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A Patient Risk Minimization Model for Post-Disaster Medical Delivery Using Unmanned Aircraft Systems

Mark J. Simpson
Embry-Riddle Aeronautical University, SIMPSM11@my.erau.edu

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By

Mark Joseph Simpson

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This dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Dothang Truong, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Aviation.

Dothang Truong Digitally signed by Dothang Truong Date: 2022.09.09 12:45:55 -04'00'

Dr. Dothang Truong
Committee Chair

John M. Robbins, Ph.D. Digitally signed by John M. Robbins, Ph.D. Date: 2022.09.14 14:26:12 -04'00'

John M. Robbins, Ph.D.
Committee Member

Dahai Liu Digitally signed by Dahai Liu Date: 2022.09.14 01:02:29 -04'00'

Dahai Liu, Ph.D.
Committee Member

Committee Member

Gregory S. Woo, Ph.D. Digitally signed by Gregory S. Woo, Ph.D. Date: 2022.09.14 21:11:40 -04'00'

Gregory S. Woo, Ph.D.
Committee Member (External)

Steven Hampton Digitally signed by Steven Hampton Date: 2022.09.17 11:51:27 -04'00'

Steven Hampton, Ed.D.
Associate Dean, School of Graduate Studies, College of Aviation

Alan J. Stolzer Digitally signed by Alan J. Stolzer Date: 2022.09.19 08:56:53 -04'00'

Alan J. Stolzer, Ph.D.
Dean, College of Aviation

Lon Moeller Digitally signed by Lon Moeller Date: 2022.09.19 10:18:10 -04'00'

Lon Moeller, J.D.
Senior Vice President for Academic Affairs and Provost

May 11, 2022

Signature Page Date

Abstract

Researcher: Mark Joseph Simpson

Title: A Patient Risk Minimization Model for Post-Disaster Medical Delivery Using Unmanned Aircraft Systems

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The purpose of this research was to develop a novel routing model for delivery of medical supplies using unmanned aircraft systems, improving existing vehicle routing models by using patient risk as the primary minimization variable.

The vehicle routing problem is a subset of operational research that utilizes mathematical models to identify the most efficient route between sets of points. Routing studies using unmanned aircraft systems frequently minimize time, distance, or cost as the primary objective and are powerful decision-making tools for routine delivery operations. However, the fields of emergency triage and disaster response are focused on identifying patient injury severity and providing the necessary care. This study addresses the misalignment of priorities between existing routing models and the emergency response industry by developing an optimization model with injury severity to measure patient risk.

Model inputs for this study include vehicle performance variables, environmental variables, and patient injury variables. These inputs are used to construct a multi-objective mixed-integer nonlinear programming (MOMINLP) optimization model with the primary objective of minimizing total risk for a set of patients. The model includes a

secondary aim of route time minimization to ensure optimal fleet deployment but is constrained by the risk minimization value identified in the first objective. This multi-objective design ensures risk minimization will not be sacrificed for route efficiency while still ensuring routes are completed as expeditiously as possible.

The theoretical foundation for quantifying patient risk is based on mass casualty triage decision-making systems, specifically the emergency severity index, which focuses on sorting patients into categories based on the type of injury and risk of deterioration if additional assistance is not provided. Each level of the Emergency Severity Index is assigned a numerical value, allowing the model to search for a route that prioritizes injury criticality, subject to the appropriate vehicle and environmental constraints.

An initial solution was obtained using stochastic patient data and historical environmental data validated by a Monte Carlo simulation, followed by a sensitivity analysis to evaluate the generalizability and reliability of the model. Multiple what-if scenarios were built to conduct the sensitivity analysis. Each scenario contained a different set of variables to demonstrate model generalizability for various vehicle limitations, environmental conditions, and different scales of disaster response.

The primary contribution of this study is a flexible and generalizable optimization model that disaster planning organizations can use to simulate potential response capabilities with unmanned aircraft. The model also improves upon existing optimization tools by including environmental variables and patient risk inputs, ensuring the optimal solution is useful as a real-time disaster response tool.

Keywords: aviation, decision science, emergency response, linear programming, Monte Carlo simulation, operations research, optimization model, risk minimization, sUAS, vehicle routing problem

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Chapter I

Introduction

Natural disasters affect approximately 210 million people each year, resulting in a global average of over 78,000 lives lost annually, according to the International Disaster Database (n.d.). Countries are responsible for developing tailored disaster response plans based on available resources, with the U.S. allocating almost $8 billion to the disaster relief fund in 2018 (Painter, 2019). Unmanned aircraft can be a valuable and inexpensive alternative to manned surveillance and delivery methods (Christie et al., 2016; Langford & Emanuel, 1993), and research on integrating small unmanned aircraft systems (sUAS) into disaster response plans have shown promising results. sUAS, commonly referred to as drones, are remotely piloted aircraft weighing less than 55 lb (24.95 kg) (sUAS Operations, 2016). In 2019, the University of Maryland used an sUAS to deliver a kidney to a critically ill patient needing a transplant (Freeman, 2019), demonstrating the reliability and feasibility of using the technology for medical delivery. UPS Flight Forward, a participant in the Federal Aviation Administration's (FAA) Integration Pilot Program, conducted the first package delivery under Title 14 C.F.R. Part 135 when medical supplies were flown to WakeMed hospital in Raleigh, North Carolina, in 2019 (FAA, 2019a). These achievements were both significant milestones in the U.S., although regulatory restrictions continue to slow industry growth in controlled airspace. A U.S.-based company, Zipline International Inc., is routinely using sUAS to deliver blood to patients in rural Rwanda, reducing the waste of blood products by more than 95% (Campanaro, 2018).

For the purpose of this research, the terminology for unmanned aircraft is unmanned aircraft systems (UAS), or sUAS for small unmanned aircraft weighing under 55 lb (24.95 kg). UAS refers to not only unmanned aircraft (UA), but the ground control station, antennas, and other support equipment needed to conduct flight operations. Historically, the term unmanned aerial vehicle (UAV) has been used as well, primarily by military operators and foreign entities. The term drone is seldom used within the industry, as it refers to platforms designed to be used in military anti-aircraft training where UA are routinely used as targets. However, the term has become synonymous with UAS in the media and general lexicon. While this study uses UAS to identify all portions of the unmanned system, previous studies use different terminology, and it should be understood that UAS, UAV, UA, and drone can be used interchangeably and are referring to the same type of technology.

The U.S. non-model fleet of sUAS is projected to reach 1,550,000 units in 2025, with a majority (65%) expected to be consumer-grade sUAS. As regulations allow for increased commercial operations, the market share for professional-grade sUAS is projected to increase as well (FAA, 2021a). Other countries are already utilizing sUAS in novel ways, partly due to the lack of regulatory restrictions in countries like Brazil, Mexico, Japan, and developing African nations (Ison et al., 2014). A 2016 study from the University of San Diego on worldwide unmanned aircraft usage found the U.S. is home to more than one-third of all commercial drone operations, and while government regulation remains scattered and inconsistent, industry trends indicate growth in UAS use for scientific research, conservation, public safety, and emergency response (Choi-Fitzpatrick et al., 2016). It has been established that UAS are beneficial in assisting with disaster recovery efforts, although researchers have determined that UAS are not being appropriately utilized due to unclear risks and the inability to receive rapid approval for operations (Clothier et al., 2015).

In the U.S., emergency response is managed by the Federal Emergency Management Agency (FEMA). According to FEMA, a successful disaster response plan requires coordination between local, state, and federal agencies. The plan should cover the four phases of emergency management: mitigation, preparedness, response, and recovery (FEMA, 2017). In the immediate aftermath of a natural disaster, emergency managers focus on providing critical care to the affected population, usually by establishing echelons of triage facilities from an identified “ground zero” location (Dara et al., 2005). This approach could leave rural areas without adequate medical attention from first responders, especially if environmental hazards do not allow for ground transportation of lifesaving medicine. According to the Rural Sociological Society, 55% of the population affected by Hurricane Katrina were categorized as non-metro residents even though a majority of the relief effort focused on the New Orleans metro area (Saenz & Peacock, 2006). Future disasters could follow similar trends, making optimization models valuable for rural emergency planning and response. Previous literature explores the imbalance between rural and urban communities regarding their ability to effectively manage the necessary emergency planning and response (Kapucu et al., 2013). This imbalance can be attributed to socioeconomic variables such as civic engagement and leadership experience, as well as environmental variables like geographic distance and natural boundaries.

Unmanned aircraft are already being used to deliver medical supplies to rural areas, with previous simulation models establishing the economic advantage of using inexpensive unmanned platforms to reduce the logistics cost per dose administered by 20% (Haidari et al., 2016). Using sUAS to deliver medical supplies to areas that would not normally be accessible due to logistical limitations is critically important. However, coordinating multiple sUASs is a complex endeavor requiring an understanding of both emergency management and sUAS operations. A useful model must include stochastic environmental variables and vehicle performance variables to ensure each sUAS is loaded with the correct medicine for multiple patients while ensuring the vehicle can return safely prior to fuel exhaustion. Previous research attempting to model airborne delivery in an emergency response system (Boutilier et al., 2017; Chowdhury et al., 2017) has been largely theoretical and does not model the necessary variables to obtain a practically useful solution. This study addresses this gap in the research literature by introducing a practical and theoretically significant optimization model with the primary objective of minimizing risk to injured patients awaiting medical treatment and a secondary objective of minimizing travel time. Minimizing the route travel time ensures optimal utilization of available assets, leading to reduced operating costs and additional flexibility for other sUAS missions.

Statement of the Problem

Previous studies on UAS routing have focused on optimizing spatial coverage for surveillance purposes (Liu et al., 2013; Liu et al., 2014) or minimizing operational costs for parcel delivery through vehicle routing problems (Karak & Abdelghany, 2019) and do not address the unique conditions present during disaster relief efforts. While some researchers have attempted to model UAS routing for medical delivery (Rabta et al., 2018), these studies have not considered important factors such as injury severity, vehicle limitations, uncontrollable environmental variables, and coordination between multiple vehicles to minimize total travel time. Optimization models need to include these variables to be useful for practical operation and allow emergency management personnel to determine the optimal routing for medicine delivery.

Determining optimal sUAS routing to minimize risk will help first responders care for the greatest number of patients with respect to the severity of their injuries. Without an optimization model that considers injury severity, a simple routing model could result in suboptimal sUAS utilization for disaster response, increasing the risk of further patient deterioration. Traditional routing problems will usually find the shortest path between injured patients within the constraints of the vehicle endurance and payload capacity, but if the last stop on a route is an epinephrine delivery to a patient having an allergic reaction, the risk of that patient deteriorating is much higher than if the epinephrine was delivered first. An operationally useful model should consider injury severity and find an optimal solution based on patient risk.

Purpose Statement

This research study focuses on developing and validating a novel, quantitative optimization model to inform decision-makers on optimal sUAS vehicle routing that minimizes the total risk to patients in the affected area within the constraints of sUAS system limitations. The model also includes the secondary objective of minimizing the total route time utilizing a multi-objective mixed integer nonlinear programming model (MOMINLP) method. The model's effectiveness, usability, and scalability are evaluated through an iterative sensitivity analysis of multiple what-if scenarios to confirm model reliability and generalizability.

Significance of the Study

This study extends previous research on unmanned routing studies by improving on existing routing models designed for parcel delivery and other non-emergency operations. Current literature indicates misalignment between current routing studies designed to optimize cost or distance and emergency response plans designed to optimize the efficiency of response in relation to injury severity. This novel decision-making model includes environmental variables and sUAS vehicle limitations to capture the conditions present during disaster response in rural areas, with the objective functions of minimizing patient risk and route time. The validated model provides researchers with a tool to answer future research questions related to the study of sUAS routing and disaster response. The theoretical significance of this study is the provision of a framework for unifying the disaster-response- and vehicle-routing disciplines within decision theory by developing an optimization model for sUAS for emergency management.

The practical significance of this study lies in the development of an optimization model that provides emergency planners with a tool to understand the capabilities of sUAS for medical delivery. The model is significant as a new capability to evaluate the benefit of purchasing additional aircraft, upgrading to more capable sUAS platforms, and studying the impact of varying environmental conditions. In addition to emergency planning, the model can assist in real-time decision-making during a natural disaster. The optimal route objectively determines how to minimize risk to the greatest number of patients and minimize travel time to those patients, increasing the effectiveness of the overall disaster response to the affected rural community and ensuring proper utilization of sUAS technology in a disaster response plan.

The National Preparedness System in the U.S., as defined by FEMA (2017), is designed to be used by the entire community, including local, state, and federal governments. This tiered approach to disaster planning means the practical applications of the model can be useful to agencies of varying scope and size. Local police agencies are already attempting to utilize unmanned technology in rural areas (Baumgarten, 2018), but coordinated sUAS response optimizing multiple aircraft for delivery or surveillance is not being utilized. During disaster response, local agencies are often the first to reach affected individuals, and this model can inform local emergency management plans. State agencies are also employing unmanned technology; the Arkansas Game and Fish Commission recently implemented a training program for utilizing sUAS for fisheries and wildlife management (Fernando et al., 2019). State responsibilities during emergency response include financial assistance and response efforts (FEMA, n.d.). On the federal level, FEMA utilizes the Unmanned Aircraft System Team to improve situational awareness through remote sensing (FEMA, 2017), indicating a commitment to employ sUAS for emergency response. Regardless of size and scope, these agencies utilize the same technology for public health and safety. This optimization model is practically significant to organizations responsible for the health and safety of rural populations in the U.S.

Research Questions

This study is designed to identify the optimal sUAS routing for medical supply delivery to minimize the health risk, with a secondary goal of achieving the minimum total travel time. The research questions (RQ) are:

RQ$_1$

What are the key variables related to sUAS medical delivery in rural areas during disaster relief efforts?

RQ$_2$

What is the mathematical relationship between the decision variables and objective variables?

RQ$_3$

What is the optimal routing solution for medical supply delivery using sUAS to minimize patient risk and travel time?

RQ$_4$

To what extent are the optimal solutions affected by various scenarios?

Delimitations

This research study focuses on the variables involved in sUAS medical delivery during disaster response in rural areas. Urban environments are generally a focal point of state and federal response to natural disasters due to population density and the availability of hospitals and shelters, which can leave rural communities to rely on the resources of local agencies, private institutions, or volunteer organizations. In addition to limited funding, these areas can also face geographical challenges resulting in longer response times, especially if a natural disaster makes traditional transportation methods difficult or impossible. Because of the challenges facing disaster response in sparsely populated and underserved communities, the model is delimited to rural environments where sUAS can be used as the optimal delivery method for time-critical medical supplies.

Because sUAS regulations can vary significantly between countries (Ison et al., 2014), the study is delimited to emergency response operations inside the U.S. National Airspace System (NAS). While the relationship between stochastic patient variables and deterministic vehicle variables remains valid for international locations, the model would require additional modification to account for regulatory changes in any environment outside the U.S. In the U.S., small UAS (sUAS) weighing less than 55 lb (24.95 kg) can legally operate at altitudes of 400 ft (121.92 m) above ground level (AGL) and below with waivers available for beyond line of sight operations (Operation and Certification of Small Unmanned Aircraft, 2016).

The scope is also limited to sUAS and does not consider variables for larger platforms due to Title 14 C.F.R. §107 regulations restricting the operation of larger vehicles without a waiver. Part 107 restrictions for altitude, airspeed, and weight limitations are also considered study delimitations. Additionally, because of the 400 ft (121.92 m) altitude restriction for sUAS operating under Part 107, this study does not consider interaction with manned aircraft assisting in other disaster response missions. Manned-unmanned separation is considered procedural, meaning the controlling agency in charge of air traffic specifies separation minimums, therefore, sense-and-avoid technology is not necessary for this type of operation. Part 107 regulations restrict flight operations in instrument meteorological conditions (IMC) or under instrument flight rules

(IFR), which require additional onboard equipment, higher altitudes for radar coverage, and indirect ATC routing. While there could be value in using sUAS to deliver medical equipment in suboptimal weather conditions when manned aviation could not operate, this study is delimited to visual operations to comply with current FAA regulations. Line of sight requirements, access to controlled airspace, and flights over populated areas are not delimitations because FAA waivers exist for these types of operations.

In the U.S., emergency responders use the Emergency Severity Index (ESI) to categorize patients according to risk. The ESI includes time-based checkpoints to help responders appropriately assess risk and assign an injury severity. For example, an injury requiring assistance within 60 min is categorized as an immediate injury. The study is delimited to patients whose injury can be categorized by the ESI, with a numerical value assigned to each injury level. Assigning a time-sensitive value to an injury severity allows for an objective assessment of overall risk in a given environment. Details on the theoretical foundation of injury severity and risk minimization are discussed in Chapter II. Numerical values for ESI categories are explained in Chapter III.

Limitations and Assumptions

Because sUAS reliability varies between platforms and accurate accident data is challenging to obtain, it is assumed that all sUAS are properly maintained and can complete each round-trip delivery without mechanical failure. Additionally, it is assumed that each mission is initiated with full fuel or battery capacity, and the endurance, speed, and payload capacity are equal and constant among all sUAS used.

During emergency response operations, multiple aircraft frequently share limited airspace. It is assumed that the FAA coordinates procedural control of the airspace over an affected area, allowing for appropriate separation between other sUAS traffic conducting similar deliveries and surveillance flights or manned medivac flights in the vicinity of the delivery area. While it is possible a patient may require multiple types of medicine or multiple patients with varying injury severities exist at a given location, for this study it is assumed that the first responders conducting the severity categorization report the most severe injury and the total required medicine.

This study does not include variables to account for the possibility of air traffic congestion delays or conflict. The scope is limited by the types of medicine that can be delivered due to the size and payload capacity of the sUAS; most antibiotics, analgesics, antiseptics, and tranquilizers are compact and lightweight, making them optimal for sUAS transport. Larger equipment such as defibrillators and ventilators might not allow for multiple stops, depending on the weight of the equipment and payload capacity of the sUAS. Previous research indicates that defibrillator delivery via sUAS can reduce response time over traditional methods (Boutilier et al., 2017; Claesson et al., 2016), but the distance to the patient is a critical variable. Heavier medical equipment is included in the study to measure how the model evaluates the delivery of a single piece of medical equipment against multiple smaller deliveries to minimize overall risk. However, the maximum gross weight (combined airframe, fuel, and payload weight) is limited to 55 lb (24.95 kg) per Part 107 regulations.

Part 107 regulations also limit spatial and environmental conditions. The FAA specifies that all sUAS must maintain separation minimums of 500 ft (152.4 m) below clouds and 2000 ft (609.6 m) horizontal separation, a maximum altitude of 400 ft (121.92 m) AGL, and a visibility of 3 statute mi (4.83 km). The model does not consider operations in adverse weather under instrument flight rules. Regulations also specify that each operator must maintain line of sight and only control one sUAS at a time. However, the model assumes the agency in charge of the disaster response has prior approval to conduct flights beyond visual line of sight, and the chosen sUAS platforms can safely and legally execute autonomous or semi-autonomous flight plans with minimal human intervention.

This study does not include time windows for each patient, as the theoretical foundation of emergency triage risk categorization only includes general guidelines for required response time. These guidelines are sufficient to correlate an injury assessment to the risk of patient deterioration but are not sufficient to determine a precise individualized delivery window. Additionally, current vertical take-off and landing (VTOL) sUAS technology is generally not capable of achieving flight times greater than 120 min while maintaining a realistic payload capacity for medical delivery. Vehicle endurance and standard triage practices require this study to be limited to fixed risk values for each route.

Because disaster response efforts are usually coordinated at an Emergency Operations Center to ensure interagency coordination (Ryan, 2013), this study includes a single depot responsible for the initiation of all sUAS flight operations. While this limits emergency responses to patients within range of the aircraft, the model can be used iteratively to achieve independent solutions at additional depots if required.

Lastly, it is assumed that sUAS transition time (climbs, descents, and time taken for the medicine to be unloaded) is uniform throughout the route due to the relatively low operating altitudes defined by FAR Part 107, and a standard time limit can be used for each transition to accurately model the battery consumption and time delay during each delivery. While larger transport vehicles like delivery trucks or helicopters can have different unload times based on payload capacity and available personnel, sUAS have relatively small payload capacity and fly at lower altitudes, per FAA requirements. Fixed values for transition times have been used in other unmanned routing problems to accurately model these variables (Chowdhury et al., 2017; Fikar et al., 2016).

Summary

The purpose of Chapter I is to provide a brief but structured introduction to this dissertation topic. This optimization model addresses the research gap of inadequate routing tools for minimizing risk to a set of patients during natural disasters. The model is theoretically and practically significant and appropriately scoped to rural areas where medical delivery and disaster response efforts are uniquely challenging. The next chapter presents a review of the relevant extant literature.

Definitions of Terms

lUAS	A large unmanned aircraft system weighing 55 lb (24.95 kg) or more including payloads, cargo, and fuel.
sUAS	A small unmanned aircraft system weighing less than 55 lb (24.95 kg) including its payload, cargo, etc. (Operation and Certification of Small Unmanned Aircraft, 2016).
Risk Minimization	The optimal UAS utilization to reach the greatest number of injured patients, using the minimal number of UAS, before the time horizon expires.

Urban	The Census Bureau considers areas populated by at least 2,500 but less than 50,000 people to be urban clusters and areas of 50,000 or more people to be urban areas.
Rural Area	All populations, housing, and territory not included within an urbanized area or urban cluster (Ratcliffe et al., 2016, p. 3).

List of Acronyms

ATC	Air Traffic Control
C.F.R.	Code of Federal Regulations
FAA	Federal Aviation Administration
FEMA	Federal Emergency Management Agency
ERAU	Embry-Riddle Aeronautical University
ESI	Emergency Severity Index
IRB	Institutional Review Board
lUAS	large unmanned aircraft system
MOMINLP	Multi-Objective Mixed-Integer Nonlinear Programming
sUAS	small unmanned aircraft system
UA	unmanned aircraft
UAS	unmanned aircraft system
UAV	unmanned aerial vehicle
VRP	vehicle routing problems

Chapter II

Review of the Relevant Literature

The current body of literature on sUAS, medical delivery, and vehicle routing studies is extensive. The following chapter begins with an overview of UAS history and significance, as well as a summary of current FAA regulations. Current research on mixed integer linear programming and solution algorithms is discussed, focusing specifically on applications in aviation. The gap in literature is identified, following a thorough review of UAS routing studies, concluding with a summary of common model variables. Lastly, emergency triage models are used to outline the theoretical foundation for risk minimization.

Significance of Small UAS

Background of Technology

The unmanned aircraft industry began with the first pilotless flight in 1918 by Lawrence and Sperry, just 15 years after the Wright brothers achieved powered heavier-than-air flight (Dalamagkidis et al., 2012). For the first half of the 20th century, unmanned aircraft were predominately used as target drones for both World War I and II, until the Cold War in the 1950s necessitated the evolution of unmanned surveillance aircraft. Industry development accelerated in the 1990s during the Gulf War (Gusterson, 2016) and became a critical tool for the U.S. military in the Global War on Terrorism with the development of weaponized UAS (Enemark, 2014).

The last decade has seen a rapid increase in UAS utilization, legislation, and research in the private and commercial sectors. In 2013, the Chinese company DJI released and marketed the Phantom sUAS to worldwide audiences, recording $130 million in sales in the first year alone (Xu & Muneyoshi, 2017). At a 2013 price point of $1,000 when comparable vehicles cost over $5,000 (McDonald, 2015), it is not an exaggeration to say DJI revolutionized the consumer-grade sUAS industry. The company currently holds a 77% share of consumer drone sales in the United States and has expanded the DJI Phantom product line to include the DJI Inspire for professional grade cinematography (Poland, 2020) and the DJI Matrice for professional industrial applications. The FAA estimates 6.4% annual growth in the recreational sUAS sector, although growth is slowing and will likely slow further as prices stabilize and the eagerness of early adopters plateaus (FAA, 2021a). The rapid rise of DJI products, and the hobbyist industry in general, necessitated additional FAA legislation to safely integrate new remote pilots into the national airspace.

FAA Legalization*.* To address industry growth and lack of federal guidance, the FAA released sUAS regulatory guidance for commercial sUAS operations under Title 14 Part 107 in 2016, resulting in over 385,000 registered sUAS by December 2019 (FAA, 2021a). The rules governing Part 107 operations, as provided in the FAA regulations, are:

- The operation must be within the U.S.;
- The unmanned aircraft must weigh less than 55 pounds;
- The aircraft must be registered, if over 0.55 lbs.;
- Must fly only in uncontrolled airspace;
- Must keep the aircraft in sight (visual line of sight);
- Must fly under 400 feet;
- Must fly at or below 100 mph;
- Must yield right of way to manned aircraft;

Additionally, all operators are required to obtain a Part 107 Remote Pilot Certificate to ensure an appropriate understanding of the national airspace environment. These regulations are designed to separate commercial operations from recreational pilots, so professional unmanned pilots are prepared to operate safely in the NAS.

The FAA also provides safety guidance in Advisory Circular 91-57B for recreational operations, with similar limitations for airspace, altitude, and vehicle registration (FAA, 2019b). The FAA stipulates the advisory circular is not legally binding and should be considered interim guidance for recreational sUAS operation.

The FAA accepts online waiver applications for certain types of operations that are outside Part 107 regulations. Night operations and operations in controlled airspace are the most commonly requested waivers (FAA, 2020a). Operations over 400 ft (121.92 m), and operations beyond visual line of sight are also requested, although the rate of approval is much lower. The FAA reports a total of 50,582 out of 78,596 waiver requests have been approved, an approval rate of approximately 64%. Requests for airspace waivers into controlled airspace below 400 ft (121.92 m) can be requested through a program called Low Altitude Authorization and Notification Capability (LAANC). Active since May 2019, LAANC is designed to automate the approval process based on prospective flight location, depending on real-time analysis of temporary flight restrictions, notice to air missions (NOTAMs), and other airspace considerations.

Part 107 waivers can be obtained for certain types of sUAS operations, but not for UAS over the 55 lb. (24.95 kg) weight limit. Approval for large UAS (lUAS) is covered under Title 49 U.S.C. §44807, which allow lUAS to be registered under Title 14 C.F.R. Part 47 and operate under Part 91 (FAA, 2021b) under risk-based safety programs. The

FAA reported 19 §44807 exemptions in 2019, mostly for agricultural purposes. The FAA 2020 fiscal forecast estimates these exemptions to increase over the next half-decade as military use stabilizes and commercial operations accelerate (FAA, 2021a).

Certification for commercial air carriers is outlined under Title 14 C.F.R. Part 135. With the recent industry push for sUAS delivery operations by companies like Amazon and the United Postal Service (UPS), the FAA began issuing Part 135 certifications for sUAS operations in 2019. Companies pursuing Part 135 sUAS certification must follow the same approval process as manned aircraft, although the FAA provides clarification for regulations that do not apply to UAS, such as carrying manuals onboard. The rigorous approval process includes a 5-phase approach that includes a design assessment of all safety processes and documentation, as well as a performance assessment for training and flight procedures (FAA, 2020b). Four types of Part 135 certificates are available: Single Pilot, Single Pilot In Command, Basic Operator, and Standard Operator. The first Part 135 single pilot certificate was issued to Wing Aviation, LLC in April 2019, followed by a standard 135 certificate for routine operations in Christiansburg, Virginia. Wing is currently partnering with FedEx, Walgreens, and local businesses to deliver goods to consumers within the service area (Hawkins, 2019). UPS Flight Forward Inc. received the first standard Part 135 certificate a few months prior to Wing in September 2019 and demonstrated its operational capability by flying medical supplies in Raleigh, North Carolina.

San Francisco-based Zipline International, which currently conducts routine UAS medical deliveries in Ghana, achieved another milestone in sUAS integration into the NAS in early 2020. During the Covid-19 pandemic in the U.S., Zipline and Novant

Health were granted an emergency Part 107 waiver from the FAA to deliver medical supplies in North Carolina (CNBC, 2020). While only two routes were initially approved, the company has plans to expand to other locations. Obtaining this type of FAA waiver for sUAS delivery during a nationwide crisis is an important validation for the routine use of sUAS during the emergency response in the U.S.

Regulatory guidance is still being refined for commercial sUAS operations as the FAA obtains additional data on common waiver requests. The FAA recently approved changes to Part 107 regulations for flights over people, night operations, and flights from moving vehicles (FAA, 2021c). Additionally, rule changes are under review to require operators to present their remote pilot certificates upon request of government officials, as well as verify the completion of additional training requirements every 24 calendar months. Another significant regulatory change currently being implemented is Remote Identification. Research has shown remote identification of sUAS improves situational awareness between manned and unmanned aircraft (Kubo et al., 2020), and is an important aspect of unmanned traffic management (UTM) (Ishihara et al., 2019). Critics have expressed concerns over the privacy of sUAS operator information (Plaza, 2019), and current research shows troubling trends in Part 107 compliance. A 2019 study from Embry-Riddle Aeronautical University (ERAU) monitored UAS activity over a 30-day period and found that 34% of the 271 flights exceeded the maximum allowable altitude under Part 107 regulations (Wallace et al., 2020).

In addition to growth in the sUAS sector, Urban Air Mobility (UAM) is another important industry segment requiring research and regulation. UAM is a system of on-demand air transportation within urban areas (Kim, 2019), with Airbus already offering

UAM solutions in Sao Paolo and Mexico City. Kim explains that while there is a vast amount of existing literature on vehicle routing problems (VRP), there are few studies on UAM optimization. However, with this present study limited to emergency responses in rural areas, UAM would not impact operations and ATC would publish Notice to Air Missions (NOTAMs) to ensure appropriate separation between sUAS deliveries and other airborne traffic in the area.

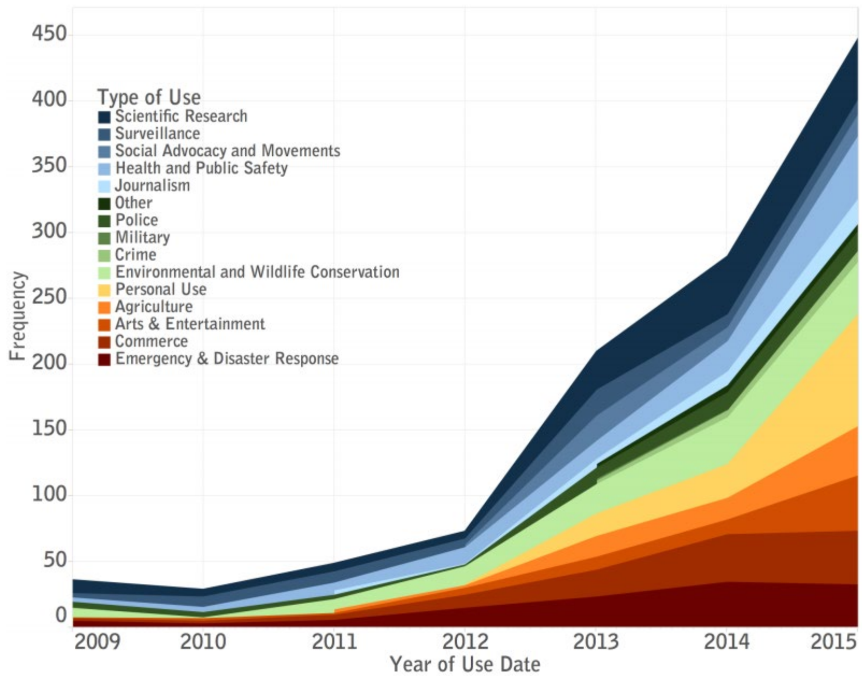
Small UAS for Disaster Response

UAS Industry Growth

A study of 1,145 reported UAS operations between 2009–2015 indicated that 12% of flights were in support of short-term emergency response and another 10% were for health and public safety (Choi-Fitzpatrick et al., 2016), and the rate of use increased significantly each year (see Figure 1). Choi-Fitzpatrick et al. hypothesize the increase is due to both an increase in large-scale natural disasters and innovative use of UAS technology. While the increase in UAS utilization is a worldwide trend, 36% of the operations were from the U.S. (see Figure 2) with approximately 40 reports of use for emergency and disaster response.

Figure 1

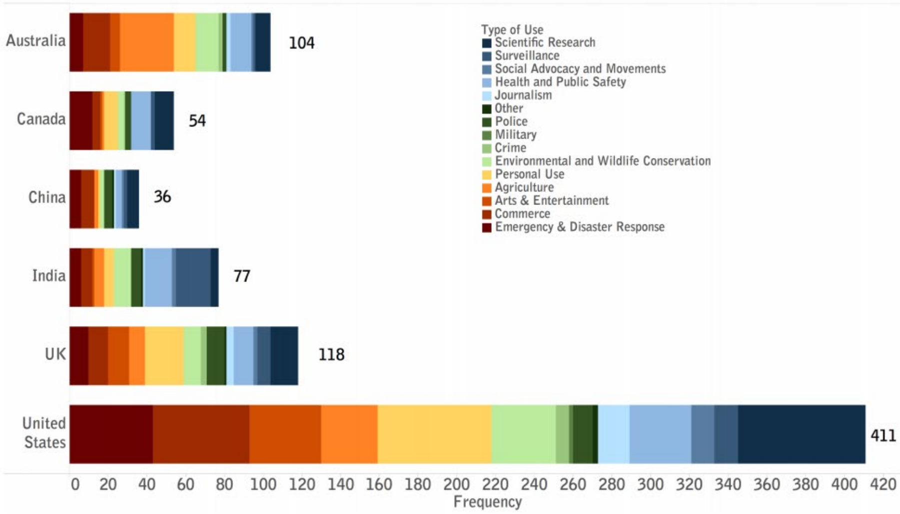
Drone Use by Type



Note. From “Up in the Air: A Global Estimate of Non-Violent Drone Use 2009-2015” by Choi-Fitzpatrick et al., 2016, p.14. Copyright 2016 by University of San Diego.

Figure 2

Drone Use by Country (Choi-Fitzpatrick et al., 2016)



Note. From “Up in the Air: A Global Estimate of Non-Violent Drone Use 2009-2015” by Choi-Fitzpatrick et al., 2016, p.18. Copyright 2016 by University of San Diego.

sUAS Medical Delivery

UAS medical delivery is particularly important for developing countries because inaccessible roads and poor infrastructure can not prevent airborne delivery of blood or medicine (Scott & Scott, 2017). However, poor road conditions can disrupt emergency operations in disaster-prone areas in the U.S. during emergency responses to natural disasters (Amin et al., 2019). Widespread sUAS medical delivery is not yet prevalent in the U.S., although Zipline is expanding on 2019 proof-of-concept flights to deliver Covid-19 medication and lab samples in North Carolina (Bright, 2020). Since 2016, Zipline has made over 14,000 shipments of blood and other critical medical supplies to low-income rural areas and is currently valued at $1.2 billion (McNabb, 2019).

Flirtey, the first UAS company to complete an FAA-certified delivery in the U.S. in 2016, announced plans to launch the first automated external defibrillator (AED) UAS delivery service in 2017 and received FAA approval for beyond line of sight AED delivery in Reno, Nevada, in 2018 (Dukowitz, 2019).

Matternet is another leader in UAS medical delivery as the first company in the world to conduct routine operations over densely populated areas in Switzerland (Matternet, 2019). Routine operations in the U.S. began in 2019 in partnership with UPS, carrying laboratory tests from WakeMed hospital in Raleigh, North Carolina, to a central laboratory for analysis. According to Matternet, the 3-min flight can take up to 30 min by traditional medical courier. In 2020, UPS, CVS, and Matternet partnered to deliver prescription drugs to retirement communities in Florida during the Covid-19 pandemic.

Wing, a subsidiary of Google, is also conducting routine sUAS delivery in Virginia. The company does not specifically focus on medical delivery, but customers in the service area have the option to purchase a limited selection of medical supplies, and Wing saw a significant increase in this area during the Covid-19 pandemic (Reichert, 2020). The current sUAS delivery efforts in the U.S. are summarized in Table 1.

Table 1

Characteristics of UAS Delivery in the U.S.

Company	Collaboration	Types of Delivered Supplies	Payload	Range
Zipline	Novant Healthcare	vaccines, blood	3.0 lb	45 mi
Flirtey	N/A	medicines, AEDs	4.4 lb	20 mi
Matternet	WakeMed Health, UPS	medicines, blood, lab samples	4.4 lb	6 mi
Wing	FedEx, Walgreens	food, medicines, household goods	3.3 lb	6 mi

Note. UAS = unmanned aerial system; N/A = not applicable.

Optimization Modeling

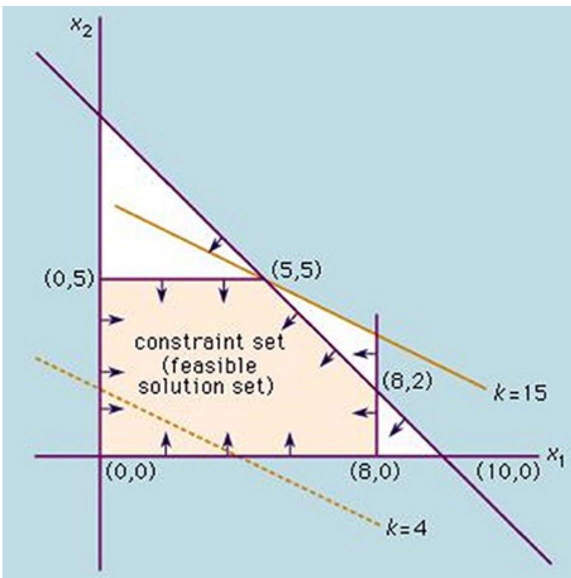
The core premise of linear programming is focused on optimization. Optimization occurs everywhere, from financial markets to engineering design, and the concept of finding an optimal solution is as old as human history itself (Yang, 2010). Yang explains Greek mathematicians solved problems that optimized time and distance, as did Kepler, Newton, Bernoulli, and Galileo. In 1917, Harris Hancock published one of the first contemporary books on optimization, called *Theory of Minima and Maxima*, building on existing concepts in the study of calculus. In the 50 years following Hancock, numerous researchers explored linear programming and optimization. Kantorovich (1939) developed a linear programming algorithm for use in the field of economics, and Koopman popularized the concept of shadow costs in linear programming during his 1941 study of merchant fleet movement during World War II (Dorfman, 1984). Dorfman explains the field of linear programming, as we know it today, was formulated by Dantzig (1951) while researching procurement and training optimization for the U.S. military. Dantzig defined the area of study as the maximization of a linear function subject to linear inequality constraints. The field of linear programming exploded in the 1970s with the advent of metaheuristic algorithms, as well as the widespread use of the modern computer to solve complex algorithms in business management, transport planning, scheduling, and communications networking (Yang, 2010).

Optimization Methods

The body of literature on linear optimization is quite large and reflects the broad operational applications of the methodology. Linear programming is one of the simplest methods to perform optimization, as solutions are obtained by combining and reducing linear relationships to an objective function. Through the use of an objective function and constraints expressed as inequalities, the Simplex method of solving linear optimization problems can be displayed graphically (see Figure 3).

Figure 3

Simplex Method Solution



Note. The constraints, visualized by the purple lines, bound the potential feasible solutions in the yellow area. The vertex of the yellow line (5,5) indicates the highest value in the constrained area, thus representing the optimal solution. From "A Review of the Use of Linear Programming to Optimize Diets, Nutritiously, Economically and Environmentally" by Van Dooren, 2018, p 48.

Linear programming methods are acceptable when every variable in the equation exhibits a linear relationship, as is sometimes the case in problems involving inventory management or manufacturing. However, modeling nonlinear relationships is often necessary for optimization problems in domains such as engineering and finance. The theory behind nonlinear programming is similar to linear programming in that the optimal solution is desired for a given function and constraints. However, nonlinear programming involves a branch of mathematics known as the calculus of variations and should be used if the objective function and/or any of the constraints are nonlinear (Massachusetts Institute of Technology [MIT], n.d.). Linear and nonlinear methods have dozens of sub-methods, including mixed integer programming and goal programming. Relevant aviation and VRP studies using these methods are discussed in additional detail in Chapter 3.

Optimization Algorithms

The discovery of linear programming was initially dominated by mathematicians and economists such as Koopmans in 1943 and Dantzig in 1951 (Dorfman, 1984). The solution space to a standard linear programming model can be defined as the point of intersection between a finite number of linear equations and/or inequalities (Gass, 2003). As operations research expanded in the 20th century and additional applications were explored, the need arose to model complex environments that exceed the limits of computational and human capability.

Research into exact algorithms can be beneficial for certain problems where the precise solution is desired. For example, Toth and Vigo (1997) developed an exact algorithm for solving a VRP with backhaul, combining an integer programming model with a Lagrangian lower bound. With a maximum computational cap of 100 min, an exact solution for 100 customers was obtained in 29 of the 34 instances. It should be noted that computing power has significantly improved since 1997, but researchers were using the model to identify a potential location for a supply depot, a decision that does not need to be made under time constraints. Baldacci et al. (2003) improved on previous research into exact solution methods, solving a capacitated vehicle routing problem (CVRP) with 135 customers using a new approach based on a two-commodity network flow formulation. The time limit for this study was 1 hr, an improvement in both processing time and model complexity over previous studies. However, the variables and constraints in exact studies are usually so complex that exact algorithms can only be used for relatively small studies. The authors explain that even the most effective exact algorithms are usually limited to about 50 customers for this type of study. These examples are only a small sample of the theoretical research being conducted on exact optimization algorithms. Kallehauge (2008) provides a more exhaustive literature review on the development of exact algorithms and their application for VRP time window (VRPTW) problems, including a summary of the seminal authors in traveling salesman problem (TSP) methods such as arc formulation, arc-node formulation, spanning tree formulation, and path formulation.

For more complex problems, heuristic methods are commonly seen as an appropriate solution for non-deterministic polynomial-time hardness (NP-hard) linear programming problems. VRPs are considered NP-hard, meaning the solution time increases significantly with problem complexity (Seshadri, 2019). When the exact solution cannot be found using the available computing power, or if the solution takes an unacceptable amount of time to be practically useful, heuristics are commonly used (Cordeau et al., 2002). The Clarke-Wright savings algorithm is one of the most popular heuristic methods (Altinel & Oncan, 2005), and was recently used to optimize vehicle capacity and fuel price for hauling sewage from wastewater treatment facilities (Passos et al., 2018). The sweep algorithm is another popular method in classical heuristics, originally developed by Gillett and Miller (1974). A modified sweep algorithm was used in a VRP with simultaneous pickup and delivery between two depots and multiple nodes (Kumar & Jayachitra, 2016), with results showing a solution can be found with over 200 nodes. Fisher and Jaikumar (1981) developed a popular two-phase cluster-based heuristic method that improved on previous methods due to its flexibility and ability to always find a solution if one exists. The method is still being utilized and improved, as researchers recently found a CVRP solution by creating node clusters of equal size, then found the optimal solution for each cluster (Sultana et al., 2017).

The use of metaheuristic methods has increased in the last 30 years and have found applications in engineering, medicine, and other sciences by utilizing a global search or local search in conjunction with a learning strategy to structure information and efficiently find near-optimal solutions (Kaveh, 2017). Local search methods include simulated annealing and tabu search, which search the solution space for an optimal solution, then proceed to search for improvements within the same neighborhood (Cordeau et al., 2002). Genetic algorithms, adaptive memory procedures, and particle swarm optimization are some of the most common global metaheuristic methods.

Optimization applications for Aviation Research

While optimization methods are determined by the types of variables and constraints in the model, solution algorithms are usually narrowly scoped for a specific environment being modeled. Current literature provides little guidance for selecting the appropriate algorithm, although Cordeau et al. (2002) explain the most important attributes for algorithm selection are accuracy, speed, simplicity, and flexibility. In aviation research, heuristic methods are usually preferred due to the stochastic nature of the environment (Scala et al., 2017). Some aviation-based problem sets require flexible models that can be quickly solved. Examples in the existing literature include studies on aircraft routing (Jamili, 2017), runway conflicts (Adacher & Flamini, 2014), and airplane deicing coordination (Norin et al., 2012). Other problems are not as time-sensitive, allowing for heuristic methods that prioritize accuracy. Examples include airport architectural designs (Braaksma & Shortreed, 1975) and ground crew scheduling (Rodič & Baggia, 2017).

Extant Routing Studies

Traveling Salesman Problem

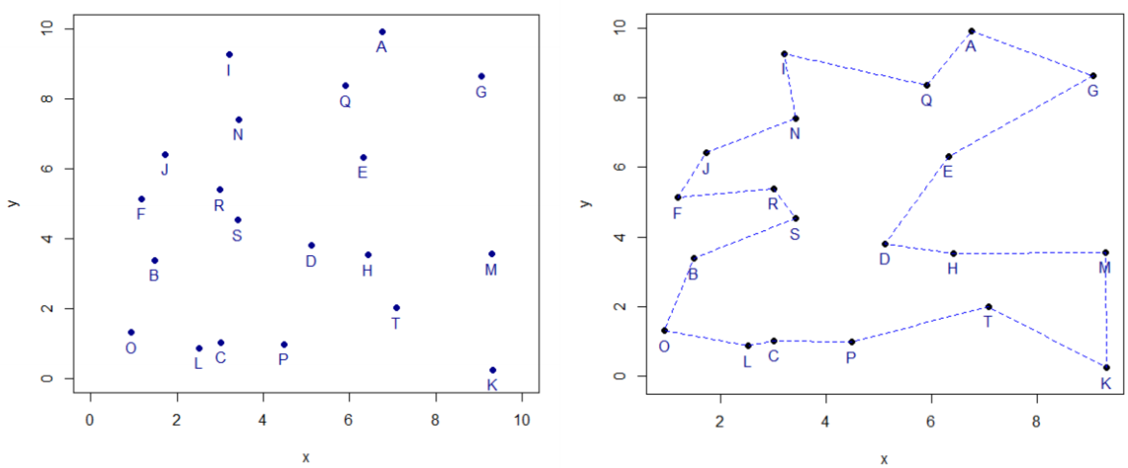
The traveling salesman problem (TSP) was originally explored by British mathematician Thomas Kirkman and Irish mathematician W.R. Hamilton in the 1800s. In a paper presented to the Royal Society in 1855, Kirkman posed the question of the shortest route between points in a polyhedron, where the circuit passes through each point only once (Biggs et al., 1986). While this is often referenced as the foundational theory for shortest-route problems (Saji et al., 2014; Vukmirović & Pupavac, 2013), Biggs et al. explain that the contributions by Kirkman were theoretical and impractical due to complicated restrictions.

Sir William R. Hamilton, a more famous mathematician during the period, expanded on Kirkman's general routing question and founded what he called the *icosian calculus*. This mathematical formula, published in *Philosophical Magazine* (Hamilton, 1856), is the basis for all future research on routing studies, and the concept of a route that passes through all vertices on a graph is now known as a Hamiltonian cycle.

Karl Menger, the famed Harvard mathematician and economist, continued the research of Kirkman and Hamilton when he posed “Das Botenproblem” (the messenger problem) at a mathematical colloquium in Vienna (Menger, 1930). He outlined a problem similar to the TSP, except the model involved delivering mail at each location, adding an additional variable for a different industry. The example TSP and solution in Figure 4 demonstrates how 20 random points on a grid can be optimized for delivery.

Figure 4

Random Nodes and Optimal Routing



Note. From “Business Analytics Applications for the Vehicle Routing Problem” by Blok, 2016.

Vehicle Routing Problem

The Vehicle Routing Problem (VRP) was first discussed by Dantzig and Ramser (1959) as a modern approach to the TSP using the example of gasoline delivery trucks.

The authors explain that both problems address a set of n nodes to be visited once, with the vehicle or salesman returning to the starting point using the most expeditious route possible. Using the gasoline truck example, they developed the first computational algorithm for vehicle routing with a vehicle capacity constraint, and proposed the following Truck Dispatching Problem (TDP):

[1] Given a, set of n "station points" P_i ($i = 1, 2 \ldots n$) to which deliveries are made from point P_o, called the "terminal point"

[2] A "Distance Matrix" $[D] = [d_{ij}]$ is given which specifies the distance $d_{ij} = d_{ji}$ between every pair of points ($i, j = 0, 1, \ldots n$)

[3] A "Delivery Vector" $(Q) = (q_i)$ is given which specifies the amount q_i to be delivered to every point P_i ($i = 1, 2 \ldots n$)

[4] The truck capacity is C, where $C >$ max. q_i

[5] Each station point P_i must be visited once by a connected route

[6] The problem is to find those values of x_{ij} which make the total distance a minimum under the conditions specific in [2] and [5]

Dantzig and Ramser (1959) outline the process of manually solving the route minimization problem while acknowledging that additional constraints or scenarios involving multiple trucks or varying capacities were not feasible with the available technology. Regardless of the relative simplicity of the algorithm, the formula is seen as the foundation of present-day linear programming methods, which still use the structure of minimizing or maximizing a variable, subject to a list of constraints.

Increasingly complicated routing problems were solved through the development of heuristic methods in the 1960s. Simple VRPs are relatively straightforward to solve with computer programs, but the solutions are usually heuristic because routing problems that accurately model a complex scenario are generally considered NP-hard. Hochba (1997) explains that if the optimal solution is unrealistic due to modeling or computational limitations, it is considered NP-hard and therefore reasonable for researchers to sacrifice optimality for efficiency through the use of an approximation algorithm. The stochastic nature of real-world delivery scheduling makes a single optimal solution extremely unlikely, as a traffic collision or other external factor will require recalculation. Heuristic methodologies acknowledge that a given solution might not be optimal but is acceptable when the alternative is no solution at all, or if the solution takes an impractical amount of time to calculate. A *greedy algorithm* is one common example, where a series of locally optimal solutions are found that contribute to a global heuristic solution (Black, 2005). Another heuristic method is the Clarke-Wright savings algorithm, in which an iterative procedure is used to select a near-optimum route (Clarke & Wright, 1964). The authors note that their formula is very similar to the algorithm by Dantzig and Ramser but point out the existing design emphasizes filling trucks to maximum capacity instead of minimizing distance. The Clarke-Wright savings algorithm computes the savings of combining two customers into the same route, with the solution being the route with the highest savings. This method can be solved by a computer or through manual calculation.

Vehicle Routing Problem Variants

Practical application is an important benefit to routing problems, as accurate models that include the appropriate environmental variables can improve efficiency in many industries. Thus, the traditional VRP has extensive variants (Ho et al., 2008) to address specific routing scenarios with different variables and constraints. A thorough literature review of 277 VRP studies between 2009–2015 indicated research was trending towards highly tailored models to accurately capture real-world variables (Braekers et al., 2016). The authors note that generic models are used infrequently, making the literature for VRP variants vast. Additionally, Liu (2019) states in a review of more recent literature that while UAS routing studies are increasing in recent years, there is still no consensus on common objectives being optimized.

VRP with capacity limits (CVRP) are common NP-hard problems to satisfy the order demands of a geographic location (Lin et al., 2019). A CVRP model was recently paired with a backtracking search algorithm to increase the efficiency of waste collection by 36%, reducing economic costs and environmental impacts (Akhtar et al., 2017).

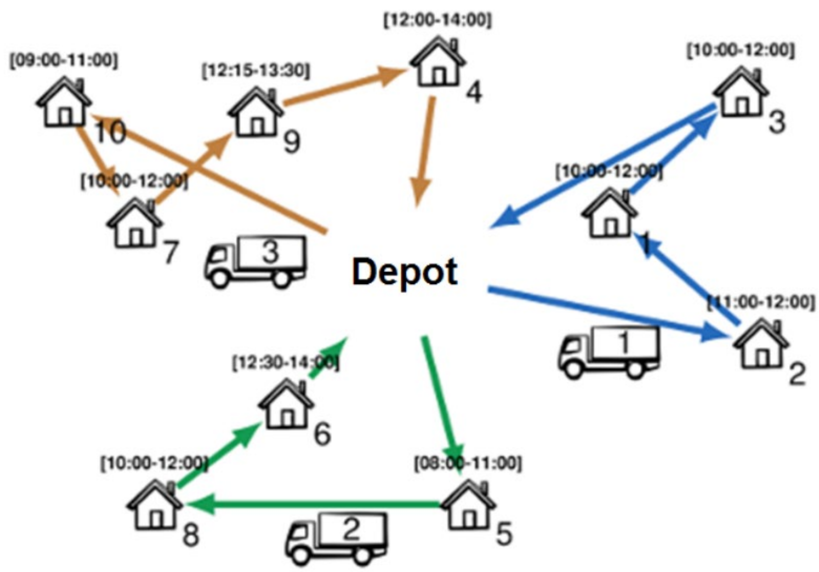
The VRP with multiple depots (VRPMD) are also common, as most real-world delivery services utilize a supply chain with more than one location to service a larger geographic area. Laporte et al. (1988) used a branch and bound tree to find an exact solution for VRPMD, but it is only computationally feasible under relatively few constraints (Crevier et al., 2007). Jordan and Burns (1984) utilized a VRPMD model to reduce the empty-truck miles by having truckers transport goods back to their home terminals.

The VRP with pickup and delivery (VRPPD) can also be found in many industries. A recent study focused on mixing pickup and delivery services in the poultry industry, as the locations that receive chicks are the same locations that require pickup of grown chickens for slaughter (Dechampai et al., 2017).

The VRP with time windows (VRPTW) are used when deliveries must be made within a specific timeframe and are also referred to as time-constrained vehicle routing problems (Kolen et al., 1987). The VRPTW studies have a wide range of operational applications as well, including bank deliveries, postal deliveries, school bus routing (Hashimoto et al., 2006), and military aircraft mission synchronization (Quttineh et al., 2013). Figure 5 is a visualization of the single depot VRP variation with time windows.

Figure 5

Vehicle Routing Problem With Time Windows



Note. From “From “Business Analytics Applications for the Vehicle Routing ” by Blok, 2016.

Many other VRP variants exist, and the most useful models include multiple VRP constraints. For example, Romero-Gelvez et al. (2019) used a capacitated vehicle routing problem with time window (CVRPTW) model to reduce the travel time of a fleet of heterogeneous vehicles. The study is practically significant because it includes real-world variables and constraints that a delivery service would encounter and it uses Google maps to model the distance matrix and a Google API to obtain real-time traffic data in the target city of Bogota, Colombia. A multi-depot vehicle routing problem (MDVRP) can be used to model package delivery scenarios with more than one pickup location (Dhall & Sharma, 2015) or a vehicle routing problem with backhaul (VRPB) can be used to study how vehicles can both deliver and pick up packages along the same route (Goetschalckx & Jacobs-Blecha, 1989). A study by Shankar et al. (2014) also includes multiple constraints to model the complexities of fleets of delivery vehicles. The researchers utilized a tabu search algorithm for a multi-depot capacitated vehicle routing problem with time window (MDCVRPTW) to obtain a near-optimal solution. Each of these routing problems can maximize or minimize a specific variable such as time, distance, or cost.

UAS Routing Studies

VRPs have been adopted by the aviation industry, as optimal routing and accurate modeling of environmental factors can significantly influence fuel burn and positively impact profit margins (Palopo et al., 2010). Ferguson and Dantzig (1956) demonstrated the application of a linear programming model for aircraft routing under uncertain passenger demand, followed by numerous stochastic transportation problems (Holmberg, 1995; Szwarc, 1964; Williams, 1963) aimed at accurately modeling the complex and dynamic variables involved in aircraft fleet management.

UAS vehicle routing studies have also been completed, with some of the major publications coming from Tianjin University of Technology, Beijing Jiatong University, and The Beijing Highway Design & Research Institute. Studies by Liu et al. (2014), Liu et al. (2013), Liu et al. (2012), and Zhang, et al. (2015) have similarities to the model developed in this present study, including the number of UAS, time constraints, and distance. However, because the UAS utilization involves gathering imagery, these studies focus on providing coverage over a designated area and are not related to delivery. They do, however, validate the multi-objective linear programming methodology as an appropriate model for sUAS routing optimization.

UAS routing studies, specifically for delivery, have also been identified, as companies like Amazon, Google, FedEx, and UPS are expanding into the UAS package delivery market. This area of study, frequently called Traveling Salesman Problem-Drone (STP-D) or vehicle routing problem-Drone (Poikonen et al., 2017 Schermer et al., 2019), contains numerous models for single-point delivery from a mobile or permanent hub. One specific TSP-D model currently being researched is the last-mile concept, where delivery trucks equipped with drones are deployed to a neighborhood or location, followed by a deployment of multiple drones to finish the individual deliveries for that coverage area (Bouman et al., 2018; Moshref-Javadi & Lee, 2017; Murray & Chu, 2015). These models are sometimes called the Hybrid Vehicle-Drone Routing Problem (HVDRP) (Karak & Abdelghany, 2019). While useful for home delivery services, most of these models do not account for multiple stops due to the assumed weight restriction of a package and vehicle limitations. One exception is modeled by Dorling et al. (2016). The researchers propose a multi-trip vehicle routing model for parcel delivery, minimizing the delivery cost subject to a time limit. However, the study focuses on battery power and consumption and ignores important environmental factors that affect sUAS endurance, making the model theoretical in nature. Sundar and Rathinam (2012) use an approximation algorithm to solve a VRP with multiple depots to improve understanding of fuel constraints, but do not address variables affecting fuel consumption, thus making the model too simplistic for practical application. A recent study by Thibbotuwawa et al. (2020) provides a thorough classification of UAS routing problems, as well as a graphical taxonomy based on current studies in the field of research. Table 2 summarizes the findings of this study, with researchers noting that models including wind considerations on vehicle energy consumption are rare.

Table 2

Overview of Vehicle Routing Problem Approaches Using UAS

Author	Approach	Objective
Shetty et al. (2008)	General VRP + multi-vehicle TSP	Maximize the total weighted service to the targets from the homogeneous fleet of UAVs
Xingyin et al. (2016)	VRP	Minimize the maximum duration of the routes (i.e., completion time)
Levy et al. (2014)	Single VRP	Find a path for the UAV so that each target is visited at least once by the vehicle, the fuel constraint is never violated along the path for the UAV, and the total fuel required by the UAV is a minimum
Casbeer (2011)	VRP with precedence constraints	Minimize the total distance traveled by a homogeneous fleet of UAVs
Klein et al. (2013)	Dynamic VRP	Minimize the time required to determine the location of the source
Arsie & Frazzoli (2008)	Dynamic VRP	Minimize the expected time between the appearance of a target point and the time it is visited by one of the agents
Avellaret et al. (2015)	Coverage problem into VRP	Minimize the time coverage of ground areas using a homogeneous fleet of UAVs equipped with image sensors
Guerrero & Bestaoui (2013)	TSP + capacitated VRP (CVRP)	Minimize the sum of travel time among waypoints
Wen et al. (2016)	CVRP	Minimize the total travel time and fleet size of the homogeneous fleet of UAVs
Savuran & Karakaya (2016)	Capacitated mobile depot VRP (C-MoDVRP)	Maximize the total number of targets visited by the UAV
Murray & Karwan (2013)	VRP with time windows (VRPTW)	Maximize the overall effectiveness of the mission; minimize changes to the initial mission plan; minimize total travel time; minimize the use of resources, payloads, and "dummy" bases
Guerriero et al. (2014)	VRP with soft time windows (VRP-STW)	Minimize the total distances traveled by the homogeneous fleet of UAVs; maximize the customer satisfaction and minimize the number of used UAVs
Kim et al. (2017)	Multi-depot VRP (MDVRP)	Minimize the operating cost of a heterogeneous fleet of UAVs; find the optimal number of UAV center locations
Habib et al. (2013)	MDVRP	Minimize the total distances traveled by a homogeneous fleet of UAVs

Note. TSP = traveling salesman problems; UAS = unmanned aerial system; UAV = unmanned aerial vehicle(s); VRP = vehicle routing problems.

Studies involving UAS for disaster response have also been completed, confirming the economic feasibility of utilizing the technology to deliver medical supplies (Haidari et al., 2016) and the use of geospatial imaging to detect survivors

(Levin et al., 2016). A recent study used a linear programming method to model the pickup of medical samples and delivery of medicine to patients in rural areas (Kim et al., 2017) which can be used to estimate the number of UAS vehicles to purchase for the operation. However, the researchers did not include environmental variables or patient priority, and routine sUAS delivery is currently illegal in the U.S. under Title 14 C.F.R. Part 107 regulations, making the model theoretical.

Models that combine VRP and disaster response variables have not been thoroughly researched. Oruc and Kara (2018) combined air and ground vehicles to provide accurate damage assessments, optimizing the routings of small UAS and motorcycles for maximum ground coverage, but the study was focused on imagery acquisition and not the delivery of supplies. One particularly relevant study to the risk minimization model is a continuous approximation model that designs an environment for UAS distribution of supplies during natural disasters but focuses on the location of distribution centers to minimize overall cost (Chowdhury et al., 2017). Their model does include the delivery of medicine or supplies, as the researchers focused on cost minimization through distribution center locations and only included UAS system limitations to model the overall cost of delivery. They specifically explain that wind is not considered in their model and state future research should include environmental variables to assess the impact on an optimization framework.

Another study focuses on the last-mile distribution of medical supplies during natural disasters but uses a linear programming model to minimize the total travel distance (Rabta et al., 2018). Their model includes recharging stations for the UAS and assumes that each location is visited once. This differs from the risk minimization research because the model only considers one vehicle at a time and does not reflect the possibility that a vehicle might not have the payload capacity to carry the necessary deliverables to all locations. It does, however, include different priority subsets, acknowledging that certain deliverables will be identified as more urgent during disaster relief operations. A similar approach is used in this risk minimization study to prioritize patient deliveries based on injury severity.

Wen et al. (2016) developed a multi-objective linear optimization model for delivering blood supplies via UAS in emergency situations, a variation of the capacity VRP (CVRP). Their study included variables to model the limited payload capacity of the vehicle and a multi-objective function, but they focused on minimizing the number of vehicles and total mileage. The assumption is that every location is visited once and does not account for environmental conditions or aircraft speed. This study is useful to identify the number of vehicles required to cover a specific area during natural disaster response, but the overly simplistic variables do not allow for practical application.

Common Objective Functions and Constraints

Although VRPs can be used to solve a variety of practical applications, commonalities can be found throughout the extant literature. True to the theoretical foundation of the original traveling salesman problem, maximization of efficiency, profit, or equipment utilization are the foundation of many aviation-based optimization problems. Minimization of time, distance, or fuel are also frequent objective functions in the aviation industry as well as unmanned VRPs. Model constraints in unmanned VRPs are also similar throughout the literature, as vehicle range, endurance, and payload capacity are constrained by technological limitations. The core premise of delivery nodes and prospective routing arcs are also included in unmanned VRPs, although differences exist between delivery models where payload capacity is critical and surveillance models that frequently prioritize maximum loiter time.

Theoretical Foundation

Mixed-Integer Nonlinear Programming

Mixed-integer nonlinear programming (MINLP) methods are frequently used in operational research due to the complexity of real-world systems. Simplistic methods such as linear programming can be suitable for theoretical problems or validation of new solution algorithms, but more advanced and practically useful models in extant literature usually include linear, nonlinear, and discrete variables. For example, aircraft avoidance is one emerging application for operations research due to the extremely complex and stochastic nature of in-flight routing (Cafieri & Omheni, 2017). The literature on MINLP methods is vast, with studies ranging from the distribution of industrial gases (You et al., 2011) to the sustainable growth of aviation infrastructure (An et al., 2019).

Emergency Management

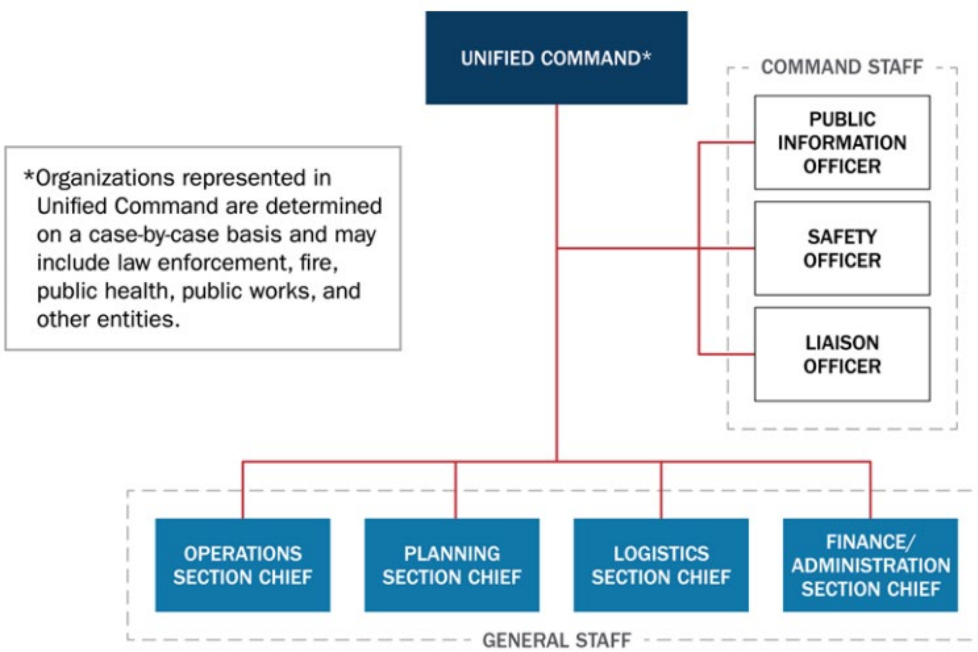
In the U.S., FEMA utilizes an all-hazards approach to emergency operations planning (Goss, 1998). In 2004, FEMA developed the National Incident Management System (NIMS) for use by individuals, families, communities, private and nonprofit sectors, faith-based organizations, and state, local, tribal, territorial, and federal governments (FEMA.com, n.d.) to ensure standardization and coordination for emergency response. NIMS outlines the structure of emergency operations centers (EOCs) and Incident Command Systems (ICS) and is built on the guiding principles of flexibility, standardization, and unity of effort (FEMA, 2017). FEMA explains in the

NIMS handbook that while the structure of emergency response in the U.S. is developed by local agencies, they should comply with federal guidelines in relation to resource management, command and coordination, and communication and information management (FEMA, 2017, p. 1-2).

Jurisdictions are responsible for planning the identification, allocation, mobilization, and deployment of available resources prior to an emergency occurring (FEMA, 2017, p. 8), and a clear chain of command through a single incident manager or unified command team (see Figure 6).

Figure 6

ICS Organizational Chain of Command

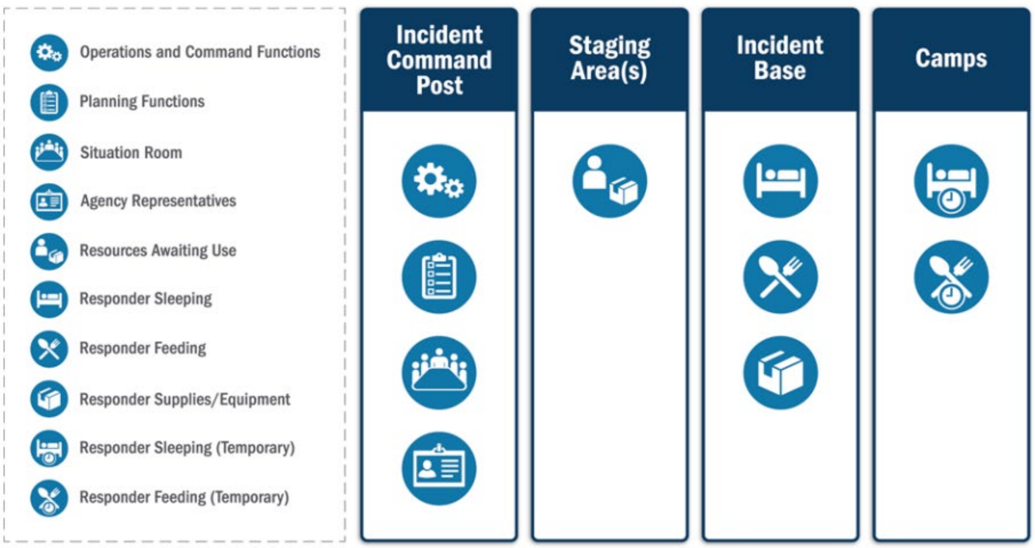


Note. ICS = Incident Command System. An example of ICS organization. From "National Incident Management System. 3rd edn." by FEMA, 2017, p. 26. In the public domain.

Paired with a common hierarchy of responsibility within the ICS are standardized ICS facilities for incident management teams, supporting staff, first responders, and equipment (see Figure 7).

Figure 7

Incident Facilities



Note. From "National Incident Management System. 3rd edn " by FEMA, 2017, p. 32. In the public domain.

Injury Classification

Emergency planning for a mass casualty incident (MCI) requires a coordinated effort between hospitals, first responders, law enforcement, U.S. National Guard, and varying levels of federal support. This coordination must occur in a "convoluted, confused, and fragmented environment" (Hoard et al., 2005, p. 118), and frequently includes an overwhelming number of victims and limited time (Killeen et al., 2006). To standardize coordination between first responders, U.S. regulatory agencies provide guidance on standard triage categories and injury assessment. Because the scope of this present study is limited to the U.S., risk and risk minimization is defined based on industry standards in the field of emergency triage.

The U.S. Department of Health and Human Services [HHS] (2019) characterizes an MCI as an event where the environment is dynamic, the number of patients far exceeds the usual resources, and conventional triage and treatment paradigms may fail. For these events, the time/treater/treatment method is used to assess a patient's likelihood of survival, where the first responder identifies the time required to provide intervention, the required healthcare provider expertise, and the required resources to stabilize the patient. This assessment informs the categorization of patients into the Emergency Severity Index (ESI) as defined by the Agency for Healthcare, Research, and Quality (see Table 3).

Table 3

Emergency Severity Index

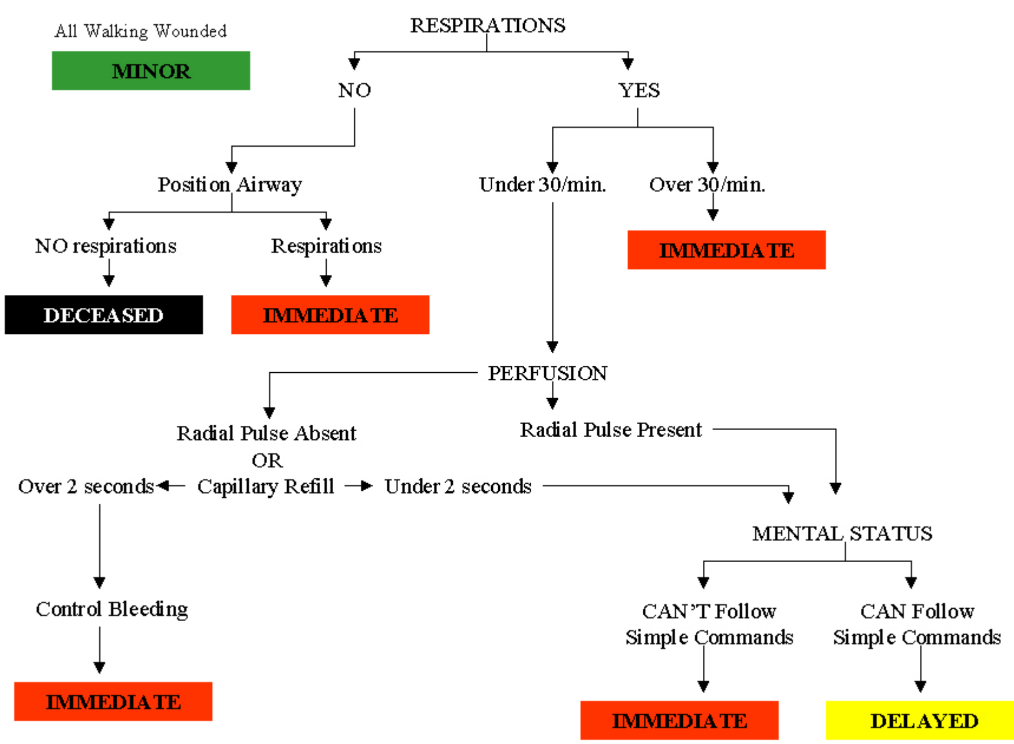
Category	Definition
Resuscitation	Immediate, life-saving intervention required without delay
Emergent	High risk of deterioration or signs of a time-critical problem
Urgent	Stable with multiple types of resources needed to investigate or treat (e.g., lab tests plus x-ray imaging)
Less Urgent	Stable with only one type of resource anticipated (e.g., only an x-ray or only sutures)
Nonurgent	Stable with no resources anticipated except oral or topical medications or prescriptions

Medical Triage

The two most common models used to assist first responders in categorizing injury severity are the START (simple triage and rapid treatment) model and the SALT (sort, assess, life-saving interventions, treatment/transport) model. The START model (see Figure 8) is widely used in the U.S. to identify the required level of medical care, while the SALT model (see Figure 9) was developed more recently in 2006 to address the lack of standardization in the mass casualty triage field.

Figure 8

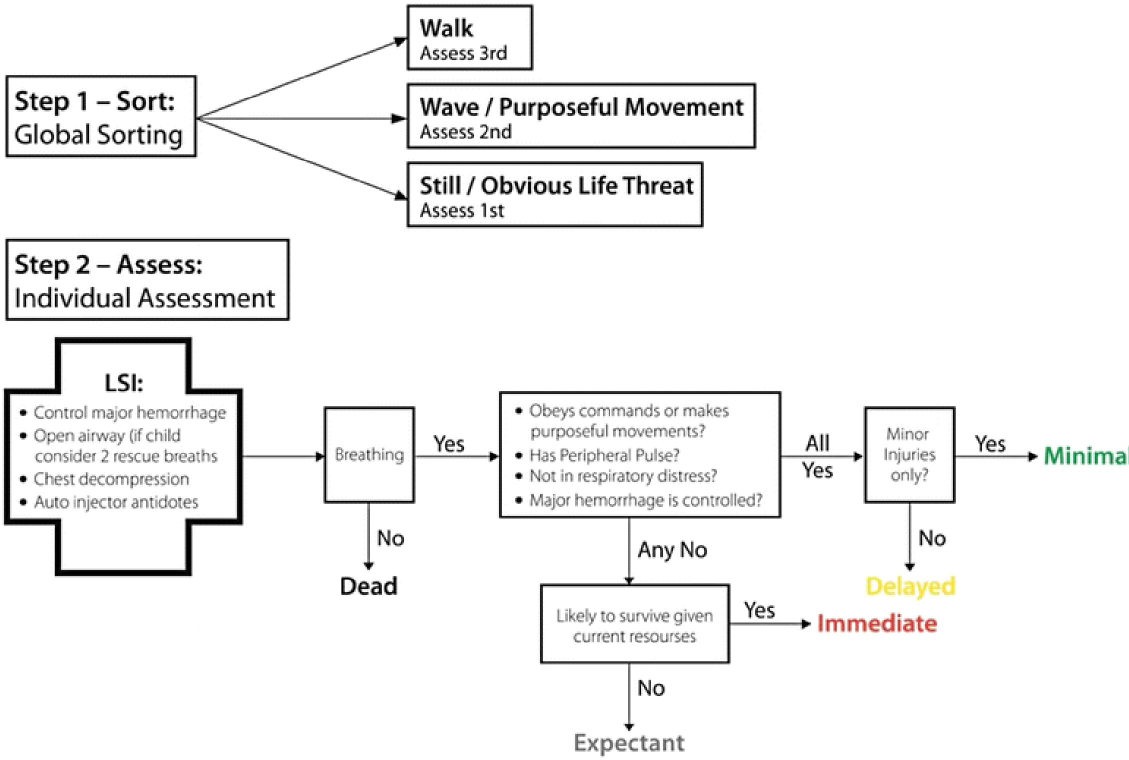
START Model



Note. START = simple triage and rapid treatment.

Figure 9

SALT Model



Note. SALT = sort, assess, life-saving interventions, treatment/transport.

Both models are similar, although the SALT model is endorsed by the American College of Emergency Physicians, American College of Surgeons Committee on Trauma, American Trauma Society, National Association of EMS Physicians, National Disaster Life Support Education Consortium, and State and Territorial Injury Prevention Directors Association. These risk minimization techniques are widely used in the triage field to categorize injured patients and align with the four major categories of injury severity outlined by U.S. disaster response agencies. Therefore, this present study utilizes the four-category risk assessment model presented in Table 4 as the theoretical foundation for minimizing risk to a group of patients.

Table 4

Risk Assessment Model

Category	Definition
Expectant/Dead	UAS-delivered medical supplies will not impact the outcome
Immediate	Medical attention is required within 60 min
Delayed	Medical attention is required within 120 min
Minor	Status is unlikely to deteriorate over multiple days, but risk of additional injury can still be minimized at a lower priority

For this model, the target risk minimization categories are the immediate, delayed, and minor categories. The usefulness of the model is based on the rapid delivery of medical supplies to multiple patients requiring lifesaving treatment. Therefore, each of these categories are given a risk value for delivery and a penalty for deliveries after the time limit has been reached. Thus, this present study defines *risk minimization* as the optimal UAS route to achieve the lowest possible penalty for missing a patient.

HHS specifies the timeframe for medical attention in the immediate category is 60 min, while the delayed category states several hours. Minor injuries are unlikely to deteriorate over several days and therefore have the lowest risk value. This definition allows for model selection of patients with minor injuries only if endurance allows and other urgent injuries are addressed. The concept of risk minimization as it applies to this study is discussed further in Chapter III.

Justification for Risk Minimization

Objective functions focused on risk minimization are not common in existing literature. A study on offshore helicopter operations found that overall transportation risk can be reduced at the expense of increased travel time (Qian et al., 2012; Qian et al., 2015). This finding is an important precedent for risk minimization, as traditional routing studies would most likely seek to reduce overall travel time and, according to this study, increase passenger risk. Risk minimization has also been used in routing problems for logistics (Giaglis, 2004) and ground-based vehicle routing for emergency response (Campbell et al., 2008). The VRP study by Campbell et al. is an important theoretical justification for prioritizing risk minimization, as the authors explain traditional cost-minimizing VRPs do not properly reflect the priorities of emergency responders during disaster relief. The Campbell et al. study focuses on alternative objective functions for minimization of the maximum arrival time and minimization of the average arrival time. However, all of these studies acknowledge the importance of quantifying total risk and provide precedent in the extant literature for a VRP that prioritizes risk minimization as the objective function (Campbell et al., 2008; Giaglis, 2004; Qian et al., 2012; Qian et al., 2015).

Gap in the Literature

The review of the relevant research literature confirms the economic feasibility of sUAS medical supply delivery, developed simplistic VRP models to deliver scheduled medical supplies and blood samples, and researched cost minimization methods for UAS delivery. However, a gap exists in the literature because no studies combine the numerous vehicle routing models with environmental variables to produce a model that is theoretically valid and operationally useful for medical delivery using multiple sUAS. Additionally, extant research focuses on the optimization of vehicle utilization. This narrow focus results in a clear gap in research, as emergency response plans must focus on providing care to the highest number of patients with respect to injury severity. This present study addresses this gap because its risk minimization model for post-disaster medical delivery using UAS is unique due to the inclusion of environmental variables to allow for real-world optimization calculations while acknowledging that the number of sUAS are limited and total travel time should be minimized as a secondary priority.

This chapter summarizes the history of sUAS and the technological impact on the emergency response industry and presents a broad overview of linear programming methodology. Each component of a multi-objective MINLP model is explained and supported by previous studies to validate the research design. The theoretical foundation for the study is identified through industry standards for medical triage, with extant literature confirming the concept of quantifiable risk minimization as it pertains to natural disasters in the U.S. While linear programming is a common approach for vehicle routing problems, the literature on sUAS technology, routing studies, and emergency response indicates a clear gap in priorities. This research addresses the research gap by developing a novel model that aligns the traditional vehicle routing problem with the goals of the emergency response industry.

Chapter III

Methodology

This chapter details the justification for selecting a multi-objective mixed-integer nonlinear programming (MOMINLP) model, including the variables that justify the use of this method. It presents the population and sample and provides detailed descriptions of the research design, relevant ethical considerations, measurement instrument, and data analysis method.

Research Method Selection

This study utilizes the MOMINLP quantitative modeling methodology. The types of variables included in the model inform the methodology selection; each variable is explained in detail to justify the decision to use this specific subset of linear modeling.

Linear Programming

Linear programming is a broad methodology with applications in manufacturing, engineering, agriculture, energy, and transportation. The methodology combines elements of mathematics, operations research, and computer science to solve real-world industry problems (Mann, 2012). Decision-making in these domains can be highly complex, often exceeding human computational power. Software can assist in identifying the optimal solution to these problems, with models focusing on the minimization or maximization of a specific variable. The minimization or maximization function, commonly referred to as the objective function, is subject to a list of constraints. The general mathematical formula for an objective function is presented in Equation 1.

$$\text{Minimize or Maximize} = \sum_{i=1}^{n} c_i X_i \tag{1}$$

where:

c_i = the objective function coefficient corresponding to the i^{th} variable, and

X_i = the i^{th} decision variable.

A simple linear programming example is provided for context: An airline company wants to maximize profit on a 416-seat Boeing 747. Market research indicates the profit for each seat:

- \$350 for each first class seat sold (x)
- \$280 for each business class seat sold (y)
- \$250 for each coach class seat sold (z)

Because the company wants to maximize profit (P), the objective function for this problem is $P = 350x + 280y + 250z$. This equation is subject to the following constraints:

- No more than 416 seats sold ($x + y + z \leq 416$)
- At least 5 first class seats, but no more than 20 ($5 \leq x \leq 20$)
- At least 20 business class seats, but no more than 50 ($20 \leq y \leq 50$)

As this example demonstrates, linear programming can be used to find the optimal solution for a problem in almost any industry, including aviation. While the optimization concept is straightforward in theory, including all the variables that influence a real-world system is challenging. This example of profit maximization could include other variables such as jet fuel consumption and crew salary, and hundreds of other constraints such as budget and aircraft range, making linear programming an ideal methodology for solving complex optimization problems.

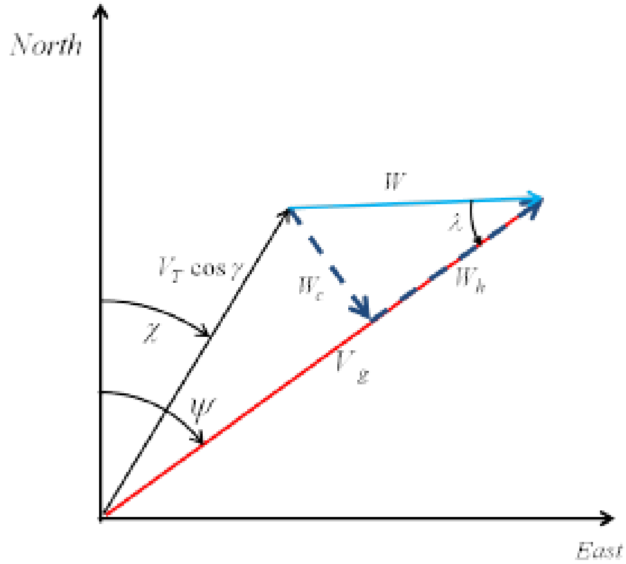
As discussed in the literature review, previous linear programming models on sUAS routing do not include essential variables that make the model practical for emergency response decision-makers. Dozens of subsets of linear programming can be used for more specific problems, including goal programming for disaster response (Ortuño et al., 2011), nonlinear programming for sUAS delivery (Chang & Lee, 2018), and integer programming for airline passenger screening (McLay et al., 2007).

Nonlinear Programming

Linear programming models are used when all variables and constraints exhibit linear relationships, where one variable directly or inversely affects other variables at a constant rate. Environmental variables are included in this study, meaning a nonlinear relationship exists between wind speed, wind direction, and groundspeed. A headwind of 20 kt reduces groundspeed by approximately 20 kt, and a tailwind increases the groundspeed by approximately 20 kt, but a crosswind of 20 kt only has a small impact on aircraft groundspeed and thus aircraft range. Figure 10 presents these variables modeled using existing mathematical calculations. The inclusion of these variables requires a nonlinear programming method. As discussed in the literature review, models that consider wind as an environmental variable affecting UAS vehicle endurance are rare (Thibbotuwawa et al., 2020).

Figure 10

Airspeed, Groundspeed, and Wind Speed Relationship



Note. The black, blue, and red lines denote horizontal component of air velocity, wind vector, and ground velocity vector, respectively. From "Vertical Trajectory Optimization for Continuous Descent Arrival Procedure " by Park & Clarke, 2012.

Mixed-Integer Programming

Integer programming is also a common subset of linear programming. Linear programming models include only continuous linear variables, such as the number of patients at a hospital or milligrams of penicillin required to treat infections. Integer programming problems include only discrete variables, such as the number of beds in a hospital or the number of doctors in a city. The risk minimization model in this present study is considered mixed-integer because it includes continuous variables such as wind speed and discrete variables such as payload capacity and injury severity.

Multiple Objectives

The risk minimization model is a multi-objective model because it includes two objective functions to minimize risk and travel time. More specifically, a goal programming methodology is utilized to ensure the model solves the primary objective of risk minimization first, followed by the secondary goal of route time minimization used to achieve the final optimal solution. For this study, the hierarchy of criticality is absolute, meaning the optimal primary objective will not be sacrificed to achieve a more optimal secondary objective. This variation is referred to as lexicographic goal programming (LGP) and has been previously used in transportation models (Quddoos et al., 2013) and models for humanitarian response after natural disasters (Ortuño et al., 2011).

Multi-Objective Mixed-Integer Nonlinear Programming

The inclusion of nonlinear environmental variables, discrete and continuous variables, and two objective functions designates the chosen model as a multi-objective mixed-integer nonlinear programming (MOMINLP). This subset of linear programming is relatively narrow, with applications ranging from supply chain problems (Chen & Lee, 2004; Wu et al., 2009) to construction site layout planning to minimize noise pollution and transport costs (Hammad et al, 2016).

Population/Sample

Population and Sampling Frame

The population for this study is all U.S. rural areas, as defined by the Census Bureau as "all population, housing, and territory not included within an urbanized area or urban cluster" (Ratcliffe et al., 2016, p. 3). The Census Bureau considers areas of at least

2,500 and less than 50,000 people to be urban clusters and areas of 50,000 or more people to be urban areas. Approximately 97% of the total U.S. land cover is considered rural, with approximately 19% of U.S. citizens residing in these rural areas.

Sample Size

Four locations fitting the Census Bureau's definition of a rural community were selected for the study sample. Geographic and demographic variation were prioritized during the selection process to ensure the sample is representative of the entire rural population of the U.S. The first location for the initial model output is Purvis, Mississippi, with a 2010-census population of 2,175 and a population density of 554 residents per square mile. Purvis is located in Lamar County, with approximately 60,000 residents in an area of 500 sq mi and a density of 112 people per square mile. The South Mississippi State Hospital is located near Purvis, a logical location to execute medical disaster response in the surrounding region. Over the last decade, the area has suffered numerous natural disasters, including multiple tornados and hurricanes. In 1908, the community was also devastated by the 8th deadliest tornado outbreak in history, resulting in 83 deaths (approximately 10% of the population) and 340 wounded. The other sample locations selected are Floyd, New York, McCall, Idaho, and Winslow, Arizona. The entire city of Purvis is small enough to meet the Census Bureau's definition of a rural area within the city limits, making it an ideal location for the initial model output. The other communities also have rural populations surrounding their city centers to meet the delimitation for this study. Table 5 presents the population data for each location in the sample.

Table 5

Sample Population Characteristics

Location	Population	Density per square mile	Region
Purvis, MS	2,175	572	Southwest
Floyd, NY	3,819	109	Northeast
McCall, ID	2,991	397	Northwest
Winslow, AZ	9,005	693	Southwest

Sampling Strategy

The sample locations were selected by both geographic location and population to ensure appropriate generalizability for the model. Floyd, McCall, and Winslow have rural communities outside their city centers, while Purvis is small enough to be considered rural even in the city center. These locations, displayed in Figure 11, show separation by both physical location and climate. The differences in climate are captured in the model sensitivity analysis by using data inputs from the historical wind data at each location.

Figure 11

Sample Locations

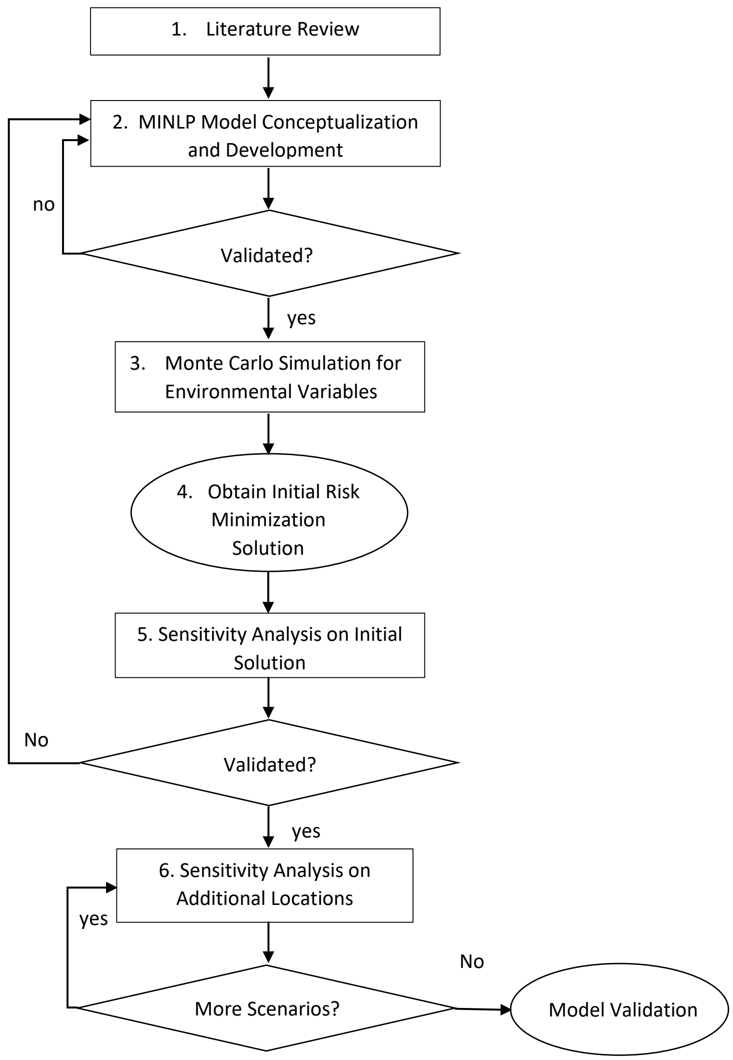
Research Procedure

Model Development Design and Procedures

The model development process was designed to analyze previous research and identify the variables influencing the disaster response system, followed by model development and validation through multiple scenarios of increasing scope. The research procedure, as illustrated in Figure 12, began with a thorough literature review of airborne vehicle routing studies and optimization models for medical delivery and disaster planning presented in Chapter II. After the decision variables and parameters were conceptualized, the risk minimization model was developed using LINGO Version 19.0 software and was validated by comparing the results to a simple scenario. The model was then tested with hypothetical scenarios in rural areas using Microsoft Excel to assign values to the stochastic environmental variables based on historical wind data and the stochastic patient variables based on random number generators.

Figure 12

Research Procedure for Optimal Solution Model Development



Note. MINLP = mixed-integer nonlinear programming.

The procedure to develop and validate the model followed six steps.

Step 1. Literature Review. As discussed in Chapter II, many UAS routing studies determine the optimal path without considering the appropriate variables. The literature review solidifies the research gap and informs the selection of variables and model constraints in subsequent steps.

Step 2. MINLP Model Conceptualization and Development. This step identifies the input variables and constraints used in the initial model. The objective function was developed, and relationships were defined based on the literature review outlined in Step 1. The model must be flexible to account for different constraints and variable values depending on the type of sUAS, available medical resources, and other event-specific considerations. Coding the variables and constraints into LINGO required an iterative process of adding data to LINGO, verifying the data through internal and external sources, and running the model through multiple iterations to ensure outputs were reliable and coded properly.

Step 3. Monte Carlo Simulation for Environmental Variables. To compute travel time between any two patients in a given scenario, groundspeed must first be calculated. The inputs required to calculate groundspeed are sUAS heading, sUAS airspeed, wind direction, and wind velocity. To ensure the reliability of the formulas and observe the distribution of groundspeed over a large sample size, two Monte Carlo simulations were utilized. The mean and standard deviation for wind velocity and wind direction were obtained using 8760 historical data points from the first model location and were used as inputs for a stochastic simulation where each trial is an independent scenario. The second Monte Carlo simulation was deterministic, with static environmental variables designed to simulate the groundspeed distributions for 5,000 patients where vehicles are subjected to the same wind conditions for every trial. For both simulations, the wind direction, wind speed, and aircraft speed were manipulated to observe the impact of changing variables on the groundspeed distribution over a large dataset.

Step 4. Obtain Initial Risk Minimization Solution. Once the necessary model input reliability was achieved through the use of Monte Carlo simulations and iterative testing during the model development, an initial optimal risk minimization solution for the first scenario was obtained. The output was validated against known route travel times for the environmental conditions used as inputs, and prioritization of injury severity is observable in a controlled 5-patient scenario.

Step 5. Sensitivity Analysis on Initial Solution. To confirm the usefulness of the model at different scales, the model was run through multiple what-if scenarios for each variable. The sensitivity analysis is an important tool for disaster planning, as decision-makers must understand the ramifications of purchasing sUAS with different payload and endurance limitations as these decisions are most likely cost-driven. The sensitivity analysis process was iterative and flexible, and additional scenarios were added based on the initial results.

The sensitivity analysis also ensures decision-makers understand the total risk minimization values across a wide range of disaster response scenarios. With the cost of a human life currently valued at over $9 million (Moran & Monje, 2016), justification for sUAS medical delivery is strengthened through research on the impact of changing variables like payload capacity and endurance. Results from the initial sensitivity analysis demonstrate model reliability, as the scenarios are designed to be small enough that the optimal route can be confirmed through manual observation. Through the process of updating sUAS and environmental variables, the generalizability of the model can also be observed.

Step 6. Sensitivity Analysis on Additional Locations. To confirm model generalizability for rural environments in the U.S., three additional locations were selected based on population and demographics. The statistics for each location are discussed in the Demographics section of this chapter. The sensitivity analyses in Steps 5 and 6 demonstrate the model is robust to changing environmental variables, vehicle variables, and across a variety of rural locations.

Apparatus and Materials

Because this research is focused on the development of an optimization model, gathering new data was not required. Existing historical data obtained from the National Oceanic and Atmospheric Administration (NOAA) Online Database (https://www.ncdc.noaa.gov/cdo-web/datasets) was used as the input for the Monte Carlo simulations for each geographic region. The rural regions were selected based on the U.S. Census Bureau definition, with priority given to areas that are particularly susceptible to natural disasters. The data source for sUAS system limitations is commercially available technical data. Although the model is platform-agnostic, for the purposes of model development and validation, industry standards were used for sUAS endurance, speed, and payload capacity.

Research Design

Solution Method

This research employs a quantitative heuristic method to achieve optimal risk minimization in a novel extension of a standard VRP. Heuristic methods are widely used in the aviation domain (Jozefowiez et al., 2013; Thengvall et al., 2001) to solve large-scale problems that do not have perfect solutions. Heuristic methodologies such as greedy algorithms and column-based algorithms are frequently used to find the best possible solution under a given set of circumstances. Because this study does not attempt to completely eliminate risk by delivering medicine to every patient, which would likely result in no solution being found or an economically infeasible number of participating sUAS during large-scale disasters, a heuristic method is appropriate to find a solution that minimizes risk. Numerous heuristic methodologies are employed to solve NP-hard VRPs, including simulated annealing, the bee colony algorithm, or population search methods.

This risk minimization study utilizes a capacitated VRP (CVRP) approach to achieve the appropriate risk minimization solution, meaning the model will constrain medicine weight to less than or equal to the maximum payload capacity of each vehicle. Thus, this research design is considered a multi-objective capacitated vehicle routing problem.

The list of assumptions and justifications for the study can are presented in Table 6. These assumptions are consistent with similar sUAS vehicle routing studies and bound the study to specific disaster response and medical delivery scenarios.

Table 6

Model Assumptions and Justifications

Assumption	Justification
Vehicle reliability is 100% and performance characteristics remain constant throughout the flight.	Failure modes and statistical probabilities for commercial sUAS are usually unavailable, but during one maximum-endurance flight cycle, variables such as airspeed and transition time normally remain constant.
Wind velocity and direction remain constant throughout the flight.	Flight time is limited to sUAS battery life. Minimal environmental changes are expected during this time.
Routing decisions are made at finite intervals.	When a given number of sUAS are prepared to fly, a snapshot of injury location and distance is used to determine optimal risk minimization at a single point in time.
The separation of manned and unmanned traffic will be managed procedurally during emergency response operations using FAA Notices to Air Missions (NOTAMs) and Temporary Flight Restrictions (TFRs).	Instructions for temporary flight restrictions and other procedures for safe airspace coordination are from the FAA Emergency Response Plan.
Times for preflight and loading required supplies are calculated at a fixed rate based on the number of sUAS executed during the mission.	Loading a single sUAS can be done at a given rate, and additional sUAS are loaded at a similar fixed rate.
Transition times (landing, offloading, taking off) at each location are calculated at fixed rates.	Flight clearance for sUAS delivery are limited to under 400 ft (121.92 m) per FAA Part 107 regulations. A small payload size should minimize variation in payload offload time. These variables are included in the model at fixed rates.
Each flight completes the entire round-trip flight from a single depot without mid-route refueling.	Some sUAS routing models include refueling depots or multiple launch/recovery points at strategic locations to increase model flexibility, but coordinating logistics of refueling locations during disaster response is unrealistic. The range constraint limits the risk minimization for each flight, but it is necessary to model a realistic environment to ensure appropriate reliability.

Decision Variables

The decision variables for the model are the possible routes to injured patients. Each route is a binary variable, with 0 indicating the patient is not selected and 1 indicating the patient is selected. The model considers the constraints and determines the optimal routing with the available sUAS to minimize risk. The second objective function of travel time minimization uses the same binary decision variable for a route being selected. The number of potential routing decisions facing emergency responders will be too complex to calculate manually, even in relatively small scenarios. For example, applying the permutation formula to a scenario with one sUAS vehicle and 10 injured people contains 10 factorial (3,628,800) potential route combinations without even considering the influence of model constraints. Table 7 lists the input and output variables for the model, their characteristics, and scales.

Table 7

Model Parameters, Input/Output Characteristics, and Scales

Parameter	Input or Output	Scale
sUAS route	Output, Binary	$x_{ij}^{k} \begin{cases} 1 \text{ if vehicle } k \text{ travels along arc } i\text{–}j \\ 0 \text{ otherwise} \end{cases}$
Injury risk	Input, stochastic	Discrete
Injury location	Input, stochastic	Discrete
Medicine weight	Input, stochastic	Discrete
Wind direction	Input, stochastic	Discrete
Wind velocity	Input, stochastic	Continuous
Available sUAS	Input, deterministic	Discrete
Airspeed	Input, deterministic	Continuous
Payload capacity	Input, deterministic	Discrete
Endurance	Input, deterministic	Continuous

Objective Function

The objective functions for the MINLP model are to minimize the total risk to injured patients and minimize travel time. The model is built to run two separate successive iterations using the following objective function:

MIN = (travel time weight * total travel time) + (penalty weight * total penalty)

The model then runs a submodel in the code twice with a different weighted value for travel time and penalty each time. The lexicographic methodology used for this study requires no combination of travel time weight and penalty weights, making the weight values binary:

1. Risk minimization solution: MIN = (0 * total travel time) + (1 * total penalty)
2. Constrain secondary solution: total risk = total penalty
3. Travel time solution: MIN = (1 * total travel time) + (0 * total penalty)

Risk Minimization

As discussed in the literature review, the theoretical foundation for risk minimization is the first responder injury scale. Although first responders classify patients into four categories, the expectant/dead category does not apply to this model, as the time horizon for these patients has passed. The three other categories of immediate, delayed, and minor all have approximate time constraints. Immediate injuries must receive additional care within approximately 60 min, delayed injuries within 120 min, and minor injuries within several days. The risk severity for each patient can be quantified by an escalating scale presented in Table 8. If a delivery is not made, the value listed in the table is assessed as a penalty. The model is then tasked with minimizing the penalty assessed.

Table 8

Individual Risk Severity

Injury Classification	Risk Value
Immediate	500
Delayed	300
Minor	100

Immediate injuries have a value of 500, meaning the model prioritizes these patients over all others. Delayed and minor injuries are valued at 300 and 100, respectively. It is important to note that these values are arbitrarily determined and a user can adjust these values if patient prioritization changes based on the type of emergency response. With the values listed in Table 8, the model will prioritize the delivery of two patients with delayed injury (missed delivery penalty = 600) over one patient with an immediate injury (missed delivery penalty = 500). However, the model was tested with various risk values during the model validation phase to confirm appropriate model flexibility. For example, if emergency responders prioritize immediate patients over any number of delayed patients, an absolute hierarchy of patient prioritization is possible by updating the risk values. For that scenario, the model user would increase the range between each category. Immediate injuries could be set to 1000, delayed injuries could be set to 100, and minor injuries could be set to 1. For these values, the model would acknowledge the weight of immediate injuries at a factor of 10, and it would require a successful delivery of 10 delayed injuries to equal one immediate injury. This model flexibility is a significant benefit in terms of operational usability.

The risk severity matrix in Table 8 quantifies the total risk (R_t) of a rural area by summing the risk of each patient (P), identified as the primary risk minimization objective (f_1), as shown in Equation 2:

$$f_1=(min)R_t=R_{S(P1)}+R_{S(P2)}+ R_{S(P3)}+\dots R_{S(Pn)} \tag{2}$$

Travel Time Minimization

The secondary objective (f_2) of minimizing total travel time (Tt) is constrained to the optimal risk minimization, meaning f_2 cannot increase f_1. Unlike weighted goal programming methodologies that use a numeric goal to find an optimal solution between conflicting objectives, this study uses lexicographic goal programming. The primary goal of risk minimization is solved first, followed by a separate optimization solution using the potential locations from f_1 as an input for f_2, as shown in Equation 3.

$$F_1=(min)T=R_{S(P1)}+R_{S(P2)}+ R_{S(P3)}+\ldots R_{S(Pn)}),\ f_2=(min)T_t \qquad (3)$$

Constraints

The list of constraints contains standard limitations for vehicle routing problems identified from the literature review and the relevant environmental constraints to ensure route completion within maximum vehicle endurance.

- Each sUAS will depart and return to the same physical location
- Each injury location can be visited only once
- Route flight time will not exceed sUAS endurance
- Maximum number of sUAS will not be exceeded
- Patient medicine demand must not exceed payload capacity

The decision variables and additional constraints demonstrate model complexity with the inclusion of stochastic environmental variables, stochastic patient data, and deterministic sUAS vehicle limitations.

In summary, this study is considered a CVRP and is solved by a MOMINLP model. The results are validated by real-world scenarios using industry-standard sUAS capabilities and average weather conditions at each location.

Sources of the Data

Demographic information for this research was collected using publicly available databases, primarily the U.S. Census Bureau (https://www.census.gov/library/visualizations/2010/geo/population-density-county-2010.html) and the NOAA historical weather (https://www.ncdc.noaa.gov/cdo-web/datasets). No original data was collected to develop the model, and demographic information was used solely for model validation.

Ethical Considerations

Because this research uses data from previous studies for the model formulation, no human subjects were necessary, and the Institutional Review Board (IRB) approval was not required. However, the practical application of this research requires decision makers to consider the ethical implications of choosing which patients receive potentially lifesaving medicine based on the model results. This consideration is outside the scope of the study, as the goal is model development and not model implementation with a rural disaster management plan.

Measurement Instrument

VRPs are considered NP-hard, meaning perfect solutions are generally not feasible under realistic constraints, and searching every potential route is not possible under normal computing conditions. Thus, heuristic algorithms are used to identify the optimal route. Even with heuristics, the process of finding an optimal solution still involves analyzing hundreds or thousands of routing possibilities. Many algorithms have been developed to optimize this process and find a suitable balance between computational time and optimality.

Multi-route improvement algorithms attempt to upgrade a feasible solution by exploring delivery point exchanges between routes and have been successfully demonstrated in multiple studies (Kindervater & Savelsbergh, 1997; Thompson & Psaraftis, 1993; Van Breedam, 1994). Another approach is cluster-first and route-second algorithms, which saves processing time by identifying geographically similar points and grouping them into clusters, followed by route selection on each individual cluster (Fisher & Jaikumar, 1981; Ryan et al., 1992).

One of the most well-known algorithms is the Clarke and Wright savings heuristic (CWSH) (Clarke & Wright, 1964). This method is advantageous due to its balance between flexibility and efficiency (Larson & Odoni, 1981), and while newer metaheuristic methods can output improved optimal solutions, they require a significant amount of time and computing power. For the optimal solution to be practically useful, the results must be obtained using relatively limited computing power available in an emergency operations center and must be obtained in the shortest time possible. While this time advantage comes at the cost of accuracy, a model used for emergency response must find the appropriate balance between speed, accuracy, flexibility, and simplicity.

The modeling software used for this research automatically assigns the solver type based on the variables included and generally will select a branch-and-bound technique for models with numerous integer variables. The underlying theory behind the branch-and-bound method is a divide-and-conquer algorithm, as searching through all potential routes is inefficient and time-consuming. This technique divides the problem into smaller sub-problems, or “branches” that are evaluated independently, and it discards solutions that could not possibly contain the optimal solution for the entire problem. This process is called bounding and fathoming. The branch-and-bound technique can be summarized by the following iterative process (Hillier & Lieberman, 1995):

Initialization: Set $Z^* = -\infty$. Apply the bounding step, fathoming step, and optimality test—as described below—to the whole problem. If not fathomed, classify this problem as the one remaining subproblem for performing the first full iteration.

- Branching: Among the remaining subproblems, select the one that was created most recently (break ties according to size). Branch from the node for this subproblem to create two new subproblems by fixing the next variable at either 0 or 1.
- Bounding: For each new subproblem, obtain its bound by applying the simplex method to its linear programming relaxation and rounding down the value of Z for the resulting optimal solution.
- Fathoming: For each new subproblem, apply the fathoming tests and discard those subproblems that are fathomed by any other tests.

While the underlying calculations for the branch-and-bound technique are complicated, the implementation of the heuristic is quite simple and has been widely used for VRPs. Utilizing this method will increase the reliability of the model over more obscure and untested metaheuristic algorithms.

Data Analysis Approach

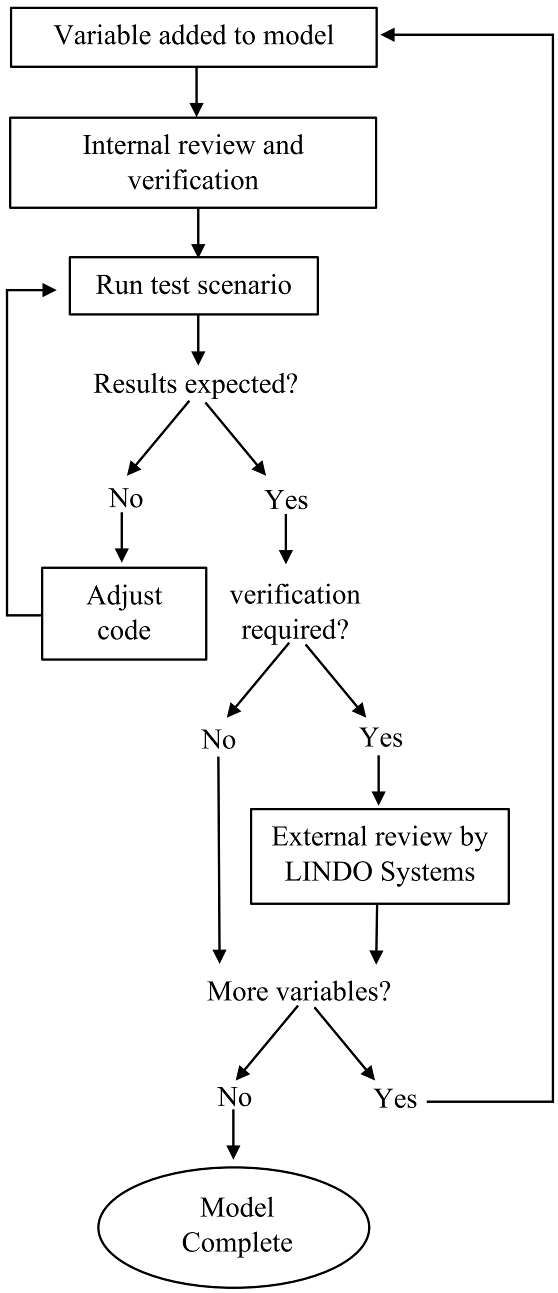
The reliability of the model was tested through iterative testing at a single location. This testing was followed by reliability and generalizability testing at three additional locations using the what-if scenarios.

Reliability Assessment Method

The reliability of the model was confirmed at multiple steps during the model development process. As the model was built in LINGO, each line of code was reviewed and verified by this researcher. The model code was then reviewed by an independent specialist from LINDO Systems, whose team of technicians confirmed model accuracy at multiple checkpoints during the construction of the final model. This process is visualized in Figure 13 and demonstrates thorough testing to confirm the model produces consistent results. During this process, a comparison was made between a simplistic scenario where the optimal route is obvious and an output from the LINGO computation being tested. Achieving the same results from both scenarios confirms the reliability of using a software program for more complex problems that cannot be solved manually. This process was repeated as new variables were added to the model to ensure the accuracy of the code during the build process.

Figure 13

Model Reliability Workflow



After confirming the reliability of the LINGO formula, the model was run through multiple iterations at the same location but with different controllable and uncontrollable variables. Comparing the model output in multiple scenarios confirms the reliability of the model, but also addresses the generalizability of the model at different scales of emergency response. For example, if the injury severity level for one patient is changed from minor to immediate and all other variables remain constant, comparing the updated model output with the original model output confirms the model is responding correctly to variation in uncontrollable inputs. This process was repeated for other controllable and uncontrollable variables. The specific locations and variations in model construction are discussed in the data analysis portion of this chapter, as well as in Chapter IV.

Reliability of Patient Variables. Existing models are used for injury risk categorization because these processes are widely used in the triage field to measure injury severity and have been studied extensively. These triage models are outlined in Chapter II as the theoretical foundation for the study. The manual manipulation of risk, location, and medicine variables was iterative, occurring during the model build process outlined above, as well as the subsequent sensitivity analysis. Table 9 shows how each patient variable was selected and manipulated during the sensitivity analysis to confirm reliability.

Table 9

Selection and Manipulation of Patient Variables

Variable	Input Type	Initial Model Output	Sensitivity Analysis
Number of Patients	Deterministic	5	7, 15
Injury Risk	Stochastic	random number generator, 100, 300, 500	random number generator
Injury Location	Stochastic	random location generator	random location generator
Required Medicine Weight	Stochastic	random number generator, 0-6	random number generator

Reliability of Environmental Variables. Groundspeed is calculated using the wind angle in reference to the direction of travel, true airspeed, and wind velocity. Using an existing formula to calculate sUAS groundspeed ensures acceptable construct reliability. For reliable input data during the what-if scenario testing and Monte Carlo simulations, NOAA databases for weather conditions were used to determine wind speed and direction for each location. Each location dataset was evaluated using SPSS Version 28 to ensure no missing data were present.

Just as the stochastic patient variables were manually manipulated during the sensitivity analysis on the initial output, the stochastic environmental variables were altered during the sensitivity analysis on additional locations. While the primary objective of testing different locations is to demonstrate model generalizability, changing the environmental conditions, as seen in Table 10, also demonstrates the reliability of the outputs with a variety of wind directions and speeds. While the historical data indicated location-specific trends for both direction and velocity, a stochastic wind direction value was obtained for the initial model output to demonstrate both reliability and generalizability. The mode of the dataset was used for the sensitivity analysis at each additional location. The wind velocity for the initial model output was set to roughly 95% of the maximum wind velocity observed in the historical data, and additional location-specific sensitivity analyses were conducted at 5% above the minimum observed wind velocity and 95% of the maximum observed wind velocity at each location.

Table 10

Stochastic Environmental Variables

Variable	Input Type	Initial Model Output	Sensitivity Analysis
Wind direction	Stochastic	Random number generator (0,360)	Mode
Wind velocity	Stochastic	10	5%, 95%

Reliability of sUAS Variables. The input reliability of aircraft performance data is defined by the end-user, including airspeed, endurance, and payload capacity variables. The what-if scenarios also use sUAS variables from commercially available platforms, and environmental conditions were retrieved for each location to ensure the model is valid for a wide range of operational uses. This ensures future scenarios of increasing complexity produce reliable results, regardless of scale. Future outputs would also be reliable due to the objective nature of mathematics. The sUAS variables for the initial output and subsequent sensitivity analysis are listed in Table 11.

Table 11

sUAS Variable Values

Variable	Input Type	Routing Model (Mississippi)	Sensitivity Analysis
Available sUAS	Deterministic	1	3
Airspeed (mph)	Deterministic	22	35
Payload capacity	Deterministic	10	15, 20
Endurance (minutes)	Deterministic	100	150

Validity Assessment Method

sUAS variables. Inputs for aircraft performance data during the model testing and validation phase were based on currently available sUAS capabilities. Because sUAS delivery is not widespread, many platforms are being custom-built by large multinational corporations who can afford the research and development costs. Amazon is currently testing a multirotor sUAS designed to carry a 5 lb (2.27 kg) package up to 15 mi (24.14 km) (Lardinois, 2019). Wing, owned by Google, is partnering with FedEx to develop an sUAS that can travel up to 60 mph (96.56 kph) and carry a 3 lb (1.36 kg) payload up to 6 mi (4.8 km) (Murphy, 2019). UPS, however, is approaching delivery service differently by partnering with Matternet, a Swiss company specializing in commercial drone technology. The Matternet M2 is currently authorized by the Swiss Aviation Authority to operate delivery services over cities and was the first platform approved by the FAA for unmanned Part 135 certification. The M2 has a range of 12 mi (19.32 km) and a payload capacity of 6 lb (2.72 kg), which is adequate to carry lightweight defibrillators along with other medical supplies.

For model construction and validation, no specific vehicle was used for the inputs of sUAS vehicle variables. While the M2 is a potential candidate for medical delivery after natural disasters because it is commercially available and has been certified by multiple federal aviation agencies, the battery limitations make delivery operations in rural areas difficult to execute. Instead of testing the model with one platform, a variety of vehicle capabilities were selected through a review of the existing technology. As technology advances and capabilities increase, the model allows for this expansion because these model constructs are manually entered by decision-makers. Adjusting the values of airspeed, payload capacity, and endurance during the sensitivity analysis demonstrates model generalizability throughout a wide range of platforms.

Patient Variables. Because the location, risk value, and medicine weight are all stochastic and obtained through random generators, these variables remain valid regardless of scenario location. However, the number of patients requires further analysis to determine model generalizability during disaster responses of differing magnitudes. For the sensitivity analysis, additional model outputs were obtained for seven and 15 patients to demonstrate model generalizability throughout varying scales of disaster response.

Environmental Variables. The location-specific sensitivity analysis for wind direction and wind velocity was conducted to determine how different environmental conditions would affect the optimal risk minimization route. The wind values for each location were selected based on 1 year of hourly environmental data from NOAA. Windspeed values at 5% and 95% of the total yearly distribution were calculated in SPSS Version 28 and used as the input variables to calculate travel time at each location during low wind and high wind conditions.

The sensitivity analysis results ensure the model is reliable and generalizable to different locations, environmental conditions, sUAS vehicles, and scope of emergency response. The results are discussed in detail in Chapter IV.

Demographics

External validity is addressed in the model validation phase through multiple what-if scenarios of varying complexity and location. The four rural locations are Purvis, Mississippi; Winslow, Arizona; McCall, Idaho; and Floyd, New York. According to the U.S. Census Bureau, the median age in rural communities is 51, and the median household income is $52,386. The average age of all four sample communities is 45, and the median salary of the sample locations is $51,678. Purvis and Floyd have relatively low average age and income, while McCall and Indian Wells have higher average ages and incomes. This broad sample of age, income, and geographic locations confirms the model can be useful in multiple disaster response scenarios within the U.S.

Modeling and Data Analysis Process

Following the identification of model variables, objective functions, and constraints, the data was coded into the appropriate LINGO syntax. For the baseline model validation, one sUAS vehicle and five randomly generated points were used to create the scenario. An online random point generator was utilized to identify the distance and bearing from the center point (sUAS hub), and the RANDBETWEEN formula in Microsoft Excel was used to randomly assign one of the injury severity categories. An example dataset is shown in Table 12 and Figure 14.

Table 12

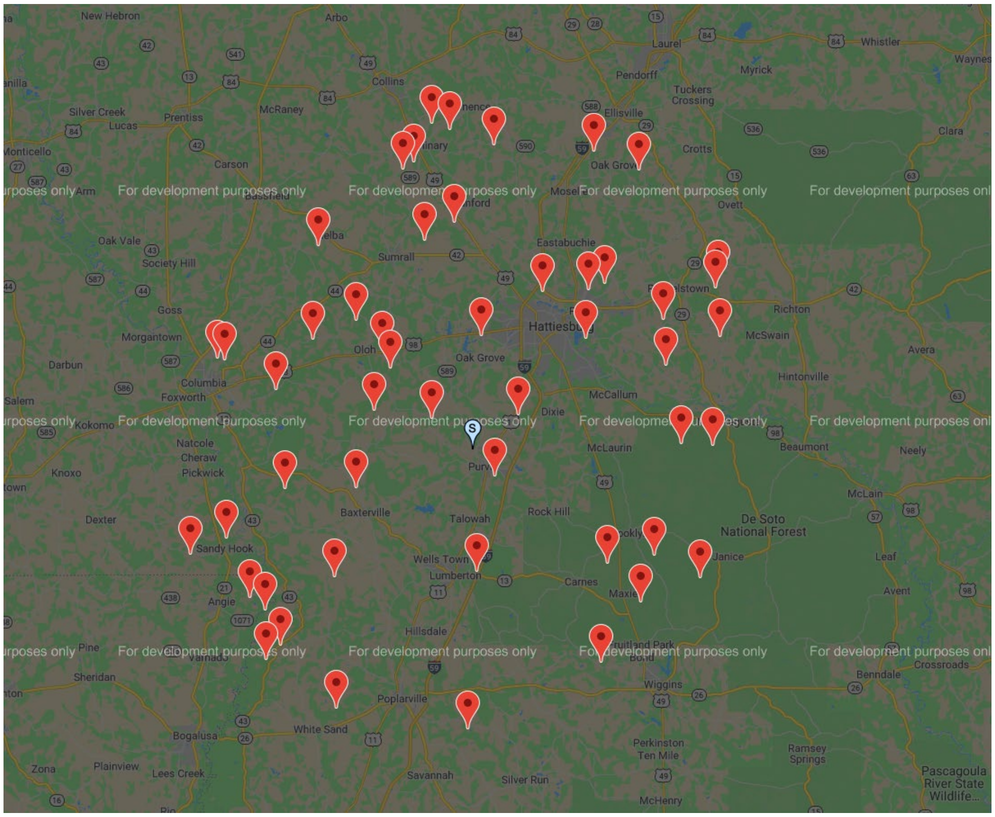
Random Injury Location and Severity

Distance	Bearing	Severity
23.7538	232.253°	Delayed
21.6651	89.155°	Minor
~~9.5199~~	~~291.378°~~	~~Expectant/Dead~~
5.0835	53.298°	Minor
15.946	130.286°	Immediate
26.6462	224.436°	Immediate
~~24.4493~~	~~65.562°~~	~~Expectant/Dead~~
3.1829	140.286°	Minor
17.6877	35.982°	Minor
26.2124	56.31°	Minor
~~10.2486~~	~~4.248°~~	~~Expectant/Dead~~
26.5086	207.831°	Immediate
~~14.2634~~	~~45.552°~~	~~Expectant/Dead~~
18.5367	286.648°	Minor
23.6032	119.452°	Delayed
19.0847	38.581°	Delayed
24.8456	224.426°	Delayed
24.2104	236.343°	Delayed
20.7218	55.801°	Minor
17.041	227.281°	Minor

Note. Strikeouts indicate patients reported as expectant/dead which will not be included in the model.

Figure 14

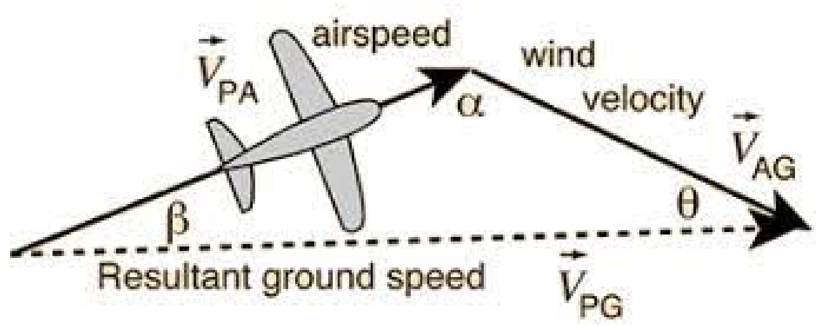
Randomly Generated Patient Locations



To determine the secondary objective of total travel time, the groundspeed of the sUAS must be calculated and converted to a travel time matrix for LINGO to calculate an optimal solution. The required variables to determine groundspeed are airspeed, heading, distance, wind speed, and wind direction. The relationship between these variables can be visualized in Figure 15, with corresponding mathematical calculations listed in the formulas below.

Figure 15

Trigonometric relationship between wind and aircraft



Note. β is the offset angle, θ is the difference between wind direction and desired bearing. V_{PG} is the resultant groundspeed vector, V_{PA} is the airspeed vector, and V_{AG} is the wind velocity vector. By Nave (n.d.). In the public domain.

Airspeed is a deterministic input, and sUAS heading and distance were determined by trigonometric calculations. The randomly generated location data was transferred to an excel spreadsheet in latitude/longitude format, where the relative heading between every combination of patient locations was calculated using Equation 4.

Heading = degrees(atan2(cos(radians(lat1))*sin(radians(lat2))-sin(radians(lat1))*cos(radians(lat2))*cos(radians(lon1-lon2)),sin(radians(lon2-lon1))*cos(radians(lat2)))) (4)

To determine groundspeed, the trigonometric function in Equation 5 was applied to each true course value.

Groundspeed = true airspeed*cos(radians(true course+degrees(asin(wind velocity*sin(radians(wind direction-true course))/true airspeed))-true course))-wind velocity*cos(radians(wind direction-true course)) (5)

The final step in calculating the travel time between each patient is the distance calculation between each point. Using the latitude and longitude of both points, plus the radius of the earth at 3443.8985 nautical miles, the formula in Equation 6 was used.

Distance = acos[(sin(lat_place_1*pi()/180)*sin(lat_place_2*pi()/180)+cos (lat_place_1*pi()/180) *cos(lat_place_2*pi()/180)*cos(lon_place_2*pi()/180-lon_place_1*pi()/180))] *3443.8985 (6)

Equations 4 to 6 that calculate distance and groundspeed between two points allow for one final calculation to be made: *Travel time= distance/speed*

The complete formula for travel time is as presented in Equation 7.

Travel time = (acos[(sin(lat_place_1 * pi()/180) * sin(lat_place_2 * pi()/180) + cos(lat_place_1 * pi()/180) * cos(lat_place_2 * pi()/180) * cos(lon_place_2 * pi()/180-lon_place_1 * pi()/180))] * 3443.8985) / true airspeed * cos(radians(true course + degrees(asin(wind velocity * sin(radians(wind direction-true course)) / true airspeed))-true course))-wind velocity * cos(radians(wind direction-true course)) (7)

Using Equations 4–7, the travel time matrix was built and transferred to LINGO to generate an optimal solution. To ensure the model remains useful to first responders, the maximum allowable computation time was limited to 180 s, or 5% of the available time to reach a patient with an immediate injury. Calculation times outside of this window are considered operationally unusable and would require model adjustments to reduce the calculation time to acceptable values under 180 s.

Model results are displayed in Chapter IV for each iteration of the reliability and generalizability test and will include the output for both objective functions. For risk minimization, results will be displayed as a penalty for each missed delivery. This value is compared to the total available risk minimization in a given set of patients to objectively evaluate the optimal route for a given set of inputs and constraints. A risk reduction of 100% would indicate that all patients received the appropriate medication.

Summary

The model constructed for this research utilizes the variables outlined in the literature review to build a mathematical formula designed to output the optimal sUAS routing to minimize risk, with a secondary goal of minimizing travel time. The routing solution is constrained by vehicle limitations, environmental conditions, patient location, and injury severity. Risk minimization is calculated based on these variables, followed by a secondary calculation to minimize total travel time for a given optimal risk minimization value.

Chapter IV

Results

The purpose of this study was to develop a risk minimization model for rural area medical deliveries after a natural disaster. To answer the research questions posed in Chapter I, a mathematical model was constructed to identify the relationships between the two objective functions and model constraints. The mathematical model was then coded into LINGO Version 19.0 with a combination of deterministic and stochastic inputs. The deterministic variables were obtained by reviewing extant literature on current sUAS capabilities and limitations such as vehicle endurance, airspeed, and payload capacity. The stochastic inputs were selected by evaluating historical climate data from Purvis, Mississippi, followed by an analysis of the dataset in SPSS Version 28 to confirm the completeness of the dataset and observe the descriptive statistics and distribution. The mean and standard deviation values from the historical climate data were then used as input variables for two Monte Carlo simulations to observe the groundspeed distribution in a large dataset. The results of the simulation, discussed later in the chapter, confirm the distribution is similar to the groundspeed values used in the LINGO model, demonstrating the mathematical formulas used to calculate the groundspeed input values are reliable.

After achieving an initial output, multiple what-if scenarios were conducted to evaluate the sensitivity of the model to changing environmental variables and a variety of sUAS capabilities. The results of the sensitivity analysis are used to demonstrate model generalizability across a wide range of disaster response scenarios.

Mathematical Model

The following mathematical model is an adaption of the standard CVRP formulation (Markov, 2015), updated to reflect the novel risk minimization variable in this study. The Markov formula has been validated in previous studies and adapted for similar routing models (Markov et al., 2017; Markov et al., 2020).

A group of sUAS $K = (k_1, \ldots, k_m)$ are available to transport medicine to a set of patients P. Let $G = (P, A)$ be a graph where $P = (P_0, \ldots P_{n+1})$ is the set of vertices representing patients (p), with $p \in P$, and $A = \{(V_i, V_j): i \neq j \wedge i, j \in V\}$ be a set of arcs representing the available routes that must start and end at the depot (i=0).

Each patient p has:

- A risk score R_p. The sum of R_p for a set of patients = R_T, representing the total risk value set P.
- A required deliverable demand q_i representing the requested medicine weight at location i.
- A fixed transition time z to land, unload medicine, depart for the next location.

Each sUAS vehicle k has:

- A travel time t from patient i to j
- A maximum payload capacity Q
- A maximum endurance k_e
- Each vehicle will depart and return to the depot i=0

X_{ijk} is a binary variable, $X_{ijk} = 1$ indicates that the sUAS k flies from i to j, otherwise, $X_{ijk} = 0$

Y_{ik} is a binary variable, $Y_{ik} = 1$ indicates that the sUAS k visits node i and fulfills the deliver requirement q_i, otherwise, $Y_{ik} = 0$

U_{ik} is the cumulative demand serviced by vehicle k when arriving at node i.

$$\text{Min} R_T = \sum_{k \in K} \sum_{i \in P} \sum_{j \in P} R_p \, X_{ijk} \tag{8}$$

Equation 8 is the objective function to minimize total patient risk (R_T) where R_p is the risk value at a patient location and $X_{ijk} = 1$ if sUAS k visits patient p along route i,j, otherwise $X_{ijk} = 0$.

$$\text{Min} T = \sum_{k \in K} \sum_{i \in P} \sum_{j \in P} X_{ijk} \, (t_{ij} + z) \tag{9}$$

Equation 9 is the objective function to minimize the sum of mission durations for all routes where sUAS k visits patient p along route i,j, with t_{ij} representing the time from i to j, and z representing the fixed constant for landing, unloading medicine, and resuming forward flight, subject to Equations 10−19.

$$\sum_{k \in K} Y_{ik} \leq 1, \quad \forall \, i \in P \tag{10}$$

Equation 10 ensures a patient only receives at most one delivery from a vehicle k. Unlike traditional CVRP models, this equation does not guarantee each patient receives a visit; only that the maximum number of visits cannot exceed 1.

$$\sum_{j \in P/\{i\}} X_{ijk} - \sum_{j \in P/\{i\}} X_{jik} = 0, \quad \forall\, i \in P,\ k \in K \tag{11}$$

Equation 11 is a path flow constraint to ensure continuity within a selected route. Each vehicle k must arrive and depart the same number of patient locations.

$$\sum_{j \in P/\{i\}} X_{0jk} - \sum_{j \in P/\{i\}} X_{j0k} = 1, \quad k \in K \tag{12}$$

Equation 12 is also a path flow constraint and ensures each vehicle k can only leave the depot once. The depot is identified as $i = 0$. The first three constraints can be summarized that for all sUAS vehicles k in the set K, a selected route must leave the depot $i = 0$ once, visit a patient p no more than once, and end at the same depot $i = 0$ where the route originated.

$$Y_{ik} = \sum_{j \in P/\{i\}} X_{ijk},\ \forall\, i \in P, k \in K \tag{13}$$

Equations 13 is a coupling constraint to ensure Y_{ik} is linked to the binary decision variable X_{ijk}.

$$X_{ijk} \in \{0,1\}, \quad \forall\, i,j \in P, k \in K \tag{14}$$

$$Y_{ik} \in \{0,1\}, \quad \forall\, i \in P, k \in K \tag{15}$$

Equations 14 and 15 ensure X_{ijk} and Y_{ik} are binary variables, as both the route X_{ijk} and the delivery Y_{ik} are either selected or not selected on a given route for vehicle k.

$$U_{ik} + q_j \leq U_{jk} + Q(1 - X_{ijk}), \forall i,j \in P,\ k \in K \tag{16}$$

Equations 16 is a subtour elimination constraint, linking the node demand for q_j with the cumulative demand U_{ik} in a big-M fashion where:

U_{ik} = Cumulative demand serviced by vehicle k when arriving at node i.

q_j = Requested medicine weight at location j.

Q = Vehicle payload capacity

$$q_i \leq U_{ik} \leq Q,\ \forall\ i \in P, k \in K \tag{17}$$

Equations 17 is also a subtour elimination constraint, and provides the lower bound for U_{ik}, ensuring vehicle capacity Q is not exceeded for a selected route where:

q_i = Requested medicine weight at location i.

U_{ik} = Cumulative demand serviced by vehicle k when arriving at node i.

Q = Vehicle payload capacity

$$X_{ijk}\,(t_{ij} + z) \leq k_e, k \in K \tag{19}$$

Equation 19 ensures the total route travel time does not exceed vehicle endurance K_e where:

t_{ij} = Travel time from patient i to patient j.

z = Fixed transition time to land, unload, and resume flight.

k_e = Maximum endurance for vehicle k

Input Variables

Purvis Mississippi was selected as the location for M_1 due to the flexibility provided by the entire city being categorized as a rural area. The three other locations are tested during the sensitivity analysis to confirm model generalizability. Five patient locations were identified within a 10-mi radius using an online random point generator. In Purvis, the local hospital was selected as the center point and depot, as emergency operations centers are frequently collocated with hospitals in disaster response plans. The center point (depot) and five simulated patient locations, listed P1–P5, are displayed in Figure 16. The complete list of model variables for the initial model scenario can be found in Table 13. The specific details for each patient are listed in Table 14.

Figure 16

Patient Locations

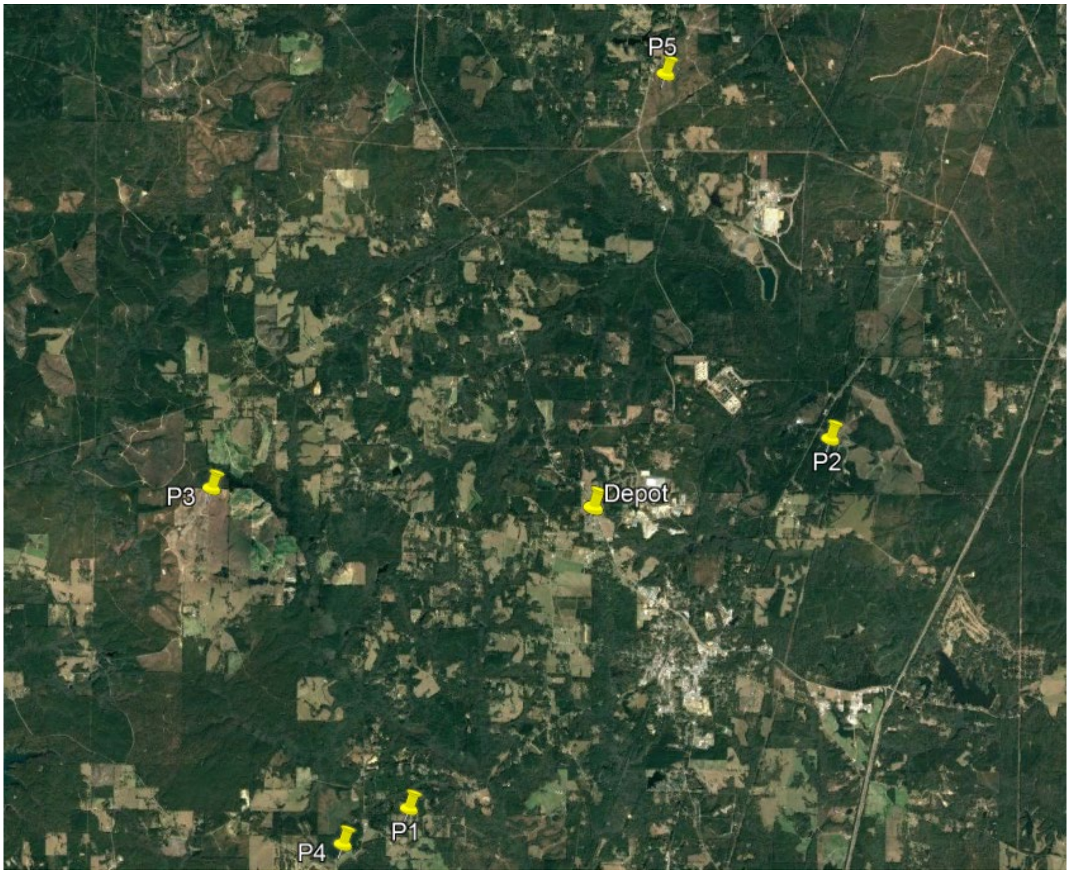


Table 13

Initial Model Variables

Variable	Value
Location	Mississippi
Patients	5
Wind direction	270
Wind velocity (mph)	10
Payload capacity	10
Total required medicine weight (sum of patient requirements in scenario)	20
Total patient risk (sum of patient risk in scenario)	1,300
Airspeed (mph)	22
Endurance (minutes)	100
Available sUAS vehicles	1

Table 14

Initial Model Patient Locations

	Longitude	Latitude	Penalty Value	Medicine Weight
Patient 1	-89.4599	31.1181	300	3
Patient 2	-89.3820	31.1776	100	6
Patient 3	-89.4971	31.1689	300	5
Patient 4	-89.4721	31.1124	100	4
Patient 5	-89.4132	31.2356	500	2
			1,300	20

For the initial scenario M_1, Patient 5 has the highest risk value and the lightest medicine weight. Patient 2 has the lowest risk value and the heaviest medicine weight. The values in Table 14 were altered during the sensitivity analysis to demonstrate model generalizability, with results discussed later in this chapter.

Monte Carlo Simulation for Environmental Variables

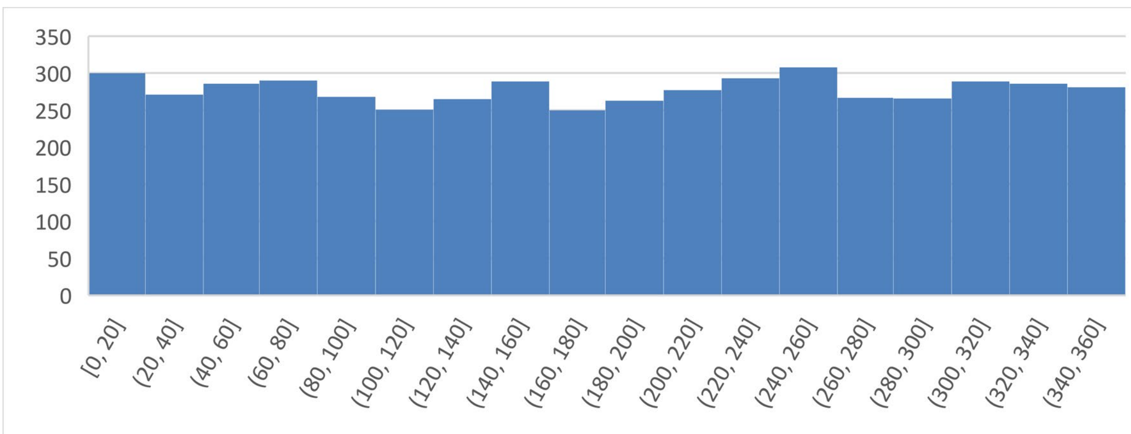
The values for all deterministic variables were selected based on a literature review of currently available commercial sUAS. The environmental variables, however, require a different approach to ensure the model is robust to a variety of potential environmental conditions and the groundspeed calculations used to determine travel time are accurate. The effects of wind velocity and wind direction on sUAS groundspeed are particularly important, as groundspeed will determine if the vehicle is able to complete a given route before maximum endurance is exceeded. To demonstrate input reliability for these stochastic variables, two Monte Carlo simulations were used, each with 5,000 trials. The descriptive statistics for the simulated dataset and actual dataset used for the M_1 results can be found in Appendix A.

Stochastic Simulation

The first test for input reliability is a stochastic simulation where every trial is independent. The data found in Figure 17 show the distribution for the heading to a patient location using the =RANDBETWEEN(0,360) formula in Excel, as there is no way to predict what heading a patient will be located at in relation to the depot. As expected for a randomly selected heading, the distribution is uniform.

Figure 17

sUAS Heading Distribution: Stochastic Simulation

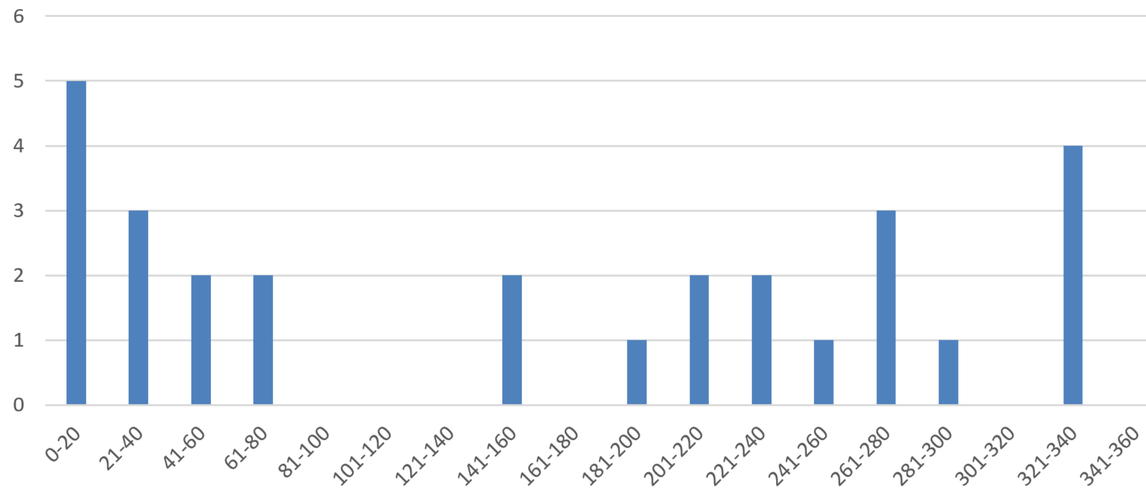


Note. sUAS = small unmanned aircraft system.

This uniform distribution can be compared to the data used in a 7-patient scenario where groundspeeds are calculated using seven randomized patient locations (see Figure 18).

Figure 18

sUAS Headings for the 7-Patient Scenario



Note. sUAS = small unmanned aircraft system.

The data for the 7-patient scenario only includes 56 data points compared to the 5,000 data points in the simulation, but both datasets have a similar distribution, as expected.

Wind direction and wind velocity for a given location are not random, and trends in weather patterns are published by NOAA in an online database for historical climate data. Hourly wind data were obtained for an entire calendar year resulting in 8,760 data points. The descriptive statistics for the nearest weather station to the four model locations can be found in Tables 15 and 16. The wind velocity values of 5% and 95% are included because the sensitivity analysis was conducted using these wind intervals to demonstrate model generalizability across a wide range of location-specific wind conditions. Histograms for velocity and direction at each location can be found in Appendix B.

Table 15

Descriptive Statistics Results for Hourly Wind Velocity (miles per hour)

Location	*M*	IQR	*SD*	Median	Min	Max	Skewness	Kurtosis	5%	95%
Jackson, MS	6.30	3.3	2.068	6.3	2.0	10.7	0.036	-0.837	3.0	9.7
Syracuse, NY	8.41	3.0	2.006	8.8	4.0	12.7	-0.259	-0.805	4.9	11.5
Boise, ID	7.83	2.0	1.474	7.4	4.9	11.7	0.78	-0.406	6.0	10.8
Winslow, AZ	7.66	3.8	2.834	6.9	3.7	15.9	0.975	0.189	4.5	13.8

Note. IQR = Interquartile range.

Table 16

Descriptive Statistics for Hourly Wind Direction (miles per hour)

Location	*M*	IQR	*SD*	Median	Min	Max	Skewness	Kurtosis
Jackson, MS	146	84	80.715	139	1	360	0.705	0.107
Syracuse, NY	257	31	28.581	262	160	314	-0.724	0.150
Boise, ID	204	177	87.38	150	1	360	0.382	-1.513
Winslow, AZ	215	52	39.046	225	7	359	-0.927	1.671

Note. IQR = Interquartile range.

Because Purvis, Mississippi is used for the initial model, the stochastic simulation trials included a random wind velocity and direction within the normal distribution by inputting the mean and standard deviation for Purvis. The wind direction formula for each of the 5,000 trials in the stochastic simulation is: *NORM.INV(RAND(),146,80.715)* The wind velocity formula for each of the 5000 trials in the stochastic simulation is: *NORM.INV(RAND(),6.3,2.0678)*

Stochastic Simulation Results

The simulation groundspeed distribution is displayed in Figure 19 and actual groundspeeds for the initial model using the seven patient locations are illustrated in Figure 20.

Figure 19

Stochastic Simulation Histogram: Groundspeed

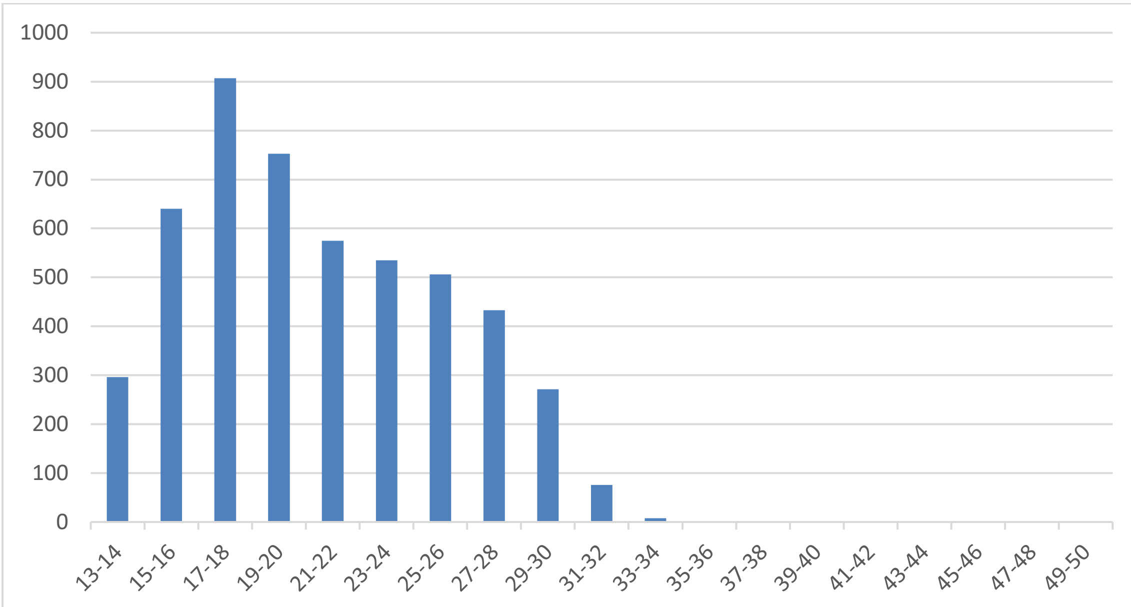
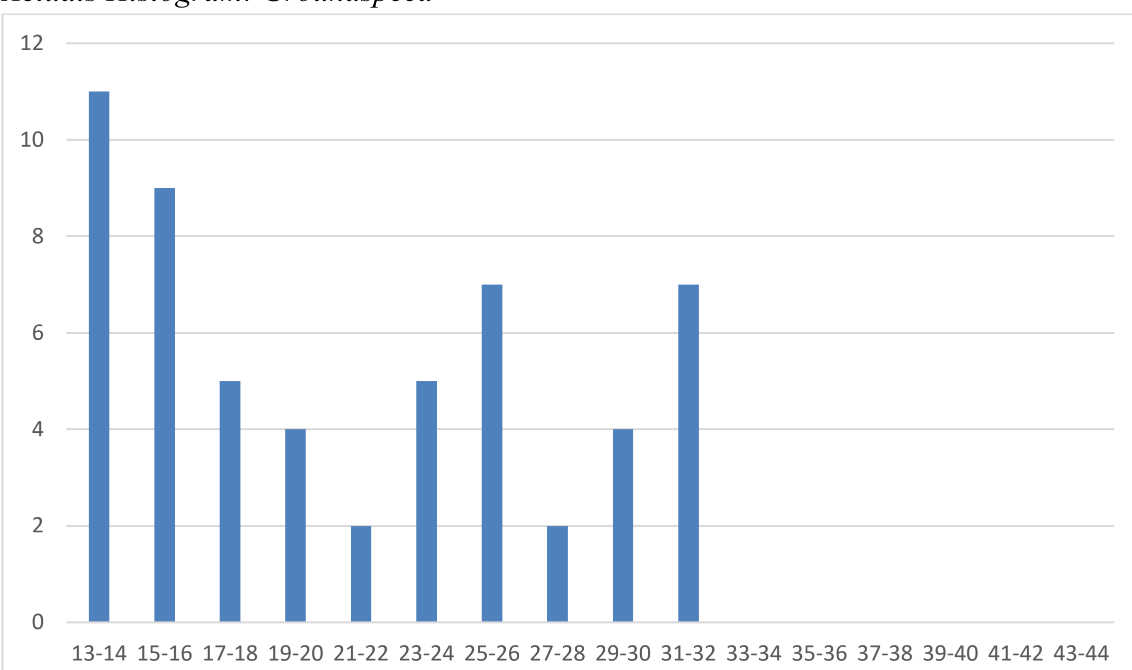


Figure 20

Actuals Histogram: Groundspeed



The groundspeed distribution on the 5,000 simulated trials has a skewness of .032 and a kurtosis of -0.935, compared to the skewness of 0.297 and kurtosis of -1.299 from the 56 data points for the 7-patient scenario. Because the mathematical equations used for both datasets are the same, differences in the distribution can be attributed to the difference in sample size. The simulation data was transferred from Excel to SPSS for further evaluation of the distribution. In the simulation options, SPSS has an option to automatically identify the distribution that most accurately fits the input data, which was used to evaluate the distribution of multiple Monte Carlo Simulation outputs. As expected, the fit statistics varied significantly depending on the simulation output; over a sample size of 10 trials, SPSS identified the distribution as lognormal 5 times, uniform 3 times, and gamma 2 times. This demonstrates the stochastic nature of the environmental variables as they influence vehicle groundspeed over a large dataset.

Deterministic Simulation

The same 5,000 trial simulation process was completed for a deterministic scenario, where the trials are *not* independent. Instead, the deterministic simulation uses the same wind direction and wind speed for all trials, simulating the environmental conditions of a specific day for all 5,000 iterations. The airspeed is also deterministic and uniform for all trials. Only the patient distance, which is limited to a 10-mi radius from the depot and required sUAS heading is stochastic. The formula used to obtain a randomized patient distance is:

*= RAND()*10+0*

And the formula used to obtain a randomized sUAS heading is:

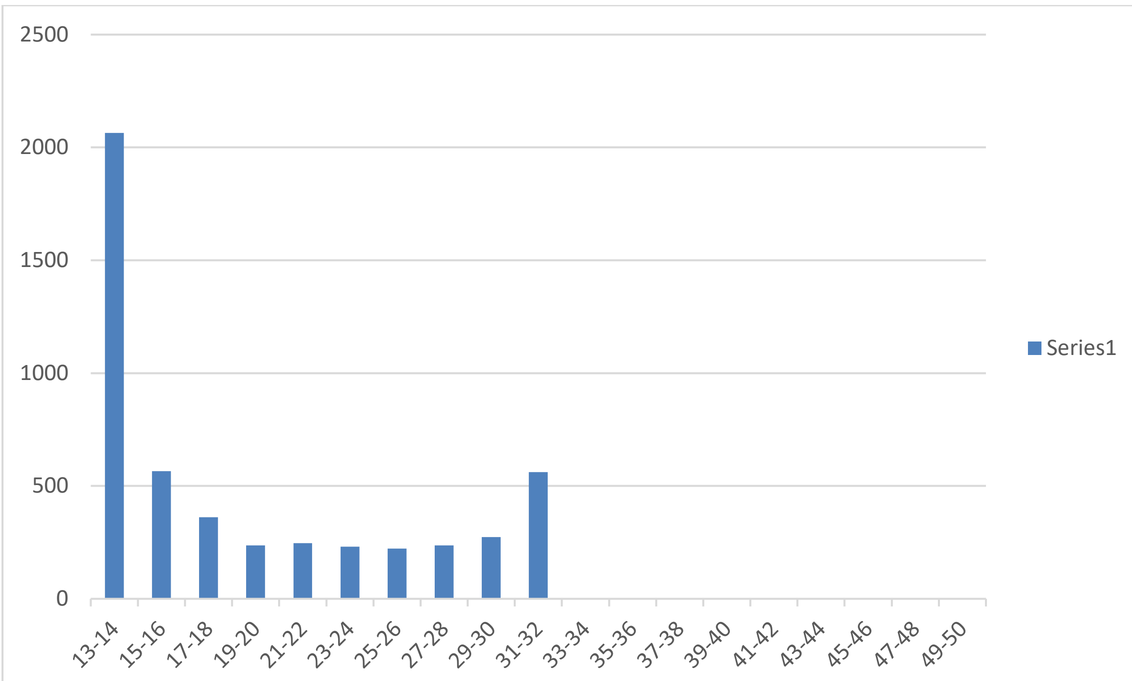
= RANDBETWEEN(0,360)

Deterministic Simulation Results

The comparison output for the 5,000-trial deterministic simulation can be found in Figure 21 and again compares the simulation to the actual initial dataset in Figure 20.

Figure 21

Deterministic Simulation



Like the stochastic simulation, the same formulas were used for both groundspeed calculations. The simulation skewness is 0.249, compared to 0.297 for the model output. The kurtosis of the simulation is -1.458, similar to the platykurtic results of the model output at -1.299. The number of trials with very high or very low groundspeeds demonstrate the nonlinear relationship between wind direction and vehicle heading in a scenario with randomized headings. Depending on the size of the airspeed and wind velocity vectors, the law of cosines is applied through the groundspeed formula shown in Equation 19 that was used for the simulation trials.

*=TAS*COS(RADIANS(HDG+DEGREES(ASIN(Wind Velocity*SIN(RADIANS(Wind Direction-HDG))/TAS))-HDG))-Wind Velocity*COS(RADIANS(Wind Direction-HDG))* (19)

A simple way to interpret the simulated groundspeed graph for the deterministic scenario is a traditional cosine wave. Changing the airspeed and wind direction simply alters the period and amplitude of the simulation data. The results of the deterministic and stochastic Monte Carlo simulations demonstrate the random nature of the groundspeed variables in a large dataset, confirming the utilization of stochastic patient locations, distances, and wind values in the LINGO model.

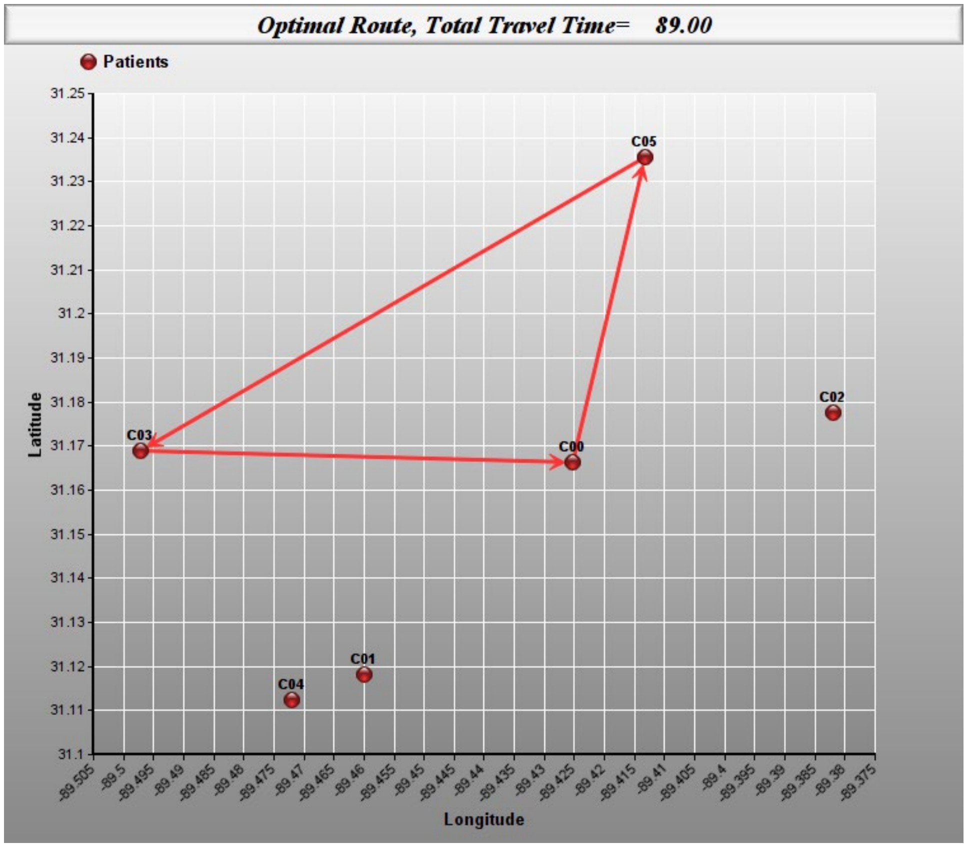
Initial Model Results

Following confirmation of input reliability from the Monte Carlo simulation results and confirmation of coding accuracy from external experts, an initial model run (M_1), was obtained in a relatively simplistic scenario. The M_1 output is used as a baseline for the sensitivity analysis discussed later in this chapter to confirm model generalizability through the use of multiple what-if scenarios. The complete LINGO code used to obtain these results can be found in Appendix C.

The results from M_1 are displayed in Figure 22. The optimal route for risk minimization is to travel to Patient 5, followed by Patient 3, and return to the depot. The total route travel time with the wind conditions set to 10 kt at a direction of 270º is 89 min and includes a 2-min transition time at each location. The total penalty for missing Patients 1, 2, and 4 is 500, for a total risk minimization value of 800. The total runtime to obtain both objective functions was 0.63 s to run 1,199 iterations.

Figure 22

Initial Model Results



A traditional routing problem with no vehicle or capacity restraints would return the shortest travel time to visit all five patients. For the set of patients in this scenario, the shortest travel time is 129.7 min, which includes a 2-min transition time at each location to account for unloading and reinitiating flight. If the model is limited by all the constraints listed in the above table *except* risk, the model returns a route to Patients 4 and 1, mirroring the results of a traditional capacitated vehicle routing problem. Delivering medicine to Patient 4 and Patient 1 only reduces the risk by 400, which is only 50% of the risk reduction obtained by M_1. Comparing the results of a traditional routing problem to the results of this model demonstrates the extent to which this model realistically captures the variables that impact sUAS delivery during disaster response.

Model Reliability and Validity

The sensitivity analysis for the model requires multiple what-if scenarios on each variable, which can be found in Table 17. Iterative sensitivity testing in small scenarios allow for observation of results with clear changes in optimality following the manipulation of a single variable. Reliability can be defined as a measure of model consistency over multiple iterations, while validity is a measure of model accuracy over multiple scenarios. Because this research is focused on developing a novel stochastic model and not improving an existing model, model reliability and generalizability will be evaluated. The structured process of building and testing the initial model increases reliability through iterative testing as each new variable is added. Model generalizability, however, requires additional sensitivity analysis through multiple what-if scenarios. As these scenarios are conducted, model reliability is also continually demonstrated through additional model iterations.

The results presented in Table 17 are a sample of scenarios to demonstrate the process of confirming model reliability and generalizability. As each variable is tested, a new value is used for the model input. The stochastic patient variables (injury risk value, injury location, required medicine weight) were tested during the initial model construction and verification process. The stochastic environmental variables and deterministic vehicle variables were evaluated during the sensitivity analysis. Observing the expected changes to the optimal route in these scenarios demonstrates model reliability, with future scenarios maintaining the same level of reliability due to the objective nature of mathematics. The process of testing the range of acceptable values for each variable also demonstrates model generalizability for a wide range of potential disaster response scenarios.

Table 17

Sensitivity Analysis Values

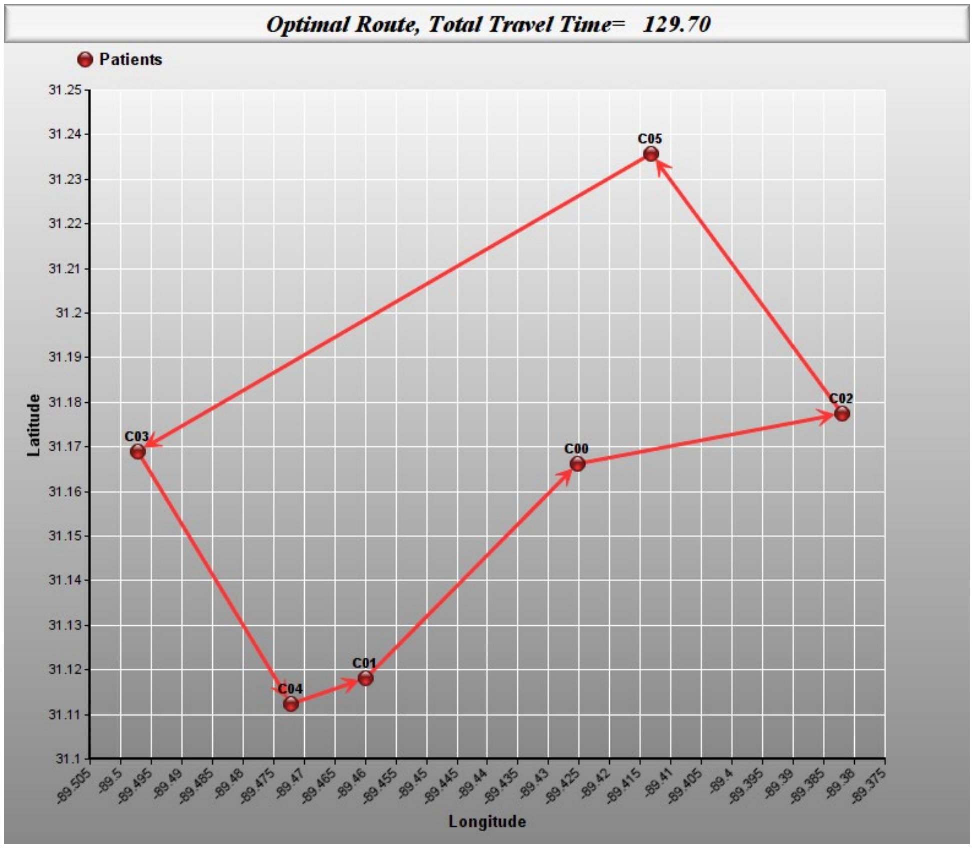
Variable	Input Type	Initial Model	Confirmatory Test
Injury risk	Stochastic	Random number generator	Model verification
Injury location	Stochastic	Random location generator	Model verification
Medicine weight	Stochastic	Random number generator	Model verification
Wind direction	Stochastic	270	Scenario 5
Number of patients	Deterministic	5	Scenario 3
Wind velocity	Stochastic	10	Scenario 2, 5
Available sUAS	Deterministic	1	Scenario 4
Airspeed	Deterministic	22	Scenario 1
Payload capacity	Deterministic	15	Scenario 4
Fuel capacity	Deterministic	100	Scenario 1

Scenario 1: Vehicle Performance Improvement

The initial model had an endurance of 100 min, which limits the route to two patients. Increasing the endurance to 150 min is a simple change to observe model reliability, as well as demonstrate generalizability for a range of sUAS endurance capabilities. The results of this change can are provided in Figure 23.

Figure 23

Endurance Increase



Increasing vehicle endurance allows for all five patients to receive medicine, with a total route time of 129.70 min. If the vehicle endurance is reduced to the original value of 100 but the speed is increased to 35 mph (56.32 kph), there is a similar result. All patients receive a delivery and the total route time is reduced to 78.6 min. These scenarios demonstrate the value of modeling potential disaster response scenarios before they occur; disaster management agencies can observe potential outcomes depending on the sUAS vehicles available. Testing these vehicle limits demonstrates model reliability because the effect of changing airspeed and endurance can be observed. This process also demonstrates model generalizability for more capable aircraft that could be available in the future.

Scenario 2: Environmental Changes

Increasing the wind value by 50% increases sUAS travel time significantly. Table 18 contains the travel time matrix used as the input for the initial scenario M_1, and Table 19 contains the travel time matrix when wind velocity is increased from 10 mph (16.09 kph) to 15 mph (24.14 kph) The wind direction remains the same at heading 270º.

Table 18

M_1 Travel Times

	Depot	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Depot	0	25.0	8.2	34.2	30.9	22.1
Patient 1	14.8	0	21.0	26.7	6.3	35.9
Patient 2	21.1	44.1	0	54.9	50.3	26.9
Patient 3	12.8	15.6	20.7	0	17.2	23.1
Patient 4	16.9	2.6	23.5	24.6	0	37.4
Patient 5	25.7	49.7	17.6	48.1	54.9	0

Table 19

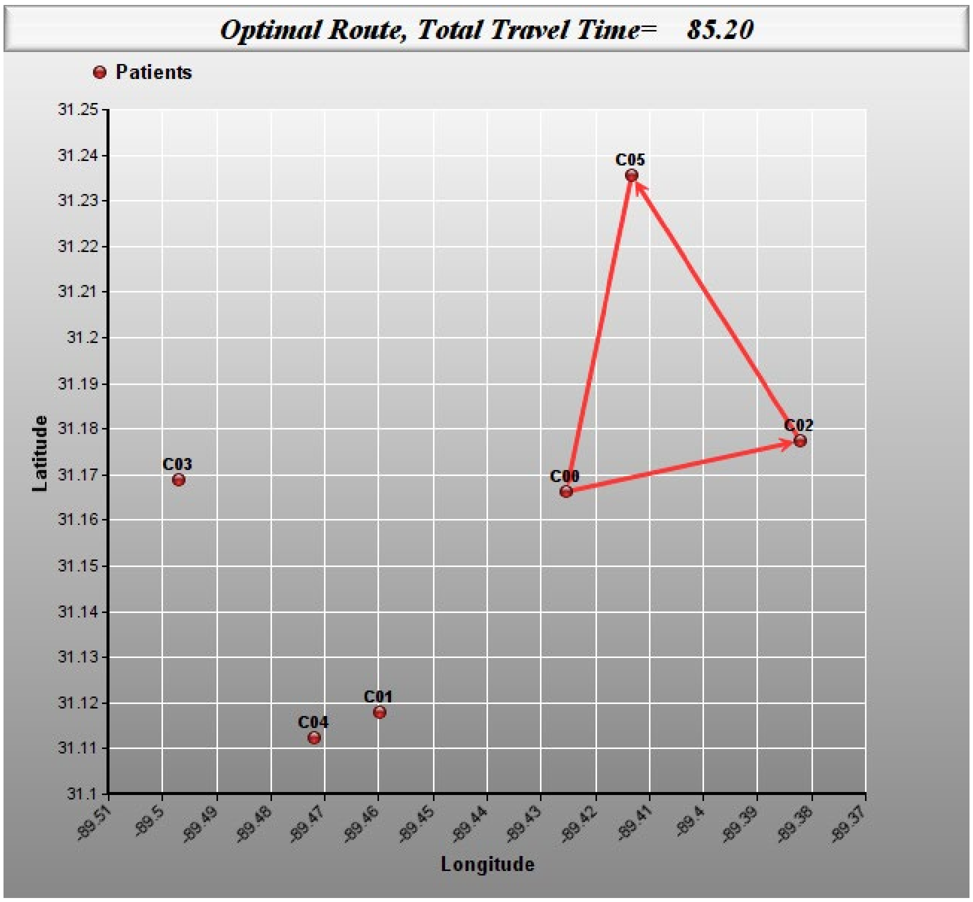
50% Wind Increase Travel Times

	Depot	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Depot	0	37.5	7.2	58.6	47.4	25.3
Patient 1	14.6	0	19.4	40.1	10.5	38.3
Patient 2	35.8	70.9	0	94.0	81.2	38.7
Patient 3	11.1	15.4	17.9	0	18.1	21.4
Patient 4	16.4	2.4	21.6	34.7	0	39.1
Patient 5	33.3	69.1	18.1	76.9	78.0	0

It is important to note the relationship between the sUAS heading, wind direction, and wind velocity. The relationship is nonlinear, and a 50% increase or decrease is not expected for each value due to the possibility of wind coming at a 90º angle related to sUAS heading. The model output for a wind value of 15 mph (24.14 kph) is shown in Figure 24.

Figure 24

Wind Increase Results



The roundtrip travel time to visit Patient 2 and Patient 5 is 85.2 min. The travel time table for this scenario lists the travel time to Patient 3 at almost an hour, 60% of the vehicle endurance to make this one delivery. Furthermore, because Patient 5 has the highest risk value, the model prioritizes this delivery. Patient 2 has the lowest risk, but deliveries to the other three patients requires a flight directly into the 15 mph (24.14 kph) headwind and the model output confirms these deliveries cannot be made. Thus, the highest risk patient receives medicine, along with Patient 2 as the only other location that is reachable in these conditions.

The travel time in a no-wind scenario is listed in Table 20. As shown in the table, without winds affecting travel time the time to reach a patient is the same length as the time to return from that location. The model output, as shown in Figure 25, finds a travel time of exactly 100 min, which coincidentally is the exact endurance limit for the sUAS in this scenario.

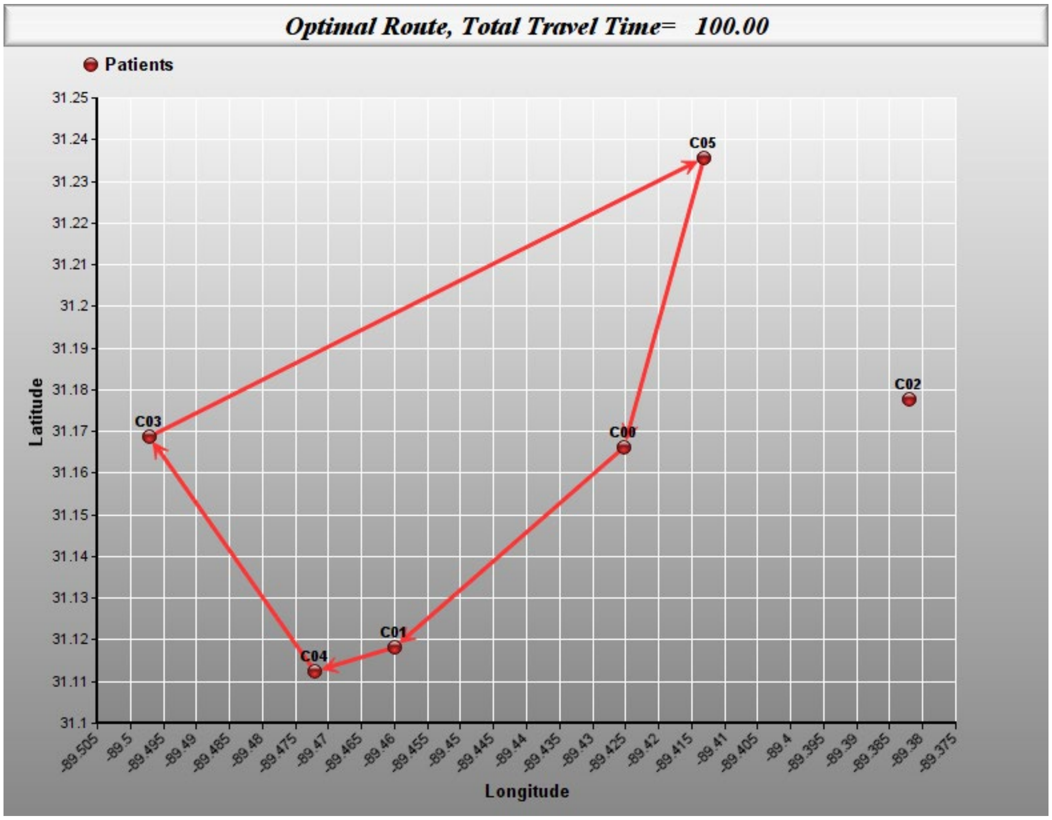
Table 20

Zero-Wind Travel Times

	Depot	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Depot	0	17.1	11.8	18.7	20.4	21.3
Patient 1	17.1	0	27.1	18.2	3.6	37.6
Patient 2	11.8	27.1	0	30.0	30.6	19.3
Patient 3	18.7	18.2	30.0	0	18.3	29.7
Patient 4	20.4	3.6	30.6	18.3	0	40.4
Patient 5	21.3	37.6	19.3	29.7	40.4	0

Figure 25

Wind Decrease Results



Patient 2 has the lowest risk value and does not receive medicine in this scenario. The total risk minimization is therefor 1,200 out of a possible 1,300 for all five patients.

Scenario 3: Patient Complexity

To demonstrate generalizability and reliability in more complex scenarios, this scenario includes a 40% increase in patients. For five patients, there are 15 potential route combinations (i.e., 5 + 4 + 3 + 2 + 1). Adding two additional patients increases the route combinations to 28, effectively doubling the complexity of the model. The two additional patients are visualized in Figure 26 and the associated risk and medicine requirements are listed in Table 21. All other values mirror the initial model scenario. As a reminder, the initial model results returned a route of D-P5-P3-D.

Figure 26

7-Patient Scenario

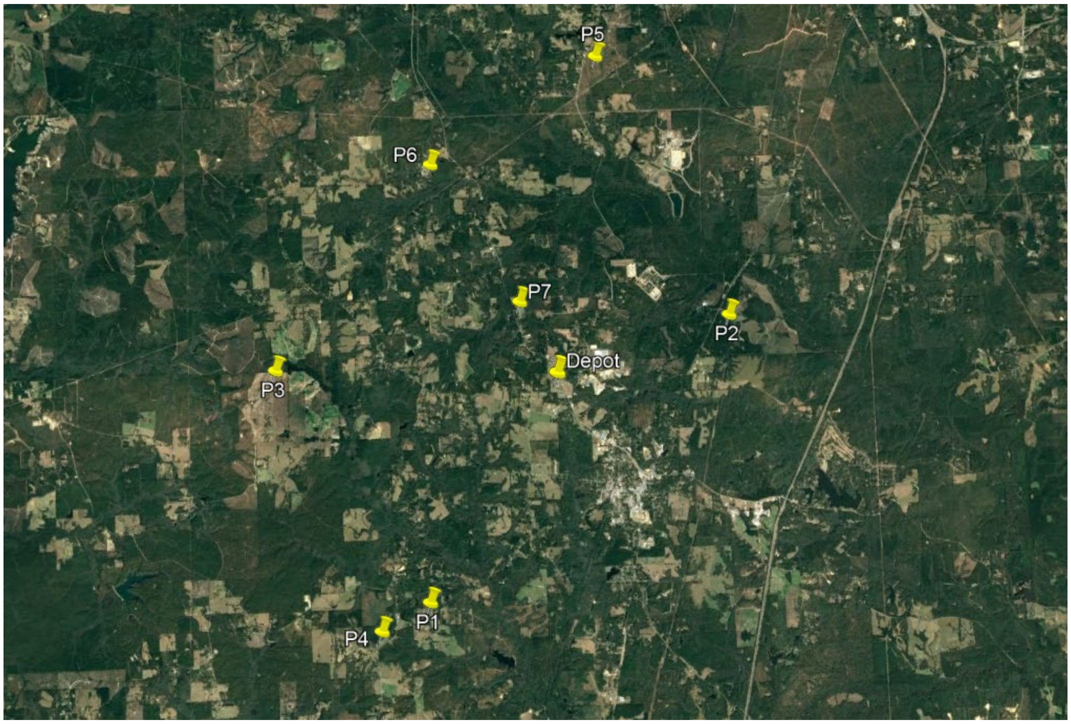


Table 21

7-Patient Risk and Delivery Requirements

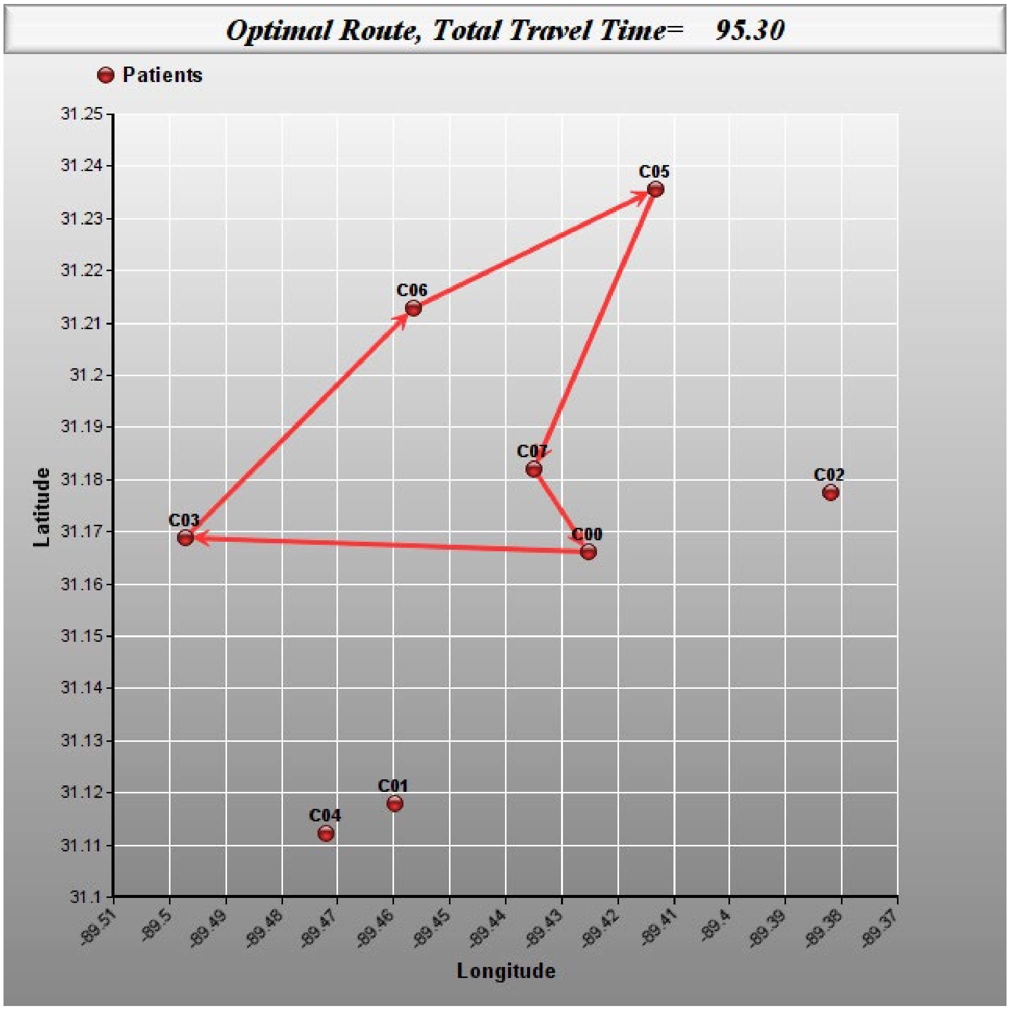
	Longitude	Latitude	Risk Value	Medicine Weight
Patient 1	-89.4599	31.1181	300	3
Patient 2	-89.3820	31.1776	100	6
Patient 3	-89.4971	31.1689	300	5
Patient 4	-89.4721	31.1124	100	4
Patient 5	-89.4132	31.2356	500	2
Patient 6	-89.4564	31.2128	100	3
Patient 7	-89.4349	31.1820	500	5
			1,900	28

The results in Table 21 demonstrate a complex scenario where the two additional patients increase total risk by 68%. It is important to recognize that the total required medicine weight of 28 is more than the payload capacity of one vehicle. Additionally, Patient 7 has the highest risk value while also requiring a high medicine weight.

As expected, the model output found in Figure 27 demonstrates the prioritization of Patient 5 and Patient 7, as they have the highest risk values. Patient 6 and Patient 3 are also visited for a total travel time of 95.3 min and a risk minimization of 1,400 out of the 1,900 possible in this scenario.

Figure 27

7-patient Results



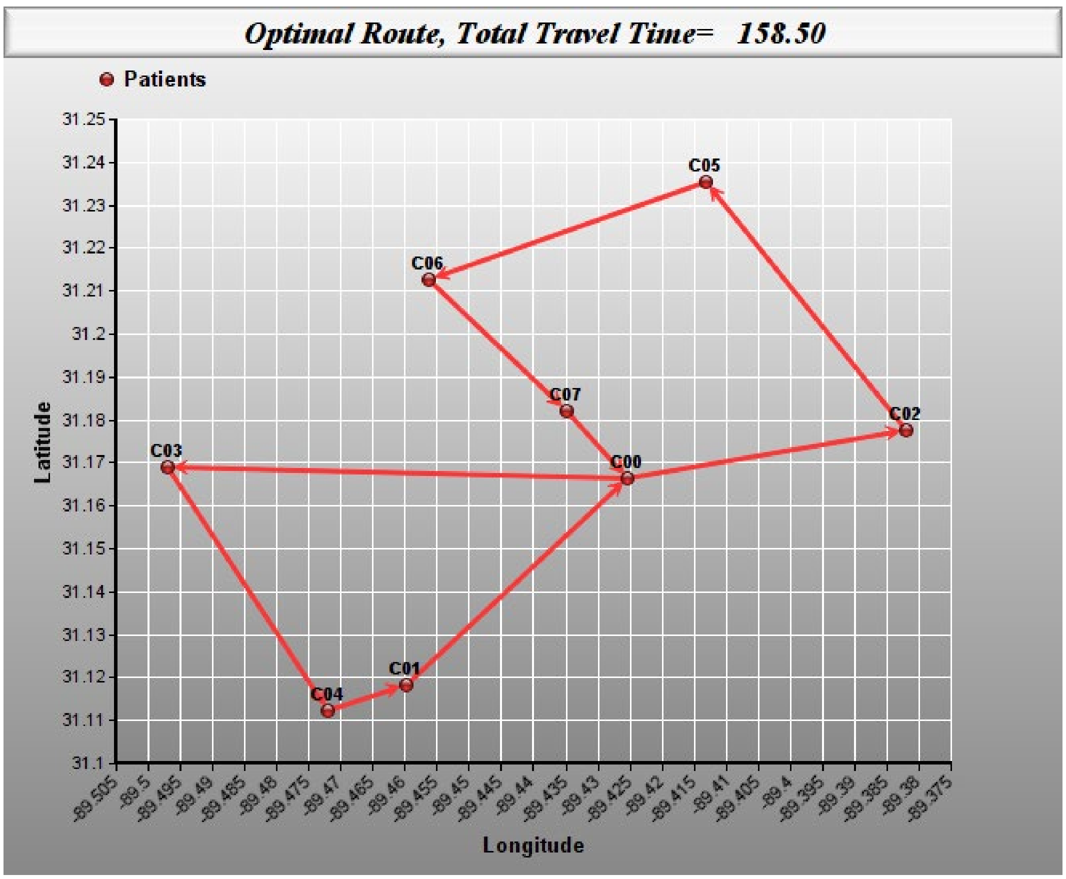
To obtain this solution, the model took 2.94 s and ran a total of 20,654 iterations. This is a significant increase from the original M_1 values of .63 s and 1,199 iterations, but still well within the 3-min threshold for calculating a useful solution.

Scenario 4: sUAS Vehicles

To demonstrate the value of adding a second sUAS, the 7-patient scenario was used to demonstrate a complex scenario with additional patients and additional sUAS. All other vehicle and environmental values were the same, with the only difference from Scenario 3 being one extra vehicle. The model output in Figure 28 shows two separate routes, with all seven patients receiving medicine for a risk minimization of 1,900 and a total travel time for both vehicles is 158.5 min.

Figure 28

Multiple sUAS Results



Note. sUAS = small unmanned aircraft system.

Scenario 4 can be used to demonstrate the value of the model for planning purposes. In this scenario with two vehicles and seven patients, an organization might be interested in a less expensive vehicle with 50% of the payload capacity (VHCAP = 10). The model provides the ideal route, as shown in Figure 29, in less than a second, with the optimal route for two sUAS visiting five of the seven patients. The organization could then use the model to simulate the use of an extra vehicle, each with the reduced payload capacity (sUAS = 3). The results of this scenario are displayed in Figure 30 and confirm all deliveries are possible with three individual routes with a total travel time of 209 min between all three vehicles.

Figure 29

Reduced Payload Capacity Results

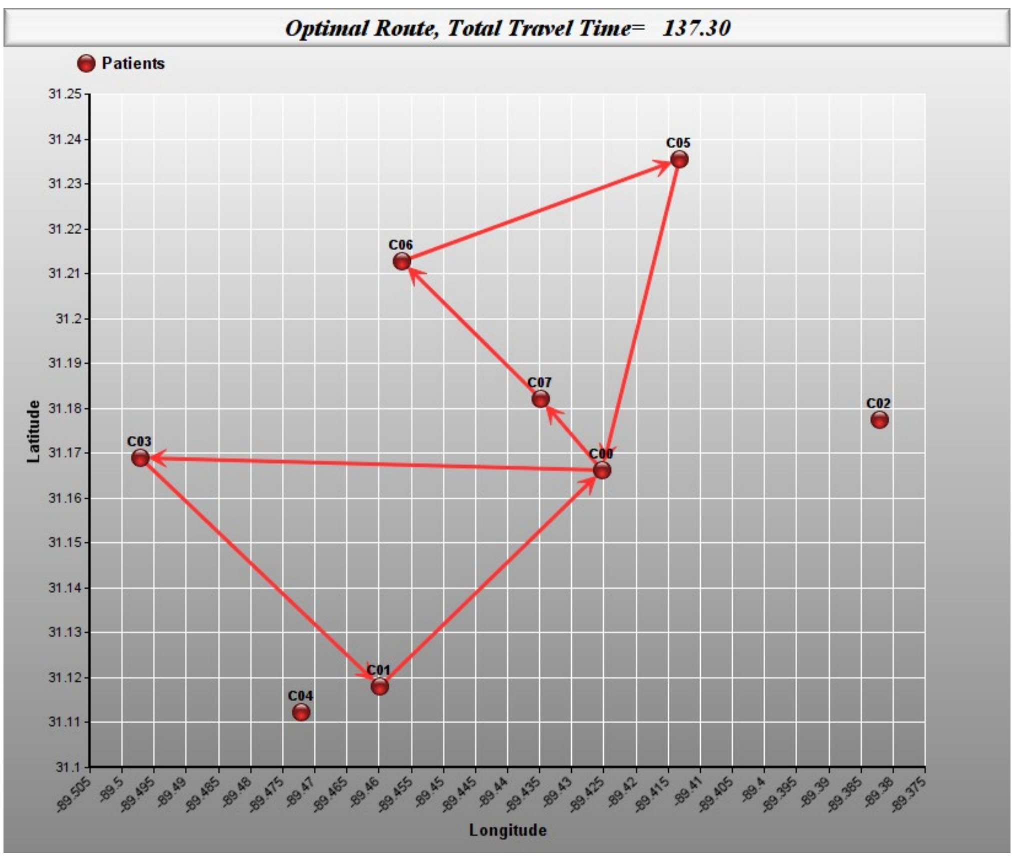
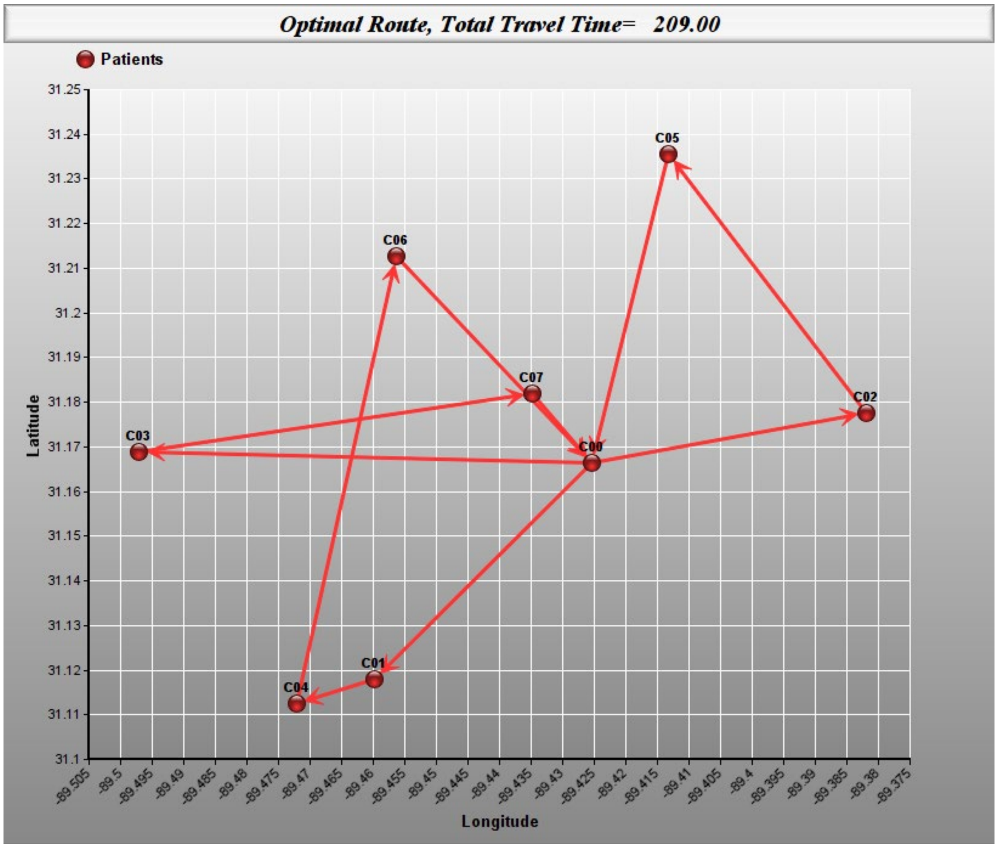


Figure 30

Reduced Payload Capacity and Increased sUAS Results



Note. sUAS = small unmanned aircraft system.

Scenario 5: Multiple Locations

The initial model run included a wind velocity of 10 kt at a heading of 270º. To demonstrate appropriate model generalizability with these stochastic variables, the model was tested with a range of headings and wind velocity values from different locations around the country. This is a particularly important element of the sensitivity analysis, as it confirms the generalizability of the model in other rural areas in the United States. While patient data for a given emergency will always be stochastic and the vehicle variables will not change based on location, the environmental conditions must be thoroughly tested to ensure generalizability. The input reliability is tested through the use of the Monte Carlo simulations, and the output generalizability is tested in this scenario. Histograms displaying the normal distribution of wind velocity and wind direction at the four locations are in Appendix B.

Because the patient location in a given scenario is randomized, the sUAS heading from a patient i to patient j is arbitrary as well, and the same set of random patient locations can be utilized for each new location. Furthermore, while the wind direction distribution at each location is different due to the impact of surrounding terrain and localized weather patterns, the relationship between an unpredictable patient location and a known wind direction remains unpredictable. Therefore, running the model with a fixed set of patients and varying wind direction and wind speed values demonstrates model reliability and model generalizability, as the only variables being tested are environmental. For each location, the mode of the wind direction dataset is used, as this is the most frequently occurring value in the historical NOAA data. For the wind velocity, the values of 5% and 95% of the historical dataset were used. The values used for the location-based sensitivity analysis are listed in Table 22 and the results are listed in Table 23.

Table 22

Wind Values for Different Locations

Location	5% Wind Velocity	95% Wind Velocity	Wind Direction Mode
Jackson, MS	3.0	9.7	155
Syracuse, NY	4.9	11.5	255
Boise, ID	6.0	10.8	132
Winslow, AZ	4.5	13.8	241

Table 23

Wind Sensitivity Analysis Results

Location	Wind Velocity (mph)	Wind Direction	Objective 1	Objective 2	Patients Visited	Route
Mississippi	3.0	155º	95.4	200	3	1,3,5
Mississippi	9.7	155º	86.4	500	2	3,5
New York	4.9	255º	97.4	200	3	1,3,5
New York	11.5	255º	96.6	500	2	3,5
Idaho	6.0	132º	98.6	200	3	1,3,5
Idaho	10.8	132º	88.9	500	2	3,5
Arizona	4.5	241º	97.2	200	3	1,3,5
Arizona	13.8	241º	80.5	700	2	2,5

In the low wind scenarios, there is no difference in the optimal route as the three patients with the highest injury value are prioritized and the differing wind values are not significant enough to impact the outcome; only small variations in total route time are observed. However, in high wind scenarios the sUAS is unable to travel to Patient 1 and return within the vehicle endurance constraint of 100 min. In the high wind scenario in Arizona, the optimal route includes Patient 2 (risk value = 100) instead of Patient 3 (risk value = 300). Patient 3 is due west of the depot, and with a wind direction of 241º and a velocity of 13.8 kt, the sUAS has a direct headwind traveling to Patient 3. The vehicle cannot deliver to Patient 5 (risk value = 500) and Patient 3 under these conditions and instead can only deliver to Patient 5 and Patient 2.

Running multiple wind scenarios using values from 8,760 hour-by-hour historical data points further demonstrates model generalizability in a variety of potential environmental conditions. Moreover, because the location-specific wind values can be compared with static depot and patient locations, small changes in optimal routing can be observed and attributed to the changing environmental variables to demonstrate model reliability as well.

Scenario 6: Maximum Calculation Time

Through multiple iterations of sensitivity analysis, each solution was achieved within the 180-second limit on a machine with an i5 6^{th}-gen processor and 8Gb RM, the model took less than 6 s for all scenarios. This time limit was implemented to ensure operational usefulness for time-sensitive deliveries, and the results of the first five scenarios indicate further analysis is necessary to determine the upper limit of model complexity. A scenario was built with 15 patients and four sUAS vehicles to determine if a measurable increase in processing time could be determined. While testing the maximum solution time was not a planned step in the sensitivity analysis, the extremely low solution times obtained in the initial output and subsequent scenarios indicate the model might be able to quickly solve increasingly complex scenarios, demonstrating additional generalizability for large-scale disaster response.

A groundspeed matrix was developed by randomly generating a travel time value between 0-60. Because the Monte Carlo simulation results indicate a uniform travel time distribution over the 5,000 trials, selecting a random travel time was acceptable for this scenario. Randomly generated patient locations were also obtained to visualize the results displayed in Figure 31. The model took 5.33 s to run the 24,282 iterations required to obtain the optimal solution for 15 patients and four sUAS vehicles, a 748% increase over the initial model solution time of .63 s. While the solution time for this scenario is measurably higher than the initial model run with five patients and one sUAS, the relatively low calculation time further demonstrates model generalizability in complex scenarios with a high number of patients and sUAS vehicles.

Figure 31

15-Patient Scenario Results

```
ROUTE 1:
           FROM           TO    LENGTH     LOAD
-----------------------------------------------
            C00          C03       0.0        5
            C03          C09       2.0       10
            C09          C00      14.0


ROUTE 2:
           FROM           TO    LENGTH     LOAD
-----------------------------------------------
            C00          C04       0.0        4
            C04          C13       9.0        5
            C13          C08      11.0        6
            C08          C05      29.0        8
            C05          C00      50.0


ROUTE 3:
           FROM           TO    LENGTH     LOAD
-----------------------------------------------
            C00          C10       0.0        3
            C10          C07      10.0        6
            C07          C06      14.0       10
            C06          C00      24.0


ROUTE 4:
           FROM           TO    LENGTH     LOAD
-----------------------------------------------
            C00          C12       0.0        2
            C12          C15      23.0        4
            C15          C01      29.0        7
            C01          C00      38.0
```

Summary

These scenarios are a small sample of the potential solutions the model can provide decision-makers in the disaster response industry. The results of the sensitivity analyses are presented in Table 24 to clearly observe the changes in the primary and secondary objective functions.

Table 24

Summary of Sensitivity Analysis Results

Scenario	Risk Minimization (visited/total)	Optimal Route (min)	Route	Notes
M1	800/1300	89	3,5	Baseline model output.
VHDIST = 150	1300/1300	129.7	1,2,3,4,5	Distance increased from 100 to 150 min and all deliveries completed.
TAS = 35	1300/1300	78.6	1,2,3,4,5	sUAS airspeed increased from 22 to 35kts and all deliveries completed.
$W_v = 15$	600/1300	85.2	2,5	Wind velocity increased from 10 to 15 kt and two deliveries completed.
$W_v = 0$	1200/1300	100	1,3,4,5	Wind velocity decreased from 10 to 0 kt and four deliveries completed.
P = 7	1400/1900	95.3	3,5,6,7	Patients increased from 5 to 7 and four deliveries completed.
VHNUMB = 2	1900/1900	158.5	1,2,3,4,5,6,7	Patients increased to 7, vehicles increased from 1 to 2, and all deliveries completed.
VHCAP = 10	1700/1900	137.3	1,3,5,6,7	Patients increased to 7, vehicles increased to 2, payload capacity reduced from 20 to 10, and five deliveries completed.
VHNUMB = 3	1900/1900	209	1,2,3,4,5,6,7	Patients increased to 7, payload capacity reduced to 10, and sUAS increased to 3.

Chapter V

Discussion, Conclusions, And Recommendations

This chapter discusses the results of this research and how they serve to answer the research questions. The practical and theoretical contributions are discussed, as are the conclusions drawn from the study. The limitations of the research and recommendations for future research are also provided.

Discussion

The study was aimed at developing and validating a quantitative optimization model to inform decision-makers on the optimal sUAS vehicle routing to minimize total risk and route travel time within the constraints of vehicle limitations. The model has improved existing vehicle routing studies by including environmental variables and patient risk values to create a novel routing model for post-disaster sUAS medical delivery in rural areas. The findings of the study are discussed in relation to the research questions listed in Chapter I.

RQ1

Research Question 1 asks What are the key variables related to sUAS medical delivery in rural areas during disaster relief efforts? Existing VRP research focusing on UAS routing and delivery was used to develop an initial list of vehicle-specific variables that impact vehicle endurance and payload capacity. Combined with this researcher's industry knowledge and discussions with subject matter experts in the field of autonomy, a list of key variables was created to answer RQ_1 (see Table 25).

Table 25

Variable Values

Variable	Input Type	Initial Model	Confirmatory Test
Injury risk	Stochastic	Random number generator	Model verification
Injury location	Stochastic	Random location generator	Model verification
Medicine weight	Stochastic	Random number generator	Model verification
Wind direction	Stochastic	270	Scenario 5
Number of patients	Deterministic	5	Scenario 3
Wind velocity	Stochastic	10	Scenario 5
Available sUAS	Deterministic	1	Scenario 4
Airspeed	Deterministic	22	Scenario 1
Payload capacity	Deterministic	15	Scenario 4
Fuel capacity	Deterministic	100	Scenario 1

These key variables can be grouped into three categories: scenario variables, vehicle variables, and environmental variables. The scenario variables are unknown prior to a natural disaster and are randomized for the purposes of model development and sensitivity analysis. The scenario variables are injury demand, injury risk, injury location, and required medicine weight. While demand and location are relatively common variables in existing routing studies, risk is used in the primary objective function as the variable to be minimized and is an important novel variable in this research. The vehicle variables are deterministic and can be updated by a user to match the limitations of the vehicle to be modeled. The deterministic variables are available sUAS, airspeed, payload capacity, and endurance. The environmental variables were selected because of their effect on aircraft groundspeed and, therefore, aircraft endurance. The environmental variables are wind direction and wind velocity, which required a Monte Carlo simulation to ensure the values used for the initial model and sensitivity analysis are valid.

RQ$_2$

Research Question 2 asks What is the mathematical relationship between the decision variables and objective variables? A thorough literature review of extant routing studies uncovered a research gap for medical delivery models, with no existing studies including patient risk as an input variable or objective function. The variables identified in RQ$_1$ were organized into a mathematical function to address the research gap and answer RQ$_2$. The optimization model was built around an objective function to minimize total patient risk (R_t) for a given set of patients (P). The variables from RQ$_1$ are listed in Table 26. The table includes a simplistic explanation of how each variable is utilized to build the objective function and constraints and answer RQ$_2$.

Table 26

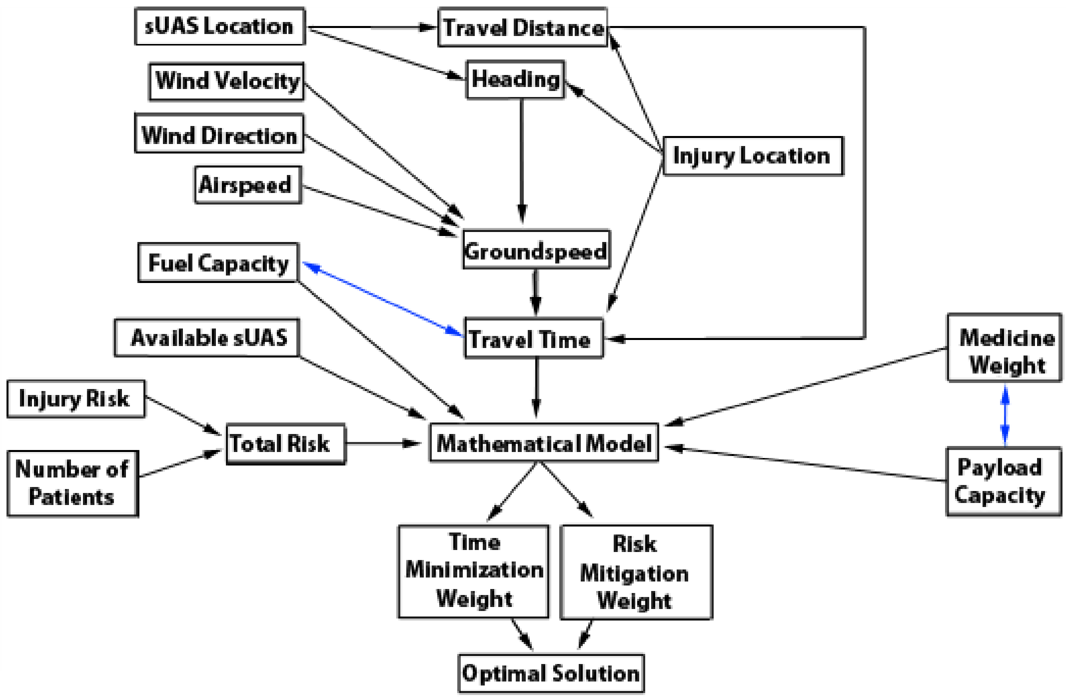
Variable-Model Relationships

Variable	Model Relationship	Explanation
injury risk	objective function	To minimize total risk.
required medicine weight payload capacity	constraint constraint	Required medicine weight for route must be less than payload capacity.
available sUAS injury location	input input	Number of routes must not exceed available sUAS.
endurance	constraint	Route time must be less than aircraft endurance.
wind direction wind velocity airspeed	input input input	Input for groundspeed calculations to determine vehicle endurance limitation. Validated through Monte Carlo simulation.
injury demand	input	Model is not constrained by number of injured patients; deliveries are not mandatory.

The relationships between the variables are illustrated in a flow chart in Figure 32 to observe the answer to RQ$_2$ and demonstrate how each input was utilized.

Figure 32

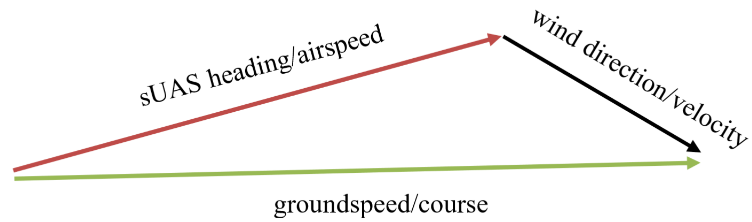
Variable Relationships Diagram



Injury location and sUAS location are used to calculate the required travel distance and relative heading. A groundspeed calculation can be computed with the necessary heading, airspeed, wind velocity, and wind direction. These four variables can be visualized as a vector and magnitude for the trigonometric groundspeed calculations in Figure 33. To validate the groundspeed calculations and compare the historical wind data to the distribution of a large dataset, a Monte Carlo simulation was utilized.

Figure 33

Groundspeed Vectors



To calculate travel time between the two patients, time = distance x groundspeed. Travel time is a primary input for the mathematical model, and the relationship between travel time and fuel capacity is noted in the flow chart (see Figure 31); the mathematical model uses flight time as a constraint for travel time (*travel time* $\leq$ *endurance*), with the fuel capacity defining the maximum possible travel time for a given vehicle.

Total risk for a given set of patients can be calculated by adding the number of patients and their individual risk values, and the resulting total risk value is used for the objective function in the mathematical model. Medicine weight and payload capacity are also required, and the relationship between the two (*medicine weight* $\leq$ *payload capacity*) is displayed in the flow chart as well. Lastly, the number of sUAS is an input into the mathematical model; however, the input is not dependent on any other variables.

The output of the mathematical model is dependent on the weighted value of the two objective functions. As described in Chapter III, these weights are binary. The primary risk minimization objective receives the full weighted value for the first calculation, followed by a subsequent calculation with travel time weight receiving the full weighted value and is constrained by the results of the first calculation, such that: *Total risk value for minimization solution* $\geq$ *Total risk value for travel time solution.*

The optimal solution for the two objective functions will therefore contain a total risk minimization value as well as a travel time to complete the route as expeditiously as possible. The relationship between these variables is the foundation for the mathematical formulation discussed in Chapter III, followed by the LINGO coding and reliability testing to obtain the initial model result for a 5-person scenario in Purvis, Mississippi.

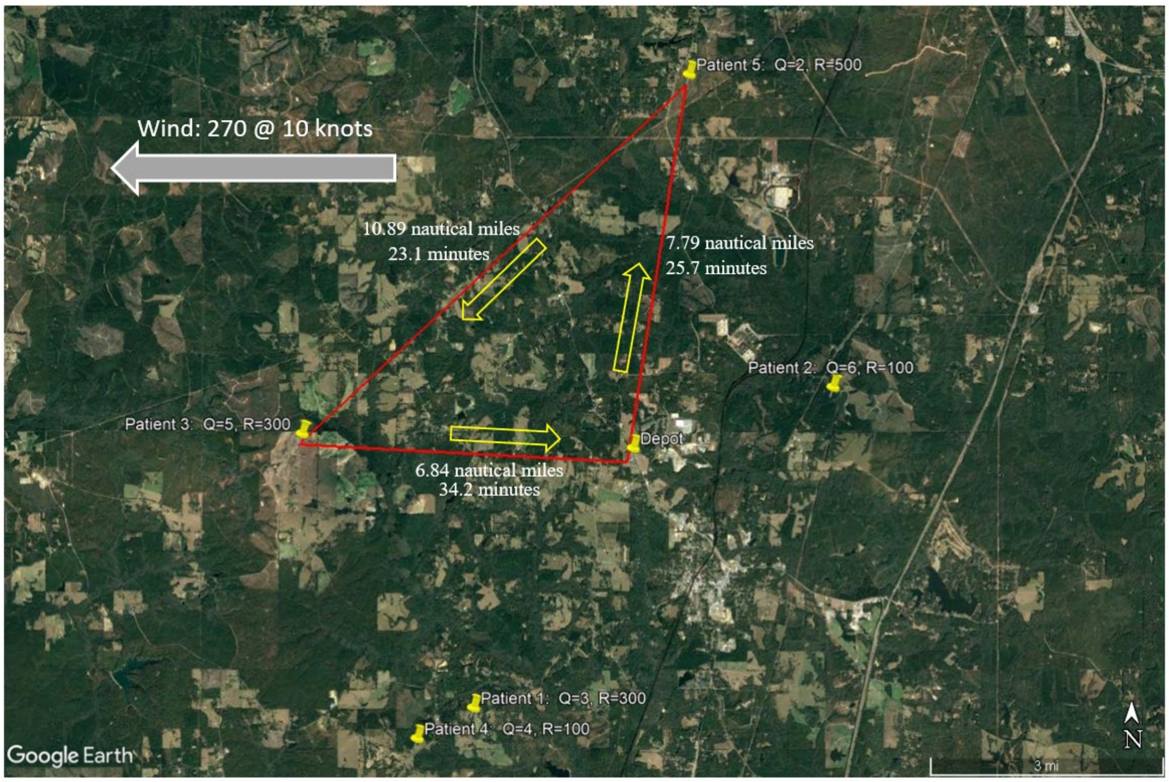
RQ3

Research Question 3 asks What is the optimal routing solution for medical supply delivery using sUAS to minimize patient health risk? To answer this question, the objective functions and constraints were used to determine the optimal route for risk minimization. Additional constraints were added to the list of variables to ensure the model output would return a complete route, and each patient would only be visited once. These constraints are not specific to the novel risk minimization model but are generic VRP constraints to ensure the formulas are bound by route-specific requirements. The full list of mathematical constraints can be found in Chapter IV.

To find the optimal routing solution for a given set of patients, deterministic values for the vehicle variables were selected based on commercially available sUAS platforms. Stochastic scenario variables were selected through random location and number generators. Stochastic environmental variables were selected based on historical weather data at the initial model location in Purvis, Mississippi. The initial model output, M_1, had an optimal risk minimization value of 800 out of 1,300. A secondary objective function was developed to ensure that after identifying an optimal route for risk minimization, the model would then prioritize sUAS travel time. The secondary solution for minimum travel time uses the primary objective as the input, so at no time will the optimal risk minimization solution be compromised in favor of improving the secondary objective. For the initial model solution M_1, the optimal secondary solution is 89 min to complete the route. The risk values, required delivery weight, and optimal route for this scenario are found in Figure 34.

Figure 34

Optimal Routing Solution Map



RQ4

Research Question 4 asks To what extent are the optimal solutions affected by various scenarios? To answer this question, multiple what-if scenarios were conducted to determine how robust the model was to changing variables. In each scenario, one variable was changed at a time to clearly observe the result of the variable being tested. These scenarios demonstrate model reliability, as more complicated calculations will be equally reliable due to the objective nature of mathematics. The scenarios also demonstrate model generalizability across a wide range of potential variable inputs. Environmental variables, vehicle variables, and scenario variables were all tested to ensure optimal solutions can be found using a variety of sUAS platforms to respond to a variety of potential disaster response scenarios.

Conclusions

Theoretical Contribution

The primary theoretical contribution of this study is the development of a novel vehicle routing model that includes variables unique to the disaster response environment. As discussed in this chapter, the conclusions from RQ_1 and RQ_2 demonstrate the theoretical contribution of the model by identifying and organizing the variables into a mathematical formula. During this process, patient injury severity was identified as a novel variable. The relationship between injury severity and other included variables is particularly important, as it is used to quantify total risk and is optimized in the primary objective function. The inclusion of injury severity provides the emergency management industry with a tool that aligns with the goals of first responders.

To ensure the model is useful for disaster management professionals, the theoretical foundation of this study is based on the START and SALT emergency triage models used by first responders in the U.S. These models, combined with the Emergency Severity Index, are used to assign objective values to patients based on injury severity and are directly correlated to the possibility of a patient succumbing to their injuries. This theoretical foundation was established through a thorough literature review, followed by the development of a mathematical model that includes injury severity as well as traditional vehicle limitations such as endurance, payload capacity, and airspeed. The inclusion of these variables and the development of the mathematical model addresses the research gap identified in Chapters I and II, as prior routing models do not include the necessary variables to accurately model vehicle route optimization when the objective is unrelated to traditional objective functions such as distance, time, or cost.

The risk minimization model for post-disaster medical delivery using unmanned aircraft systems also furthers the existing body of knowledge by combining vehicle variables with environmental variables to obtain total route travel time. As most routing studies do not include environmental variables, the inclusion of wind velocity and wind direction is an important theoretical contribution. Combining patient variables, vehicle variables, and environmental variables to minimize patient risk is a novel contribution to the field of transportation routing studies. The model can be used as a foundation for future research on sUAS route optimization, risk minimization for emergency response, or future transportation studies that require the inclusion of stochastic environmental variables to measure travel time accurately.

Practical Contribution

The inclusion of environmental variables makes the optimal route useful in various practical real-world scenarios due to the impact of wind direction and wind velocity on aircraft performance. Existing routing models rarely include environmental wind variables due to the increased complexity of the optimization calculation. While simplifying the number of variables usually allows for larger scenarios to be solved, this limits the usability and generalizability of the results. This is particularly true for sUAS operations, where relatively slow speeds and limited battery life increase the impact of wind velocity on a given route. The initial model output developed for RQ_3 and the sensitivity analysis developed for RQ_4 provide a clear example of the practical contribution of this model.

The optimal route for M_1 included two patients with a total risk minimization value of 800. The total travel time is 89 min with a 10-kt wind from heading 270º. As described in the sensitivity analysis, the scenario without wind returns a delivery route to four patients, with a total travel time of 100 min, the exact endurance of the sUAS vehicle. Table 27 compares the M_1 output and zero-wind sensitivity analysis scenario.

Table 27

Comparison of Wind Scenarios

Scenario	Risk Minimization Value	Patient Route	Route Travel Time (Wind Included)	Route Travel Time (Wind Excluded)
M_1	800/1300	3,5	89 min	105 min
Zero Wind	1,200/1,300	5,3,4,1	100 min	100 min

While the zero-wind scenario was primarily used to demonstrate the reliability of wind variables calculations and generalizability across a range of wind conditions, it also demonstrates the practical contribution of this model. If a 10 kt wind is present at the time of flight, the *actual* travel time to patients 5,3,4, and 1 is 105 min. This exceeds maximum endurance for the vehicle, and the sUAS will crash prior to completing the route. Comparing these two scenarios demonstrates the importance of including environmental input variables to ensure the model is a practically useful tool for disaster response.

The current model can also be used for disaster planning with the inclusion of the relevant environmental variables, vehicle variables, and patient variables. Organizations at the federal, state, and local level are responsible for developing cohesive disaster response plans, and decisions made by these organizations could be influenced by budget, available resources, and location-specific considerations such as the availability of hospitals and schools for disaster response. The sensitivity analysis conducted for this study is an example of the practical contribution of the model for planning purposes. Organizations can measure the impact of purchasing additional sUAS, upgrading to more capable platforms, or specific environmental conditions at a rural location. Also, most importantly, the impact of these decisions can be quantified in terms of the total risk minimization for a given scenario.

The practical contributions listed above can be utilized by numerous organizations working in the emergency management industry. As discussed in Chapter I, the primary organization responsible for disaster prevention and response is FEMA. And while FEMA is an important federal organization, they are primarily tasked with allocating funds, creating policy, and directing resources for coordinated emergency response. Local and State agencies will also directly benefit from the practical contributions of this study, as they are responsible for planning and executing local disaster response procedures. These organizations will most likely be making decisions surrounding implanting unmanned technology in their communities and will benefit from an objective tool to measure the effectiveness of different sUAS platforms.

Private companies are also frequently contracted to conduct unmanned operations and are another beneficiary of the risk minimization model. While many small companies operating sUAS have talented pilots and capable aircraft, routine sUAS operations in the U.S. is not frequent enough to require the development of fleet decision-making tools for companies with limited funds and resources. A publicly available model will assist these companies in providing a service to local communities looking to implement unmanned technology in their disaster response plans.

Private companies could modify the model formula for other business cases as well. Using this approach for non-emergency response would be possible, the values given to each patient would most likely represent something other than risk. For example, a company could assign values to each customer based on how much they are willing to pay for shipping; a customer paying a $5 delivery fee for food or a product could be prioritized over a customer paying $3 for shipping. However, this type of operation would most likely require significant modification to the mathematical code. For example, the current approach of absolute risk prioritization followed by a second objective function minimizing distance would fit the non-emergency use case. However, a company attempting this type of operation would still benefit from this research by having a valid and reliable model to use as a starting point. Non-emergency deliveries would most likely make a small modification to the existing code to apply a weight to each objective function, resulting in a more traditional goal-programming approach.

Limitations

The sensitivity analysis for multiple locations demonstrates model generalizability for rural areas in the U.S. but does not include urban areas. However, urban areas are generally the focal point of widescale disaster response, as the aftermath of Hurricane Katrina demonstrates. This could leave underserved communities vulnerable when traditional transportation methods are unavailable. While the model does not consider additional factors that could be present in urban environments, 97% of the U.S. is considered rural, and the variables included in the model were specifically designed to model the conditions in these locations.

The current model is also limited to operations in the U.S., as other countries could have conflicting regulations governing the operations of sUAS. This study was specifically designed for operations in airspace controlled by the FAA, under the guidance of Title 14 C.F.R. Part 91.137, detailing how Temporary Flight Restrictions (TFRs) in the vicinity of disaster areas can be used to restrict airspace access to aircraft participating in emergency response activities. The Emergency Severity Index, used as the theoretical foundation for risk minimization, is also specific to emergency operations in the United States. While these factors limit the study to U.S. locations, the model was designed to capture the variables present in this environment.

Recommendations

Heuristics

As stated in Chapter III, the use of heuristic algorithms is generally preferred to solve NP-hard problems, especially when a time-constrained solution is required to remain operationally useful for medical deliveries. For this study, the branch-and-bound method was used to balance accuracy and flexibility. However, even in the most complicated 15-patient scenario tested in this study, a solution was returned in approximately 5 s. Because the solution threshold for this study was set to 180 s, additional research to expand the upper limits of model complexity is recommended. This study was limited to rural environments where population density is low, but understanding how the current branch-and-bound heuristic methodology handles additional patients could indicate the model is useful for urban environments or areas of higher population density.

The other technique for solving routing problems is an exact solution framework. Exact algorithms are normally used to baseline the effectiveness of newly proposed heuristic frameworks, as solutions frequently require significant computing power and take hours to solve complex scenarios. However, with improvements in computing technology and advancements in the field of exact algorithms, it is possible that an exact algorithm could be obtained in a realistic timeframe for large-scale medical delivery. As described in Chapter III, LINGO uses a branch-and-bound heuristic. Expanding on this model by researching an exact solution method would require a different software package but could improve the overall accuracy and reliability of the output if solution times remain low. Chapter III also describes the computational architecture of this study, specifically with the wind variation calculations being made in Excel instead of LINGO. Allowing the LINGO calculation to be based on a simple table containing the travel time between each point significantly reduces the complexity of the model, thus reducing the calculation time. However, this is at the expense of additional steps in the solution process, as a user now needs to use separate programs to input the necessary values to obtain a solution.

Neural Networks and Simulations

Neural networks and other advanced solution methods have increased in popularity as computing power becomes more readily available. These types of solutions have been used to solve vehicle routing problems (Steinhaus et al., 2015), and require significantly more advanced coding techniques. These heuristic solution methods will allow researchers to include environmental conditions in the same calculations as all other routing constraints, which will result in a more streamlined process for end-users in addition to an algorithm that can handle larger and more complex scenarios.

Similarly, using methods more capable than Lingo will allow researchers to utilize a more holistic Monte Carlo simulation method. One important limitation of the LINGO software is requiring a user to click the 'calculate' button each time to obtain a solution. If a researcher was interested in comparing 1000 solutions using a randomly selected wind direction, it would require a significant amount of manual labor and time to obtain and compile the data. While this study utilized a Monte Carlo simulation for one specific variable calculation (groundspeed) to demonstrate random heading and wind values resulted in random groundspeed outputs, other VRP studies have used Python scripts to obtain a routing solution for a given set of input values. This approach can then be repeated hundreds or thousands of times using a looping script in the code, giving researchers access to metadata on the important delivery information. For example, for 5,000 delivery iterations, you could easily determine how many scenarios resulted in 100% of patient deliveries or how many scenarios resulted in less than 50% of patient deliveries. These confidence intervals are a powerful planning tool for first responders and would be an excellent future research opportunity.

A Monte Carlo Simulation approach using a Python script could also be used to measure model improvement. This research provides a new tool for the disaster management industry, but future improvements using the previously mentioned heuristic approaches should be evaluated for improvements in accuracy and solution time. For example, a comparison between the current branch-and-bound algorithm and a neural network algorithm would require a more advanced research approach that allowed for iterative model runs to objectively measure solution time and solution accuracy over a large number of model runs. It is important to note that developing an approach to evaluate confidence intervals over thousands of runs will most likely take a significant amount of computing power and time and would not be designed for first responders to use in a post-disaster environment. Instead, it would be used as a planning and research tool to evaluate how changes in variable values and stochastic scenarios such as equipment failure or changing wind conditions might impact the success of route completion.

Time Windows

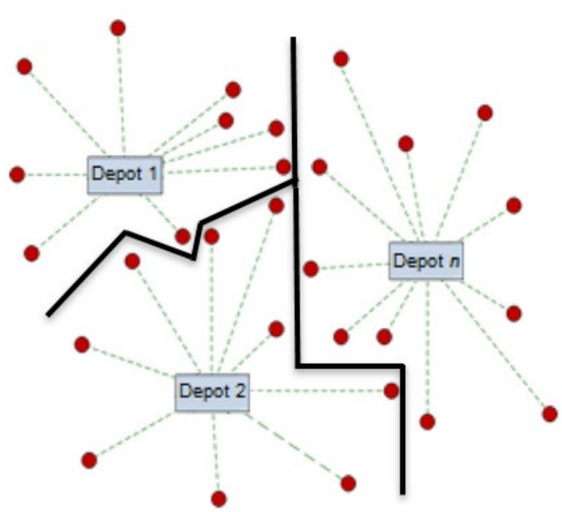
The inclusion of time limits is included in some traditional VRP models where locations have a defined window for the delivery to be completed. This significantly increases model complexity but is necessary for problems such as aircraft fleet routing or the delivery of perishable goods. Time windows were not included in this study because the theoretical foundation for risk minimization is based on time constraints that are normally outside the scope current of sUAS endurance limits. As technology improves, it could be possible to utilize an aircraft with the appropriate payload capacity and endurance where time windows would be required. However, this would also require first responders to change how they conduct medical triage. The current triage protocol is to sort patients into groups based on injury severity, and while patients are categorized based on the time required to receive additional care, a precise time is not assigned to each patient. Adding time windows to the study would require first responders to set an ‘earliest’ and ‘latest’ requirement for each patient, which could be difficult to estimate. Adding this responsibility would also raise a number of ethical questions, especially when a first responder is only aware of a small subset of patients they have seen. Standardizing time windows could prove difficult without a full operational picture of the number and extent of patient injuries. However, if sUAS endurance improvements allow for increased flight time and first responder protocol changes to clearly define time windows, the model can be expanded to include this variable.

Multi-Depot

The current model includes one depot where all sUAS begin and end their delivery route. This model can be run multiple times with different inputs for coverage over a larger area. With solution times under 5 s, it is feasible for an incident commander to coordinate boundaries between depots and have each depot obtain their own solution, as diagramed in Figure 35.

Figure 35

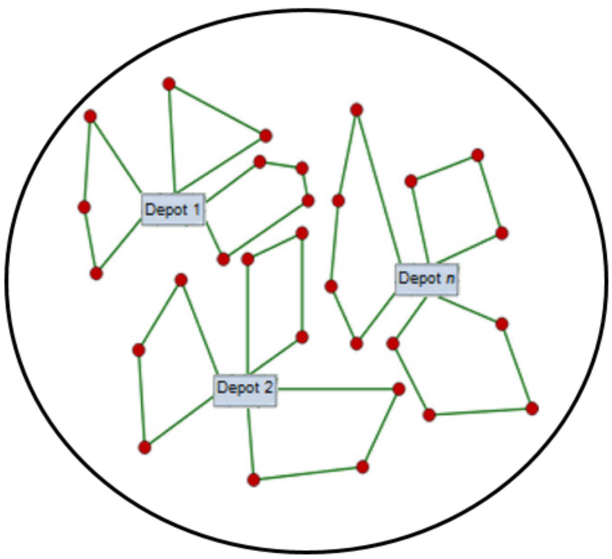
Separate Model Solutions



However, future research could expand on the existing model by incorporating multiple depots in the same model iteration, as depicted in Figure 36. This would increase model complexity and most likely increase solution time but could demonstrate a new operational use for emergency responders in large-scale disaster scenarios.

Figure 36

Multi-Depot Single Solution



Urban Environments with Route Deviations

This study was delimited to rural environments to address the possibility of inadequate medical support from local, state, and federal entities. However, future research could incorporate additional variables that accurately model urban environments. Other than population density, the main difference between urban and rural environments is the existence of obstacles and non-compliant air traffic. In rural environments, emergency response will most likely include a temporary flight restriction to ensure any air traffic in the vicinity is participating in a coordinated response to the emergency. This might not be a realistic expectation in urban environments, especially if the response area is close to a major airport. Additional stochastic variables should be added to account for unplanned route deviations to accurately model this type of environment.

Heterogenous Fleets

The current model assumes that the agency coordinating the disaster response utilizes a homogenous fleet of sUAS vehicles. Fleet routing models utilizing a set of heterogeneous ground vehicles is a well-researched topic (Singhtaun & Tapradub, 2019; Wang & Wen, 2020). Recent studies have been conducted in the aviation sector as well (Zhang & Chen, 2021). If the disaster response field adopts unmanned technology for medical deliveries, coordination between multiple agencies at the local, state, and federal levels could eventually require a model that can handle a heterogeneous fleet. While this addition will increase model complexity to account for different payload capacities, airspeeds, and endurance limitations, improvements in computer processor technology might allow for a more complex model without sacrificing model processing time.

Other Deliveries

The model developed in this study is narrowly scoped to medical delivery in rural areas during emergency response. While the study is centered around the feasibility of most medicines being a realistic size and weight to be transported by sUAS, future research could explore the possibility of delivering other items. For example, vehicle routing for non-emergency medical delivery could be explored if a different theoretical foundation was developed to measure risk minimization. If the FAA increases the maximum allowable UAS weight, platforms like the Bell Autonomous Transport Pod (see Figure 37) could be utilized for both civilian and military deliveries.

Figure 37

Bell Autonomous Transport Pod

One of the potential military applications for a platform with a payload capacity of 70 lb (31.75 kg) and a 100 mph (160.93 kph) maximum speed is ammunition delivery. The risk variable could be repurposed to measure the needs of a specific unit on the battlefield and allow the model to determine the optimal route to complete autonomous resupply missions. The new variables would need further research and validation, but the model developed in this study can be used as the foundation for future delivery studies.

The model can be modified for a variety of civilian applications as well. As discussed in Chapter II, routing models for other types of delivery have been developed but are not always inclusive of all the necessary environmental variables, limiting the accuracy and operational usability of the routing solutions. Future studies can replicate the structure of this study by calculating the environmental variables separately from the modeling software, ensuring solution times remain low. Alternatively, a more robust code can be developed to combine all of the calculations into one script using a program such as Python. Either approach would need to be thoroughly researched to understand the impact on solution time and solution accuracy. Regardless of how environmental variables are built into the model structure for more complicated scenarios, this study can be expanded to other non-emergency delivery scenarios as well. For example, the model could be modified to identify optimal routes for picking up medical samples from patients who are unable to travel to a hospital, or for UAM passenger pickup and dropoff routing optimization. While these scenarios require a different theoretical foundation for assigning values to each pickup or dropoff location, it would be possible to use a majority of the existing LINGO code to identify the optimal route of a fleet of UAM vehicles to pick up passengers based on the amount of money each passenger paid for the trip. This is essentially removing the Emergency Severity Index as the basis for prioritization and replacing it with expected profit from selecting a given location.

Improved User Interface

The construction and validation of the risk minimization model for post-disaster medical delivery using unmanned aircraft systems was completed in LINGO, which is a flexible and powerful modeling software tool. However, it is not intuitive for users who are not familiar with operational research or the syntax of model inputs. The groundspeed calculation is a relatively straightforward trigonometric relationship between airspeed, wind speed, and wind direction. LINGO is not configured to handle these types of calculations; thus, required the use of Excel formulas for this study. It is acceptable for an academic study, but future research should explore a front-end user interface and develop the appropriate software to accept basic user inputs for vehicle limitations and environmental conditions. Such an interface would allow first responders to quickly and accurately update the necessary variables to obtain an optimal route.

Additional Variables

This study includes all the appropriate variables to reliably model the conditions during post-disaster medical delivery in rural areas using sUAS. However, as the model is adapted for different use cases or more specific sUAS platforms, additional variables could be added to the model to increase accuracy. As discussed earlier in the chapter, future research opportunities include modeling more complex scenarios, and additional computing power and modeling software could also allow for stochastic environmental functions such as changing wind direction or changing wind velocity while the sUAS is en route. This would require additional data for the likelihood of a stochastic event occurring, but publicly available wind data could provide the necessary information on the possibility of wind direction and velocity changing over time for a specific area.

Future research will focus on specific sUAS airframes to increase model accuracy as specific use cases are developed, although it should be noted that this will also decrease the generalizability of the resultant model. For example, an emergency management organization in Craig, Colorado, could add a variable for performance decrease at high density altitudes due to the rural community being located at 6200’ MSL, and potentially include stochastic temperature variables to reflect the significant climatological differences between the summer and winter seasons. This would require the model to consider vehicle-specific performance characteristics but would increase the validity of the model for a specific sUAS vehicle in a specific location.

Some sUAS vehicles could necessitate the addition of variables as well. For example, a certain airframe might have the capability to carry a significant amount of weight due to the thrust and lift generated but is limited by the volume available in the payload bay. For this theoretical platform, it is possible the limiting factor is the volume of medicine compared to the volume of available payload space.

These opportunities for future research can expand on the existing study by exploring increasingly complex scenarios for the same population of rural areas in the U.S. and allow first responders to utilize the model for larger affected populations. Future research can also focus on a narrower scope for specific locations and platforms. Any mathematical changes or additional model variables should be followed by iterative and rigorous reliability and validity assessments to ensure model outputs are acceptable.

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Appendix A

Monte Carlo Simulation Descriptives

Table 1A

Stochastic Simulation Descriptives

Statistics

		Groundspeed Simulated	Groundspeed Actual
N	Valid	5000	56
	Missing	0	4944
Mean		29.8155	20.6239
Std. Error of Mean		.06664	.88048
Median		29.7573	19.5984
Mode		16.95[a]	12.01[a]
Std. Deviation		4.71216	6.58892
Variance		22.204	43.414
Skewness		.032	.297
Std. Error of Skewness		.035	.319
Kurtosis		-.935	-1.299
Std. Error of Kurtosis		.069	.628
Range		24.96	19.98
Minimum		16.95	12.01
Maximum		41.91	31.99

a. Multiple modes exist. The smallest value is shown

Table 2A

Deterministic Simulation Descriptive Statistics

		Groundspeed Simulated	Groundspeed Actual
N	Valid	5000	56
	Missing	0	4944
Mean		27.411	29.011
Std. Error of Mean		.0983	.8772
Median		25.006	28.286
Mode		25.1	20.0[a]
Std. Deviation		6.9527	6.5646
Variance		48.341	43.094
Skewness		.563	.214
Std. Error of Skewness		.035	.319
Kurtosis		-1.185	-1.340
Std. Error of Kurtosis		.069	.628
Range		20.0	20.0
Minimum		20.0	20.0
Maximum		40.0	40.0
Sum		137054.0	1624.6
Percentiles	25	20.990	23.480
	50	25.006	28.286
	75	33.789	34.072

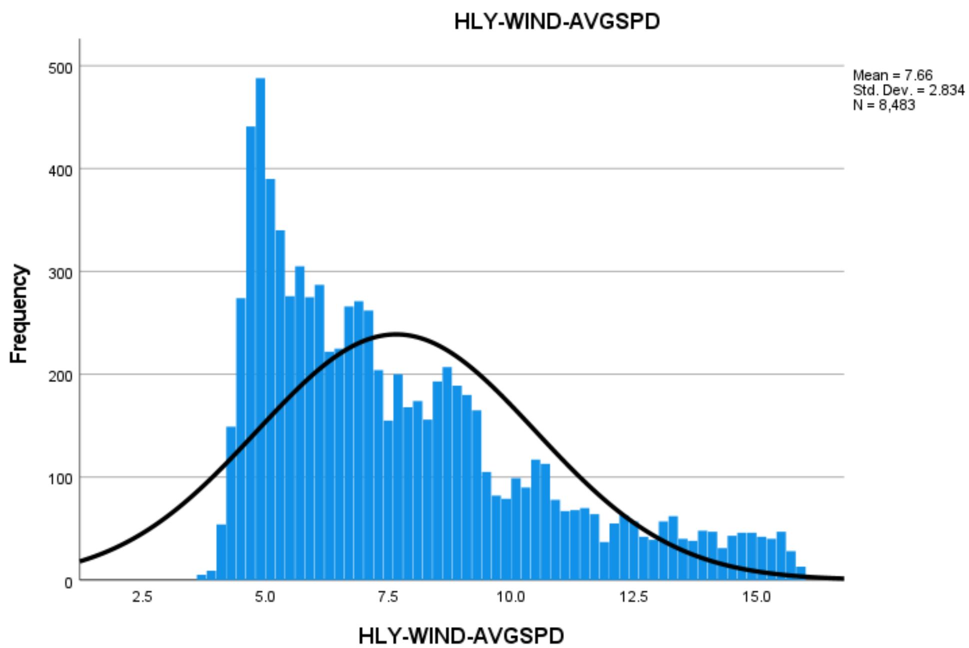
a. Multiple modes exist. The smallest value is shown

Appendix B

Historical Environmental Data

Figure 1B

Arizona



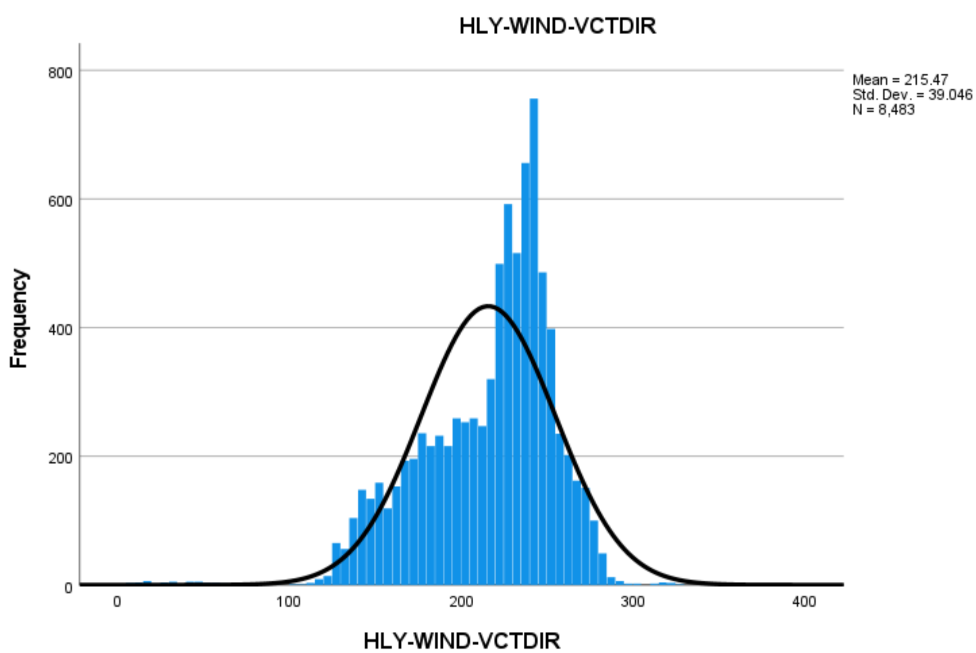
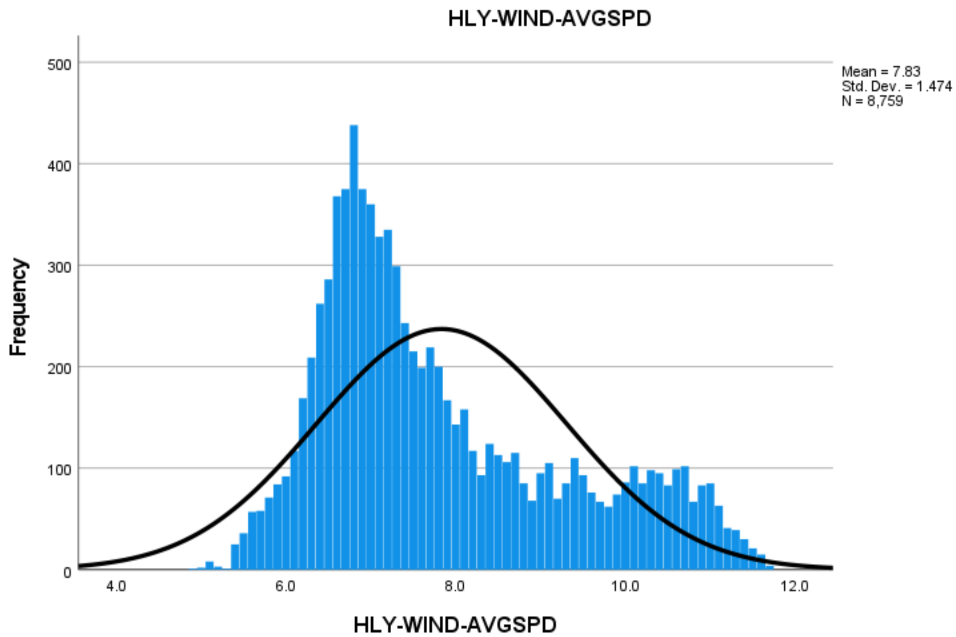


Figure 2B

Idaho



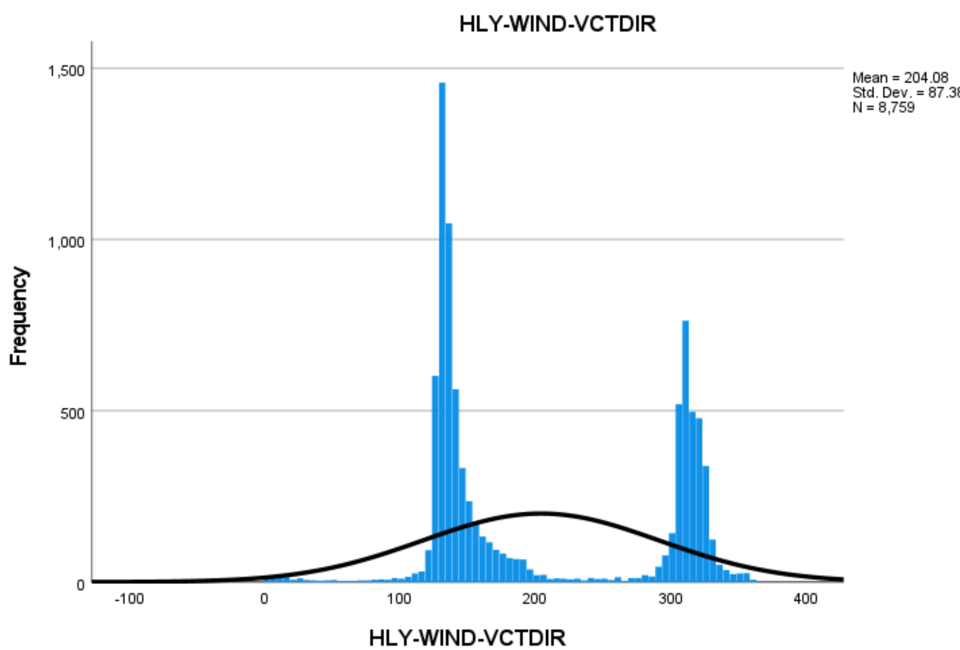
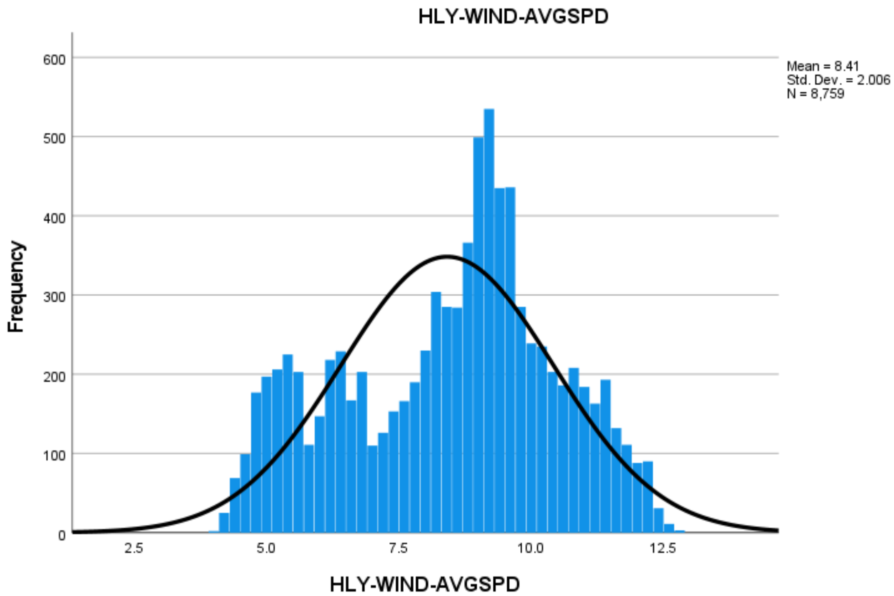


Figure 3B

New York



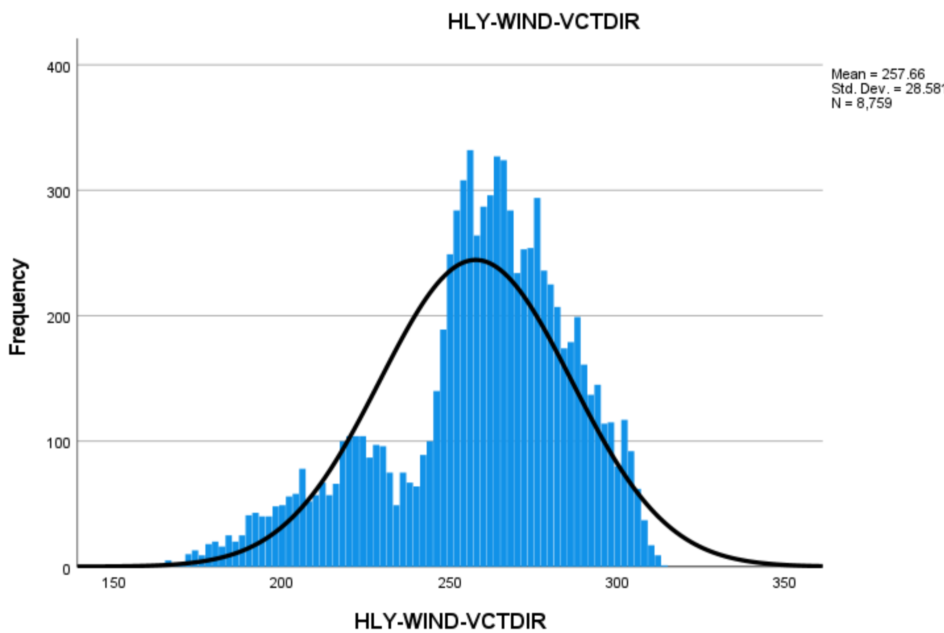
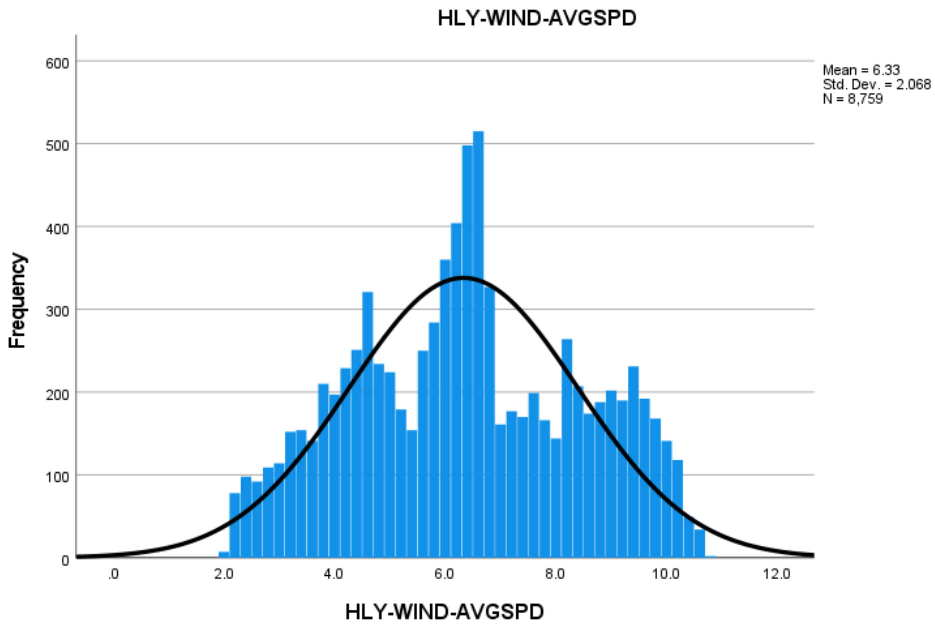
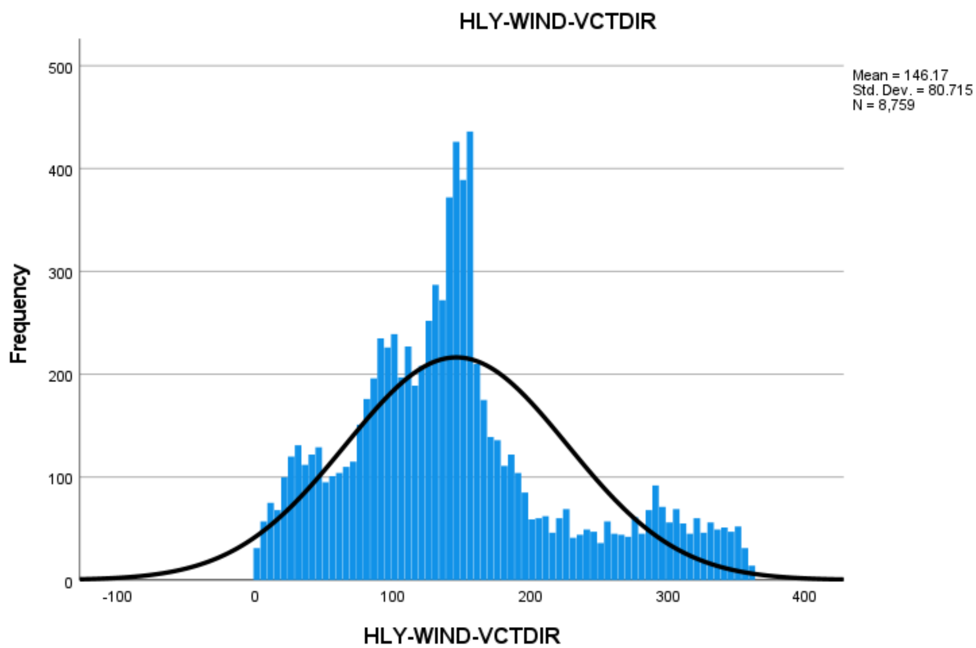


Figure 4B

Mississippi





Appendix C

M_1 Model Algorithm and Input Data

```
MODEL:
! A Vehicle Routing Problem (VRP) for sUAS medical delivery;

 SETS:
 ! Definitions

Parameters:
   Q         is the amount of medicine required at patient location I,
   VHNUM     is the maximum available sUAS,
   VCAP      is the vehicle payload capacity in grams
   VMAXT     is the total travel time available for a vehicle,
   VAL       is the value for visiting city i

Variables:
   Y(I,J)      is a binary variable: 1 if some vehicle travels from
location I to J, else 0
   U(I)        is the accumulated deliveries at location I
   T(I)        is the accumulated time at location I
   Wv          is the wind velocity
   Wd          is the wind direction
   TAS         is the sUAS airspeed
   GS          is the sUAS groundspeed from location I to location J
   LOADCUM(j)  is cumulative load on trip just after city j
   DISTCUM(j)  is cumulative distance on trip just after city j
   ZIN(K)      is binary: 1 if city K is visited
   CITYBGN     is the index of the depot
   TRANSPOSE   is binary: 1 if DISTANCE matrix should be transposed
   INFLAG(i)   is 1 if city i is to be included in the problem
   BACK21ST    is 1 if trip must return to depot
   RUNTIME(i)  is the time spent visiting city i

Time-based parameters:
   RUNTIME   is the transition time to land, unload, and take off at
location k,
   Ttot      is the accumulated travel time at city I
  ;

   CITY: Q, U, TD, TME, TML, TMV, TMA, DB4,DFT
     , RUNTIME, INFLAG, ISREALLY, SFLAG
     , VAL
     , TimEarl, TimLate
     , XCORD, YCORD
     , LOADCUM, DISTCUM
     , ZIN;
   CXC( CITY, CITY): DIST, X, FLO, DistNoWind, HDG, Wv,Wd
      , DISTANCE         ! Changeover time, excluding runtime;
      ,  CMBDIST         ! The final distance matrix;
      ,    Y             ! Y( I, J) = 1 if CXC I, J is in tour;
   ;
   CITYBGN( CITY);                      ! Identify city, or depot, at which
tour begins;
   VHTYP: VHNUM, VHCAP, VHDIST, TAS;       ! Different vehicle types;
```

```
  DUMMY/1..1/; ! For excluding/isolating a CALC or SUBMODEL.
      @FOR( DUMMY | 0:
         code to be excluded..
          );

   CXCSUB(CXC): dcity, acity, arrohd;  ! Arcs in routes used, for
graphing solution;
 ENDSETS

 DATA:
TOLRELOPT = 0.01; ! Set ending relative optimality tolerance;
TIME2ROPT = 600;  ! Time in seconds to apply optimality tolerance;
TIMETOT  = 180;   ! Upper limit on solve time seconds;
BACK21ST = 1 ;    ! > 0 means must do a changeover back to first at
end;
VHTYP = 1..1;     ! The different vehicle types;
VHCAP = 10;       ! Max capacity of each vehicle type;
VHDIST= 100;      ! Distance limit for each vehicle type;
VHNUM = 1;        ! Number vehicles available of each vehicle type;

CITY= C00   C01   C02   C03   C04   C05;
Q=    0     3     6     5     4     2;
VAL=  0     200   100   200   100   300;

CITYBGN = C00;    ! First city;
!TimEarl = 0 ;    ! Earliest arrival;
!TimLate = 99999; ! Latest arrival;
!TMV= 1000;       ! Visit time at stop k;
INFLAG= 1;        ! INFLAG(j) = 0 if city j is not to be included in
this problem instance. Else 1 ;
RUNTIME=2;        ! RUNTIME(j) = time spent at city j;


! DISTMTYP = 0: explicit distance matrix,
             1: x-y coordinates, Manhattan/L1 metric,
             2: x-y coordinates, Euclidean distance,
             3: latitude-longitude, great circle distances;

DISTMTYP = 0;
DISTANCE=

0     25.0  8.2   34.2  30.9  22.1
14.8  0     21.0  26.7  6.3   35.9
21.1  44.1  0     54.9  50.3  26.9
12.8  15.6  20.7  0     17.2  23.1
16.9  2.6   23.5  24.6  0     37.4
25.7  49.7  17.6  48.1  54.9  0



;


XCORD, YCORD =

-89.4253    31.1663
```

```
-89.4599    31.1181
-89.382     31.1776
-89.4971    31.1689
-89.4721    31.1124
-89.4132    31.2356


;
ENDDATA


SUBMODEL sUAS_OpStp:
!  Parameters:
!    DISTMAX = distance upper limit for the trip,
     NUMC = number cities, including depot, in the problem,
     CMBDIST( i, j) = distance or time from city i to city j,
     CFIRST = index of depot city,
     LenWgt = Weight applied to minimizing tour length,
     PenWgt = Weight applied to minimizing penalty for missed stops;



;

  ! Minimize Distance and penalties;
   MIN = LenWgt* TourLen + PenWgt* TourPen;
     TourLen = @SUM( CXC( i, j)| i #LE# NUMC #AND# j #LE# NUMC:
CMBDIST( i, j)* Y( i, j));
     TourPen = @SUM( CITY( I)  | i #LE# NUMC #and# i #NE# CFIRST:
VAL(i)*(1 - ZIN( i)));
     TourPen <= TourPenUL;  ! Upper limit on tour penalty;

  !  a vehicle does not travel inside itself,...;
   @FOR( CITY(k)  | k #LE# NUMC :
       Y( k, k) = 0;  ! City cannot go to itself next;
       @BIN( ZIN( k)); ! Either visit k or not;
          );

  ! For each city k, except depot....;
   @FOR( CITY( k)| k #LE# NUMC #AND# k #NE# CFIRST:
  ! a vehicle must enter city K from some city I, together
    their demands cannot exceed vehicle capacity... ;
    [MTXNTRO] @SUM( CITY( i) |  i #LE#  NUMC #AND# i #NE# k #AND# ( i
#EQ# CFIRST #OR#
                 Q( i) + Q( k) #LE# VCAP): Y( i, k)) = ZIN( k);

  ! a vehicle must leave K after service to some city J;
     [MTXITO] @SUM( CITY( j)| j #LE#  NUMC #AND# j #NE# k #AND# ( j
#EQ# CFIRST #OR#
                 Q( j) + Q( k) #LE# VCAP): Y( k, j)) = ZIN( k);

  ! LOADCUM( k) is at least amount needed at K, but can't
    exceed vehicle capacity;
     @BND( 0, LOADCUM( k), VCAP);

  ! If i precedes k, then can bound LOADCUM( k) - LOADCUM( i);
     @FOR( CITY( i)| i #LE# NUMC #AND# i #NE# k #AND# i #NE# CFIRST:
      [ULO] LOADCUM( k) >= LOADCUM( i) + Q(k)  ! Case: i precedes k;
```

```
                 - ( Q( k) + Q( i))* Y( k, i) ! Case: k precedes i;
                 - VCAP*(1- Y(i,k) - Y(k,i)) ; ! Case: neither above;
          );
       );

! If i precedes k, then can bound DISTCUM( k) - DISTCUM( i);
  ! For each city k, except depot....;
   @FOR( CITY( k)| k #le# NUMC #AND# k #NE# CFIRST:
     DISTCUM( k) >= CMBDIST( CFIRST, k)* ZIN( k); ! Assumes triangle
inequality;
     @FOR( CITY( i)| i #LE#  NUMC #AND# i #NE# k #AND# i #NE# CFIRST:
      [MTZUDO] DISTCUM( k) >= DISTCUM( i) + CMBDIST( i, k)        !
Case: i precedes k;
                 - ( CMBDIST( i, k) + CMBDIST( k, i))* Y( k, i) ! Case:
k precedes i;
                 - DISTMAX*(1- Y( i, k) - Y( k, i)) ;           ! Case:
neither above;
          );



! Cut based on CMBDIST( ) satisfying the triangle inequality;
      [OSMCUTRIMO] DISTCUM( k) >= @SUM( CITY( i) | i #LE#  NUMC #AND# i
#NE# k #AND# i #NE# CFIRST:
                            ( CMBDIST( CFIRST, i) + CMBDIST( i, k))*
Y( i, k));

      DISTCUM( k) + CMBDIST( k, CFIRST) <= DISTMAX; ! Assumes triangle
inequality;
    );

   ! Make the Y's binary;
   @FOR( CXC( i, j) | i #LE#  NUMC #AND# j #LE#  NUMC : @BIN( Y(i,j)));

   ! Maximun number vehicles allowed;
    @SUM( CITY( j) | j #LE#  NUMC #AND# j #NE# CFIRST: Y( CFIRST, j))
<= VEHNMAX;

! Some cuts;
!  Minimum no. vehicles required, fractional
    and rounded up;
   VEHCLF = @SUM( CITY( I)| i #LE#  NUMC #AND# I #NE# CFIRST: Q( I))/
VCAP;
   VEHCLR = @FLOOR( VEHCLF +.9999); ! Min vehicles needed if all cities
must be visited;

! Must send enough vehicles out of depot;
!Key; !  @SUM( CITY( j) | j #LE#  NUMC #AND# j #NE# CFIRST: Y(
CFIRST,j)) >= VEHCLR;
  VCAP * @SUM( CITY( j) | j #LE#  NUMC #AND# j #NE# CFIRST: Y(
CFIRST,j)) >=
         @SUM( CITY( i)| i #LE#  NUMC #AND# I #NE# CFIRST: Q( I)* ZIN(
i)) ;
! Some Gomory cuts on the 'send enough vehicles' cut;
!  Need a separate trip for each city requiring > 0.5 truck;
    @SUM( CITY( j) | j #LE#  NUMC #AND# j #NE# CFIRST: Y( CFIRST,j)) >=
```

```
    @SUM( CITY( i) | i #LE#  NUMC #AND# I #NE# CFIRST #AND# 2* Q( I)
#GT# VCAP: ZIN( i)) ;

   @FOR( CITY( k)  | k #LE#  NUMC #AND# k #NE# CFIRST:
! A cut: If K is 1st stop, then LOADCUM( k) = Q( k);
!Key;     LOADCUM( k) <= VCAP - ( VCAP - Q( k)) * Y( CFIRST, k);

! A cut: If K is not 1st stop...;
!Key;     LOADCUM( k) >= Q( k) * ZIN( k)
           + @SUM( CITY( i)| i #LE#  NUMC #AND# i #NE# CFIRST: Q( i) *
Y( i, k));
! A cut: If K is not last stop...;
!Key;     LOADCUM( k) <= VCAP
           - @SUM( CITY( i)| i #LE#  NUMC #AND# i #NE# CFIRST: Q( i) *
Y( k, i));
        );

  !  3 item knapsack cuts,( 2 item case Q(i) + Q(j) #GT# VCAP already
taken care of);
!Weak; @FOR( CITY( i) | i #LE#  NUMC #AND# i #NE# CFIRST:
        @FOR( CITY( j) | j #LE#  NUMC #AND#  j #GT# i:
          @FOR( CITY( k) | k #LE#  NUMC #AND# k #GT# j #AND# Q( i) + Q(
j) + Q( k) #GT# VCAP:
               Y( i, j) + Y( j, i) + Y( i, k) + Y( k, i) + Y( j, k) +
Y( k, j) <= 1;
              );
             );
          );

! Subtour size 2 cuts,( Case Q(i) + Q(j) #GT# VCAP already taken care
of);
!Key;  @FOR( CITY( i) | i #LE#  NUMC #AND# i #NE# CFIRST:
        @FOR( CITY( j) | j #LE#  NUMC #AND# j #GT# i #AND# Q( i) + Q(
j) #LE# VCAP:
            Y( i, j) + Y( j, i) <= 1;
            );
          );

 ! Subtours of size 3 cuts,( Case Q(i) + Q(j) #GT# VCAP already taken
care of);
!Key; @FOR( CITY( i) | i #LE#  NUMC #AND# i #NE# CFIRST:
        @FOR( CITY( j) | j #LE#  NUMC #AND# j #GT# i #AND# j #ne#
CFIRST #AND# Q( i) + Q( j) #LE# VCAP:
          @FOR( CITY( k) | k #LE#  NUMC #AND# k #GT# j #AND# k #ne#
CFIRST :
               Y( i, j) + Y( j, i) + Y( i, k) + Y( k, i) + Y( j, k) +
Y( k, j) <= 2;
              );
             );
          );

 ! Subtours of size 4 cuts,( Case Q(i) + Q(j) + Q( k) #GT# VCAP already
taken care of);
!Key; @FOR( CITY( i) | i #LE# NUMC #AND# i #NE# CFIRST:
        @FOR( CITY( j) | j #LE# NUMC #AND# j #GT# i #AND# j #ne# CFIRST
#AND# Q( i) + Q( j) #LE# VCAP:
```

```
          @FOR( CITY( k) | k #LE# NUMC #AND# k #GT# j #AND# k #ne#
CFIRST #AND# Q( i) + Q( j) + Q( k) #LE# VCAP:
            @FOR( CITY( h) | h #LE# NUMC #AND# h #GT# k #AND# h #ne#
CFIRST :
                Y( i, j) + Y( j, i) + Y( i, k) + Y( k, i) + Y( i, h) +
Y( h, i)
              + Y( j, k) + Y( k, j) + Y( j, h) + Y( h, j)
              + Y( k, h) + Y( h, k) <= 3;
              ); ); ); );
ENDSUBMODEL

PROCEDURE SETUPDISTMAT:
!  Setup standard from-to distance matrix from whatever initial form
the data are supplied;
 ! Outputs:
   NUMC = number of cities in problem, based on INFLAG,
   ISREALLY(j) = original index of city j in reduced problem based on
INFLAG( ),
   CMBDIST( i, j) = effective distance from i to j, including any visit
time
;
  N = @SIZE( CITY); ! Number cities in the full problem;
  NUMC = N;

! distmtyp = 0: explicit distance matrix,
             1: x-y coordinates, Manhattan/L1 metric,
             2: x-y coordinates, Euclidean distance,
             3: latitude-longitude, great circle distances,
             4: explicit matrix but also X-Y coordinates for graphing;

! If using X-Y coordinates Manhattan/L1 metric, compute the distance
matrix;
  @IFC( distmtyp #eq# 1:
    @for( CXC(i,j) | i #le# j:
      DISTANCE( i,j) = @abs( xcord(i) - xcord( j)) + @abs( ycord(i) -
ycord(j));
      DISTANCE(j,i) = DISTANCE(i,j);
        );
      );

! If using X-Y coordinates Euclidean metric, compute the distance
matrix;
  @IFC( distmtyp #eq# 2:
    @for( CXC(i,j) | i #le# j:
      DISTANCE( i,j) = (( xcord(i) - xcord( j))^2 + (ycord(i) -
ycord(j))^2 )^0.5;
      DISTANCE(j,i) = DISTANCE(i,j);
        );
      );

 @ifc( DISTMTYP #eq# 3:
! This portion calculates the distance matrix DIST(i,j) assuming XCORD
and YCORD
   are the longitude and latitude in degrees;
   D2R = @PI()/180; ! Degrees to radians conversion factor;
 ! Compute Great Circle Distances. Radius of earth = 6371 km.
  Notice this simplifies if YCORD(i) = YCORD(j) or XCORD(i) = XCORD(j);
```

```
   @FOR( CXC(i,j):
     @IFC( i #EQ# j: distance(i,j) = 0;! Get rid of trivial roundoff;
       @ELSE
        distance( i,j) =
6371*@acos(@sin(D2R*YCORD(i))*@sin(D2R*YCORD(j))+@cos(D2R*YCORD(i))*@co
s(D2R*YCORD(j))
                     *@cos(@ABS(D2R*(XCORD(i)-XCORD(j)))));
         );
       );
      ); ! End Lat-long distance calculation;


 ! Index of first/depot city;
 @FOR( CITYBGN( k): CFIRST = k);
! @write( CITyBGN( CFIRST),' is the depot with index= ', CFIRST,
@NEWLINE( 1));

@for( dummy | 0:
!  Write out part of the distance matrix;
   @for(city(j):
     @write( @format( city(j),'7s'));
       );
   @write( @newline(1));
   @for( city(i) | i #le# 24:
      @for( city(j) | j #le# 24:
        @write( @format( distance(i,j), '7.2f'));
          );
       @write( ' ',city(i),@newline(1));
        );
     );


  ! Do an in-place transpose if requested;
  @IFC( TRANSPOSE:
    @FOR( CXC( i,j) | i #LT# j #AND# j #LE# NUMC:
      TEMP = DISTANCE(i,j);
      DISTANCE(i,j) = DISTANCE(j,i);
      DISTANCE(j,i) = TEMP;
        );
      );

 ! Check if CFIRST makes sense;
  @IFC( CFIRST #GE# 1 #AND# CFIRST #LE# N:
    @IFC( INFLAG( CFIRST) #EQ# 1:
      Status = 0;
        );
     @ELSE
       Status = 1;
      );
  @IFC( Status #GT# 0:
     @WRITE(' ERROR: First task, ',CFIRST,' is not in active
set.',@NEWLINE(1));
     CFIRST = 1;
      );

  ! If need not do changeover back to CFIRST, set its changeover = 0;
  @IFC( BACK21ST #EQ# 0:
```

```
    @FOR( CITY(i):
      DISTANCE(i,CFIRST) = 0;
        );
      );

  ! Strip out the cities with INFLAG(j) = 0;
    NUMC = 0;

!  @write('ALPHA: INFLAG(2), INFLAG(3)= ', INFLAG(2), ' ', INFLAG( 3),
@newline(1));
  @FOR( CITY( j) | INFLAG( j) #GE# 1:
    NUMC = NUMC + 1;
    ISREALLY( NUMC) = j;
!    @WRITE('  j to NUMC, CFIRST = ',j,', ',NUMC,', Q( j)= ',  Q( j),
@NEWLINE(1));
    @IFC( j #EQ# CFIRST: CFIRST = NUMC);
    RUNTIME( NUMC) = RUNTIME( j);
    Q( NUMC) = Q( j);              ! Move demands down;
    VAL( NUMC) = VAL( j);          ! Move values of visiting down;
    TimEarl( NUMC) = TimEarl( j); ! Move time windows down;
    TimLate( NUMC) = TimLate( j);
!    @write( 'NUMC,Q(NUMC)= ',NUMC,' ', Q(NUMC), @newline(1));
    @FOR( CITY( k):
     DISTANCE( k, NUMC) = DISTANCE( k, j); ! Move col j early;
     DISTANCE( NUMC, k) = DISTANCE( j, k); ! Move row j early;
       );

! Assume Demands greater than vehicle capacity have been handled
beforehand;
! Subtract out obvious full loads;
!    @IFC( Q( NUMC) #GT# VCAP:
        QOVER( NUMC) = @FLOOR( Q( NUMC)/ VCAP); ! Number full loads
over;
!         Q( NUMC) = Q( NUMC) - VCAP* QOVER( NUMC); ! Remaining partial
load;
!       @ELSE
        QOVER( NUMC) = 0;
!         );
! Special case where Q = VCAP;
      );

   @WRITE( ' This problem has number cities/products(including depot)=
', NUMC, @NEWLINE(1));

   ! Turn off non-selected cities;
   @FOR( CXC(i,j) | i #GT# NUMC #OR# j #GT# NUMC:
      y(i,j) = 0;
       );

  TOTRUN = @SUM( CITY(j) | j #LE# NUMC: RUNTIME(j));

  ! Adjust for run time. Time from start of changeover to finish of run
of task;
  @FOR( CXC( i, j) | i #LE# NUMC #AND# j #LE# NUMC:
    CMBDIST( i, j) = DISTANCE(i,j) + RUNTIME(j);
      );
```

```
 ! Write distance matrix;
  @ifc( 0:
   @write(' Here is the distance matrix:', @newline(1));
   @for( city(i) | i #le# numc:
     @write( @format( city(i), '8s'))
       );
  @write( @newline(1));
   @for( city( i) | i #le# numc:
     @for( city( j) | j#le# numc:
       @write( @format( cmbdist(i,j),'8.3f'));
         );
     @write( ' ', city(i), @newline(1));
       );
      );
endprocedure

PROCEDURE DoReportArc:
      NROUTES = 0;
  ! Write a listing of the routes;
      @FOR( CITY( j):
        @IFC( Y( CFIRST, j) #GT# .5:  ! Is j a 1st city on a route?;
          NROUTES = NROUTES + 1;
          DISTCUMTRP = 0;
          LOADCUMTRP = Q( j);
          @WRITE( @NEWLINE( 2), 'ROUTE ', NROUTES, ':', @NEWLINE(  1));
          @WRITE('           FROM           TO    LENGTH     LOAD',
@NEWLINE( 1));
          @WRITE('------------------------------------------------',
@NEWLINE( 1));
          @WRITE( '   ', @FORMAT( CITY( 1),'12s'), ' ',
            @FORMAT( CITY( j),'12s'),
            @FORMAT( DISTCUMTRP, '10.1f'), ' ', @FORMAT(
LOADCUMTRP,'8.0f'), @NEWLINE( 1)
          );
          IPOS = J; ! Find remaining cities in trip until returning to
CFIRST;
          @WHILE( IPOS #NE# CFIRST:
            NLOOPS = NLOOPS + 1;
            @FOR( CITY( J2):
              @IFC( Y( IPOS, J2) #GT# .5:
                DISTCUMTRP = DISTCUMTRP + CMBDIST( IPOS, J2);
                @IFC( J2 #NE# CFIRST:
                  LOADCUMTRP = LOADCUMTRP + Q( J2);
                  @WRITE( '   ', @FORMAT( CITY( IPOS),'12s'), ' ',
                    @FORMAT( CITY( J2),'12s'),
                    @FORMAT( DISTCUMTRP, '10.1f'), ' ', @FORMAT(
LOADCUMTRP,'8.0f'), @NEWLINE( 1)
                        );
                @ELSE
                  @WRITE( '   ', @FORMAT( CITY( IPOS),'12s'), ' ',
                    @FORMAT( CITY( CFIRST),'12s'),
                    @FORMAT( DISTCUMTRP, '10.1f'), @NEWLINE( 1)
                   );
                );
                IPOS = J2;
                @BREAK;
              ); );  ); ); );
```

```
ENDPROCEDURE

PROCEDURE DoGraphArc:
 ! Display a graph of the routes;
       DISTOT = 0; ! Total distance in all trips;
 ! Loop over arcs used;
   @FOR( CXC( i, j) | i #LE# NUMC #AND# j #LE# NUMC #AND# Y( i, j) #GT#
0.5:
       iprev = isreally( i);
       jprev = isreally( j);
       DISTOT = DISTOT + CMBDIST( i, j);
       @INSERT( cxcsub, iprev, jprev);
       dcity( iprev, jprev) = iprev;  ! Departure city;
       acity( iprev, jprev) = jprev;  ! Arrival city;
       arrohd( iprev, jprev) = 1; ! Put arrowheads on this arc;
          );
   @CHARTNETNODE(
        'Optimal Route, Total Travel Time= ' + @format( DISTOT,'8.2f')
! Title of chart;
      , 'Longitude', 'Latitude' ! Labels for horizontal and vertical;
      , 'Patients'      ! Legend for arc set 1;
      , xcord, ycord        ! Coordinates of the nodes;
      , dcity, acity, arrohd);          ! Node pairs of arcs actually
used;


ENDPROCEDURE

 CALC:;
  @SET( 'TERSEO',1);    ! Output level (0:verb, 1:terse, 2:only errors,
3:none);
  @SET( 'IPTOLR', TOLRELOPT); ! Set ending relative optimality
tolerance;
  @SET( 'TIM2RL', TIME2ROPT); ! Time in seconds to apply optimality
tolerance;
  @SET( 'TATSLV', TIMETOT);   ! Solver time limit in seconds (0:no
limit) for @SOLVE's;

!  @write(' Setup distance matrix', @newline(1));
  SETUPDISTMAT; ! Setup distance matrix;
  VCAP = VHCAP(1);     ! This assumes only one vehicle type;
  DISTMAX = VHDIST(1); ! This assumes only one vehicle type;
  VEHNMAX = VHNUM(1); ! This assumes only one vehicle type;

!LS***;
! First put all the weight on minimizing the penalty for uncovered
stops;
  LenWgt = 0;
  PenWgt = 1;
! @GEN(SUAS_OpStp);  ! Generate the scalar equivalent;
  @SOLVE( SUAS_OpStp);
  ISTAT = @STATUS();
  @write( 'Status for Min Penalty solve = ', ISTAT,' Penalty= ',
TourPen, @newline( 1));

! Now constrain the Penalty for missed stops;
  TourPenUL = TourPen;
```

```
! and minimize the length;
  LenWgt = 1;
  PenWgt = 0;
  @SOLVE( SUAS_OpStp);
  ISTAT = @STATUS();
  @write( 'Status for Min Tour length solve = ', ISTAT,' Tourlength= ',
TourLen, @newline( 1));

    @IFC( ISTAT #EQ# 0 #OR# ISTAT #EQ# 4:
!   Do a report based on a solution stored in the arc variables Y( i,
j);
      DoReportArc;
!   Do a graph of the solution stored in the arc variables Y( i, j);
      DoGraphArc;
    );
 ENDCALC

 END
```