AN OPTIMIZATION MODEL FOR DETERMINING THE FLEET SIZE FOR A ROBOT-SHARING SYSTEM

by

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ABSTRACT

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Different innovative concepts are aiming to improve last-mile urban logistics and reduce traffic congestion. Congested metropolitan cities are implementing last-mile delivery robots to make the delivery cheaper and faster. A key factor for the success of Automated Delivery Robots (ADRs) in the last-mile is its ability to meet the fluctuating demand for robots at each micro-hub. Delivery companies rent robots from micro-hubs scattered around the city, use them for deliveries, and return them at micro-hubs. This paper studies the dynamic assignment of the robots to satisfy their demands between the micro-hubs. A Mixed-Integer Linear Programming (MILP) model is developed, which minimizes the total transportation costs by determining the optimum required fleet size. The result determines the number of robots required for each planning period to meet all the demands. It provides algorithms to operate and schedule the robot-sharing system in the last leg of the delivery in dense urban areas.

AN OPTIMIZATION MODEL FOR DETERMINING THE FLEET SIZE FOR A ROBOT-SHARING SYSTEM WITH TIME WINDOWS

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1. INTRODUCTION

1.1. Overview

The growth of freight transportation generates the need to improve the mobility of people and goods in metropolitan areas through innovation and technology. Urban traffic congestion, especially in commercial and business districts, is prevalent in many metropolitan areas around the country due to the high concentration of human activities within a limited transportation network. In any given community or region, transport plays an integral role in the socio-economic activity. However, conventional urban transport planning has ignored its importance and has confined its attention to the performance of the transport network itself, avoiding the socio-economic effects that are more difficult to quantify.

Freight transportation is a primary component of all supply-chain and logistics systems, and very important for any region and state. An integral part of the urban goods movement is pickup and distribution operations. Nonetheless, rapid urbanization, growing demand, and higher expectations of consumers have exacerbated the urban challenges of freight movement. By facilitating improvements in logistics, and sufficient investments in the freight transportation system help to increase efficiency. The management of the supply chain systems is logistics. It requires regulating the flow of goods, information, and other resources between the point of origin and the point of consumption in order to satisfy customer requirements. It takes considerable interaction, teamwork, networking, and expertise to get domestic or foreign freight to the proper destination on time and safely. Small packages and parcels that are common for the fulfillment of e-commerce orders can be transported and distributed using parcel carriers. The distribution of larger goods can also often be done very economically by parcel carriers (Supply Chain Quarterly, 2021).

Besides, e-commerce has a significant effect on the economy of any country in the world and gives much room for innovation in this sector, which is likely to improve the overall economic efficiency of any country. E-commerce has grown over the last couple of years, with the revolution of digital technology. In developed economies worldwide, it has influenced pricing, product supply, transportation trends, and consumer preferences. The e-commerce industry continues to grow on an annual basis, with 12.70% of total sales in 2019. The total sale has increased by more than 20% on the year 2020 due to the pandemic as the people's dependence on the e-commerce has been increasing lot more since then.

E-commerce Share of Total Global Retail Sales from 2015 to 2021

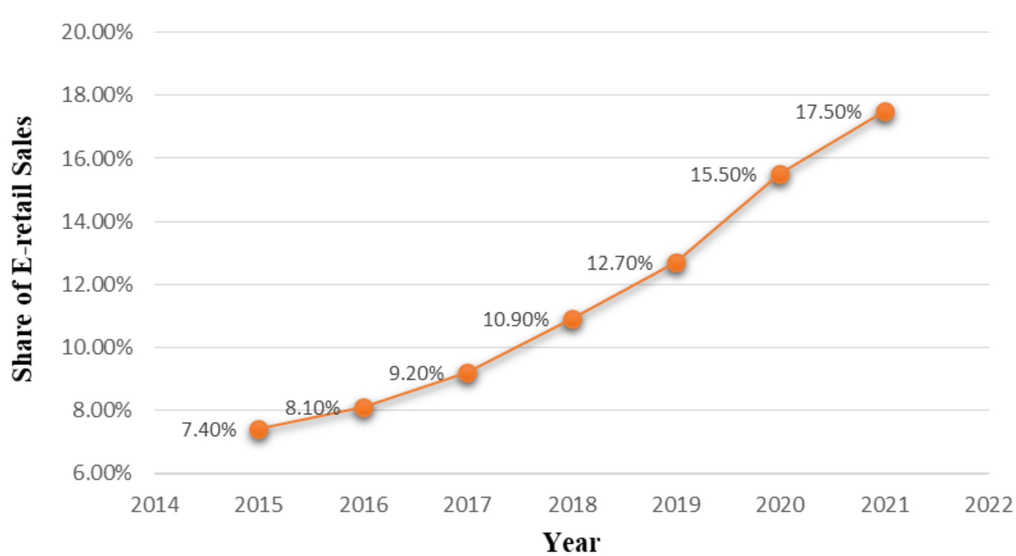
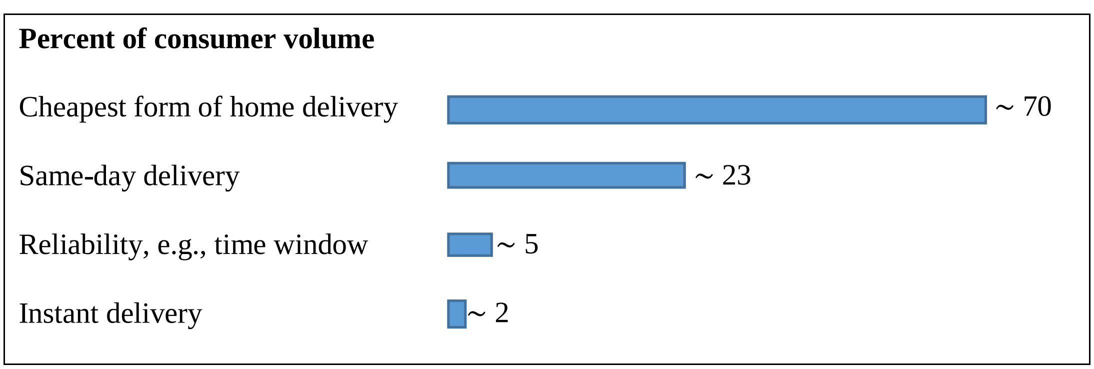


Figure-1: Global E-commerce Market Size 2015-2021

Source: Future of E-Commerce: Innovations to Watch Out For, 2021

An essential component of e-commerce is the last-mile delivery, which refers to the distribution of goods from the local distribution centers to the customers. The last-mile delivery typically varies from a few blocks to 50 or even 100 miles. The primary aim of the last-mile delivery is to deliver a package to the consumer as quickly and efficiently as possible. It is critical for any company today, from multinational business to smaller e-commerce retailers, to understand why last-mile delivery is so important for everyone selling a product, as is understanding its tremendous impact on consumer satisfaction and loyalty. A waiting period of 5-7 days for a parcel to deliver was previously considered normal; however, today if any company takes 5-7 days to deliver the shipment, it is sure to fail as there are several suppliers who are already shipping packages in the matter of a few hours (Fixlastmile, 2021). According to a report by McKinsey and Company, nearly 25 percent of customers are willing to pay a significant amount for the chance of same-day or instant delivery, but 70 percent of the consumers would still choose the option of having the cheapest delivery to their home. On the other hand, younger consumers are more inclined to prefer same-day and instant delivery over regular delivery, and this share is likely to increase day by day (McKinsey & Co, 2016).

Table-1: Share of consumers choosing different delivery options (McKinsey & Co.)



The last-mile delivery is the last leg of the whole system, and the setting up of the pickup-delivery process of the goods must be understood. The driver of the last-mile delivery van starts to look for parking near the customer's place. Sometimes, because of a lack of available parking options, the driver has to park on the road illegally. The choice of where to park requires consideration of the vehicle size, package's size and weight, and the distance to the customer's location. Once the vehicle is parked, the driver unloads the goods and walks to the customer's location. The goods must be delivered to the address mentioned by the customer. Walking to the back of a building, taking the stairs, or finding an office in a large building may be needed by the driver. If there are more deliveries within that area, the driver repeats operations until all the goods have been delivered.

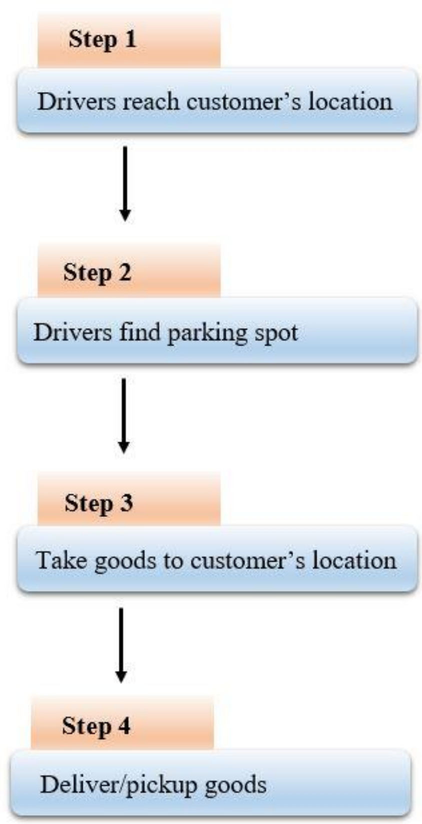


Figure-2: Process of a typical last-mile delivery

The last-mile delivery of parcels has some adverse effects of transport on road congestion, safety, and pollution in dense urban areas. According to Holguín-Veras (2019), urban freight traffic due to online shopping and e-commerce doubled between 2009 and 2018. For every 25 Americans, there was a single regular internet distribution in 2009. Today, for every eight Americans, there is one. He also says that by 2023, this traffic would again double (Curbed, 2019). According to the MHI Annual Industry Report, by the end of 2050, urban freight is projected to rise by 40 percent, which means that the number of trucks will rise, contributing to congestion in residential and downtown areas as goods are being transported and delivered by trucks mostly (MHI, 2020). According to studies from the Texas A&M University Transportation Institute, this rapid growth explains why trucks, actually 7 percent of U.S. traffic, generate 28 percent of the nation's congestion (Curbed, 2019). One of the contributing factors towards the current level of congestion in our metropolitan areas is the last-mile delivery vans and trucks which require multiple stops for completing all the deliveries. Research by the Urban Freight Lab showed that half of the trucks making deliveries in downtown Seattle were forced to park on busy streets in illegal spots or double-park creating traffic congestion in the city center (Curbed, 2019). Most packages delivered in the offices and commercial places are ordered by the consumers and are meant to be taken home. This causes an overwhelming number of packages arriving in the city centers and creating congestion. If delivery vehicles get stuck due to heavy traffic, companies spend more on fuel and labor, and congestion costs as much as 2 to 4 percent of urban GDP (Smart City Lab, 2019). In reality, last-mile delivery is seen as the most costly part of the distribution process. The cost of the last-mile can be as much as 28 percent of the cost of the entire supply chain, according to the Council of Supply Chain Management Professionals.

In the last-mile of the parcel delivery industry, technology is transforming the level of innovation in product and service offerings and changing the way delivery companies communicate with customers. The most innovative concepts are concentrating on delivering the packages to the customer with the aid of electric and autonomous vehicles to reduce last-mile congestion and costs. Big tech companies like Amazon, DHL, and UPS as well as some supply chain management companies are experimenting with drones and automated delivery robots to deliver parcels (Post & Parcel, 2020). The key players in this last-mile delivery system are the established delivery companies like UPS, FedEx, DHL, and the U.S. Postal Service. Google, Uber, Instacart, and Task Rabbit are examples of technology firms, all of which use crowdsourcing for deliveries. The most famous example of a retailer that would arrange its own logistics is Amazon. In February 2016, Google obtained a patent for an automated delivery vehicle that could carry anything from the packaged purchased online and can even deliver pizza (Arcadis, 2019). Drones are one of the first unmanned delivery ideas that have drawn attention due to Amazon's announcement as they plan to use drones to deliver goods to customers. However, they have a small carrying capacity which is ranging from 2 to 5 pounds. In addition to this, they a limited range of 10 to 30 miles they can cover (Naiop.org, 2018). In addition, drones have some drawbacks and the application of this technology is not accepted for flying in populated areas (Ansys, 2020). Larger drones need at least 21 square feet of the landing area to transport heavier parcels which is an issue in dense urban neighborhoods (Naiop.org, 2018). As a solution to this, various companies in the supply chain and logistics organizations are dealing with the last-mile automated delivery robots for congested urban environments. These are the sidewalk delivery robots that deliver products to customers without a delivery person's intervention. These robots can either be dropped off from a truck to deliver goods to the customers or can also be dispatched from micro-hubs within communities. They have a higher carrying capacity than drones and are less costly and less difficult to operate because they travel on the ground rather than by air.

There is an enormous challenge in determining how these delivery robots will be deployed on suburban and densely populated areas where trucks, cars, bikes, pedestrians and, more travel in different directions at different times. These challenges still need to be worked out before these sidewalk robots are deployed on the roads. One of the most known automated delivery robots is the Starship (created by founders of Skype) and Dispatch (created by researchers from Massachusetts Institute of Technology and University of Pennsylvania) (TechCrunch, 2020; Fast Company, 2015). These robots can be used for delivering small packages, grocery, laundry, pizza and many more. Starship automated robots are deployed on different college campuses to deliver food to the students. Well, these mobile robots have already distributed food and groceries in urban areas in the U.S. and several other parts of Europe, for example, Starship Technologies, a London-based company, revealed its delivery robots in March 2016 and partnered with Domino's to deliver pizzas to customers (Starship, 2017). Starship Technologies is currently rolling out its robot delivery services to corporate and college campuses in Washington D.C. It plans to add more cities to its list as demand for contactless delivery during the pandemic has grown exponentially (TechCrunch, 2020). Similar to drones, these sidewalk delivery robots are faster in delivering customer’s orders to their doorstep and the flexibility of choosing a convenient delivery time. The delivery cost of parcels in the delivery robots is somewhat less than the drones which is an additional benefit. But, delivery robots have a shorter range in distance covered, and sometimes, obstacles on the road like pedestrians can be a problem for them.

Figure-3: Sidewalk Delivery Robot (Source: Starship)

Such automated delivery robots can be a last-mile distribution solution, but they do have some drawbacks of their own. One of them is the operation speed of these robots is equal to a human walking speed, which is why they need to use the sidewalks. Starship and other robots compete for curbside space with pedestrians and people in wheelchairs while using the sidewalks and received disapproval for operating on sidewalks of many cities. For example, San Francisco has only legalized Postmates' robots to operate temporarily on a limited number of sidewalks for making deliveries. As a result, these automated delivery robots must move slowly in human jogging speed and be very careful of the pedestrians. Nevertheless, permission has been granted to Starship robots to work in at least eight U.S. states (Wired, 2020). Such robots have a battery life of 2 hours, which means they can run at a stretch for 6 km, and they need to return before recharging their battery (Swiss Post, 2020). Different automated delivery robots have different speeds and battery life, this determines which robots can operate on the sidewalks and which ones on the road.

1.2. Problem Statement

Most of the delivery systems which include automated delivery robots for the last leg of the delivery have been designed as a two-tier distribution system. Here, a truck brings the automated robots to a drop-off location with packages inside it; the robots are dispersed, transported, and returned to the truck after completing the delivery (Jennings et. al., 2019). Anyone living in densely populated areas is very used to the issues of commercial vehicle curbside parking. In most dense and congested urban areas, curbside parking spaces and freight loading and unloading areas are very small and usually insufficient at some times of the day. The drivers have a hard time finding a parking location near the address of the customer and for this, they are parking on-road to complete the delivery. These vehicles carrying the automated robots face some issues related to traffic flow, congestion, and transport policy. In addition, these vehicles not only suffer from the congestion in the local streets, sometimes they generate the congestion while parking at certain times of the day in densely populated areas when time window-based deliveries are expected to be fulfilled. In these cases, micro-hubs are the best solution for simplifying this problem in the last-mile of the distribution system. Micro-hubs can be fixed stores built in and around medium to high-density areas near the customer's locations allowing the distribution of last-mile parcels (Mabe, 2020). The size of the micro-hubs can vary according to the density of demand for a given area. Truck parking will not be a concern for the micro-hubs. This can also reduce the problem of creating congestion by delivery vehicles in the city centers. The parcels would be transferred from the trucks to the automated robots in the micro-hubs to allow delivery in communities nearby. The robots try to complete their deliveries until their battery drains out which can vary from 2 hours to 12 hours at a stretch which finally determines how far they can travel to complete the deliveries.

1.3. Research Objectives

The main motivation of this research lies in the fact that a large number of freight vehicles, mostly trucks in the city centers tend to create congestion when the parking spaces are limited. But the recent trends of same-day delivery has increased the number of trucks entering into the cities and thus, creating more congestion than ever. As a remedy to this problem, automated delivery vehicles are planned to be distributed in the urban cities which will reduce the congestion.

Additionally, the above mentioned traditional way of delivering goods has been creating other problems too, such as delivery delays, high level of emissions, and high operating costs. Therefore, different delivery companies like UPS, Amazon, and FedEx are supporting the initiatives of implementing automated delivery robots in the last-mile delivery. More specifically, this research focuses more on the last leg of the delivery system with sidewalk automated delivery robots, than the truckload shipments and other parts of the delivery system.

The main objective of this research is to analyze a different approach by considering an automated delivery robot-sharing network to make the last-mile delivery more convenient for the delivery companies. Therefore, we formulated a mathematical programming problem that can be applied to effectively plan the dynamic assignment of robots in a robot-sharing network between the micro-hubs for the last-mile delivery inside small communities in densely populated areas. This research aims to demonstrate the design of a robot-sharing network that reduces transportation costs by specifying the optimal size of the robot fleet by minimizing unmet demands for robots, unused robots, and the need to move empty robots between micro-hubs to meet demand.

The key contribution of this research is providing a dynamic approach for planning and analyzing robot use effectively with certain demands which can reduce the curbside parking issue for the last-mile delivery. In order to solve the proposed problem, the study followed several steps which are stated below:

a) First of all, a thorough literature review was conducted on the topics related to urban freight logistics, last-mile delivery to understand the traditional and the current practices followed to solve different issues and problems.
b) Then, the theoretical concept was developed from which the variables, parameters, and the objective function of the model were determined.
c) Then, the model was formulated that represents the problem and it was coded in an Optimization Solver.
d) Later, various experiments were conducted with different problem sizes and assumptions in order to show the effectiveness of the model.
e) Finally, the conclusions were obtained from the application of the proposed method, as well as recommendations for future research.

The figure below shows us the representation of methodology adopted for understanding, conceptualizing and formulating, and solving the problem efficiently.

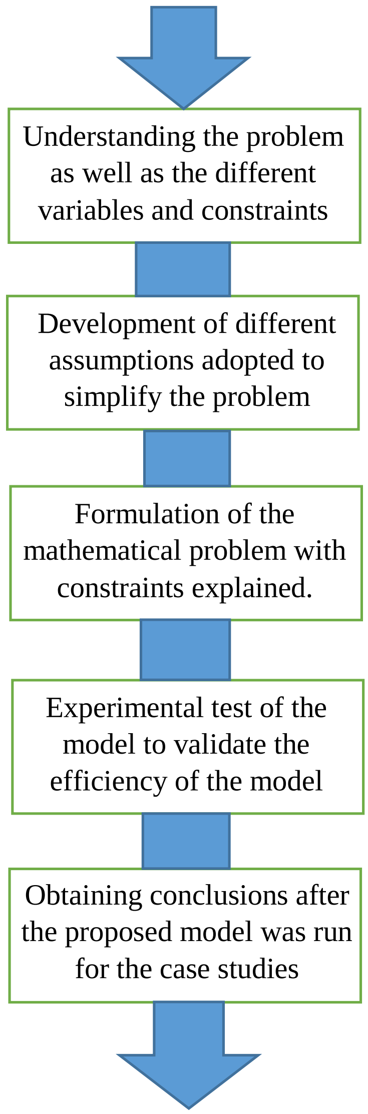


Figure-4: Illustration of the steps followed to solve the problem

1.4. Thesis Organization

The research study conducted is structured as follows: first, an introduction in Section 1; second, a literature review of studies related to last-mile delivery in urban areas, urban freight delivery methods, and recent innovations in the last-mile delivery were conducted in Section 2. Then in Section 3, the problem overview, mathematical formulation, and solution methodology of the model developed were described. Later, the model was applied in various problem sizes, and the results, along with heuristic approach, are presented and discussed in Section 4. Section 5 concluded with the findings of the research as well as the recommendations on the future work.

2. LITERATURE REVIEW

2.1. Overview

The goal of the literature review is to identify all the frameworks, methodologies and methods that have been applied in other literature. The study reviewed different research intending to obtain a better understanding of previous work carried out on this specific subject.

2.2 Urban Freight Transportation

Technology has advanced over the years and has made a significant contribution to the transport systems in making it easy to move people and goods from one location to another. Urban freight transportation is a vital component to function cities, but it is also an activity that affects the urban environment and communities. Many initiatives are being implemented to increase the performance, reliability, and efficiency of urban freight systems and to eliminate all the negative effects that may be associated with them.

Freight vehicles contribute significantly to pollution and environmental nuisances, such as emissions, noise, etc., which have a negative effect on the quality of life of urban centers. For the integrated management of urban freight transport, Crainic (2004) created an organizational and technical framework and recognized planning and operational issues. The authors have also described a formulation for one of these problems which can optimize the whole freight systems. Anderson *et. al.* (2005) evaluated how urban transportation can work in such a way that it meets urban sustainability targets that the policymakers are starting to enforce. The authors studied different distribution operations in detail and the findings from the survey indicate that the policy initiatives will differ in their operational and financial effects on distribution companies, as well as in terms of the increase in levels of vehicle pollutants.

Increased congestion in metropolitan centers during peak morning and afternoon hours is rising the cost of logistics. Improving the productivity of urban freight and commercial vehicle movements while maintaining environmental sustainability and economic development is a key challenge for transportation agencies. Therefore, Figliozzi (2011) analyzed the CO_2 emissions for different levels of congestion and time-definitive customer demands. The results indicate that suburban depots and tight time windows tend to increase emissions on average, although some other factors are contributing to the emissions of CO_2.

Another researcher, Giuliano (2012) points out that freight can be viewed as adding congestion on the major highways, though freight is a relatively minor component of the overall task of urban transport, between 10% and 15% of the volume of metropolitan road traffic. In addition, congestion impacting passenger transport on both road and rail networks can both affect, and be affected by, long-distance rail lines, dedicated truck routes and, port-related roads. Freight can cause delays at road and rail intersections, thus contributing to disputes between passengers and freight on shared routes.

Cui *et. al.* (2015) conducted a study that provides a broad discussion of the connections between urban freight transport and urban planning. The authors state that urban freight transport matters a great deal for cities and economic growth in regional, national and global contexts. Simultaneously, a discussion has also shown that the social and environmental effects of urban freight transport are of great concern to governments and the public.

Another study by Hwang *et. al.* (2015) develops an urban transportation network that incorporates the various emissions from freight vehicles with the total delivery time. This study can help policymakers to assess the effect of freight truck operations on air quality in urban areas and to develop strategies to mitigate adverse environmental impacts, particularly in the context of road congestion.

2.3. E-commerce

Currently, e-commerce tends to be one of the fastest-growing marketing tools for customers for various kinds of goods and services. Buyers and distributors engaged in retail e-commerce are no longer limited by store hours or regional marketing areas. Online shopping is a new retail channel that contributes to increased commercial traffic, congestion and, thus pollution in areas with dense populations. One of the main components of e-commerce is the last-mile delivery as it constituents 28% of the cost of the total delivery system (Fixlastmile, 2021).

Visser (2014) mentioned in a paper that the last few years have been a phase of drastic change in e-commerce and home delivery. The rise in home delivery means more freight vans in the residential areas and the city centers. There are some issues, such as congestion problems, environmental concerns, and traffic protection, about the increasing number of freight vehicles in these areas. They all contribute to changes in urban freight flow patterns and movements of vehicles in urban areas.

Pan *et. al.* (2017) developed a model which investigated the best time for successful deliveries by understanding the habits of the customers and thus determining an optimal time for them in case of delivering perishable goods. This study was among the first to integrate data mining techniques in urban freight transportation and can be generalized to all e-commerce businesses that provide home deliveries.

Research by Cárdenas *et. al.* (2017) examined the spatial distribution of e-commerce deliveries over a four months, later, they proposed a technique to measure the external costs per parcel at the national level based on the total vehicle-kilometers traveled. The results from the analysis suggest that e-commerce consumption per capita is higher in rural areas, while the total number of kilometers traveled remains close to that in urban areas.

Another study by Allen *et.al.* (2018) states the reason why e-commerce is leading to the increasing use of light goods vehicles in urban areas. The authors examined the current last-mile delivery operations for parcels and packages along with all the factors involved. Eventually, they identified several measures to enhance the quality of business-to-consumer (B2C) and business-to-business (B2B) parcel delivery in urban areas which can be used by retailers, distribution suppliers, local authorities, and the public.

Bergmann (2019) analyzed route performance in an urban distribution system that incorporates first and last-mile pickup and delivery operations. The increasing number of orders coming in from different locations can range from a few meters to a few kilometers, and they are usually defined by very short periods of time. Their findings would support logistics service providers in assessing route efficiency and traffic footprint for first and last-mile delivery operations.

In contrast, Mangiaracina (2019) indicated in a study that the last-mile is affecting the overall logistics costs. As a result, the economic viability of the last-mile distribution process of a B2C e-commerce company needs special consideration in order to be improved. The analysis emphasizes that the possibility of failed deliveries, the customer density in the distribution areas, and the degree of automation of the process are among the key factors influencing its cost.

2.4. Last-mile Delivery Innovations

With e-commerce and consumer demand continuing to develop, one of the concepts of this innovation is the use of electric vehicles for the delivery of goods (Pelletier *et. al.*, 2016). A study conducted by Siragusa *et. al.* (2019) shows that initial investment for electric vehicles is relatively high, but electric vehicles lead to a decrease in greenhouse gas (GHG) emissions by 17% to 54%, or even more if a higher daily mileage is considered.

2.4.1. Unmanned Drones

At first, it was believed that drones were very successful for the last-mile distribution. Drones usually function by launching from a truck acting as a mobile depot for drones to deliver goods to customers and is known as truck-based delivery of drones. Agatz *et. al.* (2016) developed an integer programming model and also developed several fast route first-cluster second heuristics based on local search and dynamic programming where truck collaborates with drones for the last-mile deliveries. This experiment results in a very cost-effective solution in comparison to only track-based delivery in the last-mile.

Consumers, on the other hand, have concerns regarding the delivery of drones. People, for instance, are concerned with possible military use and abuse by criminals. According to Temando’s (2016) study, 51% of the U.S. people are able to consider the delivery of drones. Many customers perceive risks and are not prepared to embrace this new technology. The factors influencing consumer acceptance of innovative services such as internet banking and smartphone apps have been analyzed in several studies, but few studies have been conducted on drone delivery services.

Vattapparamban *et. al.* (2016) surveyed to explore different aspects of drones related to cyber security, privacy, and public safety in future smart cities. They state that the use of drones in urban areas will carry many technological and societal problems as well as information security, privacy, and public security-related problems.

Yoo (2018) introduces a new paradigm through the combination of drone distribution and autonomous mobility, aimed at simultaneously solving potential consumer demand, delivery times, and traffic congestion problems of the last-mile. Accordingly, the latest Drone-Delivery using Autonomous Mobility (DDAM) is evaluated using the Guideline for Design Science Research (DSRG). The findings indicate that in high-demand seasons, the DDAM model is more feasible as an alternative distribution system in the last-mile delivery.

Some researchers in 2018 evaluated and analyzed the effects on the environment of an existing motorcycle delivery system and a new drone delivery system to distribute foods. Based on the average distribution distance in urban and rural areas, regional differences of environmental improvement impacts after drone deployment have also been assessed. The analysis indicates that drone global warming potential (GWP) was one-sixth that of motorcycle delivery, and drone delivery particulates were half that of motorcycle delivery, and in a rural area the environmental impact reduction was 13 times greater than in an urban area (Park *et. al*., 2018).

Yoo (2018) presented in a study a theoretical model of the relationships between customer adoption factors, such as intention, and determinants such as perceived attributes of innovation, perceived risks, and individual characteristics to use drone delivery. The results indicate that customers who assume that a drone will invade their privacy are less likely to use drone delivery. Drone delivery acceptance by the customers also depends on their area of residence.

In 2019, Moshref-Javadi *et. al.* developed a mixed-integer linear programming model with a synchronized truck and drone delivery where the trucks act as mobile depots. The model determines the optimal allocation of customers with trucks and drones, the optimal route sequence of the truck, and the optimal launch and return locations of the drones. They also observe that the operation of drones increase in densely populated areas like downtown and the model was finally able to reduce the customer waiting time significantly.

Kitjacharoenchai *et. al.* (2019) suggested a mixed-integer programming model and heuristic algorithms to solve the two-echelon vehicle routing problems with drones and conducted numerical experiments and sensitivity analyses on different types of problems using both mixed-integer programming and heuristics approaches. The results from the experiments compared both mixed-integer programming and heuristics and the sensitivity analyses show that the delivery times can be improved with the recommended models.

Khalid (2020) suggested a new approach where the drone will be delivering the packages by riding the existing public transportation. The authors developed an agent-based simulation models and compared it with the conventional truck-based delivery of drones. The comparison analysis was based on different indicators which finally proves more efficient and environment-friendly than the traditional truck-based deliveries.

Gonzalez-R *et. al*. (2020) formulated a truck-based drone delivery problem determining the best routes for a single truck and single drone serving several locations. The drones cannot complete the deliveries with a single battery due to having a short battery range, it was assumed that the batteries were swapped in the trucks. The heuristic approach to the model with the Branch-and-Cut method produced a good solution for similar large-sized problems.

In the same year, to understand last-mile delivery operations of a large fleet of drones in low-altitude air, She *et al*. established a steady-state traffic equilibrium model, in which each drone seeks a route that minimizes its own travel cost, while congestion is generated in areas with high drone concentration. The findings indicate that airborne distribution systems will use much less power than traditional ground-based systems if they are operated at the proper altitude.

2.4.2. Parcel Lockers

Parcel lockers installations may also be an innovative approach to this final phase of delivery from which consumers pick up their deliveries at their convenient time. The drivers do not need to make several delivery trips to the customer's home, just one stop at the parcel locker is sufficient for the delivery. These lockers allow the delivery companies to reduce the costs associated with delivering a parcel as well as productivity is increased by saving courier time (Bloq.it 2020).

Iwan *et. al.* (2015) analyzed the serviceability and efficiency of installing parcel lockers based on the Polish postal company system. They found out that parcel lockers can be a vital contributor for shaping future urban delivery networks and a high possibility to reduce the negative environmental effects and also, the most important factor for the parcel lockers to be efficiently used is the location of these lockers. The results show that 15% of consumers will use the lockers more often if their locations are improved and that most consumers prefer to use lockers near their homes.

In 2018, Yeun *et.al.* performed a survey of 164 customer's intention to use self-collection of parcels as a last-mile delivery option and analyzed the survey data using hierarchical regression analysis. The authors identified the main focus of the stakeholders should be to educate and market self-collection methods considering what the competitors are. The location of the self-collection points is also an important consideration point for customers and thus, stakeholders should continuously monitor the positions of the points of self-collection and transfer the unpopular points to a more strategic location in order to maximize utilization.

Another research work by Deutsch *et al.* (2018) focused on the design of the parcel locker network, which maximizes the overall benefit by optimizing the number, location, and size of the parcel locker facilities and solved using a linear integer program. The authors found out that the parcel lockers can be beneficial to delivery companies by reducing the number of failed deliveries and the number of delivery vehicles as well as for customers, by providing flexibility in collection hours, protection, and savings compared to daily home delivery.

Schwerdfeger *et. al.* (2020) optimized the shifting positions of lockers so that users are within a predefined range for any point during the planning horizon to minimize the locker fleet when satisfying all customers. The results indicate that more lockers are required when the lockers are mobile instead of stationary.

Some researchers determined various parcel delivery techniques with the help of a simulation tool and estimated consumer movements on the basis of actual parcel delivery trip data and parcel receiving habits statistics which finally, helps to determine the time-area requirements. The results indicate that policymakers should focus on reducing the parking at depots by the customers (Schnieder *et. al.* 2020).

Lin *et.al.* (2020) studied the locker location problem where the demand for the locker service is fixed and the service level for a customer who uses a facility is a decreasing function of the walking distance using the multinomial logit model. The results emphasized the importance of considering the customers’ choice behaviors and the difference between the traditional coverage model by other studies and this model by the authors.

In order to meet the demands of last-mile distribution, Wang *et al*. (2020) developed a non-linear integer programming model with an approach to transferring fixed lockers to mobile parcel lockers, with the aim of reducing the operating cost, location, and route optimization of mobile parcel lockers. The findings show that the model can substantially reduce delivery times and the number of vehicles used in last-mile deliveries.

2.4.3. Autonomous Sidewalk Delivery Robots

Nowadays, autonomous delivery robots are faster, more versatile, and even cheaper than ever while transporting goods to customers in the last-mile and they might reduce the need for drivers in the future (USPS, 2016). These robots, the manufacturers say, will be faster, more versatile, and even cheaper than ever while transporting goods to customers in the last-mile and they might even reduce the need for drivers in the future (Marks, 2019). Coltin *et. al* (2013) introduced an auction-based algorithm to schedule pickup and delivery problems with transfers and time windows and executed the planned scheduled on physical robots and demonstrated the efficiency of the robots in the real-world.

Delivery trucks need a curbside space to release the robots in order to complete the deliveries. Curbside parking availability is a limitation for trucks, affecting trucks' parking costs and their operations and impacting fleet sizes for the commercial vehicles (Figliozzi *et. al*, 2017). However, sidewalk robots only move at pedestrian speed, and unavailable customers can further delay the robots. The mode of operation would then cause the truck to have excessive waiting times. Small robot depots, to which the robots can return autonomously and where the truck can refill its goods for robots, seem to be the better choice (Boysen *et. al.* 2018).

For the last-mile, these delivery robots are also facing regulatory issues, which are briefly explained in some research. Hoffman *et. al.* (2018) evaluated and developed the regulatory structure for autonomous package delivery robots by highlighting legal consequences. Now, compared to the other automated delivery robots and drones, these face the fewest legal and regulatory obstacles (Marks, 2019).

A publication by Boysen, Schwerdfeger, and Weidinger (2018) focuses on concepts where delivery robots are launched from trucks, transported, and released in urban and suburban areas, allowing them to complete deliveries in the communities and return to the truck once delivery is complete. The researchers solved scheduling heuristics to minimize the number of late customer deliveries. The findings indicate that robot depots contribute greatly to an effective method of delivery. Instead, if the truck has to wait for the return of the robots, this results in significant waiting times for the truck and much more dissatisfied customers.

Bakach, Campbell, and Ehmke (2019) examined a two-tier robot delivery system consisting of trucks and robot-based delivery. This research specified the optimum number of total robot hubs and the optimum number of robots to satisfy the customers' demand considering time windows for the deliveries. This problem is solved using mixed-integer formulations with and without time windows to deliver goods to the customers. The results have shown that automated robots significantly reduce cost when the customer density is low and service expectations are high.

Another research by Poeting *et. al.* (2019) simulates the performance of a two-tiered distribution network of a robot delivery system, where a vehicle delivers the goods to local hubs and robots then deliver them to customers. The number of local depots a vehicle visit is maximized, increasing the total number of robot-delivered packages that are solved by mixed-integer programming. This enabled deliveries to be completed within a particular time slot which is chosen by the customers.

Further research by the same authors considers the minimum distance traveled by truck to all the micro-hubs, and robots complete the second tiered delivery. This problem is analogous to a traveling salesman problem and is determined by the formulation of integer programming, and the second part with the robots is solved by the simulated heuristics. The results for each of the scenarios (time-windows and on-demand) specify that the position of the micro-depots within the urban environment is the most crucial factor for delivery efficiency.

Many contributions can be found where the robots' potential to reduce last-mile travel, energy, and carbon emissions are evaluated. Figliozzi *et. al.* (2019) evaluated the performance of sidewalk autonomous delivery robots used in combination with a mother ship van to transport them to the delivery locations and could be a viable alternative to standard delivery vehicles. The authors finally concluded that the van carrying the automated robots might need more parking spaces than conventional delivery vans in the downtown areas.

Jennings *et. al.* (2019) developed a model to estimate delivery times and the number of customers served utilizing a combination of sidewalk automated delivery robots and a delivery truck. The results when compared with the conventional delivery system show that these automated delivery robots can provide sufficient cost and time savings in some of the scenarios. Additionally, the implementation of these delivery robots might significantly decrease road travel per delivered package.

Liu *et. al.* (2020) developed an optimization model of a two-echelon distribution network for efficient E-grocery delivery, where conventional trucks serve the delivery in the first echelon and automated delivery robots in the second echelon. A two-step clustering-based hybrid Genetic Algorithm and Particle Swarm Optimization algorithm are proposed to minimize the total transportation and emission cost of the robots. The results finally prove efficient on the planning of the multi-echelon sustainable E-grocery delivery networks with automated delivery robots.

Further research by Liu *et. al* (2020) where a multi-modal last-mile system as a two-echelon location-routing problem with mixed vehicles and mixed satellites is formulated to understand the characteristics of cost components and environmental impact of the automated robots. The model can also be used to develop multi-objective two-echelon location routing problems.

In another research, Sonneberg *et al.* (2019) conducted a research where the robots are released from a robot hub, complete customer demands, and return to the hub. The robots can visit multiple customers before returning to the hub, which depends on the battery range of the robots. The authors minimize the total cost of transportation, the number of hub locations and finally determines optimal routes for robots by solving a location routing problem with time windows.

At present, few papers are found concentrating on robot-based sidewalk delivery, and none of them designs robot distribution and analyzes robot-sharing network to plan robot operations. Our research is based only on the distribution of robots between micro-hubs and finding the optimum number of robots to be present in each micro-hub. This problem is very similar to the problem of bike-sharing, which specifies the optimal size of the bike fleet required and is solved by using a branch-and-bound approach to integer problems (Raviv *et. al.* 2013; Shayarshad *et. al.* 2012). All the recent studies indicate that linear integer programming models can solve the mathematical problems developed to solve the problems with robots. Our problem is, therefore also solved through mixed-integer programming.

3. METHODOLOGY

3.1. Problem Overview

The research problem addressed in this study is the optimal design of a robot-sharing network inside urban areas in order to provide an innovative and alternative method of operating the last-mile deliveries. Traditional practices involve the deployment of automated robots from the delivery trucks that travel from the distribution centers to the urban areas to deliver the parcels. This traditional delivery system has been problematic for several reasons in the urban areas, such as:

a) Traffic congestion: Cities all over the world are experiencing increased traffic as an increasing amount of delivery vehicles block their streets. As a result, the commute time for each passenger will increase within several years due to the increase of urban congestion.

b) Increased fuel cost: Fuel prices account for more than half of the transportation industry's gross operating costs. As a result, the cost of freight transportation in all modes is heavily influenced by fuel prices (Gohari *et. al.,* 2018)

c) Carbon emissions: The majority of this comes from motor vehicles, such as cars and buses, which account for forty-five percent of the total emissions. Three-quarters of all transportation pollution comes from vehicular traffic. The remaining 29.4 percent comes from freight trucks (Our World in Data, 2020).

d) Noise pollutions: Trucks are a major source of noise pollution, perhaps even more than other forms of freight transportation (OECD, 1997).

e) Customer dissatisfaction due to delays: Companies that are competitive are able to consistently offer high levels of customer satisfaction on the on-demand delivery. Unhappy consumers also leave poor reviews when delivery is delayed, which has a negative impact on online e-commerce companies.

There are many companies that follow different types of distribution for their delivery in metropolitan areas. Some companies have particular time windows for delivery. They also follow certain policies in the urban cities regarding the entrance of these trucks or vans to the downtown areas. These regulations are in effect usually in peak hours to reduce the traffic congestion and improve the fuel consumption by these vehicles. On the contrary, this study recommends an innovative approach where the robots will be dispersed from micro-hubs scattered around the cities.

In this research, a robot-sharing network has been proposed where the trucks will be delivering the packages in numerous micro-hubs located inside the cities. These robots will be completing the last leg of the delivery from the micro-hubs at any time of the day. The micro-hubs will be located within three to four miles from the customer's location. Delivery companies will decide beforehand from which micro-hub they want to dispatch their delivery. The trucks carrying the parcels will arrive at micro-hubs at the beginning of the day, rent the robots and return to the micro-hubs are completing the delivery. There will be a third entity looking over the whole system of renting robots, retuning the robot after the utilization to the micro-hubs. The robot might return to the same or different micro-hub, which depends on the demand for that particular robot. We have assumed that there could be a shortage of robots in another micro-hub, so the robot can return to that micro-hub after completing the delivery to the customers. The system charges a fee for the robot's use, depending on the use period. The system tracks the operation of the robot rental by monitoring the number of robots available at each micro-hub and the number of robots rented out. At the same time, there may be robots at various locations that are not in operation due to inconsistent demand at different times, and they will be moved to the micro-hubs where there is a shortage of robots to satisfy all the demands of robots.

The proposed model would decide how robots can be dispersed by transporting them between different micro-hubs over a specified, and optimize the usage of robots as well as reducing the transportation costs of the whole last-mile delivery using a robot-sharing system. Figure 5 provides an illustration of the robot-sharing network developed for addressing the problem and important variables incorporated in the study.

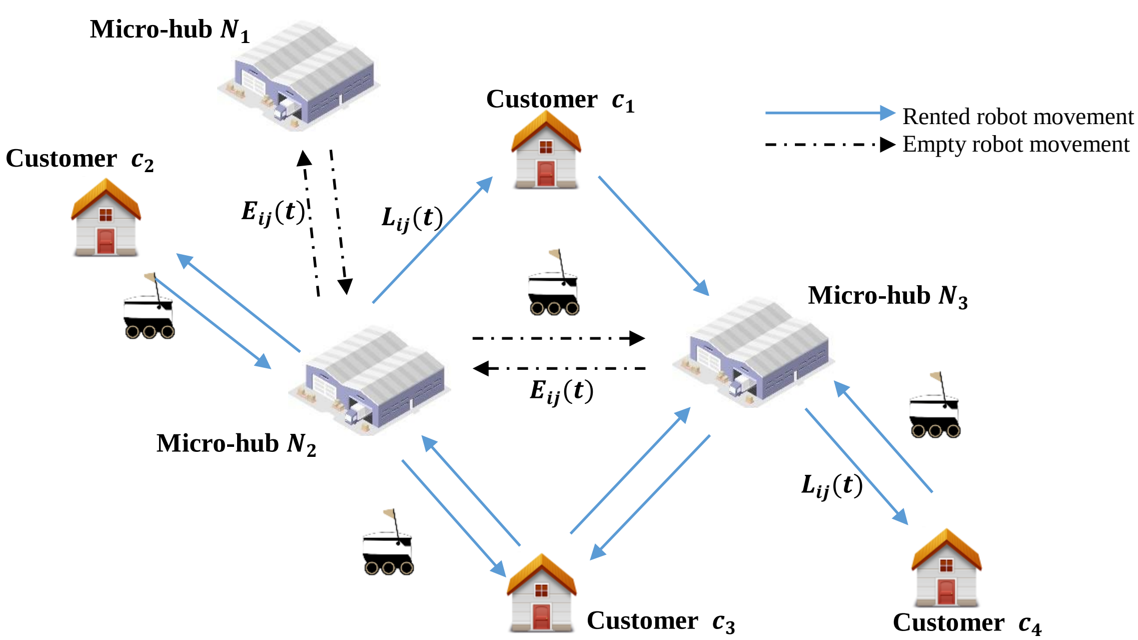


Figure-5: Illustration of the robot-sharing system

The figure above shows the robot delivery network. N denotes the set of micro-hubs or nodes from which the robots will be dispatched to complete the deliveries. The planning horizon is divided into discrete time steps, and t denotes any given time step. Thus, t = 1,2,3……T where T is the total number of time steps. As shown in Figure 5, three micro-hubs serve as both origin and destination for the delivery robots.

We denote the number of robots present at origin i is $O_i(t)$ at the beginning of time step t and at destination j is $D_j(t)$ at the beginning of time step t. A micro-hub can both serve as an origin and a destination. If a robot delivers a package to a customer c_1 from the micro-hub N_1, the number of robots dispatched from the micro-hub is denoted by $L_{ij}(t)$. The robot returns to a different micro-hub, N_2 after completing delivery to the customer c_1.

At the same time, another robot dispatched from the micro-hub N_1 returns to the same micro-hub N_1 after completing the delivery to a customer c_2. If the demand for robots in micro-hub N_1 is more than the number of robots available in N_1 then empty and unutilized robots from another micro-hub N_2 can be brought to N_1 to fulfill the demand which is denoted by $E_{ij}(t)$. At some of the time steps, there might be some demands which could not be met due to the shortage of robots, those demands will be fulfilled in the next time step but there will be some penalty p associated with it as the delivery to the customer will be late, and the unmet demand of robot is denoted by $U_{ij}(t)$.

Since delivery companies will rent the robots for a fixed period of time, the robots will have a deadline to arrive at the micro-hubs; if violated, the delivery companies will have to pay a penalty q for this. Also, the sidewalk delivery robots have a fixed battery range, for which robots need to complete the delivery and return to the micro-hubs between certain time steps. This designed system aims to show how robot-based delivery can be planned within a community in urban environments.

Apart from the practical contribution and innovation of the proposed method, the mathematical model developed to extract optimal solutions presents a novel approach for a robot-sharing system. The contributions of the framework developed are presented below:

a) The objective function of the model presents an approach that indicates that the outputs of the model are economically viable, by minimizing the total transportation costs associated with the operation of the robot-sharing system.
b) The model determines the optimal number of robots required in each micro-hub at the beginning of the day for the whole day operation which fulfills all the customers' demand for that particular day.
c) To the best knowledge of the authors, this is the first study that incorporates the moving of empty robots to the micro-hubs where there is a shortage of robots.
d) Additionally, since the parcels are delivered with the help of sidewalk robots, the study also adopts constraints related to batteries of the robots as they need to return to the micro-hubs before their battery drains out, which tells us that the customers' place needs to be within that range.

3.2. Mathematical Programming Model

This section of the study describes and illustrates the mathematical formulation and model developed to solve the problem addressed in this study. After describing the different assumptions adopted to formulate the model, it analyses the parameters and variables needed to formulate and develop the mathematical model which represents the problem accurately.

3.2.1. Assumptions

A mixed-integer linear programming model is developed with the goal of determining optimal robot fleet size in order to satisfy all the customer demands while taking into consideration the problem objective. For the formulation and development of the model, some reasonable assumptions were made:

a) A homogenous number of micro-hubs are assumed and this assumption is crucial for the development of the model, as it is used in order to calculate the transportation costs of the problem in a uniform manner.
b) The demands for robots by different delivery companies in each time step are assumed.
c) Since the sidewalk delivery robots will work according to their battery operation, it is assumed that the micro-hubs are all within two to three hours of the customers' location.
d) The operational cost of the micro-hubs is assumed to be fixed and known beforehand.
e) The time it takes to recharge the battery of the robots when they return after completing a delivery is assumed.
f) All the penalty cost, unmet demand cost, and penalty cost for arriving late to the micro-hubs after completing a delivery are all assumed to be known.
g) The cost of transporting empty robots from one micro-hub to another micro-hub are all assumed to be known.

h) It is assumed that each robot can serve only one customer at a time during a single time step.

3.2.2. Objective Function

The objective function of the model is developed to minimize the total transportation costs of the robot-sharing system. The transportation costs consists of the following terms:

i. The operating cost of rented robots,
ii. The cost of moving empty robots from j to i,
iii. The rental cost of the robots per time step,
iv. The penalty cost for unmet demand, and
v. The penalty cost for late arrival in the micro-hubs. The transportation cost is denoted by μ.

$$\mu = \sum_i \sum_j \sum_t h * L_{ij}(t) + \sum_i \sum_j \sum_t tp * E_{ji}(t) + \sum_i r * O_i(\mathrm{t}) + \sum_j r * D_j(\mathrm{t}) + \sum_i \sum_j \sum_t p * U_{ij}(t) + \sum_i \sum_j \sum_t q_j * y_{ij}(t)$$

3.2.3. Notations

The complete mathematical formulation which describes the problem is described below:

Sets:

The sets used to develop the mathematical model are as follows:

I Set of origins

J Set of destinations

T Set of time steps

Parameters:

The parameters used to develop the model are described below:

$dm_{ij}(t)$ Demand of robot movement between $i \in N$ and $j \in N$ in time step $t \in T$

r Operation cost of each robot

tp Cost of transporting an empty robot

h Renting cost per robot

p Penalty cost per unit time for one unit of unmet demand

q Penalty cost for late arrival in the micro-hubs

b Maximum operating time on one battery

ft_{ij} Travel time of each robot to return to destination j from origin i

lt_i Loading time of the parcels at location i

bt Battery charging time of the robots at location i

at_i Arrival time at an original hub i

t_j^{last} Latest arrival time at a destination micro-hub j

$\alpha_{ij}(t)$ Proportion of all utilized robots that are dispatched in time step $t \in T$ from $i \in N$ and arrive at the destination $j \in N$ *in* time step $t \in T$

$\beta_{ji}(t)$ Proportion of all unutilized robots that are dispatched in time step $t \in T$ from $j \in N$ and arrive at the destination $i \in N$ *in* time step $t \in T$

Decision variables:

The following decision variables are used to develop the mathematical programming model in this study:

$O_i(t)$ Numbers of robots present at the origin $i \in N$ at the beginning time step $t \in T$

$D_j(t)$ Numbers of robots present at the destination $j \in N$ at the beginning of time step $t \in T$

$L_{ij}(t)$ Numbers of rented robots dispatched from origin $i \in N$ to destination $j \in N$ during the time step $t \in T$

$E_{ji}(t)$ Numbers of unutilized robots transferred from origin $i \in N$ to destination $j \in N$ during the time step $t \in T$

$U_{ij}(t)$ Unmet demand of robots from origin $i \in N$ to destination $j \in N$ at the end of time step $t \in T$

$x_{ij}(t)$ Binary variable representing if a robot travels on link (i, j) at time step $t \in T$

$y_{ij}(t)$ Binary variable representing if destination j will be reached later than the rented time in $t \in T$

3.2.4. Mathematical Formulations

In this subsection, the objective function and the constraints of the developed model are presented and described,

$$\text{Minimize} \quad \sum_i \sum_j \sum_t h * L_{ij}(t) + \sum_i \sum_j \sum_t tp * E_{ji}(t) + \sum_i r * O_i(\mathrm{t}) + \sum_j r * D_j(\mathrm{t}) + \sum_i \sum_j \sum_t p * U_{ij}(t) + \sum_i \sum_j \sum_t q_j * y_{ij}(t) \quad (1)$$

Objective function (1) comprises the function of the problem stated above, with the goal to minimize the transportation costs.

Subject to:

$$U_{ij}(t) = U_{ij}(t-1) + dm_{ij}(t) - L_{ij}(t) \qquad \forall i, j, t \quad (2)$$

Constraint (2) shows the formula used to minimize the unmet demand which ultimately reduces the penalty cost associated with it. It ensures that all the deliveries of the customers are fulfilled by completing the unmet demands from the previous time step *(t-1)* in that particular period. The unmet demand is seen when there shortage of robots in the micro-hubs.

$$U_{ij}(t) \leq L_{ij}(t) \qquad \forall i, j, t \tag{3}$$

The inequality equation in Constraint (3) determines that the robots' unmet demands are less than the number of robots rented. This is because we want to minimize the unmet demand to fulfill all the deliveries to the customer. If more robots are rented out, there will be less unmet demands and thus, minimized cost.

$$L_{ij}(t) \leq dm_{ij}(t) \qquad \forall i, j, t \tag{4}$$

Constraint (4) represents the robots dispatched from the micro-hubs are less or equal to the demand so that more robots than the demands are not rented out. If more robots are rented out, this might result in more transportation costs.

$$\sum_j L_{ij}(t) \leq O_i(t) \qquad \forall i, t \tag{5}$$

$$\sum_i E_{ji}(t) \leq D_j(t) \qquad \forall j, t \tag{6}$$

Constraints (5) and (6) balances all the robots at each micro-hubs at the beginning of each time step. This shows that the number of robots rented are not greater than the number of robots present at any micro-hub at any time step. Similarly, at the same time, empty robots are not transported more than the number of robots available.

$$O_i(t) = O_i(t-1) + \sum_j \sum_t \beta_{ji}(t) * E_{ji}(t) - \sum_j L_{ij}(t-1) \qquad \forall i, t \tag{7}$$

$$D_j(t) = D_j(t-1) + \sum_i \sum_t \alpha_{ij}(t) * L_{ij}(t) - \sum_i E_{ji}(t-1) \qquad \forall j, t \qquad (8)$$

Constraints (7) and (8) maintains the flow of robots between all the micro-hubs during the planning period. These formulas ensure that the whole system operates properly with the specific number of robots assigned at the beginning of each time step.

$$at_i + lt_i + bt + ft_{ij}(t)\, y_{ij}(\mathrm{t}) \; > \; t_j^{last} \qquad \forall i, j, t \qquad (9)$$

A time window has to be maintained by robots for each delivery. The robots need to be returned to the micro-hubs within the time they are hired for. Constraint (9) represents the time window to be maintained by each robot at each time step ρ.

$$at_i + lt_i + bt + ft_{ij}(t)\, x_{ij}(t) \leq b \qquad \forall i, j, t \qquad (10)$$

Each robots have some battery limitations, so they need to complete the delivery and return to the micro-hubs before their battery drains out. Constraint (10) is the battery operation by each robot at each time step ρ. If the robots cannot return to the micro-hubs before their battery drains out, there is a penalty cost associated with it which has to be paid by the delivery companies.

$$L_{ij}(t) \geq 0, \;\; E_{ji}(t) \geq 0, \;\; U_{ij}(t) \geq 0, \;\; O_i(t) \geq 0, \;\; D_j(t) \geq 0 \qquad (11)$$

The last constraint shows that all the variables are non-negative.

From the decision variables and the constraints, we can understand the size of the problem depends on the input parameters, such as the number of micro-hubs and the total time steps. Therefore, the final formulation in order to conduct the experiment is stated below:

Minimize $\sum_i \sum_j \sum_t h * L_{ij}(t) + \sum_i \sum_j \sum_t tp * E_{ji}(t) + \sum_i r * O_i(\mathrm{t}) + \sum_j r * D_j(\mathrm{t}) + \sum_i \sum_j \sum_t p * U_{ij}(t) + \sum_i \sum_j \sum_t q_j * y_{ij}(t)$

Subject to:

$$U_{ij}(t) = U_{ij}(t-1) + dm_{ij}(t) - L_{ij}(t) \qquad \forall i, j, t$$

$$U_{ij}(t) \leq L_{ij}(t) \qquad \forall i, j, t$$

$$L_{ij}(t) \leq dm_{ij}(t) \qquad \forall i, j, t$$

$$\sum_j L_{ij}(t) \leq O_i(t) \qquad \forall i, t$$

$$\sum_i E_{ji}(t) \leq D_j(t) \qquad \forall j, t$$

$$O_i(t) = O_i(t-1) + \sum_j \sum_t \beta_{ji}(t) * E_{ji}(t) - \sum_j L_{ij}(t-1) \qquad \forall i, t$$

$$D_j(t) = D_j(t-1) + \sum_i \sum_t \alpha_{ij}(t) * L_{ij}(t) - \sum_i E_{ji}(t-1) \qquad \forall j, t$$

$$at_i + lt_i + bt + ft_{ij}(t)\, y_{ij}(\mathrm{t}) > t_j^{last} \qquad \forall i, j, t$$

$$at_i + lt_i + bt + ft_{ij}(t)\, x_{ij}(t) \leq b \qquad \forall i, j, t$$

$$L_{ij}(t) \geq 0, \; E_{ij}(t) \geq 0, \; U_{ij}(t) \geq 0, \; O_i(t) \geq 0, \; D_j(t) \geq 0$$

3.3. Optimization Platform

The CPLEX solver from IBM ILOG is a high-performance solver for Linear Programming (LP), Mixed-Integer Linear Programming (MILP), and Quadratic programming problems. It can solve large, real-world optimization problems and is a common tool for solving wide and complex problems using Mixed-Integer Programming problems. In order to find integer solutions, the CPLEX branch-and-bound algorithm for solving Mixed-Integer Programming problems uses modern features such as cutting planes and different heuristic approaches (IBM.com, 2021).

CPLEX formulates mathematical formulas using the Optimization Programming Language (OPL) and an algebraic modeling language. It has a syntax that is very similar to that of algorithm formulation, making it easy to use and understand while still allowing the user to create constraints. CPLEX Optimizer is a modular, high-performance solution for a number of constrained programming problems. The different steps followed in developing and solving the mathematical model in CPLEX are illustrated below.

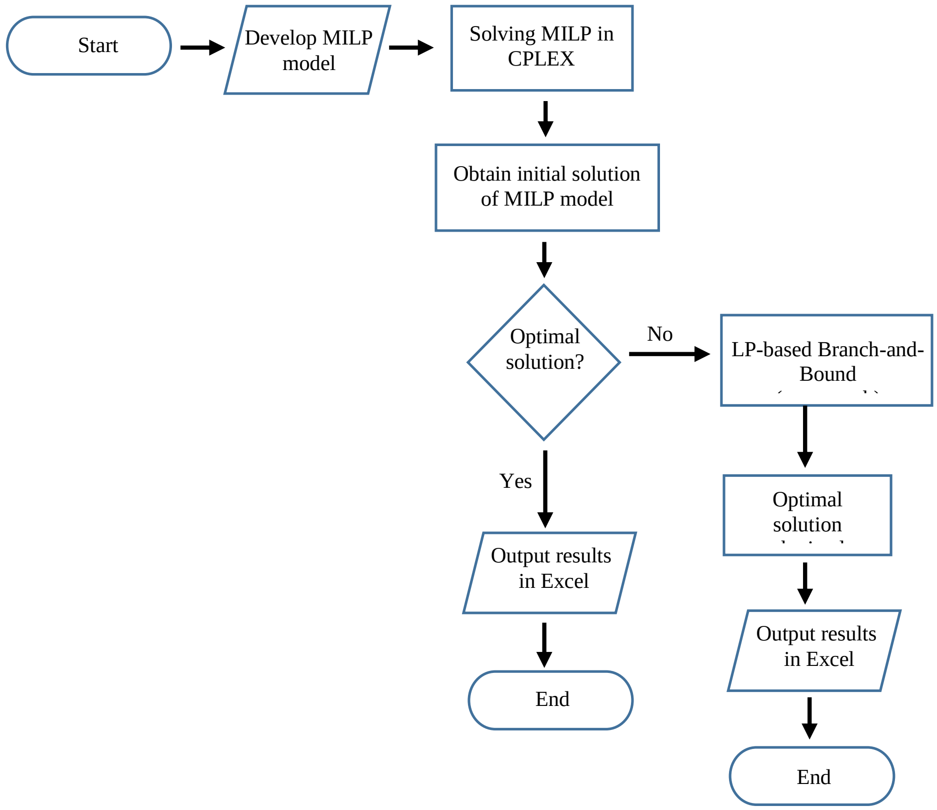


Figure-6: Flow Chart for solving the Robot-sharing problem with MILP

MILP is a computationally complex problem. It finds the best solution to a problem with a linear objective, constraints, and integer-valued variables. A linear objective function, constraints, and integer variables are all part of the model built in this research (Gurobi, 2021). Furthermore, the complex existence of our problem in this research investigated the need to determine the optimal number of automated delivery robots. The coding structure in CPLEX is very straightforward and gives a very effective approach to determining efficient solutions. The figure below shows the structure used for coding the MILP model.

```
//Expression
dexpr float cost1= sum(i in origins,j in destinations, t in time)(h*l[i][j][t]
                                  + tp*e[i][j][t] + p*u[i][j][t]+ q*y[i][j][t] );
dexpr float cost2= sum(i in origins)r*o[i][t];
dexpr float cost3= sum(j in destinations)r*d[j][t];

//Objective Function
minimize cost1+ cost2 + cost3;


//Constraints
subject to{

    constraint1:
    forall(i in origins, j in destinations, t in time)
          u[i][j][t] <= l[i][j][t];

    constraint2:
    forall(i in origins, j in destinations, t in time:(t-1) in time)
        u[i][j][t]== u[i][j][t-1] + dm[i][j][t]- l[i][j][t];

    constraint3:
    forall(i in origins, j in destinations, t in time)
          l[i][j][t] <= dm[i][j][t];
           l[1][1][1] == dm[1][1][1];


     constraint4:
    forall(i in origins,  t in time)
       sum (j in destinations)l[i][j][t] <= o[i][t];

    forall(j in destinations, t in time)
        sum (i in origins) e[j][i][t] <= d[j][t];

        constraint5:
    forall(i in origins, t in time:(t-1) in time)
    o[i][t]== o[i][t-1]+ (sum (j in destinations, t in time ) beta[i][j][t] * e[j][i][t])
                                                     - (sum (j in destinations) l[i][j][t-1]);
```

Figure-7: Example of MILP model developed in CPLEX

3.3.1. Brand-and-Bound Algorithms

The developed model in our study was first experimented with smaller datasets which allowed the model to disregard computation times and run as long as it needed to find optimal solutions to the problem. As the problem size gets bigger, it takes longer computational time for the solver to find the optimal solution. The size of the problem that we want to solve is beyond the computational limit of the solver. In such cases, we can use a heuristic algorithm - that finds a feasible solution which, in objective function terms, is close to the optimal solution. In general, a well-designed heuristic algorithm will frequently produce good quality (near-optimal) results. To find the best solution to the problem, we used the LP-Based Branch-and-Bound approach.

A branch-and-bound algorithm based on linear programming is commonly used to solve Mixed-Integer Linear Programming (MILP) problems. The method relies on accurate estimation of the lower and upper bounds of search space regions/branches. By tightening the bounds on the variables, it is often possible to enhance the linear formulation of the problem as a part of the branch-and-bound tree (Medium, 2021).

In LP-based branch-and-bound, the LP relaxations of the original Mixed-Integer Linear Programming problem are solved at first. The outcome is either the LP is infeasible, which means MILP is infeasible, or the LP has a feasible solution, which gives the optimal solution to MILP. A lower bound is obtained by finding the optimal value of an LP relaxation of a minimize MILP model. In our analysis, the LP-based Branch-and-Bound approach was able to find the optimal solution faster, while the MILP takes longer than the solver's computational time.

4. EXPERIMENTS & DISCUSSIONS

4.1. Preliminary Experimentations

The next step after the problem definition is the formulation of the mathematical model which will accurately represent the problem of this research. After that, the following step in this study would be to test the model and to conduct various experimentations with different problem sizes to know the efficacy of the model regardless of the problem size and structure.

As preliminary experimentation, we test the model with a small problem size at first. We assumed there are three micro-hubs in a community, which serve as both origins and destinations for the delivery robots. The demands from the delivery companies for the robot movements are distributed in six, five, and four time steps. The demands are all generated on the basis of community size. We determined the number of robots required in these micro-hubs at the beginning of the day and assuming the number of potential customers. The below tables will give us the number of demands of robots from the delivery companies required to complete the deliveries. This hypothetical dataset is obtained from different research on the basis of community sizes. The three tables below show the demands for robot movements for the three different time steps.

Table-2: Demand parameters for four time steps

Time Step	1	2	3	4	Total
Demands for robot movement	*dm(1,1)* = 17	*dm(1,1)* = 12	*dm(1,1)* = 18	*dm(1,1)* = 19	***66***
	dm(1,2) = 18	*dm(1,2)* = 22	*dm(1,2)* = 25	*dm(1,2)* = 24	***84***
	dm(1,3) = 18	*dm(1,3)* = 18	*dm(1,3)* = 20	*dm(1,3)* = 15	***61***
	dm(2,1) = 26	*dm(2,1)* = 19	*dm(2,1)* = 22	*dm(2,1)* = 15	***82***
	dm(2,2) = 11	*dm(2,2)* = 15	*dm(2,2)* = 12	*dm(2,2)* = 19	***49***
	dm(2,3) = 17	*dm(2,3)* = 18	*dm(2,3)* = 19	*dm(2,3)* = 20	***64***
	dm(3,1) = 26	*dm(3,1)* = 19	*dm(3,1)* = 22	*dm(3,1)* = 21	***76***
	dm(3,2) = 21	*dm(3,2)* = 22	*dm(3,2)* = 24	*dm(3,2)* = 27	***92***
	dm(3,3) = 18	*dm(3,3)* = 17	*dm(3,3)* = 22	*dm(3,3)* = 16	***72***

Table-2 shows the demands of robots at each micro-hub when there are four time steps. For instance, in the first time step, *dm(1,1)* is 17 which means, companies have requested 17 robots from micro-hub 1 and will return to the same micro-hub after completing their delivery to the customers. Similarly, *dm(2,1)* in the second time step indicates 19 robots are required from micro-hub 2 to serve customers and will return to micro-hub 1 after the delivery. Similar scenarios are seen when there are five and six time steps.

Table-3: Demand parameters for five time steps

Time Step	1	2	3	4	5	Total
Demands for robot movement	*dm(1,1)* = 13	*dm(1,1)* = 14	*dm(1,1)* = 13	*dm(1,1)* = 15	*dm(1,1)* = 11	***66***
	dm(1,2) = 17	*dm(1,2)* = 18	*dm(1,2)* = 19	*dm(1,2)* = 13	*dm(1,2)* = 17	***84***
	dm(1,3) = 10	*dm(1,3)* = 18	*dm(1,3)* = 10	*dm(1,3)* = 5	*dm(1,3)* = 18	***61***
	dm(2,1) = 20	*dm(2,1)* = 16	*dm(2,1)* = 12	*dm(2,1)* = 15	*dm(2,1)* = 19	***82***
	dm(2,2) = 11	*dm(2,2)* = 10	*dm(2,2)* = 12	*dm(2,2)* = 11	*dm(2,2)* = 5	***49***
	dm(2,3) = 17	*dm(2,3)* = 14	*dm(2,3)* = 12	*dm(2,3)* = 8	*dm(2,3)* = 13	***64***
	dm(3,1) = 16	*dm(3,1)* = 19	*dm(3,1)* = 14	*dm(3,1)* = 20	*dm(3,1)* = 7	***76***
	dm(3,2) = 18	*dm(3,2)* = 22	*dm(3,2)* = 15	*dm(3,2)* = 17	*dm(3,2)* = 20	***92***
	dm(3,3) = 15	*dm(3,3)* = 17	*dm(3,3)* = 14	*dm(3,3)* = 8	*dm(3,3)* = 18	***72***

Table-4: Demand parameters for six time steps

Time Step	1	2	3	4	5	6	Total
Demands for robot movement	*dm(1,1)* = 12	*dm(1,1)* = 10	*dm(1,1)* = 9	*dm(1,1)* = 15	*dm(1,1)* = 7	*dm(1,1)* = 13	***66***
	dm(1,2) = 17	*dm(1,2)* = 13	*dm(1,2)* = 19	*dm(1,2)* = 13	*dm(1,2)* = 17	*dm(1,2)* = 10	***84***
	dm(1,3) = 10	*dm(1,3)* = 18	*dm(1,3)* = 7	*dm(1,3)* = 5	*dm(1,3)* = 18	*dm(1,3)* = 13	***61***
	dm(2,1) = 20	*dm(2,1)* = 9	*dm(2,1)* = 10	*dm(2,1)* = 15	*dm(2,1)* = 19	*dm(2,1)* = 9	***82***
	dm(2,2) = 12	*dm(2,2)* = 8	*dm(2,2)* = 12	*dm(2,2)* = 11	*dm(2,2)* = 5	*dm(2,2)* = 9	***49***
	dm(2,3) = 16	*dm(2,3)* = 10	*dm(2,3)* = 11	*dm(2,3)* = 8	*dm(2,3)* = 13	*dm(2,3)* = 16	***64***
	dm(3,1) = 12	*dm(3,1)* = 15	*dm(3,1)* = 14	*dm(3,1)* = 20	*dm(3,1)* = 7	*dm(3,1)* = 20	***76***
	dm(3,2) = 14	*dm(3,2)* = 18	*dm(3,2)* = 5	*dm(3,2)* = 17	*dm(3,2)* = 20	*dm(3,2)* = 20	***92***
	dm(3,3) = 5	*dm(3,3)* = 17	*dm(3,3)* = 5	*dm(3,3)* = 8	*dm(3,3)* = 18	*dm(3,3)* = 20	***72***

The demands of robots from the delivery companies throughout the day are equal in all the scenarios irrespective of the time steps. For example, in all the tables above, the total number of required robots dispatching from micro-hub 1 and returning to micro-hub 1 is 66 and 89 when the robots will be dispatched from micro-hub 1 and returned to micro-hub 2. This is similar for all the rows in all the tables above which means the total demand throughout the day is equal and it is distributed randomly in each time step.

We have considered the parameter of four different types of sidewalk delivery robots, Starship, Domino's DRU, Postmates, and Dispatch's Carry. These four robots have different speeds, battery ranges, and the distance they can cover within single battery life.

Table-5: Parameters of the four types of Robots

Name	Speed	Battery Range	Battery Life
Starship	4 mph	8 miles	2 hours
Domino's DRU	12 mph	12 miles	1 hour
Postmates	3 mph	30 miles	10 hours
Dispatch's Carry	4 mph	48 miles	12 hours

The Starship and Domino's DRU need to be charged in between the deliveries as their battery life is 2 and 1 hour respectively. When running at top speed, Starship and Domino's DRU can only operate for 2 and 1 hour respectively. (Swiss Post, 2020). Postmates and Dispatch's Carry, on the other hand, can run for up to 10 and 12 hours at a time, respectively, and their batteries are recharged at night after the day's deliveries are completed (Jennings et al. 2019).

For solving the problem in this model, the parameters are assumed to be known. The operating cost of the robots is assumed to be 1.95 unit of cost per robot, and the rental cost of the robot is 1.99 unit of cost per delivery (Technical.ly, 2020). Unmet demand incurs a penalty cost of 2.99 unit of cost per time step, and arriving late at any micro-hub incurs a penalty cost of 2.95 unit of cost per time step. It is assumed that the cost of moving an empty robot from one micro-hub to another is 0.75 unit of cost per unit of time. These numbers are based on literature reviews we conducted on various topics. The distance between the customer's location and the micro-hubs are all presumed for simplification of the problem. The time for charging the battery for each robot is assumed to be 10 minutes, but the Postmates and Dispatch's Carry can operate the whole day without charging. The robots that have just arrived at the micro-hub after finishing a delivery are assumed to be not in use at the next time step, but Postmates and Dispatch's Carry can operate in the next time step as they don't need to charge their batteries in between the deliveries. All the other parameters related to time are all randomly generated while modeling the problem.

The result gives the total number of robots required at each micro-hub at the beginning of the day and the minimum transportation costs for the delivery companies when all the demands are fulfilled. The results are obtained from all the time steps considering the parameters of all the types of robots. The three tables show the robot operations when the total system of a day is divided into four, five, and six time steps. The results for all of the decision variables used in the model are shown in the tables below. In the tables, *O(i)* and *D(j)* represent the numbers of robots present at the origin and destination at the beginning of each time step. *L(i,j)* is the number of robots rented out from the origin and *E(i,j)* is the number of unutilized robots transferred in a particular time step. *U(i,j)* is the unmet demand of robots in any particular time step.

Table-6: Decision Variables for six time steps

Time Step	***O(i)***	***D(j)***	***L(i,j)***	***E(j,i)***	***U(i,j)***
1	O(1) = 59 O(2) = 65 O(3) = 58	D(1) = 0 D(2) = 0 D(3) = 0	L(1,1) = 12 L(1,2) = 15 L(1,3) = 9 L(2,1) = 18 L(2,2) = 12 L(2,3) = 13 L(3,1) = 12 L(3,2) = 12 L(3,3) = 5	E(1,1) = 0 E(1,2) = 0 E(1,3) = 0 E(2,1) = 0 E(1,1) = 0 E(1,2) = 0 E(1,3) = 0 E(2,1) = 0 E(2,2) = 0	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	182	0			
2	O(1) = 23 O(2) = 22 O(3) = 29	D(1) = 42 D(2) = 39 D(3) = 27	L(1,1) = 10 L(1,2) = 6 L(1,3) = 7 L(2,1) = 9 L(2,2) = 8 L(2,3) = 10 L(3,1) = 11 L(3,2) = 9 L(3,3) = 9	E(1,1) = 15 E(1,2) = 17 E(1,3) = 11 E(2,1) = 17 E(2,2) = 12 E(2,3) = 15 E(3,1) = 20 E(3,2) = 13 E(3,3) = 12	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	74	108			
3	O(1) = 52 O(2) = 42 O(3) = 40	D(1) = 29 D(2) = 13 D(3) = 6	L(1,1) = 9 L(1,2) = 19 L(1,3) = 7 L(2,1) = 10 L(2,2) = 12 L(2,3) = 11 L(3,1) = 14 L(3,2) = 5 L(3,3) = 5	E(1,1) = 9 E(1,2) = 11 E(1,3) = 9 E(2,1) = 7 E(2,2) = 3 E(2,3) = 3 E(3,1) = 2 E(3,2) = 1 E(3,3) = 3	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	134	48			
4	O(1) = 35 O(2) = 24 O(3) = 31	D(1) = 33 D(2) = 36 D(3) = 23	L(1,1) = 9 L(1,2) = 19 L(1,3) = 7 L(2,1) = 10 L(2,2) = 12 L(2,3) = 11 L(3,1) = 14 L(3,2) = 5 L(3,3) = 5	E(1,1) = 13 E(1,2) = 9 E(1,3) = 11 E(2,1) = 14 E(2,2) = 12 E(2,3) = 10 E(3,1) = 7 E(3,2) = 10 E(3,3) = 6	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	90	92			
5	O(1) = 36 O(2) = 31 O(3) = 27	D(1) = 39 D(2) = 31 D(3) = 18	L(1,1) = 15 L(1,2) = 13 L(1,3) = 5 L(2,1) = 10 L(2,2) = 6 L(2,3) = 8 L(3,1) = 14 L(3,2) = 12 L(3,3) = 5	E(1,1) = 12 E(1,2) = 14 E(1,3) = 13 E(2,1) = 10 E(2,2) = 14 E(2,3) = 7 E(3,1) = 10 E(3,2) = 5 E(3,3) = 3	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	94	88			
6	O(1) = 32 O(2) = 33 O(3) = 23	D(1) = 27 D(2) = 31 D(3) = 36	L(1,1) = 7 L(1,2) = 15 L(1,3) = 14 L(2,1) = 13 L(2,2) = 5 L(2,3) = 13 L(3,1) = 7 L(3,2) = 11 L(3,3) = 9	E(1,1) = 7 E(1,2) = 11 E(1,3) = 9 E(2,1) = 15 E(2,2) = 7 E(2,3) = 9 E(3,1) = 15 E(3,2) = 12 E(3,3) = 9	U(1,1) = 0 U(1,2) = 0 U(1,3) = 0 U(2,1) = 0 U(2,2) = 0 U(2,3) = 0 U(3,1) = 0 U(3,2) = 0 U(3,3) = 0
Total	88	94			

In the above table, at the very beginning, there is a need for 59 robots at $Origin(1)$, 65 robots at $Origin(2)$, and 58 robots at $Origin(3)$. To successfully plan the whole system, (59+65+58) = 182 robots are required at the beginning of the planning period which is determined by the model. It can also be seen that the total number of robots after each time step remains the same. For example, $Origin(i)$ has 74 robots and $Destination(j)$ has 108 robots, i.e. 182 robots in total. At the very beginning, no robots are present in *D(j)* that is because all the robots are in the origin micro-hub. *L(i,j)* shows the number of robots moved from one micro-hub to the other. *U(i,j)* is seen as zero in the table because the unmet demands of any particular period are fulfilled in the next time step.

When five time steps are considered keeping total demand the same, there is a need for 67 robots at $Origin(1)$, 75 robots at $Origin(2)$, and 61 robots at $Origin(3)$. A total of (67+75+61) = 203 robots are required at the beginning of the planning period to design the robot-sharing system without having many late deliveries. Again, it can be seen that the total number of robots after each time step remains the same. A time step 3, 4 and 5, the total number of robots are (134+69) = 203, (111+92) = 203, and (96+107) = 203 respectively. The *E(j,i)* is zero at the very beginning because empty robots were not moved at that time step. Similar to the previous table, the *U(i,j)* is also null in this table because the unmet demands are fulfilled in the next time step. All the values are shown in the table below.

Table-7: Decision Variables for five time steps

Time Step	***O(i)***	***D(j)***	***L(i,j)***	***E(j,i)***	***U(i,j)***
1	$O(1) = 67$	$D(1) = 0$	$L(1,1) = 13$	$E(1,1) = 0$	$U(1,1) = 0$
	$O(2) = 75$	$D(2) = 0$	$L(1,2) = 17$	$E(1,2) = 0$	$U(1,2) = 0$
	$O(3) = 61$	$D(3) = 0$	$L(1,3) = 10$	$E(1,3) = 0$	$U(1,3) = 0$
			$L(2,1) = 20$	$E(2,1) = 0$	$U(2,1) = 0$
			$L(2,2) = 11$	$E(1,1) = 0$	$U(2,2) = 0$
			$L(2,3) = 17$	$E(1,2) = 0$	$U(2,3) = 0$
			$L(3,1) = 16$	$E(1,3) = 0$	$U(3,1) = 0$
			$L(3,2) = 18$	$E(2,1) = 0$	$U(3,2) = 0$
			$L(3,3) = 15$	$E(2,2) = 0$	$U(3,3) = 0$
Total	203	0			
2	$O(1) = 27$	$D(1) = 49$	$L(1,1) = 10$	$E(1,1) = 19$	$U(1,1) = 0$
	$O(2) = 27$	$D(2) = 46$	$L(1,2) = 8$	$E(1,2) = 18$	$U(1,2) = 0$
	$O(3) = 12$	$D(3) = 42$	$L(1,3) = 9$	$E(1,3) = 12$	$U(1,3) = 0$
			$L(2,1) = 7$	$E(2,1) = 16$	$U(2,1) = 0$
			$L(2,2) = 12$	$E(2,2) = 11$	$U(2,2) = 0$
			$L(2,3) = 8$	$E(2,3) = 19$	$U(2,3) = 0$
			$L(3,1) = 5$	$E(3,1) = 8$	$U(3,1) = 0$
			$L(3,2) = 3$	$E(3,2) = 17$	$U(3,2) = 0$
			$L(3,3) = 4$	$E(3,3) = 14$	$U(3,3) = 0$
Total	66	137			
3	$O(1) = 43$	$D(1) = 22$	$L(1,1) = 9$	$E(1,1) = 8$	$U(1,1) = 0$
	$O(2) = 46$	$D(2) = 23$	$L(1,2) = 19$	$E(1,2) = 5$	$U(1,2) = 0$
	$O(3) = 45$	$D(3) = 24$	$L(1,3) = 7$	$E(1,3) = 9$	$U(1,3) = 0$
			$L(2,1) = 10$	$E(2,1) = 7$	$U(2,1) = 0$
			$L(2,2) = 12$	$E(2,2) = 8$	$U(2,2) = 0$
			$L(2,3) = 11$	$E(2,3) = 8$	$U(2,3) = 0$
			$L(3,1) = 14$	$E(3,1) = 12$	$U(3,1) = 0$
			$L(3,2) = 5$	$E(3,2) = 5$	$U(3,2) = 0$
			$L(3,3) = 5$	$E(3,3) = 7$	$U(3,3) = 0$
Total	134	69			
4	$O(1) = 35$	$D(1) = 33$	$L(1,1) = 10$	$E(1,1) = 11$	$U(1,1) = 0$
	$O(2) = 31$	$D(2) = 36$	$L(1,2) = 13$	$E(1,2) = 9$	$U(1,2) = 0$
	$O(3) = 45$	$D(3) = 23$	$L(1,3) = 12$	$E(1,3) = 13$	$U(1,3) = 0$
			$L(2,1) = 10$	$E(2,1) = 14$	$U(2,1) = 0$
			$L(2,2) = 9$	$E(2,2) = 12$	$U(2,2) = 0$
			$L(2,3) = 11$	$E(2,3) = 10$	$U(2,3) = 0$
			$L(3,1) = 16$	$E(3,1) = 7$	$U(3,1) = 0$
			$L(3,2) = 17$	$E(3,2) = 9$	$U(3,2) = 0$
			$L(3,3) = 9$	$E(3,3) = 7$	$U(3,3) = 0$
Total	111	92			
5	$O(1) = 32$	$D(1) = 36$	$L(1,1) = 11$	$E(1,1) = 12$	$U(1,1) = 0$
	$O(2) = 31$	$D(2) = 39$	$L(1,2) = 10$	$E(1,2) = 14$	$U(1,2) = 0$
	$O(3) = 33$	$D(3) = 32$	$L(1,3) = 11$	$E(1,3) = 13$	$U(1,3) = 0$
			$L(2,1) = 10$	$E(2,1) = 10$	$U(2,1) = 0$
			$L(2,2) = 13$	$E(2,2) = 14$	$U(2,2) = 0$
			$L(2,3) = 8$	$E(2,3) = 7$	$U(2,3) = 0$
			$L(3,1) = 14$	$E(3,1) = 14$	$U(3,1) = 0$
			$L(3,2) = 12$	$E(3,2) = 5$	$U(3,2) = 0$
			$L(3,3) = 7$	$E(3,3) = 3$	$U(3,3) = 0$
Total	96	107			

Similarly, the time step is reduced to four, while the total demand remains the same, and there is a need for 87 robots at $Origin(1)$, 79 robots at $Origin(2)$, and 85 robots at $Origin(3)$. To successfully plan the whole system, (87+79+85) = 251 robots are required at the beginning of the planning period.

Table-8: Decision Variables for four time steps

Time Step	***O(i)***	***D(j)***	***L(i,j)***	***E(j,i)***	***U(i,j)***
1	*O(1)* = 87	*D(1)* = 0	*L(1,1)* = 17	*E(1,1)* = 0	*U(1,1)* = 0
	O(2) = 79	*D(2)* = 0	*L(1,2)* = 18	*E(1,2)* = 0	*U(1,2)* = 0
	O(3) = 85	*D(3)* = 0	*L(1,3)* = 18	*E(1,3)* = 0	*U(1,3)* = 0
			L(2,1) = 26	*E(2,1)* = 0	*U(2,1)* = 0
			L(2,2) = 11	*E(1,1)* = 0	*U(2,2)* = 0
			L(2,3) = 17	*E(1,2)* = 0	*U(2,3)* = 0
			L(3,1) = 26	*E(1,3)* = 0	*U(3,1)* = 0
			L(3,2) = 21	*E(2,1)* = 0	*U(3,2)* = 0
			L(3,3) = 18	*E(2,2)* = 0	*U(3,3)* = 0
Total	251	0			
2	*O(1)* = 34	*D(1)* = 69	*L(1,1)* = 10	*E(1,1)* = 19	*U(1,1)* = 0
	O(2) = 25	*D(2)* = 50	*L(1,2)* = 17	*E(1,2)* = 24	*U(1,2)* = 0
	O(3) = 20	*D(3)* = 53	*L(1,3)* = 7	*E(1,3)* = 26	*U(1,3)* = 0
			L(2,1) = 7	*E(2,1)* = 16	*U(2,1)* = 0
			L(2,2) = 12	*E(2,2)* = 19	*U(2,2)* = 0
			L(2,3) = 5	*E(2,3)* = 15	*U(2,3)* = 0
			L(3,1) = 5	*E(3,1)* =17	*U(3,1)* = 0
			L(3,2) = 12	*E(3,2)* = 14	*U(3,2)* = 0
			L(3,3) = 2	*E(3,3)* = 22	*U(3,3)* = 0
Total	79	172			
3	*O(1)* = 52	*D(1)* = 22	*L(1,1)* = 17	*E(1,1)* = 8	*U(1,1)* = 0
	O(2) = 58	*D(2)* = 41	*L(1,2)* = 19	*E(1,2)* = 5	*U(1,2)* = 0
	O(3) = 64	*D(3)* = 14	*L(1,3)* = 16	*E(1,3)* = 9	*U(1,3)* = 0
			L(2,1) = 10	*E(2,1)* = 17	*U(2,1)* = 0
			L(2,2) = 12	*E(2,2)* = 18	*U(2,2)* = 0
			L(2,3) = 11	*E(2,3)* = 6	*U(2,3)* = 0
			L(3,1) = 14	*E(3,1)* = 2	*U(3,1)* = 0
			L(3,2) = 15	*E(3,2)* = 5	*U(3,2)* = 0
			L(3,3) = 12	*E(3,3)* = 7	*U(3,3)* = 0
Total	174	77			
4	*O(1)* = 27	*D(1)* = 41	*L(1,1)* = 10	*E(1,1)* = 11	*U(1,1)* = 0
	O(2) = 53	*D(2)* = 46	*L(1,2)* = 9	*E(1,2)* = 13	*U(1,2)* = 0
	O(3) = 45	*D(3)* = 39	*L(1,3)* = 8	*E(1,3)* = 17	*U(1,3)* = 0
			L(2,1) = 15	*E(2,1)* = 16	*U(2,1)* = 0
			L(2,2) = 18	*E(2,2)* = 18	*U(2,2)* = 0
			L(2,3) = 19	*E(2,3)* = 12	*U(2,3)* = 0
			L(3,1) = 16	*E(3,1)* = 13	*U(3,1)* = 0
			L(3,2) = 17	*E(3,2)* = 9	*U(3,2)* = 0
			L(3,3) = 12	*E(3,3)* = 17	*U(3,3)* = 0
Total	125	126			

As compared to the other two, the system with four time steps has the lowest transportation costs. This is because the operating costs of the robots that are considered fixed are minimized as the time step is reduced. Among the four robots, Starship and Domino's DRU have similar results for the total number of robots as well as the total transportation costs. Similarly, results for the total number of robots and the total transportation costs for Postmates and Dispatch's Carry are alike. Therefore, for further experimentation of the model, we shall only consider the parameters of Starship and Postmates robots.

From the tables, the result of each of the variables is determined. The first column is the respective time steps and the other columns are the result of the different variables. From the results, we can see that after each planning period the summation of robots in both the micro-hubs remains the same. As the time step decreases, due to the rise in demands in each time step, the number of robots increases, on the other hand, transportation costs decrease. The table below shows the size of the robot fleet and transportation costs for each time step.

Table-9: Robot fleet size and transportation costs for different time steps

Time Steps	**Starship**		**Postmates**	
	Robot Fleet Size	**Transportation Costs**	**Robot Fleet Size**	**Transportation Costs**
6	166	2036.95	182	2049.75
5	197	2063.9	203	2052.9
4	243	1829.7	251	1789.7
3	309	1929.75	331	1903.35

In the above table, we can see that the number of robots required is always less when Starship robots are used. Despite having a larger robot fleet, the Postmates robots have a lower transportation cost than the Starship robots. Therefore, the transportation costs are more dependent on the time of the robots returning to the micro-hubs as there is a penalty cost associated with it.

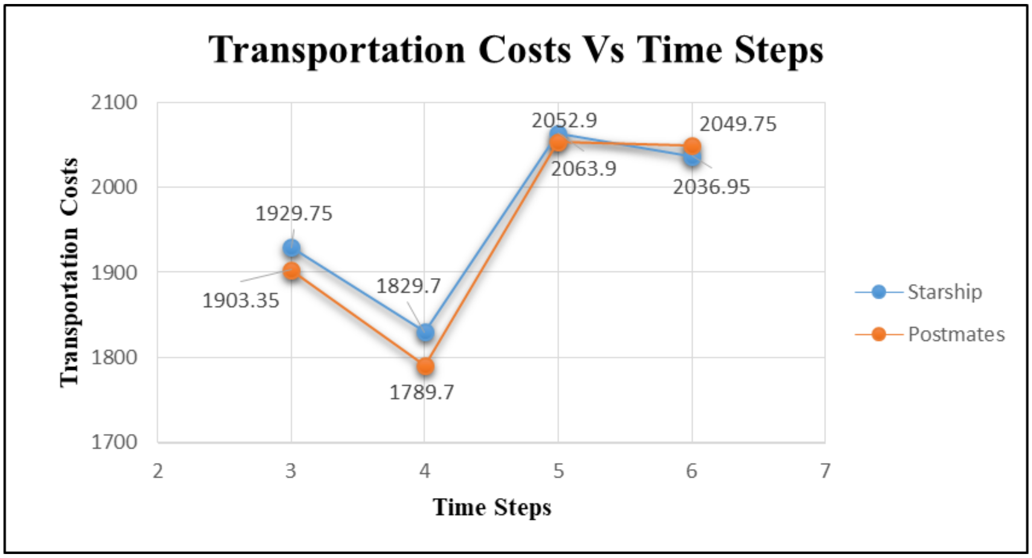


Figure-8: Transportation costs for different time steps

From the above graph, we can see that, as the number of time steps is increasing, the transportation costs are also increasing. The lowest transportation costs are seen when the operation of the whole system is divided into four time steps for both the Starship and Postmates robot. The transportation costs for the robot that need not be charged is the lowest as their latest arrival time has increased due to their battery life. The robots can have some delay while returning to the micro-hub after completing the delivery as we know, their batteries won't drain out in the middle of the road.

4.2. Case Study Applications

As the next step in this experimentation, keeping the time step fixed to four, we shall test the model by increasing the number of micro-hubs. The number of micro-hubs will be chosen according to the population density of any area. Here, we shall test the suitability of the robot-sharing system based on the population density of a community or a city. We have assumed that low-density areas having population of half a million to one million have ten to twenty micro-hubs, medium-density areas where the population is one million to five million have around 50 micro-hubs and densely populated areas where the population is five to ten million have one hundred to one hundred and fifty micro-hubs. The table below will show the distribution of micro-hubs with respect to population density.

Table-10: Number of Micro-hubs based on population density

Population Density	Micro-hubs
Low	10-20
Medium	Around 50
High	100-150

After running the models in CPLEX, we obtained the transportation costs for the different numbers of micro-hubs (10, 20, 50, 100, and 150). The models also give us the total required fleet size we need at the beginning of the day for the successful operation throughout the day. The required fleet size for the day in all the micro-hubs is given below.

Table-11: Required robot fleet size for different number of micro-hubs

Micro-hubs	Robot Fleet Size	
	Starship	Postmates
10	278	309
20	390	470
50	842	843
100	2068	2199
150	2436	2674

In the above table, it is seen that the total required fleet size for the Postmates robot is more than the Starship robot. This is because the Starship robots are returning to the micro-hubs within two hours but the Postmates robots are not as they can deliver packages to locations that are more than two hours distance. That is why more robots are needed to be present in the micro-hubs.

We calculated the transportation costs for the whole robot-sharing system with the different number of micro-hubs. Furthermore, transportation costs per robot and transportation costs per micro-hub are determined from the total. This gives a better understanding of the cost for each robot and each micro-hub. The transportation costs per robot are seen to be the lowest in the Postmates robots for all population sizes and all scenarios. The explanation for this is that there is a penalty for being late at the micro-hub; however, Postmates robots do not encounter this penalty because their battery will run for an entire day without having to be recharged. The penalty costs for unmet demands are also seen to decrease as there are more number of robots present in the micro-hubs to fulfill the demand. The graph below illustrates that transportation cost per robot reduces with the increase of the number of micro-hubs.

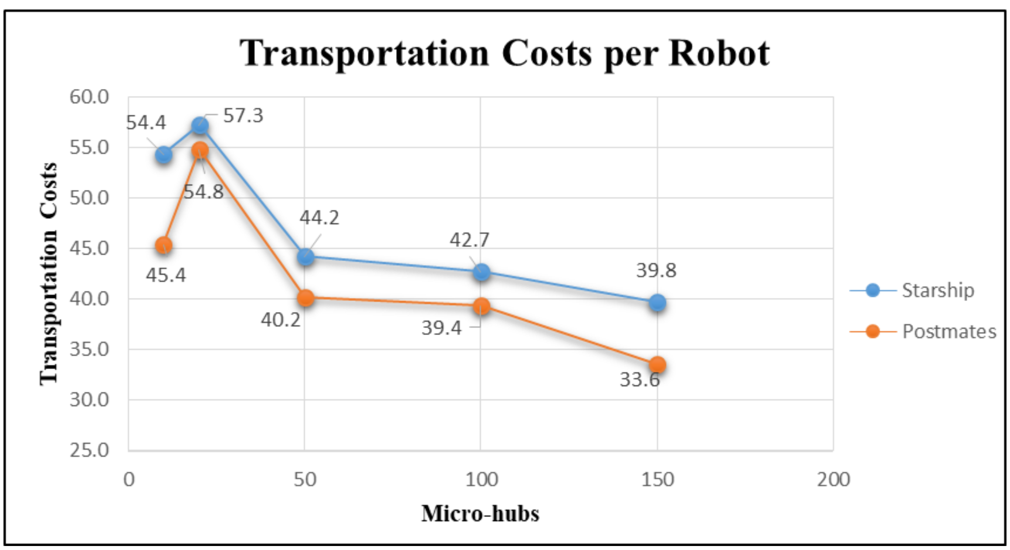


Figure-9: Transportation costs per robot

The above graph shows an improving trend in minimizing the transportation costs. The transportation costs per robot are reduced by almost 15 percent when 50 micro-hubs are set up in medium-density areas. This cost is further reduced when 50 more i.e. 100 micro-hubs are set up in high population density areas. Setting up 150 micro-hubs reduces the cost by more than 30 percent from the initial cost.

Again, if the transportation costs per micro-hub are considered, it is also seen to have a downward trend which is illustrated in the graph below. The transportation cost reduces drastically when 50 micro-hubs are installed in the medium density areas. The transportation costs per micro-hub are reduced by almost 60 percent and further by almost 10 percent when 150 micro-hubs are installed. This is illustrated in the graph below.

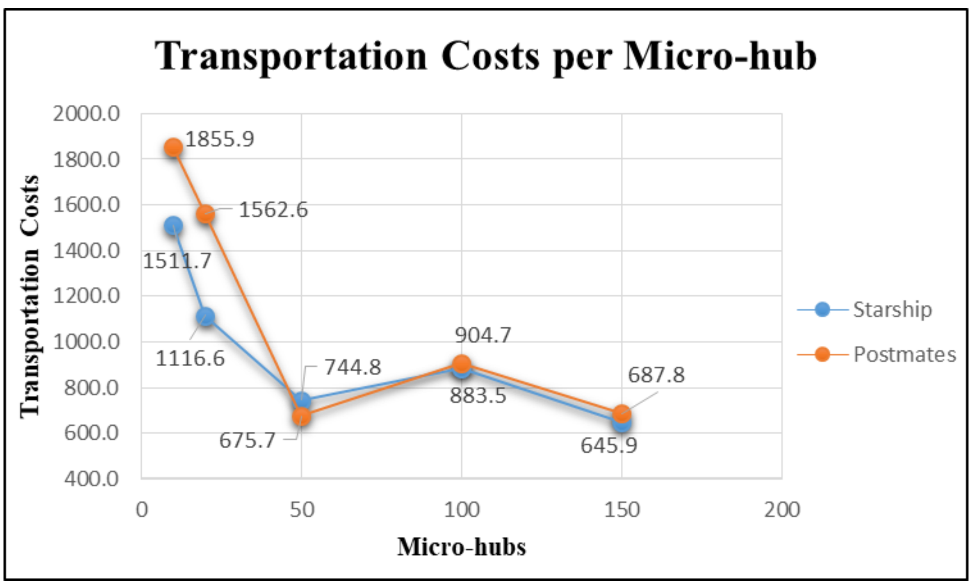


Figure-10: Transportation costs per micro-hubs

We have also compared the transportation costs of the robot-sharing system obtained from the mathematical model and the lower bound values after the LP-based Brand-and-Bound (B&B) algorithm has been applied.

Table-12: Computational results of MILP and B&B

Micro-hubs	Method	Objective Values	Comp. Time (sec)
10	MILP	15123	15
	B&B	15116	0.001
20	MILP	22335	31
	B&B	22331	0.001
50	MILP	37253	377
	B&B	37241	0.01
100	MILP	88387	3288
	B&B	88354	0.05
150	MILP	96929	8829
	B&B	96890	0.05

The above table shows the computational results of Mixed-Integer Linear Programming (MILP) and LP-based Branch-and-Bound method. By using only the Branch-and-Bound algorithm in the problem, we obtain optimal solutions in a very short time for all the micro-hubs. Finally, this heuristic algorithm can provide the lower bound values in an acceptable time than MILP for all test cases. It is worth mentioning that the Branch-and-Bound algorithm provides improved objective function values than the mathematical model. This table helps to prove the accuracy of the mathematical model developed.

5. CONCLUSIONS

5.1. Study Overview

Urban freight transportation is an integral component of cities and transportation systems as everyone is getting dependent more on e-commerce day by day. E-commerce has altered the traditional delivery of goods in our cities. Every day, more goods are delivered, more destinations are reached, and more vehicles are transported, increasing the system's complexity. These developments are accelerated by behavioral and social factors such as social trends, supply chain globalization, and consumer technology adaptation. A more innovative approach is required as the current trends seem to be inadequate as the population and urbanization are growing day by day.

This research provided an alternative method for delivering packages to customers in dense urban areas. We have studied and analyzed the potential of a robot-sharing system in reducing transportation costs for the delivery companies for any particular community, which might consist of several micro-hubs. We have considered the sharing of robots between micro-hubs where there are more demands, which has not been done in any research before. This method can also be successfully applies to bike-sharing problems where the bike can be shared between the stations.

We have formulated a new problem arising in urban settings and designed a MILP problem with objectives related to the minimization of total transportation costs. In addition, different constraints are formulated which relate to fulfilling all the unmet demands, returning the robots to the micro-hubs, and maintaining the balance of the robots throughout the day. This problem is solved using an LP relaxation-based optimization method in CPLEX optimization studio.

Various experiments were conducted using different problem sizes to observe the effectiveness of the model. The results of this research, of course, depend on the parameter values used to develop the model. Our first observation from the results gives the optimal number of robots required in each micro-hub at the very beginning. The model was able to minimize all the unmet demand from all the time steps. The number of robots at the beginning will vary with the demands of delivery and will keep fluctuating throughout the day. Although reducing the time steps increases the number of robots, it ensures the lowest cost of transportation that might bring benefits to the delivery companies.

The objectives of this study have been pursued by making some assumptions by the researchers to simplify the process of evaluation. The interpretation of the results indicates the following outcomes of the study:

a. With the smaller problem size, time step four gave us the lowest transportation costs of the whole system with the optimal number of robots required at the micro-hubs.
b. When larger problem size is considered, Branch-and-Bound gives the optimal objective function value within a time less than one second.
c. The transportation costs per robot have decreased by more than 25 percent from when this model is analyzed for densely populated areas.
d. The transportation costs per micro-hub have decreased by almost 60 percent when 100-150 micro-hubs have set installed in dense urban areas.

In summary, this robot-sharing system can perform best in dense urban areas with more number of micro-hubs. The demands of robots may change, requiring a larger fleet of robots than the model estimates. More orders from the customers will require a larger fleet size in the future. Finally, this approach is an excellent example of a robot-sharing system and it can be solved as a Mixed-Integer Linear Programming (MILP) model.

5.2. Major Contributions of the Study

An innovative approach is introduced in this study which would be beneficial for the delivery companies in reducing the transportation costs on the last-mile. The proposed model's key advantage is its ability to move unused robots from one micro-hub to another when the number of robots available is insufficient to complete deliveries. This will help to reduce the number of unmet demand and thus, reduce the transportation costs. The model is seen to be very successful in reducing the transportation costs in dense urban areas.

The contribution of this thesis can be explained in two different aspects:

a. From the theoretical concept, an innovative approach is proposed for the last-mile delivery which is advantageous for the whole urban logistics system. It can alleviate traffic congestion, mitigate environmental impacts, create the transportation system more sustainable finally, and improve freight mobility in dense urban areas.

b. From the development side of the model, it provides a novel solution to the robot-sharing system in the urban areas which can be used in the last-mile of the supply chain system.

5.3. Recommendations on Future Work

The proposed approach and the model provide a high potential for future extension which are described below.

a. These robots travel on the sidewalks, so they might stop operating when they see pedestrians or during peak hours. Some more parameters could be considered, which might affect the travel time of the robot.
b. In the near future, the model could be tested with actual data, potentially yielding more practical results.
c. Some assumptions of the problem could be reduced in order to improve its accuracy.
d. Computational times for larger problem sizes could be reduced by different heuristic approaches like genetic algorithm, tabu search, simulated annealing, etc.
e. Last but not the least, since the proposed solution is a new business concept that necessitates additional infrastructure, a feasibility study or cost-benefit analysis may be used to assess the model's performance.

REFERENCES

1. Agatz, N., Bouman, P., and Schmidt, M. (2016). “Optimization Approaches for the Traveling Salesman Problem with Drone.” SSRN Electronic Journal.
2. Allen, J., G. Thorne, and M. Browne. (2007). Good Practice Guide on Urban Freight Transport. BEST Urban Freight Solutions, Rijswijk, Netherlands.
3. Allen, J., S. Anderson, M. Browne, and P. Jones. (2000). A Framework for Considering Policies to Encourage Sustainable Urban Freight Traffic and Goods/Service Flows. Summary Report. Transport Studies Group, University of Westminster, United Kingdom.
4. Allen, J., Piecyk, M., Piotrowska, M., McLeod, F., Cherrett, T., Ghali, K., Nguyen, T., Bektas, T., Bates, O., Friday, A., Wise, S. and Austwick, M. (2018). Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: The case of London.
5. Anderson, S., Allen, J. and Browne, M. (2005). Urban logistics—how can it meet policy makers’ sustainability objectives?. Journal of Transport Geography, 13(1), pp.71-81.
6. Ansys. (2020). The Challenges to Developing Fully Autonomous Drone Technology. <https://www.ansys.com/blog/challenges-developing-fully-autonomous-drone-technology>

7. Arcadis. (2019). The future of city mobility. [online] Available at: <https://www.arcadis.com/en/united-kingdom/arcadis-blog/natalie-sauber/the-future-of-city-mobility/>
8. Bakach, I., Campbell, A., & Ehmke, J. (2020). A Two-Tier Urban Delivery Network with Robot-based Deliveries.
9. Bergmann, F., Wagner, S. and Winkenbach, M. (2019). Integrating first-mile pickup and last-mile delivery on shared vehicle routes for efficient urban e-commerce distribution. Transportation Research Part B: Methodological, 131, pp.26-62.
10. Bloq.it. (2020). Parcel Lockers – How smart lockers solve last-mile delivery issue. Available at: <https://bloq.it/parcel-lockers-how-smart-lockers-solve-last-mile-delivery-issue/>
11. Boysen, N., Schwerdfeger, S., and Weidinger, F. (2018). “Scheduling last-mile deliveries with truck-based autonomous robots.” European Journal of Operational Research. 2018; 271(3):1085-1099.
12. Cárdenas, I., Beckers, J. and Vanelslander, T. (2017). E-commerce last-mile in Belgium: Developing an external cost delivery index.
13. Crainic, T., Ricciardi, N. and Storchi, G. (2004). Advanced freight transportation systems for congested urban areas. Transportation Research Part C: Emerging Technologies, 12(2), pp.119-137.
14. Curbed. (2019). Stuck in traffic? Online shopping is partly to blame. Available at: <https://archive.curbed.com/2019/1/10/18177399/amazon-delivery-traffic-online-shopping-e-commerce>

15. Jianqiang Cui, Jago Dodson & Peter V. Hall. (2015). Planning for Urban Freight Transport: An Overview, Transport Reviews, 35:5, 583-598, DOI: 10.1080/01441647.2015.1038666

16. Dablanc, L., and A. Beziat. (2015). "Parking for Freight Vehicles in Dense Urban Centers—The Issue of Delivery Areas in Paris." Presented at 94th Annual Meeting of the Transportation Research Board, Washington, D.C.

17. Deutsch, Y., and Golany, B. (2018). "A parcel locker network as a solution to the logistics last-mile problem." International Journal of Production Research, 56:1-2, 251-261.

18. Iwan, S., Kijewska, K. and Lemke, J. (2015). Analysis of Parcel Lockers' Efficiency as the Last Mile Delivery Solution – The Results of the Research in Poland. Transportation Research Procedia, 12, pp.644-655.

19. Gurobi. (2021). Mixed-Integer Programming (MIP) - A Primer on the Basics - Gurobi. Available at: <https://www.gurobi.com/resource/mip-basics/>

20. Fast Company. (2015). No More Waiting For The FedEx Guy, This Handy Robot Delivers At Your Leisure. Available at: <https://www.fastcompany.com/3053844/no-more-waiting-for-the-fedex-guy-this-handy-robot-delivers-at-your-leisure>

21. Figliozzi, M. (2011). The impacts of congestion on time-definitive urban freight distribution networks CO2 emission levels: Results from a case study in Portland, Oregon. Transportation Research Part C: Emerging Technologies, 19(5), pp.766-778.

22. Figliozzi, M., & Tipagornwong, C. (2017). Impact of last-mile parking availability on commercial vehicle costs and operations. Supply Chain Forum: An International Journal, 18, 60 - 68.

23. Figliozzi, M., & Jennings, D. (2019). Autonomous delivery robots and their potential impacts on urban freight energy consumption and emissions. Transportation research procedia, 46, 21-28.

24. Fixlastmile. (2021). Last-mile delivery for eCommerce: Challenges, benefits, and future implications. Available at: <https://www.fixlastmile.com/blog/last-mile-delivery-for-ecommerce/>

25. Gohari, A., Matori, N., Wan Yusof, K., Toloue, I. and Cho Myint, K. (2018). Effects of the Fuel Price Increase on the Operating Cost of Freight Transport Vehicles. E3S Web of Conferences, 34, p.01022.

26. Gonzalez-R, P., Canca, D., Andrade-Pineda, J., Calle, M. and Leon-Blanco, J. (2020). Truck-drone team logistics: A heuristic approach to multi-drop route planning. Transportation Research Part C: Emerging Technologies, 114, pp.657-680.

27. Goodman, R. (2005). Whatever You Call It, Just Don’t Think of Last-Mile Logistics, Last. Global Logistics and Supply Chain Strategies, Vol. 9, No. 12 pp. 46–5.

28. Giuliano, G. (2012). Tracking environmental issues in major cities. Urban freight for livable cities (pp. 44–53). Stockholm: Capito AB.

29. Hoffmann, T., and Prause, G. (2018). “On the Regulatory Framework for Last-Mile Delivery Robots.” Machines 6(3), 33;

30. Hwang, T. and Ouyang, Y. (2015). Urban Freight Truck Routing under Stochastic Congestion and Emission Considerations. Sustainability, 7(6), pp.6610-6625.

31. Ibm.com. (2021). ILOG CPLEX Optimization Studio - Overview. Available at: <https://www.ibm.com/products/ilog-cplex-optimization-studio>

32. Jennings, D., and Figliozzi, M. (2019). “A Study of Sidewalk Autonomous Delivery Robots and Their Potential Impacts on Freight Efficiency and Travel.” Transportation Research Record: Journal of the Transportation Research Board. 2019;2673(6):317-326.

33. Khalid R., Chankov S.M. (2020) Drone Delivery Using Public Transport: An Agent-Based Modelling and Simulation Approach. In: Freitag M., Haasis HD., Kotzab H., Pannek J. (eds) Dynamics in Logistics. LDIC 2020. Lecture Notes in Logistics. Springer, Cham. https://doi.org/10.1007/978-3-030-44783-0_36

34. Kitjacharoenchai, P., Min, B. and Lee, S. (2019). Two echelon vehicle routing problem with drones in last mile delivery. International Journal of Production Economics, 225, p.107598.

35. Lastovetska, A. (2021). Future of E-commerce: 5 Incredible Tech Innovations | MLSDev. Mlsdev.com. Available at: <https://mlsdev.com/blog/future-of-e-commerce-innovations-to-watch-out-for-new>

36. Lin, Y., Wang, Y., He, D. and Lee, L. (2020). Last-mile delivery: Optimal locker location under multinomial logit choice model. Transportation Research Part E: Logistics and Transportation Review, 142, p.102059.

37. Liu, D., Deng, Z., Zhang, W., Wang, Y. and Kaisar, E. (2020). Design of sustainable urban electronic grocery distribution network. Alexandria Engineering Journal, 60(1), pp.145-157.
38. Liu, D., Deng, Z., Mao, X., Yang, Y. and Kaisar, E. (2020). Two-Echelon Vehicle-Routing Problem: Optimization of Autonomous Delivery Vehicle-Assisted E-Grocery Distribution. IEEE Access, 8, pp.108705-108719.
39. Mabe, J. (2016). "Micro Hubs and Shared Mobility: A Share Economy Concept for Same-Day Delivery - Techgistics: Technology: eCommerce: Logistics." Techgistics, Techgistics | Technology | eCommerce | Logistics, <https://www.techgistics.net/blog/micro-hubs-and-shared-mobility-logistics-share-economy-lastmile-sameday>
40. Mangiaracina, R., Perego, A., Seghezzi, A. and Tumino, A. (2019). Innovative solutions to increase last-mile delivery efficiency in B2C e-commerce: a literature review. International Journal of Physical Distribution & Logistics Management, 49(9), pp.901-920.
41. Marks, M. (2019). "Robots in Space: Sharing Our World with Autonomous Delivery Vehicles." SSRN Electronic Journal.
42. McKinsey & Company. (2016). How customer demands are reshaping last-mile delivery. <https://www.mckinsey.com/industries/travel-logistics-and-transport-infrastructure/our-insights/how-customer-demands-are-reshaping-last-mile-delivery>

43. Medium. (2021). The Branch and Bound Algorithm. Available at: <https://towardsdatascience.com/the-branch-and-bound-algorithm-a7ae4d227a69>

44. MHI. (2020). Embracing the Digital Mindset, <https://www.mhi.org/publications/report>

45. Moshref-Javadi, M., Hemmati, A. and Winkenbach, M. (2019). A truck and drones model for last-mile delivery: A mathematical model and heuristic approach. Applied Mathematical Modelling, 80, pp.290-318.

46. Naiop.org. (2018). Bringing It Home: Four Innovative Concepts for E-commerce Deliveries to Consumers | NAIOP. Available at: <https://www.naiop.org/en/Research-and-Publications/Magazine/2018/Spring-2018/Business-Trends/Bringing-It-Home-Four-Innovative-Concepts-for-Ecommerce-Deliveries-to-Consumers>

47. OECD. (1997). The Environmental Effects of Freight. <http://www.oecd.org/environment/envtrade/2386636.pdf>

48. Our World in Data. (2020). Cars, planes, trains: where do 〖CO〗_2 emissions from transport come from? Available at: <https://ourworldindata.org/co2-emissions-from-transport#:~:text=Road%20travel%20accounts%20for%20three,comes%20from%20trucks%20carrying%20freight.&text=Rail%20travel%20and%20freight%20emits,only%201%25%20of%20transport%20emissions.>

49. Pan, S., Giannikas, V., Han, Y., Grover-Silva, E. and Qiao, B. (2017). Using customer-related data to enhance e-grocery home delivery. Industrial Management & Data Systems, 117(9), pp.1917-1933.

50. Park, J., Kim, S. and Suh, K. (2018). A Comparative Analysis of the Environmental Benefits of Drone-Based Delivery Services in Urban and Rural Areas. Sustainability, 10(3), p.888.

51. Pelletier, S., Jabali, O., and Laporte, G. (2016). 50th Anniversary Invited Article—Goods Distribution with Electric Vehicles: Review and Research Perspectives. Transportation Science. 2016; 50(1):3-22.

52. Poeting, M., Schaudt, S., & Clausen, U. (2019). Simulation of an Optimized Last-Mile Parcel Delivery Network Involving Delivery Robots. In Interdisciplinary Conference on Production, Logistics and Traffic, pages 1–19. Springer.

53. Poeting, M., Schaudt, S., & Clausen, U. (2019). A Comprehensive Case Study in Last-Mile Delivery Concepts for Parcel Robots. IEEE Conference Publication.

54. Post & Parcel. (2020). Automated Vehicles: Reshaping the Logistics Industry in 2020 | Post & Parcel. Available at: <https://postandparcel.info/118617/features/e-commerce-features/automated-vehicles-reshaping-the-logistics-industry-in-2020/>.

55. Raviv, T., Tzur, M., & Forma, I.A. (2013). Static repositionRaviv, T., Tzur, M., & Forma, I.A. (2013). Static repositioning in a bike-sharing system: models and solution approaches. EURO Journal on Transportation and Logistics, 2, 187-229.

56. Sayarshad, H., Tavassoli, S., and Zhao, F. (2012). “A multi-periodic optimization formulation for bike planning and bike utilization.” Applied Mathematical Modelling. 36(10):4944-4951.

57. Siragusa, C., Tumino, A., Mangiaracina, R. and Perego, A. (2020). Electric vehicles performing last-mile delivery in B2C ranging from 2 to 5 pounds: An economic and environmental assessment. International Journal of Sustainable Transportation, pp.1-16.

58. She, R. and Ouyang, Y. (2020). Efficiency of UAV-based last-mile delivery under congestion in low-altitude air. Transportation Research Part C: Emerging Technologies, 122, p.102878.

59. Schnieder, M. and West, A. (2020). Comparison of Time-Area Requirements of Parcel Lockers vs. Home Delivery: A Cyber-Physical System of Last Mile Delivery. 2020 Forum on Integrated and Sustainable Transportation Systems (FISTS),.

60. Sonneberg, M., Leyerer, M., Kleinschmidt, A., Knigge, F., & Breitner, M. (2019). Autonomous Unmanned Ground Vehicles for Urban Logistics: Optimization of Last Mile Delivery Operations. In Proceedings of the 52nd Hawaii International Conference on System Sciences.

61. Starship. (2017). Starship Technologies launches pilot program with Domino's Pizza Enterprises. <https://www.starship.xyz/press_releases/starship-technologies-launches-pilot-program-with-dominos-pizza-enterprises/>

62. Supplychainquarterly.com. (2021). The economic impact of e-commerce. Available at: <https://www.supplychainquarterly.com/articles/507-the-economic-impact-of-e-commerce>
63. Swiss Post. (2020). FACTSHEET STARSHIP DELIVERY ROBOT, <https://webcache.googleusercontent.com/search?q=cache%3AnESLuWo6li8J%3Ahttps%3A%2F%2Fwww.post.ch%2F-%2Fmedia%2Fpost%2Fueber-uns%2Fmedienmitteilungen%2F2017%2Ffactsheet+lieferroboter.pdf%3Fla>
64. TechCrunch. (2020). Starship Technologies is sending its autonomous robots to more cities as demand for contactless delivery rises. <https://techcrunch.com/2020/04/09/starship-technologies-is-sending-its-autonomous-robots-to-more-cities-as-demand-for-contactless-delivery-rises/>
65. Technical.ly DC. (2019). "George Mason University now has a fleet of 25 food delivery robots roaming on campus." <https://technical.ly/dc/2019/01/25/george-mason-university-now-has-a-fleet-of-25-food-delivery-robots-roaming-on-campus/> (Nov. 19, 2020).
66. Temando. (2016). State of Shipping in Commerce 2016. Retrieved from Temando: https://temando.com/en/research-2016.
67. Tomorrow.Mag. (2019). The Last Mile issue: how can we solve urban delivery problems? <https://www.smartcitylab.com/blog/mobility/the-last-mile-issue-how-can-we-solve-urban-delivery-problems/>
68. USPS. (2016). Technological Disruption and Innovation in Last Mile Delivery USPS Office of Inspector General,

<https://www.uspsoig.gov/document/technological-disruption-and-innovation-last-mile-delivery>

69. Vattapparamban, E., Güvenç, İ., Yurekli, A. İ., Akkaya, K., and Uluağaç, S. (2016). “Drones for smart cities: Issues in cyber security, privacy, and public safety.” 2016 International Wireless Communications and Mobile Computing Conference (IWCMC).
70. Visser, J., Nemoto, T. and Browne, M. (2014). Home Delivery and the Impacts on Urban Freight Transport: A Review. Procedia - Social and Behavioral Sciences, 125, pp.15-27.
71. Wang, Y., Bi, M., & Chen, Y. (2020). A Scheduling Strategy of Mobile Parcel Lockers for the Last Mile Delivery Problem. Promet-traffic & Transportation, 32, 875-885.
72. Wired. (2020). Delivery Robots Aren't Ready-When They Could Be Needed Most. <https://www.wired.com/story/delivery-robots-arent-ready-when-needed-most/>
73. Yuen, K., Wang, X., Ng, L. and Wong, Y. (2018). An investigation of customers’ intention to use self-collection services for last-mile delivery. Transport Policy, 66, pp.1-8.
74. Yoo, W., Yu, E. and Jung, J. (2018). Drone delivery: Factors affecting the public’s attitude and intention to adopt. Telematics and Informatics, 35(6), pp.1687-1700.
75. Yoo, H., & Chankov, S. (2018). Drone-delivery Using Autonomous Mobility: An Innovative Approach to Future Last-mile Delivery Problems. 2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 1216-1220.