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THESIS

EFFECTIVE HUMANITARIAN LOGISTICS DELIVERY USING SPACE-FILLING CURVES

by

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March 2019

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**EFFECTIVE HUMANITARIAN LOGISTICS DELIVERY USING
SPACE-FILLING CURVES**

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Submitted in partial fulfillment of the
requirements for the degree of

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from the

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ABSTRACT

The military has increasingly been used for humanitarian assistance and disaster relief (HADR) operations over the past two decades. HADR operations are an essential component of building international relations that often falls under the responsibility of the U.S. military. Department of Defense assets deploy globally to provide relief to other nations, and first responders offer valuable aid and provide supplies. Due to the nature of these missions, there is very little time for planning to respond to specific disasters. Disaster relief missions can take place in very austere environments where infrastructure may have been destroyed, making the people who need supplies harder to reach. We propose the use of a low-cost, low-maintenance, low-tech tool based on space-filling curves for vehicle route planning in HADR operations or similar high-impact missions and use simulation experiments to assess its performance. By utilizing this space-filling curve approach for route planning, the military can achieve up to 40% savings in distance traveled, fuel used, and time to complete deliveries over base case situations. Additionally, if used in conjunction with non-traditional delivery methods like unmanned aerial vehicles, better route planning methods can reduce fuel consumption and improve delivery timeliness even further.

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LIST OF ACRONYMS AND ABBREVIATIONS

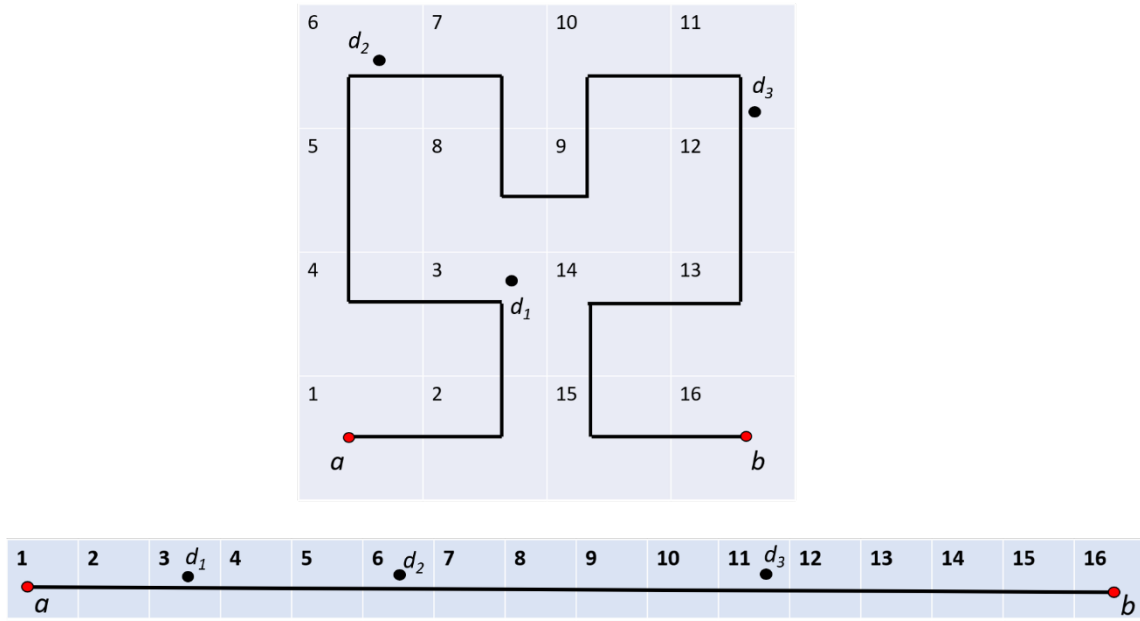
ACE	aviation combat element
ARG	amphibious ready group
AO	area of operations
DoD	Department of Defense
DOE	design of experiments
GCE	ground combat element
HADR	humanitarian assistance and disaster relief
LCE	logistics combat element
LH	Latin hypercube
MAGTF	Marine air-ground task force
MEU	Marine Expeditionary Unit
MOE	measure of effectiveness
MOW	Meals on Wheels
MTVR	medium tactical vehicle replacement
NGO	non-governmental organization
NOLH	nearly orthogonal Latin hypercube
NPS	Naval Postgraduate School
OLH	orthogonal Latin hypercube
SOP	standard operation procedure
SFC	space-filling curve
TSP	traveling salesman problem
UAV	unmanned aerial vehicles
ULS	unmanned logistics system
USMC	United States Marine Corps
USN	United States Navy
VRP	vehicle route planning

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EXECUTIVE SUMMARY

The characteristics of the United States military forces that make it an elite fighting force are also the ones that make it ideal for responding to humanitarian assistance and disaster relief (HADR) operations. The U.S. military has ground and air transportation assets for logistics and personnel movements, heavy equipment to clear roads and build or fix infrastructure, and a pre-existing command and control structure that allows for calm problem solving in the face of chaos. A low cost, low maintenance, and easy to implement vehicle routing planning tool can compound the military's existing strengths into cost-effective and more efficient logistics deliveries in HADR operations or similar mission environments. Additionally, this type of tool can be used in coordination with both governmental and non-governmental organizations (NGOs) or passed on to local authorities in a disaster area as the military leaves so continued aid delivery is uninterrupted.

The vehicle routing planning tool incorporates a space-filling curve (SFC) approach. A space-filling curve is a continuous curve whose range includes the entire 2-dimensional unit square, though more generally the range can be an n -dimensional unit hypercube. The SFC approach is adapted from a study by Bartholdi et al. (1982) where a routing system for the charity Meals on Wheels was created to heuristically solve the Traveling Salesman Problem. The objective of the Traveling Salesman Problem is to find the shortest route that passes through each of a set of points exactly once. The SFC approach consists of mapping any 2-dimensional square space to an SFC approximation of the space and assigning θ values to represent the relative locations of the curve numerically. Demands are generated on the 2-dimensional square and assigned appropriate θ values as delivery sites. Traversing the stops in order from the lowest to highest θ value is conceptually the same as straightening out the curve as if it were a linear route, as Figure 1 shows. In practice, convoy commanders must visit the sites in the order prescribed by the routes but have discretion on the actual transit between designated delivery locations.



A basic representation of how SFCs can be used to sort demands by taking a 2-dimensional space and reducing that space to a one-dimensional continuous line. The three demands here are used to show corresponding relative positions between the two spaces.

Figure 1. Example of SFC and straightened-out curve with demands.

The actual tool that could be used in the real world would consist of an SFC map overlay with θ values configured in a grid structure, a map of the region of interest, and a Rolodex system to use as an index referencing the θ value for delivery locations.

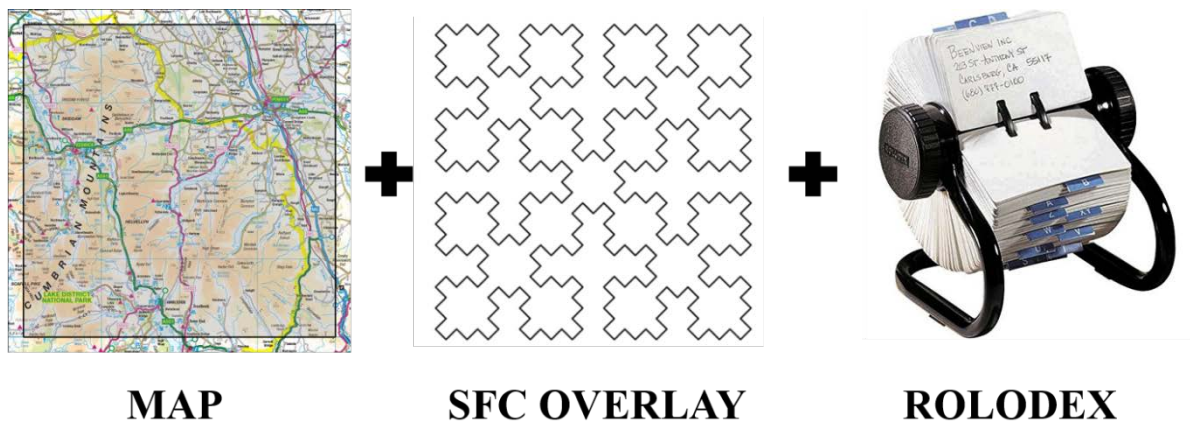


Figure 2. Components of the SFC tool.

In our study, we implement the SFC approach into a simulation called SFC-SIM and use data farming to acquire data for analysis under a variety of conditions. SFC-SIM generates random demands, assigns routes using several variants of the SFC method, and reports route characteristics. A designed experiment creates a large set of combinations of factor settings (model inputs) for the simulation runs, such as the military convoy and NGO delivery assets available, as well as the number of demands for aid. We also examine several vignettes: a base case vignette that randomly divides the delivery sites visited by military convoys into routes with roughly equal numbers of stops, and several variants that employ SFCs. The major findings from the SFC-SIM simulation and data farming analysis are as follows:

- The SFC-based vignettes consistently and significantly outperform the base case vignette, with an average savings in MOEs of 40 to 44%.
- The average distance traveled, fuel used, and time spent completing routes decreases as the number of convoys increases for all vignettes.
- Using unmanned aerial vehicles (UAVs) combined with ground transportation reveals the number of UAVs is a significant factor in determining the average total distance traveled. As the number of UAVs increases, the total distance traveled in the SFC method decreases.

The exact optimal for a Traveling Salesmen problem can only be computed if all the exact travel distances between each pair of delivery locations are known. It is unlikely to obtain this type of information during HADR operations. Some of the benefits of a low-tech tool like the SFC routing method include it being easy to implement, easy to share, and adaptable to the scenario it is used in which gives it flexibility. The SFC overlay and Rolodex components are easy to produce and provide a physical product to pass on to other organizations and ensure continuous logistics delivery planning in a region. This might improve the overall coordination capabilities between the military and NGOs in HADR operations. While the SFC method does not provide an optimal result for vehicle routing efficiency it does provide improved efficiency at an approximate minimum of 15% and value for HADR missions and similar scenarios. This improved efficiency, which results

in up to 40% savings of distance traveled, fuel usage, and time to complete deliveries, can turn the tide in saving money – and more importantly, saving lives.

Reference

Bartholdi JJ III, Platzman LK, Collins RL, Warden WH III (1982). A minimum technology routing system for Meals on Wheels. *Interfaces*, 13, 1–8.
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I. INTRODUCTION

A. PURPOSE

The efficient and timely delivery of supplies and materiel is the primary objective of any logistics organization. In the military, logistics often occurs under extreme conditions or in austere environments where every delivery could be the difference between success and failure, life and death. Since the 1990s the military has been increasingly involved in humanitarian assistance and disaster relief (HADR) operations (Hofmann and Hudson 2009). HADR operations are an essential component of building international relations that often falls under the responsibility of the U.S. military. Department of Defense (DoD) assets deploy globally to provide relief to other nations, and first responders offer valuable aid as well as provide supplies. Due to the nature of these missions, there is very little time for planning to respond to specific disasters or crises. Saving money for the DoD through effective logistics delivery, while still meeting the mission, is a critical objective as the military becomes more constrained by increasing mission requirements.

Exploring space-filling curve-based methods to determine a low-cost, low-energy tool to implement effective logistics delivery could be one solution for the DoD in HADR operations. Additionally, this tool could be passed onto the local government or non-governmental organizations (NGOs) after the military leaves, giving continuous routing capability at no extra cost or effort. This research leverages simulation, data farming, and space-filling curve (SFC) approaches to gain insight into using a low-maintenance tool to improve logistics delivery, especially in HADR operations.

B. BACKGROUND

This section covers the military role in HADR operations, a motivating example of the use of SFCs, and a brief overview of the analysis methodology.

The idea for implementing SFC methods for HADR operations first arose from a study by Bartholdi et al. (1982) on creating a routing system for a charity in Atlanta,

Georgia, to heuristically solve the Traveling Salesman Problem (TSP) (see also Bartholdi 2003). To understand how logistics operations work within HADR operations, an example of pertinent DoD organizations and equipment is explained in the this section. Using recent events in the Hurricane Maria relief efforts, the United States Marine Corps (USMC) and its relevant units will serve as a case study in this thesis.

A rudimentary discussion on SFCs is needed to understand how they can be utilized in addressing the problem. This and transportation route planning will be covered in the remainder of this section.

1. Military Role in HADR Operations

The use of military forces in HADR operations has increased in recent decades. This increase is partly due to the military having its own infrastructure that is flexible and expeditionary, especially for the Navy and Marine Corps forces which work in conjunction in Amphibious Ready Groups (ARG) and Marine Expeditionary Units (MEU). The exact structure and function of a MEU will be covered in depth in Chapter II. HADR is also used to project “soft power” diplomacy. The United States provides HADR for its allies and adversaries alike. The term soft power was first coined in the late 1980s by Dr. Joseph Nye, Jr., who described it as “the ability to get what you want through attraction rather than through coercion” (Jones 2019). The Marine Corps Operating Concept describes the future security environment being driven by complex terrain, to include being prepared to fight the “three-block war” in which humanitarian assistance is a critical component (United States Marine Corps [USMC] 2016). A third and final factor for the increased use of military for HADR is climate change and its impact on coastal regions, infrastructure, and resources. Espach et al. stated “between 1970 and 2003, more than two-thirds of the contingency-response incidents in the Pacific involved HADR conducted by the U.S. Pacific Command (USPACOM), which is the DoD joint combatant command responsible for all military operations in the theater” (2016, p. 96). The same study concluded that the storms and disasters seen today in that region alone will continue to increase with “greater average frequency and intensity” in the future (p. 89).

The military often does not act alone when responding to HADR missions. They are often working in conjunction with governmental agencies like the Federal Emergency Management Agency (FEMA) or NGOs like the Red Cross.

2. Transportation Route Planning

Transportation route planning or vehicle route planning (VRP) can be considered the bread and butter of logistics or supply chain management. A common problem within VRP is the traveling salesman problem (TSP), where the objective is to find the shortest route that passes through each of a set of points exactly once. Many factors and constraints often come into play when trying to plan routes for logistics delivery, and each one adds a layer of complexity to the problem. These factors and constraints include capacity, fuel, distance traveled, location of warehouses, location of deliveries, time constraints, available routes, traffic considerations, etc. Due to the complexity and related costs of logistics, businesses and other interested parties have been looking for optimal solutions for VRP that fit their specific needs and can increase their profit margin. The VRP problem has been studied intensely for several decades and there are many heuristic approaches to solving it to near-optimal levels (Yue et al. 2015). One of these heuristic approaches is the SFC.

Logistics delivery in HADR operations is similar to the VRP problems that plague businesses, but it also brings its own added complexity. For example, as will be discussed in Chapter II, Hurricane Maria destroyed a great deal of infrastructure and caused the roadways to be blocked by debris in Puerto Rico in 2017.

3. Motivating Example: Meals on Wheels

The “Meals on Wheels” (MOW) program is a charity that provides food for senior citizens unable to leave their homes. Volunteer drivers deliver the warm meals to 30 - 40 locations daily; these locations represent a rotating list of clientele, making routing somewhat volatile and difficult to manage. To address this issue, Bartholdi et al. (1982) developed an SFC approach that used an index system as coordinates, where a delivery location fell within the closest curve’s (x, y) coordinates. A representation of what the SFC overlay could look like appears in Figure 1. A Rolodex system was then used to keep track of the delivery locations based on these indexes and where they fell on the curve, which is

known as their Sierpinski index value (θ). The routing is based on sorting each client's θ value into a list of locations to visit from low to high values.

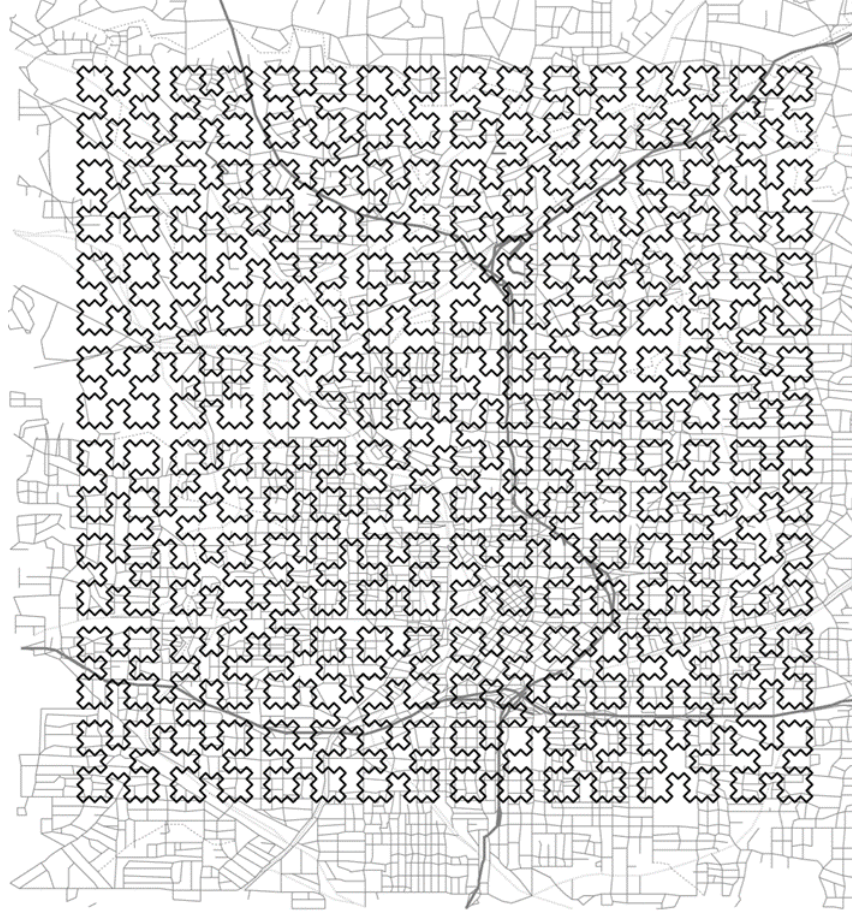


Figure 1. Example overlay of an SFC on an urban city map. Source: Bartholdi (2003).

The key takeaways from Bartholdi's 2003 study are:

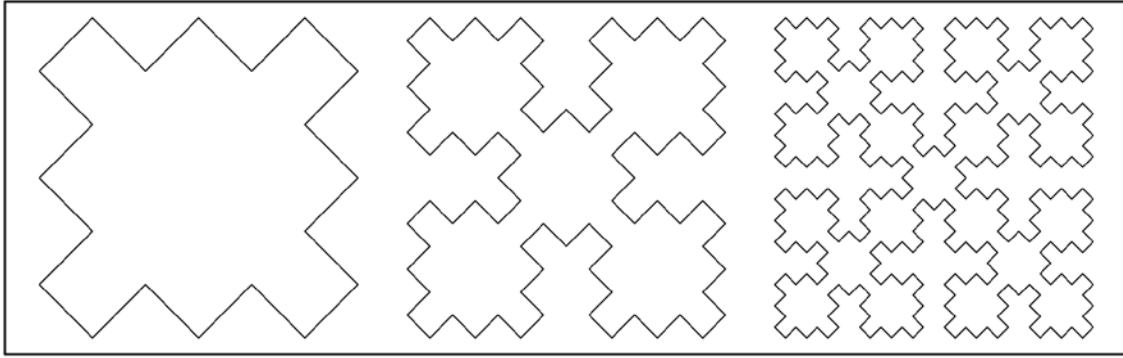
- The SFC heuristic algorithm generates tours that are only around 25 percent longer than the optimum for uniformly distributed sets of points.
- The runtime of the algorithm is $O(n \log n)$ because routing n locations requires only the $2n$ values of the coordinates (x, y) and the sorting of the Sierpinski values. This means minimal data is needed to formulate the routes and the typical $O(n^2)$ distances between points is not even required.

- Using the Rolodex index cards method made it easy to add or remove delivery locations. It is not necessary to re-solve or recalculate each time this happens.

One reason the SFC implementation for routing could be useful is once the grid of θ values is created and overlaid on a relevant map, the tool can be passed off to any organization in the area needing to make deliveries. As most NGOs are non-profit, this could ultimately save them time, money, and other resources. The military could create the map and grid combination, train pertinent NGOs in the area on how to use the routing method, and then pass on all materials for this low-cost, high-impact logistics tool.

4. Space-Filling Curves

SFCs were first discovered by the Italian mathematician Giuseppe Peano in 1890, in which he found a continuous curve that could pass through every point of a two-dimensional region. More specifically, “he constructed a continuous surjective mapping $I \rightarrow I^2$, where $I = [0,1]$ is the closed unit interval in the real line $\mathbb{R}$ and $I^2 = [0,1] \times [0,1]$ ” (Bernal-González et al. 2015, p. 58). According to Sagan (1994), the SFC was then further studied and illuminated by D. Hilbert in 1891, E.H. Moore in 1900, H. Lebesgue in 1904, W. Sierpinski in 1912, and many others since. In the MOW study, a Sierpinski curve was used for their recursion algorithm and is depicted in Figure 2 (Bartholdi 2003). An example of the Hilbert curve and its iterations can be found in Figure 3. Eventually, after so many iterations of different orders of SFCs, they would travel to every point within in a space, therefore filling that space with a continuous line.



The SFC is recursively constructed upon each preceding figure by splitting each square into quadrants and filling a smaller copy of the figure.

Figure 2. Example of an iterative Sierpinski SFC. Source: Bartholdi (2003).

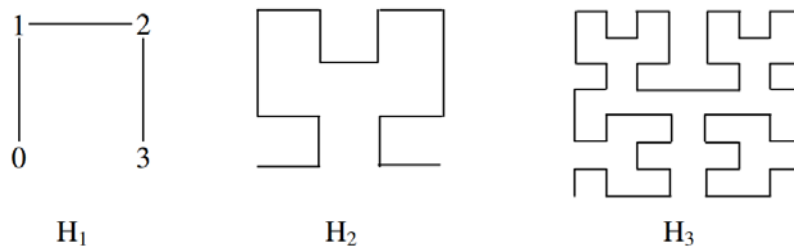


Figure 3. Hilbert curves of 1st, 2nd, and 3rd order. Source: Ali and Ladhake (2011).

Not all SFCs are necessarily created equally, because the shape of the curve does have some impact on the proximity of points. This is especially true when trying to use SFCs to come up with a delivery route. Other applications of SFCs include scheduling tasks or transactions, storing multidimensional data, searching, special access methods, indexing, and clustering (Ali and Ladhake 2011). Image browsing is one specific way SFCs can be used. Craver et al. suggest an interesting solution to boundary issues with SFCs in their paper on multi-linearization data structures for image browsing by using Hilbert and Peano curves in conjunction (1998). As can be inferred from the 3rd order Hilbert curve representation in Figure 3, two points could be right next to each other (for example, the two points nearest the center in the bottom row) and yet the curve requires a significant

distance traveled between them. The study further showed that Peano curves, however, do not have the same boundary issue, especially when overlaid with Hilbert curves (1998).

A deeper discussion on SFCs and how they are implemented in the methodology for this study is covered in Chapter III, which also includes the basics of the SFC method's algorithm and how it works.

5. Data Farming

This thesis uses a data farming approach to investigate the SFC method to see how well it is suited for HADR operations, both for ground and aerial delivery methods. Data farming involves generating (or growing) data from a simulation model by conducting large-scale designed experiments, and then using data mining methods and graphs to provide insights about how changes in the simulation model's inputs lead to changes in the model's outputs (Sanchez and Wan 2015).

C. RESEARCH QUESTIONS

Informed by past works on logistics delivery utilizing a basic space-filling curve-based method, as well as looking for improvements in HADR operations logistics delivery, this analysis will address two questions:

- Can we produce a low-cost, low-energy, and low-maintenance tool for planning that can be used by local organizations even after the military leaves the area of operations (AO)?
- How does incorporating unmanned aerial vehicle (UAV) delivery compare to traditional ground delivery?

This research attempts to answer the questions through simulating the SFC method and analyzing the resulting data, ultimately providing a tool for the military and other humanitarian aid organizations to use for effective logistics delivery in HADR or other applicable operations.

Space-filling curve-based approaches, simulation, and data farming are used to address the primary and secondary research questions. Chapter II discusses a real-world

case on recent Hurricane Maria relief operations in Puerto Rico by the 26th MEU. This case helps frame the problem and assess real world applications and approaches for the SFC method used in scenario vignettes. The exact implementation of the method is covered in detail in Chapter III. Chapter IV describes experiments used to study the vignettes, and then presents the analysis. Chapter V offers conclusions, recommendations, and potential directions for future work.

II. SCENARIO

A. HURRICANE MARIA DISASTER ASSISTANCE

Hurricane Maria made landfall in Puerto Rico on the morning of September 20, 2017 as a Category 4 storm with sustained wind speeds of 155 miles per hour and heavy rainfall for days. Ultimately, thousands of deaths and 25 to 43 billion dollars of damage occurred, and a week after Maria hit it was almost impossible to find food, water, and fuel (Cortés 2018, p.1). Initial support for hurricane relief efforts came from the 26th MEU, which was also supporting Hurricane Irma relief efforts in Florida at the same time, meaning resources and units were split between the two locations.

1. Units Involved

As part of the response to Hurricane Maria, the 26th MEU was sent to provide relief and assistance as necessary, filling in for as much destroyed infrastructure as possible, clearing vital routes and roadways, and delivering logistics for various classes of supply. A MEU is the smallest and most agile Marine air-ground task force (MAGTF) unit. More specifically, a MAGTF “is the Marine Corps principal organizational construct for conducting missions across the range of military operations” (USMC 2019, p. 2). The Marine Corps prides itself on being expeditionary and the MEU supports that mindset by providing “a forward deployed, flexible sea-based MAGTF” which can conduct many different types of operations, to include humanitarian assistance (USMC 2019, p. 4). A MEU is composed of the ground combat element (GCE), air combat element (ACE), and the logistics combat element (LCE). Additionally, the MEU is a part of the Navy-Marine Corps team where the Navy is represented by the Amphibious Ready Group (ARG). To illustrate a very basic relationship between these two units, their individual structures and command relationships are shown in Figure 4.

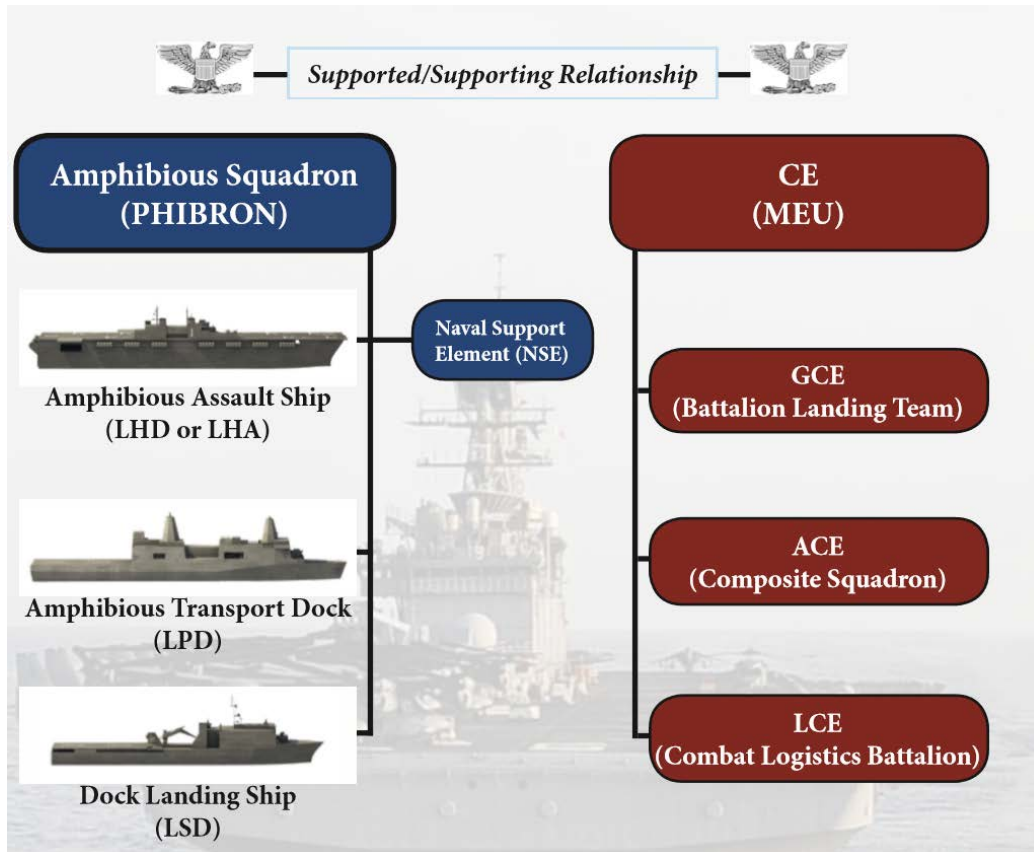


Figure 4. The Navy-Marine Corps fighting team as represented by the ARG on the left and the MEU on the right. Source: USMC (2019).

In Chapter III, the composition of equipment for the relevant elements of the MEU is discussed in deciding the model input value ranges.

2. Lessons Learned

The 26th MEU supported hurricane relief efforts for both Hurricane Irma and Hurricane Maria over a six-day period in October 2017. They were able to travel on the ground an approximate total of over five thousand miles and deliver 326 pallets of water and food, with over 750,000 pounds of aid transported for Hurricane Maria relief efforts alone (Werner 2017). To accomplish this, they had to clear more than 60 miles of roadway of storm debris. The ACE also contributed almost two hundred thousand additional pounds of aid transported with over 200 flight hours completed (Werner 2017).

B. THESIS SCENARIOS

From here on, we will refer to the method of assigning routes using a Sierpinski curve as the “SFC method.” We refer to our simulation model, that implements the SFC method and simulates its performance for randomly generated demands under a variety of situations, as “SFC-SIM.” As Chapter III will reveal, the SFC method is a heuristic approach to solving a route planning problem that can be modified to use several different employments. Five different SFC-SIM vignettes represent these different employments, to include a base case for comparative analysis, and four vignettes that use SFC heuristics. Bartholdi (2003) discusses how other heuristic methods for the TSP can yield routes that are closer to optimal, but they also were inappropriate for solving the specific problem for MOW because even the simpler ones needed a computer to solve. This thesis similarly avoids comparing the SFC routes to those of other heuristic methods, such as a greedy algorithm or nearest neighbor, because the point of this method is to be low-maintenance and low-tech in order to be used in austere environments like HADR operations.

All the vignettes in this thesis have the same basic form. A list of demand locations is provided. Each demand must be assigned to a route, either for an NGO vehicle or UAV (if one is available) or to one of several convoys. Routes for NGO vehicles or UAVs are assigned first, according to the rules for the specific vignette. The remaining demands are split roughly equally across the available convoys. Not all available convoys may be needed if the number of demands is sufficiently small. Unless otherwise specified, demands with the same θ value are consolidated into a single stop and not assigned to more than one vehicle or convoy: in other words, there are not separate stops for “repeat” demands.

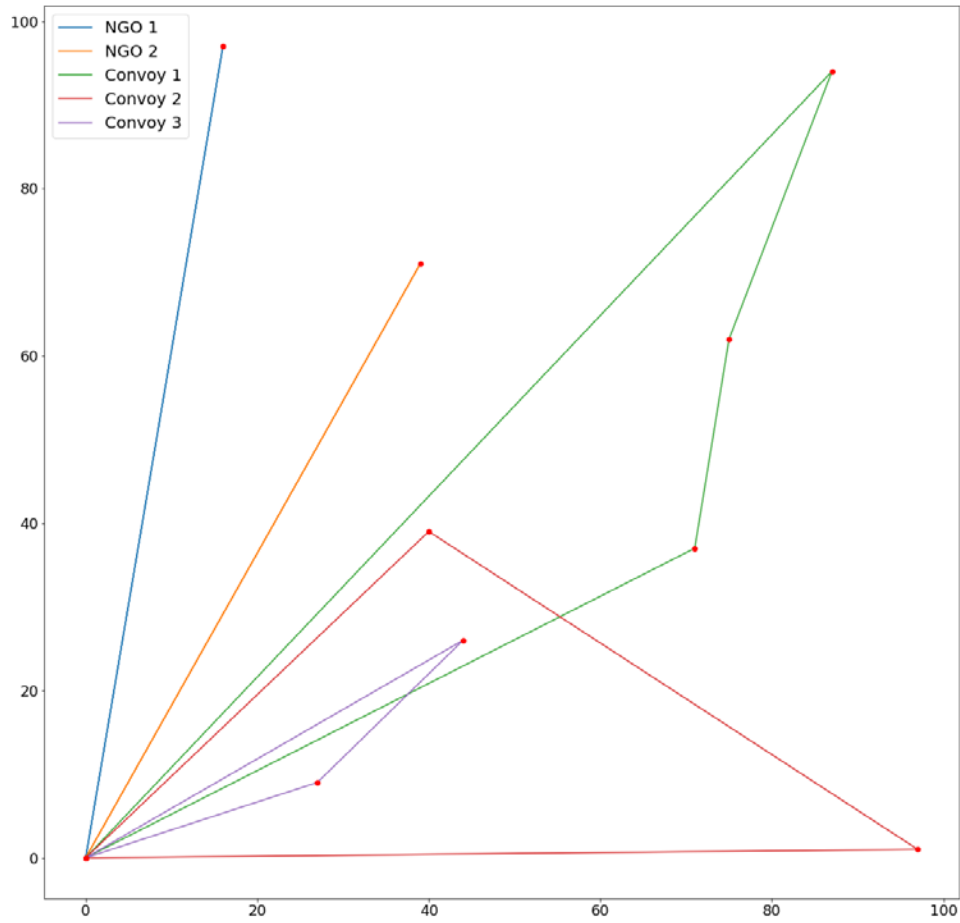
1. Vignette 0 (Base Case)

A base case vignette (Vignette 0) is used to make a comparison to the vignettes that use SFCs. This vignette assigns a random but even division of demands per route. The demands are not ordered according to distance or SFC θ values, which is where the randomness occurs. This base case does not yield the absolute worst-case scenario for VRP, which would result in a set of routes that maximize the total distance traveled. However, it

does represent a situation where little to no planning is put into use when designating routes for convoys to deliver supplies. While random assignment of demands to convoys is unlikely to occur in the real world, the chaos of HADR operations and other failures could be represented by this scenario, and it gives a baseline to measure against.

2. Vignette 1

This vignette incorporates NGO vehicle deliveries by giving them responsibility for the demand points with the lowest θ values and only one demand point per NGO vehicle. The lowest θ may not correspond to the shortest distance, as this value is simply representing the curve iteration and therefore the curve's location in the space. The remaining unassigned demands are then divided roughly equally across the convoys available. Consider the small example in Figure 5, involving nine demands, two NGO vehicles, and three convoys, for a total of five routes. Figure 6 shows what the route for the same demands in Figure 5 would look like if not split up into different routes.



This example involves 2 NGOs, 3 military convoys, and 9 demands, using a 100 by 100 grid size. The red dots represent demand locations and the colored line segments represent the Euclidean path between demand locations and origin.

Figure 5. Example routes generated using Vignette 1 SFC method.

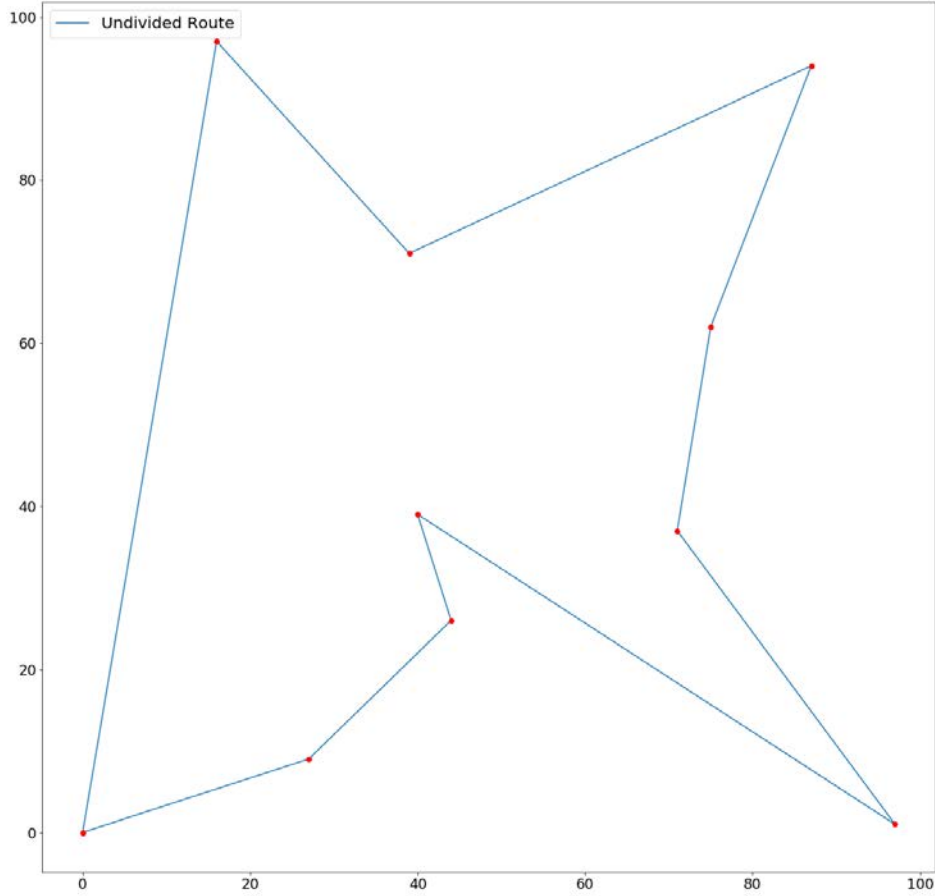


Figure 6. Example of undivided route from same demand points as in Figure 5.

3. Vignette 2

In this vignette, the NGO vehicles are assigned the points with the highest θ values, which is a different assignment priority from that of Vignette 1. The highest and lowest overall θ values in fact reside in the lower left hand of the grid. This means there is little difference in the routing for NGOs except in Vignette 1 they typically get points on the lower left-hand side of the grid and in Vignette 2 they typically get points in the lower right-hand side. Figure 7 shows the Vignette 2 routing method with the same input values from the example for Vignette 1. Although there are the same number of routes, most routes are different.

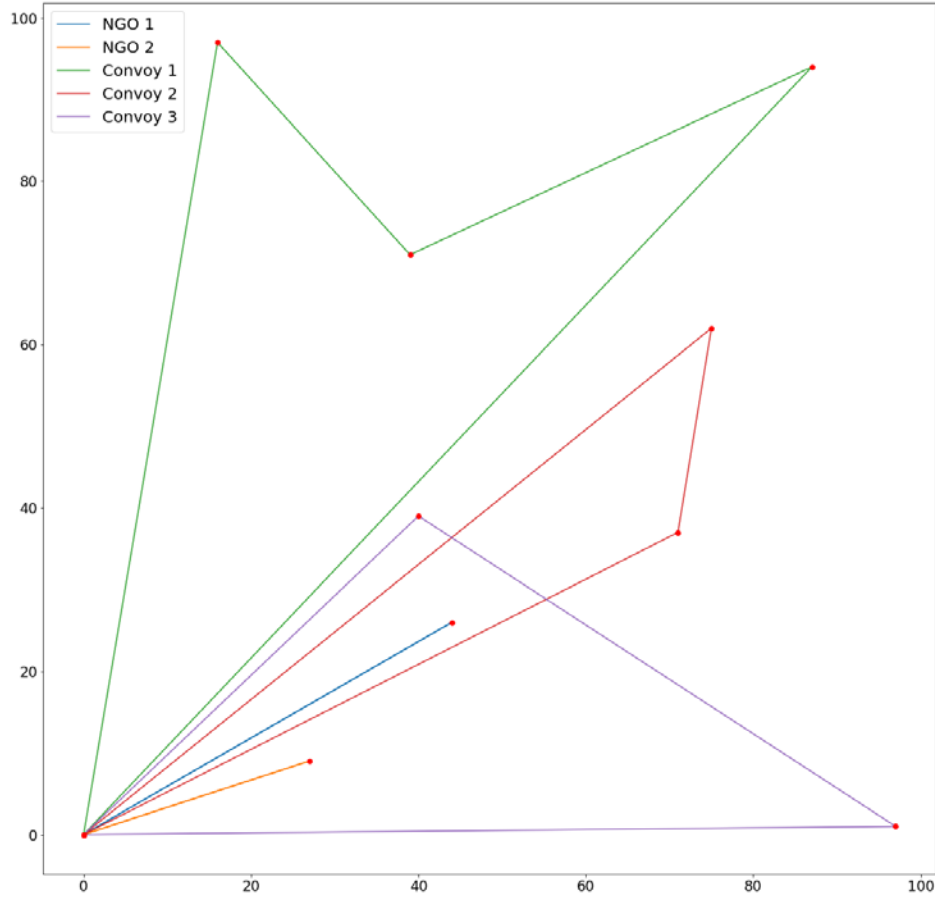
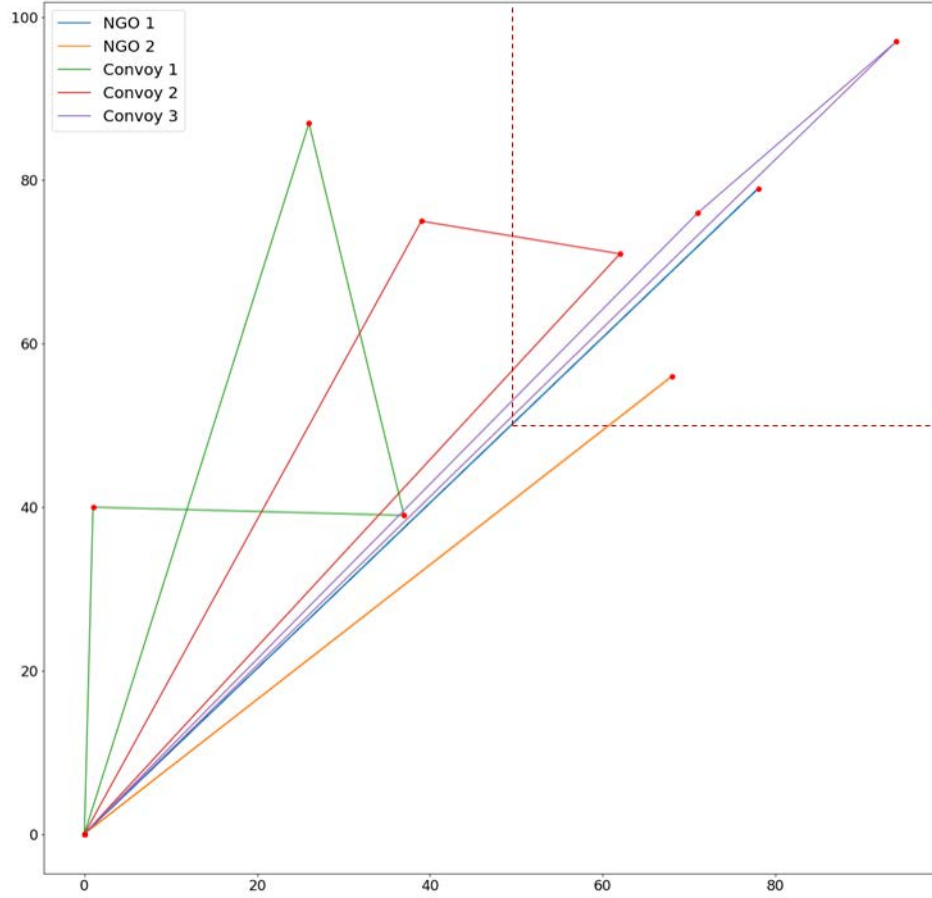


Figure 7. Example of routes using Vignette 2 SFC method.

An exploration of instead restricting the NGO vehicles to demands in the upper right corner of the grid, which then gives NGOs a farther distance routing method, is conducted in Chapter IV with modified Vignette 2 code. An example of what the routing would look like with different NGO demand locations, but otherwise the same input as examples for the other vignettes, is shown in Figure 8. Exploring both closest and farthest routing priorities for NGOs is important for determining whether there is an impact on the distance travelled by the military convoys.



Dotted red line represents border of area NGOs are restricted to making deliveries. Still the same inputs as previous vignette examples in this chapter.

Figure 8. Example of NGOs restricted to upper right quadrant in grid space for Vignette 2 exploration.

4. Vignette 3

Vignette 3 generates the requests for demands separately for the convoy elements and the NGO elements. There is no specific organization rule for giving either elements the highest or lowest θ values in this vignette like there is in Vignette 1 and 2. Figure 9 shows an example of Vignette 3.

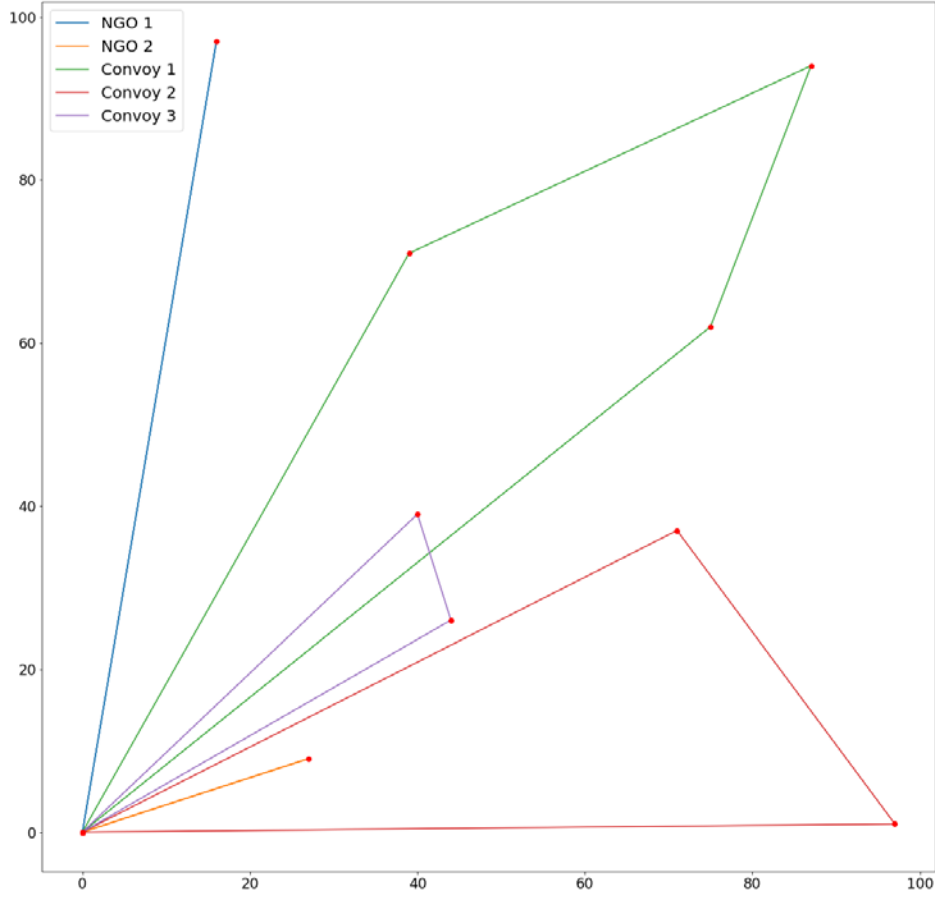


Figure 9. Examples of routes using Vignette 3 SFC-SIM.

5. Vignette 4

Vignette 4 compares UAVs to military convoys by replacing the NGO vehicle input with a UAV input instead, where the UAV is still only assigned a single demand just like the NGOs. In Vignettes 0–3, if there are repeat demands (for a given grid size) for the demand locations assigned to NGOs, then a single route is output for those demands. From a practical perspective, one NGO vehicle might be released from delivering aid and its volunteer(s) could be used to assist in other ways. In Vignette 4 the repeat demands are counted as a separate route for each vehicle (UAV) even if two are going to the same grid location. This realistically reflects capacity constraints on the UAVs, or possibly their need to carry different types of cargo. An example of Vignette 4 and its method for dealing with repeat demands in UAVs is found in Figure 10. This example used the inputs of two UAVs,

eight military convoys (though only 3 were graphed so the paths could be easily seen), 31 demands, a 10 by 10 grid size, and a random seed of 168026 since it had known repeat demands.

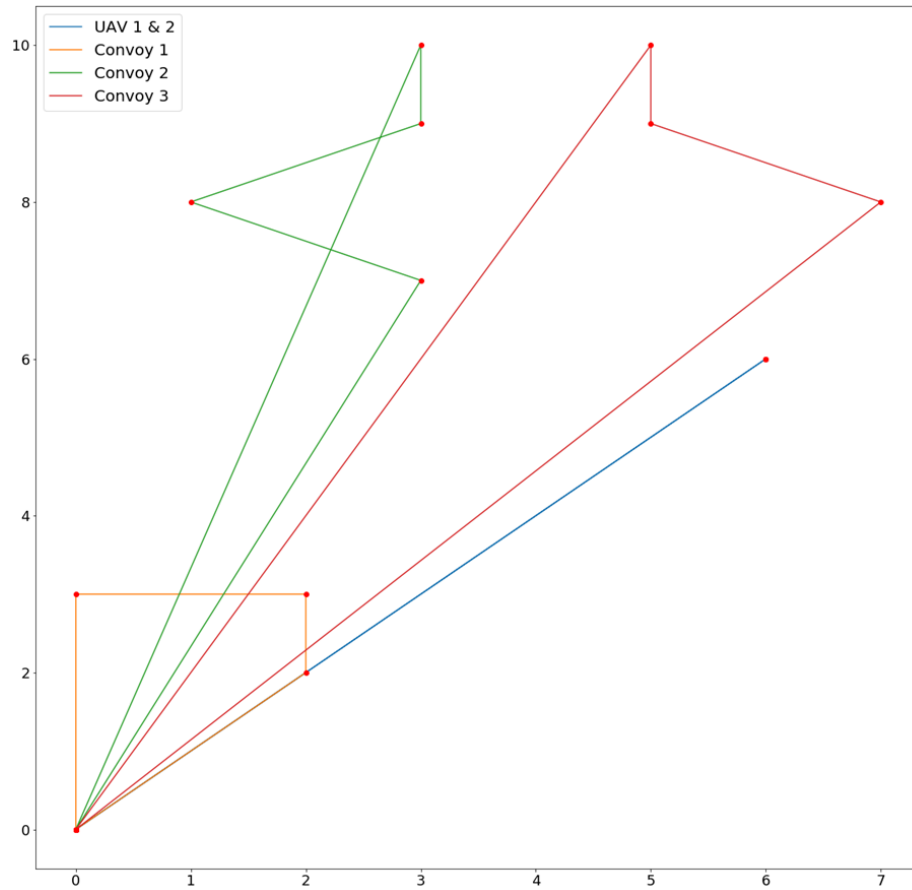


Figure 10. Example of Vignette 4 SFC-SIM which incorporates repeat demands and UAV deliveries.

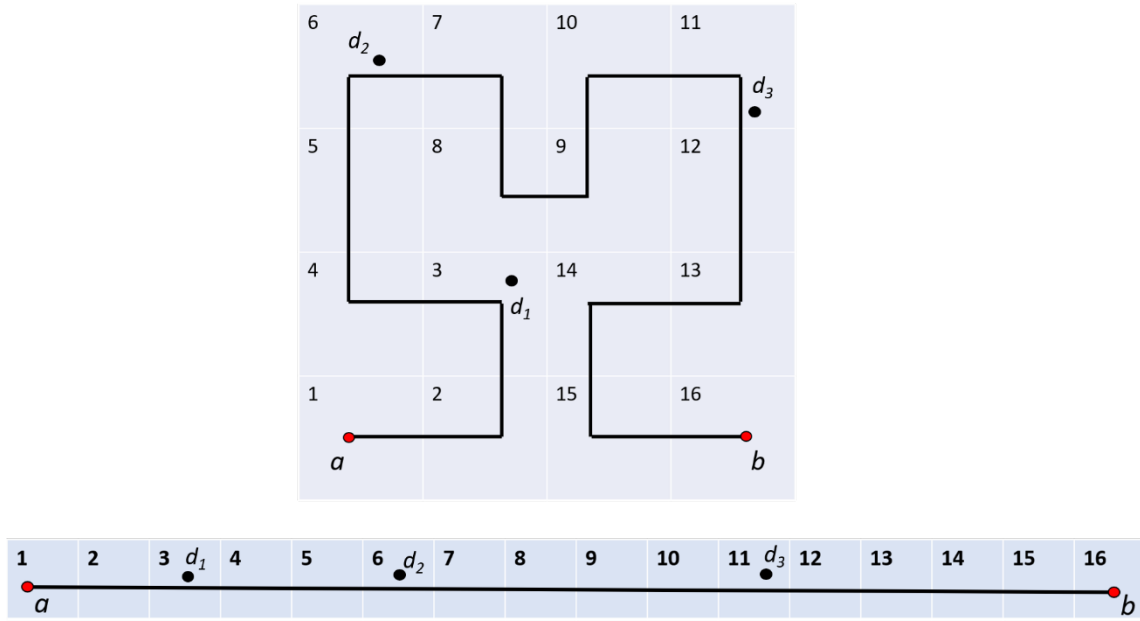
III. MODEL

A. OVERVIEW

SFC-SIM uses the Python programming language (Van Rossum 2019). It codes the algorithm that calculates a Sierpinski index value (θ) (Third Landing 2017), stores this θ in a Pandas data frame so it can be easily indexed, and extracts this θ for route creation indexing. Next, we create a randomly generated list of demands stored in a Python dictionary as the key and the θ value stored correspondingly for each demand as the dictionary's value. From there, using a simple sorting function gives the route to be traveled, going from coordinates with the lowest to highest θ value. The following sections of this chapter will discuss how specifically how heuristic approaches like SFCs method work, as well as the inputs, outputs, and logic of the SFC-SIM model.

B. SPACE-FILLING CURVES

As mentioned in Chapter I, SFCs have been used in various applications over time as they can map any n -dimensional data structure into a 1-dimensional data structure. The simplest way to think of SFCs is that they are a continuous string that can fill every space within a defined area, and the string can be straightened out to look at how specific points fall in a linear order (see Figure 11).



A basic representation of how SFCs can be used to sort demands by taking a 2-dimensional space and reducing that space to a one-dimensional continuous line. The three demands here are used to show corresponding relative positions between the two spaces.

Figure 11. Example of SFC and straightened-out curve with demands.

C. MODEL INPUTS

1. Number of Vehicles

This represents the number of NGO vehicles in Vignettes 0–4. NGO vehicles may be making deliveries in addition to military convoys during HADR operations. To account for these vehicles, it is safe to assume about 0 to 3 vehicles in an austere environment. The NGO vehicles will operate independently of one another and only make a single delivery to one point in SFC-SIM Vignettes 0–3.

In Vignette 4, the number of vehicles represents the number of UAVs, each making a single delivery. This allows for ground versus air delivery comparisons.

2. Number of Convoys

The military has a specific number of vehicles allotted to each unit and each vehicle typically can serve various missions. The USMC's standard vehicle for handling logistics deliveries and other cargo is the medium tactical vehicle replacement (MTVR), also known

as a 7-ton. The GCE typically owns 31 MTVRs and the LCE typically has 15 MTVRs (United States Marine Corps [USMC] 2019). Realistically, there will be many different taskings for those vehicles and it is rare to have all vehicles available due to maintenance issues. For this reason, it is safe to assume that between 1 and 15 vehicles are available for HADR delivery on any given day of the mission. For SFC-SIM, a convoy can be considered anything from a single vehicle making a delivery to multiple vehicles moving in conjunction.

Every unit has its own standard operating procedure (SOP) that dictates convoy operations and what parameters must be met for each convoy before executing a mission. This SOP would help specify the convoy operations in terms of convoy size, vehicle composition, maximum speed traveled, distance spacing between vehicles, how long the missions can last before fresh drivers are needed, which personnel by MOS-type should be on the convoy, example equipment and personnel manifesting documents, and many other pieces of information that ultimately play a role in logistics planning. For the simplicity of SFC-SIM, sending out 1 to 10 convoys in a single operating day is a reasonable range for this input.

3. Number of Demands

For SFC-SIM, each demand location is randomly generated using the **random** module in Python. Demands can fluctuate from low to high each day, depending on how often certain classes of supply need to be replenished, emerging crises in a post-disaster environment, and based on the ability to meet demands due to stockpile levels. Therefore, the code generates demand locations uniformly distributed over the area of operations.

4. Grid Size (Level of Refinement)

For SFC-SIM, any integer value x can be entered for the MAXINPUT and a resulting x by x grid will be the output. For example, if the MAXINPUT value is 10, then a 10 by 10 grid will be the output (see Figure 6). There is a possibility of multiple demands being at the same (grid) location, particularly if the number of demands is large relative to the grid size. The exploration of the size of refinement and how it affects distances traveled could be an interesting measure of effectiveness of the SFC method. Treating grid size as

a factor that changes during the experiment, rather than a parameter that remains fixed, will reveal whether the choice of grid size has a big impact on overall efficiency and effectiveness. It should be noted that to benchmark results, the vignette codes scale distances based off grid size. How the scaling is applied is covered in the model assumptions (Section F).

	0	1	2	3	4	5	6	7	8	9	10
10	127	129	135	152	158	159	225	231	248	254	255
9	126	124	138	149	156	161	220	234	245	252	257
8	120	117	112	144	170	167	213	208	240	266	263
7	103	106	80	79	181	184	202	207	272	277	280
6	97	92	85	74	67	190	195	309	298	284	286
5	31	33	39	56	62	63	318	312	295	289	287
4	30	28	42	53	60	446	323	330	341	348	353
3	24	21	16	48	458	440	437	335	336	362	359
2	7	10	15	464	469	423	426	400	368	373	376
1	1	3	501	490	476	417	412	405	394	380	382
0	0	510	504	487	481	415	414	408	391	385	383

Produced by SFC-SIM code in a Jupyter Notebook.

Figure 12. A 10 x 10 table with an assigned θ value for each (x, y) grid coordinate.

5. Random Seed

To facilitate comparisons among different vignettes, the analyst has the option of controlling the random number seed. A random seed is simply a number used to initialize the **random** Python module, which is in fact a pseudorandom number generator.

D. SFC-SIM ALGORITHM

To better understand how SFC-SIM works, the following pseudocode gives a step-by-step breakdown of incorporating the SFC algorithm from Bartholdi (2003) and its implementation for simulation and data farming.

1. Generate Sierpinski θ values for designated grid space.
2. Store θ values in Pandas dataframe.
3. Generate n demands.
4. Match and store related θ values to demand (x, y) coordinates.
5. Sort demands on θ value (low to high).
6. Consolidate repeat demands (demands with shared θ value).

$$n_stops = n_demands - n_repeats$$

7. Assign one stop to each NGO vehicle (or UAV), using the Vignette logic.
8. Split remaining stops ($n_stops - n_NGO_stops$, or $n_stops - n_UAV_stops$) to routes for $n_military_convoys$.
9. Output routes and associated route characteristics.

E. MODEL LOGIC

In this section we provide additional details on the underlying logic for calculating route and route characteristics.

1. Euclidean Distance

The Euclidean distance is also known as the straight-line distance or “as the crow flies” distance. More simply, it is the distance measured between two points on a plane. For example, the distance between (x, y) and (a, b) can be calculated by the following equation:

$$dist((x, y), (a, b)) = \sqrt{((x - a)^2 + (y - b)^2)} \quad (1)$$

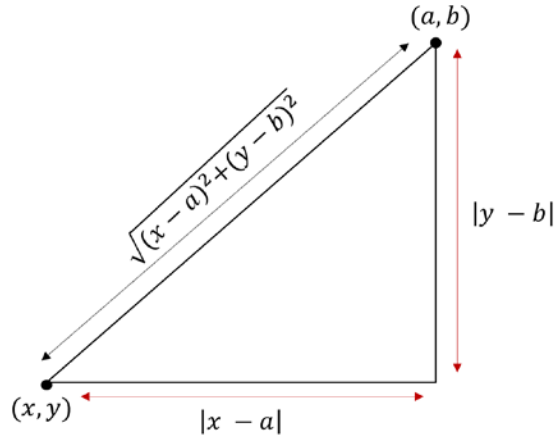
Complete routes based on Euclidean distances may be reasonable representation of distance traveled for UAVs or rural ground vehicle transport.

2. Manhattan Distance

The Manhattan distance is also known as the city block or taxi cab distance. This distance measurement is often more realistic for vehicles traveling, especially along grid-based streets in urban areas. The Manhattan distance is calculated using the following equation:

$$dist((x, y), (a, b)) = |x - a| + |y - b| \quad (2)$$

A basic comparison of the two distances can be found in Figure 13.



The “legs” of the triangle represented by red arrows are the two distances that equate to the Manhattan distance when added together. The hypotenuse of the triangle is equivalent to measuring the Euclidean distance.

Figure 13. Representation of Euclidean and Manhattan distances.

3. Repeat Demands

As discussed in Chapter II Section B and this chapter’s section D, demands can be generated with the same θ in which case they are treated as a single delivery location. Since repeat demands can be created, repeats must be tracked because they do affect the number of “stops” a convoy makes. The repetition of demands is realistic because multiple demands for one location or a cluster of nearby locations are likely.

4. Route List

The route list output helps visualize the route traveled for each simulation run and can reveal overall patterns or amplifying information.

F. ASSUMPTIONS AND LIMITATIONS

In addition to the previously stated assumptions for SFC-SIM’s input values, further assumptions and limitations shape the output of SFC-SIM.

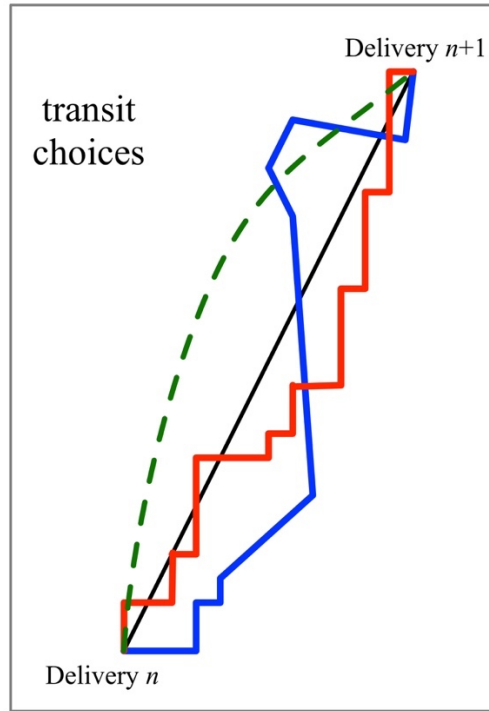
1. Model Assumptions

As statistician George Box famously quipped, “All models are wrong, but some are useful.” It is important to state the assumptions used in conjunction with SFC-SIM because

they address the gaps the model cannot cover and add clarity to the analysis of the results in Chapter IV.

- Assume all delivery routes begin and end at the same initializing point of coordinate (0,0). There would likely be different start points in the real world, especially if units are stationed at different locations, but it is not unrealistic to see a scenario where most or all supplies are stockpiled in a single location. This can be especially true when operating in a smaller AO or if the infrastructure is severely damaged.
- A follow-on to the previous assumption is that convoy will not resupply within SFC-SIM logic, meaning the convoy does not need to stop at a warehouse or stockpile at any point during their route. Once they leave the initialization point, they will complete the route as planned.
- Assume that capacity is not an issue and the number of vehicles and their corresponding bed space is sufficient to meet the demands on the route.
- Assume all the scheduling of demands and routing takes place once a day, such as the same time every morning. This is to account for all demands at once instead of constantly updating throughout the day.
- To make all runs comparative, scaling the grid size must occur when calculating distance. The code uses the square kilometer (km) area of Puerto Rico as a comparative AO, which resulted in scaling by a ratio of one hundred to the MAXINPUT.
- Convoy commanders in real world applications of the tool must visit the sites in the order prescribed by the routes.
- Convoy and other military commanders in real world applications of the tool will have discretion on transit between designated delivery locations. Consider Figure 10, the commander could choose to travel in a straight line if it was an aerial delivery (black line), along a curvy highway (green

dotted line), through urban districts that use the Manhattan distance (red line), and a combination of different roads that are known to be safe or not blocked by debris (blue line).



Possible transit paths between delivery point n and delivery point $n+1$. This allows for the routing of visiting delivery points in order but using a path that best fits each convoy's other restrictions and needs.

Figure 14. Transit discretion for convoy commander example.

2. Model Limitations

Since SFC-SIM is a simulation of HADR operations that incorporates only a heuristic solution to the TSP, it has some significant limitations to what it can represent. The complexities of the real world must be substituted with assumptions because SFC-SIM is extremely simple.

- SFC-SIM just looks at 2-dimensional rendering of space and therefore cannot account for elevation changes.

- SFC-SIM provides results for a single day.
- SFC-SIM will typically not provide an optimal solution to the TSP.

These limitations are less restrictive than they might appear at first glance. First, there are 3-dimensional versions of SFCs that could be used in locations where different or rapidly-changing elevations are a concern. Second, because the situation on the ground may be very different from day to day, it makes sense to investigate the daily variability—keeping the method simple to implement. Third, in order to calculate an optimal route for the deterministic TSP, the analyst must know the exact distances between all pairs of delivery sites—an impossible undertaking in HADR operations characterized by uncertainty and rapidly-changing conditions.

G. SIMULATION OUTPUT

The SFC-SIM Python vignette files print out identifying information for each run and then several outputs. An example of the raw output can be seen in Figure 15. The run is made by typing “`python vignette_3randseed.py 2 31 8 10 168026`” on the command line. The first line contains all header information, the second line gives the corresponding information the headers label, for example vignette number is first header title in line one and vignette number is the first value in line two of the output. The remaining lines correspond to each route produced and include the Euclidean distance, Manhattan distance, and the points visited in each route. The NGO routes are listed first, followed by the military convoy routes.

```

C:\Users\aspri\Desktop\updated rand files>python vignette_3randseed.py 2 31 8 10 168026
vignette n_NGO_convoy n_demands max_MC_convoy maxin n_routes n_stops rn_seed
3 2 31 8 10 10 28 168026
169.70562748477138 240.0 [(0, 0), (6, 6), (0, 0)]
169.70562748477138 240.0 [(0, 0), (6, 6), (0, 0)]
88.2842712474619 100.0 [(0, 0), (0, 0), (2, 2), (2, 3), (0, 3), (0, 0)]
235.2821556977404 300.0 [(0, 0), (3, 7), (1, 8), (3, 9), (3, 10), (0, 0)]
250.46553677733388 340.0 [(0, 0), (5, 10), (5, 9), (7, 8), (0, 0)]
271.8154610843157 380.0 [(0, 0), (8, 8), (9, 9), (9, 10), (0, 0)]
293.73003012496014 400.0 [(0, 0), (10, 10), (10, 7), (9, 6), (0, 0)]
194.20743220670803 260.0 [(0, 0), (7, 4), (8, 3), (8, 4), (0, 0)]
248.48857801796103 280.0 [(0, 0), (9, 4), (10, 4), (10, 0), (0, 0)]
97.0820393249937 120.0 [(0, 0), (4, 2), (4, 1), (2, 0), (0, 0)]

```

Figure 15. Example output from one run of a design point in the command terminal.

The output can be printed to a file for further analysis, rather than simply printed to the screen.

1. Measures of Effectiveness (MOEs)

In this thesis, MOEs are defined as quantifiable measurements that are related to some objective and help mark progress or make a decision.

a. *Average Distances Traveled*

A measurement that logisticians look at is distance traveled, though usually it is analyzed in relation to time and related costs. In this thesis, the comparison of two different distance measurements is evaluated for all the runs of each scenario.

(1) Euclidian Distance versus Manhattan Distance

Reporting these two different distance measurements is useful for two reasons. The Euclidean distance as previously defined and discussed gives an approximation of distance traveled for UAVs or other air-based transportation. The Manhattan distance gives an upper limit approximation of ground-based transportation because it measures in a “block” fashion.

(2) Average Time to Complete Routes

When it comes to delivering logistics, other than quantity of items delivered, the most demanding measure of effectiveness is the time it takes to complete routes. Often

there is a specific time window an item must arrive in for the delivery to be considered effective. While the assumption has been made for SFC-SIM that every item is delivered “on time,” looking for a pattern of time taken in the simulation results will be critical for measuring efficiency of SFC-SIM. We had to make some assumptions about the SOP and the operating environment for converting the distances into time for completion. A typical military convoy does not go more than 40 miles per hour (mph) or about 64.4 kilometers per hour (kph) to ensure cohesiveness of convoy and for safety. Since HADR missions occur in less than ideal conditions, there may be an additional slowing down of convoy speeds so 20 mph or about 32.2 kph is also a fair assumption. These two speeds will be used in the average time to complete routes conversion in analysis.

For the scenario in Vignette 4, the UAV fuel rate consumption is based on the values for the unmanned logistics system (ULS) which was the subject of Ekman’s NPS thesis “Simulating sustainment for an unmanned logistics system concept of operations in support of distributed operations” (2017). The values are 65 kilometers per hour (km/hr) for the small ULS, 130 km/hr for the medium ULS, and 463 km/hr for the large ULS (Ekman 2017).

b. Fuel Savings

We calculate the convoy vehicle fuel usage based on travel speeds and vehicle burn rates when combined with distance traveled. There are several variants of the MTVR used by the Marine Corps, but its most common cargo variants are the MK23 and MK25 Standard Cargo MTVR. Their fuel capacity is 78 gallons and they have a cruising range of 300 miles or 483 kilometers (Oshkosh 2010). This approximates to a fuel usage rate of 0.16 gallons per kilometer or 0.26 miles per gallon. The first rate will be used to calculate fuel usage based on outputs of SFC-SIM.

For the scenario in Vignette 4, the UAV fuel rate consumption is based off of the values for the ULS. The values are 2 gallons per hour (gal/hr) for the small ULS, 9 gal/hr for the medium ULS, and 250 gal/hr for the large ULS (Ekman, 2017).

IV. EXPERIMENT AND ANALYSIS

In this chapter, we define the design of experiments (DOEs) and post-processing of output used to farm and clean the data. Once we clean and organize the data, we use it to investigate the relationship between the factors and our previously defined MOEs of interest.

A. DESIGN OF EXPERIMENTS

Even though SFC-SIM is very simple, there is still a computational cost for running the simulation for each set of parameters. Running every combination of all levels of four factors for the vignettes would computationally grow large and take a significant amount of time to run.

1. Definitions

Some of the common terms used to describe the elements of DOE are defined in this section.

- **Factors:** This term is interchangeable with input variables or parameters, except that factors are varied in a controlled way during an experiment. Factors can take on discrete or continuous quantitative values, as well as qualitative or binary value types (Kleijnen et al. 2005). In this study, the model inputs described in this chapter are all factors. Useful simulation results often distinguish the important factors for the simulations outputs and which combination of factors influence results (Sanchez and Wan 2015).
- **Factor levels:** Each factor has two or more of these values and is usually coded numerically to make analysis easier (Kleijnen et al. 2005).
- **Design point:** a combination of the factor levels for all factors.

2. Efficiency in DOE

Once the model is built, the goal is to simulate through design points in a manner that will give the best representation of outputs so the data can be analyzed effectively. This means an efficient DOE is a critical part of any simulation and modelling study.

a. Nearly Orthogonal Latin Hypercubes

Latin hypercubes (LHs) are based off Latin square designs, which have a single sample in each row and column, and are represented in a hypercube, or a cube with more than three dimensions. LH sampling is commonly used in simulation because it can be used to screen many factors and have minimal restrictions on sampling budget (Hernandez et al. 2012). Refinements of LH sampling are the orthogonal Latin hypercube (OLH) and the nearly orthogonal Latin hypercube (NOLH), which are structured (rather than random) to eliminate unwanted characteristics of simple LHs. OLHs are defined as LHs with a correlation coefficient between all pairs of columns in the design matrix of zero (Hernandez 2008), but they do not always exist. An NOLH is defined as a “LH with a maximum pairwise correlation no greater than 0.05 between any two input variables” (Hernandez et al. 2012). NOLHs are useful because they keep the number of total design points that have to be run through a simulation manageable without reducing the analysis capability on the outputs.

The Simulation Experiments & Efficient Designs (SEED) Center for Data Farming at the Naval Postgraduate School (NPS) has many tools available to assist with data farming. These include a suite of data farming scripts that are publicly available at <https://rubygems.org/gems/datafarming> written in the Ruby programming language. We use one of these Ruby scripts, `stackednolh.rb` (Sanchez 2018) to create a stacked NOLH DOE of 113 design points. We cross that design with the one hundred random seeds using another data farming script (`cross.rb`) to give a total of 11,300 runs for the each of the four vignettes. In other words, we conduct 100 replications with common random numbers because we control the random number seed for each replication.

Table 1. Factor ranges and levels.

Factor	Range
# of NGO vehicles	[0,3]
# of convoys	[1,10]
# of demands	[10, 100]
Grid size	[10,1000]
Vignette	[0, 1, 2, 3, 4]

3. Output Post-processing

We use another Ruby file, `rundesign_general.rb`, to run the entire DOE for each of the vignettes. All runs were made on a 2.9GHz i9 MacBook Pro. Vignette 0 is the fastest (80 minutes of CPU time for the 11,300 runs) because it does not include any SFC calculations or other route planning heuristics. The other vignettes require about 15 CPU hours each. Multiple cores on the MacBook Pro make it possible to run them simultaneously.

While this process outputs the information wanted, it may not be in the format needed for analysis, especially since each design point needs to be summarized over the replications. In order to have a file that is easily read into JMP, (the statistical software we use for analysis), we must post-process the raw data output had to occur. A Ruby post-processing script reads the raw output (see Figure 15 in Chapter III, Section F) and summarizes the results of each run with statistics like the minimum, maximum, and average distance traveled for the vehicles and convoys, as well as design point and vignette identifying information.

A portion of the processed output can be seen in Figure 16, where it is formatted as a comma separated value (CSV) file and displayed in Excel. This format makes it easy to upload into statistical software like JMP and immediately analyze the data. Note that the “NaN” (not a number) entries in Figure 16 are not errors: if there are no NGOs, then there are no calculations for any of the NGO distances and “NaN” becomes a placeholder value.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
1	vignette	n_NGO	coi	n_demand	max_MC	c_maxin	n_routes	n_stops	rn_seed	n_ngo	min_d1ngo	max_d1ngc	avg_d1ngo	stdev_d1ng	min_d2ngo	max_d2ngc	avg_d2ngo	stdev_d2ng	n_mc	min_d1mc
2	1	0	20	8	629	8	20	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	103.5041	
3	1	0	26	6	319	6	26	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6	138.4348	
4	1	0	26	7	753	7	26	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	97.31789	
5	1	0	28	3	196	3	28	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	256.8992	
6	1	0	28	7	814	7	28	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	97.25554	
7	1	0	28	9	567	9	28	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	9	97.33801	
8	1	0	29	3	814	3	29	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	254.2981	
9	1	0	29	7	72	7	29	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	124.4584	
10	1	0	31	9	10	9	25	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	9	89.44272	
11	1	0	33	10	691	10	33	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	10	97.09783	
12	1	0	33	3	258	3	33	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	268.2816	
13	1	0	33	8	10	8	26	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	104.7214	
14	1	0	33	9	258	9	33	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	9	97.34084	
15	1	0	37	3	381	3	37	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3	266.1045	
16	1	0	37	9	691	9	37	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	9	112.5213	
17	1	0	41	4	567	4	41	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4	202.9074	
18	1	0	41	7	196	7	41	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	131.5548	
19	1	0	43	4	629	4	43	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4	202.8442	
20	1	0	43	9	1000	9	43	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	9	112.5558	
21	1	0	44	8	938	8	44	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8	131.4939	
22	1	0	46	7	938	7	46	100580	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	7	146.7865	
23	1	1	20	9	567	10	20	100580	1	80.46427	80.46427	80.46427	NaN	90.65256	90.65256	90.65256	NaN	9	103.3349	
24	1	1	20	9	753	10	20	100580	1	80.42197	80.42197	80.42197	NaN	90.57105	90.57105	90.57105	NaN	9	103.4699	
25	1	1	22	4	381	5	22	100580	1	80.54793	80.54793	80.54793	NaN	90.81365	90.81365	90.81365	NaN	4	201.025	
26	1	1	22	5	629	6	22	100580	1	80.5381	80.5381	80.5381	NaN	90.62003	90.62003	90.62003	NaN	5	166.6573	
27	1	1	22	7	876	8	22	100580	1	80.43046	80.43046	80.43046	NaN	90.63927	90.63927	90.63927	NaN	7	120.9016	
28	1	1	24	3	691	4	24	100580	1	70.85026	70.85026	70.85026	NaN	87.12012	87.12012	87.12012	NaN	3	209.2353	
29	1	1	24	5	10	6	21	100580	1	63.24555	63.24555	63.24555	NaN	80	80	80	NaN	5	208.3131	
30	1	1	24	5	72	6	24	100580	1	68.71843	68.71843	68.71843	NaN	83.33333	83.33333	83.33333	NaN	5	168.0211	

Figure 16. Processed output data in Excel.

B. COMPARING BASE CASE TO SFC VIGNETTES FOR DISTANCE MOES

In this section, we use partition trees, regression models, and graphical displays to obtain insight about several distance-related measures. We are particularly interested in which factors are most important, including comparisons among the vignettes.

1. Partition Tree

In JMP (2019), the partition platform splits data recursively on optimal predictors “according to a relationship between the predictors and response values.” For this thesis scenario, the partition tree is used to examine the vignettes, number of NGO vehicles, number of convoys, and number of demands to choose which are the best predictors for the minimum, maximum, and average distance traveled per route. Figure 17 depicts the latter.

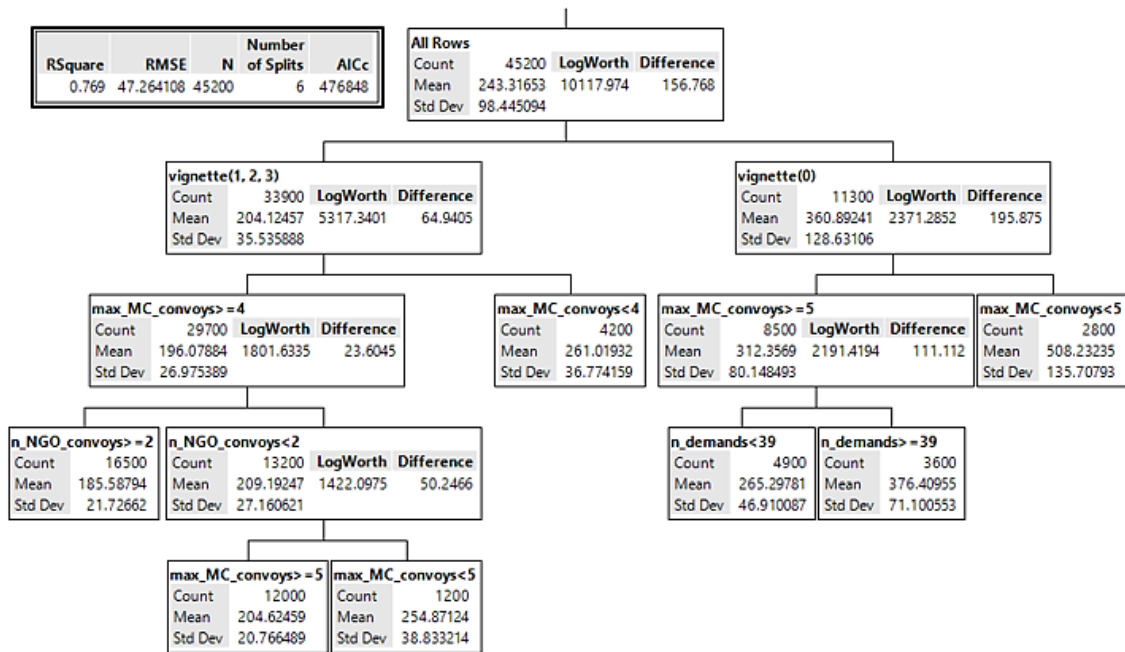


Figure 17. Partition tree for average total Euclidean distance traveled per route (avg_d1tot).

As seen in Figure 17, the first or most significant split is on the vignettes with Vignettes 1–3 being significantly different from the base case vignette. For example, the split of vignettes gives Vignettes 1–3 a mean of about 204 km and Vignette 0 a mean of about 361 km. Some of the insights from the partition tree are:

- The SFC-based vignettes (Vignettes 1–3) give a significantly lower average route distance traveled and a smaller standard deviation.
- The number of convoys is the next significant factor affecting average route distance traveled, with four or more convoys leading to better results than less than four. This is further refined two splits down with six or greater yielding better results. This finding is not surprising considering it intuitively makes sense that the more convoys there are, the shorter the distance each needs to travel.
- The number of demands and number of NGO convoys have smaller effects.
- The grid size has no effect.

With only six splits total, this partition tree has an R-squared value of 0.769. R-squared values can tell if the factors as represented in the partition tree are a good or accurate fit for the response variable. This R-squared value is reasonably high and statistically significant ($p < 0.001$), but it does not tell the whole story. The partition tree in Figure 17 can continue to be split into new branches and nodes until reaching no further splitting is possible, but that becomes unwieldy and might not provide any new insight about just how important each predictor variable is in its ability to predict the response.

2. Regression

Regression is an alternative to a partition tree that sometimes give a clearer picture of the relationship between the prediction factors and the response variable. In JMP, potential factors and their possible interactions or polynomial effects can be selected and then analyzed by a sequence of F-tests. A stepwise regression on the data helps to eliminate

some of the unnecessary terms. The results of a stepwise regression model for the response variable of average total Euclidean distance is shown in Figure 18. Our goal is to look at the four input variables and the vignette, all two-way interactions, plus the second-degree polynomial effects for the quantitative factors.

Current Estimates						
Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio" "Prob>F"
☒	☒	Intercept	319.879116	1	0	0.000 1
☐	☒	vignette{1&2&3-0}	-77.123918	10	2.783e+8	46753.62 0
☐	☒	vignette{1&2-3}	-7.5600228	5	2461153	827.009 0
☐	☒	vignette{1-2}	-0.6017096	1	8182.43	13.748 0.00021
☐	☒	n_NGO_convoys	-28.530879	7	36575694	8778.816 0
☐	☒	n_demands	4.09957388	5	54414870	18284.75 0
☐	☒	max_MC_convoys	-23.40685	7	1.115e+8	26758.20 0
☐	☒	maxin	-0.005587	5	171567.2	57.651 5.2e-60
☐	☒	vignette{1&2&3-0}*(n_NGO_convoys-1.50442)	13.6055251	1	6019704	10113.85 0
☐	☒	vignette{1&2-3}*(n_NGO_convoys-1.50442)	-3.9433695	1	463897.8	779.406 5e-170
☐	☐	vignette{1-2}*(n_NGO_convoys-1.50442)	0	1	2224.017	3.737 0.05323
☐	☒	vignette{1&2&3-0}*(n_demands-35.0619)	-2.8758238	1	23845531	40063.46 0
☐	☒	vignette{1&2-3}*(n_demands-35.0619)	-0.1344968	1	47809.92	80.327 3.3e-19
☐	☐	vignette{1-2}*(n_demands-35.0619)	0	1	1001.479	1.683 0.19458
☐	☒	vignette{1&2&3-0}*(max_MC_convoys-6.50442)	13.9901866	1	33402454	56120.28 0
☐	☒	vignette{1&2-3}*(max_MC_convoys-6.50442)	1.24423792	1	242187	406.904 4.3e-90
☐	☐	vignette{1-2}*(max_MC_convoys-6.50442)	0	1	253.8558	0.427 0.51371
☐	☒	vignette{1&2&3-0}*(maxin-505.062)	0.00330336	1	35752.26	60.068 9.4e-15
☐	☐	vignette{1&2-3}*(maxin-505.062)	0	1	18.33131	0.031 0.86069
☐	☐	vignette{1-2}*(maxin-505.062)	0	1	458.4903	0.770 0.38012
☐	☒	(n_NGO_convoys-1.50442)*(n_demands-35.0619)	-0.43984	1	452387.5	760.067 6e-166
☐	☒	(n_NGO_convoys-1.50442)*(max_MC_convoys-6.50442)	5.55895383	1	5980252	10047.57 0
☐	☒	(n_NGO_convoys-1.50442)*(maxin-505.062)	0.00220107	1	18786.04	31.563 1.94e-8
☐	☒	(n_demands-35.0619)*(max_MC_convoys-6.50442)	-0.3177187	1	1481637	2489.334 0
☐	☐	(n_demands-35.0619)*(maxin-505.062)	0	1	5386.007	9.051 0.00263
☐	☒	(max_MC_convoys-6.50442)*(maxin-505.062)	0.00086804	1	12232.24	20.552 5.82e-6
☐	☒	(n_NGO_convoys-1.50442)*(n_NGO_convoys-1.50442)	5.19074281	1	1066989	1792.673 0
☐	☐	(n_demands-35.0619)*(n_demands-35.0619)	0	1	743.5267	1.249 0.26371
☐	☒	(max_MC_convoys-6.50442)*(max_MC_convoys-6.50442)	2.15668704	1	3486699	5858.087 0
☐	☒	(maxin-505.062)*(maxin-505.062)	0.00001186	1	33500.17	56.284 6.4e-14

The unchecked boxes in the “Entered” column represent parameters that can be eliminated as reliable prediction variables.

Figure 18. Stepwise regression results example for average total Euclidean distance in JMP.

Once the stepwise model is complete, the resulting factors can be fed into a least squares linear regression model to further analyze the factors and their ability to predict the response. Figures 19 and 20 show some of the pertinent least squares results following stepwise regression.

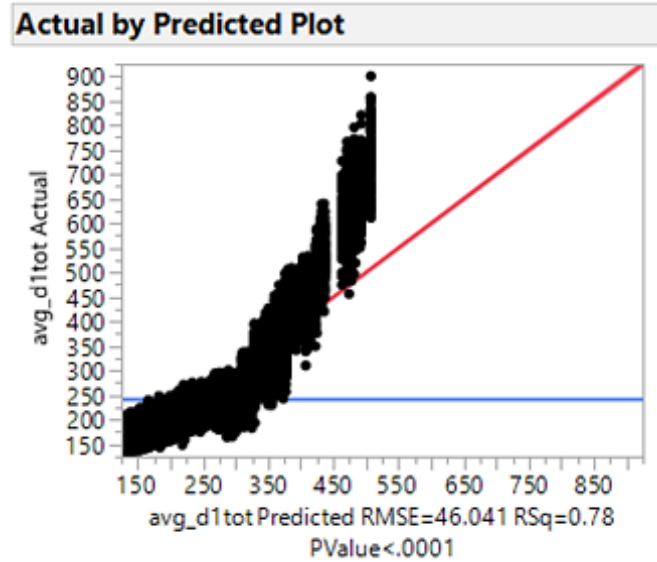


Figure 19. Actual versus Predicted Plot for average total Euclidean distance.

Effect Summary			
Source	LogWorth		PValue
vignette{1&2&3-0}	10959.58		0.00000
max_MC_convoys	4851.500		0.00000
n_demands	2483.393		0.00000
n_NGO_convoys	2131.421		0.00000
n_NGO_convoys*max_MC_convoys	599.871		0.00000
max_MC_convoys*max_MC_convoys	354.805		0.00000
vignette{1&2-3}	177.554		0.00000
n_demands*max_MC_convoys	153.123		0.00000
n_NGO_convoys*n_NGO_convoys	110.861		0.00000
n_NGO_convoys*n_demands	47.803		0.00000
maxin	7.837		0.00000
maxin*maxin	4.177		0.00007
n_NGO_convoys*maxin	2.550		0.00282
max_MC_convoys*maxin	1.797		0.01595
vignette{1-2}	1.312		0.04871

The factors and factor interactions below the red line do not seem to significantly impact the predicting power of the linear regression model.

Figure 20. Summary of factor effect in the least squares regression model.

The actual versus predicted plot in Figure 19 shows how close the least squares regression model fits the data. The R-squared value is 0.78 which is similar to that of the partition tree. However, there are two types of issues with the regression model. First, looking at the effect summary of each factor and interaction in Figure 20, anything below the red line does not appear to add significance to the model. In this case, we can remove the grid size (shown as maxin in Figure 20) as a significant prediction factor. Doing so makes no discernable difference in the Actual by Predicted plot and does not change R-squared.

The second problem is due to lack of fit. The Actual by Predicted plot in Figure 19 shows a distinct lack of fit as the data points have a slight upward exponential curve which therefore cannot have a linear fit. One way to rectify this problem is a transformation of the response (avg_d1tot). Separate application of a square root, logarithmic, and reciprocal transformation of the response each result in an improvement. The best-case regression model fit occurs with the reciprocal transformation of the response, as seen in Figure 21.

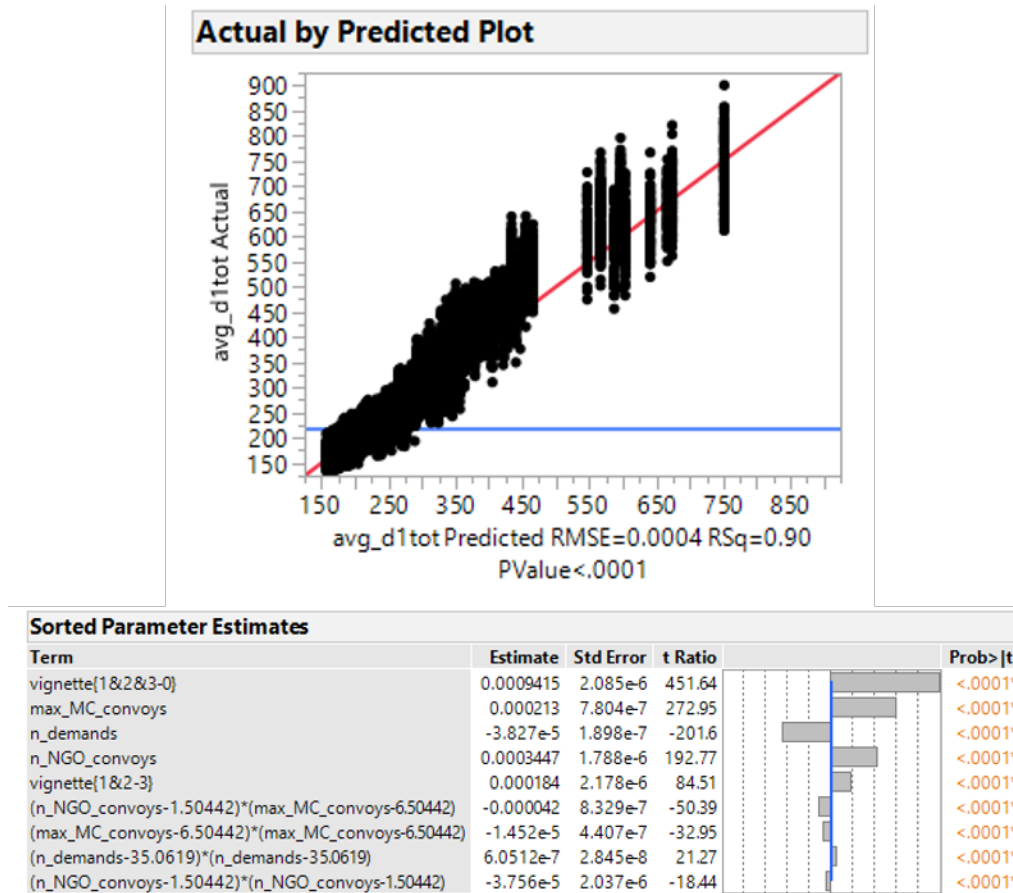


Figure 21. Final model plot and sorted parameter estimates for average route total Euclidean distance traveled.

Figure 21 shows an improved Actual versus Predicted plot with an R-squared of 0.90, which is a good indication of fit. Additionally, we would be able to reduce the terms suggested by the stepwise regression as the sorted parameter estimates show in Figure 2. We could eliminate some of the terms with small parameter estimates and still have little to no impact on the fit of the model. The order of the importance of the factors is the same as the partition tree, with vignette being the most significant and grid size having no impact.

Ultimately, we are interested in determining which factors and terms have the biggest impact on our MOEs of interest. While the regression models can give us some insight on important factors, they do not give any more information on this than the partition trees. Additionally, there is no change in the list of terms that are important between the Euclidean distance or the Manhattan distance, as they are highly correlated

($\rho > 0.999$). We will focus on the partition tree and graphical analysis for the remainder of the analysis since partition trees are simpler than the regression model and yet provide the same insight.

A quick summary of the regression model analysis and insight on which factors best predict the output:

- The stepwise regression does not eliminate many potential interactions among any of the prediction factors.
- In every follow-on least squares regression model, grid size (maxin) can be eliminated as an important predictor in the model.
- Overall, R-squared values for the regression models are consistently above 0.7 which shows a decent fit for the model.
- There is no difference between the two distance types when it comes to the important prediction factors in the regression models.
- Just like in the partition tree, the vignette is the most significant factor in determining the predicted value in the model. The second most significant factor is the number of military convoys.

3. Box Plots

With vignette type and number of military convoys consistently showing up as significant predicting factors in determining the distances traveled in the model, box plots help with visualizing the comparison between these factors. As seen in Figure 22, there are three noteworthy trends:

- There is a very clear delineation between the amount of distance traveled in Vignette 0 versus the amount of distance traveled in the SFC vignettes (Vignettes 1–3) on average.
- Among the SFC vignettes there is no discernable difference between the average distances traveled.

- As the number of convoys increases, the average distance traveled per route decreases for all vignettes.
- After seven convoys there is no significant difference among the SFC average distance traveled per route.

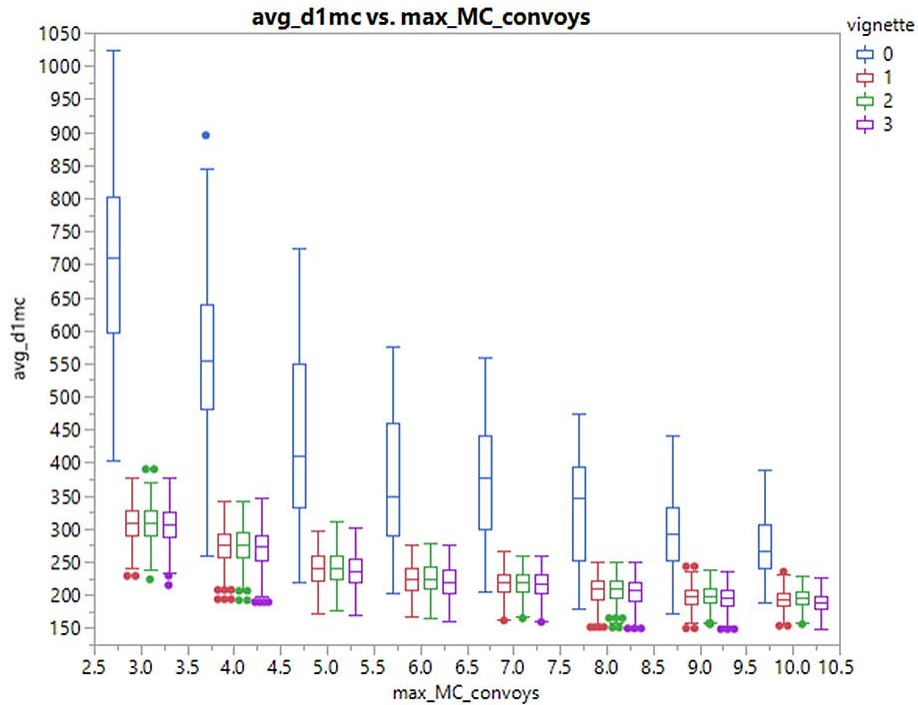


Figure 22. Average Euclidean distance traveled for military convoys versus number of military convoys in each vignette.

The trends found in Figure 22 hold true for similar box plots when minimum and then maximum distance traveled are on the y-axis, which intuitively makes sense. Also, there is no difference other than magnitude when comparing the Euclidean and Manhattan distance results. One more interesting boxplot, of total Euclidean distance traveled by number of convoys for each of the vignettes, is in Figure 23.

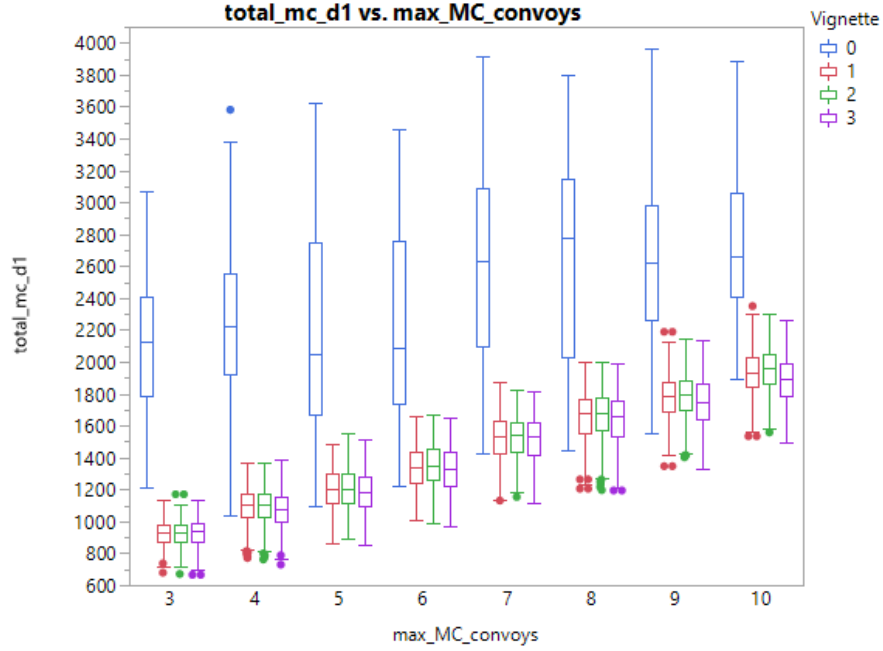


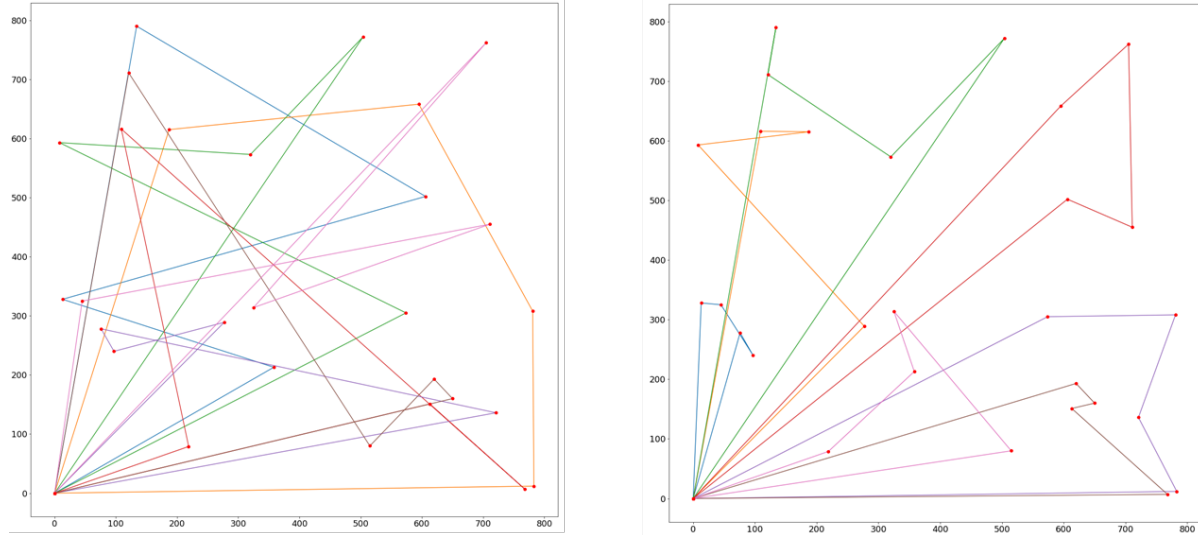
Figure 23. Total Euclidean distance traveled for military convoys versus number of military convoys in each vignette.

While Figure 22 and similarly constructed boxplots showed downward trends, Figure 23 shows that the overall distance traveled increases as number of convoys increases. It should be noted that the total does not rise at the same rate as the number of convoys. When tripling the number of convoys, the total Euclidean distance traveled approximately doubles. This holds true for all the vignettes, though once again the base case vignette (Vignette 0) has significantly higher totals. This is not at all surprising, but it is visually interesting to see how dramatically different the SFC vignettes are from the base case.

C. FUEL AND TIME MOES

While the previous section explores the MOE of average distance traveled, there are more aspects to look at. Additionally, we need to explore and analyze the other two MOEs mentioned in Chapter III, Section F: the fuel savings, average time to complete routes, and maximum time to complete routes. Consider Figure 24, which gives a side-by-

side comparison of the base case vignette (Vignette 0) and Vignette 1 for one particular set of demands.



Same input values of zero NGO vehicles, seven military convoys, 28 demands, and a grid size of 814. Vignette 0 is random demand assignment and Vignette 1 incorporates the SFC method.

Figure 24. Example of Vignette 0 (left) and Vignette 1 (right) routes for same demands in same grid space.

For the example in Figure 24, Vignette 0 scenario yields a total Euclidean distance traveled of 2312 km, while Vignette 1 returns 1483 km. Essentially, Vignette 1 reduces total convoy miles by 46% in this single instance. As was shown in the previous section, the SFC method-based vignettes regularly outperformed the base case vignette. Additional savings yielded by the SFC vignettes over the 45200 situations simulated:

- 989 total convoy miles (41%)
- 181 average convoy miles (44%)
- 210 max convoy miles (41%)

Applying the conversion values discussed in Chapter III, MOE section, we can analyze the time to complete routes and fuel savings. Figure 25 shows a comparison of the distributions of the base case and Vignette 1.

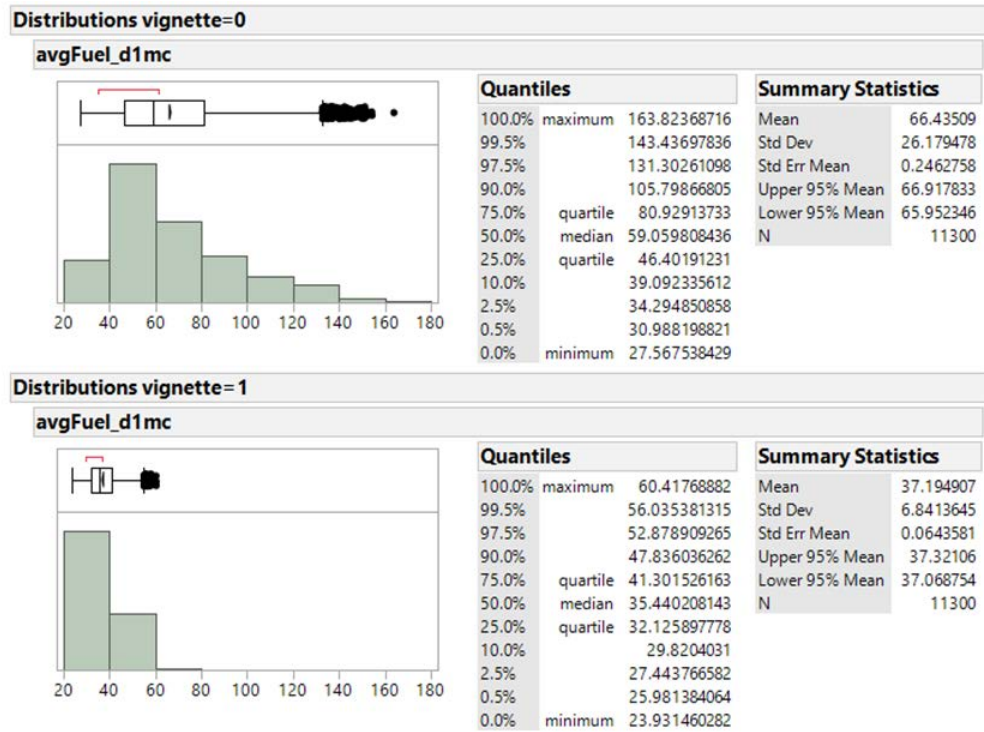


Figure 25. Comparison of distributions for average fuel (gallons) used in Euclidean distance in the base case (top) and Vignette 1 (bottom).

Overall there is a trend of the SFC vignettes yielding a fuel savings of:

- 179.7 average gallons of fuel per convoy (44%)
- 204.7 max gallons of fuel per convoy (40%)

These are just estimates based off our assumptions so more work could be done on fuel usage stochastically in the future to give more sensitive analysis of this MOE.

We now look at the speed conversions and how they affect the time to completion of routes. Summary statistics appear in Table 2.

Table 2. Summary statistics of time to complete all routes for SFC vignettes compared to base case.

	Average speed of 20 mph (Base Case)	Average speed of 40 mph (Base Case)	Average speed of 20 mph (SFC vignettes)	Average speed of 40 mph (SFC vignettes)
Average time to complete	14.8 hours	7.4 hours	6.3 hours (44% better)	3.1 hours (44% better)
Maximum time to complete	18.3 hours	9.1 hours	8.9 hours (41% better)	4.4 hours (41% better)

Practically, the ability to complete the routes faster means more time freed up to make additional deliveries, more cargo can be moved in a 24-hour period, the military convoy vehicles could be released for other missions if necessary, and most importantly it means aid supplies arrive quickly to those who desperately need it.

D. GROUND VERSUS UAV DELIVERY

Vignette 3 was slightly modified to now look at the NGO vehicles as logistic delivery UAVs where the DOE uses the UAV range as 1 to 20 but keeps the other factors ranges unchanged for a total of 11,300 scenario runs. This allows us to look at some possible impacts of UAV delivery being used in addition to ground delivery. Figure 26 shows some interesting distribution information on the average distance of UAVs traveled.

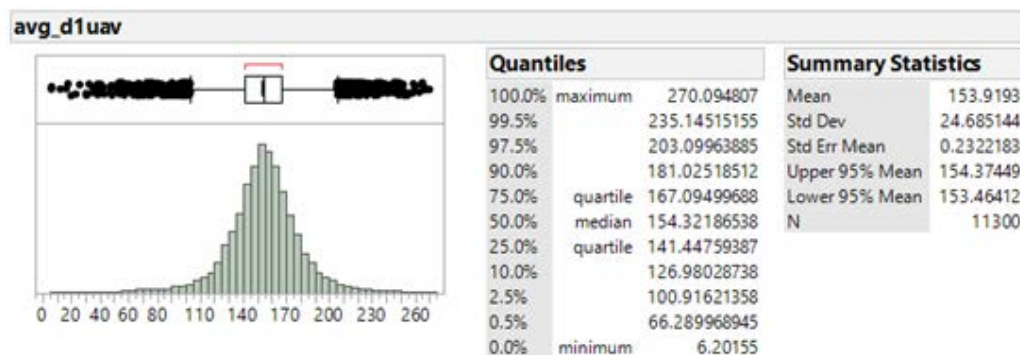


Figure 26. Distribution graph and summary statistics for average UAV distance traveled.

The distribution graph in Figure 26 appears to be very normally distributed which is different from Vignettes 1 and 2 where we always had skewed distributions. This is not surprising, though, because this exploration's methodology has no preference for specific θ values. It is interesting to see that the mean of these distances is about 154 kilometers. Figure 27 helps us see how the number of UAVs in each convoy affect the maximum distance traveled by a UAV.

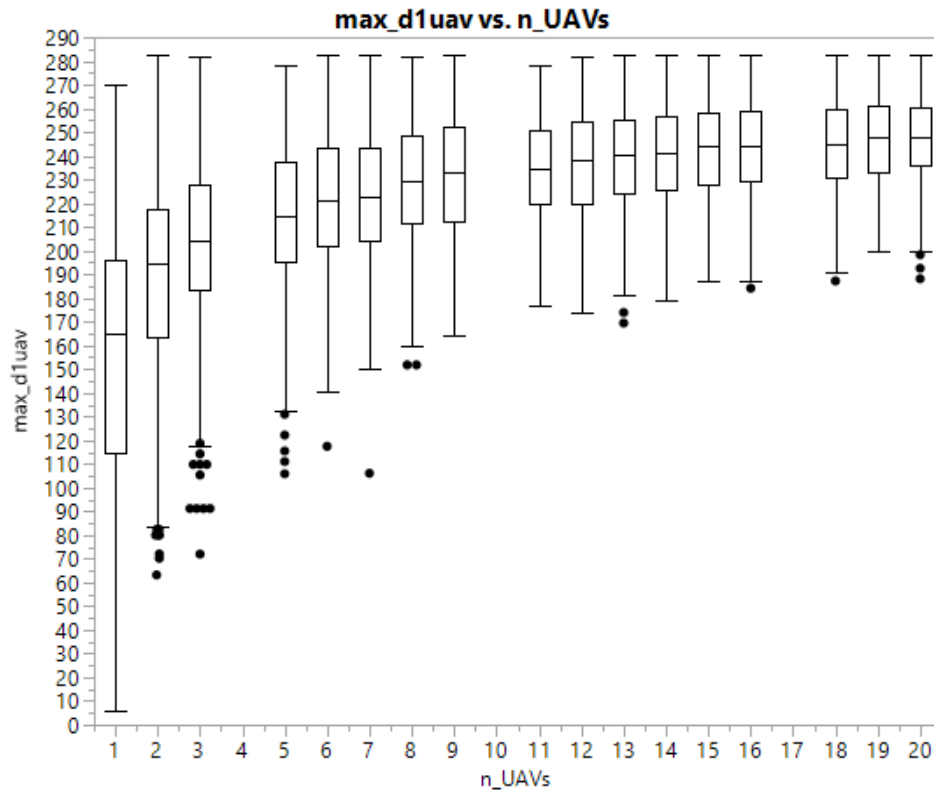


Figure 27. Maximum Euclidean UAV distance traveled per number of UAVs.

Figure 27 shows a trend of increasing max distance traveled by UAVs up until eight or nine UAVs where it stabilizes. The range of the maximum distances also gets tighter around that same number of UAVs. Another aspect to look at is how UAV use impacts total distance and military convoy distances traveled. Figure 28 gives an initial look at possible effects on the average Euclidean distance traveled by the military routes (convoys or UAVs) per the number of UAVs they have available.

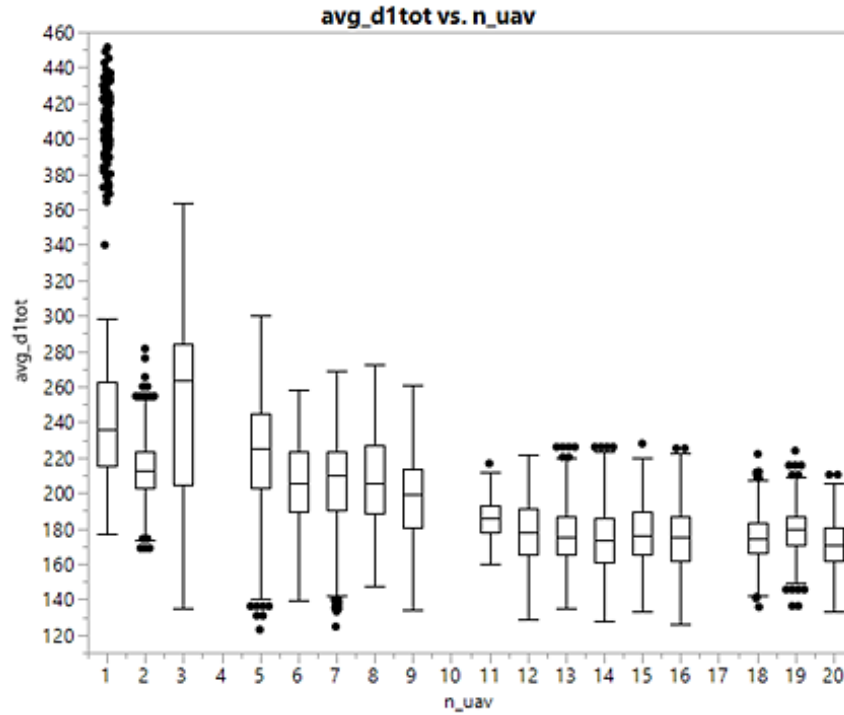


Figure 28. Average military route Euclidean distance (convoy or UAV) traveled by number of UAVs used.

Figure 28 shows there is potentially something interesting going on when only one UAV is used, a possibly bimodal distribution affected by another factor. There generally seems to be a downward trend of average total Euclidean distance traveled as the number of UAVs used increases. To further look at the relationship between the use of UAVs and the combined average distance fuel used for military convoys, we built a partition tree model (see Figure 29).

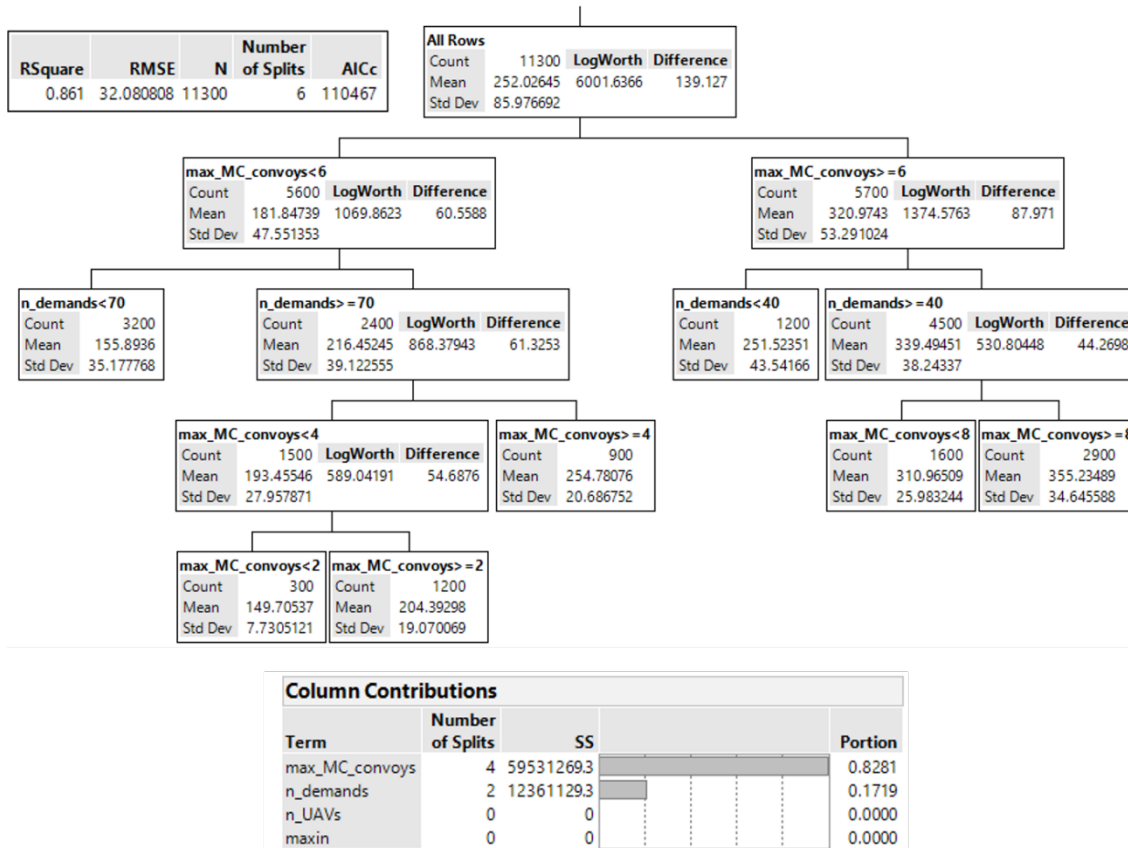


Figure 29. Partition tree and accompanying statistics for average combined distance fuel use for military convoys in UAV scenario.

The partition tree in Figure 29 shows that there is no impact of UAVs on the military convoys' distance traveled or fuel used. The "Column Contributions" section shows that the number of military convoys and number of demands are the overwhelming determining factors in the model. Overall, the partition tree model shows a decent fit with an R-squared value of 0.86.

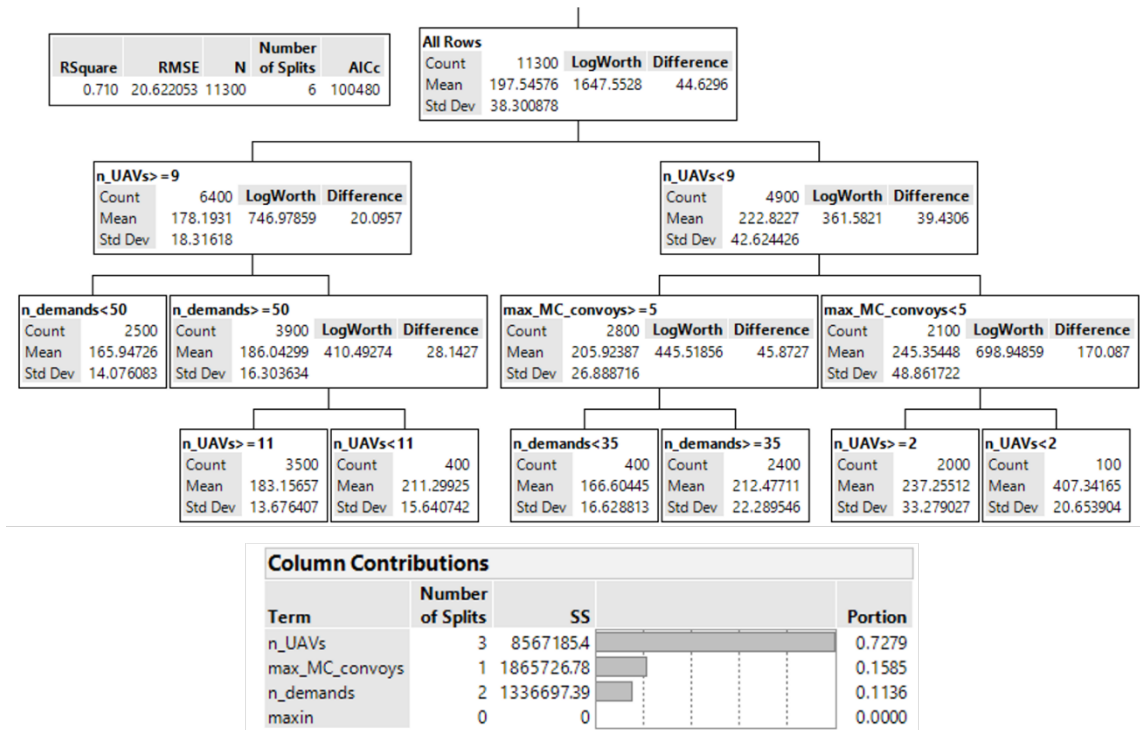


Figure 30. Partition tree for total Euclidean distance (both UAVs and military convoys)

The partition tree in Figure 30 shows that the number of UAVs is an overwhelming determining factor in predicting the final total distance traveled. The first split is on whether there are nine or more UAVs and less than nine UAVs. The former has a mean of 178 km traveled and the latter has a mean of 222 km traveled. This reinforces the findings of Figure 28 and provides quantitative measures like the means. The overall R-squared is 0.71.

Table 3. Summary statistics of UAV performance: Average time, maximum time, and total fuel measurements.

	Average time to complete (hrs)	Max time to complete (hrs)	Average Fuel Use (gal)	Max Fuel Use (gal)	Total Fuel Use (gal)
Small ULS	2.4	3.5	4.7	6.9	76.8
Medium ULS	1.2	1.7	10.7	15.6	111.7
Large ULS	0.3	0.5	83.1	121.9	871.4

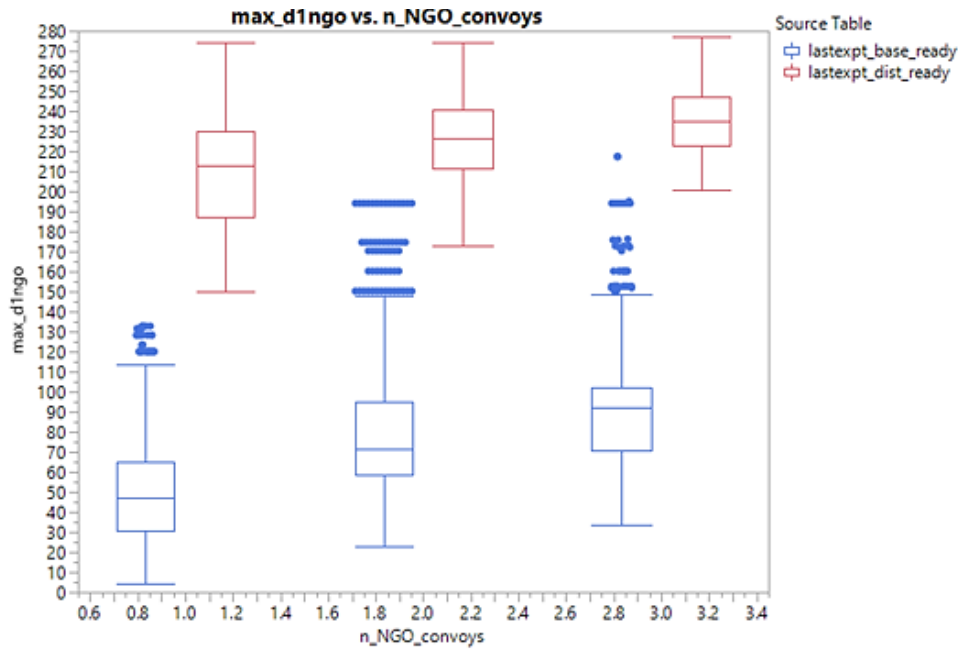
Depending on the UAV assets used there are tradeoffs between time to deliver and fuel consumption. Using UAVs to reduce fuel consumption and time to delivery could be a benefit, especially when used in conjunction with military convoys being routed via the SFC method. Overall, more in-depth analysis of UAVs using the SFC routing model could be research in future works, but even this rudimentary analysis provides several interesting insights:

- The use of UAVs significantly decreases the average total distance and maximum distance traveled per route when used in conjunction with ground transport in SFC-SIM. This decrease directly translates into faster deliveries.
- According to the partition tree model the use of UAVs is not a significant predictor for the average distance traveled for military convoys in the SFC method, as seen in Figure 29.
- The use of UAVs is an overwhelming significant predictor for the average total Euclidean distance traveled (Figure 30).

- The large ULS asset is not fuel efficient but it does deliver large amounts of cargo for one delivery at the fastest rate. The small ULS cannot hold as much cargo but is very fuel efficient relative to the other ULS assets and the ground assets (Table 3).

E. NGO CLOSEST VERSUS FARTHEST DEMAND ASSIGNMENT

As discussed in Chapter II, Section B, Vignette 2 was originally designed to look at routing based on assigning the NGO vehicles the highest θ value. However, because of the symmetry of the SFC and fact that our analysis does not include any geographic features of terrain or demand, this is essentially equivalent to assigning the NGO vehicles the lowest θ values as in Vignette 1. We now explore what would happen when NGO vehicles are restricted to the upper right quadrant of a grid space to determine any possible significant impact on either the NGOs or military convoys. In the real world there could be many reasons why NGOs may be restricted to a certain space. One example is specific supply classes might be delivered by NGOs alone, such as medical supplies to a certain area affected by a disease outbreak. It may be a cleared area, so military commanders request the NGOs to travel to that sector instead of areas that need extra equipment for route clearing. A delineated sector could also represent a more urban area that may be traversed by NGOs more easily. One of the first comparisons of the two different Vignette 2 outputs appears in Figure 32. For the figures in this section, “lastxpt_base_ready” and “lastxpt_dist_ready” respectively correspond to Vignette 2’s original method and Vignette 2’s second method of sending NGOs only to the upper right quadrant of the grid space.



Original Vignette 2 output (blue) and new quadrant restricted Vignette 2 output (red)

Figure 31. Maximum Euclidean distance traveled by number of NGO vehicles comparing outputs of Vignette 2 for two different demand patterns.

The boxplots in Figure 31 reveal significant differences in the maximum distances traveled by the NGO vehicles in Vignette 2 for the two routing protocols. The distances are larger when they can only go to the upper right quadrant (“lastexpt_dist_ready”). This intuitively makes sense, but nevertheless it is good to show it is statistically different when comparing means. We can see this in Figure 32 as well. The two circles on the right-hand side do not overlap, indicating that the mean NGO distances are significantly different for the two routing protocols ($p\text{-value} < 0.0001$). This holds the same for the minimum and average distances traveled by NGO vehicles as well.

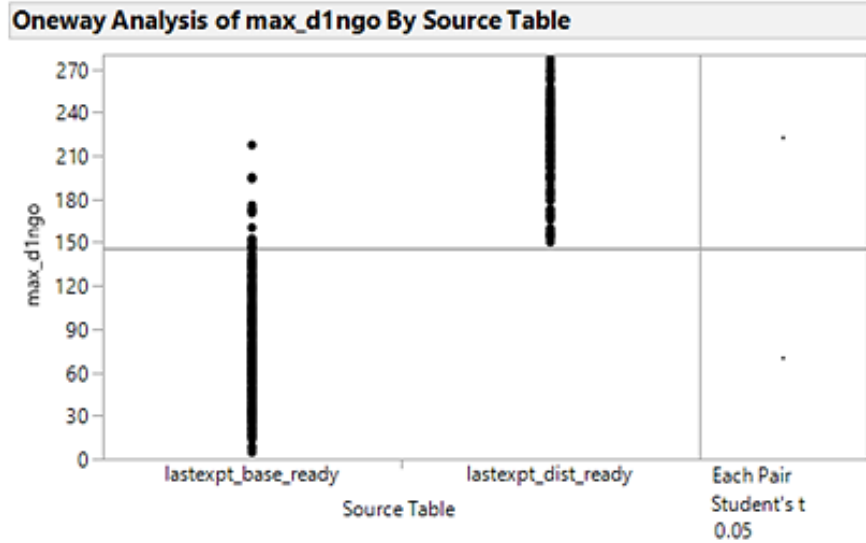


Figure 32. Student's t test comparison of means for the maximum NGO vehicle distance traveled in each Vignette 2 scenario.

The other relationship we are interested in is how the military convoy distances are affected between the two different Vignette 2 routing protocols. Figure 33 reveals there is very little difference. This exploration can ultimately assure military leaders that when coordinating with a small number of NGOs, their convoys will not substantively be impacted by the NGO routing protocols. This flexibility can help inform them on how to best work with NGOs.

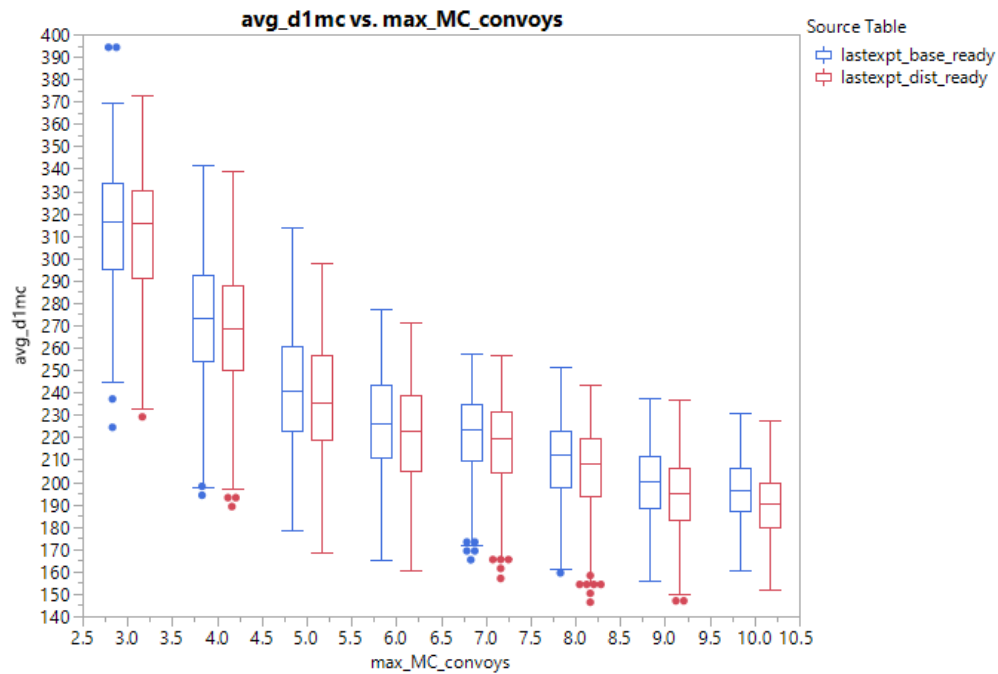


Figure 33. Average Euclidean distance traveled for military convoys comparing two demand patterns for Vignette 2.

As with all the analysis in this chapter, it is important to remember the impact it can have in real-world operations, such as the relief operations in Hurricane Maria. Many of the deaths reported and estimated after the storm were blamed on poor infrastructure and slow reaction to providing relief to where it was needed (Newkirk II 2018). While it is not clear if vehicle routing was a specific issue, the time savings, fuel savings, and ultimately the ability to free up delivery assets faster might have made a difference.

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V. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

The characteristics of the United States military forces that make it an elite fighting force are also the ones that make it ideal for responding to humanitarian assistance and disaster relief (HADR) operations. The U.S. military has ground and air transportation assets for logistics and personnel movements, heavy equipment to clear roads and build or fix infrastructure, and a pre-existing command and control structure that allows for calm problem solving in the face of chaos. A low cost, low maintenance, and easy to implement vehicle routing planning tool can compound the military's existing strengths into cost-effective and more efficient logistics deliveries in HADR operations or similar mission environments. Additionally, this type of tool can be used in coordination with both governmental and non-governmental organizations (NGOs) or passed on to local authorities in a disaster area as the military leaves so continued aid supply delivery is uninterrupted.

In this thesis, we examine the effectiveness of a potential military and civilian application for HADR operations logistics delivery. The tool involves using a space-filling curve method for vehicle route planning. Our assessment is based on the exploration of a simulation model, SFC-SIM, that generates random demands, assigns routes using several variants of the SFC method, and reports route characteristics. A designed experiment creates the combinations of military convoy and NGO delivery assets available, as well as the number of demands for aid. The significant findings from the analysis are:

- The SFC-based vignettes consistently and significantly outperform the base case vignette, with an average savings in MOEs of 40 to 44%.
- The average distance traveled per route, fuel used, and time spent completing routes decreases as the number of convoys increases for all vignettes.
- Using UAVs combined with ground transportation reveals that the number of UAVs is a significant factor in determining the average total distance traveled.

As the number of UAVs increases, the total distance traveled in the SFC method decreased.

It is important to remember the real-world savings and implications these conclusions can help inform. For example, the availability of a route planning tool in the aftermath of Hurricane Maria might have saved time, fuel, or freed up delivery assets faster and ultimately saved lives.

Another aspect of HADR that the SFC approach might improve is the coordination between the military and NGOs. Some of the benefits of a low-tech tool like the SFC routing method include it being easy to implement, easy to share, and adaptable to the scenario which gives it flexibility. The easy to share aspect means organizations working side by side can coordinate with each other and easily incorporate each other's deliveries into their organization's logistics structure. In the early stages of HADR, the route planning tool can be used by local authorities to make their portion of relief deliveries. When the military leaves, if they have not already given the tool to local authorities, they can pass the SFC routing materials they have on so there is no disruption to effective deliveries. Essentially, there is a chain reaction of benefits with the routing tool. The benefits do not just improve military convoy operations, but also simplify the planning process and allow continued improvement of routing throughout the operation.

Intangibly, there is a comfort in having a planning tool available in a situation that is often driven by chaos and confusion. When everything is an emergency, it is beneficial to stay calm and collected and tackle each problem as quickly and smoothly as possible. During HADR, there are usually several different organization structures and authorities that are all trying to plan and coordinate at the same time. Volunteers want to help during HADR operations but often get lost in the shuffle of everything going on. With a planning tool like the SFC routing approach, volunteers can take charge and make things happen.

Tying our results back to the MOW example, the SFC approach in that study was able to reduce total travel time to 30% of original travel times without the approach and their routes were at least 13% shorter as measured by Euclidean distance (Bartholdi 2003). In the MOW study they were implementing the approach in real life and could not make

an “apples to apples” comparison like we are able to do in SFC-SIM. It is telling that we are able to get around 40% savings in distance, time, and fuel by using the SFC method, which is not that far off from the real-world MOW case.

B. FUTURE WORK

Future work regarding SFC methods in VRP in military operations and NGO employment:

- Continuing to simulate and analyze the combined use of ground transportation and UAV logistics delivery assets in the SFC method. This thesis only began to scratch the surface of the potential impact of using UAVs for HADR operations and SFC-based routing.
- Look at hybrid VRP models that combine SFCs with other heuristic methods that could lead to improved efficiency and would be just as easy to implement in the real world.
- Compare different SFC designs, such as Hilbert or Peano curves, to see if they can be even more efficient and effective for VRPs. There could be added advantages to using different curves as each have their own pros and cons.
- Looking at other applications for this SFC method beyond the scenarios covered in this thesis and other organizations that could benefit from its use.
- Additional scenarios, supply class analysis, clustering of demands, and other MOEs could be added to the model.
- Implementing the model and its application in a real-world scenario to see what kind of impact it could have as a tool used in the military.

C. FINAL THOUGHTS

The exact optimal for a Traveling Salesmen problem can only be computed if all the exact travel distances between each pair of delivery locations are known. It is unlikely to obtain this type of information during HADR operations. Using an SFC overlay, map, and Rolodex can be considered a low-cost, low-maintenance tool that provides vehicle routing solutions in austere and rapidly changing environments such as HADR operations. The SFC overlay and Rolodex components are easy to produce, implement, and pass on to other organizations for continuous use in a region. While their use does not provide an optimal result for vehicle routing efficiency it does provide improved efficiency over other types of routes, such as routes that might arise using a “first come, first serve” assignment of randomly generated demands to routes. This improved efficiency, which leads to substantial savings in the distance traveled, fuel usage, and time to complete deliveries, can turn the tide in saving resources—and more importantly, saving lives.

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