2-1-2012

Analysis of resource control in nondeterministic mobile ad hoc network systems : an unmanned aerial vehicle example

Alex Fleshman

Alex J. Fleshman

Candidate

Electrical engineering

Department

This thesis is approved, and it is acceptable in quality
and form for publication:

Approved by the Thesis Committee:

Chaouki T. Abdallah, Ph.D , Chairperson

Accepted:

Dean, Graduate School

Date

ANALYSIS OF RESOURCE CONTROL IN NONDETERMINISTIC MOBILE AD HOC NETWORK SYSTEMS; AN UNMANNED AERIAL VEHICLE EXAMPLE

BY

ALEX JAMES FLESHMAN

THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

Electrical Engineering

The University of New Mexico

Albuquerque, New Mexico

December, 2011

DEDICATION

I dedicate this thesis to my family and friends for making my life enjoyable and exciting day after day.

ACKNOWLEDGMENTS

First off, I would like to express my sincere gratitude to Dr. Chaouki Abdallah who has guided throughout this trying process during a particularly interesting time in my life. He also gave me the tools and a great deal of academic freedom to investigate a topic that is fascinating to me.

Secondly, I would like to thank my family. There is no way I could have reached this level without my mother's unwavering support, my father's guidance, my brother's example for annihilating challenges and my sister's examples for passion and sense of humor. You have all built and continue to improve upon the foundation that empowers me daily.

Thirdly, thanks to my beautiful wife Stephanie. She makes me a better person every day and each morning that I wake up next to her is the luckiest day of my life. Without her inspiration, friendship and companionship, this thesis would not have been possible.

Lastly, thanks to my baby Hunter or Hailey. Your mother would not let me stop working on this paper because she wanted me to be done before you were born. I cannot wait for the challenges, fun and love that you will bring into my life.

ANALYSIS OF RESOURCE CONTROL IN NONDETERMINISTIC MOBILE AD HOC NETWORK SYSTEMS; AN UNMANNED AERIAL VEHICLE EXAMPLE

BY

ALEX JAMES FLESHMAN

THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

Electrical Engineering

The University of New Mexico

Albuquerque, New Mexico

December, 2011

ANALYSIS OF RESOURCE CONTROL IN NONDETERMINISTIC MOBILE AD HOC NETWORK SYSTEMS; AN UNMANNED AERIAL VEHICLE EXAMPLE

by: Alex J. Fleshman

B.S., Electrical Engineering, Embry-Riddle Aeronautical University, 2008

M.S., Electrical Engineering, University of New Mexico, 2011

ABSTRACT

This thesis utilized known information about a dynamic graph in which resource needy nodes act as relays for control information to a supplier node in order to characterize system performance and analyze the effects of change on the system. The connectivity, or information sharing, was based on distance and since every node moved around a defined space, the connectivity of the graph changed constantly. Several different controllers and scenarios are investigated in order to extract the uniqueness in each performance curve which created a better understanding of this near nondeterministic system. One such application for this dynamic system is the automation of Unmanned Aerial Vehicles (UAVs). This paper utilizes the UAV example in order to bring life, and motivate this research. Note that there are many other applications and problems with similar voids in understanding that this approach could be applied.

The United States Department of Defense is increasingly utilizing Unmanned Aerial Vehicles (UAVs) to support current operations. As of August 2010, there were 207

Intelligence, Surveillance, and Reconnaissance (ISR) sorties flown per day to provide essential battlespace situational awareness for Operation Enduring Freedom and Operation Iraqi Freedom [1]. This paper proposes an implementation of an autonomous UAV network that assumes cutting edge technologies can be combined to provide "infinite" ISR over a given area. The particular dynamics of this problem are characterized using systems techniques while changes to the performance factors on the system are found using information about the root system.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

I. Introduction

1.1 Problem Statement

The objective of this thesis was to determine the correlation between the connectivity and resource requirements of a dynamic, distance dependent, array of needy nodes and a supplier controller's performance in order to understand implications of change on the system.

1.2 Research Objectives

This research explored the effects of a resource controller's access to information on a nondeterministic system of needy nodes and investigated several different control methods in an effort to classify the performance of the controller algorithm. Specifically, the goals of this research are:

- Compare and contrast the performance of different resource controllers on the dynamic system of needy nodes
- Investigate the impact of available information of the system on the performance of each of the different resource controllers
- Explore the impact of eliminating needy nodes, which act as relays, on the performance of each different resource controller
- Attempt at a mathematical description of different resource controllers that defines stability conditions

1.3 Thesis Overview

Although the motivation for this research is United States ISR applications, it can be extrapolated and generalized to solve many problems. This thesis will reveal useful information in regards to controlling and understanding nondeterministic systems. This paper will show that if some boundary conditions are place upon a dynamic system, the controller may not need to know everything in order to be consistently successful. This thesis will also reinforce the concept that the more information a controller has on a system the better the controller can operate. It will also show the fine balance between connectivity, or “information” given to a supplier, and resource requirements from the users that supply the connectivity.

Nondeterministic systems greatly increase the computational complexity when searching for optimal control methods. Nondeterminism means that a state or event is not based on previous states. It does not follow the “cause and effect” rule. Therefore, a controller on a system that is nonderterministic, to be optimal, must parallel process and evaluate the system for every possible future state until an end state is found [13]. In the case of UAVs, the end state is nonexistent as the US military calls for continuous operations. This eludes to no end state and to optimally control a system of these UAVs an infinite amount of parallel processing would have to be done. This thesis eased the amount of nondeterminism by establishing certain operating rules and by characterizing the system based upon a few factors so that changes to controller attributes were able to be anticipated based on changes to the system.

Again, although this problem can be extrapolated to model many different problems, the United States ISR operations were the focus of this thesis. Irregular warfare has dictated a heavy focus on ISR in strategic doctrine because the enemies (terrorists) are disparate and in hiding within the mountainous terrains in the high desert. Even before the current war on terrorism, ISR is described in high regard. "Maintaining data on the opponent's air, space, surface, and information threats to friendly forces is the critical foundation to identifying targets and ultimately mission success [17]." UAVs have largely fulfilled the role of collecting, and dispersing data for current operations in Southwest Asia because the area is vast and has an uncontested aerial environment.

UAVs come with many perks compared to their manned counterparts. In the same platform, a UAV can hold much more equipment because there is no need for the pilot or life-support gear. Also, structurally, UAVs can be built to withstand many more G's (gravitational forces) than a pilot could ever survive allowing for more maneuverability during tactical engagements. Furthermore, these platforms are designed to have an extremely long loiter time (time in flight) and the pilots can support these marathon surveillance runs because the drivers simply switch out as they are on the ground sitting in a console. Additionally, the operator's morale remains high because they are able to conduct their mission operations from home station and not at a deployed location away from their families. Finally, according to the UAV community in a semi-humorous, but realistic mantra; it does not matter what arsenal the platform is designed to carry, in a UAV, the operator always has one more missile. In conclusion, UAVs provide a greater operational capability and facilitate happier airmen.

Another benefit to utilizing UAVs is cost savings that are incurred. The system is cheaper, training the operators is cheaper, and the risk of losing the pilot is reduced to nothing. Now that all of these improvements have been made to the Air Forces ISR resources, it is time to investigate future possibilities.

UAVs are covered with a variety of informative sensors. Why not try to eliminate some of the human resources exploiting these sensor feeds with sophisticated detection software? Currently, there are at least seven people watching each UAVs collection data; even if there is nothing of interested being sensed. It would appear prudent to automate the observations for search missions over large areas. This thesis assumes that UAVs have the capability to disperse over an area and identify if they see something "interesting" and communicate with each other for support if required. This communication network quickly becomes complex given that each UAV can only communicate within a certain distance and that the UAVs are moving in a search pattern.

With the amount of money that the military spends on ISR capabilities, it is not too obscure to think that the government is not open to different solutions. This research paper discusses the connectivity and control of the notional system of UAV sensors depicted on the next page.

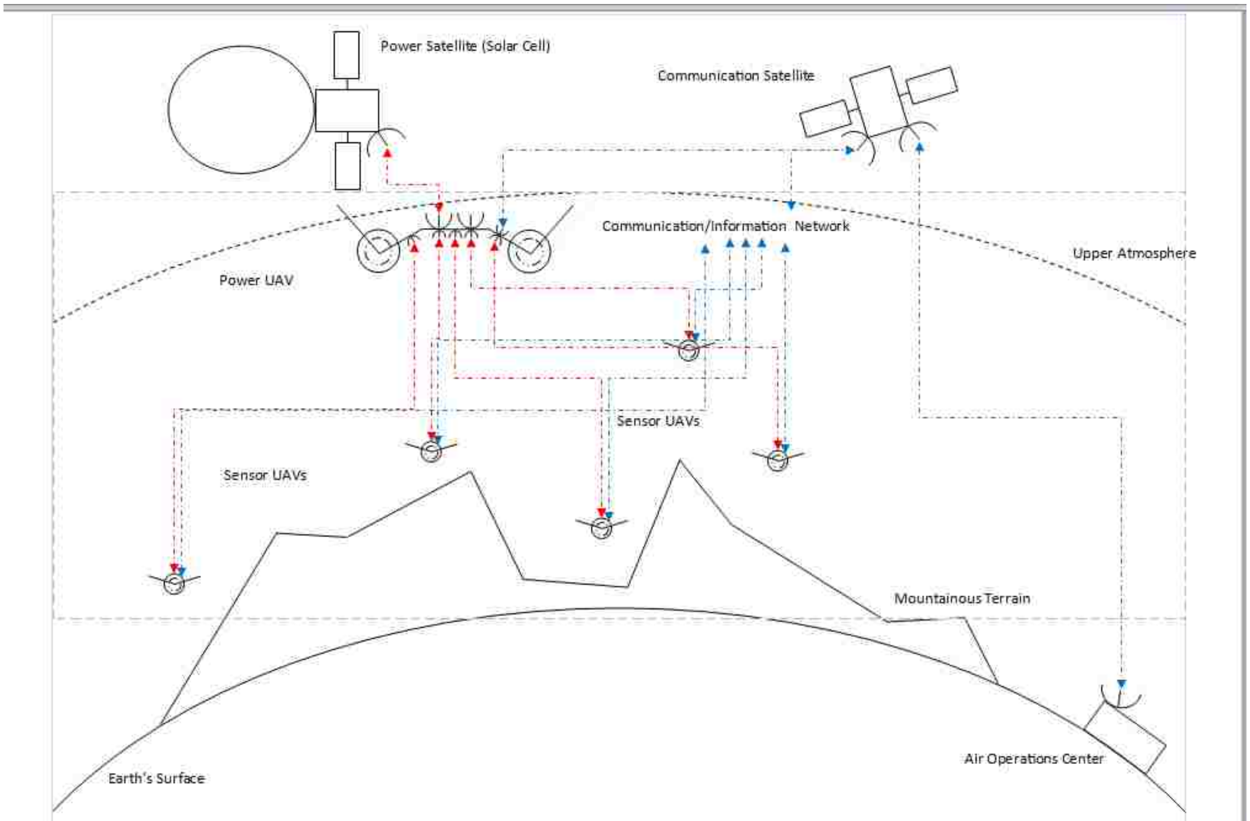

Figure 1.1 OVI Diagram of Possible Future UAV Deployment

The figure above shows the synergy of two different types of resources; power and communications. The red lined represent the power transfer. At the upper left corner, there is main source of power, the Power Satellite, which supplies power to the Power UAV. The Power UAV flies around autonomously and provides power to the Sensor UAVs. It is the controller that directs the Power UAV's flight path that this thesis investigated. On the upper right of the figure is the Communications Satellite which provides a median to pass information between the Air Operations Center (AOC) and the Communication/Information Network fed by the Sensor UAVs. This thesis assumed that the Sensor UAVs could communicate amongst each other and that the Power UAV could communicate and provide power resources to each UAV.

II. Background

2.1 Motivation

2.1.1 UAV Combat Integration

UAVs provide a unique capability in today's combat environment; however, without integration into the "bigger picture" they are useless. This is why the Air Force strives to integrate all of its new weapon systems together. Information sharing is vital to operational situational awareness in combat. UAVs currently have several ties to other systems because of their purpose to support other operations.

UAVs can currently communicate with the Air Operations Center (AOC), radios carried by Joint Terminal Attack Controllers (JTAC), and the Distributed Common Ground System (DCGS).

An AOC is the control center for the Air Force that manages all of the air assets under its respective purview. There are many stations within the AOC that supply information to the AOC Commander so that he/she can make command decisions. One such piece is the feeds that are supplied by on-station UAVs. This real-time intelligence of the battlefield is highly desired by AOC Commanders because it provides one of the only sources of ground truth data. Other information systems rely on human interaction/updates to information streaming in which injects a human error component. For example, if two radars are overlapped and relaying their information on a common operating picture (COP), what happens if the radars are not perfect? If there is a radar overlap in the region there is potential for the COP to show two tracks flying close together when in reality there is only one. This radar de-cluttering function is done by a human in the loop that may make mistakes resulting in the commander making ill-informed decisions. On the other hand, if a commander is looking at a potential target/rescue coming from a UAV providing Full Motion Video (FMV), he knows that the data is accurate and can provide confident leadership decisions.

JTACs are air traffic controller that are typically deployed with ground units that have the ability to call in air support requests from a forward operating locations. These are the men that call in air strikes if, for instance, a group of enemy tanks starts to close in on friendly positions. In the current war on terrorism, they are also travel with Special Forces teams that track high value targets. The radios that JTACs carry are equipped to receive live feeds from the UAVs. This is important because they have the ability to control (task) a UAV to look over an enemy force, or watch a high value target and provide them input so that they can either call for the right air asset (to strike the tanks) or enter the right building (to acquire a high value target).

The DCGS is a center that exploits a multitude of intelligence sources one being UAVs. The DCGS may be tasked to look for Improvised Explosive Devices (IEDs) along a well-traveled route. In this case, UAVs would fly over the route on a regular basis and DCGS personnel would analyze the feeds to see if there was suspicious activity happening roadside and even compare road footage with the previous days feed to see if there are inconsistencies that could equate to IEDs being buried.

2.1.2 Search and Rescue

UAVs are not only crucial to support combat missions, but also search and rescue. For every aircraft, whether it be an airplane or helicopter, that goes down unintentionally behind enemy lines, the Air Force has resourced an entire wing (3rd largest unit in the Air Force organizational structure [15]) to be trained and equipped to ensure the safe return of the downed crew. This mission is designed around the foundations of military heritage and the Air Force Airman's Creed that explicitly states "I will never leave and Airman behind." It gives warfighters that are going into harm's way the confidence that if something bad does happen, someone out there is doing everything they can to rescue them. This instills hope and confidence that is vital to the Air Force's effectiveness. To highlight the operational tempo and necessity of these special warriors, the 64th Expeditionary Rescue Squadron operating in Iraq made back to back CH-47 Chinook helicopter crew (5-men each) saves within 4 days of each other. The team was operating out of HH-60 Pave Hawk helicopters, but had much needed support [5]. Information is critical in a wartime environment. Utilizing High Demand/Low Density (HD/LD) assets, such as some of the Combat Search and Rescue (CSAR) equipment/personnel, it becomes extremely important to use only what is needed for the mission. ISR is the answer. Assets are more efficiently managed when there is ISR available to leadership. The current problem is the manpower and lack of assets involved with providing the ISR requested by leadership. Resolution of this problem seems to be a priority to Air Force leadership.

2.1.3 Air Force Trends

The common idiom of "put your money where your mouth is" is another way of saying that if you believe in something, you should support it, and even more literally, support it financially. Therefore this thesis uses the Air Force annual budget report from the past several years to provide a trend of UAV/ISR importance to the Air Force mission. In the FY03 AF Budget Report, written in Feb 2002, it is clear that the then newly spawned war on terrorism in the middle east was driving UAV requirements when it states that the Global Hawk is still in research and development, but has already been deployed. Early deployment is typical for capabilities that satisfy a much needed combat requirement. The trend continues in the FY08 report when it annotates a growth in the C4ISR arena, "due almost exclusively to increases in the UAS (Unmanned Arial Systems…another name for UAVs) inventory, reflects the importance of persistent surveillance to all the QDR (Quadrennial Defense Review) focus areas and it will continue to grow…" It goes on to further state, "The ability of the future force to establish an 'unblinking eye' over the battlespace through persistent surveillance will be key to conducting effective joint operations," and "UASs and space systems are essential programs in the Global Space & C4ISR (Command, Control, Communication, Computers ISR) portfolio, providing the persistent coverage that the commanders in the field increasingly demand." Finally, jumping to the most current AF Budget Overview (FY12), the Air Force not only furthered the acquisition of UAVs (now called RPAs), but is planning to make the training path for operators and support staff that was developed in 2010 more robust. This includes military construction (MILCON) projects to create the necessary facilities, revolutionary training program, and a personnel retention plan [16].

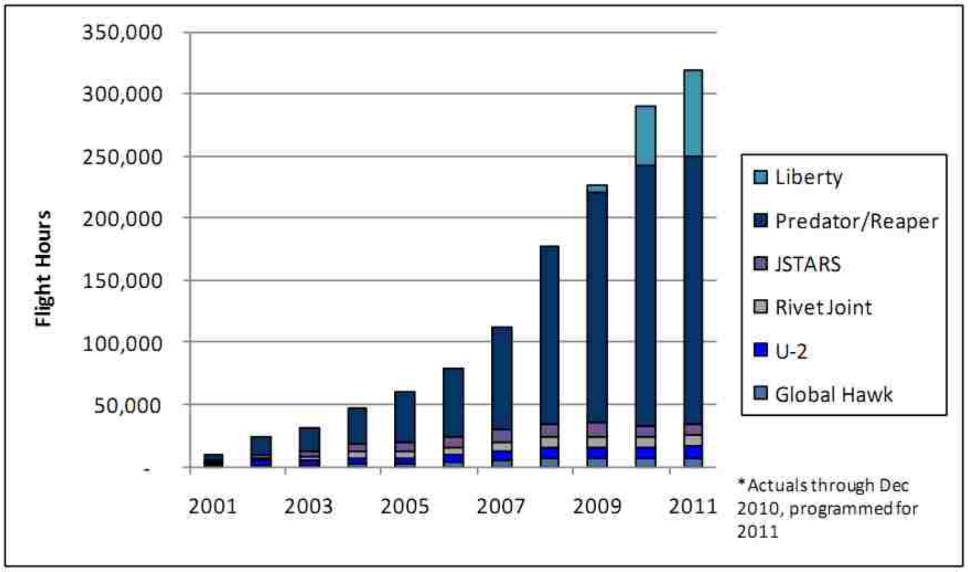

Figure 2.1 ISR Operational Growth in Flight Hours [16]

The graph above shows the increase in operational flight hours of given AF assets and highlights the increasing use of Predator/Reapers (UAVs) after the commencement of Global War on Terrorism in 2001.

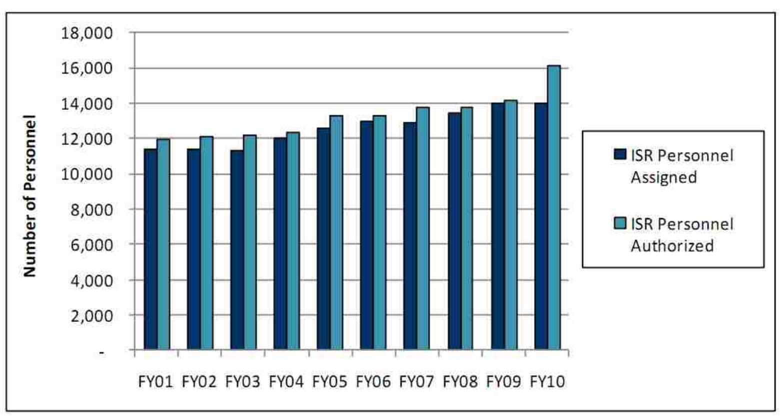

Figure 2.2 Air Force ISR Personnel Authorized and Assigned [16]

It is also important to note the jump in authorized ISR personnel from FY09 to FY10. More than 2000 additional ISR bodies were authorized in a time of force reduction. The FY12 Budget Overview then describes requirement for even more personnel to, "sustain unmatched intelligence analysis/dissemination," referencing the support needs of the Distributed Common Ground Station (DCGS), which is the center that exploits collected intelligence. In FY12, the Air Force is proposing purchasing 51 additional UAVs (48 MQ-9A Reapers and 3 RQ-4B Global Hawks) to, "locate the enemy, avert enemy plans, deliver weapons on target and assess the impact of their efforts. This persistent surveillance provides critical support to military operations and national security objectives [16]."

2.1.4 Manpower Study

This important capability comes at a great cost to the Air Force. The table below shows the number of personnel required to maintain the current (as of August 2010) coverage in support of Operation Iraqi Freedom.

Function	**Personnel Per Sortie**
Sensor Operator/Pilot	8
Exploitation	28
Overhead (support staff)	8
Sorties per Day	74
Personnel per Day	3256

Table 2.1 UAV Manpower

Considering that there are about 507,900 people in the USAF, the UAV ISR mission makes up .6% of all personnel [7]. Not only does this capability take 3256 people to execute every day, it takes 9 months for many of these warriors to receive training. It is important to note the number of people it takes to manage a UAV feed. It takes one sensor operator, one pilot, and at least seven people to exploit the intelligence that is being collected. Often times the intelligence collected is not important to the warfighter and the team is essentially waiting for a support call or something interesting to happen. If these sensors were automated to fly around and notify the proper authorities when it spotted something interesting, the UAV support team could be optimized and either cover more area, or do the same function with less people.

2.2 Problem/System Setup

Given the general operational depiction given in **Figure 1.1 OVI Diagram of Possible Future UAV Deployment**, and using the recently developed Tactics, Techniques, and Procedures (TTPs) of a Joint Fires Coordination Measure (JFCM) [6], the system was defined/implemented in the following manner.

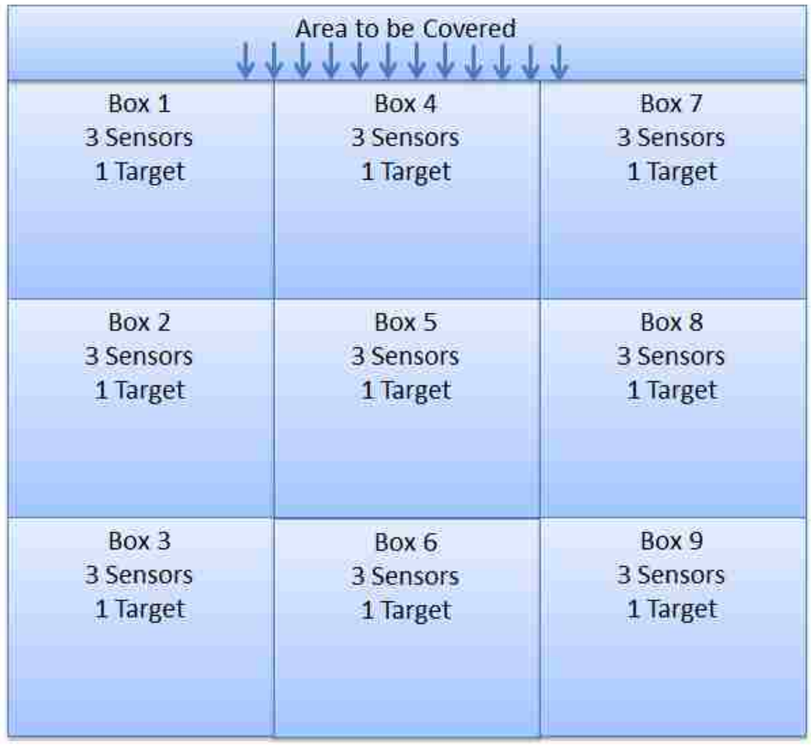

Figure 2.3 Sensor Boxes

A group of three Sensor UAVs were deployed in each of the nine JFCMs (boxes). This configuration not only eased the burden of operational command and control, but also reduced the computational burden on the system controller and enabled more solidified results because these boundaries made the system less nondeterministic. Each Sensor UAV flew in an optimal coverage pattern that consisted of a minimal spanning tree. To further optimize coverage, each of the Sensor UAVs in their respective boxes were spaced equidistant from each other as shown below [9].

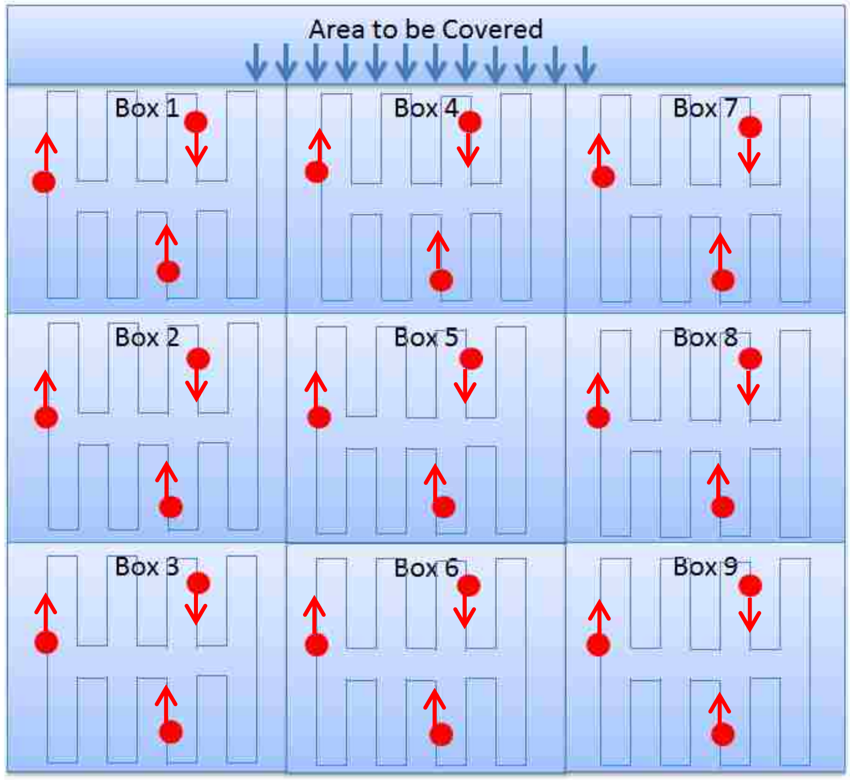

Figure 2.4 Sensor Boxes w/Equally Distributed Sensor UAVs

This thesis investigated the complex communications network created by the sensors and several control methods to keep the sensors powered. The Sensor UAVs and the Power UAV had a defined communication distance. Two variances in the simulations were executed. The first, Static Flight, acted as a control for the second and consisted of the sensors flying in their flight paths continuously. This system was deterministic and an optimum solution could theoretically be found. During this set of simulations, several complex systems attributes were calculated based upon an average taken along one full sweep of the Power UAV. The second instance of the simulation, or the Dynamic Flight, included nine semi-randomly placed targets in the operational area. When a Sensor UAV passed over a target, it communicated with the other two sensors in the box and called for support. All three Sensor UAVs loitered over the target together for five time steps to simulate the prosecution of the target. Once completed, the target disappeared (simulating that the target was either destroyed, recovered, or neglected) and the Sensor UAVs within that box redistributed themselves equally around the flight path and continue searching for more targets.

2.3 Mathematical Concepts

2.3.1 Graph Theory

A graph is a way to represent a set of vertices and their interrelationships. Graphs are used to understand and mathematically quantify complex systems. The easiest way to understand a graph is to use an example and describe it.

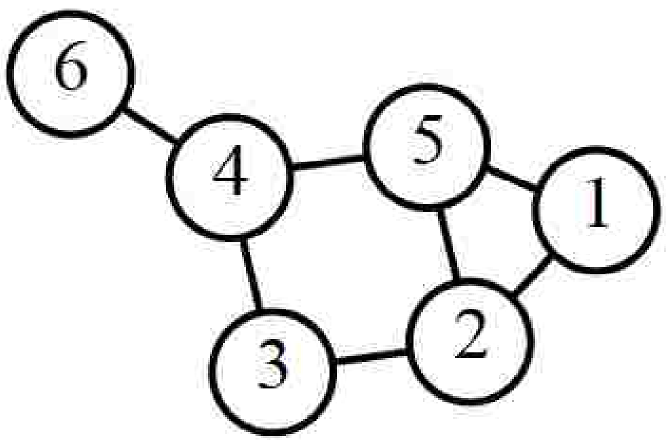

Figure 2.5 Connected Graph

The figure above represents a graph that has six vertices which are labeled one through six. A relationship between each of the vertices is defined by an edge, or the line that connects two vertices. The graph above is an undirected graph because the edges do not have a direction associated with them so it is assumed that the relationship between two connected vertices is bilateral. A directed graph would have arrow heads between the vertices annotating a one-directional relationship. Every graph used analyzed in this thesis will be undirected. The graph is also connected, meaning that every vertex is accessible by every other vertex via an edge or a series of edges. The converse is called an unconnected graph. The number of connections each vertex has is known as the valency or degree of that vertex. In the figure above, the degree of vertex four is three because it is connected to three, five and six. A complete graph is when each vertex is connected to every other vertex via an edge [12].

Graphs are used in order to mathematically quantify and analyze complex systems. For example, the internet can be represented by a huge graph of billions of nodes (computers) that are connected by the internet (wires and routers). From the graph of the internet, one could see the most critical nodes (could be a router that connects a great percentage of the computers to the internet) and provide a backup system to ensure continuity in the event of system failure so that the minimal amount of users are affected. Similarly, the power grid is a complex network that could be analyzed via graph theory to understand and allocate electric resources more efficiently. If additional users are added and connected to the network, then more power must be supplied.

2.3.1.1 Degree

The degree of a vertex is the number of edges attached to it [12].

2.3.1.2 Valency Matrix

The valency matrix of a graph is defined as a diagonal matrix that defines the degree of each vertex as shown below.

- Valency Matrix = Diag(d_1, d_2, d_3...d_n)
- Where d_1 is the degree of the first vertex, d_2 is the degree of the second vertex, etc.

The valency matrix can identify the most important (in a degree centrality sense) node in the graph as it reveals the vertex with the highest degree [12].

2.3.1.3 Mean Degree

The mean degree of a graph is the average degree over each of the vertices. The mean degree can be found using the following logic [12].

- *c = the mean degree*
- *n = the number of vertices*
- *k_i = the degree of the i^{th} vertex*

$$c = \frac{1}{n}\sum_{i=1}^{n} k_i$$

2.3.1.4 Density

The density of a graph is the number of edges present divided by the number of possible edges (excluding multiple edges and self-edges). The density of a graph can be found using the following logic. [12]

- *ρ = the density*
- *c = the mean degree*
- *n = the number of vertices*

$$\rho = \frac{c}{n-1}$$

2.3.2 Simulation Variables/Equations

Since the dynamic system under investigation is functionally nondeterministic, this thesis investigated a fair way to classify controllers that decide the Power UAV flight path as there are many solutions that could work (no loss of aircraft). The controller worked on a network that is not fully connected so it did not have all the information required to make "perfectly smart" decisions. This means that a controller was better if it could successfully manage the system while knowing the least. This is why every controller was characterized by the connectivity coefficient.

2.3.2.1 Connectivity Coefficient

The connectivity coefficient is the potential amount of knowledge the system can know divided by the potential amount of knowledge the system contains. In the case of this dynamic UAV system, the connectivity coefficient is the greatest area covered by all the sensors if they were minimally connected divided by the total area of the operational area. This idea is best represented by a picture.

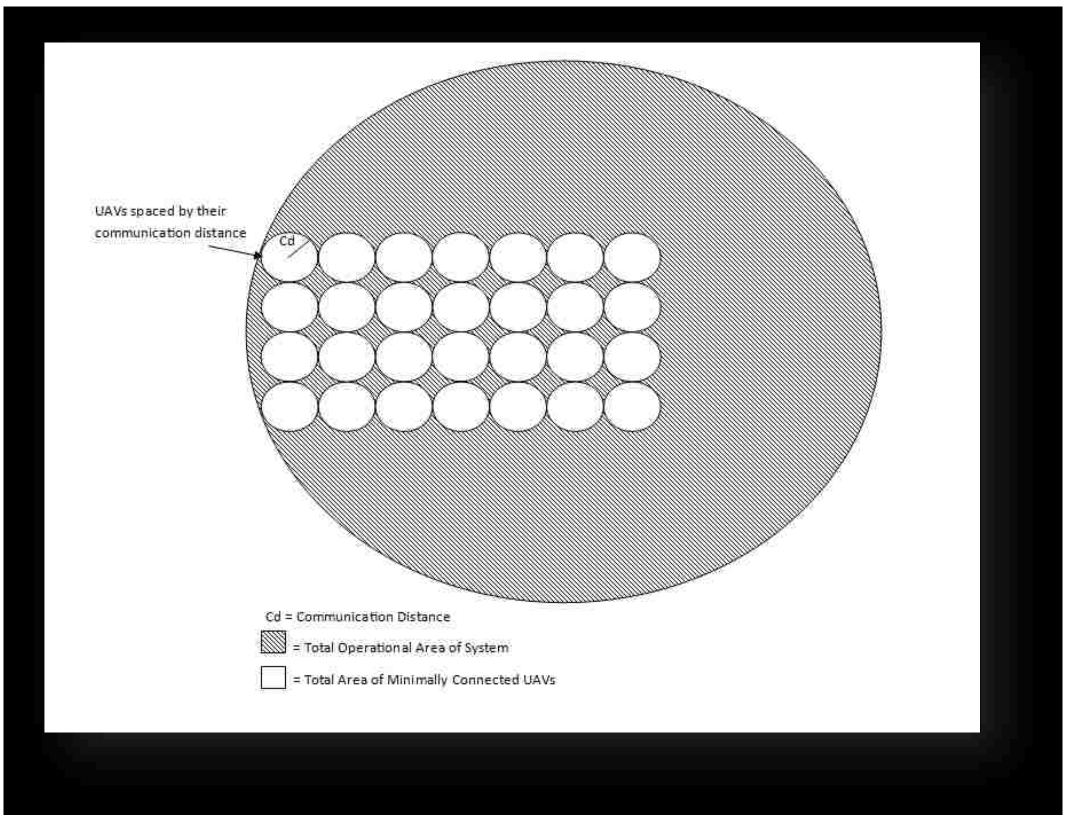

Figure 2.6 Connectivity Coefficient (Cc)

The figure above shows 28 UAVs that are communication nodes when it comes to information within the system. The connectivity coefficient goes down as the communication distance is decreased. The lower the connectivity coefficient, the less information on the system is available, therefore, the controller that can complete the mission with the lowest connectivity coefficient, is best. Using this metric for classifying controllers allows for operational flexibility when employing the UAVs because, ideally, UAV movement will be completely random within their JFCMs and the controller needs to know enough to provide necessary resources. Given **Figure 2.6 Connectivity Coefficient (Cc)**, the connectivity coefficient can be calculated as follows:

- *Cc = Connectivity Coefficient*
- N_s *= Number of Sensors*
- C_d *= Communication Distance*
- *A = Area*
- *Note: The units of the communication distance must match the units of the area*

$$Cc = \frac{N_s * C_d^2 * \pi}{A}$$

2.3.2.2 Power Coefficient

There is also a resource condition that has to be met to fully satisfy the mission requirements. During this investigation the resource, or Power Coefficient, was found and held constant throughout each respective experiment. The Power Coefficient is defined as

- *Pc = Power Coefficient*
- *PSR = Power Source Rate*
- N_s *= Number of Sensors*
- *PDR = Power Drain Rate*

$$Pc = \frac{PSR}{N_s * PDR}$$

The Power Coefficient must be greater than, or equal to one for a system to be fully sustainable. The less connected the system, the higher the Power Coefficient needs to be. If the graph is fully connected and the Power UAV can supply power to all of the Sensor UAVs, the Power Coefficient can be exactly one assuming that the Power UAV can power all Sensor UAVs simultaneously. Prior to investigating the relationship between the Connectivity Coefficient and its implications on the system, a Power Coefficient that satisfies the respective controller under scrutiny was set constant.

2.3.2.3 Communication Distance Formula

The communication distance was calculated constantly for each of the Sensor and Power UAVs throughout the simulation. The simulation assumed that the UAVs are at a high enough altitude to ensure line of sight, therefore, the communication distance was derived from free space path loss as described below [2].

- *Cd = Communication Distance*
- *Tx = Transmission Power*
- *Rx = Receiver Sensitivity*
- *Freq = Operating Frequency*

$$Cd = 10^{\frac{Tx - Rx - 32.44 - 20 * log_{10}(Freq)}{20}}$$

2.3.3 Mobile Ad-Hoc Networks

Mobile Ad-Hoc Networks (MANETs) were the next technological advancement to establishing networks after utilizing permanent infrastructures such as routers, repeaters, gateways etc. As an example, cellular phones operated with the use of permanent structures that act as routers for further communication; without the permanent antenna towers, there was no cellular phone service or network. MANETs create a network by enabling every node to act as a router in the absence of a permanent one. This solution provided extensive networks that spawn and adapt constantly as new nodes enter and exit respective networks [4].

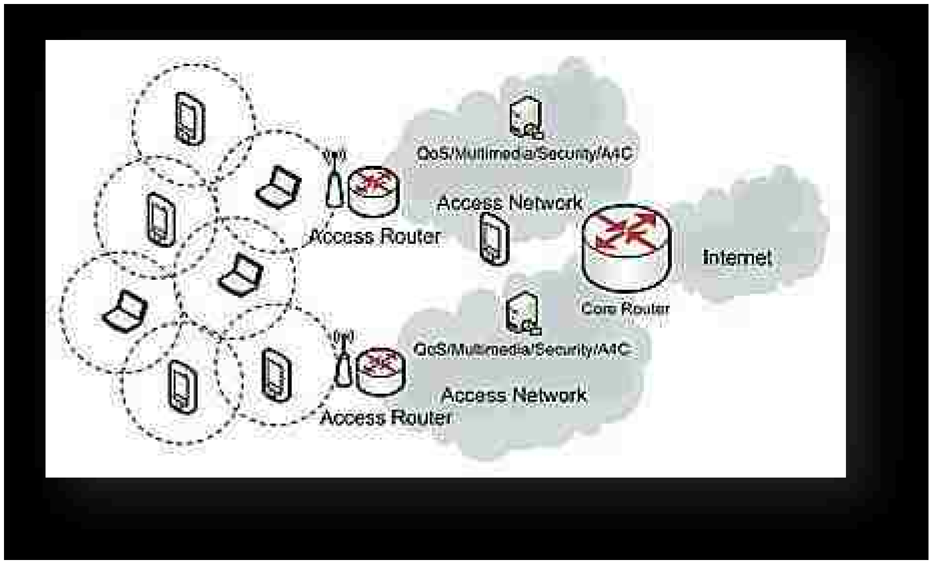

Figure 2.7 Mobile Ad Hoc Network Example [11]

As shown above, the information in this case is the internet. This figure depicts a MANET because the nodes (phones and computers) on the left hand side of the figure are acting as access points to the internet for each other so that the nodes outside of the communication distance with the permanent structures can still access the information.

III. Simulation Setup and Methodology

As discussed in section 2.2 Problem/System Setup, 27 Sensor UAVs flew in nine respective JFCMs (three Sensors per JFCM) and searched for targets. Meanwhile, the Power UAV was being implemented with different controllers that designated its refueling flight path. The Power UAV collected Sensor UAV location and power level data from other Sensor UAVs and by its own observations as the system created its own MANET. The Power UAV was controlled by two different algorithms and, when disconnected from a, or more than one, Sensor UAV(s), estimated the location and power level of the disconnected UAV(s) via two different methods.

Since there were two controllers under test and two different estimation schemes to be implemented on each controller, there were a total of four different controllers tested. Each controller/estimator pair was simulated against a scenario with zero targets and nine targets. The table on the next page outlines all simulations executed.

Controller		Simulation
Controller Algorithm	**Estimator**	**Flight**
TSP	Hold	Static
		Dynamic
	Dead Reckoning	Static
		Dynamic
DTSP	Hold	Static
		Dynamic
	Dead Reckoning	Static
		Dynamic

Table 3.1 Simulations Executed

3.1 Resource UAV Controller Algorithms

3.1.1 Traveling Salesman Problem (TSP) Controller

The TSP was one of two Power UAV controllers investigated during simulation. The TSP controller calculated and executed, based on 1000 iterations, the shortest flight path between all the Sensor UAVs and traversed this path until completion. Once all of the Sensor UAVs have been supplied, the Power UAV calculated a new shortest path trajectory that met every Sensor UAV.

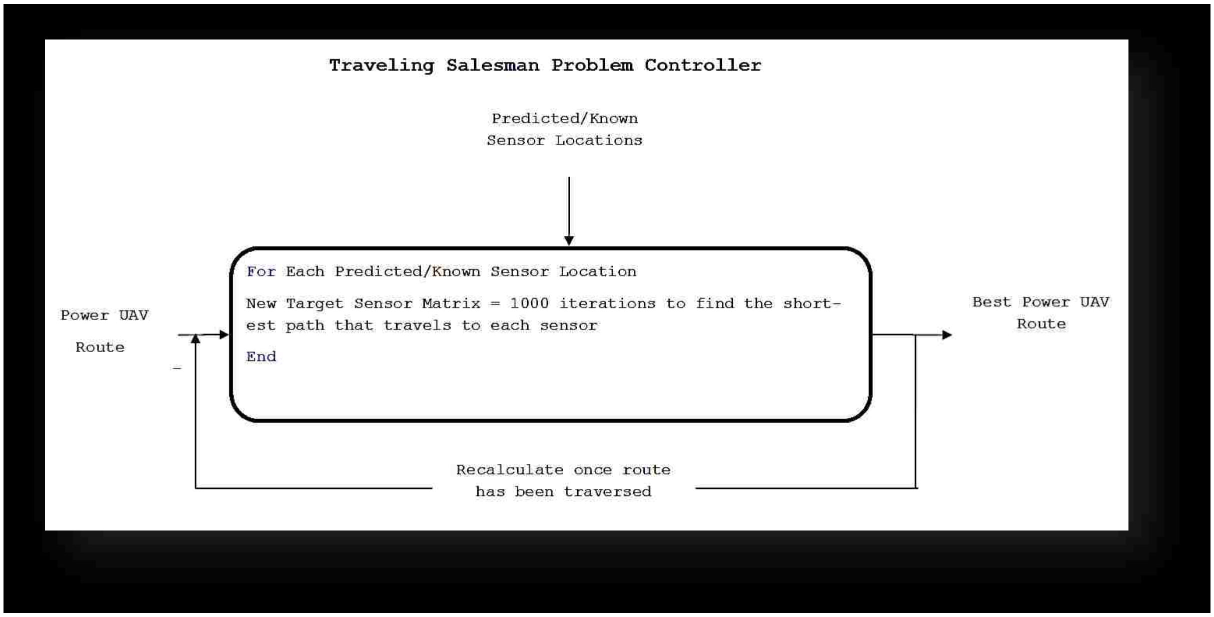

Figure 3.1 Traveling Salesmen Problem (TSP) Controller

3.1.2 Dynamic Traveling Salesman Problem (DTSP) Controller

The dynamic TSP control algorithm starts by mapping out the shortest path between all Sensor UAVs. Once the Power UAV resupplied the first Sensor UAV, the controller recalculated the shortest path between the remaining Sensor UAVs that have not yet been powered. This process continued until all Senor UAVs were powered and then the controller repeated the algorithm.

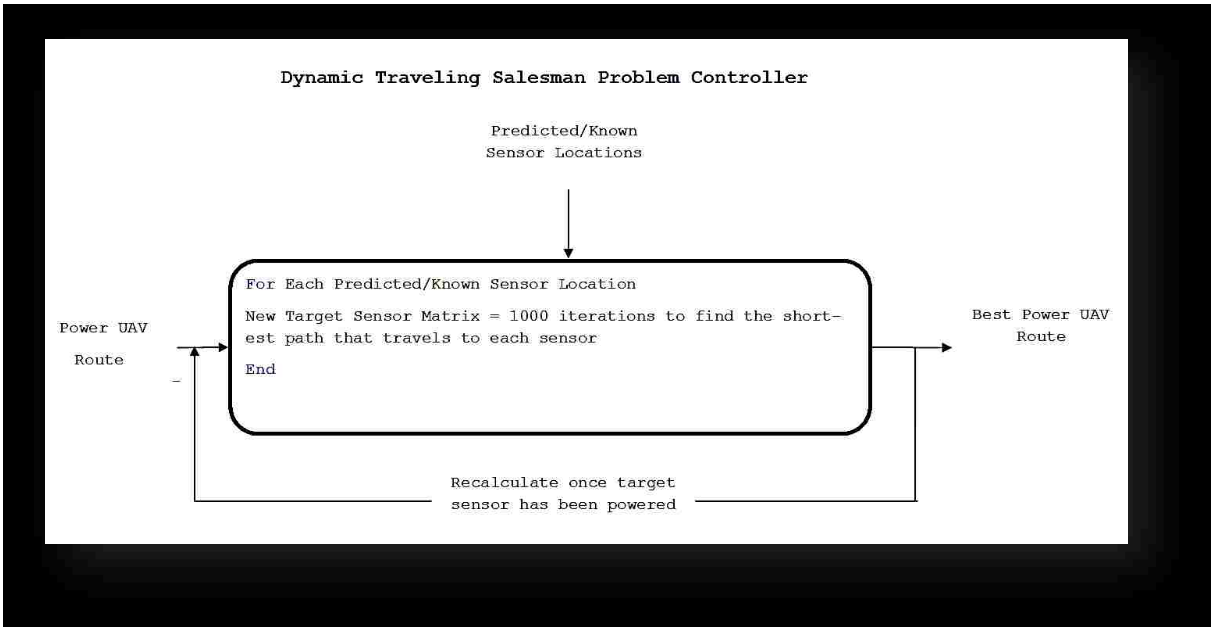

Figure 3.2 Dynamic Traveling Salesmen Problem (DTSP) Controller

3.2 Estimation

3.2.1 Background

The network of Sensor UAVs was typically not fully connected. In fact, the ability for the system to operate in a less connected system implies that the controller could function with less knowledge. The Power UAV providing resources to the Sensors needed to estimate the location and the power levels of the Sensor UAVs that were not connected so that inputs to the Power UAV controller could continue. Estimating the location of a Sensor UAV that is disconnected from the Power UAV became increasingly difficult as time passed. Sensors that are given operational agility to travel anywhere could potentially be located within a circular area with a radius governed by the equation of motion below.

- *d = distance from last known position*
- *v = velocity*

- Δt = *time from last update*

$$d = v * \Delta t$$

Using the matrix method of modeling the system as in this thesis, the UAV could travel discretely to a location defined by the equation below.

- l = *1X2 matrix location*
- n = *number of time-steps since the last update*

$$l = (2n + 1)^2$$

The equation above was a result of the Sensors moving around positions inside of a matrix one location at a time offering nine options per step. After just five time-steps the Sensor UAV could be located in any of 121 locations. This highlights the importance of connectivity and knowledge that the resource needs to have on the system to make decisions. Confining the UAVs to the JFCM put a limit on the possible locations for the UAVs.

3.2.2 Estimation Techniques

For this thesis, the power level estimator was reflective of the actual burn algorithm and therefore the Power UAV knew the power levels throughout the system. This was done to narrow the scope of this project.

3.2.2.1 Hold Estimation

Hold Estimation was one method or technique that the Power UAV controller used to make decisions. The Power UAV knew the location of all Sensor UAVs that are connected to it. During hold estimation, once the Power UAV became disconnected from a Sensor UAV, the Power UAV assumed that the Sensor UAV stopped and held its current location.

3.2.2.2 Dead Reckoning Estimation

Dead Reckoning Estimation is a method that assumed that once disconnected from any given Sensor UAV, the Power UAV estimated that the Sensor UAV flew the predetermined flight path and was not called upon to support another UAV or was re-tasked by a human in-the-loop. The Dead Reckoning Estimator reflected truth data when the simulation has no targets to be prosecuted because the Sensor UAVs did not stray from their respective flight paths.

3.3 Sensor Flight Paths

3.3.1 Static Flight Path System Rules

The Sensors are programed to follow a specific flight path that was made of a minimum spanning tree over the total area to be covered. This method ensured that the area is most efficiently covered meaning that the time unobserved over a given area is equal to every other spot in the coverage area [9].

3.3.2 Dynamic Flight Path System Rules

The dynamic flight path allowed for many uncertainties to occur within the simulations which yielded more meaningful results. It would be unrealistic to believe that the Sensor UAVs would be forced to travel a certain route without the capability of a human in-the-loop being able to take control and fly away from the fixed path, or a Sensor UAV making a decision to further investigate something that its software deems interesting. The figure on the next page depicts the dynamic flight path system rules.

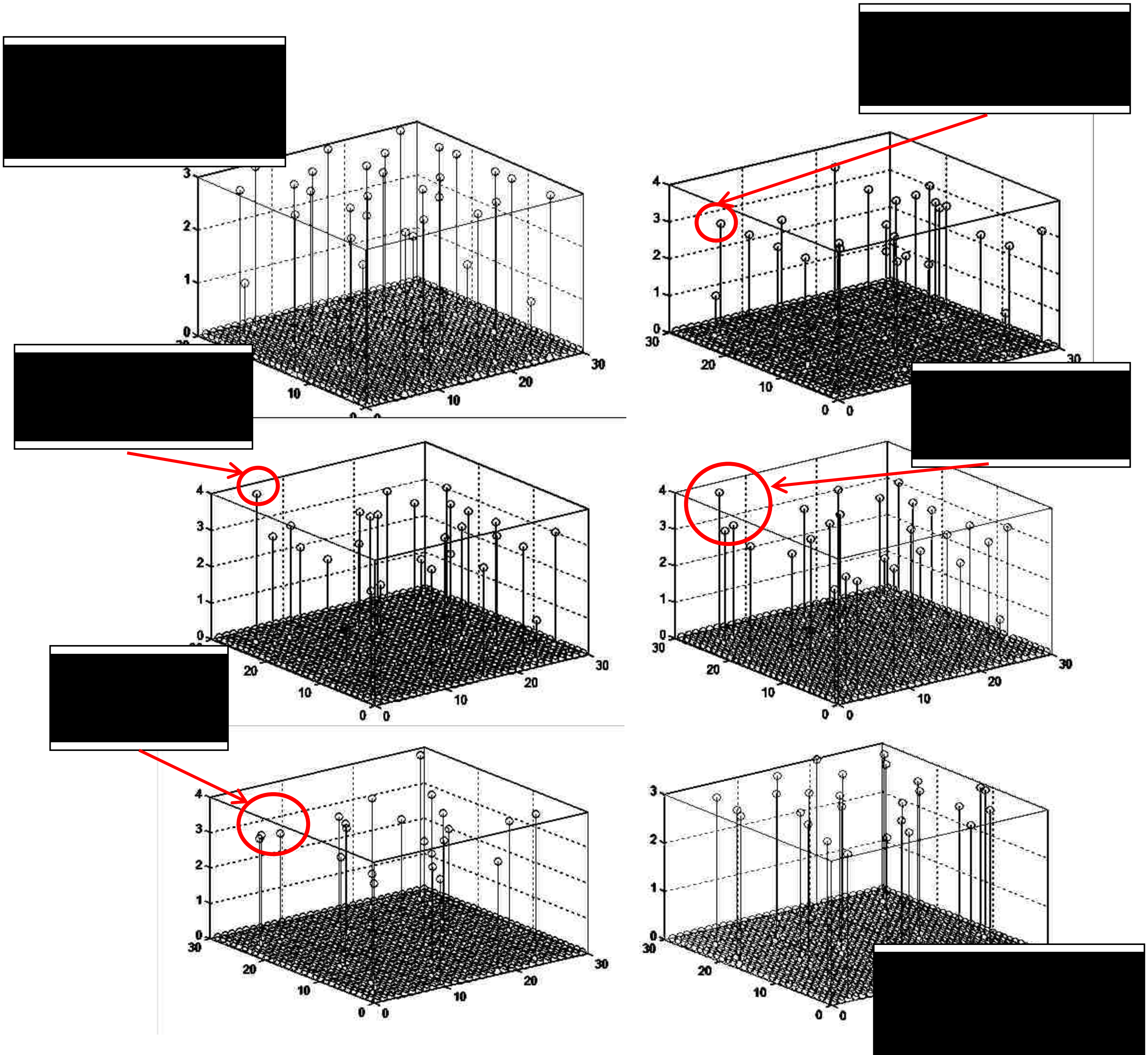

Figure 3.3 Dynamic Flight Path Depiction

As shown above, during a dynamic flight nine targets are injected semi-randomly (one target per JFCM) within the total observed area. The Sensor UAVs flew the preprogramed minimum spanning tree flight path until one observes a target. The Sensor that observed a target communicated to the other Sensor UAVs within the same JFCM.

The other Sensors converged on the target, stayed at the location for three time steps, simulating prosecution, and then redistributed themselves equally along the standard flight path and continue operations.

3.4 Simulation Rules

3.4.1 Resource Allocation

The Power UAV could only power Sensor UAVs if there was direct connectivity between the two systems. Direct connectivity is defined as the Power UAV could communicate with the Sensor without the use of another Sensor being a relay.

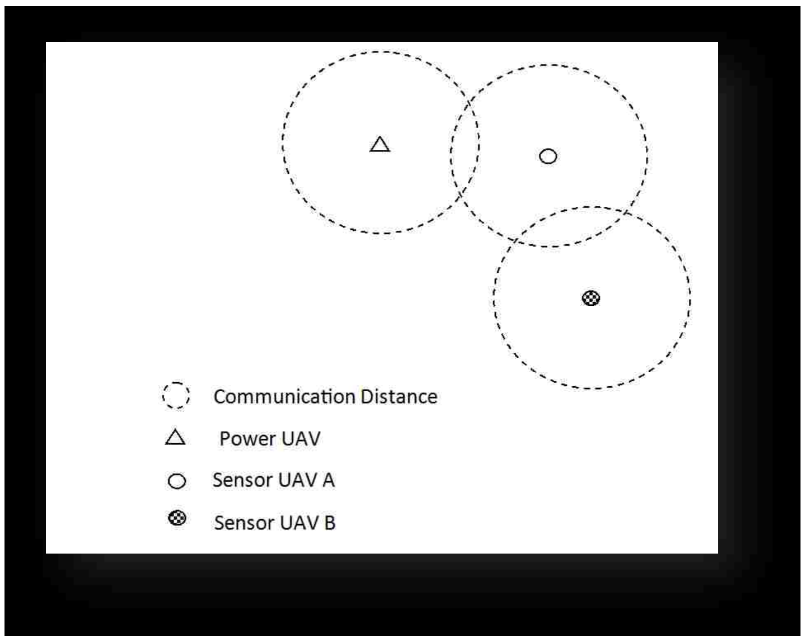

Figure 3.4 Connectivity Depiction

In the MANET above, the Power UAV is directly connected to Sensor UAV A, and therefore, can supply power to the platform. The Power UAV is not, however, directly connected to Sensor UAV B. It is connected via Sensor UAV A so the Power UAV receives updates from Sensor B, but cannot supply it power. In the case above, the Power UAV will supply its max Power Supply Rate to Sensor UAV A. The following resource allocation algorithm was used if there are more than one Sensor UAV directly connected with the Power UAV.

- *P_{2Si} = Power rate allocated to sensor i*
- *S_{Pni} = Sensor i's power requirement*
- *N = Number of sensors with direct connectivity to the Power UAV*
- *PSR = Power UAV supply rate*

$$P_{2Si} = \frac{S_{Pni}}{\sum_{i=1}^{N} S_{Pni}} * PSR$$

This algorithm allocates resources with the goal of achieving max power amongst all directly connected sensors at the same time and operates under the assumption that the Sensor UAVs may receive any Power Supply Rate.

3.5 Nodes Missing

The military exercises redundancy in all of its systems because of the possible ramifications of technical failure. The military also stresses the importance of operational agility; therefore, it is important to investigate the effects on system performance in the event of a loss or reassignment of an aircraft. This also ensures that the system is being investigated as a true MANET. During the simulation, the connectivity coefficient was altered by increasing and decreasing the communication distance and also by removing nodes from the system. The table on the following page shows which nodes were removed from the system to analyze the effects on the four different controllers.

	Nodes Missing			
	3	3 Critical	6	8
Sensor Number	3	13	3	3
	15	14	7	7
	25	15	11	11
			15	13
			21	14
			25	15
				21
				25

Table 3.2 Nodes Removed During Simulation

3.6 Data Gathering

The systems and controllers were described by several characteristics and two performance indicators during each simulation execution. For each separate controller, during each separate instance of the simulation, the following was collected:

- Minimum Sensor Power
- Minimum Sensor Average Power
- Average Mean Degree of all the Nodes
- Average Density of all the Nodes
- Average Valency Matrix
- Connectivity Coefficient
- Power Coefficient

The Minimum Sensor Power is the lowest value of sensor power that any of all the Sensor UAV has during the duration of the simulation. If the Minimum Sensor Power is less than, or equal to zero, it means that the Sensor UAV crashed and the simulation (controller, and parameters applied) is deemed a failure.

The Minimum Sensor Average Power is the lowest average sensor power across all Sensor UAVs that occurs during the duration of the simulation. This value is used to determine the effectiveness of the controller and system parameters.

The Average Mean Degree of all the nodes is the running average degree of all the nodes during the simulation. Only the value occurring after the simulation is complete is utilized.

The Average Density of all the Nodes is the running average density of all the nodes during the simulation. Only the value occurring after the simulation is complete is utilized.

The Average Valency Matrix is the running average valency matrix during the simulation. Only the matrix occurring after the simulation is complete is utilized.

The Connectivity Coefficient is defined earlier in this section.

The Power Coefficient is defined earlier in this section.

3.7 Simulation Methodology

The first step was to find a working Power Coefficient. This was done by estimation and understanding the system. The Power Coefficient, as stated previously, needed to be greater than one for the system to feasibly work. The Power Coefficient was chosen to be 2.963 based on the knowledge of the area that the Power UAV operated in is 120 X

120 time-steps and by utilizing the information found in the first simulation depicted in **Figure 4.1 TSP Hold – 0 Nodes Missing - Minimum Average Sensor Power**.

Each simulation was executed while varying the connectivity coefficient. If the simulation is successful, all targets (if there are any present) were found, prosecuted and removed and the minimum sensor power remained above zero. The data described in Section 3.6 Data Gathering was logged. Then the minimum average sensor power was plotted against the connectivity coefficients. Next, the same simulation was executed except with different nodes removed. The connectivity coefficient was again varied and plotted against the minimum average sensor power. Finally, this sequence was repeated for each of the four controller/estimator pairs.

3.7.1 Performance Parameters

The controllers were characterized based on the Cc and Pc effects on the minimum average sensor power and the minimum sensor power within the system over all time steps. The greatest minimum average sensor power that keeps the minimum sensor power above zero (no UAV crashes) was the most power efficient solution.

3.7.2 Matrix Model Advantages

Matrices provided the foundation to modeling this system. As shown in section 2.3.1 Graph Theory, graphs utilize matrices to describe complex systems to aid in representation and more importantly calculations. The first layer of the model that was created was the space matrix. The space matrix is a matrix of defined dimensions that represents the area that the Sensor UAVs, Power UAV, and Targets will interact. The size of the matrix depends on the level of fidelity that the system is to be simulated as shown below:

- *F_a = Fidelity of the Model ($m^2/cell^2$)*
- *$A_{Scenario}$ = Area of the scenario (m^2)*
- *A_{Matrix} = Area of the matrix ($cells^2$)*

$$Fa = \frac{A_{Scenario}}{A_{Matrix}}$$

The advantage to this representation is the flexibility because depending on processing power available to run the simulations and the fidelity requirement, the model can be as fine or coarse as required by the user.

The next matrix layer was two UAV location matrices. The first one was for simulation and analysis purposes as it reflected the truth data for each Sensor UAV. This truth data can be compared to the second UAV location matrix which was the observed data (what the Power UAV knows via the created MANET) used to evaluate different Power UAV estimation techniques because if the Power UAV is not connected to a Sensor UAV via a MANET, then the Power UAV had to estimate input parameters. There was also a count column associated with the estimated location matrix that captured the last time that the Power UAV received an update on the location of any given Sensor UAV. Note that the Power UAV location was included in these matrices and the estimated location is always equivalent to the truth data as the Power UAV was assumed to know where it is located at all times.

The third matrix contained the instantaneous power levels for all Sensor UAVs. This matrix also contains a “last updated” column to distinguish between truth and estimated data. It is important to capture the staleness of the data so that these parameters could be incorporated into the system controller. The controller should weigh the validity via a confidence factor with the necessity when making decisions. The estimator for power usage, for the purposes of this paper, is always perfect. Further research could be done by increasing the fidelity of this simulation in which utilizing the staleness of information would be vital.

Lastly, the direct connectivity matrix for the system was calculated for each time step and was used to determine the indirect connectivity matrix as all UAVs function as communication relays.

These were the key matrices used to formulate all of the data used to characterize system performance.

Another advantage modeling the system with matrices, besides parameter comparisons and fidelity flexibility is operational agility. For example, if real-world intelligence from other sources leads to prioritized sectors, the areas could easily be divided and incorporated to the Sensor and Power UAV implementation as shown below.

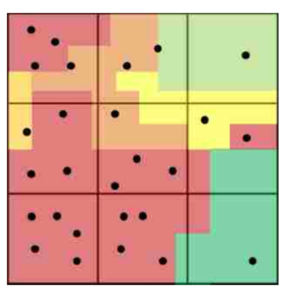

Figure 3.5 Prioritization of Area to Be Covered

Imagine intelligence sources provided a prioritization of the area to be surveyed as annotated above that marked the most likely location of the desired target or person to be rescued. Red depicts the highest probability followed by orange, yellow, light green and finally dark green depicting the lowest probability of the location. The matrix method could allow for this parameter to be taken into account and the system of systems could modify sensor locations based on these inputs. Notice that the all red JFCM has five sensors monitoring it as the bottom right JFCM has only one because it is mostly dark green. This operational optimality is achievable real-time by modifying the controller of the system by altering the state of the system based upon this input.

Furthermore, if the simulation called for a terrain mapping, the matrix approach makes it convenient to model and represent surface data such as Digital Terrain Elevation Data (DTED). The following depiction is of a randomly generated terrain compiled over the space matrix.

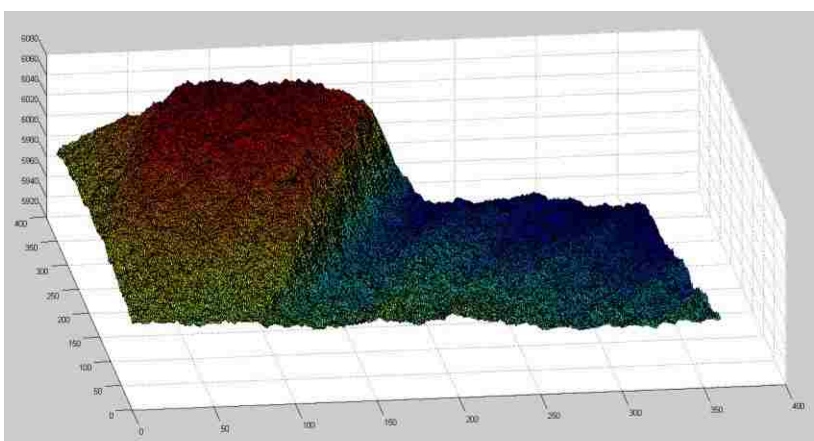

Figure 3.6 Example Terrain Mapping onto Area to Be Covered

This information could be utilized to take into account line-of-sight calculations, a realistic power usage rate, etc.

All in all, the matrix model approach enables a strong mathematically founded approach that is be built upon as further requirements, parameters and capabilities come online.

3.7.3 Justification for Parameters:

The intent of this thesis was not to investigate a real world solution to UAV operational issues. This system is too hypothetical and utilizes undeveloped capabilities so putting together a working solution would be out of scope for this paper, and therefore, several generic parameters were used.

However, there were some parameters that can be approximated based upon current capabilities.

The operational area that encompasses all nine JFCMs is 129,600 square kilometers. This number was set due to the number of UAVs and a reasonable coverage time [7]. Another parameter that was utilized was the communication frequency of the UAVs. These two parameters were investigated further because the greatly affect the connectivity of the system.

It is smart in battle to attempt to create MANETs with nodes consisting of as many weapon systems as possible. The military is looking at creating one common language to share the information from all these nodes across the MANETs. The current proposed solution to this effort is called Common Data Link (CDL). This data link will phase out existing weapon platform specific data links on legacy systems and facilitate data sharing across the battlespace. CDL is being developed to operate at around 2 GHz in order to provide higher data rates at the cost of communication distances, a shortfall that is planned to be mitigated by the integration of all systems. The frequency of 2 GHz is used in the simulations with the assumption that if something like this were to come online, it would be integrated into CDL. This frequency is pertinent to the freespace attenuation used to calculate communication distance [7].

In order to fully validate the simulation models, many more parameters would have to be identified including Sensor power burn rates, charge rates and capacity, Power UAV supply rates, capacity and number of simultaneous targets, satellite power supply rate etc.

3.8 Anticipated Results.

The following anticipated results correspond to the already introduced research goals as outlined in Section I of this paper.

3.8.1 Controller Performance

The DTSP with dead reckoning estimation will work best. This controller utilizes more calculations for the controller so that it updates its initial decision on shortest flight path continuously as the Power UAV replenishes the Sensor UAVs. The Sensor UAVs will most likely be flying their respective search patterns so the dead reckoning estimation method will prove most effective.

3.8.2 Connectivity Coefficient Dependence

The system performance will increase as the value of Cc increases. Lower values of Cc will render the simulation a failure by corresponding to a minimum sensor power of less than or equal to zero.

3.8.3 Removal of Nodes from the System

The degree centrality of the nodes that are removed will impact the jolt to the performance factors. The performance factors will decrease with the information that the controller has about the system. However, since the nodes that are taken away from the system consume resources, the performance factors will increase once the connectivity coefficient is high enough to provide the controller adequate information on the system. Combining these two factors will yield an intersection of the minimum average sensor power curves between the full system and the system with missing nodes. There will also be an intersection between the minimum sensor power curves. This intersection will define when knowledge of the system is overcome by the cost of that knowledge. Because there is a maximum sensor power, the difference between the performance parameters of the full system and the system with nodes missing will be more drastic as the points correspond to smaller values of Cc and will converge at the larger values of Cc. This will lead to a flatter full system performance parameter curve with the system with nodes missing lower on smaller values of Cc and sloping upward at a faster rate than the full system surface with creating an intersection prior to maximum system performance parameters. The slope of the system with nodes missing will depend on the amount of nodes that are missing, i.e. the fewer amount of resources to supply, and the degree centrality as compared to the rest of the nodes, or the percentage of connectivity that node supplied to the system.

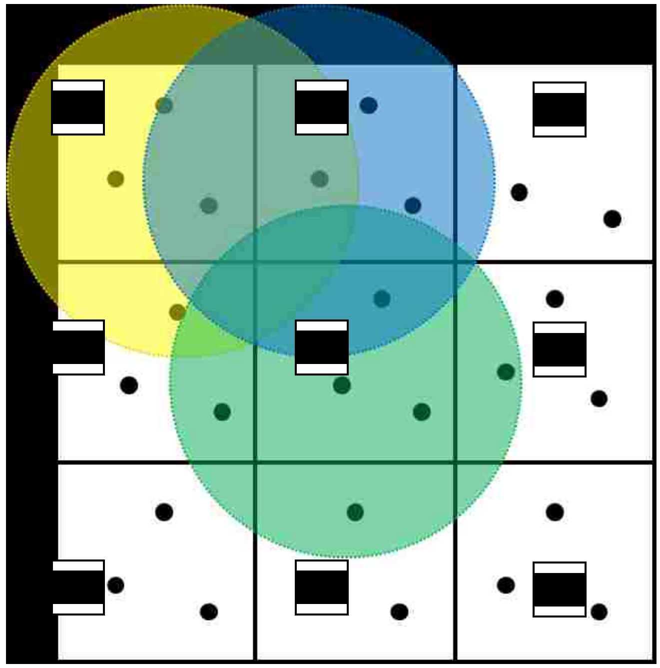

Figure 3.7 JFCM Potential Node Coverage

If there are a lot of "non-important" nodes missing with a low relative degree centrality (for instance the corner JFCMs as shown above), then the slope will be increase as the system is not losing out on much system information, but is freeing up resources for the more important nodes. The more critical the node that is missing the gentler the slop of the surface will be, as the Cc coefficient will need to be increased by a greater value to ensure the controller has adequate information on the system.

3.8.4 Stability Analysis

The stability of the system will depend on the performance of each individual controller. The stability of the system with different nodes removed will depend on the minimum Cc for stability with zero nodes missing and the degree centrality of the nodes that were removed from the system.

IV. Results and Data Analysis

4.1 Simulation Results

4.1.1 Simplifying to Two Dimensions

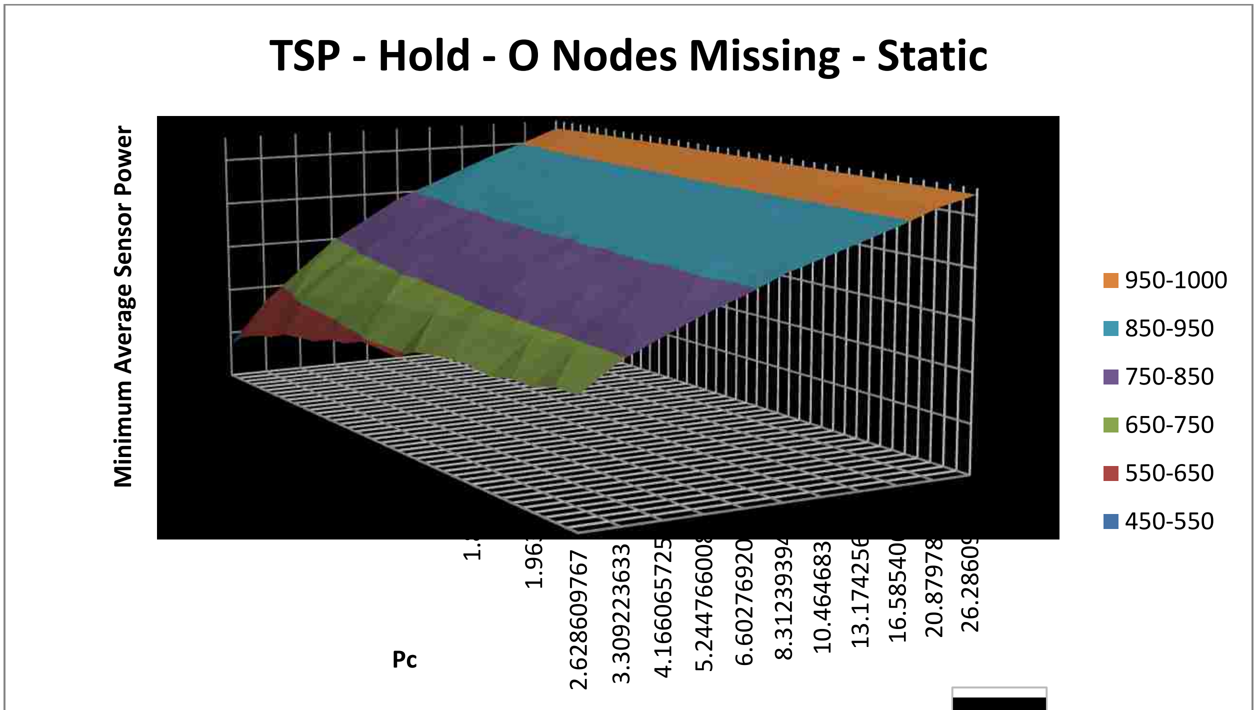

Figure 4.1 TSP Hold – 0 Nodes Missing – Static Flight Path - Minimum Average Sensor Power

The figure above shows the minimum average sensor power for the TSP Hold Estimation controller acting with all 27 nodes and zero targets. This plot shows that Cc impacts the performance of the system significantly more so than Pc. In fact, the change in Pc is almost negligible across the different Ccs. It is important to note that this is true because the values of Pc were chosen to be greater than one, meeting minimum resource requirements. If Pc were to be simulated at values less than one, the minimum average sensor power would decrease no matter what Cc was as hinted above when Pc was set to 1.296 and Cc was 2.628609. This is not only because only adequate Pcs were simulated, but because the Cc has compounding effects on the system. The Power UAV understands more of the system and can supply power more efficiently when it knows where the other nodes are located (higher Cc) and can also link up to power the Sensor nodes sooner as it can power a Sensor within its communication distance.

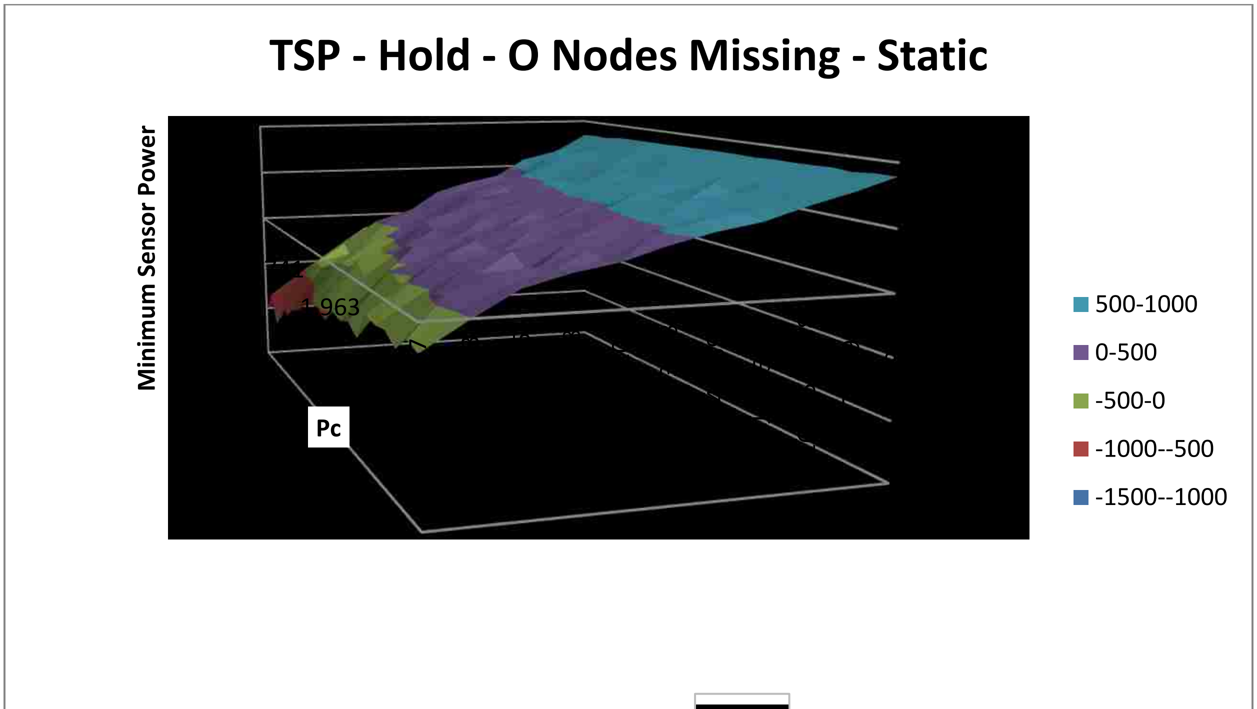

Figure 4.2 TSP Hold – 0 Nodes Missing – Static [redacted] Path - Minimum Sensor Power

The figure above represents the second performance parameter that this thesis investigated, the minimum sensor power. Again, note that the impact of Pc was not significant and the system performance was driven by Cc. This chart is important as it reveals which values of Cc and Pc work (do not lose a sensor). The minimum average sensor power, given a certain Pc and Cc may be close to maximum, but this parameter masks whether or not the Power UAV is meeting all of the sensors. For example, if the Power UAV finds an optimal resource supplying flight path that powers 26 of the 27

UAVs constantly and holds them at a there maximum power capacity of 1000, neglecting one sensor completely, the minimum average sensor power will be 814.8 after 5000 time-steps, potentially meeting minimum performance requirements. However, this data does not reveal the obvious that one sensor was buried after only 1000 time-steps and the minimum sensor power observed is -4000.

This lack of dependence on Pc leads to a simplification of the classification of the system as Pc was chosen to be held at a value of 1.593 establishing a 2-dimensional problem.

4.1.2 TSP/Hold Estimation

4.1.2.1 Static Flight Path

In order to attempt to classify this dynamic system and the effects that a particular node has on a system, the static simulation was run and the average degree centrality was calculated for each node and normalized into a percentage of the system over all of the different values of Cc. The table below represents each sensor number and its respective average percentage degree centrality against the entire system. The table also shows spatially which JFCM each sensor resides and the location of each JFCM relative to each other.

Sensor #	% Degree Centrality	Sensor #	% Degree Centrality	Sensor #	% Degree Centrality
1	0.0291	4	0.0396	7	0.0298
2	0.0298	5	0.0394	8	0.0292
3	0.0306	6	0.0410	9	0.0302
10	0.0390	13	0.0524	16	0.0413
11	0.0394	14	0.0509	17	0.0410
12	0.0401	15	0.0524	18	0.0393
19	0.0311	22	0.0415	25	0.0317
20	0.0316	23	0.0417	26	0.0318
21	0.0286	24	0.0385	27	0.0290

Table 4.1 Normalized Degree Centrality

As expected, the sensors in the center JFCM were more important when it comes to relaying information throughout the system because these sensors geographically neighbor 8 other JFCMs. Following the same logic, the next most important JFCMs were 2, 4, 6, and 8 because they all neighbor 5 other JFCMs and the corner JFCMs were least important as they neighbor only 3 other JFCMs. This table was not recreated for every controller because the degree centralities remained the same relative to their respective system.

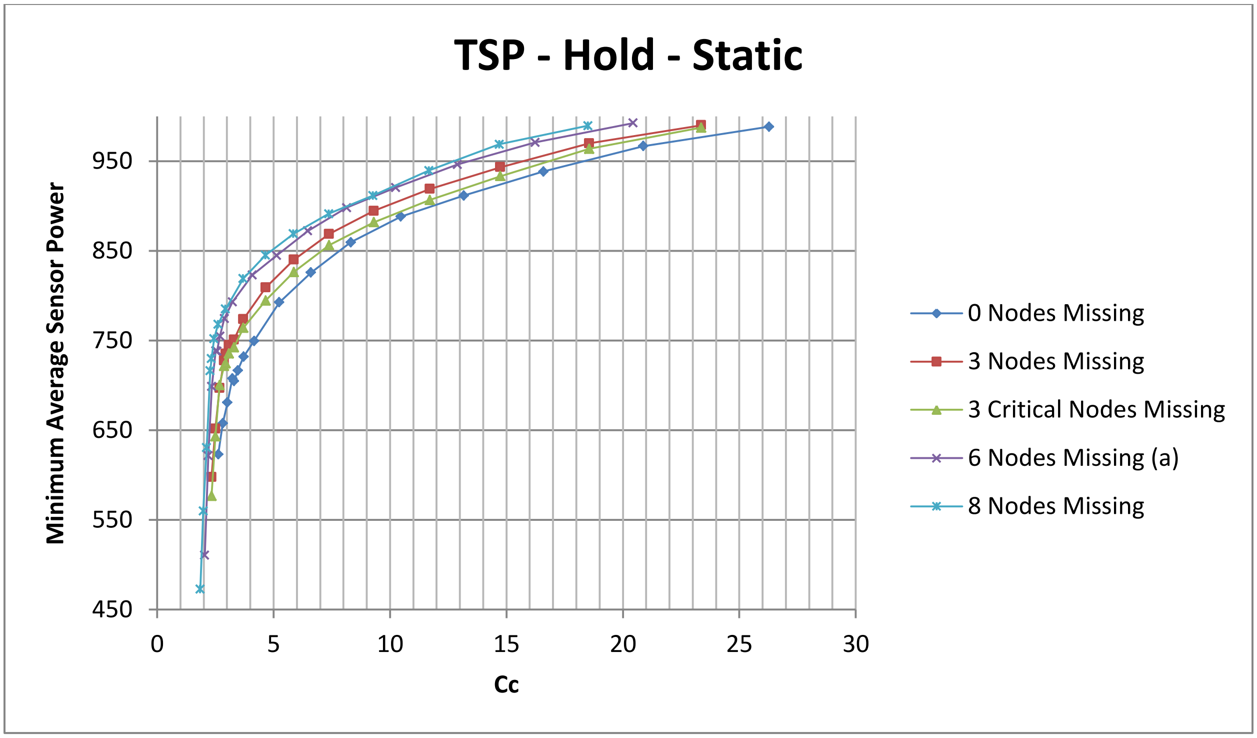

Figure 4.3 TSP- Hold – Static Flight Path - Minimum Average Sensor Power

The figure above shows the results from the first experiment. The simulation was against the TSP algorithm utilizing Hold Estimation during the Static Flight Path and plots the minimum average sensor power against Cc. The simulation was run with different nodes missing in order to investigate further dynamics of the system. Intuitively, the performance of the system should increase as Cc increases which is the case. It is also clear that the maximum minimum average sensor power would tend towards the maximum sensor power value of 1000 as Cc increases. Other interesting dynamics are pointed out in the interpreted graph below.

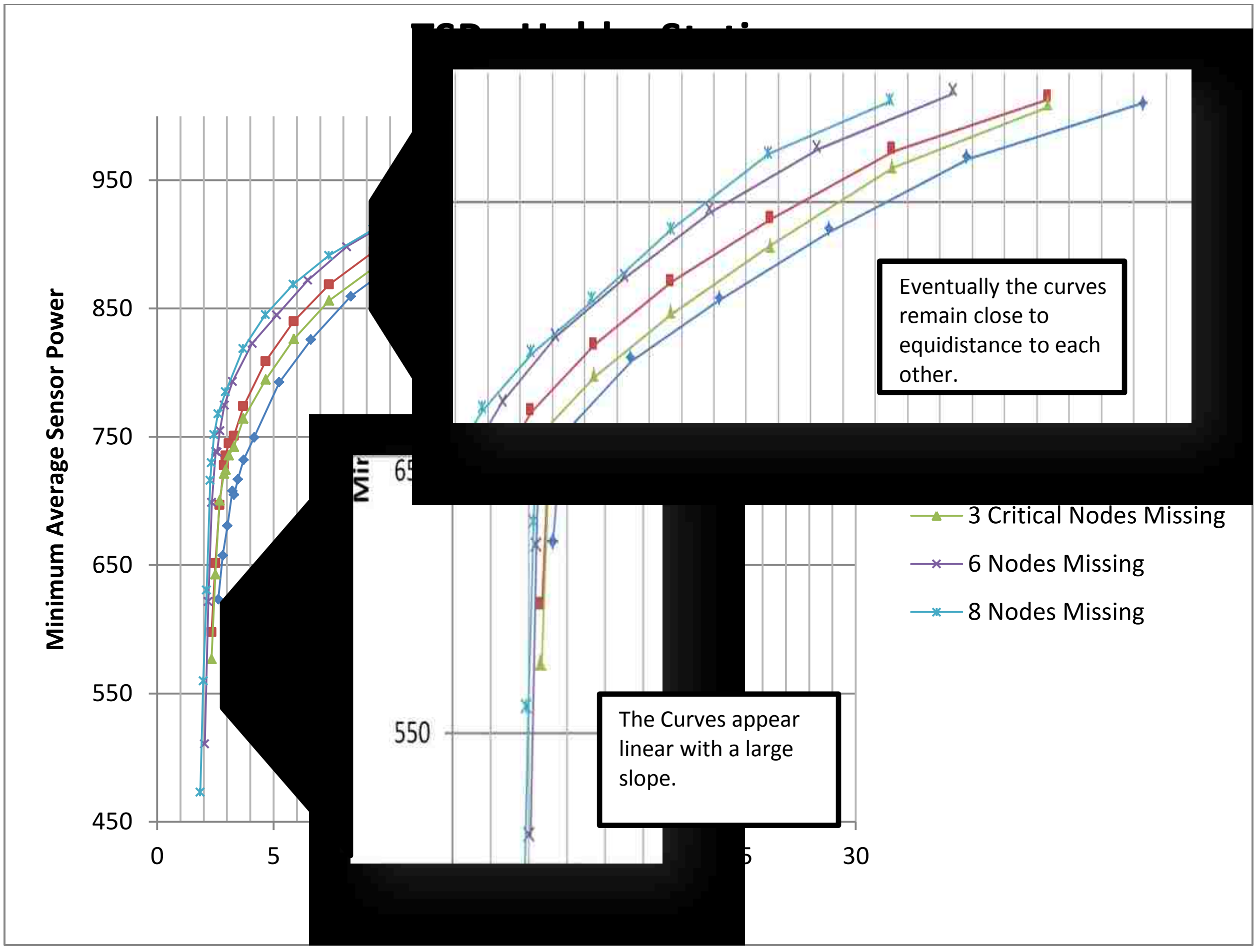

Figure 4.4 TSP- Hold – Static Flight Path - Minimum Average Sensor Power with Annotations

After splicing the chart, some interesting relationships between the fully connected and not fully connected system dynamics are revealed. The system actually performs better with more nodes missing. The reason for this is an anomaly is because Cc is related to the communication distance as well as the number of sensors in the system. Therefore, the number gives a normalized "knowledge" of the system, and in this case, if the Power UAV is just as knowledgeable about a system with less power requirements and more significantly, less potential knowledge of the system, the overall system performance increases. Even though the system appears to be performing better with nodes missing, it is important to understand that the operational performance is decreasing as the time to perform a coverage sweep is increasing. This fact is further discussed later in this thesis.

Another interesting feature is that the curves start with an almost linear slope until a certain Cc is attained, and then flatten out in a logarithmic fashion. During the logarithmic values of Cc, the curves remain equidistant to each other.

As discussed, the curves transition between the following formats after a certain value of Cc.

$$Minimum\ Average\ Sensor\ Power = m * Cc + b \quad for\ Cc < \mu$$

And

$$Minimum\ Average\ Sensor\ Power = \alpha * Log(Cc) + \beta \quad for\ Cc \geq \mu$$

Determining the value of μ is done by investigating the minimum sensor power curves.

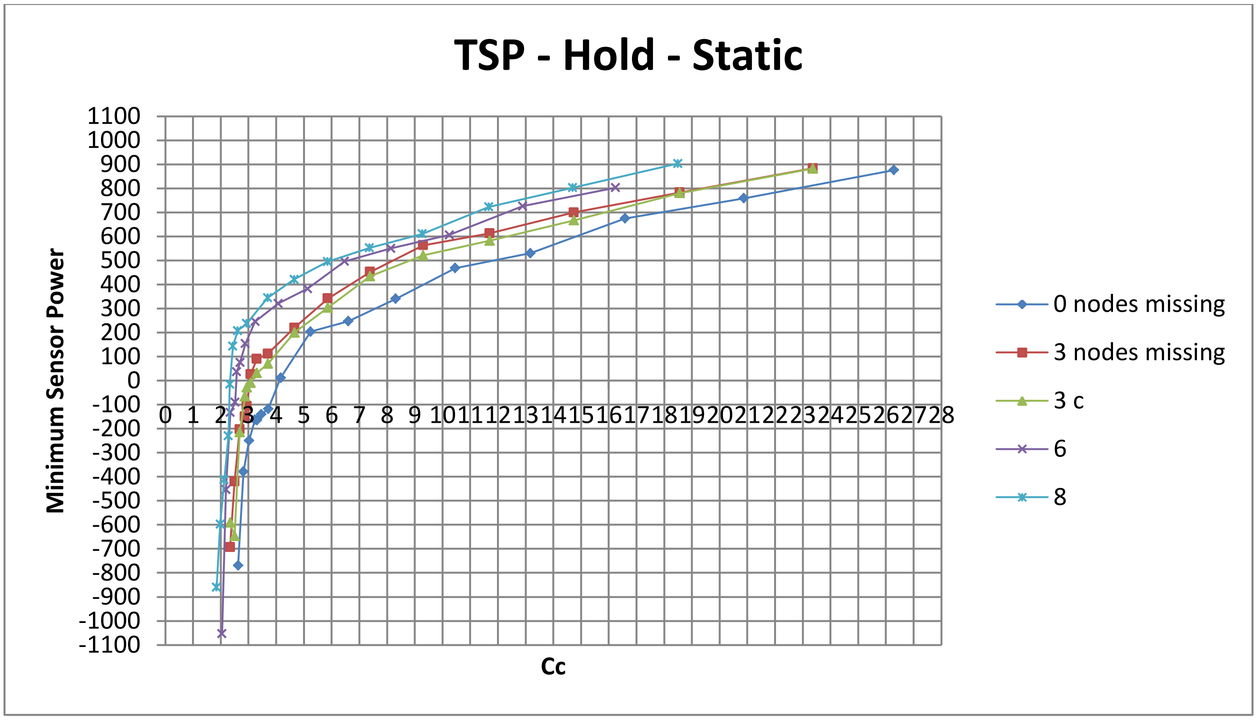

Figure 4.5 TSP- Hold – Static Flight Path - Minimum Sensor Power

This figure shows the other half of the performance characteristics, the minimum sensor power. Again, note that if Cc leads to a minimum sensor power that is below zero, this means at least one sensor crashed. These curves also show that the greater the power requirement, given an equal amount of knowledge of the system leads to a lower performance. It is, however interesting to compare the 3 Nodes Missing and the 3 Critical Nodes Missing experiments. The 3 Critical Nodes Missing leads to a lower performance because the nodes carried more information. After reviewing **Table 4.1 Normalized Degree Centrality**, the % of information taken out from the 3 Critical Nodes is right between the 3 and 6 Nodes Missing which would put the 3 Critical Nodes Missing curve right between the other two. This is not true, due to the delta in power requirements. In fact, the zero crossing of these curves can be described by the following equation.

$$\mu = \rho - \log(\sum_{f3} \gamma_3 * 39.65 + \sum_{f5} \gamma_3 * 48.57 + \sum_{f8} \gamma_3 * 15.418 + .2 * \delta)$$

Where μ is the zero crossing for a given system with N nodes missing, ρ is the zero crossing for the full system, δ is the total decreased degree centrality percentage from the full system from pulling out N nodes and $f3$, $f5$ and $f8$ correspond to the number of JFCMs that the missing sensor node could potentially impact. Referencing **Table 4.1 Normalized Degree Centrality**, $f3$ nodes come from the corner JFCMs, $f8$ nodes come from the center JFCM and $f5$ come from the other JFCMs. It is clear from table **Table 4.1 Normalized Degree Centrality**, that the degree centrality of the nodes in the center, box 5 or $f8$, are greater than those in the perimeter boxes and the next important boxes, in terms of degree centrality, are 2, 4, 6 and 8. The corner boxes are least important. Therefore, pulling out a node from box 9 will affect the system differently than pulling out a node in box 5 and must be weighted independently.

To continue the explanation of the stability equation above, the summation with $f3$, $f5$ and$f8$ is the summation of all of the γ, the decreased degree centrality percentage from the full system, of the nodes in a box with factor 3, 5 and 8 respectively.

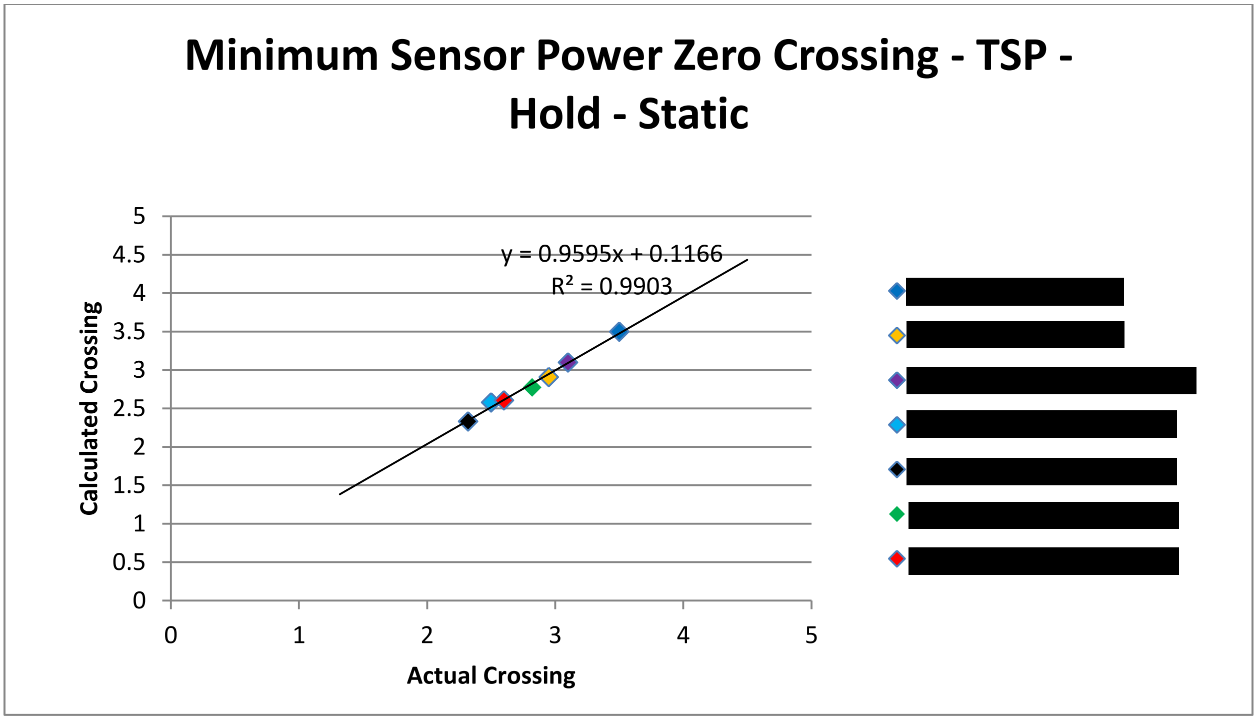

Figure 4.6 TSP- Hold – Static Flight Path - Stability Calculations Versus Actual

The correlation between the calculated crossings and the actual (simulated) crossings are very close. The slope of the line is nearly 1 with a y-intercept close to zero. To validate the stability equation on the previous page, two additional experiments were tested. The red and green data points above represent the removal of 6 and 4 Nodes respectively. The nodes that were removed are shown in the table below.

	Nodes Missing	
	4	**6**
Sensor Number	7	7
	12	12
	14	13
	27	14
		23
		27

Table 4.2 TSP- Hold – Test Nodes Removed

4.1.2.2 Dynamic Flight Path

The following figures represent the performance parameters of the TSP Hold Estimation controller that had nine total targets, one per JFCM, implanted within the simulation.

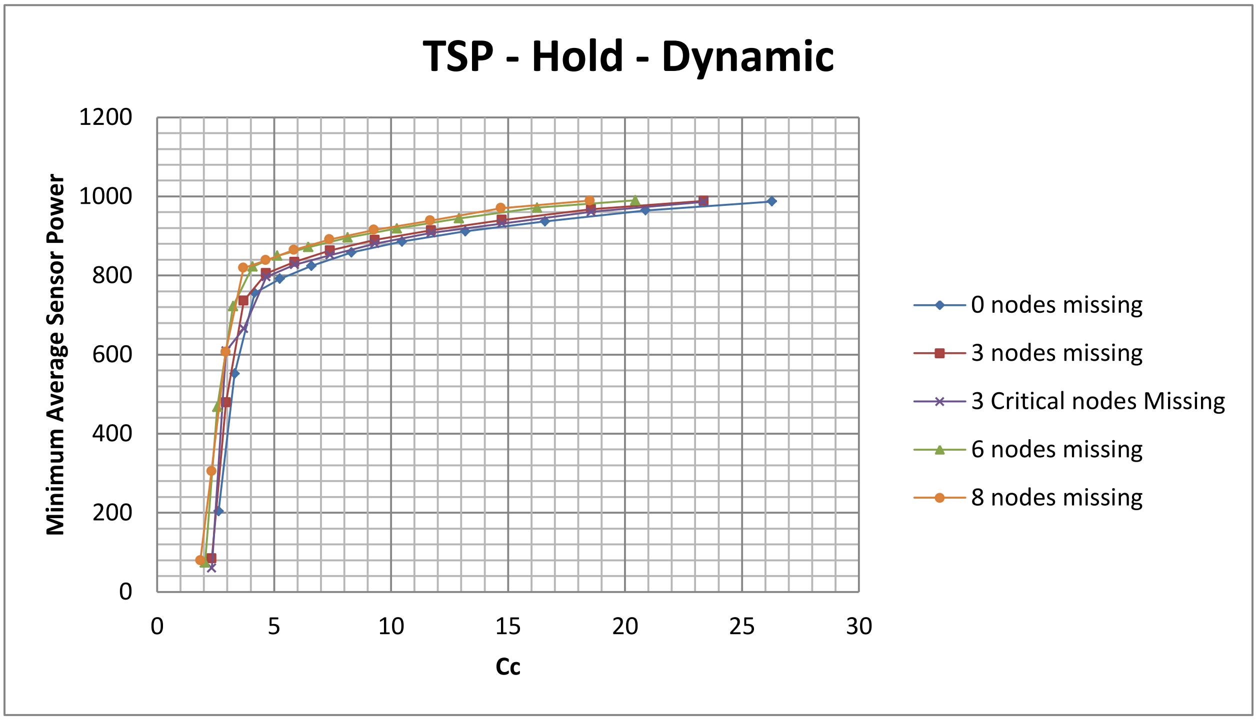

Figure 4.7 TSP- Hold – Dynamic Flight Path - Minimum Average Sensor Power

The minimum average sensor power curves, as shown above, have similar characteristics to those of the static case. When Cc is less than μ, the minimum average sensor power curve is described by a straight line and when Cc is greater than μ, the curve is logarithmic. However, as expected, by making the system more unpredictable the value of μ has increased from the static case. At higher levels of Cc, the two curves are identical as they both approach the maximum sensor power.

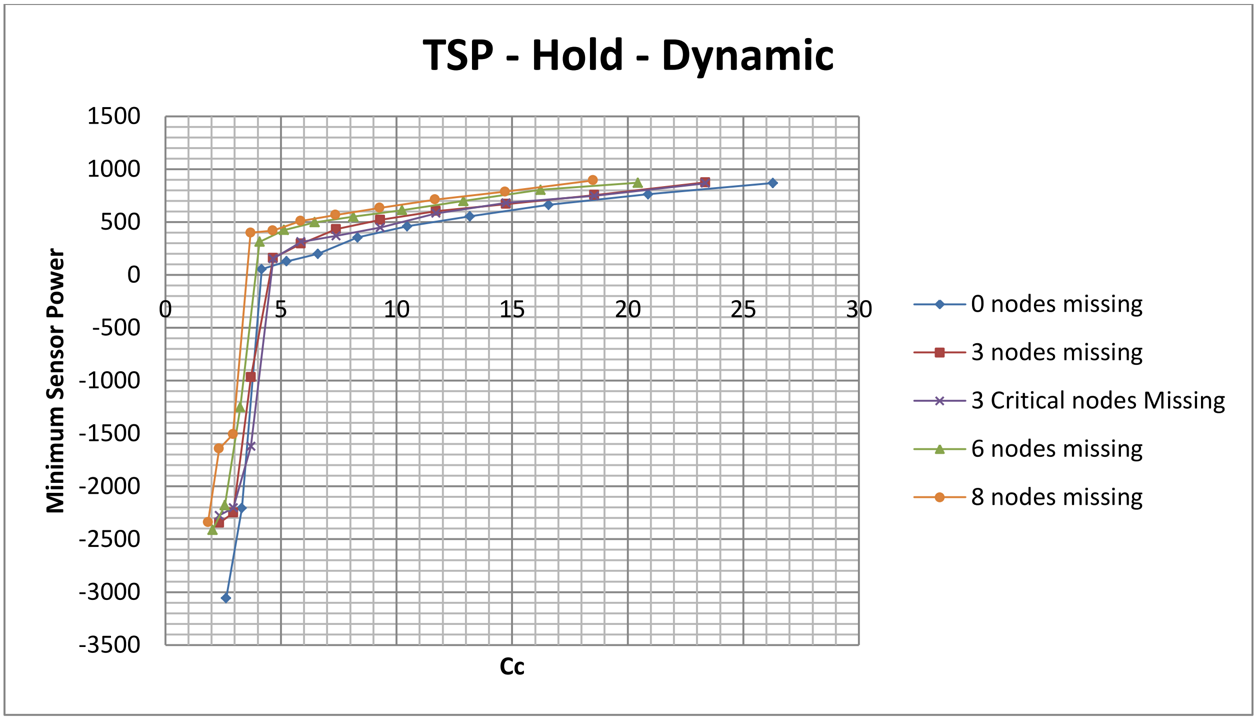

Figure 4.8 TSP- Hold – Dynamic Flight Path – Minimum Sensor Power

The figure above reveals that the system becomes stable at greater values of Cc as compared to the static case. This is true because now the simulation is more dynamic and the sensor nodes have more unpredictability. The figure also shows that unlike in the static case, the 0 nodes missing experiment does not have the greatest Cc stability requirement. Even though there is a substantial advantage because of the loss of potential knowledge on the system, both of the 3 nodes missing experiments required a higher Cc to ensure stability. This is due to the fact that with the introduction of more random sensor movement drove a greater requirement for knowledge of the system which outweighed the resource cost of only 3 additional nodes.

4.1.3 TSP/Dead Reckoning Estimation

4.1.3.1 Static Flight Path

The figure below is represents the same TSP controller as above, but implements the Dead Reckoning Sensor UAV location estimator.

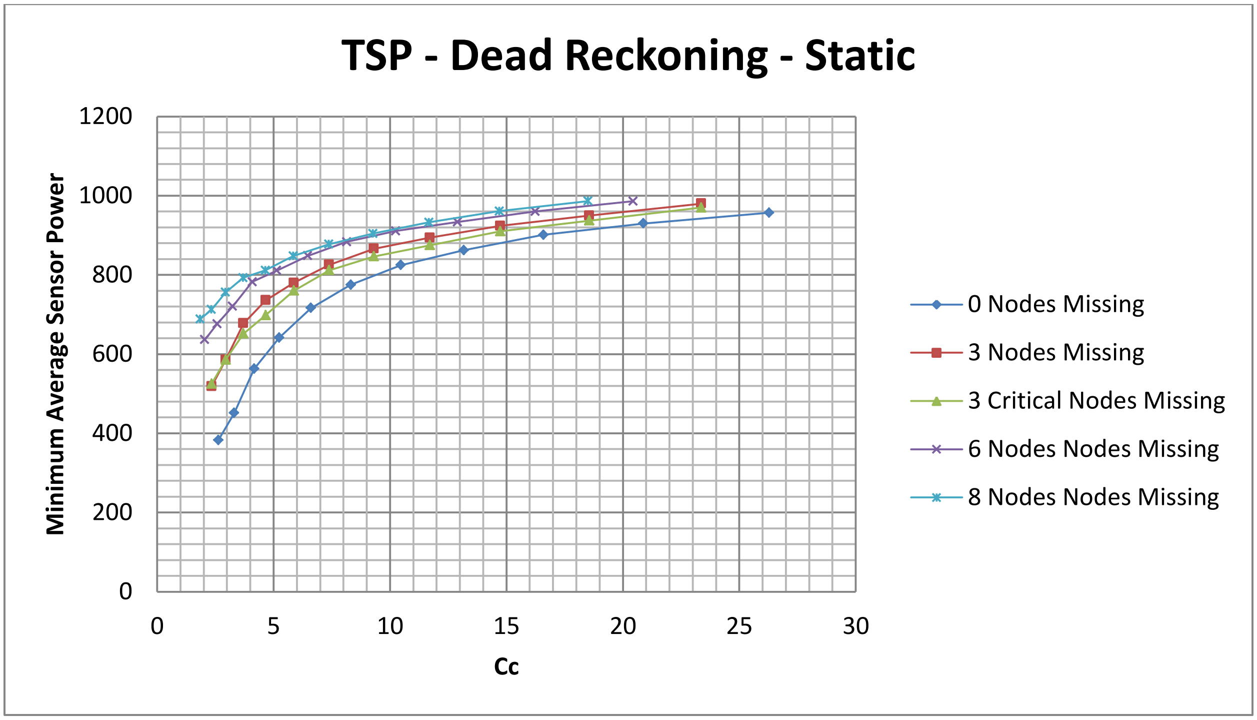

Figure 4.9 TSP- Dead Reckoning – Static Flight Path - Minimum Average Sensor Power

The figure above shows that the curves representing the minimum average sensor power are more logarithmic in shape and are absent of a linear portion at smaller values of Cc. This is due to the fact that the estimation method used is mirrored with the actual Sensor UAV locations. This simulation is the same as having an all knowing Power UAV with varying levels of Cc. Counter intuitively, the overall minimum average sensor power is lower.

The next figure reveals information about the stability of the system. When compared to the TSP Hold Estimator during Static Flight, this controller actually requires a higher Cc, for all instances of different nodes missing to obtain stability even though this system is all knowing.

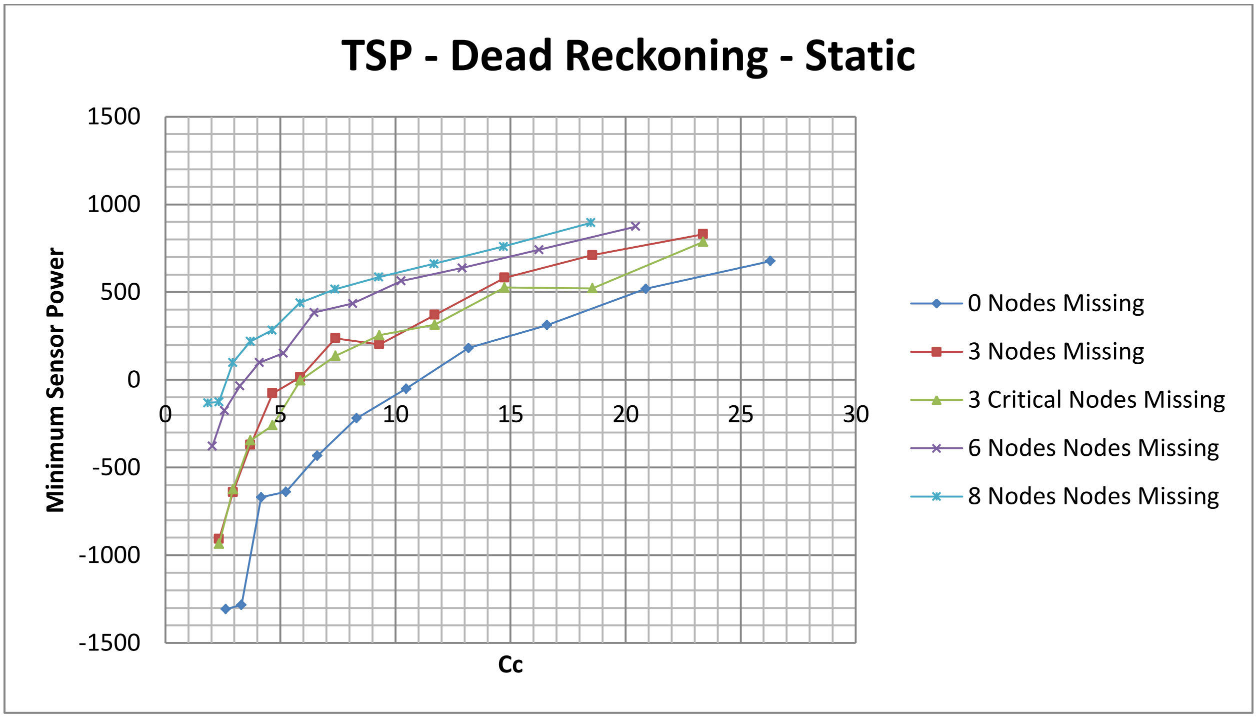

Figure 4.10 TSP- Dead Reckoning – Static Flight Path - Minimum Sensor Power

This may derive from a situation where the Power UAV starts to "chase" a Sensor UAV. This could decrease the effectiveness of the resource supplying since the Power UAV does not move on to the next Sensor UAV until it fills the Sensor's energy to capacity. After this result, an even more lucrative estimator may be to calculate where the next target Sensor UAV will be upon arrival of the Power UAV.

Even though the stability curve does not match the shape of the TSP Hold Estimator during Static Flight, the same algorithm used to calculate the minimum sensor power, for stability, was used.

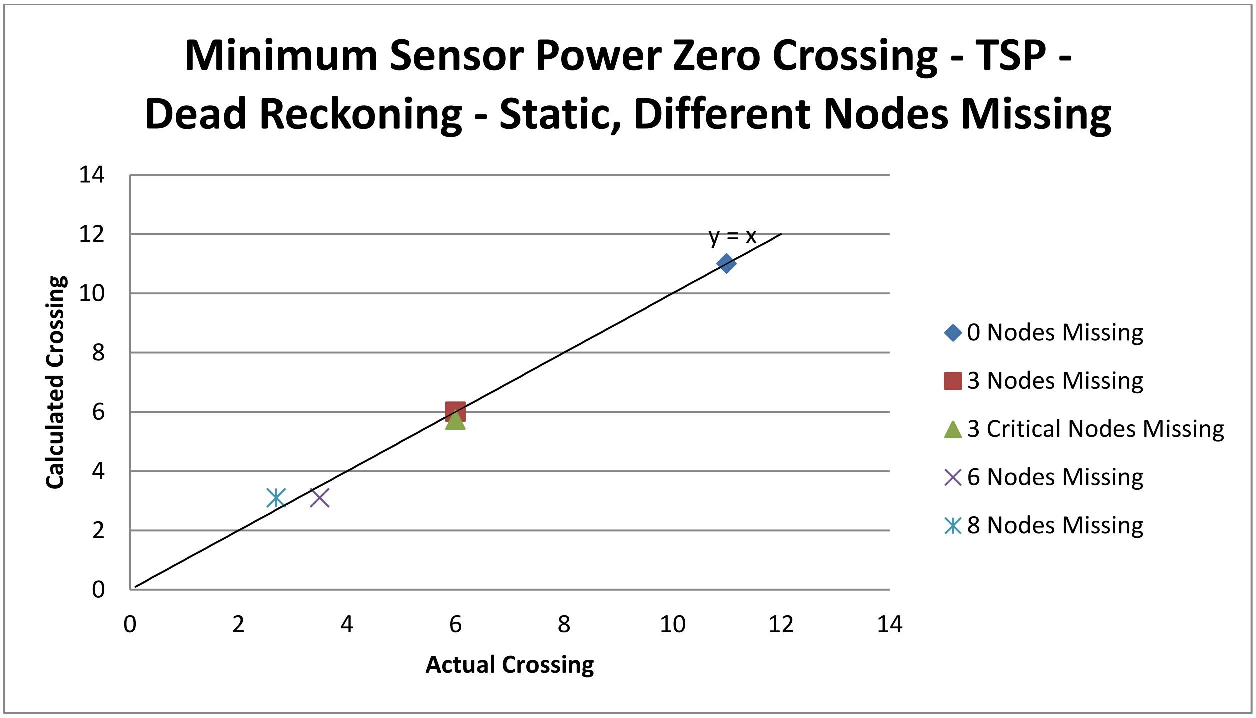

Figure 4.11 TSP- Dead Reckoning – Static Flight Path - Stability Calculations Versus Actual

The figure above represents the calculated Cc crossing based on the same stability equation found in section 4.1.2.1 after solving iteratively for different weighting factors. The calculated crossings get worse as the number of nodes missing increase.

4.1.3.2 Dynamic Flight Path

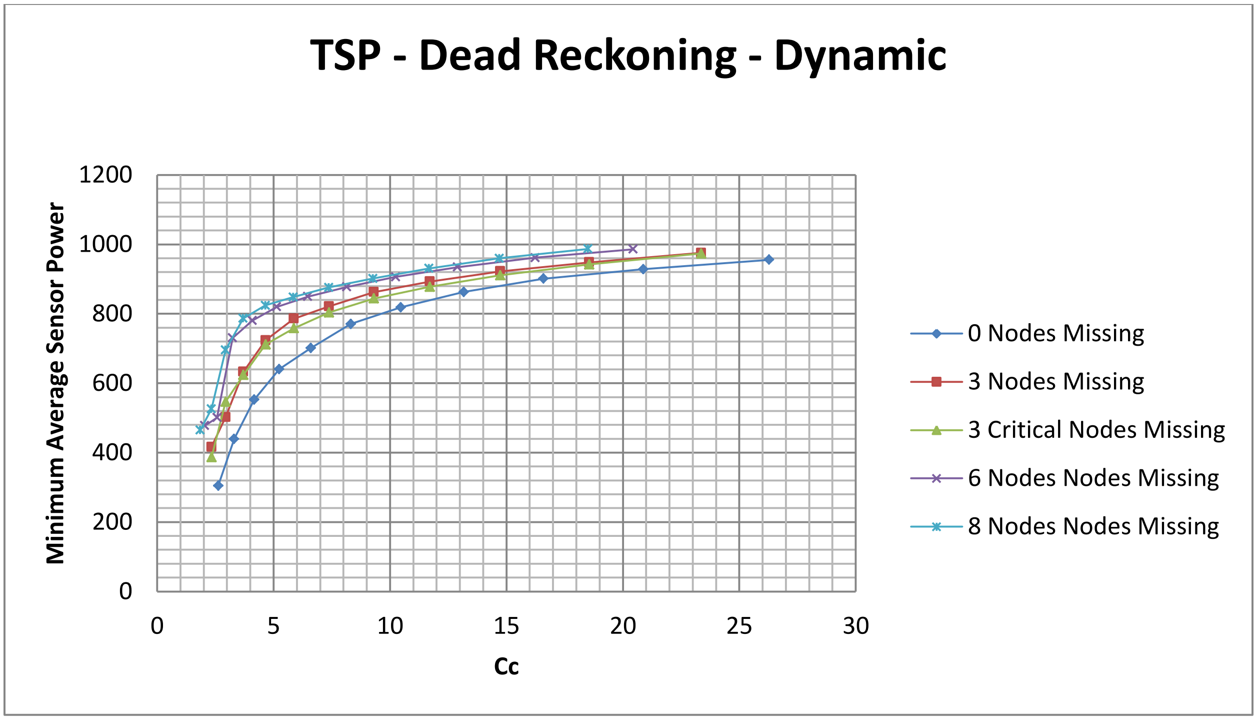

Figure 4.12 TSP- Dead Reckoning – Dynamic Flight Path – Minimum Average Sensor Power

The figure above represents another system that is not all knowing. It appears to contain characteristics of the TSP Hold Estimator and the TSP Dead Reckoning Estimator during Static Flight. The TSP Hold Estimator controller revealed two pieces to each of the curves, linear and logarithmic while the TSP Dead Reckoning Estimator only had a logarithmic. Looking at the figure above, the system goes from a similar all-knowing curve to the not all-knowing curve as the number of nodes decreases.

This same argument is true for the minimum sensor power curves.

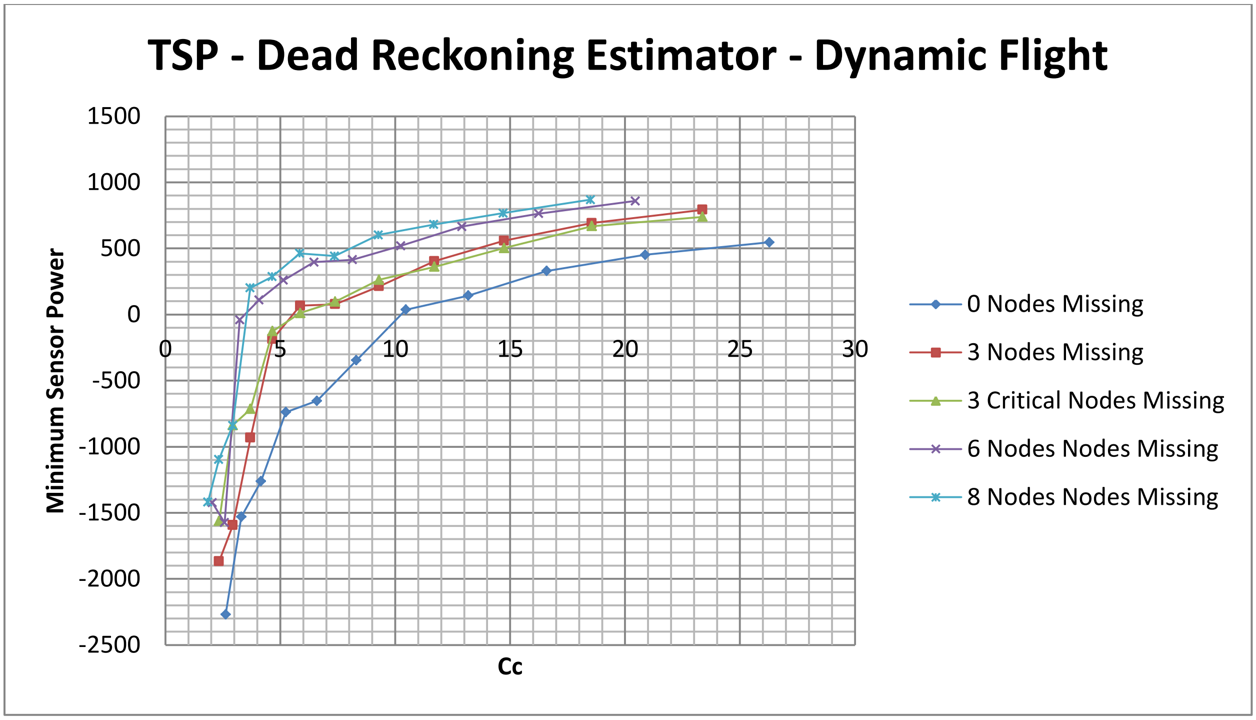

Figure 4.13 TSP- Dead Reckoning – Dynamic Flight Path – Minimum Sensor Power

The figure above shows that the minimum sensor power curves are more gradual as the number of nodes is increased.

4.1.4 DTSP/Hold Estimation

4.1.4.1 Static Flight Path

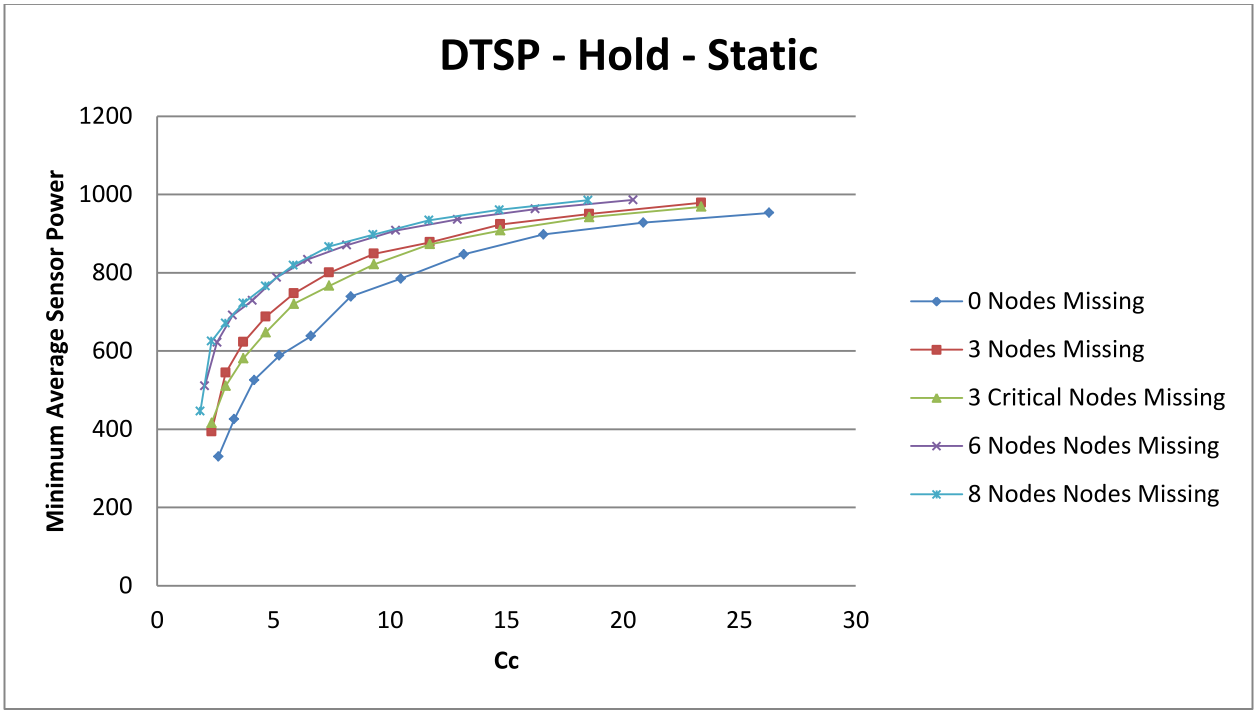

Figure 4.14 DTSP- Hold – Static Flight Path – Minimum Average Sensor Power

The DTSP Hold Estimator controller performes slightly worse that its TSP counterpart while taking more calculations to execute its algorithm. The same is true for the minimum sensor power curve that follows. It does however reveal an all-knowing (meaning no linear part at lower Ccs) shape.

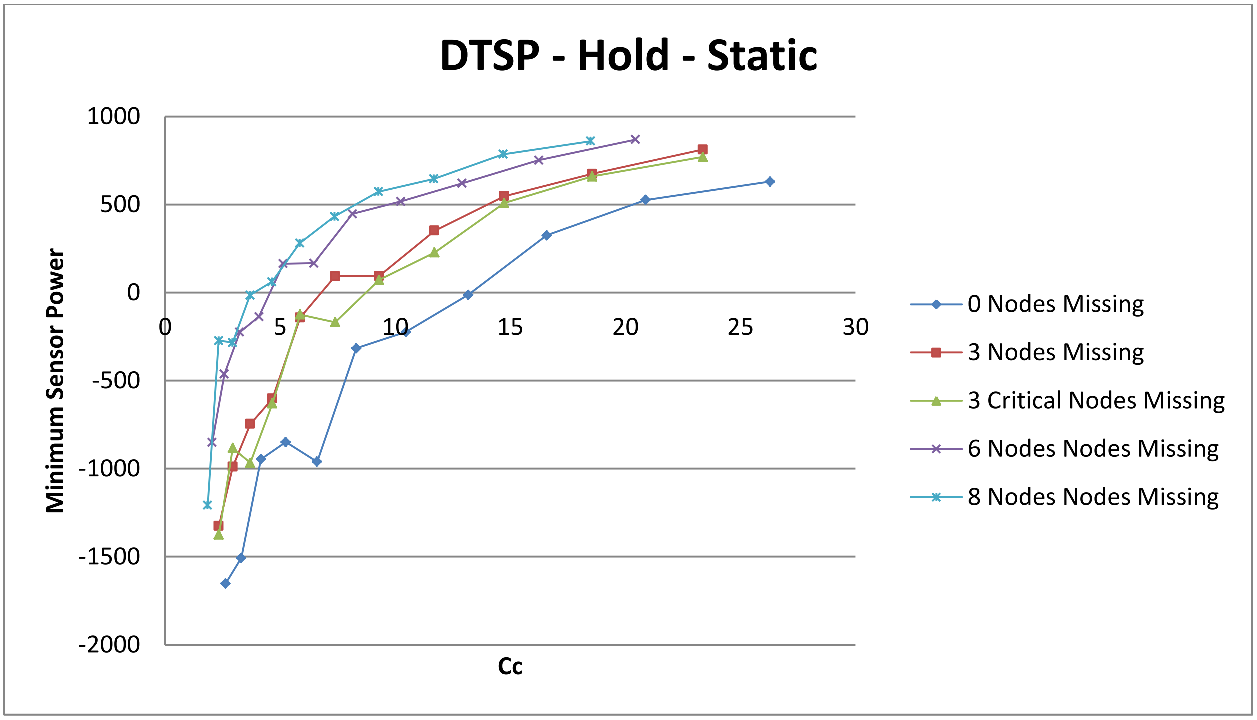

Figure 4.15 DTSP- Hold – Static Flight Path – Minimum Sensor Power

These figures show that it is better, for this system, to execute the refueling flight path to completion rather than re-computing intermittently throughout the process.

4.1.4.2 Dynamic Flight Path

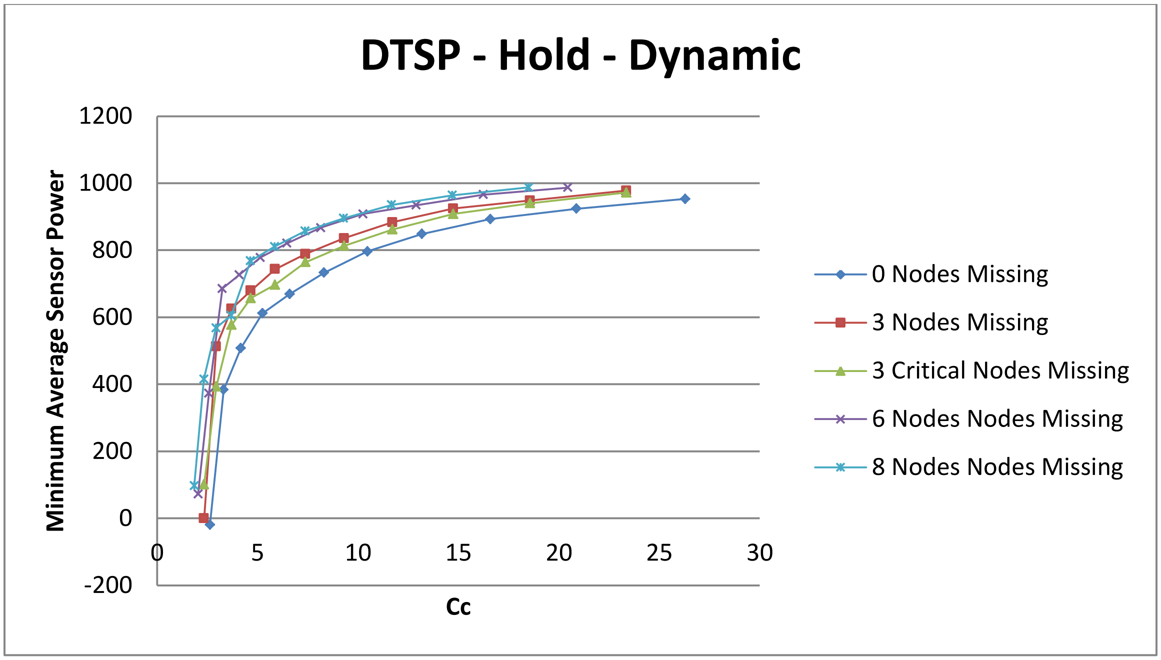

Figure 4.16 DTSP- Hold – Dynamic Flight Path – Minimum Average Sensor Power

The drastic increase at lower Cc levels shows that the system does not know enough about the system to ensure stability until a Cc of around 5. This controller estimator combination is the only one that has induced a negative minimum average sensor power.

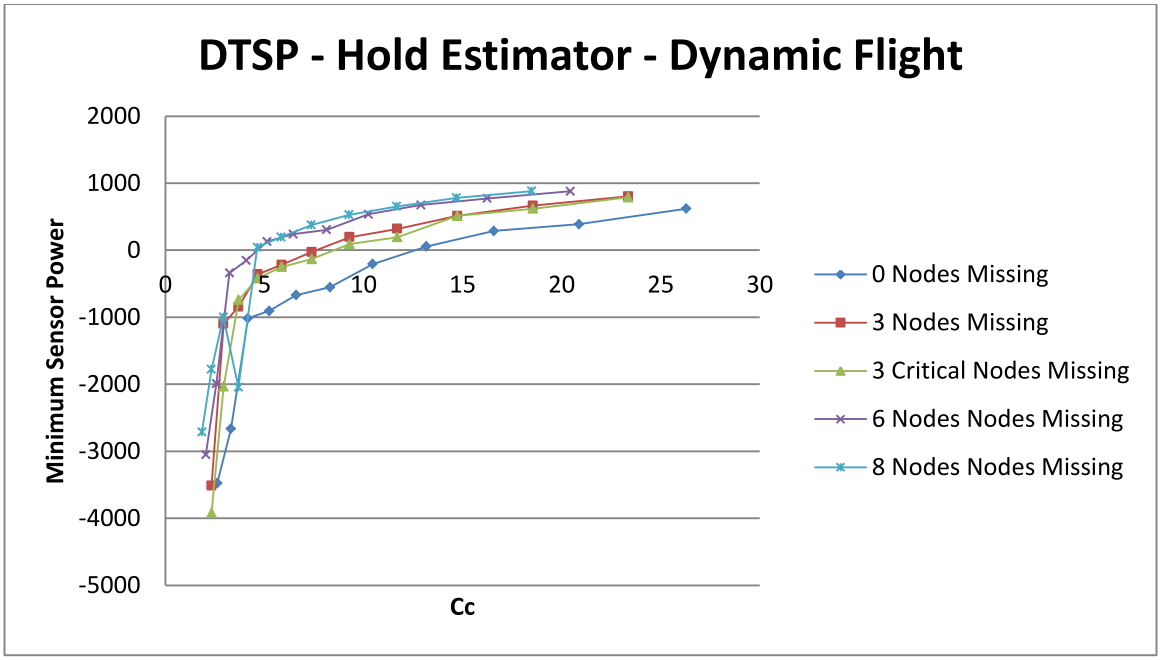

Figure 4.17 DTSP- Hold – Dynamic Flight Path – Minimum Sensor Power

Furthermore the minimum Cc for stability is the greatest of all the controllers.

4.1.5 DTSP/Dead Reckoning Estimation

4.1.5.1 Static Flight Path

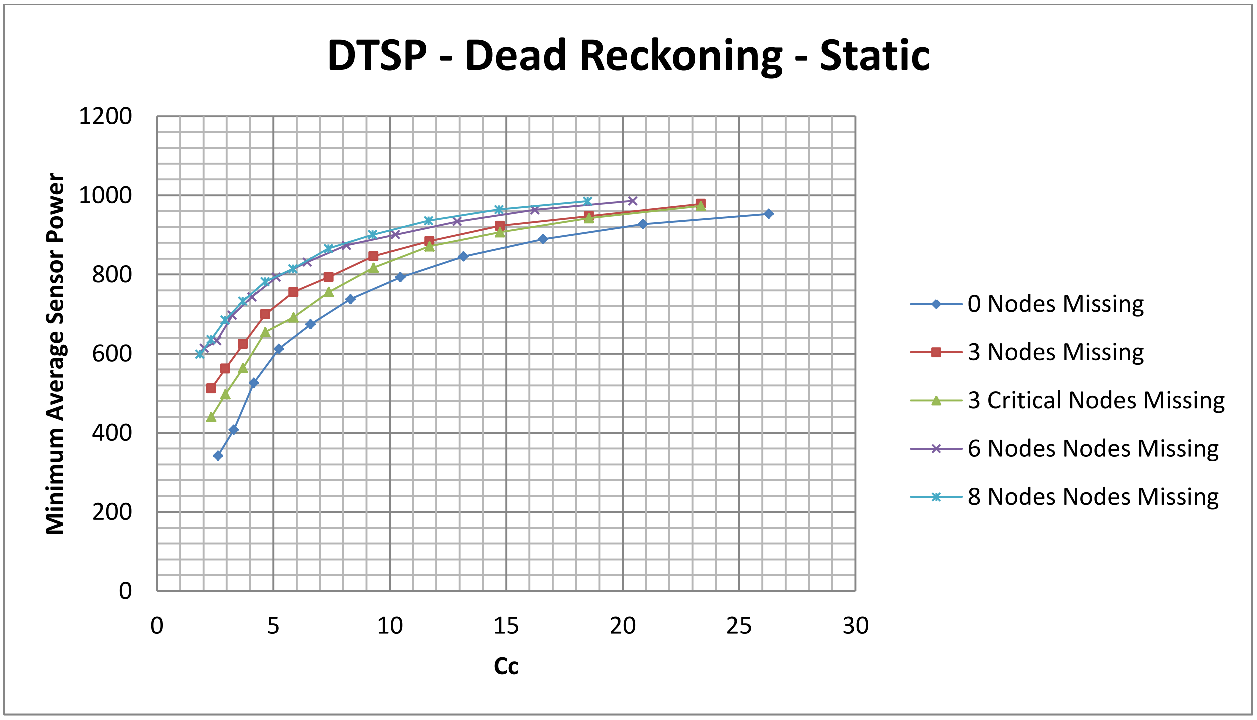

Figure 4.18 DTSP- Dead Reckoning – Static Flight Path – Minimum Average Sensor Power

The figure above shows a gradual increase in the performance of each instance as Cc is increased. This is due to the Dead Reckoning Estimator during Static flight where the system is all knowing of the Sensor UAV locations.

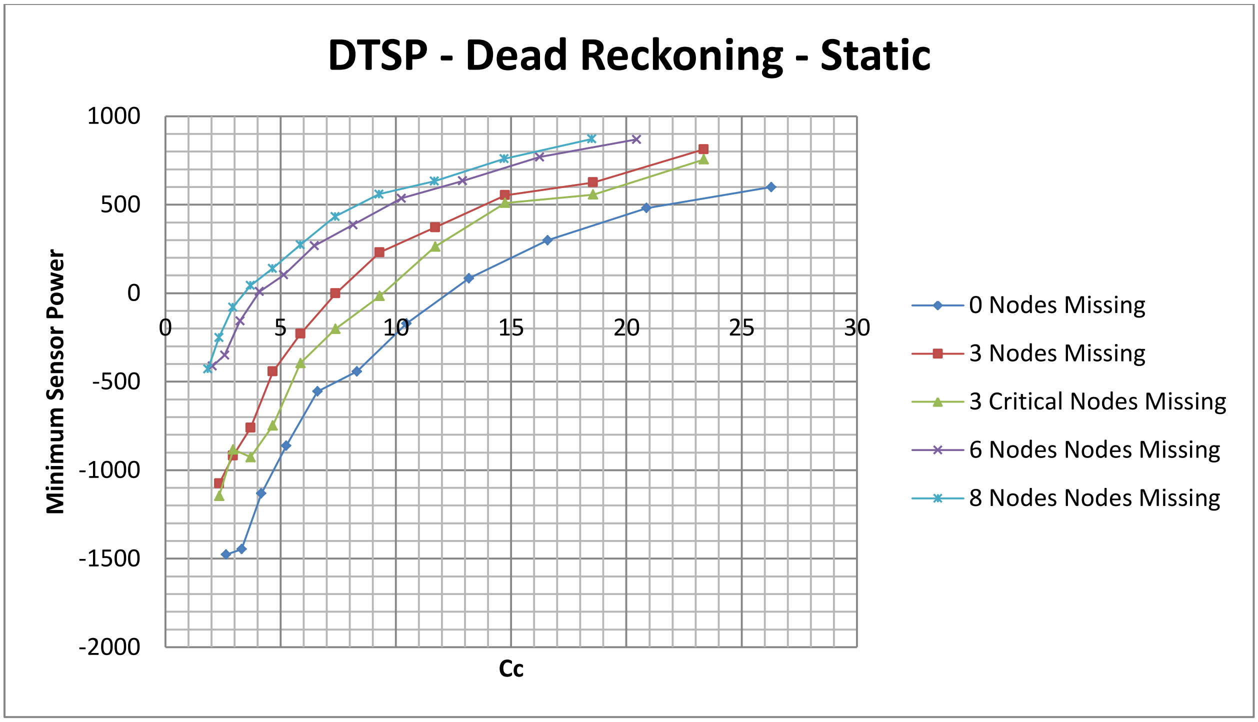

Figure 4.19 DTSP- Dead Reckoning – Static Flight Path – Minimum Sensor Power

Similarly to the minimum average sensor power curves, the minimum sensor power curves are gradually increasing as Cc increases representing no instance of when the system has adequate knowledge and a boost in performance is evident.

4.1.5.2 Dead Reckoning Flight Path

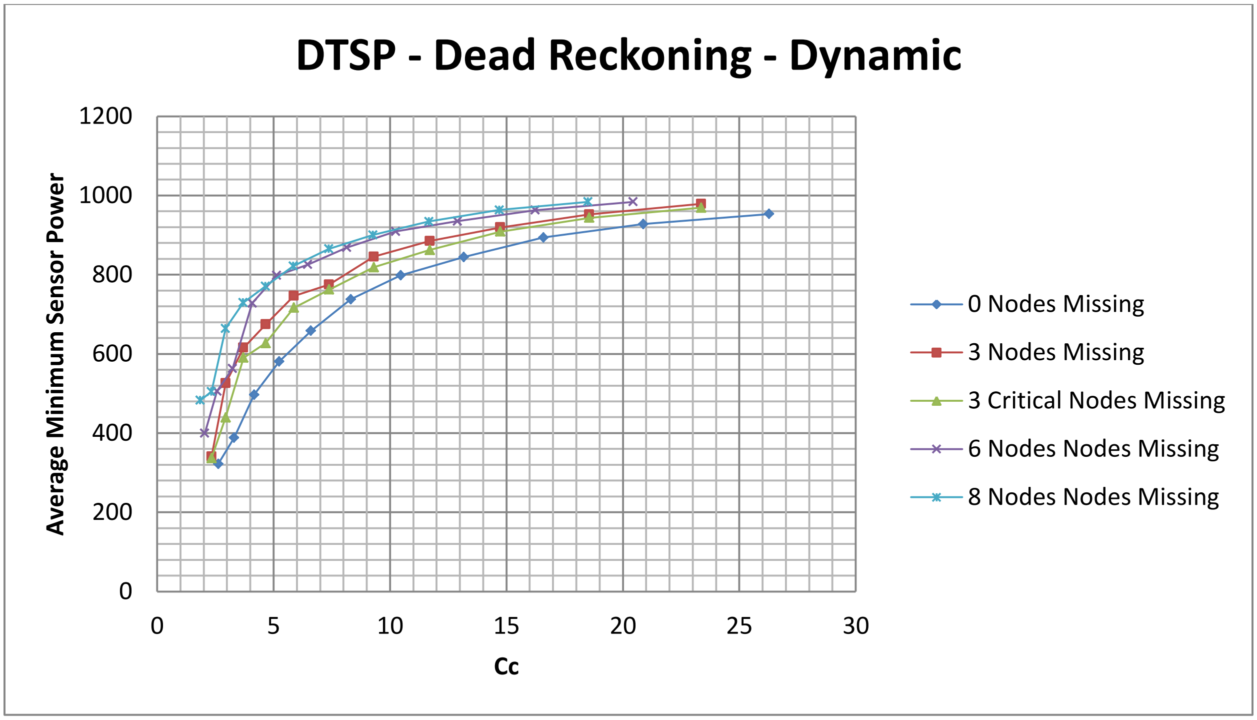

Figure 4.20 DTSP- Dead Reckoning – Dynamic Flight Path – Minimum Average Sensor Power

This controller's estimator does not guarantee an all-knowing system because of the Dynamic Flight Path and it is evident that the more nodes present, the better knowledge of the system, and the more gradual the increase in performance with an increase in Cc.

Same methodology describes the minimum sensor power figure on the next page.

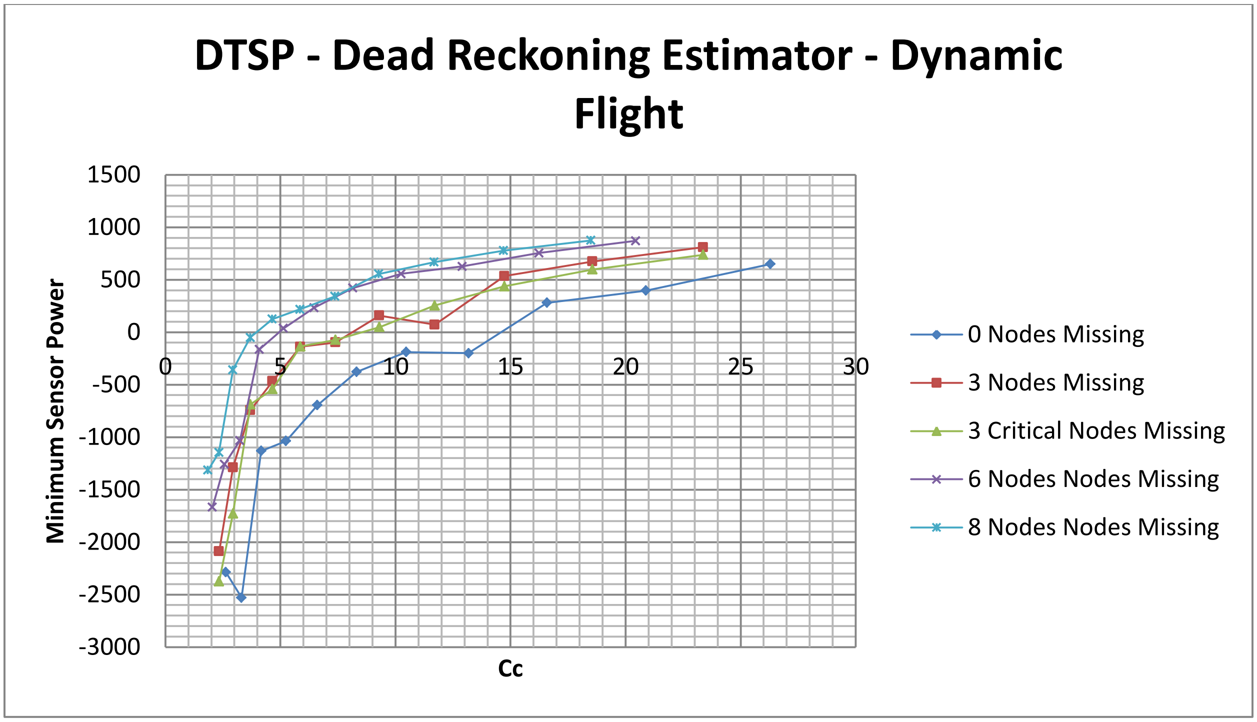

Figure 4.21 DTSP- Dead Reckoning – Dynamic Flight Path – Minimum Sensor Power

4.1.5 Controller Comparison

This section will investigate the different controllers and their performances. Only the simulations with zero nodes missing will be analyzed and compared to one another.

4.1.5.1 Static Flight

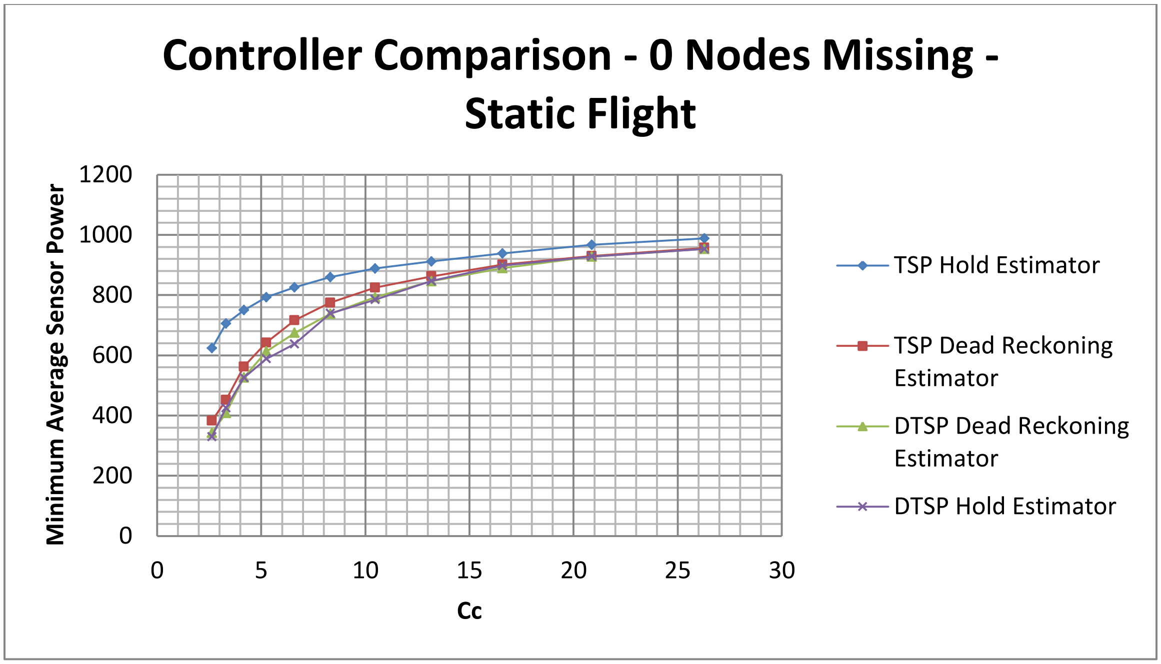

Figure 4.22 Controller Comparison – 0 Nodes Missing – Static Flight - Minimum Average Sensor Power

The controller that performed best was the least complicated algorithm to execute, the TSP Hold Estimator.

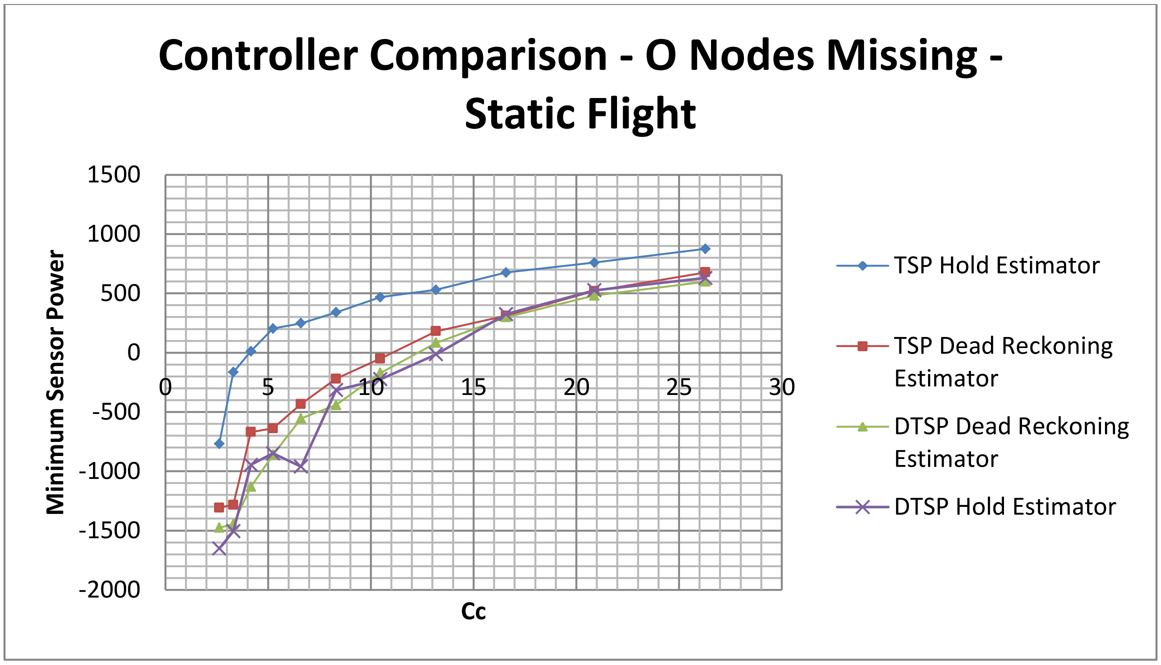

Figure 4.23 Controller Comparison – 0 Nodes Missing – Static Flight - Minimum Sensor Power

The TSP Hold Estimator had the lowest Cc for stability by more than 100% against any other controller.

4.1.5.2 Dynamic Flight

During Dynamic Flight, the TSP Hold Estimator performed the best overall.

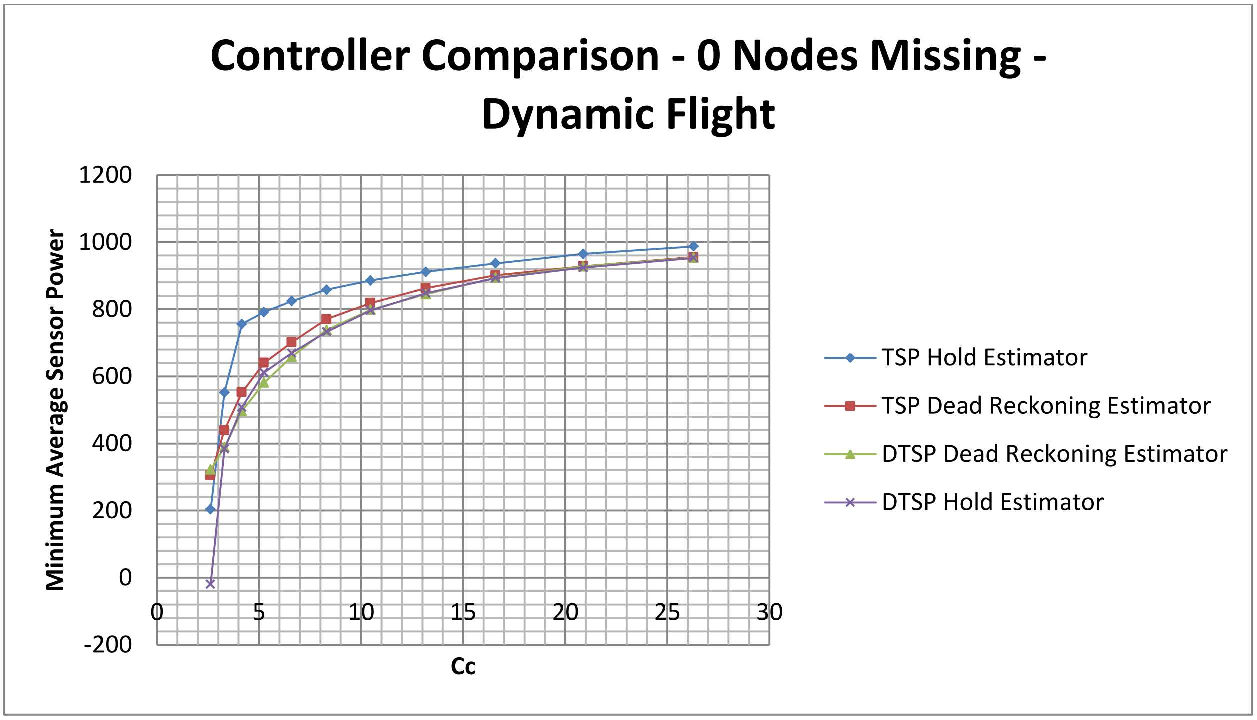

Figure 4.24 Controller Comparison – 0 Nodes Missing – Dynamic Flight – Minimum Average Sensor Power

At small values of Cc, the minimum average sensor power was actually bettered by two of the other three controllers. However, after investigating the minimum sensor power curves in the figure below, it is clear to see that for all valid and stable values of Cc, the TSP Hold Estimator controller was superior.

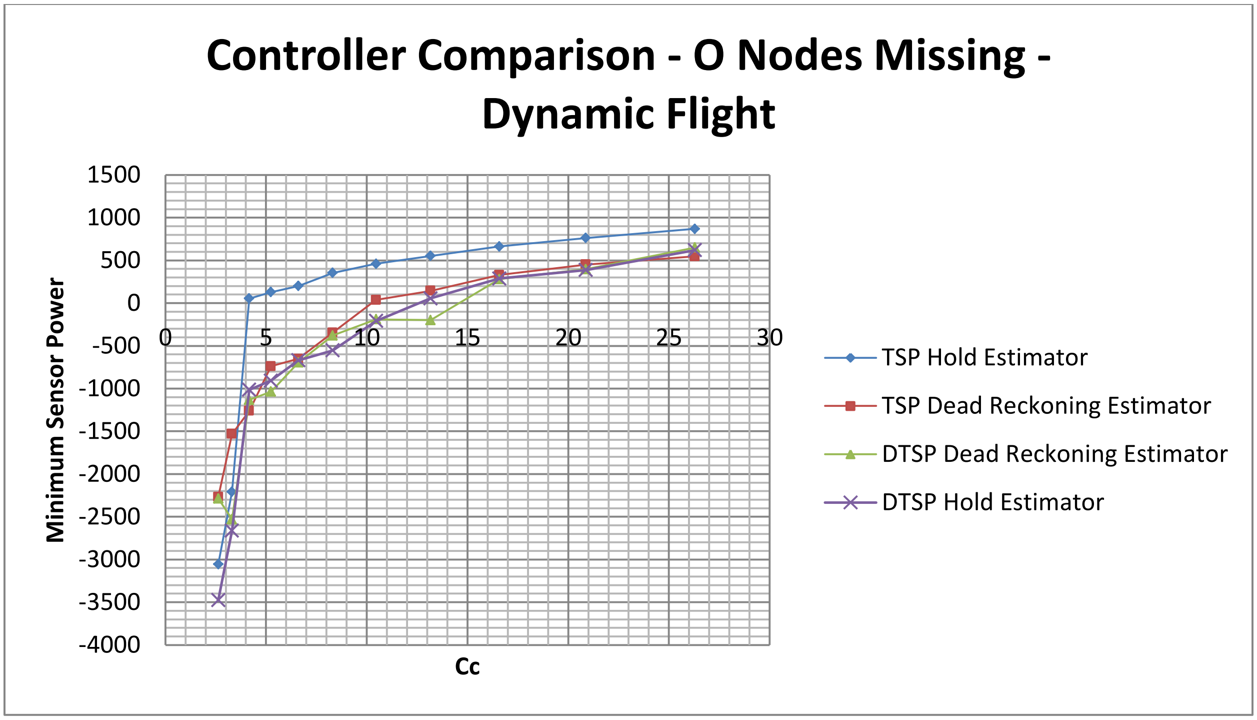

Figure 4.25 Controller Comparison – 0 Nodes Missing – Dynamic Flight – Minimum Sensor Power

Again, after investigating the cause and effects the different estimators had on the controllers, an estimator that targeted the location of where the Sensor UAV to be powered was going to be at Power UAV arrival would probably perform even better than the Hold Estimator. Notice that the TSP Hold Estimator, which is the least complicated in terms of estimation and recalculation of Power UAV flight path, is the only controller with a spike in the performance curves. This is because it is functionally superior to the other systems, but requires a certain amount of knowledge to execute effectively. The other curves gradually increase with the increase in Cc. This is because their constant recalculations are trying to make the right decisions, but the Sensor UAVs get into a race with the Power UAV.

4.1.5 Operational Efficiency

It is important to note that the simulations that compared the performance of different controllers with different nodes missing only accounted for the Cc and not operational efficiency. This is to say that when a Sensor UAV is taken from the system, its contribution to knowledge of the system might be trumped by its resource requirement and, therefore, boosting the system's performance if that Sensor UAV is taken away. However, operationally the system is operation at a lower capacity. Below is one such example that can be extrapolated to all the other controllers under investigation.

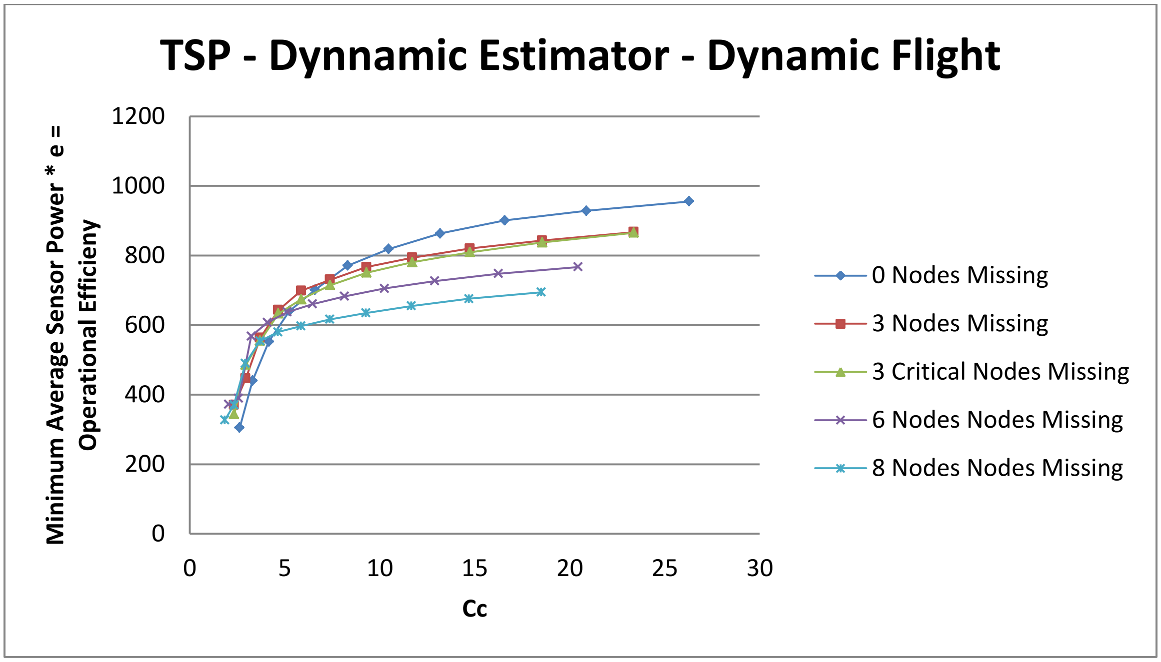

Figure 4.26 Operational Efficiency Example

One such way to account for operational efficiency is depicted in the figure above by taking the TSP Dead Reckoning Estimator during Dynamic Flight and simply multiplying each of the respective curves by their operation efficiency which is defined by the following.

- *e = efficiency*

- $N =$ *Number of total nodes in full system (always 27 for this thesis)*
- N_{NR} = *Number of nodes removed from the system*

$$e = \frac{N - N_{NR}}{N}$$

From the figure above, as Cc increases to a fully stable and operational system, the full network performs best as it can cover more ground. Prior to this section, there was no indication that losing a Sensor UAV is inherently bad because now it takes longer to traverse the area of operation.

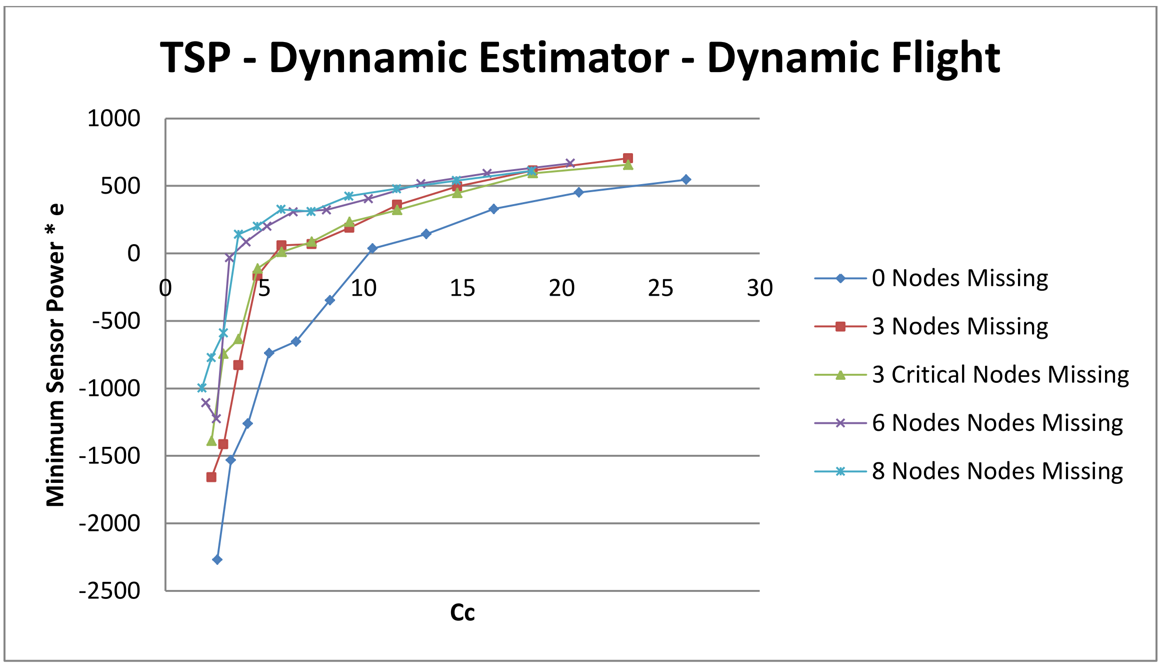

Figure 4.27 Operational Efficiency Stability Example

Note that this simple multiplication of the operational efficiency does not change the zero crossings on the minimum sensor power curves and, therefore, the stability constraints levied on Cc are the same.

4.1.6 Summary of Analysis

There were many controllers and performance curves investigated. This thesis is designed to try and understand the ties between knowledge of a system, and controller performance. The next section will summarize the findings from the other sections in Section IV Results and Analysis.

4.1.6.1 Controllers and Estimators

The TSP Hold Estimation controller had the best performance even though it was the least complicated. It had a pinnacle value of Cc that stabilized it and boosted its minimum average sensor power curve, more so than any other controller. This represented the definitive point that the system had enough knowledge to perform successfully. This controller showed this point because of its simplicity and greater requirement for knowledge. The other controllers gradually increased performance as Cc increased because of their sophistication. To articulate this point, the most complicated controller, the DTSP Dead Reckoning Estimation controller, had the most gradual performance curves. This controller would have probably trumped the TSP Hold Estimation controller had its implementation been even more sophisticated as mentioned earlier in this section.

4.1.6.2 Nodes Missing

The impact of nodes taken away from the system was dependent on many variables. The first variable is location within the total observed area which impacted the mean degree centrality. The second were the location of the other nodes that were taken out. Lastly, the number of other nodes taken out of the system impacts the performance of the resource controller. There was evidence of this three-way balancing act during analysis of the different simulations. If a corner JFCM node is taken out, the system will perform better because its contribution to knowledge does not outweigh its resource requirement. Same goes for a node that has the highest mean degree in the system because if it is the only one that is removed, then there is probably other sensors that can collect and pass on the pertinent information to the Power UAV. Problems arise when you get the wrong combination of nodes missing. Implementing this system into the JFCM approach simplifies the nondeterminism of the problem, but also allows for the wrong combination of sensors to be removed and effectively cutoff from the rest of the nodes.

4.1.6.3 Stability

The stability of the system was consequence of the Cc and the Pc. Establishing a Pc allowed this thesis to focus on the balance between the costs of knowledge versus system performance. During the experiments, the stability relied upon the controller and estimator algorithms, the number of nodes missing and Cc. Given a controller estimator pair's performance curves and algorithm for stability can be calculated as shown previously in Section IV. This algorithm will be different for every controller, but each algorithm will account for similar data.

V. Conclusions

The classification and mathematical representation of a nondeterministic system that includes needy nodes source nodes operating with given restrictions is an emerging problem. With the development of Internet 2.0 which has a cloud computing focus, and the military driving towards communication and information sharing MANETs, this problem will continue to arise in different forms and fashions. This thesis provides one way of approaching not a solution, but a way to attempt to understand the complexities. As these technologies start to develop, it is going to be increasingly important to determine a smart approach to mathematically classify these nondeterministic, infinite end state systems. This thesis used the connectivity coefficient because it can be generalized to any system by classifying the variable using the maximum potential knowledge of the controller to the maximum potential knowledge of the system. Implementing some control on this system by utilizing the JFCM operational model greatly simplified this resource allocation problem and increases the flexibility of the non all-knowing system. It ensured that the nodes were spread out over a vast area so that a functional MANET was created instead of having all the nodes move to the opposite corners of the map driving a full connectivity requirement.

This thesis focused on the case where the needy nodes and resource node were limited by communication distance. Future research could apply this model to more realistic parameters. Actual existing system parameters could be used to include a calculated mean time before failure of each of the systems to better determine the nodes that would drop out. Parameters could also include a more realistic communication distance model, actual power usage, supply and capacity, speeds and areas. This investigation could produce an actual realistic model and provide information on how many assets would be required to cover certain areas based upon a sensor coverage requirement. Another item could be to simulate terrain and model the effects on the system. This could include different altitudes amongst sensors and possible drive different power burn rates. It would also be interesting to develop another controller that takes into account a predefined importance of certain areas within the operational area and distributes the sensors accordingly and inputs this information into the resource provider.

Future research could also include an analysis of unrestricted sensor movement within the system and its effects on the connectivity coefficient.

Again, this problem investigated a MANET that required resources from a source that had limited knowledge of the system because of communication distance. The idea of utilizing the connectivity coefficient was to come up with a generalized way to classify this system so that this type of variable could be identified in other instances as it is based on knowledge. Therefore, a future project could work the same type of investigation on a different system that has knowledge based on something other than communication distance, like bandwidth restrictions, systems that gather information through data bursts, or any system that does not have full connectivity and that gets information in a random, or near random fashion.

VI. REFERENCES

[1] *Air Force Magazine.Com*. Air Force Association, 9 Sept. 2010. Web. 5 Oct. 2010. <http://www.airforce-magazine.com/DRArchive/Pages/2010/September%202010/September%2009%202010/AirSortiesfromSWA082910.aspx>.

[2] Balanis, Constantine A. Antenna Theory. 3rd ed. Hoboken (N.J.): J. Wiley-Interscience, 2005. Print.

[4] Bakht, Humayun. "Understanding Mobile Ad-hoc Networks." Computing Unplugged. Web. 5 Feb. 2011. <http://www.computingunplugged.com/issues/issue200406/00001301001>.

[5] DePalo, Lee K. *USAF Combat Search and Rescue - Untapped Combat Power*. Air Force Air University, Sept. 2005. Web. 10 Dec. 2010. <http://www.au.af.mil/au/awc/awcgate/maxwell/mp35.pdf>.

[6] Department of Defense. "Joint Publication." *Joint Fire Support* 3.09 (2006): A1-A12. *Http://www.bits.de/NRANEU/others/jp-doctrine/jp3_09(06).pdf*. Web.

[7] F, J. R. "UAV Operations in Current War on Terrorism." Personal interview. 17 Oct. 2010.

[8] Herniter, Marc E. *Programming in MATLAB*. Pacific Grove: Thomson Learning, 2001. Web.

[9] Jones, Phillip P. "Cooperative Area Surveillance Strategies Using Multiple Unmanned Systems." Thesis. Georgia Institute of Technology, 2008. Web. 3 Oct. 2010. <http://icsl.gatech.edu/aa/uploads/9/92/Pjones_proposal.pdf>.

[10] Kirk, Joseph. *Traveling Salesman Problem - Genetic Algorithm*. MATLAB Central, 16 Jan. 2007. Web. 2 Dec. 2010. <http://www.mathworks.com/matlabcentral/fileexchange/13680-traveling-salesman-problem-genetic-algorithm>.

[11] *Mobile Ad Hoc Networks (MANETs)*. Digital image. National University of Singapore, 4 July 2006. Web. 5 Mar. 2011. <http://www.comp.nus.edu.sg/~xuemingq/research.html>.

[12] Newman, M.E.J. "Mathematics of Networks." *Networks: An Introduction*. Oxford: Oxford UP, 2010. 109-52. Web.

[13] nondeterminism. (n.d.). The Free On-line Dictionary of Computing. Retrieved March 07, 2011, from Dictionary.com <http://dictionary.reference.com/browse/nondeterminism>

[14] Okamoto, Garret. Signals and Communication Technology. Berlin: Springer-Verlag, 2004. Print

[15] Powers, Rod. "Air Force Organizational Structure (Chain of Command)." *About.com*. Web. 16 Nov. 2010. <http://usmilitary.about.com/cs/airforce/a/aforganization_2.htm>.

[16] United States of America. Department of Defense. Air Force. *Air Force Budget*. Air Force Financial Management & Comptroller. Web. 21 Jan. 2011. <http://www.saffm.hq.af.mil/budget/pbfy03.asp>.

[17] USAF, comp. "Air Force Doctrine Document." *Strategic Attack* 2nd ser. 2.1 (1998): 28-31. Web.