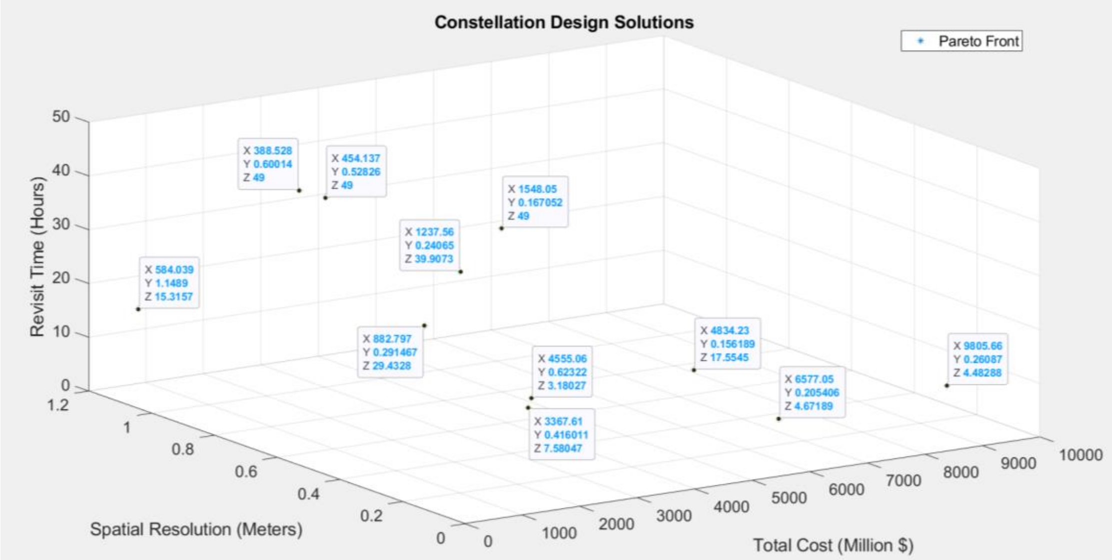

Figure 4-3: Set 2 Results for Walker Custom Constellation

It is found out that similar solution numbers in the design space are achieved with Custom Walker constellation and the tradeoff analysis of the changing parameters are similar in the same manner. The effect of the change in the constellation configuration is revealed to be minimal. It is noticed that the ratio of the number of planes and the RAAN Increment are reasonable and therefore the Custom Walker constellation design performs similar to the Delta. The changes in the constellation design is evaluated in the proceeding cases and analyzed in the analysis section. Fitness function values and the key parameters of the solutions are presented in Table 4-3.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter	Inclination	True Anomaly Increment	RAAN Increment
1	**476.53**	**0.60**	**49**	2	2	501	0.51	35	99	132
2	**542.14**	**0.53**	**49**	2	2	493	0.57	38	97	132
3	**716.04**	**1.15**	**15.32**	3	2	960	0.50	61	123	25
4	**970.8**	**0.29**	**29.43**	2	2	437	0.91	57	84	138
5	**1325.6**	**0.24**	**39.91**	2	2	459	1.16	63	26	68
6	**1636**	**0.17**	**49**	2	2	374	1.36	40	51	100
7	**3697.6**	**0.42**	**7.58**	5	3	632	0.93	65	37	120
8	**5105.1**	**0.62**	**3.18**	5	5	815	0.80	69	176	51
9	**5098.2**	**0.16**	**17.55**	3	4	360	1.40	83	66	145
10	**6929.1**	**0.21**	**4.67**	4	4	480	1.43	58	16	67
11	**10355.7**	**0.26**	**4.48**	5	5	590	1.38	65	70	67

Table 4-3: Set 2 Fitness Scores and Parameters for Walker Custom Constellation

4.1.3 Case 3 Results

In this case, the model set is changed by the bounds. The diameter length is set between 0.3 and 1.5 meters and the inclination angle is set between 0 and 100 degrees. For inclination angles bigger than 96 degrees, the orbit is defined as sun synchronous. The aim of these changes is to develop the model by including accurate orbital configuration and enlarging the design space. Previous cases demonstrated that most of the solutions are above from the desired space in the Pareto front. Then the search is focused on the smaller telescope size. As a main search question of this thesis, whether smaller size satellites can yield better performance is questioned. Figure 4-4 illustrates the findings of the set simulated with the Walker Delta constellation.

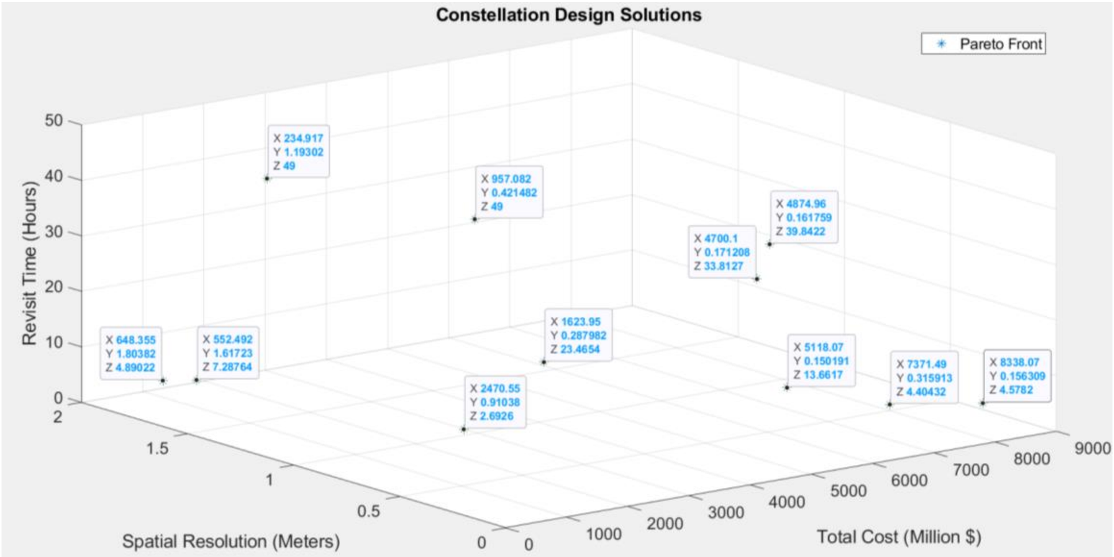

Figure 4-4: Set 3 Results for Walker Delta Constellation

With the change of the bounds, it is observed that more optimal solutions are found in the desired design space. This change in the diameter length size has affected the performance of all objective functions. As a main driver function, costs are reduced reasonably. The main tradeoff of the change in the diameter size is that as the cost of the system goes down, the resolution performance worsens. When the revisit time objective is analyzed, it is observed that with lower Altitude values, the gap duration increases. On the other hand, the size of the constellation is increased as more satellites can be added to the system provided that the cost is less for smaller satellites. The tradeoff for the revisit time is between the altitude decrease and the constellation size increase. The fitness functions and the parameters of the solutions are given in Table 4-4.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter	Inclination
1	**322.92**	**1.19**	**49**	2	2	695	0.36	29
2	**750.49**	**1.62**	**7.29**	3	3	972	0.37	56
3	**912.35**	**1.80**	**4.89**	3	4	990	0.33	56
4	**1133.08**	**0.42**	**49**	2	4	408	0.59	10
5	**1822**	**0.29**	**23.47**	3	3	374	0.79	57
6	**2910.5**	**0.91**	**2.69**	4	5	902	0.60	93
7	**4964.1**	**0.17**	**33.81**	3	4	387	1.38	66
8	**5139**	**0.16**	**39.84**	3	4	375	1.41	71
9	**5382.1**	**0.15**	**13.66**	4	3	361	1.46	73
10	**7921.5**	**0.32**	**4.40**	5	5	583	1.13	75
11	**8778.1**	**0.16**	**4.58**	5	4	369	1.44	68

Table 4-4: Set 3 Fitness Scores and Parameters for Walker Delta Constellation

The same set is simulated once more with Custom type Walker Constellation configuration. The solutions are presented in the Pareto front as in the Figure 4-5.

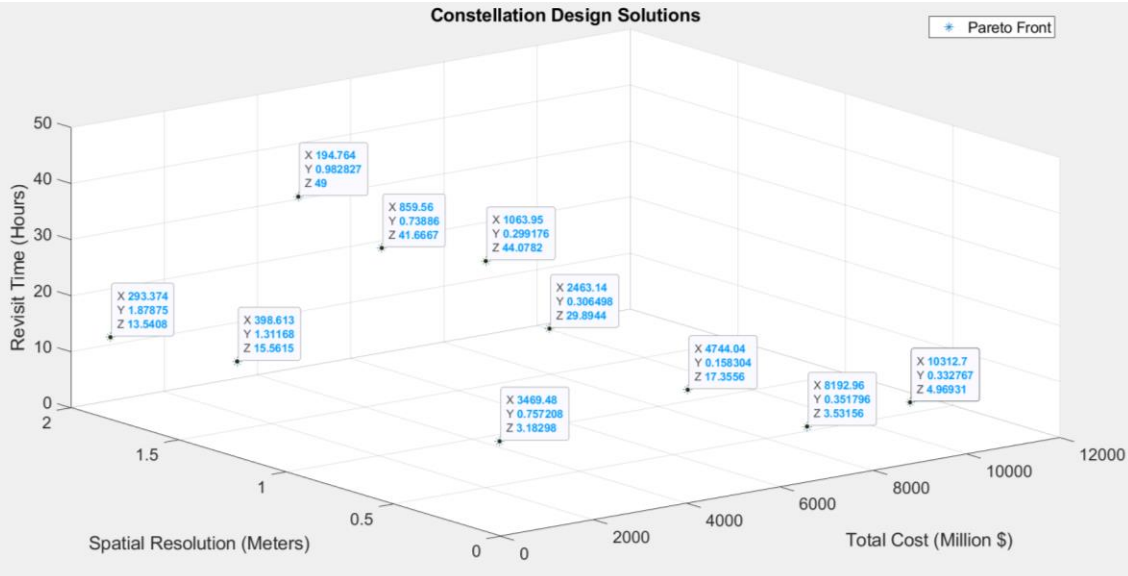

Figure 4-5: Set 3 Results for Walker Custom Constellation

As discussed earlier, the change of the constellation configuration has minimal effect on the solutions. Similar solutions in the design space are found. The scores of the solution points and the parameters are given in Table 4-5.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter	Inclination	True Anomaly Increment	RAAN Inc.
1	**282.76**	**0.98**	**49**	2	2	501	0.31	39	99	132
2	**425.37**	**1.88**	**13.54**	3	2	960	0.31	68	123	25
3	**530.61**	**1.31**	**15.56**	3	2	834	0.39	55	124	43
4	**991.56**	**0.74**	**42**	2	3	814	0.67	46	76	96
5	**1151.9**	**0.30**	**44.08**	2	2	513	1.05	85	74	113
6	**2727.1**	**0.31**	**29.89**	3	4	436	0.87	98 *	84	128
7	**4019.5**	**0.76**	**3.18**	5	5	815	0.66	77	176	51
8	**5008**	**0.16**	**17.36**	3	4	360	1.39	92	66	145
9	**8743**	**0.35**	**3.53**	5	5	700	1.21	91	143	78
10	**10863**	**0.33**	**4.97**	5	5	780	1.43	71	88	85

Table 4-5: Set 3 Fitness Scores and Parameters for Walker Custom Constellation

It is observed that a solution with a Sun Synchronous orbit type has entered the design space. Both of the solutions for Case 3 pointed out that diameter length around 0.3 meters give the optimal solutions residing in the desired design space. One observation is that the resolution is affected with the decrease of the size. The tradeoff for this case is with the Altitude value. Analyzing the effect of the Altitude for a given diameter length suggest that the resolution performance gets in the desired design space when the Altitude value decreases. Tradeoffs and analysis are discussed in detail in the following sections.

4.1.4 Case 4 Results

Case 4 consists of simulations for Sun Synchronous orbit types. The effect of the inclination for the previous cases suggest that this value should be kept in accordance with the geographic location of the targets to ensure the coverage and the required revisit time values are achieved. On the other hand, it is a common fact that Sun Synchronous orbits have significant advantages for remote sensing missions with LEO orbital configurations. Therefore, this special simulation is configured to review the effects of Sun Synchronous orbits. The solutions for the simulation with a Walker Delta Constellation are presented in Figure 4-6.

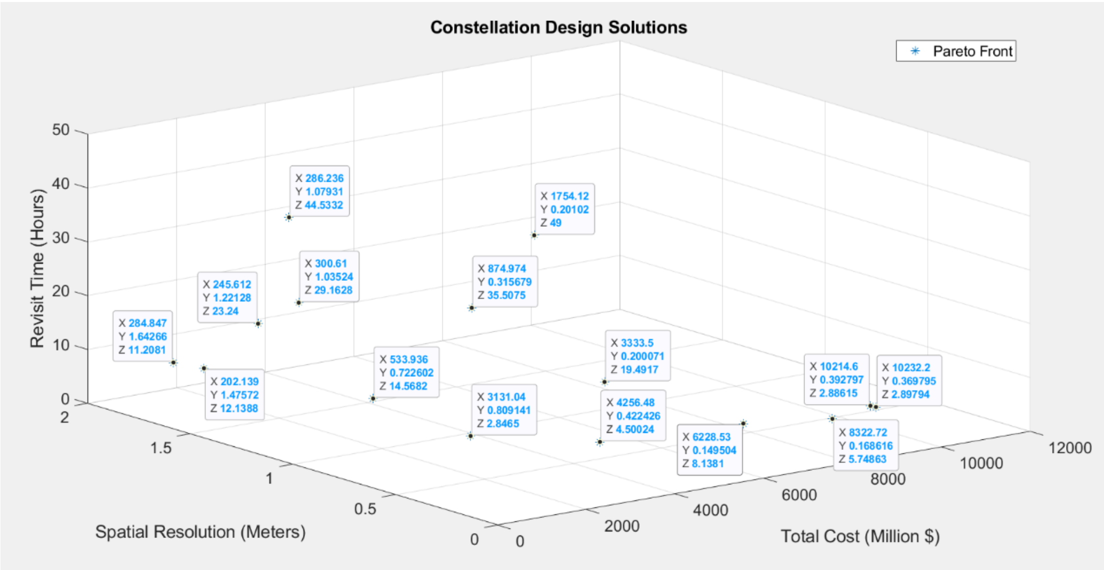

Figure 4-6: Set 4 Results for Walker Delta Constellation

Significant increase on the number of solutions that reside in the desired design space is observed with implementing Sun Synchronous orbits. Tradeoffs between the parameters and their effect on the objective functions are similar to the findings of the previous cases. As the diameter is the main driver parameter for resolution and the cost, the solution points show that the diameter length is mainly in the vicinity of two diameter values: 0.3 meters and 0.5 meters.

Having a diameter length in the vicinity of 0.3 meters, the cost of the system decreases significantly. But the tradeoff is made with the resolution. Varying with the Altitude value, the resolution value for this configuration is slightly over 1 meter. The other group of solutions in the desired space have diameter length values around 0.5 meter. In this case, the cost of the system increases, but this increase is observed to be around the minimal values of the solutions of previous test cases. For this configuration, the resolution improves depending on the altitude. One other finding is that the revisit time changes with the size of the constellation.

The significance of the Sun Synchronous orbit configurations is that the scores of the objective functions that are in the desired design space can be achieved with a smaller number of satellites concluding with less system costs. Table 4-6 illustrates the objective function scores and the parameters of the solution points.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter
1	**290.14**	**1.48**	**12.14**	2	2	772	0.32
2	**333.61**	**1.22**	**23.24**	2	2	734	0.37
3	**416.85**	**1.64**	**11.21**	2	3	822	0.31
4	**374.24**	**1.08**	**44.53**	2	2	724	0.41
5	**388.61**	**1.04**	**29.16**	2	2	719	0.42
6	**621.94**	**0.72**	**14.57**	2	2	757	0.64
7	**962.97**	**0.32**	**35.51**	2	2	470	0.91
8	**1886.12**	**0.20**	**49.00**	3	2	369	1.12
9	**3571.04**	**0.81**	**2.85**	4	5	949	0.72
10	**3531.5**	**0.20**	**19.49**	3	3	434	1.32
11	**4520.48**	**0.42**	**4.50**	4	3	889	1.28
12	**6558.53**	**0.15**	**8.14**	5	3	352	1.44
13	**8762.72**	**0.17**	**5.75**	5	4	398	1.44
14	**10764.63**	**0.39**	**2.89**	5	5	915	1.42
15	**10782.21**	**0.37**	**2.90**	5	5	862	1.42

Table 4-6: Set 4 Fitness Scores and Parameters for Walker Delta Constellation

The Sun Synchronous set is simulated once more for the Custom type Walker Constellation configuration. Together with the previous solutions of Sun Synchronous set, the results pointed out that the increase of the number of solutions in the desired space is achieved with Sun Synchronous orbit configuration. Figure 4-7 represents the solutions of the Pareto front.

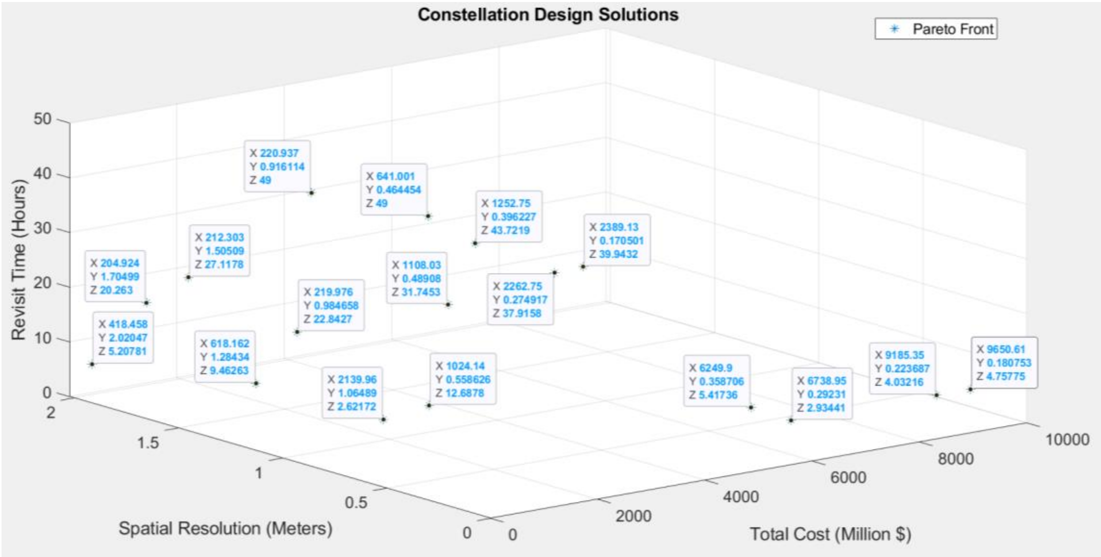

Figure 4-7: Set 4 Results for Walker Custom Constellation

The solution points suggest similar findings and tradeoffs of parameters. The effect of the change on constellation type is minimal. Table 4-7 illustrates the scores of the objective functions and the parameters of the solutions.

Analyzing the results of the Sun Synchronous sets, solutions points in the desired design space of less than a billion dollars cost, less than a 1-meter resolution and less than 10 hours of revisit time suggests that constellation designs with a diameter length around the vicinity of 0.3 meters and Sun Synchronous orbits with an Altitude around the vicinity of 600 kilometers yield optimal solutions. The validation of these findings is discussed in the following sections.

No	Cost with Launch	Resolution	Revisit Time	Number of Satellites	Number of Planes	Altitude	Diameter	True Anomaly Increment	RAAN Increment
1	**292.92**	**1.70**	**20.26**	2	2	901	0.32	125	123
2	**300.3**	**1.51**	**27.12**	2	2	816	0.33	148	130
3	**307.98**	**0.98**	**22.84**	2	2	547	0.34	156	152
4	**308.94**	**0.92**	**49.00**	2	2	511	0.34	164	156
5	**616.46**	**2.02**	**5.21**	3	3	996	0.30	42	115
6	**882.16**	**1.28**	**9.46**	3	4	681	0.32	77	23
7	**729**	**0.46**	**49.00**	2	2	554	0.73	75	77
8	**1222.14**	**0.56**	**12.69**	3	3	522	0.57	133	136
9	**1306.03**	**0.49**	**31.75**	3	3	483	0.60	144	147
10	**1384.75**	**0.40**	**43.72**	2	3	571	0.88	41	47
11	**2579.96**	**1.06**	**2.62**	4	5	952	0.55	157	37
12	**2460.75**	**0.27**	**37.92**	3	3	453	1.00	78	96
13	**2521.13**	**0.17**	**39.94**	3	2	390	1.39	33	80
14	**6799.9**	**0.36**	**5.42**	5	5	588	1.00	104	92
15	**7288.95**	**0.29**	**2.93**	5	5	506	1.06	80	105
16	**9735.35**	**0.22**	**4.03**	5	5	483	1.32	115	147
17	**10200.61**	**0.18**	**4.76**	5	5	404	1.36	84	122

Table 4-7: Set 4 Fitness Scores and Parameters for Walker Custom Constellation

4.2 Trade-offs

The results of this thesis demonstrated there are certain tradeoffs between decision parameters that affect the scores of the objective functions. Tradeoffs between the objective functions are observed as well.

Considering the tradeoffs between the objective functions, it is found that the cost is the primary driver function of the design. Better performance in terms of high resolution and low revisit times can be achieved with highly expensive systems. On the other hand, keeping the cost at lower levels and aiming for the high-resolution results with a small size constellation designs and therefore, high revisit times. Desired performance space having less than a billion dollars cost, less than 1-meter resolution and less than 10 hours of revisit times is achieved in Pareto fronts of all cases.

Analyzing the tradeoffs between the decision parameters, sensor diameter length is the primary driver of the cost and the design of the system. For solutions that have similar diameter lengths, the change of the altitude drives the performance of the resolution objective function. Revisit time performance is mainly based on the inclination parameter as well as the number of satellites and orbital planes in the design.

It is significantly found out the Sun Synchronous orbital configuration yields the maximum number of solution points in the Pareto fronts. The cost is minimized where the performance of the other objective functions can be achieved in the desired design space.

4.3 Limitations

The results of this thesis study are an implementation of MATLAB’s MOGA optimization method and STK orbital simulations that produces designs for remote sensing constellation. The design is limited by several factors of the nature of the MOGA and STK features.

For the design of the orbits, circular orbit types are used in this thesis. Realistic elliptical orbit configurations are not considered. Constellation type is configured to be Walker provided that all of the satellites are the same size. Changes on the satellite sizes are not considered. The sensor type of the satellite design is configured to be fixed and having a 30 degrees of cone half angle for the field of view. More developed sensor configurations and the usage pointing attitudes were outside of the scope of this study. For the resolution calculation, the altitude parameter is used in the equations and acquiring the actual range from the sensors to targets are not modeled in STK.

4.4 Analysis

Optimal solutions in the desired design space are found on each set. It is observed that the desired performances of objective functions can be achieved with different design parameters. The change of the bounds on decision parameters allows a wider design space and enables the solution points of the Pareto fronts to be more accurate. On the other hand, the size of the design has significant effect on the resulting computational times required to reach acceptable solutions as well as enlarging the design space to achieve accurate solution points.

The change on the Walker constellation type is found to be minimal when applied to each of the described cases. The main reason is that the algorithm mutates the Walker parameters of spacing in each iteration to find better offspring. Therefore, when comparing the Custom Walker constellation spacing parameters with the actual design of the Delta Walker constellation, it can be concluded the designs produced by the algorithm are similar to the Delta Walker constellations. Delta Walker constellations can be implemented that provide the evenly spacing of the satellites and orbital planes. One other finding of this analysis is that Delta Walker constellations are beneficial for regional coverage as well as global coverage.

For the scope of the design sets where the cost is less than a billion dollars, the resolution is less than or in the vicinity of 1 meter and revisit time less than 10 hours, it is found that satellite designs would have diameter lengths between the values of 0.3 and 0.5 meters. The altitude values for this span of diameter length varies between

600 km and 900 km to achieve the desired performance. It is also found that usage of the Sun Synchronous orbits results with better designs.

4.5 Validation

The optimal solution among the findings of the cases has diameter length value on a span of 0.3 to 0.5 meters and altitude value between 600 km to 900 km as it is stated on the Analysis section. The optimal orbital configuration to be implemented for these parameters is found to be sun synchronous. The cost of the system and the size of the system varies for the resolution and revisit time performances. But for the scope of this study where the resolution is set around 1 meter and revisit time around the vicinity of 20 hours, it is found that the desired regional coverage can be achieved with 2 to 3 satellites per plane and with a number of 2 to 3 orbital planes.

Therefore, the validation method in this study is to compare these findings with the current solutions. One issue is that the cost information of the current systems is not possible to achieve as the cost of products are kept as commercial secrets in the space industry. For this reason, the cost is not included in the comparison with the current systems.

The systems to compare with the parameters found are BlackSky's Pathfinder satellites and SkySat constellation's Terra Bella satellites [38, 39]. Both systems consist of satellites with sensor designs that the diameter length value is around the vicinity of 0.3 meters having a spatial resolution value of around 1 meter. The orbital configuration of these systems are Sun Synchronous orbits with Altitude of in the vicinity of 600 km.

The comparison of the solutions of this thesis with these systems suggest that the findings are accurate and validated. It is also significantly important that the suggested design parameters which are found among the solution points of all the test cases of the study are compatible with the actual implementation of SkySat constellation.

4.6 Summary

This chapter presented possible solutions for remote sensing constellation designs with different parameter sets and orbital configurations at LEO. The diameter length and the altitude parameters are found to be the main driver for the design of the system. The tradeoffs and analysis are presented to illustrate the perspectives of the constellation design considerations. A candidate design solution is proposed among the findings of all the cases and the validation is discussed with a comparison of the current systems. The conclusions from the results of this study are presented in the next chapter.

Chapter 5: Conclusions

The main contribution of this thesis work is the multi-objective genetic algorithm model that could be run in MATLAB, in conjunction with STK, to optimize constellation designs for desired decision parameters. Tradeoffs between the cost, resolution and revisit times are illustrated through the generated cases of constellation designs. The results showed that the model of this thesis study is capable of creating realistic solutions. The improvements of the usage of smaller satellite designs to optimize the desired performances for remote sensing constellations for regional coverage considerations are illustrated. This work can be referenced by decision makers to save money and increase the performance of constellations as this work is validated with the current space architectures that are more resilient and efficient.

5.1 Challenges

One of the most challenging parts of this research study can be listed as the limitation in the computation time. The determination of the origins of errors was difficult due to the complexity of the model. The algorithm ran overnight before a notification of an error is brought to the user. The results of the changes to the model were not observed for several hours as the algorithm ran. The issue originates from resource limitations. The performance of the algorithm can be increased by the acquisition of additional computing power and possibly a more sophisticated implementation of error handling and scripting of algorithm execution.

One other challenge is the nature of integration of STK with MATLAB. The STK tasks are run by scripts of MATLAB that would require multiple references. Tutorials and commands in example scenarios generally do not provide the adequate level of details required for a command to function. Lack of details in the error of not functioning commands made it difficult to address the cause of an error.

The last challenge to state for this work is the usage of the multi-objective genetic algorithm. The MOGA does not generates genes in integer values. Therefore, understanding the MATLAB codes for mutation and crossover functions was a challenge. For this thesis, these MATLAB code parts are used that Diniz has developed for her thesis and it was adopted for the desired decision variables [16].

5.2 Recommendations for Future Work

In this study's work, the ability for the usage of MATLAB's MOGA together with STK is demonstrated to generate remote sensing constellation designs for regional coverage considerations. Design of the algorithm can be changed for new sets of decision parameters, bounds and fitness functions in order to meet a user's priorities. MATLAB and STK connection is based on the code snippets that runs the features of STK. Other entities in the STK's library of MATLAB code snippets can be applied to numerous objectives to calculate different access report features. The utilized design tool of this thesis can be expanded and further explored for different objectives.

The size of the model can be increased to enlarge the design space of MOGA by using higher population and generation sizes. Hence, different optimization algorithms can be applied.

For the scope of this thesis, regional coverage is modeled. The model can easily be expanded to address global coverage. Analysis of modeling constellations by adding more satellites and orbital planes can be achieved with changing the targets to cover the globe or specific parts of the globe to user's choice. For the constellation model in this thesis is a single satellite design is used. For future studies, distributed models can be created by adding different designs of satellites and/or modelling for multiple orbital configurations.

A single parameter cost model is used in this study. The conceptual satellite design is based on the diameter length parameter. The model can be changed with utilization of different cost models based on mass parameter or multi-parameter cost models. The satellite design of the model can be developed by adding more decision parameters to configure the design.

The sensors of the satellite design of the model is configured to be fixed in a nadir-pointing position. The sensor pointing type can be changed from fixed to pointing and the type of the sensor can be developed in order to achieve desired solutions.

In this study modelling launch vehicles and ground architectures are not included in the design. More parts of a satellite constellation system such as these and more subsystems of the satellite model can be added to develop the design as a future study.

5.3 Conclusions

This thesis was based on the necessity of a regional remote sensing constellation design. A model of constellation design was developed for different cases in order to analyze solutions for different objectives and parameter sets. The results are presented in Pareto fronts. Tradeoffs and analysis of the findings are presented. A conceptual constellation design is proposed based on the optimal solutions. Validation of the proposed system is discussed with comparison to current systems.

In general, it is presented with this thesis that constellation designs with smaller satellites are capable of achieving the desired mission requirements. Using of small size space telescopes provided with the advancements of the technology makes it possible for better and cheaper solutions. By this work, the results are presented as tradeoffs that allow decision makers to have a broad perspective of constellation usage for remote sensing missions for their preferences.

Appendix A

MATLAB Code

A.1: MOGA.m

```
%Electro-Optic Satellite Constellation Design methodology using the MOGA tool
% GAMULTIOBJ SETUP
tic
%*************USER INPUTS***********
nvars=9; % Number of Decision Variables
generations=30;
populationsize=30;
%Fitness Functions
%Fcn1 is the cost, Fcn2 is the resolution and Fcn3 is the revisit time.
Function1 = @(x) cost(x);
Function2 = @(x) resolution(x);
Function3 = @(x) revisittime(x);
FitnessFunction = @(x) [Function1(x) Function2(x) Function3(x)];
% DV's= [num_sat, num_plane, a, e, i, raan, argofper, tranmly, diamter]
%For Walker constellation type Delta where f=1, there has to be min 2
%planes
vec=[2, 2, 350, 0, 0, 0, 0, 0, 0.5;5, 5, 1000, 0, 90, 180, 180, 180, 1.5];
lb = vec(1,:); % lower bounds on DV's
ub = vec(2,:); % upper bounds on DV's
options =
optimoptions('gamultiobj','OutputFcns',{@gaoutputfcn},'PlotFcn',{@gaplotpareto,@gaplotscorediversity},
'InitialPopulationRange',[lb;ub],'PopulationSize', populationsize, 'Generations',
generations,'CreationFcn',@int_pop,'MutationFcn',@int_mutation,'CrossoverFcn',@int_crossover);
%GAMULTIOBJ solver
try
[x,fval,exitflag,output]=gamultiobj(FitnessFunction,nvars,[],[],[],[],lb,ub,options);
modifier='success'; save(date,'x','fval','output','vec')
figurename=strcat(date,'ResultsFig');
saveas(gcf,figurename,'fig');
plot3(fval(:,1),fval(:,2),fval(:,3))
xlabel('Total Cost (Million $)')
ylabel('Spatial Resolution (Meters)')
zlabel('Revisit Time (Hours)')
title ('Constellation Design Solutions')
legend ('Pareto Front')
catch me
   modifier='failed';
   report=getReport(me);
   save('Report.mat','report')
end
```

A.2: cost.m

```
function TotCost=cost(x)
%Set Initial States for design parameters
nvars=9;
num_sat=0;
num_plane=0;
a=0;
e=0;
i=0;
raan=0;
argofper=0;
tranm=0;
diamt=0;
% setting initial values for the DV's of MOGA
num_sat=x(1);
```

```
num_plane=x(2);
a=x(3);
e=x(4);
i=x(5);
raan=x(6);
argofper=x(7);
tranm=x(8);
diamt=x(9);
% Satellite Design Cost, using Space Telescope Cost Model
TotCost = num_sat * num_plane * 250 * (diamt^1.4); % (Million $) *1e6 for $
End
```

A.3: resolution.m

```
function Spt_Res=resolution(x)
%Set Initial States for design parameters
nvars=9;
num_sat=0;
num_plane=0;
a=0;
e=0;
i=0;
raan=0;
argofper=0;
tranm=0;
diamt=0;
% setting initial values for the DV's of MOGA
num_sat=x(1);
num_plane=x(2);
a=x(3);
e=x(4);
i=x(5);
raan=x(6);
argofper=x(7);
tranm=x(8);
diamt=x(9);
%******INPUTS*********
lambda=500e-9; % visible light vavelength assumed as 500 nm
%****END INPUTS*******
Spt_Res=((1.22*lambda)/diamt)*a*1e3; % meters
end
```

A.4: revisittime.m

```
function Max =revisittime(x)
%Set Initial States for design parameters
nvars=9;
num_sat=0;
num_plane=0;
a=0;
e=0;
i=0;
raan=0;
argofper=0;
tranm=0;
diamt=0;
% setting initial values for the DV's of MOGA
num_sat=x(1);
num_plane=x(2);
a=x(3);
e=x(4);
i=x(5);
raan=x(6);
```

```
argofper=x(7);
tranm=x(8);
diamt=x(9);
intplnphsinc=1;
lambda_nm=0.5;
ang_res=1.22*lambda_nm/diamt;
try
   uiapp=actxGetRunningServer('STK12.application');
catch
   uiapp=actxserver('STK12.application');
end
root=uiapp.Personality2;
uiapp.visible=false;
root.NewScenario('ExpSTK');
root.CurrentScenario.SetTimePeriod('1 Jan 2020 11:20:00.000','3 Jan 2020 12:20:00.000');
root.CurrentScenario.Epoch = '1 Jan 2020 11:20:00.000';
root.CurrentScenario.StartTime = '1 Jan 2020 11:20:00.000';
root.CurrentScenario.StopTime = '3 Jan 2020 12:20:00.000';
EOSat = root.CurrentScenario.Children.New('eSatellite', 'EOSat');
keplerian = EOSat.Propagator.InitialState.Representation.ConvertTo('eOrbitStateClassical');
keplerian.SizeShapeType=('eSizeShapeAltitude');
keplerian.LocationType = 'eLocationTrueAnomaly';
keplerian.SizeShape.ApogeeAltitude=a;
keplerian.SizeShape.PerigeeAltitude=a;
keplerian.Orientation.Inclination=i;
keplerian.Orientation.ArgOfPerigee=argofper;
keplerian.Orientation.AscNode.Value=raan;
keplerian.Location.Value=tranm;
EOSat.Propagator.InitialState.Representation.Assign(keplerian);
EOSat.Propagator.Propagate;
sensor = EOSat.Children.New('eSensor', 'Sensor');
sensor.CommonTasks.SetPointingFixedAzEl(0,90,'eAzElAboutBoresightRotate');
sensor.CommonTasks.SetPatternSimpleConic(30.0, ang_res);
EOConst = root.CurrentScenario.Children.New('eConstellation', 'EOConst');
try
root.ExecuteCommand(['Walker */Satellite/EOSat Type Delta NumPlanes ' int2str(num_plane) '
NumSatsPerPlane ' int2str(num_sat) ' InterPlanePhaseIncrement ' int2str(intplnphsinc) ' ColorByPlane
Yes ConstellationName EOConst']);
catch
   Flag_error=1
end
areaTarget = root.CurrentScenario.Children.New('eAreaTarget', 'MidEast');
areaTarget.AreaType = 'ePattern';
root.BeginUpdate();
patterns = areaTarget.AreaTypeData;
patterns.Add(25.0, 15.0);
patterns.Add(50.0, 15.0);
patterns.Add(50.0, 55.0);
patterns.Add(25.0, 55.0);
root.EndUpdate();
CoverageRegion = root.CurrentScenario.Children.New('eCoverageDefinition','CoverageRegion');
CoverageRegion.Grid.BoundsType = 'eBoundsCustomRegions';
covGrid = CoverageRegion.Grid;
bounds = covGrid.Bounds;
bounds.AreaTargets.Add('AreaTarget/MidEast');
covGrid.Resolution.LatLon = 2.0;
try
 for x=1:num_plane
   for y=1:num_sat
      CoverageRegion.AssetList.Add(['Satellite/EOSat' int2str(x) int2str(y) '/Sensor/Sensor']);
   end
 end
catch
   Flag_error=2
end
```

```
CoverageRegion.Advanced.AutoRecompute = false;
CoverageRegion.ComputeAccesses();
fom = CoverageRegion.Children.New('eFigureofMerit','Fom');
fom.SetDefinitionType('eFmRevisitTime');
overallValDP = fom.DataProviders.GetDataPrvFixedFromPath('Overall Value');
Result_1 = overallValDP.Exec();
Max_sec = cell2mat(Result_1.DataSets.GetDataSetByName('Maximum').GetValues);
Max = Max_sec/3600; %Max GAP duration in hours
```

A.5: int_crossover.m

```
function xoverKids = int_crossover(parents,options,GenomeLength,FitnessFcn,unused,thisPopulation)
IntCon=[1,2];
nKids=length(parents)/2;
xoverKids=zeros(nKids,GenomeLength);
index=1;
for i=1:nKids
 r1=parents(index);
 index=index+1;
 r2=parents(index);
 index=index+1;
 alpha=rand;
 xoverKids(i,:)=alpha*thisPopulation(r1,:)+(1-alpha)*thisPopulation(r2,:);
end
x=rand;
if x>=0.5
 xoverKids(:,IntCon)=floor(xoverKids(:,IntCon));
else
 xoverKids(:,IntCon)=ceil(xoverKids(:,IntCon));
end
range=options.PopInitRange;
%xoverKids=checkbounds(xoverKids,range);
end
```

A.6: int_mutation.m

```
function mutationChildren=int_mutation(parents,options,GenomeLength,~,state,~,~)
IntCon=[1,2];
shrink=0.01;
scale=1;
scale=scale-shrink*scale*state.Generation/options.Generations;
range=options.PopInitRange;
lower=range(1,:);
upper=range(2,:);
scale=scale*(upper-lower);
mutationPop=length(parents);
mutationChildren=repmat(lower,mutationPop,1)+repmat(scale,mutationPop,1 ).*...
    rand(mutationPop,GenomeLength);
x=rand;

if x>=0.5
mutationChildren(:,IntCon)=floor(mutationChildren(:,IntCon));
else
mutationChildren(:,IntCon)=ceil(mutationChildren(:,IntCon));
end
%mutationChildren=checkbounds(mutationChildren,range);
end
```

A.7:int_pop.m

```
function Population=int_pop(GenomeLength,~,options)
totalPopulation=sum(options.PopulationSize);
IntCon=[1,2];
range=options.PopInitRange;
lower=range(1,:);
span=range(2,:)-lower;
Population=repmat(lower,totalPopulation,1)+repmat(span,totalPopulation,
1).*rand(totalPopulation,GenomeLength);
x=rand;
if x>=0.5
    Population(:,IntCon)=floor(Population(:,IntCon));
else
Population(:,IntCon)=ceil(Population(:,IntCon));
end
%Population=checkbounds(Population,range);
```

A.8: gaoutputfcn.m

```
function [state, options,optchanged] = gaoutputfcn(options,state,flag)
optchanged = false;
switch flag
case 'init'
disp('Starting the algorithm');
% case {'iter','interrupt'}
% disp('Iterating ...')
 case 'iter'
 genpop=state.Population
 genscore=state.Score
 gennum=state.Generation
 %genbest=state.Best
 save('genscore.mat','genscore')
 save('gennum.mat','gennum')
 save('genpop.mat','genpop')
 %save('genbest.mat','genbest')
 case 'done'
 disp('Performing final task');
end
```

Bibliography

1. Abramson, R. L., Bearden, D. A., & Glackin, D. L. (1995, December). Small satellites: cost methodologies and remote sensing issues. In *Advanced and Next-Generation Satellites* (Vol. 2583, pp. 548-564). International Society for Optics and Photonics.

2. Mosher, T. (1999). Conceptual spacecraft design using a genetic algorithm trade selection process. *Journal of Aircraft*, *36*(1), 200-208.

3. Evans, H., Renner, T., & Tuttle, R. (2014). *The Phenomenology of Intelligence-focused Remote Sensing. Volume 1: Electro-optical Remote Sensing*. Riverside Research.

4. Stahl, H. P., Henrichs, T., Luedtke, A., & West, M. (2012, September). Update on multivariable parametric cost models for ground and space telescopes. In *Space Telescopes and Instrumentation 2012: Optical, Infrared, and Millimeter Wave*(Vol. 8442, p. 844224). International Society for Optics and Photonics.

5. Budianto, I. A., & Olds, J. R. (2004). Design and deployment of a satellite constellation using collaborative optimization. *Journal of spacecraft and rockets*, *41*(6), 956-963.

6. Riddle, Ellen. 1998. "Use of Optimization Methods in Small Satellite Systems Analysis." In *Proceedings of the AIAA/USU Conference on Small Satellites*, 1–8.

7. Taylor, ER. 2000. "Evaluation of Multidisciplinary Design Optimization Techniques as Applied to Spacecraft Design." In *Aerospace Conference Proceedings, 2000 IEEE*.

8. Jilla, C., & Miller, D. (2002, May). A multiobjective, multidisciplinary design optimization methodology for the conceptual design of distributed satellite systems. In *9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization* (p. 5491).

9. Ferringer, M. P., & Spencer, D. B. (2006). Satellite constellation design tradeoffs using multiple-objective evolutionary computation. *Journal of spacecraft and rockets*, *43*(6), 1404-1411.

10. Konak, A., Coit, D. W., & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety*, *91*(9), 992-1007.

11. George, E. R. (1997). Optimization of satellite constellations for discontinuous global coverage via genetic algorithms. *Astrodynamics 1997*, 333-346.

12. Ely, T. A., Crossley, W. A., & Williams, E. A. (1999). Satellite constellation design for zonal coverage using genetic algorithms. *The journal of the Astronautical Sciences*, *47*(3), 207-228.

13. Confessore, G., Di Gennaro, M., & Ricciardelli, S. (2001). A genetic algorithm to design satellite constellations for regional coverage. In *Operations Research Proceedings* (pp. 35-41). Springer, Berlin, Heidelberg.

14. Asvial, M., Tafazolli, R., & Evans, B. (2002). Non-GEO satellite constellation design with satellite diversity using genetic algorithm. In *20th AIAA International Communication Satellite Systems Conference and Exhibit* (p. 2018).

15. Mason, W., Coverstone-Carroll, V., & Hartmann, J. (1998, August). Optimal Earth orbiting satellite constellations via a Pareto genetic algorithm. In *AIAA/AAS Astrodynamics Specialist Conference and Exhibit* (p. 4381).

16. Diniz, H., Navigation Constellation Design Using A Multi-Objective Genetic Algorithm, Wright-Patterson FB, OH: School of Engineering, Air Force Institute of Technology (AU), March 2015.

17. SSTL, “Carbonite-1” [Online]. Available: https://www.sstl.co.uk/CARBONITE-1. [Accessed October 2016].

18. Stahl, H. P., Stephens, K. R., Henrichs, T., Smart, C., & Prince, F. A. (2010). Single-variable parametric cost models for space telescopes. *Optical Engineering*, *49*(7), 073006.

19. E. Abbate, Disaggregated Imaging Spacecraft Constellation Optimization with a Genetic Algorithm, Wright-Patterson AFB, OH: School of Engineering, Air Force Institute of Technology (AU), March 2014.

20. Sellers, J. J., Astore, W. J., Giffen, R. B., & Larson, W. J. (2000). *Understanding space: An introduction to astronautics*. Primis.

21. H. Riebeek, “Catalog Earth Satellite Orbits” NASA, [Online]. Available: http://earthobservatory.nasa.gov/Features/OrbitsCatalog/ [Accessed 13 November 2016].

22. Wiesel, W. E. (1997). *Spaceflight dynamics*. McGraw-Hill Science Engineering.

23. Wertz, J. R., Everett, D. F., & Puschell, J. J. (2011). *Space mission engineering: the new SMAD*. Microcosm Press.

24. A. Kauderer, “Orbital Elements" NASA, [Online]. Available: http://spaceflight.nasa.gov/realdata/elements/graphs.html [Accessed 13 November 2016].

25. AGI, “Object Tools – Walker”, [Online]. Available: https://help.agi.com/stk/11.0.1/Content/stk/tools-12.htm [Accessed 13 November 2016].

26. Mosher, T. (1996, September). Applicability of selected multidisciplinary design optimization methods to conceptual spacecraft design. In *6th Symposium on Multidisciplinary Analysis and Optimization* (p. 4052).

27. Broder, M., Mahr, E., Barkmeyer, D., Burgess, E., Alvarado, W., Toas, S., & Hogan, G. (2009). Review of three small-satellite cost models. In *AIAA SPACE 2009 conference & exposition* (p. 6689).

28. Stahl, H. P., Henrichs, T. M., Luedtke, A., & West, M. (2013). Update to single-variable parametric cost models for space telescopes. *Optical Engineering*, *52*(9).

29. Arora, J. S. (2004). *Introduction to optimum design*. Elsevier.

30. Sobieszczanski-Sobieski, J., & Haftka, R. T. (1997). Multidisciplinary aerospace design optimization: survey of recent developments. *Structural optimization*, *14*(1), 1-23.

31. Olds, J. (1992, September). The suitability of selected multidisciplinary design and optimization techniques to conceptual aerospace vehicle design. In *4th Symposium on Multidisciplinary Analysis and Optimization* (p. 4791).

32. Darwin, C., & Bynum, W. F. (2009). *The origin of species by means of natural selection: or, the preservation of favored races in the struggle for life* (p. 458). New York: AL Burt.

33. Grignon, P. M., & Fadel, G. M. (2004). A GA based configuration design optimization method. *J. Mech. Des.*, *126*(1), 6-15.

34. H. I. Ozdemir, Constellation Design of Geosynchronous Navigation Satellites which Maximizes Availability and Accuracy over a Specified Region of the Earth, Wright-Patterson AFB, OH: School of Engineering, Air Force Institute of Technology (AU), March 2008.

35. Irvine, J. M. (1997, November). National imagery interpretability rating scales (NIIRS): overview and methodology. In *Airborne Reconnaissance XXI* (Vol. 3128, pp. 93-103). International Society for Optics and Photonics.

36. “Characterization of satellite remote sensing systems.” Satellite Imaging Corporation, [Online]. Available: http://www.satimagingcorp.com/services/resources/characterization-of-satellite-remote-sensing-systems/ [Accessed 13 November 2016].

37. AGI, “Walker (Satellites)”, [Online]. Available: https://help.agi.com/stk/11.0.1/Subsystems/connectCmds/Content/cmd_WalkerSatellites.htm#desc [Accessed 21 October 2020].

38. GSP, “BlackSky Pathfinder1, 2”, [Online]. Available: https://space.skyrocket.de/doc_sdat/blacksky-pathfinder.htm [Accessed 11 November 2020].

39. GSP, “SkySat 3 to 21”, [Online]. Available: https://space.skyrocket.de/doc_sdat/skysat-3.htm [Accessed 11 November 2020].

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 an 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)* 16-12-2020	**2. REPORT TYPE** Master's Thesis		**3. DATES COVERED** *(From – To)* Sep 2015 – Dec 2020
TITLE AND SUBTITLE Electro-Optic Satellite Constellation Design Using Multi-Objective Genetic Algorithm		**5a. CONTRACT NUMBER**	
		5b. GRANT NUMBER	
		5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Yasin Tamer, Captain, TURAF		**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/ENY) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865			**8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT-ENY-MS-20-D-071
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Intentionally left blank			**10. SPONSOR/MONITOR'S ACRONYM(S)** **AFRL/RHIQ (example)**
			11. SPONSOR/MONITOR'S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **DISTRUBTION 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

Satellite constellation design is a complex, highly constrained, and multidisciplinary problem. Unless optimization tools are used, tradeoffs must be conducted at the subsystem level resulting in feasible, but not necessarily optimal, system designs. As satellite technology advances, new methods to optimize the system objectives are developed. This study is based on the development of a representative regional remote sensing constellation design. This thesis analyses the design process of an electro-optic satellite constellation with regional coverage considerations using system-level optimization tools. A multi objective genetic algorithm method is used to optimize the constellation design by utilizing MATLAB and STK integration. Cost, spatial resolution, and coverage are computed as objective functions. A single variable Space Telescope Cost Model is used to determine the system cost. The search parameters of the optimization method are the 6 classical orbital elements, Walker constellation parameters such as number of planes and number of satellites per plane, and the sensor diameter length as the driving variable for the cost model. The results from this model will provide a trade-space for the baseline satellite design based on the sensor's diameter length and cost, versus mission requirements. Resulting tradeoffs allow decision makers to have a broad perspective of constellation usage for remote sensing missions for their preferences.

15. SUBJECT TERMS
Constellation Optimization, Remote Sensing, Multi-Objective Genetic Algorithm

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Dr. Andrew Keys, AFIT/ENY
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	U	UU	92	(937) 255-6565, ext 4747 (Andrew.Keys@afit.edu)

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