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affiliée à l'Université de Montréal

**A data-driven approach to locating and routing unmanned aerial vehicles for
disaster area reconnaissance**

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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Mai 2023

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Cette thèse intitulée :

**A data-driven approach to locating and routing unmanned aerial vehicles for
disaster area reconnaissance**

présentée par **Sean GROGAN**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

The only difference between science and screwing around is writing it down

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RÉSUMÉ

Cette thèse présente un cadre général visant l'exploitation des données météorologiques pour aider à planifier l'utilisation d'un véhicule aérien sans pilote (UAV) muni de capteurs pour aider les équipes de recherche et de sauvetage à analyser une zone impactée par une tornade. Cette thèse utilise les bases des problèmes de planification des tournées, d'assignation et de détermination dynamique des routes de véhicules. Nous nous appuyons sur ces principes en incorporant des données historiques sur les tornades afin de rechercher plus efficacement une zone impactée par une tornade. En effet, la localisation et le trajet des tornades ne sont pas totalement aléatoires. Dans cette thèse, nous cherchons à exploiter les données historiques pour développer des stratégies de recherche afin d'évaluer les zones touchées par les tornades de manière plus efficace.

Nous démontrons tout d'abord comment les données météorologiques et les données spatiales relatives aux tornades peuvent être incorporées dans les procédures de recherche et de sauvetage afin d'acheminer les UAV adéquatement. Nous développons une méthode d'acheminement des UAV à l'aide de l'ensemble des données historiques disponibles. Nous analysons également les compromis entre le temps nécessaire pour créer des points de passage et la valeur de la fonction objectif. On observe qu'il est possible d'utiliser des «méthodes exactes» pour générer des points de passage. Ainsi, l'heuristique que nous proposons permet de déployer UAV plus rapidement.

Ensuite, nous présentons une méthode et une solution pour la localisation d'UAV dans l'état d'Oklahoma à l'aide de données historiques sur les tornades, basées sur des modèles de couverture et d'acheminement des véhicules à stations multiples. Lors de l'affectation des UAV, nous découvrons qu'il faut jusqu'à 70% de UAV en plus pour obtenir une couverture suffisante, alors qu'il n'y a que 5% de chances qu'un UAV donné ne puisse pas voler.

Enfin, nous exploitons les données historiques pour identifier plus efficacement l'étendue de la zone impactée par une tornade. Nous constatons que l'utilisation des tendances historiques des tornades permet de réduire de 2% le temps nécessaire à l'identification de l'étendue de la zone touchée (30% des tournées de UAV ne sont pas du tout déterminées de manière dynamique).

Cette thèse constitue une première étape pour appuyer les chercheurs et les sauveteurs avec l'utilisation des données météorologiques et d'autres données d'experts. Cette thèse fournit également un contexte et des opportunités supplémentaires pour l'utilisation des détecteurs de signaux sans fil. Cette thèse contient également d'autres propositions, comme la quantifi-

cation du compromis entre l'utilisation de méthodes exactes et d'heuristiques et leur impact sur la mise en œuvre d'une solution, ainsi que l'utilisation de la durée totale de réalisation du VRP comme fonction objectif.

ABSTRACT

This dissertation presents a framework for using meteorological data to help plan the use of a unmanned aerial vehicle equipped with sensors to assist searchers and to assess an area that is damaged in the aftermath of a tornado. Using the vehicle routing problem’s framework, location-routing problem’s framework, and dynamic routing principals, we develop several methods using the historical data set of tornadoes to more effectively search an area impacted by a tornado. It is widely believed that the location of tornadoes are completely random. However, in this dissertation we can leverage the historical data to develop search strategies using unmanned aerial vehicles equipped with sensors to assess areas impacted by tornadoes in a more efficient manner.

We initially demonstrate how tornado weather data and spatial data can be incorporated into search and rescue procedures to route the unmanned aerial vehicles. We develop a method for routing UAVs using the historical data set and also analyze the trade-offs between time to create waypoints and the yielding objective function value. It is observed that while there is an opportunity to use exact methods to generate waypoints, our proposed heuristic is sufficient for the rapid response needed in post-disaster relief.

Next, we present a method and solution to prepositioning unmanned aerial vehicles in Oklahoma using historical tornado data based on set covering and multi-station vehicle routing models. When attempting to allocate unmanned aerial vehicles, we find that we require up to 70% more unmanned aerial vehicles to have sufficient coverage when there is as small as a 5% chance of any given unmanned aerial vehicle being unable to launch.

Finally, we leverage historical data to more efficiently identify the extent of the area damaged by a tornado. We find that using the broad historical trends in tornadoes can reduce the amount of time it takes to identify the extent of by 2% (30% off not dynamically routing at all).

This dissertation can provide an initial stepping stone for the use of meteorological and other expert data into the search and rescuers’ toolkit. This dissertation also provides further context and opportunities to use wireless sniffers. There are also other takeaways such as quantifying the trade-off between using exact methods and heuristics and their impact on implementation of a solution and the use of the VRP’s make-span as the objective function goal.

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LIST OF SYMBOLS AND ACRONYMS

CETSP	Close enough travelling salesperson problem
CEVRP	Close enough vehicle routing problem
DCVRP	Distance Constrained vehicle routing problem
EF-n	Enhanced Fujita rating of n, where n is in 1 to 5, inclusive
F-n	Fujita rating of n, where n is in 1 to 5, inclusive (before 2007)
GIS	Geographic information system
MDVRP	Multi-depot vehicle routing problem
MStC	Minimum Score to Consider
NWS	National Weather Service
LSR	Local storm reports
SAR	Search and rescue
SBWs	Storm-based warnings
tBar or $\bar{t}$	In the vehicle routing problem proposed in this dissertation, the $\bar{t}$ indicates the longest route taken in a collection of routes. This can be seen as the makespan of a project.
UAV	Unmanned aerial vehicle
USAR	Urban search and rescue
VRP	Vehicle routing problem

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CHAPTER 1 INTRODUCTION

Preparation for and responding to disasters is a major logistical challenge. Governmental organizations, nongovernmental organizations (NGO), and inter-governmental organizations devote considerable resources to preventing, mitigating, preparing, responding, and recovering from the effects of disasters. A disaster is “a shocking event that seriously disrupts the functioning of a community or society, by causing human, material, economic or environmental damage that cannot be handled by local agencies through standard procedures” [3]. Disaster response is considered a “growth industry” [4].

When a disaster occurs, organizations begin to mobilize their disaster response plans. Disaster response are the operations whose objectives is the deployment of resources to provide immediate relief to a population [3, 5].

1.1 General Context

In recent years, advances in unmanned, autonomous, and semi-autonomous vehicles have resulted in devices that are becoming cheaper and much easier to use, which results in an increased utility. The increased development and use of unmanned aerial vehicles (UAVs), commonly and colloquially known as drones, have added a new dimension to search and rescue (SAR) operations. UAVs and drones are currently being developed for applications in construction, mining, journalism, security, and even pizza delivery. In practice, the use of unmanned vehicles can be beneficial in situations where the use of human manpower can be dangerous, limited, or rapid decisions are required. The use of UAVs, flying vehicles, have the added utility of being unencumbered by infrastructure damage or other obstacles in the aftermath of a disaster. There is a large and growing body of work in using UAVs in disaster response applications, one such function is assisting SAR teams in identifying where people are in need of aid or transporting medical and first aid supplies to these people. When responding to emergencies and disasters, while there are some over-arching principals when developing SAR procedures, domain-specific data and knowledge assist rescuers in creating searches that can be conducted faster. An example of this in current practice is using the understanding of ocean currents to predict where overboard and stranded sailors may be. Tornadoes are often believed to be completely random and unpredictable phenomenon in a given region or city. However, this dissertation attempts to demonstrate that with broad understandings of tornadoes, and using the historical data available of past tornadoes, we can use this data to produce SAR operational procedures that can help responders identify and

understand the extent of the damage and assess the area impacted by tornadoes rapidly, in a much more rapid way than previously. Typically assessment of tornado damage is conducted after a tornado outbreak has subsided.

Use of UAVs (and drones) is growing rapidly in the SAR space, and with the knowledge from this dissertation we hope that the UAVs can be operated more efficiently in responding to tornadoes.

1.2 Elements of the Problem

For a detailed overview of the meteorological science of tornadoes or how the National Weather Service (NWS) uses radar and other remote sensing tools to develop their data, we direct the reader to search meteorological literature or to consult the NWS extensive online library on the subject [6–8]. However, we believe the reader would benefit knowing the following information about tornadoes, how they act, and what data is available.

A tornado is a severe weather event that is a rotating column of air that is in contact with the surface of the Earth. It is this “contact” of the "funnel cloud" to the ground that causes damage to nearby structures, which is why the damaged area is usually highly localized in this area. A visual, photographic example can be seen in Figure 1.1 [9]. Through various remote sensing tools and understanding of meteorological conditions, the National Weather Service produces spatial polygons known as storm based warnings (SBWs). Storm based warnings should not be confused with storm watches. Storm watches are alerts produced by the NWS to indicate the occurrence of severe weather. SBWs indicate a severe weather (tornadoes in this dissertation) has a high probability of immediately occurring or is actively occurring. This can be colloquially interpreted as "take shelter now!" The way the NWS vulgarizes the difference is a Tornado Watch is you have the ingredients to make tacos, while a Tornado Warning is we are having tacos now. In this dissertation, we use the SBW polygons to help delineate "search areas" to initially inspect for victims and damage.

Tornadoes have occurred almost every region in the world ¹. However, the most destructive of these storms predominately occur in North America, specifically in an area colloquially known as Tornado Alley [10]. The United States has recorded on average 1000 tornadoes per year from 1970 to 2022 with 40 of them being EF-3 (or F-3) or more destructive² [11]. Assessment of tornado damage, and determining how destructive a tornado is, is often conducted by engineers and first responders physically approaching and inspecting damaged structures [12, 13]. Aerial surveying is also conducted. However, flight time for manned aircraft is

¹A tornado has been recorded on every continent except Antarctica

²This is the destructive power where you might lose your house



Figure 1.1 An F5 tornado (upgraded from initial estimate of F4) viewed from the southeast as it approached Elie, Manitoba on Friday, June 22, 2007

expensive, and any severe weather must have completely subsided before conducting manned aerial reconnaissance. Therefore, damage assessment and location of victims can be a time-consuming and oft delayed process.

Some unique attribute to tornadoes (compared with, say, hurricanes and earthquakes) is that tornado damage is highly localized to the immediate area where the funnel cloud is in contact. This damaged area can be significantly smaller than the initial search area/SBW. Broadly speaking, tornadoes will head in a north-east direction. Damage is also in largely continuous areas; where there is damage, chances are you will see damage in adjacent areas.

Tornado strength and damage is classified by the "Enhanced Fujita Scale", formerly known as the "Fujita Scale". The Enhanced Fujita Scale is a scale of tornado damage intensity. It is **not** like the Saffir-Simpson Hurricane Wind Scale that classifies hurricanes by maximum observed wind speed (For example, Hurricane Katrina was a category 5 hurricane, Hurricane Sandy was a category 3). Rather, the Enhanced Fujita Scale uses assessment of structural damage to interpret the strength of tornadoes. The Enhanced Fujita Scale does control for the type and construction of a building when accounting for the strength of a tornado (where the former Fujita Scale would just classify damage regardless of structure type). For example, a shed built of wood without a foundation would equally likely collapse during a "weak" tornado and a "strong tornado", but a nearby modern hospital built of concrete would require a much stronger tornado event.

The UAV considered in this dissertation is based on the equipment proposed in [14]. This is a fix-winged, gas-powered, UAV with an endurance of 8 hours and a cruising speed of 80

kph (22 m/s). This UAV can be seen in Figure 1.2 [14], from [15]. The UAV uses many sensors in assisting search and rescue missions. Some proposed sensors in use are normal visual cameras and wireless sniffers. Wireless sniffers are devices that are able to passively detect wireless signals, such as those from cell phones, to detect the presence of people (under the belief that people will be close to their wireless devices such as cell phones). The use of wireless sniffers is important and disruptive because it allows the UAVs to passively detect and interpret where people may be located. Previously, any kind of aerial reconnaissance could only be limited to what could be seen from above, with line of sight being limited once a building or other structures damage was in the way. Wireless sniffers allow for people to be passively detected. If we extend this idea that wireless devices indicate the presence of people and we can overlap this wireless sensor identification with where damaged structures are, we can interpret this as where on the ground rescuers should prioritize their SAR efforts.

Broadly speaking, the research in this dissertation lies at the intersection of vehicle routing problems and location-decision problems. The objectives are twofold: 1) decide the best location to preposition the UAVs in advance of a tornado disaster through a region, state and 2) find the best way to route one or more UAVs over an area impacted by a tornado in order to identify the location of and extent of tornado damage.

A detailed overview of how "waypoints" are generated can be seen in Chapter 4. Waypoints can be thought of the customers in the vehicle routing problem or the cities in the travelling salesperson problem. In this dissertation, the objective is for the waypoints to be the center of circles that are the minimum covering set where the circles are covering all the sections of named roads. Given the UAV having a "scanning radius" r_{scan} , we attempt to generate a collection of waypoints for the search and rescue process. We use the road network as an approximation of where people might be in the event of a severe weather event, that is, we assume that people will be within r_{scan} distance of a named road. The waypoints are a



Figure 1.2 A visual example of the UAV proposed in ©2014 ING Robotic Aviation Inc

minimum covering set of circles with a radius r_{scan} that covers the entire road network of an area. We use the road network to help create waypoints to visit because if an SBW is created over an area without much in the way of human infrastructure, the likelihood of a person being there in the aftermath of a severe disaster would be low

The waypoints can broadly be thought of as customers in a vehicle routing problem, where the demand for services are unknown until the waypoint is visited. Throughout this dissertation, we progressively increase the amount of information the operator will get from visiting a waypoint, and incorporate this information into the UAVs' decision-making process.

The vehicle routing problem in this dissertation is a variation on the open vehicle routing problem. The open vehicle routing problem is defined as the "vehicle [not returning] to the depot after servicing the last customer on a route" [16]. In our variation, the objective function value does not need to include the final arc (from the last waypoint back to the depot), however this arc must be included in the feasibility of the solution. If the objective is to reduce the time it takes for a UAV to survey an area, it is wise to first identify the shortest route that passes through all designated waypoints, and then factor in the return journey to ensure that the UAV can safely make its way back to the depot or base. As a future consideration, it may be possible for a UAV to land at a safe location for subsequent retrieval instead of returning all the way to base.

Broadly, the goals are to assess a damaged area in the least amount of time as possible. For instance, if multiple UAVs are simultaneously (or asynchronously) sent out over an area, the length of any one route does not matter. What is being optimized and minimized would be the longest route. This can be akin to minimizing the makespan of a project.

1.3 Research Objectives

Tornadoes are widely considered to be unpredictable phenomenon. To a certain extent they are. In a given region of the United States, say the state of Oklahoma or Mississippi, every square kilometer of those states are equally likely to experience a tornado. Given the size of the actual area impacted by the tornado, the damaged area can be incredibly small on the backdrop of the state or region. However, this dissertation aims to demonstrate that historical understandings of tornadoes can be leveraged to help SAR personnel make better decisions, especially when including the disruptive technologies of easy-to-operate UAVs and wireless sniffers. Can we use the notable historical trends of tornadoes, specifically in "Tornado Alley" of the United states, leverage the this information and the UAV tool proposed in [14] to identify the location and extent of the damage incurred by a tornado as quickly as possible?

To accomplish this, we breakdown this dissertation into sub-objectives. We want to :

1. Sub-objective 1 : define concepts and frameworks for creating "search areas";
2. Sub-objective 2 : develop an approach for initially identifying areas to deploy a SAR UAV;
3. Sub-objective 3 : use the historical data to allocate SAR UAVs in advance of a tornado occurring; and
4. Sub-objective 4 : using the historical data to help the UAV identifying the extent of the damage as quickly as possible.

1.4 Dissertation outline

The dissertation is divided into seven chapters. Chapter 2 contains the literature review. Chapter 3 presents an overview of the three themes explored in this dissertation and how they are related to each other. Chapters 4, 5, and 6 are the three main contributions of the dissertation related to the sub-objectives mentioned in the previous section. Chapter 4 introduces the concept of using tornado weather related data to route unmanned aerial vehicles after a tornado. Chapter 5 builds upon theme one where we try to adequately position UAVs in advance of a tornado occurring, we also begin to leverage historical information to position these UAVs. Chapter 6 proposes a way of assessing damage in the aftermath of a tornado in a shorter amount of time. In this chapter, we also leverage the use of historical trends in tornado damage to a better searching method. Chapter 8 summarizes the work proposed in this dissertation and provides some avenues of future research.

There are seven appendices in this dissertation. Appendix A presents data and tools used in Chapter 4. Appendix B indicates the location of data used in Chapter 5. Appendix C shows the pseudocode and the algorithms used in Chapter 5. Appendix D describes the mathematical models used in Chapter 5. Appendix E presents some additional results for Chapter 6.6. Appendix F indicates the location of data used in Chapter 6. Appendix G is a collection of implementation notes and other ideas that may not have formally been presented in this dissertation, but could be beneficial to the reader to understand why some decisions were made when producing this dissertation.

CHAPTER 2 LITERATURE REVIEW

In this broad literature review, we wish to provide an overview of the literature dealing with search and rescue operations and the underlying and relevant operations research models (that is, the vehicle routing problem and location problems). The chapters 4, 5, and 6 have their own literature reviews with specific breakdowns that are relevant to each chapter.

We break down the literature review into six sub-sections: Operational Environments in SAR Operations; Uses of Wireless Sniffers; The Vehicle Routing Problem and SAR operations; Other modes and models to solve SAR operations; Use of meteorological data in routing; Location problems

2.1 Operational Environments in SAR Operations

In the literature, there were three main operational environments that were used by authors to help contextualize their problems: Urban Search and Rescue (USAR), Wilderness Search and Rescue (WiSAR), and Air-Sea Rescue (ASR) operations. These three are all SAR mission in an urban, wilderness, and maritime context, respectively. USAR operations aim to locate and provide aid to multiple, stationary victims in a constrained search environment [17–31]. Causes of USAR missions are in earthquake response [14, 32–35] or hurricanes [36, 37]. WiSAR operations aim to locate one specific victim or a small group of victims in an unbounded environment. [38, 39] consider using mobile phone detection in aerial search and rescue operations in a WiSAR operation. As the name implies, this would typically be in a wilderness environment (forest, mountains, desert) [40] or, broadly, missing people [41]. There is also [42] who uses a team of UAVs in WiSAR operations. ASR operations are similar to WiSAR, but are strictly for victims lost or stranded at sea, such as the event of a crashed plane or shipwreck. UAVs are also used in management of hazards to monitor and immediately dispatch crews if needed [43], but this paper focuses more on location problems.

The use of ground based unmanned vehicles outnumber the aerial based tools [17, 19–21, 25, 27, 29, 31, 44–48]. These land-based vehicles are preferred or required to complete their missions as they navigate an interior, building environment and require a navigable path to a victim to be found [17, 19, 25, 27, 45–47]; similarly a city based environment that requires carrying a payload that would be infeasible for a UAV to carry [20, 21, 29, 31]; or are to be deployed as semi-permanent installations such as creating mobile ad-hoc networks (where a UAV 'hovering' would consume too much fuel) [25, 44–46]. While these situations differ in

the equipment used, we can use a simplified version of methods in this literature as a basis for UAV operations.

The literature on the use of UAVs in various applications is extensive. Initially, researchers focused on exploring the capabilities of single UAVs or drones, as demonstrated in studies such as [39, 49–51]. These works delve into topics such as target localization [39, 50], target tracking [51], and propose routing strategies using algorithms like ant colony optimization [49] or generating Moore Curves (Closed Hilbert curves) [50].

Subsequently, the exploration expanded to incorporate multiple UAVs or drones to achieve UAV-related goals, as highlighted in publications like [42, 52, 53]. These papers collectively acknowledge the importance of utilizing multiple UAVs to swiftly assess an area in post-disaster scenarios.

2.2 Uses of Wireless Sniffers

Another key piece of literature in this domain is in [54] where authors analyze the feasibility of using WiFi detection in WiSAR operations. Most importantly, the authors deem the technology feasible. In [55], authors use wireless sensor networks to help in crisis management. Another is in [39, 50] where the authors use the wireless sensor to develop a probability map of the location of a lost individual.

2.3 The Vehicle Routing Problem and SAR operations

SAR missions are often interpreted as a vehicle routing problem (VRP) [39, 52, 53, 56, 57] or variations of the Travelling Salesperson Problem (TSP) [57–61]. One or more UAVs are launched from one or more depots to fly over an area, usually defined as a collection of destinations.

In the search phase of SAR operations, the UAV’s objective is not to directly visit each potential victim location, but rather to approach them within a certain detection range. This problem is commonly referred to as the ‘Close Enough Travelling Salesperson Problem’ (CETSP) [57–61], or alternatively, the ‘Close Enough VRP’ (CEVRP) [57]. The dissertation [57] specifically focuses on addressing the ‘Close Enough VRP’ (CEVRP) and highlights the utilization of UAVs in surveillance scenarios, employing the CEVRP formulation for routing UAVs in such situations. Notably, in the literature review of [57], the author does not differentiate between the CEVRP and CETSP literature when searching for research on the CEVRP, suggesting that methods developed for CETSPs can be applicable to CEVRPs.

However, in [56], the authors approach their problem as the distance-constrained capacitated vehicle routing problem (DCVRP), without considering the concept of traveling only "close enough" to a customer or target.

Since the VRP is a generalization of the TSP, one – and past authors [61,62] – can claim that the CEVRP is an extension of the CETSP. Therefore, the research here draws specifically on the works of [61] and [62] where they identify regions of overlap in service areas which are known as Steiner zones. The idea is that the customers in the TSP can be serviced if the Salesperson is within a certain distance of the customer. Any overlapping customers create what is known as a Steiner zone which is a region the Salesperson (vehicle) must pass within this zone to visit all associated customers. However, neither of these papers addresses the comparison of methods to build Steiner zones and [61] mentions their method performs poorly when addressing homogeneous customer radii.

2.4 Other modes and models to solve SAR operations

After graph-based formulations, another common model formulation is set covering methods [21,44]. It is a formulation well suited to monitoring procedures as set covering formulations attempt to allocate the robots over a disaster scene to ensure connectivity [44] or to ensure an area is adequately searched [21].

In addition to the mathematical optimization models proposed, several robot task allocation models and methods were used in the literature [14,24,31,45]. Robot task allocation can be implemented in a decentralized way and enable real time reactions to new information present in the environment.

When it comes to a centralized method for optimizing the formulations outlined in the previous subsection, ant colony optimization (ACO) appears to be a common method [20,23,49,63]. The ACO method uses multiple agents (ants) to find an optimal path from a start to a goal objective. Both [23,63] use ACO to optimize multiple land robots to find a specific target location. [49] uses ACO to find the most efficient traversal of a tour in their TSP formulation.

Another optimization procedure that makes multiple appearances is particle swarm optimization (PSO) [21,31,44,46]. PSO is a subset of population based algorithms that is based on how animals will work both cooperatively and competitively to find food in an environment. The agents of the population will alert the population to the best known solution, and then the agents will make a decision to improve their optimal value. In addition to the PSO method, [22,42] explores a genetic algorithm method and differential evolution to optimize

the path-finding mission outlined in their paper.

In a decentralized manner to solve the robot task allocation methods, auction based optimization methods appears to be a common choice [19, 24, 64] since they are easy to decentralize (each agent of a robotic swarm makes their own decision) and easy to implement (one asks the robot to predict how much it will cost to perform a task, the cheapest one executes the task).

In addition to the well-established procedures outlined previously, some authors attempt stochastic optimization techniques such as Markov Decision Process [29, 39, 47, 55].

2.5 Use of meteorological data in routing

There has been research in incorporating uncertainty in weather conditions into routing UAVs [65], although they strictly look at wind conditions. In addition, one can see routing of trucks and other land-based transportation during severe weather events [66] using the Travelling Salesperson Problem (TSP) as a foundation. The case study in [66] studies a severe weather event that includes tornadoes; however, the method they use to update their travel times between cities revolves around perception (rain, snow, etc.) and fog causing delays in transportation, not tornadoes. There is research in formulating capacitated arc routing problems to respond to winter weather where trucks are required to "grit" roads (sometimes known as sanding roads); there is the addition of these trucks dynamically re-routing after receiving weather updates [67]. There are many papers that do reference snow clearing operations, but they all appear to lack dynamically responding/re-routing based on new information or observing changing conditions [68–70] and are all ground-based operations.

2.6 Location problems

Station location and resource allocation problems are used in the aspects of SAR operations. These problems have been broadly studied from two perspectives: deterministic and stochastic. Deterministic models include covering, center, and median models. Covering problems are very common in the emergency services field [71, 72]. Stochastic models deal with the allocation of resources in a stochastic environment, e.g., in cases where customer demands, distances, or costs are random [73]. Stochastic models also consider multiple future scenarios with respect to customer demand [74] and treat the travel distance as uncertain, e.g., depending upon the time of day for the ambulance location problem. Most of the literature surrounds the distribution of Maritime SAR helicopters for various maritime security and search and rescue forces [73, 75, 76].

2.7 Analysis and gaps of the literature

Prior to 2021 [2, 77, 78], there existed no literature where SAR teams were responding specifically to tornado disasters. When a tornado strikes, the impacted area is smaller than the area impacted of an earthquake or hurricane. This smaller area of damage presents a unique opportunity for using classic operations research tools in new ways. By borrowing wilderness and maritime SAR principals with the tools provided by the literature in preparing for hurricanes and earthquakes, we can adapt the literature to work in the tornado niche.

Some of the literature relevant to SAR operations involving collapses structures [14, 17–35]. However, most of these pieces of literature still involve a SAR person or robot being close to a victim in need for various reasons [17–31]. There are some that do conduct aerial surveillance [14, 32–35], with very few that use the "wireless sniffer" to help identify people [14, 32, 33]. Further use and demonstration of the "wireless sniffer" mounted to a UAV can be seen [14, 32, 33, 39, 50, 54, 55]. Tests using the "wireless sniffer" seem to be promising in particular for identifying and counting people in an area.

For SAR formulations, the VRP and TSP are often used as these frameworks identify the SAR vehicle as the vehicle in the VRP or the salesperson in the TSP, where the customers or cities represent victims or people in need of aid [39, 52, 53, 56, 57, 57–61]. In addition, the variations known as the CEVRP and CETSP are suited quite well for the searching part of SAR operations as UAVs do not need to visit every structure, location, etc. as cameras (as well as the wireless sniffer) can remotely sense or identify the information needed [56, 57, 57–61]. However, the previous literature all optimizes a global objective: minimize the travel time, fuel consumption of all vehicles. When using multiple vehicles, SAR personnel only are concerned with how long it takes to complete the entire of the mission; in a multi-UAV mission, if one UAV takes a marginally more inefficient route, as long as it is not the longest route, this route would not have a bearing on the overall mission completion time.

In preparation for SAR operations, there appears to be a gap in land-based allocation problems. There is use in the maritime contexts [73–76] and they even include uncertainty with respect to the availability of aircraft (for example, due to unplanned maintenance) [73, 76]. However, these models assume that distress calls are responded to directly; that is, when a distress call is received, they deploy the appropriate aircraft to conduct their response mission. In addition, they assume multiple aircraft available at each depot [73, 75, 76]. These pieces of literature do not cover instances where the depot cannot respond, all aircraft are 'down' (such is the potential in a tornado if the tornado hits the UAV depot or people operating the depot are victims themselves) or where the aircraft (or multiple aircraft) have to

spend time searching an area for stranded vessels or sailors.

CHAPTER 3 DISSERTATION OVERVIEW AND ORGANIZATION

This dissertation is a dissertation by paper. Chapters 4, 5, and 6 are published journal articles. In this chapter, we will introduce and briefly discuss these three papers presented in this dissertation as well as their relationship with the broader proposition in this dissertation.

This dissertation's research objective was to developing fast and efficient UAV routing models to assess areas after a tornado. We breakdown this dissertation into sub-objectives. We want to :

1. Sub-objective 1 : define concepts and frameworks for creating "search areas";
2. Sub-objective 2 : develop an approach for initially identifying areas to deploy a SAR UAV;
3. Sub-objective 3 : use the historical data to allocate SAR UAVs in advance of a tornado occurring; and
4. Sub-objective 4 : using the historical data to help the UAV identifying the extent of the damage as quickly as possible.

We have three main deliverables: The Chapter 4 accomplishes sub-objective 1 and 2; Chapter 5 accomplishes sub-objective 3; and Chapter 6 accomplishes sub-objective 4. Each chapter and the links between them are described in the following sub sections.

3.1 Overview of Using tornado-related weather data to route unmanned aerial vehicles to locate damage and victims (Chapter 4)

In Chapter 4, we present a first paper whose objective is to lay foundations of the use of tornado-related weather data in disaster response. This theme outlines the decision to use Storm Based Warnings as search areas and how to create waypoints for use in Chapters 5 and 5.

In addition to its direct application to the remaining themes in this dissertation, this chapter also sheds light on an aspect often proposed but rarely quantified by OR practitioners in their research: the trade-off analysis when employing heuristics or metaheuristics in solution methods. This study highlights the significance of time in this particular context, emphasizing the time required to solve the problem versus the time needed for a team to effectively operate

the solution. By addressing this critical trade-off, the paper provides valuable insights into the practical implications of using heuristics or metaheuristics in solving real-world problems.

Search and Rescue operations provide a strong base to conduct this research. Time spent planning and time spent executing the plan is important. Specifically, in our paper the objective function of the model proposed is in units of time, and the time value is on the order of several hours, which means there is a quantifiable and obvious relationship between time spent planning (solving the mathematical model) and the time executing the plan. In the paper, we can see solution methods that can be resolved in a “reasonable” time (less than a hour), but potentially are not “worth it” because a solution that solves in minutes yields a solution that is about 20 minutes longer. Explicitly from one test :

- Heuristic solution, takes 15 seconds to solve, solution is of 3h28m.
- Metaheuristic solution, takes 6m8s to solve, solution is of 3h28m (does not find a better solution than the heuristic to the precision of a minute).
- Exact solution, takes 40m17s to solve, yields a solution of 3h09m.

For disaster response practitioners, we hope this poses some creative use of well known and recorded data and novel equipment to respond to disasters.

This article appeared in OR Spectrum titled "Using tornado-related weather data to route unmanned aerial vehicles to locate damage and victims" [77].

3.2 Location of disaster assessment UAVs using historical tornado data (Chapter 5)

In Chapter 5, we begin to leverage historical data to produce an efficient use of resources in preparing for tornadoes. One pragmatic shortcoming of Chapter 4 [77] is that we assumed that any fire station, depot can be used. This was an over-estimation (and over-use) of resources.

Tornadoes' location and path can be random. From a responder's viewpoint, this means that with some non-negligible chance a search and rescue team may not be able to adequately respond to a tornado disaster. This can be due to unplanned maintenance, flight crew not being able to make it to the launch station, or the station itself being struck by a tornado. This paper contributes to the growing body of literature on robustifying solutions against events that have a reasonable chance of occurrence yet are unknown in their time or severity. Within the context of this paper, an initial assumption could be that we have

perfect knowledge of what stations will be active and inactive at any given time, that is, we plan for 100% uptime and ability to respond from any depot. Historically speaking, about 1 in every 25 tornadoes that occurred intersected a fire station in the state of Oklahoma. Assuming that even minor tornadoes can interfere with flight operations, this can mean that there is a 4% chance of a tornado impacting the ability for SAR personnel to respond to a tornado. Considering this, plus the chance of unplanned maintenance or flight operators themselves being victims of the tornado, this could lead to a chance of not being able to adequately respond to a tornado.

For disaster response practitioners, we hope this poses some creative use of well-known and recorded data into their decision-making toolkit. We also pose a framework for trading off the ability to adequately respond to disasters versus the number of stations. Depending on the assumptions made surrounding the chance a station cannot respond to a disaster, the number of stations required could be anywhere from 30% to 80% more stations.

This article appeared in *Geomatics, Natural Hazard, and Risk* and is titled "Location of disaster assessment UAVs using historical tornado data" [2].

3.3 Using historical data to dynamically route post-disaster assessment UAVs in the context (Chapter 6)

The final exploration in this dissertation is if we can further leverage historical tornado data in order to identify the extent of the damage in as short time as possible. In Chapter 6, we develop the idea using broad trends in historical tornadoes to accomplish this goal. This paper also develops a method for creating artificial cases to increase the number of tests available for development and further testing of dynamic routing problems.

Recall from the outset the goal of this dissertation is to attempt to effectively identify people in need. UAVs also provide the opportunity to allow for algorithmic decision making to efficiently operate the UAV. In both Chapters 4 and 5, we assume the UAV will fly over and assess the entire area delineated by the SBW. In Chapter 6, we develop a method to prioritize areas that are identified to be impacted by the tornado. The sooner the tornado is identified and the extent of the damage of the tornado is identified, the sooner on-the-ground rescue teams can be deployed to identify people who might be in need of aid.

We develop a rule-set that allows for the UAV to re-route and decide on new waypoints to visit as the UAV begins to uncover damage. We specifically leverage the broad trend of tornadoes moving from a south-west to north-east direction. We found that using this information can help identify the location of damage in a shorter amount of time and identify the extent of

the damage in a shorter amount of time.

This article was submitted to "Applied Sciences, Special Issue 'Advanced Research and Application of Unmanned Aerial Vehicles'" and is titled "Using Historical Data to Dynamically Route Post-disaster Assessment Unmanned Aerial Vehicles in the Context of Responding to Tornadoes" [78].

3.4 Data Information and Use

This dissertation relies heavily on the use of real world, historical data. To better grasp what data is being used and where, we have created a flowchart in Figure 3.1 to help identify what data is being used and where and (broadly) in which algorithms. Blue rectangles represent data sources. The red elongated hexagons represent some broad algorithms/concepts used in each paper.

"Fire Stations" or "Fire Depots" [79, 80] – that is, places that store and dispatch firefighting equipment – were used as candidate depots for the UAV tool used in this dissertation. They were selected because 1) their prevalence through the state(s) and 2) operated under the assumption that fire stations would be already located in locations that ensured adequate coverage of emergency services.

"Road Data" was used as an indication of where people might be in the event of a tornado occurring. If the detection range of the UAV was sufficiently large such as on the order of 10^2 meters (or more), we assume that potential victims of a storm will be "within range" of a named road. We largely use the road network in the generation of waypoints (Due to the number of locations road data was pulled from, see Appendix F for a list of internet locations that contained the road data used in this dissertation).

In this dissertation, we use two types of tornado tracks. The first is what we denote as "schematic tornado tracks" [81]. This is a list produced by the Storm Prediction Center, National Oceanic and Atmospheric Administration of recorded tornadoes from 1950 until present (Specifically 2021 for this dissertation). Among details about damage to life, crops, and building, we mainly focus on the information that indicates a "start point", an "end point", a "width", and the "severity" (EF- n /F- n scale). We do not use more than the "start point" until Chapter 6, the "schematic tornado tracks" is limited to identifying which SBWs are being used in the waypoint and routing algorithm. We denoted them as "schematic tornado tracks" because in comparison to the "detailed tornado tracks", the "schematic tornado tracks" are much simpler.

The second type is the "detailed tornado tracks" [82]. In comparison to the "schematic

tornado tracks", the "detailed tornado tracks" will contain spatial polygons to the extent of the damage a tornado may cause. These tracks will better render the path the tornado took (as tornadoes do not follow a line). This data set was used uniquely in Chapter 6 to better understand the performance of the dynamic routing algorithm. By the nature of the additional detail represented by the "detailed tornado tracks", there are less events in this dataset than the "detailed tornado track".

Finally, we have the Storm Based Warning (SBW) data [83]. We briefly introduced this data in Chapter 1 and in conjunction with the data from "schematic tornado tracks" in Chapter 4 and Chapter 5 as well as the "detailed tornado tracks" in Chapter 6, we use these SBWs to indicate the use of the SBWs as an initial search area.

In addition to the contributions of the next three chapters in this dissertation, there is a progression in the amount of data – tornado events – used in each chapter. As we grew more confident in our understanding and use of the data we began to incorporate more data/tornado events. Chapter 4 only considers three events, two from the state of Oklahoma and one from Texas. We had to manually choose the tornado events in question to ensure that the disparate data sets were appropriately matched. In Chapter 5 we allowed a more algorithmic approach to aligning the "schematic tornado tracks" and SBWs which allowed for 124 events. In Chapter 6, we increased the scope of locations to include road data from several states (Texas, Oklahoma, Arkansas, Louisiana, Mississippi, Tennessee, Kentucky, Alabama, Georgia, South Carolina, and Florida), SBWs in the region indicated, and the "detailed tornado tracks". This intersection allowed the development of 182 events.

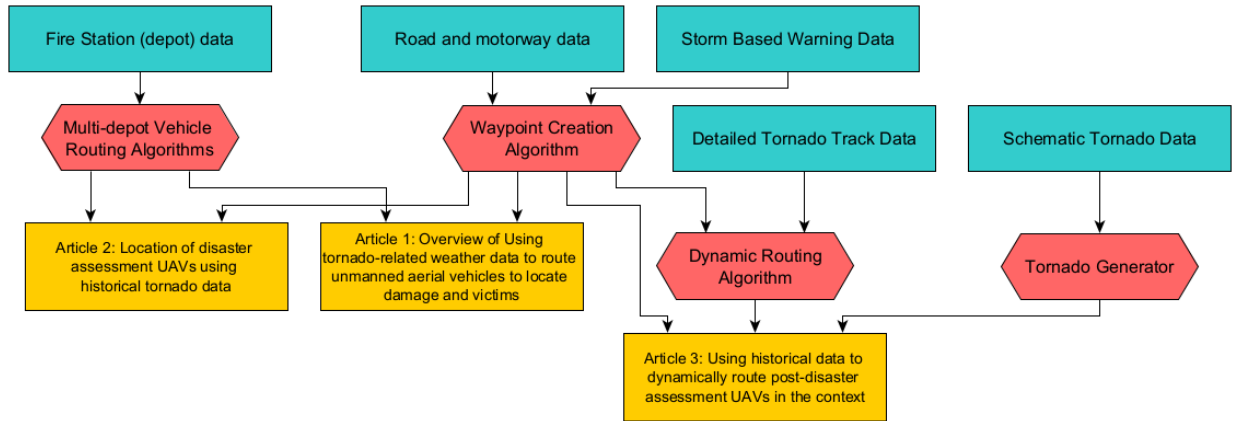


Figure 3.1 A flow chart showing the algorithms and data used in each project. Blue rectangles represent data sources, orange circles represent any filters placed on the data sources. The red elongated hexagons represent some broad algorithms used in each paper.

CHAPTER 4 ARTICLE 1: USING TORNADO-RELATED WEATHER DATA TO ROUTE UNMANNED AERIAL VEHICLES TO LOCATE DAMAGE AND VICTIMS

This article, titled "*Using tornado-related weather data to route unmanned aerial vehicles to locate damage and victims*" was published in *OR Spectrum* on June 30 2021. This paper was co-authored by Robert Pellerin and Michel Gamache [77].

4.1 Abstract

This chapter presents a framework for the use of unmanned aerial vehicles (UAVs) equipped with cameras and wireless sensors to search an area after the occurrence of a tornado. This chapter attempts to demonstrate how tornado weather data can be incorporated into search and rescue procedures to allocate and route the UAVs. Traditionally, the time to assess and search an area after a tornado strikes is on the order of several days. Incorporating UAVs into a search and rescue team's available tools can reduce this time span to the order of hours. These methods are applied and model in this project to three real-world cases. Several methods for creating "waypoints," points of interest for the UAVs to inspect, to route the UAVs were tested. An analysis was performed to compare the time it took to generate the waypoints and the resulting objective function value. It is observed that while there is an opportunity to use exact methods to generate waypoints, our proposed heuristic is sufficient for the rapid response needed in post-disaster relief.

4.2 Introduction

The response to disasters, man-made or natural, is a major logistical challenge. First responders and rescue teams are under pressure to rapidly identify areas to search for people in need of aid. Speed is of the essence. In recent years, technological advances in unmanned, autonomous and semiautonomous vehicles have increased their utility and ease of operator use while also reducing capital and operational costs. The utility of unmanned vehicles (land-based or aerial) stems from their use in situations where rapid calculated decisions are required, human manpower is limited, or the environment is too dangerous for direct human intervention, such as in the aftermath of a disaster. One sub-classification of these vehicles is unmanned aerial vehicles (UAVs), commonly and colloquially known as drones. UAVs are currently being developed and have found use in applications such as construction,

mining, journalism, security, and even pizza delivery. UAVs have the added ability versus their land-based counterparts to traverse over uncertain and impassable terrain to attain their objectives [14, 84].

The traditional sensors urban search and rescue (USAR) personnel use in their search procedures are acoustic sensors, optical cameras, infrared (heat sensing) cameras, and trained dogs. With the exception of using infrared cameras, many of these tools require a line of sight (optical camera) or the sensing device to be within close proximity of the victim to detect them (such as the dog nose or a ‘snake camera’). Therefore, this limits UAVs to visual assessment destruction of disasters rather than aid rescuers in locating victims.

However, in the past decade, there has been an explosion in the adoption and use of the personal cell phone around the world. In 2015, there were approximately 95 mobile subscriptions per 100 people in the world International Telecommunication Union [85], with 103 cell phone subscriptions per 100 people in the USA The International Association for the Wireless Telecommunications Industry [86]. Cellphones emit a host of signals by being on and active. Some authors have begun to explore the ability to passively or actively detect in interact these signals. This device is known as a wireless sensor. In general, the wireless sensor is the term for a device that attempts to detect the existence of wireless signals, much the same way a laptop seeks Wi-Fi signals and attempt to connect to them. Some authors have begun to explore the use of detecting these signals to identify the location of people in disaster scenarios [14, 19, 32, 39, 55].

Among the types of disasters that have been studied in the literature, the UAV tool outlined here has been proposed to be used in hurricane response [36, 37] and earthquake response [14, 32–35, 87, 88]. This chapter will expand into using this tool in the aftermath of tornado disasters.

For an overview of the meteorological attributes of tornadoes, we direct the reader to search meteorological literature or to consult the National Weather Service (NWS) extensive online library on the subject. Storm-based warnings (SBWs), Local storm reports (LSRs), tornado tracking (abilities and limitations) are the primary data elements that can be exploited.

Since 2007, SBW is locations indicated by meteorologists to alert the public to the potential of any severe weather that may occur. These warnings can indicate the imminent occurrence of thunderstorms, hail, snow, floods, and others. They are created by using the skills, remote sensing tools, and expertise of meteorologists. LSRs are sightings of a severe weather event, in this chapter an actual tornado touchdown. In short, SBWs are geospatial polygons generated from the NWS that indicate the potential of severe weather and LSRs are actual weather sightings by trained spotters in the field [7, 89]. SBW predictions for tornadoes have become

good enough that the probability of detection has exceeded 90% for all tornadoes and (since 1997) is near 100% for EF-4 and EF-5 tornadoes (the most damaging tornadoes) and above 95% for EF-3 tornadoes (where EF- n is the Enhanced Fujita scale with n being a ranking of 1 to 5) [90]. That is, when the most damaging tornadoes occur that will cause structural damage to buildings and residences, one can reasonably expect a SBW to have existed to predict it.

Unfortunately, the only reliable way to track a tornado's path is visually or with post-damage assessment. While Doppler radar and other remote sensing tools can be used to aid in prediction, these tools cannot reliably track the tornado once it has occurred. The traditional 'funnel cloud' has to be in contact with the ground for the tornado to damage structures, which is difficult to determine remotely with Doppler radar [6].

This chapter is organized as follows: Section 4.3 is a review of relevant literature. Section 4.4 outlines the mathematical model and the data that is incorporated into the mathematical model. Section 4.5 demonstrates the proposed method of generating waypoints and a solution. Next, in Section 4.6 we apply the model and method to three experimental data sets. Finally, we conclude this chapter in Section 4.7.

4.3 Literature Review

A detailed breakdown of the use of UAVs in disaster response and SAR can be found in [14] and [84]. It appears that the use of UAVs for SAR operations appears in wilderness search and rescue [41], earthquake response [14, 32–35], and hurricane response [36, 37]. There has been a growing body of knowledge in using UAVs and other unmanned vehicles to locate victims using wireless – cellphone – technology in the aftermath of disasters. The following papers demonstrate the feasibility of the UAV equipped with the wireless sensor for mapping victim location [14, 27, 32, 33, 50, 55]. Specifically, [14] dives into how a mixed fleet of UAVs in the aftermath of the 2010 Haitian earthquake would aid rescuers and aid workers in managing their response.

However, there is a lack of literature in the use of active and granular meteorological data (such as tornado watches and warnings) in routing UAVs. There has been research in incorporating uncertainty in weather conditions into routing UAVs [65], although they strictly look at wind conditions. In addition, one can see routing of trucks and other land-based transportation during severe weather events [66] using the Travelling Salesperson Problem (TSP) as a foundation. The case study in [66] studies a severe weather event that includes tornadoes, however, the method they use to update their travel times between cities revolves

around perception (rain, snow, etc.) and fog causing delays in transportation, not tornadoes. For the vehicle routing problem (VRP), formulations offered in [91] use a singular depot. In [56], the authors formulate their problem as the distance-constrained capacitated vehicle routing problem (DCVRP). Their approach does not consider the idea of only needed to travel "close enough" to a customer – or target.

In the search part of SAR operations, the UAV does not need to visit each potential victim location directly but rather must get close enough (within detection range) to a potential victim. Broadly this is known as the 'Close Enough Travelling Salesperson Problem' (CETSP) [57–61] or the 'Close Enough VRP' (CEVRP) [57]. The dissertation [57] focuses on solving the 'Close Enough VRP' (CEVRP). The author highlights the use of UAVs in surveillance and the use of the CEVRP formulation in routing UAVs in this situation. In the literature review of [57], they do not make a distinction between the CEVRP and the CETSP literature when seeking research for the CEVRP, implying that methods developed in the CETSPs can be applied to CEVRPs. However, [57] only explores the use of the Steiner zone, does not consider other means of computing the CEVRP.

Since the VRP is a generalization of the TSP, one – and past authors [61,62] – can claim that the CEVRP is an extension of the CETSP. Therefore, the research here draws specifically on the works of [61] and [62] where they identify regions of overlap in service areas which are known as Steiner zones. The idea is that the customers in the TSP can be serviced if the Salesperson is within a certain distance of the customer. Any overlapping customers create what is known as a Steiner zone which is a region the Salesperson (vehicle) must pass within this zone to visit all associated customers. However, neither of these addresses the comparison of methods to build Steiner zones and [61] cites that their method performs poorly when addressing homogeneous customer radii.

4.4 Mathematical Model

The goal of this chapter is to demonstrate the use of weather data from the National Oceanic and Atmospheric Administration (NOAA) and Geographic Information System (GIS) data from various state-level administrations to allocate search pattern of a small fleet of UAVs to search for potentially those in need of aid after a tornado disaster.

This section aims to demonstrate the following:

1. A new take on a distance constrained multi vehicle routing problem with multiple depots that is applicable to damage assessment and search operations;

2. How to prepare data and use data for the distance constrained multi-vehicle routing problem with multiple depots that is based on data from NOAA and GIS data from the states of Oklahoma and Texas.

The mathematical model is based on previous Distance Constrained VRP's and Multi-Depot VRP's. The underlying assumptions and rules for the mathematical model are as follows:

1. The fleet of N UAVs is homogeneous and has homogeneous flight and detection characteristics. Ideally, the same or similar tools will be deployed by governments
2. The mathematical model is based on distance constrained VRPs. UAVs have a hard endurance constraint (fuel tank, battery life) and will crash if the UAV does not safely land close to the launch point. Let E be the maximum amount of time a UAV can fly.
3. The model is attempting to minimize a continuous variable $\bar{t}$ which is the longest tour any one UAV takes, this is equivalent to minimizing the makespan of a project.
4. Each UAV has a scanning radius r_{scan} which is the range of detection for the devices on board the UAV to identify damage and victims (such as cameras and wireless sniffers).
5. The model assume that in the event of a severe weather event, most people will be inside their homes, places of work, or in their vehicles. If r_{scan} is sufficiently large (on the order of 10^2 meters, literature indicates 300 meters), The model assumes that these places will be within r_{scan} of the road network.
6. The model creates a collection of waypoints (customers) based on the geospatial road data that exists within the bounds of the search area (bounds created by the weather data). See Section 4.5 for details on waypoint creation.
7. The model assumes a simultaneous launch time, once the severe weather has subsided. The simultaneous launch time is because once the severe weather has subsided, the launch points can then (simultaneously) launch the UAVs over the search area. The model assumes simultaneous launches as any given UAV would not be able to engage with the area subject to severe weather
8. Each UAV is allocated to its specific depot.
9. Only one UAV per depot. The UAV to be used requires a two to three person team to set up, launch, and operate the UAV. Additional UAVs per depot would require at least one operator according to the specifications provided by the manufacturer. In

addition, if UAVs start at separate locations, should mechanical failures or other loss of a single launch point would cause all the UAVs to be inoperable. That is, The model is managing to spread the risk of failure over many depots

10. The mission is round trip, UAVs will return to its depot (launch point) after its search pattern .
11. This last leg (the arc defined by a waypoint to depot) is not included into the calculation of $\bar{t}$, as the last leg does not have an effect on the time it takes to search the area.

The differentiation here from common VRP formulations is the objective function which is equivalent to a makespan of a project. The makespan of a project is the time it takes to complete all tasks of a project. The main objective in a search-and-rescue operation is to minimize the time the teams will to cover the search area. The time it takes for any individual SAR team member or sub-team takes is relatively meaningless to the amount of time the entire team takes to search a region. For example, if Team A takes 60 minutes to search its area, whether Team B takes 50 or 60 minutes has little meaning to the goal of covering the entire area. Traditionally, VRP problems often attempt to minimize the total cost, the total travel time, or the total distance of all vehicles and all routes. The objective of the proposed model function consists of minimizing a continuous variable $\bar{t}$, which is linked to the rest of the model with a typical VRP distance traveled constraint. That is, this constraint attempts to calculate the time $\bar{t}_i$ a specific UAV_{*i*} takes to cover a route.

Sets, parameters, and variables of the mathematical model are defined as follows:

Let $G = (W \cup S, A)$ be a directed graph. We denote W as the set of *waypoints* (traditionally called customers) and S as the set of *fire stations* (commonly called depots in VRPs) where drones are launched from and subsequently recovered from. Let $W_s = W \cup \{s\}; \forall s \in S$ be union of waypoints and stations. Let A be the set of arcs (i, j) where $i, j \in W \cup S$

Let E be the endurance of the UAV, i.e. the time a UAV can be aloft. Let t_{ij} be the time it takes for a UAV to fly from waypoint or station i to j . Any $t_{ij} > E$ is removed from the model. Let K be the maximum number of UAVs that can be airborne for any incident. The following formulation uses an indicator variable and that indicator has a big- M constraint. To ensure numerical stability in exact methods, the minimum value of M should be the maximum t_{ij} in the model or the endurance E of the UAV, whichever is less.

The binary variable x_{ijs} takes the value of 1 if UAV from station s is flying from i to j , 0 otherwise. The variable z_{is} is a continuous variable that indicates the total time traveled by the UAV of station s at waypoint i . The singular variable, $\bar{t} \in \mathbb{R}^+$ interpreted as the length of time it takes for the longest route of a UAV from any station to visit all of its waypoints.

Given a set of waypoints and a set of depots where drones are based, the problem then consists in determining a set of routes, each performed by a drone that starts and ends at its own depot, such that all waypoints of the affected area are visited, all the operational constraints are satisfied, and the length of time for the longest search route of a drone is minimized.

The problem can be formulated as follows:

$$\min \bar{t} \tag{4.1}$$

$$\sum_{s \in S} \sum_{j \in W \setminus i} x_{ijs} = 1 \quad \forall i \in W \tag{4.2}$$

$$\sum_{s \in S} \sum_{i \in W \setminus j} x_{ijs} = 1 \quad \forall j \in W \tag{4.3}$$

$$\sum_{i \in W_s \setminus j} x_{ijs} - \sum_{p \in W_s \setminus j} x_{jps} = 0 \quad \forall s \in S, j \in W \tag{4.4}$$

$$\sum_{i \in W_s} \sum_{j \in W_s \setminus i} t_{ij} x_{ijs} \leq E \quad \forall s \in S \tag{4.5}$$

$$\sum_{i \in W_s} \sum_{j \in W_s \setminus \{i, s\}} t_{ij} x_{ijs} \leq \bar{t} \quad \forall s \in S \tag{4.6}$$

$$\sum_{j \in W_s} x_{sjs} \leq K \quad \forall s \in S \tag{4.7}$$

$$z_{ss} = 0 \quad \forall s \in S \tag{4.8}$$

$$(z_{is} + t_{ij} - z_{js}) - M(1 - x_{ijs}) \leq 0 \quad \forall i \in W_s, j \in W, i \neq j, s \in S \tag{4.9}$$

$$(z_{is} + t_{ij} - z_{js}) + M(1 - x_{ijs}) \geq 0 \quad \forall i \in W_s, j \in W, i \neq j, s \in S \tag{4.10}$$

$$x_{ijs} \in \{0, 1\} \forall i, j \in W_s, \forall s \in S; z_{is} \in \mathbb{R}^+ \forall i \in W_s, \forall s \in S; \bar{t} \in \mathbb{R}^+ \tag{4.11}$$

Where (4.1) is the objective function. Constraints (4.2) and (4.3) ensure each waypoint is visited and constraints (4.4) ensure precedence is appropriately maintained. Constraints (4.5) ensure the UAVs return to their departing station within the endurance limit. Constraints (4.6) assures the time $\bar{t}$ is equal to the time it takes for the UAV with the longest route to visit all its waypoints in the problem. Note that constraints (4.6) does not include the arc where the UAV flies back to base. Constraint (4.7) limits the number of UAVs used. Finally, constraints (4.8), (4.9), and (4.10) are used together to eliminate subtours and calculate the load on the route. Constraints (4.9) and (4.10) are linearized from (4.12). Finally, (4.11) are the domains of the variables for this model.

$$\sum_{i \in W_s} \sum_{s \in S} x_{ijs}(z_{is} - z_{js} + t_{ij}) = 0 \quad \forall j \in W \quad (4.12)$$

4.5 Solution Method

The procedure to solve this problem is twofold: first the model generates waypoints to be visited, then generate a route to visit these waypoints. These steps are broken down in this section into the following subsections : *Waypoint Generation Methods* (4.5.1) which breaks down the methods tested for this paper and *Route Generation Method* (4.5.2) for how the UAV is routed over the area.

Waypoints are locations that aim to route the UAVs through the potential disaster area. Waypoints can be thought of as the center of a disk with the radius of r_{scan} that contains some number of points of interest. The method here generates waypoints from these "points of interest." Broadly, points of interest is defined as being indications of where people might be in the event of a tornado. For this paper, we use the data provided by each state's road network, road geospatial shape files. This paper assume that in the event of severe weather most of the population will be within r_{scan} distance (300m) of a surveyed road.

All the geospatial data is converted into the The Universal Transverse Mercator (UTM) and distances between any points are computed by finding the euclidean distance between the points. Performing calculations using UTM as a reference grid will have a maximum distortion of about 0.1%, or one meter for every kilometer of distance

4.5.1 Waypoint Generation Methods

In this section we explore the waypoint generation methods used in this paper for comparison. They are:

- Regular Rectangular Generation Method 4.5.1.1
- Regular Hexagonal Generation Method 4.5.1.2
- Generating Waypoints using minimum set covering, Steiner Method 4.5.1.3
- Heuristically generating a minimum set covering 4.5.1.4

4.2.1.1 Rectangular

Of the tests, rectangular generation method is naive and straightforward. This method converts the points of interest, the roads, into a regular rectangular grid of waypoints, where the grid of waypoints represent the center of a scanning region and the UAVs will visit all these waypoints. The rectangular generation method ensures that all the points of interest are within r_{scan} units of distance from any waypoint. Given a scanning radius of r_{scan} , round the points of interest to the nearest integer part of $\sqrt{2} \times r_{scan}$ meter using built-in `round(n)` functionality. Given a function `round(n)` that rounds the number `n` to the nearest integer value, define the function to round the elements of the coordinate as `round( $\sqrt{2} \times r_{scan}/n$ )  $\times$  n`

It might be naive to round to the nearest $2 \times r_{scan}$, however, given a circular detection range, this will leave a gap in the diagonal between four developed waypoints. Figures 4.1 and 4.2 illustrate this. For example, if a scanning range is 300 meters, round each point of interest to the nearest 424 meter interval (not 600 meter) on the UTM coordinate system.

The algorithm is in $O(n)$ time as it takes one pass through the points of interest to generate the waypoints. That is, take each point of interest in the points of interest and round the coordinates to the nearest $\sqrt{2} \times r_{scan}$. This will place the centers of these waypoints at the nearest $\sqrt{2} \times r_{scan}$. Add each point to the collection of waypoints, discarding duplicates. The algorithm is more formally defined below in Algorithm 1.

This algorithm leads to an inefficient packing of the waypoints. That is, there is a great overlap in each waypoint's range (once again, refer to Figure 4.2). However, as tests will show, this will yield a near-instantaneous waypoint generation method.

A sample visualization of this method can be seen in Figures 4.3 and 4.4

Algorithm 1 Rectangular Waypoint Grid

```

1: Given  $r_{scan}$ , PointsOfInterest
2: Waypoints = Set()
3: ScanningDiameter = IntegerPart( $\sqrt{2} \times r_{scan}$ )
4: for point in PointsOfInterest do
5:   x, y = point
6:   waypoint_x, waypoint_y = round x and y to the nearest ScanningDiameter
7:   Waypoints.add((waypoint_x, waypoint_y))
8: end for
9: return Waypoints

```

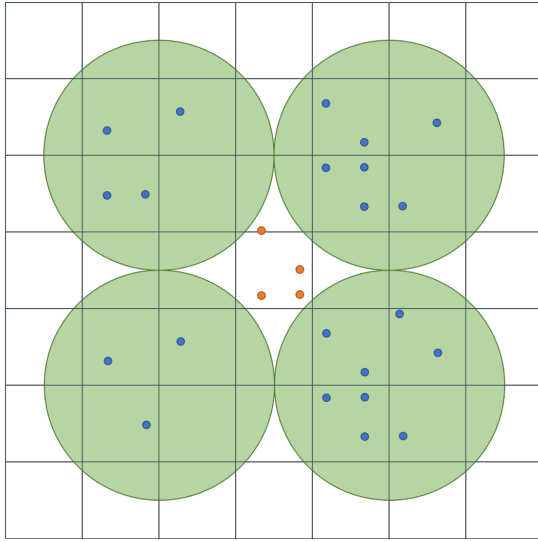


Figure 4.1 When rounding to the nearest $2 \times r_{scan}$ point, this figure shows missed points of interest assuming a circular detection range (figure is for illustrative purposes, not to scale)

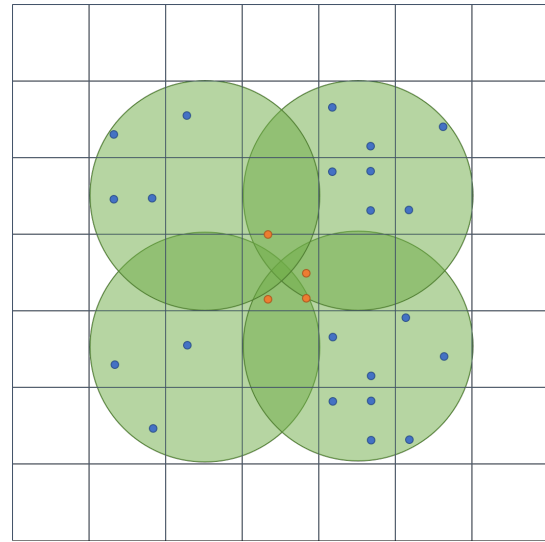


Figure 4.2 When rounding to the nearest $\sqrt{2} \times r_{scan}$ point, this figure shows all points of interest covered (figure is for illustrative purposes, not to scale)

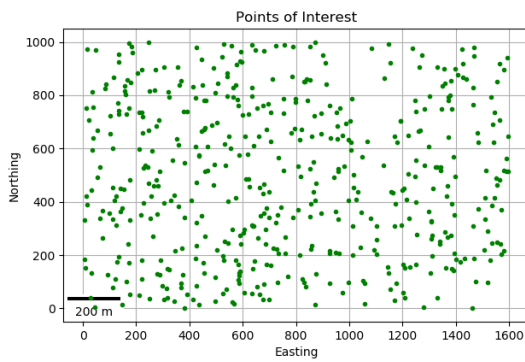


Figure 4.3 Sample Points of Interest

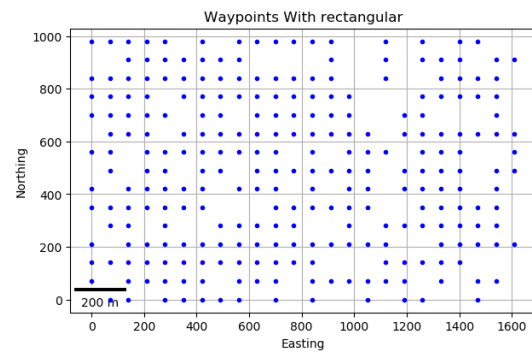


Figure 4.4 Sample Rectangular-grid Waypoints

4.2.1.2 Hexagonal

The second method tested was a hexagonal packing method. Hexagon tiling has been shown to be very efficient [92] and some CETSP implementations have used or discussed its use [60]. The hexagonal method will create waypoints that align with the centers of a hexagon tile. Such an example of the hexagon tiling can be seen in Figure 4.7, and a sample of the tiling method can be seen in Figures 4.5 and 4.6.

The algorithm to generate the hexagonal pattern is as follows: given a r_{scan} and **points_of_interest**, define R as the major axis of the hexagon and set it to r_{scan} and r as the minor axis of the hexagon set to $r_{scan} \times \sqrt{3}/2$. For each point, round each **points_of_interest** to its closest position on the hexagon tile. This is done by rounding one element of the coordinate to its closest $2 \times R$ unit. Let this number be e . Round the other coordinate to the nearest $2 \times r$ if $e/(2R)$ is an even number, otherwise round the coordinate to the nearest $2 \times r$ and then add an r . An example of the hexagonal pattern can be seen in Figure 4.7.

More explicitly, the algorithm to generate the pattern is described in Algorithm 2

The hexagon will have a much greater packing efficiency and in turn, often yielding a shorter tour. However, the distribution of **points_of_interest** is not uniform nor random. The **points_of_interest** follow the roads in the region. Due to land planning in the United States in the 19th and early 20th centuries, often major and minor roads will follow a north to south or east to west direction. This can yield a pattern where if a road is parallel to the major axis of the hexagons in the hexagon pattern, the waypoints generated can force the UAV to fly in a zig-zag pattern over the road, rather than a more linear path over the roads. An example of this can be seen in Figure 4.8.

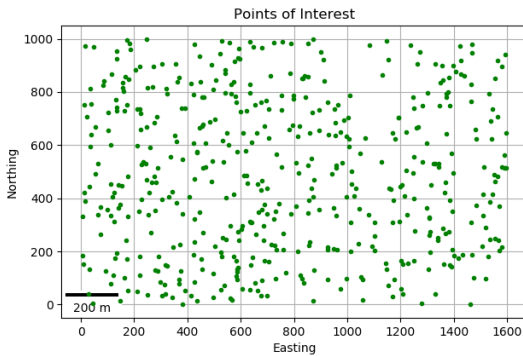


Figure 4.5 Sample Points of Interest

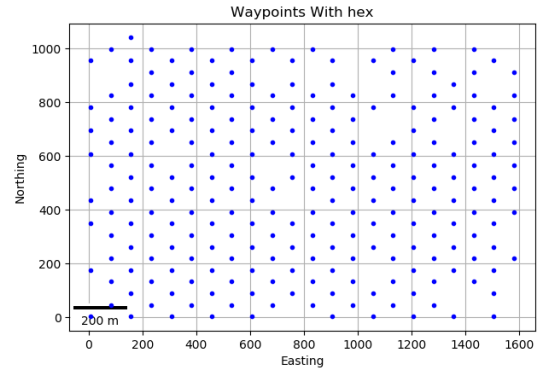


Figure 4.6 Sample Hexagon-grid Waypoints

Algorithm 2 Hexagonal Waypoint Algorithm

```

1: Given  $r_{scan}$ , PointsOfInterest
2: Waypoints = Set()
3: for point in PointsOfInterest do
4:   easting, northing = point
5:   newEasting = round easting to the nearest  $2 \times R$ 
6:   newNorthing = round nothing to the nearest  $2 \times r$ 
7:   if newEasting  $/ 2 \times R \bmod 2 == 0$  then newNorthing +=  $r$ 
8:   end if
9:   Waypoints.add((newEasting, newNorthing))
10: end for
11: return Waypoints
  
```

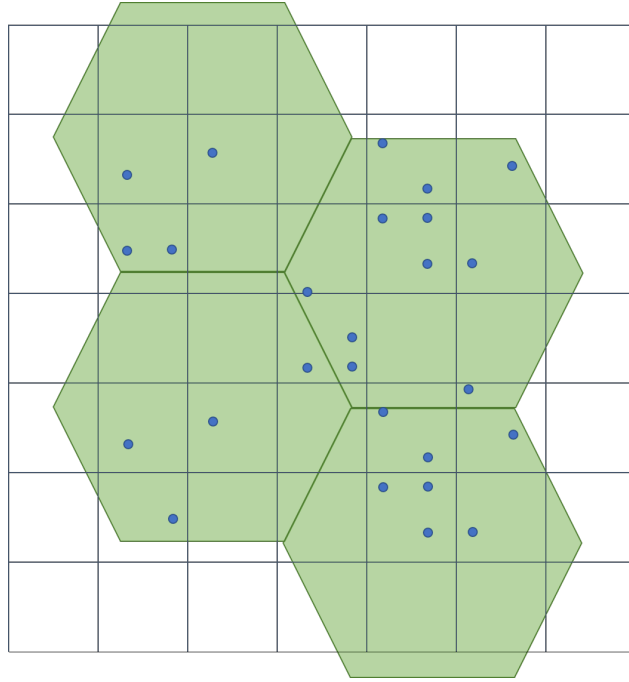


Figure 4.7 Hexagonal Pattern (figure is for illustrative purposes, not to scale)

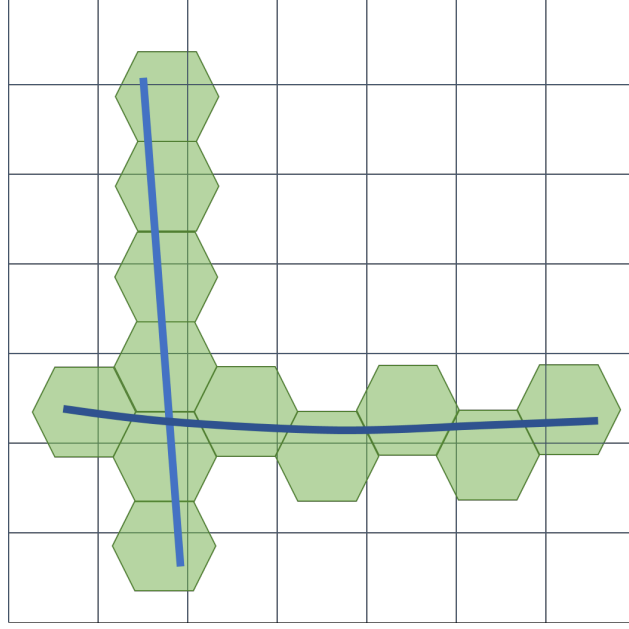


Figure 4.8 An example of a hexagonal pattern with associated roads in blue, the east-west road generates a zig-zag while the north-south road generates a rather linear pattern. The path will follow the center points of the hexagons (figure is for illustrative purposes, not to scale)

4.2.1.3 Steiner Zone

As used in [61], the authors apply the idea of a minimum set covering to the CETSP. A demonstration of the waypoints created can be seen in Figure 4.10. For them, the authors denote a collection of customers as N and a collection of potential Steiner Zones (sets) as M . The objective (4.13) is to minimize the number of sets $x_j \forall j \in M$ to cover all the customers N , where j is defined as a waypoint that is the center of M . They also denote the binary parameter s_{ij} as 1 if customer (point of interest in the case) $i \in N$ is covered by set $j \in M$, s_{ij} takes 0 otherwise. This relationship is defined in (4.14) which ensures that each customer is associated with one set. Finally, $x_j \forall j \in M$ is defined as a binary variable in (4.15).

$$\min z_{(MSC)} = \sum_{j \in M} x_j \quad (4.13)$$

$$\sum_{j \in M} s_{ij} x_j \geq 1 \quad \forall i \in N \quad (4.14)$$

$$x_j \in \{0, 1\} \quad \forall j \in M \quad (4.15)$$

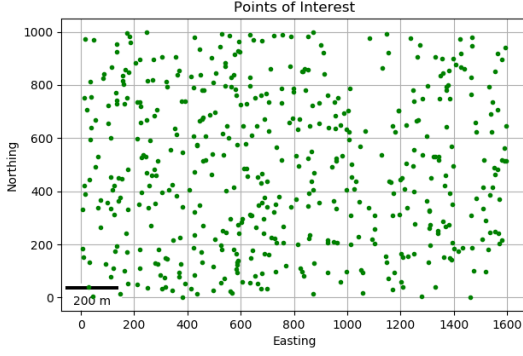


Figure 4.9 Sample Points of Interest

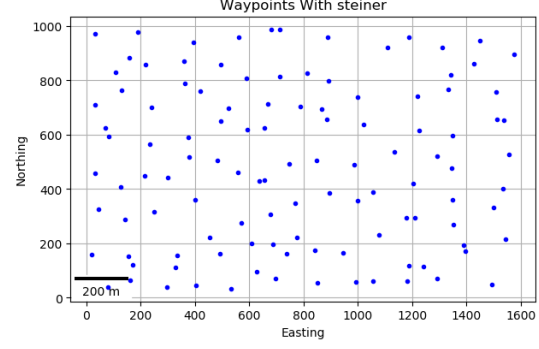


Figure 4.10 Sample Steiner-Zone Waypoints

To generate the collection of sets M , [61] proposes a heuristic. We attempt to make a more complete discovery of the sets leveraging multi-processing tools at our disposal. The parameters s_{ij} are computed by iterating through all the **points of interest** and finding the group of **points of interest** that lie in a minimum bounding circle of radius r_{scan} . We use the Welzl algorithm developed by [93] to find the minimum enclosing disk in average $O(n)$ time. The algorithms to define these sets is depicted in Algorithm 3.

Algorithm 3 Determining Membership of Sets

```

1: Given  $r_{scan}$ , PointsOfInterest
2: groups = set()
3: for each Point in PointsOfInterest do
4:   Execute the following (lines 5-7) on separate processes
5:   neighborhoodPoints = all PointsOfInterest within  $2 \times r_{scan}$  units of Point
6:   Generate subGroups of neighborhoodPoints such that none of the minimum bounding
   circles of the subGroup in subGroups are larger than  $2 \times r_{scan}$ 
7:   Return subGroups from process
8:   groups.update(subGroups)
9: end for
10: return groups

```

After the groups are created, the groups are transformed into the integer program defined by Equations (4.13) to (4.15) and solved. The center point of the identified groups from the integer program are then identified and used as the Waypoints for the UAVs.

However, the method outlined here should yield the most efficient packing of waypoints and minimize the number of waypoints, it can take a long time to execute an exact implementation using commercial solving software. In addition, the use of commercial software could be a

barrier for some organizations¹. Therefore, we also implement a heuristic with the concept of Steiner Zones.

4.2.1.4 Steiner Zone Heuristic

This method attempts to implement the concepts from the previous method but heuristically. The `point_of_interest` are iterated over and are attempted to be added to covering sets based on if they can be added via the minimum enclosing disk demonstrated in [93]. If a specific `point_of_interest` can be added to a covering set in the solution, it is added and the loop proceeds to another `point_of_interest`. If the `point_of_interest` cannot be added anywhere - a new covering set is created and the current `point_of_interest` is added. Since this is a heuristic creation that largely depends on the order of the waypoints, a tabu search is also (optionally) implemented to see if an improvement can be made to the solution. A sample of the waypoints generated can be seen in Figure 4.12

The tabu search is implemented as follows: Covering sets are ordered in descending order by number of points in the group (the idea is that more densely packed covering sets are more likely in more urban or suburban areas, and have more options for movement). The densest, non tabu covering set is selected. Members of the selected covering set are then attempted to be added to other groups. Covering sets are passed over if they are in the most recent half of the tabu list to avoid cycling of points between groups. If there are any remaining points left, they are added back into the solution in their original set and their covering set is now tabu for up to a number of iterations that is the same as the number of initial covering sets. If a covering set is completely empty, we have found a new best solution and the new best

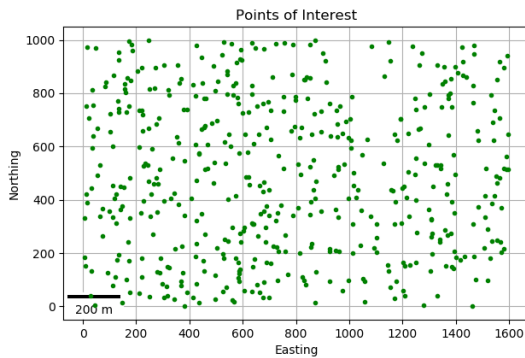


Figure 4.11 Sample Points of Interest

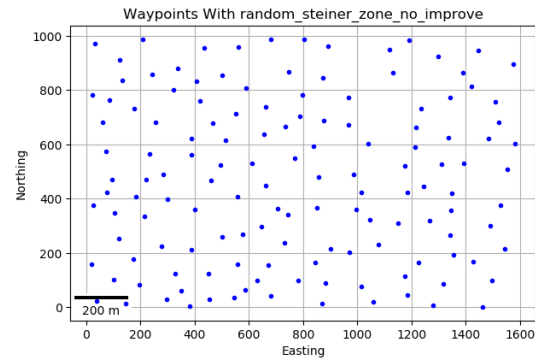


Figure 4.12 Sample Steiner-Zone Heuristic Waypoints

¹Although there are freeware or open source implementations such as COIN-OR

solution counter is reset and the covering set ID is permanently discarded. If all moves are tabu, the tabu list is emptied and the process continues. Stopping criteria are (all optionally) a time limit, a maximum number of iterations, and a maximum number of iterations without improvement. Globally, the tabu search is re-executed until no better solution is found.

Algorithm 4 Steiner Zone Heuristic

```

1: Given  $r_{scan}$ , PointsOfInterest
2: groups = set()
3: while length(PointsOfInterest)  $\geq 0$  do
4:   tempGroup = set()
5:   tempGroup.add(PointsOfInterest.pop())
6:   for Point in PointsOfInterest do
7:     if distanceFunction(Point, tempGroup)  $\leq r_{scan}$  then
8:       tempGroup.add(Point)
9:       PointsOfInterest.remove(Point)
10:    end if
11:  end for
12:  groups.add(tempGroup)
13: end while
14: return groups

```

4.5.2 Route Generation Methods

The mathematical model in Section 4.4 is based on the class of problems known as the VRP. The VRP is well known as being NP-Hard [91]. Since this paper aims to generate the waypoints and deploy the UAVs in a short time frame, constructive heuristics will be used to minimize distance of the longest tour. Due to the timeliness and speed at which post-disaster response must be executed, a cluster first route second generation heuristic was implemented [94].

As the method suggests, a cluster-first route-second (CFRS) method was utilized as a constructive heuristic for the problem. The CFRS method implemented here is based on the work in [94]. Cluster first was done with **k-means++** clustering as it is good at creating clusters from convex data-sets and the **n_clusters** is directly related to the number of depots K .

After assigning waypoints to clusters, the routes are created. The route method is the minimum insertion heuristic is used [95] with the exception that the initial arc selected is the arc between the two waypoints with the longest time, i.e. the constructive heuristic created will chose two waypoints i and j in a given cluster with the greatest t_{ij} . This is selected because the objective function minimizes the one way route from the station through all the

waypoints. The final arc does not have an effect on the objective function. The minimum insertion heuristic adds the remaining waypoints to the tour. The next waypoint to be inserted is the one that is closest to the waypoints in the current route and is positioned in the place that minimizes the $\bar{t}_i$ for the tour i . This process repeats until all waypoints are inserted into the route.

Then the routes are assigned a fire station based on the minimum cost to insert the fire station. That is, we find the single fire station from the collection of fire stations with the minimum cost to insert. The outline of the CFRS can be seen in algorithm 5.

Algorithm 5 Cluster First Route Second

```

1: Waypoints, FireStations, K
2: clusters = k_means(numberOfClusters=k, data=Waypoints)
3: for cluster in clusters do
4:   route = []
5:   for waypoint in cluster do
6:     idx = findMinCostInsertion(waypoint, route)
7:     route.insert(waypoint, idx)
8:   end for
9:   station = findMinCostStation(FireStations, route)
10:  solution[station] = route
11: end for
12:

```

4.6 Results

This section is devoted to testing the methods outlined to three experimental data sets. The first one is the Moore-Newcastle Tornado May 20, 2013 [96], second is the May 9, 2016 Katie, Oklahoma tornado [97], and the third one is from a collection of tornadoes in East Texas on April 29, 2017 [98].

The computer used for these tests are in Table 4.1.

Table 4.1 Computer Specifications

Processor	AMD A8-7600 Radeon R7, 4 Cores 3.10 GHZ
RAM	16.0 GB installed (15.0 GB usable)
OS	Windows 10, 64-Bit
Language	Python 3.7.5

4.6.1 Heuristic Comparison to Exact method

The CEVRP is known to be NP-Hard. We compared the proposed heuristic to smaller problem sizes (on the order of 10's of waypoints and two depots). We ran these models on the above computer with the parameters in Table 4.2 passed to the solver.

The smaller problems were created by randomly generating a 'square SBW' in a random location in Oklahoma.

Summary statistics can be seen in Table 4.3, 70 instances were created ranging from 4 to 19 waypoints. All exact methods terminated via the time constraint (2000 seconds), while the heuristic completed in seconds. On average, the optimality gap was 1.75%. Occasionally, the heuristic approach finds a better solution than the one found by the optimal approach within its allotted time. For these instances, the solution was on average 2.23% better than the one found the exact approach.² Excluding instances where the heuristic found a better solution, the heuristic produces solution that are on average 4.48% longer than the one produced by the optimal approach. There was little effect on the percent difference among the waypoint generation methods. A scatter plot of the tests can be seen in Figure 4.13.

Table 4.2 Parameters for Gurobi solving the CEVRP exactly

Parameter	Value	Interpretation
Version	8.1.1	
MIPGap	0.1	10%
MIPFocus	1	finding feasible solutions quickly ³
Method	2	Barrier Simplex
TimeLimit	2000	seconds, 33m20s
Cuts	2	Aggressive

Table 4.3 Summary of Heuristic vs. Exact Tests

Case	Value
Average Difference	1.86%
Average Difference (Only exact is better)	4.48%
Average Difference (Only heuristic is better)	-2.23%
Rectangular	2.45%
Hexagon	1.37%
Mean Shift	1.44
Steiner Exact	2.63%
Steiner Heuristic	1.93%

²Implementation Note : Warm starts were rejected by the Solver

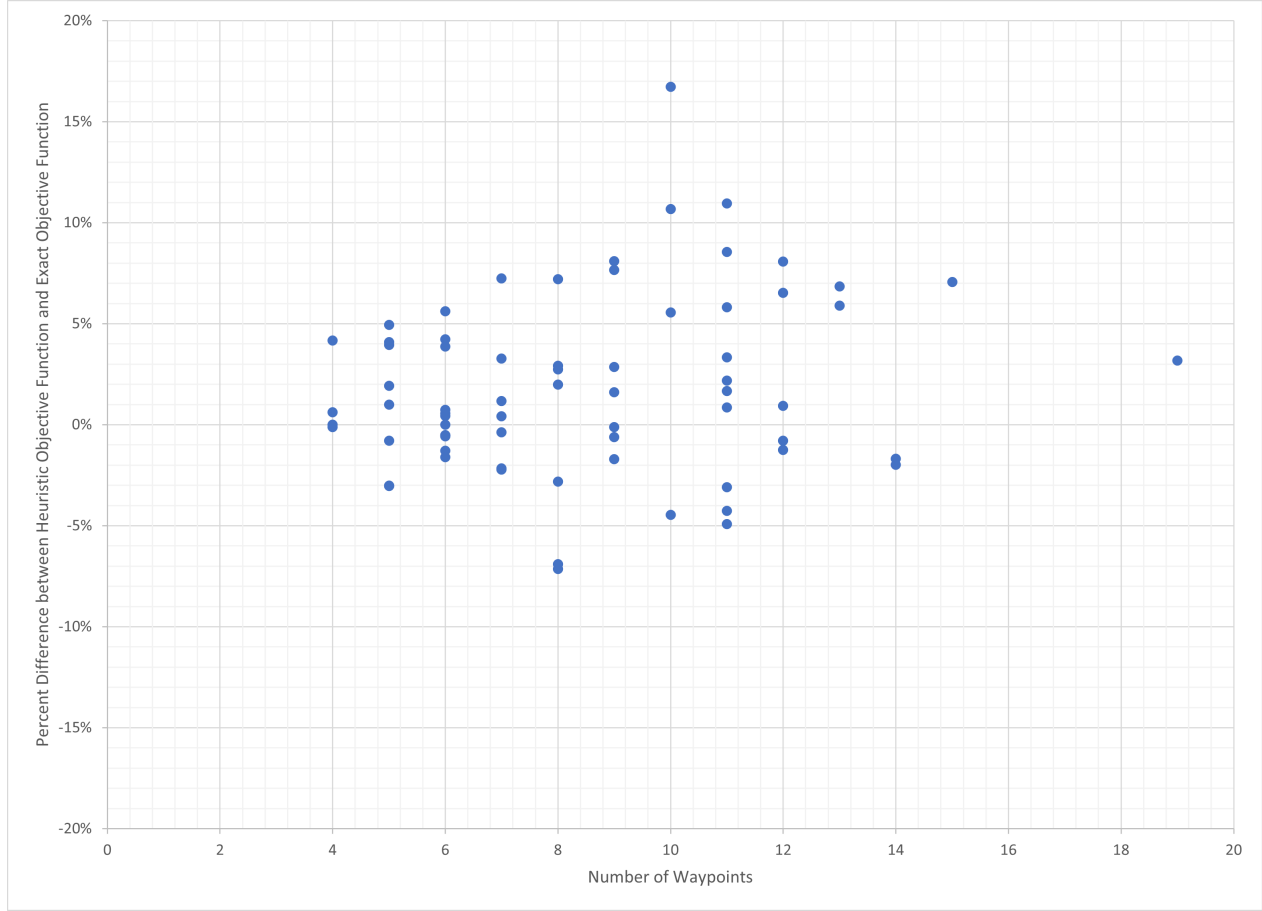


Figure 4.13 Percent difference between heuristic and exact objective functions, and the number of waypoints in the solution

4.6.2 Experimental Data Sets

The first two data sets are two major tornadoes that struck the state of Oklahoma in the past decade. We consider professional, non-volunteer fire stations in the state of Oklahoma as potential depots for the UAVs. Geospatial road information was also pulled from the government’s public databases. Both pieces of information were pulled from the Oklahoma Office of Geographic Information, Oklahoma GIS Data Clearinghouse web site [80].

The East Texas tornadoes in 2017 used similar data from the Texas General Land Office [99] and the Texas DOT [100]. However, fire stations were pulled from the ArcGIS Open Data Hub [101]. The file here contains Fire Station data for the United States in its entirety. A breakdown of parameters used are in Table 4.4 and Table 4.5.

⁴Number of UAVs Launched was determined from approximately 600 waypoints per UAV by the rectangular method for Moore-Newcastle and Katie. East Texas was increased to about 400 waypoints per UAV to account for the number of disjointed search areas

Table 4.4 Parameters for the tests⁴

	Moore-Newcastle	Katie	East Texas
Date	May 20, 2013	May 9, 2016	April 29, 2017
State	Oklahoma	Oklahoma	Texas
Initial Number of Fire Stations	513	513	1150
Number of UAVs Launched, K	4	20	10

Table 4.5 Parameters for Steiner inspired methods⁵

Steiner Exact		Steiner Heuristic with Tabu improvement	
Solver	Gurobi 8.1.0	Max Time (First pass)	Infinite
Solver Time Limit	600s	Max Time (Subsequent passes)	60s
Gap	1%	Maximum Iterations	10,000
		Maximum Iterations Without Improvement (First pass)	500
		Maximum Iterations Without Improvement (Subsequent passes)	200

4.6.3 The Tests

Results : Waypoint Generation

Tables 4.6, 4.7, and 4.8 contain the results for testing the three data sets with the five waypoint generation methods. They all contain identical columns respectively: the generation method, the number of waypoints that were generated with the method, the percentage increase of number of waypoints from the best method (Steiner Zone Exact), the time (in seconds) it took to create the waypoints, and the makespan $\bar{t}$ in hours (objective function value). The last column compares the waypoint generation methods to the naive method (Rectangular). This value is the ratio of the additional time it takes to generate waypoints and reduction in solution value, which is also recorded in units of time. Greater the value in this column the better the result is. Any value greater than 1.0 means for every second

⁵Please note the *Solver Time Limit* in this table is strictly the time it takes to solve the set-covering problem that was passed to Gurobi, this does not including the generation of the sets. This stopping criteria was not triggered in the data sets outlined, only the gap.

we spent on generating the waypoints we saved more than one second on $\bar{t}$. If proportion is negative, that means time was lost on $\bar{t}$ for each second generating waypoints. This is interesting because the objective of this paper is to launch the UAVs as soon as possible with data that is reported in real time. That is, we can plot the trade-off between the time it takes to find a solution and the value of the objective function.

We can see that almost all of the Steiner-inspired methods offer significant improvements on the solution value. However, trying to offer a tabu-search improvement of the Steiner Zone Heuristic offers limited improvement in only one case (reducing the number of waypoints) while requiring a significant time commitment to attempt the method. The difference between the proposed heuristic and the exact method is between 11% and 26% reduction in number of waypoints, but the reduction in objective function value $\bar{t}$ is between 5% and 18%.

In this section we showed the different waypoint generation methods, the time it takes to generate waypoints from each method, the objective value $\bar{t}$ for each method, and the time it takes to run each method, and the trade-off between objective function value and time it takes to run. In Figure 4.14, we see when fewer waypoints are generated, there is a reduction in the objective value $\bar{t}$. However, this reduction comes at a cost of generation time. From Tables 4.6, 4.7, and 4.8, we can see that heuristically generating the waypoints (Steiner Zone Heuristic (No Tabu)) is a much better use of the time in the event of a disaster than any other method. While for smaller instances, generating the waypoints with an exact method can offer a positive return on the objective function, the speed of the heuristic far outweighs the time the exact method takes.

Route Generation and Program Execution Times

This subsection is devoted to route generation and overall program execution times. The data for these times can be seen in Tables 4.9, 4.10, 4.11. A brief inspection, it appears that there is a strong correlation between the number of waypoints and the time it takes for the heuristic to route the UAV.

Table 4.6 Moore-Newcastle 2013 Waypoints

	Number of Waypoints	Waypoint Increase %	Generation Time (s)	$\bar{t}$	$\bar{t}$ savings over additional generation time
Rectangular	2653	96%	0.08	4h41m	
Hexagon	2349	73%	239.97	4h34m	1.84
MeanShift	2501	84%	55.42	4h18m	24.95
Steiner Zone Heuristic (No Tabu)	1712	26%	15.96	3h28m	278.98
Steiner Zone Heuristic (With Tabu)	1709	26%	367.94	3h28m	11.99
Steiner Zone Exact	1357	0%	2,417.54	3h09m	2.29

Table 4.7 Katie 2016 Waypoints

	Number of Waypoints	Waypoint Increase %	Generation Time (s)	$\bar{t}$	$\bar{t}$ savings over additional generation time
Rectangular	8247	103%	0.17	4h38m	
Hexagon	8211	102%	450.46	5h07m	(3.96)
MeanShift	7980	96%	59.70	4h28m	9.54
Steiner Zone Heuristic (No Tabu)	4638	14%	64.27	3h48m	46.35
Steiner Zone Heuristic (With Tabu)	4638	14%	1,162.94	3h43m	2.83
Steiner Zone Exact	4069	0%	1,308.28	3h03m	4.33

Table 4.8 East Texas 2017 Waypoints

	Number of Waypoints	Waypoint Increase %	Generation Time (s)	$\bar{t}$	$\bar{t}$ savings over additional generation time
Rectangular	6777	89%	0.20	6h10m	
Hexagon	7075	97%	2,192.31	7h50m	(5.16)
MeanShift	5526	54%	194.51	5h18m	(11.17)
Steiner Zone Heuristic (No Tabu)	3982	11%	64.69	4h40m	1.10
Steiner Zone Heuristic (With Tabu)	3982	11%	2,621.36	4h40m	0.03
Steiner Zone Exact	3592	0%	10,738.59	4h25m	0.09

Looking at Table 4.12, we can see that when we look at the summation of the waypoint generation time and the routing time, we continue to find a middle ground with the using the Steiner Zone Heuristic without an improvement step. While the route generation time is largely irrelevant for the smaller, Moore-Newcastle data set, the larger data set we can see that there is a significant cost to running the routing heuristic on these larger waypoint counts. We can say that with the order of magnitude increase in the number of waypoints, we see an order of increase in the routing time.

A visualization of the routes for the Moore-Newcastle case can be seen in Figures 4.15, 4.16, 4.17, 4.18, and 4.19

4.6.4 Summary of results

As we have shown in Section 4.6, there is a trade-off between waypoint generation time, routing time, and objective function value. The additional waypoints of some methods do yield a greater time to create routes, but this only becomes a factor with the larger, real-world data sets (Katie and East Texas), largely because the number of waypoints is nearly double the best case scenarios. Although a reduction in number of waypoints yields a reduced objective function, it can happen at a cost of additional generation time. While it is atypical to directly compare objective function values and solution times, we believe it is an appropriate analysis here due to the nature of SAR operations – there is a pertinent need to analyze the trade-off between spending more time planning and taking action on a plan. Or more generally – there

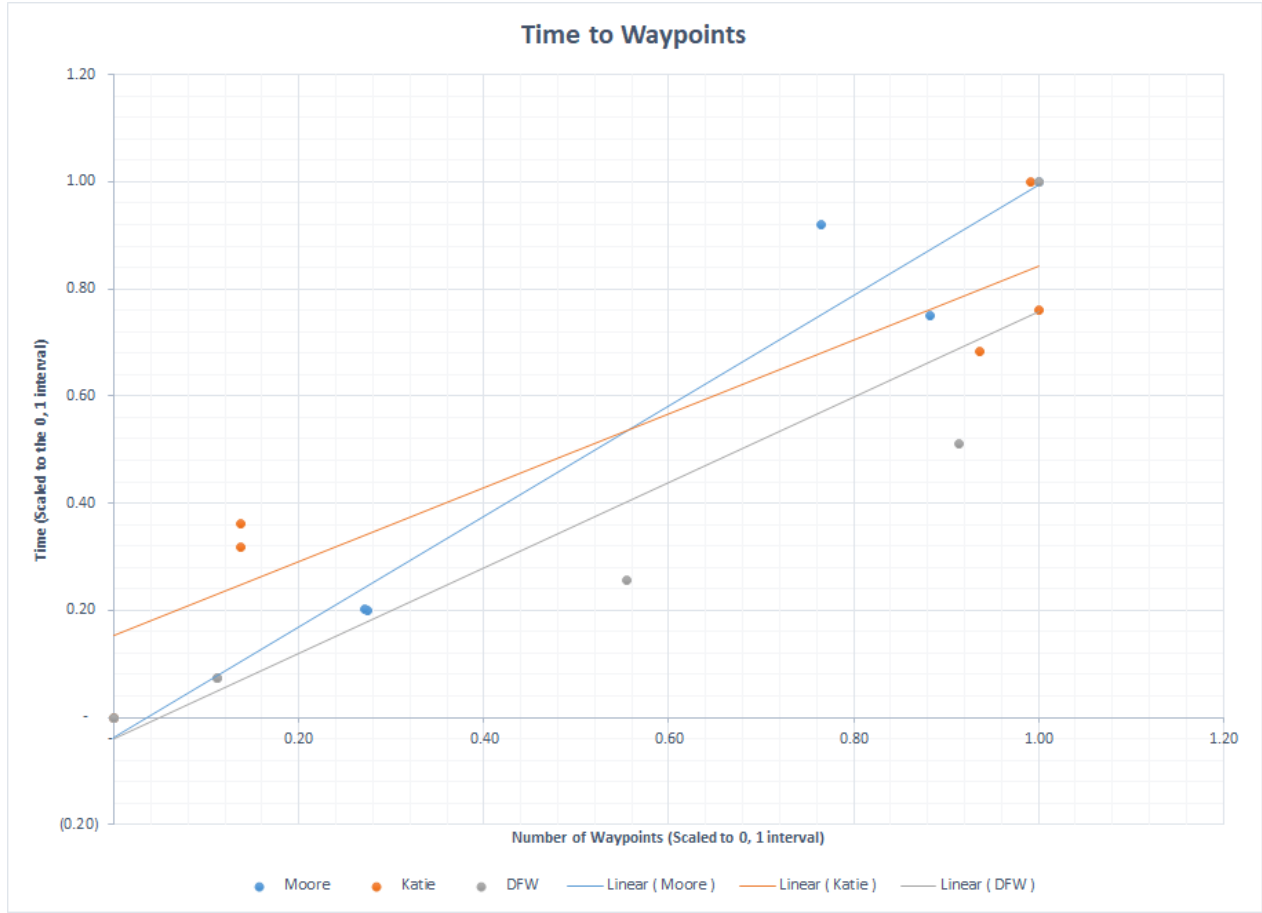


Figure 4.14 Relationship between $\bar{t}$ to Waypoints

is a need to know the relationship between solving this problem to optimality and how much time it takes to optimize. Further research into trade-offs between generation of solution and objective function is warranted. However, in situations and industries where time is of the essence, even tractable exact solutions must be cast aside for a good enough solution. Search and rescue operations provide a unique opportunity to analyze this trade-off explicitly as the objective is to usually complete a mission in the shortest time, rather than other VRPs, TSPs where costs associated are often in monetary values or distance values.

4.7 Conclusion

This chapter uses meteorological data in routing UAVs in the aftermath of tornadoes. This chapter explored the use of various methods to generate waypoints and analyzed the trade-offs between time to create waypoints and the yielding objective function value.

To the best of our knowledge, there is no research being conducted in the operations research

Table 4.9 Moore-Newcastle 2013 Route Generation Time

Moore-Newcastle (2013) Times in Seconds					
	Rectangular Grid	Hexagonal Grid	Steiner Zone Heuristic	Steiner Zone Heuristic (Tabu)	Steiner Zone Exact
Reading Files	40.46				
Processing Files	20.19				
Generating Waypoints	0.08	239.97	15.96	367.94	2417.54
Routing	181.31	168.61	108.53	111.45	74.96

Table 4.10 Katie 2016 Route Generation Time

Katie (2016) Times in Seconds					
	Rectangular Grid	Hexagonal Grid	Steiner Zone Heuristic	Steiner Zone Heuristic (Tabu)	Steiner Zone Exact
Reading Files	30.82				
Processing Files	65.47				
Generating Waypoints	0.17	450.46	64.27	1162.94	1308.28
Routing	1523.92	1608.11	419.70	284.25	111.03

literature incorporating meteorological data from the National Weather Service, specifically tornado information, to aid rescuers in their decision making process. Granted, this is potentially due to the recent innovations with UAV technology and remote sensing on the UAVs as well as the digitization of the severe weather data being a relatively recent decision (limited digitized data appears before 2012). That is, it is traditionally quicker to wait for rescuers to drive out or wait for citizens to "call in" need rather than go out looking for the tornado damage.

It is typical that when fewer waypoints are generated, the resulting amount of time it takes to search the area is reduced. This does come at a cost of time to create the waypoints. Typically, the implementation of the "Steiner zone heuristic" method has the best trade off

Table 4.11 East Texas 2017 Route Generation Time

East Texas (2017) Times in Seconds					
	Rectangular Grid	Hexagonal Grid	Steiner Zone Heuristic	Steiner Zone Heuristic (Tabu)	Steiner Zone Exact
Reading Files	30.82				
Processing Files	65.47				
Generating Waypoints	0.20	2192.31	64.69	2,621.36	10,738.59
Routing	528.28	729.73	432.94	209.00	208.81

Table 4.12 Time Analysis

Data set	Waypoints	Generating Waypoints (s)	Routing (s)	Total Time (s)	Waypoint Count
Moore	Rectangular	0.10	181.31	181.42	2,653
	Hexagon	297.33	168.61	465.94	2,349
	Steiner Zone Heuristic	16.90	108.54	125.44	1,712
	Steiner Zone Heuristic (Tabu)	396.42	111.46	507.88	1,709
	Steiner Zone Exact	3,696.19	74.97	3,771.16	1,357
East Texas	Rectangular	0.23	528.29	528.52	8,247
	Hexagon	2,813.46	729.73	3,543.20	8,211
	Steiner Zone Heuristic	67.22	209.00	276.22	4,638
	Steiner Zone Heuristic (Tabu)	2,769.65	208.81	2,978.46	4,638
	Steiner Zone Exact	11,680.09	166.59	11,846.69	4,069
Katie	Rectangular	0.13	1,523.93	1,524.06	6,777
	Hexagon	449.91	1,608.11	2,058.02	7,075
	Steiner Zone Heuristic	65.01	419.70	484.72	3,982
	Steiner Zone Heuristic (Tabu)	1,194.10	284.25	1,478.35	3,982
	Steiner Zone Exact	1,861.06	111.03	1,972.09	3,592

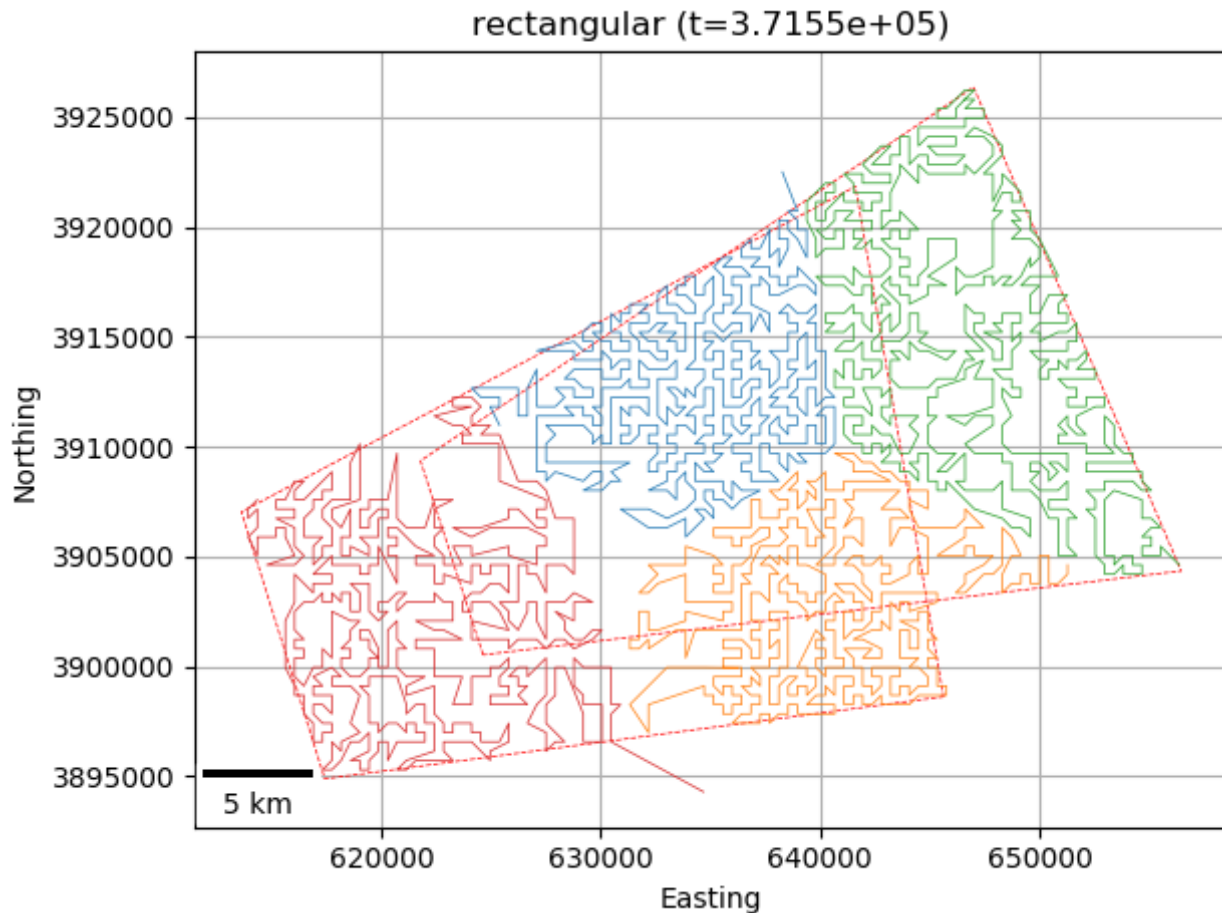


Figure 4.15 Route for Moore-Newcastle using rectangular waypoints

between time to create waypoints with the $\bar{t}$ value. Clearly, solving the method exactly would yield the best results, but often at an order of magnitude additional time.

There is plenty of low hanging fruit for future exploration.

Some limitations of the research include the legal and data hurdles that may exist outside of The United States, such as some governments' restrictions or bans on UAV operations or this chapter may not be effective in locations where GIS and meteorological data may not be as detailed or freely available. However, we encourage the reader to explore how to use expert-generated data and the flexibility wireless sniffers can provide members of the search and rescue community. One example to get data of where people may be is to use light maps and imagery from artificial satellites. One such idea to identify bounding locations for search areas is via observation towers (such as those tracking forest fires) and triangulating a search area from observers.

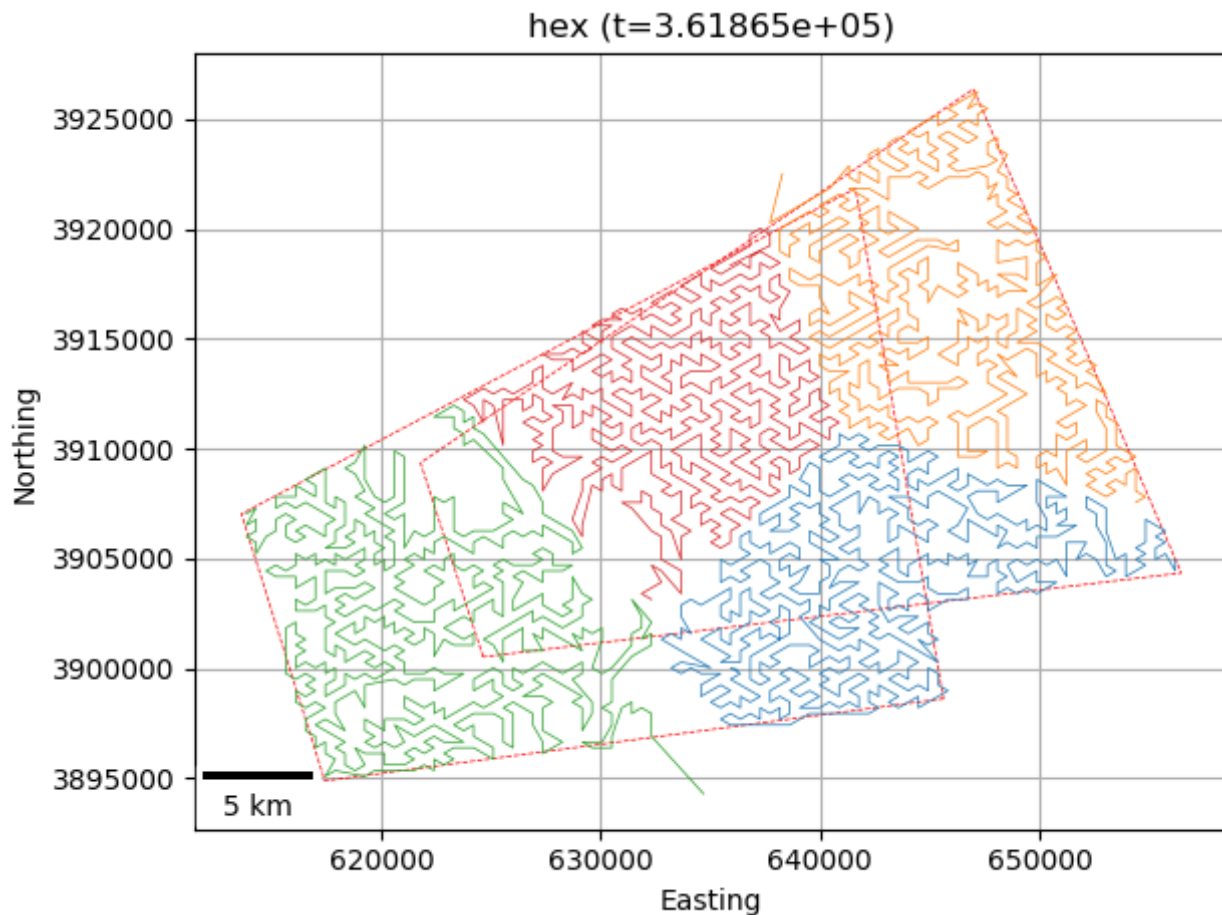


Figure 4.16 Route for Moore-Newcastle using hexagonal waypoints

The first is that these waypoints can be pre-computed exactly and issued to the disaster response bodies.

Additionally, the method in this chapter has tasked the UAV(s) to search the entire area; often times, the damage associated with the tornado is a small part of this initial search area. For instance, in the context of the Moore-Newcastle tornado, the initial search area is approximately 700km^2 while the tornado path area is approximately 70km^2 with the most damage (EF-4 and EF-5 damage) done in an area approximately 20km^2 . While the objective of this chapter was to scan the entire search area in as short amount of time - in practice the objective should be to *find the damaged area as quickly as possible*. Knowledge that tornadoes typically move from west-by-south-west to east-by-north-east pattern (from approximately the eight o'clock to two o'clock on a clock face, where twelve is north) intuitively means that a pattern that goes from north to south to north could decrease the time it takes to find the damaged area.

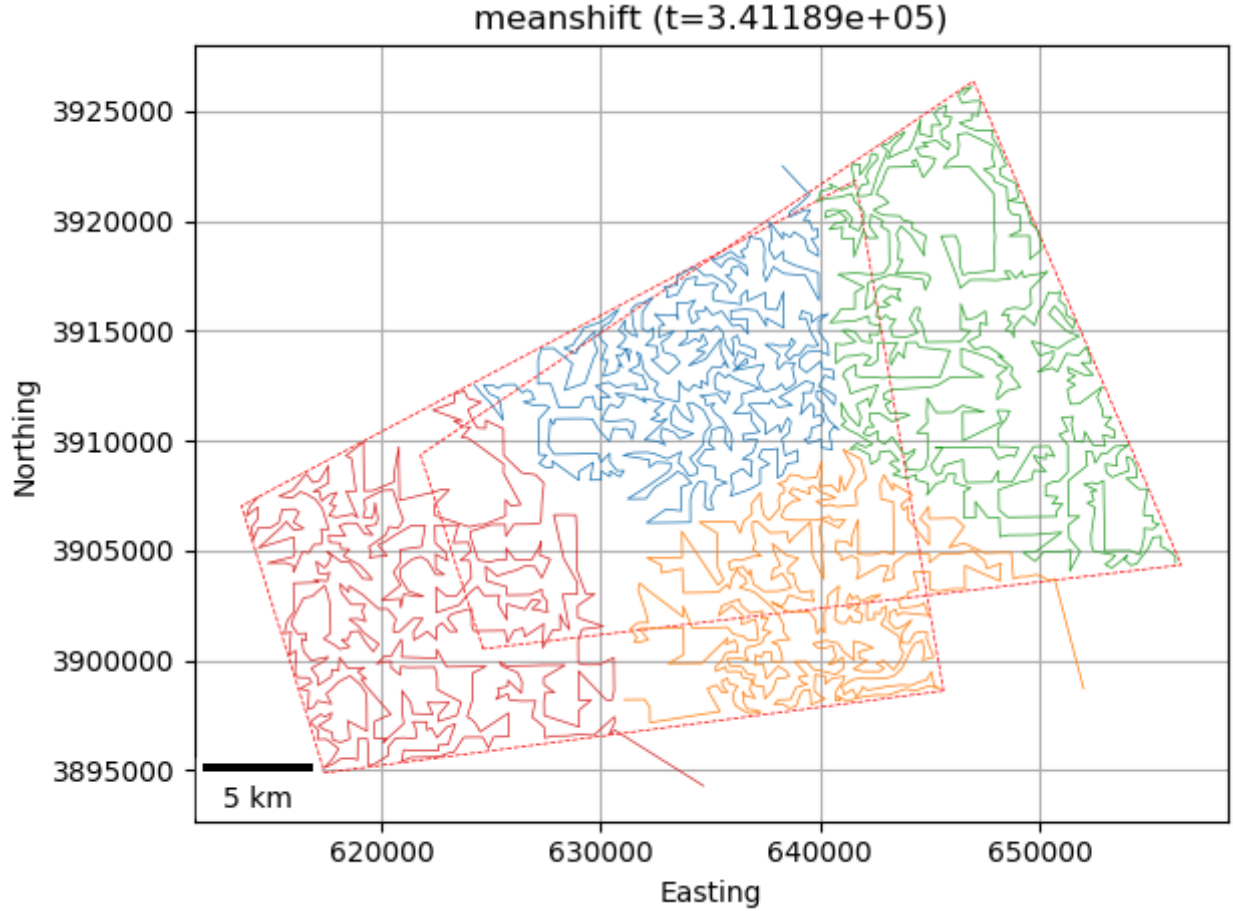


Figure 4.17 Route for Moore-Newcastle using mean-shift waypoints

Our model forces the UAVs to return to base. In practice, manned aircraft must always return to base, but the smaller UAVs could potentially land away from base in safe zones and be picked up by a staff member. Such examples could be a school's athletic field, parking lot, or other depot. This could extend the effective range of the UAV and allow for a "one-way-mission." In addition, allowing inter-depot refuelling (which has been explored in the literature) can allow for UAVs to extend their range, although the immediate response needed for the UAV to be present in the disaster area might make the practical implementation of layovers to be unnecessary.

There may also be a chance to explore asynchronous launches if a depot can send a UAV from a sufficiently far or safe distance from a severe tornado event; however, we do believe that we would run into similar issues with inter-station refueling.

Due to the nature of the objective function, further explorations of heuristics should be done to potentially find a better trade-off between solution generation time and $\bar{t}$ and route time.

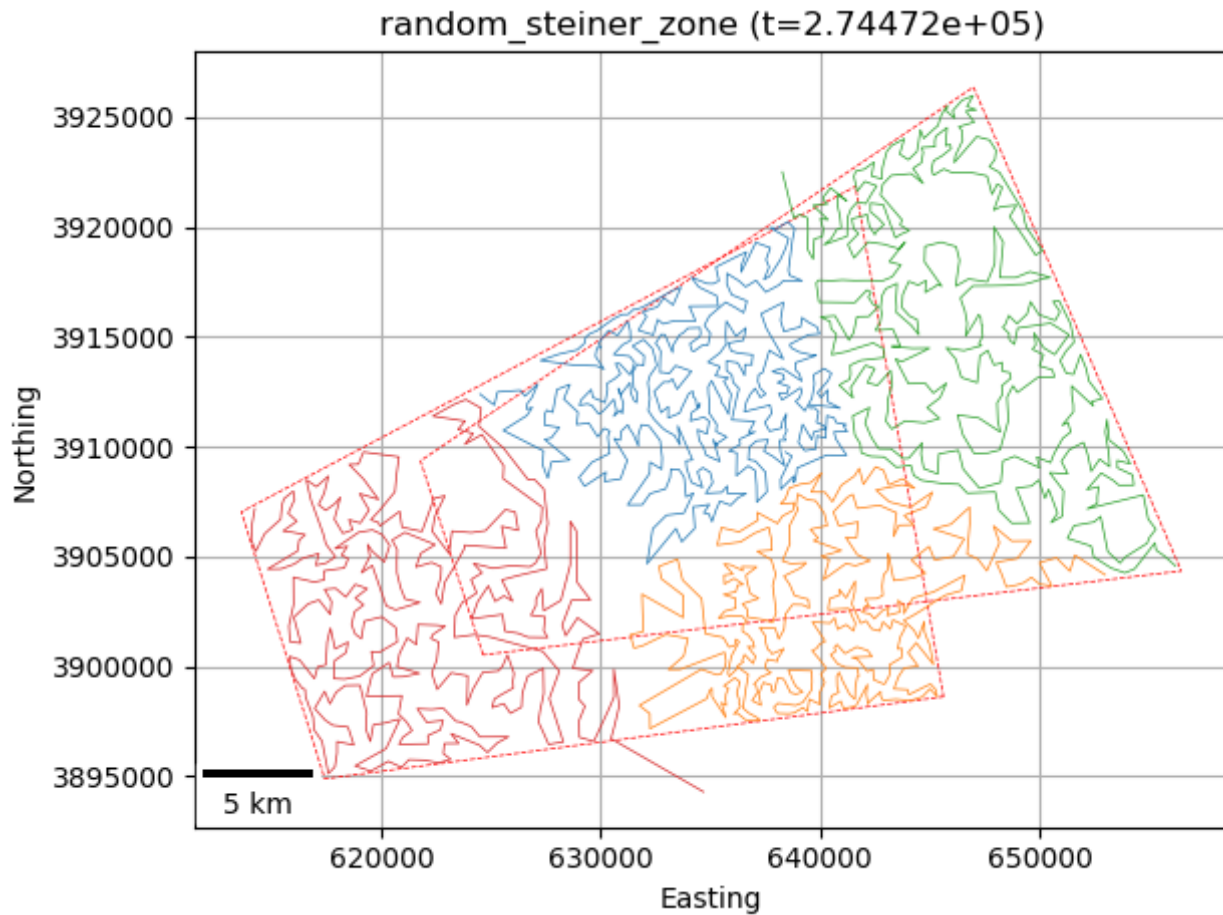


Figure 4.18 Route for Moore-Newcastle using Steiner zone heretic waypoints

This chapter assumes all depots have a UAV. While the UAVs in this chapter are inexpensive compared to manned counterparts, their costs are not negligible. Allowing for alternative recovery procedures could continue to minimize the number of UAVs to initially purchase by governing bodies or rescue groups

We hope that this publication can serve as a starting point for using tornado data in the operations research literature and potentially using the make-span of a VRP in the Search and Rescue operations literature.

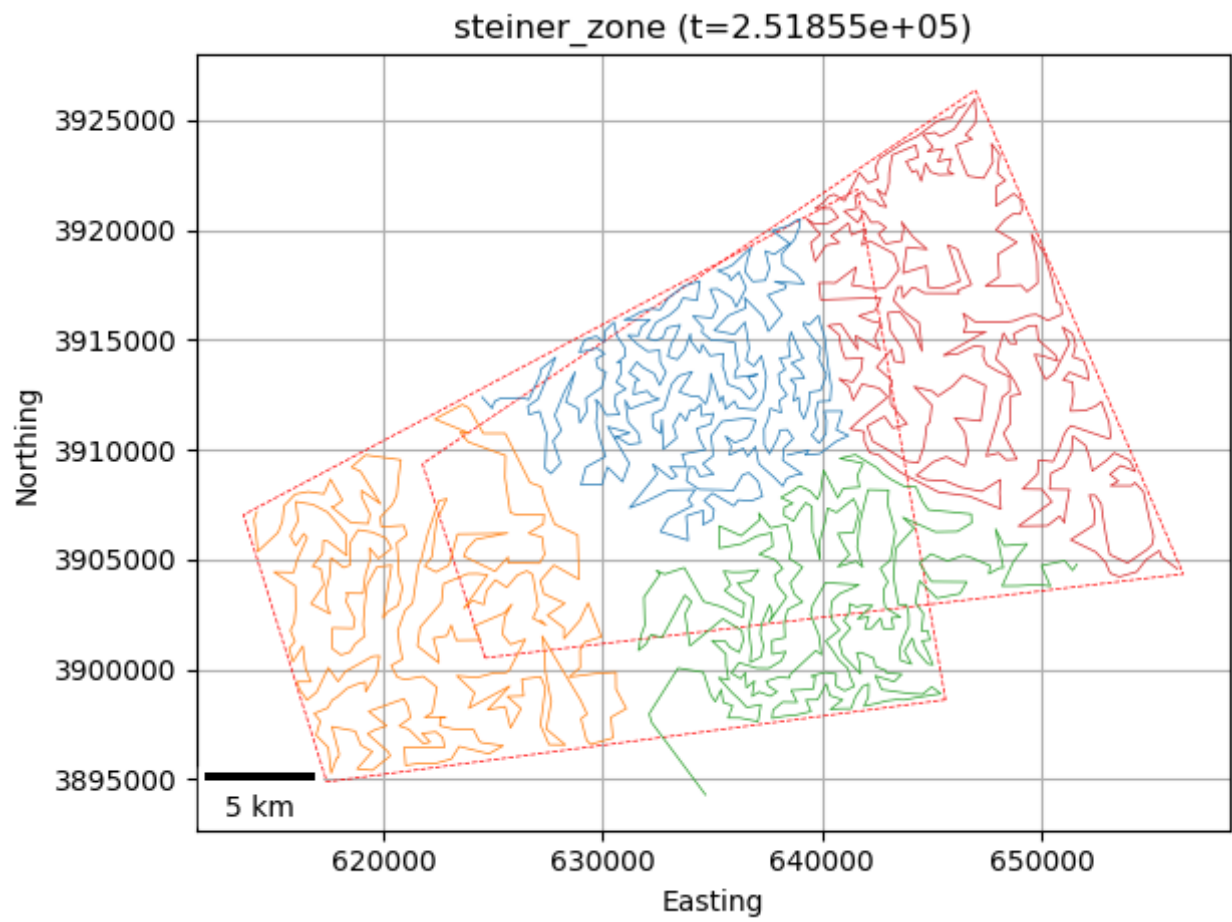


Figure 4.19 Route for Moore-Newcastle using Steiner zone exact waypoints

CHAPTER 5 ARTICLE 2: LOCATION OF DISASTER ASSESSMENT UAVS USING HISTORICAL TORNADO DATA

This article, titled "*Location of disaster assessment UAVs using historical tornado data*" was published in *Geomatics, Natural Hazards and Risk* on September 11, 2022. This paper was co-authored by Nathalie Perrier, Michel Gamache, and Robert Pellerin [2].

5.1 Abstract

Preparing and responding to disasters is a complicated task. One must balance coverage of SAR resources versus preparation cost. This chapter presents a method and solution to prepositioning UAV damage assessment and search teams in Oklahoma using historical tornado data. The approach is based on set covering and multi-station vehicle routing models. It also presents a method to robustify the solution in the event a UAV team cannot be activated to respond to the disaster. This can simulate a team unable to respond. Results show 70% more stations and teams being required when chance of a depot failure goes from 0 to 5% and 90% more stations required when 0–10%. We find that when trying to use a solution that does not account for depot failure, the system of UAVs cannot meet search completion targets in 3–4% of cases. These results demonstrate accounting for the chance of teams not being able to respond to domestic disasters is important and failing to do so means an increased chance of not being able to respond adequately to disasters and incorporating the chance of station failure has a profound impact on the number of stations needed.

5.2 Introduction

Preparing for disasters and the subsequent Search and Rescue (SAR) operations involves a variety of decision problems that can be addressed with operations research methodologies [102, 103]. SAR operations present a variety of decision-making problems at the strategic, tactical, and operational levels. These problems include determining the number and type of resources used in an SAR operation (e.g., helicopters, fixed wing aircraft, Emergency Medical Technicians and other first responders), locations for these teams and tools, and identifying search teams' needs and capabilities. The strategic aspect of SAR operations concerns the determination of the locations of guard and search team stations and resources depots or launch points. The strategic level also includes long-run planning problems, such as enhancing the capabilities of the SAR fleet in terms of flight crew number or increasing

the number of stations that can be activated. All these decisions are often done in advance of a disaster occurring.

One aspect of the emergency response systems, e.g., SAR operations, includes resource allocation. Resource deployment decisions are often made in conjunction with computer-assisted modeling of the probability of detection under various deployment scenarios [76]. This can be compared to and contrasted with operational decisions that are guided via established survival tables to guide the SAR routing efforts and advanced technology designed to maximize the probability of detecting a point of interest.

Procedures at the strategic, tactical, and operational level have been developed. The traditional approach has been to deal separately and sequentially with each problem or planning level. Once the station locations are chosen at the strategic level, the actual allocation of resources to each station can be determined, and the airborne vehicle routes are determined last.

In recent years, many developments in SAR airborne technologies have increased to improve operations and reduce the time span to assess and search a damaged area in real-time. These technologies include airplanes and helicopters equipped with numerous sensors as well as Unmanned Aerial Vehicles (UAVs), also called drones, equipped with cameras and wireless sniffers to detect the presence and roughly the proximity to a cellular device. The reasoning is that knowing where people are in the event of a disaster with structural destruction means rescue teams can triage where to initially focus their efforts. The support provided by UAVs, as well as the use of wireless sniffer sensors, can allow rescuers to better prioritize areas to conduct SAR operations.

The problem studied in this chapter is an application of the location and routing problem. We are trying to solve strategic questions in the SAR operation. Here we determine the choice and location of stations that search teams will be allocated to before a tornado disaster. We develop a metaheuristic to choose what stations are selected to get a permanent UAV search team. We use metaheuristics as the location-routing problem is NP-hard [71, 72]. We then test the solution on various artificial scenarios to determine the effectiveness of the selected stations when considering different failure criteria. We leverage the past work of [77] to conduct the routing algorithms of this problem.

We also aim to answer the question what if there is a situation where UAV is unable to launch to respond to a tornado. Such scenarios could be the station itself was struck by the tornado and the crew is unable to launch the UAV due to damage, the UAV was undergoing routine maintenance off site and does not exist at the station, or crew members themselves are victims of the tornado striking (such as they are trapped at home or en route to a station

to operate the UAV). We therefore aim to robustify the solution against this uncertainty. Robust optimization is often juxtaposed to stochastic optimization where the latter attempts to optimize an expected value, where the former attempts to identify solutions that are likely to still give quality solutions

The remainder of the chapter is as follows. Section 5.3 presents a brief literature review on UAV routing for SAR operations. Then, Section 5.4 provides a definition of the problem and its context. Section 5.5 outlines the data used and methods for solving the problem, while Section 5.6 outlines the testing procedure. Section 5.6 discusses the results before concluding the chapter in Section 5.7 with a general discussion and identifying future research perspectives.

5.3 Literature Review

A detailed breakdown of the use of UAVs in disaster response and SAR operations can be found in [14] and [84]. The use of UAVs for SAR operations also appears in wilderness search and rescue [41], earthquake response [14, 32–35], mountain rescue operations [40] and hurricane response [36, 37]. The only work so far that incorporates UAVs in response to tornadoes is in [77].

Other work has also discussed the use of UAVs in monitoring application and management of natural hazards [43]. Within that literature, routing problems and facility location problems form an important aspect of SAR operations planning. Routing problems for SAR operations consist of determining a set of routes, each performed by a drone that starts and ends at its own depot (launch point), such that all points of interest of the affected area are visited, all the operational constraints are satisfied, and the length of time for the longest search route of a drone is minimized. UAVs have a hard endurance constraint (fuel tank, battery life) and will crash if the UAV does not safely land close to its launch point. Furthermore, each UAV requires a two-to-three-person team to setup, launch, and operate the UAV.

The literature in UAV routing for SAR operations highlights the use of the close enough vehicle routing problem formulation in routing UAVs, since the UAV does not need to visit each potential victim location directly but rather must get close enough (within detection range) to a potential victim. In addition, the feasibility of the UAV equipped with the wireless sensor for mapping victim location has been demonstrated in the literature [14, 27, 32, 33, 50, 55].

Station location and resource allocation problems concern the strategic and tactical aspects of SAR operations. These problems have been broadly studied from two perspectives: deter-

ministic and stochastic. Deterministic models include covering, center, and median models. Covering problems are very common in the emergency services field [71,72]. Stochastic models deal with the allocation of resources in a stochastic environment, e.g., in cases where customer demands, distances, or costs are random [73]. Stochastic models also consider multiple future scenarios with respect to customer demand [74] and treat the travel distance as uncertain, e.g., depending upon the time of day for the ambulance location problem.

We are unable to find any location and allocation research conducted at the intersection of tornado preparations, UAV usage, and locating the UAV tool in preparation of tornadoes occurring. In addition, very little work has been published concerning station location, resource allocation, and routing problems for SAR operations. In our case, we draw upon and adapt the research that use the context of maritime security forces to prepare for distress calls from ocean vessels. For example, [73,75,76] try to optimize the distribution of Maritime SAR helicopters along the coasts of Canada, the United States, and Turkey, respectively. These three papers use simulations based on past distress calls to allocate the helicopters. In these papers, when a distress call is received, SAR helicopters are dispatched directly to a distress call. [75] presented a decision support system for SAR operations. The system allows to determine the dimension and location of the search area and the search sub-areas and the assignment of the available SAR units to their corresponding sub-areas. [76] proposed a simulation and optimization-based approach that enables the determination of robust locations for coast guard stations in the presence of uncertainty in distress call locations, i.e., such that the stations are adequately located with respect to distress calls that vary over time. First, distress call locations are simulated based on a real data set of distress calls. These patterns then serve as input to a p-uncapacitated facility location problem to determine p locations for responding stations. The approach also provides guidance to the tactical question of how the resources (e.g., helicopters, fixed wing aircraft) should be allocated across stations. [73] formulated a p-median model for allocating helicopter resources to candidate stations with the objective of minimizing total response time to incidents (distress calls). The model determines the stations to be activated as well as the number and type of helicopters to be deployed at each station [73] also included probability distributions of helicopter failure rates, maintenance period distributions—a helicopter is inoperable during maintenance time—and inclement weather suspending operations. Still, at the strategic and tactical levels, [104] proposed a methodology for delineating priority sectors of spatial coverage for the UAV in order to support SAR operations. Sectors with high probability of containing the signal of a missing person are defined to optimally allocate resources, and consequently shorten the field search.

While these works offer a great starting point for this chapter, there is a lack of literature in

the use of active and granular meteorological data (such as tornado watches and warnings) in locating UAV depots. In addition these papers lack the necessity of conducting a ‘search’, all the helicopters are dispatched directly to the distress call rather than having to identify the location of a distress call.

There has been research in incorporating uncertainty in weather conditions into routing UAVs [65], although a look is strictly given at wind conditions. [66] studied a severe weather event that includes tornadoes; however, the method they use to update the travel times between cities revolves around perception (rain, snow, fog, etc.) causing delays in transportation, not assessing the damage caused by tornadoes. In addition, most resource allocation models involving ‘server-to-customer’ type operations, such as firefighting, emergency incident response, first aid (ambulance services), and SAR at sea, do not account for the effects of unexpected equipment breakdown and weather condition issues to the performance of the optimal solution. In most real-life situations, the performance is affected due to unexpected delays or unavailability of scarce resources.

Recently, [77] proposed using a combination of UAVs and meteorological data from the National Weather Service (NWS) to identify the location of a potential assessment area after a tornado occurs. Powerful tornadoes are frequent in large parts of the central United States. A tornado is a rotating column of air that can cause severe destruction to property and loss of life when the rotating column is in contact with the ground. It is difficult to track this path of destruction remotely, as well it is impossible to know the scale of the tornado until after surveying the destruction. A search area is selected from a combination of data from the NWS called a storm-based warning (SBW) and a local storm report (LSR). The SBW is a polygon where potential severe weather might occur, and the LSR is the occurrence of a severe weather event. The search area is further delineated by the assumption that most people in need of aid will be in close proximity to a named road (i.e., a road in the official road network of a state). This combination of a delineated search area, a road network to further limit the search area, and a UAV that can identify where people might be in need is used in unison to deploy UAVs in the aftermath of a tornado.

5.4 Problem description and context

The problem can be defined as follows. Given the use of UAVs for assessing damage and identifying areas to deploy SAR teams in the aftermath of a tornado, where should state officials preposition these teams in such a way to minimize the number of UAVs deployed/prepositioned while ensuring a maximum amount of time to assess an area. The UAV in question was defined in [14]. The UAV is a fixed-wing gas-powered aircraft, a wingspan of 3.3m, a top speed

of 22m/s, and an endurance of 8hr.

In addition, given the probability of a UAV not being able to launch, how do we account for and plan for this happenstance.

In this context, fire stations can be used as depots to locate UAV teams. To solve this problem, we propose a stochastic scenario-based model that considers multiple historical tornado scenarios and treat the UAVs locations as uncertain, e.g., depending on if one or more UAVs is not able to provide services in the case of equipment breakdowns. We seek the determination of robust locations for stations, i.e., locations that are robust over the tornado scenarios in the presence of equipment breakdowns.

Therefore, to identify the location of a potential assessment area after a tornado occurs, [77] proposes using a combination of a UAV tool and meteorological data from the NWS. The UAV tool used was proposed in [14] and is a fixed-wing, unmanned, and remotely controlled aircraft equipped with cameras and a wireless sniffer. The wireless sniffer is a generic term for a device to detect the presence of, direction to, and distance to a cellular device. In combination with observing a damaged or destroyed structure, using a wireless sniffer means first responders can estimate where and how many people require aid in the event of a disaster. A search area is selected from a combination of data from the NWS called a SBW and an LSR. The SBW is a polygon where potential severe weather might occur and the LSR is the occurrence of a severe weather event (specifically a tornado occurring). The search area is further delineated by the assumption that most people in need of aid will be in close proximity to a named road (i.e., a road in the official road network of a state). This combination of a delineated search area, a road network to further limit the search area, and a UAV that can identify where people might be in need is used in unison to create a search tool to aid first responders in identifying people in need of aid.

To solve the problem, we interpret the goal as a location problem and use techniques for the location and routing problem and/or a multi-depot vehicle routing problem where it is not required to use every depot. A full breakdown of the notation used in this document can be found in Table 5.1. From the collection of depots D , we assign at most one UAV team to a depot. While UAVs have become easier to use, there is still no fully autonomous solution and still require operators to maintain, launch, operate, and retrieve the UAVs. Because of these hands-on requirements of operating UAVs, there is a chance that a UAV may not be able to launch. This could be because operators may not be able to make it to a fire station because they are victims themselves, or a fire station could be damaged because of the storm. We define this chance as a probability of a station being “down” as p_{down} . To solve the location problem, we use the collection of historical tornado events $e \in TE$ to define

the routes and/or service area of each historical scenario. Let $\bar{T}_{target}$ be a service time upper bound within which we want to complete a search.

Our focus is on the state of Oklahoma. There are 1185 fire stations listed in the state of Oklahoma, and previous work has noted that any and all of the fire stations in the state can be used as a depot [77]. It is financially unlikely to fund a UAV team for each depot. The next section describes our data preparation process and solving approach.

5.5 Data and methods

To generate the selection of fire stations for this chapter, we decompose the problem into three parts: Section 5.5.1 where we discuss the Generation of waypoints; Section 5.5.2 where we generate an initial solution with a Selection of Depots Heuristic; finally, Section 5.5.3 where we present how to solve the Station-Location Problem. After we have solution(s) generated from the method outlined in Section 5.5.3, we test the quality of the solution against artificial cases generated from real-world data. This procedure is outlined in Section 5.5.4.

5.5.1 Generation of waypoints

Points of interest are indications of where people might be in the event of a natural disaster. These points are generally aggregated into sectors called waypoints. In this chapter, waypoints are created based on the geospatial road data that exists within the bounds of the search area (bounds created by the weather data). Waypoints can be thought of as the center of a disk that contains a number of points of interest. The demand for each point of interest can be considered to be equal, although this could be changed to model situations where different distress calls receive more weight (or a priority) according to population density or the severity of the damage observed.

To generate the waypoints for each disaster, we use the work by [77]. We assume that people in need of aid will be on or near the public road network in the case of a tornado disaster. We decompose the road network into “points of interest.” This decomposition occurs by converting the “polyline” geospatial data that represents the road network in the state of Oklahoma into discrete points. A polyline here is a spatial geometry that is created by a sequence of coordinates that typically make up the centerline of a road. We use these centerline points as “points of interest” and if any pair of points on the polyline is greater than the scanning radius r_{scan} of our device, we place additional points on the line between the two points such that no two points are more than the scanning radius r_{scan} apart. All these points are used as “points of interest” for creating the waypoints. The creation of

Table 5.1 The Notation and Meaning in this theme

Notation	Meaning
D	Collection of candidate depots
p_{down}	The probability (percentage) chance that any given station $s \in S$ will not be able to launch
r_{scan}	The parameter defined as the scanning radius (range) of the UAV. In this chapter, r_{scan} is 300 meters
TE	Collection of historical tornado events
e	Lowercase e, a specific scenario in a collection of scenarios TE
$T_i, i \in D$	Defined as the time (cost) it takes a specific route i to complete its route
T	In the context of a vehicle routing problem, $\bar{T}$ (Tee Bar) represents the time (or any cost metric) of the route with the maximum distance (or cost). In mathematical notation: $\bar{T} = \max\{T_i\} \forall i \in D$. $\bar{T}$ can be similarly interpreted to the makespan of a project. In the context of this chapter, this is the time it takes the UAV (of all UAVs launched) with the longest time to complete its route
$\bar{T}_{target}$	Defined as the maximum value $\bar{T}$ can take and a solution be feasible.
S_k	The solution (collection of depots) that are selected for testing. The subscript k represents the iteration of the metaheuristic
$\S_{p_{down}, F_{target}}$	The final solution from our metaheuristic with the parameters p_{down} and F_{target}
N_{feas}	A counter that keeps track of the number of historical tornado events TE that are covered by the solution S_k
F_{target}	A minimum percentage of historical tornado events TE that are adequately covered by the solution S_k

waypoints is an extension of the set covering problem. Due to the set covering being NP-Hard and the number of sets being very large, we use the Steiner Zone Heuristic developed in [77]. The Steiner Zone Heuristic selects a point of interest at random (i.e., a portion of the road network in this case) and creates a temporary group. From the selected group, the algorithm will continually add points of interest from the road network that are within r_{scan} of all other points of interest in the temporary group. Once there are no further points to add, the center of the smallest enclosing circle is then used as a “waypoint.” After this has been completed, all the points from in the temporary group are removed from the initial collection of points of interest. The heuristic then selects a new initial point of interest, and the process repeats until all points of interest are at most r_{scan} from a waypoint. For our instance, we have set $r_{scan}=300$ m. For a detailed description of the Steiner Zone Heuristic see Algorithm 1 in Appendix A.

5.5.2 Selection of depots heuristic

The proposed strategy to find the minimum number of depots (fire stations) consists of solving a set covering problem and a vehicle routing problem. We define the mathematical model for this problem in Appendix B.

To generate an initial and a well-balanced set of fire stations, we used a greedy heuristic based on solving a multi-knapsack problem. The multi-knapsack problem is an extension of the knapsack problem where one tries to find the greatest value of items to carry in multiple knapsacks while taking into account the knapsacks’ capacities. In our problem, each knapsack will represent a depot, and we attempt to minimize the number of depots while ensuring all the items (waypoints) can be carried. The capacity of our knapsacks is fixed and homogeneous, the value of each item is homogeneous, and the weight of the items varies based on the knapsack it is being placed in.

Applied to our case, the weight of the items is the distance from the waypoints to each fire station and the capacity of the knapsack is expressed as a maximum total distance that cannot be exceeded. Practically speaking, all waypoints will have a different weight (distance) depending on which knapsack (fire station) it is assigned to. We solve this problem heuristically by assigning the item (waypoint) with the smallest weight to the knapsack (fire station). We then continue to add items (waypoints) that have the smallest weight (distance) to the knapsack (fire station) until it is full. We then repeat the process by selecting the next item-knapsack (waypoint-fire station) pair with the minimum weight (distance). The pseudocode for this algorithm can be seen in Appendix A, Algorithm 2: Multi-knapsack inspired initial solution.

This heuristic works well for our specific needs. The classical knapsack and multi-knapsack problems have homogeneous weights and values, and given binary decision variables, these problems are NP-Hard (Rinnooy Kan et al. 1993). However, since our weights vary depending on the knapsack the item is placed in, there will typically be a ‘best knapsack’ an item can be placed in. Because of this, our greedy heuristic can find a solution rather quickly that matches the number of stations an exact solver solution that has been running for over a day.

5.5.3 Solving the station-location problem

To solve the Station-Location Problem, we use the data generated from the previous sections and we propose a ‘station removal heuristic’. We formally define the deterministic version of our model in Appendix B. Our objective is to minimize the number of fire stations that are selected to ensure that UAVs can scan a tornado search area in approximately $\bar{T}_{\text{target}}$. We see $\bar{T}_{\text{target}}$ as the upper bound on the amount of time we want the entire area to be searched. We define T_i as the time it takes UAV i to complete its search and $\bar{T}$ is the maximum T_i . We want $\bar{T} \leq \bar{T}_{\text{target}}$. We define a target feasibility rate F_{target} as a percentage of historical cases that are served in under the $\bar{T}_{\text{target}}$. Finally, we define the p_{down} as a probability that any given station would not be able to launch their UAVs for any reason, that is the chance a fire station is “down” (such as, but not limited to: the fire station being struck by a tornado, operational staff not being able to reach the fire station, operational staff required to attend other duties in an emergency).

To find the solution to our interpretation of the station location problem, we propose a ‘station removal heuristic’ which is a neighborhood search heuristic. This heuristic has a tabu list to ensure a diverse search of local neighborhoods. The heuristic starts with an initial solution, which can be the collection of all possible stations; however, in order to reduce the computational search, the initial solution consists of selecting a small subset of stations that are ideally well distributed across the state using the heuristic from Section 5.5.2 (which generates a solution with about 20% of the full collection of potential stations).

Each current solution (i.e., a selection of stations) is tested using the collection of historical tornado events TE . For each historical tornado event $e \in TE$, the heuristic goes through the list of fire stations and generates a random number for each station. If this number is greater than p_{down} , then the station is ‘up’ and can dispatch a UAV. This process creates the set of available stations. The next step consists of evaluating if the available stations can respond to the tornado event under the $\bar{T}_{\text{target}}$. This procedure is done N_{Tests} times for each tornado event to ensure robustness against failure. A counter denoted N_{feas} tracks the number of times a selection of fire stations successfully responds in under $\bar{T}$ target (i.e., N_{feas}

increments by 1 if the response is under $\bar{T}_{target}$, 0 otherwise). If the number of feasible tests is greater than the feasibility target, i.e., $N_{feas}(N_{tests} \times \|TE\|) \geq F_{target}$, the current solution is accepted as a feasible solution.¹ If the number of stations is less than the one obtained in the best solution, the solution is accepted as a new best solution.

Next, a perturbation is applied to the current solution. These solution perturbations can be one of three possible perturbations: (1) removing a station from the solution, (2) swapping a station in the solution with a station outside the solution, and (3) adding a station to the solution. The “station removal heuristic” gets its name from the “removing station” neighborhood, which is further subdivided into three sub-neighborhoods: (1.1) random removal where each station has a random chance of being removed; (1.2) least often removal where the heuristic first calculates for each fire station the frequency at which it is used for all tornadoes and the selection of the station to be removed is carried out randomly, but the chance of being selected is weighed on their frequency; (1.3) most often removed is similar to the least often removed, but with an increased likelihood given to stations selected more often in a solution. These neighborhoods are randomly selected, and their weights are defined by whether the last solution is feasible or not. If the current solution is feasible, we place heavier weights on the ‘station removal neighborhoods’. If the solution S_k (where k is a solution iteration counter) is feasible and also the current best solution, we know that the number of stations in the best solution must be less than the number of stations in S_k . If the current solution S_k is infeasible, but $S_k - 1$ is feasible, one station larger (i.e., $|S_k - 1| = |S_k| + 1$), and is the same size as the best solution, so if a better solution exists, then it must be the size of $|S_k|$, therefore the “station swapping” neighborhood is prioritized as that will maintain the same cardinality. Whether the solutions are feasible or infeasible, there is a small chance that a station will be added back to the solution as to increase the diversity of the solutions.

At each step, the solution is stored in a tabu list to avoid coming back to the same solution for a short amount of time (iterations). The heuristic allows infeasible solutions to become the current solution.

In short, the stopping criteria is iterations without improvement for each local iteration and iterations where the solution is infeasible to stop the global iterations. Every time a solution is denoted as infeasible (that is, the value of $N_{feas}(N_{tests} \times |TE|) < F_{target}$), the infeasibility counter increases by 1. Once the maximum number of infeasible solutions is reached, the heuristic is reset with the current best solution and starts again. The global reset is repeated a minimum of $MinGlobalIters$ times. At that point, the global reset is done again if a new best solution is found in the last global iteration. Once a global iteration has completed without a new best solution, the program terminates and returns the current best solution.

The heuristic is tuned to solve this strategic problem. That is, there is no intention to use this models in a real time manner. We developed the stopping criteria is tuned in such a way to allow the metaheuristic to run longer in an effort to uncover better solutions.

Detailed results (including execution time) can be seen in Table 5.2 (in seconds) and Table 5.3 (same data but in hours:minutes:seconds).

Table 5.2 Time (s) from station-location heuristic (average:26367s).

		Target feasibility										
		100%	99%	98%	97%	96%	95%	94%	93%	92%	91%	90%
Depot failure rate	0%	15028	15174	15171	14850	15375	1605	1982	1803	2717	1931	1891
	1%	42265	25336	28712	24528	35688	32048	33697	26004	25820	29427	30458
	2%	26343	22665	27395	28931	19895	31354	24307	37977	27892	23276	28258
	3%	30836	29717	25267	25536	24232	22908	23720	30002	31110	33638	34890
	4%	49044	24579	22889	26667	19208	23450	30555	21364	24383	24574	36943
	5%	39787	36246	25260	21560	29291	39379	24621	32308	30030	38465	32484
	6%	50221	27748	20648	23012	22139	26573	23719	26984	28046	37879	29711
	7%	51226	15282	15040	22600	19988	31386	20685	25905	40616	29081	30124
	8%	32130	18437	28750	25785	22620	29164	29735	24111	31046	30514	26904
	9%	27187	15362	24029	23263	27729	23666	32069	33454	32503	33028	35215
	10%	36504	33085	26149	23702	16660	27105	27551	16200	24039	25363	24061

Table 5.3 Time (hms) from station-location heuristic (average:7h19m27s).

		Target feasibility										
		100%	99%	98%	97%	96%	95%	94%	93%	92%	91%	90%
Depot failure rate	0%	04h10m28s	04h12m54s	04h12m51s	04h07m30s	04h16m15s	00h26m45s	00h33m02s	00h30m03s	00h45m17s	00h32m11s	00h31m31s
	1%	11h44m25s	07h02m16s	07h58m32s	06h48m48s	09h54m48s	08h54m08s	09h21m37s	07h13m24s	07h10m20s	08h10m27s	08h27m38s
	2%	07h19m03s	06h17m45s	07h36m35s	08h02m11s	05h31m35s	08h42m34s	06h45m07s	10h32m57s	07h44m52s	06h27m56s	07h50m58s
	3%	08h33m56s	08h15m17s	07h01m07s	07h05m36s	06h43m52s	06h21m48s	06h35m20s	08h20m02s	08h38m30s	09h20m38s	09h41m30s
	4%	13h37m24s	06h49m39s	06h21m29s	07h24m27s	05h20m08s	06h30m50s	08h29m15s	05h56m04s	06h46m23s	06h49m34s	10h15m43s
	5%	11h03m07s	10h04m06s	07h01m00s	05h59m20s	08h08m11s	10h56m19s	06h50m21s	08h58m28s	08h20m30s	10h41m05s	09h01m24s
	6%	13h57m01s	07h42m28s	05h44m08s	06h23m32s	06h08m59s	07h22m53s	06h35m19s	07h29m44s	07h47m26s	10h31m19s	08h15m11s
	7%	14h13m46s	04h14m42s	04h10m40s	06h16m40s	05h33m08s	08h43m06s	05h44m45s	07h11m45s	11h16m56s	08h04m41s	08h22m04s
	8%	08h55m30s	05h07m17s	07h59m10s	07h09m45s	06h17m00s	08h06m04s	08h15m35s	06h41m51s	08h37m26s	08h28m34s	07h28m24s
	9%	07h33m07s	04h16m02s	06h40m29s	06h27m43s	07h42m09s	06h34m26s	08h54m29s	09h17m34s	09h01m43s	09h10m28s	09h46m55s
	10%	10h08m24s	09h11m25s	07h15m49s	06h35m02s	04h37m40s	07h31m45s	07h39m11s	04h30m00s	06h40m39s	07h02m43s	06h41m01s

5.5.4 Generation of artificial tornado instances

To generate the solutions, we use the collection of 124 tornado incidents from 2002-04-18 to 2019-12-28. While this might be sufficient for identifying the fire stations that will be selected, these cases cannot be used to test the solutions. We built an “Artificial Tornado Generator” to create new tornado instances. This generator creates these new cases by taking a current historical tornado incident and randomly placing it somewhere else in the state. Once it is in a new location, we solve the multi-depot-routing problem as previously proposed [77].

5.6 Experiments and results

To validate the approach, two broad tests are conducted. The first is to assess the sensitivity to the two main parameters: the probability of depot failure p_{down} and the target feasibility F_{target} . The former could be approximated yet is still largely uncertain; the latter is defined as an objective from decision-makers. The second experiment is to demonstrate the quality of the solutions against unknown cases. We use the method outlined in Section 5.5.4 to generate unknown tornado events to see if the station positioning matches the target feasibility rate.

5.6.1 Sensitivity of feasibility versus depot failure

The sensibility of two parameters denoted as ‘depot failure rate’ and ‘target feasibility rate’ are tested in this section. The depot failure rate is largely unknown and can be largely affected by the structural stability of the depot and staffing policies. The target feasibility rate is a policy decision where the decision-makers can tune the number of operational stations based on the number of historical instances that are adequately served by the solution.

Table 5.5 shows the results of this sensitivity analysis. First, it validates the efficiency of the heuristic proposed in Section 5.5.3: the greater the chance of failure, the more stations are required for an adequate response; the higher the feasibility rate, the more stations required to provide an adequate response.

A question that can be raised here is why one would choose a feasibility rate lower than 100%. As can be seen from Table 5.5 there is a marked reduction in the number of stations from when the feasibility target from 100 to 99%. This can be accounted for the rare times when the size of the search area (number of waypoints) is so numerous that many more depots are required to ensure adequate coverage in the event of a disaster. Considering the number of stations deployed, desiring a targeted feasibility of 100% would require 30% more stations and resources versus a 99% feasibility target. This increases up to an 85% increase in the

number of depots when we assume any chance of failure. This sensibility analysis can be useful if the decision-makers decide that responding to the largest tornado outbreaks would be better served by fewer UAVs in the air and having people respond in other ways. As shown in Figure 5.1, most instances contain less than 10,000 waypoints. A lower feasibility target effectively ignores these larger tornado events.

The following figure, Figure 5.2, also validates what we expect from a solution to solve where to preposition these UAVs. Regardless of the parameters of the solution we are looking at, we see clusters of stations in the dense metropolitan centers of Oklahoma City in the center of the state and Tulsa in the northeast. When there is no chance of failure, we see an even distribution of stations. As the failure increases, we begin to see clusters of stations form in parts of the state, such as the western panhandle and around the metro Tulsa and Oklahoma City area. Conversely, as we lower the feasibility targets: the number of stations in the sparsely developed eastern portion of the state is also reduced. Note the roads in blue in Figure 5.2 do not represent the totality of the road data used to create the waypoints. The roads displayed are the highways and interstate motorways in Oklahoma. They are displayed to help orient the reader.

5.6.2 Testing the solution on the artificial tornadoes

The second test demonstrates the need to account for the failure rate in the solution method. We denote the solutions as $S_{p_{down}, F_{target}}$ which should be read as the solution in with the failure rate of p_{down} and the feasibility rate of F_{target} . For simplicity, we take the number as an integer. To ensure the reliability of the solutions, we take the solutions $S_{0,100}$, $S_{5,100}$, $S_{10,100}$, $S_{0,99}$, $S_{5,99}$, $S_{10,99}$, $S_{0,98}$, $S_{5,98}$, $S_{10,98}$ and place them up against 250 randomly generated tornado cases. When solving the tornado case, we apply the failure rate indicated by the solution. For example, $S_{0,100}$ gets a 0% failure rate, $S_{5,98}$ is 5%, and so forth.

We also demonstrate the need to account for the chance of failure when deciding what stations to select as a depot for the UAVs. To conduct this demonstration, we take the solutions $S_{0,100}$, $S_{0,99}$, $S_{0,98}$, and put these solutions in a situation where they have a chance of failure—that is, before solving a tornado case, we apply a 5% and 10% chance of failure. The results of these tests can be seen in Table 5.4.

In our first batch of tests, accounting for failure, the solutions generated by our initial solution method appears to largely match the feasibility goal of the solution. All the solutions are within 1.0% of the feasibility rate.

While using the solutions not accounting for failure there is a minor, yet consistent short-

coming of the solutions not considering depot failure. We see a feasibility drop off 3% versus the solutions accounting for failure and nearly a 4% drop considering the feasibility targets.

5.7 Summary and conclusion

The problem studied in this chapter is an application of the location and routing problem where we are trying to determine the choice and location of stations that search teams will be allocated before a tornado disaster. We considered historical weather data and the potential for equipment breakdowns to choose the depots. We also offered a parameter called “feasibility target” to allow decision-makers to tune and reduce the number of stations in their final solution. This allows for the rare times when the size of the search area (number of waypoints) is so numerous that many more depots are required to ensure adequate coverage in the event of a disaster.

We first demonstrated the relationship between the number of depots in a solution, the chance of depot failure, and a feasibility target. This validates the proposed heuristic (higher depot failures require more depots, lower feasibility targets yield fewer depots) and shows the conservative nature of assuming the need for 100% feasibility (needing 30–80% more stations than even 99% feasibility targets).

Next, we assessed the quality of the solution against unknown tornado cases. When accounting for depot failure, our solutions are within 1% of the target feasibility rates. We also compared the effect of using solutions that do not account for depot failure when depot failure is present. We missed the target feasibility rates by 4% in this case.

There is still plenty of research opportunities. In a sparsely populated state like Oklahoma, most fire stations are volunteer. There could be work on balancing the tradeoff between using professional versus volunteer fire stations and/or having differing probabilities for a fire station being ‘down’ as a function of its type or location. In addition, methods could be developed to ensure that station choices do not ‘clump’ together in high station failure rate

Table 5.4 Results of tests against the artificial cases

		Accounting for failure			Not accounting for failure		
		100%	99%	98%	100%	99%	98%
Chance of depot failure	Feasibility goal						
	0%	99.6%	98.0%	98.0%			
	5%	100.0%	98.4%	97.4%	97.6%	96.8%	96.4%
	10%	100.0%	97.8%	98.8%	96.8%	95.6%	95.6%

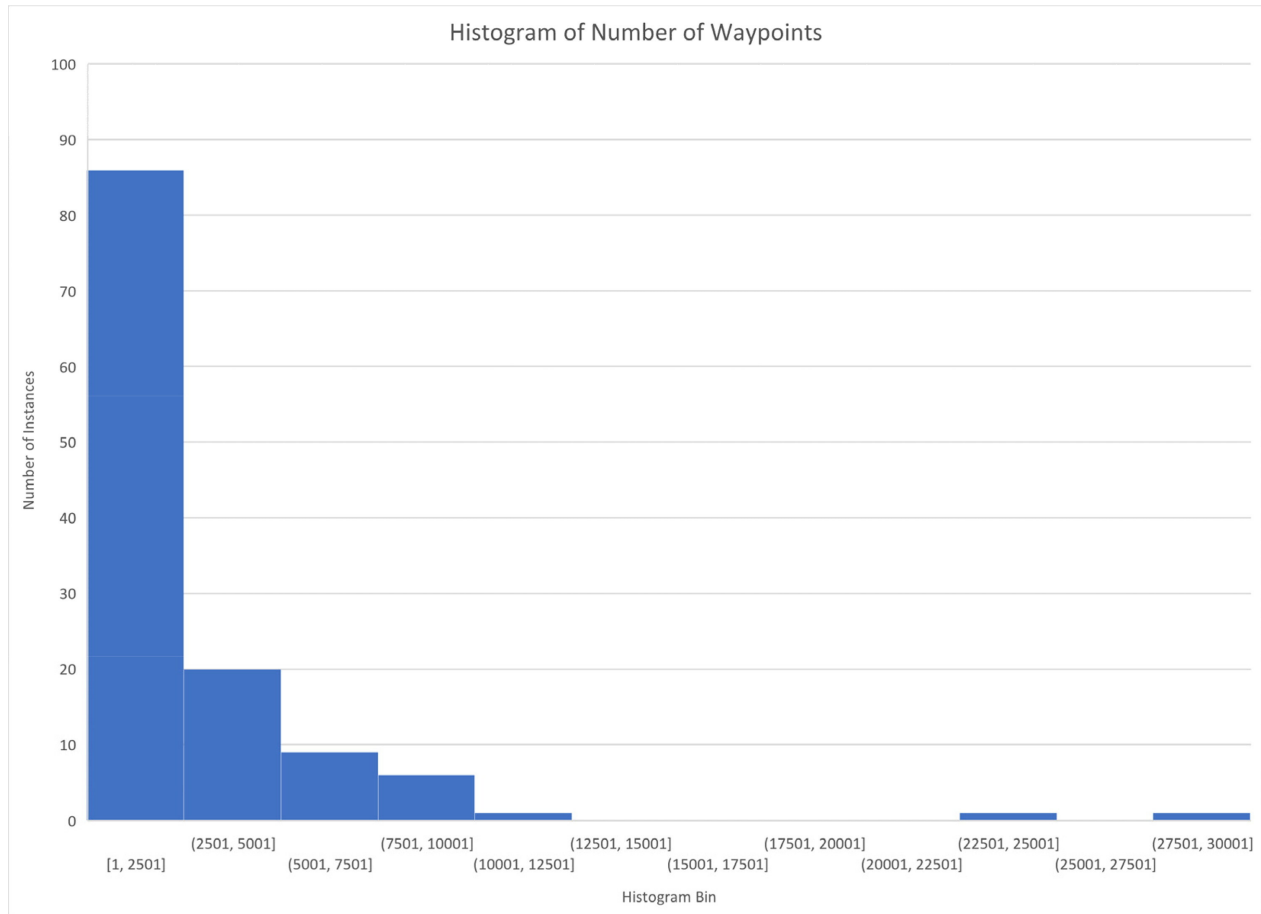


Figure 5.1 Histogram of number of waypoints versus number of occurrences

Table 5.5 Sensitivity of depot failure rate versus feasibility rate

		Target feasibility										
		100%	99%	98%	97%	96%	95%	94%	93%	92%	91%	90%
Depot Failure Rate	0%	101	77	67	41	38	32	30	30	28	28	28
	1%	104	82	65	41	38	35	31	32	29	30	27
	2%	135	85	69	43	41	37	31	32	32	31	29
	3%	141	82	67	44	41	39	35	33	33	32	30
	4%	129	89	72	46	42	39	33	36	33	31	32
	5%	173	88	70	48	41	40	36	35	35	34	32
	6%	166	91	73	48	44	41	39	37	35	34	33
	7%	173	96	75	49	45	42	40	39	34	36	34
	8%	176	99	75	53	48	44	42	38	35	37	35
	9%	177	98	80	53	46	44	40	40	38	36	36
	10%	194	104	80	55	50	46	43	40	40	38	37



Figure 5.2 Visualization samples of solutions for station locations within the state

situations. Stronger methods for generating artificial tornado storms could provide (artificial data sets) could provide better solutions—both in generating the station-location solution as well as testing the station location solution.

CHAPTER 6 ARTICLE 3: USING HISTORICAL DATA TO DYNAMICALLY ROUTE POST-DISASTER ASSESSMENT UNMANNED AERIAL VEHICLES IN THE CONTEXT OF RESPONDING TO TORNADOES

This article, titled "*Using Historical Data to Dynamically Route Post-Disaster Assessment Unmanned Aerial Vehicles in the Context of Responding to Tornadoes*" was published in *Applied Sciences* on March 25 2023. This paper was co-authored by Michel Gamache and Robert Pellerin [78].

6.1 Abstract

Responding to tornado disasters resides at a unique intersection of search and rescue operations: it has attributes of wilderness and maritime search and rescue operations and search and rescue operations in the aftermath of earthquakes and hurricanes. This chapter presents a method of attempting to leverage historical data to more efficiently identify the extent of the area damaged by a tornado. To assist in building and understanding the historical data, we also develop a method to generate tornado areas that react similarly to the limited historical data set. The chapter successfully demonstrates the method of creating artificial tornado instances that can be used as a testing sandbox for the further development of tools when responding to tornado-type disasters. These artificial instances perform similarly in some important metrics to the historical database of tornado instances that we produced. This chapter also shows that the use of historical tornado trends has an impact on the response method outlined in this chapter, typically reducing the standard deviation of the time it takes to fully identify the extent of the damage.

6.2 Introduction and Literature Review

The majority of search and rescue (SAR) literature, in particular when using unnamed aerial vehicles (UAVs) in assisting SAR personnel, typically responds to disasters that involved earthquakes or hurricanes. A detailed breakdown of the use of UAVs in disaster response and SAR operations can be found in the previous literature [14, 84]. The two main axes of the use of UAVs for SAR operations can be separated into locating missing individuals or post-disaster damage assessment. Examples of the former can be broken down into wilderness SAR operations [41] and mountain rescue operations [40]. Examples of the latter, UAVs were

used in earthquake response [14, 32–35] and hurricane response [36, 37]. There is a limited amount of work incorporating UAVs in response to tornadoes [2, 77]. Therefore, when UAVs are being used in assisting SAR personnel in disaster assessment operations, most of the literature aims at responding to disasters that involved earthquakes or hurricanes.

How UAVs can be incorporated into the response to tornadoes can be found in the intersection of the two axes. There are many overlaps of wilderness SAR, maritime SAR operations, and earthquake/hurricane response and the response to tornadoes; post-tornado search and rescue operations provide a unique setting that is ripe to develop dynamic routing algorithms to more effectively search an area that has been impacted by a tornado.

Wilderness and maritime SAR operations often involve systematically searching an area to identify a single entity (vessel in distress, missing hikers) or responding directly to a distress call. There exist search rules that searchers will use to effectively cover an area and ensure that searchers rigorously examine an area and that the human searchers balance the time investigating any given small area versus the overall potential area a person in aid might be. In addition, knowledge of general ocean currents can aid searchers in their efforts by allowing searchers to prioritize their areas of inspection [105].

In response to large-scale disasters (such as earthquakes, hurricanes), search and rescue operations are often conducted as damage assessment operations from the sky and/or require the use of search dogs, cameras, and reports of where missing people may be [14, 106]. However, there is a growing body of work proposing the use of “wireless sniffers” to help identify where victims may be by passively detecting cell phones [14, 27, 39, 50]. Even with this innovative technology, the response (search) in the aftermath of earthquakes or hurricanes will still involve assessing an area on the size of a city, county, province, department, or region.

Tornadoes, and responding to tornadoes, provide a situation that is not adequately covered by the response literature. One of the ways of allocating search areas is by using meteorological data for creating a search area [77] (For a deeper understanding of the meteorological attributes of tornadoes, we direct the reader to search meteorological literature or to consult the National Weather Service (NWS) extensive online library on the subject). Previous work used storm-based warnings (SBWs) and local storm reports (LSRs) to identify and route post-disaster UAVs. SBWs are polygons that are drawn over an area that meteorologists expect there could be severe weather. SBWs can indicate many kinds of severe weather; however, we are only explicitly looking at the SBWs that are drawn to indicate the presence of tornadoes (not severe thunderstorms, not hail, not snowstorms). LSRs are observations to where severe weather is presently occurring. Their paper only considers LSRs observations to indicate the presence of tornadoes. The intersection in both time and space of this spatial

information delineates the search area [77].

The strategic aspect of SAR operations—such as the location and allocation of SAR teams, vehicles, and equipment—can be seen in previous works [2, 76]. Specifically, there is a discussion of the location of United States Coast Guard helicopters that conduct SAR operations in the Atlantic Ocean [76]. In other literature, the search area is further identified by the named road network under the assumption that anyone in need of rescue would be close to the road network of a state. That is, in areas where there are large open fields, the UAV would not search throughout a—for example—cornfield. They used the road network to create a series of waypoints that can be used to route one or several UAVs through a disaster area [2].

Where tornado response begins to differentiate from other SAR response operations is that the area impacted by a tornado (that is, where people may be in need of aid) is significantly smaller than the search area in an earthquake, hurricane, or even the area defined in previous work. Only about 1–5% of the area defined by a SBW is damaged. This aligns more with the wilderness and maritime SAR operations as rescuers are trying to identify a missing person or vessel in distress and identifying this is disproportionally smaller than the area needed to be searched, that is, like a “needle-in-a-haystack”. However, wilderness and maritime SAR operations fall short because once a portion of the damaged area has been identified, the extent of the damage must also be identified.

When formulating the problem as a mathematical optimization problem, the most common formulations appear to be in the form of a traveling salesperson problem [48, 49], a vehicle routing problem [52], or as a simpler shortest path problem or pathfinding problem—where returning to the start is unnecessary [42, 47, 63, 107]. While the latter papers in the literature may on the surface appear simple, the goals put forth in the papers are often to create a coverage network in an attempt to identify victims and find paths to them [25, 47], or to set up a connectivity network to a victim [19, 42].

After graph-based formulations, another common model formulation is a set covering method [21, 44]. It is a formulation well-suited to monitoring procedures as set covering formulations attempt to allocate the robots over a disaster scene to ensure connectivity [44] or to ensure an area is adequately searched [21]. Swarm-based methods (such as ant colony optimization or particle swarm optimization) are frequently used when multiple UAVs are used in completing their mission [21, 44, 46, 108, 109].

In addition to the mathematical optimization models proposed, several robot task allocation models and methods were used in the literature [14, 24, 31, 45]. Robot task allocation can be implemented in a decentralized way and enable real-time reactions to new information present in the environment. The advantage of most robot task allocations (such as in [14, 31, 45])

is that they allow for the decentralized operation of many robots. Conversely, [24] allow for robots to compete for performing the next task.

In addition to the well-established procedures outlined previously, some authors attempt stochastic optimization techniques such as Markov Decision Process [29, 39, 47, 55].

One method of Markov Decision Processes is using a random forest to determine the next area for the UAV to explore to find a lost hiker [39]. However, the method they propose works well in spatially small search areas and the attraction of the WiFi sensor helps triangulate the missing person(s). There is also use a Markov Decision Process using land-based robots are navigating an interior environment (i.e., office space, school) [29]. There is also a Markov model attempting to predict the rescuer's needs and to deploy a UAV with wireless sensor networks and cellular networks to focus on maintaining connectivity for rescuers in a search area [55]. Markov Decision Processes can also be used to consider and map an unknown interior environment [47].

There is a large and growing body of work in using UAVs in disaster response applications, in particular with assisting SAR teams in identifying where people are in need of aid or transporting medical and first aid supplies to people in need of aid. The advent of wireless sniffer technologies allow for SAR UAVs to detect the presence of wireless devices (i.e., cell phones). With the adoption of cell phones in much of the world, the combination of these two technologies allows for the use of UAVs in responding to emergencies where people in need of aid may not have line-of-sight to the sky. When responding to emergencies and disasters, while there are some over-arching principals when developing SAR procedures, domain-specific data and knowledge can go a long way in creating searches that can be conducted faster (e.g., understanding ocean currents to identify where overboard and stranded sailors may be). In the context of searching after a tornado strikes, we can use broad understandings of tornadoes to better capture and identify the extent of the damage. A UAV equipped with wireless sniffers can also estimate the number of people that may be in need of aid at any given area, even if they are buried. To the best of our knowledge, there is very little research in utilizing meteorological and tornado data to help rescuers identify where victims may need aid [2, 77]. In addition, these past works do not attempt to identify the extent of the damage as quickly as possible; they simply assume the entire area must be assessed.

This chapter presents a method of attempting to identify the damaged area of a tornado quicker than trying to search the entire area. It also attempts to demonstrate that intelligently incorporating historical data into the decision-making process can assist the tools to make better decisions. The remainder of the chapter is broken down into five sections. Section 6.3 contains the problem context and other rules and assumptions that are used in this

chapter. Section 6.4 discusses how the dynamic program will work. Section 6.5 details the experimentation, including a method for generating “artificial tornado instances” to provide additional cases for the chapter. We test the method developed on historical cases in Section 6.6. We then conclude this chapter in Section 6.7 by outlining our contribution and discussing research opportunities. Appendix E has additional results for Section 6.6 and Appendix F outlines the location of the publicly available data this chapter building on.

6.3 Problem Context

Given the existence and use of UAVs for assessing damage and identifying areas to deploy SAR teams to in the aftermath of a tornado, multiple methods can be used for routing deployed UAVs to identify damaged areas as quickly as possible. For example, the UAVs may be routed through the entire identified search area [77]. However, the actual damaged area is significantly smaller than a proposed search area.

An example of such an area can be seen in Figure 6.1. Here, we have a red polygon, which represents an area that may have tornado damage, with the cyan polygon representing the actual damage caused by the tornado. The objective of this chapter is to identify the area denoted in cyan, in relation to the initial search area outlined in red. Note that the tornado damage area may not be totally encompassed by the SBW.

To effectively search the area, previous works assume that people in need of aid would be within some radius of a road, which has been denoted r_{scan} . The performance metrics outlined in [2, 14, 33, 77] yield an r_{scan} of 300 m. Using the road network as a proxy for the location of people (as in [77]), and heuristically finding the minimum number of waypoints with a radius of r_{scan} that can cover the road network in a given area. An example of these waypoints can be seen in Figure 6.2. Given the context of Figure 6.2, a UAV that is scanning the area is attempting to identify the waypoints in green by searching through the collection of blue waypoints. The waypoints in green will not be known when the UAV is launched. Previously, the UAV only considers waypoints inside the SBW and will never inspect the damaged waypoints outside the SBW [2, 77]. That is, “damaged waypoints” outside the SBW (for example, the waypoints west of the red box outlined in Figures 6.1 and 6.2) would never be inspected in the previous literature. This chapter attempts to allow the UAV to scan the entire area as well as identify damage that may occur outside of a search area.

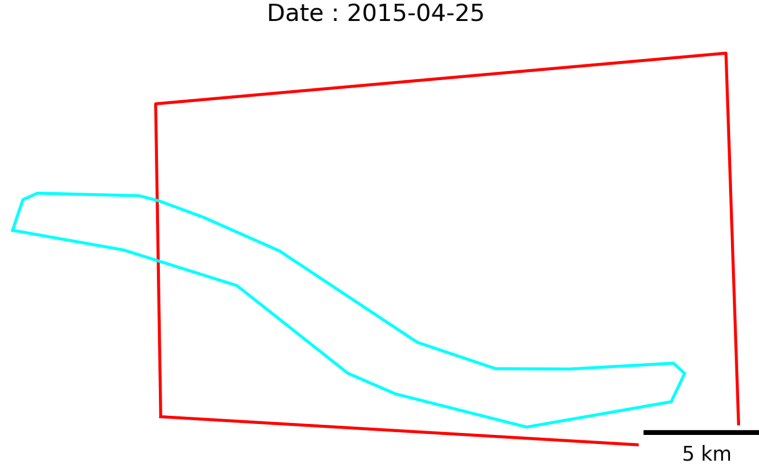


Figure 6.1 An example of a tornado damage area (cyan) and a SBW (red).

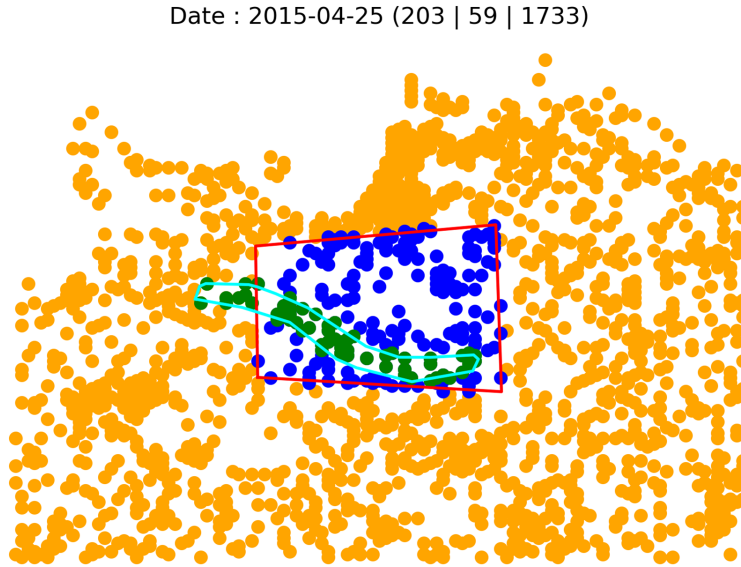


Figure 6.2 Example of waypoints in the vicinity of the tornado, Green dots represent waypoints within the damage, blue dots represent waypoints within the search area that do not correspond to damage, orange dots represent waypoints outside the damage area and outside the search area. Note: the size of the waypoints are not to the scale of r_{scan} .

6.4 Model Concepts and Dynamic Routing Setup

The following section breaks down the concepts and steps included in the dynamic routing of the UAV over the search area. The concepts are broken down into five sections. First, we

propose a concept called the “base score of a waypoint”. The next section is a concept of an “Influence matrix”, which determines how much information gained from one waypoint has on another waypoint. The “influence matrix” and “base score” are combined to determine the “Computed Score of a Waypoint”, which is discussed in the third subsection. The next subsection discusses the details of how the UAV will route itself to its next waypoint(s) based on its computed score. Finally, “Evaluation of the quality of the solution” discusses the objective of the routing algorithm (find the extent of the damage as quickly as possible) and how this chapter determines what subset of parameters works toward this goal.

6.4.1 Base Score of a Waypoint

Each waypoint receives a “Base Score” that follows a basic decision tree (the following decision tree is graphically represented in Figure 6.3 to aid the reader) based on the following attributes: whether the UAV has visited the waypoint or not (unvisited), whether the waypoint is initially in an SBW or not, and whether there is damage in the waypoint area. If a waypoint is not in the search area and not visited, the base score is 0.0. If a waypoint is in the search area and not visited, the base score is 0.5. If the waypoint is visited and not damaged, the waypoint base score is 0.0. If the waypoint is visited and damaged, the waypoint is given a base score of 5.0 (This value was initially set to 1.0; however, with initial testing, we quickly realized the score of 1.0 would not be sufficient). The base score is dynamic, but it only changes upon visitation with the UAV. Waypoints outside the SBW can be visited if the dynamic program decides to visit the waypoint, but will never receive the base score of 0.5: either the visitation will affirm the waypoint’s base score of 0.0 (no damage), or it will receive the damaged score of 5.0. A decision tree of this process can be seen in Figure 6.3.

6.4.2 Influence Matrix

The base score of a waypoint exerts influence on its neighbor waypoints as a function of distance. Waypoints that are spatially “close” to each other will more likely have the same attribute of being damaged or undamaged. The influence of one waypoint on another is a function of the distance between the waypoints. Let an influence matrix $\mathbb{I}$ be a $n \times n$ matrix that can be referenced as the influence waypoint j has on waypoint i . The value of any element $\mathbb{I}_{ij}$ is in the range of 0 to 1. For this chapter, we used a linear relationship of influence; however, other functions (say, logarithmic or exponential) can be used. The objective is to inform the solver of the likelihood a nearby waypoint will share the same state (damaged or undamaged). We use the parameters minimum influence range (the distance from a waypoint where the influence is 1.0, typically r_{scan}) and maximum influence range

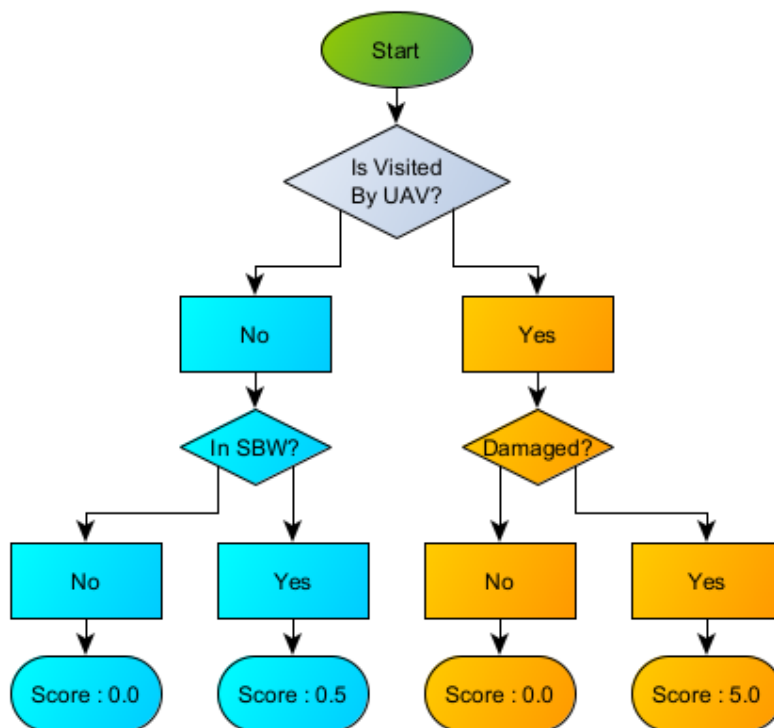


Figure 6.3 Decision tree for determining the base score of a waypoint; once the waypoint has been visited (i.e., the right, orange part of the, the score is fixed for the remainder of the scenario).

(where waypoints beyond have an influence of 0.0). Samples of the symmetric case can be found in Figure 6.4.

In addition to the previous “symmetric influence matrix”, we have also developed a data driven influence matrix where the samples can be seen in Figure 6.5. Here, we use the historical data set of tornadoes to create an elongated matrix (along the 35-215 to 50-230 degree directions, south-west to north-east) to better reflect the typical direction a tornado might travel. The idea behind this data driven influence matrix is that since most tornadoes traverse along this half, there will be a greater chance of waypoints along this path to have identical conditions, attributes. Samples of this matrix can be found in Figure 6.5.

This is generated by using the frequency of the direction of tornadoes from the historical tornado database from 1950 until 2021. The radial histogram of this can be found in Figure 6.6. Here, the direction of a tornado is simply what is recorded as the start point and the end point, and the direction between those two points. This is the same direction used in this data driven influence matrix. It will not necessarily capture the path of tornado might take that may look like an S or something else.

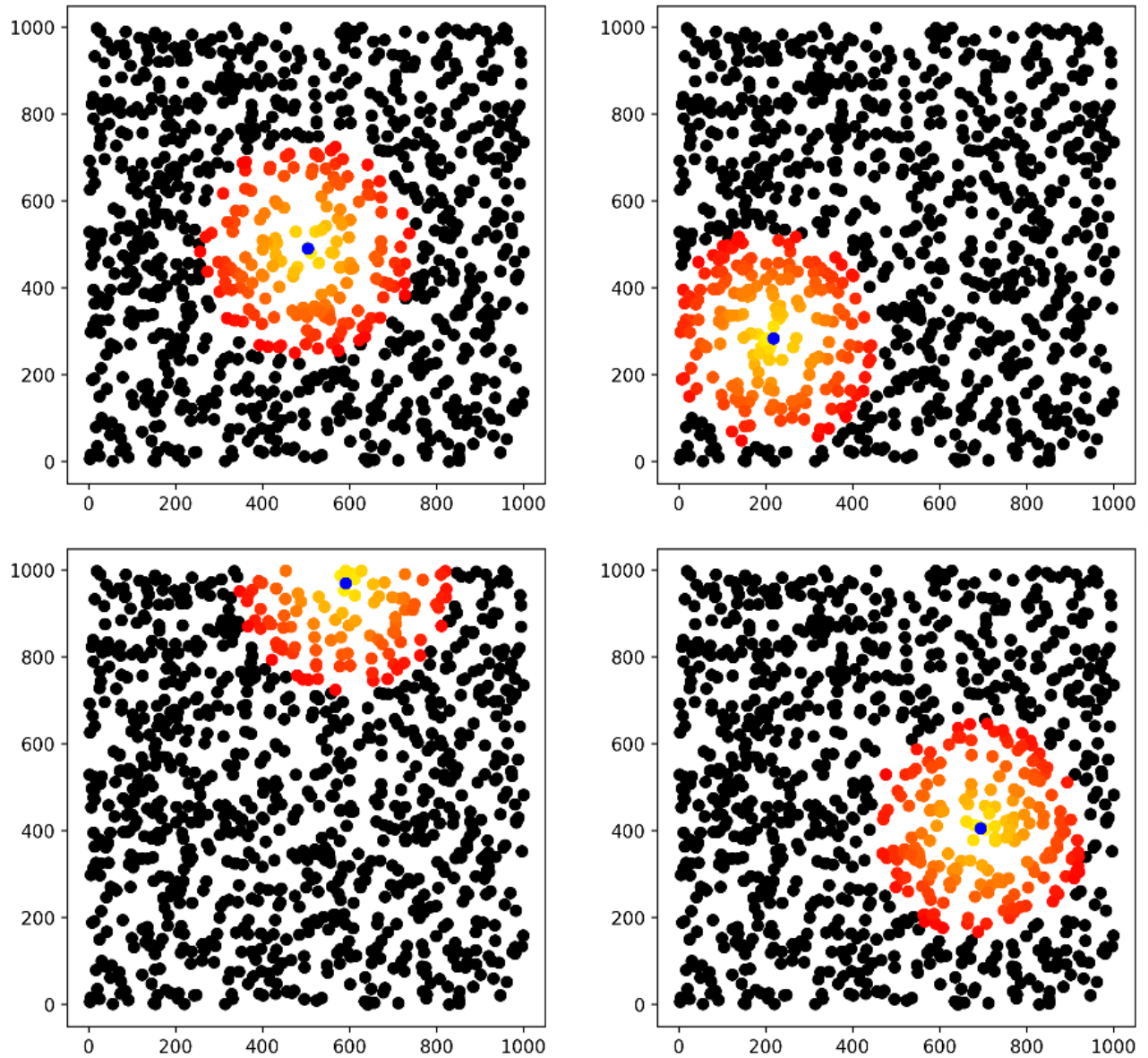


Figure 6.4 Visual samples of an “influence matrix” for a random waypoint (in blue) where yellow dots indicate high influence (close to 1.0), red dots indicate a lower influence (close to 0.0), and black dots indicate no influence (that is, 0.0).

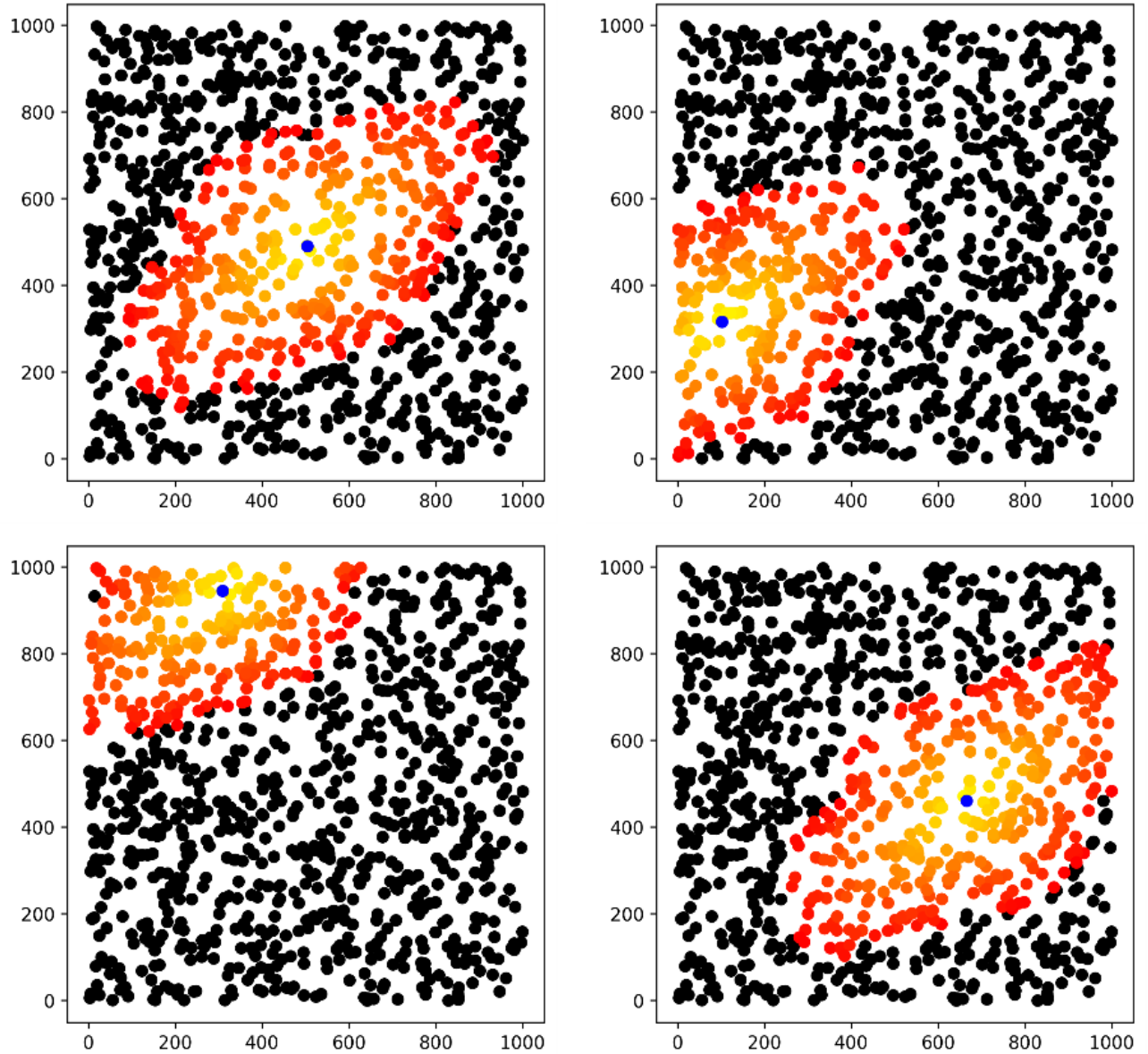


Figure 6.5 Visual samples of an “Data-driven influence matrix” for a random waypoint (in blue) where yellow dots indicate high influence (close to 1.0), red dots indicate a lower influence (close to 0.0), and black dots indicate no influence (that is, 0.0).

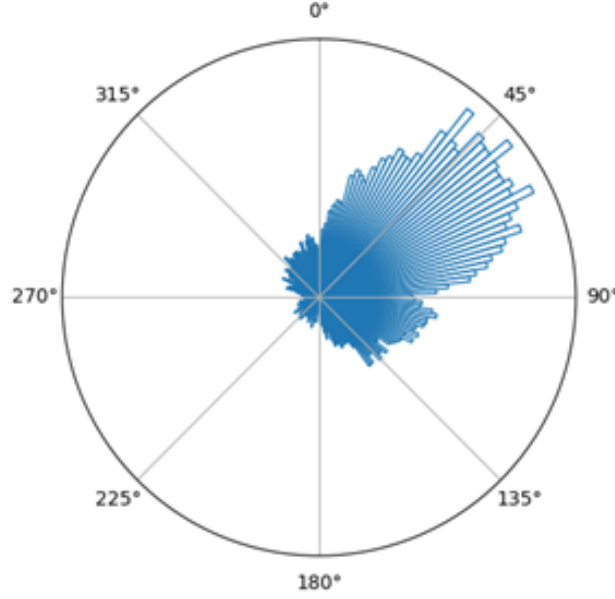


Figure 6.6 Radial histogram of the direction of tornadoes with the length indicating of tornadoes in each direction. Note: this chart does not indicate intensity of the tornado, nor does it give any indication of the length or width the tornado took.

6.4.3 Computed Score of a Waypoint

In addition to the base score of each waypoint, each waypoint also has a computed score. The computed score is between 0.0 and 1.0 and is only computed and applied for unvisited waypoints. The computed score of a waypoint is used in the dynamic routing of the UAV. Simply, the computed score of a waypoint is the weighted average of all the waypoints weighted by the influence matrix score. Mathematically, let the computed score of waypoint i be s_i , the base score of waypoint j be B_j , and the influence of waypoint j on waypoint i be $\mathbb{I}_{ij}$. The computed score of waypoint s_i is $s_i = \frac{\sum_j \mathbb{I}_{ij} B_j}{\sum_j \mathbb{I}_{ij}}$.

6.4.4 Routing the UAV: Parameters and Considerations

The overarching idea behind dynamically routing the UAV is for the UAV to fly directly to the waypoint with the highest computed score. If multiple waypoints have the highest computed score, the closest one is selected. In practice, waypoints along the route will have the ability to be scanned while a UAV is on route from waypoint k to the waypoint with the highest computed score (waypoint $k + 1$). The decision was to include waypoints that are within a rectangle whose width is $2 \times \epsilon$ and length l is the length of the line between waypoint k and waypoint $k + 1$. The value of ϵ is the minimum of the length of $\frac{\ell}{2}$ or

$2 \times r_{scan}$, $\epsilon = \min \left[\frac{\ell}{2}, 2 \times r_{scan} \right]$. Figure 6.7 illustrates the area and the waypoints that will be considered.

There is also the concept of Minimum Score to Consider (MStC). Given a computed score s_j , if the score is below a MStC, the waypoint is ignored, and not considered in determining the next waypoint to visit. Once all waypoints with a computed score above a MStC are visited, the UAV is considered to have completed its mission. This is an extension of the idea that once you have enough information about a waypoint's neighbor waypoints, you can potentially safely ignore these waypoints even if they have not been visited. By default, the MStC is 0.0 (for example, waypoints outside of the initial search area have 0.0s and will be below or equal to the MStC). MStC was selected and tuned in this chapter to ensure that all damaged waypoints inside a SBW would be identified.

There is also the option to give an initial route. The initial route is a minimum Hamiltonian path through all the way points in the search area. This initial route was the standard search pattern in [2, 77]. There are two options in the testing of this dynamic program on the historical and artificial test cases. Having the initial route allows for a systematic and shortest route to search an area. However, offering no initial route would allow the UAV to inspect the center of the search area and work outward. However, this may cause the UAV's traveled route to cross itself searching for damaged areas.

Finally, given our two types of influence matrices (data driven and symmetric), we have four variations of the two influence matrices at our disposal: using symmetric the entire time; using the data driven matrix the entire time; starting with the symmetric and then switching to the data driven once damage is uncovered; and then using data driven and then switching to symmetric once damage is uncovered.

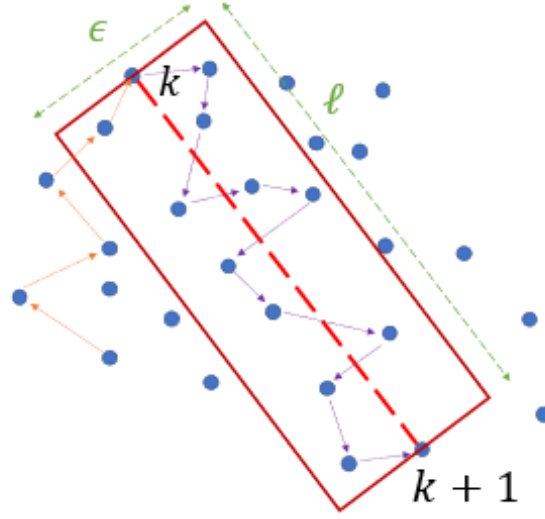


Figure 6.7 How waypoints enroute to the next waypoint are selected and routed, orange arrows is the route as traveled by the UAV, purple is the determined route between k to $k + 1$ waypoint.

6.4.5 Evaluation of the quality of the solution

There are three attributes to assess the quality of the dynamic routing problem:

- How quickly the damaged area is identified;
- How quickly the extent of the damage is identified; and
- How quickly the UAV finishes assessing the area (confirms there is no more damage in the area).

To calculate how quickly the damaged area is identified and how quickly the UAV finishes scanning the area, we define the metric “Score of Finding Damage” and “Score of Completing route”. The former is the distance the UAV takes until the first damaged waypoint is uncovered divided by the number of waypoints initially in the SBW; the latter is the distance the UAV takes to complete its entire route divided by the number of waypoints initially in the SBW. This is to normalize the distance traveled to the number of waypoints, as there may be disparities between the initial number of waypoints initially in the SBW, which may have

grave effects on the length of the route. How quickly the extent of the damage is identified is defined as a “Score of Identifying Damage” and is computed by the distance the UAV took from identifying the first damaged waypoint to the last damaged waypoint divided by the minimum length that the Hamiltonian path would have taken to identify all the damaged waypoints. A score of 1.0 would be a perfect score and means that the path the program took matched the minimum Hamiltonian path; a score of 5.0 would mean the distance the program found was five times as long as the minimum Hamiltonian path.

6.5 Experimentation

While we have historical data for more than 300 tornadoes, we developed the ability to create a larger, artificial data set in order to test the routing algorithm that is developed. The method that we propose for creating these new scenarios is based on historical data (such as the direction, length, and width of historical tornadoes) in order to obtain realistic scenarios. These scenarios will be used as test cases with historical scenarios for the development of more advanced/better routing algorithms.

Due to the limited number of historical cases available for testing, we developed a method for generating cases based on real world data for use in initial parameter tuning and testing. Due to the customizability of these generated cases, we were able to develop smaller tests sizes (that is, typically fewer waypoints). In this section, the subscript GC (Generated Case) is added to variable names to differentiate them from notations elsewhere.

The data used in this chapter draws from the data set denoted "Schematic Tornado Data" [81]

6.5.1 Generated Cases

A “Generated Case” is randomly created using a five-step approach, where Figure 6.8 graphically depicts this five-step process. In Step 1, some number of points $n_{points,GC}$ are randomly and uniformly generated within a bounding box (represented as blue points in Figure 6.8). These points are akin to the waypoints from the historical cases. In Step 2, a search area SBW_{GC} is generated by creating a concave quadrilateral that is encapsulates between 33% and 67% of the $n_{points, GC}$ (represented as a red polygon in Figure 6.8). This is akin to the SBW. In the next three steps, a polygon to represent the damaged area is created. These steps of the process are using the base database of tornadoes from 1950–2021 [81]. Only tornadoes that have a start point and an end point were considered. In Step 3, a point is randomly selected within the search area (represented as a red triangle in Figure 6.8).

Next, in Step 4, a "direction" is randomly selected from the NWS's tornado database from 1950–2021. Finally, in Step 5, the widths and lengths of each tornado in the database were normalized to the range of the randomly generated points (the minimum axis of the bounding box). A random length and width are selected from this database. The damaged area is the rectangle created by the centerline defined by the randomly selected start point, the randomly selected length, and randomly selected direction. The sides of this rectangle are defined by offsetting the centerline half the randomly selected width, perpendicular to the centerline (represented a yellow line and polygon in Figure 6.8).

6.5.2 Testing on Generated Cases

To test our algorithm, the following procedure was used. First, an initial Generated Case is created as outlined in Section 6.5.1. Then, eighteen subcases were created based on three parameters : whether an initial route is used (Yes, No); the type of influence matrix policy used (data-driven-first, data-driven, symmetric-first, symmetric); and the minimum score to consider (0.0, 0.1, 0.2). The combination of the three tested parameters yields 24 subcases; however, when using an "initial route", the change of use of matrix before identifying damage is meaningless, removing these parameter combinations we are left with 18 subcases. Using this procedure, 1000 cases were generated.

6.5.3 Results on the Generated Cases

The first analysis is testing the efficacy of the method to identify the extent of the damage. Precisely, we define this metric as the distance the UAV took from identifying the first damaged waypoint to the last damaged waypoint over the length of minimum Hamiltonian path it would take to identify all the damaged waypoints. Recall a score of 1.0 would be a perfect score and a score of 5.0 would mean the distance the program found was five times as long as the minimum Hamiltonian path. Table 1 has the average and standard deviation of the 1000 cases.

Broadly speaking, the use of either the data-driven-first (symmetric second) or using the symmetric matrix for the entire program yields higher quality results than using data-driven matrices second (after the damage is uncovered). However, what is potentially more interesting is that when using the data-driven-first (symmetric second) matrices produce a markedly lower standard deviation than their symmetric only counterparts; three of the four lowest standard deviations are from the data-driven-first matrices. This can be viewed as the method that produces more consistent results. Given the information in Table 6.1 it is reasonable to draw the conclusion that the quality of this solution based on this metric is

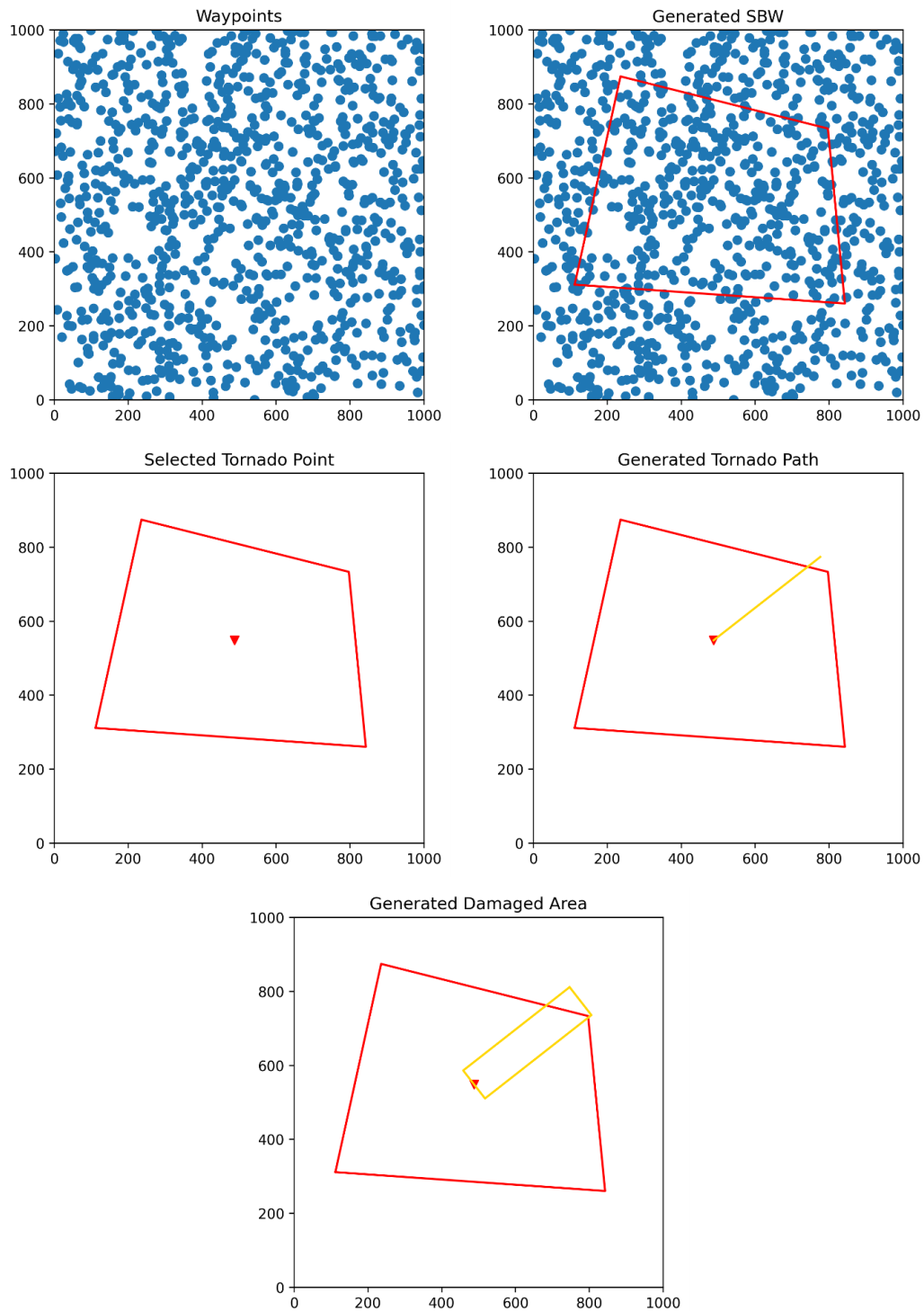


Figure 6.8 Step-by-step process on creating a random case.

unaffected using initial route and the use of the MStC.

Next, we assess the quality of dynamic program to identify the damage and to complete its route (assert that there is no further damage to be identified). To complete this analysis, the distance of the route when the damage is first uncovered is divided/normalized by the number of waypoints in the SBW is one metric; likewise the distance of the route when completed is divided/normalized by the number of waypoints in the SBW is the other metric. These results are shown in Table 6.2 and Table 6.3

As expected, the relationship between not using an initial route and how quickly damage is identified is incredibly stark. It is additionally readily apparent that using data-driven influence matrices to identify damage is marginally better than using the symmetric to identify the damage areas. Visually inspecting the resulting route does demonstrate that the data-driven influence matrix forces the UAV to fly perpendicular to the common orientation of tornadoes.

Also as expected, allowing the UAV to terminate early allows the program to terminate once the computed scores of unvisited waypoints are sufficiently low. Implementation notes: Internal preliminary tests showed that when the MStC was 0.25 or greater, it was common for the UAV to miss damaged waypoints. In the 1000 tests executed, the UAV did not miss any waypoints up to the a MStC 0.20. As for why using an initial route, symmetric matrix (or a data-driven matrix), and a MStC of 0.10 performs similarly to using a MStC of 0.20, it is believed that the systemic search of the search area allows for many waypoints with no damage to be identified and excluded from the search in later stages.

Overall, these test cases demonstrate that our parameters operate as expected: Higher MStC yields a search that is terminated earlier; not using a seeded route yields identifying damage quicker, using an initial route can help the search terminate earlier; and using a data driven search method has an effect and that effect largely helps initially identify the damage, but is detrimental after the damage is identified.

6.6 Testing on Historical Data

With a basic understanding of what parameters work better for the generated cases, we also run these on the collections of historical cases.

Table 6.1 Assessment of quality of method

Initial Route?	Matrix Type	MStC	Mean Score	Std Dev.
FALSE	data-driven-first	0.10	3.2596	1.8526
TRUE	symmetric	0.20	3.3282	3.1588
FALSE	data-driven-first	0.00	3.3695	2.1064
FALSE	symmetric	0.10	3.3883	2.6931
FALSE	data-driven-first	0.20	3.4128	2.5698
TRUE	symmetric	0.00	3.4198	3.5320
FALSE	symmetric	0.20	3.4329	2.3417
TRUE	symmetric	0.10	3.4422	4.1455
FALSE	symmetric	0.00	3.4642	3.1460
TRUE	data-driven	0.10	3.8732	3.1936
TRUE	data-driven	0.20	3.8860	3.0132
FALSE	data-driven	0.20	3.9305	3.7456
TRUE	data-driven	0.00	3.9545	3.2255
FALSE	symmetric-first	0.10	3.9703	3.7709
FALSE	data-driven	0.10	4.0058	3.8564
FALSE	symmetric-first	0.20	4.0516	3.8829
FALSE	data-driven	0.00	4.0698	4.3266
FALSE	symmetric-first	0.00	4.1296	4.9137

6.6.1 Data and creation of the Historical Cases

The data was pulled from the historical meteorological data from March 2008 to June 2019 (inclusive) for the Weather Forecast Offices with the ID code of: OUN, TSA, AMA, SHV, LZK, LCH, LIX, JAN, MEG, HUN, BMX, MOB, FFC, TAE, JAX, CHS, PAH, OHX, MRX, LMK, JKL (which encompasses the US States of Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Oklahoma, South Carolina, Tennessee, and Texas)¹. This and the location of all data used in this chapter is in Appendix F in Table F.1. There were 182 days with tornadoes in this region. Of these 182 days, several had multiple tornadoes in multiple areas. If we separate these instances where multiple tornadoes occurred on the same day, we find there are 415 unique cases.

We applied the procedure explained before. The first analysis is testing the efficacy of the method to identify the extent of the damage, again the distance the UAV took from identifying the first damaged waypoint to the last damaged waypoint divided by the minimum Hamiltonian path to identify all the damaged waypoints. The table summarizing these results can be found in Table 6.4.

¹A map and list of WFO offices can be found at <https://www.weather.gov/srh/nwsoffices>

Table 6.2 Scores of Finding Damage

Initial Route?	Matrix Type	MStC	Mean Score	Score Find Damage
FALSE	data-driven-first	0.20	3.4128	7,592
FALSE	data-driven	0.20	3.9305	7,592
FALSE	data-driven-first	0.10	3.2596	7,614
FALSE	data-driven	0.10	4.0058	7,614
FALSE	data-driven-first	0.00	3.3695	7,733
FALSE	data-driven	0.00	4.0698	7,733
FALSE	symmetric	0.10	3.3883	8,001
FALSE	symmetric-first	0.10	3.9703	8,001
FALSE	symmetric	0.20	3.4329	8,043
FALSE	symmetric-first	0.20	4.0516	8,043
FALSE	symmetric	0.00	3.4642	8,071
FALSE	symmetric-first	0.00	4.1296	8,071
TRUE	symmetric	0.20	3.3282	9,377
TRUE	symmetric	0.10	3.4422	9,377
TRUE	symmetric	0.00	3.4198	9,377
TRUE	data-driven	0.10	3.8732	9,377
TRUE	data-driven	0.20	3.8860	9,377
TRUE	data-driven	0.00	3.9545	9,377

Table 6.3 Scores of Finishing the Route

Initial Route?	Matrix Type	MStC	Mean Score	Score Finish Route
TRUE	symmetric	0.20	3.3282	36,269
TRUE	data-driven	0.20	3.8860	36,619
FALSE	data-driven	0.20	3.9305	38,403
FALSE	symmetric-first	0.20	4.0516	38,469
TRUE	symmetric	0.10	3.4422	40,480
FALSE	data-driven-first	0.20	3.4128	41,301
FALSE	symmetric	0.20	3.4329	41,349
TRUE	data-driven	0.10	3.8732	43,395
FALSE	symmetric-first	0.10	3.9703	48,069
FALSE	data-driven	0.10	4.0058	48,101
FALSE	data-driven-first	0.10	3.2596	49,230
FALSE	symmetric	0.10	3.3883	49,263
TRUE	symmetric	0.00	3.4198	50,218
FALSE	symmetric	0.00	3.4642	60,850
TRUE	data-driven	0.00	3.9545	60,895
FALSE	data-driven-first	0.00	3.3695	60,926
FALSE	symmetric-first	0.00	4.1296	64,801
FALSE	data-driven	0.00	4.0698	65,037

It is immediately apparent that: 1) data-driven-first and symmetric influence matrices continue to be better than using data driven; 2) the lack of initial route is much more positively impactful in the historical cases than in the artificial cases; and 3) there is very little difference in the scores of some of the several pairs of cases.

Next, we assess the quality of dynamic program to identify the damage in historical cases and to complete its route (assert that there is no further damage to be identified). These values are computed likewise to the generated cases. To complete this analysis, the distance of the route when the damage is first uncovered is divided/normalized by the number of waypoints in the SBW (metric 1); likewise, the distance of the route when completed is divided/normalized by the number of waypoints in the SBW (metric 2). These results are shown in Table 6.5 and Table 6.5.

Reflecting the Generated Cases, the relationship between not using an initial route and how quickly damage is identified is similar between the Generated Cases and the Historical Cases (Table 6.5). It is also apparent, however, that the MStC is a stronger indicator of a lower score to find damage than the matrix type.

Also reflecting the results from the Generated Cases, allowing the UAV to terminate early allows the program to terminate once the computed scores of unvisited waypoints are sufficiently low (Table 6.6). Once again using a symmetric matrix and a MStC of 0.10 performs similarly to using a MStC of 0.20.

Overall, these test cases demonstrate that our parameters operate as expected: Higher MStC yields a search that is terminated earlier; not using a seeded route yields identifying damage quicker; and using a data driven search method has an effect and that effect is largely helps initially identify the damage but may be detrimental after the damage is identified.

As indicated previously, there are some instances where multiple tornado tracks do appear. We have separated these and denoted them as simple (one track) and complex (multiple tracks), while the explicit numerical values do change between simple and complex cases and performance of “complex” cases are worse than “simple” cases, the substantive takeaways remain. A separation of these data is shown in Appendix E Table E.1 and Table E.2 as reference.

6.6.2 Comparison of results

To easily compare both the historical cases and the generated cases, Table 6.7 indicates which parameters the end user should use to achieve a specific goal. In Table 6.7, we have used boldface type to indicate matching parameters. The parameters that match both Historical

Table 6.4 Assessment of quality of method, historical cases

Initial Route?	Matrix Type	MStC	Mean Score	Std Dev.
FALSE	data-driven-first	0.20	6.3817	4.6151
FALSE	symmetric	0.20	6.5051	4.3033
FALSE	data-driven-first	0.10	6.7603	5.0457
FALSE	symmetric	0.10	6.7777	4.6675
FALSE	symmetric	0.00	7.1567	5.3666
FALSE	data-driven-first	0.00	7.1678	5.3796
TRUE	symmetric	0.20	7.4841	14.1935
TRUE	symmetric	0.10	8.0410	16.4381
TRUE	symmetric	0.00	9.2208	18.1696
TRUE	data-driven	0.20	10.0360	13.7550
FALSE	data-driven	0.20	11.1705	12.5204
FALSE	symmetric-first	0.20	11.4753	13.2841
TRUE	data-driven	0.10	11.6901	18.0052
FALSE	data-driven	0.10	12.0320	13.8424
FALSE	symmetric-first	0.10	12.1197	14.4577
FALSE	symmetric-first	0.00	12.8923	15.4161
FALSE	data-driven	0.00	12.9564	14.8083
TRUE	data-driven	0.00	15.3768	33.8396

cases and Generated cases are: To minimize the distance/time it takes to uncover extent of tornado, use data-driven-first or symmetric influence matrix; To reduce the standard deviation of distance/time it takes to uncover extent of tornado use a data-driven-first influence matrix; To minimize the distance/time it takes to initially identify tornado, do not use an initial route; and to minimize the distance/time it takes to complete the mission, use a higher MStC.

For reducing “the standard deviation of distance/time it takes to uncover extent of tornado”, the effect of data-driven-first versus the symmetric influence is less pronounced on historical cases than it is on the artificially generated cases.

6.7 Conclusion

This chapter presents both a (1) method of attempting to identify the extent of the damaged area in the aftermath of a tornado as quickly as possible and (2) a method for creating artificial cases that can be used to increase the number of cases available for testing. We have demonstrated that intelligently incorporating historical data into the decision-making process can assist the dynamic routing method to route and reroute a damage assessment UAV to

Table 6.5 Scores of Finding Damage, historical cases

Initial Route?	Matrix Type	MStC	Mean Score	Score Find Damage
FALSE	data-driven-first	0.20	6.3817	615
FALSE	data-driven	0.20	11.1705	615
FALSE	symmetric	0.20	6.5051	641
FALSE	symmetric-first	0.20	11.4753	641
FALSE	data-driven-first	0.10	6.7603	666
FALSE	data-driven	0.10	12.0320	666
FALSE	symmetric	0.10	6.7777	684
FALSE	symmetric-first	0.10	12.1197	684
FALSE	symmetric	0.00	7.1567	702
FALSE	symmetric-first	0.00	12.8923	702
FALSE	data-driven-first	0.00	7.1678	709
FALSE	data-driven	0.00	12.9564	709
TRUE	symmetric	0.20	7.4841	814
TRUE	symmetric	0.10	8.0410	814
TRUE	symmetric	0.00	9.2208	814
TRUE	data-driven	0.20	10.0360	814
TRUE	data-driven	0.10	11.6901	814
TRUE	data-driven	0.00	15.3768	814

Table 6.6 Scores of Finishing the Route, historical cases

Initial Route?	Matrix Type	MStC	Mean Score	Score Finish Route
TRUE	symmetric	0.20	7.4841	3,456
FASLE	data-driven-first	0.20	6.3817	3,631
FASLE	symmetric	0.20	6.5051	3,658
TRUE	data-driven	0.20	10.0360	3,984
TRUE	symmetric	0.10	8.0410	4,083
FASLE	data-driven	0.20	11.1705	4,206
FASLE	symmetric-first	0.20	11.4753	4,261
FASLE	data-driven-first	0.10	6.7603	4,481
FASLE	symmetric	0.10	6.7777	4,517
TRUE	data-driven	0.10	11.6901	4,816
FASLE	data-driven	0.10	12.0320	5,304
FASLE	symmetric-first	0.10	12.1197	5,347
FASLE	data-driven-first	0.00	7.1678	6,890
FASLE	symmetric	0.00	7.1567	6,892
TRUE	symmetric	0.00	9.2208	7,255
TRUE	data-driven	0.00	15.3768	8,172
FASLE	symmetric-first	0.00	12.8923	8,194
FASLE	data-driven	0.00	12.9564	8,203

Table 6.7 Summary and comparison of historical and generated cases.

Goal	In Generated Cases	In Historical Cases
Minimize the distance/time it takes to uncover extent of tornado	Use data-driven-first or symmetric influence matrix	Use data-driven-first or symmetric influence matrix
Reduce the standard deviation of distance/time it takes to uncover extent of tornado	Use data-driven-first matrix and not using an initial route	Do not use an initial route and use a data-driven-first or symmetric influence matrix
Minimize the distance/time it takes to initially identify tornado damage	Use data-driven-first or data-driven matrix Do not use an initial route and all else being equal a higher MStC helps	Do not use an initial route Use a higher MStC
Minimize the distance/time it takes to complete the mission	Use a higher MStC Using an initial route	Use a higher MStC

determine the extent of damage as quickly as possible. In addition, we have developed a method for creating artificial instances that react similarly for key goals (that is, identifying the extent of tornado damage). The difficulty we encountered was that we successfully developed the algorithm to use only one UAV in identifying damage (rather than multiple UAVs in the previous literature).

These artificial instances perform similarly in some important metrics to the historical database of tornado instances that we produced; however, there is a gap that needs to be addressed. From the outset, we aimed to create a method to “Minimize the distance/time it takes to uncover extent of tornado” and the generated cases perform similarly. Recall this was our primary goal. However, the other goals outlined in this chapter have slight differences between parameters in the historical cases data set versus the generated cases data set. For instance, using a data-driven influence matrix first helps identify damage in the generated cases, but this has less of an impact on the actual historical data set. This is possibly because the number of waypoints is larger than the generated cases. The nature of the data driven matrix strongly encourages the UAV to travel perpendicular to the typical direction of

tornadoes before damage is beginning to be identified. That is, before damage is identified, the influence matrix encourages the UAV to fly in a northwest-to-southeast direction. This makes intuitive sense as, if you are trying to initially identify something that will typically be in a northeast-to-southwest orientation, you would systematically search in a northwest-to-southeast direction. The additional waypoints and size of the search area curtails this effect.

Second, we also show that the use of historical tornado trends has an impact on the response method outlined in this chapter. The method is interesting as the historical data typically has a positive impact on the discovery of damaged areas and a reduction in the standard deviation of uncovering damaged areas. That is, once the damage has begun to be uncovered, the information gained from the route prior to identifying damage can help (typically) reduce the extremes in time/distance it takes identifying the extent of the damage. However, using the data driven matrix after damage is identified performs worse regardless of any other parameters used.

Tornadoes are broadly considered to be a random and unpredictable phenomenon that are hard to predict and simulate. This chapter demonstrates that, even given the unpredictable nature of tornadoes, the intelligent and directed use of historical tornado damage can help rescuers identify the area impacted by a tornado in a much more efficient manner.

Some main limitations and avenues for future research to still be explored include further sensitivity on the setup of the influence matrix (as a larger range of influence may be desired for spatially larger cases). The method outlined here is also ripe for introducing more real-time data into the method. For example: the press, storm chasers, or emergency calls reporting impacted areas can convert a waypoint with unknown attributes into a known waypoint, which can be updated immediately in the dynamic routing algorithm. We use one UAV to assess an area; practically, multiple UAVs can reduce the time it takes to search the entire area, and as indicated in the previous literature, when flying multiple UAVs over a disaster area the UAV with the greatest time aloft is what we attempt to minimize [77]. However it remains unknown how multiple UAVs would effectively assess the extent of a damaged area within the context outlined in this chapter. In addition, it remains an open question if using/flying multiple UAVs over a disaster area would be better served by multiple UAVs assessing the same area or multiple UAVs assessing their own areas. The influence matrix only considers direction and frequency; the influence matrix lacks any context on tornado width and length. While the direction histogram remains constant through most of the contiguous United States, length, width, and severity vary with the tornado location so sensitivity of data used based on location can be performed. The minimum score to consider

has the potential to be adaptive. Presently, there is also a lack of adequate research on whether these wireless sniffers can be used in practice. Assessing whether a waypoint is “damaged” is still a manual process, and aerial assessment may result in inaccurate damage reporting for some structures.

CHAPTER 7 GENERAL DISCUSSION

This dissertation presented three articles in Chapters 4, 5, and 6.

In Chapter 4, we introduced the foundation for utilizing tornado-related weather data in tornado disaster response efforts. Our approach involves the use of UAVs equipped with cameras and wireless sensors to survey areas that may contain individuals in need of assistance after a tornado. We integrate meteorological data with the existing road network to determine the most optimal routes for UAVs during post-tornado scenarios. This chapter explained the reasoning behind using SBWs as search areas and provided a detailed explanation of the process for generating waypoints, which will be utilized in Chapters 5 and 6. We also discussed the fundamental concepts related to utilizing tornado-related weather data for effective disaster response. Specifically, we focused on the decision to employ SBWs as search areas and the methodology for generating waypoints, both of which will play a crucial role in Chapters 5 and 6. Furthermore, we proposed a method of utilizing tornado sightings along with their corresponding SBWs to identify an initial search region.

By combining these factors, we proposed methods to ensure efficient and targeted deployment of UAVs, facilitating swift response and aid delivery to affected areas.

Additionally, we provide an analysis of the trade-off between route planning and the actual execution of those routes. This chapter sheds light on a common discussion among OR practitioners, namely, the challenge posed by problems that may be too complex to be solved precisely, leading to the utilization of (meta)heuristics as problem-solving approaches.

Many research studies in operations research highlight the gaps that often exist between heuristic solutions and exact solutions, yet fail to thoroughly explore the practical trade-offs in terms of time constraints. In the context of search and rescue operations, examining the trade-off between seeking an "optimal route" and efficiently executing that route becomes particularly relevant. This trade-off encompasses the time required to solve the problem versus the time needed for a team to effectively operate the solution.

By considering the practical aspects of time trade-offs, we aim to provide valuable insights into the dynamic interplay between route optimization and real-world implementation, particularly in the context of search and rescue scenarios.

Chapter 5 uses historical data to optimize allocation of UAVs in tornado preparedness. One practical limitation identified in Chapter 4 was the assumption that any (and every) fire station or depot could be utilized, leading to an overestimation and excessive utilization of

resources.

In Chapter 5, we propose an alternative approach that uses historical data to effectively allocate UAVs to depots, taking into account the uncertainties surrounding depot capabilities to respond adequately to tornado events. We address the potential issue of a depot being unable to provide an adequate response by introducing robustness into the solution. Our analysis reveals a probability of over 1 in 25 for inadequate tornado response, assuming every depot operates with 100% uptime.

To ensure sufficient response capabilities for tornado events, we determine that an additional 30% to 80% more stations need to be established to guarantee appropriate response times. Considering the random nature of tornadoes in terms of location and path, it becomes evident from a responder’s perspective that there is a non-negligible probability that a search and rescue team may not be able to respond adequately to a tornado disaster. This could result from unforeseen maintenance requirements, flight crew unavailability at the launch station, or the station itself being affected by a tornado strike.

In Chapter 6, we delve into the final exploration of this dissertation, aiming to further use historical tornado data for efficient damage assessment. Our objective is to identify the extent of damage in the shortest possible time frame.

Within this chapter, we introduce an approach that utilizes broad trends observed in historical tornadoes to accomplish this goal. By intelligently integrating historical data into the decision-making process, our dynamic routing method enables the routing and rerouting of a damage assessment UAV, optimizing the process of determining the extent of damage as swiftly as possible.

Additionally, we present a novel method for generating artificial cases, which serves to expand the available testing scenarios for the development and evaluation of dynamic routing problems. Through our analysis, we have observed that these artificially generated instances exhibit comparable performance in key metrics when compared to the existing historical database of tornado instances.

By incorporating historical data and creating additional testing scenarios, our research contributes to the advancement of efficient damage assessment techniques, ultimately enabling rapid response and effective decision-making in the aftermath of tornado events.

CHAPTER 8 CONCLUSION AND RECOMMENDATIONS

This dissertation showed that the intelligent application of historical tornado data in key ways can provide search and rescue teams the opportunity to identify the location of people in need of aid. We began by demonstrating the broad usage of spatial data (such as roads) and the storm based warnings to generate search areas for UAVs to conduct their assessment missions. We then addressed a shortcoming with the original chapter to identify what potential stations would be used to station UAVs to adequately cover the state of Oklahoma. In addition to locating the UAVs in advance of a tornado event we also robustified our selection of depots to account for a chance of a depot not being able to launch their UAV. We finally use the historical tornado data to prioritizing identifying the extent of the damage with the aim of alerting on-the-ground rescuers where to prioritize their searching.

8.1 Summary of Works

In Chapter 4 we introduce a framework for the use of UAVs equipped with cameras and wireless sensors to search areas where there may be people in need of aid after a tornado. We used a combination of meteorological data and the road network to route UAVs in the aftermath of tornadoes. Specifically, we proposed using tornado sightings and their associated SBWs to identify an initial area to assess damage.

We also analyze the trade-off between routing and executing that route. This chapter also demonstrates the trade-off OR practitioners often discuss that a problem may be too hard to solve exactly, and the use of (meta)heuristics to solve a problem. Often these pieces of research have gaps between the heuristic solution and an exact solution, but no (or limited) discussion about the practical time trade-offs. Search and rescue operations can provide a very fertile ground for analyzing the trade-off between trying to find an "optimal route" and executing that route (the time it takes to solve this problem versus the time it takes for a team to operate the solution).

In Chapter 5 we begin to leverage historical data to produce an efficient use of resources in preparing for tornadoes. We propose an approach that uses historical data to allocate UAVs to depots. We also robustify the solution against the uncertainty that a depot may not be able to respond to a tornado adequately. We can find over a 1 in 25 chance of not adequately responding to a tornado if we assume that every depot had 100% uptime.

To adequately respond to these tornadoes, we find anywhere between 30% to 80% more

stations need to be established to ensure adequate response times.

In Chapter 6, we further leverage the historical tornado data set in order to identify the extent of the damage in as short as possible. We have demonstrated that intelligently incorporating historical data into the decision-making process can assist the dynamic routing method to route and reroute a damage assessment UAV to determine the extent of damage as quickly as possible.

We also develop a method for creating artificial cases that can be used to increase the number of cases available for testing. We found these artificial instances perform similarly in some important metrics to the available historical database of tornado instances.

8.2 Response to Research Objectives

This dissertation's research objective was to developing fast and efficient UAV routing models to assess areas after a tornado. We broke down this research objective into four research sub-objectives:

1. Sub-objective 1 : define concepts and frameworks for creating "search areas";
2. Sub-objective 2 : develop an approach for initially identifying areas to deploy a SAR UAV;
3. Sub-objective 3 : use the historical data to allocate SAR UAVs in advance of a tornado occurring; and
4. Sub-objective 4 : using the historical data to help the UAV identifying the extent of the damage as quickly as possible.

In response to sub-objective 1 and sub-objective 2: Chapter 4 defined the search areas as the intersection of a tornado event and the road network to produce a search plan. We limited our testing to only three historical events as we began to understand the data we had at our disposal.

As confidence and understanding was gained, we were able to increase the impact of sub-objective 1 and sub-objective 2 in Chapter 5 and Chapter 6 by incorporating many more events – 124 and 182 respectively. These counts represent the summation of all available data for the regions (states) explored. In analyzing the trade-off between naive implementation(s) of creating a search area (rectangular and hexagonal patterns), exact methods of creating a search area (the minimum set covering/minimum number of Steiner zones), and heuristic

implementations (the Steiner zone heuristic), we find that the heuristic provides the best tradeoff in "planning" and executing the plan.

Sub-objective 3 was explored entirely and uniquely in Chapter 5. Sub-objective 3 explored a pragmatic shortcoming of Chapter 4 where Chapter 4 assumed any (and every) fire station could be a depot. In addition to contributing to the understanding of planning in disaster preparation/response, the decision tool necessitated the use of more historical tornado events to be used. Adequate prepositioning of disaster response tools allows rescuers to respond adequately and efficiently to a tornado occurring.

Finally Chapter 6 explores sub-objective 4 by proposing a means efficiently assess an area. The goal is to primarily identify the extent of tornado as quickly as possible. The quicker the affected area can be identified, the quicker on-the-ground rescuers can be deployed to people in need of aid.

8.3 Limitations

Some pragmatic limitations of the research include the legal and data limitations that may exist in other jurisdictions, such as some governments' restrictions or bans on UAV operations, use of the "wireless sniffer technology", or GIS and meteorological data may not be as detailed or freely available.

However, we encourage the reader to explore how to use expert-generated data and (if legal) the flexibility wireless sniffers can provide members of the search and rescue community. One example to get data of where people may be is to use nighttime imagery from artificial satellites that may display "light maps" of dwellings or other infrastructure. An idea to identify bounding locations for search areas could be using observation towers (such as those tracking forest fires) and triangulating a search area from observers.

All the research in this dissertation assumes synchronous launches. However, asynchronous launches can be leveraged to allow for UAVs from further away to be launched when weather permits.

While record keeping has improved throughout the years, the historical database of tornadoes is still quite limited. For instance, Chapter 6 we were only able to create about 400 instances for a large swath the south-eastern USA (where there are the most frequent and severe tornadoes in the world).

While the use of cellular phones has skyrocketed around the world, there are still populations of people that may not have (or have the means to own and use) cellular or wireless devices. For example: children, the elderly, the poor. Pragmatic decisions about prioritizing areas

that potentially have these populations would be prudent.

8.4 Future Research

There are plenty of low hanging fruit for future research. First, a lot of homogeneity is in this dissertation. We assume similar UAVs are at all stations with a similar sensor set and operational characteristics. We (intentionally) made very few assumptions on the cost of establishing and running these UAVs. In the context of Chapter 5, there is a big difference between the types of fire stations that are throughout the state. For example fire stations that are in more rural and sparsely portions of the state are often volunteer, they do not have a full time staff. So staffing these fire stations could be more expensive than staffing stations in cities. A future research idea could be to better account for the discrepancy between fire station types, such as applying a penalty function to the selection of depots (prefer professional fire stations).

There may be an opportunity to explore the use of asynchronous launches in the aftermath of a tornado. For example, launching a UAV from an area where the weather is good enough and letting it fly into an area where the severe weather is subsiding, colloquially speaking an area that is "clearing up".

All the research in this dissertation assume the UAVs will return to base. In practice, manned aircraft must always return to base, but UAVs could potentially land away from their base stations in safe zones and be picked up by a rescuer at a later date. For example: an athletic field, parking lot, or other depot.

Broadly, there is no reason why the methods in Chapters 4 and 5 cannot be applied or adapted to include other meteorological conditions or response operations. Tornadoes were selected because they were under-represented in the literature (versus hurricanes, earthquakes) and I do believe they provide a very unique testing opportunity and implementation of the methods from other disasters. However, Chapter 6 would have limited utility outside of tornadoes.

However, the method proposed in Chapter 6 could be adjusted to incorporate historical data from uniquely the area that is being planned. For example, SAR planners in West Virginia could limit the database to tornadoes that occurred in the state as tornadoes tend to be shorter in states near the Appalachian Mountains.

Advancements in simulating tornadoes – and tornado events – could produce many more instances that can be used in the development of SAR tools. The method in Chapter 5 is quite rudimentary (and does not consider tornadoes' damage at all) and the method in Chapter 6 introduces a "sandbox" for testing, there is still limited relationship between the

tornado that is artificially generated and its real world counterpart.

Given the context of Chapter 6, the waypoints could be updated (identified as damaged and undamaged) any number of ways. One obvious example is someone calling 911 and alerting emergency responders to the location of a destroyed structure; the algorithm proposed can easily incorporate this data and the UAV can be updated with the additional information.

Chapter 6 also neglected to use multiple UAVs in their assessment; more UAVs can be utilized to assess an area in (typically) a faster time, the dynamic algorithm does not perform well when there are areas with no reported damage (whereby, the minimum Hamiltonian path will typically perform best assessing these areas). Research has to be conducted to see if there is a good trade-off between efficiently identifying damage when it occurs, while efficiently affirming damage does not exist when it does not exist.

In addition to using multiple UAVs, different operators may interpret the identification of damage in different ways. To put it more mathematically, the identification of damage (The waypoint contains damage or does not contain damage) could be probabilistic rather than deterministic. Whether the UAVs would be better used to scan unique areas or allow multiple UAVs to scan the same area to ensure an area is appropriately identified remains an open question.

We assume that waypoints are equally likely to contain people; however, knowledge of people's movements throughout the day could help prioritize waypoints/locations. For example, a tornado that occurs in the evening or morning could prioritize areas known to have dwellings while areas that are commercial can be prioritized during the midday hours.

Finally, the dissertation assumes, but does not define the creation of a "priority heat map" of wireless signals. The dissertation assumes that the UAV would report the number and intensity of wireless signals. This is useful for identifying singular devices (say in a WiSAR situation), but it remains an open question about the practical reporting of data to first responders, and further if this data can be used to help the UAVs complete their mission more effectively.

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APPENDIX A LOCATION OF DATA AND TOOLS USED IN CHAPTER 4

The source code for the chapter can be found at:

<https://github.com/seangrogan-researchprojects/tornado-and-routing-project-2021>.

The final version of this software was coded in Python 3.7 [110]. In addition to the Python standard library, this chapter and research utilize the following packages: Matplotlib [111] for outputting images and graphics. Images with satellite imagery were generated using Google Earth Pro [112]. PyShp [113] from Geospatial Python for reading, processing, and manipulating ESRI shape files such as the LSR, SBW, and road files. Clustering algorithms (K-Means++, DBSCAN, and Mean Shift) were imported from Scikit-learn [114]. Tabu Search uses Pandas, the Python Data Analysis Library [115] as an underlying data structure for identifying neighbor solutions. Calculations between points on the Earth were calculated with the Great Circle Calculator [116]. Testing the model with exact solution methods was done with GUROBI 8.1 Gurobi Optimization, and the model was generated with the PuLP library [117].

Data for this chapter are all open source and available on government websites or the ArcGIS open data hub. Specifically, road data for Oklahoma [80], road data for Texas Texas Department of Transportation [100], The Texas General Land Office [99], Fire station location data can be found here [79], all SBWs and LSRs were pulled from the historic data on the NWS Chat service [118].

APPENDIX B LOCATION OF DATA USED IN CHAPTER 5

Data	Location	Notes
Storm Based Warnings (SBWs) and Local Storm Reports (LSRs)	https://mesonet.agron.iastate.edu/	Weather Forecast Offices: OUN, TSA, AMA, SHV Dates:
Simplified tornado tracks	https://www.spc.noaa.gov/gis/svrgis/	
Road data for the state of Oklahoma	https://okmaps.org/ogi/search.aspx	ODOT Local Roadways ODOT Roadways ODOT Highways Oklahoma Fire Stations

APPENDIX C PSEUDOCODE AND ALGORITHMS USED IN CHAPTER 5

Algorithm 6 Steiner Zone Heuristic

```

1:  $r_{scan}$ , PointsOfInterest
2: groups = set()
3: random.shuffle(PointsOfInterest)
4: while length(PointsOfInterest) >= 0 do
5:   tempGroup = set()
6:   tempGroup.add(PointsOfInterest.pop())
7:   for point in PointsOfInterest do
8:     if distanceFunction(point, point2)  $\leq r_{scan}$  for all point2 in tempGroup then
9:       tempGroup.add(point)
10:      PointsOfInterest.remove(point)
11:    end if
12:  end for
13:  groups.add(tempGroup)
14: end while
15:

```

Algorithm 7 Multi-knapsack initial solution generator

```

1: waypoints, fireStations, maxKnapsackSize
2: solution = dict()
3: while length(waypoints)  $\geq 0$  do
4:   find (station in fireStations, waypoint in waypoints) pair with the minimum distance
   between them
5:   solution[station] = [waypoint, ]
6:   waypoints.discard(waypoint)
7:   fireStations.discard(station)
8:   while sum(distance(station, wpt) for wpt in solution[station])  $\leq$  maxKnapsackSize
   do
9:     find waypoint2 in waypoints with the minimum distance between the waypoint
   and the station
10:    solution[station].append(waypoint2)
11:    waypoints.discard(waypoint)
12:   end while
13: end while

```

Algorithm 8 Heuristic to solve the location problem

```

1: Given depotFailureRate; targetFeasibilityPct; allStations; initialSolution
2: Parameters:  maxNumberOfInfeasibleSolutions; minimumNumberOfGlobalIters; num-
   berOfTestsForEachTornadoEvent; targetTBar; ScanningDiameter =  $2 \times r_{scan}$ 
3: runsCounter = 0
4: infeasibilityCounter = 0
5: currentSolution, bestSolution = initialSolution, allStations
6: newBest = False
7: while True do
8:   while infeasibilityCounter < maxNumberOfInfeasibleSolutions do
9:     targetFeasibilityTracker = list()
10:    for each historicalTornadoEvent in historicalTornadoEvents do
11:      while i < numberOfTestsForEachTornadoEvent do
12:        i+=1
13:        operationalStations = GetOperationalStations(currentSolution, depotFail-
   ureRate)
14:        tBar = GetTBarForEvent(operationalStations, historicalTornadoEvent,
   targetTBar, ScanningDiameter)
15:        if tBar <= targetTBar then
16:          targetFeasibilityTracker.append(True)
17:        else
18:          targetFeasibilityTracker.append(False)
19:        end if
20:      end while
21:    end for
22:    if sum(targetFeasibilityTracker) / len(targetFeasibilityTracker) >= targetFeasi-
   bilityPct then
23:      if len(currentSolution) < len(bestSolution) then
24:        newBest = True
25:      end if
26:      if len(currentSolution) <= len(bestSolution) then
27:        bestSolution = currentSolution
28:      end if
29:    else
30:      infeasibilityCounter += 1
31:    end if
32:  end while
33:  runsCounter += 1
34:  if (not newBest) and (runsCounter > minimumNumberOfGlobalIters) then
35:    return bestSolution
36:  end if
37: end while

```

Algorithm 9 GetTBarForEvent() Algorithm to identify TBar

```

1: Given operationalStations; historicalTornadoEvent; targetTBar; ScanningDiameter ->
    $2 \times r_{scan}$ 
2: Waypoints = historicalTornadoEvent.getAssociatedWaypoints()
3: ExpectedLengthOfAllWaypoints = ScanningDiameter * len(Waypoints)
4: numStationsNeeded = math.ceiling(ExpectedLengthOfAllWaypoints/targetTBar)
5: while True do
6:   distanceMatrix = []
7:   selectedStations = closest stations in distanceMatrix[], i.e. the minimum distances
8:   dMax = max(D[s in selectedStations])
9:   if dMax + (ExpectedLengthOfAllWaypoints/numStationsNeeded) <= targetTBar
   then
10:    return selectedStations
11:   else if len(operationalStations) < numStationsNeeded + 1 then
12:    return operationalStations
13:   else
14:    numStationsNeeded += 1
15:   end if
16: end while

```

APPENDIX D MATHEMATICAL MODELS IN CHAPTER 5

$$\min \sum_{i \in S} y_i \tag{D.1}$$

$$\sum_{i \in S} x_{ij} = 1 \forall j \in W \tag{D.2}$$

$$\left(\sum_{j \in W} d_{ij} x_{ij} \right) - K y_i \leq 0 \forall i \in S \tag{D.3}$$

$$y_i \in \{0, 1\} \forall i \in S \tag{D.4}$$

$$x_{ij} \in \{0, 1\} \forall i \in S, j \in W \tag{D.5}$$

Where $i \in S$ is the collection of stations (knapsacks), $j \in W$ is the collection of waypoints (items), d_{ij} is the distance metric from station i to waypoint j (the weight of putting item j in knapsack i), K is the capacity of the stations (capacity of the knapsacks). The binary variable y_i takes the value of 1 if station i is used, 0 otherwise. The binary variable x_{ij} takes the value of 1 if waypoint j is assigned to station i , 0 otherwise. The objective function D.1 consists in minimizing the number of stations, the first constraint D.2 ensures each waypoint is assigned to a station, the second set of constraints D.3 links the stations to the waypoints and sets the maximum number of waypoints that can be assigned to each station. The last set of constraints D.4 and D.5 defines both y_i and x_{ij} as binary variables.

APPENDIX E ADDITIONAL RESULT TABLES FOR CHAPTER 6

As indicated in Section 6.6, some cases have multiple tornado tracks. We have separated the data into “simple” (Table E.1) and “complex” (Table E.2) here, with similar tables above.

Table E.1 Results table, Historical Cases, Simple Cases.

Initial Route?	Matrix Type	MStC	Mean Score	Std Dev.	Score, Find Damage	Score, Finish Route
FALSE	data-driven-first	0.20	4.8922	4.2596	694	3624
FALSE	symmetric	0.20	5.0110	3.7612	735	3664
FALSE	data-driven-first	0.10	5.0967	4.5166	770	4542
FALSE	symmetric	0.10	5.1201	3.8677	798	4592
FALSE	symmetric	0.00	5.2522	4.5352	826	7089
FALSE	data-driven-first	0.00	5.3132	4.6398	832	7083
TRUE	symmetric	0.20	6.4050	17.0184	962	3481
TRUE	symmetric	0.10	6.5172	19.5489	962	4116
TRUE	symmetric	0.00	6.7681	20.7267	962	7608
TRUE	data-driven	0.20	9.5569	16.3940	962	4061
FALSE	data-driven	0.20	10.8395	14.7529	694	4269
TRUE	data-driven	0.10	10.9968	21.4810	962	4923
FALSE	symmetric-first	0.20	11.3058	15.7532	735	4349
FALSE	data-driven	0.10	11.4801	16.3374	770	5378
FALSE	symmetric-first	0.10	11.6730	17.1360	798	5445
FALSE	symmetric-first	0.00	12.1823	18.2321	826	8476
FALSE	data-driven	0.00	12.2794	17.4458	832	8478
TRUE	data-driven	0.00	14.2036	40.4971	962	8643

Table E.2 Results table, Historical Cases, Complex Cases.

Initial Route?	Matrix Type	MStC	Mean Score	Std Dev.	Score, Find Damage	Score, Finish Route
FALSE	data-driven-first	0.20	9.3606	3.7923	457	3647
FALSE	symmetric	0.20	9.4933	3.7334	453	3645
TRUE	symmetric	0.20	9.6422	4.3476	519	3406
FALSE	data-driven-first	0.10	10.0876	4.3673	458	4360
FALSE	symmetric	0.10	10.0928	4.3638	455	4367
FALSE	data-driven-first	0.00	10.8769	4.8211	462	6504
FALSE	symmetric	0.00	10.9658	4.8593	455	6500
TRUE	data-driven	0.20	10.9943	5.4299	519	3830
TRUE	symmetric	0.10	11.0887	5.7820	519	4018
FALSE	symmetric-first	0.20	11.8142	5.8025	453	4086
FALSE	data-driven	0.20	11.8323	5.9181	457	4079
FALSE	symmetric-first	0.10	13.0132	6.2842	455	5150
TRUE	data-driven	0.10	13.0765	6.9395	519	4601
FALSE	data-driven	0.10	13.1357	6.3262	458	5158
TRUE	symmetric	0.00	14.1262	9.8253	519	6550
FALSE	data-driven	0.00	14.3103	6.8814	462	7655
FALSE	symmetric-first	0.00	14.3124	6.7930	455	7632
TRUE	data-driven	0.00	17.7232	12.3189	519	7229

APPENDIX F DATA LOCATIONS, CHAPTER 6

Table F.1 Location of data used in Chapter 6.

What?	Where?	When?	Notes
Weather SBW Data	https://mesonet.agron.iastate.edu/	2022-06	For the WFOs: OUN, TSA, AMA, SHV, LZK, LCH, LIX, JAN, MEG, HUN, BMX, MOB, FFC, TAE, JAX, CHS, PAH, OHX, MRX, LMK, JKL
Road data for South Carolina	http://info2.scdot.org/GISMapping/Pages/GIS.aspx	Last Updated 2022-05-02	Statewide Highways; Statewide Other Roads
Road data for Texas	https://gis-txdot.opendata.arcgis.com/datasets/d4f7206d27af4358acb70cb1cc819d10_0/explore?location=31.008846%2C-100.055172%2C6.28	File Created 2022-06-07	
Road data for Oklahoma	https://okmaps.org/OGI/search.aspx	Accessed 2022-06-19	ODOT Roadways; ODOT Highways; ODOT Local Roadways
Road data for Kentucky	https://transportation.ky.gov/Planning/Pages/Centerlines.aspx	Last Modified 2022-05-29	Centerline Network > All Roads
Road data for Arkansas	https://gis.arkansas.gov/product/arkansas-road-inventory/	Updated 2020-10-30	
Road data for Tennessee	https://tn-tnmap.opendata.arcgis.com/datasets/37229399437446b9acd653f353f7decc_0/explore?location=35.785027%2C-85.962491%2C7.72	Created 2022-06-03	
Road data for Alabama	https://data-algeohub.opendata.arcgis.com/search?groupIds=b54e33ef0a114bacb2fa059fc0bf1340	Accessed 2022-06-19	Need to download each county separately
Road data for Mississippi	https://www.maris.state.ms.us/HTML/DATA/data_Transportation/MDOTRoadCenterlines.html#gsc.tab=0	Last Updated 2022-02-23	
Road data for Georgia	https://www.sciencebase.gov/catalog/item/5a5f36bee4b06e28e9bfc1ba	Last Modified 2022-06-15	TRAN_Georgia_State_Shape > Shape/Trans_RoadSegment_0.shp; and TRAN_Georgia_State_Shape > Shape/Trans_RoadSegment_1.shp
Road data for Florida	https://www.sciencebase.gov/catalog/item/5a86ea14e4b00f54eb3a1b55	Last Modified 2022-06-15	TRAN_Florida_State_Shape > Shape/Trans_RoadSegment_0.shp and TRAN_Florida_State_Shape > Shape/Trans_RoadSegment_1.shp; and TRAN_Florida_State_Shape > Shape/Trans_RoadSegment_2.shp
Road data for Louisiana	https://www.sciencebase.gov/catalog/item/5a5f36c4e4b06e28e9bfc1ca	Last Modified 2022-06-15	Trans_RoadSegment

APPENDIX G RANDOM THOUGHTS, IMPLEMENTATION NOTES, AND OTHER THINGS THAT I WISH I KNEW OR BETTER UNDERSTOOD BEFORE UNDERTAKING THIS PROJECT

The term "Unmanned Aerial Vehicle" and "UAV" were used and preferred over the term "drone" to evoke a vision of a larger fixed-wing aircraft (which is the tool being used) while "drone" often can be in reference in both colloquial and professional speaking/writing to those battery-powered quad-copter's you can get at Best Buy and the larger fixed-wing aircraft (like the US's Predator Drone). There is no official, legal, nor technical differences between the terms UAV and Drone, this is more of a consistent term choice I made and the way that reference documents, academic literature, and media often uses those terms.

A lot of spatial data is provided in WGS84 (EPSG:4326), which is the typical "latitude-longitude" coordinates – or more specifically, (`longitude`, `latitude`). If you are conducting research like this in the future, I highly recommend using the data in some kind of equal area conic projected coordinate, in particular one with meters as a base unit. I used Universal Transverse Mercator (UTM) coordinate system for Chapter 4, specifically in reference to the UTM zone 14 that encompasses most of the state of Oklahoma. Later chapters/projects used the "NAD 1983 USGS Contiguous USA Albers" (ESRI:102039) as this was encompassing the entirety of the continental United States. Using these coordinate systems posed three advantages: First, EPSG:4326 coordinates must use decimal points (4 to 5) to represent a location on the earth with any form of reasonable precision; this makes calculations susceptible to floating point errors; ESRI:102039 are (by default) in meters so we can store a coordinate as an integer without loss of spatial precision at the scales we're working at. Second, calculations of using ESRI:102039 are (by default) in meters and given the (relatively) short distances calculated between any two points in ESRI:102039 we can use the calculation to calculate the distance between any two points; e.g. if $p_1 = (1000, 1000)$ and $p_2 = (4000, 5000)$, the distance can be simplified to $d = \sqrt{(4000 - 1000)^2 + (5000 - 1000)^2} = 5000, 5000$ meters¹. Third, distance calculations using the euclidean norm are easily vectorizable over data; attempting to compute great circle calculations would take longer to compute.

Point: This matches largely what the colloquial definition of "point", a point in a spatial file represents an x and y location (sometimes a z, elevation/altitude is included). When using WGS84/EPSG:4326/Latitude and Longitude coordinates, the Point is in (Lon, Lat), (x, y), (east/west, north/south). This is to what might be expected because most people get

¹This would not be accurate over vast distances, such as New York City to Los Angeles

points read off to them in "latitude and longitude". Speaking of which: Latitude, flat-itude. Longitude lines go up and down.

PolyLine: A PolyLine is an ordered set of vertices that consists of one or more parts. A part is a connected sequence of two or more points.

Polygon: A polygon consists of one or more rings. A ring is a connected sequence of four or more points that form a closed, non-self-intersecting loop. A polygon may contain multiple outer rings. The order of vertices or orientation for a ring indicates which side of the ring is the interior of the polygon. The neighborhood to the right of an observer walking along the ring in vertex order is the neighborhood inside the polygon. Vertices of rings defining holes in polygons are in a counterclockwise direction. Vertices for a single, ringed polygon are, therefore, always in clockwise order. The rings of a polygon are referred to as its parts.

Road Data for all cases studied were found by conducting a web search for the state in question along with various keywords such as "Road shapefile", "Department of transportation", "DOT", "Road data". I prioritized website from state level sources and used the federal level sources if no state level source was identified. All the road shapefiles used in this dissertation were formatted as PolyLine's of the centerlines of the roads.