

DRONE DELIVERY OF MEDICAL BLOOD PRODUCTS IN SMART CITIES: AN ARTIFICIAL INTELLIGENCE APPROACH

BY

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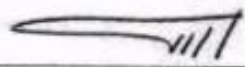
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I dedicate this thesis to my parents, my wife Habiba, and my beloved daughter Wasn. Their love, support, and inspiration have been the driving force behind my academic journey

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LIST OF ABBREVIATIONS

DSS	:	Decision Support System
UML	:	Unified Modeling Language
UAVs	:	Unmanned Aerial Vehicles
DBMS	:	Database Management System
ILP	:	Integer Linear Programming
DDP	:	Drone-Only Delivery Problem
VRP	:	Vehicle Routing Problem
S/N	:	Signal-To-Noise Ratio
ProMut	:	Probability of Mutation
NumPop	:	Population Size
ProCro	:	Probability of Crossover
ProGS	:	Probability of Greedy Search
IntGS	:	Intensity of Greedy Search
NR	:	Number of Refueling Station
NL	:	Number of Launching Station

ABSTRACT

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[In several countries, multiple factors pose challenges to the accessibility of blood groups and associated products, including the intricate supply chain, limited product shelf-life, unpredictable demand at hospitals, and delay in product accessibility. Although drones have been employed in certain countries to enhance the availability and delivery time of blood products to remote healthcare centers, the traditional emergency vehicle delivery system is still constrained due to the centralization of blood supply centers for economic reasons and the mounting traffic congestion. To tackle these challenges and further enhance blood supply logistics, this study proposes a decision support system (DSS) that centralizes the transportation of blood supplies to healthcare facilities using drones. The primary goal of the system is to minimize logistics costs by strategically locating launch and refueling stations and assigning requests to these stations. This approach utilizes integer binary linear programming to provide four possible scenarios that take into account the drone's flight range capacity and the supply node's capacity. The scenario-based analysis results demonstrate that the adoption of refueling stations is a promising strategy for extending the mission range and broadening the coverage of blood supply in non-emergency situations. Furthermore, given the complexity of the NP-hard problem, we suggest using a genetic algorithm in conjunction with Greedy Search to establish an optimal drone-based

logistics network for blood supplies. The algorithm leverages natural selection processes to converge toward a near-optimal solution that considers the drone's flight range capacity and the supply node's capacity. The scenario-based analysis reveals that the adoption of refueling stations is a promising strategy for extending the mission range and broadening the coverage of blood supply in non-emergency situations, which can prevent operational interruptions such as launch station closures. The proposed methodology offers a near-optimal solution with a small discrepancy between the CPLEX optimal and algorithmic solution, demonstrating its effectiveness and potential for improving the delivery of blood in a cost-effective manner.

|

ملخص الرسالة

الاسم الكامل: محمد رياض صالح صياد

عنوان الرسالة: توصيل فصائل الدم بواسطة الطائرات بدون طيار في المدن الذكية: منهج الذكاء الاصطناعي

التخصص: الهندسة الصناعية والنظم

تاريخ الدرجة العلمية: مايو / 2023

في العديد من البلدان، هناك العديد من العوامل التي تعيق الوصول إلى فصيلة الدم ومشتقاته، بما في ذلك سلسلة التوريد المعقدة، وقصر عمر المنتج، وتقلب الطلب على مستوى المستشفى، والوصول في الوقت المناسب. على الرغم من أن بعض البلدان حاولت تحسين توافر منتجات الدم وأوقات تسليمها إلى مرافق الرعاية الصحية البعيدة من خلال استخدام طائرات بدون طيار، إلا أن نظام توصيل المركبات في حالات الطوارئ التقليدية لا يزال معوقًا بسبب مركزية مرافق إمدادات الدم لأسباب اقتصادية وزيادة مستويات حركة المرور. لمواجهة هذه التحديات وتعزيز لوجستيات إمدادات الدم، تقترح هذه الدراسة نظام دعم القرار الذي يركز على نقل إمدادات الدم إلى مرافق الرعاية الصحية باستخدام الطائرات بدون طيار. الهدف الأساسي للنظام هو تقليل التكاليف اللوجستية من خلال التحديد الاستراتيجي لمحطات الإطلاق والتزود بالوقود وتعيين الطلبات لهذه المحطات. يستخدم هذا النهج البرمجة الخطية الثنائية الصحيحة لتوفير أربعة سيناريوهات محتملة تأخذ في الاعتبار سعة نطاق طيران الطائرة بدون طيار وقدرة عقدة الإمداد. تظهر نتائج التحليل القائم على السيناريو أن اعتماد محطات التزود بالوقود هو استراتيجية واعدة لتوسيع نطاق المهمة وتوسيع تغطية إمدادات الدم في الحالات غير الطارئة. علاوة على ذلك، نظرًا لتعقيد المشكلة في علم التعقيد الحسابي، نقترح استخدام خوارزمية جينية بالاشتراك مع البحث الجشع لإنشاء شبكة لوجستية مثالية قائمة على الطائرات بدون طيار لإمدادات الدم. تستفيد الخوارزمية من عمليات الاختيار الطبيعي للتلاقي نحو حل شبه مثالي يأخذ في الاعتبار قدرة نطاق طيران الطائرة بدون طيار وقدرة عقدة الإمداد. يكشف التحليل القائم على السيناريو أن اعتماد محطات التزود بالوقود هو استراتيجية واعدة لتوسيع نطاق المهمة وتوسيع تغطية إمدادات الدم في الحالات غير الطارئة، والتي يمكن

أن تمنع الانقطاعات التشغيلية مثل إغلاق محطة الإطلاق. تقدم المنهجية المقترحة حلاً شبه مثالي مع وجود تباين بسيط بين حل CPLEX الأمثل والحل الحسابي، مما يدل على فعاليتها وإمكانية تحسين توصيل الدم بطريقة فعالة من حيث التكلفة وسرعة الحل.

CHAPTER 1

INTRODUCTION

1.1 Overview

The emergence of intelligent cities is an increasingly prevalent trend across the globe, with smart mobility constituting a crucial component. Enhancing the quality of life in urban areas hinges significantly on the incorporation of smart mobility and transportation logistics. By leveraging cutting-edge technologies like digitalization, artificial intelligence, and information technologies, smart mobility can streamline logistics operations. Information technologies, such as artificial intelligence, cloud computing, 5G communication networks, blockchain, and the Internet of Things (IoT), can help tackle challenges arising from urbanization and conventional road networks, as well as expedite logistics processes.

One of potential area of interest in smart city is health care logistics as shown in Figure 1. Saudi Arabia is a relatively new market for using drone aircraft to deliver healthcare services. Drones can be used both for mobility and logistics. Drones are a practical option for health service providers to boost their capacity and efficiency to give services to its patients.

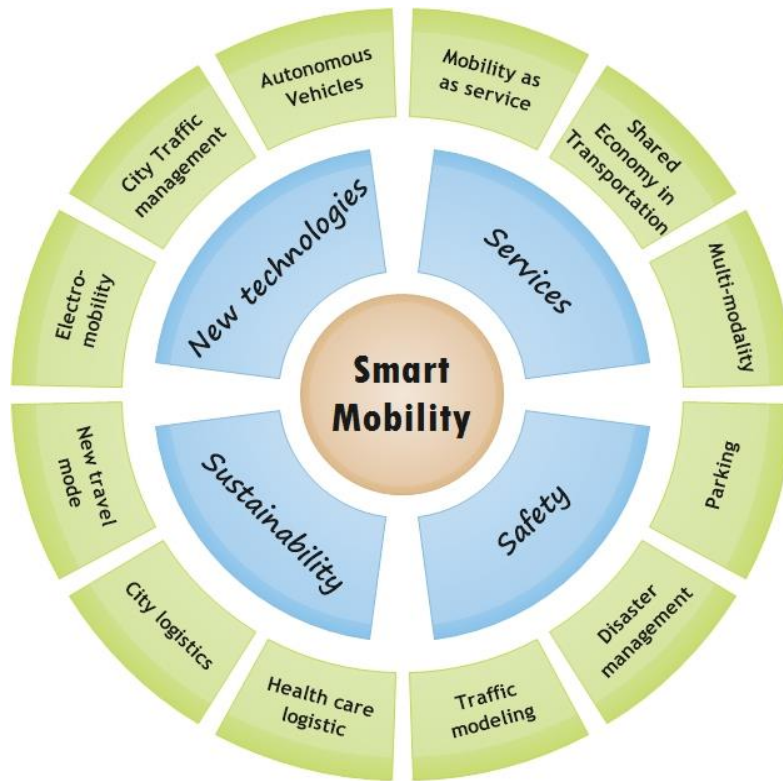


Figure 1.Exploration of Recent Technologies and Issues in Smart Mobility

Drones were traditionally exclusive to military use, but they have recently gained popularity in commercial and scientific fields due to their cost-effectiveness. Drones can be particularly useful in providing medical services to remote areas and disaster-stricken regions, where they can aid in assessments and deliver essential supplies like blood, vaccines, and medication. They also have the potential to conduct tests and procedures on patients suffering from cardiac arrest. In geriatric healthcare, drones are already being used to deliver mobility aids to the elderly and may be utilized in the future for imaging tests in rural areas. A recent survey [1] explored the collaborative use of drones and IoT in enhancing smart city intelligence, opening up new possibilities for drone technology.

Drones are being utilized for more than just transporting perishable goods, as they are now being used to transport essential medical supplies and drugs. [2] has proposed a customized drone prototype for transporting vaccines to remote areas in Nepal. It is crucial to handle blood products, particularly those with a limited lifespan, with care during delivery. To ensure proper handling, drones are being deployed to distribute blood supplies, which is a relatively new application in Saudi Arabia.

The utilization of unmanned aerial vehicles (UAVs) for delivering blood and blood products to medical facilities in urban areas is an emerging technology known as drone delivery of blood group in smart cities. This innovative approach to blood transportation has the potential to transform the delivery of blood to patients in need, as it provides a rapid and efficient method for transportation. The primary objective of the study conducted by [3] was to provide a comprehensive overview of the current and possible applications of drone technology in emergency medication, while also identifying the obstacles and prospects that may be encountered in the future.

According to [4], traditional ground-based delivery systems for blood products can be slowed down by traffic congestion and road closures during emergencies. However, using drones for blood supply chain management is a promising solution that can reduce response times and be cost-effective. By delivering blood directly to its intended destination, drone delivery can avoid the delays caused by ground-level traffic and roadblocks, especially in densely populated urban areas where healthcare facilities are located. The increasing traffic levels in these areas have made it challenging for emergency responders to reach their destination quickly. This issue can be resolved by using drones to deliver blood products in smart cities.

The delays in transporting blood supplies can be attributed in part to the reliance on traditional emergency vehicles, which are often ineffective and costly. As a solution, some healthcare organizations are considering using drones for delivery. Drones are a faster and more agile option that can avoid traffic and reduce costs. This makes them an appealing choice for healthcare facilities looking to improve their supply chain management [5].

The use of drones in blood delivery has several advantages. Firstly, it reduces the time it takes to transport blood products, which is critical in emergencies where time is of the essence. Secondly, drones can transport blood products to hard-to-reach locations, such as remote areas or disaster-stricken areas where road access is limited. By improving the speed and efficiency of blood delivery, this technology has the potential to save lives, particularly in emergency situations. It could also help to reduce the burden on medical transportation systems, enabling medical facilities to provide better care to patients. Lastly, drone delivery can reduce transportation costs and help medical facilities to maintain adequate supplies of blood group. Moreover, drones offer a diverse range of advantages, spanning from enhanced response times in medical emergencies, leading to an increase in saved lives, to their eco-friendly nature, with lower CO₂ emission levels compared to traditional transportation methods. The implementation of drone technology has revolutionized the healthcare sector, and in Africa, it is imperative to promote inclusive innovation to ensure the continued development of this technology, making it more secure and widely accepted[6], [7].

Although there are potential benefits to using drone delivery for blood products in smart cities, there are also several challenges that must be addressed. The main hurdle is regulatory compliance, as drones are subject to strict safety regulations and airspace

restrictions. Advanced navigation and collision-avoidance systems are also necessary to ensure the safe operation of drones in urban environments.

Alongside these challenges, there are ethical and social implications that need to be considered. The potential impact on employment is a concern, as drone delivery may replace some jobs in the transportation sector. Additionally, privacy concerns arise from the use of drones equipped with cameras and sensors, which may infringe on people's privacy.

To further support the challenges of using unmanned aerial vehicles (UAVs) for medical product transport, a study by [8] discusses technical issues, weather conditions, and the need for appropriate infrastructure and logistics support. Despite these challenges, successful UAV-based medical product transport programs have been implemented, demonstrating the potential benefits of using drones in the transportation of medical products.

To address these concerns, it is important to engage with stakeholders, including medical professionals, regulators, and the general public, to ensure that the implementation of drone delivery of blood group in smart cities is done in a way that is ethical, safe, and socially responsible.

Many healthcare facilities have adopted the cost-saving measure of centralizing their blood supply facilities. This entails consolidating the storage and distribution of blood products into a single central location rather than dispersing them across multiple sites. While this approach can effectively reduce costs and enhance the efficiency of blood supply

management, it has also caused significant delays in traditional emergency vehicle delivery.

To overcome this challenge, [9] proposes a decision support system (DSS) for coordinated disaster relief distribution. The DSS is designed to help humanitarian organizations manage disaster relief efforts by providing real-time decision-making support. The DSS is designed to centralize the transportation of blood supplies by strategically locating launch and refueling stations and assigning requests to these stations. This process ensures that blood supplies are delivered to healthcare facilities promptly and efficiently, thereby reducing the likelihood of delays that could have negative consequences for patients.

1.2 Thesis Objectives

The primary aim of this investigation is to create mathematical models that utilize integer programming to develop a dependable and effective drone-based blood group supply network for the healthcare sector, considering specific variables. By incorporating additional charging stations into the framework, the reliable network's service area can be expanded. This study seeks to explore the feasibility of using drones for last-mile deliveries in the healthcare sector while ensuring that blood supplies are delivered quickly and reliably to their intended destinations. The particular goals of the planned research endeavor are listed as follows:

1. This study introduces a decision support system (DSS) framework that centralizes the transportation of blood supplies to healthcare facilities via drones. The primary objective of this system is to provide input parameters to the models and generate a decision about the logistics process. The system's decision determines the optimal

locations for launch and refueling stations, as well as where the drone should make stops and assign blood requests to these optimal location stations.

2. This study is focused on addressing a real-world issue in healthcare, namely the efficient transportation of blood group supplies to healthcare facilities through the use of drones. To accomplish this, the research will utilize an optimization process to determine the optimal locations for drone launching stations. The development of a DSS framework that comprises four mathematical models, including network design models, is the primary objective of the study. Through the use of these models, healthcare requests will be allocated to routes instead of facility locations, resulting in a reduction of complexity by decreasing the number of variables and constraints involved. This approach differs from traditional facility location problems that rely on covering and median problems, making it a unique and innovative solution.
3. This study utilizes a Genetic Algorithm, which is capable of providing rapid and efficient decision-making solutions for complex problems within a limited timeframe.
4. One of the objectives for this study is to enhance the genetic algorithm's effectiveness by integrating a greedy search mechanism. This modification is intended to generate solutions with computational efficiency and quality that are comparable to the optimal Cplex solution. By minimizing the number of suboptimal solutions generated, this modified genetic algorithm is expected to improve efficiency and enable the efficient resolution of large-scale real-world problems.

1.3 Significance of the Study

The adoption of drone technology for blood supplies in healthcare has numerous benefits, such as navigating through traffic and bypassing road closures to reduce delivery times and ensure timely delivery of critical blood supplies. This is particularly crucial in emergency situations where delays can be life-threatening. In addition, the use of drones can minimize the risk of damage or spoilage during transportation, ensuring the blood's highest quality upon arrival at the hospital. The findings of this research work will be significant for patients, governments, and communities. Patients will benefit from a reliable and efficient drone-based blood supply network that delivers critical blood supplies quickly and reliably, reducing complications and improving healthcare outcomes. Governments can also benefit from cost savings, improved efficiency in the healthcare supply chain, and enhanced disaster response capabilities. Furthermore, the use of drones can promote sustainability by reducing traffic congestion, carbon emissions, and enhancing the availability of life-saving blood transfusions in remote and rural areas. The adoption of drone technology for blood supplies in smart cities can improve the efficiency and reliability of the healthcare supply chain, ultimately leading to better healthcare outcomes for patients, a cleaner environment, and a more sustainable healthcare infrastructure.

1.4 Thesis organization

In the MS thesis, there are five chapters that are arranged as follows. In CHAPTER 1, an outline of the subject is presented, along with the main objectives and the study's significance. CHAPTER 2 provides a comprehensive review of the literature on the drone

logistic network models used in this study and any relevant research. CHAPTER 3 presents a complete, journal article on a decision support system framework for centralizing the transportation of blood group supplies to healthcare facilities via drones. CHAPTER 4 presents another journal article that discusses the use of a genetic algorithm with a greedy search approach to establish a drone-centric logistics system for delivering blood supplies. Finally, CHAPTER 5 concludes the thesis by summarizing the primary findings and offering suggestions for future research in the field of smart mobility and logistics in the healthcare industry. |

CHAPTER 2

LITERATURE REVIEW

2.1 The Application of Drone in Modern Healthcare Industry

Healthcare is one of the most attractive applications of smart technologies and logistics in a global economy that is growing at an alarming rate. The costs of healthcare care are on the rise due to the increasing demand for services, demographic changes, and new medical treatments. The health care systems of many nations strive to be high quality, efficient, effective, cheap, and convenient. An intelligent healthcare logistics operation can save time, and money, and increase productivity in an environment where workers are limited. This leads to an increased level of efficiency and automation within the healthcare sector. Consequently, it promised to improve healthcare logistics processes. As a result of the COVID-19 outbreak, public health providers are required to use smart technology [10]. In same line, [11] aimed to examine the impact of the COVID-19 pandemic on healthcare logistics and supply chain networks. They suggested the utilization of unmanned aerial vehicles (UAVs) for the transportation of polymerase chain reaction (PCR) testing samples between medical facilities and laboratories. This proposed solution could significantly enhance the healthcare system's effectiveness by decreasing the risk of transmission and minimizing the time required for sample transportation. As stated by [12], Smart technologies can improve healthcare delivery and logistics by connecting people, data, medical gear, and mobile applications. Some of the emerging technologies that have made

a significant contribution in the fight against pandemics include artificial intelligence, machine learning, the Internet of Things, 5G, big data, robots, and drones.

The global employment of drones has surged in humanitarian logistics, which aims to deliver prompt medical assistance and resources to disaster-stricken areas. Medical essentials like medication, blood, vaccines, and defibrillators have been effectively delivered via drones by various companies. At Delft University, scholars have devised an innovative Ambulance Drone model capable of dispensing automated defibrillators in emergency situations. [13]. Since 2016, Zipline, situated in the Bay Area, has employed fixed-wing drones to distribute medical resources in Rwanda and Ghana[14]. This achievement has resulted in the quest for fresh opportunities. Zipline obtained consent from the US Federal Aviation Administration (FAA) to distribute medical supplies and personal protective equipment (PPE) to healthcare facilities in North Carolina in response to the Covid-19 pandemic [15]. Matternet has collaborated with UPS to ship prescription drugs from a CVS pharmacy to a retirement home in Florida, endorsing the cost-efficient conveyance of time-sensitive medicines and encouraging social distancing[16]. A German logistics company, Deutsche Post DHL, has stepped into the arena of drone delivery by releasing four iterations of delivery drones, called Parcelcopters [17]. In a six-month experimental phase, Parcelcopter 4.0 effectively distributed medication to an island in Tanzania's Lake Victoria [18]. The employment of these drone transportation services has demonstrated exceptional potential to expedite the delivery of medical resources and assistance to the distressed, especially during moments of emergency.

The healthcare industry relies heavily on the healthcare supply chain to operate efficiently. During health crises, the need for medical services surges, necessitating an upgrade of the

current healthcare delivery system. [19] emphasize the crucial interconnections between the primary components of the intelligent healthcare supply chain by applying the concept of Industry 4.0. According to research by the American Heart Association, the logistics management of the healthcare supply chain is the primary factor propelling the integration of Industry 4.0 in organizations. This development is encouraging news for policymakers and other decision-makers searching for means to optimize the operations of healthcare facilities.

The healthcare supply chain falls short of other industries' delivery networks regarding efficiency and adherence to guidelines. However, the application of digitalization initiatives by management can address this deficiency and boost the performance of the healthcare supply chain. [20] has devised a comprehensive scheme to incorporate digital solutions to capitalize on the advantages of digitalization while enhancing healthcare delivery. This approach encompasses both internal and external avenues for digitalization.

Recent studies reveal that advanced technologies such as automated guided vehicles (AGVs), radio frequency identification (RFID), and the Internet of Things (IoT) have the potential to significantly enhance healthcare delivery in hospitals. The implementation of AGVs, for example, streamlines hospital flow management, cutting down on operational expenses, while also freeing up care personnel from logistical tasks, allowing them to concentrate on providing top-notch patient care [21]. The benefits of using AGVs go beyond cost savings since staff members can concentrate on their primary function, which is providing exceptional patient care, resulting in better patient service. The introduction of such initiatives is a positive indication of significant investment in the digitalization of

the healthcare industry, with RFID technology and AGVs serving as prime examples of digitalization in practice[22].

The COVID pandemic has brought to light disparities in healthcare logistics, necessitating the implementation of measures to enhance hospital efficiency. A fresh and secure healthcare logistics framework is imperative to improve hospital performance. The study presented by[23] proposes an intelligent system, which can be used to identify logistics shortcomings in hospital flows and to suggest solutions based on industry 4.0 and the lean manufacturing approach. The ways in which artificial intelligence (AI), the Internet of Things (IoT), big data, and analytics are applied should be considered in addition to social, societal, and environmental factors. Integration of digital transformation methodologies and smart software solutions may improve healthcare logistics operations. It will also help to reduce the amount of time nurses, caregivers, and physicians waste while improving patient user satisfaction.

The relationship between logistics and healthcare costs is a complex one, as states with more logistics activity tend to experience higher healthcare expenses due to increased carbon emissions, fuel imports, and economic activity tied to logistics. However, this phenomenon hinders the pursuit of sustainability in healthcare as it results in more carbon emissions, fuel imports, and continued economic activity. To address this issue, researchers have proposed the use of smart transportation methods, as demonstrated in a study by Zhao et al [24]. The study found that a combination of economies of scale, transportation structure, and transportation technology could significantly reduce carbon emissions associated with transportation. This highlights the need for smart vehicle modifications to promote both environmental sustainability and logistical efficiency

In a broad survey of 131 countries, Zaman et al.[25] concentrated on logistics performance activities and how they affect long-term healthcare. Through a critical examination of the logistics sector, it was discovered that a significant contributor to carbon dioxide emissions is the transportation of delivery goods using unsustainable fuel, posing a threat to both environmental quality and healthcare sustainability objectives. Greening the supply chain process, according to the conclusions of this research, will help increase vehicle efficiency, reduce fuel imports, and reduce energy consumption on the way to sustainable healthcare practices.

To address the need for a more adaptable healthcare logistics system, the researchers suggest integrating unmanned aerial systems (UASs) into the supply chain. To test this concept, they developed three different scenarios tailored to the specific logistics needs of Valencia, Spain. They conducted various flights, including those in densely populated areas and regulated airspace, all of which adhered to safety standards established by the Specific Operations Risk Assessment (SORA) method. Notably, these successful test flights demonstrated that medical supplies could be delivered quickly and efficiently without the need for costly and specialized infrastructure. [26].

Over the last decade, smart cities have become increasingly relevant due to their ability to intelligently and cooperatively function as sustainable resource ecosystems while improving the lives of people and saving lives. Figure 2 demonstrates that drones and the Internet of Things can form a powerful partnership that allows for a wide range of applications in smart cities, including border surveillance, large-area monitoring, obstacle avoidance, public safety, data collection, and disaster management [27]. The survey generated a lot of interest because it highlights how the collaboration between drones and

the Internet of Things enhances the intelligence of smart cities in areas such as privacy and security, data collection, public safety, energy consumption, and quality of life. Its primary objective is to quantify the level of intelligence of smart cities in relation to environmental concerns, living standards, public safety, and emergency management.

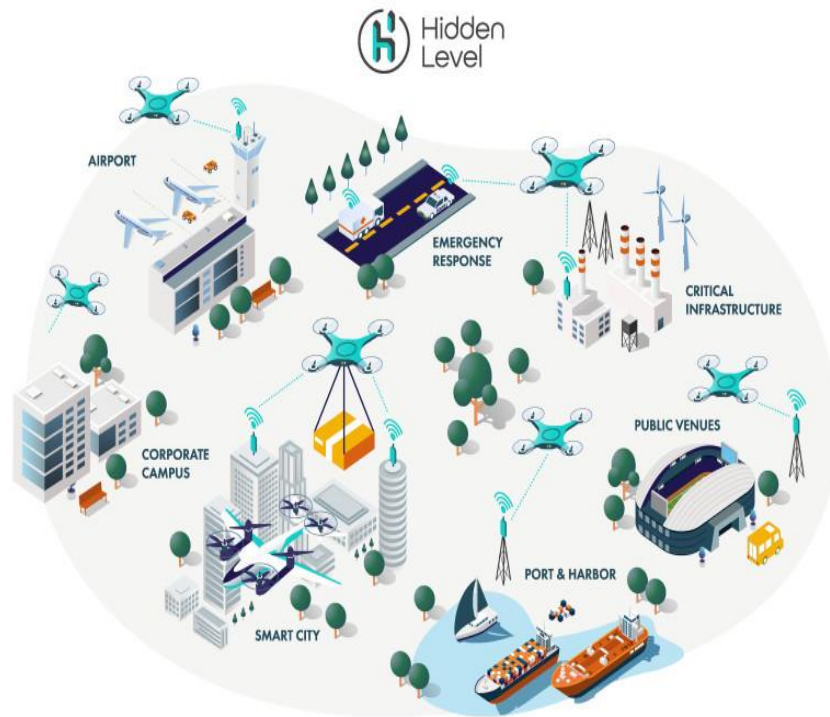


Figure 2 : Drones in Smart City

As stated by [28], drones are becoming more popular in innovative technology ideas and smart city. Drones monitor and provide services in healthcare, mobility, supply chain management, and security. They help to build a city's key infrastructure. The drone may be used in nine different ways in Smart Cities as follows:

1. Transportation system for monitoring for real-time forecasting and elimination of traffic congestion, finding a parking spot, and developing a traffic system model.

2. Healthcare distribution of cardiac pacemakers and health products, as well as ambulance service using an drone.
3. Crowd surveillance, an example, police in the United Kingdom employed a drone to discover a car thief; the drone tracks a crowd using abnormal motion detection or online streaming.
4. Core Infrastructure evaluation is used to assess issue spots such as roads, tankers, power lines, and housing.
5. Monitoring of emissions, pollution, and the management of limited resources;
6. Tourism, including the use of a drone.
7. Support of Geographic Information Systems, geodetic work for remote sensing, and 3D models;
8. Disaster prevention and response, such as fires, earthquakes, and floods;
9. The use of drones and WSN (Wireless Sensor Network) to deliver goods, communicate wirelessly, and collect data.

Drones for diagnostic applications have several economic and health benefits, including urgent help, shorter transit times to the patient, fewer issues for serious injuries reduce the amount of time to wait for rescue, support and development of basic operations of health emergency team members, and the ability to reach areas unreachable by conventional forms of medical travel. [20] calls for three questions and offers a comprehensive overview of them. (a) What are the medical supplies that are carried in the air by drones? (a) And what were the issues or potential restrictions associated with employing drones for delivery? (c) What are the potential benefits of healthcare drones? .[21] findings that drones can transport medical supplies. These are divided into (1) emergency aid supplies,

(2) medical assistance and human organs, (3) protective equipment, and (4) others in priority order.

Because of technical improvements, people can now carry items on demand, supply blood in metropolitan areas, and save themselves from drowning. Using drones to transport blood products could be a feasible option, according to [22]. The delivery of blood samples and analysis materials by drone has been established at two hospitals in Switzerland. A drone carrying less than 2 kilograms and moving at 36 km/h can carry light loads. When a machine fails, it comes equipped with a parachute that allows it to fall safely to the ground [29]. In the same way, a separate Polish effort called Air Vein is developing a method that will make blood exchange between hospitals and regional blood centers significantly more efficient. They intend to build a fleet of unmanned aerial aircraft as well as a terrestrial infrastructure that includes a navigation system, blood storage and transport modules, and a computer system that coordinates blood delivery and distribution[30], [31].

There have been few historical researches on supply chain sustainability and carbon footprint. For example, research has provided evidence that drones can make delivering goods to customers faster, easier and more efficient. Drones assist to lower the ecological footprint while promoting sustainable development by minimizing energy consumption and greenhouse emissions [32], [33]. The model developed by [34] for using drones for last-mile parcel delivery exploits the sustainability aspects of mixed-integer green routing. To solve the complex model efficiently, a genetic algorithm is developed. Furthermore, the [35]work is to assess and contrast the environmental implications of a current motorbike delivery mechanism with a new drone delivery method for food delivery.

Out-of-hospital cardiac arrests continue to be a major public health problem in the United States. According to a 2017 American Heart Association research, roughly 356,000 people are impacted each year, with an 11.4 percent survival rate following emergency medical services (EMS) care[36]. In their carefully designed study, [37]found that drone defibrillator delivery networks on a broad scale have the ability to greatly boost OHCA survival time and still being cost-effective with correct integration into current systems. Researchers in public health should explore lobbying for feasibility studies and policy development in the area of drones. Similarly to [37], [38] assumption is that OHCA response times could be significantly improved by establishing a nationwide aerial drone network. Using the location of public access defibrillators and ambulance services, the system provides real-time location information. To calculate the strategic number and position of drone installations, genetic algorithms were established.

The increasing demand for transportation and traffic congestion have led to the exploration of aerial distribution as an alternative. Drones have been identified as a viable option for the delivery and collection of drugs and test kits for people with chronic illnesses. To optimize the number of drone center locations, two models have been proposed in the study. The first model involves multi-depot path planning problems that account for both pickup and delivery requests, while the second model deals with multi-depot vehicle routing problems with pickup and delivery demands. In order to improve the efficiency of the proposed method, a pre-processing strategy, a partition method, and a Lagrangian relaxation (LR) approach have been developed. Additionally, the research by [39] has highlighted the use of heuristic evolutionary algorithms to determine the optimal number and placement of drone launching and recharging stations. Given that drones have a limited

endurance, they may have to visit multiple charging stations to reach their intended destination.

2.2 Enhancing Healthcare Logistics through Optimization Models for Last-Mile Delivery Using Drone

Healthcare supply chain management is a complex and critical process that requires efficient logistics and transportation systems to ensure timely delivery of medical supplies and equipment. The use of Unmanned Aerial Vehicles (UAVs) in healthcare supply chain management has emerged as a promising solution for overcoming the challenges of traditional transportation methods, such as traffic congestion, long delivery times, and poor accessibility. In this literature review, we will explore the existing literature on modeling supply chain networks using UAVs in healthcare systems.

The surge in interest in delivery drones has stimulated the development of optimization models to tackle the logistical challenges associated with drone-based delivery systems. Notably, the literature on last-mile drone delivery has primarily centered on devising solutions for routing and scheduling issues, frequently modeled as variations of the Traveling Salesman Problem or the Vehicle Routing Problem [34], [40]–[42]. However, given the limited carrying capacity of drones, which typically allows for the transportation of only one package per trip, each delivery requires a distinct trip. This factor renders routing models insufficient in fully accounting for the complexities of drone-based delivery systems. The objective, therefore, is to efficiently schedule and sequence a set of trips to effectively serve all demand locations.

The application of unmanned aerial vehicles (UAVs) in last-mile delivery is limited by their operational range, which has prompted researchers to explore the integration of UAVs with traditional land vehicles, particularly trucks. The synchronized truck-drone last-mile delivery approach was first proposed by [43], who introduced the flying sidekick TSP and parallel drone scheduling TSP models. Since then, subsequent research studies have extended and built upon these two models to develop hybrid truck-drone delivery systems [44]–[49]. In contrast to previous systems, [50] proposed a new approach for joint drone and truck employment in same-day delivery, where drones regularly resupply the load of a delivery truck. However, in numerous hybrid delivery scenarios that involve both trucks and drones, coordinating the schedules of these vehicles is crucial, and this coordination adds a significant level of computational complexity to the routing models used in such operations.

Operations research and optimization modeling are commonly used in various fields, including healthcare and logistics for humanitarian aid purposes [51], [52]. The delivery of medical supplies and services is often complicated and involves several challenges, including problems related to scheduling [53], supply chain integration [54], and routing [55]. The prospect of utilizing drone-based delivery systems for emergency packages has recently captured the attention of researchers. In the context of disaster management, [56] has developed a facility location model that incorporates the motion components of drone transportation, with the aim of minimizing a complex cost function. Meanwhile, [57] has proposed a multi-objective formulation for capacitated vehicle routing problems to optimize the distance and number of drones employed for delivering blood during emergencies. This formulation takes into account external environmental factors, heating

devices, and time, in order to ensure the maintenance of blood temperature. Furthermore, to address the uncertainty of drone operating conditions, [58] has introduced a chance constraint programming approach to optimize the location of drone launch platforms for disaster relief management. To contend with the unpredictable fluctuations in battery consumption that can lead to flight distance uncertainty, the researchers devised a strategy. Additionally, in a recent study, [59] put forth two optimization models designed for the emergency delivery of perishable goods via drones. The initial model seeks to minimize the total disutility value by identifying optimal platform locations and demand assignments. The second model expands upon this approach by accounting for a two-period problem, in which the relocation of platforms becomes a viable option after the first period.

To speed up the delivery and receiving of COVID-19 kits to potentially infected individuals, [60] have introduced an innovative approach. Their flexible network utilizes a combination of four vehicle routing algorithms, including greedy, intra-path, and tabu algorithms, to optimize drone routing, which minimizes flying time and improves distance. The system's artificial intelligence algorithm intelligently determines the best timing for supplying the test kits, making it an advanced system that contributes to the development of smart healthcare. In addition, this system offers the added benefit of reducing carbon footprints, which is particularly advantageous for developing countries struggling with outdated delivery vehicles and transportation systems that hinder their efforts to reduce carbon footprints.

Moreover, in times of pandemics like the COVID-19 outbreak, the healthcare system, which is one of the essential components of modern civilization, faces unprecedented and severe stress. To support healthcare systems, smart mobility and logistics systems can

leverage the flexibility of UASs by rapidly deploying an air delivery network in high-pressure situations. [34] have introduced a novel approach called Concept of Operations (ConOps) for UAS BVLOS deliveries within regulated airspace and large cities to create an upgraded ground logistics network. They have shown that the UAS delivery ConOps is a viable option that can be quickly deployed without requiring any specialized infrastructure or external support services, except for the ground logistics network. This could serve as a reliable ground transport support system during emergencies

The potential of unmanned aerial vehicles (UAVs) to transform logistics and delivery has been a topic of interest in recent years. Among the many applications of UAVs, delivering medical supplies to hospitals in urban areas is a particularly promising one. A study by [61] explores the economic benefits of using UAVs for this purpose, and proposes a strategic model that employs a facility location algorithm to optimize the infrastructure configuration for speedy and efficient delivery between hospitals. By analyzing the costs associated with implementation and conducting a case study based on the National Health Service (NHS) hospitals in London, the research concludes that utilizing UAVs for delivery can significantly reduce operational costs compared to the current system. Furthermore, the study highlights the importance of optimal hub placement in determining the success of UAV-based delivery systems.

[62] conducted an extensive literature review on the current and potential uses of drones in the field of medicine, hoping to encourage further research in this area. Building upon this foundation, [63] aimed to optimize the deployment of UAVs to ensure maximum coverage for all vehicles. Similarly, [64] described the development and testing of a hybrid vertical takeoff and landing UAV for delivering emergency supplies to local communities, while

[65] designed UAV networks for transporting biomedical materials in line with the Drone4Care project.

Furthering the discussion, [66] presented a detailed study on the air-to-ground channel parameters, including measurement campaigns, limitations, and future research directions, and [67] investigated drone path planning architecture for efficient medical emergency response in future networks. [68] proposed a novel timeslot formulation to schedule and sequence trips for serving multiple demand locations.

Additionally, [69] described how to ensure safety using the AntHocNet ant-based routing technique by considering each UAV's residual energy level. Altogether, these studies contribute to the ongoing exploration of drones' potential in medical applications, providing insights into both the technical and logistical aspects of UAV deployment.

[70] conducted a study in low-income countries and found that the use of UAVs could increase truck-space utilization, leading to a reduction in delivery time, costs, and carbon dioxide emissions. [8] investigated the use of UAVs in delivering medical products, including blood derivatives and pharmaceuticals, to hospitals and emergency scenes, including offshore vessels, during critical demand. The study demonstrated that UAVs have the potential to overcome logistical barriers and deliver medical products rapidly, especially in remote and hard-to-reach areas.

In low-income countries, [70] conducted a study indicating that drone have the potential to enhance truck-space utilization, thereby reducing delivery time, costs, and carbon dioxide emissions. Additionally, [8] investigated the applicability of UAVs in delivering medical products, including blood derivatives and pharmaceuticals, to hospitals and emergency

locations, such as offshore vessels, during times of critical demand. The findings suggested that UAVs could effectively overcome logistical challenges and facilitate the rapid transportation of medical products, particularly in remote and hard-to-reach areas.

A comparable study conducted by [71] sought to explore the influence of drones on the environmental sustainability, service time, and delivery expenses of the delivery fleet. The results indicated that the incorporation of drones led to a significant decrease in CO² emissions by 9%, a 12% reduction in service time, and a 5.6% reduction in cost per item. These findings suggest that the integration of drones can enhance the overall efficiency of the delivery system.

[72] suggested that delivery drones could have the same transformative effect on traditional transportation infrastructure as the mobile phone had on personal communication. The potential impact of UAVs on healthcare supply chains is significant, particularly in low-income countries, where transportation infrastructure and resources may be limited

The Flying Sidekick Traveling Salesman Problem is a delivery optimization process that utilizes both a truck and a drone. Two studies, [43] and [47], present this problem and propose an improved formulation by introducing three-indexed and two-indexed formulations, as well as a set of inequalities that can be resolved using a branch-and-cut approach. The proposed methods were successful in achieving optimal solutions in most cases. The study explores two versions of the problem, with one version permitting the drone to wait at customer locations and the other only allowing waiting during flight. The solving techniques were customized for both versions, and an evaluation was conducted to determine their effectiveness.

CHAPTER 3

JOURNAL ARTICLE 1

A Framework of Decision Support System for Optimizing the Logistic Network of Blood Group Supply Transportation via Drones to Healthcare Facilities

3.1 Abstract

The delivery of blood group from blood banks to hospitals is a critical aspect of the healthcare system, given the perishable nature and complex storage requirements of certain blood products. However, centralizing blood supply facilities for economic reasons and increasing traffic levels have led to significant delays in traditional emergency vehicle delivery. This research proposes a decision support system (DSS) that centralizes the transportation of blood supplies to healthcare facilities using drones. The system aims to minimize logistics costs by strategically locating launch and refueling stations and assigning requests to these stations. The approach employs integer binary linear programming to offer four possible scenarios that consider the drone's flight range capacity and the supply node's capacity. The results of the scenario-based analysis indicate that the adoption of refueling stations constitutes a promising strategy for enhancing the mission range and expanding the coverage of blood supply in non-emergency scenarios. Gradually implementing refueling stations can prevent operational interruptions like launch station closures. This, along with reduced delivery times and delay mitigation, could save lives.

Refueling stations have significant benefits for blood supply management and the logistics industry.

Keywords: Drone, Healthcare logistics optimization, Blood group delivery, Decision support system, Network design, launching station, Refueling station.

3.2 Introduction

The timely and efficient delivery of blood products is crucial in saving lives, making the distribution of blood and its components an essential aspect of modern healthcare systems. However, there are several challenges in transporting blood products, especially in areas with difficult terrain, limited access to healthcare facilities, and poor road infrastructure. Drone technology offers a promising solution to these challenges. Drones possess unique capabilities that can fly quickly over long distances and bypass traditional transportation paths. These capabilities can help blood banks and hospitals enhance the speed and reliability of their supply chains, leading to better patient outcomes. This innovative technology has the potential to transform medical logistics and increase efficiency and automation in the healthcare sector.

Moreover, the COVID-19 pandemic has emphasized the need for smart technology in public health, prompting healthcare providers to adopt drones to improve supply chain efficiency. For instance, [10] highlights the significance of utilizing smart technology, including drones, to ensure timely and efficient delivery of medical supplies. In the same vein, [73] propose the use of drones to enhance the efficiency and effectiveness of supply chains for humanitarian aid, particularly during crises. It is worth noting that healthcare professionals on the front line perceive the use of drones differently from the general

public. Consequently, the integration of drone technology in medical logistics processes promises to revolutionize healthcare delivery and improve patient outcomes.

The use of drones for the transportation of blood and medical supplies offers several advantages, as highlighted in multiple studies. [74] discovered that drones can efficiently transport blood and medical supplies to hospitals and sites in a specific zone. [5] found that drones can provide just-in-time delivery of blood through a push-method delivery system, reducing inventory and expenditures on blood. Despite the considerable weight of RBC liquid storage, [75] discovered that drones can travel over seven kilometers. Drones can also effectively transport medical products to distant or inaccessible locations where truck or human movement is impracticable, as reported by [76].

Researchers are investigating new models of transportation, combining traditional truck-based distribution with upcoming technologies like drones and autonomy transport vehicles, for last-mile delivery, as described in recent studies. The use of drones in emergency medicine has significant potential to revolutionize emergency treatment, as highlighted in [29] and [77]. [78] suggest that drones should be used to complement existing transportation systems.

Despite the potential benefits of drone delivery, there have been no studies investigating frontline health professionals' perceptions of public attitudes towards drone delivery. [79] investigate emergency healthcare clinicians' perspectives on drones' potential application in providing medical assistance in England and Scotland. They also examine the technical and environmental elements that affect drone flying and contribute to higher costs when transporting emergency medical items by drone, as reported by [80].

[81] discuss the challenges and difficulties of using Zipline drones for collecting samples from probable COVID-19 patients. This technology has been one of the most significant partners in the fight against Coronavirus during the period of public isolation in response to SARS-COV-2. [82], [7], and [83] (2020) report other significant achievements in this field. However, [84] found no studies investigating the influence of drone delivery on blood products, which could be a potential obstacle to the deployment of drones for blood delivery.

In their study, [85] employed a framework consisting of two distinct methodologies to calculate UAV flight durations and ground transfer durations. Meanwhile, [86] conducted 16 experiments to evaluate the viability of their intelligent capsule in facilitating the delivery of medical test samples, both inside buildings and during flights. In a separate study, [87] aimed to assess the cost-effectiveness of using drones for transportation compared to traditional ambulance transportation. Finally, [88] examined the effect of drone carriage material on the delivery of biological samples.

Based on the scientific literature on drone transportation network design, [89] and [46] have shown that Variable Neighborhood Search and Large Neighborhood Search are two effective optimization methods that can be used for creating transportation drone networks. These studies have concluded that mathematical modeling on a smaller scale can solve the problem optimally, while for larger-scale problems, metaheuristics based on VNS and LNS have been developed to provide approximate solutions.

In recent years, there has been a surge of interest in designing UAV networks that can improve the speed, efficiency, and affordability of healthcare delivery. Several innovative

drone delivery architecture models have emerged, such as those proposed by [72]. [90] introduced two models aimed at addressing the challenges associated with utilizing drone-based transportation to deliver medical supplies to remote regions. The proposed models aim to optimize routine healthcare services, including the utilization of set covering to identify optimal drone center locations, and multi-depot routing to minimize costs while delivering medication and picking up exam kits such as blood and urine samples. The proposed models have the potential to enhance healthcare accessibility and affordability for individuals residing in remote areas

In their study, [65] performed scenario-based analyses in distinct case studies to develop UAV networks that could be used for transporting biomedical materials as part of the Drone4Care initiative. The model and results obtained from this research serve as essential decision-support resources for deploying Unmanned Aerial Vehicles networks for the transportation of biological materials. These resources enable the assessment of strategic decisions related to UAV network deployment by evaluating the potential outcomes of such decisions. The model proposed by the authors is thus a crucial tool for decision-makers and stakeholders who need to make informed choices about the deployment of UAV networks.

The design and planning of logistics models centered around drones is an increasingly active area of research. In this regard, [40] has advanced a comprehensive methodology aimed at pinpointing drone-based delivery systems, along with the attendant routing challenges. Another noteworthy contribution is [68], which has introduced a novel timeslot structure to facilitate the scheduling of flights aimed at fulfilling multiple requests.

Furthermore, [92] has devised a spatial optimization framework, known as the backup coverage location problem with complementary coverage, to underpin the implementation of healthcare drones outfitted with automated external defibrillators (AEDs). Lastly, [93] has endeavored to grapple with the challenges posed by probabilistic demand for drone delivery across diverse geographical areas.

Overall, there is a growing body of literature exploring the design and implementation of UAV networks for healthcare delivery, with a focus on optimizing routing, scheduling, and demand forecasting. These studies hold great promise for enhancing healthcare delivery, particularly in remote or hard-to-reach areas.

In the pursuit of enabling the establishment of a recharging station infrastructure to support commercial UAV delivery services, [94] has put forward a location model for recharging stations. This model incorporates insights from prior studies on planar-space routing, range-restricted flow-recharging stations, and maximum coverage, among other relevant research areas. Meanwhile, [95] emphasized the importance of justifying the use of drone ports as a practical and effective method for positioning drones, highlighting the need for real-world evaluation. Together, these works provide valuable insights for advancing research in the spatial configuration of recharging station infrastructure for commercial UAV delivery services and can inspire new ways to optimize design and deployment.

[96] provide a comprehensive solution for unmanned aerial vehicle base stations' localization and capacity allocation challenges. They review the optimization of UAV-BSs in NGWNs in [97]. [47] propose a truck-drone system to bypass flying restrictions and develop a binary integer programming

paradigm. [98] develop two heuristic algorithms and local search techniques to solve this problem. [99] suggest a mixed-integer linear programming (MILP) model for designing UAV routing and charging stations, with a focus on belt conveyor inspection. These studies provide valuable insights and potential inspiration for optimizing the design and deployment of UAVBS systems in practical settings.

A mathematical model proposed by [100] based on scientific literature research can minimize the costs associated with an aerial delivery system including drone acquisition, refueling stations, warehousing, and shipping. The approach suggested by the study is practical and effective. Similarly, [101] proposed an optimization approach to minimize the total cost of the network while taking into account flow boundaries, capacity constraints, and power constraints. Their method involved an integrated base station and path design, and it can help provide efficient path planning for real-time medical care delivery as indicated by [67]. In addition, [102] developed a model that optimizes drone delivery of light-weight relief packages in disaster-prone areas.

One innovative solution for last-mile delivery involves combining a ground vehicle with a drone to make deliveries. [103] introduced a novel approach to combine a vehicle with a drone, creating a new type of traveling salesman problem (TSP). To tackle this problem, [104] proposed a new heuristic method. Meanwhile, [105] addressed a variant of the TSP that includes drone resupply and delivery release dates. Additionally, [106] focused on the multi-visit traveling salesman problem with multi-drones, with the goal of reducing the time it takes to service clients with a truck and multiple drones. To solve these problems,

[44] developed an integer program that employs path-first, cluster-second heuristics based on local searching and dynamic programming.

These studies focus on decision support systems for drone logistics. [107] introduced StarVis and BarVis, two visualizations that inform operators about schedule issues and outcomes of modifications. [108] proposed a decision support system for estimating rental drone fleet size for small- to medium-sized businesses.[109] developed a mixed integer programming model and a scheduling decision support system using a genetic algorithm to minimize drone usage in a depot with unique package release time, distance, and deadline. [110] created a decision support model using graph theory and a matrix approach to select the ideal drone for healthcare supply accessibility based on criteria and sub-criteria.

The objective of this study addresses the gap in the transportation of blood group to healthcare facilities by designing a drone network with a decision support system. The traditional emergency vehicle delivery system has significant delays due to centralized blood supply facilities and increasing traffic levels. The proposed framework introduces four scenarios that centralize the transportation of blood supplies to healthcare facilities using drones to minimize logistics costs by strategically locating the launch and refueling stations. Our research makes a methodological contribution by presenting network design scenarios that incorporate a decision support system, which assigns blood group requests to a path rather than to a blood bank facility. This approach results in a reduction of variables and constraints as compared to conventional routing and location problems. The application of suggested framework of DSS holds promise in addressing delays, shortening

delivery times, and potentially saving lives in critical situations. This proposed solution offers an effective means to optimize blood group transportation, ultimately enhancing the efficiency of the healthcare system.

The organization of this paper consists of the following sections: Section 1 serves as an introduction and provides an overview of the problem under consideration. Section 2 presents the problem definition and highlights the challenges associated with it. Section 3 presents various scenario formulations that were considered to address the problem. The section highlights the assumptions made for each scenario. Section 4 provides details of the computational experiments conducted to analyze the scenarios, discussing the simulation model and the inputs used to test each scenario. Section 5 presents an analysis and discussion of the results obtained from the computational experiments, examining the performance of each scenario and identifying the most effective approach. Section 6 includes additional experiments that were performed to validate the proposed models within a decision support system. Finally, Section 7 concludes the paper by summarizing the key findings and the contributions of the study, while also highlighting the limitations of the study and providing suggestions for future research.

3.3 Problem Definition

The healthcare industry heavily relies on the timely and efficient delivery of blood supplies to different facilities. To streamline this process, a centralized (DSS) has been proposed, allowing healthcare professionals to request blood groups and have them delivered by drones. However, the success of this system depends on the optimal location of launching

and refueling stations, which must consider the flight range capacity of drones and the capacity of each supply node in the decision support system.

The objective of this research is to design a logistic network for the transport of blood groups that minimizes the total logistics costs, including the construction costs of launching and refueling stations and the delivery costs between different locations. Several factors will be considered in this study, such as the flight range capacity of drones, the capacity of each supply node, and the characteristics of the drone's flight, such as position, flight video, and parameter status.

The proposed solution will be a decision support system that uses optimization methodology to determine the most suitable scenario for each blood request, considering the request's specifications, location, and blood bank location. The system will determine the optimal location for launching and refueling stations and provide real-time updates to healthcare professionals on the drone's flight progress. The summary of the proposed scenarios concept, along with the decision support system, is shown **Figure 3**.

Real-time updates will be provided to healthcare professionals to monitor the progress of the drone's flight and ensure that the blood supplies are delivered on time. The system will also monitor the status of the drones, including battery charge and maintenance needs, to ensure that they are in good operating condition for each mission.

The successful implementation of this study will result in a more efficient and cost-effective transportation system for blood supplies, potentially saving lives by reducing

delivery times and minimizing the risk of delays due to traffic congestion or other unforeseen circumstances

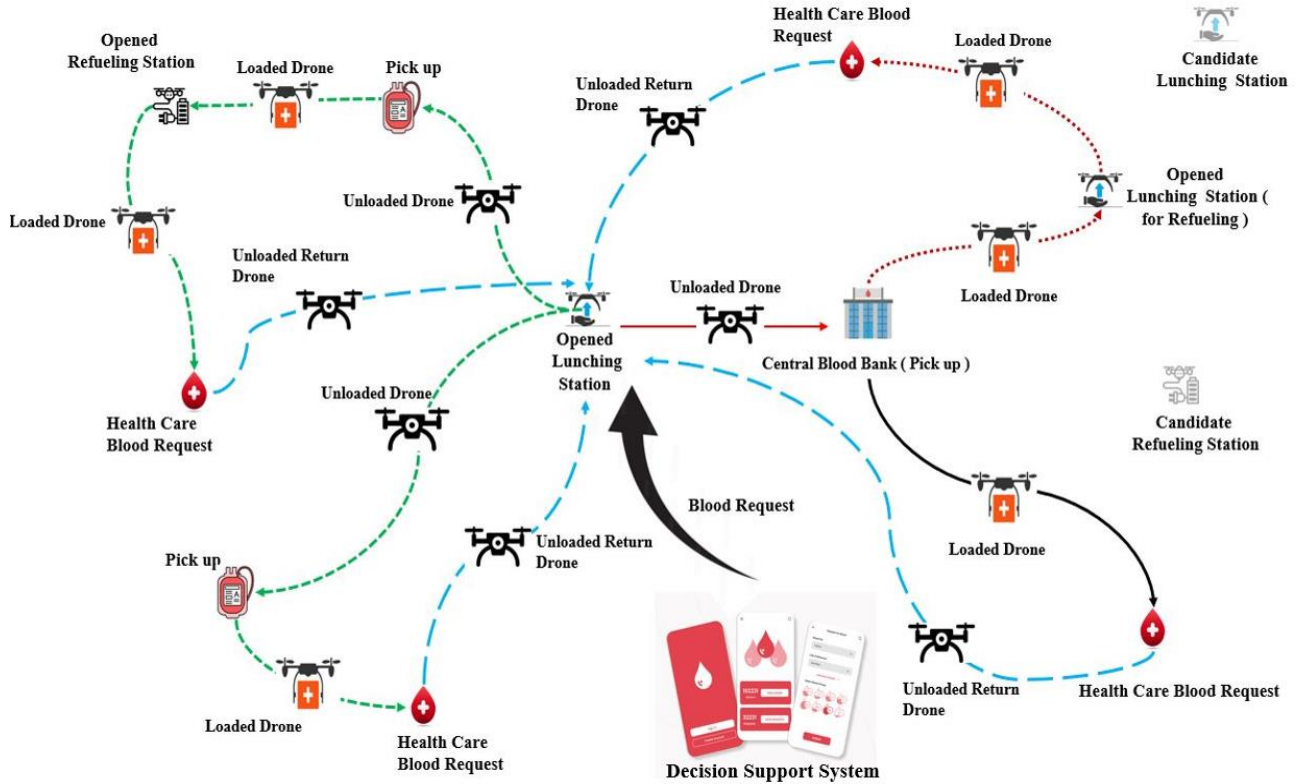


Figure 3. Network concept of transport of the blood group unit between the location of health care in the smart city

3.4 Components of the Decision Support System (DSS)

This section, we will look at the fundamental constituents of the proposed DSS. DSSs are generally categorized based on different system characteristics, such as their support for collaborative or individual decision-making, and can also be distinguished as desktop or web-based applications depending on their intended purpose. Despite these variations, all DSSs share basic attributes. In particular, a standard DSS should comprise four main constituents: the data component, the model component, the decision component, and the interface component.

The structure of the proposed DSS is elucidated in this study through the application of a UML class diagram as depicted in **Figure 4**. Each class is represented by a rectangular box that comprises of multiple sections. The first section consists of the class name, while the second section contains the attributes, and the last section depicts the operations. Attributes refer to the specific property values that define the features of a class, whereas operations describe the actions or behavior of the class. Furthermore, different types of relationships between classes can be exhibited, which are represented by various graphic connections such as aggregation (solid line with a clear diamond at one end), inheritance or generalization (solid line with a clear triangle at one end), and dependency (dashed line with an arrow at one end). The interconnections and types of objects that exist within the system can be demonstrated by depicting each component as an individual class.

The DSS components showed in **Figure 4** will be briefly specified as follows.

- **Data Component:** The system's data component categorizes data into three types. The first type is managed by the DBMS, which stores internal data for the decision-making and optimization models, including input data, internal variables, and model outputs. The DBMS also manages the queue of requests, their status, and optimization results, as well as model descriptions. The Data System contains the second and third types, namely internal and external data. Internal data describes internal procedures, like logistic network distances, blood bank units, and healthcare locations. External data is real-time, e.g. blood group units, drone travel costs, and launching and refueling expenses.
- **Model Component:** The fundamental aspect of this component is centered around a mathematical model that are specifically customized to scrutinize the impact of

varied choices on the system's performance. These models delineate the operations taking place at different tiers of management, and the essence of their functions varies according to the specific operation they facilitate. The most significant contribution of this study is the model component, which features an optimization module that combines four scenarios formulated as integer linear programming (ILP) within the decision support system. Each scenario plays a crucial role in the proposed system for transporting blood groups essential for healthcare purposes.

- **Interface Component:** The DSS module being discussed is a critical element that enables the exchange and collaboration between the decision support system (DSS) and decision makers (DMs). The module holds immense importance because the effectiveness of the model is determined by the quality of its interface, which takes precedence over the quantity and quality of available data. The module is designed to include an Information Communication System (ICS) that effectively interfaces with the actual system, thereby ensuring consistency between the system's stored data and its real-world counterpart.
- **Decision Component:** At the second level of the system, there are two distinct classes, namely the operational decision class and the strategic decision class. The former is responsible for generating decisions related to blood requests, such as the selection of launching stations, takeoff and collection locations for drones, refueling points, and logistics endpoint. Meanwhile, the latter involves the selection of appropriate locations for launching and refueling stations. Key performance indices are integrated into both classes to guide the decision-making process. To ensure optimal decision-making, the decision support system (DSS) must collect

the optimization procedures and decision rules that are contingent on both the performance indices and the nature of the decision being made.

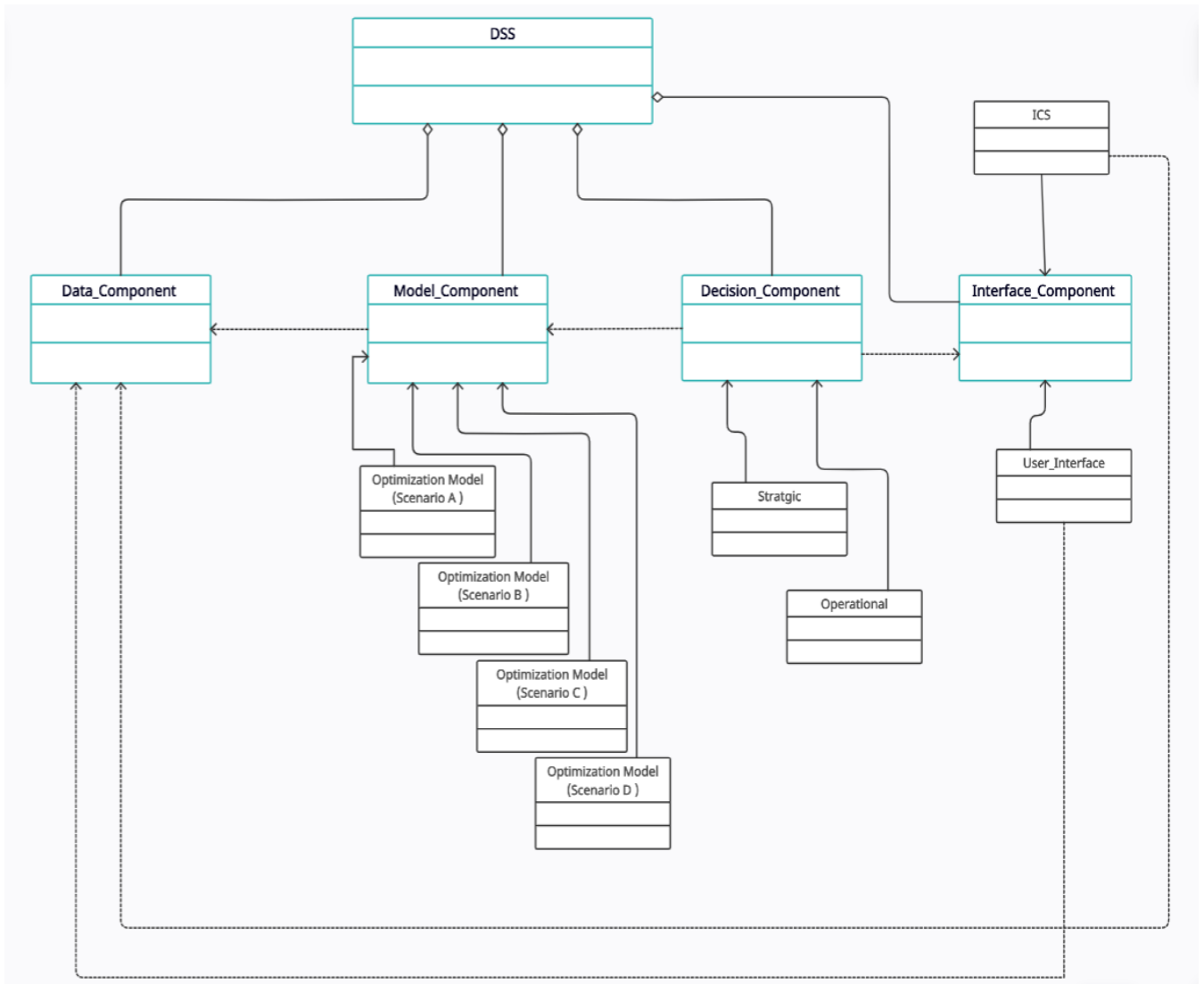


Figure 4. Visualizing the structure of a decision support system with UML

3.5 Scenario Formulation

Our study assumes that an infinite number of homogeneous drone fleets will be deployed at several candidate launching stations $j, \forall j \in M = \{1, 2, \dots, m\}$. In response to user requests, the decision support system will determine the location of the blood group pick-up point as well as the healthcare demand for the blood. The healthcare request for the blood group is predictable and known, and is expressed in terms of the number of packages for certain blood group p to transport within the stipulated period on path $i, \forall i \in N = \{1, 2, \dots, n\}$ & $p \forall \in P = \{A+, A-, B+, B-, O+, O-, AB+, AB-\}$. The objective is to set up the location of the launching station (and refueling stations) and allocate the requests to those locations in order to minimize overall logistic and construction costs of the launch and refueling stations.

Four scenarios are formulated as integer linear programming (ILP) within the decision support system. Each scenario plays a role in the proposed system for the transportation of health care blood transportation. In the first Scenario, because the flight range capacity of drone is assumed to be unbounded, all requests for blood must be met, resulting in a 100% satisfaction rate. Furthermore, drones are required to return to their original launching station when delivering blood packages. In other Scenarios, this restriction is eliminated. Despite this, the costs of repositioning drones in the event of an imbalance are not considered. In the second, drones have the option to end their logistical trip at nearby launching locations. In the third and fourth Scenarios, the flight range capacity is considered in terms of distance in kilometers. Ultimately, in Scenario 4, the ability to recharge and swap the battery of a drone during a mission is considered. Refueling may be performed at a launching station, where the operator of the launching station is expected to

have the ability to handle the refueling operation using existing facilities. **Table 1** outlines assumptions for four different scenarios (A, B, C, D) related to formulation, including satisfaction rates, flying range, and station usage. The notation sets and parameters for the mathematical formulation in each Scenario are shown in **Table 2**.

Table 1.Scenarios' assumptions

Assumptions	Scenario A	Scenario B	Scenario C	Scenario D
Drone returned to origin launching station	Applicable	Not Applicable	Not Applicable	Not Applicable
Refueling station opened	Not Applicable	Not Applicable	Not Applicable	Applicable
Satisfaction rate	100%	100%	< 100%	$\leq 100\%$
Flying range	Unbounded	Unbounded	35 km	35 km
Blood group {A+, A-, B+, B-, O+, O-, AB+, AB-}	All of them can be requested	All of them can be requested	All of them can be requested	All of them can be requested

Table 2.Scenarios' Parameters and Set Notation

Sets	
N	Set of the healthcare request
M	Set of the possible launching station
P	Set of the blood group
f	Set of the possible location of the refueling station
Parameters	
B_{ip}	The requested units of blood group on the path i for blood group p
d_i^{ph}	The distance between the pickup location of path i and the location of the medical blood request
d_{ij}^{lp}	The distance between the pick-up location on path i and the launching station j
d_{ij}^{hl}	The distance between the health care blood request of path i and launching station j
d_{if}^{pr}	The distance between the pickup location of path i and the refueling station f
d_{if}^{rh}	The distance between the health care blood request location of path i and refueling station f
l_j	The fixed operating costs of launching station j
R_f	The fixed operating costs of refueling station f
α	Fixed costs per kilometer of unloaded drone
β	The fixed costs per kilometer of loaded drone
τ	The satisfaction rate of the health care request
δ	The flying range limit for drone

3.5.1 Scenario A

In this Scenario, when the request comes from health care is emergency this model allows the decision support system to activate Scenario A in order to satisfy the request with 100%. Regardless of where the drones end their trip, they are allowed to do so. The binary decision variables for this Scenario are introduced as follows:

$$\omega_j = \begin{cases} 1 & \text{if the launching station } j \text{ is selected to be opened } \forall j \in M \\ 0 & \text{Otherwise} \end{cases}$$

$$\chi_{ijp} = \begin{cases} 1 & \text{if route } i \text{ begins at launching station } j \text{ for blood type } p \\ & \forall i \in N, j \in M, p \in P \\ 0 & \text{Otherwise} \end{cases}$$

The objective function is formulated as follows:

$$\text{Min} \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} (\alpha (d_{ij}^{lp} + d_{ij}^{hl}) + \beta d_i^{ph}) + \sum_{j=1}^m l_j \omega_j \quad (1A)$$

Subject to:

$$\sum_{j=1}^m \chi_{ijp} = 1 \quad \forall i \in N, p \in P \quad (2A)$$

$$\sum_{i=1}^n \chi_{ijp} \leq \omega_j \sum_{i=1}^n B_{ip} \quad \forall j \in M, p \in P \quad (3A)$$

$$\omega_j, \chi_{ijp} \in \{0,1\} \quad \forall i \in N, j \in M, p \in P \quad (4A)$$

The objective function of the total cost of transportation and the construction of the launching station is represented by Equation (A1). The first component of (1A) indicates the transportation cost of an unloaded drone from the origin launching station to the pickup

location, from the health care request location to the original launching station, and the transportation cost of a loaded drone on the path between pick up and health care; the second term represents the fixed running costs. Constraint (2A) ensures that each path of request i and blood group p are assigned to only one launching station. Constraint (3A) states that the launching station j is selected to be opened if the path i uses the launching station j for a given blood group p . Constraint (4A) guarantees the optimal value of decision variables is binary.

3.5.2 Scenario B

This scenario bears resemblance to the one previously described in Scenario A, with the exception that the drone is granted the liberty to return to a nearby launching station to complete its logistical task. As a result, a new binary variable is introduced to model this scenario, as follows:

$$Y_{ijp} = \begin{cases} 1 & \text{if route } i \text{ end at launching station } j \text{ for blood type } p \\ & \forall i \in N, j \in M, p \in P \\ 0 & \text{Otherwise} \end{cases}$$

$$\begin{aligned} \text{Min } & \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_{ij}^{lp} + \beta \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_i^{ph} + \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} Y_{ijp} d_{ij}^{hl} \\ & + \sum_{j=1}^m l_j \omega_j \end{aligned} \quad (1B)$$

Subject to:

$$\sum_{j=1}^m \chi_{ijp} = 1 \quad \forall i \in N, p \in P \quad (2B)$$

$$\sum_{i=1}^n \chi_{ijp} \leq \omega_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad (3B)$$

$$\sum_{i=1}^n Y_{ijp} \leq \omega_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad (4B)$$

$$\sum_{j=1}^m Y_{ijp} = \sum_{j=1}^m \chi_{ijp} \quad \forall \quad i \in N, p \in P \quad (5B)$$

$$Y_{ijp}, \omega_j, \chi_{ijp} \in \{0,1\} \quad \forall \quad i \in N, j \in M, p \in P \quad (6B)$$

The objective function of the total cost of transportation and the construction of the launching station is represented by Equation (A1). The transport costs of an unloaded drone from the source launching station to the pickup location are represented by the first component of the objective function (1B), the transportation costs of a loaded drone on the used path are represented by the second component, the transportation costs of an unloaded drone from the health care request to the nearby launching station are characterized by the third component, and the fixed running costs of the launching station are calculated by the fourth component. Constraint (2B) indicates that the request of health care for a given blood group must be met. Constraints (3B) & (4B) states that the launching station j is selected to be opened if the path i uses the launching station j for a given blood group p . Constraint (5B) guarantees that the drone will take path i , which carries blood group p , must return to any nearby open launching station to end the trip. Constraint (6B) determines the domain of the decision variables.

3.5.3 Scenario C

This Scenario is constrained by the drone's flight range per kilometer, which is not appropriate for an emergency blood request. Consequently, we introduce a parameter $\tau \in [0,1]$, which represents the stratification rate for the request. Moreover, the drone is allowed to end its trip at a nearby open-air launching station. The mathematical model in Scenario B will be used in this Scenario with some modifications. Only constraint (2B) in Scenario B is replaced with the two constraints (1C), which states that a percentage of blood request must be met, and (2C), which ensures that a request has to be assigned to only one launching station. Also, a new constraint (3C) is added to the model to consider the flight range.

$$\sum_{i=1}^n \sum_{j=1}^m B_{ip} \chi_{ijp} \geq \tau \sum_{i=1}^n B_{ip} \quad \forall p \in P \quad (1C)$$

$$\sum_{j=1}^m \chi_{ijp} \leq 1 \quad \forall i \in N, p \in P \quad (2C)$$

$$\sum_{j=1}^m \chi_{ijp} d_{ij}^{lp} + d_i^{ph} \sum_{j=1}^m \chi_{ijp} + \sum_{j=1}^m d_{ij}^{hl} \gamma_{ijp} \leq \delta \quad \forall i \in N, p \in P \quad (3C)$$

3.5.4 Scenario D

The option to refuel the battery throughout the flight is addressed in Scenario 4, either at the open launching station (which has machinery already installed) or at certain refueling stations with a built-in battery charger. For paths without recharging stations, a dummy refueling station with index $(m + 1)$ is added to set M . As such, the distance between the pickup location of path i and the dummy refueling station equal to zero ($d_{i \rightarrow (m+1)}^{pr} = 0$) and the distance between the health care request of path i and the dummy refueling station equal

to the distance between the pickup location of path i and the location of the health care blood request location ($d_{i \rightarrow (m+1)}^{rh} = d_i^{ph}$). The new binary decision variables are introduced to this Scenario as follows:

$$K_f = \begin{cases} 1 & \text{if the refueling station } f \text{ is selected to be opened } \forall f \in M \\ 0 & \text{Otherwise} \end{cases}$$

$$E_{ifp} = \begin{cases} 1 & \text{if route } i \text{ used refueling station } f \text{ for blood type } p \\ & \forall i \in N, f \in M \cup \{m+1\}, p \in P \\ 0 & \text{Otherwise} \end{cases}$$

The objective function is modeled as follows:

$$\begin{aligned} \text{Min } & \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_{ij}^{lp} + \beta \sum_{i=1}^n \sum_{f=1}^{m+1} \sum_{p \in P} B_{ip} E_{ifp} (d_{if}^{pr} + d_{if}^{rh}) \\ & + \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \gamma_{ijp} d_{ij}^{hl} + \sum_{j=1}^m l_j \omega_j + \sum_{j=1}^m R_j K_j (1 - \omega_j) \end{aligned} \quad (1D)$$

In the objective function (1D), the first term indicates the costs of transporting an unloaded drone from its starting point to the pickup location. If transportation between launching stations is accomplished by transferring through a refueling station, the second component corresponds to the transportation cost of loaded drones from the pickup site to the refueling station and from the refueling station to the healthcare request locations; other than that, it directly correlates to the transportation cost of loaded drones from the pickup to the request location of the path i . The third component (1D) refers to the cost of transporting the returned, unloaded drones from the requested location to a nearby launching station. Because it involves the product of two binary variables in last term in the objective function, hence the model becomes nonlinear. To solve this issue, we introduce a new

binary variable represented by $\tilde{\varphi}_j$ such as $\tilde{\varphi}_j = K_j \omega_j \quad \forall j \in M$. Thus, the objective function for Scenario D can be modeled as follows:

$$\begin{aligned}
\mathbf{Min} \quad & \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_{ij}^{lp} + \beta \sum_{i=1}^n \sum_{f=1}^{m+1} \sum_{p \in P} B_{ip} E_{ifp} (d_{if}^{pr} + d_{if}^{rh}) \\
& + \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \Upsilon_{ijp} d_{ij}^{hl} + \sum_{j=1}^m l_j \omega_j + \sum_{j=1}^m R_j K_j - \quad (2D)
\end{aligned}$$

Constraints (3B), (4B), (5B), (1C), and (2C) are added to the model in addition to the following constraints.

$$\sum_{f=1}^{m+1} E_{ifp} = \sum_{j=1}^m \chi_{ijp} \quad \forall \quad i \in N, p \in P \quad (3D)$$

$$\sum_{i=1}^n E_{ijp} \leq K_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad (4D)$$

$$\sum_{j=1}^m d_{ij}^{lp} \chi_{ijp} + \sum_{f=1}^m d_{if}^{pr} E_{ifp} \leq \delta \quad \forall \quad i \in N, p \in P \quad (5D)$$

$$\sum_{j=1}^m d_{ij}^{hl} \Upsilon_{ijp} + \sum_{f=1}^m d_{if}^{rh} E_{ifp} \leq \delta \quad \forall \quad i \in N, p \in P \quad (6D)$$

$$\sum_{j=1}^m d_{ij}^{lp} \chi_{ijp} + d_i^{ph} E_{i(m+1)p} + \sum_{j=1}^m d_{ij}^{hl} \Upsilon_{ijp} \leq \delta(2 - E_{i(m+1)p}) \quad \forall \quad i \in N, p \in P \quad (7D)$$

$$\tilde{\varphi}_j \leq \omega_j \quad \forall \quad j \in M \quad (8D)$$

$$\tilde{\varphi}_j \leq K_j \quad \forall \quad j \in M \quad (9D)$$

$$\tilde{\varphi}_j \leq K_j + \omega_j - 1 \quad \forall \quad j \in M \quad (10D)$$

$$\chi_{ijp}, \Upsilon_{ijp}, \omega_j, K_j, E_{ijp} \in \{0,1\} \quad \forall \quad i \in N, j \in M, p \in P \quad (11D)$$

Constraints (3D) allow for only one refueling station on Path i and no refueling stations are permitted if path i is not serviced. As stated in constraint (4D), a refueling station is usable if the launching or refueling station is opened. Constraints (5D) And (6D) guarantee that the path between and to the refueling station does not violate the flight distance capacity for a drone, whereas constraint (7D) is the flight range limit for a path that does not involve an intermediate refueling station. Constraints (8D), (9D) and (10D) are formulated to control the decision variable $\tilde{\varphi}_j$ to be binary. Constraints (8D), (9D) enforce $\tilde{\varphi}_j$ to become zero if one of the decision variables K_j or ω_j are zero. Constraints (10D) enforce $\tilde{\varphi}_j$ to become 1 if one of the decision variables K_j and ω_j are 1. Constraints (11D) restrict the domain of decision variables to be binary.

3.6 Computational Experiments

To ensure the precision and dependability of the proposed mathematical models and gather valuable insights for developing effective heuristics to tackle larger-scale problems, optimization techniques were employed for testing. This enabled us to comprehensively assess the models' performance and gain a deeper understanding of the underlying system dynamics, which helped identify potential limitations and opportunities for improvement. The results of this testing played a crucial role in refining the models and enhancing their predictive capabilities, thus contributing to more effective decision-making in practical applications. The optimization process was conducted on a personal computer equipped with a 3.7 GHz Intel Xeon® processor and 32 GB of RAM, using the CPLEX 22.1.8 solver and Windows 10 operating system. Given the need to solve binary programming models,

we employed the Pyomo library in conjunction with the classical branch-and-cut CPLEX solver in python.

3.7 Analysis & Discussion

3.7.1 Scenario A

This Scenario assumed that the drone's flight range was extensive enough to cover all incoming requests, ensuring comprehensive coverage of the geographical region. Consequently, an optimal solution was achieved within a relatively short period of time (46.7 seconds), resulting in a total cost of 253289.284 \$, which includes both the transportation cost and the fixed cost of constructing the launching station. It is pertinent to mention that the drone returned to its initial launching after completing its delivery task, thereby covering a total of 50 requests. These requests were obtained from different

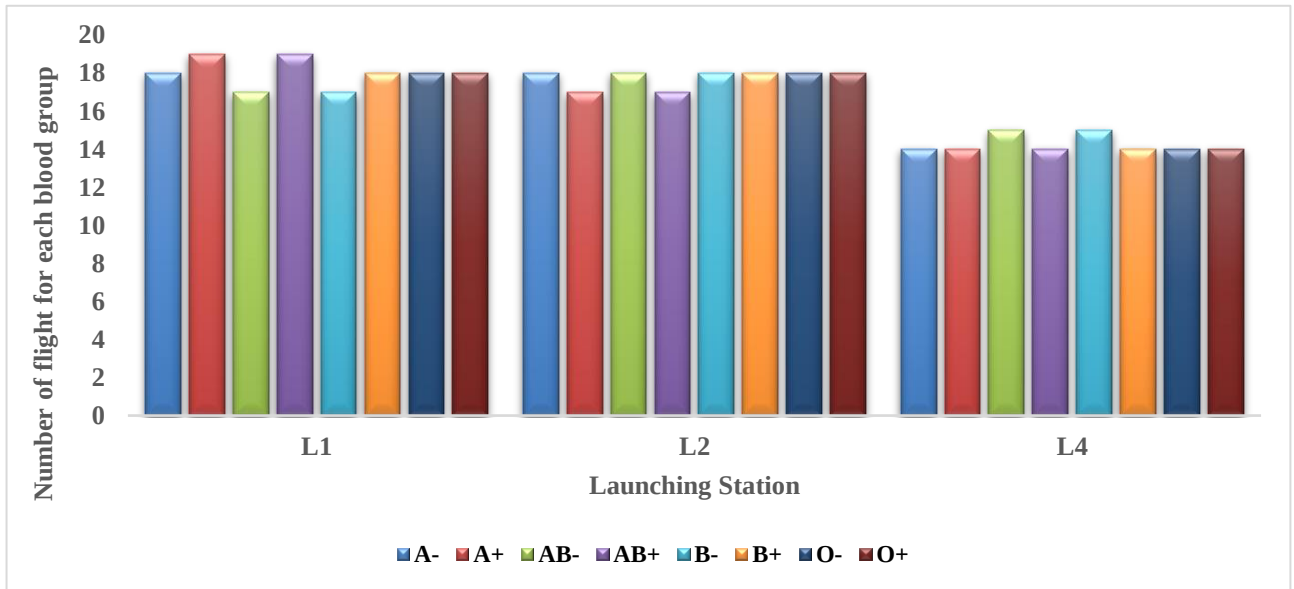


Figure 5. The number of flights departing from the open launching station for each blood group (Scenario A)

healthcare locations, each containing eight blood groups. The study's results are further demonstrated in **Figure 5**, where the number of trips taken at varying distances is represented along with the corresponding launching station.

The depicted **Figure 6** offers a visual representation of a fully operational drone network comprising three launching stations. Each of these stations serves distinct purposes in facilitating the transportation of blood group supplies. The first launching station, identified as L1, is responsible for covering a set of designated requests, including R13, R15, R18, R19, R20, R25, R29, R30, R34, R35, R36, R38, R42, R44, R47, R48, R49, R6, and R7. This set encompasses a total of 144 paths across all blood groups. The second station, L2, serves as a point of contact for hospitals and specifically caters to requests including R1, R11, R14, R16, R17, R21, R22, R24, R27, R28, R3, R31, R33, R34, R35, R40, R41, R45, and R46. In total, L2 serves 142 unique paths required to fulfill the designated requests. Similarly, the third launching station, L4, also serves hospital requests, albeit with a different set of required samples, including R10, R12, R2, R23, R26, R32, R34, R37, R39, R4, R43, R5, R50, R8, and R9. To cover these designated requests, L4 encompasses a total of 114 unique paths.

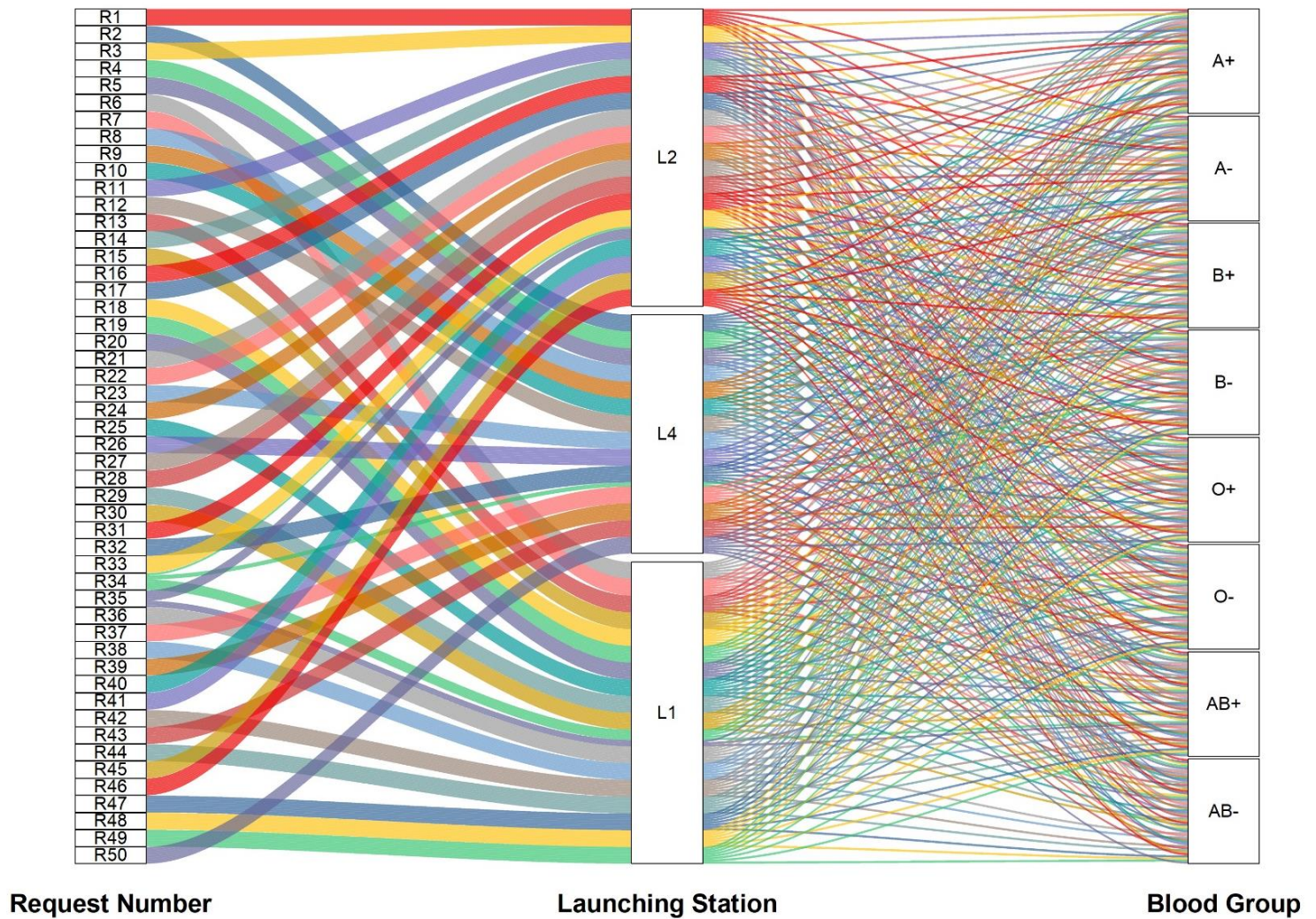


Figure 6.The optimal configuration of the logistic network for Scenario A.

3.7.2 Scenario B

This Scenario showed that equipping drones with extensive flight range would ensure comprehensive coverage of a geographical region, resulting in the attainment of an optimal solution within a duration of 82.6 seconds. The cost of this solution, which includes both transportation and fixed costs, amounted to \$245294.561.

An essential benefit of this approach is that the drone need not return to its initial launching after each delivery, leading to a cost reduction compared to Scenario A. The study's findings are graphically

represented in **Figure 7**, displays the number of flights departing from the opened launching station at varying distances, as well as the corresponding launch station.

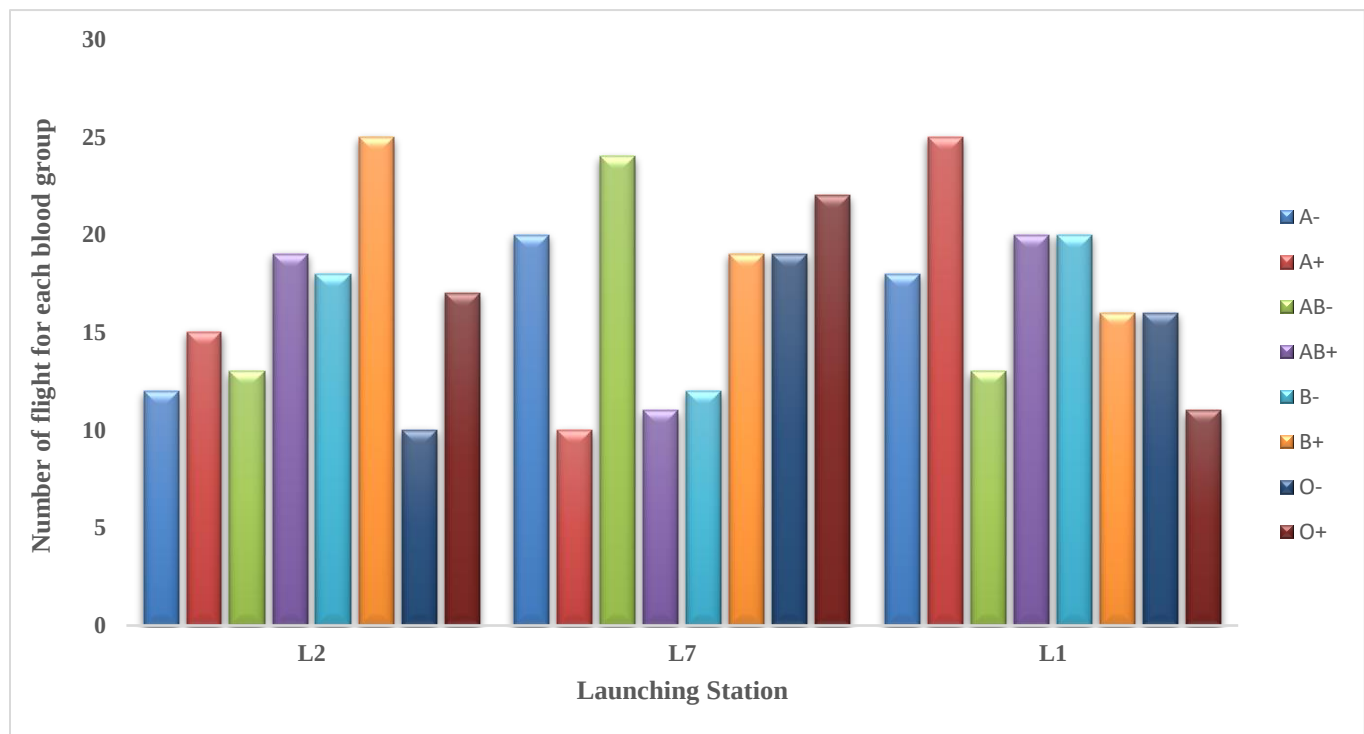


Figure 7.The number of flights departing from the open launching station for each blood group (Scenario B)

The illustrated **Figure 8** shows a sophisticated drone system, comprising three launch stations operating in tandem to transport critical blood group supplies efficiently. Each launch station is specifically designed to ensure the timely and effective delivery of these vital medical resources. The design of each launch station guarantees the quick and efficient delivery of vital medical supplies. To meet the high demand for blood transportation, the system has decided to transport in total 128 units from launching station 1, 120 units from launching station 2, and 152 units from launching station 7.

It is noteworthy that upon completing a mission, a drone must return to a nearby launch station before it can be deployed for another task. Close examination revealed that certain launch stations, particularly L7, have an inadequate number of drones to facilitate the distribution of blood groups to various locations, while other launch stations have a surplus of drones. Specifically, L1 receives 151 flights, L2 receives 159,

and L7 receives 90. This observation emphasizes the critical need for precise and strategic distribution of drones to optimize the performance and efficacy of the drone system.

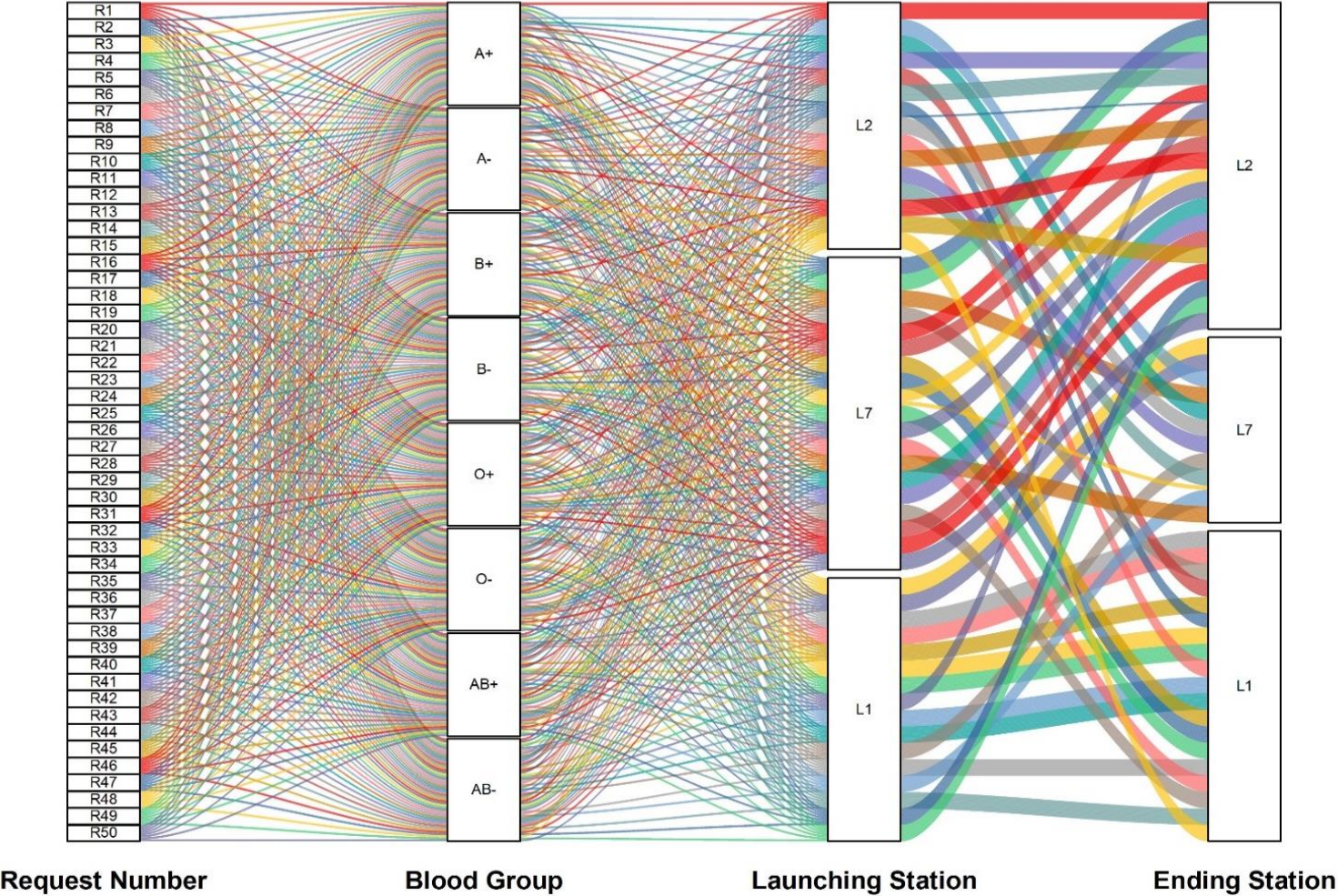


Figure 8.The optimal configuration of the logistic network for Scenario B

3.7.3 Scenario C

This scenario aims to assess the feasibility and efficacy of a drone-based blood delivery system, which has a flying range limitation of 35 km from the launch station to the final destination, where the drone will conclude its trip. The results of this Scenario c, illustrated in **Figure 9**, indicate that the drone system can effectively serve up to 70% of the blood requests, which corresponds to a total of 280 blood groups out of 400 requests. Moreover, all the solutions were obtained within a reasonable time frame of less than 148 seconds.

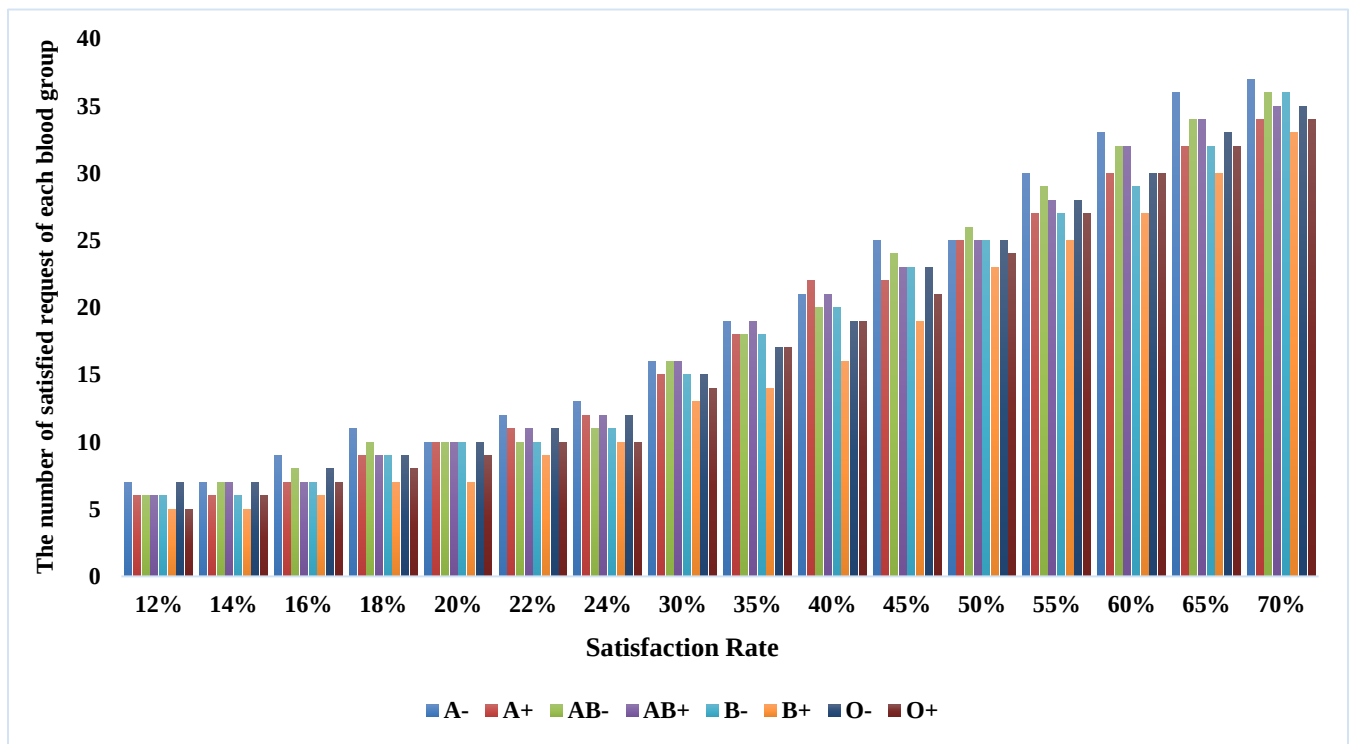


Figure 9. The number of satisfied requests from each blood group for the corresponding satisfaction rate (Scenario C).

When the satisfaction rate was at 12%, the optimization model recommended the selection of only two launching stations to cover the 48 requested paths, with a total cost of 31307.191 \$. At a satisfaction rate between 14% and 20%, the locations of the bases remained constant, allowing for a gradual increase in activity. The total number of transported blood groups increased to 76 at a satisfaction rate of 20%. However, from 22%

to 55% satisfaction rate, it was necessary to open four launching stations to maximize the coverage of the request path.

As the satisfaction rate approached 60%, the optimal solution had not yet been achieved. Nonetheless, the model accepted a solution with a very small gap of less than 0.1%. At a satisfaction rate of 70%, which is close to the maximum flying range of the drone, the model recommended the opening of five launching stations to cover the longest distances. The total cost, which included transportation and the setup of the stations, was evaluated for each satisfaction rate and is presented in **Figure 10**^{Error! Reference source not found.} The red columns from 60% to 70% represent the best bound for the total cost at a given satisfaction rate, indicating a relatively small gap.

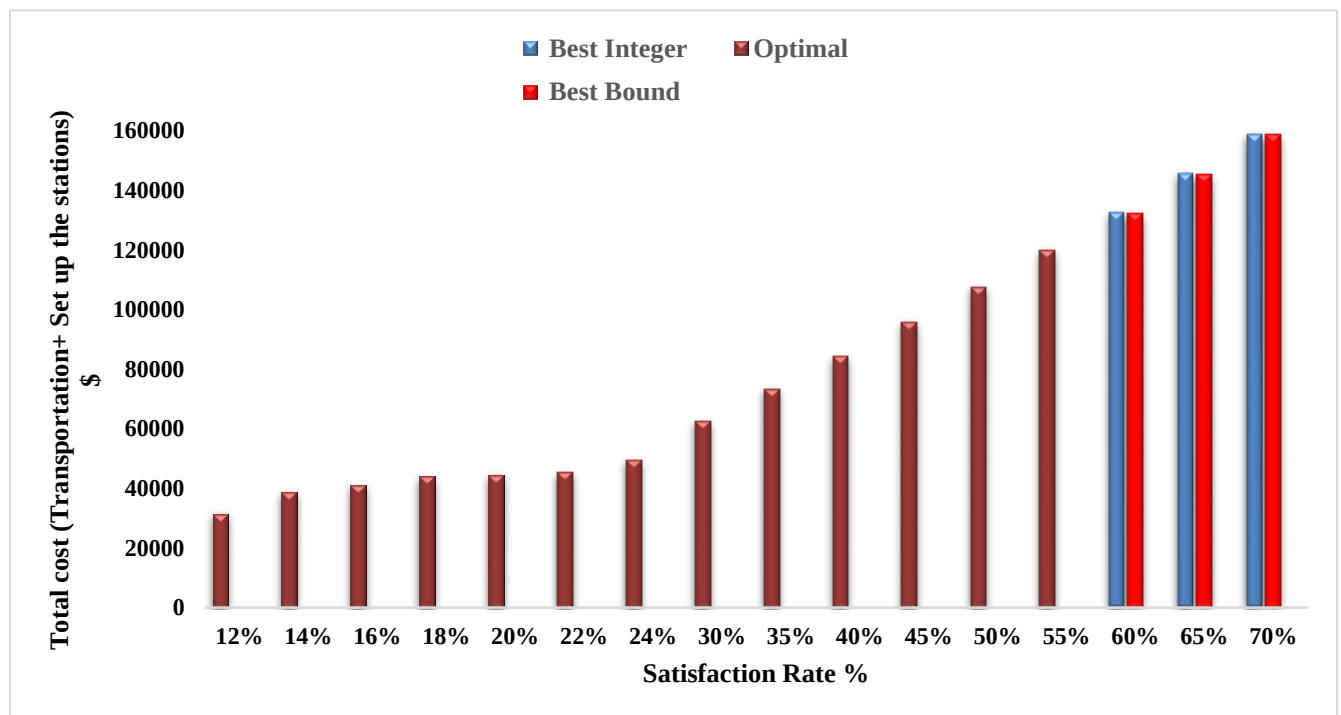


Figure 10. Logistic Network Cost Based on Satisfaction Level (Scenario C)

Figure 11 shows a sample solution for Scenario C, wherein the system receives 50 requests with the goal of fulfilling 30% of blood group requests. The proposed solution involves the utilization of four launching stations, with the majority of requests departing from stations L1 and L4, as recommended by the model. It is worth noting that the drones can discontinue their tasks at any open nearby launching station, leading to a significant number of drones being allocated to stations L1 and L7.

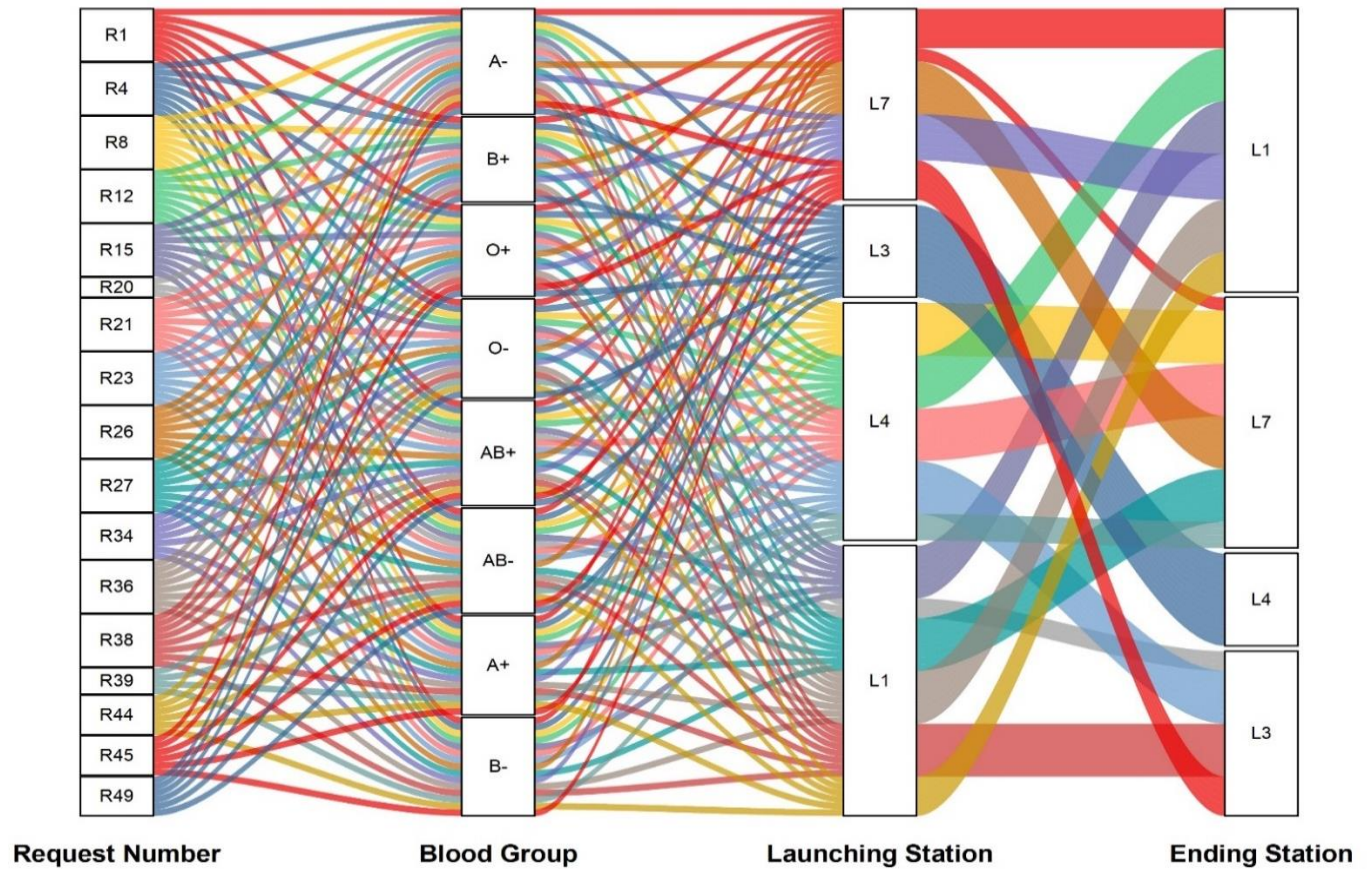


Figure 11. Optimal Configuration for 30% Satisfaction in Scenario C's Logistics Network

3.7.4 Scenario D

The ability to refuel the drones has the potential to significantly increase the coverage of blood requests in healthcare delivery systems. According to **Figure 12**, by enabling the refueling of drones, the coverage of blood requests can be extended from in scenario C

from 70% to 94%, where the number of requests for each blood group that have been fulfilled is illustrated. Moreover, it is possible to achieve full coverage of 100% by establishing multiple refueling stations or by utilizing existing launch sites. The findings of the study indicate that the solution time required to achieve the results for the given scenario is less than 185 seconds, with an insignificant gap of less than 0.1%.

In Scenario D, where 75% coverage is required, the optimal configuration entails opening three launch stations labeled L2, L6, and L7, along with two refueling stations located at RE1 and RE3. This configuration can be achieved optimally within 155.17 seconds and at a cost of 202192.226 \$, which includes the cost of transportation and setting up the launching and refueling stations. By utilizing seven stations, including five launching stations and two refueling stations, with two of the stations serving both as a launching and refueling station, 85% of the demand can be fulfilled at a cost of 210590.507 \$ within 179 seconds. However, in this, 94% of the demand can be met only if launching and refueling stations with low activity rates are opened, as some healthcare locations are situated close to the flying range limit, as shown in **Figure 14**. This results in a substantial increase in costs compared to the results obtained in Scenario C, as depicted in **Figure 13**.

In summary, the ability to refuel drones has the potential to increase the coverage of blood requests, especially in remote areas or in emergency situations. However, in determining the optimal configuration of launching and refueling stations, various factors such as the coverage required, the number of stations, and the distance between the stations must be considered. The results of this study highlight the importance of these considerations in optimizing the delivery of healthcare services using drone technology.

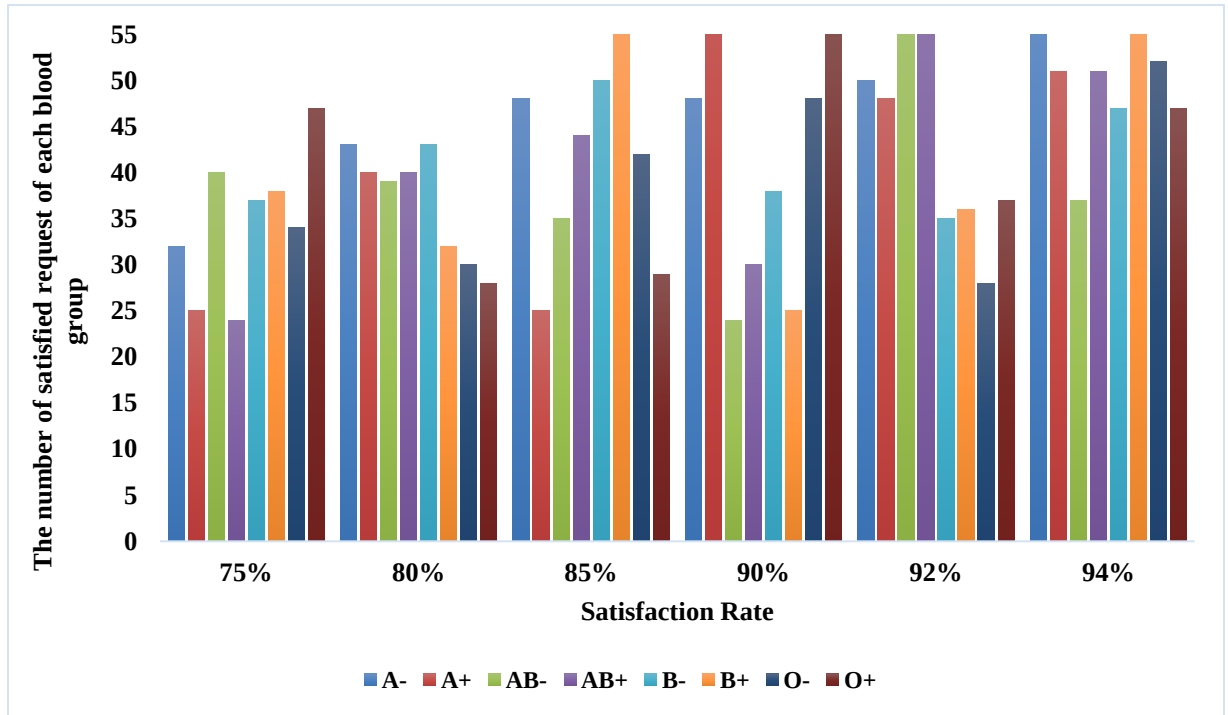


Figure 12. The number of satisfied requests from each blood group for the corresponding satisfaction rate (Scenario D)

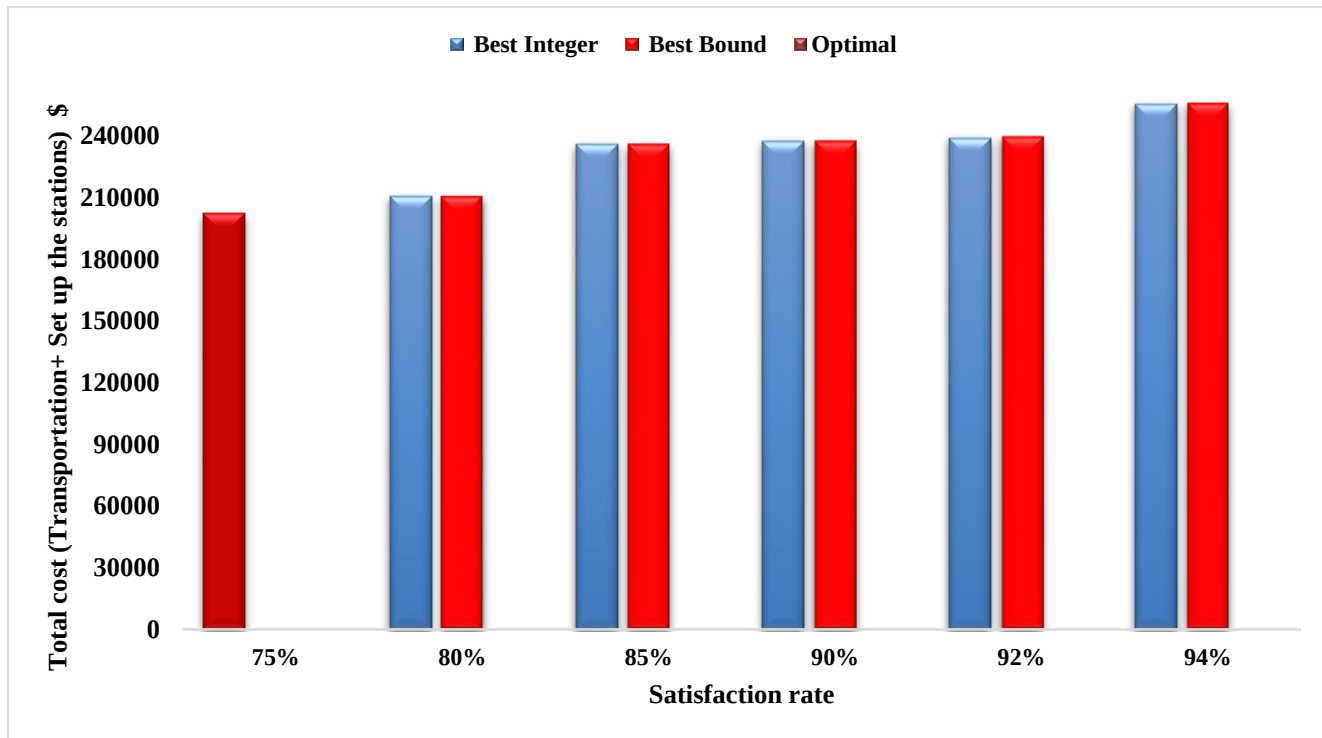


Figure 13. Logistic Network Cost Based on Satisfaction Level (Scenario D)

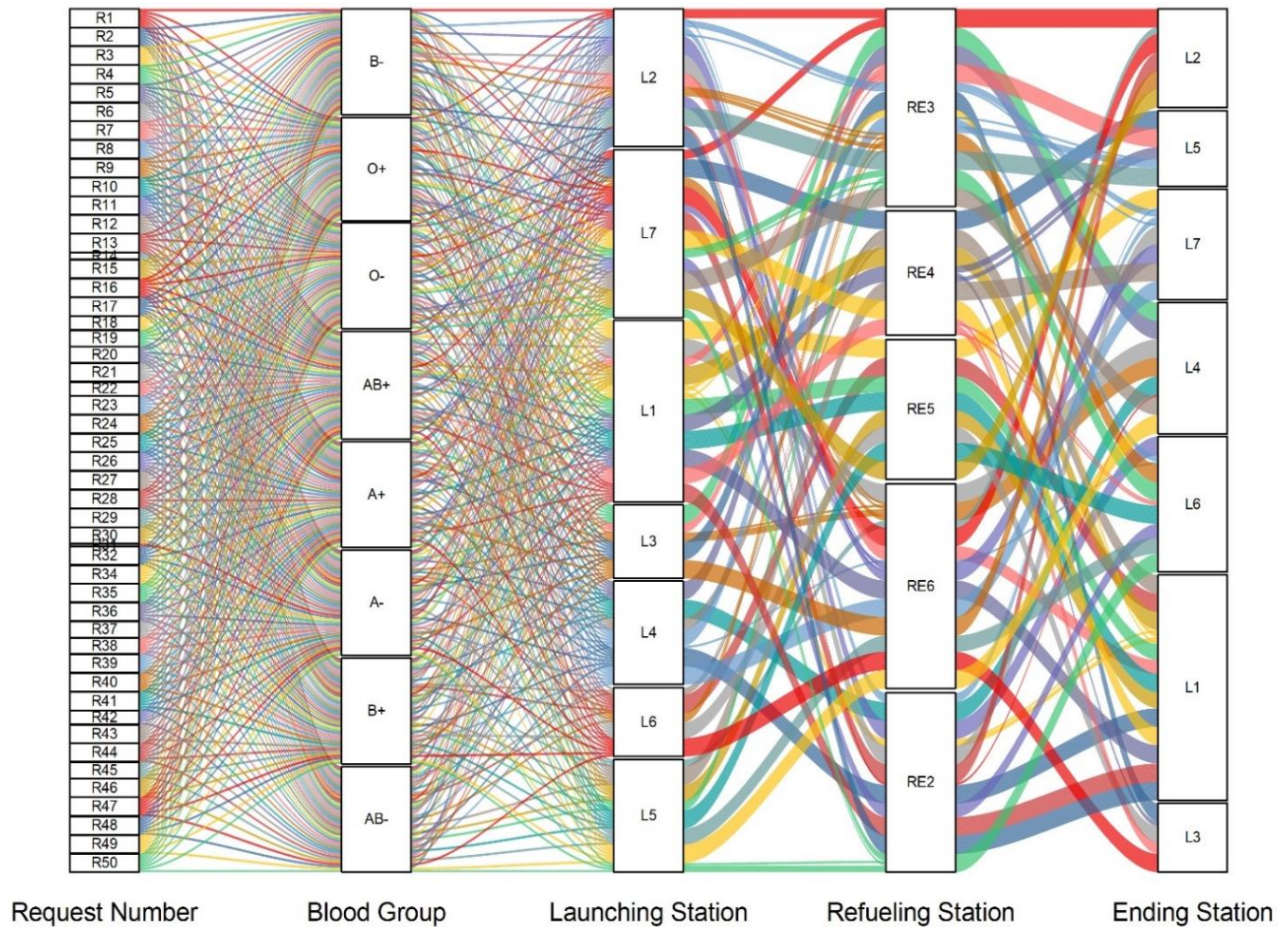


Figure 14. Optimal Configuration for 94% Satisfaction in Scenario D's Logistics Network

3.7.5 Summary

This study aimed to analyze the blood group transportation system's central decision-making process, specifically the optimal configuration of launching and refueling stations for healthcare request locations. The study analyzed 50 blood group requests in the system and presented the findings in **Table 3**, which highlighted two critical parameters: NL and NR. NL represents the ideal number of launching stations, while NR represents the number of refueling stations located away from optimal launching locations.

The study's analysis provides valuable insights into the optimal placement of launching and refueling stations for blood group transportation in different scenarios. The results presented in **Table 3** offer decision-makers a clear indication of the most appropriate number of stations required to achieve optimal outcomes. Additionally, the information on refueling station locations enables effective resource distribution. This study adds to the existing knowledge in the field of resource allocation and logistics optimization and provides a useful reference point for future research.

The study's outcomes underline the importance of informed decision-making regarding the placement of launching and refueling stations for blood group transportation from the blood bank. **Table 3** provides a summary of key performance indicators, such as total logistics cost, number of open stations, and optimal logistic network configurations for different satisfaction rates. The finding aims to provide healthcare professionals with a quick overview of the system's performance, enabling them to make informed decisions about blood supply transportation. The study's findings have broad implications for various applications, including emergency response, military operations, and transportation, making them vital in guiding decision-making processes and improving the overall performance of blood group transportation systems.

Table 3. Results Summary of Case Study (50 Requests)

Scenario	Flying Distance (Km)	Satisfaction rate %	Total cost (Transportation & Setting up the stations)	NL	NR	C.T (s)	Best Integer	Best Bound	Gap %
A	∞	100%	253289	3		46.7			
B	∞	100%	245295	3		82.6			
C	35	12%	31307	2		20			
		14%	38780	3		30.75			
		16%	41000	3		33.65			
		18%	43886	3		43.5			
		20%	44500	3		40.3			
		22%	45296	4		48.1			
		24%	49518	4		48.3			
		30%	62586	4		56.71			
		35%	73232	4		51.8			
		40%	84304	4		72.6			
		45%	95798	4		102.3			
		50%	107639	4		120			
		55%	119881	4		99			
		60%	132538	5		142.5	132538	132413	0.09
		65%	145619	5		148	145619	145508	0.08
		70%	158786	6		140	158786	158758	0.02
D	35	75%	202192	3	2	155.17			
		80%	210591	5	2	179.5	210591	210423	0.08
		85%	235857	6	3	150.22	235857	235713	0.06
		90%	237446	6	4	180.25	237446	237311	0.06
		92%	238959	6	5	162.58	238959	239363	0.03
		94%	255499	7	5	185.6	255499	255477	0.09

3.8 Description of the Additional Experiments

To assess the efficiency and effectiveness of a blood transportation network, we employed a unique approach known as Random Geographic Coordinates Sampling. This technique involves generating random coordinates for potential pickup blood bank and healthcare request location within specified minimum and maximum ranges for longitude and latitude

values ([46.653, 55.150] and [25.36, 29.744], respectively). The aim was to evaluate the network's efficacy across diverse locations.

To avoid redundancy, we excluded blood bank and healthcare request location pairs with identical locations. Furthermore, to ensure a comprehensive evaluation, we randomly selected 15, 25, and 35 stations to open and generated random blood group requests ranging from 1 to 1000 for each selected station. The 15-experiment conducted are summarized in

Table 4.

Table 4.Experiment's Description

Experiment label	Available Stations	Number of Request
S-15-R-143	15	143
S-15-R-342	15	342
S-15-R-585	15	585
S-15-R-692	15	692
S-15-R-889	15	889
S-25-R-282	25	282
S-25-R-355	25	355
S-25-R-413	25	413
S-25-R-685	25	685
S-25-R-779	25	779
S-35-R-242	35	245
S-35-R-407	35	407
S-35-R-560	35	560
S-35-R-722	35	722
S-35-R-904	35	904

We conducted a performance evaluation of a medical drone to determine its operating range and costs. The drone demonstrated an impressive flying distance of 40 km, with an estimated operating cost of \$0.699 per km when empty and \$0.702 per km when loaded. In addition, we conducted a random selection of the costs associated with establishing a launching station, which ranged uniformly between \$3000 and \$8000. Similarly, the cost range for a refueling station was between \$2000 and \$5000.

To expand the drone's range capabilities, we conducted additional tests under scenario C and D. These tests were designed to evaluate the drone's potential to increase its range to 52 km, which could be achieved through advancements in technology or payload reduction. To ensure reliable and getting fast results, we implemented a solver time limit of one hour (3600s) or an acceptable solution gap of less than 0.1%. These measures were put in place to optimize the accuracy and efficiency of the performance evaluation.

To optimize the accuracy and efficiency of the performance evaluation, we implemented two measures: a solver time limit of one hour (3600s) and an acceptable solution gap of less than 1%. These measures were put in place to ensure reliable and timely results. By limiting the solver time and setting an acceptable solution gap, we were able to mitigate the risk of lengthy solving time to reach the optimal solution. This problem could have negative implications for healthcare decisions maker, especially in emergency situations to deliver blood request. Therefore, these measures were crucial to the success of our performance evaluation.

3.8.1 Scenario A

Table 5 presents the results of 15 tests, where the first 4 and the test labelled as S-25-R-413 were able to achieve the optimal solution within the given computation time limit.

However, for the rest of the tests, the optimal solution was not reached within the given time limit. In such cases, the solver was instructed to return solutions with a gap of less than 1%.

The assessment of the obtained solutions can be performed by referring to **Table 5**, which includes data on the optimal integer, optimal bound, and the gap of CLPEX. These metrics can aid in determining the degree of proximity between the achieved solutions and the optimal.

It should be emphasized that the failure to obtain an optimal solution within the allocated time frame can stem from either the intricacy of the problem or the limited computational resources. In these situations, a solution with a gap of under 1% may still be valuable for practical applications.

In addition, it is crucial to consider the balance between computation time and the quality of the solution. Sometimes, it may be preferable to obtain a solution within a specified timeframe, even if it is not optimal, rather than investing more time in obtaining the optimal solution. The result provides useful insights for assessing the solver's performance and the resulting solutions. The statement underscores the importance of evaluating the balance between solution quality and computation time in practical situations.

Table 5. Additional Experiment Results for Scenario A

Experiments	Optimal total cost (Transportation & Setting up the stations)	NL	Best Integer	Best Bound	Gap %	C.T (s)
S-15-R-143	658761.856	3				64.6

S-15-R-342	1566689.33	6				91.5
S-15-R-585	2719980.74	7				165.5
S-15-R-692	3227167.25	7				177.5
S-15-R-889	-	10	4148430	4128567.865	0.98	342.25
S-25-R-282	-	5	1291783	1287877.642	0.3	258
S-25-R-355	-	10	1608988	1608835.009	0.21	221
S-25-R-413	1880399.13	12				281
S-25-R-685	-	11	3148518	3142252.387	0.2	420.6
S-25-R-779	-	15	3584655	3571317.48	0.37	341.8
S-35-R-242	-	6	1096585	1088214.459	0.76	345.21
S-35-R-407	-	10	1850730	1837805.698	0.7	578.5
S-35-R-560	-	12	2565466	2544400.68	0.82	287.64
S-35-R-722	-	20	3303399	3279182.133	0.73	685.69
S-35-R-904	-	22	4154625	4134655.032	0.48	855.6

3.8.2 Scenario B

One way to improve the efficiency of drone operations is by relaxing the constraints related to the destination launching station. Instead of mandating that the drone returns to the same launching station it departed from, as assumed in scenario A, the drone can be allowed to return to any nearby open launching station. This modification not only provides more flexibility in drone operations but also results in reduced computation time required for path planning, as shown in **Table 6**. By reducing computation time, drone operators can plan more complex paths with multiple stops, leading to better operational efficiency.

Table 6. Additional Experiment Results for Scenario B

Experiments	Optimal total cost (Transportation & Setting up the stations)	NL	Best Integer	Best Bound	Gap %	C.T (s)
S-15-R-143	620339.105	6				45
S-15-R-342	1476581.58	7				88.3
S-15-R-585	2544825.39	10				87.65
S-15-R-692	-	11	3016676.005	3004698.477	0.4	111.6
S-15-R-889	-	11	3915089.329	3888145.734	0.69	108
S-25-R-282	-	7	1208215.69	1197475.226	0.89	144.81
S-25-R-355	-	10	1522324.092	1514283.257	0.53	186.75
S-25-R-413	-	10	1785015.7	1770334.855	0.82	173.91
S-25-R-685	-	14	2973400.992	2966048.18	0.25	350.6
S-25-R-779	-	18	3399149.68	3378702.305	0.6	300.38
S-35-R-242	-	10	1029710.928	1019501.246	0.89	300.51
S-35-R-407	-	12	1748650.406	1736475.378	0.7	411.9
S-35-R-560	-	15	2423839.14	2404122.565	0.81	247
S-35-R-722	-	15	3134350.657	3109827.056	0.78	420.2
S-35-R-904	-	17	3952754.103	3914845.815	0.96	693.6

3.8.3 Scenario C

In scenario C, experiments were conducted to address the problem of blood delivery. The experiment involved setting the satisfaction rate to 40%, 60%, and 80%, with an initial flying range distance of 40 km. The main objective was to identify optimal of feasible

solutions to the problem. However, if infeasible solutions were encountered at the initial flying range of 40 km, the flying range was extended to 52 km to achieve an 80% coverage of blood requests.

Unfortunately, in the S-15-R-889 experiment, no solution was found in either case. This outcome can be attributed to one of two factors. Firstly, it is possible that the number of launching stations was not sufficient to cover 80% of the blood requests. Alternatively, it could be that the flying range was relatively small, making it difficult to cover the distance required to reach the designated locations. Thus, to identify the root cause of the problem and devise a suitable resolution, additional further investigation is necessary. **Table 7** presents the findings of the study. Notably, when the problem was addressed with a flight range of 52 km, the computational time increased. This can be attributed to the fact that a larger flying range results in a more complex and challenging problem, necessitating more time and resources to solve

The results of the experiment show that increasing the flying range can lead to improved solutions and higher coverage rates. However, this comes at the cost of increased computation time, which may not be feasible in real-world applications where time is critical. Therefore, it is important to carefully consider the trade-off between flying range, computation time, and solution quality when designing and implementing blood delivery systems.

Furthermore, the experiment highlights the importance of finding feasible solutions to the problem of blood delivery. Infeasible solutions may lead to delays and inefficiencies in the delivery process, which can have serious consequences for patient health and safety. Therefore, it is important to use effective methods for finding feasible solutions, such as

the approach used in this experiment of extending the flying range if infeasible solutions are encountered.

Table 7. Additional Experiment Results for Scenario C

Experiment	Satisfaction rate %	40 Km						52 Km				
		Optimal	NL	Best Integer	Best Bound	Gap %	C.T (s)	NL	Best Integer	Best Bound	Gap %	C.T (s)
S-15-R-143	40	205522	4				981					
	60	325889	4				1020					
	80	465396	6				986					
S-15-R-342	40	463627	6				723					
	60	-	8	754594.3	750092	0.6	852					
	80			INFS				9	1086745	1081459	0.49	871
S-15-R-585	40	-	5	785220.4	781762	0.44	1021					
	60	-	10	1275620	1269271	0.5	1000					
	80			INFS				9	1859080	1851657	0.4	762
S-15-R-692	40	919799	9				764					
	60	-	9	1509919	149.8595.37	0.75	650					
	80			INFS				11	2196818	2189262	0.34	680.8748.6
S-15-R-889	40	-	9	116555.3	1170685	0.5	848					
	60			INFS				14	1941834	1938475	0.17	1021
	80			INFS						INFS		
S-25-R-282	40	385823	6				1012					
	60	-	7	621942.4	618648	0.53	2119					
	80			INFS				6	897834	888884	1	2554
S-25-R-355	40	-	7	481358.3	477826	0.73	2000					
	60	-	8	777886.2	772856	0.65	2100					
	80			INFS				9	1122540	1115212	0.65	2537
S-25-R-413	40	-	7	557760.3	554123	0.65	2282					
	60	-	9	903044.5	895832	0.8	2344					
	80			INFS				12	1310402	1298610	0.9	2631

S-25-R-685	40	-	9	907975.8	900233	0.85	2033						
	60	-	12	1490739	1478039	0.85	1790						
	80			INFS				13	2173093	2156447	0.77	853	
S-25-R-779	40	-	9	1027586	1019321	0.8	2200						
	60			INFS				16	1702914	1680784	1.3	3600	
	80			INFS				20	2473265	2463403	0.4	3600	
S-35-R-242	40	331388	5				926						
	60	-	8	538869.8	527444	0.21	1753						
	80	-	12	541074.2	527461	0.9	2100						
S-35-R-407	40	-	8	552871.3	537244	2.1	3600						
	60	-	14	899133.4	875020	2.68	3600						
	80			INFS				14	1287282	1269867	1.35	3600	
S-35-R-560	40	-	12	748110	731333	2.24	3600						
	60	-	16	1231642	1202471	2.37	3600						
	80			INFS				16	1784343	1756436	1.56	3600	
S-35-R-722	40	-	13	957069.2	935903	2.21	3600						
	60			INFS				13	1563218	1543440	1.27	3600	
	80			INFS				20	2294569	2261732	1.43	3600	
S-35-R-904	40	-	15	1194990	1171028	2	3600						
	60			INFS				18	1975712	1943872	1.61	3600	
	80			INFS				21	2885702	2853767	1.11	3600	

3.8.4 Scenario D

The results of the optimization process are presented in **Table 8** for satisfaction rates that vary from 80% to 100% at 10% intervals, with the drone being rechargeable at any launch or refueling station. The NR columns indicate the number of refueling stations located at positions different from the optimal launch site. The satisfaction rate increases when

refueling stations are included, compared to scenario C, as they offer more flexibility in path planning and allow blood to be delivered to a larger area

In some experiment cases, two infeasible solutions appeared in the 40 km flying range with a large number of requests and 15 launching stations, as seen in experiments (S-15-R-692, S-15-R-889). This issue was resolved through increasing the flying range to 52 km, resulting in a feasible solution. Interestingly, the 80% satisfaction rate was infeasible in scenario C under the 40 km flying range, but it became a feasible solution in scenario D with the same number of launching stations. Scenario D added refueling stations or allowed for the reuse of the launch station in the configuration, resulting in a slight increase in the objective function cost due to the open refueling station. Experiment S-15-R-889 with a satisfaction rate of 80% and a flying range of 40 km and 52 km serves as an example where the solution was infeasible in both cases. However, scenario D was able to achieve a solution in the case of a 40 km flying range, which indicates the effectiveness of the model.

It is worth noting that the inclusion of refueling stations in scenario D not only increases the feasibility of the solutions but also improves the operational efficiency of drone delivery systems. With refueling stations, drone systems can cover all requests coming to the system up to 100%, providing a higher level of service. Moreover, the flexibility provided by refueling stations allows for the delivery of blood to a larger area, which is crucial in emergency situations. In this way, Scenario D simulates the real case of the drone system that can play a critical role in providing timely and efficient blood delivery services.

Table 8. Additional Experiment Results for Scenario D

Experiment	Satisfaction Rate %	40 Km						52 km					
		NL	NR	Best Integer / Optimal	Best Bound	Gap %	C.T (s)	NL	NR	Best Integer / Optimal	Best Bound	Gap %	C.T (s)
S-15-R-143	80	6	0	465389.9			910.36						
	90	8	4	590149.7	586623	0.6	1050.7						
	95	10	6	607823.4	605669	0.35	985.5						
	100			INFS				13	9	632819	631023	0.28	652.6
S-15-R-342	80	9	3	1150395	1140489	0.86	2468.4						
	90	9	5	1322528	1303155	1.46	3600						
	95	11	6	1381966	1375150	0.49	1254.6						
	100			INFS				12	9	1408948	1402585	0.45	1402
S-15-R-585	80	9	5	1891416	1877720	0.72	2854.6						
	90	11	7	2173569	2144817	1.32	3600						
	95	13	7	2315256	2297544	0.77	3600						
	100			INFS				14	9	2396765	2391978	0.2	2221
S-15-R-692	80	10	5	2228085	2214957	0.59	2145.5						
	90	12	9	2491299	2478926	0.1	892.36						
	95			INFS				14	10	2621549	2610720	0.41	1654
	100			INFS				14	11	2769383	2764557	0.17	870.5
S-15-R-889	80	12	8	2804692	2788735	0.57	1398.5						
	90	12	9	3225376	3200370	0.78	1752.6						
	95			INFS				13	9	3386805	3367079	0.58	932.6
	100			INFS				13	10	3575088	3560802	0.4	1185
S-25-R-282	80	6	3	933655.8	919016	1.57	3600						
	90	13	8	1036839	1023258	1.31	3600						
	95	17	10	1093051	1087587	0.5	809.45						
	100			INFS				17	13	1135283	1129702	0.49	980.1

S-25-R-355	80	9	4	1143010	1123570	1.7	3600	20	15	1403449	1398910	0.32	1366
	90	18	9	1293080	1280648	0.96	3600						
	95	18	12	1337579	1329416	0.61	1785.7						
	100	INFS											
S-25-R-413	80	12	5	1392112	1384509	0.59	920.89	18	15	1614915	1608615	0.39	983.1
	90	16	10	1477398	1457923	1.32	3600						
	95	18	11	1565918	1549052	1.08	3600						
	100	INFS											
S-25-R-685	80	13	5	2287908	2276768	0.53	2985.6	20	17	2469481	2458297	0.45	698.7
	90	18	15	2338779	2328207	0.45	1006.9						
	95	INFS											
	100	INFS											
S-25-R-779	80	20	10	2557300	2544958	0.52	1395.8	22	18	2618080	2609057	0.34	1116
	90	22	16	2649374	2641950	0.28	722.36						
	95	INFS											
	100	INFS											
S-35-R-242	80	12	5	781764.6	774402	0.94	3600	22	19	2775321	2772884	0.09	936.5
	90	17	12	874771.1	868153	0.76	773.55						
	95	21	14	936195.7	930011	0.66	1147.3						
	100	INFS											
S-35-R-407	80	14	9	1385716	1355709	2.33	3600	22	17	982459	975572	0.7	1889
	90	20	16	1434284	1419153	1.05	3600						
	95	20	16	1495153	1484997	0.68	3600						
	100	INFS											
S-35-R-560	80	16	8	1816948	1795453	1.25	3600	22	18	2136695	2123172	0.63	648.4
	90	20	10	1993525	1956181	1.87	3600						
	95	22	14	2064252	2035984	1.37	3600						
	100	INFS											
S-35-R-722	80	20	10	2360795	2345190	0.72	3600						

S-35-R-904	90	21	15	2460918	2430095	1.25	3600	27	18	2746036	2737225	0.32	1825
	95	25	16	2611734	2589657	0.85	3600						
	100	INFS											
	80	21	11	2987806	2919623	2.45	3600						
	90	22	13	3123467	3044382	2.53	3600						
	95	24	16	3251225	3199374	1.59	3600						
	100	INFS											

3.9 Conclusion

The healthcare industry's timely and efficient blood supply delivery can be enhanced through the implementation of a centralized decision support system using drones. The success of the system relies on the optimal location of launching and refueling stations, considering the flight range capacity of drones and the capacity of each supply node in the decision support system. The objective of the research is to design a logistic network that minimizes total logistics costs, including construction costs and delivery costs between locations. Real-time updates will be provided to healthcare professionals to monitor the progress of the drone's flight and ensure that the blood supplies are delivered on time. The implementation of this system could result in a more efficient and cost-effective transportation system for blood supplies, potentially saving lives by reducing delivery times and minimizing the risk of delays.

The present study formulates four combinatorial optimization location models and demonstrates their practical application in the transportation of blood groups. Our investigation highlights the crucial role of technical features, such as range, speed, and payload, in determining the optimal location for launching stations. Through the utilization

of decision support systems, our research findings reveal that imposing a return to the launching base results in increased total distance and emphasizes the limited range of drones. However, relaxing this constraint may require repositioning of drones to address imbalances. Moreover, our study indicates that the deployment of refueling stations can increase mission ranges and improve the fulfillment of coverage requests. Additionally, our results demonstrate the possibility of a gradual implementation of the launching process without significant modifications, such as the closure of a launching station.

In addition to exploring additional variables and factors, future research could also focus on optimizing the computational efficiency of our models. The use of CPLEX for solving our combinatorial optimization problems can be time-consuming, particularly when dealing with larger-scale problems. Therefore, exploring alternative heuristic algorithms or developing customized algorithms that can better handle large-scale problems could be a valuable avenue for future research. Additionally, it would be worthwhile to investigate the feasibility of implementing our proposed models in real-world scenarios and assessing their impact on the transportation of blood groups. Such studies could help validate the practicality and efficacy of our decision support system and identify potential areas for improvement.

CHAPTER 4

JOURNAL ARTICLE 2

A Drone-Based Logistics Network for Blood Supplies: A Genetic Algorithm Based on Greedy Search

4.1 Abstract

The delivery of blood group to healthcare facilities poses a challenge due to the short product lifetime, fluctuating demand, and limited accessibility of these areas. Drone-based delivery systems have emerged as a promising solution to improve the availability and delivery times of blood products. To further enhance the efficiency of blood supply logistics, this study proposes a drone-based logistics network for transporting blood groups from blood banks to hospitals. The proposed methodology employs a genetic algorithm with Greedy Search to establish an optimal drone-based logistics network. The algorithm considers the allocation of blood requests to launching and refueling stations and determines the most efficient routes for drones. The objective is to minimize total logistics costs, including the construction costs of launching and refueling stations, as well as delivery costs between locations. The algorithm utilizes natural selection processes, including selection, reproduction, and mutation, to converge towards a near-optimal solution. Results demonstrate that the proposed algorithm is more computationally efficient than the CPLEX solver for solving the integer linear programming problem. Moreover, the methodology provides a near-optimal solution with a small gap between the

CPLEX optimal and algorithm solution, indicating its effectiveness and potential to improve blood product delivery in a cost-effective manner.

Keyword:

Blood delivery, Drones, Logistic network, Genetic Algorithm, Greedy Search, Location-Routing Problem.

4.2 Introduction

Epidemics and pandemics like the 1976 Ebola outbreak, 2009 H1N1, 2003 SARS, and the current global COVID-19 pandemic have had a significant impact on public health and social advancement. The use of medical supplies is a vital measure to limit the transmission of infectious diseases and ensure the safety and well-being of people during such outbreaks. Nevertheless, logistics decision-makers face the challenge of making the best use of limited resources and time to allocate scarce resources such as finances and time to manage the distribution of medical supplies effectively.

The need for a swift and reliable mode of transportation for medical supplies like blood samples and medicine is imperative due to their high value and urgent nature, compounded by their small size and limited weight. In response to this challenge, the use of drones has emerged as a promising solution. For example, Matternet, a company based in Maseru, Lesotho, has successfully employed drones to transport blood samples for HIV/AIDS tests from clinics to hospitals, resulting in a notable decrease in delivery time compared to conventional terrestrial transportation modes [111]. This development has proved especially beneficial in areas with a limited road infrastructure, which would otherwise cause significant delays in the delivery of these critical supplies[112]. Additionally,

research has demonstrated that building a comprehensive network of drone stations and maintaining a corresponding fleet of drones is a more economical solution compared to investing in physical road infrastructure.

Matternet has also utilized drones for the distribution of humanitarian supplies during natural disasters, such as the 2012 earthquake that affected Haiti and the Dominican Republic[113]. To enhance its drone-based services in Switzerland, Matternet recently launched the "Matternet base stations," which come equipped with an automatic battery-swapping feature[114], [115]. The implementation of such delivery systems offers a reliable and efficient means of transporting medical and humanitarian supplies to areas with a deficient road infrastructure.

Zipline, a company that employs drones for delivery purposes, has been providing an average of 1400 blood samples daily to hospitals within a radius of 75 kilometers from a central distribution center situated in Muhanga, Rwanda [116]. The delivery system, which uses drones capable of traveling at an approximate speed of 80 miles per hour, has significantly reduced the delivery time from 4 hours to less than 30 minutes [117]–[119].

The proposed system is expected to be scaled up to meet the needs of the entire country, with a population of 11 million people, providing not just blood samples but also medical essentials such as vaccines, treatments for rabies, and anti-venom medications [120]. Zipline is also extending its services to Tanzania, a country with an area 38 times larger than Rwanda and only 8% of paved roads, with the aim of delivering 2,000 packages daily from various distribution centers [121]. Additionally, in collaboration with Novant Health,

Zipline successfully carried out the delivery of COVID-19 medical supplies in North Carolina, USA [122].

Transportation expenses and challenges in meeting demands are common in the healthcare supply chain [123]. Annually, the National Health Service (NHS) requires 1.6 million blood units to attend to over 5 million patients, and due to the high perishability of the units, there is an estimated 3% to 5% wastage rate [124], [125].

The primary focus of this review is centered on the utilization of drone-based delivery systems, which are considered the most suitable option for facilitating prompt and reliable inter-urban hospital deliveries. This is largely attributed to the fact that the distances between hospitals are relatively short, and the deliveries are often of an urgent nature[126].

Regarding urban deliveries, a hierarchical facility location method that considers recharge considerations was proposed by [39], while [90] presented a comparable approach for healthcare deliveries focused on chronic disease patients in rural settings. However, the assumptions of infinite capacity for the hubs used in these studies are not practical for urban hospitals due to the limited availability and high cost of land. Moreover, the operational costs in these studies are oversimplified as they do not consider fluctuations in occupancy level

To meet the demands of disaster relief operations, a study by [127] investigated the creation of a flexible UAV blood supply network for use during emergency situations. Meanwhile, [57] put forward a vehicle routing model that incorporates the impact of temperature fluctuations on blood products during transportation, taking into consideration the quantity of blood being transported and the length of each trip. In a similar vein, [128] developed a

location-routing algorithm for drone-based distribution of relief supplies that integrates energy management and recharging capabilities.

To optimize this system, numerous studies have been undertaken. In one such study, a drone delivery vehicle routing problem model was proposed in [40], consisting of two distinct models. The first model aimed to minimize the overall operating expenses while adhering to delivery time constraints, while the second model aimed to optimize delivery time while considering budget constraints. The work of [40] was expanded by [129] through the incorporation of a non-linear function that accounted for the drone's power consumption based on the payload and travel time. To account for the non-linear function, the researchers implemented logical and sub-gradient cuts and employed the branch-and-cut algorithm to solve the problem.

In [56], the drone fleet size was optimized for an automated drone delivery system, where all customers had identical demands. They considered the relationship between battery capacity, payload, and flight range. On the other hand, a mathematical model was developed in [130] that enabled drones to share various sites and optimized the weighted sum of the overall number of covered tasks and the total travel distance. Additionally, loading capacity and flight time were considered to facilitate the logistics of drone delivery. A proposed solution by [131] aimed to increase efficiency and reduce costs in warehouse material transfer systems through a drone scheduling problem. A study conducted by [132] aimed to improve drone delivery using location routing problems through an integer linear programming model. The study's goal was to maximize the importance values for all covered nodes, which was achieved using an ant colony optimization meta-heuristic

algorithm. However, in medical supply delivery, it is not acceptable to disregard nodes with low importance values.

The use of operations research techniques and optimization modeling in drone applications for healthcare and humanitarian logistics has been on the rise in recent years[133], [134]. A study conducted by [102] investigated the integration of drones in last-mile delivery for humanitarian logistics in a network consisting of multiple nodes and a single depot. Their model was designed to minimize travel distance, while also ensuring adherence to payload and energy limitations.

Drones have been increasingly utilized in healthcare and humanitarian logistics, particularly in the last-mile delivery of goods and services. Several studies have focused on optimizing drone operations and their capacity to cover large areas. The coverage path planning problem for a multi-UAV area in the context of maritime search and rescue was studied by[135]. They proposed a two-stage approach that consisted of decomposition and optimization to minimize the time while achieving optimal coverage. Their methodology involved two distinct stages, namely decomposition and optimization. The main objective was to find an optimal coverage path planning solution that minimizes the time taken while guaranteeing complete coverage of the area.

Another research work by [136] presented two models that can be used to find the optimal number of drone centers and route planning for drone-aided healthcare services in rural areas. In addition, [57] put forward a capacitated VRP model to deal with blood supply concerns during emergencies, with distance cost and flight times as optimization goals.

The effect of specific factors on drone trajectories, such as battery recharging and drone hovering, has also been investigated in the literature. In the context of post-disaster inspection, a fixed-fleet drone routing problem was optimized in a study by [137] using an MIP model to minimize inspection costs. On the other hand, [56] utilized a continuous approximation model to determine the optimal location of a distribution center, along with emergency inventory and service area.

Recently, there has been a notable increase in interest regarding the application of drones in healthcare and humanitarian logistics. One area of focus has been the capacity location problem with drones, which has been studied by [58], [59], [138]. Each study aimed to optimize different objectives. [138] conducted a study exploring the use of drones for logistics, with the goal of reducing facility construction and drone procurement costs, while ensuring that the necessary number of customers are served. Meanwhile, [58] incorporated the uncertainty surrounding the drone's flight distance caused by fluctuations in battery consumption into their modeling framework.

Furthermore, the challenge of limited battery life during medical supplies transportation has been addressed in several studies. For instance, researchers such as those in [65], [68] and [128] have developed methods to optimize the location selection of charging stations or tactical centers, along with the drone route. Through these optimization approaches, scholars aim to improve the effectiveness and efficiency of drone-based operations in the fields of healthcare and humanitarian logistics.

The utilization of drones for the task of pickup and delivery poses a challenging optimization problem that can be categorized as an NP-hard problem [139]. In addressing

this problem, researchers have turned to metaheuristics due to their ability to provide near-optimal solutions within reasonable time constraints and acceptable quality [140], especially when dealing with multiple objectives. For example, [141], [142] utilized the simulated annealing algorithm to solve VRP with pickup and delivery, while [143], [144] improved the tabu search metaheuristic. In their work, [145] put forward a composite algorithm that integrates the ant colony system and the virtual transformation method, and [146], [147] sought to enhance the adaptive large neighborhood search metaheuristic to investigate the optimal solution for VRP with pickup and delivery.

The genetic algorithm (GA) has proven to be effective in solving both single-objective and multi-objective vehicle routing problems (VRPs)[148]. In recent studies by [149], [150] , GA was utilized to minimize the operating costs of VRP with pickup and delivery (VRPSPD). Moreover,[139], [151] utilized an improved version of NSGA-II and a clustering algorithm to address the multi-objective VRPSPD in a two-echelon distribution system. [138] chose NSGA-II and NSGA-III for the bi-objective location problem in drone delivery. For the dynamic bi-objective routing problem, [152] introduced a customized genetic algorithm that employed NSGA-II as the base multi-objective evolutionary algorithm. The experimental results suggest that NSGA-II is effective in solving complex models for real-world problems.

The present study's principal contribution lies in proposing a drone network to address the challenge of transporting blood groups to healthcare facilities. The traditional emergency vehicle delivery system encounters significant delays due to the centralized blood supply facilities and rising traffic levels. To overcome this limitation, the study introduces a mathematical model that centralizes the transportation of blood supplies to healthcare

facilities using drones. The proposed framework aims to minimize logistics costs by strategically locating launch and refueling stations and assigning blood requests to selected stations. In addition, the research presents a network design model that assigns blood group requests to a path, reducing the number of variables and constraints compared to traditional routing and location problems.

Existing literature on location routing problems primarily proposes heuristic algorithms and mathematical programming to solve practical issues, with only a few adopting exact algorithms. Despite their efficiency in terms of solution time, heuristic algorithms fail to guarantee an optimal solution. Therefore, this paper modifies the heuristic algorithm by incorporating a greedy search to improve the performance of the genetic algorithm (GA) in computational time and quality of the solution close to the optimal Cplex solution. This modification significantly enhances the algorithm's efficiency by reducing the number of suboptimal solutions, making it possible to efficiently solve real large-scale problems.

The following sections of this academic paper have been arranged in the subsequent manner: In Section 2, a concise overview of the issue is presented, along with some indispensable assumptions. Section 3 offers a mathematical model to tackle the problem at hand. Section 4 provides a comprehensive explanation of the solution methodology employed, which involves merging a Genetic algorithm with a greedy search. Section 5 present the computational result and performance of the proposed methodology by solving problems of various sizes. Lastly, Section 6 of this manuscript offers a summary of the principal findings and provides recommendations for future research directions.

4.3 Problem Statement

4.3.1 Problem Description

The delivery of blood from blood banks to hospitals is a critical requirement that this paper aims to address. To meet this demand, the proposed solution is the use of drones to efficiently assign the blood request to the appropriate path and launching station. The algorithm selects the optimal assignment of the blood request to the launching and refueling stations from a set of candidate stations. Drones are equipped with specific requirements such as batteries, take-off and landing pads, and charging facilities to transport blood stock from the blood banks to the hospital request location. After each delivery, drones return to their respective nearby launching stations for maintenance until the next delivery request. The proposed model for designing a logistics network for delivering blood to hospital locations is shown in **Figure 15**.

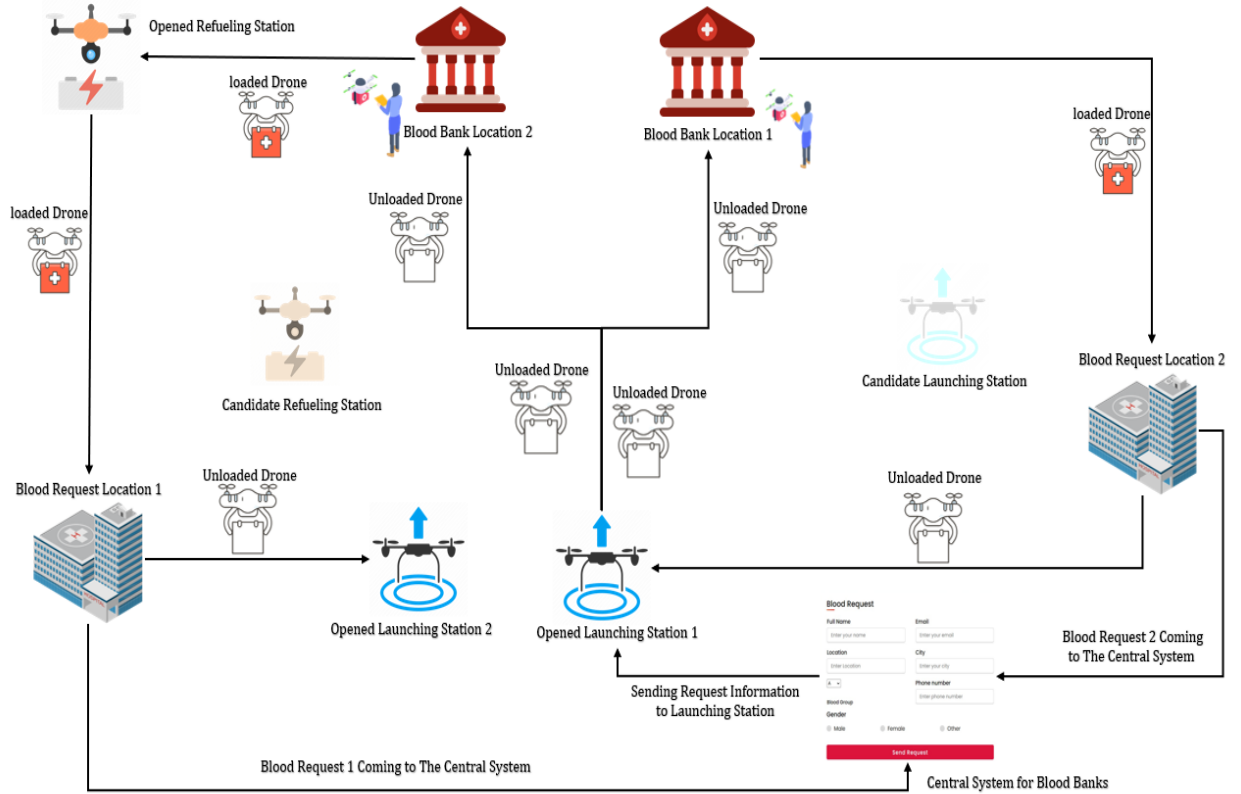


Figure 15. The Proposed Model for Delivering Blood Requests to Hospitals Using Drone Technology

Moreover, the paper aims to solve the path assignment problem for an infinite number of homogeneous drone fleets transporting blood group units from a central blood bank to various medical facilities. The path design stage utilizes the flight distance requirements of drones to determine candidate stations and ensure that most hospitals are within the operational range of drones. The launching and refueling selection stage address a facility location optimization problem. To tackle the critical problem of blood group distribution in emergency situations, the paper proposes dispatching a fleet of drones to medical facilities. A mathematical model is used to determine the most efficient routes for the drones and minimize logistics costs. The objective of this research is to design a logistic network for the transportation of blood groups that minimizes the total logistics costs,

including the construction costs of launching and refueling stations and the delivery costs between different locations. Communication systems for order requests between hospitals and the central system are not included in this paper. The utilization of UAVs to deliver blood groups can enhance patient care and response time by providing on-demand and efficient delivery services.

4.3.2 Assumption

The model presented on the paper is based on a set of underlying assumptions that are fundamental to its effectiveness.

- It is assumed that the pick-up location of the blood bank and the healthcare facility requesting the blood are known, and the distance between the two can be calculated using Euclidean distance.
- The model assumes that all blood groups are in high demand during major public health emergencies, while other medical materials are not included. This assumption is necessary to keep the scope of the model focused on the specific problem of blood group distribution.
- The requested units of blood group are deterministic.
- The model assumes that refueling stations for the drones can either use existing launching stations as refueling stations at no additional cost or open new refueling stations with setup costs. This assumption allows for a cost-effective approach to the problem of drone refueling.
- It is assumed that the drones are only able to fly for a limited distance before they require refueling or recharging.

- The satisfaction rate of blood requests is less than or equal to 100. This assumption recognizes the potential limitations of drone flying range and the possibility that not all requests for blood may be fulfilled. It is crucial to note that these assumptions are fundamental to the validity and accuracy of the model presented in this paper.

Overall, the assumptions underlying the model presented in this paper play a critical role in ensuring its validity and effectiveness. By acknowledging and accounting for these assumptions, the model provides a practical and effective solution to the problem of blood group distribution in emergency situations.

4.3.3 Mathematical Model Formulation

This study aims to optimize the deployment of homogeneous drone fleets at various candidate launching stations, denoted by $j, \forall j \in M = \{1, 2, \dots, m\}$. The healthcare demand for blood groups is expressed in terms of the number of packages to transport on path $i, \forall i \in N = \{1, 2, \dots, n\}$ & $p \forall p \in P = \{A+, A-, B+, B-, O+, O-, AB+, AB-\}$.

The primary objective of this study is to minimize the overall logistic and construction costs of launch and refueling stations by allocating requests to the optimal launching station. To achieve this objective, we seek to establish the location of the launching and refueling stations while considering the healthcare demand for blood groups and the associated transportation costs. To this end, we formulate the problem as an integer linear programming (ILP) model.

a. Sets

- N : Set of the healthcare request
- M : Set of the possible launching station
- P : Set of the blood group
- f : Set of the possible location of the refueling station

b. Parameters

- B_{ip} : The number of units of blood group daily on the path i for blood group p
- d_i^{ph} : The distance between the pickup location of path i and the location of the medical blood request (**Km**)
- d_{ij}^{lp} : The distance between the pick-up location on path i and the launching station j (**Km**)
- d_{ij}^{hl} : The distance between the health care blood request of path i and launching station j (**Km**)
- d_{if}^{pr} : The distance between the pickup location of path i and the refueling station f (**Km**)
- d_{if}^{rh} : The distance between the health care blood request location of path i and refueling station f (**Km**)
- l_j : The fixed operating costs of launching station j (\$)
- R_f : The fixed operating costs of refueling station f (\$)
- α : Fixed costs per kilometer of unloaded drone (\$)
- β : The fixed costs per kilometer of loaded drone (\$)
- τ : The satisfaction rate of the health care request (%)
- δ : The flying range limit for drone in (**Km**)

c. Binary Decisions Variables

$$\omega_j = \begin{cases} 1 & \text{if the launching station } j \text{ is selected to be opened } \forall j \in \mathbf{M} \\ 0 & \text{Otherwise} \end{cases}$$

$$\chi_{ijp} = \begin{cases} 1 & \text{if route } i \text{ begins at launching station } j \text{ for blood type } p \\ & \forall i \in \mathbf{N}, j \in \mathbf{M}, p \in \mathbf{P} \\ 0 & \text{Otherwise} \end{cases}$$

$$\Upsilon_{ijp} = \begin{cases} 1 & \text{if route } i \text{ end at launching station } j \text{ for blood type } p \\ & \forall i \in \mathbf{N}, j \in \mathbf{M}, p \in \mathbf{P} \\ 0 & \text{Otherwise} \end{cases}$$

$$\mathbf{K}_f = \begin{cases} 1 & \text{if the refueling station } f \text{ is selected to be opened } \forall f \in \mathbf{M} \\ 0 & \text{Otherwise} \end{cases}$$

$$\mathbf{E}_{ifp} = \begin{cases} 1 & \text{if route } i \text{ used refueling station } f \text{ for blood type } p \\ & \forall i \in \mathbf{N}, f \in \mathbf{M} \cup \{\mathbf{m} + 1\}, p \in \mathbf{P} \\ 0 & \text{Otherwise} \end{cases}$$

d. Formulation

The problem at hand addresses the option to recharge the battery during a flight. This can be done either at the open launching stations, where the necessary machinery is already installed, or at specific refueling stations that have a built-in battery charger. For paths that do not have any recharging stations, a dummy refueling station with index $(\mathbf{m} + 1)$ is added to set $\mathbf{M}$. The distance between the pickup location of path i and the dummy refueling station is set to zero ($d_{i \rightarrow (\mathbf{m} + 1)}^{pr} = 0$), while the distance between the healthcare request of path i and the dummy refueling station is equal to the distance between the pickup location of path i and the location of the healthcare blood request location ($d_{i \rightarrow (\mathbf{m} + 1)}^{rh} = d_i^{ph}$).

The objective function is modeled as follows:

$$\begin{aligned}
\text{Min} \quad & \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_{ij}^{lp} + \beta \sum_{i=1}^n \sum_{f=1}^{m+1} \sum_{p \in P} B_{ip} E_{ifp} (d_{if}^{pr} + d_{if}^{rh}) \\
& + \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \gamma_{ijp} d_{ij}^{hl} + \sum_{j=1}^m l_j \omega_j + \sum_{j=1}^m R_j K_j (1 - \omega_j) \quad \text{Eq(1)}
\end{aligned}$$

The objective function, denoted as **Eq (1)**, is used to minimize the total cost of transporting blood products using drone fleets. The first term of **Eq (1)** represents the cost of transporting an empty drone from its starting point to the pickup location.

If transportation between launching stations is achieved through a refueling station, the second component of the objective function represents the cost of transporting loaded drones from the pickup location to the refueling station and from the refueling station to the healthcare request locations. On the other hand, if refueling is not required, the second component of the objective function directly relates to the transportation cost of loaded drones from the pickup location to the requested location on the path i .

The third component of **Eq (1)** reflects the cost of transporting the returned, unloaded drones from the healthcare request location to the nearest launching station. It is important to note that the last term of the objective function, which involves the product of two binary variables, causes the model to become nonlinear. In order to address this challenge, we propose the introduction of a new binary variable, denoted as $\tilde{\varphi}_j$ such as $\tilde{\varphi}_j = K_j \omega_j \quad \forall j \in M$. By incorporating this variable into the model, we can then formulate the objective function as follows:

$$\begin{aligned}
\text{Min } & \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \chi_{ijp} d_{ij}^{lp} + \beta \sum_{i=1}^n \sum_{f=1}^{m+1} \sum_{p \in P} B_{ip} E_{ifp} (d_{if}^{pr} + d_{if}^{rh}) \\
& + \alpha \sum_{i=1}^n \sum_{j=1}^m \sum_{p \in P} B_{ip} \Upsilon_{ijp} d_{ij}^{hl} + \sum_{j=1}^m l_j \omega_j + \sum_{j=1}^m R_j K_j - \sum_{j=1}^m R_j \tilde{\varphi}_j \quad \text{Eq(2)}
\end{aligned}$$

subject to

$$\sum_{i=1}^n \chi_{ijp} \leq \omega_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad \text{Eq(3)}$$

$$\sum_{i=1}^n \Upsilon_{ijp} \leq \omega_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad \text{Eq(4)}$$

$$\sum_{j=1}^m \Upsilon_{ijp} = \sum_{j=1}^m \chi_{ijp} \quad \forall \quad i \in N, p \in P \quad \text{Eq(5)}$$

$$\sum_{i=1}^n \sum_{j=1}^m B_{ip} \chi_{ijp} \geq \tau \sum_{i=1}^n B_{ip} \quad \forall p \in P \quad \text{Eq(6)}$$

$$\sum_{j=1}^m \chi_{ijp} \leq 1 \quad \forall i \in N, p \in P \quad \text{Eq(7)}$$

$$\sum_{f=1}^{m+1} E_{ifp} = \sum_{j=1}^m \chi_{ijp} \quad \forall \quad i \in N, p \in P \quad \text{Eq(8)}$$

$$\sum_{i=1}^n E_{ijp} \leq K_j \sum_{i=1}^n B_{ip} \quad \forall \quad j \in M, p \in P \quad \text{Eq(9)}$$

$$\sum_{j=1}^m d_{ij}^{lp} \chi_{ijp} + \sum_{f=1}^m d_{if}^{pr} E_{ifp} \leq \delta \quad \forall i \in N, p \in P \quad \text{Eq(10)}$$

$$\sum_{j=1}^m d_{ij}^{hl} \gamma_{ijp} + \sum_{f=1}^m d_{if}^{rh} E_{ifp} \leq \delta \quad \forall i \in N, p \in P \quad \text{Eq(11)}$$

$$\sum_{j=1}^m d_{ij}^{lp} \chi_{ijp} + d_i^{ph} E_{i(m+1)p} + \sum_{j=1}^m d_{ij}^{hl} \gamma_{ijp} \leq \delta(2 - E_{i(m+1)p}) \quad \forall i \in N, p \in P \quad \text{Eq(12)}$$

$$\tilde{\varphi}_j \leq \omega_j \quad \forall j \in M \quad \text{Eq(13)}$$

$$\tilde{\varphi}_j \leq K_j \quad \forall j \in M \quad \text{Eq(14)}$$

$$\tilde{\varphi}_j \leq K_j + \omega_j - 1 \quad \forall j \in M \quad \text{Eq(15)}$$

$$\chi_{ijp}, \gamma_{ijp}, \omega_j, K_j, E_{ijp} \in \{0,1\} \quad \forall i \in N, j \in M, p \in P \quad \text{Eq(16)}$$

The constraints **Eq(3)** and **Eq(4)** specify that the launching station j will be opened if the path i utilizes that particular station for a given blood group p . This ensures that the appropriate launching station is selected for each path and blood group combination.

Constraint **Eq(5)** ensures that the drone follows the designated path i , which carries blood group p , and returns to any nearby open launching station to complete the trip. This ensures that the drone is not left stranded at the healthcare facility after delivering the blood product, and can easily return to a launching station for subsequent trips.

Constraints **Eq(6)** specify that a certain percentage of blood requests must be fulfilled. This ensures that the model optimizes the allocation of resources to meet the minimum blood demand required by healthcare facilities.

Constraints **Eq(7)** ensure that each request is assigned to only one launching station. This prevents duplication of resources and ensures that each request is assigned to the most optimal launching station for the given path and blood group.

Constraints **Eq(8)** ensure that only one refueling station is allowed on Path i , and if Path i is not serviced, then no refueling stations are permitted. This prevents unnecessary use of resources and ensures that the model allocates refueling stations only when needed.

As stated in constraint **Eq(9)**, a refueling station is usable if the corresponding launching or refueling station is opened. This ensures that refueling stations are allocated only when the corresponding launching or refueling station is operational.

Constraints **Eq(10)** and **Eq(11)** guarantee that the distance between the launching or refueling station and the refueling station, as well as the distance between the refueling station and the healthcare request location, do not exceed the maximum flight distance capacity of the drone. This ensures that the drones can complete their assigned tasks within their operational limits.

Constraint **Eq(12)** specifies the maximum flight range limit for a path that does not involve an intermediate refueling station. This constraint ensures that the drones can complete their assigned tasks without exceeding their operational range limit.

Constraints **Eq(13)** , **Eq(14)** , and **Eq(15)** are designed to ensure that the decision variable $\tilde{\varphi}_j$ is binary. Constraints **Eq(13)** and **Eq(14)** stipulate that if either K_j or ω_j is zero, then $\tilde{\varphi}_j$ must also be zero. Conversely, constraint **Eq(15)** mandates that if K_j and ω_j is one, then $\tilde{\varphi}_j$ must also be one. Finally, constraint **Eq(16)** control the decision variables χ_{ijp} , Υ_{ijp} , ω_j , K_f , E_{ijp} to be binary.

4.4 A Heuristic Approach Based on Genetic Algorithm Optimization

This section introduces a more efficient and effective method for solving the integer linear programming model proposed in Section 4.3.3, which involves optimizing the location of stations and assigning blood requests to their corresponding drone paths. This problem is known to be an NP-hard [153], and thus requires a suitable methodology for its solution. To address this issue, we have chosen to use a genetic algorithm (GA) as the primary metaheuristic tool for establishing a drone-based logistics network for blood supplies. The genetic algorithm is inspired by the process of evolution in natural species over generations and was first proposed by John Holland [154]. Since then, numerous researchers have employed the genetic algorithm in their studies, including [100], [149], [155]–[157]).

To address the NP-hard nature of the problem of transporting blood group units between health facilities, exact solution methods such as branch and bound can be excessively time-consuming, particularly for larger cases. One approach to finding near-optimal solutions in a reasonable timeframe for complex problems is the use of meta-heuristic methods, such as the genetic algorithm. This algorithm employs natural selection processes, such as selection, reproduction, and mutation, to produce offspring that are more fit and move

towards a near-optimal solution. The two-point crossover operator is used for reproduction, while the random resetting mutation operator is used for mutation

4.4.1 Method for Constraint Handling

Constraint handling is an essential aspect of mathematical modeling and optimization problems with algorithm approach. It encompasses various techniques and methods that are utilized to manage and incorporate constraints into the problem-solving process. The ultimate objective of constraint handling is to ensure that the solutions obtained satisfy the given constraints.

One common technique used in constraint handling involves converting constrained problems into unconstrained ones by penalizing the objective function. This transformation allows for more straightforward optimization since it eliminates the need to satisfy explicit constraints, while still ensuring that the solution meets the constraints in an implicit manner[158]. This approach is particularly useful in complex optimization problems where constraints can be difficult to manage.

$$f(\vec{x}) = f(\vec{x}) + Penalty \quad \text{Eq(16)}$$

The penalty term in this context is calculated by adding up the total amount of violation for each individual constraint that has been violated. This penalty component is then addressed in the following manner:

$$Penalty = Max(0, \sum_{k=1}^K Max\{0, g_k(\vec{x})\} + \sum_{e=1}^E Max(0, |h_e(\vec{x})| - \varepsilon)) - Tol \quad \text{Eq(17)}$$

Where $g_k(\vec{x})$ represents the k th constraints expressed as inequalities, $h_e(\vec{x})$ represents the k th constraints expressed as equalities and the tolerance value (Tol) is adjusted using the equation **Eq(18)**.

$$Tol = \begin{cases} Initia_{Tol} & \text{if } t \leq n1 \\ Initia_{Tol} - Initia_{Tol} \times \left(\frac{t - n1}{n2} \right) & \text{if } t > n1 \end{cases} \quad \text{Eq(18)}$$

The parameter $Initia_{Tol}$ represents the penalty imposed on the top $\theta - th$ individual, where θ is calculated as $\theta = (0.2 \times \text{Population Size (PS)})$, t the number that identifies generation. The values of $n1$ and $n2$ correspond to 15% and 35% of the maximum number of generations (Tol_{max}) allowed. As a result, when the generation number reaches 50% of Tol_{max} , the Tol parameter becomes zero. The concept is relatively comparable to the approach employed in the $\epsilon - \text{Constraint}$ methodology[159].

4.4.2 GA Representation

The healthcare logistics environment under consideration is characterized by numerous blood requests, multiple launch and refueling stations spanning a wide geographical area, making the genetic algorithm a well-suited technique for resolving this problem. To enhance the algorithm's efficiency, a stop condition is implemented that limits its runtime to 3,600 seconds or until no further improvements in the solution are observed after 15% of the total iterations have been executed. The following steps are involved in the implementation of the GA:

1. **Initialization:** This step involving setting up the GA parameters. These parameters include the population size (**NumPop**), the maximum allowable number of iterations (**MaxIter**), crossover probability (**ProCro**), mutation probability

(**ProMut**), as well as the probability (**ProGS**) and intensity (**IntGS**) of carrying out a greedy search.

2. **Initial Population:** This step is to generate a collection of solutions randomly. This group is called the initial population, and each solution is denoted by a chromosome. The n th gene of the chromosome represents the status of the n th candidate's location, with three potential categories: Starting Launching Station (L), Refueling Station (R), or Ending Station (E), as illustrated in **Figure 16(A)**.
3. **Fitness Function Evaluation:** The process involves evaluating the fitness function of the logistics network system. This includes determining the allocation of blood requests to the selected launching stations based on proximity using the closest neighborhood assignment technique, once the starting, refueling, and ending stations have been identified. The Euclidean distance is calculated to determine the distance between each node and the available station. The fitness value of the logistics network system is obtained by multiplying the cost associated with each decision variable with its value, and penalty costs are imposed on the fitness function if the solution violates any constraints. Solutions are ranked based on their fitness function.
4. **Parent Selection:** The process of generating offspring/children in a genetic algorithm involves selecting a predetermined number of solutions to act as parents. To determine the parents, the roulette wheel selection method is employed, giving more weight to individuals with higher rankings in the fitness function.
5. **Crossover Operator:** The chosen parents are matched and subjected to a crossover procedure, which leads to the creation of two fresh offspring. **Figure 16(B)**

demonstrates that a crossover point is randomly selected along the selected parents' length, causing them to be divided into two distinct sections. The second sections of the chromosomes are subsequently interchanged, creating two unique solutions. The amount of offspring generated from the crossover process is influenced by crossover probability. The enlarged population is then arranged according to their ranking, and the most exceptional individuals are picked as the following generation.

6. **Mutation Operator:** A specific number of parents are chosen to be subjected to the mutation operator, and this number is determined by the mutation probability (**ProMut** × **NumPop**). Four distinct mutation types may be randomly chosen and implemented on the chosen solution (parent). The mutate operator randomly selects multiple genes and changes their values. The reverse operator selects two locations on the chromosome and flips the order of the genes between them. The swap operator randomly selects two genes and exchanges their positions, while the insertion operator randomly selects one gene and inserts it into a new location (as shown in **Figure 16(C)**).
7. **Greedy Search:** To enhance the performance of the GA, a greedy search algorithm was incorporated as some operational facilities did not augment the fitness value. The greedy algorithm randomly selects a certain number of solutions, as decided by **ProGS**, and downgrades a predetermined number of genes (**IntGS**) in the chromosome. This involves either closing the gene completely or transforming launch stations to refueling stations. If the fitness function of the solution is improved, the previous solution is replaced with the superior one.

8. **Population Updating Process:** The produced offspring is added to the initial population, and the population is sorted based on the rank of the individuals. Then, to maintain the population size at its initial value, only the top-performing solutions are retained, while the rest are discarded.
9. **Stopping Condition:** The termination condition of the algorithm is marked by reaching the predefined maximum number of iterations (**MaxIter**). **Figure 17** presents Algorithm 1, which details the pseudocode for the proposed combination of Genetic Algorithm and Greedy Search. **Figure 18** illustrates the flowchart of the combined approach.

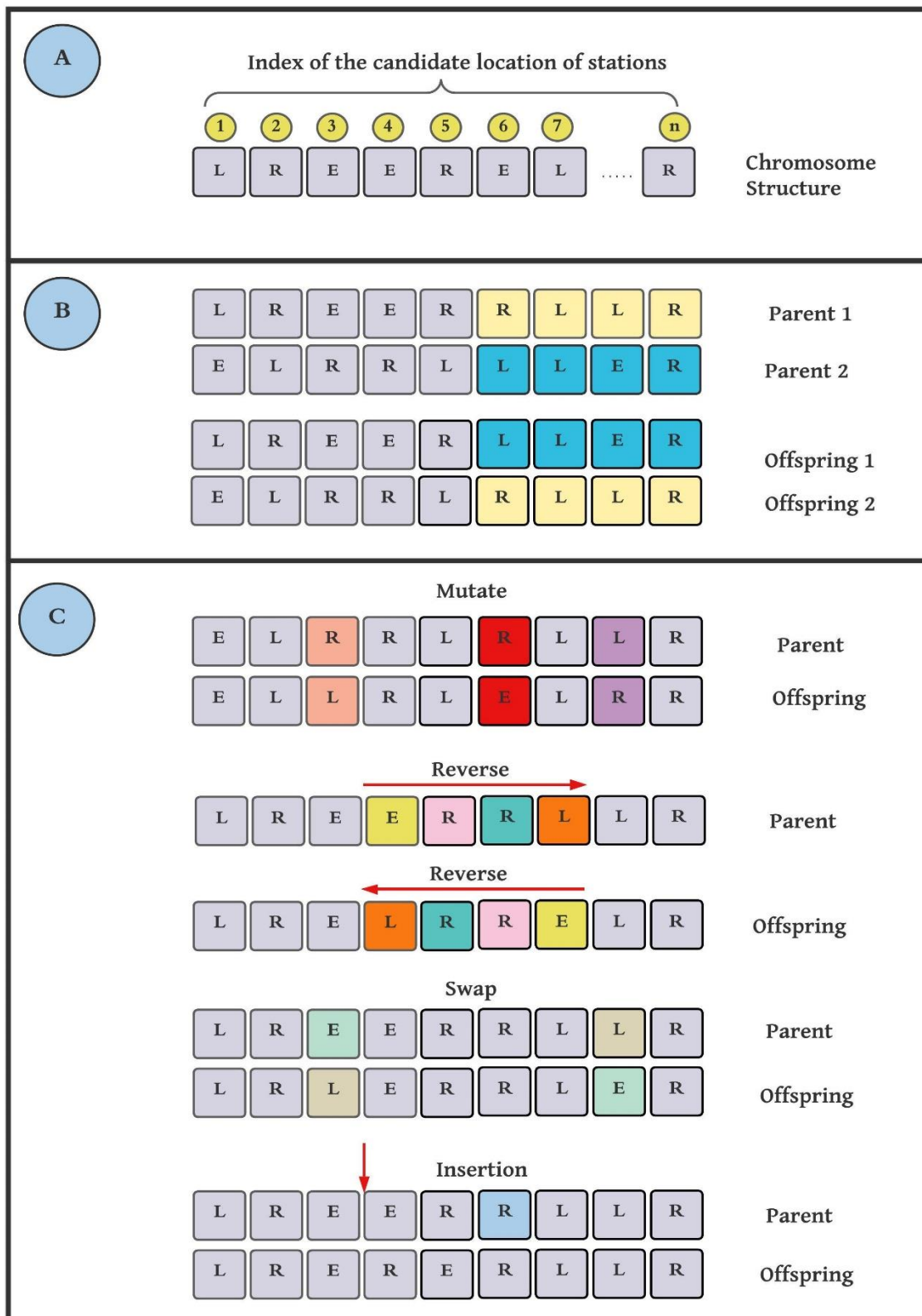


Figure 16.(A) The solution representation, (B) Crossover operation, (C) Mutation operation.

Algorithm 1: Genetic Algorithm with Greedy Search

```
1   $t \leftarrow 0$ 
2   $P(t) \leftarrow 0$  Individuals generated randomly
3  Cal [ $P(t)$ ] : Calculate the fitness function for each individual
4  Best  $\leftarrow$  Best value of individual
5  While  $t < \text{MaxIt}$  do
6       $S \leftarrow$  Choose individuals  $\in P(t)$ 
7       $Q \leftarrow$  Crossover ( $S$ )  $\cup$  Mutation( $S$ ) : Creating Offspring
8       $S^* \leftarrow$  Choose individuals  $\in P(t)$ 
9       $S^* \leftarrow$  Local search : Applying Greedy Search
10      $S \leftarrow$  Solution  $\in P(t)$ 
11      $I \leftarrow$  Randomly chosen location set  $\in S$ 
12     For  $i \in I$ 
13          $P \leftarrow S$ 
14         If allele ( $i$ ) = W
15             allele ( $i$ ) = R
16         Else
17             allele ( $i$ ) = C
18         End
19         If Cost ( $S$ ) < Cost ( $P$ )
20              $P \leftarrow S$ 
21         End
22     End
23     Return  $P$ 
24      $P(t) \leftarrow [P(t) + S^*(t)]$ 
25     Cal [ $P(t)$ ]
26     Update Best
27      $P(t+1) \leftarrow$  Choose best individuals  $\in P(t)$ 
28      $t \leftarrow t+1$ 
29 End
30 Return Best
```

Figure 17.The pseudocode for the proposed GA with Greedy Search

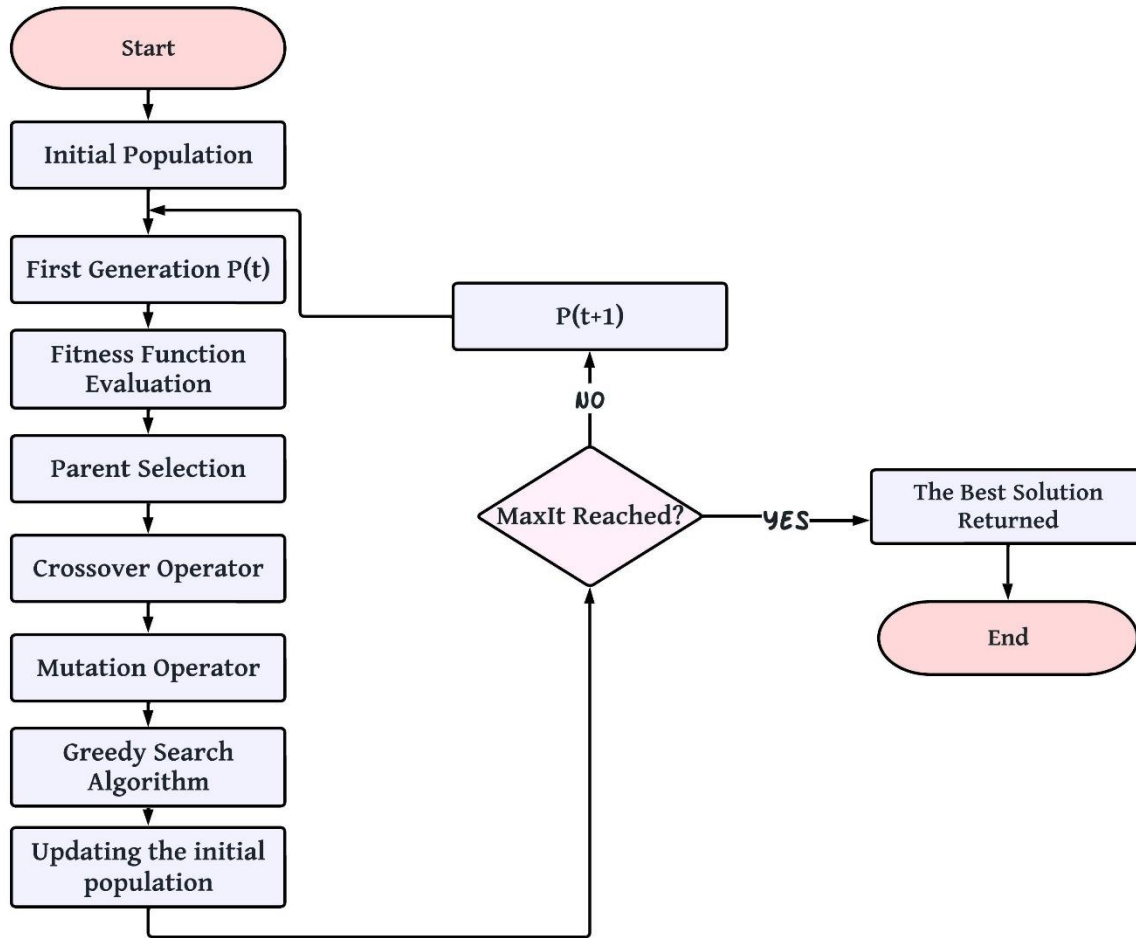


Figure 18.The Flow Chart of GA Combined with Greedy Search

4.4.3 Hyperparameter Optimization

The efficient and effective performance of metaheuristic algorithms is heavily dependent on their parameters. Thus, in order to achieve the desired level of efficacy, it is imperative to appropriately adjust these parameters prior to their implementation. The Taguchi method is a widely used technique for parameter tuning in metaheuristic algorithms. The utilization of orthogonal arrays in the Taguchi method allows for the investigation of numerous controllable factors, while concurrently reducing the impact of noise through a limited

number of experiments.[160], [161]. The response variation is evaluated by means of the signal-to-noise ratio (S/N), which is computed using **Eq (19)**.

$$S/N = -10 \times \log \left(\frac{S(Y^2)}{n} \right) \quad \text{Eq(19)}$$

Where the response value is denoted by Y, while the number of orthogonal arrays is represented by n.

Table 9 presents the parameters and their corresponding ranges applied in the research. To evaluate the performance of the GA with the integrated greedy search, five trials were conducted on ten distinct problems that vary in size and specifications. The resulting average objective values were then utilized in the Taguchi analysis. The S/N ratios obtained from the GA with greedy search are represented in **Figure 19**, which allowed for the identification of the best parameter combinations for each algorithm. In order to determine the optimal values for the various parameters under consideration, measurements were taken for the highest dot corresponding to each parameter. Specifically, parameter **A (NumPop)** and parameter **D (MaxIter r)** were found to perform best at the second level, while parameter **B (ProCro)**, parameter **E (ProGS)**, and parameter **F (IntGS)** found the optimal performance at the first level. Finally, parameter **C (ProMut)** demonstrated superior performance at the third level. **Table 10** contains further information about the Taguchi design and its associated GA outcomes.

Using Minitab 17, the Taguchi method was executed, and the parameter-tuned algorithms were created in Python and performed on a computer having a 3.7 GHz Intel Xeon® processor and 32 GB of RAM operating on the Windows 10 system.

Table 9. Parameter Levels of Combined GA with Greedy Search

Factor (Parameters)	Parameter range	Level 1	Level 2	Level 3
A: NumPop	[300 – 700]	300	500	700
B: ProCro	[0.5 – 0.9]	0.5	0.7	0.9
C: ProMut	[0.4 – 0.8]	0.4	0.6	0.8
D: MaxIter	[500 – 1000]	500	750	1000
E: ProGS	[0.2 – 0.7]	0.2	0.45	0.7
F: IntGS	[0.3 – 0.8]	0.3	0.55	0.8

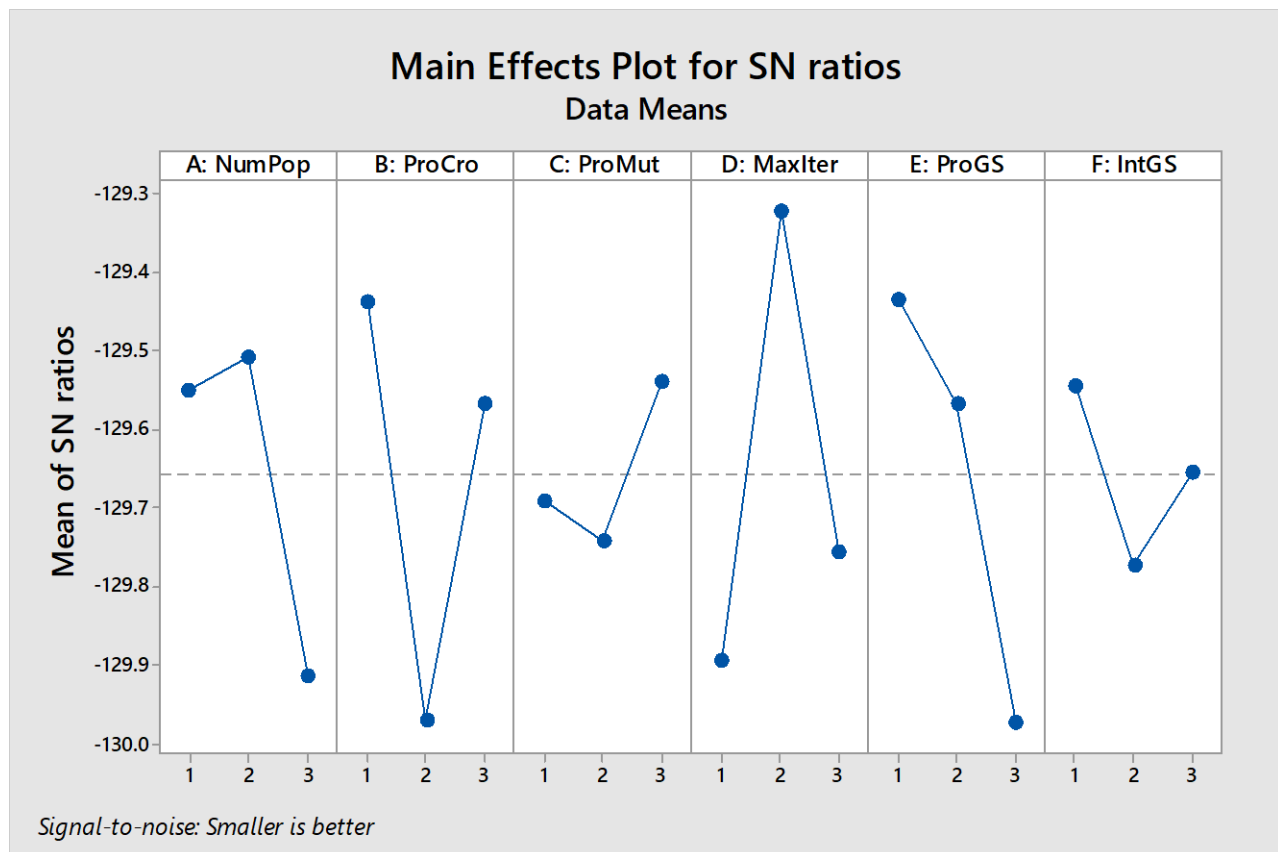


Figure 19. S/N Ratios Plot for Tuning the Parameters in GA with Greedy Search Algorithm

Table 10.Optimizing Algorithm Performance: Computational Results for Tuning Parameters

Run	Factor Level						Fitness Value
	A	B	C	D	E	F	
1	1	1	1	1	1	1	3118461.173
2	1	1	1	1	2	2	2850463.000
3	1	1	1	1	3	3	3097076.454
4	1	2	2	2	1	1	2986724.087
5	1	2	2	2	2	2	3052541.825
6	1	2	2	2	3	3	3034164.820
7	1	3	3	3	1	1	3169608.846
8	1	3	3	3	2	2	2880018.639
9	1	3	3	3	3	3	2855476.172
10	2	1	2	3	1	2	2876731.154
11	2	1	2	3	2	3	2911314.579
12	2	1	2	3	3	1	3146492.902
13	2	2	3	1	1	2	2893329.589
14	2	2	3	1	2	3	3724861.381
15	2	2	3	1	3	1	2872277.239
16	2	3	1	2	1	2	2744693.420
17	2	3	1	2	2	3	2917483.673
18	2	3	1	2	3	1	2909251.329
19	3	1	3	2	1	3	2999446.627
20	3	1	3	2	2	1	2871365.582
21	3	1	3	2	3	2	2820858.071
22	3	2	1	3	1	3	3101676.202
23	3	2	1	3	2	1	2887936.107
24	3	2	1	3	3	2	3996316.860
25	3	3	2	1	1	3	2802361.757
26	3	3	2	1	2	1	3067516.054
27	3	3	2	1	3	2	3867516.054

4.5 Computational Result

In order to assess the performance of the blood transport network using the proposed methodology, we utilized a unique technique called Random Geographic Coordinates Sampling. This method involves generating random coordinates within specific ranges for longitude and latitude values ([46.653, 55.150] and [25.36, 29.744], respectively) to represent potential blood bank pickup locations and healthcare request locations. Our goal was to evaluate the network's efficiency across various locations. To prevent redundancy,

we eliminated pairs of blood bank and healthcare request locations that were identical. To ensure a comprehensive evaluation, we randomly selected 15, 25, and 35 stations to be opened and produced blood group requests ranging from 1 to 1000 for each selected station. The details of the selected instances are summarized in **Table 11**.

Table 11. Instances Description

Instance Code	Available Stations	Number of Request
S-15-R-143	15	143
S-15-R-342	15	342
S-15-R-585	15	585
S-15-R-692	15	692
S-15-R-889	15	889
S-25-R-282	25	282
S-25-R-355	25	355
S-25-R-413	25	413
S-25-R-685	25	685
S-25-R-779	25	779
S-35-R-242	35	245
S-35-R-407	35	407
S-35-R-560	35	560
S-35-R-722	35	722
S-35-R-904	35	904

Each of the test instances was resolved through the utilization of the proposed meta-heuristic implementation and the ILP solver CPLEX 22.1.0. The formulation outlined in Section 4.3.3 was employed for this purpose. The optimal parameter of GA combined with the greedy search identified in Taguchi analysis, was employed to solve these instances.

To guarantee dependable and expeditious outcomes from CPLEX, we established a solver time limit of 1.5 hours (5400s). This yielded a satisfactory solution gap of less than 1%.

Our study evaluated the performance of a medical drone in terms of its operating range and associated costs. The drone's flying distance was an impressive 40 km, with operating costs estimated at \$0.699 per km when empty and \$0.702 per km when loaded. Additionally, we randomly selected the costs associated with establishing a launching station, which ranged between \$3000 and \$8000, and a refueling station, which ranged between \$2000 and \$5000. In cases where the 40 km range was deemed infeasible, we conducted further tests to explore the drone's potential to increase its range to 52 km. This goal could be achieved through technological advancements or payload reduction.

The outcomes of two optimization techniques, CPLEX and GA with Greedy Search, used to address a location-routing problem at the strategic and tactical planning levels, are presented in **Table 12**. The issue involved strategic planning for station selection and operational planning for optimum delivery tours, and different instances of the problem were solved to compare the quality of the solutions and the computational times of the two methods. The instances are identified by a code that includes the number of facilities (S-15 or S-25), the number of blood request (R-143, R-342, R-585, R-692, or R-889). The table provides the total cost of each solution as well as the CPU time (in seconds) required to find each solution. Additionally, the table presents the number of launching station (NL) and number of refueling station (NR) that are selected in order to assign blood request to them. The last column in the table presents the gap percentage represents the difference between the CPLEX and the GA with Greedy Search solution as a percentage of the GA

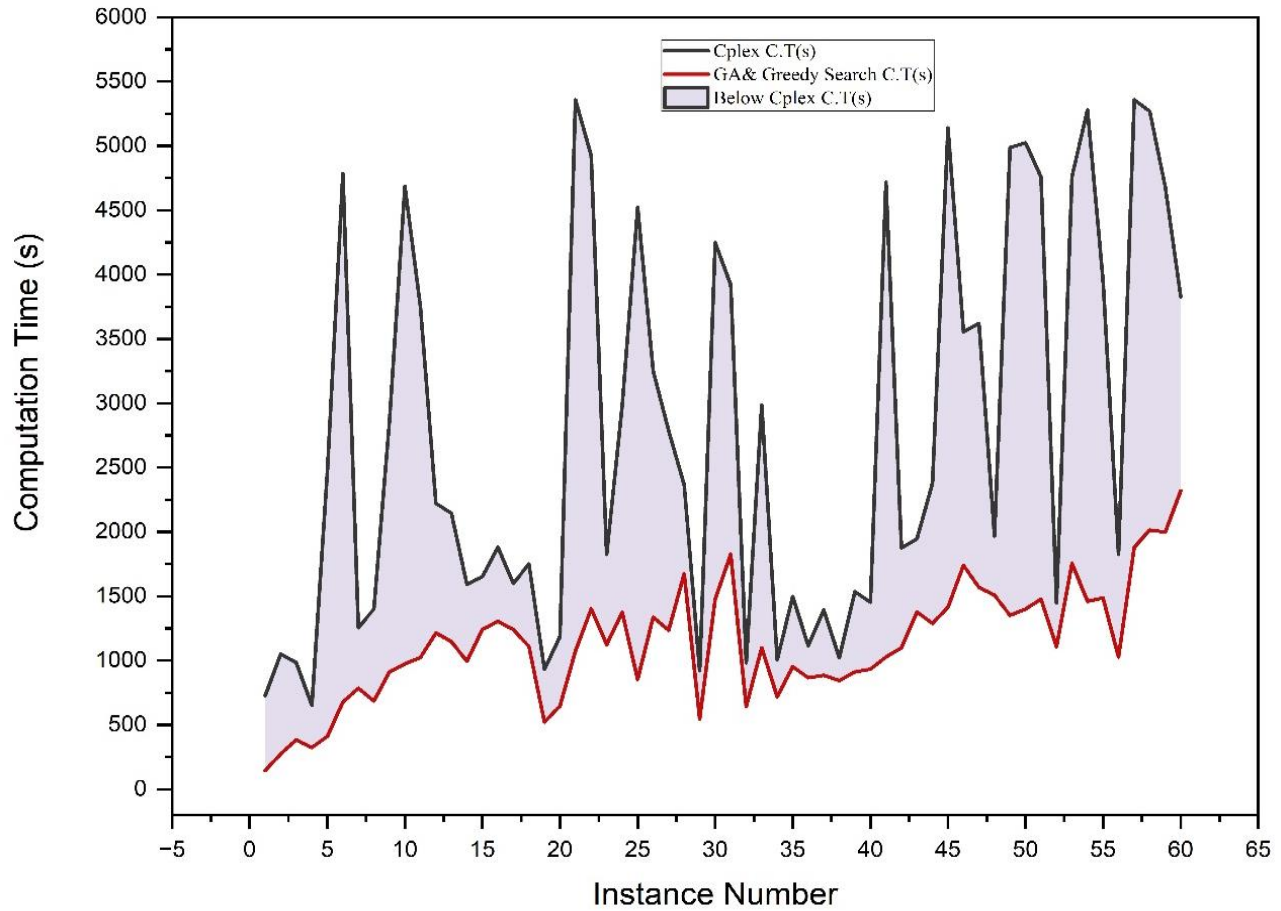
with Greedy Search. The gap percentage is equal to $(\frac{CP-GA}{GA})$, where GA and CP are GA with Greedy Search algorithm and optimal CPLEX solution, respectively.

The findings of this study suggest that the GA with Greedy search algorithm outperforms CPLEX in terms of computational time and solution quality. As shown in **Figure 20**, the y-axis represents the computational time required to solve 60 instances, while the x-axis displays the instances that were solved using both CPLEX and the GA. The computational time required by CPLEX is observed to be higher than that of the GA, indicating that CPLEX requires a longer time to solve the same instances as the GA with Greedy Search algorithm. This observation is significant because it suggests that the GA with Greedy Search algorithm is a more efficient optimization algorithm than CPLEX in terms of computational time.

Furthermore, the curve of the GA with Greedy Search algorithm appears to be consistent throughout the instances, whereas the curve of CPLEX shows more variation. This variability in CPLEX's curve suggests that it may be more sensitive to certain types of instances, which could lead to longer computational times for these instances. In contrast, the GA with Greedy Search algorithm can handle larger problem sizes compared to CPLEX. This finding is significant because it offers an alternative approach to solving complex optimization problems that may be more efficient and effective than traditional methods.

Overall, these findings have significant real-world implications, particularly in fields such as healthcare. Faster and more accurate decision-making can be achieved through the use

of efficient optimization algorithms like the GA with Greedy Search, which can ultimately lead to improved patient outcomes and resource utilization.



[Figure 20.Comparison of Computational Performance between CPLEX and GA with Greedy Search]

The proposed GA with Greedy Search algorithm performs well and finds solutions near to the optimal in comparison to CPLEX for most of the 60 instances tested (**Figure 21**). The cost of the objective function for both CPLEX and GA with Greedy Search is shown on the y-axis, while the x-axis represents the 60 different test instances. As shown in the **Figure 21**, the GA with Greedy Search algorithm can obtain near-optimal solutions for most of the test instances, as the cost of the objective function is close to that of CPLEX. Additionally, **Figure 22** provides insight into the accuracy of the GA with Greedy Search

algorithm in comparison to CPLEX. The graph shows the calculated gap percentage between the solutions obtained by both algorithms and the best CPLEX solution found within an hour and a half for each test instance. The gap percentage is shown on the y-axis, while the x-axis represents the different test instances. The graph indicates that the GA with Greedy Search algorithm performs well for most of the test instances, as the gap percentage between the solutions obtained by both algorithms is low.

However, for larger instances with more facilities and blood requests like instances 24 and 25, the GA with Greedy Search algorithm is observed to be slightly less accurate, as evidenced by higher gap percentages between the solutions obtained by the two algorithms. The maximum gap percentage between CPLEX and GA with Greedy Search is 14.9%, which is observed for instance 25, while the minimum gap percentage is 4.1%, observed for instance 14. These results highlight the need for further improvements in the proposed algorithm to enhance its performance for larger instances.

If the proposed algorithm generates a solution where all flights have the same options for choosing launching and refueling stations, with identical costs and distances, we employ the TOPSIS method to evaluate and rank these solutions based on several sustainable indicators. The importance of these indicators is determined based on relevant literature and expert opinions. Using the TOPSIS method, each candidate point is assessed and weighted according to these indicators. The objective is to select an alternative that minimizes the geometric distance from the positive ideal solution and maximizes the geometric distance from the negative ideal solution.

On a related note, increasing the flying range of drones has the potential to enhance the coverage of blood requests in healthcare delivery systems, by achieving full coverage of 100%. These findings shed light on the effectiveness of various optimization algorithms for location-routing problems and emphasize the trade-offs between solution quality and computational time. Overall, the results suggest that the GA with Greedy Search is an efficient and effective method for solving the proposed model with fast decision-making, particularly in healthcare applications.

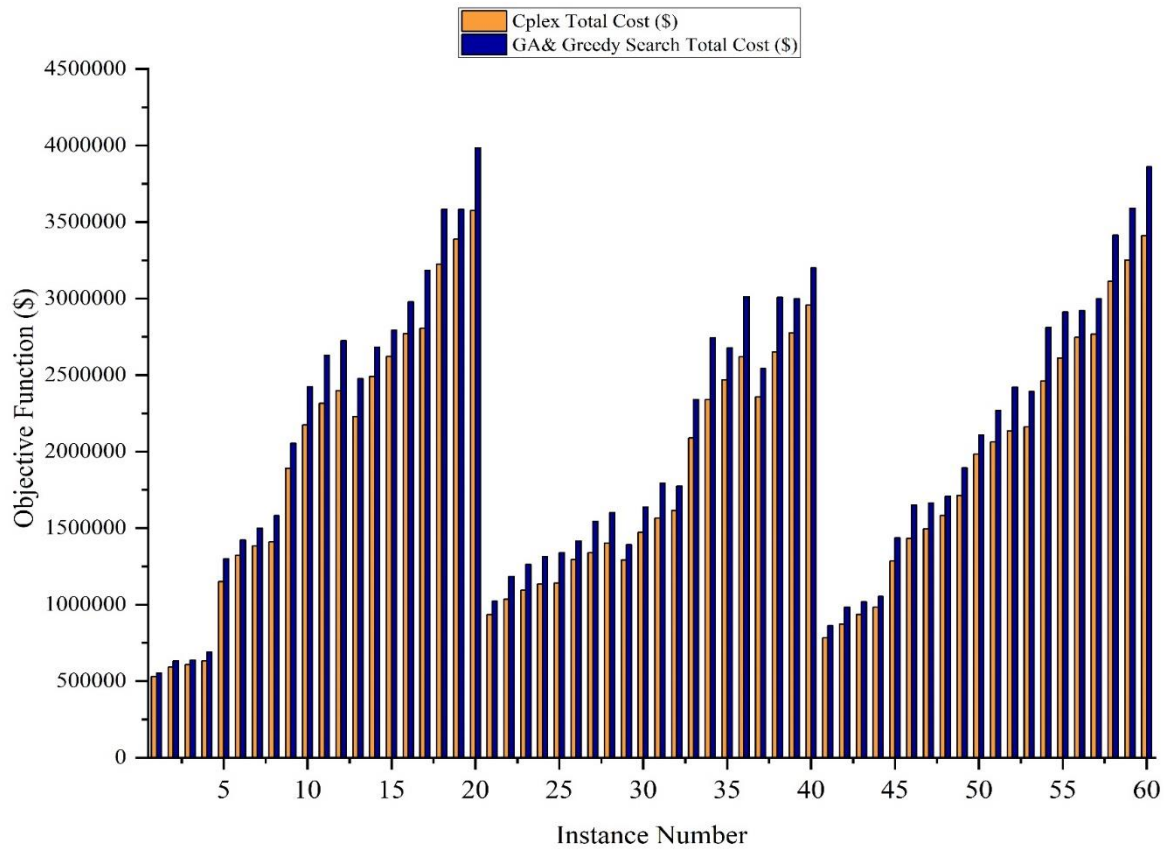


Figure 21. Comparison of Objective Function Cost for GA with Greedy Search and CPLEX

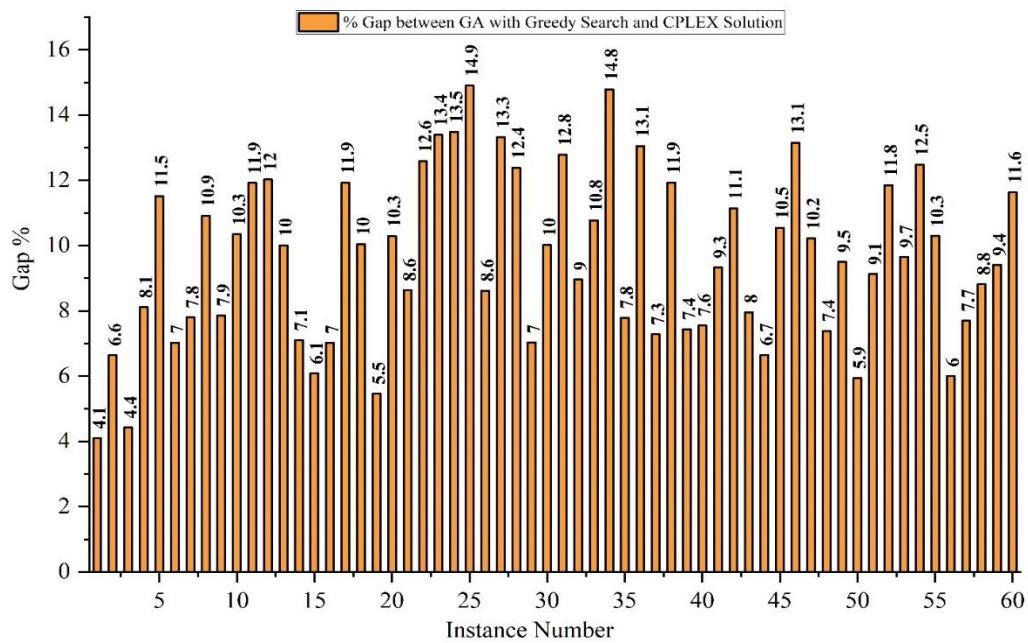


Figure 22. Percentage Gap in Solution Accuracy between GA with Greedy Search and CPLEX

Table 12.The Experiment Results of CPLEX and the Proposed Algorithm

Instance Number	Instance Code	δ	τ	CPLEX Solution				GA with Greedy Search Solution				Gap %
				NL	NR	Total cost (\$)	CPU time (s)	NL	NR	Total cost (\$)	CPU time (s)	
1	S-15-R-143	40	80	7	3	529651.85	725.36	8	3	552307.71	144.68	4.1
2			90	8	4	590149.67	1050.7	8	4	632133.27	274.52	6.6
3			95	10	6	607823.43	985.5	10	7	635943.22	384	4.4
4		52	100			INFS				INFS		
5	S-15-R-342	40	80	13	9	632819.066	652.63	15	10	688715.02	324.8	8.1
6			90	9	5	1150394.674	2468.38	9	6	1300110.88	411.58	11.5
7			95	9	5	1322422.73	4785.36	10	5	1422312.73	677.32	7.0
8		52	100	11	6	1381965.904	1254.6	11	7	1498875.714	785.2	7.8
9	S-15-R-585		100			INFS				INFS		
10		40	80	12	9	1408948.43	1402.36	13	9	1581542.55	685.32	10.9
11			90	11	7	1891415.811	2854.6	11	9	2052716.811	911.36	7.9
12			95	11	7	2172469.45	4687.3	11	8	2423229.45	974.65	10.3
13	S-15-R-692		100	13	7	2315155.904	3750.6	14	7	2628425.904	1024.36	11.9
14		40	80			INFS				INFS		
15			90	14	9	2396765.198	2221.47	14	8	2724325.118	1214.3	12.0
16		52	100	12	7	2228085.4	2145.5	13	8	2475975.78	1147.8	10.0
17	S-15-R-889		95	12	9	2491299.074	1592.36	12	10	2681819.074	995.68	7.1
18			100			INFS				INFS		
19		52	95			INFS				INFS		
20			100	14	10	2621549.36	1654.3	15	11	2791329.36	1242.36	6.1
21	S-15-R-282		95	14	11	2769383.044	1880.52	15	11	2978353.84	1305.6	7.0
22		40	80	12	8	2804692.416	1598.45	13	8	3184472.83	1240.74	11.9
23			90	12	8	3225376.39	1752.6	13	7	3585216.39	1110.39	10.0
24			95			INFS				INFS		
25	S-25-R-355		100			INFS				INFS		
26		52	95	13	9	3386805.306	932.6	14	10	3582415.22	522.54	5.5
27			100	13	10	3575088.22	1185.41	14	10	3985158.34	647.2	10.3
28		40	80	12	6	933210.79	5357.44	14	8	1021410.79	1074.36	8.6
29	S-25-R-282		90	13	8	1034772.932	4924.85	15	8	1183712.51	1402.3	12.6
30			95	17	10	1093051.36	1824.3	20	1	1262011.12	1124.3	13.4
31			100			INFS				INFS		
32		52	100	17	13	1135283.336	2980.14	17	13	1312273.536	1374.5	13.5
33	S-25-R-355	40	80	15	8	1140510.335	4521.68	16	10	1340322.821	855.3	14.9
34			90	18	9	1293189.75	3250.7	22	11	1415179.221	1337.41	8.6
35			95	18	12	1337578.57	2785.65	22	12	1543178.135	1236.2	13.3
36			100			INFS				INFS		
37	S-25-R-355	52	100	20	15	1402128.722	2365.854	23	18	1600329.722	1675.3	12.4
38		40	80	16	10	1292112.48	920.89	19	12	1389772.48	547.36	7.0

30		90	16	10	1473447.71	4247.36	20	12	1637457.25	1478.5	10.0
31	S-25-R-413	95	18	11	1563518.27	3920.8	22	15	1792718.57	1826.3	12.8
		100			INFS				INFS		
32		52 100	18	15	1614914.712	983.14	24	18	1773914.322	644.21	9.0
33		40 80	18	12	2087907.538	2985.6	20	12	2339917.847	1100.3	10.8
34		90	18	15	2338778.55	1006.91	21	16	2744578.33	720	14.8
	S-25-R-685	95			INFS				INFS		
		100			INFS				INFS		
35		52 95	20	17	2469270.22	1498.68	23	17	2677720.22	954.14	7.8
36		100	22	18	2618079.93	1115.54	23	20	3011099.17	867.21	13.1
37		40 80	22	14	2357300.359	1395.8	22	16	2542380.359	886.51	7.3
38		90	22	16	2649374.48	1022.36	23	18	3008254.98	845.3	11.9
	S-25-R-779	95			INFS				INFS		
		100			INFS				INFS		
39		52 95	22	19	2775320.77	1536.45	24	20	2998310.85	911.3	7.4
40		100	22	19	2958210.91	1453.6	24	21	3199817.91	933.54	7.6
41		40 80	15	9	781436.59	4717.71	17	10	861838.79	1028.21	9.3
42		90	17	12	873321.79	1874.55	18	13	982721.29	1100.55	11.1
43	S-35-R-242	95	21	14	936195.65	1947.3	25	18	1017145.45	1377.3	8.0
		100			INFS				INFS		
44		52 100	22	17	982458.65	2378.65	22	18	1052458.65	1288.65	6.7
45		40 80	16	10	1283215.85	5140.25	18	12	1434512.74	1414.64	10.5
46		90	20	16	1433173.85	3556.38	25	18	1650123.85	1741.3	13.1
47	S-35-R-407	95	20	16	1494143.14	3620.8	27	18	1664223.88	1568.5	10.2
		100			INFS				INFS		
48		52 100	22	17	1581413.22	1968.65	28	20	1707423.44	1508.11	7.4
49		40 80	16	8	1712248.497	4987.54	19	8	1892129.3	1351.5	9.5
50		90	20	10	1982824.518	5024.6	24	12	2107934.728	1400.21	5.9
51	S-35-R-560	95	22	14	2062221.81	4759.62	27	18	2269371.81	1478.3	9.1
		100			INFS				INFS		
52		52 100	22	18	2134498.78	1448.36	28	20	2421338.78	1108.36	11.8
53		40 80	20	12	2160688.704	4763.47	20	15	2391668.704	1755.3	9.7
54		90	21	15	2460538.36	5279.58	22	17	2811337.1	1459.5	12.5
55	S-35-R-722	95	25	16	2611123.757	3957.3	25	17	2911003.757	1488.3	10.3
		100			INFS				INFS		
56		52 100	27	18	2746036.2	1825.41	27	20	2921532.47	1028.12	6.0
57		40 80	19	10	2767806.05	5358.6	22	14	2998526.45	1880.37	7.7
58		90	21	13	3111466.895	5269.56	22	15	3412479.255	2014.65	8.8
59	S-35-R-904	95	24	16	3251224.81	4681.36	26	16	3588925.21	1998.44	9.4
		100			INFS				INFS		
60		52 100	26	18	3412458.68	3825.5	28	20	3861721.38	2320.5	11.6

4.6 Conclusion

The focus of this research is to address the challenge of efficiently transporting blood supplies in the healthcare network. Specifically, the paper aims to leverage refueling stations to expand the coverage of drones in the last leg of the logistics chain, subject to certain parameters. To design a reliable network, an integer linear programming model is formulated, and a genetic algorithm combined with a greedy search technique is applied to solve it. The proposed algorithm optimizes the location of stations and assigns blood requests to corresponding drone paths, considering multiple launch and refueling stations and an unlimited number of identical drone fleets. This approach is well-suited for resolving the NP-hard problem of transporting blood group units between healthcare facilities. By utilizing natural selection processes, the algorithm produces offspring that are better adapted to the problem and progressively moves towards nearly optimal solutions.

In terms of the optimization algorithm, the GA with Greedy Search outperforms CPLEX in terms of computational time for all of the test instances. The algorithm can obtain near-optimal solutions for most instances, with low gap percentages between the solutions obtained by both methods. However, for larger instances, the algorithm's accuracy is slightly reduced, suggesting the need for further improvements. The study's findings have significant real-world implications, particularly in healthcare, where efficient and accurate decision-making is crucial. The use of efficient optimization algorithms like the GA with Greedy Search can lead to improved patient outcomes and resource utilization by achieving full coverage of blood requests in healthcare delivery systems. Therefore, the study's results

can be used as a basis for future research on the optimization of healthcare delivery systems using drones and other innovative technologies.

To improve the effectiveness of the GA with Greedy Search algorithm, additional research could concentrate on incorporating auxiliary heuristics or optimization techniques that are more appropriate for handling the greater complexity of larger instances. The combination of metaheuristic algorithms like simulated annealing or tabu search with the GA may result in more efficient exploration of the solution space and a higher chance of achieving superior quality solutions. Moreover, implementing local search strategies, such as 2-opt or 3-opt, may help to fine-tune the solutions produced by the GA and reduce the gap percentages even further. Such improvements could have significant practical implications in various fields, particularly in healthcare, where the efficient and accurate transport of medical supplies is of utmost importance. Consequently, there is a pressing need for further academic inquiry into the optimization of drone-assisted healthcare delivery systems, utilizing advanced algorithms and state-of-the-art techniques to tackle the complex and dynamic nature of this challenging problem

Chapter 5

Conclusions and Recommendations

5.1 Conclusions

The healthcare industry can improve the timely and efficient delivery of blood supplies through the implementation of a centralized decision support system utilizing drones. The system's success relies on the optimal placement of launching and refueling stations while considering the drones' flight range capacity and the supply node capacity in the decision support system. The objective of the research is to design a logistics network that minimizes total logistics costs, including construction and delivery costs. Healthcare professionals will receive real-time updates to monitor the drone's flight and ensure on-time delivery of blood supplies. Implementing this system could result in a more efficient and cost-effective transportation system for blood supplies, potentially saving lives by reducing delivery times and minimizing the risk of delays.

The study formulates four combinatorial optimization location models and demonstrates their practical application in the transportation of blood groups. Our investigation highlights the critical role of technical features such as range, speed, and payload in determining the optimal location for launching stations. Through the utilization of decision support systems, our research findings reveal that imposing a return to the launching base results in increased total distance and emphasizes the limited range of drones. However, relaxing this constraint may require repositioning of drones to address imbalances. Furthermore, our study suggests that the use of refueling stations can extend mission ranges

and augment coverage requests. Additionally, our results demonstrate the possibility of a gradual implementation of the launching process without significant modifications, such as the closure of a launching station.

To address the NP-hard problem of transporting blood units between healthcare centers, the study utilizes a genetic algorithm in combination with a greedy search method. The proposed algorithm optimizes the placement of stations and assigns blood requests to corresponding drone paths while considering multiple launch and refueling stations as well as an infinite number of identical drone fleets. This method is highly suitable for addressing the problem's complexity. Through natural selection processes, the algorithm generates offspring that are better equipped to handle the problem and progressively moves towards achieving nearly optimal solutions.

Regarding the optimization algorithm, the GA with Greedy Search outperforms CPLEX in terms of computational time for all test instances. The algorithm can obtain nearly optimal solutions for most instances, with low gap percentages between the solutions obtained by both methods. However, for larger instances, the algorithm's accuracy is slightly reduced, suggesting the need for further improvements. The study's findings have significant real-world implications, particularly in healthcare, where efficient and accurate decision-making is crucial. The use of efficient optimization algorithms like the GA with Greedy Search can lead to improved patient outcomes and resource utilization by achieving full coverage of blood requests in healthcare delivery systems. Therefore, the study's results can serve as a basis for future research on optimizing healthcare delivery systems using drones and other innovative technologies.

5.2 Recommendations

The experimental study procedures suggest the following recommendations for future research:

- Evaluating the impact of the proposed decision support system on different stakeholders, including healthcare providers, patients, and blood suppliers. This would involve assessing factors such as accessibility, affordability, and equity, as well as identifying potential barriers and challenges to adoption and implementation.
- Conducting a feasibility study to evaluate the costs and benefits of implementing a centralized decision support system for blood supply delivery using drones. This would involve assessing the financial and technological resources required, as well as the potential impact on patient outcomes and healthcare delivery.
- One could explore the intricate routing of public transportation systems in large cities as a basis for constructing an intelligent transport network within the smart cities framework. This network would include the deployment of drones for the purpose of last-mile delivery, with a particular focus on healthcare delivery, specifically with respect to addressing concerns around hospital order density and drone distribution imbalances originating from their launch sites in the formulation of the problem.
- Metaheuristic algorithms such as simulated annealing or tabu search may be combined with the GA for more effective exploration of the solution space and achieving high-quality solutions.

- Local search strategies, such as 2-opt or 3-opt, may fine-tune the solutions produced by the GA and reduce gap percentages even further.

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