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"Last-mile Delivery Using Drones in the Healthcare Supply Chain Management "

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Firma dello studente

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I am dedicating this thesis to the courageous women, girls, and young people in Iran.

I thank every single person who made it possible to reach this destination for walking with me on this path.

Sahel

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Abstract

Healthcare supply chain management has many challenges, especially when it comes to last-mile delivery, where rising costs, environmental issues, and complexity are big problems. The study demonstrates that the use of drone technology can address fundamental logistical problems with the last-mile delivery of healthcare items. This innovative technology enables faster, more affordable, and more sustainable last-mile delivery options, which is a major benefit. Furthermore, by effectively delivering essential supplies during emergencies, drones improve community resilience, especially in disaster-stricken areas where traditional transportation is limited. The objective of our work is to enhance the efficiency of last-mile medical drone delivery with the consideration of a drone battery constraint such as limitation of drone battery life and charging time. Therefore, our study is concerned with ensuring higher demand satisfaction rates and decreasing battery degradation rates by improving recharging and distribution operations in the drone hub dispatching drones to hospitals that generate stochastic demands and are located at different geographic locations. To achieve this objective, Discrete Event Simulation methodology is used to model and analyze complex, stochastic systems by tracking discrete events over time. The simulation was based on a real-world case study of Zipline's drone-based medical supply delivery system across Rwanda, Africa. By implementing a DES model, two different operational scenarios and some experimental analyses were compared to identify the most advantageous approaches to using drones and recharging them. Regarding different scenarios, we discovered that they behave in the same way and there is no significant improvement in the second scenario compared to the first scenario. Concerning various experiments about charging strategies, it has been found that it is most effective to recharge a drone when the battery threshold is 24% or less immediately after returning the drone from the mission. Furthermore, we analyzed the number of drones and the results showed that a fleet size of 30-35 can guarantee a high level of demand satisfaction rate besides lowering the number of drone charging cycles.

Notably, the findings of this study highlight how the stochastic nature of healthcare demands and the limitation of drone battery life can be addressed when formulating strategies for using drones in last-mile delivery in healthcare logistics. Moreover, by creating a strategic methodology for effective drone hub operations and concentrating on charging and allocation strategies that best suit the stochastic demands of healthcare delivery and the limitation of drone battery life, this thesis makes a significant contribution to the field of last-mile delivery in healthcare supply chain research. This approach improves operational efficiency as well as resource utilization.

Introduction

In recent years, the healthcare industry has increasingly explored innovative solutions to enhance supply chain management, with a particular focus on last-mile delivery (Akbari et al., 2017). The delivery of goods to the end consumer, which is also known as last-mile delivery, is considered to be one of the most complex and expensive parts of supply chain management (Akbari et al., 2017, Ha et al., 2022). Traditional delivery approaches face some challenges like traffic congestion, accessibility to remote locations, and environmental impact (Mohammad et al., 2023). These challenges are particularly noticeable in health systems where timely delivery of medical supplies and other requirements is necessary because the quality of care provided depends on it (Costin 2010).

Drones or Unmanned Aerial Vehicles (UAVs) have been introduced as a potential solution to the last-mile delivery challenges (Amirsahami et al., 2023; Mohammad et al., 2023). They are especially well-suited for carrying medical supplies to hard-to-reach locations because of their capacity to avoid conventional transportation routes as well as their speed and agility (Amirsahami et al., 2023). Drone technology can get critical products like medicine, blood, and vaccines to remote areas within the shortest time and at a minimal cost thereby making available essential healthcare resources to even the most hard-to-reach areas (Asadi et al., 2022).

In order to address the last-mile delivery problem within the healthcare supply chain, this thesis evaluates the potential applications of drone technology. The goal of the research is to determine the best practices for charging and distribution operations to increase the efficiency of deliveries made using drones. This study uses the Discrete Event Simulation model as a methodology to investigate various scenarios and experimental analysis in order to determine the best practices for assigning and using a fleet of drones to meet the stochastic demands of hospitals. The main goal of this study is to examine the most effective recharging and allocation strategies that will ensure that the maximum demand satisfaction rate is achieved with the minimum fleet size while decreasing the number of charging cycles of drones to reduce battery degradation. Overall, this research aims to add to the existing knowledge about the uses of drone technology for logistics with an emphasis on the effective implementation of drone technology into the health sector supply chain.

The first chapter of the research gives a theoretical context to supply chain management and logistics, the problems with last-mile deliveries in the healthcare sector, and the use of drones for medical deliveries as a novel solution. Chapter two focuses on the method used which is Discrete Event Simulation (DES), the reasons for choosing DES, and how we used Python and SimPy as software to model drone operations. Furthermore, the data collection and conceptual modeling are introduced in this chapter. The third chapter concerns the experimental analysis. We performed different experimental analyses to find the best configuration for the recharging and distribution of the drones, and the optimal drone fleet size to improve the last-mile delivery efficiency. Lastly, in the final chapter, we provide a conclusion that is based on our analysis, address the limitations encountered during the course of the research, and present recommendations and directions for further research.

CHAPTER 1 - Theoretical Background

Recently, there has been a growing interest in utilizing drone technology for medical deliveries within the healthcare sector (Munawar et al., 2022). A potential advantage of drones is that they can quickly deliver medical supplies in a way that is both cost-effective and environmentally friendly (Mohammad et al., 2023). Moreover, drones can quickly get to hard-to-reach places, which is especially important during sensitive situations or natural disasters (Munawar et al., 2022).

According to Communication (2022e), delivery and transportation are essential parts of supply chain management and logistics, therefore it is important to initially understand their concept and then go over why drones are important in these areas. In this chapter, we delve into more detail about supply chain management and logistics concepts and provide clear definitions and explanations. Then, we go into great depth about drone applications for last-mile delivery in these areas, with a particular focus on their applications within healthcare items delivery. Finally, in the last part, we discuss our research question and the methodology we will use to investigate the research question.

1.1. Supply Chain (SC) and Supply Chain Management (SCM)

1.1.1. Definition of Supply Chain and Supply Chain Management

Over the past few decades, the concepts of supply chain (SC) and supply chain management (SCM) have undergone significant transformation. Before the term "supply chain management" gained popularity in the late 1980s and became extensively used in the 1990s, businesses largely utilized terminology like "logistics" and "operations management" instead (Hugos, 2011). According to Croom et al. (2000), the literature on supply chain management uses a confusing number of terms with similar meanings, consequently, a variety of labels on supply chains and supply chain management practices can be found in the literature. These labels include integrated purchasing strategy, value-added chain, lean chain approach, supply pipeline management, supply network, supply stream, supply base management, supplier integration, supplier partnership, supply chain synchronization, and network supply chain (Croom et al., 2000).

There are several ways to define supply chain and supply chain management, and each one emphasizes specific aspects of the complex network that is involved in introducing goods or services to the market.

Here are some examples of their various definitions:

- "A supply chain is the alignment of firms that bring products or services to market" (Lambert et al., 1998).
- "A supply chain consists of all stages involved, directly or indirectly, in fulfilling a customer request. The supply chain not only includes the manufacturer and suppliers, but also transporters, warehouses, retailers, and customers themselves" (Chopra & Meindl, 2003).
- Moreover, Ganeshan & Harrison (1995) proposed that "A supply chain is a network of facilities and distribution options that performs the functions of procurement of materials, the transformation of these materials into intermediate and finished products, and the distribution of these finished products to customers".

If this is the definition of a supply chain, then supply chain management is the activity of managing and supervising the movement of goods from their point of manufacture to their point of sale or use. It covers all of the actions we take to guarantee the efficient and effective operation of the supply chain. As an example, we may schedule the manufacturing, shipping, and storage of the goods. We also work out how to make the supply chain better so that it can deliver the outcomes we want. Several definitions of supply chain management are provided below:

- "The systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole" (Mentzer el al., 2001).

- "Supply chain management is the coordination of production, inventory, location, and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served" (Hugos, 2011).

- Tan et al. (1998) stated that supply chain management includes materials/supply management from the procurement of basic raw materials to the discovery of products (and potential recycling and repurposing). The field of supply chain management is centered on how businesses leverage the capabilities, technologies, and processes of their suppliers to gain a competitive edge. According to Tan et al. (1998), it is a management philosophy that goes beyond conventional intra-enterprise operations by uniting trading partners around the shared objectives of efficiency and optimization.

- Moreover, Berry et al. (1994) defined it as developing new products, reducing the supplier base to a single OEM (original equipment manufacturer), and fostering trust are the goals of supply chain management. This allows management resources to be allocated toward creating deep, lasting relationships (Berry et al., 1994).

Hugos (2011) asserted that supply chain management is different from traditional logistics since it covers a wider range of tasks. While supply chains involve networks of companies working together to get products to market, logistics usually concentrates on activities within a single enterprise. Supply chain management encompasses marketing, new product development, finance, and customer service, while traditional logistics focuses primarily on inventory management, distribution, procurement, and maintenance (Hugos, 2011). Croom et al. (2000) further emphasized that the term "supply chain management" refers to a variety of inter-organizational, strategic challenges that go beyond logistics. It might refer to non-vertical integration organizational alternatives or characterize the relationships a business establishes with its suppliers.

1.1.2. The Origins of Supply Chain Management

According to Hugos (2011), the terms "supply chain" and "supply chain management" gained popularity in the late 1980s and had a significant increase in usage in the late 1990s, marking an important period (Min et al., 2019). Globalization and the transfer of market power from manufacturers to retailers were the two main features of this era. Expectations for specialized products tailored to their individual requirements and tastes increased as consumers in the supply chain started to expect better value for their money. Companies tried to geographically expand to achieve either reduced production costs or improved quality as a result of the increased competition brought about by globalization (Min et al., 2019).

Supply chain management (SCM) strategies became increasingly popular among the 500 largest organizations in the late 1990s as new developments in information technology appeared. To reduce inventory levels, this involved exchanging demand data with other parties in the supply chain. The period marked a turning point for supply chain management (SCM), as businesses realized they had to revise 1950s normative declarations to reflect the reality of increased global competitiveness. The SCM landscape is about to enter a new, transformative phase as we move into the current era of Industry 4.0, which is defined by the quick development of information-led technologies (Min et al., 2019).

It's clear from thinking about supply chain management dynamics that theoretical development in the late 1990s trailed behind real-world improvements in supply chain operations. As a result, there was a lack of widespread adoption of SCM across various industries and businesses of different sizes due to the fragmented nature of its expertise. The gap incited scholars to define supply chain management (SCM) explicitly and create detailed frameworks to explain its complexities, which in turn encouraged more research projects. As a result, researchers must continuously assess how dynamic and static supply chain management is in order to forecast the future path of market dynamics (Min et al., 2019).

1.1.3. Five Phases of Supply Chain Management

A supply chain manager's responsibilities go beyond the traditional domains of procurement and logistics; they also include the complex task of improving operational effectiveness, reducing expenses, and reducing the possibility of shortages and unplanned disruptions. Fernando (2024) points out that the supply chain management (SCM) process is a complex undertaking that consists of five separate phases as you can see in Fig. 1 These stages involve precise coordination of tasks from planning and sourcing to manufacturing, delivery, and returns. Moving forward, each section will be discussed from Fernando's (2024) perspective.

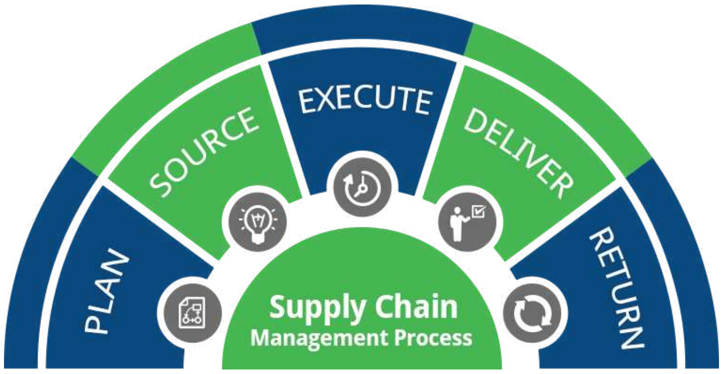

Fig. 1. Five phases of Supply Chain Management.
Source: Communication (2022e).

Planning

Getting the best results in supply chain management (SCM) usually starts with careful planning to match supply with manufacturing and consumer needs. It is essential for businesses to forecast future needs since it helps them predict demand and modify their plans accordingly. This entails determining the number of raw materials or components required at different stages of production, taking into account the limitations and capacity of the equipment, and estimating the number of employees needed. To integrate and streamline these planning procedures, a lot of big businesses use enterprise resource planning (ERP) software (Fernando, 2024).

Sourcing

For supply chain management (SCM) procedures to work well, strong supplier relationships are essential. Working with suppliers to get the supplies required for production is known as sourcing. The general objective of SCM sourcing does not change, even if different sectors may have different requirements. This ensures that:

- Components or raw materials meet the manufacturing requirements necessary to produce items.
- Negotiated prices with vendors are in line with what the market is currently expecting.
- Vendors exhibit the ability to deliver emergency supplies quickly in the event of unanticipated circumstances.
- Suppliers have a record of achieving quality requirements and making on-time deliveries of items.

Supply chain management becomes even more crucial, especially when it comes to situations where perishable items are involved. Companies need to think about things like lead times and the supplier's ability to meet their needs efficiently while sourcing products (Fernando, 2024).

Manufacturing (or Executing)

The manufacturing stage, which is the central component of the supply chain management process, involves a company using its personnel and equipment to transform components or raw materials that are purchased from suppliers into final goods. Although the finished product represents an important turning point in the production process, supply chain management is not over. Numerous additional operations, including assembling, testing, inspection, and packing, are performed during the production process. Companies need to be on the lookout for things like waste production and unanticipated resource constraints that could cause them to move away from their initial goals during these procedures. For example, in order to make sure that the SCM framework is in line with the company's goals, it is necessary to quickly deal with any increase in raw material utilization that results from inadequate staff training (Fernando, 2024).

Delivery

It becomes essential for a business to effectively deliver its items to its clients when sales transactions are finished. Strong logistical skills and well-established delivery routes are important parts of supply chain management, which ensures the timely, safe, and economical delivery of goods. In the case that one means of transportation becomes momentarily unavailable, it is necessary to implement alternate or diversified distribution systems as backup plans (Fernando, 2024).

Returns

When the product is delivered to the customer, the supply chain management process is not over. It includes managing client returns and providing product assistance. Handling returns is never ideal, particularly when the reason for the return is a company error. This part of the process, known as reverse logistics, entails the business having the necessary resources to accept returned goods and accurately process refunds. Resolving the transaction with the consumer is essential, regardless of the nature of the problem (a product recall or a customer complaint). Returns can also offer insightful input that helps the business identify any shortcomings in its products and implement the required fixes. However neglecting to deal with the underlying reason behind client returns suggests an error in the supply chain management procedure, which will probably result in future return problems (Fernando, 2024).

1.2. Healthcare Supply Chain Management

Scholars, researchers, governments, and providers are paying growing attention to the healthcare supply chain since it is an essential tool for controlling costs and improving the quality of healthcare (Elmuti et al., 2013). This supply chain includes the lifecycle procedures or routes that goods take from the place of production to the locations of use and payment. According to Elmuti et al. (2013), the healthcare supply chain consists of knowledge-based, financial, informational, and physical flows that are intended to meet end-user needs across several interconnected supplies.

In order to ensure quality and customer satisfaction while keeping costs under control, effective management of this complex chain requires the prompt and efficient coordination of its various components (Elmuti, 2002). Key players in the domain of healthcare supply chains include producers of pharmaceuticals, medical devices, and hospital supplies; distributors; providers of medical services; insurers; governments; employers; regulators; and recipients of healthcare services (Burns & Lee, 2008). Healthcare supply chains can directly improve patient care by minimizing risks, lowering errors, doing away with operating room delays and cancellations, and shortening hospital stays by optimizing the delivery of materials and information precisely when and where needed (Elmuti et al., 2013).

Several research works claim that supply chain tools can result in lower organizational costs, shorter cycle times, and improved performance without sacrificing quality (Elmuti et al., 2013). But when it comes to putting these technologies into practice, the healthcare industry continuously falls behind the commercial sectors (Kwon et al., 2016). Furthermore, there are still misconceptions regarding the foundations of the supply chain. For example, healthcare professionals frequently mistake supply chain management for contract and purchasing management, ignoring the larger logistical dimensions of the discipline (Kwon et al., 2016). It is necessary to address problems such as a lack of standardization in processes and a lack of cooperation among stakeholders in order to overcome obstacles to successful healthcare supply chain management (Nachtmann & Pohl, 2009).

Improving productivity and patient care at the same time depends on allocating funds released from supply chain optimization to cutting-edge healthcare fields (Kwon et al., 2016). Supply chain optimization in healthcare can be achieved through strategic areas such as supplier relationship management, logistics operating tools, and process optimization—all of which are modeled after effective commercial supply chain strategies (Kwon et al., 2016).

The manufacture, distribution, and dispensing of pharmaceuticals and medical supplies to patients on time is the responsibility of the complex network known as the healthcare supply chain (HSC) (Tyagi, 2023). In contrast to other supply chains, the healthcare supply chain is more complex because it depends heavily on human interaction and requires accurate, appropriate medical products that are customized to meet patient demands (Tyagi, 2023). The coordination of the movement of medical information and supplies between suppliers, providers, customers, and patients is essential for effective HSC management. This coordination includes sourcing, production, distribution, delivery, tracking of consumption, cost monitoring, and disposal (Tyagi, 2023).

Inadequate supply chain management in the healthcare industry can result in high expenses, inadequate inventories, delayed deliveries, and environmental damage (Hossain & Thakur, 2021). On the other hand, efficient management may cut down on waste, increase productivity, decrease mistakes, provide correct product information, and guarantee on-time delivery (Singh & Singh, 2019; Essila, 2022). However, a lot of hospitals struggle with outdated equipment combined with inadequate inventory management systems, which makes it difficult for them to streamline procedures related to procurement, transportation, and inventory handling (Tyagi, 2023).

In recent years, the field of healthcare research within operations and supply chain management has experienced substantial growth (Ali & Kannan, 2022). In order to convert raw materials into completed goods and facilitate their flow to end users, a network of healthcare providers, pharmaceutical manufacturers, drug suppliers, distributors, and logistics service providers is included in healthcare OSCM (Ali & Kannan, 2022). Healthcare supply chain management, despite its particular complexity, can benefit from ideas, procedures, and models from other industries to enhance service delivery and operational effectiveness (De Vries & Huijsman, 2011). However, current supply chain management paradigms must be expanded upon and adjusted due to the dynamic interaction of stakeholders, technologies, and operational features unique to the healthcare industry (De Vries & Huijsman, 2011). Therefore, even if the healthcare supply chain management has particular difficulties, it can profit from knowledge gained from other industries, which will encourage creativity and effectiveness in the provision of healthcare services.

1.3. Logistics in Supply Chain Management

These days, most people only think about logistics in terms of business and industrial logistics, since those areas control the market and have made the most progress (Kukovič et al., 2014). Logistics, or logistics management, is the part of supply chain management that plans, carries out, and keeps an eye on the safe transport and storage of goods, services, and information related to them from where they are made to where they are used, all with the goal of meeting customer needs quickly and correctly (Kukovič et al., 2014). According to Hugos (2011), a significant distinction can be seen between supply chain management and logistics. Logistics mostly deals with activities that happen inside one company, while supply chains are made up of related networks of companies working together to get a product to market. Logistics tasks like purchasing, distributing, maintaining, and managing goods have been around for a long time. Supply chain management, on the other hand, includes these more general logistics tasks as well as marketing, new product creation, finance, and customer service (Hugos, 2011). In the next few parts, we'll go into more detail about logistics to show how it works and what it means in the context of supply chain management.

1.3.1. Definitions of Healthcare (Hospital) Logistics

The critical role of logistics is to supervise the smooth movement of materials. This procedure includes the movement of materials from suppliers into the organization's operations and finally to the end user (D. Waters, 2003). As you can see in Fig. 2, inbound or inward logistics, is concerned with the flow of materials from suppliers into the company. Outbound or outward logistics involves moving items from the company to its clients. Meanwhile, "materials management" refers to the organization's careful coordination of material movement. These interrelated logistics elements work together to create an effective material flow that supports businesses in satisfying client needs (D. Waters, 2003).

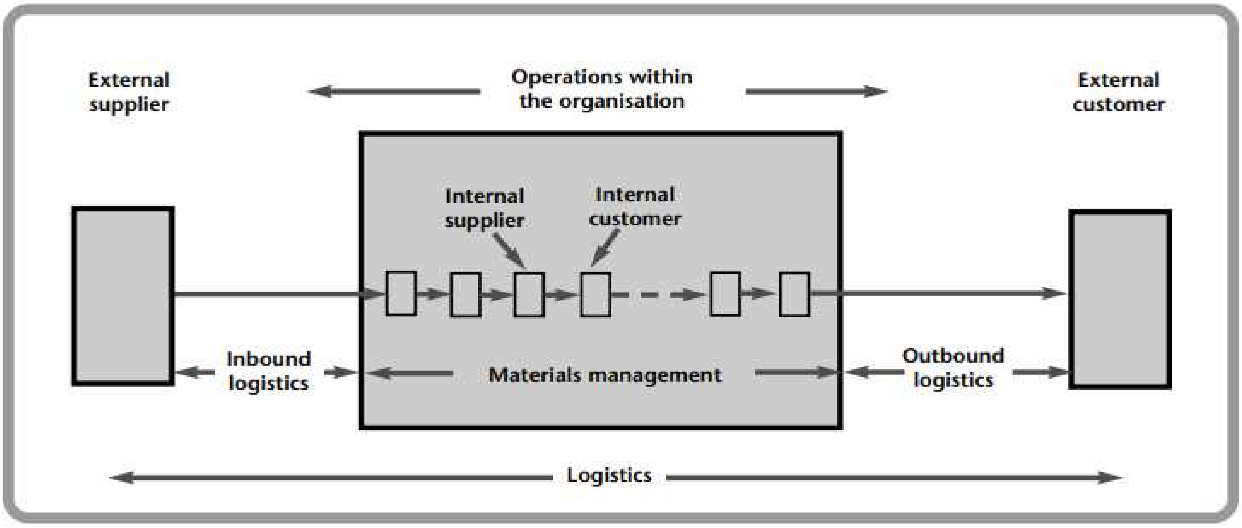

Fig. 2. The role of logistics.
Source: D. Waters (2003).

By analyzing the logistics procedures in the healthcare industry, Kaya (2023) sheds light on the complex web of actions that occur between producers and final consumers. The logistics chain in the healthcare sector involves multiple parties, such as distributors, carriers, manufacturers, warehouses, and, in the end, payers and patients. Moreover, it can be seen that in Fig. 3 delivery has an important role in healthcare logistics to transport supplies from one destination to another. Healthcare logistics encompasses an intricate network of activities that are designed to guarantee the prompt and effective provision of medical services, ranging from acquiring medical supplies to overseeing patient interactions and recycling procedures (Kaya, 2023). Furthermore, hospital logistics' primary goal, as stated by Costin (2010), is to provide all hospital stakeholders with the resources they need to do their tasks well. Hospital logistics essentially makes sure that the appropriate resources and information are available to care units at the appropriate times, allowing them to provide patient care effectively and economically. In order to maximize patient outcomes while reducing costs, this entails coordinating operations and controlling the flow of both information and physical resources (Costin, 2010).

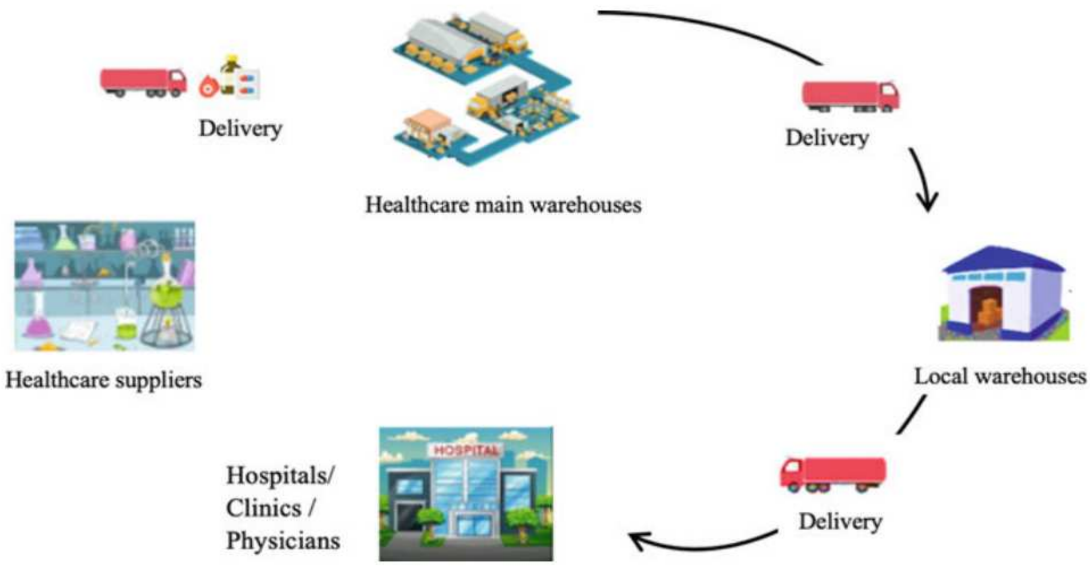

Fig. 3. Healthcare logistics networks.
Source: Umoren et al. (2021) & Kaya (2023).

Analyzing healthcare logistics reveals the complexity and intricacy of this field, making it challenging to comprehensively describe its full scope and details. In order to provide a framework for the field of logistics, Kukovič et al. (2014) underlined how crucial it is to define the connections between the parts of logistics and its subcategories. Logistics is becoming more and more important in a variety of fields, as evidenced by the way it has changed over time—from its roots in military operations to its incorporation into businesses and service sectors (Colin, 2015). Logistics plays a crucial role in overseeing the movement of supplies, information, and services, especially in the healthcare industry, to guarantee the effective provision of patient care (Kukovič et al., 2014).

Moreover, Jawab et al. (2018) emphasize hospital logistics (the details of hospital logistics are shown in Fig. 4) as an essential part of the hospital budget that handles receiving, inventory management, and procurement. There is a great deal of room for improvement in service quality and cost savings through effective hospital logistics management.

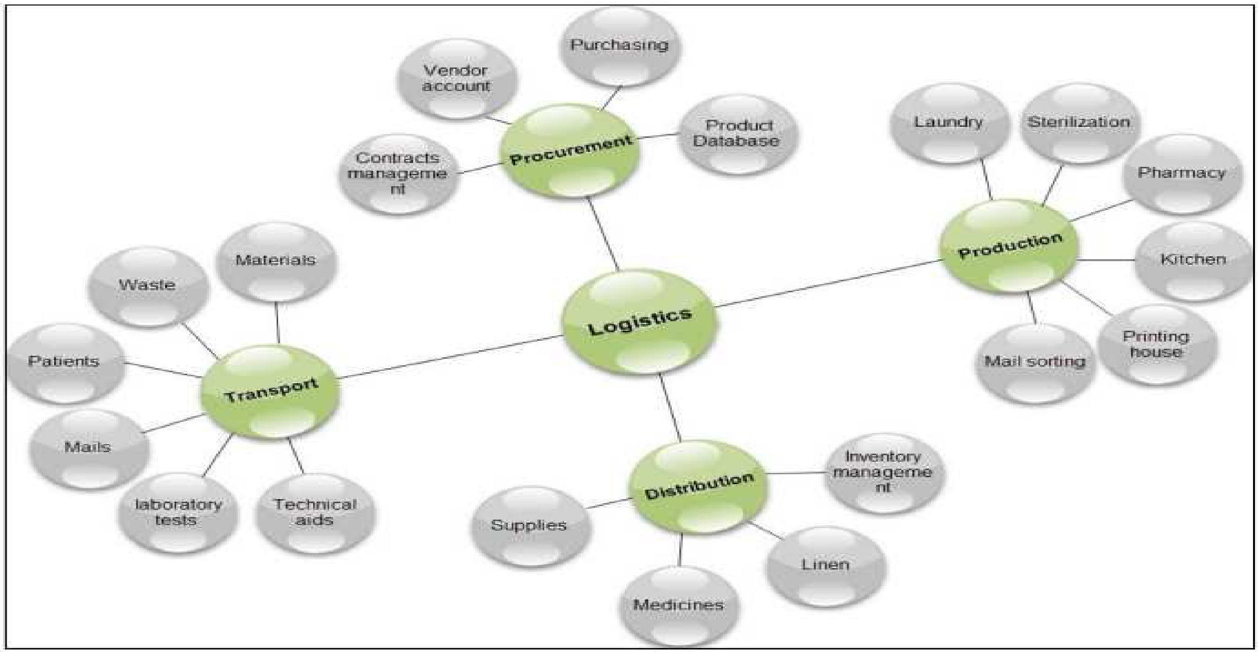

Fig. 4. Hospital logistics dimensions.
Source: Jawab et al. (2018).

The complex nature and multifunctionality of hospital logistics are highlighted via a variety of viewpoints. Hospital logistics include the management of patient, product, and material flows, guaranteeing quality and safety throughout the care process, according to the French Association of Supply Chain and Logistics (ASLOG) (Jawab et al., 2018). To maximize resource efficiency and organizational effectiveness, Ducasse (1995) offers a comprehensive view of hospital logistics that includes engineering techniques that optimize organizational efficiencies through the use of advanced distribution technologies and flow modeling techniques; managerial techniques that prioritize redesigning hospital operations, and medical products to comply with environmental standards; and traditional activities which emphasizes material management, such as the production, distribution, and procurement of supplies needed for patient care (Sampieri-Teissier, 2002).

To summarise, the various viewpoints and interpretations around healthcare logistics highlight its importance as a vital element of the healthcare delivery system. Logistics is a crucial component of healthcare settings, as it is used to optimize resource utilization, improve service quality, and improve patient outcomes.

1.3.2. Logistics-related Challenges in the Healthcare SCM

Healthcare logistics is a complex and critical field that faces significant challenges, particularly due to the rising costs of healthcare (Volland et al., 2017). Volland et al. (2017) highlighted that logistics expenses rank as the second highest cost category in hospitals, following personnel costs. Despite this, logistics and material management have historically received limited attention in hospital management research, primarily because healthcare supply chains are viewed as intricate and not directly contribute to the primary objective of effective patient treatment (Volland et al., 2017). However, in recent years, logistics has emerged as a crucial tool for controlling healthcare costs, with potential savings of up to 50% when logistics costs are efficiently managed (De Vries, 2011; Dacosta-Claro, 2002; Volland et al., 2017). As the pressure to improve quality and coverage grows while managing limited resources, healthcare organizations look for ways to cut costs without lowering the level of care or making it harder for people to get it (Beaulieu et al., 2012). Therefore, in this situation, better healthcare logistics methods look like a good way to cut costs and improve service levels (Velasco et al., 2018). Logistics activities that are well handled in hospitals can help the organization in many ways, including financially and medically (Velasco et al., 2018).

A lot of people have different opinions on whether or not logistics ideas from other fields can be used in healthcare. Most scholars think that they might be useful, but they also point out big problems that need to be solved (Volland et al., 2017). Still, everyone agrees that industrial methods like lean thinking, theory of constraints, Six Sigma, and scenario modeling can be used in healthcare, though they need to be put into practice in steps (Young et al., 2004). Using these methods to solve problems in healthcare situations is harder, because of the complicated operations and organizational problems that come up in hospital logistics (Volland et al., 2017).

1.4. Last-mile Delivery

1.4.1. Definition of Last-mile Delivery

It was the telecommunications industry that was the first to introduce the term "last-mile delivery" to characterize the final leg of delivering services to end-users (Phuong, 2020; Barton, 2016). Since then, the notion of "last-mile delivery" has seen substantial development.

According to Akbari et al. (2017), last-mile delivery has become more important in the field of logistics and supply chain management acting as delivering the goods to the end users, which is the last step in the supply chain as a result of the development of global supply chains. It can be seen in Fig. 5 that this delivery stage is important since it is the point at which items arrive at their final destination.

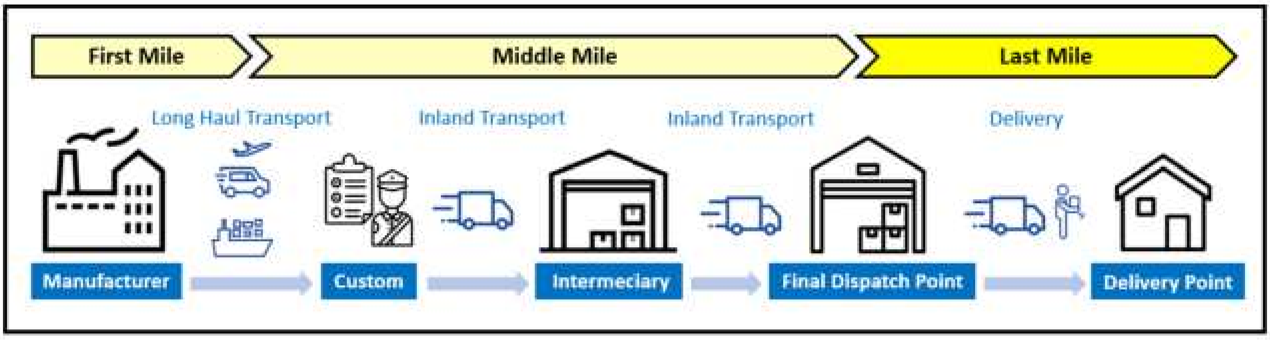

Fig. 5. Last-mile delivery structure.
Source: Castillo and Jain (2019) & Motavallian (2019).

The precise definition and extent of last-mile delivery continue to be difficult, despite the fact that it is of great significance (Olsson et al., 2019). This is due to the variety of perspectives that can be found in the literature. The definitions of "last mile delivery" change depending on the context of the supply chain (Akbari and Ha, 2020). These meanings come from the point of view of business-to-business (B2B), business-to-consumer (B2C), or consumer-to-consumer (C2C) (Akbari and Ha, 2020).

A variety of modes, including electric vehicles, bicycles, and drones, are included in the concept of "last-mile delivery". This concept reflects the changing landscape of delivery techniques (Ha et al., 2022). Because preventative measures have transformed consumer behavior and accelerated the transition toward online buying, the appearance of the COVID-19 pandemic has further shed light on the significance of last-mile delivery (Barnes, 2020).

In order to meet the expectations of customers, the switch to e-commerce platforms has increased the demand for efficient last-mile delivery services. These services are characterized by shorter delivery times and more flexible options (United Nations, 2020). According to Bauer et al.'s research from 2020, "last mile delivery" has evolved from being merely a support capability to becoming a key component of business models. This is because it is essential for increasing customer happiness and loyalty.

This is especially true in locations with a high population density (Mohammad et al., 2023). Traditional delivery methods are having difficulty keeping up with the ever-increasing demand for their services as online retail continues to see explosive growth. Innovative logistics solutions such as drone delivery, smart parcel stations, and crowdsourcing have emerged as viable alternatives to traditional truck-based home delivery. These solutions reflect the dynamic nature of last-mile delivery, which is a response to evolving consumer preferences and technological advancements (Mohammad et al., 2023). To address these challenges, innovative logistics solutions have emerged as viable alternatives.

1.4.2. Challenges of Last-mile Delivery

The Fourth Industrial Revolution, or Industry 4.0, is the change from traditional steam engines to cyber-physical systems. As a result, transportation has become an important part of urban progress, allowing modeling and prediction to improve efficiency (Mohammad et al., 2023). However, this change has brought up some big problems for logistics in cities, including increased air pollution from delivery vehicles and the difficulty of finding parking in congested areas (Mohammad et al., 2023).

The last mile of transportation is the most polluting, inefficient, and expensive part of the supply chain around the world (Mangano and Zenezini, 2019; Boysen et al., 2020; ShipHero, 2019). These problems are made worse by the rising demand for home deliveries (Ha et al., 2022). Studies show that last-mile transport costs can be as high as 75% of all supply chain costs. This puts a big financial strain on businesses that want to meet customer needs while keeping costs low (Millar, 2016; Skiver and Godfrey, 2017). Fig. 6 shows the five main problems that come up with last-mile delivery issues (Boysen, Fedtke, and Schwerdfeger, 2021).

Fig. 6. The five main challenges in Last-Mile Delivery.
Source: Boysen et al. (2021).

To explain more in detail about the challenges of last-mile delivery first, we should mention the increasing volume of shipments. The rising number of packages is because more people are moving to cities and more people are shopping online, which increases the need for last-mile delivery services. The number of people living in cities has grown a lot because of urbanization. By 2050, it is expected that about 70% of the world's population will live in cities (Bretzke, 2013). Furthermore, E-commerce has grown very quickly, with a 23.3% rise around the world in 2018. This has led to a lot more online sales, which has made package deliveries faster (Mohammad et al., 2023).

Moreover, there are worries about sustainability because the growing need for last-mile delivery means more delivery vehicles, which makes environmental, health, and infrastructure problems worse and also makes traffic more serious. The fast growth of delivery services has caused traffic jams in cities, which has an effect on the health and happiness of people who live there. Customers who are more aware of environmental issues and government rules have forced transport services to change their ways to be more eco-friendly and long-lasting (Mohammad et al., 2023).

Another important aspect as mentioned before is cost since standard delivery trucks are expensive. Traditional van deliveries can cost anywhere from 2€ to 6€, based on how dense the area is (Punakivi et al., 2001). Also, prices go up when there is a lot of traffic and not enough parking spots on busy city streets. Delivery drivers have to deal with not knowing exactly where to park, what customers' names are, and when customers are available (Mohammad et al., 2023).

Time pressure is another challenge of last-mile delivery. As e-commerce grows and more packages are sent, there is more pressure to get them delivered quickly. This is why many companies offer next-day or same-day delivery services. Last-mile delivery companies have to meet tight deadlines while their workloads change all the time. For modern transportation methods to work well with these changing needs, they need to be flexible and scalable (Mohammad et al., 2023).

The last challenge is the aging workforce. There needs to be more people working as parcel deliverers because the job is physically hard and the urban workforce is getting older (Peterson, 2018). Since e-commerce has become so popular, transportation technology has also improved. For example, self-driving cars and package lockers make delivery faster and more convenient for customers. These new technologies cut down on or get rid of human contact, which is especially important at the end of the package delivery process when customer satisfaction depends on how well and professionally the package is delivered (Mohammad et al., 2023).

These problems make it clear how important it is for people involved in logistics to fix inefficiencies, improve operations, and come up with new ideas to keep up with changing customer needs while keeping costs low and service high in the last part of the delivery process. These challenges underscore the urgent need for novel solutions to optimize last-mile logistics, balancing environmental concerns, cost-effectiveness, and customer satisfaction in urban settings (Mohammad et al., 2023). In the following section, we discuss drone delivery as an innovative approach to overcoming these difficulties.

1.5. Drone Delivery

As Ha et al. (2022) pointed out, last-mile delivery is part of the logistics and supply chain that is generally seen as the most expensive, inefficient, and harmful to the environment. This is because traditional transport methods pollute the environment and cost a lot of money, therefore, drones could be a solution to these issues (Mohammad et al., 2023; Garg et al., 2023). The fact that drones are used as a mode of transportation a lot in the papers shows that big shipping companies are starting to use them more (Mohammad et al., 2023). Drones, which are short for unmanned aerial vehicles (UAV), are basically planes that can fly without a pilot. They can be programmed to do different tasks on their own or can be managed by a person (Mohammad et al., 2023). In recent years, drones have found a lot of new uses in areas like healthcare, business, and humanitarian logistics. Reasons for using drones include faster shipping of goods, steady high speeds, not needing any road facilities, and not having to deal with traffic jams (Amirsahami et al., 2023).

This popularity shows that drone study is well developed in both academic literature and real-world business applications (Mohammad et al., 2023). Along with drones, other new technologies like robots, electric cars, and parcel lockers were also often brought up. This shows that a wide range of solutions are being considered to solve the problems of last-mile delivery, however, as you can see the rate of usage of different delivery methods to solve the challenges of last-mile delivery in Fig. 7, drone gets a better rate than others (Mohammad et al., 2023). Our discussion of drone technology in logistics will get more in-depth in the parts that follow. We talk about its potential uses, challenges, and how it will change the future of last-mile transport and supply chain operations.

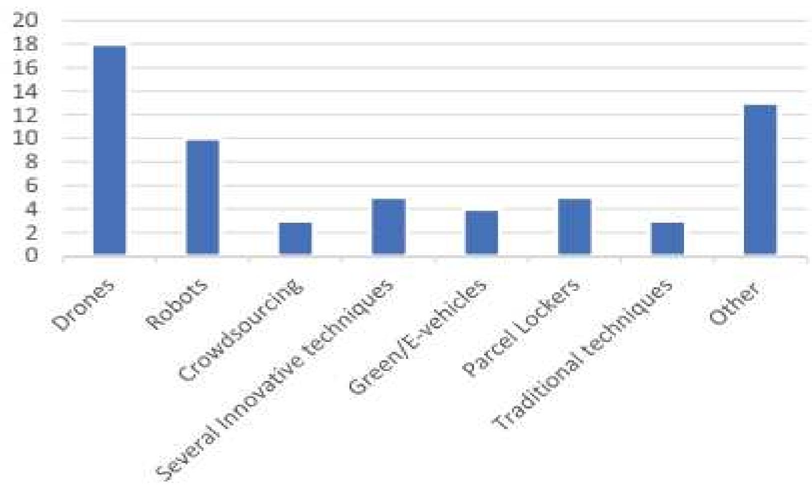

Fig. 7. Different delivery method rates to solve the last-mile delivery challenge.
Source: Mohammad et al. (2023).

1.5.1. Drone Application, General Concept

Drone technology appears to be a promising solution for last-mile delivery due to the increasing demand for faster, more cost-effective, and environmentally friendly delivery methods (Amirsahami et al., 2023). As Garg et al. (2023) mentioned, drones could change the last mile of e-commerce goods and have big benefits for the environment, transportation systems, and being able to handle disasters. New studies say that within the next five years, drones will be used for more than 20% of deliveries (Garg et al., 2023). Their ability to improve community resilience, especially in disaster-stricken areas where traditional transportation may be restricted is shown by how well they work in transporting essential supplies during crises (Garg et al., 2023). The COVID-19 pandemic has accelerated the development of drone transportation systems. As a result, 18 countries have invested in this technology to make it easier to get food and medicine to people faster (Takefman, 2021).

Drones, also called unmanned aerial vehicles (UAVs), are being used more and more in many different fields. Drones have many benefits because they can fly autonomously, which saves a lot of time and energy even though they are still in the early stages of widespread application and implementation (Mohammad et al., 2023). They could make a big difference in the growth of smart cities by making smart package deliveries possible, which would make scheduling and sending packages to many places much easier (Mohammad et al., 2023). Some of the benefits of drone package deliveries are less traffic, less pollution, faster arrival times, and lower shipping costs (Emergen Research, 2022). Customers are willing to pay more for deliveries made by self-driving vehicles. This preference is driven by two main factors: the reduced risk of infection and the increased speed of delivery compared to traditional delivery trucks (Kreier, 2022).

While drones offer numerous advantages, their use also presents certain challenges. Mohammad et al. (2023) proposed Unmanned Aerial Vehicles (UAVs) could be used in delivery systems, but there are a lot of technical and legal problems that need to be solved first. Airspace management bodies are very worried about how widely drones are being used and stress how important it is to have clear rules about how they can be used. Setting up unmanned traffic control platforms in many areas is necessary to make scheduling and drone operations easier, especially since safety and airspace congestion are becoming bigger issues (Alfandari et al., 2022). Urban places, in particular, pose big problems because of strict rules, limited space, and short travel distances (Chung et al., 2020). Also, drone flights are limited by their battery life, flying speed, and payload capacities. This shows how important it is to come up with new ways to make operations last longer (Murray and Chu, 2015). An example to get around these problems in rural places, researchers are looking into delivery systems that use both drones and trucks. These kinds of systems use trucks as mobile charging sites to keep drone batteries charged so they can fly longer (Kellermann et al., 2020). Implementing these kinds of systems, like JD Logistics' work in Guangam, Sichuan, shows that drones and trucks can work together to meet transport needs quickly, especially in remote areas (Sun et al., 2021).

Although deploying drone technology presents some challenges, as previously mentioned, this technology has sparked a lot of interest and funding from big companies in many fields when it comes to last-mile delivery solutions (Mohammad et al., 2023). Jeff Bezos, the visionary CEO of Amazon, predicted that unmanned aerial vehicles (UAVs) would play a major role in delivering small packages as early as 2013 (60 Minutes, 2013). This prediction came true with the launch of Amazon Prime Air in 2016, which aims to bring packages weighing up to 5 pounds by air within 30 minutes of an order. In 2017, Google launched its own drone delivery service called "WING". At the same time, DHL improved its last-mile delivery method in urban China, cutting delivery times from 40 minutes to 8 minutes and lowering costs by an amazing 80% (DHL, 2019). Moreover, a group of well-known drone delivery services, such as Prime Time Air, FedEx, UPS Flight Forward, and others, are leading the way in changing the last-mile operations process (Emergen Research, 2022). Drone deliveries are a good alternative to standard express delivery methods because they are much easier to use and cheaper. They offer faster services at a fraction of the cost (Tavares & Brussels, 2019). This low cost not only caters to specific markets but also starts a new era of environmentally friendly last-mile operations, making drones key players in changing the way global supply chains work.

Drones can be used in many fields, from healthcare to transporting emergency supplies. They could make it much easier to reach patients and faster to respond to emergencies (Bahrainwala et al., 2020; Saeed et al., 2021b). In addition to drone business use, partnerships like the one between Zipline (Lyons, 2020) and the Rwandan government show that drones can also be used for medical items delivery. They can help get medical goods to areas that need them quickly and easily (Toor, 2016). Drones have shown how useful they can be by making time-sensitive medical transfers possible, like moving blood in 30 minutes instead of a whole day with traditional methods (Kretchmer, 2020). They can also bring important medical supplies like PPE (Personal Protective Equipment) kits and nasal swabs, which is especially helpful during public health emergencies (Saeed et al., 2021a). In the following section, we will explore the use of drone delivery systems within the healthcare sector.

1.5.2. Drone Application in Healthcare

Adding drones to healthcare systems opens up a lot of ways to improve services, especially in areas that are hard to get to or are in rural areas. Drones are used by many businesses and groups, such as Vanuatu's Ministry of Health and Civil Aviation (Kent, 2019), Zipline (Lyons, 2020), Matternet (Matternet, 2020), and Manna Aero (Chandler, 2020), to help transport and distribute important medical supplies like vaccines, medicines, and blood units. These projects show that drone technology has the ability to solve problems with logistics and make it easier for people to get to important healthcare resources. Some examples of how drones are used in healthcare settings are shown below.

Drone-based solutions are new ways to get medical care to people, especially during emergencies like the COVID-19 outbreak. Proposed systems, such as the drone-based sample collection method for COVID-19 self-testing kits, aim to reduce face-to-face contact while still giving people in need prompt medical help at home (Munawar et al., 2022). Drones with medical supplies can give important help to patients using AI and machine learning algorithms. This makes healthcare systems and staff less reliant on traditional methods.

According to Frigstad et al. (2023), drones have become useful tools for emergency medical services (EMS) because they can quickly transport life-saving devices like Automated External Defibrillators (AEDs) to people who are having an out-of-hospital cardiac arrest (OHCA). Through the joint operation of adaptive dispatching drones and volunteer people's help, drones could greatly cut down on reaction times and improve the health of patients in urgent situations.

In addition, drones are a key part of changing the logistics of blood transportation and making sure that people in need get blood products on time. Drones are a quick, reliable, and inexpensive way to get important medical goods like blood transfusions to people who need them because they can easily get through both crowded and unpopulated areas. Recently done studies have shown that it is possible, efficient, and safe to use drones to move blood (Amirsahami et al., 2023). This opens the door for using drones in medical logistics.

Gao et al. (2023) also say that UAVs are changing the way emergency services respond by making it possible to send them quickly and adding to what they can already do. Drones might contribute to reducing the effects of crises like opioid overdoses by letting bystanders help and allowing early intervention in medical situations. This is important because patients need to get life-saving drugs like naloxone right away to survive. Drones help improve emergency reaction times and patient outcomes in critical situations by adding new UAVs to existing emergency medical service (EMS) systems.

1.6. Research Question

In this chapter, we presented the aspect that drone delivery is on the rise in solving last-mile delivery problems in healthcare SCM since drones are quicker, more affordable, and environmentally friendly modes of transportation (Mohammad et al., 2023). Nevertheless, to optimally realize the benefits of these technologies in facilitating healthcare delivery, more research needs to be conducted (Gao et al., 2023). As stated by Asadi et al. (2022), given the growing utilization of drone delivery, it is necessary to effectively manage the internal operations of drone hubs to achieve optimal performance. To ensure the efficient operation of a fleet of drones, it's important to consider several battery-related constraints. Some of these are the limited flight range, the long charging process, the high cost, and the short battery life (Asadi et al., 2022).

The objective of our work is to enhance the efficiency of last-mile medical drone delivery with the consideration of a critical constraint such as the limitation of drone battery life and charging time. In order to approach this task in the most effective way, we will concentrate on the following research question:

How can drone hub charging and distribution operations be improved to enhance the efficiency of last-mile delivery of medical supplies?

To address the core research question, this research aims to present a strategic methodology for the efficient charging and allocation of drones to enhance resource utilization and address the unpredictable stochastic demands that come from hospitals. The main objective is to determine which charging and allocation strategies result in the highest demand satisfaction rate with a minimum number of drones while at the same time using minimum drone charging cycles.

Therefore, we will examine a drone hub tasked with dispatching drones to meet stochastic demands for medical supplies from hospitals at different distances from the drone hub. The drone hub operates by delivering drones to destinations within their operational range, which is determined by the battery's level of charge. This situation is challenging because the allocation of drones to do missions and recharging them depends on their level of charge and the battery charge can vary from 0 to 100%. Therefore, we need to consider multiple combinations of charge levels to fulfill the unpredictable demands from locations at varying distances from the hub as well as find a good strategy for recharging the drones.

In order to comprehensively investigate the research question our methodology entails the Discrete Event Simulation and analysis of various operational scenarios and experiments for the drone hub. The objective is to determine the most effective scenario for successfully managing the internal activities of the drone hub to increase the demand satisfaction rate of the hospitals located in various geographical areas with the minimum number of drones and decrease the number of charging cycles of drones to reduce their battery degradation rate.

1.7. Conclusion

The concept of supply chain management (SCM) has developed a lot since it became popular in the 1990s and recently, it has gained more attention in the healthcare system since has become a key tool for cutting costs and improving quality in that field (Min et al., 2019; Elmuti et al., 2013). Healthcare supply chain management has many challenges, especially when it comes to logistics, where rising costs and complexity are big problems (Volland et al., 2017).

One area in SCM and logistics that needs more attention is last-mile delivery, which is marked by inefficiencies, cost, and environmental issues (Ha et al., 2022). In reaction to these challenges, drones have emerged as a promising solution due to their potential to offer faster, cheaper, and more environmentally friendly delivery options (Mohammad et al., 2023). While drones have shown their ability to improve healthcare delivery by facilitating the agile transportation of vital medical supplies, such as vaccines and blood products (Garg et al., 2023; Frigstad et al., 2023), further research is necessary to fully use their benefits and transform healthcare delivery (Gao et al., 2023). One of these areas that needs to be considered is drone battery-related constraints (Asadi et al., 2022). Therefore, our research goal is to underscore the importance of improving drone hub charging and distribution operations to enhance the efficiency of last-mile medical drone deliveries. By employing Discrete Event Simulation methodology to analyze various operational scenarios and charging strategies, we aim to develop charging and allocation strategies that maximize demand satisfaction rate with the minimum number of drones and decrease the drone's charging cycles, thus addressing constraints that come from drone’s battery such as limitation of drone battery life and charging time.

In the next chapter, we will delve deeper into our selected methodology and explain more about Simulation methodology and Discrete Event Simulation. Besides, we provide a comprehensive overview of the data we will use for our scenario analysis and the Conceptual model of our study.

CHAPTER 2 - Methodology

In this chapter, we describe the method used in this research. We chose simulation as our approach since it is suited for the modeling of dynamic, complex systems like the operation of drone hubs (Robinson, 2014). Through simulation, we are able to examine the stochastic nature of demands together with the interactions between the drone allocation, battery level, and charging procedures. Furthermore, Discrete Event Simulation enables us to develop and analyze various scenarios and experiments to assess their effectiveness without disrupting real-world operations (Robinson, 2014). It offers a strong basis for decision-making and the improvement of medical supply last-mile delivery.

Further in this chapter, we begin with introducing Simulation approaches, differentiating the various types of Simulation, with a focus on Discrete Event Simulation, on which the given methodology is based. Next, we will describe the conceptual model that serves as the foundation for this simulation study and upon which the subsequent research will be based. Subsequently, we will introduce different types of simulation software; afterward, we will discuss the chosen software in detail. Lastly, we presented the data that will be utilized in the experimental study and scenario analysis.

2.1. Simulation

In this section, we explore the fundamental concepts of simulation as described in Robinson's (2014) book. Our objective is to provide a clear description of simulation and explain its importance within the framework of our study.

2.1.1. What is Simulation?

Simulation models are extensively employed in various fields, demonstrating the commonplace notion of simulation in our everyday existence. For example, Meteorologists utilize simulations to forecast weather patterns, whereas video game consoles provide simulations that enable players to perform various roles such as racing drivers or city managers (Robinson, 2014). Based on the definition provided by Wikipedia contributors (2024), “A simulation is an imitative representation of a process or system that could exist in the real world”. Robinson (2014) also provides a more general and concise explanation, referring to it as "An imitation of a system". In order to gain a deeper understanding of the notion of simulation, Shannon (1975) defines simulation as "Simulation is the process of designing a model of a system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system". Computer-aided design (CAD) systems and business process maps are instances of technologies that simulate real-world functionalities, making them forms of simulation in a wide sense (Robinson, 2014).

As described by Pidd (2003), the objective of simulation models is to assist in gaining a better understanding of actual systems, making improvements, and gaining control over them. The use of simulations also has a key application towards our ability to understand systems such that we can make the right decisions in real systems. Managers of simulation models change the inputs and other scenes to review the outcomes in an effort to enhance their understanding and possibly make modifications to real systems. Thus, simulations serve as a tool that helps in the decision-making process without substituting the decision-maker (Robinson, 2014).

Furthermore, there is a clear differentiation between static and dynamic simulations. Static simulations represent a system at a certain instant, while dynamic models illustrate the progression of a system over time, such as the motion of weather or trains (Law and Kelton, 2000). The main focus of our study is to examine dynamic simulations, specifically those that are performed using computers.

2.1.2. Why Simulate?

Operating systems are naturally complex, interconnected, and variable making it challenging to predict performance. Variability includes both predictable changes, such as the number of drones at distribution centers, and unexpected ones, such as the number of demands from hospitals. The interconnection implies that changes in one place affect others, leading to results. Moreover, the systems display a mix of complexity from component combinations and dynamic complexity from prolonged interactions as described by Sterman (2000).

Simulation models effectively tackle these complexities by projecting performance, examining designs, and assessing policy effects. They offer benefits over real-world trials that are expensive, disruptive, and time-consuming. Modifications can be made to simulations without affecting ongoing activities and can be viable even in the absence of actual systems. They create controlled environments and necessitate fewer assumptions making them trustworthy and understandable for the general public through representations (Robinson, 2014).

Despite their advantages, simulations come with drawbacks. They can be costly, time-consuming, and data-intensive, requiring extensive organization and analysis. Developing models necessitates a variety of abilities, such as statistical analysis and validation processes. Moreover, simulations may give a sense of accuracy; hence warranting evaluation of their validity and underlying assumptions (Robinson, 2014).

An examination of simulation studies' benefits and drawbacks shows that they can be quite helpful in certain industries, including ours. For instance, compared to direct system experimentation, simulation studies offer the benefit of requiring only a minimal cost input. If the simulations are effective, this approach not only lowers the possibility of large financial losses imposed by bad decisions but also has the potential to increase profits.

2.2. Different Types of Simulations

In this section, we discuss in greater detail several simulation approaches that are illustrated in Fig. 8 and their real-world uses. Next, we go into more detail on the particular kind of simulation that was selected for our study, emphasizing its advantages over alternative approaches in the context of our particular case study.

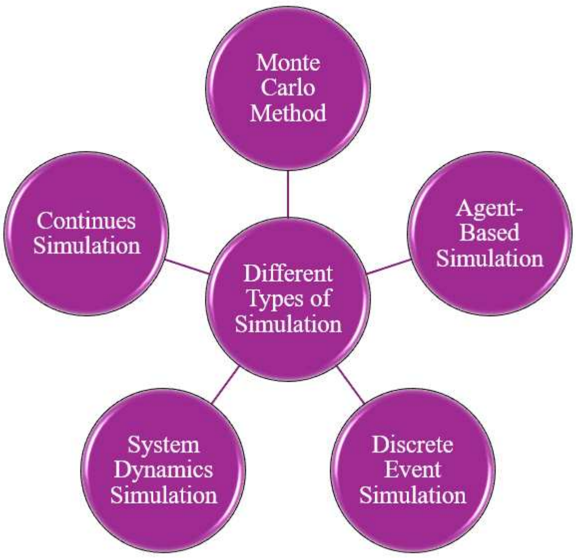

Fig. 8. Different Types of Simulation.
Source: Based on own investigation.

The Monte Carlo method: This method evaluates uncertainties and potential threats through the use of probability distributions, and is utilized in risk analysis for large-scale projects. It improves risk awareness and is used in the manufacturing, finance, and oil and gas sectors (LLC, 2023).

Agent-Based Simulation: This technique utilizes behavioral rules to imitate how individual agents, such as workers or machinery, affect a system. It is helpful in identifying opportunities and threats while exploring biological, social, and physical systems (LLC, 2023).

System Dynamics Simulation: Focuses on the interactions that occur inside a system over time, predicting behaviors and examining trade-offs through the use of feedback loops (Karunathilake et al., 2020). According to Karunathilake et al. (2020), it offers insights at the aggregate level for long-term strategic planning.

Continuous Simulation: Models involve factors that are constantly changing over time, such as water levels or the altitude of an airplane. This type of simulation typically uses differential equations to model how state variables change over time (Wikipedia authors, 2023).

Discrete Event Simulation (DES): This method of system simulation monitors changes in state during specific events while taking into account resources such as expenses and equipment. It employs a three-phase method to enhance event processing and is very adaptable, particularly in the manufacturing and healthcare industries (Allen et al., 2015).

2.2.1. Discrete Event Simulation as Our Selected Methodology

In this research, our main goal is to determine the best charging and allocation strategies for drones that yield the highest demand satisfaction rate with the fewest number of drones while also utilizing the least drone charging cycles. We have determined that Discrete Event Simulation (DES) is the best choice for modeling stochastic processes within our case study in the healthcare system after carefully examining various simulation models and their real-world applications.

This conclusion is derived based on multiple factors. The Continuous Simulation approach lacks applicability and practical significance for our particular case study because it works well for a system that is always changing. We are more concerned with the moment at which an event, like charging or allocation, occurs than with our system's continuous capture. On the other hand, the Monte Carlo simulation method is used more for risk analysis which is not our main object and it is too simplistic for our needs. Agent-based Simulation assesses the impact of a new agent or element on the system that is not our goal and fails to sufficiently account for the concept of process. System Dynamics operates at a deterministic and macroscopic level that may not include all the details of the model. Discrete Event Simulation is widely recognized as the most versatile and commonly used approach, providing extensive applicability and the adaptability to incorporate with other modeling techniques where appropriate (Robinson, 2014). DES is the most suitable framework for our needs, as it offers a comprehensive platform for capturing the complex dynamics of stochastic systems.

Discrete Event Simulation (DES), according to Stamatti (2024), is based on simulating dynamic systems by tracking discrete events as they take place at particular periods. This approach works especially well for modeling and examining systems whose behavior is subject to quick shifts, concentrating on key events that impact the system's behavior.

To explain DES's fundamental ideas, entities, events, a simulation clock, and queues are the core components of DES (Stamatti, 2024):

Entities are the objects or components of the system that are being examined (Stamatti, 2024). The entities that make our model consist of:

- **Drones:** These are the main objects that interact in the simulation, carrying out tasks like charging and delivery.

- **Hospitals:** Although not specifically specified as objects, hospitals are characterized by their data (name, distance, and demand) and are represented by their stochastic demands for drone deliveries.

Events are actions brought about by entities that change the system's conditions or state (Stamatti, 2024). In our model, events are actions that are mainly started by the entities and modify the drones' states or situations. Notable events consist of:

- **Starting a delivery:** Triggered when a drone starts flying to a destination to do a mission.

- **Completing a delivery:** Triggered when a drone completes the mission and comes back to the hub.

- **Start charging:** Begins when the drone's battery needs to be recharged.

- **Complete charging:** This ends when a drone’s battery is fully charged.

- **Demand generation:** Hospitals request medical items over time based on the non-homogeneous Poisson Process.

To help with the simulation's time flow, the simulation clock keeps track of the moments when events happen (Stamatti, 2024). The simulation clock in our model is controlled by the SimPy environment, which monitors the simulation time evolution. It is necessary for planning and carrying out every event, including demand generation, drone arrivals and departures, and charging. In part 2.4 of this chapter, we go into SimPy environments in further detail.

Queues serve as holding places where entities wait to be processed or served and are essential for handling and arranging entities (Stamatti, 2024). Although a queue structure is not mentioned specifically in our model, it functions in our model since drones in scenario 2 are sorted and dispatched according to their charge level and status. We discuss further scenario 2 in section 2.3 of this chapter.

At a higher level of abstraction, sources, servers (which might or might not include queues), and sinks are common components of DES (Stamatti, 2024):

- Sources create entities and add them to the simulation; they have settings that control when and how many arrive (Stamatti, 2024).
  The sources in our simulation are places at which new demands are generated. Demand originates from the hospitals and the frequency of demands is determined by the non-homogeneous Poisson Process representing their average daily demands.

- Servers are entities that are temporarily retained by the system, usually for a predefined amount of time for processing (Stamatti, 2024).
  Drones are the servers in our study. By flying to hospitals and delivering whatever is required, they meet the requests. Their operational parameters—such as charging time, range, and speed—determine how they execute tasks and organize their workflow.

- Sinks are endpoints where entities can be removed from the system. They are also important places to collect information about the length of time an entity has been in the system as well as general performance metrics (Stamatti, 2024).
  Sinks are not shown explicitly in our study. In our case, this can theoretically entail the efficient delivery of goods to hospitals or it can be the unsatisfied demands that are removed from the system or even a reporting system that records deliveries that are finished or other metrics, "removing" these events from the system so that they can be analyzed.

2.3. Simulation Study Setup: Development of the Conceptual Model

The outline of a simulation study is illustrated in Fig. 9 below, which was largely inspired by the work of Robinson (2014) and Landry et al. (1983). The boxes are the key stages in a simulation study and illustrate the important deliverables:

- Conceptual Model: Creating a comprehensive overview of the model in development, including its theoretical foundations and operational characteristics, is the purpose of this stage.

- Computer Model: This step, which comes after conception, focuses on actually putting the simulation model into practice on a computing platform.

- Solutions and/or Understanding: This critical stage entails analyzing the results derived from rigorous experimentation within the model.

- Improvement in the Real World: The last phase converts the knowledge and solutions obtained from the simulation into workable improvements in real-world applications.

The graphic, which links these phases, emphasizes the ease of transitioning between several stages of simulation research by using arrows to represent the dynamic processes enabling stage transitions.

According to Robinson (2014), the process of conceptual modeling is crucial to simulation research and is frequently considered its most important component. A well-designed model is essential to the simulation's effectiveness, highlighting the importance of simplicity while fulfilling the goals of the research. Conceptual modeling is defined by Robinson (2014) as “A non-software specific description of a computer simulation model (that will be, is or has been developed), describing the objectives, inputs, outputs, content, assumptions, and simplifications of the model”. A simulation study is typically prompted by the identification of a real-world problem. This problem could be related to a proposed system or it could be an issue with an existing one. For instance, a supermarket may face issues with long customer queues, or there might be design concerns for a new store. It is the modeler's responsibility to fully understand the issue and create a model that is appropriate for solving it. Accordingly, conceptual modeling entails the following processes (Robinson, 2014):

- Gaining an extensive understanding of the current issue.
- Setting clear modeling objectives.
- Creating the conceptual model and outlining its assumptions, simplifications, content, and inputs and outputs.
- Gathering and analyzing data essential for developing the model.

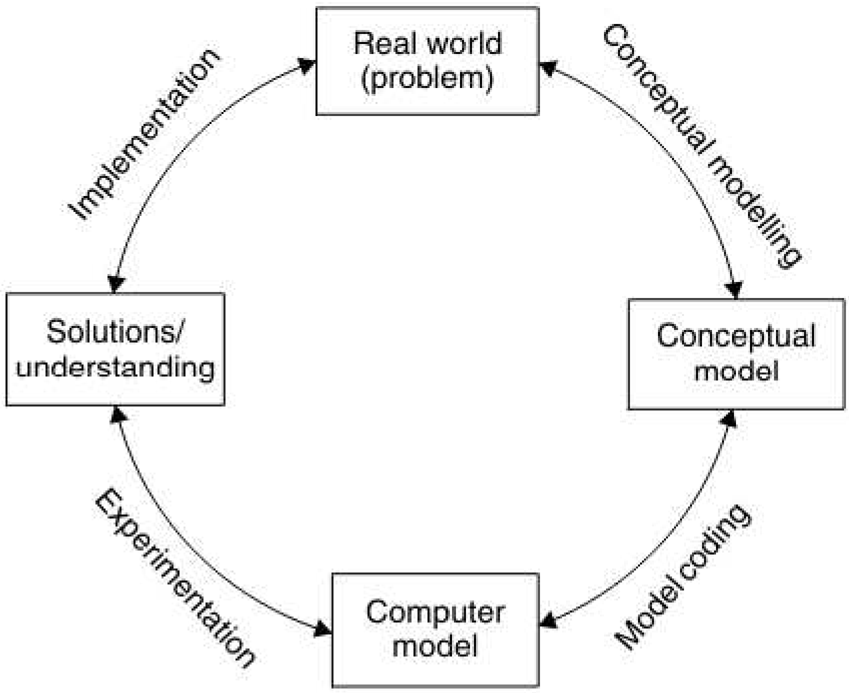

Fig. 9. An outline of a Simulation study: Key Stages and Processes.
Source: Robinson (2014).

2.3.1. Conceptual Model of Our Study

The Conceptual Model of our drone delivery simulation study is as follows:

Problem Description and Objectives

- Our Simulation study will analyze a drone hub's operation of dispatching drones to meet stochastic demand for medical supplies, including blood units, from hospitals located at varying distances from the drone hub. Every hospital generates stochastic demands independently within 24 hours. Following receiving a demand, the drone hub initiates by verifying the availability of drones with sufficient charge to fulfill the demand of the specified hospital. We examine two distinct scenarios concerning the allocation of drones to meet demand. The primary difference between these scenarios lies in the method of drone assignment. In the first scenario, upon receiving a demand, the drone hub checks for idle drones and dispatches the first available drone that has enough charge to fulfill the demand. The second scenario introduces a new rule to this model. Here, when a demand is received, the drone hub checks for idle drones with sufficient charge sorts them according to their charge levels, and then dispatches the drone with the minimum charge necessary to meet the demand. In both scenarios, if no drone with adequate battery power is available, the demand remains unsatisfied.

Furthermore, the drone hub has to recharge drones when it is necessary. To achieve this, the hub monitors idle drones every minute. If it identifies a drone with a charge level below a designated threshold and the drone has been idle for a specified duration, the hub recharges the drone to full capacity.

Our study aims to enhance the last-mile delivery of medical items using drones by improving the charging and distribution operations of the drone hub when considering the drone's battery limitations. Therefore, our objective is to determine the most effective recharging algorithm and distribution operation that may optimize the utilization of the drone's energy. Simultaneously, we hope to enhance the hospital demand satisfaction rate and reduce the rate of battery degradation. In other words, we aim to identify potential bottlenecks and areas for drone charging and distribution operations and improve them.

To achieve our objectives, we must implement recharging protocols that prioritize two key performance indicators (KPIs): enhancing the average demand satisfaction rate and promoting drone battery longevity by reducing the average number of charging cycles per drone per day. To this end, we will conduct experimental analyses to identify the optimal recharging strategies, which include the recharging threshold and the duration of drone idle time before recharging. These experiments will help us determine the most effective recharging rules for improving our KPIs.

Inputs

- Hospital Data: Includes hospital names, distances from the drone hub, and average daily demand for medical supplies. This data is loaded from an Excel file.

- Drone Specifications: Drone's operation range, speed, and charging time. These parameters affect the drone's ability to deliver and its operational efficiency. In our study, we consider the Zipline drone specifications for our analysis.

- Drone Fleet Size: Initially, we do our research and analysis using a fixed number of drones. Once the optimal configuration has been determined, we examine the number of drones needed to achieve the highest KPIs rates.

- Simulation Duration: Determination of adequate simulation length and replication count to ensure reliable results.

Outputs

- Demand Satisfaction Rate: Percentage of demands that are successfully met within the time constraints.

- Average Number of Charging Cycles per Drone per Day: Indicates the average number of charging operations required for each drone on a daily basis.

Content (Scope and Level of Detail)

- The simulation focuses on the operational aspect of drone delivery from a single drone hub to multiple hospitals.

- Includes basic drone operations like checking the drone charge level for each demand, flying to destinations to deliver supplies, and charging operations of drones.

Assumptions

- The simulation starts with drones at 100% battery capacity.

- Hospitals' demands follow a non-homogeneous Poisson Distribution related to the average demands per day for each hospital (Exponential Distribution for the time between demand arrival is used).

- No failures or maintenance issues affect the drones during the simulation period.

Simplifications

- Simplifications include assuming perfect flight conditions and ignoring potential real-world issues like drone maintenance, weather conditions, and emergency prioritization.

- The traffic conditions or other real-time challenges affecting drone speed or route are not considered.

- Charging drones until they become fully charged. Interruption during charging is not considered. The rationale behind this simplification is that if interruption during the charging process is allowed, we should track the drone battery's charge level every moment during the charging process. To do this we should have precise information about the SOC (State of Charge) of the Zipline drone. But we do not have precise information about the SOC of Zipline drone charging, therefore, we are unable to follow the drone's momentary charge during the charging.

2.3.2. Process Flow Diagram and Logic Flow Diagram

Representing the conceptual model's content correctly is essential when it comes to project specification. The process flow diagram and the logic flow diagram are the two main techniques utilized for this (Robinson, 2014).

A process flow diagram, sometimes referred to as a process map, shows the order in which the system components are set up to physically depict the conceptual model. This approach describes the model's details using straightforward visual cues like boxes for processes and circles for queues. Process flow diagrams are useful tools for showing how processes flow within a system because of their simple, intuitive design (Robinson, 2014).

In logic flow diagrams, standard flow diagram symbols are used to depict the model's logic as opposed to the process flow. These graphics work especially well at conveying the complex logic of a system. The notation is frequently recognizable and simple for users to understand. However, unlike process flow diagrams, logic flow diagrams may get rather big and complicated, especially for large-scale models. This makes them harder to manage and understand (Robinson, 2014).

To simply show our conceptual model, we illustrate the general structure of our approach in Fig. 10 and 11 here with a simple process flow diagram and logic flow diagram.

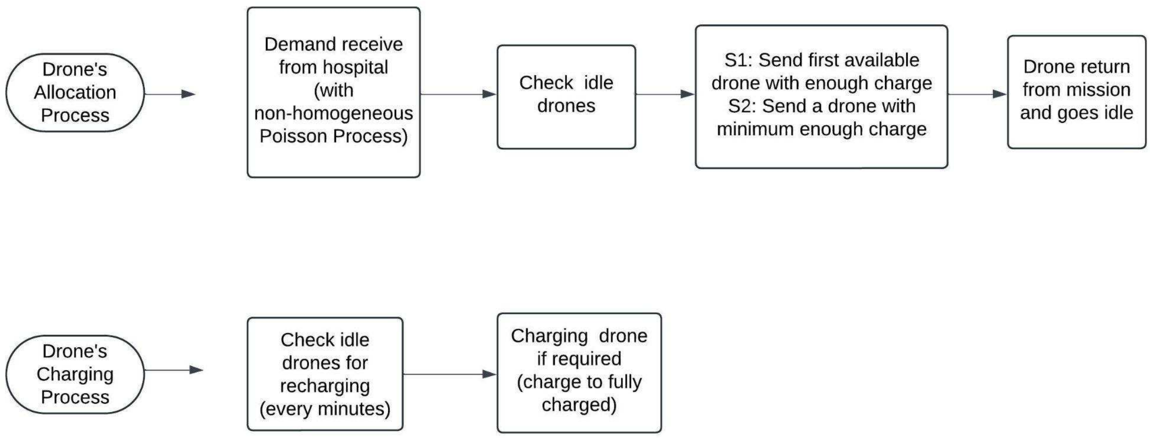

Fig. 10. Process flow diagram of our study.

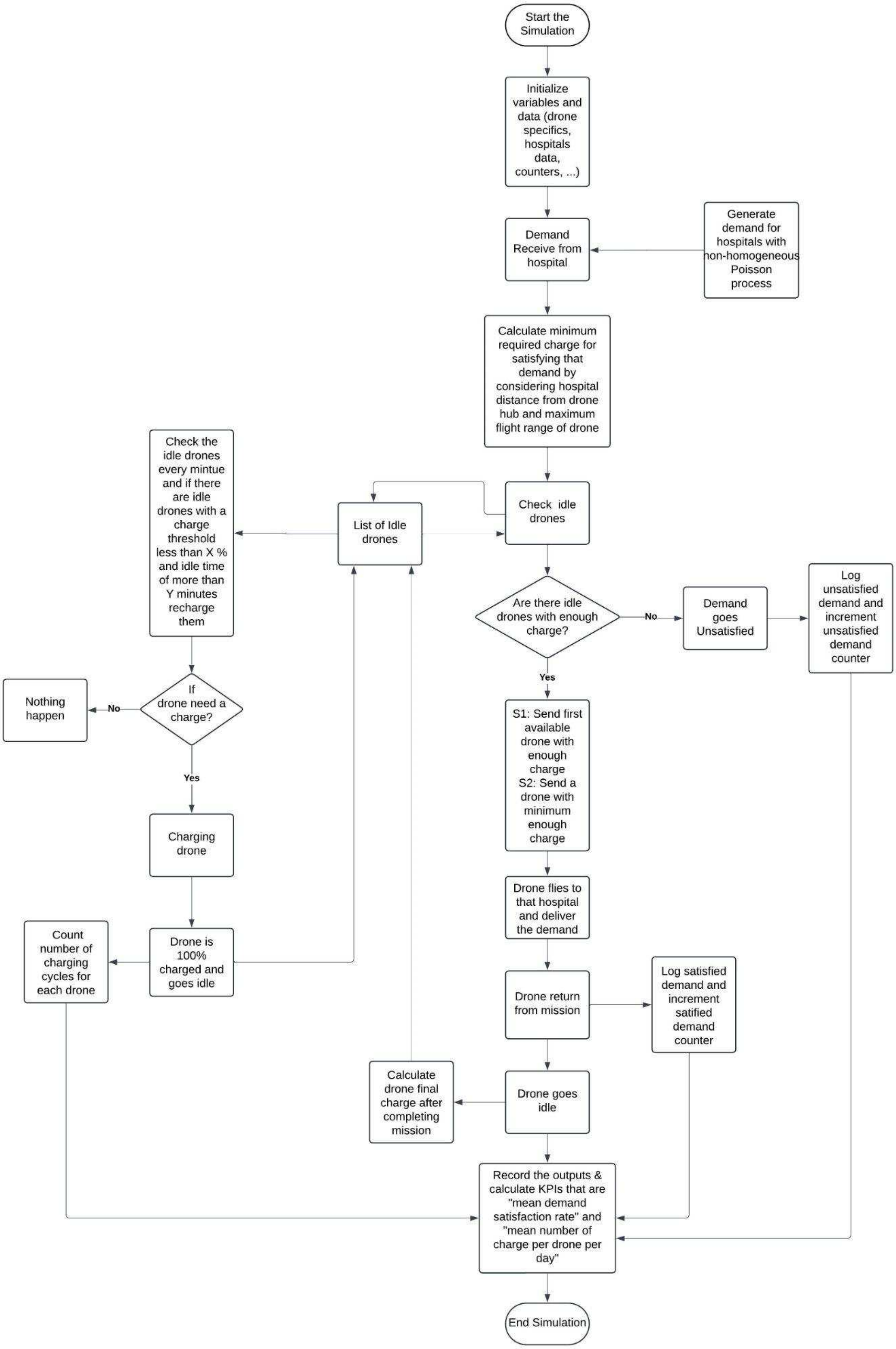

Fig. 11. Logic flow diagram of our study.

2.4. Simulation Software

Discrete Event Simulation programs include SIMUL8, AnyLogic, Arena, and Simio, among many others. These platforms are primarily designed for commercial use and are typically not open source (Wikipedia writers, 2024c). For our research on discrete event simulation, we decide to use the SimPy package in combination with the Python programming language. The reasons behind our selection of SimPy as our simulation tool and the ways in which SimPy and Python can be combined to imitate discrete events are covered in the following parts.

2.4.1. Python and SimPy Library for Discrete Event Simulation

Python is a versatile programming language suitable for a wide range of applications, though it may not always be the first choice for developing Discrete Event Simulation (DES) models. The software platforms available today provide effective drag-and-drop interfaces for developing DES that are easy to use (Al-Muzaki, 2024b). However, building a model in Python offers substantial benefits in post-simulation stages like result gathering, visualization, validation, and optimization, even if it is more complicated and requires a less intuitive approach than specialist tools. Python's capabilities also make it easier to integrate simulation with machine learning, which could improve interoperability between both technologies (Al-Muzaki, 2024b). Furthermore, Python is more affordable than other commercial software because it is an open-source and free tool (Al-Muzaki, 2024b).

We leverage SimPy, a robust library for DES recognized for its reliability and open-source availability (Al-Muzaki, 2024b). Unlike continuous simulation, in which variables change continuously over time, SimPy focuses on the simulation of discrete-event systems, in which changes happen at discrete moments.

As identified by Kumar (2024), SimPy is quite distinct due to the following characteristics:

- Process: In SimPy, the entities to be simulated whether people waiting in line, cars on a road, or the operation of a computer system are modeled as processes. These are created using the generator functions in Python and this makes it easy to model complex and sequential tasks.

- Events: The basic element in the use of the SimPy framework is an event that can be fixed at certain conditions or time intervals. This scheduling is necessary for determining the flow of simulation and for triggering state modifications in the system.

- Resources: SimPy addresses cases where there are entities that need to share scarce resources. The resource class is introduced which helps to simulate the allocation and contention of the resource which is critical in cases such as data centers and manufacturing plants.

- Statistics and Data Collection: During the simulation, various resources for data collection and monitoring are offered to the library. This feature is required for monitoring the time that entities spend in certain states as well as for obtaining other data that are essential for understanding and analyzing the performance of the system.

- Integration: Another advantage of using SimPy is that it supports integration with other Python tools, including NumPy and Pandas. In other words, it helps to make analytics-driven decisions and evaluate the results of simulations.

With these features, SimPy extends Python's more powerful data handling and analyzing function, and provides a solid basis for the modeling of discrete-event systems.

2.5. Data Collection

To model our Discrete Event Simulation and subsequent analysis of various scenarios and experiments, it is crucial to collect specific data about drone operations. This contains information on the drone's speed, range of operation, and charging time. Furthermore, data about drone hub location, hospitals' distance to the drone hub, and the frequency of requests from individual hospitals are crucial. Our study utilizes data referenced from research conducted by Asadi et al. (2022), that provides a real-world case study utilizing Zipline drones, which are used in Rwanda, Africa to carry medical supplies. The initial section of this part will introduce the Zipline Company, followed by detailed data that will support our case study.

2.5.1. Zipline Company

Zipline, a California-based company founded in 2014, is well-known throughout the world for its creative approach to manufacturing and design, with the primary goal of improving healthcare delivery in remote areas (Callaghan, 2023). The business uses drone technology to deliver necessary medical supplies, such as blood units, plasma, infusions, and more recently, COVID-19 test kits, and vaccines. Their advanced 'Platform 1' drone which is illustrated in Fig. 12 is mostly used for this, as it drastically cuts down on delivery times when compared to conventional ground transportation techniques, which is vital in saving lives in remote areas (Callaghan, 2023).

Since its establishment, Zipline has gradually expanded its services around the world. In 2016, it started by distributing blood and medical supplies in Rwanda, Africa. The business currently handles large-scale shipments of a variety of things beyond healthcare, including food, retail items, veterinary and agricultural supplies, and retail goods (Tactis, 2021).

The ambitious objective of Zipline is to create a logistics system that is inclusive to all, leaving a substantial impact in eight nations on four continents. With over 60 million miles of autonomous commercial flights, Zipline is revolutionizing the distribution of healthcare and consumer goods, along with food supplies (Zipline Drone Delivery & Logistics, nd).

The company utilizes two distinct drone platforms: one for long-range deliveries and another for precise home delivery (Zipline Drone Delivery & Logistics, nd). They deliver directly to homes, hospitals, and companies throughout a wide range of nations, including the USA, Rwanda, Ghana, Nigeria, Cote d'Ivoire, Kenya, and Japan (Tactis, 2021). In addition to accelerating vital deliveries, these initiatives promote economic expansion, environmental sustainability, and the development of innovative logistical solutions (Zipline Drone Delivery & Logistics, nd).

The capabilities of Zipline's Platform 1, designed for long-distance commercial deliveries, will be specifically examined in our research. The drone has an amazing operational range of more than 120 miles per round trip (193 km), and it can attain speeds of up to 60 miles per hour (96.5 km/h) (Zipline Drone Delivery & Logistics, nd). Additionally, the 90-minute intervals give drones enough time to charge (McNabb, 2020).

Fig. 12. Zipline Drone Platform 1.
Source: (Callaghan, 2023).

2.5.2. Data

In our research, a real-world case study of Zipline's drone-based medical supply delivery system across Rwanda, Africa, is examined. The primary operational hub for these drones is situated in Muhanga district, west of Kigali, the capital of Rwanda. The study examines how these drones satisfy the variable demand for blood supply required by Rwandan hospitals. The names and locations of hospitals, their distances from the drone hub, the population each hospital serves, and the daily demands for blood units and flights are all included in the input data, as shown in Table 1. Notably, the data utilized in our study originates from the publication of Asadi et al. (2022). Asadi et al. (2022) collected the data for their study through a combination of real-world case study related to the operations of Zipline drones, which are delivering medical items in Rwanda, Africa and theoretical modeling that I explain in detail.

The Haversine formula, first proposed by Sinnott (1984) and acknowledged by Asadi et al. (2022), is a typical method for determining the distance between two places on the Earth's surface, and it is used in the geographical calculation of the distances between the hospitals and the station. Asadi et al. (2022) also incorporates regulatory considerations, such as the Rwandan Civil Aviation Authority's (2021) mandate that prohibits drone flights within a 10 km radius of airports. To ensure that drones do not violate airspace limits, modifications are made to the travel routes to hospitals such as Kiziguro and Rwamagana in order to comply with these laws. The layout of these geographical elements is displayed in Fig. 13.

Additionally, Asadi et al. (2022) developed an approach to calculate the daily blood unit required. The first step in this method is to estimate the hospital user population using district population information. The population of a district with many hospitals is distributed equally among them. The World Health Organization (WHO) recommends that 2% of hospital users require blood each year, which is the assumption used to compute the yearly need for blood units (Dhingra, 2010). In order to account for the possibility of unplanned demand rises, this estimate is considered cautious. To find each hospital's daily blood unit requirement, divide the annual demand by 365. Asadi et al. (2022), also considered the drones' capacity limitations that each can carry only two units of blood (Baker, 2017), then they used average daily demand for blood units to determine the necessary number of daily flights to each hospital.

In line with findings from Swartzman (1970) and Armony et al. (2015), the study models the number of demand arrivals from hospitals using a non-homogeneous Poisson Process. We use the pattern of demand arrivals from hospitals, consistent with Green et al. (2007), Tiwari et al. (2014), and Jones et al. (2007), to derive the mean demand for blood units of each hour over a day. The results as you can see in Fig. 14 show a trend of increasing arrivals from early morning (6.00 am) until noon at peak, followed by a reduction till early the next morning. Moreover, a significant operational limitation highlighted by the research is that any excess demand for blood units cannot be satisfied when there are not any drones available to meet that demand. The system does not support backlog or deferral of unmet demands, emphasizing the urgency and critical nature of medical deliveries by drones.

Moreover, the study excludes three of the 33 hospitals surveyed—Kirehe, Nyagatare, and Mibilizi—because their locations fall outside of the drones' 193 km operating range, making them unreachable for medical assistance. These hospitals are removed from the analysis due to this constraint.

Table. 1. The data related to blood unit delivery using Zipline drones in Rwanda, Africa.
Source: Asadi et al. (2022).

Hospital name	District	Dist. to Zipline station (km)	Pop. reach the hospital	Pop. need blood unit/year	Pop. need blood unit /day	Rounded # of flights needed/day
Nyamata	Bugesera	34.3	361914	7238.3	19.8	10
Butaro	Burera	73.5	336582	6731.6	18.4	10
Nemba	Gakenke	47.8	169117	3382.3	9.3	5
Ruli	Gakenke	27.6	169117	3382.3	9.3	5
Kiziguro	Gatsibo	75.8	216510	4330.2	11.9	6
Ngarama	Gatsibo	77.5	216510	4330.2	11.9	6
Byumba	Gicumbi	61.3	395606	7912.1	21.7	11
Gakoma	Gisagara	34.9	161253	3225.1	8.8	5
Remera Rukoma	Kamonyi	20.3	340501	6810.0	18.7	10
Kibuye Referral	Karongi	48.2	110603	2212.1	6.1	4
Kirinda	Karongi	22.6	110603	2212.1	6.1	4
Mugonero	Karongi	55.6	110603	2212.1	6.1	4
Gahini	Kayonza	85.4	172079	3441.6	9.4	5
Rwinkwavu	Kayonza	94.0	172079	3441.6	9.4	5
Kirehe	Kirehe	99.6	340368	6807.4	18.7	10
Kabgayi	Muhanga	5.2	319141	6382.8	17.5	9
Kibungo	Ngoma	85.1	336928	6738.6	18.5	10
Muhororo	Ngororero	22.6	333713	6674.3	18.3	10
Shyira	Nyabihu	46.0	294740	5894.8	16.2	9
Nyagatare	Nyagatare	104.9	465855	9317.1	25.5	13
Kaduha	Nyamagabe	40.8	170746	3414.9	9.4	5
Kigeme	Nyamagabe	53.8	170746	3414.9	9.4	5
Kibogora	Nyamasheke	77.5	190902	3818.0	10.5	6
Nyanza	Nyanza	31.9	323719	6474.4	17.7	9
Munini	Nyaruguru	76.8	294334	5886.7	16.1	9
Kabaya	Rubavu	44.7	201831	4036.6	11.1	6
Gitwe	Ruhango	22.4	159943	3198.9	8.8	5
Ruhango	Ruhango	19.8	159943	3198.9	8.8	5
Kinihira	Rulindo	50.7	143841	2876.8	7.9	4
Rutongo	Rulindo	41.9	143841	2876.8	7.9	4
Mibilizi	Rusizi	107.3	200429	4008.6	11.0	6
Murunda	Rutsiro	48.3	324654	6493.1	17.8	9
Rwamagana	Rwamagana	73.7	313461	6269.2	17.2	9

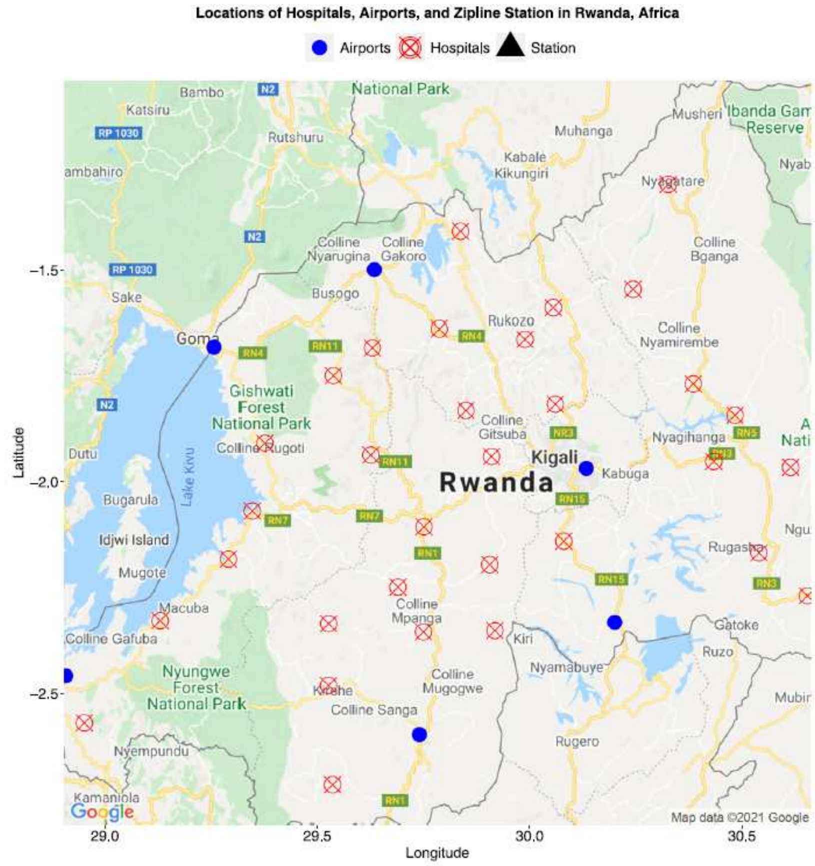

Fig. 13. Locations of airports in Rwanda, hospitals (demand nodes), and the swap station located in the Zipline drone hub.

Source: Asadi et al. (2022).

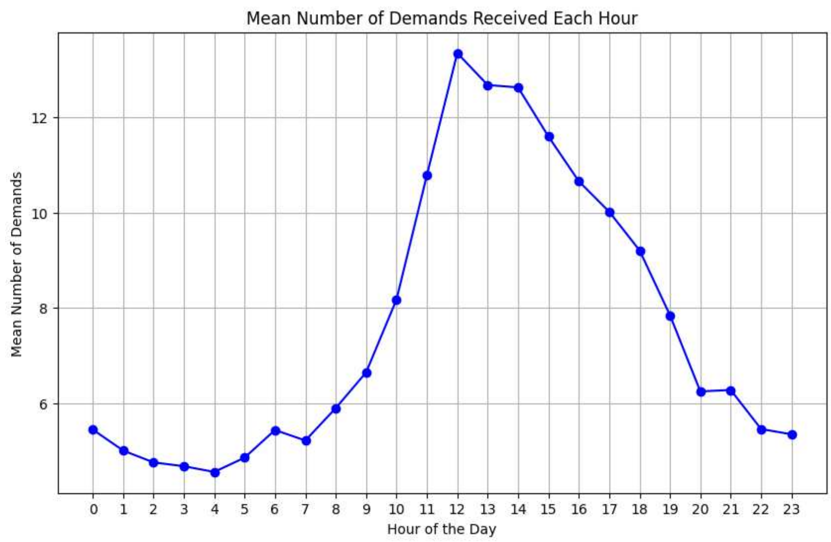

Fig. 14. The pattern of the average number of demands received each hour of the day.

Source: Based on own investigation.

2.6. Conclusion

In this chapter, we have thoroughly described the methodology and data that will be employed in our simulation modeling efforts. We also detailed the specific problem and objectives of our study and developed a conceptual model which is a crucial element in simulation studies as noted by Robinson (2014).

Moving forward, in the subsequent chapter, we will delve deeper into our investigation through the execution of computer-based simulation modeling. We will introduce our experimental design, perform experiments, and present the result of scenario analysis and experiments. This will enable us to evaluate the results and identify the most effective scenario for our research.

CHAPTER 3 - Experimental Analysis

In the previous chapters, we have detailed our problem statement and research question, along with a thorough explanation of our methodology. Additionally, we have introduced our conceptual model to be prepared for model coding.

According to Robinson (2014) and Landry et al. (1983), the next step involves experimentation and understanding the solution. Therefore, this chapter focuses on advancing our investigation through computer-based simulation modeling results. Further in this chapter, we will outline our experimental design, conduct various experiments, and present the results of our studies across different scenarios. This approach will allow us to evaluate the outcomes and determine the most effective scenario and optimal setup to find the best results for our research.

3.1. Experimental Design

The study aims to enhance drone performance in delivering medical supplies through the last mile by improving the charging and distribution operation of the drone hub while considering limitations in batteries. Our goals are to determine an effective recharging algorithm and distribution plan for drones' energy usage, as well as increase hospital demand satisfaction rates and mitigate battery degradation. Battery deterioration is defined as a process whereby the efficiency of a battery diminishes through time since it cannot retain as much power capacity as before. This degradation means that over time, a fully charged battery will not provide the same range as it initially did (Battery Degradation: Maximizing Battery Life & Performance, nd). Some of the key factors that affect battery degradation are the temperature, usage patterns, voltage, and depth of charge/discharge, along with the number of charging cycles (Topalov, 2021; Battery University, 2023; Wikipedia contributors, 2022b; Luo et al., 2023). In order to lower the rate of battery degradation, we aim to minimize the number of charging cycles for drones in our study.

To provide a comprehensive explanation of our study, our simulation will analyze the operations of a drone hub dispatching drones to fulfill stochastic demands for medical supplies, such as blood units, from hospitals at varying distances. Each hospital generates stochastic demands within a 24-hour period, and the drone hub checks the availability of drones with sufficient charge to meet these demands.

We will examine two drone allocation scenarios. The first scenario involves dispatching a random available drone with enough charge to meet the demand. The second scenario improves on this by sorting idle drones based on their charge levels and dispatching the drone with the minimum necessary charge. If no drone with adequate battery power is available, the demand remains unsatisfied in both scenarios. Additionally, the drone hub will monitor and recharge drones as necessary. The hub will check idle drones every minute and recharge those with a charge level below a designated threshold if they have been idle for a specified duration.

To achieve our objectives, we will implement recharging protocols prioritizing two key performance indicators (KPIs): increasing the average demand satisfaction rate and extending drone battery longevity by reducing the average number of daily charging cycles per drone. We will conduct experimental analyses to identify optimal recharging strategies, including the recharging threshold and the necessary duration of drone idle time for recharging. These experiments will help us determine the most effective recharging rules for improving our KPIs. As mentioned, the two variables in our study are the ‘charging threshold’ and ‘drone idle time’. The charging threshold indicates the charge level at which a drone should be recharged, while drone idle time refers to the duration a drone remains idle after completing a mission before being recharged. To identify the optimal values for these variables, we will run experiments with different combinations of these values and assess which combination results in better KPIs.

Values for the ‘charging threshold’ as you can see in Table 2, are chosen based on the number of locations a drone can cover with that charge level. For drone idle time, we will experiment with a minimum of 0 minutes and increments of 15 minutes up to a maximum of 60 minutes. If the optimal idle time is found to be 60 minutes, further experiments will be conducted with longer idle times. The 0 minutes means recharging a drone immediately upon return if its charge level is below the threshold. The 60 minutes means that when a drone returns from a mission with its charge level below the designated charging threshold, it is not recharged immediately. Instead, the drone must remain idle for a period of 60 minutes before it can be recharged.

To conduct our experiments, we aim to test all combinations of 'charging threshold' and 'drone idle time' across both scenarios. Prior to executing these experiments, it is crucial to establish the warm-up period, determine the appropriate run length, and decide on the number of replications for each scenario. Once these preliminary steps are completed, we will proceed with the experiments and present the results.

Table. 2. The maximum number of locations that a drone with each charge level can cover.
Source: Asadi et al. (2022) & based on own investigation.

Charge Threshold %	Number of Locations Can be Covered
6	1
21	2
22	3
24	6
29	7
33	8
36	9
37	10
43	11
44	12
47	13
48	14
50	16
51	17
53	18
56	19
58	20
64	21

3.1.1. Warm-up Period and Run Length

Finding a warm-up period for our model is necessary because it is a non-terminating simulation with steady-state Key Performance Indicators (KPIs). The ‘warm-up period’ indicates the initial stage of a simulation run, during which the system is allowed to move from an arbitrary or non-representative starting state to a more stable and normal operating condition (Robinson, 2014). During this time frame, the simulation results frequently do not accurately reflect the long-term patterns of the system, resulting in what is referred to as initialization bias. The main objective of the warm-up period is to reduce the impact of initialization bias, ensuring that the data obtained after this period accurately represents the system's stable performance (Robinson, 2014).

In our study, we must initially identify the warm-up period for each scenario. Once the warm-up period is determined, the data corresponding to this period should be excluded, and only the simulation results obtained post-warm-up should be considered. Additionally, to establish an appropriate run length for the model, it should be at least ten times the duration of the warm-up period, as suggested by Robinson (2014). Subsequently, we will calculate the warm-up period and the run length for both scenarios.

To determine the appropriate warm-up period, we begin by running the system and monitoring the resulting time series data for both KPIs. This enables us to determine the duration of the warm-up period. However, our goal is to determine the optimal 'charging threshold' and 'drone idle time' using our experimental analysis. The challenge lies in deciding which values of 'recharging threshold' and 'drone idle time' to use in our model to accurately determine the warm-up period. To address this, we conduct simulations across various configurations to observe their KPIs time series data and identify the configuration that presents more fluctuations or initial biases. This configuration will provide a reliable warm-up period that can be applied to other configurations as well. To conduct some experiments to identify an appropriate setup for finding the warm-up period, we choose various 'charging thresholds' from Table 2, taking into account the minimum, average, and the maximum number of hospitals that can be covered by that charging threshold: 6% (which can cover 1 hospital), 37% (which can cover 10 hospitals), and 58% (which can cover 20 hospitals). Regarding the 'drone idle time,' we select 0 minutes, 30 minutes, and 60 minutes to represent minimum, middle, and maximum idle times, respectively. Furthermore, in these experiments, we consider a scenario where Zipline operates a fleet of 15 drones (Staedter, 2016).

In this study, we explored nine different combinations for each scenario and conducted experiments to visualize their KPIs time series. By visually examining these time series across various configurations, we observed consistent patterns in both scenarios for all configurations. The comprehensive time series graphs are included in the appendix.

Our analysis found no significant variations in the time series patterns for different 'drone idle times' (0 minutes, 30 minutes, 60 minutes), therefore, the value we choose for 'drone idle time' does not affect the determination of our warm-up period. Following analyzing different 'charging thresholds', it was shown that a 6% threshold displayed an initial bias in both Key Performance Indicators (KPIs) time series. For alternative thresholds (37%, 58%), KPI 1, which measures the mean demand satisfaction rate, did not exhibit an initial bias. However, KPI 2, which measures the average number of charges per drone per day, did show an initial bias, similar to the 6% threshold.

The initial bias observed for KPI 1 at the 'charging threshold' of 6%, compared to other thresholds, can be attributed to the starting conditions of the simulation. In the beginning, all drones are fully charged at 100%, enabling them to meet most hospital demands effectively. When the 'recharging threshold' is set to a higher value, drones recharge more quickly, maintaining high charge levels and thus consistently fulfilling demands. However, at a 6% threshold, drones recharge more slowly, which reduces their ability to meet demand as efficiently as they did at the initial fully charged state.

Fig. 15 and 16 depict the time series of both the key performance indicators (KPIs) for scenario 1 with a 6% and 37% charging threshold and a drone idle time of 60 minutes. Due to the consistent trends observed across multiple time series, we have chosen not to include all of them in this section. For a comprehensive review of the additional time series, please refer to the appendix.

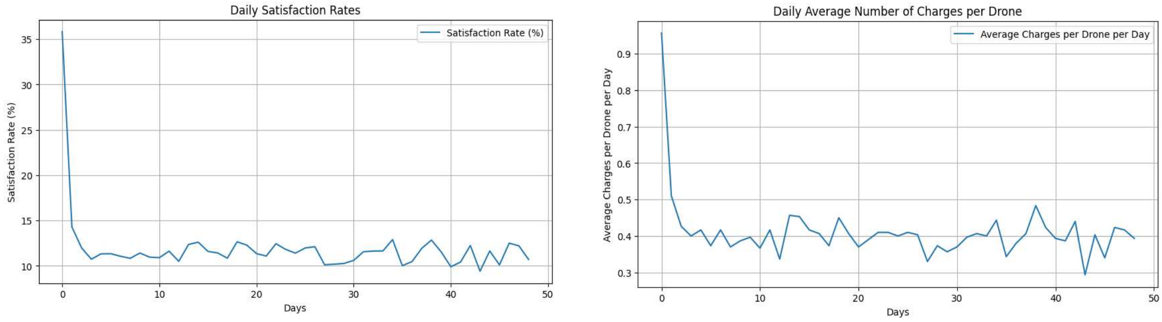

Fig. 15. The time series of simulation output for a charging threshold of 6 % and drone idle time of 60 minutes.

Source: Based on own investigation.

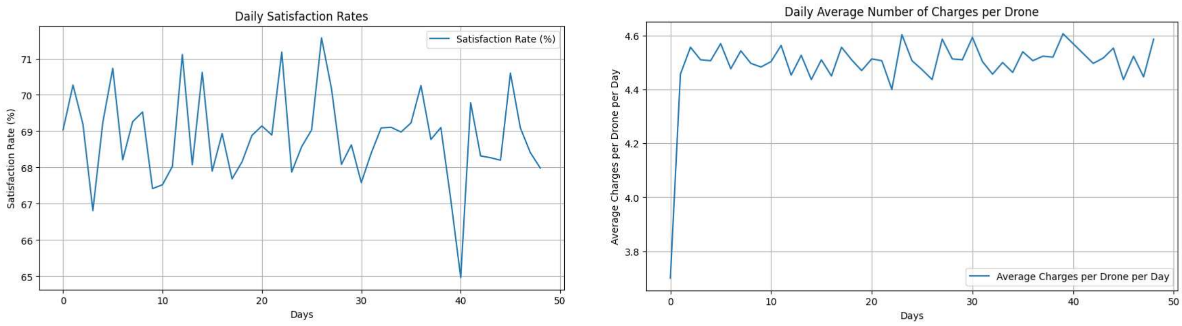

Fig. 16. The time series of simulation output for a charging threshold of 37 % and drone idle time of 60 minutes.

Source: Based on own investigation.

To determine the warm-up period and run length, we chose to run the simulation with a 'charging threshold' of 6% and a 'drone idle time' of 60 minutes. This configuration was selected since it presented an initial bias in the time series of results for both key performance indicators (KPIs) while in other configurations with different 'charging thresholds', we had an initial bias in the time series of results just for KPI 2. In all other configurations, the patterns of the time series remained the same, therefore, we determined the warm-up period for one specific configuration using a threshold of 37% and a duration of 60 minutes. This was done to illustrate that the warm-up period is shorter compared to the 6% threshold and remains constant across all other configurations.

To determine the warm-up period with our two configurations, we utilized the Marginal Standard Error Rule (MSER). This method allowed us to precisely identify the necessary warm-up period for each scenario. For the first scenario, we conducted 20 replications over 15 days run length to smooth the time series. Similarly, for the second scenario, we performed 20 replications over 18 days run length before applying the MSER formula to ascertain the warm-up periods for both configurations.

In Scenario 1, as depicted in Fig. 17 and 18, with a 'charging threshold' set at 37% and a 'drone idle time' of 60 minutes, the warm-up period was zero day for KPI 1 and one day for KPI 2. With a 'charging threshold' of 6% and the same 'drone idle time,' the warm-up periods were two days for KPI 1 and one day for KPI 2. We adopted the maximum warm-up period, which is two days, leading to a new run length of 20 days, adhering to the guideline that the run length should be at least ten times the warm-up period (Robinson, 2014).

For Scenario 2, as shown in Fig. 19 and 20, with a 'charging threshold' of 37% and a 'drone idle time' of 60 minutes, the warm-up period was zero day for KPI 1 and one day for KPI 2. For the configuration with a 'charging threshold' of 6% and the same 'drone idle time,' the warm-up periods were five days for KPI 1 and four days for KPI 2. Again, we selected the maximum warm-up period, which is five days, resulting in a new run length of 50 days.

Having established the warm-up periods and run lengths for both scenarios, the next step is to determine the appropriate number of replications for each scenario. This will enable us to proceed with all subsequent experiments.

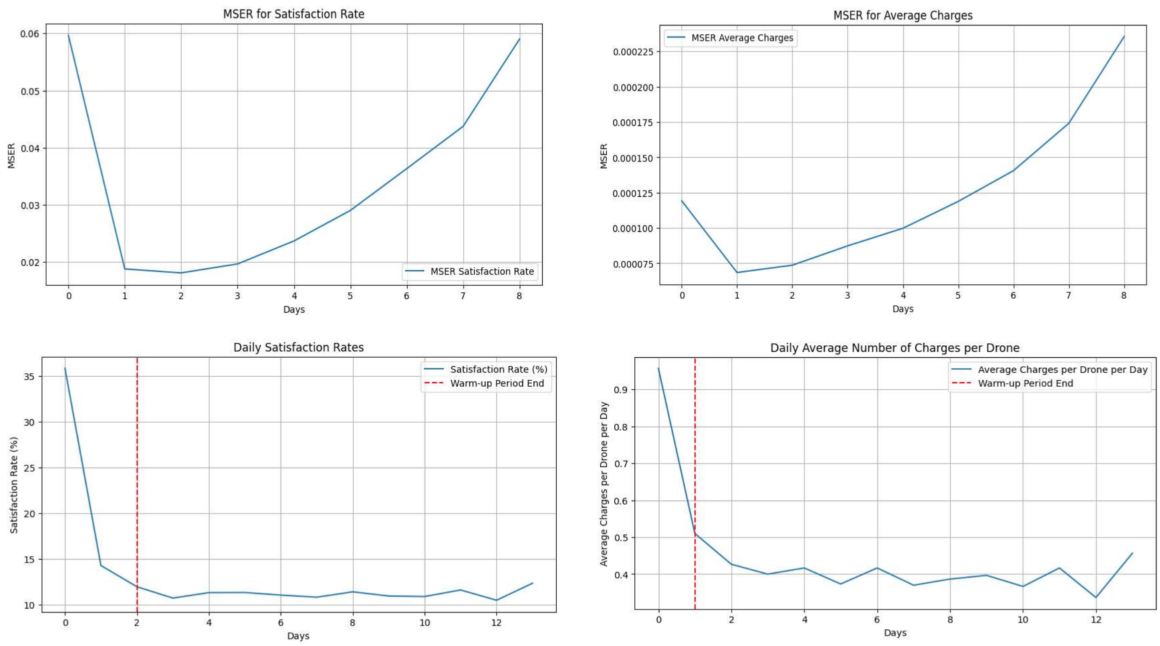

Fig. 17. MSER graph and warm-up period for the time series of simulation output with a charging threshold of 6% and a drone idle time of 60 minutes in Scenario 1.
Source: Based on own investigation.

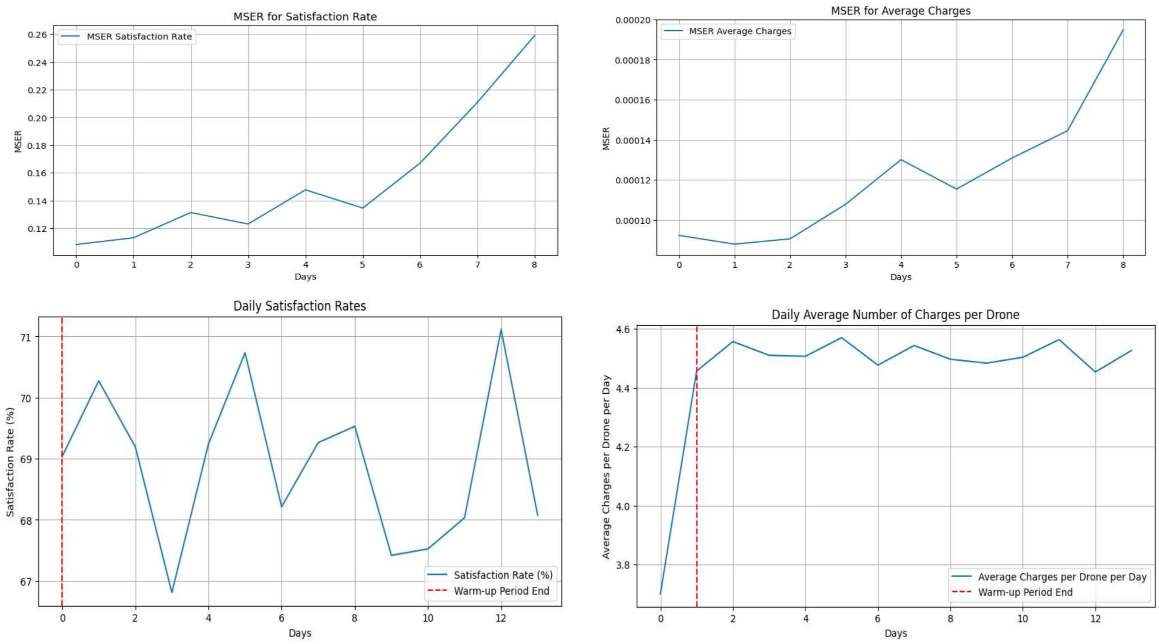

Fig. 18. MSER graph and warm-up period for the time series of simulation output with a charging threshold of 37 % and a drone idle time of 60 minutes in Scenario 1.

Source: Based on own investigation.

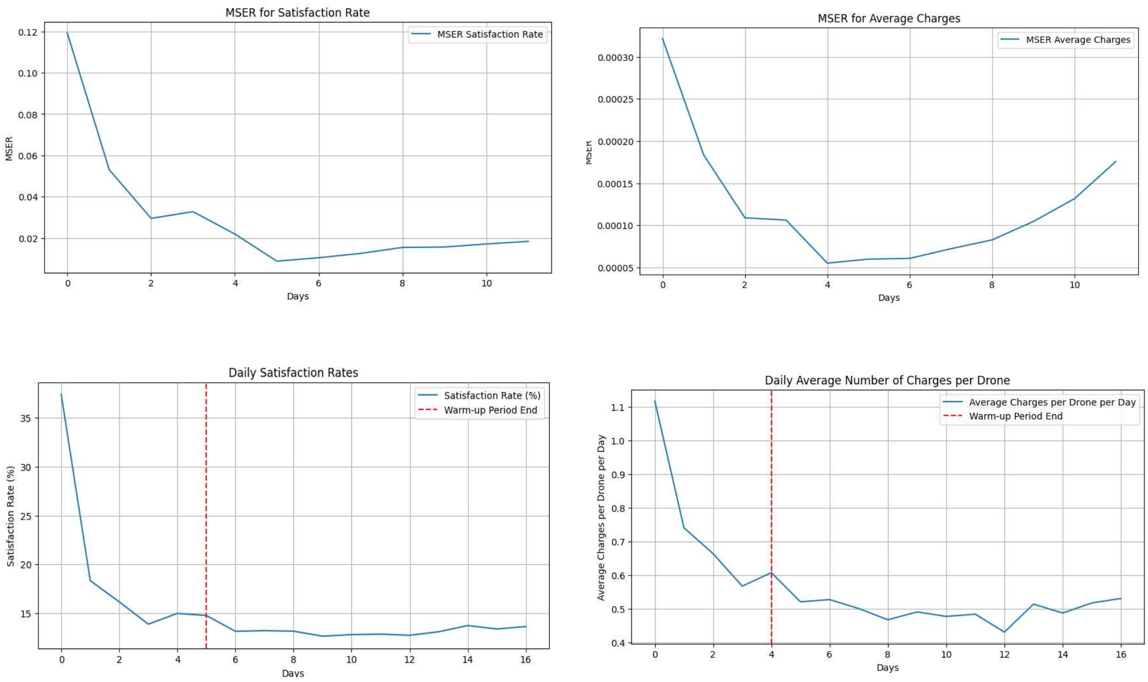

Fig. 19. MSER graph and warm-up period for the time series of simulation output with a charging threshold of 6% and a drone idle time of 60 minutes in Scenario 2.

Source: Based on own investigation.

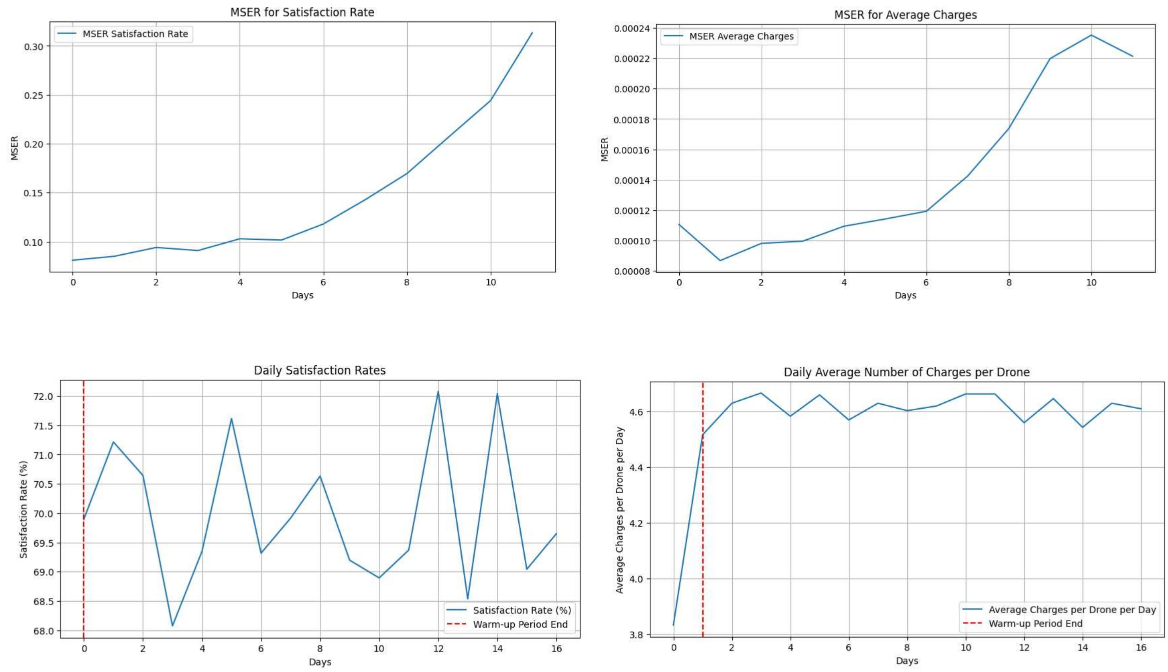

Fig. 20. MSER graph and warm-up period for the time series of simulation output with a charging threshold of 37 % and a drone idle time of 60 minutes in Scenario 2.
Source: Based on own investigation.

3.1.2. Number of Replications

The input for our model, which represents demand, is derived from a probability distribution function, making it inherently random. Consequently, the outcome of our analysis is also random. To address this issue, we construct confidence intervals. Ensuring that the width of these confidence intervals, relative to the average, remains sufficiently small requires an adequate number of simulation replications. To determine if the number of replications is sufficient, we must execute our simulation with the predetermined number of replications and then calculate the 'relative error' of the confidence interval's half-width using the specified formula below. The number of replications should be incremented until the 'relative error' is less than 0.05 (Robinson, 2014).

In our study, to determine the warm-up period, we carried out 20 simulation replications and calculated the average daily Key Performance Indicators (KPIs) to smooth the time series data. To identify the necessary number of replications to achieve a sufficiently narrow width of the confidence interval relative to the average of all daily KPIs, first, we excluded the warm-up period observations, and then, we calculated the mean and variance of the remaining daily KPIs. For KPI 2, the variance was found to be zero in both scenarios, indicating no variation among the data points and resulting in a relative error of zero. As a result, the number of replications was considered adequate for KPI 2. Next, we calculated the relative error for KPI 1 in both scenarios using the 20 replications, applying the Formula. 1 provided below. The relative error was less than 0.05 (approximately 0.03 for scenario 1 and 0.04 for scenario 2), indicating that the number of replications was sufficient. Based on these results, we maintained the 20 replications for our analysis.

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S_n^2/i}}{|\bar{X}_n|}$$

Formula. 1. Relative Error.

3.2. Experimental Studies

Given that we now have the optimal warm-up period, run length, and number of replications for both scenarios, we can now undertake our experiments with a 15-drone fleet size. In these experiments, 'charging threshold' and 'drone idle time' values will be varied to cover all feasible combinations according to our assumption. Based on the settings of the experiments, we will seek to identify which scenarios and which of the combinations of 'charging threshold' and 'drone idle time' produce the best results for our KPIs. The outcomes of these experiments are provided below, in Table 3 for scenario 1 and Table 4 for scenario 2.

Table. 3. The results of the experiments in scenario 1.
Source: Based on own investigation.

Scenario 1				
Num of EXP	**Charging Threshold**	**Drone Idle Time**	**Mean Demand Satisfaction Rate %**	**Mean Number of Charge**
0	6	0	11.34	0.4
1	6	15	11.6	0.4
2	6	30	11	0.38

3	6	45	11.02	0.38
4	6	60	11.39	0.4
5	21	0	65.42	3.97
6	21	15	65.24	3.89
7	21	30	62.87	3.74
8	21	45	61.73	3.64
9	21	60	60.83	3.57
10	22	0	69.8	4.35
11	22	15	68.02	4.22
12	22	30	67.18	4.12
13	22	45	65.2	3.94
14	22	60	63.22	3.81
15	24	0	75.43	5.06
16	24	15	73.19	4.82
17	24	30	71.31	4.61
18	24	45	69.11	4.44
19	24	60	67.16	4.25
20	29	0	75.74	5.21
21	29	15	74.1	5
22	29	30	71.8	4.73
23	29	45	69.88	4.54
24	29	60	67.91	4.35
25	33	0	75.96	5.37
26	33	15	74.42	5.08
27	33	30	72.45	4.83
28	33	45	70.28	4.61
29	33	60	68.03	4.38
30	36	0	76.15	5.42
31	36	15	74.44	5.12

32	36	30	72.77	4.86
33	36	45	70.35	4.64
34	36	60	68.2	4.44
35	37	0	76.41	5.6
36	37	15	74.83	5.28
37	37	30	72.89	4.99
38	37	45	70.78	4.75
39	37	60	68.66	4.51
40	43	0	75.99	5.73
41	43	15	75	5.37
42	43	30	73.37	5.07
43	43	45	70.71	4.79
44	43	60	68.9	4.57
45	44	0	76.12	5.77
46	44	15	75.1	5.37
47	44	30	73.05	5.1
48	44	45	71.15	4.81
49	44	60	68.77	4.55
50	47	0	75.84	5.9
51	47	15	74.99	5.46
52	47	30	73.09	5.13
53	47	45	71.32	4.87
54	47	60	68.83	4.62
55	48	0	75.7	5.91
56	48	15	75.11	5.51
57	48	30	73.21	5.17
58	48	45	71.09	4.87
59	48	60	68.97	4.65
60	50	0	75.18	6.02

61	50	15	75.17	5.57
62	50	30	73.15	5.22
63	50	45	71.15	4.93
64	50	60	69.21	4.65
65	51	0	74.95	6.14
66	51	15	74.86	5.64
67	51	30	73.23	5.27
68	51	45	71.42	4.97
69	51	60	68.85	4.68
70	53	0	74.66	6.23
71	53	15	75.01	5.72
72	53	30	72.85	5.3
73	53	45	71.32	5.01
74	53	60	69.04	4.73
75	56	0	73.98	6.33
76	56	15	74.66	5.79
77	56	30	73.23	5.36
78	56	45	71.13	5
79	56	60	69.17	4.76
80	58	0	73.33	6.48
81	58	15	74.43	5.82
82	58	30	73.25	5.42
83	58	45	71.2	5.06
84	58	60	69.06	4.76
85	64	0	72.98	6.61
86	64	15	74.52	5.91
87	64	30	73.03	5.43
88	64	45	71.22	5.1
89	64	60	68.87	4.78

Table. 4. The results of the experiments in scenario 2.
Source: Based on own investigation.

Scenario 2				
Num of EXP	**Charging Threshold**	**Drone Idle Time**	**Mean Demand Satisfaction Rate %**	**Mean Number of Charge**
0	6	0	13.25	0.5
1	6	15	13.21	0.5
2	6	30	13.23	0.5
3	6	45	13.22	0.5
4	6	60	13.1	0.49
5	21	0	76.11	4.99
6	21	15	73.48	4.76
7	21	30	71.05	4.52
8	21	45	68.84	4.35
9	21	60	66.55	4.15
10	22	0	76.9	5.16
11	22	15	74.7	4.91
12	22	30	72.26	4.67
13	22	45	69.76	4.47
14	22	60	67.5	4.27
15	24	0	77.44	5.44
16	24	15	75.61	5.15
17	24	30	73.13	4.89
18	24	45	70.81	4.65
19	24	60	68.54	4.43
20	29	0	77.42	5.54
21	29	15	75.65	5.22
22	29	30	73.25	4.94

23	29	45	71.07	4.7
24	29	60	68.57	4.48
25	33	0	77.38	5.61
26	33	15	75.69	5.27
27	33	30	73.39	4.99
28	33	45	71.15	4.73
29	33	60	68.67	4.5
30	36	0	77.3	5.64
31	36	15	75.56	5.3
32	36	30	73.49	5
33	36	45	71.16	4.74
34	36	60	68.75	4.51
35	37	0	76.98	5.76
36	37	15	75.53	5.38
37	37	30	73.56	5.06
38	37	45	71.14	4.79
39	37	60	68.87	4.54
40	43	0	76.64	5.85
41	43	15	75.56	5.44
42	43	30	73.51	5.09
43	43	45	71.1	4.81
44	43	60	69.01	4.56
45	44	0	76.41	5.88
46	44	15	75.62	5.44
47	44	30	73.48	5.09
48	44	45	71.15	4.82
49	44	60	68.97	4.56
50	47	0	76.05	5.96
51	47	15	75.59	5.48

52	47	30	73.4	5.14
53	47	45	71.23	4.84
54	47	60	68.97	4.57
55	48	0	76.01	6.01
56	48	15	75.47	5.51
57	48	30	73.32	5.15
58	48	45	71.28	4.85
59	48	60	68.82	4.59
60	50	0	75.54	6.08
61	50	15	75.36	5.54
62	50	30	73.4	5.19
63	50	45	71.21	4.87
64	50	60	68.78	4.6
65	51	0	75.26	6.18
66	51	15	75.16	5.61
67	51	30	73.43	5.2
68	51	45	71.23	4.88
69	51	60	68.86	4.61
70	53	0	74.71	6.28
71	53	15	75.02	5.65
72	53	30	73.48	5.23
73	53	45	71.1	4.91
74	53	60	68.88	4.62
75	56	0	74.17	6.39
76	56	15	75.02	5.7
77	56	30	73.31	5.25
78	56	45	71.01	4.92
79	56	60	68.97	4.63
80	58	0	73.5	6.52

81	58	15	74.91	5.74
82	58	30	73.29	5.28
83	58	45	71.12	4.94
84	58	60	68.9	4.64
85	64	0	72.93	6.62
86	64	15	74.95	5.77
87	64	30	73.14	5.3
88	64	45	71.08	4.94
89	64	60	68.94	4.65

3.3. Analysis of Scenarios

In this section, we assessed two different scenarios in order to determine the optimal approach for our objectives. The primary distinction between these scenarios is based on the approach used to assign drones in order to fulfill hospital demands. In the first scenario, the first available drone that has enough battery charge is dispatched. However, the second scenario sorts idle drones based on their charge levels and sends out the one with the minimum necessary charge. If there is no drone with sufficient battery capacity, the demand will not be fulfilled in both scenarios.

The experimental results of both scenarios do not show any significant differences. In order to explore this further, a statistical test was done using a Confidence Interval Between Two Means, which is suggested by the Formula. 2 below, to discover that exists any differences between the above-mentioned scenarios.

$$CI = \bar{X} - \bar{Y} \pm t_{2n-2,1-\alpha/2}\sqrt{\frac{S_X^2+S_Y^2}{n}}$$

Formula. 2. Confidence Interval Between Two Means.

Statistical Hypothesis:

Our null hypothesis (H0) states that there is no difference between the two scenarios. In order to evaluate this hypothesis, we computed the 95% confidence intervals for both Key Performance Indicators (KPIs).

Confidence Interval Between Two Means Analysis:

- **Confidence Interval of KPI 1 (Mean Demand Satisfaction Rate %)**: [−2.88, 5.39]
- **Confidence Interval of KPI 2 (Mean Number of Charges)**: [−0.24, 0.47]

Since both confidence intervals contain the value zero, we cannot reject the null hypothesis with a confidence level of 95%. Therefore, we conclude that there is no statistically significant difference between Scenario 1 and Scenario 2 for both KPIs. The statistical test findings reveal that our rule in scenario 2 does not improve the model, as there is no statistically significant difference between scenarios 1 and 2. This is likely because, in scenario 1, the closest available drones, which often have lower charge levels, are allocated first. Consequently, drones stationed farther away with higher charge levels remain idle until a demand requires more charge than the closest available drones. This logic effectively aligns scenario 1 with scenario 2.

While both scenarios behave in a similar manner, there is no notable distinction in choosing to proceed with either scenario. Therefore, we decided to proceed with scenario 2 for additional analysis.

3.4. Optimal Configuration Analysis

In this section, our goal is to determine the optimal values for the 'charging threshold' and 'drone idle time' that yield the best Key Performance Indicators (KPIs). Specifically, we aim to identify a configuration that maximizes our first KPI, the 'mean demand satisfaction rate', while simultaneously minimizing our second KPI, the 'mean number of charges per drone per day'. To achieve this, we created a scatter plot (refer to Fig. 21) that displays all experimental results, with each point representing an experiment number from Table 4, with a combination of 'charging threshold' and 'drone idle time' from scenario 2. The optimal points are those closest to the upper-left corner of the plot (0, 100), indicating the highest satisfaction rates coupled with the lowest number of charges.

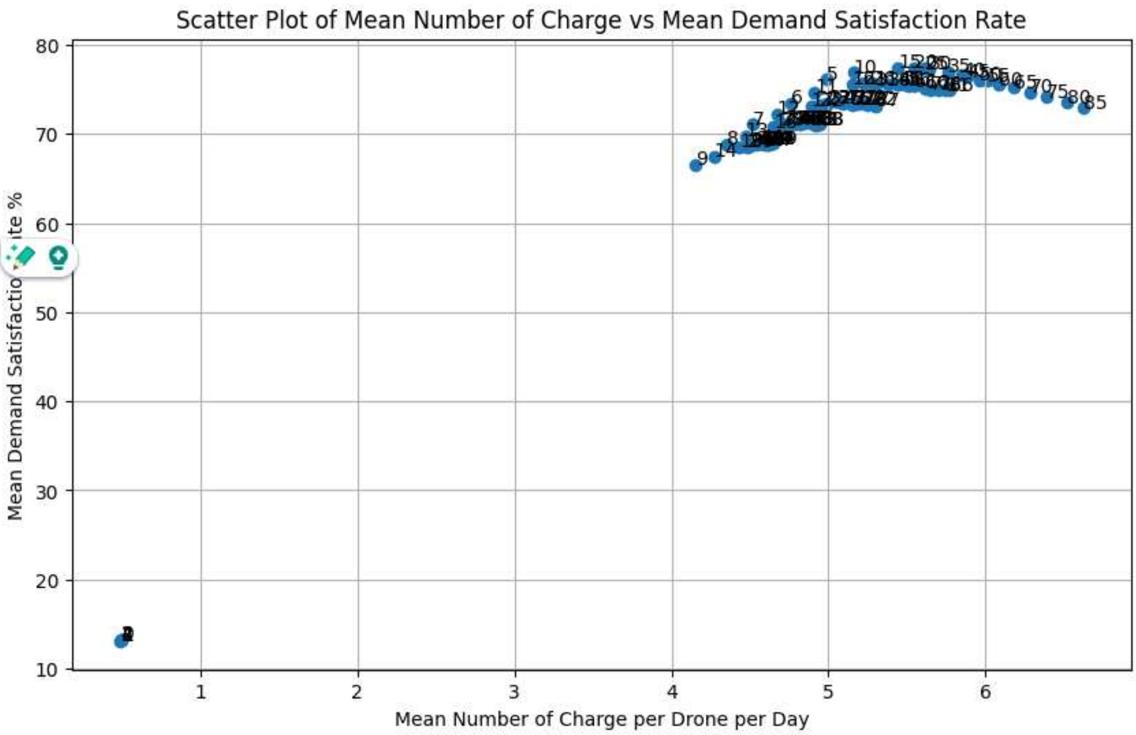

Fig. 21. Scatter plot of all experimental results in scenario 2.
Source: Based on own investigation.

To enhance the clarity of the data points in Fig. 21, we have divided the original plot into two separate graphs. The first graph displays data with a ‘mean number of charges per drone per day’ less than 1, while the second graph presents the remaining data. The revised plots are shown in Fig. 22 and 23.

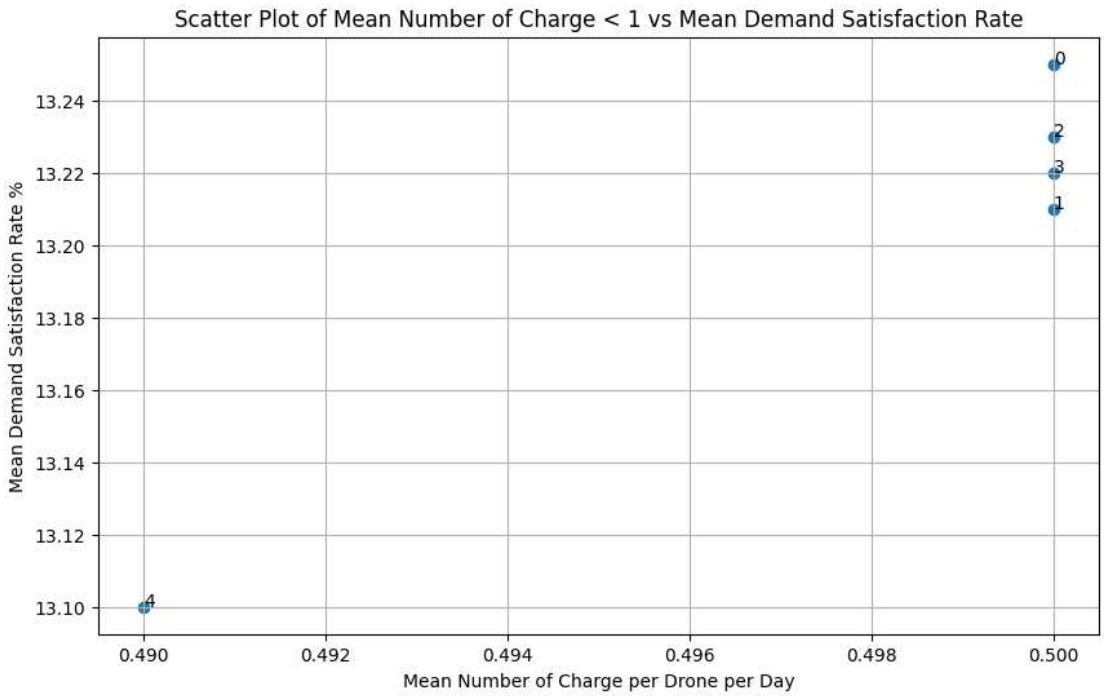

Fig. 22. Scatter plot of experimental results with a 'Mean Number of Charge' less than 1 in scenario 2.
Source: Based on own investigation.

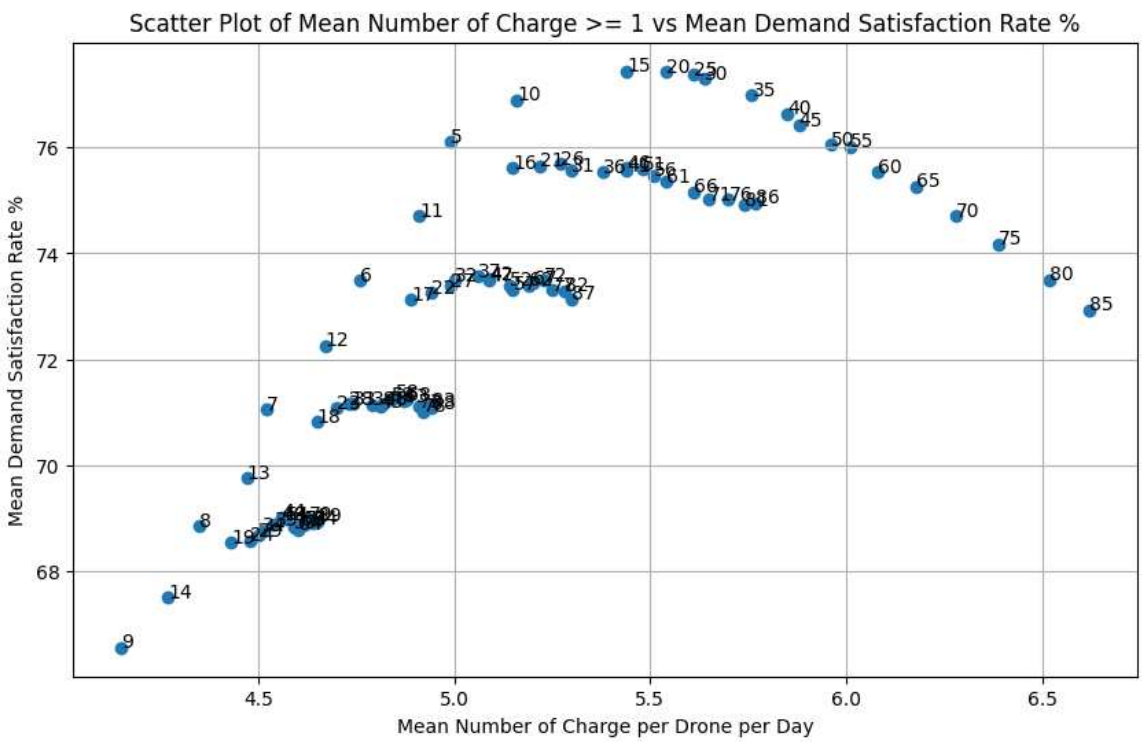

Fig. 23. Scatter plot of experimental results with a 'Mean Number of Charge' more than 1 in scenario 2.
Source: Based on own investigation.

To pinpoint the optimal configuration, we calculated the Euclidean distance of each point from the upper-left corner (0, 100). By sorting these distances in ascending order, we identified the points nearest to this ideal location as the best options. The top five optimal points are presented in Table 5 and illustrated in Fig. 24.

Table. 5. Euclidean distance of top 5 points from the upper-left corner (0, 100).
Source: Based on own investigation.

Num of EXP	Charge Threshold %	Idle Time (min)	Mean Demand Satisfaction Rate %	Mean Number of Charge	Distance
15	24	0	77.44	5.44	23.20661975
20	29	0	77.42	5.54	23.24968817
25	33	0	77.38	5.61	23.3052891
30	36	0	77.3	5.64	23.39016032
10	22	0	76.9	5.16	23.66929657

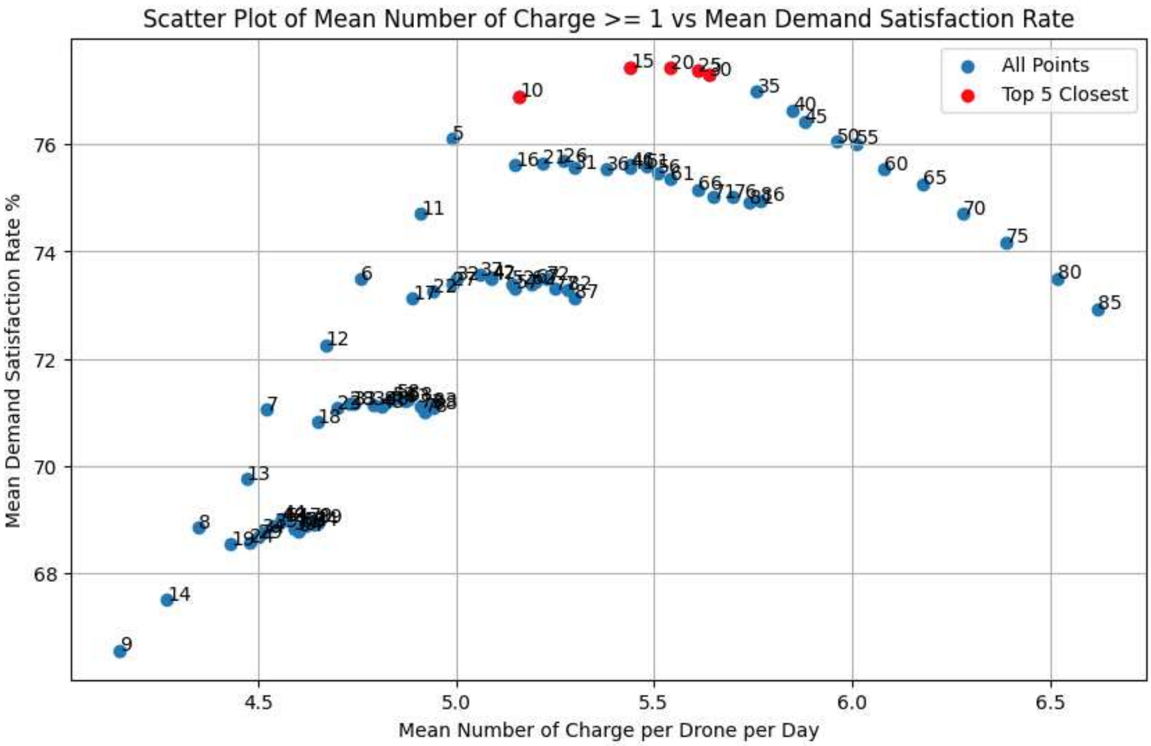

Fig. 24. The top 5 points according to their Euclidean distance from the upper-left corner (0, 100).
Source: Based on own investigation.

Based on the scatter plot analysis and the calculated distances, experiment number 15 emerges as the optimal point, being the closest to the upper-left corner coordinates (0, 100). This experiment, which involves a 'charging threshold' of 24% and a 'drone idle time' of 0 minutes, yields the best Key Performance Indicator (KPI) results.

For subsequent analyses aimed at determining the optimal number of drones, we will utilize this configuration. The results of the analysis will be presented in the following section.

3.5. Number of the Drones Analysis

As for all earlier experiments, we presumed that Zipline operates with a fleet of 15 drones (Staedter, 2016). In this section, we also examine the relationship between the number of drones and KPIs with a ‘charge threshold’ of 24% and ‘drone idle time’ of 0.

As illustrated in Table 6, we conducted experiments where the size of the drone fleet ranged from 15 to 50 units. The findings indicate that as the number of drones increases, the 'mean demand satisfaction rate' also rises, while the 'mean number of charges' decreases. Notably, with a fleet of 45 drones, the hub can meet 100% of demands, however, acquiring additional drones entails significant costs, and there is a risk of many drones remaining idle. Therefore, it is crucial to determine the optimal fleet size that allows the drone hub to efficiently meet hospitals' demands while effectively using drones. Following the section, we present an analysis of the number of drones and their impact on Key Performance Indicators (KPIs), ultimately determining the optimal drone fleet size.

Table. 6. Values of Key Performance Indicators (KPIs) corresponding to the increasing number of drones.
Source: Based on own investigation.

Num Drones	Mean Demand Satisfaction Rate %	Mean Number of Charge
15	77.44	5.44
16	80.24	5.32
17	82.86	5.18
18	85.01	5.04
19	86.99	4.91
20	88.92	4.77
21	90.34	4.65
22	91.89	4.52
23	93.1	4.4
24	94.28	4.26
25	95.24	4.15
26	96.09	4.04
27	96.92	3.92
28	97.43	3.81
29	98.08	3.7
30	98.5	3.61
31	98.85	3.49

32	99.13	3.4
33	99.39	3.31
34	99.56	3.21
35	99.65	3.14
36	99.78	3.05
37	99.84	2.98
38	99.89	2.89
39	99.92	2.82
40	99.95	2.75
41	99.97	2.68
42	99.97	2.63
43	99.99	2.56
44	99.99	2.51
45	100	2.44
46	100	2.39
47	100	2.35
48	100	2.29
49	100	2.25
50	100	2.2

To determine the optimal number of drones, it is crucial to achieve a balance between maximizing the 'demand satisfaction rate' and minimizing the 'number of charges'. Initially, we visualized these metrics against the number of drones to identify trends and potential optimal point. This analysis aids in pinpointing the ideal number of drones that achieve both objectives effectively.

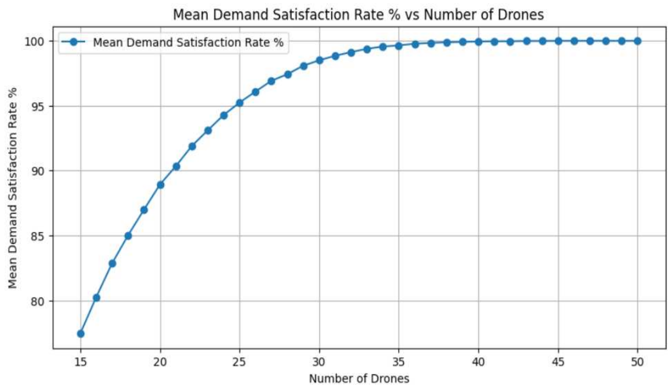

Fig. 25. The ‘mean demand satisfaction rate’ against the number of drones.
Source: Based on own investigation.

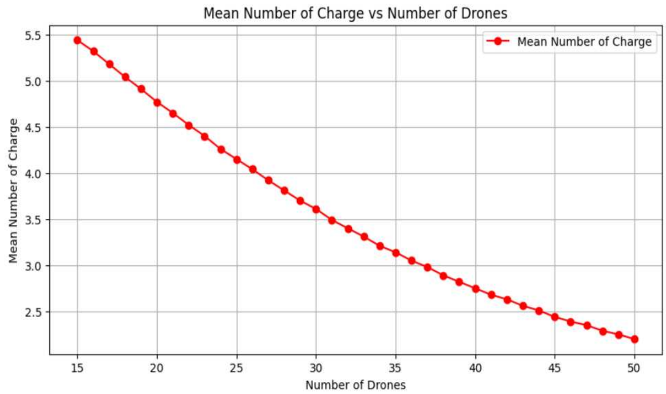

Fig. 26. The ‘mean number of charges per drone per day’ against the number of drones.
Source: Based on own investigation.

Based on our analysis of the plots, the following insights were obtained:

- **Mean Demand Satisfaction Rate % vs. Number of Drones:**
  Fig. 25 demonstrates a significant increase in the 'mean demand satisfaction rate' as the number of drones increases from 15 to 35. However, beyond 35 drones, this rate begins to stabilize, showing minimal improvement up to 50 drones. Moreover, the incremental positive changes in the 'mean demand satisfaction rate' for each additional drone are clearly depicted in Fig. 27. Remarkably, after the deployment of 35 drones, the increase in the 'mean demand satisfaction rate' becomes negligible.

- **Mean Number of Charges vs. Number of Drones:**
  The plot in Fig. 26 shows that the mean number of charges required decreases as the number of drones increases. This is anticipated because a larger fleet can distribute the workload more evenly, reducing the frequency with which each drone needs to recharge. Notably, the slope of the graph is steeper from 15 to 30 drones, indicating a more rapid decrease in the number of charges. After 30 drones, the slope becomes less steep, suggesting a slower rate of decrease in charging frequency.

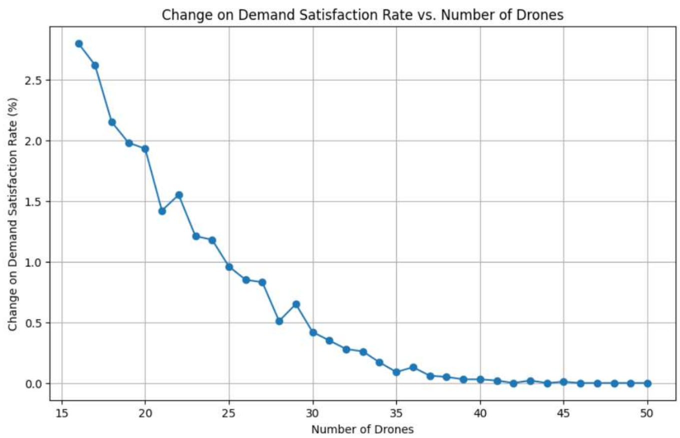

Fig. 27. The amount of incremental positive change in the 'demand satisfaction rate' by increasing the number of drones.
Source: Based on own investigation.

Based on the insights obtained from the visualizations, the optimal number of drones appears to be around 30 to 35. By taking into account the cost of adding drones, this fleet size efficiently balances the goals of maximizing the demand satisfaction rate and the minimization of the number of charges.

3.6. Conclusion

This chapter is dedicated to providing a detailed overview of an experimental study conducted to further advance our work on the last-mile delivery of medical supplies using drones. Building on the methodology and conceptual model outlined in previous chapters, we focused on the experimental design, execution, and evaluation of simulation results to identify optimal strategies for drone recharging and distribution.

We designed our experiments to test different 'charging thresholds' and 'drone idle times', aiming to enhance key performance indicators: demand satisfaction rate and the number of charging cycles per drone per day. Our simulations evaluated the impact of various configurations on the operations of a drone hub serving stochastic hospital demands for medical supplies.

Through precise experimental setup, including the determination of warm-up periods, run lengths, and number of replications, we ensured robust data collection. Then we implement all our experiments with both scenarios and after that, we compare our two different scenarios. The experiments revealed that no significant difference existed between the two drone allocation scenarios tested. Thus, we proceeded with scenario 2, which prioritized dispatching drones based on minimal required charge. Furthermore, our analysis identified the optimal recharging configuration with a 24% charge threshold and 0 minute idle time, which achieved the best balance between a high demand satisfaction rate and a minimum number of charging drones to decrease the battery degradation rate. Moreover, further analysis explored the impact of fleet size, revealing that increasing the number of drones significantly improved demand satisfaction rates up to 35 drones, after which the benefits are not considerable.

In conclusion, the optimal setup for our drone hub to optimally recharge drones involves a charge threshold of 24% and drone idle time of 0 minutes, with a recommended fleet size of 30-35 drones to effectively balance operational efficiency and resource utilization.

CHAPTER 4

4.1. Conclusion

The concept of supply chain management (SCM) has developed a lot since it became popular in the 1990s, and in recent years has become a significant theory in the healthcare industry as it has become one of the primary tools to drive efficiency and reduce cost in the system (Min et al., 2019; Elmuti et al., 2013). Healthcare SCM also has many issues, especially in logistics, as costs and their complexity continue to rise (Volland et al., 2017). Another under-researched domain within SCM & logistics is last-mile delivery which has been known to be inefficient, costly, and environmentally unsustainable (Ha et al., 2022). As a result of these challenges, drones have been deemed a viable solution as they can provide faster, cheaper, and eco-friendly delivery services (Mohammad et al., 2023). However, more study is required to fully realize their benefits and transform the delivery of healthcare (Gao et al., 2023). According to Asadi et al. (2022), a significant issue that needs consideration is the restrictions associated with drone batteries such as limitation of drone battery life and its charging time. In this research, the application of drones in last-mile delivery systems for the healthcare supply chain has been investigated, specifically looking at drone's recharging and distribution methods to improve their effectiveness and address battery-related limitations. To achieve this goal, Discrete Event Simulation methodology was used to track discrete events across time to model and analyze complex, stochastic systems. This approach, which focuses on significant events influencing system dynamics, works well for analyzing systems with rapid behavioral changes (Stamatti, 2024, Robinson, 2014). Additionally, the data used in our analysis is sourced from a study by Asadi et al. (2022), which offers a real-world case study utilizing Zipline drones, which are used to transport medical supplies in Rwanda, Africa. Based on a DES approach, we evaluated various recharging strategies (that include different charging thresholds and drone idle time before recharging them) to assess the effects on the identified KPIs like demand satisfaction rate and the number of charging cycles per drone per day. Moreover, our experimental design involved two primary scenarios for drone dispatching: In the first scenario, to fulfill the demand, the drone hub checks for idle drones and dispatches the first available drone that has enough charge. In the second scenario, the drone hub checks for idle drones with sufficient charge sorts them according to their charge levels, and then dispatches the drone with the minimum charge necessary to meet the demand. Having modeled and analyzed both scenarios, we could not detect a difference between the two, as a result, there is no significant difference to continue with each scenario. Hence, we moved to the second scenario to examine it for further analysis.

Our simulations showed that the best configuration for recharging was when the battery threshold level was at 24 % or less and the drone's idle time of 0 minutes. This configuration was optimal in achieving a high demand satisfaction rate while at the same time, the charging frequency was low enough to decrease the battery degradation rate. Furthermore, the results of the analysis of the optimal number of fleets showed that the addition of more drones has a positive effect on the number of drone charging cycles and also increases the demand satisfaction rate to an optimal of 35 drones after which the rate stabilizes. Therefore, it was advised that a fleet of 30 to 35 drones is the most suitable when it comes to effectiveness and efficiency.

This research highlights the significance of proper drone management when it comes to last-mile delivery especially in the health sector due to the need for quick delivery of medical supplies. The study also underscores the importance of precision in charge strategies of the drones which would significantly enhance the service delivery. In conclusion, this research shows that drone-based delivery solutions are feasible and have tangible benefits in the context of healthcare supply chain management. When recharging and distribution strategies are well coordinated, it becomes easy to overcome the challenges of last-mile delivery, thereby improving health delivery systems.

4.2. Limitations of the Study and Recommendations

To improve the reliability and relevance of the results, it is recommended that future research attempts overcome the many constraints of this study. First of all, the study's simulation model assumes that all flying circumstances are ideal and ignores possible real-world problems like severe weather conditions, the need for maintenance, and the order in which drone operations should be prioritized in an emergency. To present more real-life cases, these elements have to be regarded in the future study. Second, the model also does not capture changes in the performance of the drones and their batteries over time, since it is framed with the drones maintaining constant performance throughout the course of the study. This work reduces the impact of battery degradation and its influence on drone reliability and range to a basic level. For a better understanding of the impact of battery degradation and maintenance schedules on operation efficiency, it is recommended to include more detailed models of these components in future research. Furthermore, we do not account for waiting times for demands, and if a demand is made and there are not any drones available, it cannot be completed. Future research can add backlogging unsatisfied demands if it suits the application.

In conclusion, as this study provides useful information concerning how to increase the effectiveness of the use of drones for last-mile delivery in the healthcare sector, addressing these challenges and exploring the recommended fields will contribute significantly to enhancing the efficiency of future research and practical application of drone technology in supply chain management.

Appendix

Appendix I - The time series of simulation output with different configurations that are used to determine the best configuration to find the warm-up period. The source of all figures is based on our own investigation.

For Scenario 1:

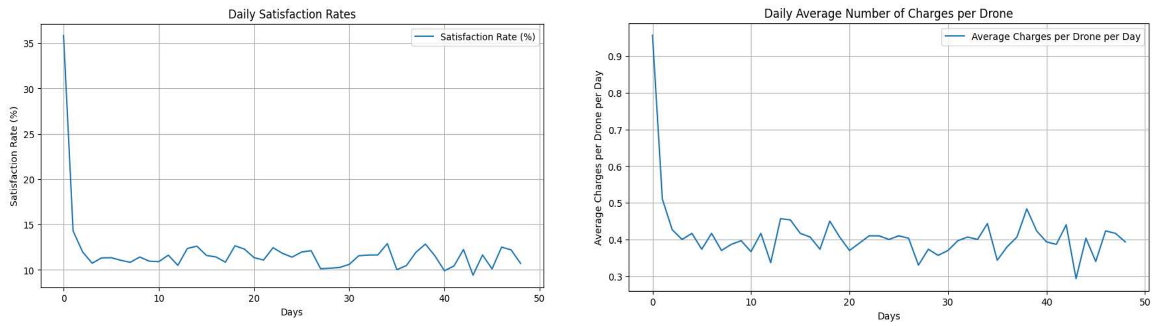

Fig. 28. The time series of simulation output for a charging threshold of 6 % and drone idle time of 60 minutes.

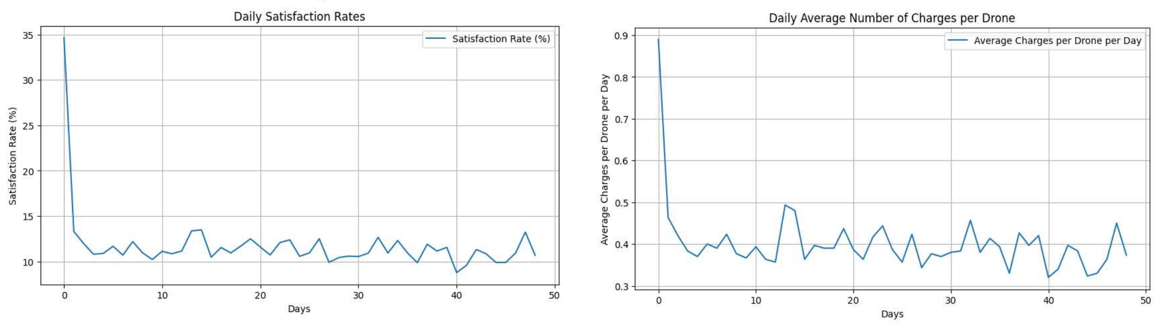

Fig. 29. The time series of simulation output for a charging threshold of 6 % and drone idle time of 30 minutes.

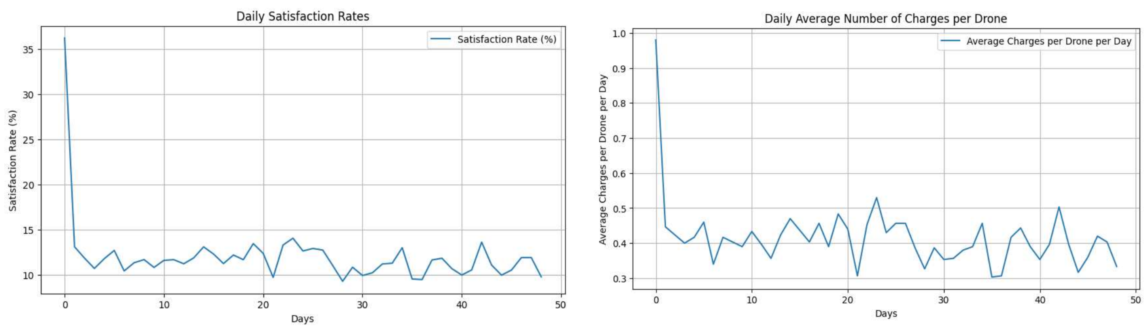

Fig. 30. The time series of simulation output for a charging threshold of 6 % and drone idle time of 0 minutes.

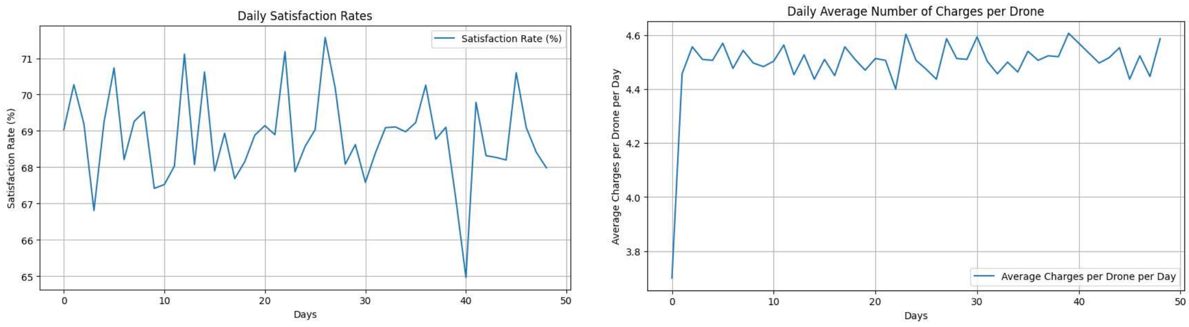

Fig. 31. The time series of simulation output for a charging threshold of 37 % and drone idle time of 60 minutes.

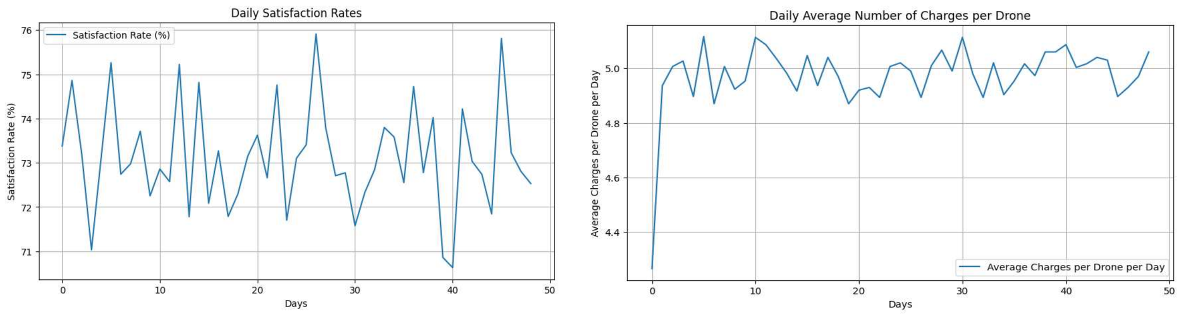

Fig. 32. The time series of simulation output for a charging threshold of 37 % and drone idle time of 30 minutes.

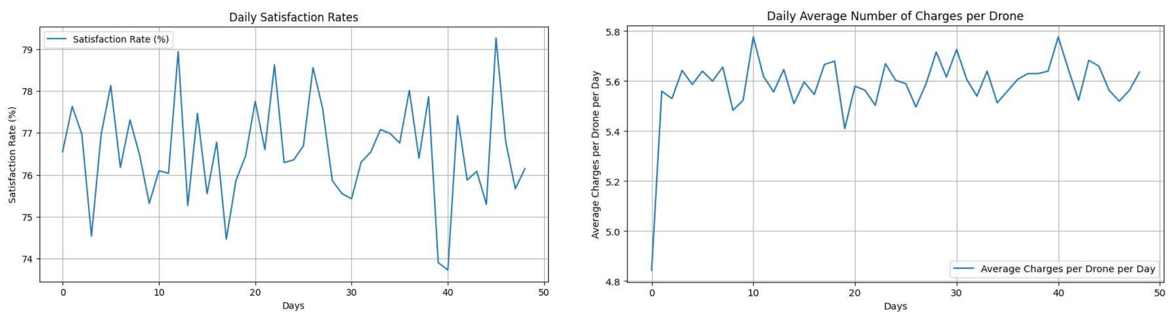

Fig. 33. The time series of simulation output for a charging threshold of 37 % and drone idle time of 0 minutes.

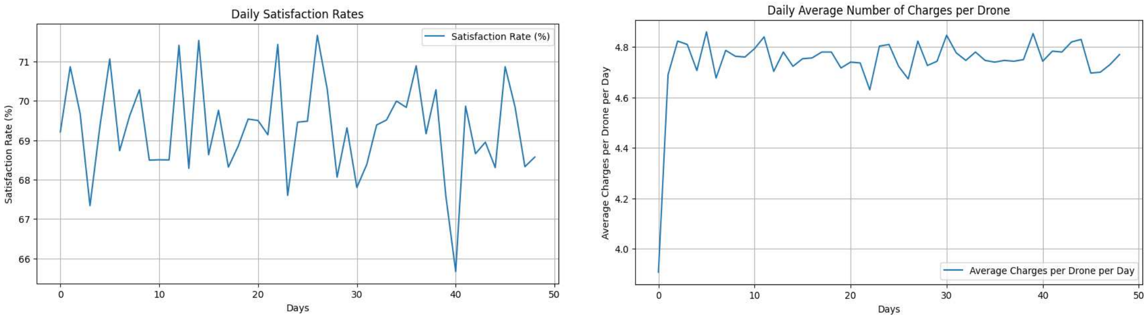

Fig. 34. The time series of simulation output for a charging threshold of 58 % and drone idle time of 60 minutes.

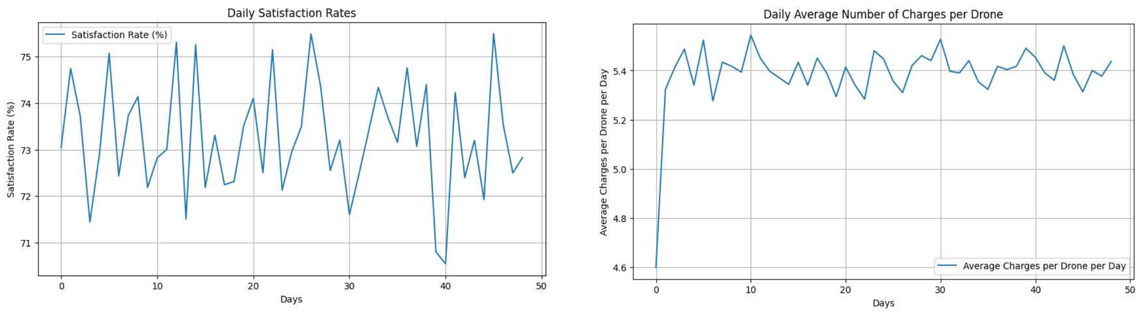

Fig. 35. The time series of simulation output for a charging threshold of 58 % and drone idle time of 30 minutes.

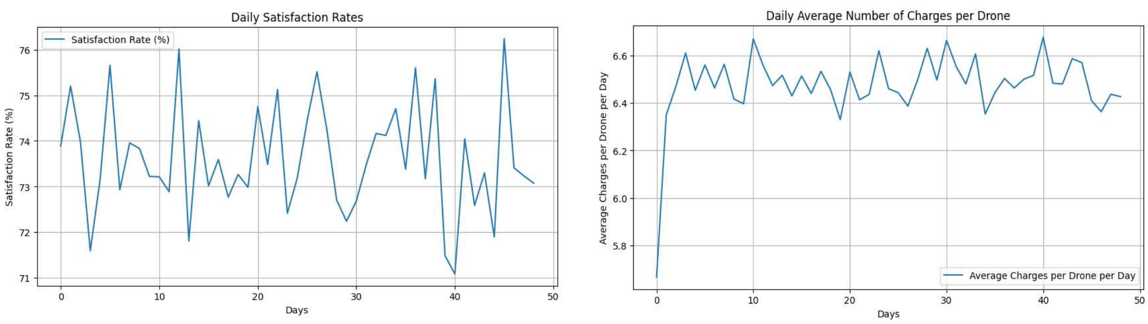

Fig. 36. The time series of simulation output for a charging threshold of 58 % and drone idle time of 0 minutes.

For Scenario 2:

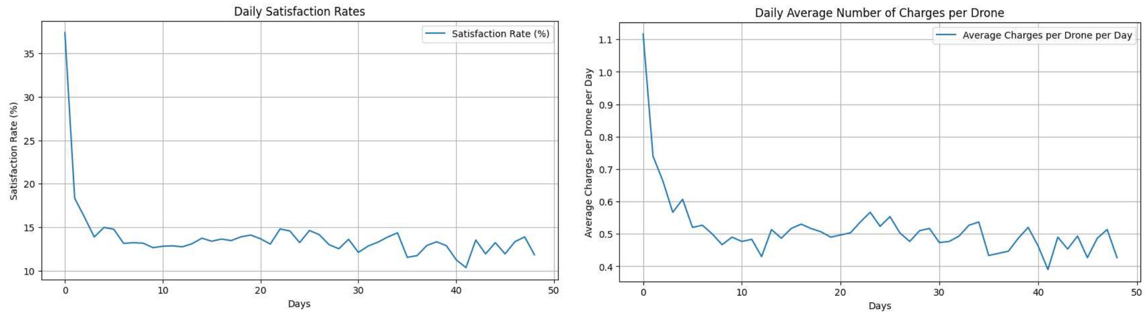

Fig. 37. The time series of simulation output for a charging threshold of 6 % and drone idle time of 60 minutes.

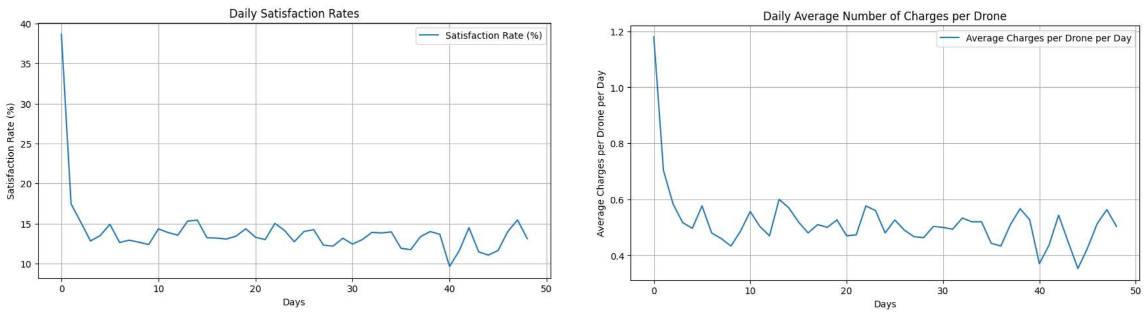

Fig. 38. The time series of simulation output for a charging threshold of 6 % and drone idle time of 30 minutes.

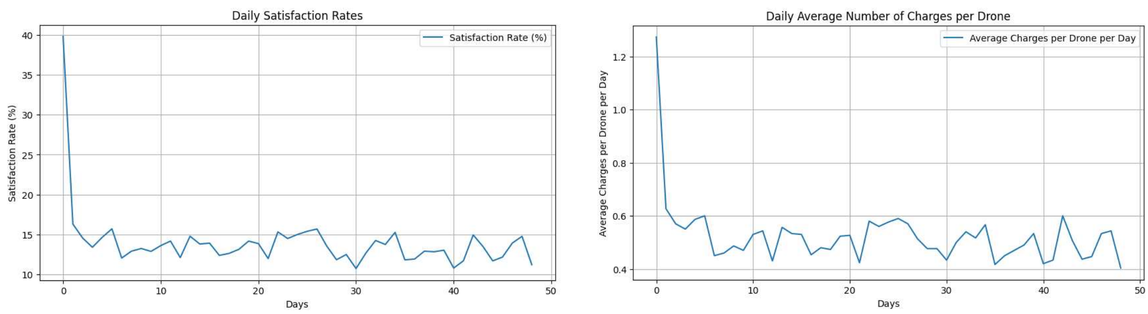

Fig. 39. The time series of simulation output for a charging threshold of 6 % and drone idle time of 0 minutes.

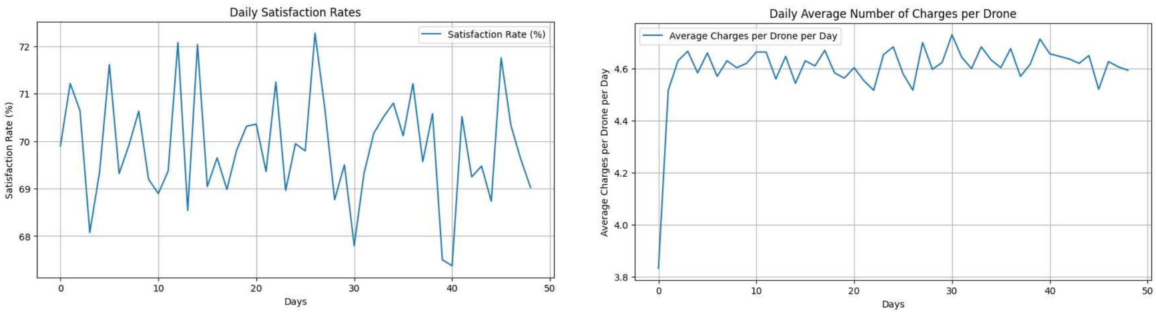

Fig. 40. The time series of simulation output for a charging threshold of 37 % and drone idle time of 60 minutes.

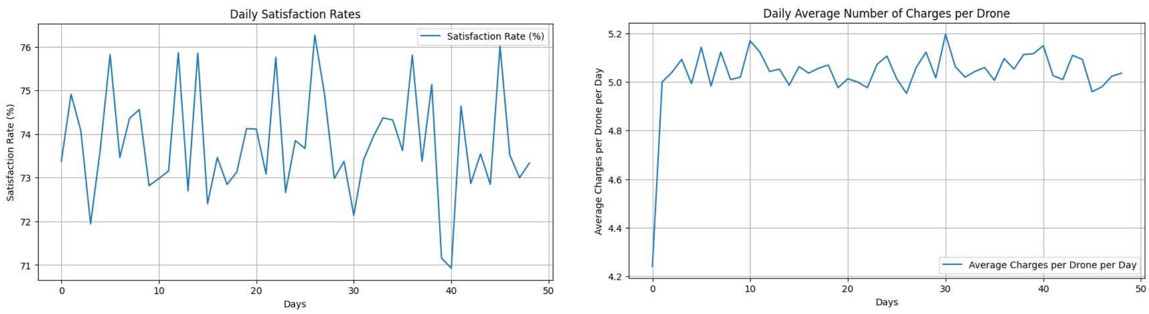

Fig. 41. The time series of simulation output for a charging threshold of 37 % and drone idle time of 30 minutes.

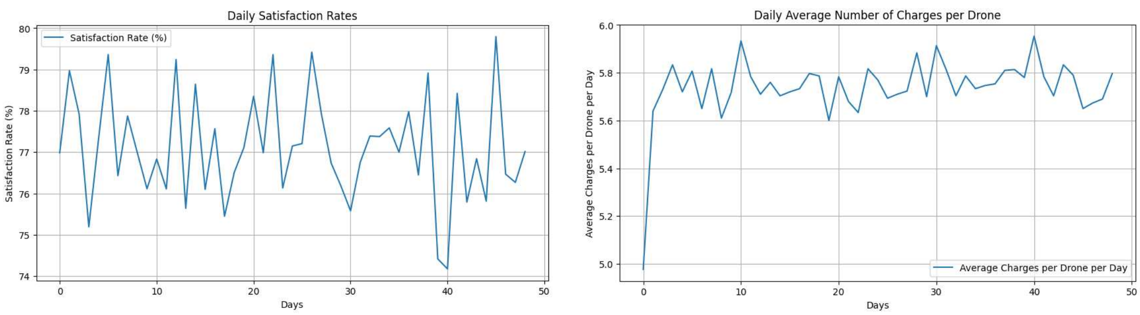

Fig. 42. The time series of simulation output for a charging threshold of 37 % and drone idle time of 0 minutes.

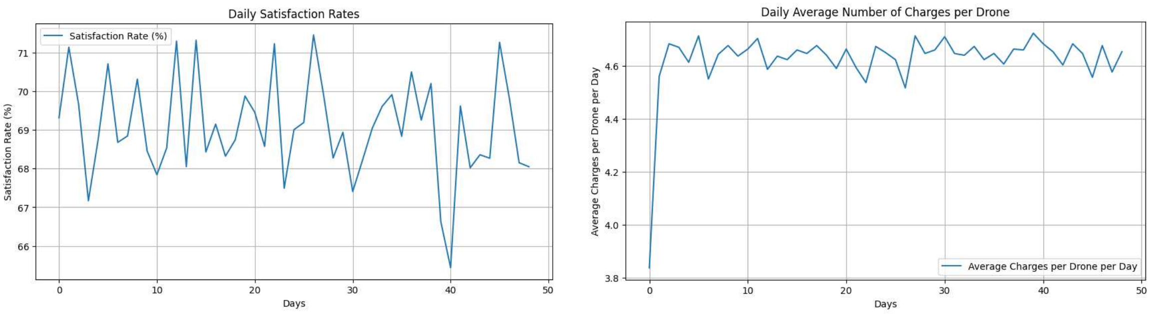

Fig. 43. The time series of simulation output for a charging threshold of 58 % and drone idle time of 60 minutes.

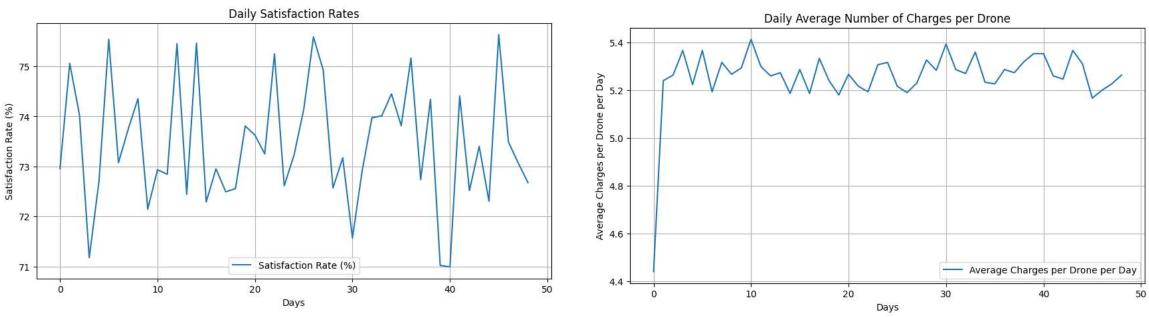

Fig. 44. The time series of simulation output for a charging threshold of 58 % and drone idle time of 30 minutes.

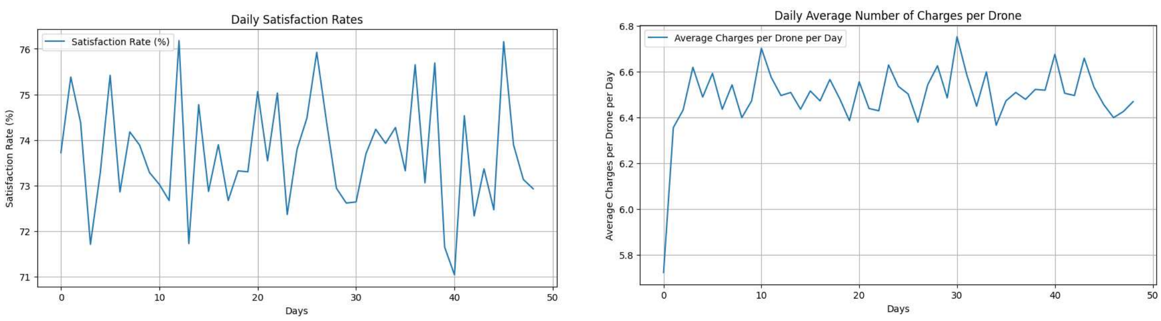

Fig. 45. The time series of simulation output for a charging threshold of 58 % and drone idle time of 0 minutes.

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