Investigation in Crowdshipping Enabled Urban and Last-mile Delivery Paradigms

by

Sudheer Ballare
B.E., Civil Engineering, Mumbai University, India 2003
M.Tech., Environmental Engineering, Mumbai University, India 2007
MSc. Transport & the Environment, Newcastle University, UK 2012

THESIS

Submitted in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy in Civil Engineering
to the Graduate College of the
University of Illinois at Chicago, 2020

Chicago, Illinois

Defense Committee:
Jane Lin, Chair and Advisor
Abolfazl (Kouros) Mohammadian
Bo Zou
Sybil Derrible
Mengqi Hu, Department of Mechanical and Industrial Engineering

ACKNOWLEDGMENT

This thesis would most definitely not have been successfully completed without the constant support, encouragement and advice of several individuals. Though no words should suffice but I wish to express my sincere heartfelt gratitude for the support of all those who helped me in completing this dissertation.

First and foremost, I would like to express my gratitude to my PhD. supervisor and mentor Professor Jane Lin for having provided me this wonderful opportunity to be part of her research group and pursue my PhD. degree under her guidance. She continues to be a great advisor and a mentor to our entire research group and has constantly provided advice towards my personal and professional growth. I completely appreciate all her contributions of time, energy, innovative ideas, and funding towards making my Ph.D. experience at UIC productive, enjoyable and stimulating. Her enthusiasm towards research in urban logistics is exceptional and was a source of motivation for me during the tough phase of my Ph.D. journey. I will always be indebted to Prof. Lin for sharing her knowledge and being patient with me, for all the accolades and awards received, and the overall PhD experience.

I want to also extend my gratitude to Dr. Kouros Mohammadian, Dr. Bo Zou, Dr. Sybil Derrible and Dr. Mengqi Hu for agreeing to serve on my dissertation committee and for the invaluable guidance I have received from them. Their input in this work is highly appreciated.

I am also grateful to the faculty of the Department of Civil and Materials Engineering and the College of Urban Planning and Policy at UIC, whose courses I have taken. All these courses were interesting and rewarding and contributed to a better understanding of my research questions.

The research in this dissertation was partially supported by the National Science Foundation, award number 1534138, on the Smart CROwdsourced Urban Delivery (CROUD) System.

I also wish to extend my gratitude to Dr. Darrell Sonntag and the entire MOVES team at the U.S. Environmental Protection Agency's Ann Arbor office for having provided me an opportunity to be a research participant in their ongoing project activities.

I would also like to thank all my friends and colleagues at the University of Illinois at Chicago who made my graduate studies more enjoyable. My time at UIC was also enriched by the Graduate Student Council, UIC-ITE Student chapter and the UIC Toastmasters club. And last but not the least, I would like to express my deepest gratitude to my wife and my family, whom I missed every moment being miles away. Thank you, for your love and encouragement.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

SUMMARY

Urban logistics, especially the last mile delivery, is a major urban challenge due to the high density in cities and the use of diesel-powered freight vehicles, resulting in traffic congestion and other negative impacts such as air and noise pollution. With the rise of e-commerce and customer expectation of express delivery, the metropolitan areas are seeking innovative ways to better manage urban freight movement and create an efficient and environment friendly transportation system. Information and communication technology advancement is ushering in a new era of mobility, changing the way people and goods move.

Traditionally, freight movement takes the so-called hub-and-spoke delivery model. While the hub-and-spoke model is proven efficient with the economies of scale, it is ill-suited for fulfilling the increasing demand for same-day and even one-hour delivery in urban areas with the inflexible structure and is restricted by the hub capacity.

Using real-time information technology for speedy coordination, crowdshipping brings reduction in the transportation costs for the last mile. Crowdshipping provides a feasible alternative in the first and last mile deliveries, provides flexibility of delivery time windows and uses a variety of transport modes for the delivery, for e.g. personal automobiles, taxis, bicycles, cargo cycles, walking etc. In Chapter 3 of this dissertation, an empirical investigation is presented of an existing crowdsourcing delivery company with respect to the operational factors such as parcel size, delivery distance, demand frequency and distribution, the user characteristics including customer and driver profiles, and the pricing model. Both quantitative and qualitative analyses are performed to shed light on the market demand trending and growth opportunities in crowdsourcing deliveries.

Another solution to reducing truck trips into busy urban centers is the use of Automated Parcel Station (APS). APS is an automated parcel collection (and sometimes dispatch as well) station located in public spaces. For the ease of access, these APS' are located at shopping centers, transit stations, gas stations, etc. Parcel recipients travel on foot or by car to collect their parcels from an APS. In Chapter 4 of this dissertation, we propose, formulate, and evaluate a new and innovative delivery paradigm where the last-mile demand fulfilment is done through Microhubs with Crowdshipping (M+C). In this paradigm, an urban service area is divided into a number of smaller service zones (e.g., by zipcode). Within each zone, there is a microhub to temporarily store inbound and outbound parcels of small to medium size. These parcels are collected or distributed by automobile or bicycle crowdshippers between customers (shippers and end receivers) and the zonal microhub. Commercial trucks are dispatched periodically to visit the microhubs in the service area to transfer parcels to their respective destination microhubs. Though, an initiative involving microhubs and dedicated freight bikes has been field tested recently in the Citylab project in Europe for the first time, the performance of a microhubs and crowdshipping paradigm has not been analytically assessed before this dissertation.

In Chapter 5 we show that the proposed M+C paradigm is a Many-to-Many Split Pickup and Delivery Problem (M-MSPDP) for truck routing between microhubs. We present a general formulation of M-MSPDP and a Maximum Split-Benefit with Tabu Search (MS-BTS) heuristic to solve the large-scale M-MSPDP. MS-BTS is evaluated with the exact solution methods and other existing heuristics. We further apply the MS-BTS heuristic to solve for two applications of the M-MSPDP: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bike rebalancing in a bike-sharing system (i.e., M-MSPD-OC). The computation time of MS-BTS is considerably improved over the other methods while maintaining a comparable level of the solution quality.

Lastly, Chapter 6 considers a futuristic delivery paradigm where all stages of the last-mile demand fulfillment are handled without any involvement of human factor, including for parcel loading/unloading, sorting and transportation between hubs and the customers. This Chapter presents a brief commentary on the impacts of such a proposed delivery paradigm.

Chapter 1 Introduction

1.1 Background

Urban logistics is complicated due to the high density in cities and the use of diesel-powered freight vehicles, resulting in congestion and other negative effects like air and noise pollution (Browne et al., 2011; Dablanc, 2007). The last-mile deliveries consist of a significant part of the entire transportation cost of a delivery (Arvidsson et al., 2013). In addition, due to the nature of the deliveries in urban areas, which include short trips, frequent stops, and a low load factor, the costs are even higher (Zunder and Ibanez, 2004; Filippi et al., 2010; Stathopoulos et al., 2012). A variety of restrictions are put in place by the local authorities to manage urban deliveries. These include loading and unloading time-windows, designated low emission zones, consolidated distribution of goods, vehicle restrictions by weight and size, use of information and communication technologies (Anderson et al., 2005; Muñuzuri et al., 2005).

With the requirement of just-in-time/express last-mile urban deliveries on one hand and the negative externalities associated with freight transportation on the other, there is a need for a fast, flexible, and sustainable urban delivery paradigm. The traditional Hub-and-Spoke paradigm (H+S hereafter) is ill-suited for fulfilling the express last-mile delivery demand for its fixed centralized structure. H+S represents centralized control at one or more transshipment centers (or hubs), with spokes spread over the delivery service area (Klincewicz, 1998; Zäpfel, & Wasner, 2002; Elhedhli and Hu, 2005). The shipment between any two nodes is transferred from the spokes connecting the nodes through the transshipment center. This in turn induces additional delay at the hub and transportation costs for the last-mile deliveries (Pohl, 2013; Chen and Lin, 2014).

With an increase in urban population density, more freight is expected to travel within urban areas, posing a tough challenge to the cities (Lerner and Van Audenhove, 2012). Information and communication technology advancement is ushering in a new era of mobility, changing the way people and goods move (Trentini and Mahléné, 2010). The new urban mobility solutions are now required to be sustainable, and address the environmental and energy concerns (Ohnishi, 2008). Freight transport in the United States is a major contributor of greenhouse gas (GHG) emissions, air pollutants like Nitrogen Oxide (NO_X) and Particulate Matter (PM_{10}) (Browne et al., 2011; Braunstein, 2015; Thompson, 2015). Freight transport also accounts for over two-thirds of the transportation energy consumption and two-fifths of the operating cost for the trucking industry (Crainic et al., 2009; Sahin et al. 2009).

1.2 Research Motivation

The traditional Hub-and-Spoke paradigms rely mostly on trucks to carry out the deliveries, which cause space and parking shortage, and worsen urban congestion and air pollution. Strategies to mitigate such problems include better routing algorithms, smaller and cleaner vehicle fleet, off-peak deliveries, freight partnerships, and consolidated delivery (Verlinde et al., 2012; Holguín-Veras et al., 2017). Another way to increase the efficiency of transport systems is by using a combination of two or more modes, also referred to as co-modality (European Commission, 2006). This includes non-motorized transport modes like bicycles, tricycles, and even pedestrians. Use of cargo cycles and electric vehicles for the last-mile deliveries reduces the vehicle miles travelled, and corresponding CO_2 emissions in very congested cities like New York (Leonardi et al., 2012; Koning and Conway, 2015; Conway et al., 2017). Co-modality can also include use of public transportation modes such as trains, trams, buses or taxis, which combine transport of goods and passengers (Thompson and Taniguchi, 2014; Ronald et al., 2015).

The rapid advancements in information technology and ubiquitous computing offer opportunities to enable better coordination between demand and supply in the freight sector. Driven by the notion of shared economy, creative ways are being implemented to feasibly and profitably share underutilized resources, with the shared economy expected to reach $335 billion globally by 2025 (Belk, 2014; Cohen and Kietzman, 2014; Malhotra and Van Alstyne, 2014; Bothun and Liebermann, 2015). Crowdshipping involves fulfilling the delivery demand by everyday individuals with spare time and capacity (Howe, 2006; Rai et al., 2017). Using real-time information technology for speedy coordination, crowdshipping brings reduction in the transportation costs for the last-mile (Behrend, 2011). Crowdshipping provides a feasible alternative in the first and last mile deliveries, and uses a variety of transport modes for the delivery, for e.g. personal automobiles, taxis, bicycles, cargo cycles, walking etc. (Marjanovic et al., 2012). Crowdshipping also provides the customers with the flexibility of selecting their preferred delivery time windows and reduces the negative externalities for the urban areas (Lan et al., 2010; Rougès and Montreuil, 2014; McKinnon et al., 2015; Paloheimo et al., 2016). In addition, crowdsourcing offers an opportunity to make more social connections for users (Bellotti et al., 2015; Hamari et al., 2015; McKinnon et al., 2015; Piscicelli et al., 2015).

Another solution to reduce truck trips into busy urban centers is the use of Automated Parcel Station (APS). APS is an automated parcel collection (and sometimes dispatch as well) station located in public spaces. Parcel collection from APS is made possible by entering a mobile phone number and the access code. For the ease of access, these APS' are located at shopping centers, transit stations, gas stations, etc. Parcel recipients travel on foot or by car to collect their parcels from an APS. The first APS network in the world was deployed in Poland in 2009 by InPost Ltd (Moroz and Polkowski, 2016). Another example of APS is the Amazon Lockers, which are secure, self-service kiosks that allow the customers to pick up their Amazon.com parcels at a convenient time. These kiosks also allow process the return of any previous Amazon.com purchases that the customer no longer requires (Amazon, 2018). As part of the EU-funded Civitas Citylab project (Citylab, 2018), Amsterdam has recently field tested a system of city center microhubs in combination with freight bikes, which has led to reduction in delivery van stops and other negative effects.

The classical Vehicle Routing Problem (VRP) strategies typically limit the visit to a customer once and only once. The implication of that is that the entire demand at the customer must be picked up at that single visit, i.e. no splitting of loads is allowed. Dror and Trudeau (1989) introduced the split delivery vehicle routing problem (SDVRP) in which the total demand at the customer could be served by multiple visits from the vehicles. Though this appears to lead to an increase in the total costs due to a greater number of visits, but this allows for dividing and allocating the customer demand (load) in such a way that vehicle capacity can be best utilized to serve the customer. The number of vehicles and the total cost of transportation can thus be reduced. The benefits of the split deliveries have been shown already by several studies (Dror et al., 1994; Frizzell and Giffin, 1995; Sierksma and Tijssen, 1998; Archetti et al., 2006; Nowak et al., 2008).

1.3 Research Objectives

Driven by the need of a reliable, robust and environment-friendly urban delivery paradigm, this dissertation focuses on understanding and assessment of new last-mile delivery paradigms such as crowdshipping and the use of microhubs.

Crowdshipping

Crowdshipping involves making use of everyday individuals with spare time and capacity to fulfill the variable delivery demand generated by e-commerce. Coordination occurs through real-time web or mobile based technology, bringing reduction in the cost of transportation and associated negative environmental impacts. This study performs preliminary investigation of an existing crowdsourcing delivery company with respect to the operational factors such as parcel size, parcel delivery distance, customer demand frequency and distribution, the user characteristics including customer and driver profiles, and the pricing model. Both quantitative and qualitative analyses are performed to shed light on the market demand trending and growth opportunities in crowdsourcing deliveries. Detailed overview of the case-study crowdsourcing delivery service, research questions, data analysis and findings, and key conclusions are presented in Chapter 3.

Microhubs with crowdshipping without split loads

Building on the Citylab project (Citylab, 2018) and Amazon lockers and extending them to both pickup and drop-off services at any APS – call it a microhub and coupled with crowdshipping to provide door-to-door service – presents an emerging delivery paradigm. Though, an initiative involving microhubs and dedicated freight bikes has been field tested recently in the Citylab project for the first time, the performance of a microhubs and crowdshipping paradigm has not been analytically assessed before. In light of the potential benefits of microhubs and crowdshipping as discussed earlier, we propose a new and innovative delivery paradigm where the last-mile demand fulfilment is done through Microhubs with Crowdshipping (M+C). In this paradigm, an urban service area is divided into a number of smaller service zones (e.g., by zipcode). Within each zone, there is a microhub to temporarily store inbound and outbound parcels of small to medium size. These parcels are collected or distributed by automobile or bicycle crowdshippers between customers (shippers and end receivers) and the zonal microhub. Commercial trucks are dispatched periodically to visit all the microhubs in the service area to transfer parcels to their respective destination microhubs. It was observed in the past that the cost of the Vehicle Routing Problem (VRP) can be even halved by allowing split deliveries (Archetti, Savelsbergh, & Speranza, 2006). Hence, this study considers two variations of the M+C delivery model. The first variation does not allow the split pick up or deliveries between the microhubs for the trucks. The second variation of the M+C model allows this. Detailed problem definition, research contributions, model formulation, and evaluation are presented in Chapter 4.

Many-to-Many Split Pickup and Delivery Problem (M-MSPDP)

The second variation of the M+C delivery model allows split deliveries between the microhubs for the trucks. Each microhub can be visited by several trucks and the same truck can visit more than one microhub. Previous studies have already established the benefits of the split deliveries (Dror et al., 1994; Frizzell and Giffin, 1995; Sierksma and Tijssen, 1998; Archetti et al., 2006; Nowak et al., 2008). However, solving VRP with split loads is more difficult that solving a classical VRP. In this dissertation, we introduce the general case of Many-to-Many Split Pickup and Delivery Problem (M-MSPDP) for truck routing between microhubs and present the evaluation of a Maximum Split-Benefit with Tabu Search (MS-BTS) heuristic to solve large scale problems, using randomly generated datasets. We further apply the MS-BTS heuristic to solve for two applications of the M-MSPDP: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bike rebalancing in a bike-sharing system (i.e., M-MSPD-OC) in Chapter 5.

The research objectives of this study are:

1) to empirically investigate the business model and operational characteristics of an existing crowdshipping delivery startup, including
    a. to identify the attributes associated with the successfully completed deliveries during the study period to better understand the factors to the success, and
    b. to identify the socio-demographic factors behind the motivation of participants (senders and drivers) in the crowdsourced delivery system.
2) to define and formulate an innovative last mile delivery paradigm – M+C - that combines microhubs with crowdshipping and exploits co-modality; and
3) to investigate the feasibility of M+C as a viable alternative to urban last mile delivery by analyzing the effects of key operational factors on the performance of M+C and comparing it with the current state-of-the-practice.

4) to formulate and construct a heuristic solution method for a general case of the Many-to-Many Split Pickup and Delivery Problem (M-MSPDP).

1.4 Research Significance and Contributions

The successful outcomes of this research contribute to the understanding of the new last-mile delivery paradigms. Individual chapters will detail the research contributions for each of the last-mile and urban delivery paradigms analyzed in this dissertation. We briefly describe the research significance and contributions here.

This dissertation makes a significant contribution in the crowdshipping literature in the following aspects: (1) analyzing the operational performance of a crowdsourced delivery company and (2) identification of attributes associated with successfully completed deliveries. The findings of this study will provide insights to crowdsourcing companies to develop pricing & matching mechanisms as well as reevaluate the existing strategies to reduce overall operational costs, improve performance, attract participation and secure a bigger market share.

The significant contributions of the study on Microhubs with Crowdshipping (M+C) are two-fold: (1) the proposed M+C paradigm is an innovative new business model that combines a network of microhubs with crowdshipping in urban areas and exploits co-modality; and (2) to the best of our knowledge, this is the first analytical investigation of microhubs paradigm with crowdshipping.

This study also contributes to the vehicle routing literature by introducing a heuristic for solving the general case of Many-to-Many Split Pickup and Delivery Problem (M-MSPDP). We present the MS-BTS heuristic to solve large scale M-MSPDP and evaluate it by applying the MS-BTS heuristic to randomly generated datasets.

The results of the evaluation of the proposed M+C delivery paradigm would help the city agencies to possibly reduce the negative externalities associated with freight transport in urban areas. To the authors' best knowledge, this is also the first study to quantitatively investigate this new paradigm of Microhubs with Crowdshipping.

1.5 Organization of the Dissertation

This dissertation defense report contains 6 chapters and is organized in the following order:
Chapter 1 provides an introduction to the new last-mile delivery paradigms addressed in this work and outlines the research objectives. Chapter 2 introduces the literature review for the current and emerging state-of-the-art last-mile delivery paradigms. Chapter 3 details an overview of the case study for the crowdsourcing delivery company's delivery service as well as the pricing model employed by the company. A set of research questions to be answered in this study are presented, followed by an overview of the crowdsourcing data shared by the company, to be used to find answers for the research questions. The detailed data analysis and findings are presented next, followed by a further discussion of potential market growth opportunities for the case study crowdsourcing company and others in general. Chapter 4 presents the conceptual design of microhubs with crowdshipping delivery paradigm. Detailed model formulation for both the H+S

and the M+C operation are also presented with a description of the hypothetical numerical example to compare the performance of the proposed M+C delivery paradigm with the H+S delivery paradigm. A series of sensitivity analyses for the performance of the proposed delivery paradigm is discussed with respect to the key factors described above. Chapter 5 presents the heuristic solution to a general case of Many-to-Many Split Pickup and Delivery Problem (M-MSPDP) and quantifies the benefits of splitting the loads. The evaluation of the MS-BTS heuristic is presented with its application to randomly generated datasets. The Chapter 6 considers a futuristic delivery paradigm where all stages of the last-mile demand fulfillment are handled without any involvement of human factor and presents a brief commentary on the impacts of such a proposed delivery paradigm. Lastly, Chapter 7 provides a commentary on the proposed direction of future research work.

Chapter 2 Literature Review of Last-mile and Urban Delivery Paradigms

2.1 Introduction

The relevant literatures for this dissertation can be classified into the following areas: crowdshipping, new last-mile delivery paradigm without split pick-up and deliveries, and new last-mile delivery paradigm with split pick-up and deliveries. Additional literature review is provided in Chapter 6 to assess the impact of automation in future on the freight and logistics industry.

2.2 Crowdshipping

Crowdshipping involves making use of everyday individuals with spare time and capacity to fulfill the variable delivery demand generated by e-commerce (Howe, 2006; Rai et al., 2017). Using real-time information technology for speedy coordination (see Figure 2-1), crowdshipping brings reduction in the transportation costs for the last-mile (Behrend, 2011). Crowdshipping also offers an opportunity to lower the last-mile delivery costs by employing occasional drivers and not the regular professional drivers who work full-time (Archetti et al., 2016), by allocating fewer resources (Rougès and Montreuil, 2014) and by using a variety of transport modes for the delivery, for e.g. personal automobiles, taxis, bicycles, cargo cycles, walking etc. (Marjanovic et al., 2012). Customers are also offered the flexibility to select the time windows for either pickup or for their parcels (Goetting and Handover, 2016; Punel and Stathopoulos, 2017; Le and Ukkusuri, 2019). Using the drivers already on the road, crowdshipping can reduce the VMT as well as the vehicle-trips, especially in the congested urban areas (McKinnon et al., 2015; Chen et al., 2016). This translates into fuel-savings, reduction in congestion and promotion of active modes of travel (Rougès and Montreuil, 2014; Kafle et al., 2017). Lastly, crowdsourcing offers an opportunity to make more social connections for users (Bellotti et al., 2015; Hamari et al., 2015; McKinnon et al., 2015; Piscicelli et al., 2015).

There are already several crowdsourcing delivery startup companies operating in this domain providing domestic as well as international shipping options with long-haul, short haul and last-mile delivery options. These include but are not limited to Postmates, Uber Rush, Deliv, Piggy Bee, Instacart, Amazon Flex, Friendshippr etc. Efforts in crowdsourced delivery have been made by retailers such as Walmart and Walgreens, technology companies like Google, e-retailers such as Amazon and eBay and even by traditional logistics companies like DHL and UPS (Rogues and Montreuil, 2014; Janjevic et al., 2013; IEEE 2017). However, crowdsourcing delivery service is still young and not well understood.

Existing studies on crowdshipping focus on distributing the delivery tasks among the crowdshippers to minimize the additional travel effort (Archetti et al., 2016, Wang et al., 2016, Arslan et al., 2018, and Kafle et al., 2017). Several studies explore the successful implementation of dynamic ride-sharing in passenger travel (Attanasio et al., 2004; Agatz et al., 2011; Chan and Shaheen, 2012; Furuhata et al., 2013; Ma et al., 2013). Other studies examine the ideas of crowdsourced-delivering library books (Paloheimo et al., 2014), collecting e-commerce reverse flows by taxis (Chen et al., 2016), using trucks as a network of transshipment points for crowdshippers (Kafle et al., 2017), using occasional drivers for making deliveries (Archetti et a., 2016), and combining people and parcel flows using taxis (Li et al., 2014).

The success of a crowdshipping model is dependent on the availability of a willing crowd to perform the services (Erickson and Trauth, 2013) and the area of operation (Chen et al., 2016). Crowdshipping requires a critical mass of participants, both senders and drivers, to be available in any area of operation to be successful and offer any cost savings (Archetti et al., 2016). The performance of crowdshipping is found to improve in dense urban areas (Li et al., 2014). The successful factors behind successful platforms were found to be “happy crowd” (38.24%), “good service” (27.36%), and “maximum profit” (18.32%) for platforms (Rai et al., 2018) and “compensation” (45.36%), “good working environment” (27.05%), and “good platform operation” (16.88%) for drivers (Stathopoulos et al., 2018) of a crowdsourced delivery system.

Privacy concerns continue to be a major concern among users of crowdshipping services (Rougès and Montreuil, 2014). In addition, other concerns include loss, theft or damage to the parcels (Furuhata et al., 2013). Also, lack of access to technology could be considered a barrier for a segment of population to use crowdsourced delivery service (Punel and Stathopoulos, 2017).

There is still a shortage of crowdshipping literature that addresses the behavior, motivation and goals of the participants (senders and drivers) of a crowdsourced delivery system.

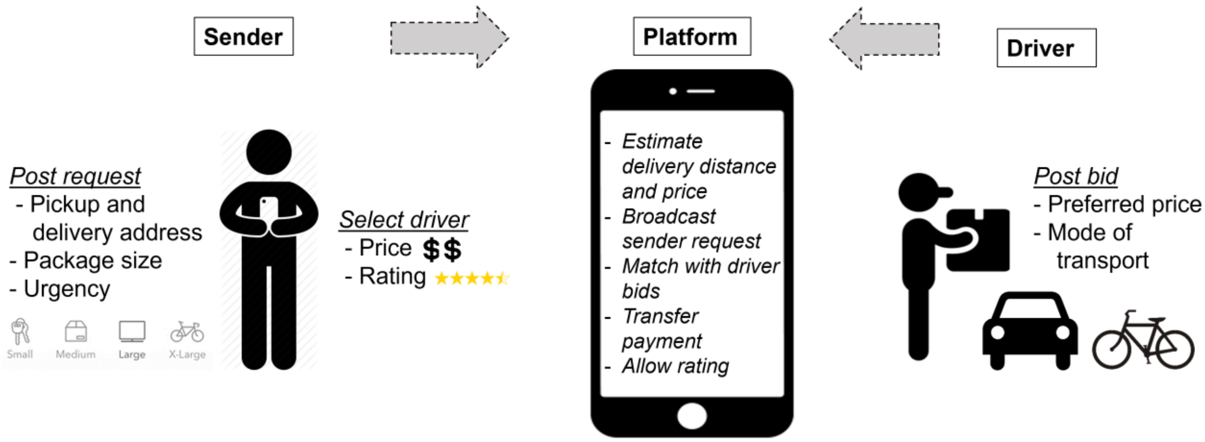


Figure 2-1: Crowdsourced parcel delivery system

2.3 Microhubs with crowdshipping delivery paradigm without split pick-up and deliveries

A recent solution to H+S in last-mile delivery is the concept of microhub. A microhub is a small-scale logistics facility usually located in the centre of an urban environment like city center, from which the local distribution demand is served by employing environment-friendly modes of transport (Janjevic and Ndiaye, 2014). A system of city center microhubs was recently field tested in Amsterdam as part of the EU-funded Civitas Citylab project (Citylab, 2018). Seven microhubs in the city of Amsterdam were carefully selected among the existing locations of the international postal mail service provider, PostNL in the city center. The microhubs were served by 50-60 freight bikes to pick up or deliver parcels from or to the microhubs. This design was a result of an investigation with the partnering postal companies (e.g. PostNL), which contributed a large number of vehicle trips in the cities. It was the first of its kind field test at such a scale. The field test showed a reduction of the delivery van stops in the city center - a total of 2,000 van stops were accounted to have been reduced during the field test. Based on the results, PostNL decided to upscale the existing system in Amsterdam and rolled out similar system in other Dutch cities. The microhubs are located at existing PostNL locations and are maintained by PostNL but are also shared with other logistics service providers.

An Automated Parcel Station (APS) is considered to be the main physical element of a microhub (see Figure 2-2 for an example). The customers can either pick up or drop off their parcels (small parcels) at the APS without any manual intervention. The customers enter a mobile phone number and a personal code to access the APS for parcel drop or collection. Customers travel on foot or by car to collect their parcels from the APS, which are located in accessible public areas like shopping centers, transit stations, gas stations, etc. The first APS network in the world was deployed in Poland in 2009 by InPost Ltd (Moroz and Polkowski, 2016). A large network of automated parcel stations is being operated in Germany, France, Sweden and Poland by the local operators (Ducret, 2014; Morganti et al., 2014; Moroz and Polkowski, 2016). These initiatives consist of relatively small parcels and light-duty freight vehicles (Augereau and Dablanc, 2008; Gonzalez Feliu et al., 2012). The benefits of using the parcel stations include reduction in the parcel turnaround time and the delivery failure rate (Punakivi et al., 2001; Punakivi, M. and Tanskanen, 2002; Weltevreden 2008), reduction in vehicle miles traveled (VMT) (Brummelman et al., 2003; Folkert and Eichhorn, 2007), substitution of car trips with non-motorized trips (McLeod et al., 2006), and a decreased risk of parcel thefts (McLeod and Cherrett, 2009). Research has shown that these alternative delivery options could be self-sufficient by earning revenue from subscription, advertisements and increased visits from potential customers (Bilik, 2014).

On the other hand, crowdshipping is gaining traction in last-mile delivery in recent years for its relatively low delivery cost and flexibility (Rai et al., 2017). It is generally believed that crowdshipping may enhance customer experience in terms of greater convenience, faster delivery, and cheaper delivery fee, and thus help retain and even expand market share of a business establishment (Punel et al., 2018). Crowdshipping may also bring about reduction in VMT, peak hour congestion, and emissions in urban areas by promoting active modes of the first and last mile delivery (e.g., by bicycle or by walking) (Gdowska et al., 2018).

In light of the potential benefits of microhubs and crowdshipping as discussed above, we propose this new urban delivery paradigm where the last-mile demand fulfilment is done through a network of microhubs coupled with crowdshipping (or M+C for short hereafter). In this paradigm, an urban service area is divided into a number of service zones (e.g., by zipcode). Within each zone, there is a designated microhub to temporarily store inbound and outbound parcels. In this study, the parcels are assumed of a typical online shopping parcel size, e.g., the commonly seen Amazon parcels which can be carried by a regular passenger vehicle. These parcels are either collected or distributed by crowdshippers between the customers (shippers and end receivers) and the microhub of a zone. Two types of crowdshippers are considered: automobile drivers and bicyclists. Commercial trucks are dispatched periodically to visit only the microhubs in the service area to transfer parcels to their respective destination microhubs. By doing so, truck traffic on busy and often narrow city streets can be largely avoided.

Figure 2-2: A PostNL parcel station in Amsterdam (Ref: PostNL, 2019)

2.4 Microhubs with crowdshipping delivery paradigm with split pick-up and deliveries

Dror and Trudeau (1989, 1990) introduced the Split Delivery Vehicle Routing Problem (SDVRP) which has since received much attention, especially in recent years. SDVRP is found to reduce the routing cost compared to the case where each customer is visited only once in the traditional VRP (Frizzell and Giffin, 1992). The cost can even be halved by allowing split deliveries (Archetti et al., 2008). Archetti and Speranza (2012) provide a survey of the SDVRP and its variants. In the existing SDVRP literature, it considers only delivery tasks and does not consider the pairwise Pickup-and-Delivery operation during routing. Nor is it an M-M problem. Different from the traditional PDVRP (Pickup and Delivery Vehicle Routing Problem), the Split Pickup and Split Delivery Vehicle Routing Problem (SPSDVRP) requires a decision variable of the quantity of demand transported between each pickup and each delivery point.

Splitting of demand is generally observed in the transportation and deliveries of bulk commodities, e.g. cement, grains, crude oil, and natural gas (Archetti and Speranza, 2012). Another common practice in freight transport is parcel shipments by truck among distribution centers (DCs), between producers and DCs, or between producers/DCs and retail stores (Battara et al., 2014; Wang et al., 2017). Though branch-and-cut exact algorithms can solve small to medium size SDVRPs, meta-heuristic algorithms (simulated annealing, tabu-search, adaptive neighborhood etc.) are necessary to solve for large scale problems (Archetti and Speranza, 2012).

Bicycle rebalancing can be formulated as a many-to-many SDVRP. Consider a fleet of bicycle shipping vans tour around the bike sharing stations, loading and unloading bicycles to redistribute the bicycles in response to the demand dynamics at the stations. For a given van, partial loading and unloading of bicycles may take place at a bike sharing station. For a given bike sharing station in need of bicycles, those bicycles may be unloaded from multiple vans that collect bicycles from multiple stations; for a station that has spare bicycles for redistribution, those extra ones may be split into multiple vans and distributed to multiple stations. Therefore, this problem represents a Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP), where both the pickup and the delivery demand are allowed to be split, and the pickup-delivery pairs are many-to-many (Tang et al., 2019). Some meta-heuristics proposed to provide an optimal solution for the BRP are: bee-colony algorithm (Szeto and Shu, 2018), destroy and repair algorithm (Dell’Amico et al., 2016), Dantzing-Wolfe and Benders' decomposition-based heuristics (Contardo et al., 2012) and the Markov Decision Process (Brinkmann et al., 2018).

Consider another example of the PostNL parcel stations in Amsterdam (PostNL.com, 2019). Self-service parcel lockers were launched by the Dutch postal operator (PostNL) at several locations (for e.g. train stations) to allow customers to pick up parcel and commerce purchases as well as send parcels, 24 hours a day. Once the parcel is delivered to a secure PostNL parcel station, the customer receives a notification informing them of where to collect their parcel. Parcel stations allow reduction in missed deliveries and allow easy returns for the customers. At a given station, all its outgoing parcels may be loaded into more than one truck and distributed to more than one destination. Similarly, the incoming parcels to a station may come from multiple truckloads of multiple origins. It represents another application of the M-MSPDP.

Note that these two applications represent two variants of the M-MSPDP. In the parcel station application, the demand between any pair of stations is known at a given time point because the origin and destination of each parcel is given. In other words, the pairwise pickup-delivery demand is pre-determined. We call the parcel station problem a Many-to-Many Split Pickup-and-Delivery Problem with Fixed Pairwise Demand (M-MSPD-FPD). In contrast, in the bike rebalancing problem, the load (i.e., the number of bicycles) between one station to any other station is a decision variable. We call the bike rebalancing problem a Many-to-Many Split Pickup-and-Delivery Problem with One Commodity (M-MSPD-OC).

In this study, we focus on the static case of M-MSPDP, though the solution methods can be easily applied to a dynamic case. The static case of the Bike-sharing Rebalancing Problem (BRP) was first defined and solved by Chemla et al. (2013) and Raviv et al. (2013). Chemla et al. (2013), proposed a combination of branch-and-cut algorithms with tabu search algorithm for solving a deterministic static single vehicle BRP on instances of up to 100 bike stations. The relaxations considered by them including allowing vertices to be visited more than once by the vehicle and allowing split deliveries. For the same problem, a 3-step mathematic programming-based heuristic is presented by Forma et al. (2015) by using a decomposing approach to first form clusters and then determining optimal routes among these clusters to maintain inventory levels for each station.

The optimal route is calculated by using an exact method for the single-vehicle BRP in Erdogan et al. (2015) for instances up to 60 bike stations. A solution to the multi-vehicle static BRP is proposed by Raviv et al. (2013) to minimize the system-wide ‘user dissatisfaction’ and ‘operational costs’. This variant of the problem permits the bike stations to be visited multiple times, allows transshipment and considers a time limit for all routes. A single-vehicle BRP is formulated based on minimizing the user dissatisfaction by Di Gaspero et al. (2013), which determines the user dissatisfaction as the total deviation from the target inventory levels at each bike station. The authors (Di Gaspero et al., 2015) further propose a constraint programming model with Large Neighborhood Search (LNS) for the same problem, determining the routes by keeping the target inventories as given (Schuijbroek et al., 2017).

An approach based on several construction (meta) heuristics is proposed by Rainer-Harbach et al. (2014) to jointly address inventory balancing and vehicle routing with the objective to minimize the weighted sum of (a) the deviation from a given target inventory level for each station, (b) the number of (un)loading operations, and (c) total work time. The initial solution is improved by applying problem-specific local search moves to obtain high-quality solutions (Schuijbroek et al., 2017). Similar problem is solved by Di Gaspero et al (2013) by combining a CP optimization model with Ant colony Optimization with the objective to minimize the weighted sum of the deviation from target inventory levels and total work time. A cluster first route-second approach, incorporating an exact algorithm and utilizing Benders composition, is developed by Kloimüllner et al. (2015) with the objective to maximize the number of stations visited over a fixed time window (Schuijbroek et al., 2017).

The routes and the respective quantities for loading and unloading are determined by making use of set of loading and unloading strategies embedded in a bee-colony algorithm (Szeto and Shu, 2018). The objective of the problem is set to minimize the positive deviation from the tolerance of 'total demand dissatisfaction' and the service times (Dell'Amico et al., 2018). A hybrid large neighborhood search approach is used by Ho and Szeto (2017) to solve a multi-vehicle static BRP. A set of four mathematical formulations for multiple-vehicle static BRP is proposed by Dell'Amico et al. (2014) and solved by using the branch-and-cut algorithm. Dell'Amico et al. (2016) provides the solution to the multiple-vehicle static BRP with route duration constraints by implementing the destroy and repair algorithm.

Contardo et al. (2012) considers the dynamic version of BRP with a heterogenous fleet of vehicles and proposes a solution to the time-indexed formulations by using Dantzing-Wolfe and Benders' decomposition-based heuristics. A mixed integer linear programming formulation and math-heuristic approach is proposed by Zhang et al. (2017) which considers the level of the inventory and the forecast of the arrival of the users in a time-space network flow model. A dynamic green bike repositioning problem is introduced by Shui and Szeto (2017) which minimizes the total unfulfilled demand as well as the cost of the fuel and CO_2 emissions for the repositioning the vehicle. A hybrid rolling horizon artificial bee colony algorithm is proposed for solving this problem (Dell'Amico et al., 2018).

Several studies also attempt to address the stochastic version of the BRP. The stochastic information is considered implicitly as part of their penalty function by Raviv et al. (2013). Wang and Wang (2013) provide an analysis on bike repositioning strategies using real-time and historical data in a simulation environment. Regue and Recker (2014) solve a dynamic BRP, where demand estimation is carried out be entering the historical data into a forecasting model. An hourly demand estimation is used in a proposed mathematical formulation by Saharidis et al. (2014) for making decisions about the locations and capacity of the bike-stations. Schuijbroek et al. (2017) models the bike-sharing inventory as a non-stationary Markov chain to determine bounds on inventory quantities and use them in MILP models. Another study (Brinkmann et al., 2018) models a stochastic-dynamic BRP as a Markov decision process and anticipates future demands by presenting a dynamic lookahead policy to minimize the expected unsatisfied demands (Dell'Amico et al., 2018).

Dror et al. (1994) presents a mixed integer programming (MIP) formulation to obtain the exact solution for the SDVRP with an unlimited vehicle fleet. Another method to obtain the exact solution was proposed by Belenguer et al. (2000) using a cutting-plane based algorithm. Jin et al.

(2007) propose a two-phase exact algorithm for the SDVRP with a limited vehicle fleet, while Jin et al. (2008) propose a column generation algorithm for the same problem. A cut-and-price based approach is proposed by Moreno et al. (2010) for the SDVRP with a limited vehicle fleet. Further, a branch-cut and-price algorithm is developed by Archetti et al. (2012) for the SDVRP. Another method to obtain the exact solution for VRPSPSD for bike-sharing is proposed by Casazza (2016).

Dror et al. (1994) notes that SDVRP is more difficult to solve for optimality than the traditional VRP, which is NP-hard (Lenstra and Kan, 1981). Hence, heuristic solution methods have been developed to solve SDVRP. A three-phase Tabu Search heuristic for SDVRP with unlimited vehicle fleet is proposed by Archetti et al. (2006). Chen et al. (2007) propose a hybrid algorithm for the SDVRP with an unlimited vehicle fleet. This hybrid algorithm is a combination of a MILP formulation, a savings-based heuristic and a record-to-record procedure. A Scatter Search based heuristic algorithm is proposed by Campos et al. (2008) for the SDVRP with a limited vehicle fleet. A Memetic Algorithm with population management is developed by Boudia et al. (2007) for the SDVRP with an unlimited vehicle fleet. Another hybrid combination of a tabu search heuristic and an integer programming formulation is proposed by Archetti et al. (2008). Aleman et al. (2010) presents constructive and local search procedures for the SDVRP with a limited vehicle fleet, whereas Aleman and Hill (2010) implement a TS heuristic with vocabulary building for the SDVRP with an unlimited fleet. Derigs et al. (2010) compare the performance of several local search-based metaheuristics for the SDVRP with an unlimited vehicle fleet. A two-phase constructive procedure as well as a Genetic Algorithm for the SDVRP with a limited vehicle fleet is proposed by Wilck IV and Cavalier (2012).

The VRP with Split Pickups and Deliveries problem (VRPSPDP), with paired loads, is a more complex problem than the regular SDVRP, but some of the approaches used for solving SDVRP are applicable and should be considered. The first attempt at solving the VRPSPDP appears in Mitra (2005). This paper considers the problem of supplying finished goods to multiple delivery points and picking up returnable items for a set of customers using a homogenous fleet of vehicles. Thus, each customer can have demand for both pick-up and delivery and the demand can be more than the capacity of the vehicle. Split pick-ups and deliveries are allowed, implying that a vehicle could visit the same customer multiple times and each customer could be visited by multiple vehicles. The objective of the problem simultaneously determines the minimum number of vehicles required to fulfill the customer demand (pick-up and delivery) as well as to identify the routing strategy to minimize the total route cost. No constraints on time windows or the length of the route are considered. The paper presents a MILP formulation for the problem and proposes a heuristic (constructive algorithm) that first determines the minimum number of required vehicles and then creates routes based on the cheapest insertion criterion (Archetti and Speranza, 2012). An alternative formulation is proposed in Mitra (2008) for the same problem with an improved faster heuristic (parallel clustering). Nowak et al. (2008) present the formulation for a one-to-one pick-up and delivery problem and quantify the benefit of using split loads. According to the paper, the maximum benefit is achieved when the size of the load is just above one-half of the vehicle capacity. The paper presents a heuristic based on tabu search and simulated annealing to solve the problem of pick-up and delivery loads with split loads. Wang et al. (2012) developed a hybrid heuristic algorithm to solve the VRP with simultaneous deliveries and pickups with split loads and time windows (VRPSDPSLTW) and test it on modified Solomon datasets. Sahin et al. (2013)

proposes a heuristic based on tab search and simulated annealing which improves the initial solution determined from Clark and Wright's saving heuristic.

The Table 2-1 provides the summary of the relevant literature review that is available for problems with fixed origins and destinations:

Table 2-1. Literature Review

Study	Structure	Split	Paired demand	Variant	Solution
Archetti et al., 2011 Archetti et al., 2006 Wilck IV and Cavalier, 2012	One to Many	Yes	Yes	SDVRP	Branch and cut algorithm Heuristic using tabu search algorithm Heuristic using Genetic Algorithm
Casazza et al., 2016	Many to Many	Yes	No	VRPSPSD	Exact solution using Dantzig-Wolfe decomposition and column generation

Mitra, 2005	One to One	Yes	Yes	VRPSDPDP	Constructive algorithm
Mitra, 2008	One to One				Parallel clustering algorithm
Nowak et al., 2008	One to Many				Tabu search with simulated annealing
Wang et al., 20012	One to One				Hybrid heuristic method
Sahin et al., 2013	One to One				Heuristic combining Tabu Search and Simulated Annealing

Chapter 3 Preliminary Investigation of a Crowdsourced Parcel Delivery System: A Case Study

Ballare, S. and Lin, J., 2018. Preliminary investigation of a crowdsourced parcel delivery system: A case study. *City Logistics 3: Towards Sustainable and Liveable Cities*, pp.109-128.

3.1 Introduction

The rise of e-commerce (US Census, 2016) and the trend of on-demand deliveries has led to the urban retail sector reexamining the efficiency of the associated vehicle fleet to satisfy this variable demand. The traditional "hub and spoke" distribution model being used extensively by large carriers (e.g. Fedex and UPS) is not built to cater to such variable express demand. In addition, much of the trunk space of passenger vehicles during routine journeys is mostly unused. The retail sector is feeling the need for an innovative urban mobility solution that provides reliability of transportation, while ensuring environmental sustainability and reduction in the cost of the last mile deliveries (Lee et al., 2001; Munuzuri et al., 2005; Crainic et al., 2009; Quak and Koster et al., 2009).

This chapter is organized as follows. First, an overview is provided of the case study crowdsourcing delivery company's delivery service as well as the pricing model employed by the company. Next, a set of research questions to be answered in this study are presented, followed by an overview of the crowdsourcing data shared by the company, to be used to find answers for the research questions. The detailed data analysis and findings are presented next, followed by a further discussion of potential market growth opportunities for the case study crowdsourcing company and others in general. The chapter ends with the key conclusions from the study.

3.2 Overview of the Case Study

3.2.1 Types of Delivery Service

The studied crowdsourcing technology company provides matching of the unused capacity in passenger vehicles with the delivery requests across the United States. The name of the company is kept confidential due to the non-disclosure agreement involved. The company's delivery model enables efficient, express, flexible and low-cost delivery for customers and rewards the participating drivers for trips they were already scheduled to take. Several of crowdsourcing delivery companies operate at a regional level (for e.g. Dolly in Chicago and Wagon in Seattle), but the crowdsourcing technology company considered in this study operates nationally. It has been introduced as a shipping network between neighbors connecting the senders with drivers with spare capacity in their vehicles headed in the same direction. A delivery mobile app connects users (called "customers") needing to send something with those who are willing to transport it to the specified destination (called "drivers"). The company's business model differs from the traditional "hub and spoke" model in the way that there does not exist a centralized dispatch or consolidation center ("hub"), neither are the individuals transporting the parcels considered to be employees of the company. Thus, the company offers a more flexible and cost-effective alternative to traditional delivery methods. The company's initial targeted market is intercity delivery and expedited or same-day delivery service. The crowdsourced delivery company also offers several incentives to the drivers in terms of roadside discounts, free road-side assistance, and tax write-offs on miles driven. It is a new smartphone app now addressing the issue by providing services that operate like ridesharing (for e.g. Uber and Lyft), only it transports parcels instead of people.

Both the customers and drivers are required to pre-register themselves with the company by providing basic information including preferred pickup locations. This is done by downloading and registering with the delivery ridesharing app of the company on their smartphones. This application allows the customers to post details and pictures of the goods to be transported and enables the drivers to choose between the various delivery service requests in their vicinity. The app also provides information on the location, size, price, ratings and reviews to enable both customers and drivers to make the right choice.

For convenience of the customers and drivers, the parcels are identified based on their size rather than their weight. The parcels are classified into five sizes – small, medium, large, extra-large and super-large. The small and the medium parcel sizes can be accommodated on the front passenger seat whereas the medium size in the backseat of a normal passenger car. The extra-large and super-large parcel sizes however would require a SUV or a pickup truck to accommodate them. In addition to normal parcels, the company also offers transfer of pets through its delivery system, however such deliveries have not been considered as part of this study. The company does offer specific instructions on permissible parcel contents. It specifies that all customers are prohibited from including in any parcel, and all drivers are prohibited from knowingly accepting, picking-up, carrying or delivering any parcel containing any illegal or contraband items, as listed on the company website.

The process is initiated when a customer submits a request for parcel pickup and delivery through the app, with user-specified information including the parcel size, pickup and drop off location, and delivery time windows etc. This posted request is marked by the app as *published*. The app then estimates the delivery fee based on the parcel size and the requested delivery distance and broadcasts the published request along with the delivery fee to all eligible drivers. Any driver can submit a bid in response to the published delivery request, upon which the customer has the choice to accept or decline the bid while also considering the ratings and reviews of the driver. Once the customer accepts the bid submitted by the driver, the status of the request changes to *accepted*. When the driver picks up the parcel and completes the delivery, the status of the delivery request changes to *delivered*. However, there may be cases where no driver responds to a published delivery request before the expiration of the specified delivery time window. In this case, the status of the delivery request changes to *expired*. If either customer or driver decides to refuse the request at any point in time before the delivery is carried out, the request is marked as *cancelled*. Users, both customers and drivers are allowed a total of 3 cancellations of *accepted* requests by the company, before their user profiles are deactivated, to deter malicious users messing with the system. Figure 3-1 describes the process from creation and fulfillment of a delivery request.

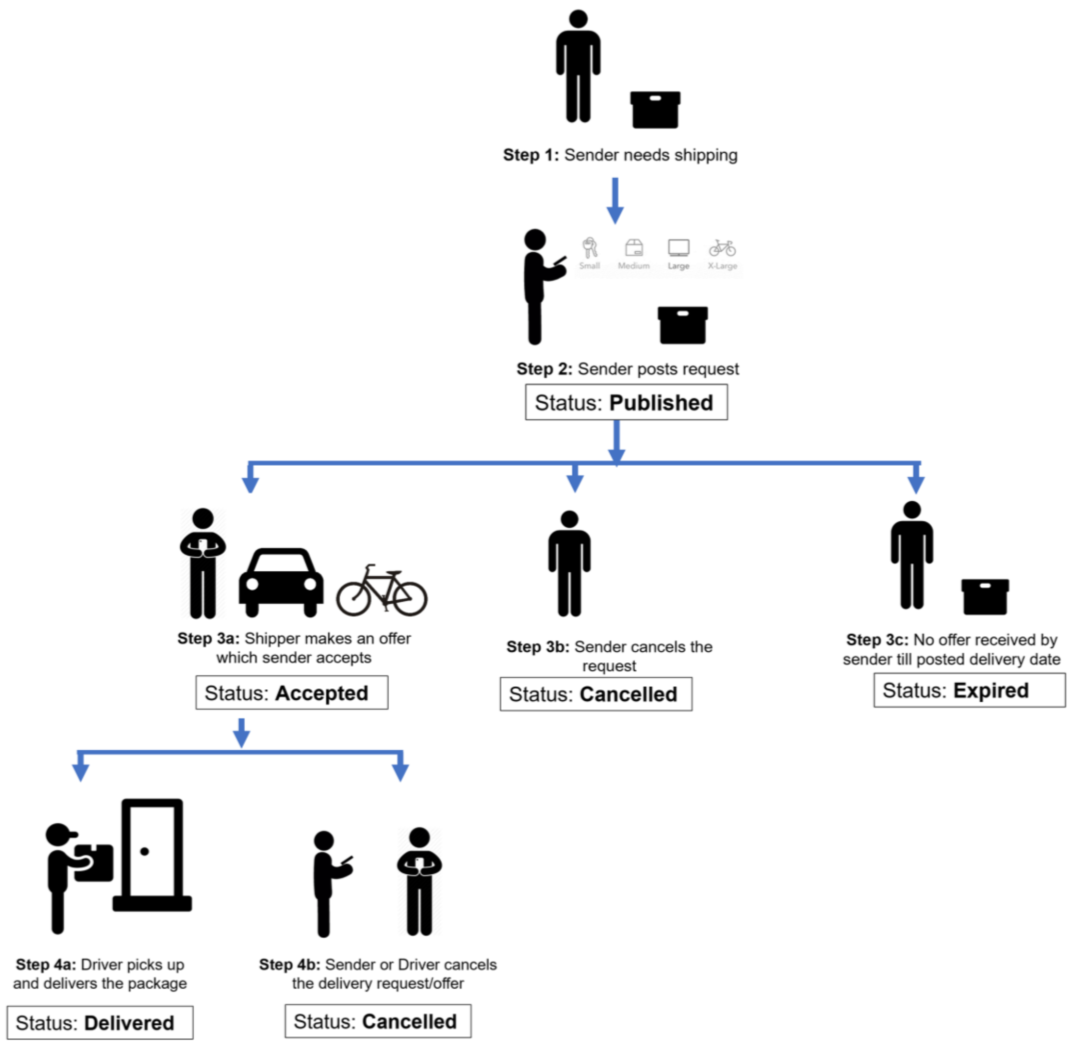


Figure 3-1: Flowchart of crowdsourced delivery system

Delivery integrity is considered to be one of the most important attributes for the customers to select traditional couriers (Gibson et al., 2015). Hence, to ensure customer confidence, all the deliveries made through the app are insured by the company up to $500. Customers can purchase additional insurance depending on the self-declared value of the transported goods. Registered drivers must provide information about their vehicle type, driver's license and insurance. They can start operating only after verification of these details by the company.

During the study period, between January 2015 and August 2018, a total of 380,951 users were registered with the company, including customers and drivers. For the same period, a total of 107,505 delivery requests were received by the company, including deliveries which were completed, cancelled or were in process of being accepted for delivery. These deliveries, in total, accounted for a revenue of more than $53.8 million.

3.2.2 Pricing Model

For every delivery service request received, the delivery app estimates the delivery fee depending on several factors, including size of the parcel to be delivered, delivery distance and urgency status, with a specified minimum and maximum fee for the selected parcel size. Once the customer accepts the bid posted by the driver against the estimate fee and the delivery has been completed, the driver receives 80% of the agreed fee whereas the company receives 20% of the fee. It is important to note here that the pricing model does not intend to fully cover the transportation expenses of the selected driver, rather it aims to offset a part of her/his expenses towards a journey which they were already undertaking irrespective of the delivery request. A safety fee of $1 is applied to each delivery irrespective of the parcel size or the delivery distance, and this fee as well as the insurance amount is not shared with the driver. As can be seen from the Figure 3-2, the price of sending a parcel increases with an increase in parcel size as well as the delivery distance.

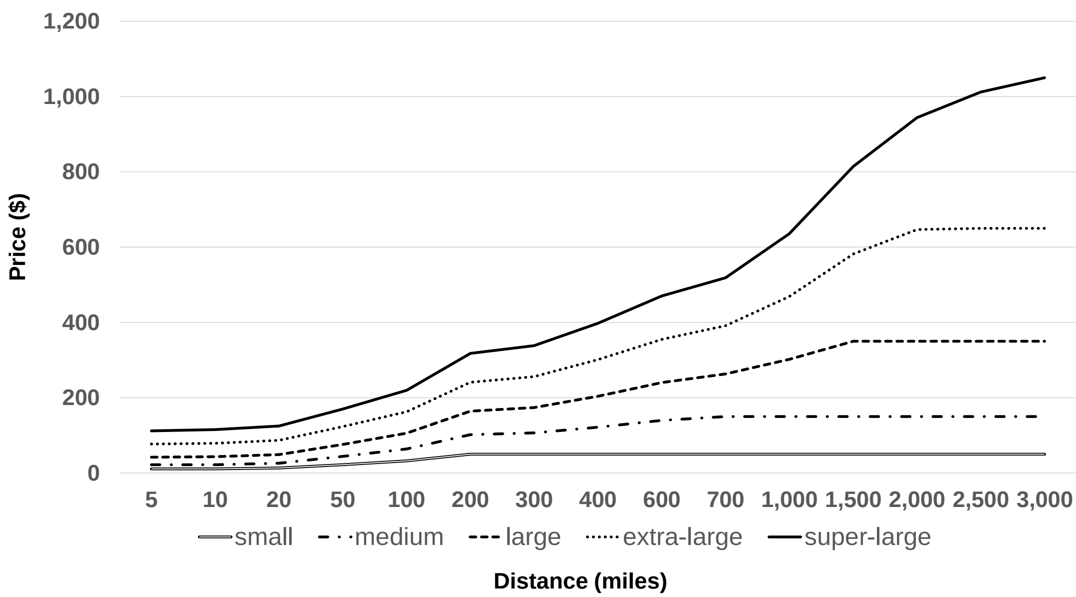


Figure 3-2. Pricing model used for different parcel sizes

3.3. Research Questions

The success of crowdshipping depends upon timely identification of preferences of customers and drivers and providing motivation to all users for participation in such a delivery system. This also enables the company to not only maintain the critical mass for such a delivery system, but also helps it to forecast the demand (Rouges and Montreuil, 2014).

This study answers research questions which are of importance to the existing logistics companies as well as new startups which wish to employ crowdsourcing for the first or last-mile delivery. The research questions have been clustered under the appropriate headings – delivery attributes, user characteristics, market opportunities and qualitative assessment of service. The research questions are as follows:

1. What is the success percentage for the delivery requests received so far and the reasons behind the fulfillment/unfulfillment of these requests?

2. Who are the regular users (customers and couriers) of a crowdsourcing delivery system and what are their characteristics?

3. Which are the parcel sizes and delivery distance which are popular among the customers and the couriers respectively?

4. What are the features of the pricing model and the virtual platform provided by the company to match the customers with interested couriers?

5. What are the socio-demographic characteristics behind the motivation of users to participate in crowdsourced delivery system?

6. How can the current crowdsourcing delivery system be improved?

Under delivery attributes, this study answers basic questions regarding the delivery service requests created on the ridesharing app, including their current trend. The study also investigates the percentage of successful and unsuccessful deliveries, and the reasons behind them on the basis of the average delivery distance requested and the delivery price. For user characteristics, this study explores the user base for such a delivery system, including the customers and drivers. The study first investigates the trend of registration among the users, registered locations, age profiles for the most active customers and drivers, and identifies these as businesses or individuals. The study then uses the socio-demographic characteristics extracted from census data for zip codes to identify factors behind behavior of users of the crowdsourced delivery system. The study also investigates the interdependency between the zipcodes in terms of spatial autocorrelation by using the zipcode level parcel flows – both inbound and outbound.

Further, for market opportunities, the study explores the preferences of the customers in terms of the parcel sizes as well as the delivery distance. This section answers the important question regarding what the potential future strategy of the company, including which parcel sizes and the delivery distance will provide the company a bigger market share. Under qualitative assessment of service, the study explores the perceived strengths and improvement areas for the business model employed by the crowdsourced delivery company. Comments are provided on the entire delivery system, as well as the delivery ridesharing app itself.

3.4. Data

The data used in this study is obtained from one of the largest crowdsourced delivery companies in the United States providing coverage across the entire geographic area. For this study, the data was downloaded from the company database for the past three and a half year's operations. From the company database, the data for all the delivery requests and registered users was extracted in the CSV format for further analysis, using a free software – DB visualizer. The data was present in the two following subsets as shown in the Figure 3-3. The header fields present in the delivery data subset, user data subset and their respective description is provided in the Table 3-1 and Table 3-2.

.

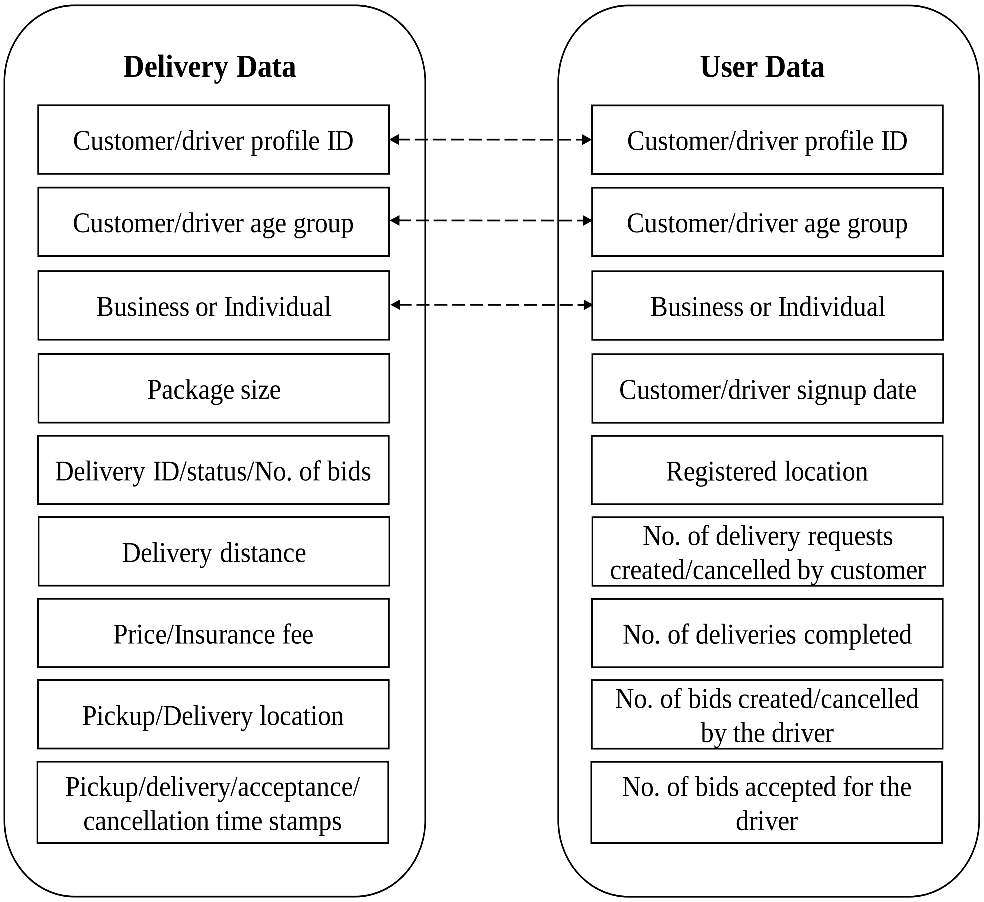


Figure 3-3. Data structure and organization

Table 3-1. Description of the field names present in the delivery data

Sr. No.	**Field Name**	**Description**
1	Delivery Id	Serial number of the delivery request.
2	Parcel Size	Size of the goods to be transported as defined by the company.
3	Delivery Status	Status of the delivery request.

4	Delivery deadline	Date and time when delivery time-window ends.
5	Insured value	Self-declared insurance value of the goods to be transported.
6	Total price	Total price of the delivery as estimated by the delivery ridesharing app.
7	Insurance fee	Insurance fee for delivery if selected by the customer.
8	Total distance	Distance between the pickup and the delivery point of the delivery as estimated by the app.
9	Customer profile id	Registered identification number of the customer.
10	Customer age group	Pre-defined age group bracket of the customer.
11	Driver profile id	Registered identification number of the driver.
12	Driver age group	Pre-defined age group bracket of the driver.
13	Pickup city/state/zip/MSA	City/state/US Zip code/Metropolitan Statistical Area where the pickup of the delivery is scheduled.
14	Delivery city/state/zip/MSA	City/state/US Zip code/Metropolitan Statistical Area where the delivery is scheduled.
15	Published date	Date and time when the delivery request is posted by the customer.
16	Cancelled date	Date and time of cancellation of a delivery request.
17	Accepted date	Date and time when the delivery request is accepted by the driver and the customer.
18	Started/Pickup date	Date and time when the driver initiates/completes the pickup of the delivery.

19	Delivery date	Date and time when the driver completes the delivery.
20	Sender business	True or False choice based on if the customer has declared itself to be a business or an individual.
21	Driver business	True or False choice based on if the driver has declared itself to be a business or an individual.
22	Destination Lat/Lon	Latitude/Longitude of the delivery point.
23	Pickup Lat/Lon	Latitude/ Longitude of the pickup point.
24	Bids	Number of bids from drivers received per delivery request.

Table 3-2. Description of the field names present in the User data

Sr. No.	**Field Name**	**Description**
1	Profile id	Registered identification number of the user.
2	Signup date	Date and time of registration of the user.
3	Age group	Predefined age group bracket of the user.
4	Registered city/state/zip/MSA location	Preferred city/state/zip code/Metropolitan Statistical Area of operation for user.
5	Is driver	True or False choice (if the user is a driver or customer).

6	Is customer	True or False choice (if the user is a customer or a driver).
7	Business/Individual	True or False choice (if the user is a business or an individual).
8	Created/Delivered/Cancelled	Number of delivery requests created/completed/cancelled by the user.
9	Created/Cancelled bids	Number of bids created/cancelled by the driver.
10	Accepted bids	Number of bids accepted for the driver.

The delivery dataset contains the primary details about the goods transported including the parcel size, declared value and registration details for the customer and the driver. Detailed information about the pickup and the drop off locations is provided in terms of the zip code, city and state as well as geographical coordinates. Additionally, the data contains information about the distance between the pickup and drop off points, and the total fee charged by the company for the respective delivery. Other details include time stamps for generation of delivery service request, its completion, pickup of the parcel and its delivery. The user data contains the profile information of both customers and drivers for each completed delivery in terms of the age group, registered location, individual or business etc. It also contains the number of delivery requests and their status for the customer and the number of bids created and their respective status for the drivers. The socio-demographic data for the zip codes is obtained from the 2017 American Community Survey (U.S. Census, 2019). It is not mandatory for users, both senders and drivers, to provide their preferred zip code for participation in the delivery.

3.5. Analysis Findings

Only the delivery service requests that were completed, cancelled, expired, and are in progress or awaiting pick up or delivery during this period were considered for analysis in this study. No cargo consolidation is considered for this data and each delivery is assumed to be an isolated set of pickup and delivery case between a customer and the driver involved.

a) Delivery attributes

A large number of delivery requests (72.56%) were successfully completed between 2015 and 2018. However, 22.33% of the delivery requests have also been cancelled, in addition to 5.04% of delivery requests that expired due to not being accepted by any of the drivers before the delivery deadline. Overall, the completed deliveries account for only 49.48% of the total price, with the cancelled and expired delivery requests accounting for 49.97% of the total price combined. There has not been a significant change from the numbers between 2015 and 2016 (when we first performed the analysis), with 73.18% of deliveries successfully completed, 19.11% of delivery requests cancelled and 6.68% of the delivery requests expired. Between 2015 and 2016, the completed deliveries accounted for 47.10% of the total price, with the cancelled and expired delivery requests accounting for 48.98% of the total price combined.

The completed delivery requests between 2015 and 2018 account for a total of 34.16% of the total miles travelled with an average of 63.98 miles per delivery request. Whereas, the cancelled and expired delivery requests account for 65.20% of the (expected) total miles travelled with an average of 322.69 miles per delivery. This indicates that the service requests for a longer delivery distance have a difficulty finding a driver willing to complete the delivery. This is also confirmed in Figure 3-4, which shows that the average miles travelled and the average price ($) per delivery request for the completed deliveries is lower than those cancelled or expired. Between 2015 and 2016, the completed delivery requests accounted for a total of 31.77% of the total miles travelled with an average of 71.04 miles per delivery request. The cancelled and expired delivery requests between 2015 and 2016 accounted for 63.33% of the (expected) total miles travelled with an average of 401.09 miles per delivery.

The published delivery requests are from the period between July and August 2018. These are the delivery requests which have not yet received a response from the drivers. These have a high average delivery distance in miles and a high average price ($) per delivery. This also represents delivery requests for a high percentage (71.74%) of extra-large and super-large parcel sizes which generally have a higher delivery distance requested in comparison to the small, medium and large parcel sizes. The high average delivery distance for the published delivery requests during this period may be due to a new customer signing up to use the crowdshipping service for long distance deliveries. In absence of detailed information available for the customers, it is difficult to speculate the exact reason for this high average delivery distance for the published delivery requests.

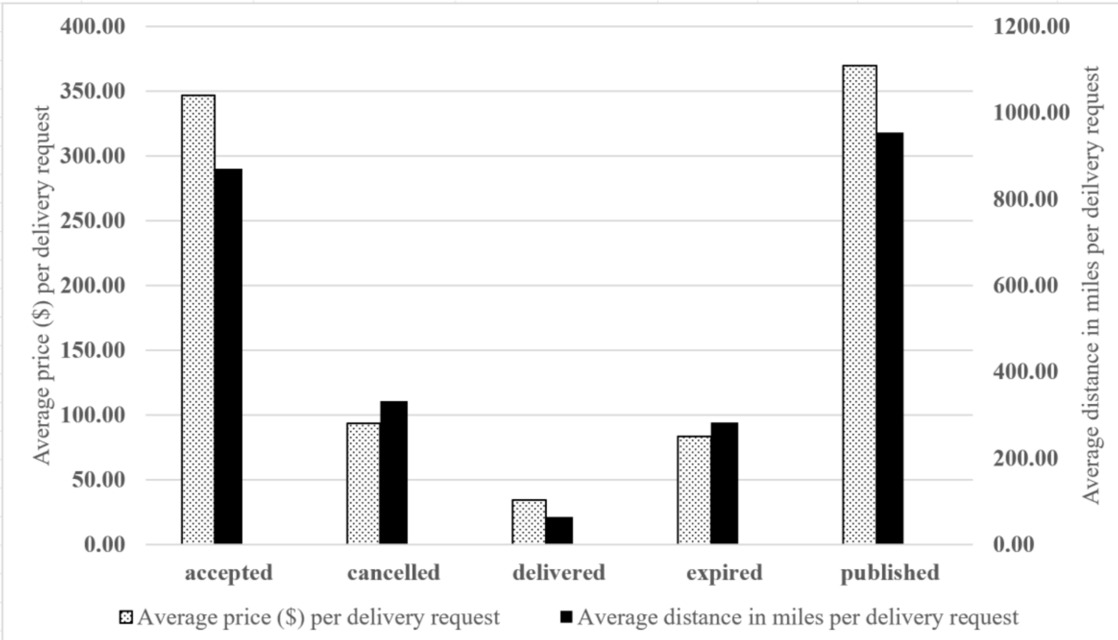


Figure 3-4. Performance parameters for the different delivery request status

A total of 77,845 deliveries were recorded as completed between the period of 2015-18 for the company. Figure 3-5 provides the growth trend for the number of deliveries, miles travelled and the total price during the study period. This translates to an average of approximately 5,200 number of parcels delivered every quarter representing a cumulative delivery distance of 332,715 miles and a total fee collection of $177,655. It shows a healthy growth in the number of completed deliveries for the company and is an indicator that such a delivery service system is acceptable to customers. Further investigation is needed to explore which parcel sizes and what delivery distance is popular among the customers, and also the nature of users responsible for the success of such a delivery system. Figure 3-6 shows a constant growth in delivery requests for all the parcel sizes, however the largest growth is observed in the medium parcel size over the study period.

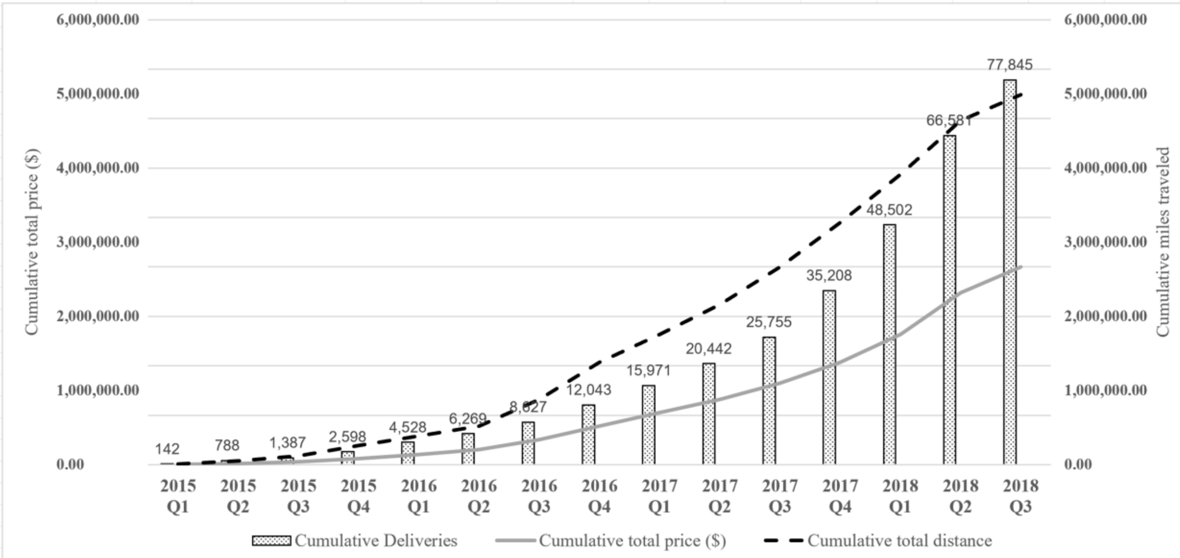


Figure 3-5. Growth trend for the number of completed deliveries

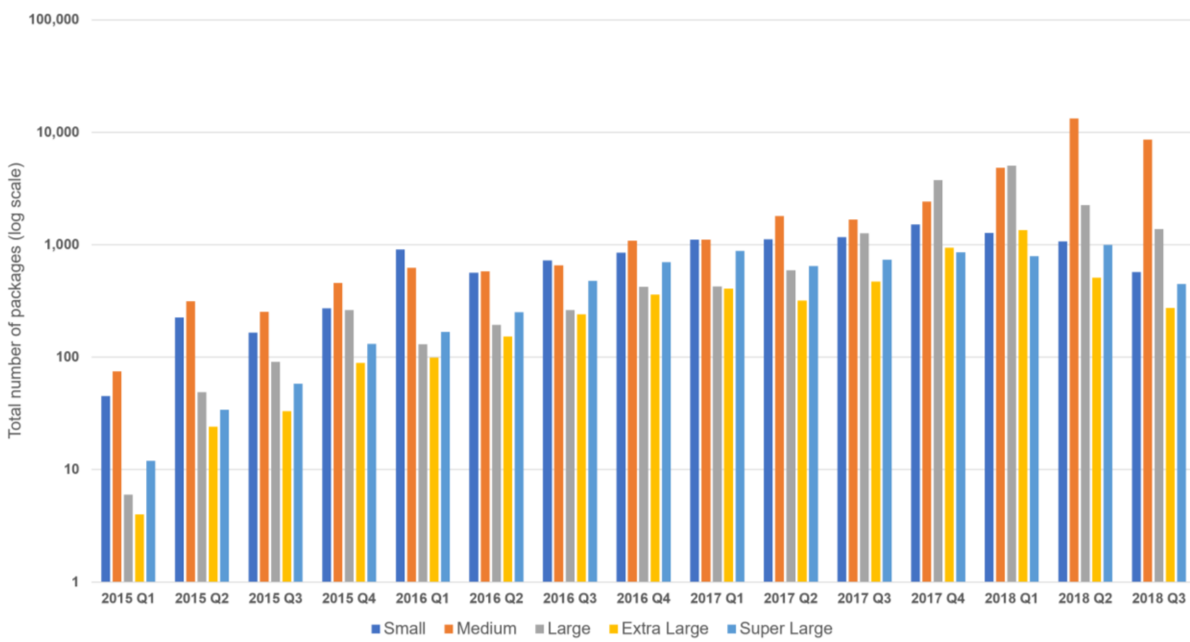
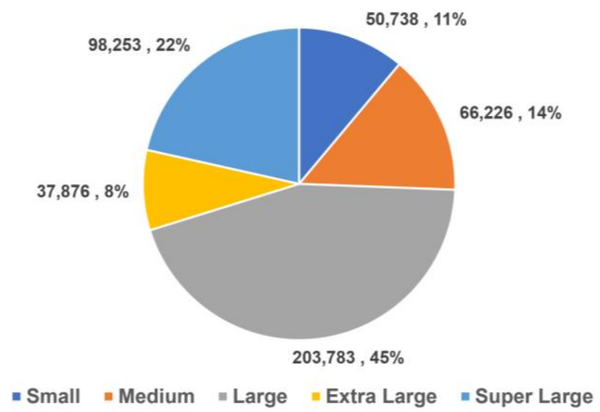


Figure 3-6. Growth trend for the number of completed deliveries

Figure 3-7 presents the distribution of the total fee collected according to the various parcel sizes. There is an increase in the share of the total fee collected from the medium, extra-large and super large parcel sizes between 2015-2018 as compared to between 2015-2016, whereas there is a decrease in the share of total fee collected from the small and large parcel sizes.



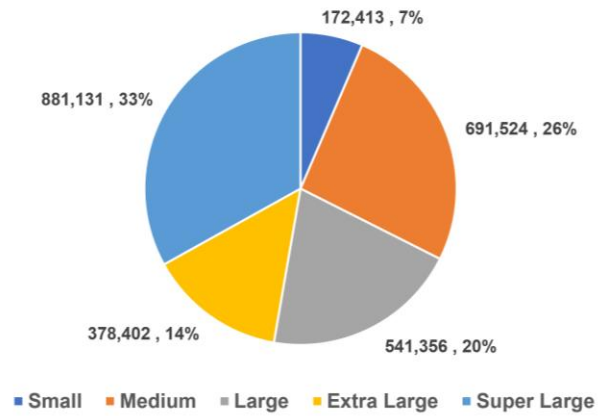
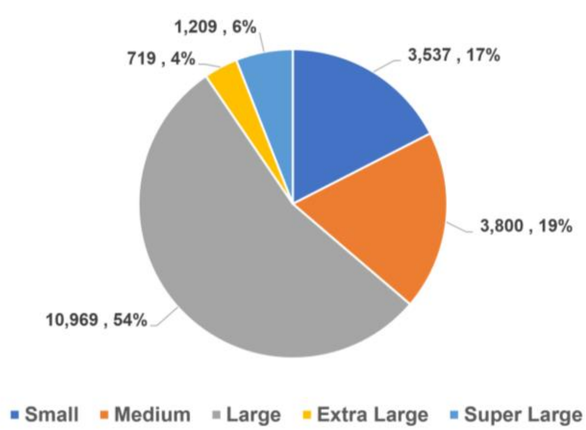


Figure 3-7. Distribution of total fee collected: (a) between 2015-2016; (b) between 2015-2018

Figure 3-8 presents the distribution of total completed deliveries according to the various parcel sizes. The large parcel size appears to be popular between 2015-2016, whereas the medium parcel size appears to be the most popular between 2015-2018. There is a considerable decrease in the share of the large parcel sizes, whereas there is a small increase the other parcel sizes except the small parcel size.



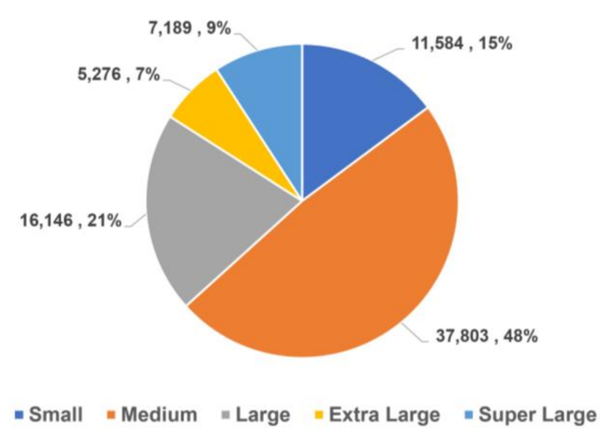


Figure 3-8. Distribution of completed deliveries: (a) between 2015 -16; (b) between 2015-18

Figure 3-9 presents the performance metrics for the different parcel sizes for all the completed deliveries.

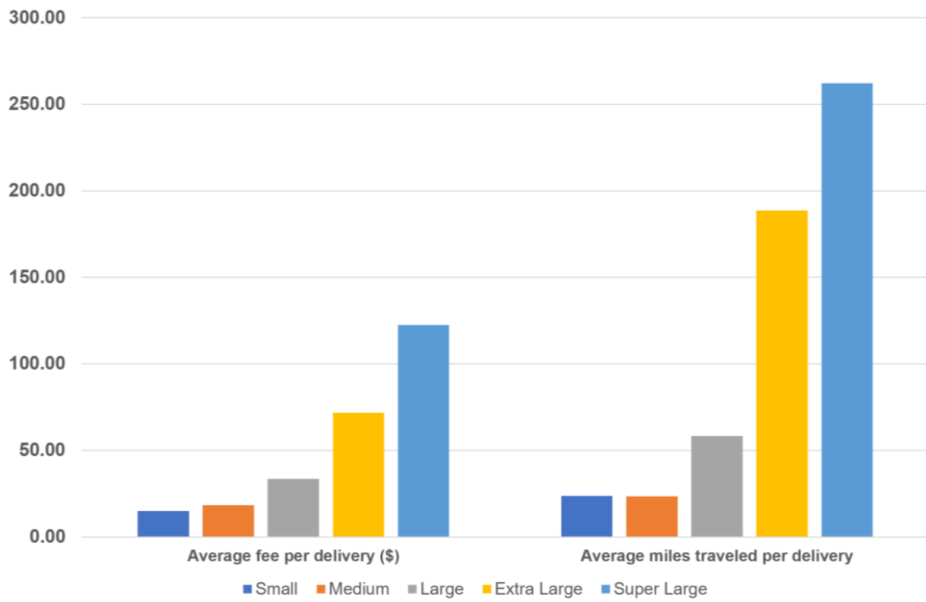


Figure 3-9. Performance metrics for the completed deliveries

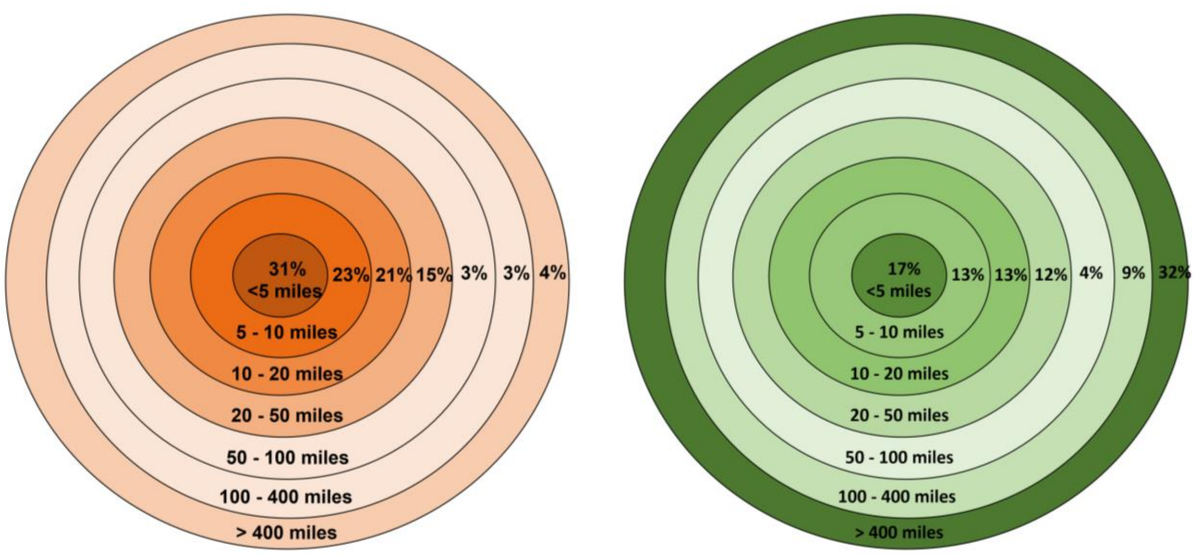


Figure 3-10. Distribution by distance: (a) total completed deliveries by number; (b) by total fee collected

Figure 3-10 shows that majority of the deliveries (90%) and the total fee collected (55%) collected are restricted within a delivery distance of less than 50 miles indicating intracity travel. At the same time, a small percentage of deliveries (4%) over a distance of 400 miles account for a large portion (32%) of the total fee collected.

Table 3-3 provides the distribution of the delivered parcel sizes based on the delivery distance.

Table 3-3. Distance distribution for completed deliveries by parcel size

	Percentage of total deliveries completed					
Distance in miles	Small	Medium	Large	Extra-large	Super large	**Total**
0 to 5	3.13%	15.85%	8.87%	1.71%	1.64%	**31.20%**
5 to 10	2.86%	12.63%	5.64%	1.20%	1.00%	**23.34%**
10 to 20	4.43%	11.58%	2.49%	0.70%	1.30%	**20.50%**
20 to 50	3.93%	6.67%	1.70%	0.87%	1.52%	**14.68%**
50 to 100	0.28%	0.77%	0.49%	0.43%	0.52%	**2.50%**
100 to 400	0.15%	0.56%	0.67%	0.78%	1.18%	**3.33%**
400 +	0.08%	0.41%	0.84%	1.07%	2.05%	**4.45%**
Total	**14.85%**	**48.47%**	**20.70%**	**6.76%**	**9.22%**	**100%**

Figure 3-11 shows that the medium and large parcel sizes have a large share in deliveries less than 100 miles, whereas the extra-large and super-large parcel sizes have a larger share in deliveries more than 100 miles. The medium parcel size continues to remain popular irrespective of the delivery distance.

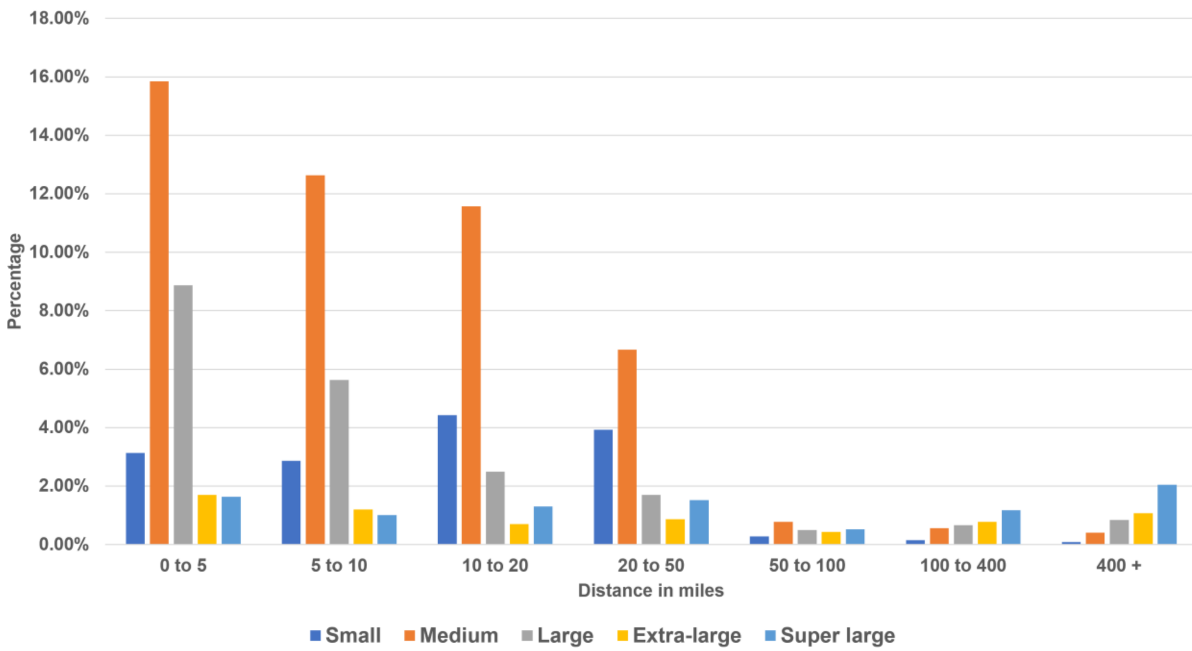


Figure 3-11. Distribution of delivered parcels based on size and delivery distance

b) User characteristics

Figure 3-12 provides the trend for the new user registrations, both as customer and driver, for the eight quarters of the study period. After an initial increase in the second and the third quarter of 2015, a decline in the number of new user registrations is observed. The number of new registrations appear to be stable over the recent years.

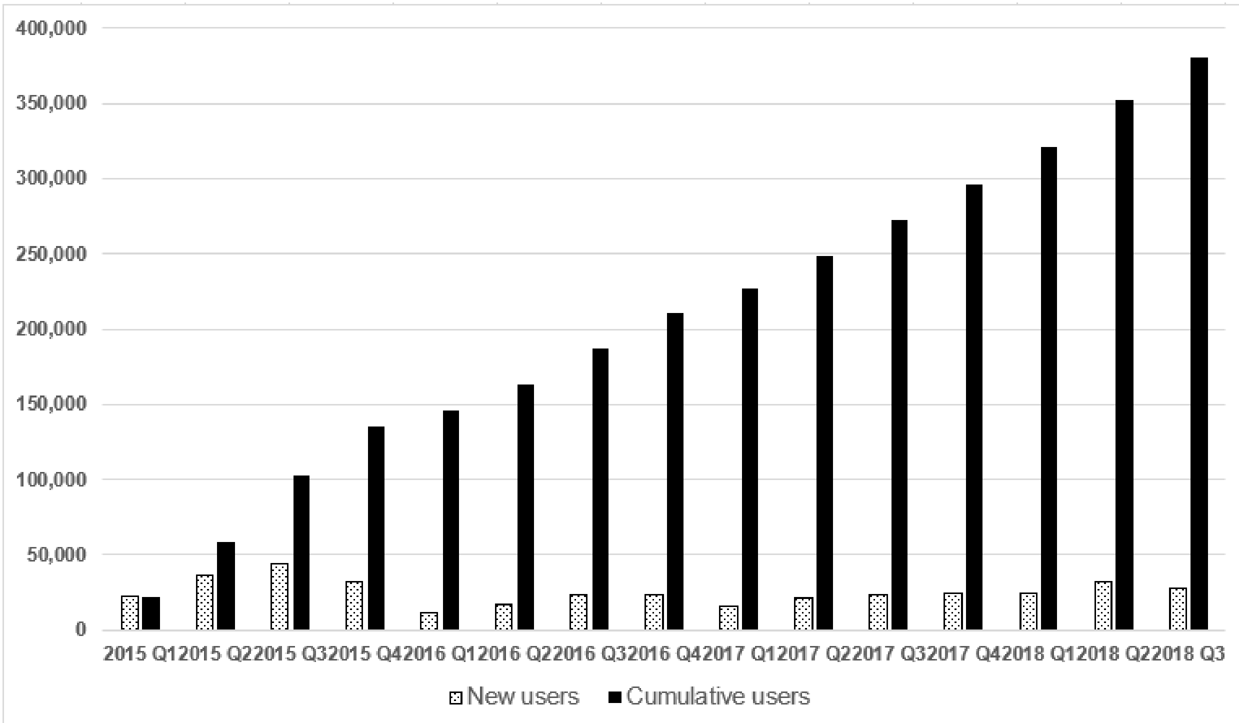


Figure 3-12. Trend for registration of users on the delivery ridesharing app

From the age group distribution for the registered customers and the drivers of the completed deliveries, it was found that the age group of 35-44 years is popular among both the customers and the drivers. A large number of customers have not provided their age details as it is not a mandatory requirement by the company app, whereas it is a mandatory requirement for the drivers and hence a relatively low amount of undeclared age numbers for drivers. More than half of the customers who have provided their age details fall into the age group of 25-44 years, whereas more than 79% of the drivers fall in the age range of 24-54 years. This has been found in other studies as well (Ermagun and Stathopoulos, 2018). The age-group of 35-44 years comprises mostly of working individuals who are internet savvy and open to opportunities to experiment with a new delivery system as well as participate as a driver in such a system to supplement their income. This has been found true for other collaborative systems making use of technology, where younger population form a large share of the user base (Panda et al., 2015; Rayle et al., 2015; Shaheen et al., 2016).

Most of the completed delivery requests have been made by users identifying themselves as businesses (95.5%) rather than individuals (4.5%) among the customers who have provided this declaration to the company. Less than 1% of the drivers making these deliveries have identified themselves as business, whereas 2.61% of the drivers identify themselves as individuals. A high percentage (96.8%) of them have not declared themselves to be either business or individual. This also indicates that the crowdsourced delivery is best suited for the Business to Consumer (B2C) model which focuses on business transactions between a business and a consumer via an e-commerce website (Rougès and Montreuil, 2014). Thus, it is in the best interests of the company to provide a separate incentivized pricing model for the businesses interested in making use of the crowdsourced delivery services.

Socio-economic information is sourced from the census data (U.S. Census, 2017) for the top 100 zip codes each (majority from Atlanta region in Georgia), where the greatest number of delivery pick up requests have been generated from as well as where the most active drivers are registered. Two Regression models are developed with the number of pickup and deliveries for each zipcode and the number of drivers registered in each zipcode as the dependent variables. A total of 22 independent variables are selected from the census data for each of the zip codes. These include population, median age, number of establishments, percentage of high school graduates or higher, number of household units, median household income ($), individuals below poverty level, number of households with no car, number of households with one car, number of households with two cars, number of households with three or more cars, percentage of individuals working from home, percentage of individuals driving to work alone, percentage of individuals working outside resident county, average travel time to work, percentage of individuals in services and transportation occupation, percentage of individuals in the transportation industry, percentage of private wage workers, percentage of self-employed working individuals, unemployment rate and percentage of full time workers.

For both the regression models, we begin by calculating the correlations between the independent variables and the dependent variable as well as between the independent variables. We then select the independent variable which is the most correlated with the dependent variable and not highly correlated with other independent variables. We begin by running a linear regression and check for the significance of the dependent variable, sign of the coefficient and the R-square value. We then run a logarithmic regression if the results are not satisfactory. We keep on adding the independent variables to the model, which are correlated to the dependent variables existing in the model equation. We remove an independent variable if it is not statistically significant or does not improve the R-square value. Once, all the independent variables expected to impact the dependent variable have been tried in the model equation, the final results are checked for heteroscedasticity (Breusch-Pagan Test) and multi-collinearity.

The Table 3-4 shows the results of the model with number of pickups and deliveries per zipcode as dependent variable.

Table 3-4: Deliveries/ Parcels Sent – Log Regression

Variables	Coefficient Estimate	Std. Error	p value
(Intercept)	-2.994	12.393	0.809
log (Percentage of High School Graduate and above)[a]	3.738	1.710	0.03
log (No. of Housing Units)[a]	0.668	0.193	0.7×10^{-3}
log (Percentage of Private wage worker)[a]	5.178	1.997	0.010
log (Median Household Income)[a]	-2.424	0.470	0.8×10^{-6}
log (Percentage of people working outside resident county)[a]	0.394	0.092	3.99×10^{-5}
log (Transportation Occupation)[a]	-1.218	0.262	7.71×10^{-6}
log (Driving Alone Percentage)[a]	-2.395	0.773	0.002
log (Unemployment rate)[a]	-0.893	0.337	0.009
R-squared: 0.4494			
Adjusted R-squared: 0.413			
Studentized Breusch-Pagan test			
BP = 11.772, df = 9, p-value = 0.2264			

[a]Significant at 95% confidence level

The estimated model has a R-square value of 0.45, which is not great but can be considered reasonable for a real-world data analysis. As the p-value from Breusch-Pagan test is above 0.05, alternative hypothesis can be rejected that heteroscedasticity is present. Percentage of high school graduates or higher, number of housing units, percentage of private wage workers, percentage of households with two or more vehicles and the percentage of individuals working outside the resident county have a positive sign in relation to the number of pickups and deliveries in a zipcode. As crowdshipping requires the use of technology, it is not surprising to observe percentage of high school graduates or higher being significant for the number of pickups from a zipcode (Punel et al., 2018). The household density intuitively acts to increase the demand for crowdshipping in an area. And finally, individuals working outside the resident county or private wage workers may have limited time to use traditional logistics services and might be attracted by the flexibility provided by crowdshipping.

Median household income has a negative sign in relation to the number of pickups and deliveries in a zipcode. Households with higher median household income may not find the lower costs associated with crowdshipping attractive. This is consistent with other studies which found to have connection between the income and the use of a shared system (Efthymiou et al., 2013; Dias et al., 2016; Rayle et al., 2016). In addition, the percentage of workers involved in transportation occupation, percentage of workers driving alone to work, and the unemployment rate have a negative sign in relation to the number of pickups and deliveries in a zipcode. The workers involved in transportation occupation or driving alone to work may choose to travel to the traditional logistics service centers to fulfil their requirements. The negative sign of unemployment rate is intuitive, as unemployed individuals may not have parcels to be sent.

The Table 3-5 shows the results of the model with number of drivers registered per zipcode as dependent variable.

Table 3-5: Drivers- Log Regression

Variables	Coefficient Estimate	Std. Error	p value
(Intercept)[a]	25.3919	5.3778	5.86×10^{-6}
log (No. of Establishments)[a]	0.7288	0.186	1.42×10^{-4}
log (Driving Alone Percentage)[a]	-3.3479	0.8995	2.91×10^{-4}
log (Percentage of people working outside resident county)[a]	0.7537	0.1285	3.38 x 10-8
log (Transportation Occupation)[a]	1.2169	0.2746	1.93 x 10-5
log (Self Employed Workers Percentage)[a]	0.7273	0.3352	0.031
log (Median Household Income)[a]	-1.9956	0.4889	7.68×10^{-5}
log (Full Time Workers Percentage)[a]	-2.0244	1.1271	0.074742
R-squared: 0.3949			
Adjusted R-squared: 0.363			
Studentized Breusch-Pagan test			
BP = 11.96, df = 7, p-value = 0.102			

[a]Significant at 95% confidence level

The estimated model above has a R-square value of 0.39, which is again reasonable for a real-world data analysis. As the p-value from Breusch-Pagan test is above 0.05, alternative hypothesis can be rejected that heteroscedasticity is present. The number of establishments, the percentage of individuals working outside resident county, percentage of self-employed workers and percentage of individuals in the transportation occupation have a positive sign in relation with the dependent variable. Self-employed workers percentage is also found to be significant in other studies (Punel et al., 2018). We speculate that the number of establishments would indicate an employment zone, where workers are inclined to engage in crowdshipping during their trips from home to work and vice versa. The high amount of travel incurred by the percentage of individuals working outside resident county and the percentage of individuals involved in the transportation occupation would make participation in crowdshipping attractive.

The percentage of workers driving alone, the median household income and the percentage of full-time workers have a negative sign in relation with the dependent variable. The median income has already been found to have little connection with participation in crowdshipping (Rayle et al., 2016; Punel 2018). The workers driving alone and the full-time workers may not have enough spare time to participate in crowdshipping (Le and Ukkusuri, 2019).

The drivers participating in the crowdsourced delivery are generally either professional drivers (working for themselves or for a traditional logistics carrier) or members of the public (e.g. commuters, students etc.) (Botsman, 2014).

The high frequency pickup zip codes have a lower average population than the driver zip codes indicating that they are situated in non-residential areas. Based on a two-sample t-test, it was found that the difference in the median household incomes for customers and drivers was not significant (p=0.346), however it is less than the national average of $53,889 (U.S. Census, 2016). This is consistent with other studies which found to have little connection between the income and the use of a shared system (Efthymiou et al., 2013; Dias et al., 2016; Rayle et al., 2016).

Both customer and driver zip codes show a similar level of literacy in terms of percentage population having a bachelor's degree or higher, as this indicates the IT literate users who participate in online commerce activities. Though, it still lower than the national average of 29.8% (U.S. Census, 2017). Again, similar trend is observed in a study addressing shared personal mobility (Rayle et al., 2016) with more literate population being the most likely users. The dominant employment sectors for the pickup zip codes include hospitality, retail and manufacturing sector.

Thus, the users registering as drivers are from neighborhoods that have a large population but are economically better than the neighborhoods where the customers are registered at. This is due to the customers being in the commercial and industrial neighborhoods with the drivers based out of residential areas. This is consistent with other studies that indicate that places with high job accessibility support crowdshipping (Mladenow et al., 2016). The difference also indicates that most of the drivers are professionals either from passenger transport or delivery business, looking for an additional income.

3.6. Further Discussion

3.6.1 Market Opportunities

As seen in **Error! Reference source not found.** and **Error! Reference source not found.**, the me dium and large parcel sizes accounts for 69% of the deliveries and 46% of the total fee collected. Additionally, Figure 3-10 indicates that more than 90% of the completed deliveries are restricted within a delivery distance less than 50 miles. This also represents more than 55% share of the total fee collected for the completed deliveries. Thus, initial market opportunities in new markets are in shorter delivery distances and with the medium and large parcel sizes preferred.

Figure 3-4 shows that the average delivery distance requested for the cancelled and the expired delivery requests is more than 200 miles. In addition, from Figure 3-9, it can be seen that the extra-large and super-large parcel sizes have the largest per mile revenue among all parcel sizes. Table 3-3 shows that the extra-large and super-large deliveries tend to longer distance deliveries (> 50 miles), indicating inter-city travel. Thus, the future market growth areas are in deliveries over longer distance and for extra-large and super-large parcel sizes.

As majority (95.5%) of the active customers are registered as businesses, small businesses present a potential growth area both in the present and future markets. Also, as most of the participants in crowdshipping are considered young, the demand for crowdshipping can be assumed to grow with this generation becoming older.

We also conduct an investigation in the spatial autocorrelations between and among the outbound and inbound parcel deliveries, at the zipcode level for all parcel deliveries in the United States. We adopt a generally used standard measure of spatial autocorrelation, called Moran's I statistic (Thompson et al., 2018) for our study. Global Moran's I statistic is defined as follows:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{3.1}$$

Where,

N: Number of spatial units indexed by *i* and *j*;

w_{ij} : Spatial weight (connectivity) between units *i* and *j*;

y_i , y_j : Attribute value of unit *i* and *j*, respectively;

$\bar{y}$: Mean value of the attribute of interest.

The value of the Global Moran's I ranges between -1 (negative spatial autocorrelation) and +1 (positive autocorrelation), with 0 indicating randomness. In our study, the value of N is equal to the number of zipcodes having inbound and/or outbound parcels. The spatial weight matrix can be created based on the distances between the centroids of individual zipcodes. y_i (or y_j) represents the inbound or outbound parcels in zipcode *i* (or *j*). We use the above to calculate the multivariate Moran's I to determine the spatial autocorrelation as well as cross-correlation among the inbound and outbound parcels at zipcode level. Furthermore, to evaluate the significance of spatial autocorrelation at a local scale, we also determine the local indicators of spatial association (LISA) (Anselin et al., 2006). LISA visualizes the spatial autocorrelation as either the High-High and Low-Low combination (positive autocorrelation) or High-Low and Low-High combination (negative autocorrelation). We make use of the *GeoDa* (Ruan and Lin et al., 2010, Nguyen and Vu, 2019) software in this study to determine the global autocorrelation and LISA. The weight matrix for the study is created based on the distance using the k-nearest neighbors' option.

The total number of parcel deliveries is analyzed, and two major parcel delivery types are identified as food and flower delivery. Together, these represent approximately one third of all the deliveries made in the study. The bivariate Global Moran I value for the food deliveries is 2.47x $x \ 10^{-6}$ and the flower deliveries is 2.74×10^{-7}. The Global Moran I values provide an explanation of the extent to which the outbound parcels from a zipcode are correlated with the inbound shipments to the zipcode from other nearby zipcodes. As the Global Moran I values for both food and flower deliveries is closer to 0 than +1 or -1, it indicates no spatial autocorrelation. This is understandable as food and flowers are examples of final products ready for consumption by customers and hence do not require any processing downstream, thus eliminating any dependence on any intermediate location or services (except transportation) before reaching the customer.

Figure 3-13 and Figure 3-14 capture the local component of spatial autocorrelation using Local Moran's I for food and flower delivery respectively. As seen from the two plots, we do not observe any significant amount of local autocorrelation for either food or flower delivery. We also did not observe any spatial concentration of the food and delivery parcels, as these economic activities are generally not clustered. More information is required about the remaining parcels delivered to identify the kind of products being delivered and to conduct a spatial autocorrelation for these based on the new information.

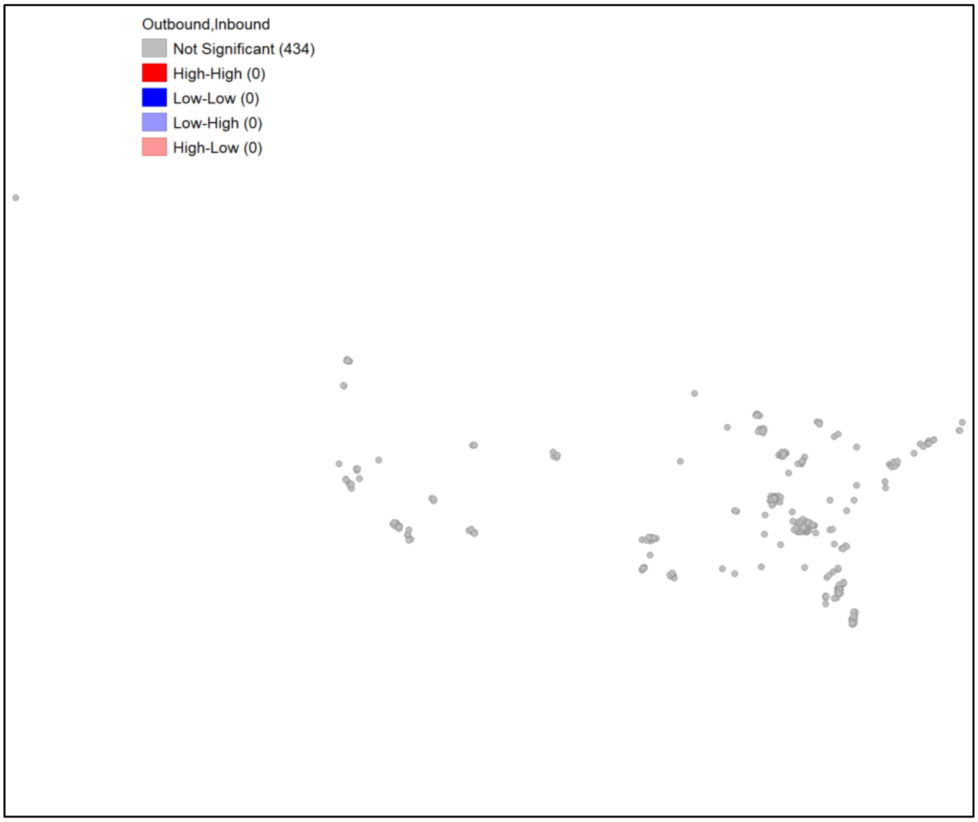


Figure 3-13. Result of the bivariate LISA for food deliveries (Outbound – Inbound)

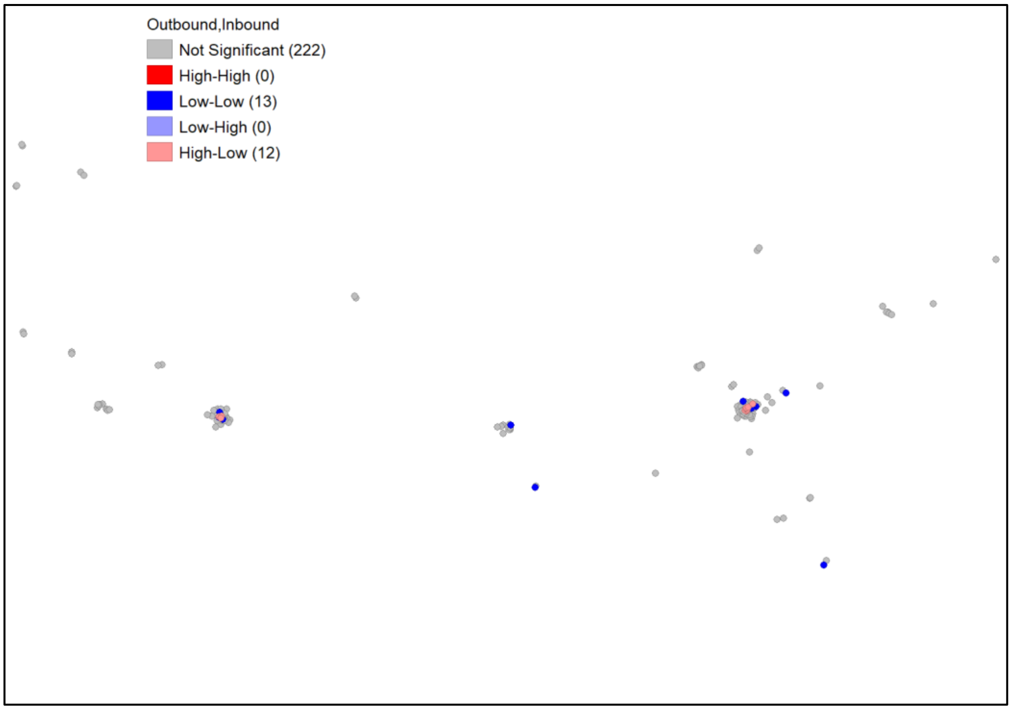


Figure 3-14. Result of the bivariate LISA for flower deliveries (Outbound – Inbound)

3.6.2 Qualitative Assessment of Service

The usability of the crowdshipping platform, customer trust and satisfaction (Frehe et al., 2017), safety of parcels and the quality of pickup and delivery (flexible, personalized) (Rai et al., 2018; Le and Ukkusuri, 2018) are the factors considered to play an important role for customer demand. The business model deployed by the crowdsourcing delivery company has several good features. The easy to use mobile app classifies the parcels based on sizes rather than weight to make it simple for customers to post their delivery service requests. Unlike ride-sharing the customer gets to pick the driver for a delivery from the choices available. Only the verified drivers are eligible to submit a bid against a delivery request. The information regarding a particular driver's bid, availability, rating and review are available on the app for the customers, which improves the quality of the service. The customer and driver can also communicate about the flexibility of pickup and delivery timings, availability and parcel details over the app. The app also helps the customer in deciding upon the parcel size and provides an estimate of the fee to be expected for the delivery.

The company ensures the safety of the delivery by verifying the driver details as well as provides a standard insurance with the option of purchasing more insurance for the parcel. The provision of rating and review system for users has been found to ensure the quality of the service and is an indicator of the user performance (Esper et al., 2003; Cabral and Hortacsu, 2010; Panda et al., 2015). The company has a system in place to discourage cancellations, either by customers or drivers, once the delivery request has been accepted. Overall, the system is transparent, safe, efficient and most importantly flexible, both for the customers and the drivers.

Several areas of improvement for the company's business model are identified. Most importantly, the delivery ridesharing app makes it possible for the customer and driver to negotiate their own terms and arrange payment outside of the app, once the initial contact has been made. This results in a loss to the company if both the parties choose to make payment outside the app, as well as is a potential safety concern for the customers as well as the drivers. Drivers may also form a temporary coalition to bid higher than the fee estimate which would make the delivery system less attractive. Since there is no mechanism to verify the contents of the parcel, the risk of delivering contraband items arises. In the absence of consolidation capability provided by the app, there is a loss in system efficiency as some delivery requests on the same route remain unfulfilled due to the discretion of the driver. There is also a possibility of the sender being inundated with bids from numerous drivers and the need to invest considerable time in evaluating and responding to the communication from the drivers.

3.7. Conclusion

Crowdshipping has been on rise in the last few years, and both industry and academics have been equally interested in analyzing this new delivery paradigm. Crowdsourced delivery offers a potential solution to mitigate the negative impacts of urban logistics, with more flexibility and lower cost than traditional delivery options. 90% of the deliveries are within a distance of 50 miles accounting for 55% of the total revenue indicating that initial market opportunities in new markets are in the shorter delivery distances. The medium and large parcel sizes are most popular as they account of 69% of deliveries and 46% of the total revenue. Future market growth areas are in deliveries over longer distances and for extra-large and super-large parcel sizes. As majority of current active customers are registered as businesses, small businesses should be the target customer population for the deliveries.

With all its advantages, many potential challenges are also identified. Crowdsourcing may suffer from issues such as safety, privacy concerns, damaged parcels, matching algorithm constraints, liability, additional insurance costs, unexpected delays and transport of contraband (Schreieck et al. 2016; Marx, 2016; Heller, 2017). In addition, the success of crowdsourcing delivery system depends on achieving and maintaining critical mass of the customers and drivers due to the reliance on occasional drivers (Rouges and Montreuil, 2014; Archetti et al., 2016). The challenge lies in identifying the behavior and motivation of crowdshipping participants, both senders and drivers, as well as the correct pricing and compensation mechanism (Ermagun and Stathopoulos, 2018).

Another area of concern is the rebound effect of increased vehicle miles for monetary compensation, thus negatively impacting the targeted environmental benefits (Paloheimo et al., 2014). Crowdsourcing is a very disruptive service and is likely to be impacted by regulations in the future, as has been the case in the ride-sharing and housing rental sector.

The existing logistics providers may see crowdsourcing both as a threat in terms of competition for the market share and an opportunity in terms of opening up new possibilities. Insights should be drawn from the performance of and challenges faced by ridesharing and housing rental sectors. This study adds to the literature of crowdshipping and illustrates the operational performance of a real-world crowdshipping company. This would be of use to academic researchers to improve their model assumptions regarding user behavior, delivery distances, parcel sizes etc. For industry and startups, by providing the first-hand observations of crowdsourcing delivery operations, the findings of this study will help understand the demand for and the growth areas of crowdsourcing delivery service.

Chapter 4 A Last-mile Delivery Paradigm using Microhubs with Crowdshipping

4.1 Introduction

Although microhubs have been implemented in several European cities, its combination with crowdshipping to provide the door-to-door service has not been field tested. By providing this last-leg service, it gives even greater convenience to customers and may further attract more customers to use this service. It also consolidates the parcel pickup and drop-off trips and thus reduces the VMT otherwise incurred by customers individually. Moreover, the performance of microhubs coupled with crowdshipping has not been analytically assessed in the literature.

In light of the potential benefits of microhubs and crowdshipping as discussed earlier, we propose this new urban delivery paradigm where the last-mile demand fulfilment is done through a network of microhubs coupled with crowdshipping (or M+C for short hereafter). In this paradigm, an urban service area is divided into a number of service zones (e.g., by zipcode). Within each zone, there is a designated microhub to temporarily store inbound and outbound parcels[1]. These parcels are either collected or distributed by crowdshippers between customers (shippers and end receivers) and the zonal microhub. The crowdshippers may be automobile drivers or cyclists. Commercial trucks are dispatched periodically to visit only the microhubs in the service area to transfer parcels

[1] In this study, the parcels are assumed of a typical online shopping parcel size, e.g., the commonly seen Amazon parcels. They can be carried by a regular passenger vehicle.

to their respective destination microhubs. Thus, truck traffic and VMT on busy and often narrow city streets can be largely avoided.

In this proof-of-concept paper, we first define the M+C paradigm and its operating characteristics, then formulate the paradigm mathematically and solve for its optimal vehicle and crowdshipper dispatching and routing strategies. To evaluate the cost and other operational aspects (e.g., VMT, fuel consumption, fleet size, floor area) of the M+C, we compare it with the traditional H+S paradigm (e.g., FedEx, UPS, USPS), in which all parcels must be collected and shipped to a sorting center (i.e., the central hub) to be sorted before being shipped out to their respective final receivers. The performance metrics used for comparison in this study are labor cost associated with travel time, number of trucks or crowdshippers dispatched, total vehicle miles traveled (VMT), total daily operating cost, and fuel consumption. They will be defined later in the chapter.

In addition, this study investigates the effects of the following key factors on the performance of M+C:

- *Service area size*: keeping the customer demand and other parameters constant, how does the network size affect the performance of M+C?
- *Number of customers*: keeping the size of the service area and other parameters constant, how does the number of customers affect the M+C operation? This and the service area size investigation are equivalent to looking into the effect of customer density (the economy of scale) on the M+C operation.

- *Crowdshipper compensation*: how does the crowdshipper compensation affect the performance of M+C? Is there a tipping point at which M+C becomes either more or less costly to operate?
- *Penalty rate*: crowdshippers may receive monetary penalty if they pick up or deliver parcels outside the preferred windows by the customers. How is the on-time performance of M+C? How does the penalty rate affect its overall operating cost?

The chapter is organized as follows. After the introduction, Section 4.2 presents the conceptual design of microhubs with crowdshipping delivery paradigm. Detailed model formulation for both the M+C and the H+S operation are presented in sections 4.3 and 4.4. Section 4.5 describes the hypothetical numerical example to compare the performance of the proposed M+C delivery paradigm with the H+S delivery paradigm. Section 4.6 discusses a series of sensitivity analyses for the performance of the proposed delivery paradigm with respect to the key factors described above. Lastly, research conclusion is drawn in Section 4.7 with future research work.

4.2 Conceptual Design of Microhubs with Crowdshipping (M+C)

In this study setting, the service area covered by a logistics carrier is divided into so-called the 'service zones' and each zone has a designated microhub that handles the parcels in and out of the zone. Figure 4-1 is an example of the service area, service zones, and microhubs. In this example, the entire service area (the square) is divided into nine service zones. Each zone has a microhub located at the zonal centroid.

Specifically, the M+C consists of the following elements.

Service area: service area is a predefined region of service by a carrier of interest. In this study, we focus on an urban area of service.

Service zone: a service area is divided into a number of smaller geographic service zones according to a predefined criteria. For example, these zones may be defined by zipcode. A service zone is the smallest geographic area served by a designated microhub.

Microhub: a microhub is a designated zonal transshipment center equipped with APS, where parcels going to and coming from other zones are sorted and stored in *lock boxes* labeled by the destination zipcode after the first mile or before the last mile of delivery. There are two basic functions of a microhub: sorting and storing.

- Sorting at the microhub is completed by depositing the parcels into respective *lock boxes* labeled by the destination zipcode. This sorting task can be readily automated with barcode (or RFID code) on the parcel and a barcode or RFID reader. This is carried out by the crowdshippers every time when they collect and bring the parcels to the microhub. In other words, sorting in the M+C paradigm is also crowdsourced to the individual crowdshippers at individual microhubs. This is in contrast to H+S, where sorting takes place centrally at the hub (also called sorting center or transshipment center). This crowdsourced sorting model in the M+C enables shorter parallel processing (sorting) time, and hence faster throughput and reduced delay.

- After the parcels are sorted at the microhub, they are temporally stored at the microhub till they are picked up and transshipped to their respective destination microhubs (zipcodes) by truck.

Figure 4-1 illustrates the relationships between service area, service zones, and microhubs. In this example, the entire service area is divided into nine service zones; each zone has a microhub to serve the customers in the zone. Parcels are collected and stored at microhubs, and transshipped (indicated by the blue arrows) among them.

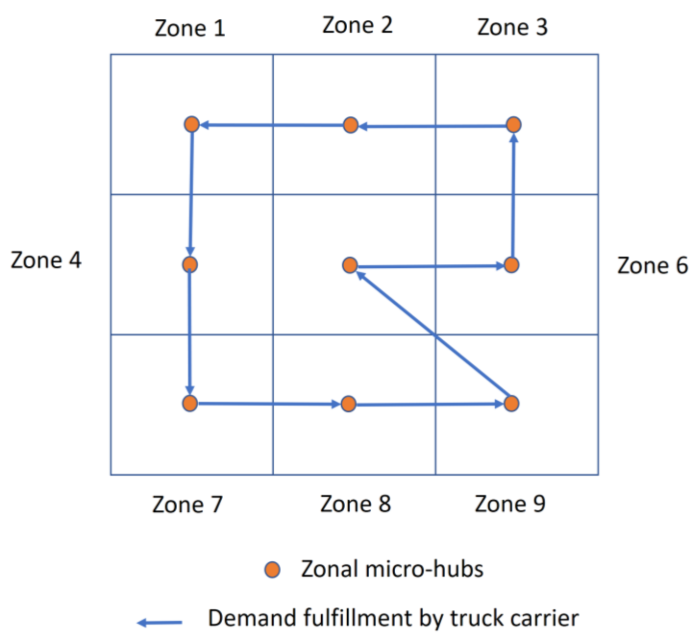


Figure 4-1. Microhubs, service zones, and truck routing in M+C

Request: all parcel pickup and delivery requests are classified into two categories according to the zonal relationship between the pickup and the delivery location: *intra-zonal* and *inter-zonal* requests.

- An *intra-zonal* request refers to one in which both the pickup and delivery addresses are within the same service zone (e.g., (P1,D1), (P2,D2), and (P3,D3) in Figure 4-2). For this type of request, transshipment may not take place. That is, an intra-zonal parcel may be picked up and delivered en-route by a single crowdshipper without going through the zonal microhub, e.g., (P1,D1) and (P2,D2) in Figure 4-2. On the other hand, if the destination address is not on the current crowdshipper's best route, then the parcel would be deposited in the microhub and delivered by another crowdshipper, e.g., (P3,D3) in Figure 4-2.
- An *inter-zonal* request refers to one in which the pickup and delivery addresses are not in the same service zone. For this type of request, transshipment service is necessary; in other words, an inter-zonal parcel is picked up by a crowdshipper at its shipper's and deposited in its microhub of origin, and then transferred by truck to its microhub of destination, and finally delivered by another crowdshipper to its final receiver.

Courier. In M+C, there are two types of couriers, namely *trucks* and *crowdshippers*.

- Delivery trucks belong to a carrier's fleet and carry out routine visits to microhubs only to pick up and deliver parcels among the microhubs. In other words, delivery trucks in the M+C paradigm do not navigate the busy and often narrow city streets to visit end customers (both shippers and receivers who can be either residents or business entities); the only places the trucks visit are the microhubs in the service area. As such, congestion due to truck traffic or truck parking on urban streets could be largely avoided. Figure 4-2 graphically illustrates the truck routing among microhubs. As we describe later in Section 3, this is a Many-to-Many Split Pickup and Delivery Problem (M-MSPSDP).

- In M+C, the first and last mile deliveries within a service zone are performed by crowdshippers. Crowdshipper routing is a vehicle routing problem (VRP). That is, a crowdshipper is assumed to start and end a route at the microhub, and visit multiple customers to pick up and/or drop off parcels. Figure 3 illustrates crowdshipper routing in a service zone. It could be a pure pickup (or delivery) routing problem (e.g., the routing of P3 and P4), a pairwise pickup-delivery routing problem (e.g., the routing of P1 and D1), or a mixed pickup and delivery routing problem (e.g., the routing of D5, P2, and D2), all of which have been extensively studied in the literature. It is assumed that a crowdshipper visits only customers within the same service zone on a service route. In other words, any crowdshipping route does not cross zonal boundaries.

Figure 4-2 illustrates the kinds of crowdshipper routing in a service zone. It could be a pure pickup (or delivery) routing problem (e.g., the routing of P3 and P4), or a pairwise pickup-delivery routing problem (e.g., the routing of P1 and D1), or a mixed pickup and delivery routing problem (e.g., the routing of D5, P2, and D2), all of which have been extensively studied in the literature. It is assumed that a crowdshipper visits only customers within a service zone on a route. However, there is no restriction for a crowdshipper to move to another service zone after completion of his/her previous routing to look for more work.

A crowdshipper can be an automobile driver, a bicyclist, or even a pedestrian. A crowdshipper's travel speed, payload capacity, service range, and compensation rate vary by the mode of transportation.

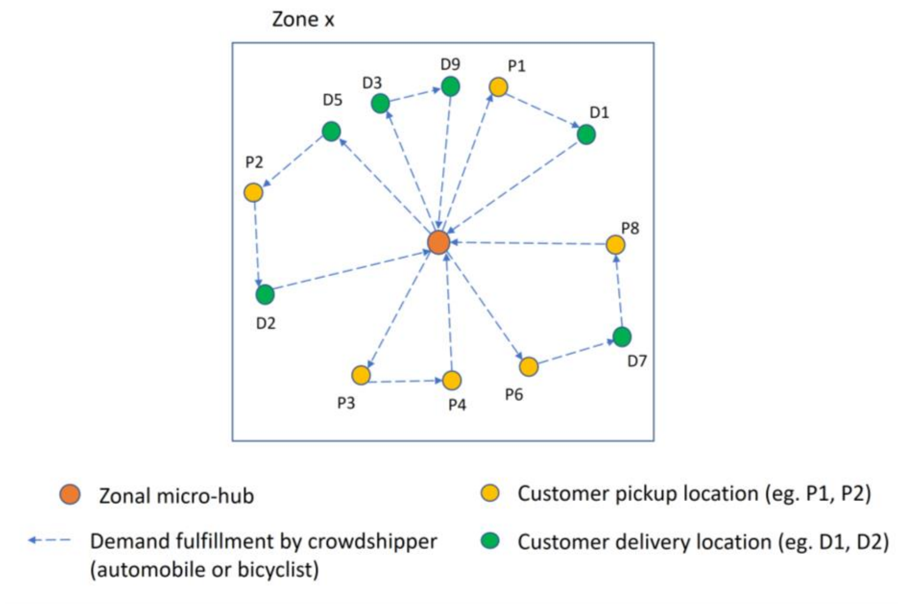


Figure 4-2. Crowdshipper routing in M+C

Based on the above description, we formulate the M+C paradigm as two separate and connected routing problems. One concerns the crowdshipper routing within a service zone; and the other concerns the truck routing among microhubs. The complete model formulations are provided next in Section 4.3.

4.3 Model Formulation and Solution Method

The formulation presented in this study is a static problem in which all shipment requests within a service area and the crowdshippers are known in advance. Each shipment request consists of the quantity, the pickup and delivery addresses, and the customer-preferred pickup time window within one-hour limit. We assume that the microhubs have sufficient capacity to temporarily store all the inbound and outbound parcels.

Observe that the crowdshipper routing within a service zone is independent of any other service zones. Therefore, crowdshipper routing is formulated and solved at the zonal level independently. Between crowdshippers and trucks, we further assume the following about their daily operations in this study for simplicity:

- Trucks visit the microhubs only after all crowdshippers have completed their first mile pickup tasks. In other words, all the parcels that must route through the microhubs in the service area have been collected and deposited at their respective origin microhubs.
- Crowdshippers carry out their last mile delivery tasks after the trucks have completed all transshipments among the microhubs. That is, all parcels have been transferred from their origin microhubs to their destination microhubs.

Thus, truck routing and crowdshipper routing can be formulated and solved separately. Their formulations are presented in Sections 4.3.1 and 4.3.2.

First, we define the general model notations as follows:

$\mathbf{H}$ set of microhubs or zones (one designated microhub per zone), $\mathbf{H} = \{1,2, \dots i, \dots j \dots., r\}$

$\mathbf{H_0}$ set of all microhubs and truck depot $\{0\}$, $\mathbf{H_0} = \mathbf{H} \cup \{0\}$

$\mathbf{N_h}$ set of all customers in zone h ($\in \mathbf{H}$) including intra-zonal pairs (i.e., both pickup and delivery customers are in zone h) and inter-zonal customers (shippers or receivers), $\mathbf{N_h} = \{1,2, \dots i, \dots j \dots., n_h\}$

$\mathbf{N_{h0}}$ set of all nodes associated with zone h ($\in \mathbf{H}$) including the customers, the zonal microhub, and the truck depot, $\mathbf{N_{h0}} = \mathbf{N_h} \cup \{h\} \cup \{0\}$

$\mathbf{N}$ set of all nodes in the network including all customers, all microhubs, and the truck depot, $\mathbf{N} = \cup\, \mathbf{N_h} \cup \mathbf{H_O}$

$\mathbf{A_h}$ set of all possible links in zone h ($\in \mathbf{H}$), $\mathbf{A_h} = \{(i, j), \forall\, i, j \in \mathbf{N_{h0}}, i \neq j\}$

$\mathbf{A_H}$ set of all possible links connecting all microhubs, $\mathbf{A_H} = \{(i, j), \forall\, i, j \in \mathbf{H_O}, i \neq j\}$

$\mathbf{A}$ set of all possible links in the network, i.e., $\mathbf{A} = \cup\, \mathbf{A_h} \cup \mathbf{A_H}, \forall h \in \mathbf{H}$

$\mathbf{F}$ set of available trucks, $\mathbf{F} = \{1, 2, \ldots, \mathrm{M}\}$, where M is the maximum number of trucks

S_h^{A} maximum number of automobile crowdshippers in zone h ($\in \mathbf{H}$)

S_h^{B} maximum number of bicycle crowdshippers in zone h ($\in \mathbf{H}$)

d_{ij} length of link $(i, j)(\in \mathbf{A})$

t_{ij} travel time on link $(i, j)(\in \mathbf{A})$; $t_{ij} = d_{ij}/V_T$ for both truck and automobile at a constant speed of V_T – assuming truck and automobile travel at the same speed, and $t_{ij} = d_{ij}/V_B$ for bicycle at constant speed of V_B.

t_c pickup or drop-off handling time at a customer location (assumed fixed)

t_h pickup or drop-off handling time at a microhub (assumed fixed)

q_i parcel weight at node i ($\in \mathbf{N_{h0}}$); $q_i > 0$ for pickup demand and $q_i < 0$ for delivery demand; $q_0 = 0$ at the depot (i.e., $i = 0$)

q_{ij} pairwise demand from origin microhub i to destination microhub j

K_T truck capacity

K_A automobile crowdshipper capacity

K_B bicycle crowdshipper capacity

C_T truck operating cost per hour

C_A hourly compensation rate to automobile crowdshippers

C_B hourly compensation rate to bicycle crowdshippers

E_i, L_i desired earliest and latest pickup time, respectively, for customer i ($\in \mathbf{N_h}$)

P constant hourly penalty rate

<u>Decision variables</u>

t_i^v arrival time at microhub i ($\in \mathbf{H}$) by truck v ($\in \mathbf{F}$)

l_{ij}^v load of truck v ($\in \mathbf{F}$) when traversing on link (i,j) ($\in \mathbf{A_H}$)

x_{ij}^v binary variable, $x_{ij}^v = 1$ if truck v ($\in \mathbf{F}$) traverses on link (i,j) ($\in \mathbf{A_H}$), and $x_{ij}^v = 0$ otherwise

p_{ij}^v binary variable, $p_{ij}^v = 1$ if transshipment from microhub i to microhub j is done by truck v, and $p_{ij}^v = 0$ otherwise.

t_i arrival time at node i ($\in \mathbf{N_{h0}}$) by a crowdshipper

l_{ij} crowdshipper load on link (i,j) ($\in \mathbf{A_h}$)

y_{ij}^{A} binary variable, $y_{ij}^{\mathrm{A}} = 1$ if an automobile crowdshipper traverses on link (i,j) ($\in \mathbf{A_h}$), and $y_{ij}^{\mathrm{A}} = 0$ otherwise

y_{ij}^{B} binary variable, $y_{ij}^{\mathrm{B}} = 1$ if a bicycle crowdshipper traverses on link (i,j) ($\in \mathbf{A_h}$), and $y_{ij}^{\mathrm{B}} = 0$ otherwise

$\pi(t_i, E_i, L_i)$, penalty for early/late service of customer i ($\in \mathbf{N_h}$), which is a function of the crowdshipper arrival time t_i, and the preferred time window E_i, and L_i, i.e.,

where,

$$\pi(t_i, E_i, L_i) = \begin{cases} \mathrm{P} \times (t_i - L_i), & \text{for } t_i > L_i \\ \mathrm{P} \times (E_i - t_i), & \text{for } t_i < E_i \\ 0, & \text{for } E_i < t_i < L_i \end{cases}$$

4.3.1 Crowdshipper Routing

Observe that crowdshipper routing of the first and the last mile is a mixed pickup and delivery VRP. We make the following assumptions/constraints to simplify the model formulation in this study:

1. There are two types of crowdshippers, automobile drivers and bicyclists;
2. There are sufficient numbers of automobile and bicycle crowdshippers;
3. Crowdshippers of the same type are homogeneous and heterogeneous across types, in terms of travel speed, load capacity, service range and compensation rate;
4. The crowdshipper assignment and routing are centrally determined by the carrier in advance to the crowdshippers' routing activities;
5. All crowdshippers within a service zone start and end their routes at the designated zonal microhub;
6. A crowdshipper has an initial empty load departing the microhub at the start of the first mile routing;
7. A crowdshipper has an empty load returning to the microhub at the end of the last mile routing;
8. A crowdshipper must pay penalty for late pickup (i.e., outside the user specified time window); there is no penalty for delivery so long as the parcel is delivered by the end of the daily operation (i.e., same day delivery) in this study;
9. A crowdshipper only serves one service zone at a time; after a route is completed, a crowdshipper may move to another service zone;
10. There is an 8-hour work limit for crowdshippers.

As explained earlier, crowdshippers of a service zone operate exclusively and independently of any other zones. Hence, it suffices to present crowdshipping for a given zone h ($\in \mathbf{H}$) within the service area as follows.

The objective function minimizes the total payment made to the crowdshippers in zone h and the late pickup penalty cost:

$$MinZ_h = \sum_{(\forall i,j\, \epsilon\, \mathbf{N_{h0}})} \left(C_A y_{ij}^{\mathrm{A}} + C_B y_{ij}^{\mathrm{B}}\right)(t_{ij} + t_c) + \sum_{(\forall i\, \epsilon\, \mathbf{N_{h0}})} \pi(t_i, E_i, L_i) \tag{4.1}$$

s.t.,

(i) Crowdshipper route constraints:

$$\sum_{(\forall i\, \epsilon\, \mathbf{N_h}, i \neq j)} y_{ij}^{\mathrm{A}} \leq 1 \qquad \forall j \in \mathbf{N_h} \tag{4.2}$$

$$\sum_{(\forall i\, \epsilon\, \mathbf{N_h}, i \neq j)} y_{ij}^{\mathrm{B}} \leq 1 \qquad \forall j \in \mathbf{N_h} \tag{4.3}$$

$$\sum_{(\forall (i,j) \epsilon\, \mathbf{A_h})} \left(y_{ij}^{\mathrm{A}} + y_{ij}^{\mathrm{B}}\right) \leq 1 \tag{4.4}$$

$$\sum_{(\forall j\, \epsilon\, \mathbf{N_h})} y_{0j}^{\mathrm{A}} \leq \mathrm{S}_h^{\mathrm{A}} \tag{4.5}$$

$$\sum_{(\forall j\, \epsilon\, \mathbf{N_h})} y_{0j}^{\mathrm{B}} \leq \mathrm{S}_h^{\mathrm{B}} \tag{4.6}$$

$$\sum_{(\forall i \epsilon\, \mathbf{N_{h0}})} y_{ij}^{\mathrm{A}} = \sum_{(\forall i \epsilon\, \mathbf{N_{h0}})} y_{ji}^{\mathrm{A}} \qquad \forall j \in \mathbf{N_{h0}} \tag{4.7}$$

$$\sum_{(\forall i \epsilon\, \mathbf{N_{h0}})} y_{ij}^{\mathrm{B}} = \sum_{(\forall i \epsilon\, \mathbf{N_{h0}})} y_{ji}^{\mathrm{B}} \qquad \forall j \in \mathbf{N_{h0}} \tag{4.8}$$

(ii) Crowdshipper schedule constraints:

$$t_j = (t_i + t_c + t_{ij})(y_{ij}^{\mathrm{A}} + y_{ij}^{\mathrm{B}}) \leq 8 \quad \forall i,j \in \mathbf{N_{h0}} \tag{4.9}$$

$$t_i < t_j \quad \text{if } i \text{ and } j \text{ are a pickup-delivery pair in zone } h,\ i,j \in \mathbf{N_h} \tag{4.10}$$

(iii) Crowdshipper load and capacity constraints:

$$\sum_{(j \in \mathbf{N_h})} l_{hj}(y_{hj}^{\mathrm{A}} + y_{hj}^{\mathrm{B}}) = 0 \quad \text{for first mile routing} \tag{4.11a}$$

or,

$$\sum_{(j \in \mathbf{N_h})} l_{jh}(y_{jh}^{\mathrm{A}} + y_{jh}^{\mathrm{B}}) = 0 \quad \text{for last mile routing} \tag{4.11b}$$

$$l_{ij} = \left(\sum_{\forall s \in \mathbf{N_{h0}}, s \neq i} l_{si} x_{si} + q_i \right) y_{ij}^{\mathrm{A}} \leq K_A \quad \forall i,j \in \mathbf{N_{h0}} \tag{4.12}$$

$$l_{ij} = \left(\sum_{\forall s \in \mathbf{N_{h0}}, s \neq i} l_{si} x_{si} + q_i \right) y_{ij}^{\mathrm{B}} \leq K_B \quad \forall i,j \in \mathbf{N_{h0}} \tag{4.13}$$

$$(l_{ij} + q_j - l_{jk})(y_{jk}^{\mathrm{A}} + y_{jk}^{\mathrm{B}}) \geq 0 \quad \forall i,j,k \in \mathbf{N_{h0}} \tag{4.14}$$

(iv) Non negativity and binary constraints of decision variables:

$$y_{ij}^{\mathrm{A}}, y_{ij}^{\mathrm{B}} \in \{0,1\} \quad \forall i,j \in \mathbf{N_{h0}} \tag{4.15}$$

$$l_{ij}, t_i \geq 0 \quad \forall i,j \in \mathbf{N_{h0}} \tag{4.16}$$

Eqs (4.2) through (4.8) ensures that (i) each customer is visited once and only once by any crowdshipper regardless of its type (A or B); (ii) the number of crowdshippers on duty does not exceed the maximum available number of crowdshippers for both types; and (iii) the inflow and outflow at any node are balanced. Eq.(4.9) restricts crowdshipper's working hours to 8 hours in a day. Eq.(4.10) ensures that the pickup of a parcel occurs prior to its delivery (for intra-zonal demand). Eqs (4.11a) and (4.11b) satisfy the empty load assumption at the start of the first mile and at the end of the last mile. Eqs (4.12) and (4.13) ensure a crowdshipper's load does not exceed its capacity. Eq.(4.14) ensures the load conservation.

4.3.2 Truck Routing

As described in Section 4.2, in the M+C paradigm, a truck v

- always starts and ends at the truck depot $\{0\}$;
- has empty load leaving and returning to the depot; in other words, at end of the route truck v must deliver all parcels it collects on the route to their designated destination microhubs;
- at each microhub *h*, first unloads all the parcels bounded for *h* (if not zero), and then loads the outgoing parcels from *h*, if not zero, as permitted by its remaining capacity.

As such, this truck routing differs from the classical VRP in three key aspects:

(1) *Many-to-many pickup and delivery*: each microhub can be an origin to many destination microhubs and at the same time a destination to many origin microhubs;

(2) *Split pickup*: at each microhub i, the total pickup demand ($\sum_{\forall j \in \mathbf{H}} q_{ij}$) may exceed the available capacity of a single truck and therefore not all parcels will be picked up by one truck visit; and

(3) *At least one visit to a microhub by any truck*: a microhub may be visited by more than one truck. This is due to the split pickup operation described in (2).

This truck routing defines a Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP). In the classical Vehicle Routing Problem (VRP) where a set of known customers with fixed demand are served by a fleet of capacitated vehicles, the objective is to minimize the total route cost such that each customer is visited by only one vehicle. This implies that (1) no splitting of loads is allowed; and (2) it is a one-to-one shipment problem (either depot-to-customer for a delivery problem, or customer-to-depot for a pickup problem, or customer-to-customer for a pairwise pickup-delivery problem). Though, in the real world, truck operators allow the excess capacity in the truck to be filled using partial loads in order to use the truck capacity more efficiently. This may require multiple trips by trucks to service the same load by allowing the load to be split such that a dedicated trip to deliver the load may be avoided.

In the Split Delivery Vehicle Routing Problem (SDVRP), the restriction that each stop, which can be a customer, a warehouse, a distribution center, etc., needs to be visited only once is dropped. That is, split deliveries are permitted to better utilize the capacity of the delivery fleet. Because the demand (total load) at a stop may at times be greater than the delivery vehicle's available capacity, splitting the demand among the vehicles may be a better strategy in terms of minimizing the total travel cost of the delivery fleet. As such, the stop may be visited by multiple vehicles if found to be beneficial. Several (one-to-many) studies have found that the SDVRP reduces the routing cost compared to the case where only a single visit to each customer is imposed in the traditional VRP (Frizzell and Giffin, 1995; Archetti and Speranza, 2008).

M-M VRP Problems have been studied in the literature, such as the Swapping Problem (Anily and Hassin, 1992). However, in a typical M-M setting, demand does not split at any customer point.

On the other hand, Split Delivery Vehicle Routing Problem (SDVRP) has also been studied (see a literature survey on the subject by Archetti and Speranza (2008)). Though branch-and-cut exact algorithms are able to solve small to medium size SDVRPs, meta-heuristic algorithms (simulated annealing, tabu-search, adaptive neighborhood etc.) are more popular in obtaining optimal solution for large problem sizes (Archetti and Speranza, 2012).

In this investigation, we simplify the truck routing by requiring that a truck visit all microhubs (total of r) at least once on its route unless there is no pickup nor delivery demand at a microhub. In other words, each truck will visit all microhubs in the service area and complete all transshipments among them in the same route.

In addition to the truck operation activities described above, we assume in this study that the pairwise demand q_{ij} is known and fixed, and that q_{ij} cannot be split when shipped between microhubs i and j. In other words, each pairwise demand q_{ij} is the smallest quantity in transshipment and cannot be split any further– it must be either picked up as a whole by a truck or left entirely to another truck. In other words, while the total pickup demand at a microhub i ($\sum_{\forall j} q_{ij}$) can be split, each pairwise demand q_{ij} that makes up the total pickup demand cannot be split – it must be either picked up as a whole by a truck or left entirely to another truck. On the other hand, the total pickup demand at a microhub i ($\sum_{\forall j} q_{ij}$) can be split – a partial sum of the total pickup demand may be picked up by a truck at a time. To facilitate the demand split, a new binary decision variable p_{ij}^{v} is introduced in the model. p_{ij}^{v} takes the value of 1 if demand q_{ij} is picked up by truck v at microhub i; and zero otherwise.

We further assume a fixed loading and unloading time at a microhub (t_h), and that the trucks have the same operating parameters (capacity, hourly rate, work hour limit, etc.).

The objective function for the truck routing among the microhubs minimizes the total truck driver's cost:

$$MinZ_H = \sum_{\forall (i,j)\,\epsilon\,\mathbf{A_H}} \sum_{\forall v \in \mathbf{F}} C_T(t_{ij} + t_h)x_{ij}^v \tag{4.17}$$

s.t.,

(i) Truck routes constraints:

$$\sum_{(\forall i\,\epsilon \mathbf{H})} \sum_{\forall v \in \mathbf{F}} x_{ij}^v \geq 1 \qquad \forall j \in \mathbf{H} \tag{4.18}$$

$$\sum_{\forall j \in \mathbf{H_O}} x_{ij}^v \geq 1 \qquad \forall i \in \mathbf{H_O}, v \in \mathbf{F} \tag{4.19}$$

$$\sum_{(\forall j\,\epsilon\,\mathbf{H})} x_{0j}^v \leq \mathrm{M} \qquad \forall v \in \mathbf{F} \tag{4.20}$$

$$\sum_{(\forall i,j\,\epsilon\,\mathbf{H})} x_{ij}^v \leq 2r - 2 \qquad \forall v \in \mathbf{F} \tag{4.21}$$

$$\sum_{(\forall i \epsilon\,\mathbf{H_O})} x_{ij}^v = \sum_{(\forall i \epsilon\,\mathbf{H_O})} x_{ji}^v \qquad \forall j \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.22}$$

(ii) Truck schedule constraints:

$$t_j^v = \left(t_i^v + t_h + t_{ij}\right)x_{ij}^v \leq 8 \qquad \forall i,j \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.23}$$

(iii) Truck load and capacity constraints:

$$\sum_{(j\,\in\,\mathbf{H})} l_{0j}^{v}\, x_{0j}^{v} \;= 0 \qquad \forall v \in \mathbf{F} \tag{4.24}$$

$$\sum_{(j\,\in\,\mathbf{H})} l_{j0}^{v}\, x_{j0}^{v} \;= 0 \qquad \forall v \in \mathbf{F} \tag{4.25}$$

$$\sum_{\forall j \in \mathbf{H}} q_{ij} p_{ij}^{v} \leq \sum_{\forall j \in \mathbf{H}} q_{ij} \qquad\qquad \forall i \in \mathbf{H}, \forall v \in \mathbf{F} \tag{4.26}$$

$$\sum_{\forall v \in \mathbf{F}} p_{ij}^{v} = 1 \qquad \forall i, j \in \mathbf{H} \tag{4.27}$$

$$l_{ij}^{v} = \left(\sum_{\forall s \in \mathbf{H_O}} l_{si} x_{si}^{v} + \sum_{\forall k \in \mathbf{H}} q_{ik} p_{ik}^{v} - \sum_{\forall k \in \mathbf{H}} q_{ki} p_{ki}^{v} \right) x_{ij}^{v} \leq \; K_T \qquad \forall i, j \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.28}$$

$$\left(l_{ij}^{v} + \sum_{\forall k \in \mathbf{H}} q_{jk} p_{jk}^{v} - \sum_{\forall k \in \mathbf{H}} q_{kj} p_{kj}^{v} - \; l_{jk} \right) x_{jk}^{v} \geq 0 \qquad \forall i, j, k \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.29}$$

(iv) Non negativity and binary constraints of decision variables:

$$x_{ij}^{v}, p_{ij}^{v} \in \{0,1\} \qquad \forall i, j \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.30}$$

$$l_{ij}^{v}, t_{i}^{v} \geq 0 \qquad \forall i, j \in \mathbf{H_O}, \forall v \in \mathbf{F} \tag{4.31}$$

Only the differences from a classical VRP are highlighted here. Eq.(4.18) says that each microhub must be visited at least once; Eq.(4.19) ensures that each microhub be visited by the same truck at least once – in other words each truck must visit all the microhubs. Eq.(4.21) says that a truck needs to traverse at most $2(r-1)$ number of links to visit all microhubs and complete its tasks, where r is the number of microhubs. This is a direct derivation from the truck routing operation described above. Eq.(4.26) ensures that all the demand picked up by a truck at a microhub is no greater than the total pickup demand at the microhub. Lastly, Eq.(4.27) ensures that the pairwise demand between any two microhubs is only fulfilled once. This is a direct derivation of the assumption that the pairwise demand q_{ij} cannot be split.

4.3.3 Solution Method

For the crowdshipper routing problem presented in Section 4.3.1, it is a classical mixed integer programming (MIP) problem and is solved exactly using the MOSEK solver in Matlab environment.

For the truck routing problem presented in Section 4.3.2, it is a special case of the Many-to-Many (M-M) Split Pickup-and-Delivery Problem (M-MSPDP), because in this study we assume that each truck must visit all the microhubs at least once until it delivers all the pairwise transshipment demand that it carries. As a result, the minimum-cost routing among all microhubs can be easily determined. Generally speaking, Dror et al. (1994) finds that SDVRP is more difficult to solve for optimality than the traditional VRP, which is NP-hard (Lenstra and Kan, 1981). Some exact solution methods for the SDVRP have been suggested in the literature (Dror et al., 1994; Belenguer et al., 2000; Jin et al., 2007, 2008; Moreno et al., 2010; Archetti et al., 2012; Casazza, and Ceselli, 2016).

4.4 Comparison Baseline: Hub-and-Spoke

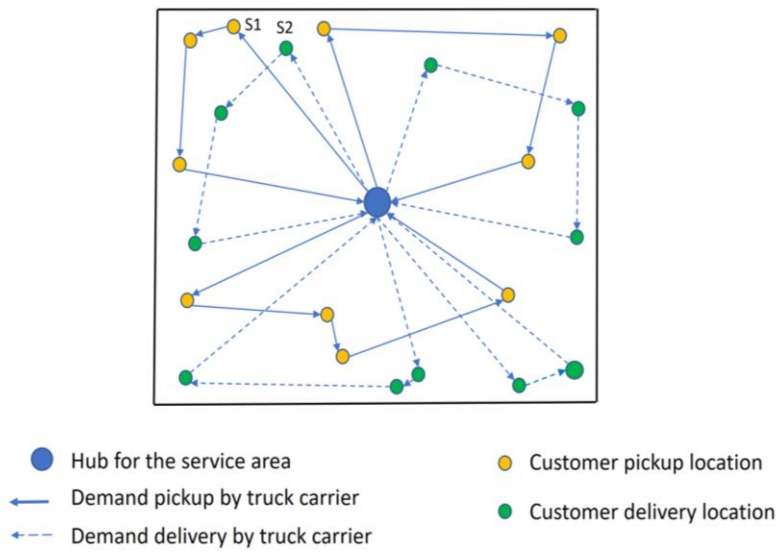


Figure 4-3. Hub and Spoke delivery paradigm considered in this study

Figure 4-3 illustrates the H+S paradigm considered in this paper. In this paradigm, there are only one type of couriers, i.e., trucks belonging to a carrier's fleet. The truck fleet serves the entire service area with peddling runs to minimize the total labor cost (truck driver cost) associated with travel time. In this study, we consider that the trucks start at the hub where the sorting center and truck depot are located and visit the customers to perform either the pickup or the delivery tasks. All parcels must be transshipped via the central hub between the shippers and receivers in the service area.

Specifically, this study considers the following daily operation by the trucks in H+S:

- All trucks start and end their routing at the central hub (which is also where the truck depot is located);

- Truck routing consists of inbound and outbound routing:
  - *Inbound routing* involves dispatching trucks at the start of the operation to collect parcels at the customers' and bringing them to the central hub. For simplicity this study assumes that trucks are dispatched with an empty load and inbound routing involves only pickup activities.
  - *Outbound routing* involves dispatching trucks to deliver parcels to their final destinations after being sorted at the hub. Similar to the inbound routing, only delivery activities are involved during outbound routing. At the end of the routing, trucks return to the depot (hub) empty loaded.

As such, the above defined inbound and outbound routing can each be formulated as a classical vehicle routing problem (VRP) with pickup or delivery. The objective function is to minimize the total daily operating cost. The inbound and outbound routing are solved separately with the same formulation used for both.

The model notations are listed below, followed by the formulation.

$\mathbf{N_c}$ customer set, $\mathbf{N_c} = \{1,2, \ldots i, \ldots j \ldots., n\}$

$\mathbf{N}$ set of all nodes including all customers and the hub $\{0\}$, i.e., $\mathbf{N} = \mathbf{N_c} \cup \{0\}$

$\mathbf{A}$ set of all possible links, i.e., $\mathbf{A} = \{(i,j), \forall\, i,j \in \mathbf{N}, i \neq j\}$

F set of at most M trucks in the fleet

t_{ij} truck travel time on link $(i,j) \in \mathbf{A}$; $t_{ij} = D_{ij}/V_T$, where D_{ij} is the distance between nodes and V_T is the truck velocity in miles per hour.

t_c Pick up or drop off handling time (fixed minutes per customer location)

q_i parcel weight (demand) at customer i ($\in \mathbf{N_c}$); $q_i > 0$ for pickup demand and $q_i < 0$ for delivery demand

K_T truck capacity

C_T truck operating cost per hour ($/hour)

E_i, L_i desired earliest and latest pickup time, respectively, for customer i ($\in \mathbf{N_c}$)

P constant penalty rate ($/hour)

<u>Decision variables</u>

t_i arrival time at customer $i \in \mathbf{N_c}$; start time at the hub $\{0\}$ is set at zero: $t_0 = 0$ for all trucks

l_{ij} truck load on link (i, j)

x_{ij} binary variable taking value 1 if link (i, j) is traversed, and 0 otherwise

$\pi(t_i, E_i, L_i)$ Penalty for early/late service of customer i ($\in \mathbf{N_c}$), which is a function of the truck arrival time t_i, and preferred time window E_i, and L_i.

where,

$$\pi(t_i, E_i, L_i) = \begin{cases} \mathrm{P} \times (t_i - L_i), & \text{for } t_i > L_i \\ \mathrm{P} \times (E_i - t_i), & \text{for } t_i < E_i \\ 0, & \text{for } E_i < t_i < L_i \end{cases}$$

The objective function aims to minimize the total inbound or outbound drivers' cost and the penalty accrued:

$$MinZ_1 = \sum_{(\forall i,j \in \mathbf{N})} C_T t_{ij} x_{ij} + \sum_{(\forall i \in \mathbf{N})} \pi(t_i, E_i, L_i) \quad (4.32)$$

s.t.,

(i) Truck routes constraints:

$$\sum_{(\forall i \in \mathbf{N_c})} x_{ij} \leq 1 \qquad \forall j \in \mathbf{N_c} \tag{4.33}$$

$$\sum_{(\forall j \in \mathbf{N_c})} x_{0j} \leq \mathrm{M} \tag{4.34}$$

$$\sum_{(\forall i \in \mathbf{N})} x_{ij} = \sum_{(\forall i \in \mathbf{N})} x_{ji} \qquad \forall j \in \mathbf{N} \tag{4.35}$$

(ii) Truck schedule constraints:

$$t_j = \left(t_i + t_c + t_{ij}\right) x_{ij} \leq 8 \qquad \forall i, j \in \mathbf{N} \tag{4.36}$$

(iii) Truck load and capacity constraints:

$$\sum_{(\forall j \in \mathbf{N_c})} l_{0j}\, x_{0j} = 0 \qquad \text{for inbound routing} \tag{4.37a}$$

or,

$$\sum_{(\forall j \in \mathbf{N_c})} l_{j0}\, x_{j0} = 0 \qquad \text{for outbound routing} \tag{4.37b}$$

$$l_{ij} = \left(\sum_{\forall s \in \mathbf{N}} l_{si} x_{si} + q_i\right) x_{ij} \leq K_T \qquad \forall i, j \in \mathbf{N} \tag{4.38}$$

$$\left(l_{ij} + q_j - l_{jk}\right) x_{jk} \geq 0 \qquad \forall i, j, k \in \mathbf{N} \tag{4.39}$$

(iv) Non negativity and binary constraints of decision variables:

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in \mathbf{N} \tag{4.40}$$

$$l_{ij}, t_i \geq 0 \qquad \forall i, j \in \mathbf{N} \tag{4.41}$$

Similar to the crowdshipper routing problem, we obtained the optimal solutions for H+S using the MOSEK solver in the Matlab environment.

4.5 Numerical Experiments

We evaluate the performance of the proposed M+C paradigm by comparing it with the H+C paradigm described in Section 4.4, through numerical examples. We first define the operational measures in Section 4.5.1, followed by the numerical example settings in Section 4.5.2. We also perform a series of sensitivity analyses to investigate the M+C operational characteristics. The setup of sensitivity analysis is described in Section 4.5.3.

4.5.1 Operational measures

The operational measures considered are

- daily operating cost defined below,
- vehicle miles traveled (VMT),
- number of trucks and crowdshippers dispatched respectively, and
- fuel consumption.

Total vehicle miles traveled (VMT) pertains to trucks and crowdshippers in the study. Number of trucks dispatched reflects the level of capital investment in the fleet size.

The total daily operating cost consists of three parts:

(1) the daily total routing cost as determined in the routing models presented earlier,

(2) the lease and operation and maintenance costs of a hub (i.e., the central hub in H+S and the microhubs in M+C), and

(3) the labor and administrative cost at a hub. In H+S, this includes labor costs associated with sorting and other administrative support. In M+C, sorting at the microhubs is handled in a decentralized fashion by crowdshippers; we also assume there is negligible administrative/staff cost at a microhub. In other words, this cost is zero in M+C.

Specifically, the total daily operating cost for the M+C and H+S delivery paradigms, respectively, is given by:

$$Z_{M+C} = \underbrace{\{Z_h + Z_H\}}_{(1)} + \underbrace{\{N_P A_P (C_L + C_{OM})\}}_{(2)} + \underbrace{\{\left(C_A N_p^A + C_B N_p^B\right) t_s\}}_{(3)} \tag{4.42}$$

$$Z_{H+S} = \underbrace{\{Z_1\}}_{(1)} + \underbrace{\{N_P A_P (C_L + C_{OM})\}}_{(2)} + \underbrace{\{N_P A_P C_H\}}_{(3)} \tag{4.43}$$

where the additional notations are as follows,

N_P Total number of parcels processed,

N_p^A Total number of parcels picked up by automobile crowdshipper (A),

N_p^B Total number of parcels picked up by bicyclist crowdshipper (B),

A_P Hub area required for every parcel processed (sq.ft./parcel),

C_L Per square foot hub leasing rate ($/sq.ft.),

C_{OM} Per square foot hub operation and maintenance ($/sq.ft.),

C_H Per square foot labor cost for activities associated with the central hub operation and maintenance such as sorting and administrative support in H+S ($/sq.ft.),

t_s Sorting time in minutes per parcel.

The floor area of a hub (in sq.ft.) is assumed to be proportional to the number of parcels processed at the hub. The floor area and the total number or parcels processed in a day is obtained from the literature (Janjevic and Ndiaye, 2017) to derive A_P. Multiplying this metric with the number of parcels to be processed provides the required floor area of the central hub in the H+S and the floor area of the microhubs in the M+C.

The fixed costs associated with the hub – lease cost and operation and maintenance (O&M) costs, are derived in a similar way. The following metrics, (a) C_L - per square foot hub leasing rate ($/sq.ft.) and (b) C_{OM} - per square foot hub operation and maintenance ($/sq.ft.), are derived as averages from the leasing rates and the annual operating and maintenance rates for such facilities/distribution centers in the United States (Distribution group, 2018). The annual costs are divided by 365 to arrive at the daily cost.

The third cost associated with parcel processing at the hub is the daily labor cost. For the H+S, C_H is again calculated by using the average of values available for such facilities/distribution centers in the United States (Distribution group, 2018). This metric, when multiplied with the facility size of the hub provides the absolute value of the labor cost associated with the hub. The annual costs are again divided by 365 to arrive at the daily cost. For the M+C, the daily labor cost associated with the microhubs is calculated based on the sorting effort needed at the microhubs. Assuming a standard sorting time ($\boldsymbol{t_s}$) of 1 min per parcel (USPS, 2018), the value of time spent by the crowdshippers in sorting parcels at a microhub is calculated by multiplying the number of parcels processed in a day at the microhub by either crowdshipper (automobile or bicycle) and the respective crowdshipper compensation (C_A/C_B).

Lastly, fuel consumption is determined in Eq. (4.44) adopted from Barth et al. (2005) and Barth and Boriboonsomsin (2009):

$$E = \sum_{\forall i,j \in \mathbf{N}} \left[(w + l_{ij})(a_{ij} + g sin\theta_{ij} + g C_r cos\theta_{ij}) d_{ij} + 0.5 C_d A \rho v_{ij}^2 d_{ij} \right] \tag{4.44}$$

where w is the vehicle curb weight (tons); l_{ij} is the vehicle load (in tons) on link (i,j), a_{ij} is the link acceleration rate (m/s^2); g is the gravitational constant (m/s^2); C_r is the coefficient of rolling resistance; θ_{ij} is the road slope of link (i,j); d_{ij} is the link length (miles); C_d is the coefficient of rolling drag; A is the frontal surface area of a vehicle (m^2); ρ is the air density (kg/m^3); and v_{ij} is the vehicle speed on link (i,j) (mph). Fuel consumptions of both trucks and crowdshipping automobiles are calculated with Eq.(4.44).

4.5.2 Network Setting

A default numerical example is generated for a study area of 15 miles by 15 miles, similar in size to the City of Chicago, which has an area of 234 square miles. A total of 900 sender-receiver pairs or 1,800 customer points are randomly and uniformly distributed in the study area. The parcels to be delivered in the study are assumed to be small in size and vary between 1 and 30 lbs. A single truck depot is located at the center of the study area. Euclidean distances are used.

In the H+S, the truck depot is also where the central hub is located. The truck fleet is assumed homogeneous in size and capacity. For simplicity, a constant travel speed is assumed for all links. This can be easily relaxed to incorporate time varying speeds (see Zhou et al., 2017).

In the M+C, the study area is further divided into service zones; the default number of zones in the experiment is a 3 x 3 grid resulting in nine zones (Figure 4-4). A designated microhub exists at the centroid of each zone. The customer points in the study area are randomly distributed across the entire study area. For the customers located in a given zone, there are randomly generated paired intra-zonal customers, with pickup and corresponding drop-off points within the zone. For the remaining customer points in the zone, half of them are considered pickup points with the corresponding drop-off points outside the zone, and the other half as delivery points with their pickup points from the other zones. Constant travel speed is assumed among the trucks and the crowdshippers, respectively.

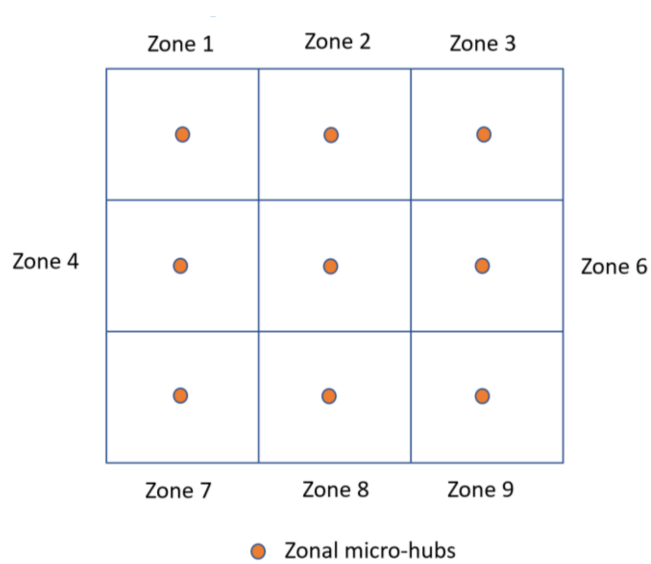


Figure 4-4. M+C numerical network

Table 4-1 summarizes the parameter values assumed in the numerical examples.

Table 4-1. Model parameter values

Parameter	Description	Value	Source
C_T	Hourly truck driver wage ($/hr)	16.73	(Bls.gov, 2018a)
C_A	Automobile crowdshipper hourly compensation ($/hr)	13.54	(Bls.gov, 2018b)
C_B	Bicyclist crowdshipper hourly compensation ($/hr)	10.74	(Bls.gov, 2018b)
K_T	Truck capacity (lbs)	3,200	(Isuzu, 2017)
K_A	Carrying capacity of automobile crowdshipper (lbs)	50	(Uberrush, 2017)
K_B	Carrying capacity of bicyclist (lbs)	30	(Uberrush, 2017)
V_T	Speed of the Truck and automobile (mph)	20	(Lee et al., 2013)
V_B	Speed of the bicyclist crowdshipper (mph)	10	(Jensen et al., 2010)
P	Penalty rate ($/hr)	3	(Postmates, 2016)
q_i	Parcel weight (lbs) at customers	[1,30]	(Uberrush, 2017)
A_P	Per parcel required hub area (sq.ft./parcel)	2.74	(Janjevic, and Ndiaye, 2017)

C_L	Hub annual leasing rate ($/sq.ft.)	10.8	(Distribution group, 2018)
C_H	Hub annual labor cost ($/sq.ft.)	15.94	(Distribution group, 2018)
C_{OM}	Hub annual operation and maintenance ($/sq.ft.)	54.41	(Distribution group, 2018)
t_c	Pick up or drop off handling time (minutes/customer	2	(USPS, 2018)
t_s	Sorting time (minutes/parcel)	1	(USPS, 2018)
t_h	Truck handling time at each microhub (fixed minutes)	10	Assumption
C_d	Coefficient of air drag	0.7 (truck) 0.29 (car)	(Akçelik and Besley, 2003) (Toyota, 2017)
A	Frontal surface area (m^2)	5 (truck) 2.09 (car)	(Akçelik and Besley, 2003) (Toyota, 2017)
a	Acceleration (m/s^2)	0	(Genta, 1997)
θ_{ij}	Road angle (degree)	0	(Genta, 1997)
ρ	Air density (kg/m^3)	1.2041	(Genta, 1997)
C_r	Rolling resistance	0.01	(Genta, 1997)
g	Gravitational constant (m/s^2)	9.81	
w	Curb weight (lbs)	8,800 (truck)	(Isuzu, 2017)

		2,840 (car)	(Toyota, 2017)

4.5.3 Sensitivity Analysis

The M+C is compared with the H+S for their operational differences in a series of sensitivity analyses of key operational factors of interest. They are: number of customers, service area size, crowdshipper compensation rate, and late pickup penalty rate. Table 4-2 summarizes the sensitivity analyses (scenarios) performed in this study.

Table 4-2. Sensitivity Analysis (values in bold are defaults)

Scenario ID	Factor	Values to be tested
1 to 7	Number of customers	108, 180, 432, **1,800**, 18,000, 180,000 and 1,800,000
8 to 13	Service area (square miles)	**15 mi × 15 mi**, 18 mi × 18 mi, and 23 mi × 23 mi
14 to 19	Crowdshipper compensation ($/hr)	Automobile: $12.54, **$13.54**, and $14.54; Bicycle: $9.74, **$10.74**, and $11.74
20 to 22	Penalty rate ($/hr)	$2.00, **$3.00**, and $4.00

A service area of 15 mi × 15 mi is equivalent to the size of City of Chicago (234 sq. mi.). The service areas of 18 mi × 18 mi and 23 mi × 23 mi represent the cities of New York (area = 301.5 sq. mi.) and Los Angeles (area = 468.7 sq. mi.) respectively.

For each scenario tested, 30 instances of randomly distributed customer locations with respective random demand and pick up time windows are generated and solved. These customer locations are randomly spread out across the entire service area. The pickup time window is limited to a one-hour interval, and randomly generated between 9:00AM and 03:00 PM. A $3/hr penalty fee applies after the time window expires. For example, suppose the pickup window at a customer location is between 10:00 and 11:00 AM. If the pickup takes place between 11:01 AM and 12:00AM, a penalty charge of $3 is applicable. For the pickup between, 12:01 and 01:00 PM, the penalty charge would be an additional $3 and so on for every hour.

4.6 Results and discussion

4.6.1 Effect of Number of Customers

In this analysis, the service area is set at 15 mi × 15 mi. The total number of customers in the service area varies from 108 to 1,800,000 according to Table 2.

The results are shown in both Table 4-3 and Figure 4-5. The total VMT is sum of miles traveled by trucks, and automobile and bicycle crowdshippers. If normalized by the number of customers, we find that per customer fleet size (trucks and crowdshippers) and per customer VMT generally hold constant or even go down slightly. This indicates the economies of scale for the M+C.

Table 4-3. Effect of number of customers on the M+C fleet size and total VMT

ID	# customers	# trucks dispatched	# auto crowdshippers dispatched	# bike crowdshippers dispatched	Total VMT (std dev)
1	108	2	8 -13	13 to 24	183 (7.8)
2	180	2	15 to 20	27 to 36	230 (8.5)
3	432	4	35 to 51	61 to 93	617 (35.5)
4	1,800	16	155 to 166	312 to 345	2,479 (15.2)
5	18,000	160	1,517 to 1,618	3101 to 3249	25,054 (301.0)
6	180,000	1600	14,858 to 15,645	29,474 to 31,248	247,512 (2,444.2)
7	1,800,000	16,000	158,376 to 162,727	329,689 to 347,868	2,489,852 (12,828.4)

Figure 4-5 shows the normalized fuel consumption in gallons per mile (gal/mi) and daily operating cost in $ per mile ($/mi). Except when the number of customers is low (108 and 180), per mile fuel consumption and per mile daily operating cost are fairly consistent across all of the number of customers scenarios. This feature also works in favor of the M+C as a feasible alternative to the last mile delivery service.

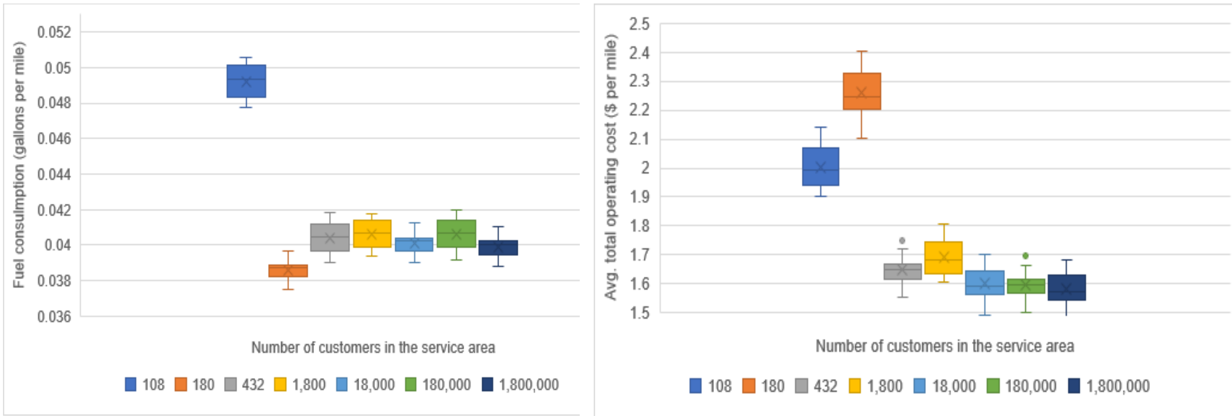


Figure 4-5: Effect of number of customers on the M+C: (a) fuel consumption (gal/mi) and (b) daily operating cost ($/mi)

<u>*Comparison with H+C*</u>

As compared to the H+S, the M+C delivers 63-81% reduction in the number of trucks dispatched, 43-60% reduction in total VMT (Figure 4-6), and 54-70% reduction in both total fuel consumption (gallons) and in gallons per dollar of daily operating cost (Figure 4-7), respectively, across all customer sizes considered.

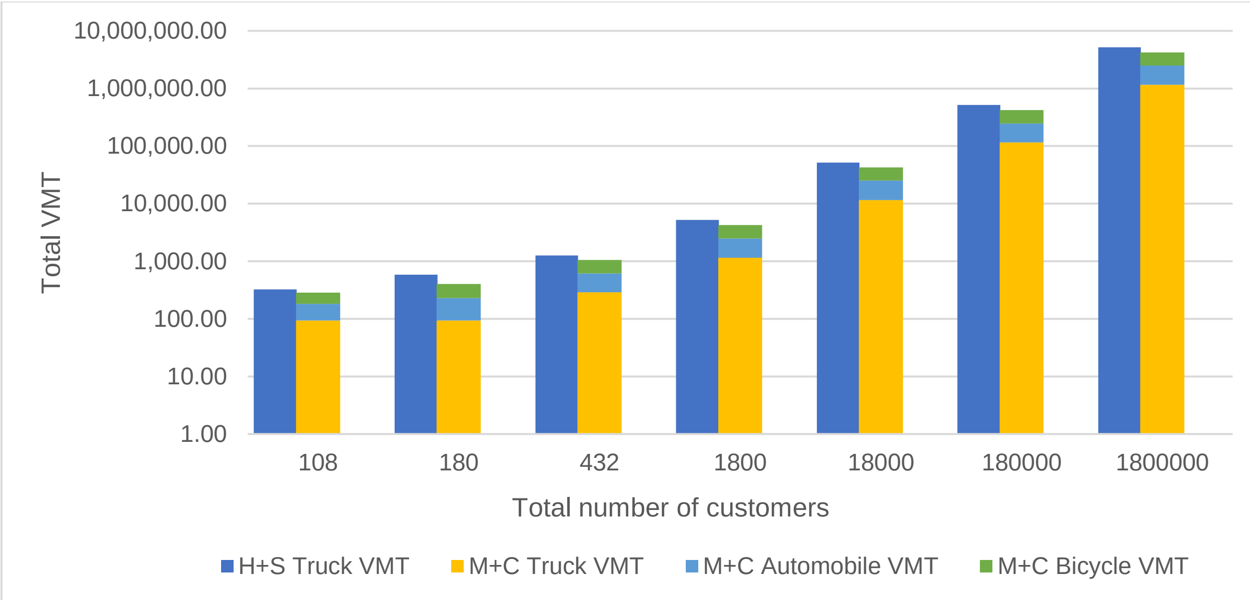


Figure 4-6: Comparison of the effect of number of customers on VMT (in Log scale)

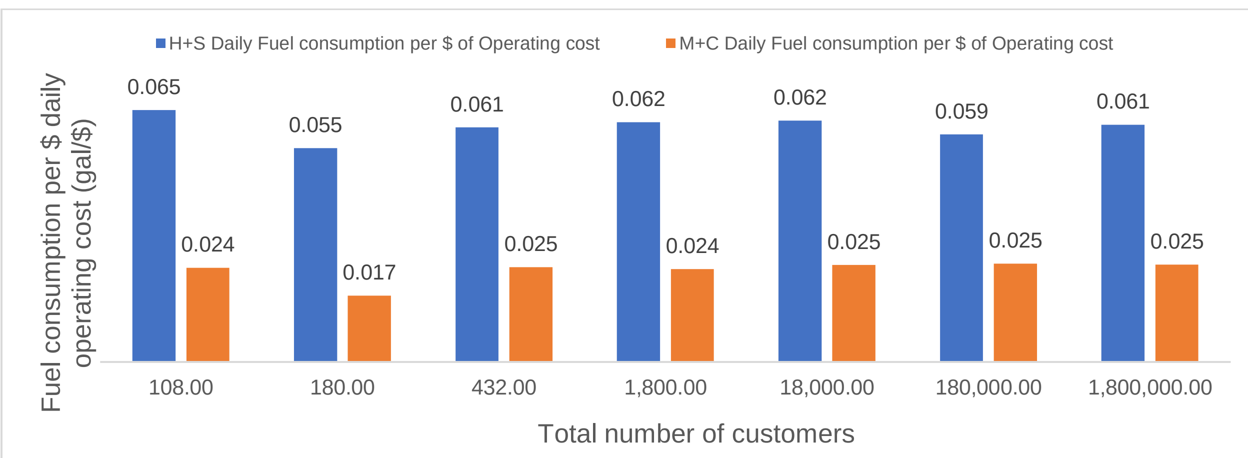


Figure 4-7: Comparison of the effect of number of customers on fuel consumption per dollar of daily operating cost (gal/$)

As in Figure 4-8, the M+C paradigm initially witnesses an increase (21.08%) in total daily operating cost from the H+S when the number of customers is low (108 customer locations in the service area). As the number of customers increases, the M+C has a lower average daily operating cost than the H+S paradigm. The saving rises as the number of customers increases.

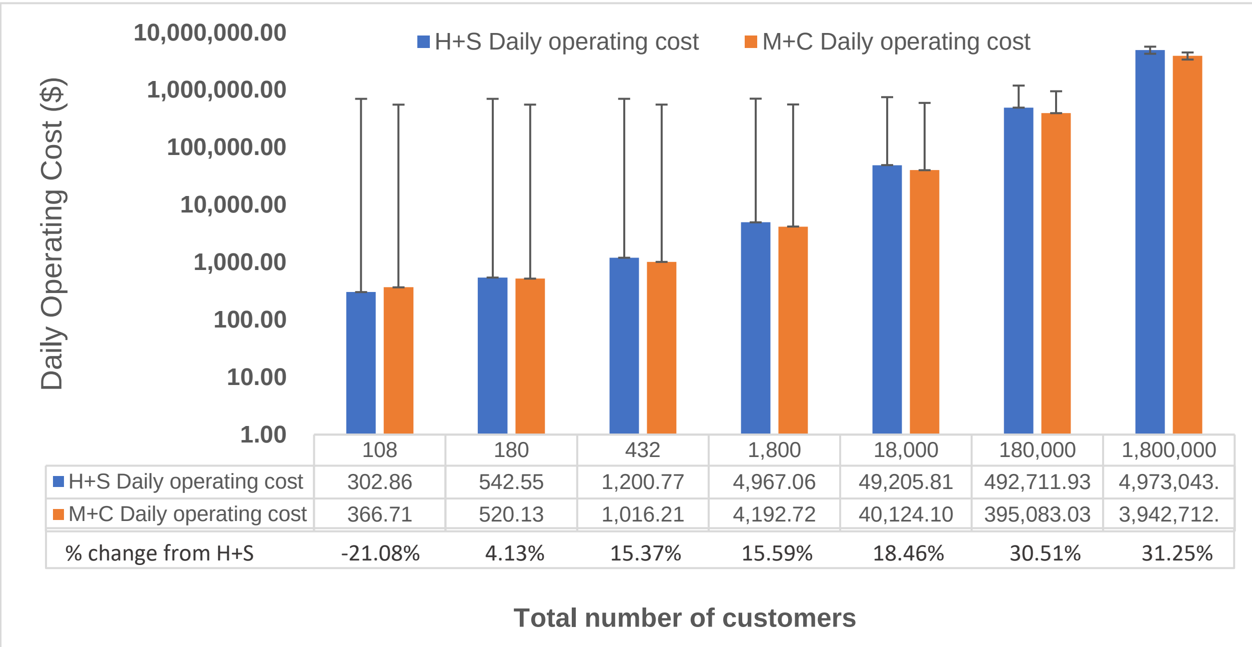
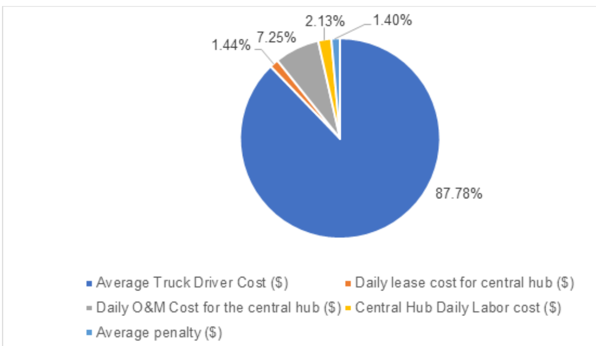
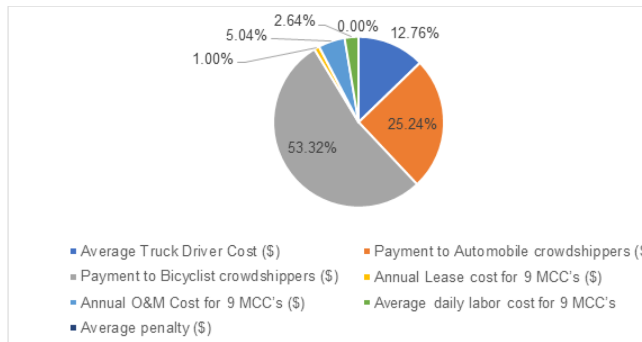


Figure 4-8: Comparison of the effect of number of customers on daily operating cost (in Log scale)

Figure 4-9 presents the average breakdowns of the total daily operating cost in the H+S and the M+C. For the H+S, the only courier cost is of the truck drivers, accounting for almost 88% of the daily operating cost (Figure 10(a)). For the M+C, the courier cost is about 91% of the daily operating cost, splitting among the truck drivers (12.76%) and the crowdshippers (25.24% for automobile crowdshippers and 53.32% for bicycle crowdshippers) (Figure 10(b)).

The lease and the O&M costs account for a small portion of the overall total daily operating cost for both the H+S (8.7%) and the M+C (6%). Therefore, the distributed nature of microhubs does not appear to impose cost burdens on the entire system.





(a) H+S (b) M+C

Figure 4-9: Distribution of total daily operating cost

Overall the results reveal that the M+C gains increasing cost advantage over the traditional H+S as the number of customers increases. When the number of customers is low, the H+S is evidently more cost efficient.

4.6.2 Effect of Service Area Size

4.6.2.1 with a fixed number of microhubs in the service area

In this analysis, operational measures are generated for three square service area sizes, 15 mi × 15 mi, 18 mi × 18 mi, and 23 mi × 23 mi, with a fixed number of 1,800 customers distributed randomly across the entire service area. A total of 9 microhubs are located in each of the service area sizes as shown in Figure 4-10.

Table 4-4. Effect of the service area size on the M+C fleet size

ID	Service area (sq. mi.)	# microhubs	# trucks dispatched	# auto crowdshippers dispatched	# bike crowdshippers dispatched
8	15 x 15	9	16	155 - 168	312 - 345
9	18 x 18	9	16	239 - 268	401 - 456
10	23 x 23	9	16	388 - 422	698 - 792

As shown in Table 4-4, despite the increase in service area, the number of trucks dispatched does not increase; instead, the absolute number of crowdshippers, both automobile and bicycle, increases. However, if normalizing the number of crowdshippers by service area, the value remains fairly consistent:

- Number of automobile crowdshippers per sq. mi.: 0.69 – 0.75, 0.74 – 0.83, and 0.73 – 0.80, respectively.
- Number of bicycle crowdshippers per sq. mi.: 1.39 – 1.53, 1.24 – 1.41, and 1.32 – 1.50, respectively.

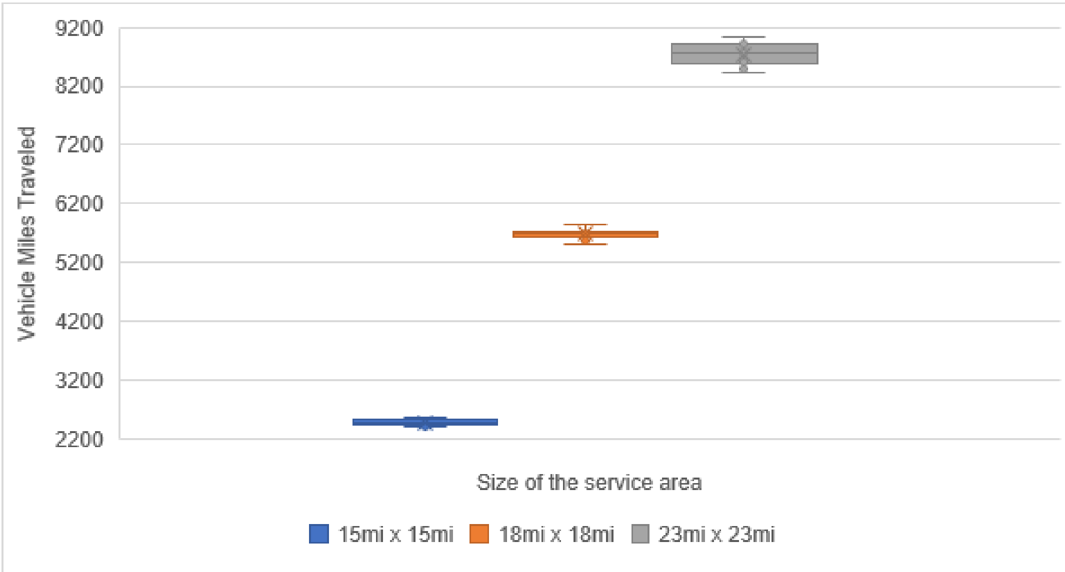


Figure 4-10: Effect of service area size on the M+C total VMT

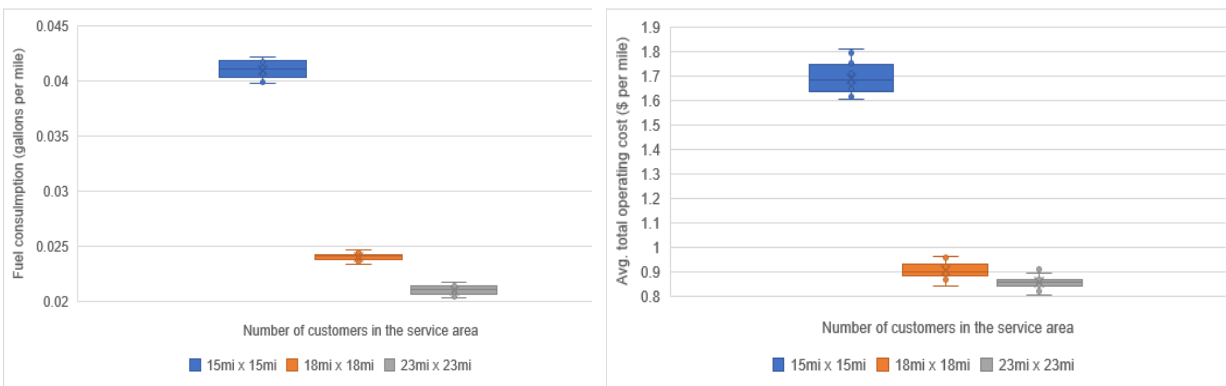


Figure 4-11:. Effect of service area size on the M+C: (a) fuel consumption (gal/mi) and (b) daily operating cost ($/mi)

As expected, the total VMT increases significantly as the service area expands (Figure 4-10). On the other hand, on a per mile basis, both the fuel consumption (gal/mi) and the daily operating cost ($/mi) for the M+C show significant reductions as the service area expands (Figure 4-11). Again, this is a desirable feature for the M+C.

Comparison to H+C

Compared to the H+S, the M+C delivers a large reduction in the number of trucks dispatched (77%, 84% and 90%, respectively for the three service area sizes), average VMT (60%, 59% and 61%, respectively), and total fuel consumption (70%, 73% and 78%, respectively). These translate into considerable reductions in the daily operating cost (4%, 8%, 13%, respectively). More importantly, the cost reduction increases as the service area grows.

There is no penalty incurred in the M+C, however, penalty is incurred in the H+S for the service areas of 18 mi by 18 mi and 23 mi by 23 mi, increasingly as the service area expands.

The average floor area of the central hub in the H+S is 2,466.7 sq.ft. with the associated daily labor cost of $107.72 at the hub. The average floor area of the 9 microhubs in the M+C is 1,316.6 sq.ft. with the associated daily labor cost of $684.58 at the microhubs.

Figure 4-12 demonstrates that the M+C has the cost advantage over the H+C in terms of both per customer daily operating cost ($/cu) and per mile daily operating cost ($/mi) when the customer density is sufficiently large, i.e., the economies of scale. When the customer density is low, the traditional H+C is more cost efficient.

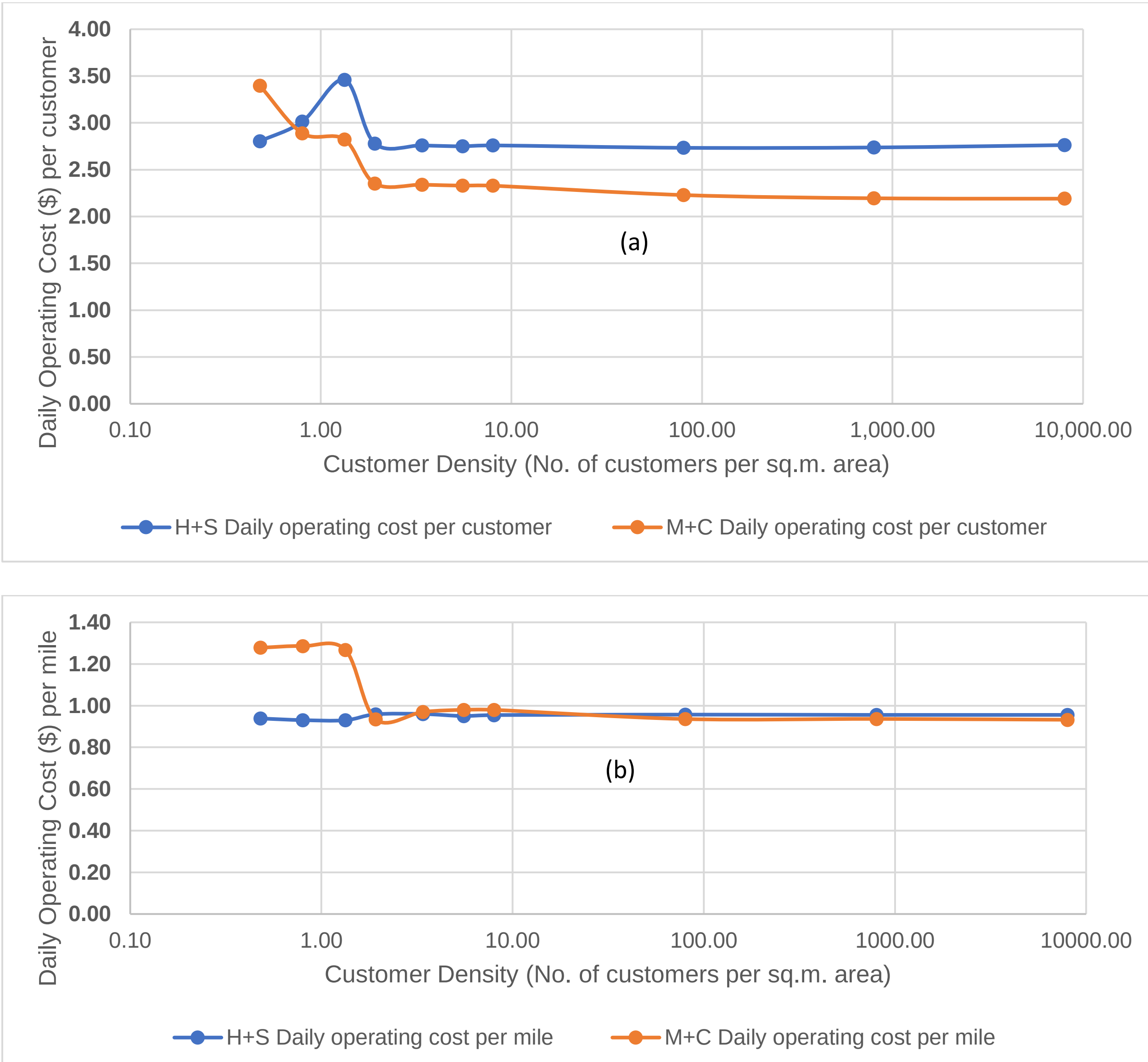


Figure 4-12. Comparison of the effect of customer density on daily operating cost: (a) \$/customer and (b) \$/mile

Overall the findings confirm that the M+C delivery paradigm may be a feasible alternative to the traditional H+S delivery paradigm with the economies of scale.

4.6.2.2 with a constant zone area served by each microhub

In Section 4.6.2.1, the number of microhubs is fixed despite the increase in service area. In this section, we vary the number of microhubs in keeping the zone area nearly constant, for the same three square service area sizes, 15 mi × 15 mi, 18 mi × 18 mi, and 23 mi × 23 mi. The total of customers is kept at 1,800 distributed randomly across the entire service area.

Specifically, there are a total of 9 microhubs in the 15 mi × 15 mi service area. This gives an average of 25 sq. mi. in each zone. Keeping the zone area as close to constant as possible, we determine that it results in 12 zones for the 18 mi × 18 mi and 21 zones for the 23 mi × 23 mi, as defined in Figure 4-13.

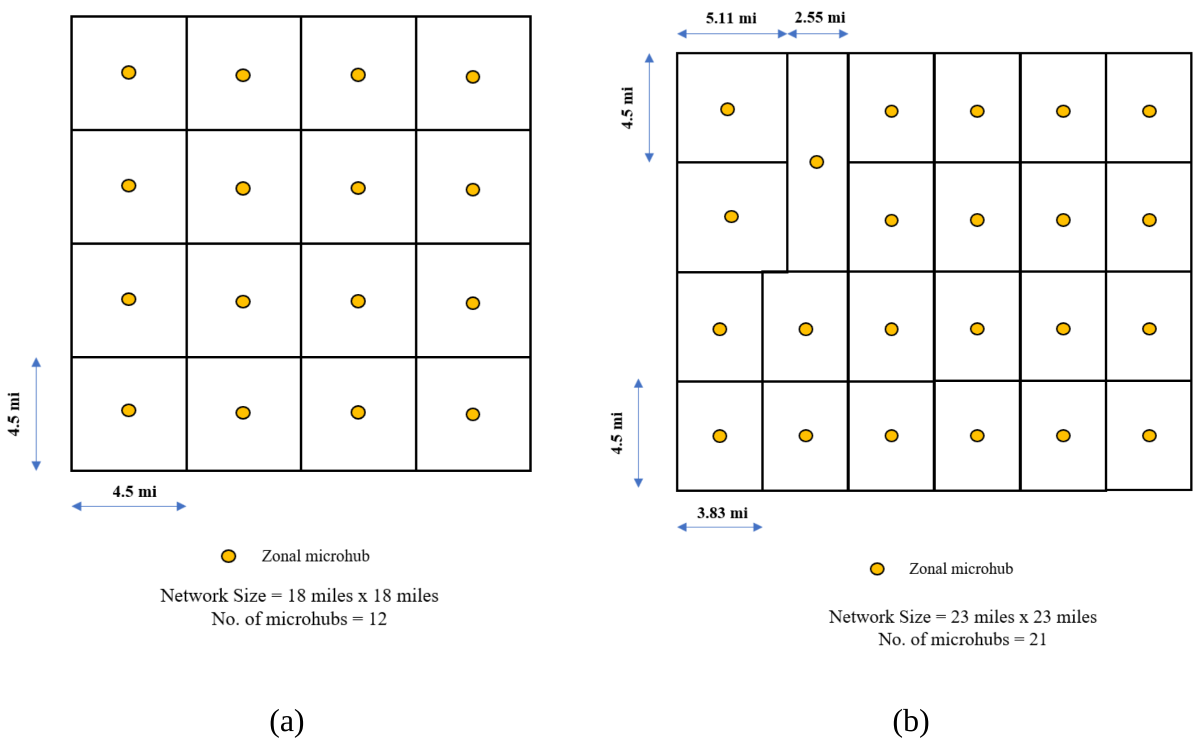


Figure 4-13. Location of M+C microhubs in service area of (a) 18 mi x 18 mi and (b) 23 mi x 23 mi

The results presented in Table 4-5 are found to be very close to those presented in Table 4-4. Even the total floor area of the microhubs remains constant at 1,316.6 sq. ft. with $684.58 of the labor cost. Noticeably the numbers of automobile crowdshippers and bicycle crowdshippers decrease from Table 4-4 as a result of keeping the zone areas near constant, which effectively increases the customer density.

Again, similar patterns are found in VMT, per mile fuel consumption, and per mile daily operating cost as shown in Figures 4-10 and 4-11 of Section 4.6.2.1.

Table 4-5. Effect of service area size on the M+C fleet size

ID	Service area (sq. mi.)	# microhubs	# trucks dispatched	# auto crowdshippers dispatched	# bike crowdshippers dispatched
11	15 x 15	9	16	155 - 168	312 - 345
12	18 x 18	12	16	203 - 247	386 - 435
13	23 x 23	21	16	379 - 411	671 - 756

4.6.3 Effect of Crowdshipper compensation

In this investigation, the service area is kept at 15 mi by 15 mi with 1,800 customer locations in the service area. The automobile and the bicycle crowdshipper compensation rates vary separately accordingly to the values shown in Table 2.

4.6.3.1 Effect of automobile crowdshipper compensation rate

As seen in Table 4-6, when the automobile crowdshipper compensation rate goes up, the number of automobile crowdshippers is reduced by about 3.58% to 4.64%, as expected, while the number of bicycle crowdshippers goes up slightly by 1.86% to 1.37%. This implies that a portion of the delivery jobs are shifted from automobile to bicycle crowdshippers. The average VMT initially goes up when the automobile crowdshipper compensation rate goes up and then drops slightly as the compensation rate continues to go up, but the changes are statistically insignificant (Figure 4-14). The total fuel consumption, on the other hand, decreases significantly as the automobile crowdshipper compensation increases resulting in the reduction of automobile crowdshippers dispatched (Figure 4-15a). However, that reduction in the number of automobile crowdshippers dispatched is not enough to offset the increases in the automobile crowdshipper compensation rate and the number of bicycle crowdshippers dispatched. As a result, the total daily operating cost goes up by 1.34 - 6.07% (Figure 4-15b).

Table 4-6. Effect of the automobile crowdshipper compensation on the M+C fleet size

ID	Auto crowdshipper compensation ($/hr)	# trucks dispatched	# auto crowdshippers dispatched	# bike crowdshippers dispatched
14	12.54	16	161 - 174	307 - 338
15	13.54	16	155 - 168	312 - 345
16	14.54	16	147 - 161	317 - 349

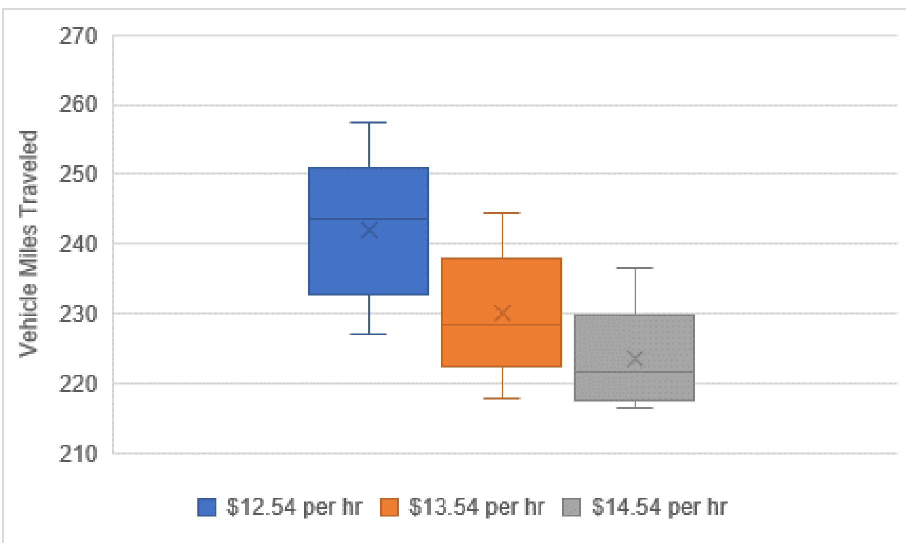
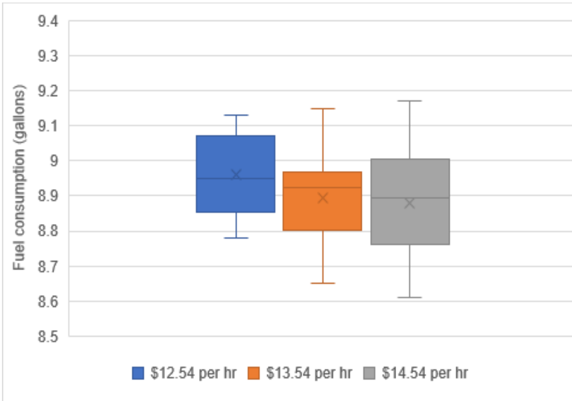


Figure 4-14. Effect of automobile crowdshipper compensation rate on the M+C total VMT



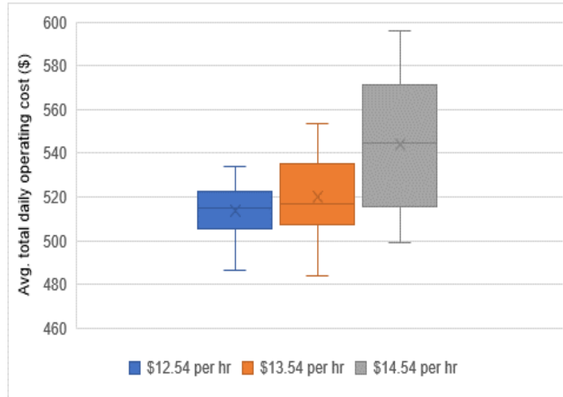


Figure 4-15. Effect of automobile crowdshipper compensation on the M+C: (a) fuel consumption (gallons) and (b) daily operating cost ($)

4.6.3.2 Effect of bicycle crowdshipper compensation rate

With an increase in the bicycle crowdshipper compensation rate, a slight decrease (2.52-2.74%) is observed in the number of bicycle crowdshippers dispatched and at the same time a slight increase (2.79-3.19%) in the number of automobile crowdshippers dispatched (Table 4-7). The VMT increases significantly when the compensation rate increases from $9.74 to $11.74 (Figure 4-16); there is little effect on fuel consumption (Figure 4-17a) or daily operating cost (Figure 4-17b). This may be due to the very slight changes in the overall fleet size dispatched.

Table 4-7. Effect of bicycle crowdshipper compensation rate on the M+C fleet size

ID	Bike crowdshipper compensation rate ($/hr)	# trucks dispatched	# auto crowdshippers dispatched	# bike crowdshippers dispatched
17	9.74	16	151 - 162	319 - 355
18	10.74	16	155 - 168	312 - 345
19	11.74	16	159 - 173	302 - 337

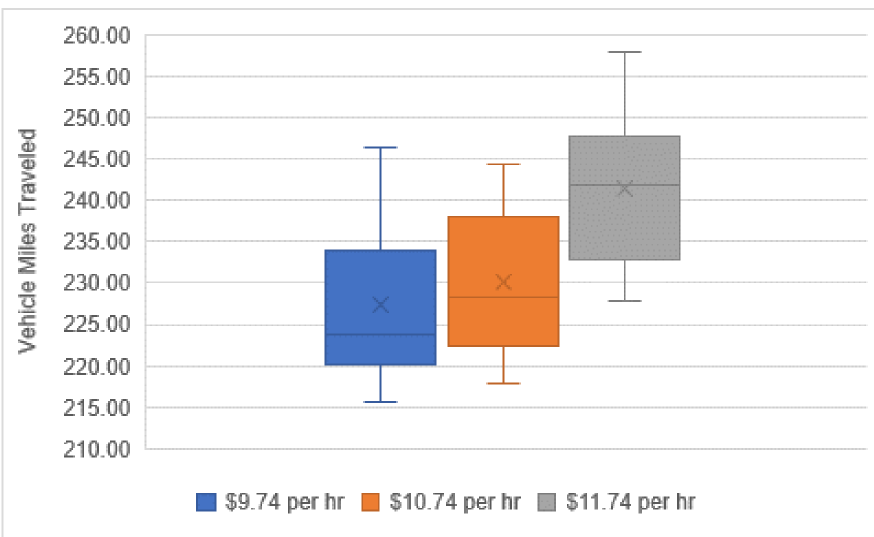


Figure 4-16. Effect of bicycle crowdshipper compensation rate on M+C total VMT

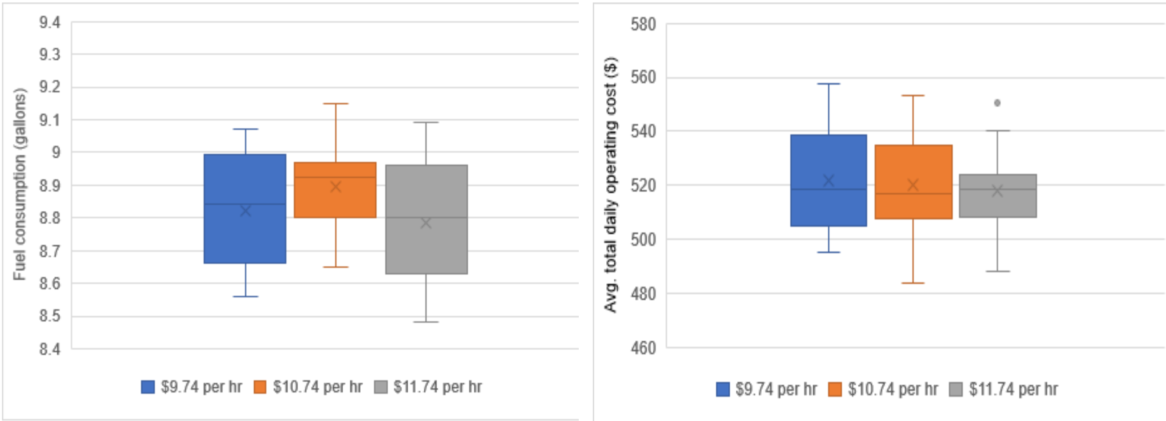


Figure 4-17. Effect of bicycle crowdshipper compensation rate on the M+C: (a) fuel consumption (gallons) and (b) daily operating cost ($)

4.6.4 Effect of Late Pickup Penalty Rate

For this analysis, the service area size is maintained at 15 mi × 15 mi with 1,800 customers. The late pickup penalty rate changes from $2/hr to $3/hr and $4/hr sequentially.

For the M+C, no penalty incurs in any of the three penalty rate scenarios. This may be due to the flexibility of crowdshippers and the assumption that there are always sufficient crowdshippers available for delivery, which is not an impractical one as in the case of Uber drivers. Therefore, crowdshipping does provide the advantage of being flexible.

In contrast, for the H+S, the average penalty ($/mi) increases by 50% and 100% respectively with the increases in the penalty rate (Table 4-8). This results in an increase in the respective daily operating cost ($/mi) for the H+S.

Table 4-8. Effect of late pickup penalty rate on the H+S

ID	Penalty rate ($/hr)	# trucks dispatched	Fuel consumption (gal/mi)	Penalty ($/mi)	Daily operating cost ($/mi)
20	2	82 to 92	0.059	0.0086	0.951
21	3	82 to 92	0.059	0.0129	0.955
22	4	82 to 92	0.059	0.0172	0.959

4.6.5 Summary findings

According to our study, as the customer demand increases with the fixed network size, all performance measures increase due to the additional customer locations that need to be served. The M+C delivery paradigm proves to incur more cost than the H+S paradigm for low customer demand. A minimum customer demand is therefore needed for the M+C to be more attractive than the H+S paradigm. Beyond this minimum customer demand, the percentage of savings in the average total daily operating cost achieved by using the M+C paradigm over the H+S paradigm increase with an increase in the customer demand. This suggests that the M+C delivery paradigm may be a feasible alternative to the conventional H+S delivery paradigm for customer demand beyond a certain minimum customer demand only and the savings in the total daily operating cost increase with an increase in customer demand.

Our study shows that as the network size increases, with the number of customer locations per zone maintained constant, all the performance measures increase as well due to the additional distance needed to be travelled to serve the customer locations. A slight reduction is achieved in the number of crowdshippers, average total fuel consumption, average VMT and average total daily operating cost if the number of microhubs is increased in proportion to the network size. The percentage of savings in the average total daily operating cost achieved by using the M+C paradigm over the H+S paradigm remains approximately constant, even with an increase in network size. In addition, larger network size with a low customer density still does not incur any penalty cost. This suggests that the M+C delivery paradigm may be a feasible alternative to the conventional H+S delivery paradigm irrespective of the network size and customer density.

According to our study, an increase in the automobile and bicyclist compensation results in the decrease in the number of the respective crowdshippers and an increase in the number of the alternate crowdshippers. Simultaneously, it results in an increase in the average total daily operating cost making the M+C paradigm less attractive than H+S paradigm.

Lastly, our study shows that increasing the penalty rate makes the M+C paradigm more attractive than the H+S paradigm.

4.7 Conclusion

This study first proposes and formulates a combined microhubs with crowdshipping (M+C) last mile delivery paradigm, and then evaluates its operational characteristics as a feasible alternative to the traditional hub-and-spoke paradigm. It is a special case of the Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP), because in this study we assume that each truck must visit all the microhubs at least once until it delivers all the pairwise transshipment demand that it carries. That allows us to solve it exactly even though the general M-MSPDP is NP hard. The operational measures used for comparison include total vehicle miles traveled (VMT), number of trucks and crowdshippers dispatched, total daily operating cost and total fuel consumption. Sensitivity analysis is conducted to investigate the effect of key operational factors such as the size of the service area, the number of customers, crowdshipper payment and penalty rate. The study considers time windows for the customer demand and cost of central hub and microhubs.

The analysis results demonstrate that the M+C could be a feasible alternative to the traditional H+C in that

(1) the M+C gains cost advantage over the H+C with the economies of scale;
(2) using crowdshippers gives flexibility to the M+C in meeting the customer time window constraints over the H+C;
(3) the M+C significantly reduces the number of trucks dispatched and the associated truck VMT, as well as total VMT, which is good for truck parking challenges and congestion in urban areas;
(4) consequently, the M+C consumes less fuel than the H+S, which is good for the environment and sustainability in general; and
(5) the M+C requires less floor area of the microhubs than that of the central hub in the H+C, which makes the M+C attractive in space limited urban areas.

On the other hand, the M+C is more costly to operate when the number of customer (or customer density) is low than the H+S.

The M+C delivery paradigm could be made more cost-competitive by suitably locating the microhubs in the urban areas based on the historical demand data. This initiative may find support in the urban areas by displaying the reduction in the truck VMT and associated congestion. In addition, with the rise in demand for the same-day deliveries, crowdshipping is expected to become more competitive due to the economies of scale.

The presented research could be extended in several directions. Crowdshippers are not restricted to one mode of transport and every mode of transport provides a different carrying capacity to the crowdshipper. Thus, it is important to study the impact of a heterogeneous fleet available to crowdshippers. This could include cleaner electric vehicles, as well as the walking mode. Another study area, includes the possibility of a relay between the crowdshippers, thus extending the service area for a respective zone. In addition, routing of crowdshippers could be performed with the objective of minimizing the emissions in the urban areas. A hybrid hub-and-spoke model combined with crowdshipping may also be studied in future for comparison.

Chapter 5 Many-to-Many Split Pickup-and-Delivery Problem

5.1 Introduction

In the classical Vehicle Routing Problem (VRP), (1) no splitting of customer loads is allowed; and (2) it is a one-to-one shipment problem (either depot-to-customer for a delivery problem, or customer-to-depot for a pickup problem, or customer-to-customer for a pairwise pickup-delivery problem). Though, in the real world, truck operators allow the remaining capacity in the truck to be filled with partial customer loads in order to use the truck capacity more efficiently. This may require multiple trips by a single truck or multiple trucks to service the demand at a given customer's by allowing the demand to be split.

Figure 5-1 illustrates the benefit of split load. In this example, there are three origin customers, A, B, and C. Each has a demand equivalent to 0.6 Truck Loaded (TL) Capacity. There is one common destination customer D. There is one single truck serving all customers. When split load is not allowed, it takes three direct shipments (A-D, B-D, and C-D) and seven trips (defined between two stops) for the truck to complete the deliveries. When split load is allowed, the truck goes to A to pick up the 0.6 TL, then goes to B to pick up an additional 0.4 TL before heading to D; after that, the truck returns to B to pick up the remaining 0.2 TL and heads to C to pick up the 0.6 TL. In the latter, the truck capacity is much better utilized. If the origin customers are relatively close to each other, compared to D, the latter strategy (with split load) also results in VMT savings.

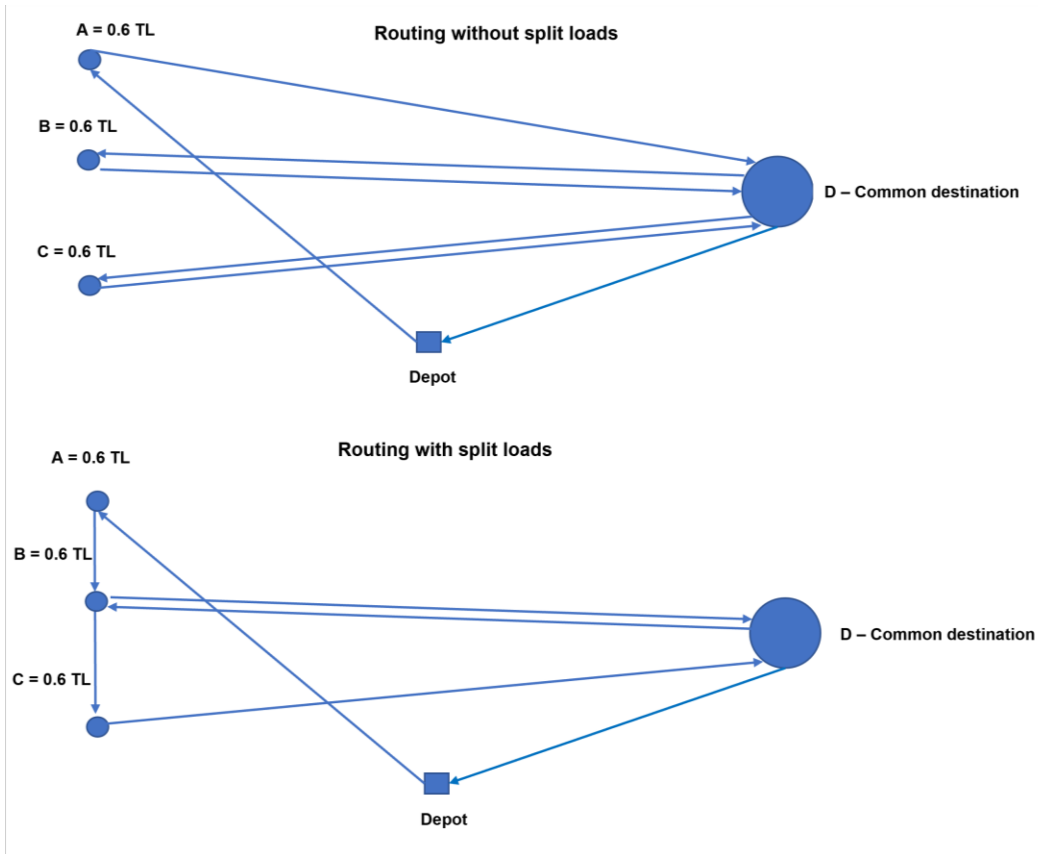


Figure 5-1: Illustration of benefit of split loads

To the best of our knowledge, a general case of Many-to-Many Split Pickup and Delivery Problem (M-MSPDP) has not been investigated in the literature. To this end, we define a general Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP) in this paper. Because the problem is NP-hard (Dror et al., 1994), we propose a heuristic called Maximum Split-Benefit with Tabu Search (MS-BTS) to efficiently solve for a large-scale M-MSPDP-FPD, which can be applied iteratively to solve for M-MSPD-OC. We then apply the MS-BTS to solve for two applications: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bike rebalancing in a bike-sharing system (i.e., M-MSPD-OC). This study contributes to the vehicle routing literature by introducing a heuristic for solving the general case of M-MSPDP.

This chapter is organized as follows. Section 5.2 defines a general M-MSPDP. Section 5.3 presents the Maximum Split-Benefit with Tabu Search (MS-BTS) heuristic. Section 5.4 investigates the performance of MS-BTS via numerical experiments. Section 5.5 presents the results of two application case studies: bike rebalancing in a bike-sharing system and parcel pickup and delivery with microhubs. Finally, Section 5.6 presents the conclusions.

5.2 Problem Definition

A general Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP) consists of a single truck depot (0), a truck fleet ($\mathbf{V} = \{v_l, \forall l \in (1,2,\dots,m)\}$, where m is the upper bound of the fleet size), and a set of customers (or parcel stations) ($\mathbf{C} = \{c_i, \forall i \in (1,2,\dots,n)\}$, where n is the total number of customers). Note that each customer can be a shipper of goods (pickup point) to one or more other customers, and a receiver of goods (delivery point) from one or more other customers at the same time, and hence it is a Many-to-Many Pickup-and-Delivery problem. We denote the pickup (or outgoing) demand as p_i and delivery (or incoming) demand as q_i at customer c_i ($\in \mathbf{C}$). (Note that $p_0 = q_0 = 0$ at the depot 0). We further denote the pairwise demand q_{ij} from customer c_i to customer c_j. In other words, $p_i = \sum_{j=1}^{n} q_{ij}$, and $q_j = \sum_{i=1}^{n} q_{ij}$.

Furthermore, at each customer c_i, both the total outgoing demand and incoming demand can be handled by multiple visits of either a single truck or multiple trucks. Specifically, for the outgoing demand, $p_i = \sum_{l=1}^{m} \sum_{k=1}^{n} p_{ik}^{l}$, where p_{ik}^{l} is the load shipped from c_i to c_k by truck v_l; similarly for the incoming demand, $q_j = \sum_{l=1}^{m} \sum_{k=1}^{n} p_{kj}^{l}$. In other words, for a given pair of pickup and delivery demand, $q_{ij} = \sum_{l=1}^{m} p_{ij}^{l}$, i.e., the demand is split into m truck shipments. The split load p_{ij}^{l} is a decision variable.

A truck v_l always starts and ends at the truck depot $\{0\}$ empty. In other words, all parcels collected on the route by v_l must be delivered to their designated destinations by end of the route. At each customer c_i, truck v_l unloads all of the onboard parcels bounded for c_i, i.e., $\sum_{k=1}^{K_i} p_{ki}^{l}$, and then loads outgoing parcels from c_i, i.e., $\sum_{k=1}^{K_{io}} p_{ik}^{l}$, as permitted by its remaining capacity.

In general, M-MSPDP is represented with a directed complete graph, $\mathbf{G} = \{\mathbf{N}, \mathbf{A}\}$, where $\mathbf{N}$ is a set of vertices, $\mathbf{N} = \mathbf{C} + \{0\}$, and $\mathbf{A}$ is a set of edges, $\mathbf{A} = \{a_{ij} = (c_i, c_j), \forall c_i, c_j \in \mathbf{C}, i \neq j\}$. For each edge a_{ij}, there is a cost associated with it. This cost can be measured in terms of distance or travel time between c_i and c_j, or labor cost (driver's wage), or some generalized cost. Thus, solving the M-MSPDP finds a strategy of truck dispatching and routing and load splitting in order to minimize total cost incurred by truck routing.

Other model notations are defined as follows:

F set of available trucks, $\mathbf{F} = \{1,2, \dots, \mathrm{M}\}$, where M is the maximum number of trucks

d_{ij} length of link $(i,j)(\in \mathbf{A})$

t_{ij} travel time on link $(i,j)(\in \mathbf{A})$; $t_{ij} = d_{ij}/V_T$ for the truck at a constant speed of V_T.

q_i parcel weight at node i $(\in \boldsymbol{C})$; $q_i > 0$ for pickup demand and $q_i < 0$ for delivery demand; $q_0 = 0$ at the depot (i.e., $i = 0$)

K_T truck capacity

Decision variables

t_i^v arrival time at customer i ($\in$ **C**) by truck v ($\in$ **F**)

l_{ij}^v load of truck v ($\in$ **F**) when traversing on link (i, j) ($\in \boldsymbol{N}$)

x_{ij}^v binary variable, $x_{ij}^v = 1$ if truck v ($\in$ **F**) traverses on link (i, j) ($\in \boldsymbol{N}$), and $x_{ij}^v = 0$ otherwise

p_{ij}^v binary variable, $p_{ij}^v = 1$ if transshipment from customer i to customer j is done by truck v, and $p_{ij}^v = 0$ otherwise.

The objective function for the truck routing to serve all the customers minimizes the total truck driver's cost:

$$MinZ = \sum_{\forall (i,j) \in \mathbf{A}} \sum_{\forall v \in \mathbf{F}} C_T(t_{ij}) x_{ij}^v \tag{5.1}$$

s.t.,

(i) Truck routes constraints:

$$\sum_{(\forall i \in \mathbf{C})} \sum_{\forall v \in \mathbf{F}} x_{ij}^v \geq 1 \qquad \forall j \in \mathbf{C} \tag{5.2}$$

$$\sum_{(\forall j \in \mathbf{C})} x_{0j}^v \leq \mathrm{M} \qquad \forall v \in \mathbf{F} \tag{5.3}$$

$$\sum_{(\forall i \in \boldsymbol{N})} x_{ij}^v = \sum_{(\forall i \in \mathbf{N})} x_{ji}^v \qquad \forall j \in \mathbf{N}, \forall v \in \mathbf{F} \tag{5.4}$$

(ii) Truck schedule constraints:

$$t_j^v = \left(t_i^v + t_{ij}\right) x_{ij}^v \leq 8 \qquad \forall i, j \in \mathbf{N}, \forall v \in \mathbf{F} \tag{5.5}$$

(iii) Truck loading and capacity constraints:

$$\sum_{(j \in \mathbf{C})} l_{0j}^v \, x_{0j}^v = 0 \qquad \forall v \in \mathbf{F} \tag{5.6}$$

$$\sum_{(j \in \mathbf{C})} l_{j0}^v \, x_{j0}^v = 0 \qquad \forall v \in \mathbf{F} \tag{5.7}$$

$$\sum_{\forall j \in \mathbf{C}} q_{ij} p_{ij}^v \leq \sum_{\forall j \in \mathbf{C}} q_{ij} \qquad \forall i \in \mathbf{C}, \forall v \in \mathbf{F} \tag{5.8}$$

$$\sum_{\forall v \in \mathbf{F}} p_{ij}^v = 1 \qquad \forall i, j \in \mathbf{C} \tag{5.9}$$

$$l_{ij}^v = \left(\sum_{\forall s \in \boldsymbol{N}} l_{si} x_{si}^v + \sum_{\forall k \in \mathbf{C}} q_{ik} p_{ik}^v - \sum_{\forall k \in \mathbf{C}} q_{ki} p_{ki}^v \right) x_{ij}^v \leq K_T \qquad \forall i, j \in \mathbf{N}, \forall v \in \mathbf{F} \tag{5.10}$$

$$\left(l_{ij}^v + \sum_{\forall k \in \mathbf{C}} q_{jk} p_{jk}^v - \sum_{\forall k \in \mathbf{C}} q_{kj} p_{kj}^v - l_{jk} \right) x_{jk}^v \geq 0 \qquad \forall i, j, k \in \mathbf{N}, \forall v \in \mathbf{F} \tag{5.11}$$

(iv) Non negativity and binary constraints of decision variables:

$$x_{ij}^v, p_{ij}^v \in \{0,1\} \qquad \forall i, j \in \boldsymbol{N}, \forall v \in \mathbf{F} \tag{5.12}$$

$$l_{ij}^v, t_i^v \geq 0 \qquad \forall i, j \in \boldsymbol{N}, \forall v \in \mathbf{F} \tag{5.13}$$

Only the differences from a classical VRP are highlighted here. Eq.(5.2) says that each customer must be visited at least once. Eq.(5.8) ensures that all the demand picked up by a truck at a customer is no greater than the total pickup demand at the customer. Lastly, Eq.(5.9) ensures that the pairwise demand between any two microhubs is only fulfilled once. This is a direct derivation of the assumption that the pairwise demand q_{ij} cannot be split.

5.3 Maximum Split-Benefit with Tabu Search (MS-BTS) Heuristic

We propose the Maximum Split-Benefit with Tabu Search (MS-BTS) heuristic to solve the M-MSPDP (Many to Many Split Pickup and Delivery Problem). MS-BTS is built on the Pickup and Delivery Problem with Split Loads (PDPSL) heuristic presented in Nowak et al. (2008). The primary difference between PDPSL heuristic and the MS-BTS heuristic is that while a load is randomly selected to be split in the PDPSL heuristic, in the MS-BTS heuristic, the selection of the load follows a hierarchical order based on the savings delivered if that load is selected (in a descending order of savings).

In the rest of the section, we first briefly describe the PDPSL heuristic presented in Nowak et al. (2008) that is used as the basis for our MS-BTS heuristic. We then explain in detail how MS-BTS works.

5.3.1 The PDPSL Heuristic

The PDPSL heuristic is presented by Nowak et al. (2008) to solve pickup and delivery problems with split loads. The general idea of the PDPSL heuristic is as follows.

Step 1: First, an initial solution is generated by creating dedicated routes for each pickup-delivery pair in the problem, with load splits being considered whenever the load is larger than vehicle capacity.

Step 2: A load is then randomly selected to be split, and the additional cost associated with generating the split is recorded in the tabu list.

Step 3: The routes are then combined based on the reduction in cost and subject to vehicle capacity along the route, using the Clarke and Wright's savings algorithm with the combinations leading to a reduced cost and subject to vehicle capacity along the route. The Clark and Wright Savings algorithm uses a criterion based on the savings in cost achieved by combining two routes and using one vehicle instead of two, to investigate the feasibility of merging of any sub-tours (Doyuran, and Çatay 2011).

Step 4: Local search techniques then follow to improve the solution: intra-route load swaps, inter-route load swaps, intra-route load insertions, inter-route load insertions, reordering of origins and destinations.

Step 5: Another load not present in the tabu list is selected and the process is repeated from Step 2.

The heuristic is developed to solve large scale problems within reasonable amount of time and has been tested on hypothetical problem sets. Nowak et al. (2008) show that savings of up to 50% are achieved by allowing split loads.

5.3.2 Proposed Maximum Split-Benefit with Tabu Search (MS-BTS) Heuristic

5.3.2.1 Theorem on optimal split load size

Nowak et al. (2008) present and prove the following theorem on the optimal split load size.

Theorem 1: *Given the origin and destination locations of a set of k loads (where load is defined as the set of origin and destination), a vehicle of capacity Q, and a very small value, ε, let v(PDPSL) be the cost of the optimal Pickup and Delivery Problem with Split Loads (PDPSL) solution to deliver these loads and v(PDP) be the cost of the optimal Pickup and Delivery Problem (PDP) solution. Then the ratio of v(PDP)/v(PDPSL) is maximized when the loads are all of size* $Q/2+\varepsilon$ *as* $k \rightarrow \infty$.

What this Theorem reveals is that, when the loads are slightly over half of vehicle capacity, the optimal split load pickup and delivery strategy will yield the maximum cost saving from the baseline optimal pickup and delivery strategy without split loads.

Similar to Nowak et al. (2008), we conduct an experiment to test the PDPSL heuristic and quantify the benefits of allowing split loads, by generating random sets of problems. Three problem sizes are considered with 5 origins and 15 (75 requests), 20 (100 requests) and 25 (125 requests) destinations, all randomly generated with uniform distribution over a grid of [-40,40] with depot located at [0,0]. Every origin-destination combination is allocated an equal load from a preselected load range (as fraction of the Truck Loading Capacity, TL). The load range is randomly selected for each set and is either less than or equal to TL. Eight ranges are used to bound the load sizes, with five different sets of load sizes generated for each range. These ranges indicate the upper and lower bound (inclusive of the bound) on the fraction of the vehicle capacity that the load can occupy, and these are [0.11-0.2], [0.21-0.3], [0.31-0.4], [0.41-0.5], [0.51-0.6], [0.61-0.7], [0.71-0.8], and [0.81-0.9]. The load sizes are randomly generated over each range with a uniform distribution. The vehicle is considered to have a unit capacity. The problem is solved using the PDPSL heuristic and by omitting the split loads steps in the PDPSL heuristic to compare the cost for with and without allowing split loads. Each of the three location configurations is matched with each of the five load sets within a load range, resulting in 15 different instances for each load range, and 120 instances overall. For detailed experimental design, please refer to Nowak et al. (2008).

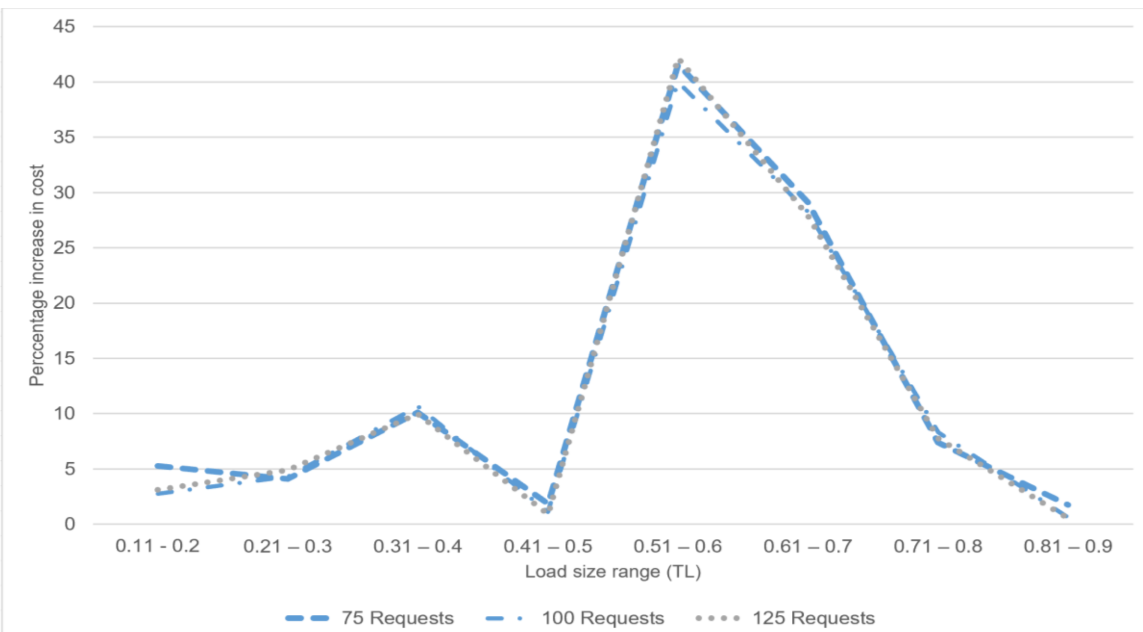


Figure 5-2: Average percentage cost increase without split loads relative to cost with split loads in three O-D matrices for 75, 100 and 125 pairs

Figure 5-2 presents the average percentage increase in cost when split loads are not allowed for the 75, 100 and 125 request problem sets with different load size ranges for an average of 30 instances for each load range of every problem set. The costs both with and without split loads are based on the distance traveled by the vehicle. These numerical results support the theoretical result presented earlier. That is, the most significant benefit with split load is found when the load sizes are just above one half of vehicle capacity, in the range [0.51-0.6]. When splitting is allowed with these load sizes, two of these load sizes are combined to fill the truck capacity, with the remainder of the loads delivered on an additional route. The benefit becomes almost negligible in the range [0.41-0.5] as two loads can be simultaneously serviced by the vehicle without any splitting. The loads are large enough that when two unsplit loads are placed on the vehicle, there is little room for a split load to be inserted. The benefit increases in the range [0.31 – 0.4], as there is more space for split loads when two unsplit loads are simultaneously on the vehicle. Further decreasing the load sizes results in less of a need for splitting, as unsplit loads can more easily be combined on a capacitated vehicle. The PDPSL heuristic is able to find more benefit with split loads for smaller load sizes as there are more potential combinations of loads to be placed on the vehicle at the same time, even without splitting. A similar result is shown empirically for the Split Delivery VRP in Archetti et al. (2006).

Building on the above theorem, we propose our MS-BTS heuristic as follows.

5.3.2.2 MS-BTS heuristic

The general idea of MS-BTS is as follows.

First, an initial solution is generated by creating dedicated routes for each pickup-delivery pair in the problem.

Second, these routes are split and consolidated by performing the following.

i. Based on the Theorem in 4.2.1, a random load is selected from the range of 0.51 – 0.6 TL to be considered for split, based on the additional cost of generating the split. The load and the associated cost are recorded in the tabu list to prevent the same load being selected repeatedly.
ii. The routes are then combined based on the reduction in cost and subject to vehicle capacity along the route. This is similar to the Clarke and Wright's savings algorithm.
iii. The local search techniques are applied in the following order:

    1) Intra-route load swaps
    2) Inter-route load swaps
    3) Intra-route load insertions
    4) Inter-route load insertions
    5) Reordering of the origins and destinations

iv. Once the loads in the range of 0.51 – 0.6 TL are exhausted, loads are selected from the range of 0.61 – 0.7 TL and the above process is repeated. This is followed by selection of loads from the range of 0.31 – 0.4 TL and finally 0.71 – 0.8 TL.

The tabu list is maintained for a number of iterations to avoid selecting the same loads repeatedly and to allow search of a broader neighborhood within the solution space. The tabu list only records the first and the second loads being split as Nowak (2005) has shown that there is no benefit from recording beyond the second loads being split.

A pseudo code is presented here for the MS-BTS heuristic. The variables used are as follows:

range – variable that defines the load-range to be used in the loop

range1 – range of loads between the range of 0.51 – 0.6 TL

range 2 - range of loads between the range of 0.61 – 0.7 TL

range 3 - range of loads between the range of 0.31 – 0.4 TL

range 4 - range of loads between the range of 0.71 – 0.8 TL

iter1 - counter for the number of iterations for first split load generated

iter2 - counter for the number of iterations for second split load generated

iter3 - counter for the number of iterations before a restart is forced

iter4 - counter for the number of iterations for improvements to be made

ITERMAIN1 - upper bound on the number of iterations for *iter1*

ITERMAIN2 - upper bound on the number of iterations for *iter2*

ITERMAIN3 - upper bound on the number of iterations for *iter3*

ITERMAIN4 - upper bound on the number of iterations for *iter4*

TEMPCOST - cost of the solution that is being updated

BASECOST - cost of a solution with no split loads created

GOODCOST - cost of the best-known solution for the current first and second split loads created

BESTCOST - cost of the best-known solution overall

WORKCOST - cost used for comparison to determine if improvements were made after *iter4* loop

---

Algorithm MS-BTS

Input: *range, range1, range2, range3, range4, iter1, iter2, iter3, iter4, ITERMAIN1, ITERMAIN2, ITERMAIN3, ITERMAIN4, TEMPCOST, BASECOST, GOODCOST, WORKCOST*

Output: BESTCOST

Generate routes: Create (dedicated) feasible initial solution, base solution

Set GOODCOST=BESTCOST=BASECOST and *iter1= iter2= iter3= iter4=0*

while (*iter1 < ITERMAIN1*) and (*iter2 < ITERMAIN2*)

Set *TEMPCOST = BASECOST*

    while (*iter3 < ITERMAIN3*)

    Set *WORKCOST = TEMPCOST*

        while (*iter4 < ITERMAIN4*)

        Set *range = range1*

        Create Split Loads: Update TEMPCOST

        if *iter1>0 and iter4=0,* add split load created to *tabulevel1*

        if *iter2>0 and iter1=0,* add split load created to *tabulevel2*

        if *iter4=0*, add split load created to *tabulevel3*

            Combine Routes: Update TEMPCOST

            Intra-Route Load Swap. Update *TEMPCOST*.

            Intra-Route Load Insertion. Update *TEMPCOST*.

18: **Inter-Route Load Swap**. Update *TEMPCOST*.

19: **Inter-Route Load Insertion**. Update *TEMPCOST*.

20: Increment *range*

21: Increment *iter4*.

22: if *TEMPCOST* < *WORKCOST*, *GOODCOST* = *TEMPCOST*, and *iter3* = 0.

23: if *TEMPCOST* ≥ *WORKCOST*, increment *iter3* and *TEMPCOST* = *GOODCOST*.

24: if *GOODCOST* < *BESTCOST*, *BESTCOST* = *GOODCOST*.

25: *iter2* = *iter2* + 1 and *iter3* = 0

26: *iter1* = *iter1* + 1

27: **end while**

28: **return** *BESTCOST*

We now describe the procedures involved in the proposed MS-BTS heuristic in detail.

Step 1. Initial solution: dedicated route Generation (Line 3 of the pseudo code)

For a dedicated route for each load request equal to or below the truck capacity, a route is created starting from the depot and traveling through the origin and destination returning to the depot. When the load request is greater than the truck capacity, the load request is split into fully-loaded truck routes until the remaining load request becomes equal to or smaller than the truck capacity.

Step 2 Creating Split Loads (Line 11 of the pseudo code)

The loads are randomly selected from the load range in the following order: 0.51 – 0.6 TL, 0.61 – 0.7 TL, 0.31 – 0.4 TL and finally 0.71 – 0.8 TL. Once the load is selected from the load range, it is compared to all other route segments having excess capacity. If the selected load is found to be greater than the excess capacity on any of the route segments, the load may be then split. The load is split in such a way that the excess capacity identified on another route segment is satisfied, while the original load reduces by the excess capacity. The split load can be either moved to another route or moved to another position in the same route. By intuition, the split load cannot be added to the end of the route as the excess capacity in this case would be equal to the truck capacity. Before moving the split load, it is checked with the tabu list and confirmed to have not been moved earlier in a fixed number of iterations. Loads previously selected and rejected are also not considered. A load previously inserted as part of the insertion local improvement technique is also not considered. The modification of the route can be rejected if the maximum route length is exceeded.

If the load split has not been recently considered and is not present in the tabu list, the route modification costs (≥ 0) are calculated due to the load split. A random number is generated based on the ratio of the route modification cost to the overall route cost. This random number is used to select the split load that generates the smallest route modification cost.

Once the load to be split is selected, it is tested for maximum route length constraint and then recorded in the *tabulevel1* list. The first split load is tracked using the *tabulevel1* list and the second split load is tracked using the *tabulevel2* list. If the maximum route length constraint is not met, the load selected is rejected and another load is considered. This process is determined for a fixed number of iterations. If during these fixed number of iterations, an appropriate load to be split cannot be determined, the algorithm moves to the local improvement phase, before looking for loads to be split again. The algorithm also moves forward once all the loads to be split have been considered, and no more iterations are repeated.

Step 3 Combining routes (Line 15 of the pseudo code)

The cost of combining the selected routes is first determined and then routes are combined. The routes can either be combined by placing them one after the another or a route may be inserted after an origin or a destination of another route, subject to truck capacity constraints at all locations within the route. This process of combining routes is similar to the Clarke and Wright's algorithm. Before combining the routes, the length of the new route is checked for the maximum route length limitation. Only the route combinations are selected that have not been previously selected and rejected for maximum route length violation. During the route combination stage, the new route is tested for the maximum route length with allowance for a small buffer, while no buffer allowance is provided during the testing in the local improvement stage. This allows those route combinations to be tested which may exceed the maximum route length criteria during the route combination stage but might benefit from the route length reduction during the local improvement stage.

A list of all the feasible route combinations with associated reduction in cost is created. The route combination with the maximum reduction in the overall cost is selected. This is followed by a local improvement step of swapping origins or destinations along the new route. Only consecutive origins and destinations are swapped resulting in no impact on the truck capacity constraint. This step is computationally less intensive and is repeated after every local search improvement step (load swap and insertions). This process is repeated until all feasible route combinations have been tested.

Step 3(a) Intra-route insertion of load (Line 17 of the pseudo code)

A loaded segment of any route is defined as the segment of the route where the truck is empty before and after the segment (for e.g. the route starting with an empty vehicle serving a customer pick up origin followed by visiting customer delivery destination to empty the load). This means that any changes to the loading within a loading segment will result in impacting that segment, without impacting the entire route. The insertion of load requires the entire selected load to be moved to another part of the route. This step is only carried out if there are more than two or more loaded segments on the route.

Before carrying out the insertion of the load, the truck capacity constraints are checked to not be violated along the route. It is also checked if the insertion move of the particular load has been attempted previously, or if the insertion move would result in returning a previously split load back to its original position. Once these conditions are satisfied, the load to be inserted can be inserted anywhere within the loaded segment. Insertion of the load requires its origin and destination to be placed consecutively in the loaded segment. The origin and destination of the inserted load are removed from their previous positions in the earlier loaded segment.

The feasible load insertion moves are determined with the reduction in overall cost. The load insertion move with the maximum reduction in the overall cost of the route is selected. The selected load insertion move is tested for truck capacity constraint violation. Swapping of origins and destinations is carried out as the local improvement step. The swapping move resulting in the reduction in the route length is selected. The loads insertion moves are evaluated and conducted for each route until there is no further improvement in the overall route cost.

Step 3(b) Intra-route swapping of loads (Line 16 of the pseudo code)

This local improvement step considers the potential swapping of loads between two loaded segments of a route. This requires the position of origins and destinations to be swapped between the two loads selected in the different loaded segments. The origins and destinations of the selected loads may either be located consecutively or may have other stops in between. If an origin has more than one load to be picked up, the other loads are retained in the loaded segment or else the origin of the load in the first loaded segment is replaced by the origin of the load from the second loaded segment. Same is true for the destinations.

The load-swap move between the loaded segments is evaluated for having been considered earlier and for violations of the truck capacity along the route. A recent load-swap move is also rejected. The reduction in cost is estimated for all feasible load-swap moves and the move with the maximum reduction in the overall route cost is selected. Swapping of origins and destinations is carried out as the local improvement step and the swapping move resulting in the reduction in the route length is selected. The load-swap moves are evaluated and conducted for each route until there is no further improvement in the overall route cost.

Step 3(c) Inter-route insertion of loads (Line 19 of the pseudo code)

This local improvement step is similar to the intra-route insertion of loads, except that instead of inserting loads between loaded segments, in this case the loads are inserted from one route to another. A load-insertion move involves moving the entire load including the load origin and destination from one route to another. All the possible load-insertion moves are evaluated for the truck capacity constraints. The load-insertion move is rejected if it was attempted recently or would result in returning a split load back into its original position.

The reduction in cost is estimated for all feasible load-insertion moves and the move with the maximum reduction in the overall cost is selected. Swapping of origins and destinations is carried out as the local improvement step and the swapping move resulting in the reduction in the route length is selected. The load-insertion moves are evaluated and conducted for each route until there is no further improvement in the overall route cost.

Step 3(d) Inter-route swapping of loads (Line 18 of the pseudo code)

This local improvement step is similar to the intra-route swapping of loads, except that instead of swapping loads between loaded segments, in this case the loads are swapped between two routes. A load-swapping move involves moving the entire load including the load origin and destination from one route to another, thereby replacing the respective origin and destination of the load being swapped out with the origin and the destination of the load being swapped in. All the possible load-swapping moves are evaluated for the truck capacity constraints. The load-swapping move is rejected if it was attempted recently or would result in returning a split load back into its original position.

The reduction in cost is estimated for all feasible load-swapping moves and the move with the maximum reduction in the overall cost is selected. Swapping of origins and destinations is carried out as the local improvement step and the swapping move resulting in the reduction in the route length is selected. The load-swapping moves are evaluated and conducted for each route until there is no further improvement in the overall route cost.

Step 4 Go back to Step 2 until no further improvement in the overall cost can be made.

5.3.3 Number of iterations

The number of iterations govern the loads to be selected for split in the heuristic. Nowak et al. (2008) observed that tracking split loads beyond the second split load brought minimal improvement to the solution while also increased the computational time. The maximum number of iterations are set by the four iteration parameters of the heuristic. The first iteration parameter (*iter1*) controls the variations of the first split load created so that the same first split load is not repeated, while the second iteration parameter (*iter2*) controls the variations of the second split load created. The first split load is tracked using the *tabulevel1* list and the second split load is tracked using the *tabulevel2* list. Solution reset is dictated by the third iteration parameter(*iter3*), which forces the heuristic to start again from an earlier solution if no improvement in solution is observed after the specified number of iterations. The first split load attempted after this reset is tracked using the *tabulevel3* list, thus ensuring that the same split load is not created for an older solution after the reset. And finally, a fourth iteration parameter (*iter4*) controls the number of times a solution undergoes the split load creation and local improvement procedure.

After finishing all the iterations of the fourth inner loop, the solution may either improve or not. If the solution has improved the iteration counter for the third loop is reset to zero to allow more improvements in the solution. The new solution is recorded as the new best solution and the procedures for split load creation and local improvements continue. However, if no improvement in solution is observed, the iteration counter for the third loop is incremented and the previous best solution is reinstated as the new best solution. If after all the iterations of the third loop have been completed and no improvement in the solution is observed, this solution is compared against the overall best solution determined so far. This process is repeated as the algorithm continues to select different loads to be split at the first and the second level.

The maximum number of iterations and the order of the local improvement procedures is selected as stated by Nowak (2005). These were finalized by Nowak (2005) through testing and considering cost improvements and computation time burden. The maximum number of iterations for the first, second, third and the fourth loop were selected at 10, 10, 5 and 10 respectively. In local improvement procedures, intra-route and swapping procedures were performed before inter-route and insertion procedures.

5.4. Numerical Experiment

5.4.1. Experimental Design

The experimental design is maintained similar to the one given in Nowak (2005) to allow fair comparison between the MS-BTS and the PDPSL heuristic. Fourteen scenarios of different transportation requests are tested as given in Table 5-1. Each transportation request comprises of the location of the origin and destination pair and the demand relative to the truck capacity (i.e., one full truck loading capacity or TL). The coordinates for the origins and destinations are randomly and uniformly generated over the range of [-40,40] (miles) for both X and Y coordinates. The depot is located at [0,0] for all scenarios and Nowak (2005) states that relocating the depot has no significant impact on the results.

Each origin-destination pair has a load demand generated randomly and uniformly between the range of 0.1 – 0.9 TL. The minimal total length of the route obtained at the end is considered the final solution. The maximum route length is set at 500 miles which is similar to Nowak (2005). For each scenario, a total of 30 instances were generated.

Table 5-1: Fourteen scenarios considered

Scenario ID	**Total number of nodes**	**Number of origins x Number of destinations**
1	20	5 x 15
2	30	10 x 20

3	60	20 x 40
4	90	30 x 60
5	100	30 x 70
6	110	40 x 70
7	120	40 x 80
8	130	50 x 80
9	140	50 x 90
10	150	60 x 90
11	200	80 x 120
12	250	110 x 140
13	300	120 x 180
14	350	150 x 200

In addition to the PDPSL heuristic, the performance of the M-MSPDP heuristic is also compared with the heuristic provided in Sahin et al. (2013), which uses a Tabu search and simulated annealing based (TESA) heuristic to improve the initial feasible solution computed from Clark and Wright's savings algorithm.

The heuristics are coded in Matlab environment and all experiments are run on 2.60 GHz Intel core i7 processor with 16 GB RAM. The exact solution for feasible cases is obtained using the MOSEK Solver.

5.4.2. Experimental Results

Tables 5-2 to 5-19 present the results of the evaluation of MS-BTS heuristic in comparison with the PDPSL heuristic and the exact solution (where available) in terms of solution quality and computational time.

Table 5-2: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality for Scenario 1

		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	**Exact Soln.**	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	Error w.r.t. PDPSL Soln.
1	294.91	294.91	0.00%	294.91	0.00%	0.00%
2	268.73	268.73	0.00%	275.18	2.40%	2.40%
3	269.59	269.59	0.00%	291.74	8.22%	8.22%
4	295.62	295.62	0.00%	314.54	6.40%	6.40%
5	277.86	277.86	0.00%	297.7	7.14%	7.14%
6	285.86	285.86	0.00%	285.86	0.00%	0.00%
7	261.77	261.77	0.00%	281.28	7.45%	7.45%
8	263.11	263.11	0.00%	273.11	3.80%	3.80%
9	281.93	281.93	0.00%	281.93	0.00%	0.00%
10	274.14	274.14	0.00%	283.18	3.30%	3.30%
11	268.93	268.93	0.00%	268.93	0.00%	0.00%
12	297.31	297.31	0.00%	308.31	3.70%	3.70%

13	268.31	268.31	0.00%	268.31	0.00%	0.00%
14	262.95	262.95	0.00%	276.36	5.10%	5.10%
15	297.8	297.8	0.00%	297.8	0.00%	0.00%
16	283.97	283.97	0.00%	295.61	4.10%	4.10%
17	292.13	292.13	0.00%	292.13	0.00%	0.00%
18	270.04	270.04	0.00%	284.43	5.33%	5.33%
19	278.92	278.92	0.00%	294.49	5.58%	5.58%
20	271.54	271.54	0.00%	294.69	8.53%	8.53%
21	274.36	274.36	0.00%	274.36	0.00%	0.00%
22	282.99	282.99	0.00%	282.99	0.00%	0.00%
23	283.84	283.84	0.00%	298.88	5.30%	5.30%
24	287.74	287.74	0.00%	300.92	4.58%	4.58%
25	279.41	279.41	0.00%	279.41	0.00%	0.00%
26	291.2	291.2	0.00%	300.81	3.30%	3.30%
27	291.56	291.56	0.00%	293.56	0.69%	0.69%
28	288.75	288.75	0.00%	311.98	8.05%	8.05%
29	265.97	265.97	0.00%	279.27	5.00%	5.00%
30	295.64	295.64	0.00%	310.31	4.96%	4.96%
Average	**280.23**	**280.23**	**0.00%**	**289.77**	**3.43%**	**3.43%**

Table 5-3: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of computational time for Scenario 1

	Computational Time (min)					
		PDPSL Heuristic		MS-BTS Heuristic		
Instance No	Exact Soln.	PDPSL heuristic Soln.	Improvement w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Improvement w.r.t. Exact Soln.	Improvement w.r.t. PDPSL Soln.
1	5.85	1.01	-82.74%	0.94	-83.93%	-6.93%
2	6.84	1.48	-78.36%	1.31	-80.85%	-11.49%
3	4.58	0.86	-81.22%	0.75	-83.62%	-12.79%
4	6.26	1.01	-83.87%	0.92	-85.30%	-8.91%
5	6.41	0.8	-87.52%	0.73	-88.61%	-8.75%
6	6.79	0.89	-86.89%	0.8	-88.22%	-10.11%
7	7.86	1.41	-82.06%	1.28	-83.72%	-9.22%
8	4.67	1.27	-72.81%	1.12	-76.02%	-11.81%
9	6.51	1.24	-80.95%	1.13	-82.64%	-8.87%
10	4.12	1.03	-75.00%	0.92	-77.67%	-10.68%
11	6.3	0.91	-85.56%	0.77	-87.78%	-15.38%
12	5.51	0.85	-84.57%	0.78	-85.84%	-8.24%
13	7.24	1.27	-82.46%	1.09	-84.94%	-14.17%
14	6.21	1.43	-76.97%	1.23	-80.19%	-13.99%
15	6.11	0.79	-87.07%	0.68	-88.87%	-13.92%
16	6.98	0.84	-87.97%	0.75	-89.26%	-10.71%
17	6.91	1.24	-82.05%	1.1	-84.08%	-11.29%

18	5.75	0.84	-85.39%	0.77	-86.61%	-8.33%
19	5.66	1.5	-73.50%	1.34	-76.33%	-10.67%
20	5.26	0.8	-84.79%	0.69	-86.88%	-13.75%
21	4.67	1.17	-74.95%	1.03	-77.94%	-11.97%
22	6.51	1.53	-76.50%	1.39	-78.65%	-9.15%
23	4.12	1.11	-73.06%	1.02	-75.24%	-8.11%
24	4.58	0.98	-78.60%	0.85	-81.44%	-13.27%
25	6.26	0.93	-85.14%	0.83	-86.74%	-10.75%
26	6.41	1.39	-78.32%	1.24	-80.66%	-10.79%
27	7.86	1.04	-86.77%	0.9	-88.55%	-13.46%
28	4.67	1.03	-77.94%	0.93	-80.09%	-9.71%
29	5.85	1.5	-74.36%	1.35	-76.92%	-10.00%
30	6.25	0.88	-85.92%	0.75	-88.00%	-14.77%
Average	**5.97**	**1.10**	**-81.11%**	**0.98**	**-83.19%**	**-11.07%**

Table 5-4: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality for Scenario 2

		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	**Exact Soln.**	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	Error w.r.t. PDPSL Soln.
1	706.56	706.56	0.00%	706.56	0.00%	0.00%
2	675.33	675.33	0.00%	740.62	9.67%	9.67%
3	681.88	681.88	0.00%	732.88	7.48%	7.48%

4	718.2	718.2	0.00%	738.96	2.89%	2.89%
5	675.73	675.73	0.00%	749.85	10.97%	10.97%
6	675.99	675.99	0.00%	703.97	4.14%	4.14%
7	720.74	720.74	0.00%	747.98	3.78%	3.78%
8	695.09	695.09	0.00%	719.52	3.51%	3.51%
9	721.81	721.81	0.00%	705.56	-2.25%	-2.25%
10	700.61	700.61	0.00%	692.86	-1.11%	-1.11%
11	714.01	714.01	0.00%	736.24	3.11%	3.11%
12	691.15	691.15	0.00%	747.65	8.17%	8.17%
13	701.94	701.94	0.00%	741.42	5.62%	5.62%
14	683.61	683.61	0.00%	703.03	2.84%	2.84%
15	677.81	677.81	0.00%	729.17	7.58%	7.58%
16	700.02	700.02	0.00%	715.3	2.18%	2.18%
17	716.26	716.26	0.00%	701.72	-2.03%	-2.03%
18	712.04	712.04	0.00%	739.07	3.80%	3.80%
19	688.95	688.95	0.00%	736.47	6.90%	6.90%
20	697.54	697.54	0.00%	704.51	1.00%	1.00%
21	703.64	703.64	0.00%	699.14	-0.64%	-0.64%
22	682.79	682.79	0.00%	742.31	8.72%	8.72%
23	685.75	685.75	0.00%	731.07	6.61%	6.61%
24	693.16	693.16	0.00%	711.37	2.63%	2.63%
25	718.35	718.35	0.00%	714.22	-0.57%	-0.57%
26	704.49	704.49	0.00%	717.91	1.90%	1.90%
27	716.54	716.54	0.00%	710.44	-0.85%	-0.85%
28	692.66	692.66	0.00%	734.09	5.98%	5.98%

29	700.19	700.19	0.00%	729.35	4.16%	4.16%
30	697.01	697.01	0.00%	708.17	1.60%	1.60%
Average	**698.33**	**698.33**	**0.00%**	**723.05**	**3.59%**	**3.59%**

Table 5-5: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of computational time for Scenario 2

	Computational Time (min)					
		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	Exact Soln.	PDPSL heuristic Soln.	Improvement w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Improvement w.r.t. Exact Soln.	Improvement w.r.t. PDPSL Soln.
1	36.4	7.67	-78.93%	8.22	-77.42%	7.17%
2	38.49	7.98	-79.27%	7.36	-80.88%	-7.77%
3	37.89	8.32	-78.04%	8.83	-76.70%	6.13%
4	41.5	7.36	-82.27%	7.64	-81.59%	3.80%
5	36.92	7.4	-79.96%	8.5	-76.98%	14.86%
6	39.89	8.51	-78.67%	7.39	-81.47%	-13.16%
7	38.62	6.28	-83.74%	7.68	-80.11%	22.29%
8	36.55	8.76	-76.03%	8.95	-75.51%	2.17%
9	43.58	7.78	-82.15%	7.25	-83.36%	-6.81%
10	39.54	8.58	-78.30%	8.16	-79.36%	-4.90%
11	37.85	7.91	-79.10%	6.58	-82.62%	-16.81%
12	41.45	7.02	-83.06%	9.44	-77.23%	34.47%
13	42.74	6.01	-85.94%	9.11	-78.69%	51.58%

14	37.72	7.64	-79.75%	8.31	-77.97%	8.77%
15	42.79	8.65	-79.78%	8.5	-80.14%	-1.73%
16	38.37	6.21	-83.82%	8.71	-77.30%	40.26%
17	40.66	8.93	-78.04%	8.16	-79.93%	-8.62%
18	41.09	7.33	-82.16%	8.42	-79.51%	14.87%
19	41.94	6.09	-85.48%	7.1	-83.07%	16.58%
20	42.95	6.68	-84.45%	8.23	-80.84%	23.20%
21	41.18	6.71	-83.71%	8.82	-78.58%	31.45%
22	42.99	6.65	-84.53%	8.6	-80.00%	29.32%
23	42.86	8.55	-80.05%	7.96	-81.43%	-6.90%
24	40.61	6.2	-84.73%	8.03	-80.23%	29.52%
25	41.77	7.75	-81.45%	8.82	-78.88%	13.81%
26	42.18	8.95	-78.78%	7.92	-81.22%	-11.51%
27	37.89	7.25	-80.87%	8.14	-78.52%	12.28%
28	41.97	6.12	-85.42%	8.13	-80.63%	32.84%
29	40.28	6.59	-83.64%	8.91	-77.88%	35.20%
30	38.81	8.53	-78.02%	7.92	-79.59%	-7.15%
Average	**40.25**	**7.48**	**-81.34%**	**8.19**	**-79.59%**	**11.51%**

Table 5-6: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality for Scenario 3

		PDPSL Heuristic		MS-BTS Heuristic		
Instance No	**Exact Soln.**	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	Error w.r.t. PDPSL Soln.
1	1,763.10	1,763.10	0.00%	1,847.73	4.80%	4.80%
2	1,739.64	1,739.64	0.00%	1,739.64	0.00%	0.00%
3	1,669.20	1,669.20	0.00%	1,784.12	6.88%	6.88%
4	1,779.30	1,779.30	0.00%	1,829.12	2.80%	2.80%
5	1,697.88	1,697.88	0.00%	1,774.28	4.50%	4.50%
6	1,771.14	1,771.14	0.00%	1,854.38	4.70%	4.70%
7	1,791.66	1,791.66	0.00%	1,871.20	4.44%	4.44%
8	1,691.70	1,691.70	0.00%	1,763.20	4.23%	4.23%
9	1,786.44	1,786.44	0.00%	1,786.44	0.00%	0.00%
10	1,632.12	1,632.12	0.00%	1,714.94	5.07%	5.07%
11	1,597.56	1,597.56	0.00%	1,597.56	0.00%	0.00%
12	1,608.66	1,608.66	0.00%	1,718.61	6.83%	6.83%
13	1,756.80	1,756.80	0.00%	1,815.32	3.33%	3.33%
14	1,739.82	1,739.82	0.00%	1,848.57	6.25%	6.25%
15	1,573.20	1,573.20	0.00%	1,573.20	0.00%	0.00%
16	1,579.20	1,579.20	0.00%	1613.94	2.20%	2.20%
17	1,583.82	1,583.82	0.00%	1687.36	6.54%	6.54%
18	1,700.70	1,700.70	0.00%	1,700.70	0.00%	0.00%

19	1,782.54	1,782.54	0.00%	1,782.54	0.00%	0.00%
20	1,719.42	1,719.42	0.00%	1821.82	5.96%	5.96%
21	1,694.52	1,694.52	0.00%	1755.77	3.61%	3.61%
22	1,694.16	1,694.16	0.00%	1,694.16	0.00%	0.00%
23	1,707.12	1,707.12	0.00%	1767.35	3.53%	3.53%
24	1,793.76	1,793.76	0.00%	1924.17	7.27%	7.27%
25	1,722.12	1,722.12	0.00%	1,722.12	0.00%	0.00%
26	1,660.50	1,660.50	0.00%	1695.35	2.10%	2.10%
27	1,634.04	1,634.04	0.00%	1759.08	7.65%	7.65%
28	1,723.98	1,723.98	0.00%	1832.93	6.32%	6.32%
29	1,738.38	1,738.38	0.00%	1811.16	4.19%	4.19%
30	1,749.12	1,749.12	0.00%	1856.81	6.16%	6.16%
Average	**1702.72**	**1702.72**	**0.00%**	**1764.79**	**3.65%**	**3.65%**

Table 5-7: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of computational time for Scenario 3

	Computational Time (min)					
		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	Exact Soln.	PDPSL heuristic Soln.	Improvement w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Improvement w.r.t. Exact Soln.	Improvement w.r.t. PDPSL Soln.
1	79.43	16.53	-79.19%	15.33	-80.70%	-7.26%
2	109.13	20.3	-81.40%	17.65	-83.83%	-13.05%
3	73.46	15.03	-79.54%	12.84	-82.52%	-14.57%

4	64.16	11.17	-82.59%	9.63	-84.99%	-13.79%
5	94.24	19.73	-79.06%	17.31	-81.63%	-12.27%
6	88.99	15.68	-82.38%	13.64	-84.67%	-13.01%
7	87.59	16.73	-80.90%	15.21	-82.64%	-9.09%
8	88.21	16.31	-81.51%	13.82	-84.33%	-15.27%
9	107.54	20.25	-81.17%	18.46	-82.83%	-8.84%
10	97.83	20.5	-79.05%	18.81	-80.77%	-8.24%
11	85.14	18.62	-78.13%	16.33	-80.82%	-12.30%
12	75.90	14.14	-81.37%	12.51	-83.52%	-11.53%
13	99.65	17.22	-82.72%	15.51	-84.44%	-9.93%
14	105.92	16.49	-84.43%	14.33	-86.47%	-13.10%
15	86.38	22.63	-73.80%	19.85	-77.02%	-12.28%
16	98.67	23.06	-76.63%	20.59	-79.13%	-10.71%
17	77.33	13.01	-83.19%	11.21	-85.50%	-13.77%
18	95.46	21.47	-77.51%	19.58	-79.49%	-8.80%
19	89.82	14.91	-83.40%	13.32	-85.17%	-10.66%
20	95.48	18.77	-80.34%	17.06	-82.13%	-9.11%
21	90.04	21.7	-75.90%	19.2	-78.68%	-11.52%
22	98.96	20.83	-78.95%	18.27	-81.54%	-12.29%
23	82.76	17.54	-78.81%	15.12	-81.73%	-13.80%
24	87.50	17.36	-80.16%	15.23	-82.59%	-12.27%
25	94.97	18.11	-80.93%	16.08	-83.07%	-11.21%
26	94.51	21.83	-76.90%	18.82	-80.09%	-13.79%
27	84.55	21.33	-74.77%	18.71	-77.87%	-12.28%
28	81.13	14.23	-82.46%	12.94	-84.05%	-9.07%

29	76.52	11.7	-84.71%	10	-86.93%	-14.53%
30	89.66	19.18	-78.61%	17.6	-80.37%	-8.24%
Average	**89.36**	**17.88**	**-80.02%**	**15.83**	**-82.32%**	**-11.55%**

Table 5-8: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality for Scenario 4

		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	Exact Soln.	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	Error w.r.t. PDPSL Soln.
1	3,272.91	3,283.80	0.33%	3,396.62	3.78%	3.44%
2	3,376.08	3,572.88	5.83%	3,572.88	5.83%	0.00%
3	3,382.38	3,383.40	0.03%	3,430.17	1.41%	1.38%
4	3,348.45	3,538.32	5.67%	3,791.85	13.24%	7.17%
5	3,365.84	3,479.52	3.38%	3,608.26	7.20%	3.70%
6	3,371.52	3,399.92	0.84%	3,399.92	0.84%	0.00%
7	3,337.73	3,512.52	5.24%	3,744.63	12.19%	6.61%
8	3,293.49	3,296.24	0.08%	3,476.72	5.56%	5.48%
9	3,360.86	3,527.16	4.95%	3,527.16	4.95%	0.00%
10	3,390.70	3,416.28	0.75%	3,416.28	0.75%	0.00%
11	3,339.29	3,487.92	4.45%	3,794.63	13.64%	8.79%
12	3,341.09	3,411.96	2.12%	3,674.92	9.99%	7.71%
13	3,382.32	3,382.44	0.00%	3,382.44	0.00%	0.00%
14	3,293.17	3,348.96	1.69%	3,626.69	10.13%	8.29%

15	3,346.22	3,585.12	7.14%	3,585.12	7.14%	0.00%
16	3,356.46	3,472.20	3.45%	3,809.00	13.48%	9.70%
17	3,258.02	3,334.32	2.34%	3,334.32	2.34%	0.00%
18	3,372.79	3,474.36	3.01%	3,474.36	3.01%	0.00%
19	3,399.10	3,420.24	0.62%	3,590.47	5.63%	4.98%
20	3,367.10	3,376.76	0.29%	3,396.76	0.88%	0.59%
21	3,329.94	3,335.60	0.17%	3,565.12	7.06%	6.88%
22	3,398.56	3,398.52	0.00%	3,398.52	0.00%	0.00%
23	3,387.28	3,395.20	0.23%	3,556.22	4.99%	4.74%
24	3,370.67	3,397.84	0.81%	3,429.13	1.73%	0.92%
25	3,317.96	3,528.48	6.34%	3,528.48	6.34%	0.00%
26	3,380.72	3,396.40	0.46%	3,459.46	2.33%	1.86%
27	3,364.82	3,569.40	6.08%	3,851.38	14.46%	7.90%
28	3,327.65	3,332.48	0.15%	3,656.98	9.90%	9.74%
29	3,288.79	3,299.16	0.32%	3,508.01	6.67%	6.33%
30	3,323.31	3,410.16	2.61%	3,627.64	9.16%	6.38%
Average	**3,348.17**	**3,425.59**	**2.31%**	**3,553.80**	**6.15%**	**3.75%**

Table 5-9: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of computational time for Scenario 4

		Computational Time (min)				
		PDPSL Heuristic		**MS-BTS Heuristic**		
Instance No	Exact Soln.	PDPSL heuristic Soln.	Improvement w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Improvement w.r.t. Exact Soln.	Improvement w.r.t. PDPSL Soln.
1	159.33	44.02	-72.37%	39.4	-75.27%	-10.50%
2	165.65	46.58	-71.88%	42.01	-74.64%	-9.81%
3	158.1	47.05	-70.24%	44.74	-71.70%	-4.91%
4	150.18	46.59	-68.98%	45.93	-69.42%	-1.42%
5	155.03	45.61	-70.58%	44.45	-71.33%	-2.54%
6	159.83	44.14	-72.38%	39.51	-75.28%	-10.49%
7	152.45	46.59	-69.44%	40.67	-73.32%	-12.71%
8	157.21	45.03	-71.36%	42.74	-72.81%	-5.09%
9	154.01	45.6	-70.39%	43.29	-71.89%	-5.07%
10	160.53	47.16	-70.62%	39.87	-75.16%	-15.46%
11	155.52	46.03	-70.40%	38.57	-75.20%	-16.21%
12	165.52	45.98	-72.22%	41.37	-75.01%	-10.03%
13	156.26	47.46	-69.63%	39.46	-74.75%	-16.86%
14	154.66	49.13	-68.23%	40.04	-74.11%	-18.50%
15	160.3	50.6	-68.43%	42.19	-73.68%	-16.62%
16	158.77	46.39	-70.78%	43.57	-72.56%	-6.08%
17	160.06	49.74	-68.92%	40.82	-74.50%	-17.93%

18	155.44	44.5	-71.37%	41.96	-73.01%	-5.71%
19	158.83	51.46	-67.60%	42.95	-72.96%	-16.54%
20	157.25	44.02	-72.01%	42.36	-73.06%	-3.77%
21	160.66	51.89	-67.70%	41.22	-74.34%	-20.56%
22	164.67	49.8	-69.76%	43.27	-73.72%	-13.11%
23	158.62	50.29	-68.30%	40.6	-74.40%	-19.27%
24	158.51	47.88	-69.79%	43.38	-72.63%	-9.40%
25	154.17	46.69	-69.72%	43.32	-71.90%	-7.22%
26	159.02	46.57	-70.71%	42.85	-73.05%	-7.99%
27	158.04	45.85	-70.99%	38.08	-75.90%	-16.95%
28	159.07	48.02	-69.81%	40.08	-74.80%	-16.53%
29	159.6	44.07	-72.39%	39.75	-75.09%	-9.80%
30	160.41	50.33	-68.62%	39.17	-75.58%	-22.17%
Average	**158.26**	**47.17**	**-70.19%**	**41.59**	**-73.70%**	**-11.64%**

Table 5-10: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 5

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	3,711.01	3,705.93	-0.14%	60.19	49.03	-18.54%
2	3,656.33	3,873.27	5.93%	57.68	48.1	-16.61%
3	3,693.20	3,715.93	0.62%	53.83	46.45	-13.71%

4	3,659.62	3,820.48	4.40%	59.32	52.38	-11.70%
5	3,776.80	3,770.45	-0.17%	59.34	50.61	-14.71%
6	3,673.34	3,873.28	5.44%	59.03	50.56	-14.35%
7	3,652.68	3,764.52	3.06%	50.47	51.55	2.14%
8	3,606.51	3,726.82	3.34%	52.05	50.07	-3.80%
9	3,641.25	3,808.56	4.59%	61.94	48.81	-21.20%
10	3,600.19	3,774.52	4.84%	55.73	45.21	-18.88%
11	3,693.93	3,838.98	3.93%	56.71	49.23	-13.19%
12	3,646.73	3,789.78	3.92%	52.65	47.62	-9.55%
13	3,619.62	3,797.62	4.92%	56.75	51.4	-9.43%
14	3,585.44	3,796.10	5.88%	50.37	47.44	-5.82%
15	3,651.42	3,826.59	4.80%	54.8	46.29	-15.53%
16	3,743.37	3,741.62	-0.05%	55.95	49.73	-11.12%
17	3,698.11	3,763.96	1.78%	54.23	46.87	-13.57%
18	3,664.47	3,766.05	2.77%	56.25	49.97	-11.16%
19	3,693.04	3,825.91	3.60%	50.6	47.99	-5.16%
20	3,600.89	3,785.62	5.13%	54.45	48.23	-11.42%
21	3,594.62	3,892.00	8.27%	52.91	49.18	-7.05%
22	3,788.68	3,811.20	0.59%	50.37	48.99	-2.74%
23	3,567.65	3,817.38	7.00%	53.37	45.64	-14.48%
24	3,757.58	3,813.31	1.48%	57.18	49.18	-13.99%
25	3,752.95	3,785.90	0.88%	58.81	52.42	-10.87%
26	3,557.44	3,822.98	7.46%	58.72	52.14	-11.21%
27	3,572.45	3,828.14	7.16%	51.45	47.72	-7.25%
28	3,568.73	3,753.48	5.18%	54.41	46.07	-15.33%

29	3,721.40	3,895.29	4.67%	58.73	46.63	-20.60%
30	3,610.77	3,750.35	3.87%	55.07	47.27	-14.16%
Average	**3,658.67**	**3,797.87**	**3.84%**	**55.45**	**48.76**	**-11.83%**

Table 5-11: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 6

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	3,734.78	3,815.56	2.16%	62.92	55.07	-12.48%
2	3,768.05	3,816.49	1.29%	68.32	58.79	-13.95%
3	3,660.09	3,887.74	6.22%	59.75	57.99	-2.95%
4	3,686.55	3,833.84	4.00%	66.46	60.78	-8.55%
5	3,788.70	3,886.90	2.59%	59.37	58.63	-1.25%
6	3,728.63	3,911.29	4.90%	67.91	57.08	-15.95%
7	3,656.11	3,838.30	4.98%	69.72	61.11	-12.35%
8	3,676.06	3,842.40	4.52%	65.25	58.79	-9.90%
9	3,741.61	3,900.61	4.25%	66.6	56.2	-15.62%
10	3,674.72	3,838.74	4.46%	58.31	58.11	-0.34%
11	3,666.63	3,916.90	6.83%	60.14	54.85	-8.80%
12	3,672.76	3,929.14	6.98%	59.76	58.92	-1.41%
13	3,731.31	3,922.07	5.11%	59.17	52.61	-11.09%
14	3,713.28	3,858.92	3.92%	66.32	55.91	-15.70%
15	3,721.39	3,825.60	2.80%	59.52	52.07	-12.52%

16	3,707.46	3,784.38	2.07%	66.92	56.47	-15.62%
17	3,702.67	3,914.97	5.73%	58.21	58.01	-0.34%
18	3,794.95	3,882.25	2.30%	58.46	50.54	-13.55%
19	3,733.62	3,763.90	0.81%	68.67	52.19	-24.00%
20	3,672.38	3,813.48	3.84%	59.98	56.75	-5.39%
21	3,686.55	3,940.18	6.88%	58.23	51.39	-11.75%
22	3,662.24	3,810.90	4.06%	64.63	57.91	-10.40%
23	3,709.84	3,756.44	1.26%	58.01	57.22	-1.36%
24	3,709.55	3,880.16	4.60%	61.19	60.96	-0.38%
25	3,778.53	3,786.24	0.20%	70.57	54.51	-22.76%
26	3,722.94	3,875.37	4.09%	65.54	52.41	-20.03%
27	3,703.55	3,774.71	1.92%	70.66	58.66	-16.98%
28	3,707.42	3,924.34	5.85%	63.73	51.93	-18.52%
29	3,725.86	3,795.50	1.87%	71.89	57.26	-20.35%
30	3,685.18	3,851.98	4.53%	71.09	54.79	-22.93%
Average	**3,710.78**	**3,852.64**	**3.83%**	**63.91**	**56.26**	**-11.57%**

Table 5-12: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 7

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	4,062.94	4,136.58	1.81%	66.17	58.78	-11.17%
2	4,105.36	4,150.86	1.11%	70.99	59.67	-15.95%

3	4,041.58	4,187.32	3.61%	71.48	62.95	-11.93%
4	4,103.43	4,115.54	0.30%	69.32	62.35	-10.05%
5	3,958.35	4,103.14	3.66%	66.35	59.86	-9.78%
6	3,997.05	4,228.75	5.80%	68.80	59.70	-13.23%
7	4,015.04	4,175.86	4.01%	73.42	63.78	-13.13%
8	3,942.98	4,240.96	7.56%	71.81	59.52	-17.11%
9	3,967.38	4,145.75	4.50%	66.78	61.66	-7.67%
10	4,006.17	4,193.24	4.67%	66.32	59.36	-10.49%
11	3,974.47	4,178.22	5.13%	67.00	62.55	-6.64%
12	4,112.17	4,285.05	4.20%	71.17	60.07	-15.60%
13	4,027.25	4,187.23	3.97%	71.66	63.23	-11.76%
14	3,955.58	4,190.89	5.95%	70.37	62.46	-11.24%
15	3,900.54	4,060.85	4.11%	70.77	62.75	-11.33%
16	3,922.35	4,108.47	4.75%	68.76	61.14	-11.08%
17	4,096.72	4,134.51	0.92%	66.63	59.35	-10.93%
18	3,952.37	4,135.29	4.63%	71.83	62.14	-13.49%
19	4,057.65	4,224.04	4.10%	69.47	60.86	-12.39%
20	3,993.65	4,203.30	5.25%	71.93	61.30	-14.78%
21	4,144.29	4,147.38	0.07%	66.14	59.05	-10.72%
22	3,962.55	4,179.52	5.48%	69.08	58.46	-15.37%
23	4,125.89	4,285.60	3.87%	72.63	63.36	-12.76%
24	4,139.59	4,262.91	2.98%	70.80	59.96	-15.31%
25	3,940.68	4,100.78	4.06%	66.41	63.36	-4.59%
26	3,925.71	4,073.46	3.76%	70.85	62.48	-11.81%
27	4,021.38	4,231.97	5.24%	72.84	59.12	-18.84%

28	3,994.27	4,149.59	3.89%	71.91	61.50	-14.48%
29	4,116.81	4,239.73	2.99%	68.15	59.09	-13.29%
30	4,076.00	4,178.51	2.51%	69.36	64.34	-7.24%
Average	**4,021.34**	**4,174.51**	**3.83%**	**69.64**	**61.14**	**-12.14%**

Table 5-13: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 8

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	5,129.37	5,298.82	3.30%	72.88	64.02	-12.16%
2	5,119.94	5,364.72	4.78%	73.83	61.06	-17.30%
3	4,888.57	5,340.70	9.25%	71.20	65.55	-7.94%
4	5,146.61	5,381.17	4.56%	71.09	62.09	-12.66%
5	5,097.99	5,368.44	5.31%	72.52	62.12	-14.34%
6	5,147.77	5,151.27	0.07%	72.46	63.95	-11.74%
7	5,081.18	5,393.06	6.14%	73.89	64.90	-12.17%
8	4,943.34	5,186.25	4.91%	75.58	62.67	-17.08%
9	4,857.30	5,176.94	6.58%	75.19	66.72	-11.26%
10	5,033.84	5,119.13	1.69%	70.92	61.28	-13.59%
11	5,146.55	5,298.54	2.95%	76.14	67.92	-10.80%
12	4,997.09	5,072.03	1.50%	73.68	62.72	-14.88%
13	5,071.45	5,378.05	6.05%	73.63	64.35	-12.60%
14	5,177.03	5,183.37	0.12%	73.62	62.27	-15.42%

15	5,055.79	5,246.01	3.76%	70.36	65.11	-7.46%
16	4,855.86	5,171.84	6.51%	71.00	63.99	-9.87%
17	4,974.97	5,394.29	8.43%	72.06	66.74	-7.38%
18	5,148.02	5,295.42	2.86%	75.43	65.50	-13.16%
19	5,109.94	5,395.42	5.59%	75.74	67.44	-10.96%
20	4,835.62	5,180.08	7.12%	74.65	62.93	-15.70%
21	5,023.75	5,249.27	4.49%	70.84	62.63	-11.59%
22	5,188.67	5,236.13	0.91%	70.02	65.29	-6.76%
23	5,083.43	5,132.95	0.97%	73.80	61.29	-16.95%
24	4,900.44	5,185.15	5.81%	73.87	63.87	-13.54%
25	4,875.05	5,113.56	4.89%	75.70	65.01	-14.12%
26	4,970.73	5,311.50	6.86%	73.77	65.71	-10.93%
27	5,110.93	5,117.31	0.12%	72.68	66.73	-8.19%
28	5,167.09	5,176.97	0.19%	71.88	66.81	-7.05%
29	5,167.62	5,232.33	1.25%	72.29	61.97	-14.28%
30	4,976.56	5,199.68	4.48%	72.88	64.17	-11.95%
Average	**5,042.75**	**5245.01**	**4.05%**	**73.12**	**64.23**	**-12.13%**

Table 5-14: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 9

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	5,795.22	5,780.54	-0.25%	81.09	70.70	-12.81%

2	5,486.83	5,804.22	5.78%	83.64	71.59	-14.41%
3	5,480.74	5,908.79	7.81%	82.17	71.09	-13.48%
4	5,710.17	5,767.62	1.01%	83.32	74.57	-10.50%
5	5,749.00	5,835.75	1.51%	81.02	72.25	-10.82%
6	5,706.07	5,945.60	4.20%	81.10	74.57	-8.05%
7	5,628.00	5,808.81	3.21%	83.32	74.06	-11.11%
8	5,510.37	5,913.87	7.32%	81.40	70.38	-13.54%
9	5,630.82	5,801.51	3.03%	82.73	71.25	-13.88%
10	5,677.29	5,879.54	3.56%	82.34	72.49	-11.96%
11	5,647.02	5,952.59	5.41%	80.11	72.26	-9.80%
12	5,491.81	5,880.49	7.08%	83.36	71.96	-13.68%
13	5,477.47	5,704.30	4.14%	83.66	70.83	-15.34%
14	5,601.73	5,953.02	6.27%	80.83	70.86	-12.33%
15	5,592.23	5,816.07	4.00%	83.24	74.30	-10.74%
16	5,636.87	5,925.95	5.13%	84.64	73.36	-13.33%
17	5,610.59	5,826.27	3.84%	82.58	73.22	-11.33%
18	5,615.15	5,888.02	4.86%	82.10	71.18	-13.30%
19	5,769.86	5,955.16	3.21%	80.62	74.43	-7.68%
20	5,746.27	5,828.32	1.43%	82.87	70.20	-15.29%
21	5,519.70	5,933.91	7.50%	83.80	71.25	-14.98%
22	5,527.33	5,936.69	7.41%	80.88	74.59	-7.78%
23	5,559.88	5,829.27	4.85%	83.47	72.47	-13.18%
24	5,684.28	5,768.05	1.47%	80.78	72.90	-9.75%
25	5,752.81	6,056.04	5.27%	80.84	72.20	-10.69%
26	5,698.27	5,912.62	3.76%	80.11	71.11	-11.23%

27	5,735.21	5,854.13	2.07%	83.37	71.98	-13.66%
28	5,619.59	5,738.99	2.12%	81.38	70.28	-13.64%
29	5,573.76	5,922.75	6.26%	84.71	71.96	-15.05%
30	5,555.86	5,857.41	5.43%	79.62	71.03	-10.79%
Average	**5,626.34**	**5,866.21**	**4.29%**	**82.17**	**72.18**	**-12.14%**

Table 5-15: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 10

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	7,149.41	7,152.09	0.04%	93.31	77.80	-16.62%
2	6,819.61	6,992.54	2.54%	90.38	80.40	-11.04%
3	6,918.09	7,043.71	1.82%	90.76	80.90	-10.86%
4	6,589.25	7,130.05	8.21%	89.87	80.97	-9.90%
5	6,683.59	7,120.43	6.54%	89.55	81.28	-9.24%
6	7,120.51	7,130.56	0.14%	88.13	78.65	-10.76%
7	6,917.81	7,113.65	2.83%	94.01	79.09	-15.87%
8	6,674.57	7,002.81	4.92%	89.64	79.91	-10.85%
9	6,511.64	6,923.27	6.32%	93.79	80.89	-13.75%
10	6,734.04	6,918.12	2.73%	92.24	79.65	-13.65%
11	6,526.20	7,034.24	7.78%	89.62	81.59	-8.96%
12	6,580.55	7,052.85	7.18%	91.26	81.86	-10.30%
13	6,553.77	6,951.46	6.07%	88.30	81.65	-7.53%

14	6,889.91	7,038.82	2.16%	88.25	78.58	-10.96%
15	6,911.72	7,146.47	3.40%	93.46	80.43	-13.94%
16	6,719.36	7,177.09	6.81%	88.87	76.02	-14.46%
17	6,647.21	7,118.26	7.09%	94.78	80.34	-15.24%
18	6,950.92	7,137.00	2.68%	94.82	81.50	-14.05%
19	6,585.61	7,194.47	9.25%	90.25	82.14	-8.99%
20	6,720.19	7,234.52	7.65%	91.03	80.43	-11.64%
21	7,161.53	7,228.25	0.93%	88.27	82.05	-7.05%
22	6,850.46	6,868.17	0.26%	93.23	79.35	-14.89%
23	6,740.91	7,225.05	7.18%	88.38	80.36	-9.07%
24	6,840.57	7,149.45	4.52%	93.51	79.54	-14.94%
25	7,015.51	7,212.06	2.80%	93.11	79.72	-14.38%
26	6,650.47	6,885.43	3.53%	94.47	80.11	-15.20%
27	6,383.38	6,770.65	6.07%	92.63	77.67	-16.15%
28	6,759.34	7,053.01	4.34%	90.93	80.83	-11.11%
29	6,901.03	6,960.10	0.86%	92.10	81.63	-11.37%
30	7,073.14	7,252.97	2.54%	90.65	79.86	-11.90%
Average	**6,786.01**	**7,073.92**	**4.31%**	**91.32**	**80.17**	**-12.16%**

Table 5-16: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 11

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	12,692.11	12,692.11	0.00%	104.69	91.83	-12.28%
2	12,514.82	13,753.79	9.90%	115.24	103.82	-9.91%
3	12,502.44	12,865.01	2.90%	171.18	148.85	-13.04%
4	12,147.43	12,499.71	2.90%	121.77	104.08	-14.53%
5	11,130.27	11,942.78	7.30%	134.87	120.42	-10.71%
6	11,674.09	11,674.09	0.00%	138.26	123.45	-10.71%
7	11,512.19	12,329.55	7.10%	154.32	134.19	-13.04%
8	12,329.85	13,673.80	10.90%	126.40	115.97	-8.25%
9	12,331.13	12,331.13	0.00%	94.42	80.02	-15.25%
10	12,128.21	13,474.44	11.10%	128.80	117.09	-9.09%
11	11,328.92	11,328.92	0.00%	117.41	100.35	-14.53%
12	11,747.15	12,404.99	5.60%	86.64	73.42	-15.26%
13	12,449.89	12,449.89	0.00%	136.63	123.09	-9.91%
14	12,168.79	12,168.79	0.00%	152.52	134.98	-11.50%
15	11,571.14	11,571.14	0.00%	92.45	81.81	-11.51%
16	12,618.21	13,690.75	8.50%	144.67	124.71	-13.80%
17	12,625.04	12,625.04	0.00%	101.06	89.44	-11.50%
18	12,397.34	12,397.34	0.00%	129.69	114.77	-11.50%
19	12,530.63	13,520.55	7.90%	113.11	103.77	-8.26%

20	11,666.40	11,666.40	0.00%	119.77	102.37	-14.53%
21	12,279.44	12,979.36	5.70%	90.58	83.11	-8.25%
22	11,905.21	11,905.21	0.00%	103.21	90.53	-12.29%
23	11,725.36	12,886.17	9.90%	107.93	92.25	-14.53%
24	11,594.64	12,638.15	9.00%	167.68	145.81	-13.04%
25	12,032.09	12,032.09	0.00%	163.82	138.83	-15.25%
26	11,489.54	12,075.51	5.10%	162.23	146.15	-9.91%
27	11,340.88	12,055.35	6.30%	131.19	116.10	-11.50%
28	11,505.35	12,138.14	5.50%	105.26	89.97	-14.53%
29	12,640.42	14,081.43	11.40%	105.96	92.95	-12.28%
30	12,539.60	14,132.13	12.70%	101.46	88.13	-13.14%
Average	**12,037.29**	**12,599.46**	**4.66%**	**124.11**	**109.08**	**-12.13%**

Table 5-17: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 12

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	16,448.70	17,344.39	5.45%	146.03	135.24	-7.39%
2	16,664.84	17,330.22	3.99%	149.53	129.12	-13.65%
3	16,554.90	17,420.89	5.23%	146.23	128.94	-11.82%
4	16,364.89	17,426.98	6.49%	149.87	132.45	-11.62%
5	16,513.64	17,499.84	5.97%	150.46	130.04	-13.57%
6	16,742.23	17,505.25	4.56%	148.83	128.57	-13.61%

7	16,241.31	17,214.73	5.99%	149.39	130.15	-12.88%
8	16,698.19	17,230.02	3.18%	147.92	133.84	-9.52%
9	16,330.71	17,260.35	5.69%	147.29	130.50	-11.40%
10	16,375.74	17,468.93	6.68%	151.36	130.85	-13.55%
11	16,598.21	17,384.14	4.74%	152.10	135.66	-10.81%
12	16,748.68	17,492.10	4.44%	150.57	131.14	-12.90%
13	16,404.68	17,271.92	5.29%	146.56	132.39	-9.67%
14	16,667.67	17,422.09	4.53%	149.30	135.13	-9.49%
15	16,504.55	17,379.06	5.30%	148.57	133.18	-10.36%
16	16,736.51	17,485.92	4.48%	148.26	132.75	-10.46%
17	16,567.80	17,464.26	5.41%	151.14	134.46	-11.04%
18	16,547.50	17,290.28	4.49%	148.34	133.81	-9.80%
19	16,607.77	17,249.53	3.86%	149.72	130.59	-12.78%
20	16,688.93	17,456.60	4.60%	149.64	134.66	-10.01%
21	16,538.47	17,394.29	5.17%	153.48	133.48	-13.03%
22	16,740.60	17,447.84	4.22%	155.83	129.73	-16.75%
23	16,316.44	17,250.65	5.73%	145.42	129.20	-11.15%
24	16,514.28	17,347.22	5.04%	147.67	129.63	-12.22%
25	16,454.66	17,388.26	5.67%	145.81	130.58	-10.45%
26	16,325.06	17,226.84	5.52%	147.33	130.49	-11.43%
27	16,298.11	17,360.70	6.52%	149.41	129.25	-13.49%
28	16,325.27	17,481.64	7.08%	148.11	132.56	-10.50%
29	16,535.59	17,422.10	5.36%	148.55	135.34	-8.89%
30	16,655.07	17,162.26	3.05%	149.38	127.47	-14.67%
Average	**16,523.70**	**17,369.31**	**5.12%**	**149.07**	**131.71**	**-11.63%**

Table 5-18: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario 13

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	19,025.33	19,826.26	4.21%	165.10	146.63	-11.19%
2	18,932.06	20,142.85	6.40%	165.70	146.20	-11.77%
3	19,118.93	20,099.39	5.13%	160.60	146.54	-8.75%
4	18,966.48	20,439.20	7.76%	161.26	142.91	-11.38%
5	19,085.09	19,967.92	4.63%	161.56	145.24	-10.10%
6	19,041.32	20,238.21	6.29%	161.31	141.61	-12.21%
7	19,083.59	19,931.45	4.44%	163.83	144.03	-12.09%
8	19,166.49	19,962.56	4.15%	160.42	142.86	-10.95%
9	19,010.35	19,859.09	4.46%	162.54	147.51	-9.25%
10	19,215.63	20,083.07	4.51%	165.89	144.78	-12.73%
11	19,104.13	20,490.16	7.26%	162.93	143.68	-11.81%
12	19,037.09	20,052.23	5.33%	162.67	144.35	-11.26%
13	18,900.12	19,952.96	5.57%	165.33	146.71	-11.26%
14	18,976.26	19,850.08	4.60%	164.88	140.94	-14.52%
15	19,196.43	19,705.50	2.65%	166.59	143.26	-14.00%
16	18,955.63	19,967.54	5.34%	161.17	141.74	-12.06%
17	19,114.28	20,256.23	5.97%	162.05	140.86	-13.08%
18	19,196.55	20,342.51	5.97%	160.05	141.62	-11.52%
19	19,248.75	19,906.26	3.42%	166.68	143.57	-13.86%

20	19,105.76	20,100.13	5.20%	163.21	143.59	-12.02%
21	19,159.74	19,733.72	3.00%	160.96	141.67	-11.98%
22	19,219.21	19,962.24	3.87%	165.07	140.39	-14.95%
23	19,241.82	19,802.70	2.91%	164.99	144.37	-12.50%
24	18,662.29	20,408.78	9.36%	161.83	141.94	-12.29%
25	19,220.50	19,990.23	4.00%	161.45	143.81	-10.93%
26	19,078.35	19,712.15	3.32%	161.64	142.06	-12.11%
27	18,995.56	19,961.85	5.09%	163.59	145.55	-11.03%
28	19,123.95	20,079.42	5.00%	161.24	141.60	-12.18%
29	18,916.57	19,915.16	5.28%	164.53	146.18	-11.15%
30	18,229.24	19,836.75	8.82%	162.73	144.30	-11.33%
Average	**19,044.25**	**20,019.22**	**5.13%**	**163.06**	**143.68**	**-11.88%**

Table 5-19: Comparison of the MS-BTS heuristic and the PDPSL heuristic in terms of solution quality and computational time for Scenario14

	Solution Quality			**Computational Time**		
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	PDPSL heuristic	MS-BTS heuristic	Improvement w.r.t. PDPSL
1	20,758.02	22,013.29	6.05%	187.57	167.54	-10.68%
2	21,514.44	22,652.99	5.29%	186.88	167.34	-10.46%
3	21,164.65	22,593.26	6.75%	194.11	165.68	-14.65%
4	20,455.04	21,716.88	6.17%	194.44	164.04	-15.63%
5	20,660.69	22,605.58	9.41%	192.34	169.62	-11.81%
6	20,560.16	22,010.69	7.06%	186.96	169.05	-9.58%

7	21,124.16	22,536.12	6.68%	194.07	165.06	-14.95%
8	21,625.63	22,565.72	4.35%	190.21	170.68	-10.27%
9	20,451.21	22,331.59	9.19%	188.55	169.31	-10.20%
10	21,480.83	22,184.52	3.28%	193.04	168.60	-12.66%
11	21,563.32	22,437.36	4.05%	188.60	163.37	-13.38%
12	22,137.74	22,374.90	1.07%	190.64	164.47	-13.73%
13	21,357.43	21,573.75	1.01%	191.08	170.34	-10.85%
14	20,571.23	22,108.18	7.47%	193.48	168.21	-13.06%
15	22,360.17	22,514.46	0.69%	187.82	166.32	-11.45%
16	20,958.80	21,612.04	3.12%	189.76	169.68	-10.58%
17	22,414.47	22,539.76	0.56%	186.26	168.60	-9.48%
18	22,493.62	23,406.05	4.06%	189.43	166.18	-12.27%
19	21,305.20	22,186.10	4.13%	184.68	163.68	-11.37%
20	20,896.06	23,452.47	12.23%	191.12	165.79	-13.25%
21	20,337.41	22,821.14	12.21%	181.16	162.77	-10.15%
22	21,548.81	21,642.20	0.43%	186.10	168.79	-9.30%
23	20,542.98	22,140.22	7.78%	186.02	163.63	-12.04%
24	21,611.71	21,927.45	1.46%	193.90	163.30	-15.78%
25	20,758.33	22,194.67	6.92%	187.58	166.39	-11.30%
26	20,718.23	21,753.92	5.00%	189.79	164.23	-13.47%
27	20,720.74	23,090.94	11.44%	188.54	166.19	-11.85%
28	20,889.70	22,101.78	5.80%	185.02	168.32	-9.03%
29	22,301.95	22,505.29	0.91%	186.17	164.80	-11.48%
30	21,186.17	21,194.58	0.04%	185.88	164.84	-11.32%
Average	**21,215.63**	**22,292.93**	**5.15%**	**189.04**	**166.56**	**-11.87%**

We successfully obtain the exact solution for up to 90 nodes, beyond which the computational time to determine the exact solution becomes excessive. For the larger problems, the comparison of the MS-BTS heuristic is done with the results of the PDPSL heuristic. Table 5-2 to Table 5-19 provide the results regarding the solution (route cost) and the computational time for exact solution (Branch and Bound method), PDPSL heuristic and the MS-BTS heuristic. The PDPSL heuristic is able to obtain the exact solution for the smaller cases, unlike the MS-BTS heuristic. Overall, the MS-BTS heuristic delivers an inferior solution to the PDPSL heuristic but is faster. This indicates that there is some potential for improvement in the MS-BTS heuristic.

Tables 5-20 – 27 present the comparison of the performance of the PDPSL and M-MSPDP heuristic with TESA heuristic from Sahin et al. (2013) for selected small size (Case 1 and Case 4) and large size (Case 10 and Case 14).

Table 5-20: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of solution quality for Scenario 1

	Solution						
Instance No	Exact Soln.	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	TESA heuristic Soln.	Error w.r.t. Exact Soln.
1	294.91	294.91	0.00%	294.91	0.00%	294.91	0.00%
2	268.73	268.73	0.00%	275.18	2.40%	268.73	0.00%
3	269.59	269.59	0.00%	291.74	8.22%	269.59	0.00%
4	295.62	295.62	0.00%	314.54	6.40%	299.41	1.28%

5	277.86	277.86	0.00%	297.7	7.14%	281.92	1.46%
6	285.86	285.86	0.00%	285.86	0.00%	285.86	0.00%
7	261.77	261.77	0.00%	281.28	7.45%	261.77	0.00%
8	263.11	263.11	0.00%	273.11	3.80%	263.11	0.00%
9	281.93	281.93	0.00%	281.93	0.00%	281.93	0.00%
10	274.14	274.14	0.00%	283.18	3.30%	278.14	1.46%
11	268.93	268.93	0.00%	268.93	0.00%	268.93	0.00%
12	297.31	297.31	0.00%	308.31	3.70%	297.31	0.00%
13	268.31	268.31	0.00%	268.31	0.00%	271.55	1.21%
14	262.95	262.95	0.00%	276.36	5.10%	262.95	0.00%
15	297.8	297.8	0.00%	297.8	0.00%	298.99	0.40%
16	283.97	283.97	0.00%	295.61	4.10%	283.97	0.00%
17	292.13	292.13	0.00%	292.13	0.00%	292.13	0.00%
18	270.04	270.04	0.00%	284.43	5.33%	274.62	1.70%
19	278.92	278.92	0.00%	294.49	5.58%	278.92	0.00%
20	271.54	271.54	0.00%	294.69	8.53%	271.54	0.00%
21	274.36	274.36	0.00%	274.36	0.00%	274.58	0.08%
22	282.99	282.99	0.00%	282.99	0.00%	282.99	0.00%
23	283.84	283.84	0.00%	298.88	5.30%	283.84	0.00%
24	287.74	287.74	0.00%	300.92	4.58%	292.21	1.55%
25	279.41	279.41	0.00%	279.41	0.00%	279.41	0.00%
26	291.2	291.2	0.00%	300.81	3.30%	292.30	0.38%
27	291.56	291.56	0.00%	293.56	0.69%	296.34	1.64%
28	288.75	288.75	0.00%	311.98	8.05%	288.75	0.00%
29	265.97	265.97	0.00%	279.27	5.00%	265.97	0.00%

30	295.64	295.64	0.00%	310.31	4.96%	295.64	0.00%
Average	**280.23**	**280.23**	**0.00%**	**289.77**	**3.43%**	**281.28**	**0.37%**

Table 5-21: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of computational time for Scenario 1

	Computational Time						
Instance No	Exact Soln.	PDPSL heuristic	Improvement w.r.t. Exact Soln.	MS-BTS heuristic	Reduction w.r.t. Exact Soln.	TESA heuristic	Improvement w.r.t. Exact Soln.
1	5.85	1.01	-82.74%	0.94	-83.93%	0.99	-83.08%
2	6.84	1.48	-78.36%	1.31	-80.85%	1.44	-78.95%
3	4.58	0.86	-81.22%	0.75	-83.62%	0.86	-81.22%
4	6.26	1.01	-83.87%	0.92	-85.30%	0.95	-84.82%
5	6.41	0.8	-87.52%	0.73	-88.61%	0.80	-87.52%
6	6.79	0.89	-86.89%	0.8	-88.22%	0.84	-87.63%
7	7.86	1.41	-82.06%	1.28	-83.72%	1.37	-82.57%
8	4.67	1.27	-72.81%	1.12	-76.02%	1.27	-72.81%
9	6.51	1.24	-80.95%	1.13	-82.64%	1.18	-81.87%
10	4.12	1.03	-75.00%	0.92	-77.67%	1.00	-75.73%
11	6.3	0.91	-85.56%	0.77	-87.78%	0.86	-86.35%
12	5.51	0.85	-84.57%	0.78	-85.84%	0.84	-84.75%
13	7.24	1.27	-82.46%	1.09	-84.94%	1.21	-83.29%
14	6.21	1.43	-76.97%	1.23	-80.19%	1.32	-78.74%
15	6.11	0.79	-87.07%	0.68	-88.87%	0.73	-88.05%

16	6.98	0.84	-87.97%	0.75	-89.26%	0.80	-88.54%
17	6.91	1.24	-82.05%	1.1	-84.08%	1.16	-83.21%
18	5.75	0.84	-85.39%	0.77	-86.61%	0.81	-85.91%
19	5.66	1.5	-73.50%	1.34	-76.33%	1.47	-74.03%
20	5.26	0.8	-84.79%	0.69	-86.88%	0.76	-85.55%
21	4.67	1.17	-74.95%	1.03	-77.94%	1.12	-76.02%
22	6.51	1.53	-76.50%	1.39	-78.65%	1.47	-77.42%
23	4.12	1.11	-73.06%	1.02	-75.24%	1.06	-74.27%
24	4.58	0.98	-78.60%	0.85	-81.44%	0.96	-79.04%
25	6.26	0.93	-85.14%	0.83	-86.74%	0.93	-85.14%
26	6.41	1.39	-78.32%	1.24	-80.66%	1.36	-78.78%
27	7.86	1.04	-86.77%	0.9	-88.55%	1.01	-87.15%
28	4.67	1.03	-77.94%	0.93	-80.09%	1.02	-78.16%
29	5.85	1.5	-74.36%	1.35	-76.92%	1.49	-74.53%
30	6.25	0.88	-85.92%	0.75	-88.00%	0.86	-86.24%
Average	**5.97**	**1.10**	**-81.11%**	**0.98**	**-83.19%**	**1.06**	**-81.71%**

Table 5-22: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of solution quality for Scenario 4

	Solution						
Instance No	Exact Soln.	PDPSL heuristic Soln.	Error w.r.t. Exact Soln.	MS-BTS heuristic Soln.	Error w.r.t. Exact Soln.	TESA heuristic Soln.	Error w.r.t. Exact Soln.
1	3,272.91	3,283.80	0.33%	3,396.62	3.78%	3537.68	8.09%

2	3,376.08	3,572.88	5.83%	3,572.88	5.83%	3475.96	2.96%
3	3,382.38	3,383.40	0.03%	3,430.17	1.41%	3468.65	2.55%
4	3,348.45	3,538.32	5.67%	3,791.85	13.24%	3451.78	3.09%
5	3,365.84	3,479.52	3.38%	3,608.26	7.20%	3503.66	4.09%
6	3,371.52	3,399.92	0.84%	3,399.92	0.84%	3463.38	2.72%
7	3,337.73	3,512.52	5.24%	3,744.63	12.19%	3492.57	4.64%
8	3,293.49	3,296.24	0.08%	3,476.72	5.56%	3541.69	7.54%
9	3,360.86	3,527.16	4.95%	3,527.16	4.95%	3498.76	4.10%
10	3,390.70	3,416.28	0.75%	3,416.28	0.75%	3488.86	2.89%
11	3,339.29	3,487.92	4.45%	3,794.63	13.64%	3499.25	4.79%
12	3,341.09	3,411.96	2.12%	3,674.92	9.99%	3457.97	3.50%
13	3,382.32	3,382.44	0.00%	3,382.44	0.00%	3454.45	2.13%
14	3,293.17	3,348.96	1.69%	3,626.69	10.13%	3539.03	7.47%
15	3,346.22	3,585.12	7.14%	3,585.12	7.14%	3511.68	4.94%
16	3,356.46	3,472.20	3.45%	3,809.00	13.48%	3502.53	4.35%
17	3,258.02	3,334.32	2.34%	3,334.32	2.34%	3454.11	6.02%
18	3,372.79	3,474.36	3.01%	3,474.36	3.01%	3539.32	4.94%
19	3,399.10	3,420.24	0.62%	3,590.47	5.63%	3528.18	3.80%
20	3,367.10	3,376.76	0.29%	3,396.76	0.88%	3480.50	3.37%
21	3,329.94	3,335.60	0.17%	3,565.12	7.06%	3541.01	6.34%
22	3,398.56	3,398.52	0.00%	3,398.52	0.00%	3511.80	3.33%
23	3,387.28	3,395.20	0.23%	3,556.22	4.99%	3495.41	3.19%
24	3,370.67	3,397.84	0.81%	3,429.13	1.73%	3497.00	3.75%
25	3,317.96	3,528.48	6.34%	3,528.48	6.34%	3489.54	5.17%
26	3,380.72	3,396.40	0.46%	3,459.46	2.33%	3535.73	4.59%

27	3,364.82	3,569.40	6.08%	3,851.38	14.46%	3466.53	3.02%
28	3,327.65	3,332.48	0.15%	3,656.98	9.90%	3485.90	4.76%
29	3,288.79	3,299.16	0.32%	3,508.01	6.67%	3547.21	7.86%
30	3,323.31	3,410.16	2.61%	3,627.64	9.16%	3512.17	5.68%
Average	**3348.17**	**3425.59**	**2.31%**	**3553.80**	**6.15%**	**281.28**	**4.52%**

Table 5-23: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of computational time for Scenario 4

	Computational Time						
Instance No	Exact Soln.	PDPSL heuristic	Improvement w.r.t. Exact Soln.	MS-BTS heuristic	Reduction w.r.t. Exact Soln.	TESA heuristic	Improvement w.r.t. Exact Soln.
1	159.33	44.02	-72.37%	39.4	-75.27%	41.79	73.77%
2	165.65	46.58	-71.88%	42.01	-74.64%	45.80	72.35%
3	158.1	47.05	-70.24%	44.74	-71.70%	47.15	70.18%
4	150.18	46.59	-68.98%	45.93	-69.42%	44.09	70.64%
5	155.03	45.61	-70.58%	44.45	-71.33%	42.82	72.38%
6	159.83	44.14	-72.38%	39.51	-75.28%	43.23	72.95%
7	152.45	46.59	-69.44%	40.67	-73.32%	46.08	69.77%
8	157.21	45.03	-71.36%	42.74	-72.81%	47.46	69.81%
9	154.01	45.6	-70.39%	43.29	-71.89%	41.84	72.83%
10	160.53	47.16	-70.62%	39.87	-75.16%	45.50	71.66%
11	155.52	46.03	-70.40%	38.57	-75.20%	47.25	69.62%
12	165.52	45.98	-72.22%	41.37	-75.01%	41.00	75.23%

13	156.26	47.46	-69.63%	39.46	-74.75%	43.93	71.89%
14	154.66	49.13	-68.23%	40.04	-74.11%	45.63	70.50%
15	160.3	50.6	-68.43%	42.19	-73.68%	45.53	71.60%
16	158.77	46.39	-70.78%	43.57	-72.56%	46.27	70.86%
17	160.06	49.74	-68.92%	40.82	-74.50%	44.96	71.91%
18	155.44	44.5	-71.37%	41.96	-73.01%	41.69	73.18%
19	158.83	51.46	-67.60%	42.95	-72.96%	44.63	71.90%
20	157.25	44.02	-72.01%	42.36	-73.06%	42.43	73.02%
21	160.66	51.89	-67.70%	41.22	-74.34%	42.58	73.50%
22	164.67	49.8	-69.76%	43.27	-73.72%	44.22	73.15%
23	158.62	50.29	-68.30%	40.6	-74.40%	44.68	71.83%
24	158.51	47.88	-69.79%	43.38	-72.63%	42.63	73.11%
25	154.17	46.69	-69.72%	43.32	-71.90%	42.86	72.20%
26	159.02	46.57	-70.71%	42.85	-73.05%	42.33	73.38%
27	158.04	45.85	-70.99%	38.08	-75.90%	46.33	70.68%
28	159.07	48.02	-69.81%	40.08	-74.80%	46.10	71.02%
29	159.6	44.07	-72.39%	39.75	-75.09%	44.90	71.87%
30	160.41	50.33	-68.62%	39.17	-75.58%	43.48	72.89%
Average	**158.26**	**47.17**	**-70.19%**	**41.59**	**-73.70%**	**44.31**	**71.99%**

Table 5-24: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of solution quality for Scenario 10

	Solution				
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	TESA heuristic	Error w.r.t. PDPSL
1	7,149.41	7,152.09	0.04%	7,191.34	0.59%
2	6,819.61	6,992.54	2.54%	6,965.80	2.14%
3	6,918.09	7,043.71	1.82%	7,072.82	2.24%
4	6,589.25	7,130.05	8.21%	7,073.19	7.34%
5	6,683.59	7,120.43	6.54%	7,103.26	6.28%
6	7,120.51	7,130.56	0.14%	7,188.98	0.96%
7	6,917.81	7,113.65	2.83%	7,158.07	3.47%
8	6,674.57	7,002.81	4.92%	6,971.35	4.45%
9	6,511.64	6,923.27	6.32%	7,117.66	9.31%
10	6,734.04	6,918.12	2.73%	7,081.45	5.16%
11	6,526.20	7,034.24	7.78%	7,050.83	8.04%
12	6,580.55	7,052.85	7.18%	7,149.44	8.65%
13	6,553.77	6,951.46	6.07%	7,078.65	8.01%
14	6,889.91	7,038.82	2.16%	7,098.72	3.03%
15	6,911.72	7,146.47	3.40%	7,001.34	1.30%
16	6,719.36	7,177.09	6.81%	7,146.30	6.35%
17	6,647.21	7,118.26	7.09%	6,935.72	4.34%
18	6,950.92	7,137.00	2.68%	6,955.16	0.06%
19	6,585.61	7,194.47	9.25%	7,078.69	7.49%

20	6,720.19	7,234.52	7.65%	6,924.35	3.04%
21	7,161.53	7,228.25	0.93%	7,213.59	0.73%
22	6,850.46	6,868.17	0.26%	6,907.48	0.83%
23	6,740.91	7,225.05	7.18%	7,029.09	4.28%
24	6,840.57	7,149.45	4.52%	6,910.49	1.02%
25	7,015.51	7,212.06	2.80%	7,097.40	1.17%
26	6,650.47	6,885.43	3.53%	6,949.91	4.50%
27	6,383.38	6,770.65	6.07%	7,136.19	11.79%
28	6,759.34	7,053.01	4.34%	6,936.61	2.62%
29	6,901.03	6,960.10	0.86%	7,079.25	2.58%
30	7,073.14	7,252.97	2.54%	7,084.78	0.16%
Average	**6,786.01**	**7,073.92**	**4.31%**	**7,056.26**	**4.06%**

Table 5-25: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of computational time for Scenario 10

	Computational Time				
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	TESA heuristic	Improvement w.r.t. PDPSL
1	93.31	77.80	-16.62%	87.11	-6.64%
2	90.38	80.40	-11.04%	83.03	-8.13%
3	90.76	80.90	-10.86%	89.34	-1.56%
4	89.87	80.97	-9.90%	86.28	-3.99%
5	89.55	81.28	-9.24%	90.36	0.90%
6	88.13	78.65	-10.76%	85.81	-2.63%

7	94.01	79.09	-15.87%	87.96	-6.44%
8	89.64	79.91	-10.85%	87.86	-1.99%
9	93.79	80.89	-13.75%	91.24	-2.72%
10	92.24	79.65	-13.65%	85.52	-7.29%
11	89.62	81.59	-8.96%	84.34	-5.89%
12	91.26	81.86	-10.30%	83.23	-8.80%
13	88.30	81.65	-7.53%	90.59	2.59%
14	88.25	78.58	-10.96%	87.82	-0.49%
15	93.46	80.43	-13.94%	90.05	-3.65%
16	88.87	76.02	-14.46%	91.90	3.41%
17	94.78	80.34	-15.24%	91.99	-2.94%
18	94.82	81.50	-14.05%	84.34	-11.05%
19	90.25	82.14	-8.99%	85.66	-5.09%
20	91.03	80.43	-11.64%	88.30	-3.00%
21	88.27	82.05	-7.05%	91.93	4.15%
22	93.23	79.35	-14.89%	85.26	-8.55%
23	88.38	80.36	-9.07%	91.44	3.46%
24	93.51	79.54	-14.94%	86.27	-7.74%
25	93.11	79.72	-14.38%	89.67	-3.69%
26	94.47	80.11	-15.20%	90.07	-4.66%
27	92.63	77.67	-16.15%	84.17	-9.13%
28	90.93	80.83	-11.11%	83.06	-8.66%
29	92.10	81.63	-11.37%	88.23	-4.20%
30	90.65	79.86	-11.90%	85.53	-5.65%
Average	**91.32**	**80.17**	**-12.16%**	**87.61**	**-4.00%**

Table 5-26: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of solution quality for Scenario 14

	Solution				
Instance No	PDPSL heuristic	MS-BTS heuristic	Error w.r.t. PDPSL	TESA heuristic	Error w.r.t. PDPSL
1	20,758.02	22,013.29	6.05%	21,647.50	4.28%
2	21,514.44	22,652.99	5.29%	21,733.22	1.02%
3	21,164.65	22,593.26	6.75%	21,564.27	1.89%
4	20,455.04	21,716.88	6.17%	21,800.42	6.58%
5	20,660.69	22,605.58	9.41%	21,628.96	4.69%
6	20,560.16	22,010.69	7.06%	21,833.85	6.19%
7	21,124.16	22,536.12	6.68%	21,784.92	3.13%
8	21,625.63	22,565.72	4.35%	21,744.78	0.55%
9	20,451.21	22,331.59	9.19%	21,922.51	7.19%
10	21,480.83	22,184.52	3.28%	21,642.41	0.75%
11	21,563.32	22,437.36	4.05%	21,687.51	0.58%
12	22,137.74	22,374.90	1.07%	22,576.45	1.98%
13	21,357.43	21,573.75	1.01%	21,932.53	2.69%
14	20,571.23	22,108.18	7.47%	21,812.49	6.03%
15	22,360.17	22,514.46	0.69%	22,702.59	1.53%
16	20,958.80	21,612.04	3.12%	21,932.53	4.65%
17	22,414.47	22,539.76	0.56%	22,818.81	1.80%
18	22,493.62	23,406.05	4.06%	22,595.79	0.45%

19	21,305.20	22,186.10	4.13%	21,626.94	1.51%
20	20,896.06	23,452.47	12.23%	21,816.53	4.40%
21	20,337.41	22,821.14	12.21%	21,535.81	5.89%
22	21,548.81	21,642.20	0.43%	21,645.21	0.45%
23	20,542.98	22,140.22	7.78%	21,654.79	5.41%
24	21,611.71	21,927.45	1.46%	22,603.49	4.59%
25	20,758.33	22,194.67	6.92%	21,707.23	4.57%
26	20,718.23	21,753.92	5.00%	21,524.14	3.89%
27	20,720.74	23,090.94	11.44%	21,627.28	4.38%
28	20,889.70	22,101.78	5.80%	21,759.62	4.16%
29	22,301.95	22,505.29	0.91%	22,825.38	2.35%
30	21,186.17	21,194.58	0.04%	21,876.18	3.26%
Average	**21,215.63**	**22,292.93**	**5.15%**	**21,918.80**	**3.36%**

Table 5-27: Comparison of the MS-BTS heuristic, PDPSL heuristic and the TESA heuristic in terms of computational time for Scenario 14

Instance No	PDPSL heuristic	M-MSPDP heuristic	Error w.r.t. PDPSL	TESA heuristic	Error w.r.t. PDPSL
1	187.57	167.54	-10.68%	173.96	-7.26%
2	186.88	167.34	-10.46%	177.35	-5.10%
3	194.11	165.68	-14.65%	177.91	-8.35%
4	194.44	164.04	-15.63%	182.87	-5.95%
5	192.34	169.62	-11.81%	173.21	-9.95%
6	186.96	169.05	-9.58%	178.60	-4.47%

7	194.07	165.06	-14.95%	176.20	-9.21%
8	190.21	170.68	-10.27%	171.42	-9.88%
9	188.55	169.31	-10.20%	175.31	-7.02%
10	193.04	168.60	-12.66%	176.75	-8.44%
11	188.60	163.37	-13.38%	181.67	-3.67%
12	190.64	164.47	-13.73%	174.25	-8.60%
13	191.08	170.34	-10.85%	181.19	-5.18%
14	193.48	168.21	-13.06%	182.13	-5.87%
15	187.82	166.32	-11.45%	181.96	-3.12%
16	189.76	169.68	-10.58%	179.63	-5.34%
17	186.26	168.60	-9.48%	171.27	-8.05%
18	189.43	166.18	-12.27%	179.28	-5.36%
19	184.68	163.68	-11.37%	180.92	-2.04%
20	191.12	165.79	-13.25%	172.65	-9.66%
21	181.16	162.77	-10.15%	177.53	-2.00%
22	186.10	168.79	-9.30%	172.95	-7.07%
23	186.02	163.63	-12.04%	180.85	-2.78%
24	193.90	163.30	-15.78%	174.61	-9.95%
25	187.58	166.39	-11.30%	176.59	-5.86%
26	189.79	164.23	-13.47%	175.71	-7.42%
27	188.54	166.19	-11.85%	177.33	-5.95%
28	185.02	168.32	-9.03%	177.59	-4.02%
29	186.17	164.80	-11.48%	172.80	-7.18%
30	185.88	164.84	-11.32%	175.39	-5.64%
Average	**189.04**	**166.56**	**-11.87%**	**177.00**	**-6.35%**

5.4.2.1 Comparison to the exact solution method

The comparison between the MS-BTS heuristic and the exact solution method is limited to the scenarios no more than 90 number of nodes (i.e., Scenarios 1 through 4 in Table 5-1), since the computation time for the exact solution is found to be more than 6 hours after 90 nodes.

Figure 5-3 shows the total vehicle miles traveled (VMT) obtained by MS-BTS in comparison to the exact solution method in the MOSEK solver. As observed, the MS-BTS heuristic solution coincides with the exact solution for the small-scale problems and the error in the MS-BTS heuristic solution w.r.t the exact solution varies between 3-8% for larger problem sizes.

Figure 5-4 shows the average computation time (in minutes) of the MS-BTS heuristic of 30 instances for each scenario. The MS-BTS heuristic delivers 73-83% savings in the computation time compared to the exact solution.

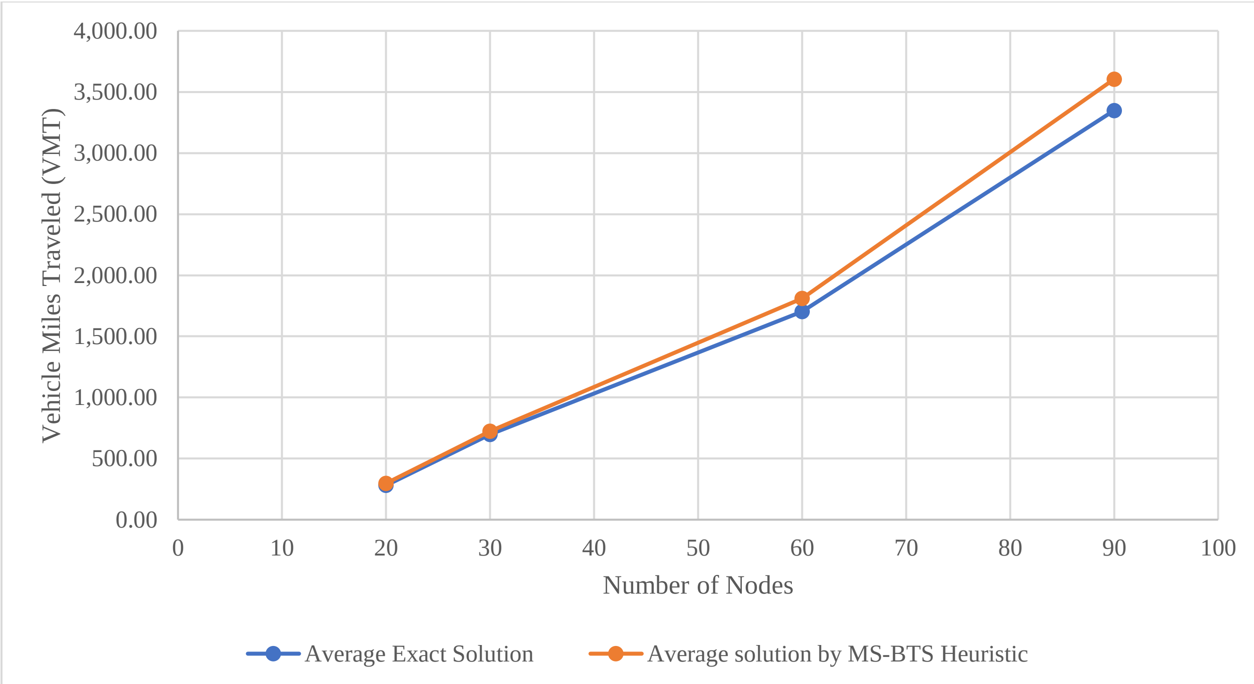


Figure 5-3. Solution of the MS-BTS heuristic in comparison to the exact solution

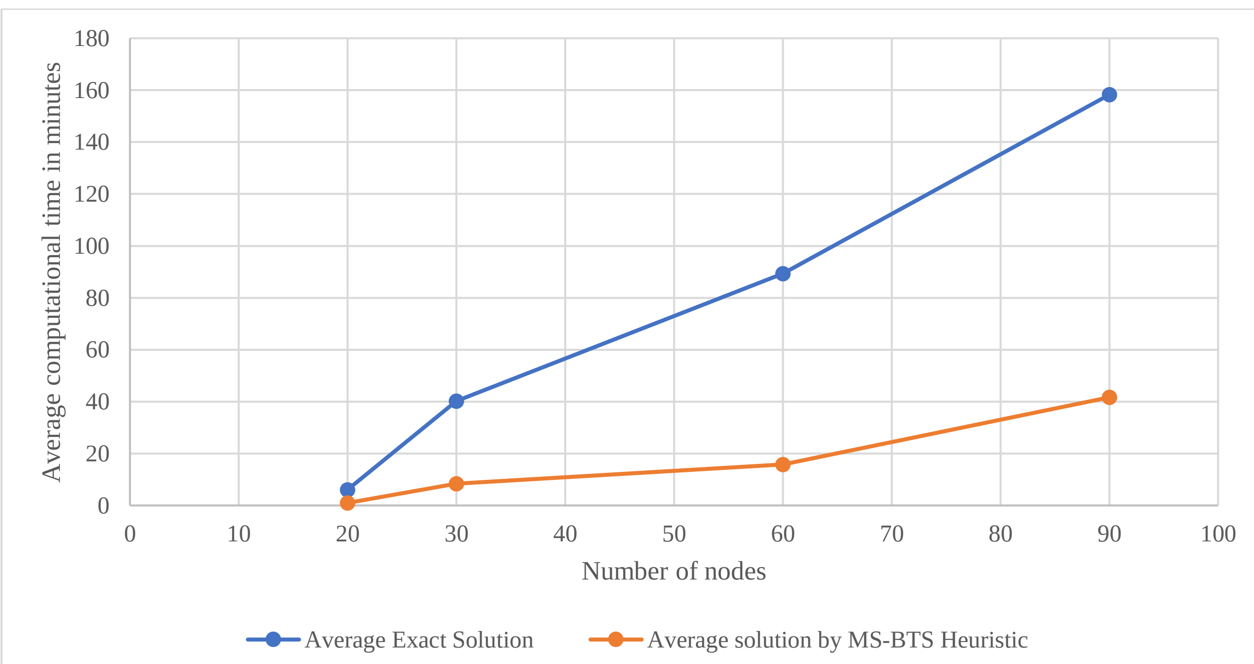


Figure 5-4. Computational time of the MS-BTS heuristic in comparison to the exact solution

5.4.2.2 Comparison between MS-BTS and other heuristics (PDPSL and TESA)

Table 5-2 presents the results of MS-BTS and PDPSL and TESA in terms of solution quality and computational time. Each scenario is again run for 30 instances and the average results are presented in Table 5-28. Figures 5-5 and 5-6 display the relative difference (% difference in VMT and % difference in computational time) of MS-BTS with respect to PDPSL and TESA.

In terms of VMT, the relative difference is within 8%. Specifically, the average % difference of MS-BTS relative to PDPSL is 5.13%, and 1.16% relative to TESA. That is, MS-BTS gives an average 5.13% higher VMT than PDPSL, and 1.16% higher VMT than TESA. Noticeable, Figure 5-5 shows that when the number of nodes increases after 200 the relative differences are stabilized, an indication of convergence among the heuristics.

In terms of computation time, MS-BTS outperforms both PDPSL and TESA by an average of 10.14% and 5.91%, respectively. In other words, on average MS-BTS takes 10.14% less time to find the solution than PDPSL, and 5.91% less time than TESA. Again, Figure 5-6 shows the convergence when the number of nodes is greater than 100.

Based on the two-sample t-test, it is found that the differences in the solution and the computation time for the MS-BTS heuristic and the TESA heuristic are not significant ($p > 0.05$).

Table 5-28: Comparison among MS-BTS, PDPSL and TESA

SID	No. nodes	O x D	VMT			Computation Time (minutes)		
			MS-BTS (A)	PDPSL (B)	TESA (C)	MS-BTS (A)	PDPSL (B)	TESA (C)
1	20	5 x 15	297.05	280.3	291.68	0.98	1.10	1.10
2	30	10 x 20	723.41	698.33	720.54	8.34	7.48	7.64
3	60	20 x 40	1,809.54	1,702.72	1,780.63	15.83	17.88	16.22
4	90	30 x 60	3,604.60	3,348.17	3,582.25	41.65	47.16	48.20
5	100	30 x 70	3,799.29	3,658.79	3,759.79	48.89	55.45	52.04
6	110	40 x 70	3,852.91	3,710.79	3,817.48	56.52	63.91	59.33
7	120	40 x 80	4,338.51	4,021.34	4,208.24	61.19	69.64	65.81
8	130	50 x 80	5,246.98	5,042.75	5,238.46	64.25	73.12	68.29
9	140	50 x 90	5,867.71	5,626.34	5,777.76	72.19	82.17	77.37
10	150	60 x 90	7,078.49	6,786.01	7,061.52	80.22	91.32	87.06
11	200	80 x 120	12,598.23	12,037.29	12,427.64	109.08	124.11	117.09
12	250	110 x 140	17,369.71	16,523.7	17,229.88	131.73	149.07	142.52
13	300	120 x 180	20,021.22	19,044.25	19,860.99	143.69	163.06	152.88
14	350	150 x 200	22,308.23	21,215.63	21,928.47	166.60	189.04	177.75

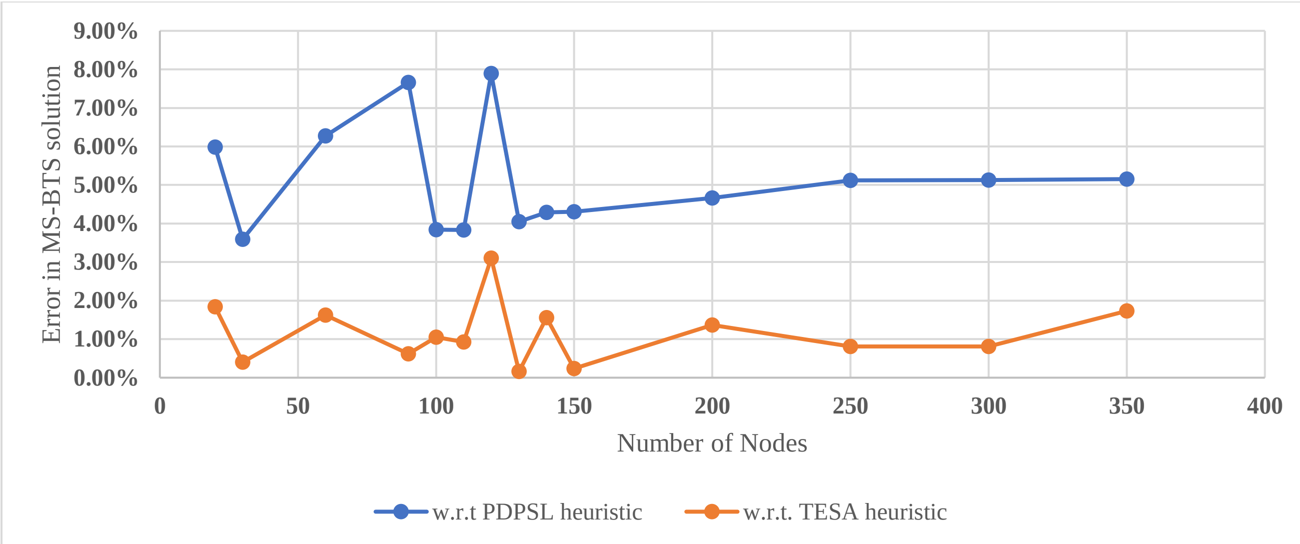


Figure 5-5. Solution quality of the MS-BTS heuristic in % difference with respect to that of the PDPSL and the TESA heuristic

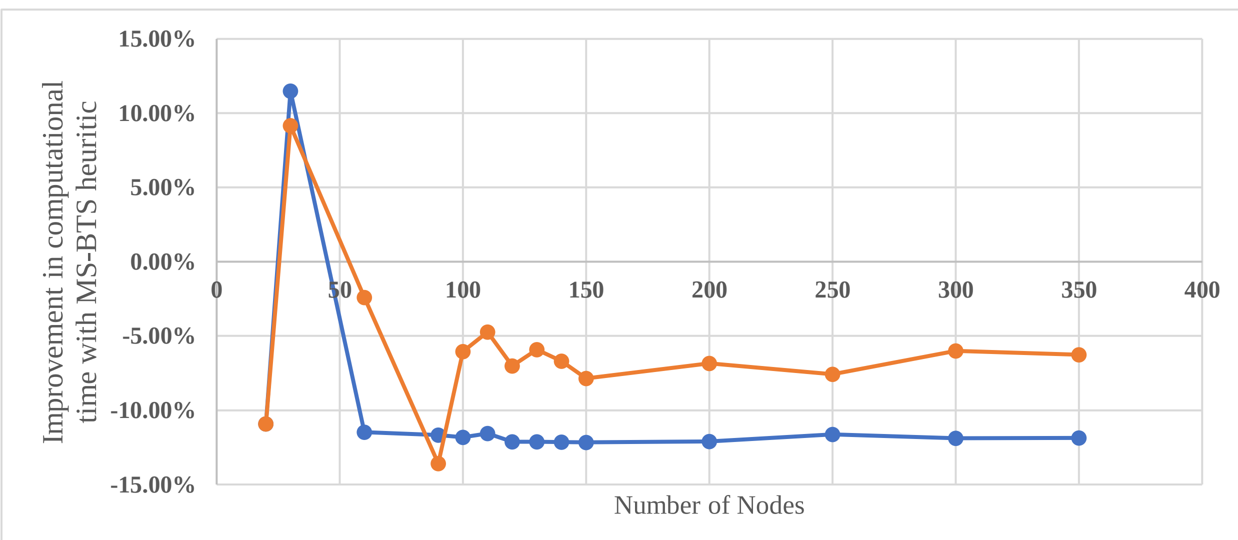


Figure 5-6. % computational time savings of the MS-BTS heuristic with respect to that of the PDPSL and the TESA heuristic

5.5. Case Studies

In this section, we apply the MS-BTS heuristic to solve for two case studies of the M-MSPDP: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bicycle rebalancing in a bike-sharing system (i.e., M-MSPD-OC).

5.5.1 Case Study 1: Parcel Station Pickup and Delivery

An emerging last-mile delivery paradigm is the concept of microhub. A microhub is a small-scale logistics facility usually located in the centre of an urban environment like city center, from which the local distribution demand is served by employing environment-friendly modes of transport (Janjevic and Ndiaye, 2014). The field test of a system of microhubs implemented in the city of Amsterdam showed a reduction of the delivery van stops in the city center - a total of 2,000 van stops were accounted to have been reduced during the field test as part of the EU-funded Civitas Citylab project (Citylab, 2018). At the same time, crowdshipping is gaining traction in last-mile delivery in recent years for its relatively low delivery cost and flexibility (Rai et al., 2017).

In light of the potential benefits of microhubs and crowdshipping, we propose this new urban delivery paradigm where the last-mile demand fulfilment is done through a network of microhubs coupled with crowdshipping (or M+C for short hereafter). In this paradigm, an urban service area is divided into a number of service zones (e.g., by zipcode). Within each zone, there is a designated microhub to temporarily store inbound and outbound parcels[2]. These parcels are either collected

[2] In this study the parcels are assumed of a typical online shopping parcel size, e.g., the commonly seen Amazon parcels. They can be carried by a regular passenger vehicle.

or distributed by crowdshippers between customers (shippers and end receivers) and the zonal microhub. The crowdshippers may be automobile drivers or cyclists. Commercial trucks are dispatched periodically to visit only the microhubs in the service area to transfer parcels to their respective destination microhubs. Thus, truck traffic and VMT on busy and often narrow city streets can be largely avoided.

In this study setting, the service area covered by a logistics carrier is divided into smaller so-called 'service zones' and each zone has a designated microhub that handles the parcels in and out of the zone. Figure 5-7 is an example of the service area, service zones, and microhubs. In this example, the entire service area (the square) is divided into nine zones. Each zone has a microhub located at the centroid of the zone.

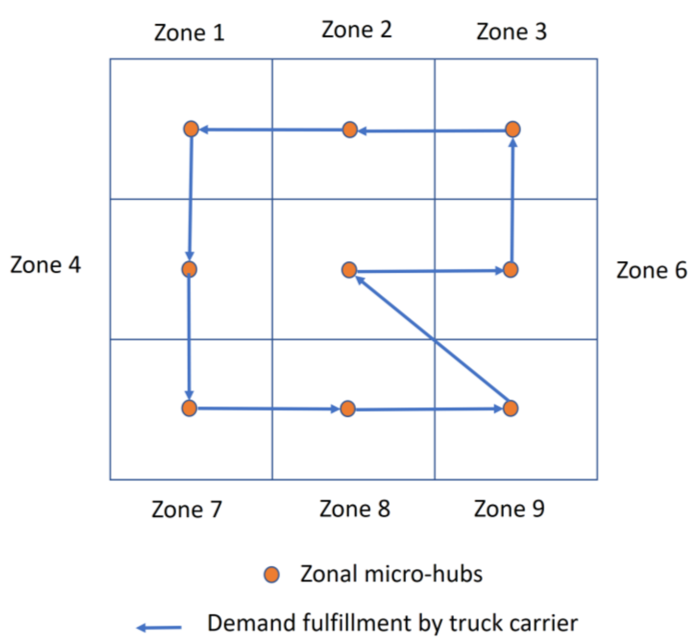


Figure 5-7. Service Area, service zones, microhubs, and truck routing in M+C

All parcel pickup and delivery requests are classified into two categories according to the zonal relationship between the pickup and the delivery location: *intra-zonal* and *inter-zonal* requests. An *intra-zonal* request refers to one in which both the pickup and delivery addresses are within the same service zone (e.g., (P1,D1), (P2,D2), and (P3,D3) in Figure 5-8). For this type of request, transshipment may not take place. An *inter-zonal* request refers to one in which the pickup and delivery addresses are not in the same service zone. For this type of request, transshipment service is necessary; in other words, an inter-zonal parcel is picked up by a crowdshipper at its shipper's and deposited in its microhub of origin, and then transferred by truck to its microhub of destination, and finally delivered by another crowdshipper to its final receiver.

Delivery trucks belong to a carrier's fleet and carry out routine visits to microhubs only to pick up and deliver parcels among the microhubs. As such, congestion due to truck traffic or truck parking on urban streets could be largely avoided. Figure 5-7 graphically illustrates the truck routing among microhubs in M+C. In M+C, the first and last mile deliveries within a service zone are performed by crowdshippers. A crowdshipper can be an automobile driver, a bicyclist, or a pedestrian. A crowdshipper's travel speed, payload capacity, service range, and compensation rate vary by the mode of transportation. Figure 5-8 illustrates the kinds of crowdshipper routing in a service zone. It is assumed that a crowdshipper visits only customers within the same service zone on a route. However, there is no restriction for a crowdshipper to move to another service zone after completion of his/her previous routing to look for more work.

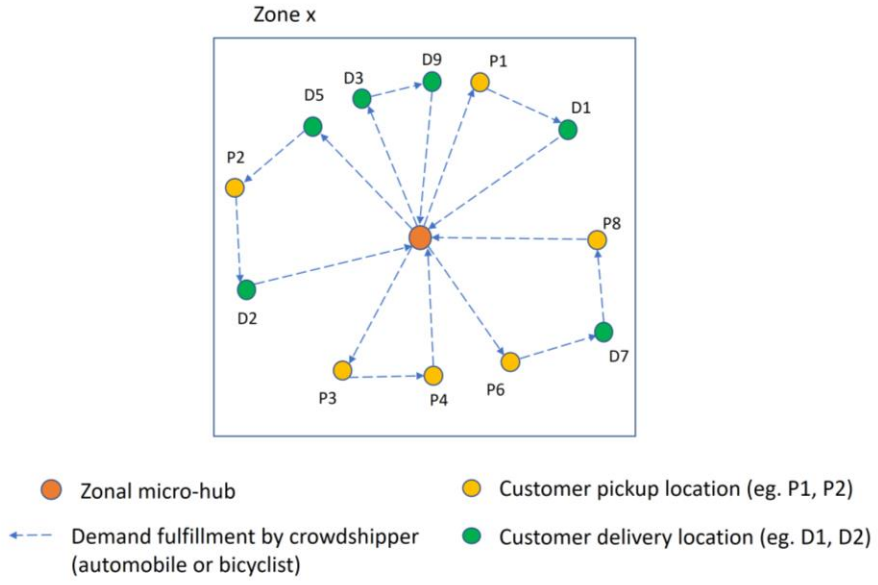


Figure 5-8: Crowdshipper routing in a service zone in M+C

Based on the above description, we formulate the M+C paradigm as two separate and connected routing problems. One concerns the crowdshipper routing within a service zone; and the other concerns the truck routing among microhubs.

The truck routing in M+C paradigm a Many-to-Many (M-M) Split Pickup-and-Delivery Problem (M-MSPDP) as follows:

(4) *Many-to-many pickup and delivery*: each microhub can be an origin to many destination microhubs and at the same time a destination to many origin microhubs;

(5) *Split pickup*: at each microhub i, the total pickup demand may exceed the available capacity of a single truck and therefore not all parcels will be picked up by one truck visit; and

(6) *At least one visit to a microhub by any truck*: a microhub may be visited by more than one truck. This is due to the split pickup operation as considered in this study.

As a comparison baseline, we consider a special case of truck routing in M+C where no splitting of loads is allowed at the microhubs and each truck must visit all the microhubs at least once until it delivers all the pairwise transshipment demand that it carries. The experimental setup is described in detail in Lin and Ballare (2020). We then apply the MS-BTS heuristic to the general case of M-MSPDP to obtain a solution (M+C with split loads allowed), while keeping all model parameters the same.

After that, we compare the performance of the M+C delivery paradigm w/o split loads (special case) and the M+C delivery paradigm with split loads (using the MS-BTS heuristic). The performance parameters selected for the comparison are the number of trucks dispatched, average total fuel consumption and average total VMT.

Table 5-29 presents the results of the solution for the M+C delivery paradigm by using the MS-BTS heuristic (allowing split loads).

Table 5-29: Results for the M+C delivery paradigm by using the MS-BTS heuristic (standard deviation in parenthesis)

Demand (# of customers in the service area)	**#trucks dispatched**	**Avg. total fuel consumption (gallons)**	**Average VMT**
108	2	8.09 (0.15)	177.10 (8.29)

180	2	9.78 (0.12)	241.16 (8.38)
432	4	24.31 (0.19)	624.86 (33.92)
1,800	16	106.49 (1.96)	2,648.77 (14.58)
18,000	158	961.73 (17.81)	23,478.51 (277.27)
180,000	1,583	10,074.99 (96.79)	225.063.64 (2,465.41)
1,800,000	15,781	98,110.36 (469.98)	2,670,731.03 (11,817.33)

As observed from Table 5-3, the performance parameters for M+C paradigm – the number of trucks dispatched, and the average total fuel consumption increase with the number of customers in the service area.

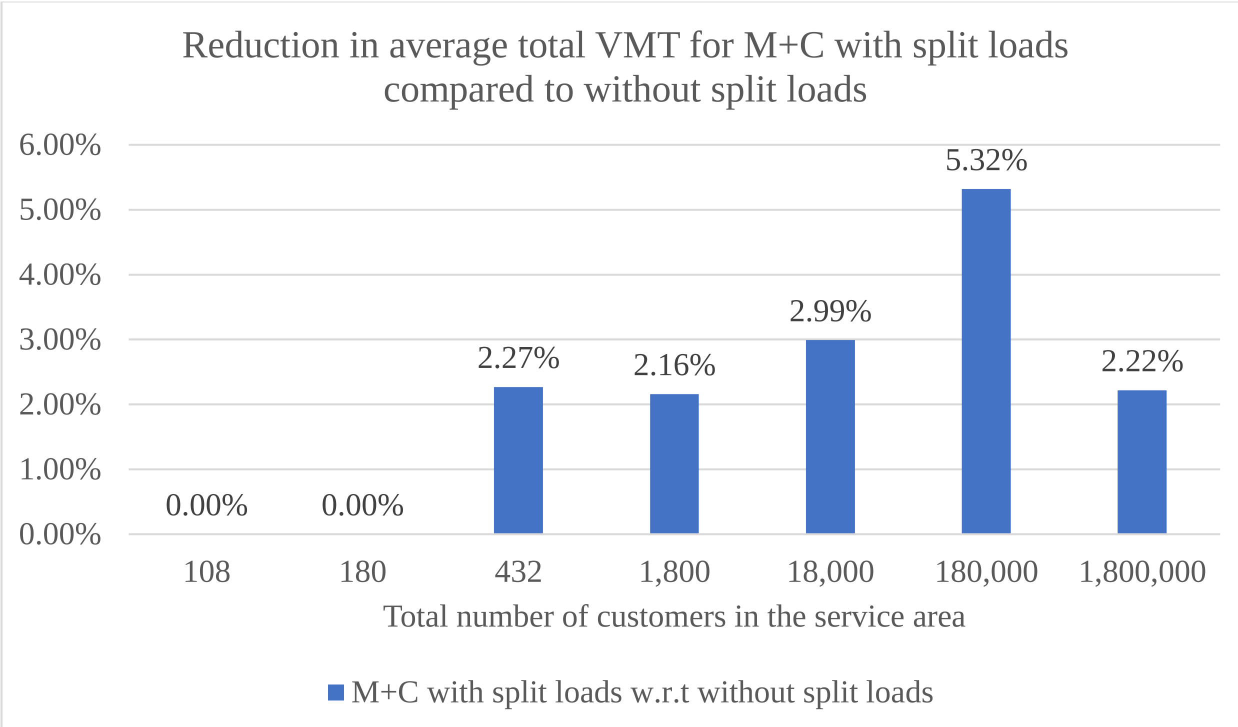


Figure 5-9. Reduction in the average total VMT for the M+C paradigm with split loads compared to without split loads

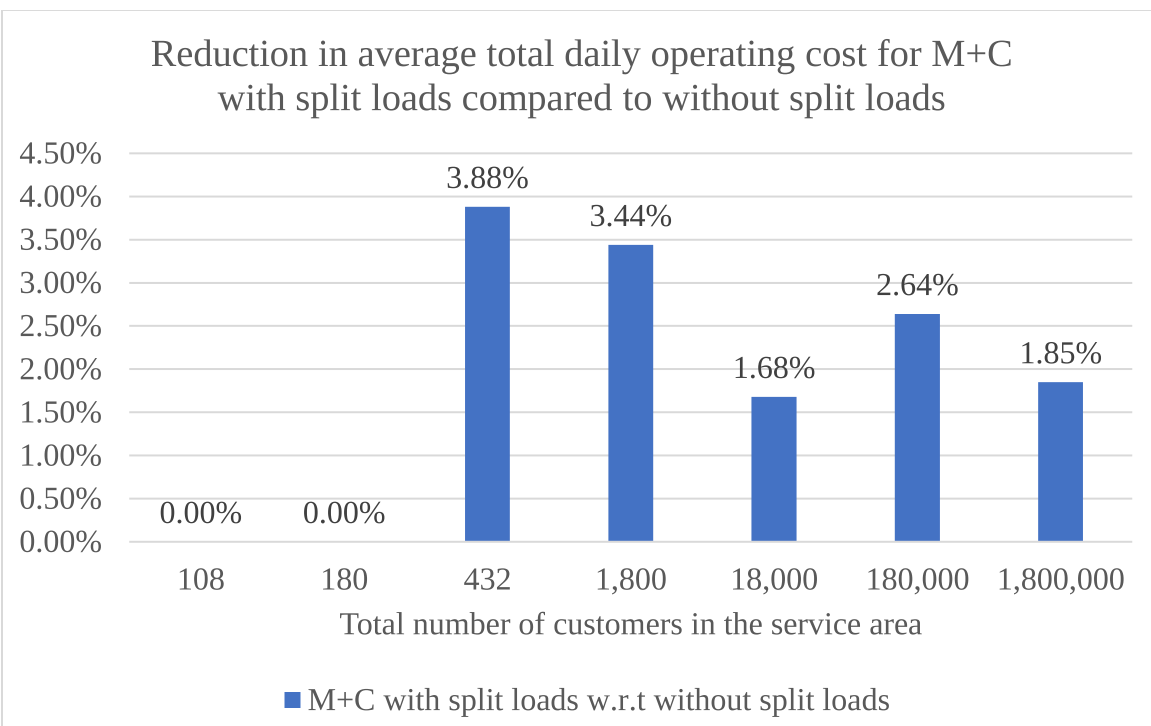


Figure 5-10. Reduction in the average total daily operating cost for the M+C paradigm with split loads compared to without split loads

From Figures 5-9 and 5-10, it is observed the M+C delivery paradigm with split loads delivers a reduction in the average total VMT and the average total daily operating cost as compared to the M+C delivery paradigm without split loads. As compared to the case of M+C delivery paradigm without split loads, the M+C with split loads allowed paradigm delivers a small reduction in the number of trucks dispatched (1.25-1.37%), average VMT (2.16-2.99%), and total fuel consumption (1.16-3.19%) for the large customer demands. The results for both scenarios are similar for the smaller customer demand as it represents a smaller opportunity for feasible loads to be split. The M+C with split loads allowed paradigm also witnesses a decrease in the average total daily operating cost in comparison with the M+C without split loads when the customer demand is large (1.68-3.88%). Thus, it is observed from the comparison of the results between the two cases of M+C delivery paradigm, allowing loads to be split brings a reduction in the number of trucks required to serve the total demand, as well as reduces the truck VMT, fuel consumption and the daily operating cost. It is important to note that there is no impact on the performance characteristics of the crowdshippers as the split loads are only being considered for the truck routing between the microhubs.

5.5.2 Case Study 2: Bike Rebalancing in a Bike-sharing System

In the second case study, we apply the MS-BTS heuristic to the Bike-sharing Rebalancing Problem (BRP). In this case study, we use the same problem setting described in Dell'Amico et al. (2016) and compare our MS-BTS solution with theirs.

The problem setting is described as follows. The BRP consists of a set of 250 bike stations and a depot. The coordinates for the bike stations are randomly generated and uniformly distributed over the range [-40,40] for both X and Y coordinates. The depot is located at [0,0]. For each bike station, requests for bike pick up or drop off are generated, which could be either positive or negative. A positive request indicates that the bike station has bikes available to be picked up for transshipment while a negative request indicates that the bike station is need of bikes to be dropped off. Bike stations with positive requests are considered as pickup stations and bike stations with negative requests are considered as delivery stations. The load demand is interpreted in terms of the number of bikes needed to be picked up or dropped off and the truck loaded capacity (TL) is restricted to the number of bikes that can be stored in the truck for transshipment. to maintain a specific service level. As is the case with the BRP literature, a station with no demand is also scheduled to be visited by the truck to allow routine inspection of bikes and stations. No temporary transshipment is considered between the bike stations and the trucks leave and return empty from/to the depot. The objective of the problem is to minimize the routing cost of the trucks to serve the demand at all bike-stations. For further details regarding the problem, please refer to Dell'Amico et al. (2016).

Dell'Amico et al. (2016) use the Destroy and Repair (D&R) metaheuristic algorithm to solve the problem of routing a fleet of capacitated vehicles to redistribute bicycles among the bike-stations of a bike-sharing system. The D&R algorithm is briefly described below. For detailed information on the heuristic, please refer to Dell'Amico et al. (2016).

Step 0. Initial solution by applying the Clark and Wright Savings algorithm, and the concept of ‘loss of flexibility’ (Dell'Amico et al., 2016) for merging of the routes. At first, dedicated routes to each bike station are created. This is followed by iteratively selecting two routes at a time to merge them into one, if feasible considering the positive and the negative requests and the truck load constraints. Dell'Amico et al., 2016 first introduced the concept of ‘feasibility’ of paths in BRP based on the properties such as removing or inserting a bike station, swapping two bike stations or merging two (partial) routes. ‘Loss of Flexibility’ for a merged route is then defined as the difference between the amount of feasibility for the resulting route (Dell'Amico et al., 2016).

Step 1. “Destroy”. That is, a number of bike stations (number is randomly selected with a uniform probability in a predefined interval [0.6582, 4] (Dell'Amico et al., 2016)) are randomly selected, one at a time, independent of each other and with uniform probability and are removed from the existing solution.

Step 2. “Repair”. This is carried out in two ways. The first involves evaluating the feasibility and the cost of inserting each of the non-assigned vertices (left from the destroy step) in any position of the route or creating a dedicated route and selecting the option with the minimum cost till all vertices are assigned. The second is to make use of the same Clark and Wright Savings Algorithm as in the first step.

Step 3. A set of local search techniques are employed to improve the current solution.

Step 4. Go back to Step 2 and repeat until no further improvement can be achieved.

Since the MS-BTS heuristic is developed to solve the Many-to-Many problem with fixed origins and destinations, we make certain changes to the problem for fair comparison between the two heuristics. The load demand for the transportation requests is generated randomly and is uniformly distributed between the range of 0.1 – 0.9 TL with the truck capacity being 1.0 TL. Instead of the unpaired demands at each bike station considered by Dell'Amico et al., 2016 to create the initial solution, we generate the requests such that each request has an origin and a destination bike station allocated. Thus, each bike-station in our problem could be an origin and destination for other bike-stations, including more than one bike-station. This is then provided to the D&R meta-heuristic as the initial solution with paired pickup and delivery bike stations. The same is also solved using the MS-BTS heuristic, which addresses this problem as a many-to-many BRP with fixed origins and destinations.

We consider the problem with 250 bike-stations to compare the performance between the D&R meta-heuristic and the MS-BTS heuristic. The parameters for the D&R meta-heuristic are kept the same as given in Dell'Amico et al. (2016).

Table 5-30present the results of the evaluation of destroy and repair meta-heuristic in comparison with the MS-BTS heuristic in terms of solution quality and computational time.

Table 5-30: Comparison of the M+C special case and the M+C with split loads allowed delivery paradigm (standard deviation in parenthesis)

Instance no.	VMT			Computational Time		
	Destroy and Repair (A)	MS-BTS (B)	Difference $\frac{A-B}{B}\%$	Destroy and Repair (C)	MS-BTS (D)	Difference $\frac{C-D}{C}\%$
1	263.1	262.23	0.33%	23.55	22.60	4.04%
2	272.26	268.58	1.35%	32.15	31.35	2.48%
3	265.27	265.27	0.00%	28.26	27.68	2.07%
4	307.31	299.63	2.50%	25.65	25.22	1.68%
5	277.93	268.79	3.29%	25.01	24.19	3.28%
6	345.98	335.57	3.01%	28.93	28.10	2.86%
7	317.19	317.19	0.00%	21.38	21.01	1.73%
8	322.96	318.08	1.51%	32.95	32.22	2.21%
9	346.68	343.14	1.02%	31.33	30.86	1.50%
10	249.38	244.17	2.09%	26.67	26.08	2.20%
11	279.36	271.45	2.83%	31.91	31.55	1.12%
12	265.76	265.76	0.00%	21.92	21.42	2.27%
13	330.36	330.36	0.00%	33.33	32.18	3.45%

14	246.79	246.30	0.20%	24.42	23.70	2.94%
15	274.74	269.22	2.01%	24.12	23.63	2.02%
16	308.66	301.44	2.34%	21.27	20.46	3.82%
17	327.75	327.75	0.00%	33.4	32.25	3.43%
18	263.99	256.41	2.87%	27.9	26.80	3.95%
19	257.93	250.97	2.70%	23.56	22.97	2.49%
20	283.41	274.88	3.01%	34.85	33.73	3.21%
21	343.3	343.30	0.00%	25.94	25.20	2.86%
22	304.5	303.59	0.30%	21.64	20.58	4.89%
23	308.6	299.56	2.93%	24.48	23.62	3.51%
24	321.8	319.97	0.57%	29.25	28.78	1.61%
25	294.99	294.99	0.00%	24.78	24.24	2.18%
26	292.75	292.75	0.00%	33.46	32.42	3.11%
27	329.43	316.52	3.92%	25.22	24.31	3.59%
28	311.19	301.39	3.15%	23.98	23.15	3.46%
29	268.12	268.12	0.00%	26.15	24.95	4.58%
30	299.32	292.76	2.19%	25.65	24.59	4.12%
Average	**296.03 (± 29.32)**	**291.67 (± 29.17)**	**1.47%**	**27.10 (±4.04)**	**26.33 (±3.99)**	**2.86%**

Thus, from the above table we can observe that on average the MS-BTS delivers a better solution in slightly lesser time as compared to the Destroy and Repair meta-heuristic. Both heuristics show a similar performance in 8 out of the 30 instances. However, the MS-BTS heuristic delivers a smaller solution (0.20-3.92%) as compared to the Destroy and Repair meta-heuristic for the remaining 22 instances and consumes less (1.02-4.89%) computation time. The MS-BTS could be improved further by exploring other local search techniques.

7. Conclusion

In this study, we introduce the Many-to-Many Split Pickup and Delivery problem. We develop a MS-BTS heuristic based on our understanding of the maximum benefits achieved by allowing split loads that can solve large problems requiring a reasonable amount of computational time. Split loads to be generated were decided from the tabu list maintained allowing the space in the solution space to be searched. A modified form of the Clarke and Wright's savings algorithm is used to make local improvements. Further local improvements are made possible by swap and insertion moves.

We evaluate the performance of the MS-BTS heuristic with randomly generated data in comparison to the exact solution method as well as two existing heuristics, PDPSL and TESA. We find that the MS-BTS heuristic performs well with an acceptable error in the solution quality than the exact solution (with an average of 5.87%), the PDPSL heuristic (with an average of 5.13%), and the TESA heuristic (with an average of 1.16%). On the other hand, MS-BTS out performs those methods in terms of computation time by 5.91% (TESA), 10.14% (PDPSL), and 79.79% (the exact solution method).

We further apply the MS-BTS heuristic to solve for two applications of the M-MSPDP: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bike rebalancing in a bike-sharing system (i.e., M-MSPD-OC). We find the MS-BTS to be useful in solving large scale problems for both applications.

This research indicates that the M-MSPDP should be further explored, with opportunities to decide the order of splitting the loads to search the solution space more efficiently. Research may also be conducted in the local improvement techniques order to improve the vehicle routing.

Chapter 6 Future Logistics: Impact of automation

In light of the potential benefits and implications of complete automation in freight handling and delivery, we also consider a futuristic delivery paradigm where all stages of the last-mile demand fulfillment are handled without any involvement of human factor. In this paradigm, the parcels are sorted, loaded onto and unloaded from trucks at the central hub using robots or machines which are fully automated and require minimum human intervention. In addition, all vehicles transporting freight between the customer and the central hub are fully automated/self-driving. We assume that no human decision maker is present in the entire system which completes the tasks based on the pre-programmed rules. A brief commentary on the impacts of such a proposed delivery paradigm is presented here.

6.1 Introduction

Automation is expected to have an impact on the way we go about our day to day lives, including how we work and commute. Recent developments in artificial intelligence (AI), advanced robotics, 3D printing, deep learning, and the Internet of Things (IoT) have made it feasible for these technologies to be adapted in our workplaces (Baker, 2004; Klumpp, 2018). From virtual assistants to self-driving vehicles, some levels of automation have already penetrated our lives, while improving our efficiency but also posing a threat to our livelihoods itself at the same time (Klumpp, 2018).

With the rapid developments in technology, significant research has also been conducted on the potential positives and negatives of automation in the future. Most researchers agree on two possible future scenarios (Arntz et al., 2016). The first scenario results in several negative outcomes of automation, including a threat to the labor workforce. In this scenario, due to most of the jobs being undertaken by robots and artificial intelligence, a permanent rate of high unemployment is predicted. The second scenario delivers the benefits of automation – safer workplace, cleaner environment, more productive and prosperous society. In this scenario, most of the displaced workers are able to be reskilled and find alternative or better jobs (Acemoglu, and Restrepo, 2017).

Automation helps in increasing labor productivity, quality of products, employee safety and reduce labor cost and lead time (Groover, 2008). Though, automation also suffers from various problems. These include high cost of equipment, lack of flexibility, integration into existing systems, maintenance issues and need for training of workforce etc. (Dadzie and Johnston, 1991; Naish and Baker, 2004; Baker and Halim, 2007). Automation in the logistics industry involves applications such as automated loading and unloading systems, conveyor belts, bar code systems, sorting or screening systems, item picking systems etc. (Dadzie and Johnston, 1991; Öjmertz, 1998; Frazelle and Frazelle, 2002; Baker, 2004; Echelmeyer et al., 2008).

6.2 Automation in the logistics industry

In the United States, motorized freight has been dominating the vast and growing freight transportation market. By 2045, the transportation sector is expected to represent \$1.6trillion of total GDP for the United States with over 40% increase in freight movement tonnage for the trucking industry alone (US DOT, 2018). Low wages, long work hours and related health impacts has led to a high voluntary in the trucking industry, which also suffers from hours of service violations and has witnessed an increase in large truck-related crashes in the recent years (Tompkins et al., 2010). With the rising public concern regarding environmental, labor and safety issues, and the reluctance of the government to add capacity to the existing highway network, it is prudent to consider other alternatives to the traditional freight transport (Sharma et al., 2015).

Automation is already present in significant amounts in most of the modern industries worldwide and has been integrated with the traditional operations. This level of automation has resulted in a considerable rise in the productivity of these industries. However, no or limited progress can be observed in automating trucks, where the established labor-intensive practices pose a challenge to enhancing productivity levels. The present highway system would remain adequate for considerable period in the future with no new investment required, if only the trucks on the highway system could be displaced by automation. With automation of the trucks, a reduction in traffic congestion and an improvement in the highway safety would be expected with reduced wear and tear of the highway infrastructure (Winroth et al., 2007; Nowakowski, 2015).

As freight and logistics solutions are getting smarter and connected, researchers are increasingly faced with the question as to how it would transform the logistics industry in the future. Automated warehouses and ports may reduce the number of jobs available, potentially save lives and increase the operation efficiency of the facility several folds. Gantry cranes, transport vehicles and stacking cranes can all be completely and remotely operated by software, reducing the number of errors. Also, human workers need not be present in more dangerous areas of the port where goods are being loaded and unloaded, and the entire operations can be sped up considerably. Automated freight trucks, on the other hand could bring a reduction in operational cost, thereby allowing more capital to be invested in improving operations and enhancing capabilities (Gregor et al., 2017).

Apart from the Automated Parcel Lockers which would be described in detail in Chapter No. 4, other examples of automation in urban logistics are presented below.

Warehousing operations

Modern warehouses already deploy autonomous vehicles to pickup, position and parcel products inside the warehouse. These vehicles follow a preprogrammed route which requires a relatively low investment for adapting the warehouse infrastructure. The vehicles reply on inputs received from the cameras and lasers installed on them to navigate the warehouse environment (Mora et al., 2006). The vehicle is able to create a 3-D map of its surroundings from the inputs received from the cameras and lasers and the next generation vehicles are even able to have more navigational freedom and independent decision-making authority to serve a wide variety of applications (Zhou et al., 2017).

Autonomous loading and transport

Deployment of self-driving vehicles in a warehouse environment allows for optimization of the loading and unloading process, thereby increasing the overall efficiency as well as safety. For e.g. consider the KARIS PRO System developed by the Karlsruhe Institute of Technology (KIT), Germany. In this system, a fleet of a number of small autonomous vehicles are deployed to transport goods in coordination with each other to form a continuous conveyer system (Di et al., 2017; Zhou et al., 2017).

Self-driving vehicles

Google is already testing technology with driverless cars on the road. It can be reasonably assumed that after overcoming the regulatory and labor organization barriers, driverless trucks would soon be deployed on the roads. Other than reducing the transportation costs, this would also eliminate the need for the restriction on hours of service and maintaining log-books, improving the overall supply-chain efficiency (Zhou et al., 2017). Japan has successfully conducted trials on coordinating a fleet of vehicles to identify self- position and potential obstacles, allowing them to travel close to each other to take advantage of reducing aerodynamic drag to reduce fuel costs up to 15% (NEDO, 2019).

Even, the loading and unloading process for a truck can be completely automated once the truck has arrived at a distribution center or a customer facility. This is already being implemented by Amazon for their several distribution centers in the United States. The robotic system deployed by Amazon enables the product shelves to be brought directly to the human handler saving the time for locating the product on the aisles (Zuden et al., 2004; Zhou et al., 2017).

Although, there is still time for the regulations to allow traffic to share the roads with fully-automated trucks, the main argument for their adoption would be improved road safety. Several fatal incidents are a result of preventable human driver-error (distracted driving, reduced blind spot visibility etc.), which can be significantly reduced by a driverless vehicle (Fagnant et al., 2015).

6.3 Possible impacts of automation in the logistics industry

Adoption of automation is driven by the inherent labor and cost efficiencies. Several potential outcomes of automation have been identified by the researchers, including significant health benefits for the environment and the population but with unprecedented workforce related challenges (Baker, 2006). With the recent advances in automation, data analysis will allow to increase the efficiency in routine tasks in transportation and warehousing thereby threatening jobs (Baker, 2006). However, the World Economic Forum (WEF) estimates the creation of new jobs due to the new skillsets required to manage the digital platforms, thus resulting in a net positive impact on jobs (Baker and Halim, 2007; WEF, 2019). It is believed that automation will bring about a net benefit to the society though with some detrimental impacts. A report by the National Bureau of Economic Research outlining the impacts of automation in the United States workforce did not estimate any gains in employment due to automation. According to the study, the automation not only resulted in loss of employment in most scenarios but also a reduction of wages for occupations where automation was not deployed (Dadzie and Johnston, 1991).

The degree of autonomy in the vehicles will also decide the magnitude of impact that it will have. The trucking industry will start benefitting even with the smallest amount of automation for truck-driving, leading to a decrease in the shortage of drivers and their turnover due to their improved wellness. At the same time, more comfortable conditions, technology-adoption and associated higher driving wages (due to the advanced skills required to manage an autonomous driving truck) in truck-driving will attract newer drivers (Mora et al., 2017). In the future, platooning of autonomous trucks is possible where the lead truck may be either controlled from the operations center or the truck depot or might be driven by a human while focusing on planning and logistics during motion (Di et al., 2017). However, adoption of the automated technologies in the trucking industry is directly dependent on the scale of investment, applicable legislations in place, as well as how the support infrastructure evolves, thus almost requiring a decade to achieve full automation (Zuden et al., 204).

The most obvious benefit to the society from automation will be through improvement health of the environment and the population through reduced emissions, and considerable improvement in workplace safety, especially in hazardous occupations and also bring a reduction in road fatalities (Eden and Gaggl, 2018). Automation will also contribute to the improved public heath not just through reduction in emissions and workplace accidents, but also by expediting the health-care delivery by implementing AI leading to reduced workload and increased productivity for the medical staff (Baker, 2006; Eden and Gaggl, 2018). Automation is expected to have several environmental benefits as well other than the reduced emissions. Approximate, 8.5 % reduction in global emissions has been estimated by WEF due to the implementation of automation in automotive, electricity and logistics industries by 2025 (WEF, 2019). The improved efficiency in all sectors will also have the benefit of reduction in the consumption of natural resources but will add to the growing e-waste issues especially in developing and under-developed countries (Zuden et al., 2017).

Along with the positives, several social concerns exist with the increased automation. Changes in the employment profiles to the scale of those observed during the industrial revolution are anticipated. During the industrial revolution, agricultural workers were increasingly replaced by the steam-powered machines, but at the same time created much larger number of employment opportunities in the factories where these machines were assembled, overall resulting in an improved standard of living. Automation is expected to bring about a similar change in the employment markets with opportunities arising in production, programming, sales, service and maintenance of automated machines. There are also discussions at the workplace to investigate collaboration opportunities between automated machines and human workers at larger scale. At the same time, health issues related to unemployment and anxiety may witness a rise due to the increase in automation worldwide (Frazelle and Frazelle, 2001). With all its positives and negatives, there is still clarity on the long-term implications to incorporating automation in the logistics sector. Automation in the logistics sector will no doubt improve operational efficiencies, add value to the service, delivery better economic returns and create higher value-adding employment opportunities.

6.4 Future Trends

3D printing technology (additive manufacturing) has witnessed some serious investments from global manufactures in recent times, due to the rapid progress made by the technology. However, the possible impact of 3D printing on the supply chains globally is not known at present. 3D printing is not yet mature to threaten the benefits delivered by the economies of scale in several sector (Economidou et al., 2018). The cost of the raw material used in the 3D printing machines is quite expensive compared to the conventional production lines built for handling high-volume of raw materials at present. With the fall in price of the raw material for the 3D printing machines in future, other factors may dictate the nature of the supply chains for e.g. urgency, acceptable quality, flexibility etc. (Balletti et al., 2017).

Chapter 7 Future Work

In this dissertation we have examined a range of methods of increasing the efficiency and reducing the cost of the last-mile delivery in urban areas. In this chapter we also identify several other areas which may be explored for further research in future. This proposed future work is presented in the following sections.

7.1 Crowdsourced delivery

In this study, we analyze the performance of an existing crowdsourced company. Further research should be conducted on identifying the behavior and motivation of crowdshipping participants, both senders and drivers, as well as the correct pricing and compensation mechanism to increase participation is such a system. The success of the crowdsourcing delivery system depends on achieving and maintain critical mass of customers and drivers, and thus efforts to attract participation from them should be investigated. It will also be interesting to obtain details of what is being transported in the parcels (for e.g. raw materials, spare components etc.) to analyse spatial autocorrelation trends in the neighboring areas. At the same time, insights should be drawn from other shared economy examples like ridesharing (Uber, Lyft etc.) and housing (AirBnB) to identify potential challenges for the crowdsourced delivery system.

7.2 Microhubs with Crowdshipping

Here, we analyze the performance of a proposed delivery paradigm that combines microhubs with crowdshipping. Though, we consider a static problem in our study, a dynamic problem can be considered in the future. A bidding process also can be considered for the compensation mechanism of the crowdshippers. In future, a relay between the crowdshippers can be considered to extend the range of delivery for crowdshippers. Crowdshippers with variable carrying capacity and using other modes like walking or e-scooters should also be explored. The microhubs also do not have to be located at a fixed position but could dynamically change their position based on the demand, i.e. facility location problem (Kafle et al., 2017). Also, we did not consider any failed deliveries and any potential parcel returns which may be considered in the future. Additionally, we could consider road network condition to see the real impact of the M+C delivery paradigm for on-time delivery. Furthermore, the environmental impact analysis of the crowdsourced delivery system could be conducted in future. And finally, a fully automated scenario could be considered where parcels are delivered by autonomous vehicles and parcel sorting is done without human effort at the microhubs.

7.3 Many-to-Many Split Pickup-and-Delivery Problem

We present a heuristic solution to solve introduce the general Many-to-Many Split Pickup-and-Delivery Problem (M-MSPDP). We also apply the MS-BTS heuristic to solve for two applications of the M-MSPDP: parcel pickup and delivery among parcel stations (i.e., M-MSPDP-FPD) and bike rebalancing in a bike-sharing system (i.e., M-MSPD-OC). In future, further applications of the MS-BTS heuristic could be investigated. We did not consider time windows during our evaluation of the heuristic, but this could be addressed in the future. Also, compensation and operating hours constraints for the truck drivers could be considered in the future. The tabu search heuristic could also be used to improve the local neighborhood search than just for simply deciding the selection of the split loads.

7.4 Future automated logistics

Automated logistics in the future is expected to improve the transparency, safety and overall efficiency of the entire supply chain. However, research needs to be conducted in evaluating how this would impact the human workforce, customer expectations of data privacy and security, and bring changes in the regulatory environment. In addition, questions regarding the rate of adoption of automation technology by the logistics companies and addressing the liability issues also need to be investigated. Automation in logistics is expected to bring a reduction in the workforce requirement but will also create a need for a more skilled workforce to oversee the automated operations. In addition, the scale of technology adoption (both automation and 3-d printing) at which the transportation costs will become equal or lesser than the conventional delivery paradigm needs to be investigated.

Cited Literature

Acemoglu, D. and Restrepo, P., 2017. Robots and jobs: Evidence from US labor markets.

Agatz, N. A., Erera, A. L., Savelsbergh, M. W., and Wang, X. Dynamic ride-sharing: A simulation study in metro Atlanta. *Transportation Research Part B*: *Methodological*, vol. 45 no. 9, 2011, p. 1450–1464.

Akçelik, R., Besley, M. Operating cost, fuel consumption, and emission models in aaSIDRA and aaMOTION. In: 25th Conference of Australian Institutes of Transport Research (CAITR 2003). University of South Australia, Adelaide, Australia, 2003.

Aleman, R.E. and Hill, R.R., 2010. A tabu search with vocabulary building approach for the vehicle routing problem with split demands. *International Journal of Metaheuristics*, 1(1), pp.55-80.

Aleman, R.E., Zhang, X. and Hill, R.R., 2010. An adaptive memory algorithm for the split delivery vehicle routing problem. Journal of Heuristics, 16(3), pp.441-473.

Amazon.com. (2018). Amazon.com: Amazon Locker Delivery. [online] Available at: https://www.amazon.com/b?ie=UTF8&node=6442600011 [Accessed 17 Jul. 2018].

Anderson, S., Allen, J., & Browne, M. Urban logistics—how can it meet policy makers' sustainability objectives? *Journal of Transport Geography*, Vol. 13, No. 1, 2005, pp. 71-81.

Anily, S. and Hassin, R. 1992. The swapping problem, *Networks* 22 419–433

Anselin, L., Syabri, I. and Kho, Y., 2006. GeoDa: an introduction to spatial data analysis. *Geographical analysis*, *38*(1), pp.5-22.

Archetti, C. and Speranza, M. G. 2008. "The Split Delivery Vehicle Routing Problem: A Survey," The Vehicle Routing Problem: Latest Advances and New Challenges," Operations Research/Computer Science Interfaces Series, Vol. 43, Part I, pp. 103-122.

Archetti, C. and Speranza, M.G., 2012. Vehicle routing problems with split deliveries. International transactions in operational research, 19(1-2), pp.3-22.

Archetti, C. and Speranza, M.G., 2012. Vehicle routing problems with split deliveries. International transactions in operational research, 19(1-2), pp.3-22.

Archetti, C., Bianchessi, N. and Speranza, M.G., 2014. Branch-and-cut algorithms for the split delivery vehicle routing problem. *European Journal of Operational Research*, *238*(3), pp.685-698.

Archetti, C., Savelsbergh, M., Speranza, G. The Vehicle Routing Problem with Occasional Drivers. *European Journal of Transportation Research,* vol. 254 no. 2, 2016, p. 472-480.

Archetti, C., Speranza, M.G. and Hertz, A., 2006. A tabu search algorithm for the split delivery vehicle routing problem. *Transportation science*, 40(1), pp.64-73.

Arntz, M., Gregory, T. and Zierahn, U., 2016. The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment, and Migration Working Papers, (189), p.0_1.

Arslan, A.M., Agatz, N., Kroon, L. and Zuidwijk, R., 2018. Crowdsourced Delivery—A Dynamic Pickup and Delivery Problem with Ad Hoc Drivers. *Transportation Science*.

Arvidsson, N., Woxenius, J. and Lammgård, C., 2013. Review of road hauliers' measures for increasing transport efficiency and sustainability in urban freight distribution. *Transport Reviews*, 33(1), pp.107-127.

Attanasio A., Cordeau, J.-F., Ghiani, G., and Laporte, G. Parallel tabu search heuristics for the dynamic multi-vehicle dial-a-ride problem. *Parallel Computing,* vol. 30 no. 3, 2004, p. 377–387.

Augereau, V., & Dablanc, L. An Evaluation of Recent Pick-up Point Experiments in European Cities: the Rise of two Competing Models? in Innovations in City Logistics, ed. Taniguchi, E., & Thomson, R.G., *Nova Science*, 2008, pp. 301-320.

Baker, P. and Halim, Z., 2007. An exploration of warehouse automation implementations: cost, service and flexibility issues. Supply Chain Management: An International Journal, 12(2), pp.129-138.

Baker, P., 2004. The adoption of innovative warehouse equipment. In Logistics Research Network 2004 Conference Proceedings (pp. 25-35).

Baker, P., 2006. Designing distribution centres for agile supply chains. *International Journal of Logistics*, *9*(3), pp.207-221.

Balletti, C., Ballarin, M. and Guerra, F., 2017. 3D printing: State of the art and future perspectives. Journal of Cultural Heritage, 26, pp.172-182.

Barth, M., & Boriboonsomsin, K. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment*, Vol. 14, No. 6, 2009, pp. 400-410.

Barth, M., & Boriboonsomsin, K. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment*, Vol. 14, No. 6, 2009, pp. 400-410.

Barth, M., Younglove, T., & Scora, G. Development of a heavy-duty diesel modal emissions and fuel consumption model. California Partners for Advanced Transit and Highways (PATH), 2005.

Battarra, M., Cordeau, J.F. and Iori, M., 2014. Chapter 6: pickup-and-delivery problems for goods transportation. In Vehicle Routing: Problems, Methods, and Applications, Second Edition (pp. 161-191). Society for Industrial and Applied Mathematics.

Behrend, T. S., Sharek, D. J., Meade, A. W. & Wiebe, E. N. The viability of crowdsourcing for survey research. *Behavior research methods*, vol. 43 no. 3, 2011, p. 800-813.

Belenguer, J.M., Martinez, M.C. and Mota, E., 2000. A lower bound for the split delivery vehicle routing problem. *Operations research*, 48(5), pp.801-810.

BELK, R. You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, vol. 67 no. 8, 2014, p. 1595-1600.

Bellotti, V., Ambard, A., Turner, D., Gossmann, C., Demkova, K., & Carroll, J. M. A muddle of models of motivation for using peer-to-peer economy systems. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, April 2015, pp. 1085-1094. ACM.

Bilik, J. Parcel machines-green solution for green cities. In Presentation at 1st International Conference Green Logistics for Greener Cities, Szczecin, 2014.

Blocken, N. M. P., Short, S. W., Rana, P., & Evans, S. A literature and practice review to develop sustainable business model archetypes. *Journal of cleaner production*, Vol. 65, 2014, pp. 42-56.

Bls.gov. (2018a). Light Truck or Delivery Services Drivers. [online] Available at: https://www.bls.gov/oes/current/oes533033.htm [Accessed 1 Jan. 2018].

Bls.gov. (2018b). Couriers and Messengers. [online] Available at: https://www.bls.gov/oes/current/oes435021.htm#ind [Accessed 1 Jan. 2018].

Bothun, D., & Lieberman, M. "Consumer Intelligence Series: The Sharing Economy." PwC. http://www.pwc.com/us/en/industry/entertainment-media/publications/consumer-intelligenceseries/assets/pwc-cis-sharing-economy.pdf, 2015.

Botsman, R., 2014. Crowdshipping: using the crowd to transform delivery. *AFR Boss Magazine*, (September 12).

Boudia, M., Prins, C. and Reghioui, M., 2007, October. An effective memetic algorithm with population management for the split delivery vehicle routing problem. In International Workshop on Hybrid Metaheuristics (pp. 16-30). Springer, Berlin, Heidelberg.

Braunstein, L., 2015. E-Commerce Giants Battling for the "Last Mile" of Delivery. The magazine of the urban land institute.

Brinkmann, J., Ulmer, M.W. and Mattfeld, D.C., 2019. Dynamic lookahead policies for stochastic-dynamic inventory routing in bike sharing systems. *Computers & Operations Research*, *106*, pp.260-279.

Browne, M., Allen, J., & Leonardi, J. Evaluating the use of an urban consolidation centre and electric vehicles in central London. *IATSS research*, Vol. 35, No. 1, 2011, pp. 1-6.

Brummelman, H.J., Kuipers, B., Vale, N., 2003. Effecten Van Packstations Op Verkeersbewegingen [Impacts of Locker Points on Mobility] TNO Inro, Delft (in Dutch)

Cabral, L., & Hortacsu, A. The dynamics of seller reputation: Evidence from eBay. The Journal of Industrial Economics, vol. 58 no. 1, 2010, p. 54-78.

Campos, V., Corberán, A. and Mota, E., 2008. A scatter search algorithm for the split delivery vehicle routing problem. In Advances in computational intelligence in transport, logistics, and supply chain management (pp. 137-152). Springer, Berlin, Heidelberg.

Casazza, M. and Ceselli, A., 2016. Exactly solving packing problems with fragmentation. *Computers & Operations Research*, *75*, pp.202-213.

Casazza, M., 2016. Exactly solving the Split Pickup and Split Delivery Vehicle Routing Problem on a bike-sharing system (Doctoral dissertation, Universita degli Studi di Milano; Universite Paris 13).

Chan, N. D., and Shaheen, S. A. Ridesharing in north America: Past, present, and future. *Transport Reviews*, vol. 32 no. 1, 2012, p. 93–112.

Chemla, D., Meunier, F. and Calvo, R.W., 2013. Bike sharing systems: Solving the static rebalancing problem. *Discrete Optimization*, *10*(2), pp.120-146.

Chen, C., Pan, S. Wang, Z., and Zhong, R. Y. Using taxis to collect citywide e-commerce reverse flows: a crowdsourcing solution. *International Journal of Production Research*, vol. 55 no. 7, 2016, p. 1833-1844.

Chen, Q., & Lin, J. A Preliminary Investigation of Sustainable Urban Truck Routing Strategies Considering Cargo Weight and Vehicle Speed. In the 2014 *Transportation Research Board Annual Meeting*, Washington DC, paper (No. 14-3300), 2014.

Chen, S., Golden, B. and Wasil, E., 2007. The split delivery vehicle routing problem: Applications, algorithms, test problems, and computational results. *Networks: An International Journal*, 49(4), pp.318-329.

Citylab-project.eu. (2018). Amsterdam. [online] Available at: http://www.citylab-project.eu/amsterdam_workshop.php [Accessed 8 Mar. 2018].

Cohen, B., & Kietzmann, J. Ride on! Mobility business models for the sharing economy. *Organization & Environment*, vol. 27 no. 3, 2014, p. 279-296.

Contardo, C., Morency, C. and Rousseau, L.M., 2012. *Balancing a dynamic public bike-sharing system* (Vol. 4). Montreal, Canada: Cirrelt.

Conway, A., Cheng, J., Kamga, C. and Wan, D. 2017. Cargo cycles for local delivery in New York City: Performance and impacts. *Research in Transportation Business & Management*, 24, pp.90-100.

Conway, A., Fatisson, P.-E., Eickemeyer, P., Cheng, J., & Peters, D. Urban micro-consolidation and last mile goods delivery by freight-tricycle in Manhattan: Opportunities and challenges. Paper presented at the Conference proceedings, *Transportation Research Board* 91st Annual Meeting 2012, 2011.

Crainic, T. G., Gendreau, M., Potvin, J. Y. Intelligent freight-transportation systems: Assessment and the contribution of operations research. *Transportation Research Part C*: *Emerging Technologies,* vol. 17 no. 6, 2009, p. 541–557.

Dablanc, L., 2007. Goods transport in large European cities: Difficult to organize, difficult to modernize. *Transportation Research Part A: Policy and Practice*, 41(3), pp.280-285.

Dadzie, K.Q. and Johnston, W.J., 1991. Innovative automation technology in corporate warehousing logistics. Journal of Business Logistics, 12(1), p.63.

Dell, M., Iori, M., Novellani, S. and Stützle, T., 2016. A destroy and repair algorithm for the bike sharing rebalancing problem. *Computers & operations research*, *71*, pp.149-162.

Dell'Amico, M., Hadjicostantinou, E., Iori, M. and Novellani, S., 2014. The bike sharing rebalancing problem: Mathematical formulations and benchmark instances. *Omega*, *45*, pp.7-19.

Dell’Amico, M., Iori, M., Novellani, S. and Subramanian, A., 2018. The bike sharing rebalancing problem with stochastic demands. *Transportation research part B: methodological*, *118*, pp.362-380.

Derigs, U., Li, B. and Vogel, U., 2010. Local search-based metaheuristics for the split delivery vehicle routing problem. *Journal of the Operational Research Society*, 61(9), pp.1356-1364.

Di Gaspero, L., Rendl, A. and Urli, T., 2013, May. A hybrid ACO+ CP for balancing bicycle sharing systems. In *International Workshop on Hybrid Metaheuristics* (pp. 198-212). Springer, Berlin, Heidelberg.

Di Tria, F., Lefons, E. and Tangorra, F., 2017. Cost-benefit analysis of data warehouse design methodologies. Information Systems, 63, pp.47-62.

Dias F.F., Lavieri P.S., Garikapati V.M., Astroza S., Pendyala R.M., and Bhat C.R. A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services. Technical paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, August 2016

Distributiongroup.com. (2018). [online] Available at: http://www.distributiongroup.com/articles/DCM0310we_boyd.pdf [Accessed 1 Jan. 2018].

Doyuran, T. and Çatay, B., 2011. A robust enhancement to the Clarke–Wright savings algorithm. *Journal of the Operational Research Society*, *62*(1), pp.223-231.

Dror, M. and Trudeau, P., 1989. Savings by split delivery routing. Transportation Science, 23(2), pp.141-145.

Dror, M. and Trudeau, P., 1990. Split delivery routing. Naval Research Logistics (NRL), 37(3), pp.383-402.

Dror, M., Laporte, G. and Trudeau, P., 1994. Vehicle routing with split deliveries. *Discrete Applied Mathematics*, 50(3), pp.239-254.

Ducret, R. (2014) Parcel deliveries and urban logistics: Changes and challenges in the courier express and parcel sector in Europe—The French case. *Research in Transportation Business & Management*, Vol. 11, pp. 15-22.

Echelmeyer, W., Kirchheim, A. and Wellbrock, E., 2008, September. Robotics-logistics: Challenges for automation of logistic processes. In Automation and Logistics, 2008. ICAL 2008. IEEE International Conference on (pp. 2099-2103). IEEE.

Economidou, S.N., Lamprou, D.A. and Douroumis, D., 2018. 3D printing applications for transdermal drug delivery. International Journal of Pharmaceutics.

Eden, M. and Gaggl, P., 2018. On the welfare implications of automation. Review of Economic Dynamics, 29, pp.15-43.

Efthymiou, D., C. Antoniou, and D P. Waddell. Factors Affecting the Adoption of Vehicle Sharing Systems by Young Drivers. *Transport Policy*, Vol. 29, 2013, pp. 64-73

Elhedhli, S., & Hu, F. X. (2005). Hub-and-spoke network design with congestion. *Computers & Operations Research*, Vol. 32 No. 6, pp. 1615-1632.

Erdoğan, G., Laporte, G. and Calvo, R.W., 2014. The static bicycle relocation problem with demand intervals. *European Journal of Operational Research*, *238*(2), pp.451-457.

Erickson, L.B. and Trauth, E.M., 2013, May. Getting work done: evaluating the potential of crowdsourcing as a model for business process outsourcing service delivery. In Proceedings of the 2013 annual conference on computers and people research (pp. 135-140). ACM.

Ermagun, A. and Stathopoulos, A., 2018. To bid or not to bid: An empirical study of the supply determinants of crowd-shipping. *Transportation Research Part A: Policy and Practice*, *116*, pp.468-483.

Esper, T. L., Jensen, T. D., Turnipseed, F. L., Burton, S. The last mile: an examination of effects of online retail delivery strategies on consumers. *Journal of Business Logistics* vol. 24 no. 2, 2003, p. 177–203

European Commission. Directorate-General for Energy. (2006). Keep Europe moving: sustainable mobility for our continent: mid-term review of the European Commission's 2001 Transport White Paper. Office for Official Publications of the European Communities.

Fagnant, D.J. and Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, pp.167-181.

Filippi, F., Nuzzolo, A., Comi, A. and Delle Site, P., 2010. Ex-ante assessment of urban freight transport policies. *Procedia-Social and Behavioral Sciences*, 2(3), pp.6332-6342.

Folkert, S., Eichhorn, C., 2007. Innovative Approaches in City Logistics: Alternatives Solution for Home Delivery Policy Notes. Disponível Em, pp. 4. http://www.Nichestransport.Org/Fileadmin/Archive/DeliverablesD.

Forma, I.A., Raviv, T. and Tzur, M., 2015. A 3-step math heuristic for the static repositioning problem in bike-sharing systems. *Transportation research part B: methodological*, *71*, pp.230-247.

Frazelle, E. and Frazelle, E., 2002. World-class warehousing and material handling (Vol. 1). New York: McGraw-Hill.

Frehe, V., Mehmann, J. and Teuteberg, F., 2017. Understanding and assessing crowd logistics business models–using everyday people for last mile delivery. *Journal of Business & Industrial Marketing*, *32*(1), pp.75-97.

Frizzell, P.W. and Giffin, J.W., 1995. The split delivery vehicle scheduling problem with time windows and grid network distances. Computers & Operations Research, 22(6), pp.655-667.

Furuhata, M., Dessouky, M., Ordez, F., Brunet, M.-E., Wang, X., and Koenig, S. Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological*, vol. 57, 2013, p. 28 – 46.

Gdowska, K., Viana, A. and Pedroso, J.P., 2018. Stochastic last-mile delivery with crowdshipping. *Transportation research procedia, 30*, pp.90-100.

Genta, G. Motor Vehicle Dynamics: Modelling and Simulation. World Scientific Publishing, Singapore, 1997.

Gevaers, R., Van de Voorde, E., & Vanelslander, T. (2009). Assessing characteristics of innovative concepts in last-mile logistics and urban distribution. In Conference proceedings of Metrans 2009, Long Beach, USA (pp. CD-ROM).

Gibson, B.J., Defee, C.C., and Ishfaq, R. The State of Retail Supply Chain: Essential Findings of the Fifth Annual Report. 2015: RILA, Dallas, TX.

Goetting, E. and Handover, W.N., 2016. Crowd-shipping: Is crowd-sourced the secret recipe for delivery in the future?. German Industry and Commerce Ltd./GCC.

Gonzalez Feliu, J., Ambrosini, C., & Routhier, J. L. (2012). New trends on urban goods movement modelling: proximity delivery versus shopping trips.

Gregor, T., Krajčovič, M. and Więcek, D., 2017. Smart connected logistics. Procedia engineering, 192, pp.265-270.

Groover, M.P. (2008) Automation, Production Systems, and Computer-Integrated Manufacturing, 3rd edition. Pearson Education Inc., Upper Saddle River, NJ.

Hamari, J., Sjöklint, M., Ukkonen, A. The Sharing Economy: Why People Participate in Collaborative Consumption. *Journal of the Association for Information Science and Technology*, vol. 67 no. 9, 2015, p. 2047-2059. DOI: 10.1002/asi.23552

HB Rai, S Verlinde, J Merckx, and C Macharis. Crowd logistics: an opportunity for more sustainable urban freight transport? - *European Transport Research Review*, 2017

Heller, N. (2019). *Is the Gig Economy Working?* [online] The New Yorker. Available at: https://www.newyorker.com/magazine/2017/05/15/is-the-gig-economy-working [Accessed 10 Aug. 2019].

Ho, S.C. and Szeto, W.Y., 2017. A hybrid large neighborhood search for the static multi-vehicle bike-repositioning problem. *Transportation Research Part B: Methodological*, *95*, pp.340-363.

Holguín-Veras, J., Campbell, S., Kalahasthi, L., & Wang, C. Role and potential of a trusted vendor certification program to foster adoption of unassisted off-hour deliveries. *Transportation Research Part A: Policy and Practice*, Vol. 102, No.C, 2017, pp. 157-171.

Howe, J. The rise of crowdsourcing. *Wired magazine*. Vol. 14, No. 6, 2006, pp. 1-4.

Ieeexplore.ieee.org. (2017). Connected shared mobility for passengers and freight: Investigating the potential of crowdshipping in urban areas - IEEE Conference Publication. [online] Available at: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8005629 [Accessed 26 Dec. 2017].

Isuzu.itruckwebsite.com. (2017). New 2014 Isuzu Reach Walk-in Van Specifications | HUSKY TRUCKS ISUZU. [online] Available at: http://www.isuzu.itruckwebsite.com/new-model-isuzu-2014-reach-walk-in-van-specifications [Accessed 27 Jul. 2017].

Iwan, S., Kijewska, K., & Lemke, J. Analysis of parcel lockers' efficiency as the last mile delivery solution–the results of the research in Poland. *Transportation Research Procedia*, Vol. 12, 2016, pp. 644-655.

Janjevic, M. and Ndiaye, A. (2017). Investigating the financial viability of urban consolidation centre projects. *Research in Transportation Business & Management*, 24, pp.101-113.

Janjevic, M. and Ndiaye, A. B., 2014. Development and application of a transferability framework for micro-consolidation schemes in urban freight transport. *Procedia-Social and Behavioral Sciences*, *125*, pp.284-296.

Janjevic, M., Kaminski, P., Ndiaye, A.B. Downscaling the consolidation of goods–state of the art and transferability of micro-consolidation initiatives. *Eur. Transp./TrasportiEuropei* Vol. 54, no. 13, 2013, pp. 1–21.

Jensen, P., Rouquier, J. B., Ovtracht, N., & Robardet, C. Characterizing the speed and paths of shared bicycle use in Lyon. *Transportation Research Part D: Transport and Environment*, Vol. 15, No. 8, 2010, pp. 522-524.

Jin, M., Liu, K. and Bowden, R.O., 2007. A two-stage algorithm with valid inequalities for the split delivery vehicle routing problem. *International Journal of Production Economics*, 105(1), pp.228-242.

Jin, M., Liu, K. and Eksioglu, B., 2008. A column generation approach for the split delivery vehicle routing problem. *Operations Research Letters*, 36(2), pp.265-270.

Jin, M., Liu, K. and Eksioglu, B., 2008. A column generation approach for the split delivery vehicle routing problem. *Operations Research Letters*, 36(2), pp.265-270.

Kafle, N., Zou, B., & Lin, J. Design and modeling of a crowdsource-enabled system for urban parcel relay and delivery. *Transportation Research Part B: Methodological*, Vol. 99, 2017, pp. 62-82.

Kedia, A., Kusumastuti, D. and Nicholson, A. (2017). Acceptability of collection and delivery points from consumers' perspective: A qualitative case study of Christchurch city. *Case Studies on Transport Policy*, 5(4), pp.587-595.

Klincewicz, J. G. Hub location in backbone/tributary network design: A review. *Location Science*, Vol. 6, No. 1, 1998, pp. 307-335.

Kloimüllner, C., Papazek, P., Hu, B. and Raidl, G.R., 2015, February. A cluster-first route-second approach for balancing bicycle sharing systems. In *International Conference on Computer Aided Systems Theory* (pp. 439-446). Springer, Cham.

Klumpp, M., 2018. Innovation Potentials and Pathways Merging AI, CPS, and IoT. Applied System Innovation, 1(1), p.5.

Koning, M., & Conway, A. (2015). Biking for goods is good: An assessment of CO2 savings in Paris. Compendium of papers, TRB 94th annual meeting, January 11–15, 2015. Washington, D.C.

Lan, X., Changchun, G. Crowdsourcing Changes Enterprise's Innovation Model [J]. *Shanghai Journal of Economics* vol. 3, 2010, p. 35-41.

Le, T.V. and Ukkusuri, S.V., 2019. Modeling the willingness to work as crowd-shippers and travel time tolerance in emerging logistics services. *Travel Behaviour and Society*, *15*, pp.123-132.

Lee, D. Y., Thomas, V. M., & Brown, M. A. Electric urban delivery trucks: Energy use, greenhouse gas emissions, and cost-effectiveness. *Environmental Science & Technology*, Vol. 47, No. 14, 2013, pp. 8022-8030.

Lee, H.L. and S. Whang. Winning the last mile of e-commerce. *MIT Sloan Management Review*, vol. 42 no. 4, 2001, p. 54-62

Lemke, J., Iwan, S. and Korczak, J. (2016). Usability of the Parcel Lockers from the Customer Perspective – The Research in Polish Cities. *Transportation Research Procedia*, 16, pp.272-287.

Lenstra, J.K. and Rinnooy Kan, A.H.G. (1981), Complexity of Vehicle and Scheduling Problems, *Networks* 11, 221-227.

Leonardi, J., Browne, M., & Allen, J. Before-after assessment of a logistics trial with clean urban freight vehicles: A case study in London. *Procedia-Social and Behavioral Sciences*, Vol. 39, 2012, pp. 146-157.

Lerner, W. and Audenhove, V.F., 2012. The future of urban mobility: towards networked, multimodal cities in 2050. *Public Transport International*, (2).

Li, B., Krushinsky, D., Reijers, H. A., and Van Woensel, T. The share-a-ride problem: People and parcels sharing taxis. *European Journal of Operational Research*, vol. 238 no. 1, 2014, p. 31–40.

Lin, J. and Ballare. S., 2020. A Last Mile Delivery Paradigm using Microhubs with Crowdshipping. *Transportation Science*, under review.

Ma, S., Zheng, Y., & Wolfson, O. T-share: A large-scale dynamic taxi ridesharing service. In Data Engineering (ICDE), 2013 IEEE 29th International Conference on April 2013, p. 410-421. IEEE.

Malhotra, A., & Van Alstyne, M. The dark side of the sharing economy and how to lighten it. *Communications of the ACM*, vol. 57 no. 11, 2014, p. 24-27.

Marjanovic, S., Fry, C. and Chataway, J. “Crowdsourcing based business models: in search of evidence for innovation 2.0”, *Science and Public Policy*, vol. 39 no. 3, 2012, p. 318-332.

Marx, P., 2016.The Gig Economy has Grown Big, Fast - and That's a Problem for Workers. Recode (accessed: 2017-06-28).

McKinnon, A., Browne, M., Whiteing, A., Piecyk, M. Green Logistics: Improving the Environmental Sustainability of Logistics. Kogan Page Publishers, 2015, p. 333.

McLeod, F., Cherrett, T., Song, L., 2006. Transport impacts of local collection/delivery points. Int. J. Logist. Res. Appl. 9 (3), 307–317. http://dx.doi.org/10.1080/13675560600859565.

McLeod, F.N., Cherrett, T.J., 2009. Quantifying the environmental benefits of collection/ delivery points. OR Insight 22 (3), 127–139. http://dx.doi.org/10.1057/ori.2009.2.

Mitra, S., 2005. An algorithm for the generalized vehicle routing problem with backhauling. *Asia-Pacific Journal of Operational Research*, *22*(02), pp.153-169.

Mitra, S., 2008. A parallel clustering technique for the vehicle routing problem with split deliveries and pickups. *Journal of the operational Research Society*, *59*(11), pp.1532-1546.

Mladenow, A., Bauer, C. and Strauss, C., 2016. "Crowd logistics": the contribution of social crowds in logistics activities. *International Journal of Web Information Systems*, *12*(3), pp.379-396.

Mora, M.C., Armesto, L. and Tornero, J., 2006. Management and transport automation in warehouses based on auto-guided vehicles. IFAC Proceedings Volumes, 39(15), pp.671-676.

Moreno, L., De AragãO, M.P. and Uchoa, E., 2010. Improved lower bounds for the split delivery vehicle routing problem. *Operations Research Letters*, 38(4), pp.302-306.

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. The impact of e-commerce on final deliveries: alternative parcel delivery services in France and Germany. *Transportation Research Procedia*, Vol. 4, 2014, pp.178-190.

Moroz, M., & Polkowski, Z. The last mile issue and urban logistics: choosing parcel machines in the context of the ecological attitudes of the Y generation consumers purchasing online. *Transportation Research Procedia*, Vol. 16, 2016, pp. 378-393.

Muñuzuri, J., Larrañeta, J., Onieva, L. & Cortés, P. Solutions applicable by local administrations for urban logistics improvement, *Cities*, Vol. 22, No. 1, 2005, pp. 15-28.

Naish, S. and Baker, P., 2004. Materials Handling-Fulfilling the Promises. Logistics and Transport Focus, 6(1), pp.18-27.

NEDO (2019). *New Energy and Industrial Technology Development Organization*. [online] Available at: https://www.nedo.go.jp/english/ [Accessed 10 Aug. 2019].

Nguyen, T.T. and Vu, T.D., 2019. Identification of Multivariate Geochemical Anomalies Using Spatial Autocorrelation Analysis and Robust Statistics. *Ore Geology Reviews*, p.102985.

Nowak, M., Ergun, Ö. and White III, C.C., 2008. Pickup and delivery with split loads. *Transportation Science*, *42*(1), pp.32-43.

Nowak, M.A., 2005. The pickup and delivery problem with split loads (Doctoral dissertation, Georgia Institute of Technology).

Nowakowski, C., Shladover, S.E. and Tan, H.S., 2015. Heavy vehicle automation: Human factors lessons learned. *Procedia Manufacturing*, 3, pp.2945-2952.

Ohnishi, H., 2008. Greenhouse gas reduction strategies in the transport sector: preliminary report. Tech. rep., OECD/ITF Joint Transport Research Centre Working Group on GHG Reduction Strategies in the Transport Sector, OECD/ITF, Paris.

Öjmertz, B. (1998) Materials Handling from a Value-Adding Perspective. Doctoral thesis, Department of Transportation and Logistics, Chalmers University of Technology, Göteborg, Sweden.

Paloheimo, H., Lettenmeier, M., Waris, H., 2016. Transport reduction by crowdsourced deliveries – a library case in Finland. *Journal of Cleaner Production* Vol. 132, 240–251. http://dx.doi.org/10.1016/j.jclepro.2015.04.103.

Panda, R., Verma, S., Mehta, B. Emergence and Acceptance of Sharing Economy in India: Understanding Through the Case of Airbnb. *International Journal of Online Marketing*, vol. 5 no. 3, 2015, p. 1-17. DOI: 10.4018/IJOM.2015070101

Piscicelli, L., Cooper, T., Fisher, T. The Role of Values in Collaborative Consumption: Insights from a Product-Service System for Lending and Borrowing in the UK. *Journal of Cleaner Production*, vol. 97, 2015, p. 21-29.

Pohl, G., 2013. Zipments thesis. New North Center.

Postmates, 2016. How do you Determine the Delivery Fee? Available at https://help.postmates.com/hc/en- us/articles/219625788- How- do- you- determine- the-Delivery-Fee-(accessed09.28.2016).

PostNL (2019). *PostNL starts installing Parcel Lockers at main NS stations and Schiphol*. [online] PostNL. Available at: https://www.postnl.nl/en/about-postnl/press-news/press-releases/2014/october/postnl-starts-installing-parcel-lockers-at-main-ns-stations-and-schiphol.html [Accessed 10 Aug. 2019].

Punakivi, M. and Tanskanen, K. (2002), "Increasing the cost efficiency of e-fulfilment using shared reception boxes", *International Journal of Retail & Distribution Management*, Vol. 30 No. 10, pp. 498-507.

Punakivi, M., Yrjölä, M. & Holmström, J. (2001). Solving the last mile issue: reception box or delivery box? *International Journal of Physical Distribution and Logistics Management*, 31(6), 427-439.

Punel, A. and Stathopoulos, A., 2017. Modeling the acceptability of crowdsourced goods deliveries: Role of context and experience effects. *Transportation Research Part E: Logistics and Transportation Review*, 105, pp.18-38.

Punel, A., Ermagun, A. and Stathopoulos, A., 2018. Studying determinants of crowd-shipping use. *Travel Behaviour and Society*, *12*, pp.30-40.

Quak, H. J., De Koster, M. R. B. Delivering goods in urban areas: how to deal with urban policy restrictions and the environment. *Transportation Science*, vol. 43 no. 2, 2009, p. 211-227.

Rai, H.B., Verlinde, S. and Macharis, C., 2018. Shipping outside the box. Environmental impact and stakeholder analysis of a crowd logistics platform in Belgium. *Journal of cleaner production*, *202*, pp.806-816.

Rai, H.B., Verlinde, S., Merckx, J. and Macharis, C., 2017. Crowd logistics: an opportunity for more sustainable urban freight transport? *European Transport Research Review*, *9*(3), p.39.

Rainer-Harbach, M., Papazek, P., Raidl, G.R., Hu, B. and Kloimüllner, C., 2015. PILOT, GRASP, and VNS approaches for the static balancing of bicycle sharing systems. *Journal of Global Optimization*, *63*(3), pp.597-629.

Raviv, T. and Kolka, O., 2013. Optimal inventory management of a bike-sharing station. *Iie Transactions*, *45*(10), pp.1077-1093.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy*, Vol. 45, 2016, p. 168–178.

Regue, R. and Recker, W., 2014. Proactive vehicle routing with inferred demand to solve the bikesharing rebalancing problem. *Transportation Research Part E: Logistics and Transportation Review*, *72*, pp.192-209.

Ronald N, Thompson R, Winter S (2015) Simulating demand-responsive transportation: a review of agent-based approaches. *Transport Reviews* 35(4):404–421

Rougès, J., Montreuil, B. Crowdsourcing delivery: New interconnected business models to reinvent delivery. 1st International Physical Internet Conference, Quebec City, Canada, May 28-30, 2014, p. 1-19.

Ruan, M. and Lin, J., 2010. Synthesis framework for generating county-level freight data using public sources for spatial autocorrelation analysis. *Transportation Research Record*, *2160*(1), pp.151-161.

Saharidis, G., Fragkogios, A. and Zygouri, E., 2014. A multi-periodic optimization modeling approach for the establishment of a bike sharing network: a case study of the city of Athens. In *Proceedings of the International MultiConference of Engineers and Computer Scientists* (Vol. 2, No. 2210, pp. 1226-1231).

Sahin, B., Yilmaz, H., Ust, Y., Guneri, A.F. and Gulsun, B., 2009. An approach for analysing transportation costs and a case study. *European Journal of Operational Research*, 193(1), pp.1-11.

Şahin, M., Çavuşlar, G., Öncan, T., Şahin, G. and Aksu, D.T., 2013. An efficient heuristic for the multi-vehicle one-to-one pickup and delivery problem with split loads. *Transportation Research Part C: Emerging Technologies*, *27*, pp.169-188.

Schreieck, M., Wiesche, M. and Krcmar, H., 2016. Design and governance of platform ecosystems–key concepts and issues for future research.

Schuijbroek, J., Hampshire, R.C. and Van Hoeve, W.J., 2017. Inventory rebalancing and vehicle routing in bike sharing systems. *European Journal of Operational Research*, *257*(3), pp.992-1004.

Shaheen, S. A., Chan, N. D., Gaynor, T. Casual Carpooling in the San Francisco Bay Area: Understanding User Characteristics, Behaviors, and Motivations. *Transport Policy*, vol. 51, 2016, p. 165-173. http://dx.doi.org/10.1016/j.tranpol.2016.01.003

Shui, C.S. and Szeto, W.Y., 2018. Dynamic green bike repositioning problem–A hybrid rolling horizon artificial bee colony algorithm approach. *Transportation Research Part D: Transport and Environment*, *60*, pp.119-136.

Sierksma, G. and Tijssen, G.A., 1998. Routing helicopters for crew exchanges on off-shore locations. *Annals of Operations Research*, *76*, pp.261-286.

Song, L., Cherrett, T., McLeod, F., & Guan, W. (2009). Addressing the last mile problem: transport impacts of collection and delivery points. *Transportation Research Record: Journal of the Transportation Research Board*, (2097), 9-18.

Stathopoulos, A., Valeri, E. and Marcucci, E., 2012. Stakeholder reactions to urban freight policy innovation. *Journal of Transport Geography*, 22, pp.34-45.

Szeto, W.Y. and Shui, C.S., 2018. Exact loading and unloading strategies for the static multi-vehicle bike repositioning problem. *Transportation Research Part B: Methodological*, *109*, pp.176-211.

Tang, Q., Fu, Z. and Qiu, M., 2019. A bilevel programming model and algorithm for the static bike repositioning problem. *Journal of Advanced Transportation*, *2019*.

Thompson, E.S., Saveyn, P., Declercq, M., Meert, J., Guida, V., Eads, C.D., Robles, E.S. and Britton, M.M., 2018. Characterisation of heterogeneity and spatial autocorrelation in phase separating mixtures using Moran's I. *Journal of colloid and interface science*, *513*, pp.180-187.

Thompson, R.G. and E. Taniguchi, (2014). Future Directions, Chapter 13, In City Logistics: Mapping the Future, (E. Taniguchi and R.G. Thompson, Eds.), CRC Press, Taylor & Francis, Boca Raton, 201-210

Thompson, R.G., 2015. Vehicle orientated initiatives for improving the environmental performance of urban freight systems. *In Green Logistics and Transportation* (pp. 119-129). Springer, Cham.

Tompkins, J.A., White, J.A., Bozer, Y.A. and Tanchoco, J.M.A. (2010) Facilities Planning, 4th edition. John Wiley & Sons, Hoboken, NJ.

Toyota (2017). [online] Available at: https://pressroom.toyota.com/releases/2017-toyota-corolla-product-specs.download [Accessed 27 Mar. 2018].

Trentini, A. and Mahléné, N., 2010. Toward a shared urban transport system ensuring passengers & goods cohabitation. Tema. *Journal of Land Use, Mobility and Environment*, 3(2).

U.S. Census Bureau report (2016), Quarterly retail e-commerce sales, 2014, http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf, last accessed January 20, 2017.

U.S. Census Bureau Report. Quarterly retail e-commerce sales, 2014, http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf, 2016.

U.S. Census. American Factfinder. Community facts, 2017, https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml, 2017.

UberRUSH. (2017). FAQ – UberRUSH. [online] Available at: https://rush.uber.com/faq/ [Accessed 28 Jul. 2017].

US Department of Transportation. (2018). DOT Releases 30-Year Freight Projections. [online] Available at: https://www.transportation.gov/briefing-room/dot-releases-30-year-freight-projections [Accessed 31 May 2018].

USPS. (2018). The Right Sort of Sorting | USPS Office of Inspector General. [online] Uspsoig.gov. Available at: https://www.uspsoig.gov/blog/right-sort-sorting [Accessed 9 Jan. 2018].

Verlinde, S., Macharis, C., & Witlox, F. How to consolidate urban flows of goods without setting up an urban consolidation centre?. *Procedia-Social and Behavioral Sciences*, Vol. 39, 2012, pp. 687-701.

Wang, I.L. and Wang, C.W., 2013, August. Analyzing bike repositioning strategies based on simulations for public bike sharing systems: Simulating bike repositioning strategies for bike sharing systems. In *2013 Second IIAI International Conference on Advanced Applied Informatics* (pp. 306-311). IEEE.

Wang, J., Jagannathan, A.K.R., Zuo, X. and Murray, C.C., 2017. Two-layer simulated annealing and tabu search heuristics for a vehicle routing problem with cross docks and split deliveries. *Computers & Industrial Engineering*, *112*, pp.84-98.

Wang, K. and Ye, C., 2012. The Competitive Decision Algorithm for the Vehicle Routing Problem with Simultaneous Delivery and Pickup. *Journal of Computational Information Systems*, *9*(8), pp.3189-3198.

Wang, K. and Ye, C., 2013. The Competitive Decision Algorithm for the Vehicle Routing Problem with Simultaneous Delivery and Pickup. *Journal of Computational Information Systems*, *9*(8), pp.3189-3198.

Wang, Y., Zhang, D., Liu, Q., Shen, F., Lee, L.H., 2016. Towards enhancing the last-mile delivery: an effective crowd-tasking model with scalable solutions. *Transp. Res. Part E Logist. Transp. Rev*. 93, 279–293. http://dx.doi.org/10.1016/j.tre.2016.06.002

WEF. (2019). *The World Economic Forum*. [online] Available at: https://www.weforum.org/ [Accessed 10 Aug. 2019].

Weltevreden, J. W. J. (2008). B2C e-commerce logistics: the rise of collection-and-delivery points in the Netherlands. *International Journal of Retail & Distribution Management*, 36(8), 638-660

Wilck IV, J.H. and Cavalier, T.M., 2012. A genetic algorithm for the split delivery vehicle routing problem. *American Journal of Operations Research*, 2(02), p.207.

Winroth, M., Säfsten, K. and Stahre, J. (2007) 'Automation strategies: existing theory or ad hoc decisions?', International Journal of Manufacturing Technology and Management, Vol. 11 No. 1, pp. 98-114

Zäpfel, G., & Wasner, M. Planning and optimization of hub-and-spoke transportation networks of cooperative third-party logistics providers. *International Journal of Production Economics*, Vol. 78, No. 2, 2002, pp. 207-220

Zhang, D., Yu, C., Desai, J., Lau, H.Y.K. and Srivathsan, S., 2017. A time-space network flow approach to dynamic repositioning in bicycle sharing systems. *Transportation research part B: methodological*, *103*, pp.188-207.

Zhou, W., Piramuthu, S., Chu, F. and Chu, C., 2017. RFID-enabled flexible warehousing. Decision Support Systems, 98, pp.99-112.

Zunder, T.H. and Ibanez, J.N., 2004. Urban freight logistics in the European Union.

Copyright Agreement

JOHN WILEY AND SONS LICENSE
TERMS AND CONDITIONS

Mar 25, 2020

This Agreement between Sudheer Ballare ("You") and John Wiley and Sons ("John Wiley and Sons") consists of your license details and the terms and conditions provided by John Wiley and Sons and Copyright Clearance Center.

License Number	4741431303668
License date	Jan 03, 2020
Licensed Content Publisher	John Wiley and Sons
Licensed Content Publication	Wiley Books
Licensed Content Title	Preliminary Investigation of a Crowdsourced Package Delivery System: A Case Study
Licensed Content Author	Sudheer Ballare, Jane Lin
Licensed Content Date	Jun 1, 2018
Licensed Content Pages	20
Type of use	Dissertation/Thesis
Requestor type	University/Academic
Format	Electronic
Portion	Text extract
Number of Pages	15
Will you be translating?	No
Title of your thesis / dissertation	Investigation of crowdshipping-enabled delivery paradigms
Expected completion date	Jan 2020
Expected size (number of pages)	150
Requestor Location	Sudheer Ballare 1198 Windham Lane

	ELK GROVE VILLAGE, IL 60007 United States Attn: Sudheer Ballare
Publisher Tax ID	EU826007151
Billing Type	Invoice
Billing Address	Sudheer Ballare 1198 Windham Lane ELK GROVE VILLAGE, IL 60007 United States Attn: Sudheer Ballare
Total	0.00 USD

Terms and Conditions

TERMS AND CONDITIONS

This copyrighted material is owned by or exclusively licensed to John Wiley & Sons, Inc. or one of its group companies (each a"Wiley Company") or handled on behalf of a society with which a Wiley Company has exclusive publishing rights in relation to a particular work (collectively "WILEY"). By clicking "accept" in connection with completing this licensing transaction, you agree that the following terms and conditions apply to this transaction (along with the billing and payment terms and conditions established by the Copyright Clearance Center Inc., ("CCC's Billing and Payment terms and conditions"), at the time that you opened your RightsLink account (these are available at any time at http://myaccount.copyright.com).

Terms and Conditions

- The materials you have requested permission to reproduce or reuse (the "Wiley Materials") are protected by copyright.
- You are hereby granted a personal, non-exclusive, non-sub licensable (on a stand-alone basis), non-transferable, worldwide, limited license to reproduce the Wiley Materials for the purpose specified in the licensing process. This license, **and any CONTENT (PDF or image file) purchased as part of your order,** is for a one-time use only and limited to any maximum distribution number specified in the license. The first instance of republication or reuse granted by this license must be completed within two years of the date of the grant of this license (although copies prepared before the end date may be distributed thereafter). The Wiley Materials shall not be used in any other manner or for any other purpose, beyond what is granted in the license. Permission is granted subject to an appropriate acknowledgement given to the author, title of the material/book/journal and the publisher. You shall also duplicate the copyright notice that appears in the Wiley publication in your use of the Wiley Material. Permission is also granted on the understanding that nowhere in the text is a previously published source acknowledged for all or part of this Wiley Material. Any third party content is expressly excluded from this permission.
- With respect to the Wiley Materials, all rights are reserved. Except as expressly granted by the terms of the license, no part of the Wiley Materials may be copied, modified, adapted (except for minor reformatting required by the new Publication), translated, reproduced, transferred or distributed, in any form or by any means, and no derivative works may be made based on the Wiley Materials without the prior permission of the respective copyright owner.**For STM Signatory Publishers clearing permission under the terms of the STM Permissions Guidelines only, the terms of the license are extended to include subsequent editions and for editions in other languages, provided such editions are for the work as a whole in situ and does not involve the separate exploitation of the permitted figures or extracts,** You may not alter, remove or suppress in any manner any copyright, trademark or other notices displayed by the Wiley Materials. You may not license, rent, sell, loan, lease, pledge, offer as security, transfer or assign the Wiley Materials on a stand-alone

basis, or any of the rights granted to you hereunder to any other person.

- The Wiley Materials and all of the intellectual property rights therein shall at all times remain the exclusive property of John Wiley & Sons Inc, the Wiley Companies, or their respective licensors, and your interest therein is only that of having possession of and the right to reproduce the Wiley Materials pursuant to Section 2 herein during the continuance of this Agreement. You agree that you own no right, title or interest in or to the Wiley Materials or any of the intellectual property rights therein. You shall have no rights hereunder other than the license as provided for above in Section 2. No right, license or interest to any trademark, trade name, service mark or other branding ("Marks") of WILEY or its licensors is granted hereunder, and you agree that you shall not assert any such right, license or interest with respect thereto

- NEITHER WILEY NOR ITS LICENSORS MAKES ANY WARRANTY OR REPRESENTATION OF ANY KIND TO YOU OR ANY THIRD PARTY, EXPRESS, IMPLIED OR STATUTORY, WITH RESPECT TO THE MATERIALS OR THE ACCURACY OF ANY INFORMATION CONTAINED IN THE MATERIALS, INCLUDING, WITHOUT LIMITATION, ANY IMPLIED WARRANTY OF MERCHANTABILITY, ACCURACY, SATISFACTORY QUALITY, FITNESS FOR A PARTICULAR PURPOSE, USABILITY, INTEGRATION OR NON-INFRINGEMENT AND ALL SUCH WARRANTIES ARE HEREBY EXCLUDED BY WILEY AND ITS LICENSORS AND WAIVED BY YOU.

- WILEY shall have the right to terminate this Agreement immediately upon breach of this Agreement by you.

- You shall indemnify, defend and hold harmless WILEY, its Licensors and their respective directors, officers, agents and employees, from and against any actual or threatened claims, demands, causes of action or proceedings arising from any breach of this Agreement by you.

- IN NO EVENT SHALL WILEY OR ITS LICENSORS BE LIABLE TO YOU OR ANY OTHER PARTY OR ANY OTHER PERSON OR ENTITY FOR ANY SPECIAL, CONSEQUENTIAL, INCIDENTAL, INDIRECT, EXEMPLARY OR PUNITIVE DAMAGES, HOWEVER CAUSED, ARISING OUT OF OR IN CONNECTION WITH THE DOWNLOADING, PROVISIONING, VIEWING OR USE OF THE MATERIALS REGARDLESS OF THE FORM OF ACTION, WHETHER FOR BREACH OF CONTRACT, BREACH OF WARRANTY, TORT, NEGLIGENCE, INFRINGEMENT OR OTHERWISE (INCLUDING, WITHOUT LIMITATION, DAMAGES BASED ON LOSS OF PROFITS, DATA, FILES, USE, BUSINESS OPPORTUNITY OR CLAIMS OF THIRD PARTIES), AND WHETHER OR NOT THE PARTY HAS BEEN ADVISED OF THE POSSIBILITY OF SUCH DAMAGES. THIS LIMITATION SHALL APPLY NOTWITHSTANDING ANY FAILURE OF ESSENTIAL PURPOSE OF ANY LIMITED REMEDY PROVIDED HEREIN.

- Should any provision of this Agreement be held by a court of competent jurisdiction to be illegal, invalid, or unenforceable, that provision shall be deemed amended to achieve as nearly as possible the same economic effect as the original provision, and the legality, validity and enforceability of the remaining provisions of this Agreement shall not be affected or impaired thereby.

- The failure of either party to enforce any term or condition of this Agreement shall not constitute a waiver of either party's right to enforce each and every term and condition of this Agreement. No breach under this agreement shall be deemed waived or excused by either party unless such waiver or consent is in writing signed by the party granting such waiver or consent. The waiver by or consent of a party to a breach of any provision of this Agreement shall not operate or be construed as a waiver of or consent to any other or subsequent breach by such other party.

- This Agreement may not be assigned (including by operation of law or otherwise) by you without WILEY's prior written consent.

- Any fee required for this permission shall be non-refundable after thirty (30) days from receipt by the CCC.

- These terms and conditions together with CCC's Billing and Payment terms and conditions (which are incorporated herein) form the entire agreement between you and WILEY concerning this licensing transaction and (in the absence of fraud) supersedes all prior agreements and representations of the parties, oral or written. This Agreement may not be amended except in writing signed by both parties. This Agreement shall be binding upon and inure to the benefit of the parties' successors, legal representatives, and authorized assigns.

- In the event of any conflict between your obligations established by these terms and conditions and those established by CCC's Billing and Payment terms and conditions, these terms and conditions shall prevail.
- WILEY expressly reserves all rights not specifically granted in the combination of (i) the license details provided by you and accepted in the course of this licensing transaction, (ii) these terms and conditions and (iii) CCC's Billing and Payment terms and conditions.
- This Agreement will be void if the Type of Use, Format, Circulation, or Requestor Type was misrepresented during the licensing process.
- This Agreement shall be governed by and construed in accordance with the laws of the State of New York, USA, without regards to such state's conflict of law rules. Any legal action, suit or proceeding arising out of or relating to these Terms and Conditions or the breach thereof shall be instituted in a court of competent jurisdiction in New York County in the State of New York in the United States of America and each party hereby consents and submits to the personal jurisdiction of such court, waives any objection to venue in such court and consents to service of process by registered or certified mail, return receipt requested, at the last known address of such party.

WILEY OPEN ACCESS TERMS AND CONDITIONS

Wiley Publishes Open Access Articles in fully Open Access Journals and in Subscription journals offering Online Open. Although most of the fully Open Access journals publish open access articles under the terms of the Creative Commons Attribution (CC BY) License only, the subscription journals and a few of the Open Access Journals offer a choice of Creative Commons Licenses. The license type is clearly identified on the article.

The Creative Commons Attribution License

The Creative Commons Attribution License (CC-BY) allows users to copy, distribute and transmit an article, adapt the article and make commercial use of the article. The CC-BY license permits commercial and non-

Creative Commons Attribution Non-Commercial License

The Creative Commons Attribution Non-Commercial (CC-BY-NC)License permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.(see below)

Creative Commons Attribution-Non-Commercial-NoDerivs License

The Creative Commons Attribution Non-Commercial-NoDerivs License (CC-BY-NC-ND) permits use, distribution and reproduction in any medium, provided the original work is properly cited, is not used for commercial purposes and no modifications or adaptations are made. (see below)

Use by commercial "for-profit" organizations

Use of Wiley Open Access articles for commercial, promotional, or marketing purposes requires further explicit permission from Wiley and will be subject to a fee.

Further details can be found on Wiley Online Library
http://olabout.wiley.com/WileyCDA/Section/id-410895.html

Other Terms and Conditions:

v1.10 Last updated September 2015

Questions? customercare@copyright.com or +1-855-239-3415 (toll free in the US) or +1-978-646-2777.

VITA

Name : Sudheer Ballare

1. Professional Preparation

- B.E. Civil Engineering, University of Mumbai, India, 2003.
- M.Tech. Environmental Engineering, University of Mumbai, India, 2007.
  Advisor: Dr. Prashant Bhave
- MSc. Transport & the Environment, Newcastle University, UK, 2012.
  Advisor: Dr. Anil Namdeo
- Project Research Associate, Center for Environmental Science and Engineering, Indian Institute of Technology Bombay, India, September 2014 - July 2015.
- Ph.D., Civil Engineering (Transportation), University of Illinois at Chicago, Chicago, 2019 (ongoing).
  Advisor: Prof. Jane Lin.

2. Appointments

- December 2019 – September 2020: ORISE Research Participant at U.S. Environmental Protection Agency, Ann Arbor, MI.
- July 2018 – July 2019: ORISE Research Participant at U.S. Environmental Protection Agency, Ann Arbor, MI.
- September 2015 – June 2018: Teaching/Research Assistant, University of Illinois at Chicago, Chicago, IL
- October 2014 – August 2015: Project Research Associate, Indian Institute of Technology – Bombay, Mumbai, India
- February 2013 – August 2014: Corporate Sustainability Manager, Larsen & Toubro Ltd., Mumbai, India
- July 2009 – September 2010: Assistant Manager – Corporate Sustainability, Larsen & Toubro Ltd., Mumbai, India
- August 2007 – June 2009: Environmentalist, Global Industries Offshore LLC, Mumbai, India
- July 2005 – May 2007: Teaching Assistant, Veermata Jijabai Technological Institute, Mumbai, India
- August 2003 – January 2005: Technical Engineer, Degussa Creating Essentials GmbH, Mumbai, India

3. Awards

- 2019: Illinois Institute of Transportation Engineers – Graduate Student Scholarship, Chicago.
- 2019: Outstanding paper award at the 11th International City Logistics conference, Dubrovnik, Croatia.
- 2018: George Krambles Transportation Scholarship Award, University of Illinois at Chicago.
- 2018: University of Illinois at Chicago (UIC) Chancellor's Student Service Award.
- 2012: AMEY Award for the best MSc. student at Newcastle University, United Kingdom.

4. Refereed Publications

(a) Refereed Journal Publications

1. Namdeo, A., **Ballare, S.**, Job, H. and Namdeo, D. (2016). Commuter Exposure to Air Pollution in Newcastle, U.K., and Mumbai, India. *Journal of Hazardous, Toxic, and Radioactive Waste*, 20(4), p.A4014004.

Refereed Journal Publications (under review or revision, or submission in the near future)

1. **Ballare, S.**, Lin, J. (under review) A Last Mile Delivery Paradigm Using Microhubs with Crowdshipping. *Transportation Science*.
2. **Ballare, S.**, Lin, J. (in preparation) Many to Many Split Pickup and Deliveries.
3. **Ballare, S.**, Sonntag, D. (in preparation) MOVES activity updates using fleet DNA: vehicle speed distributions.

(b) Refereed Copy-righted Conference Proceedings Publications

1. Bharadwaj, S., **Ballare, S.**, Rohit and Chandel, M. (2017) Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region. *Transportation Research Procedia*, 25., pp.3538-3551.
2. Ballare, S., Lin, J. (accepted) Investigating the use of microhubs and crowdshipping for last mile delivery, *Transportation Research Procedia*.

(c) Refereed Book Chapters

1. **Ballare, S.**, Lin, J. (2018) Preliminary Investigation of a Crowdsourced Parcel Delivery System: A Case Study, Chapter 6 in *City Logistics 3: Towards Sustainable and Livable Cities*, ed. Taniguchi and Thompson: 109-128, ISTE Ltd and John Wiley & Sons, Inc. https://doi.org/10.1002/9781119425472.ch6.

5. Conference Presentations

(a) by invitation

1. Ramjerdi, F. (2015) Coping with Climate: Assessing Policies for Climate Change Adaption and Transport Sector Mitigation in Indian Cities. *Climate Adaptation in the Transport Sector: Accelerating Global Efforts Transport Events at COP21,* December 9, 5-7, 2015, Paris.
2. Ramjerdi, F. (2015) Coping with Climate: Assessing Policies for Climate Change Adaption and Transport Sector Mitigation in Indian Cities in the CLIMATRANS study. *Delhi Sustainable Development Summit,* February 5-7, 2015, Delhi, India.
3. Beardsley, M., Brown, J., Han, J., Roberts, S., Sandhu, G., Sonntag, D., **Ballare, S**. (2019) Updates to EPA's Motor Vehicle Emission Simulator (MOVES). *29th CRC Real World Emissions Workshop*. March 10-13, 2018, Long Beach, CA.

(b) with peer-reviewed full paper submission

1. **Ballare, S.**, Bharadwaj, S. Chandel, M. and Rohit (2016). Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region. *14th World Conference on Transport Research*, July 10-15, 2016 Shanghai, China.
2. **Ballare, S.**, Lin, J. (2017) Case Study of a Crowdsourced Parcel Delivery System, *2017 International City Logistics Conference*, Phuket, Thailand, June 14-16, 2017.
3. Lin, J., and **Ballare, S.** (2017) Crowdshipping Consolidation in Urban Logistics. *INFORMS 2017*. 22-25, October 2017, Houston, TX.
4. **Ballare, S.**, Mueller, S. and Lin, J. (2018) The Impact of Higher Ethanol Blend Levels on Vehicle Emissions in Five Global Cities. *97th* Air *and Waste Management Association (A&WMA) Annual Conference*, June 25-28, 2018, Hartford, CT.

5. Conlon, J., **Ballare, S.**, Lin, J. (2018) Analysis of Fuel Consumption and Greenhouse Gases of Autonomous Vehicles at a Network Scale, *97th Transportation Research Board Annual Meeting*, Washington D.C., January 7-11, 2018.
6. **Ballare, S.**, Lin, J. (2019) Investigating the use of microhubs and crowdshipping for last mile delivery, *11th International Conference on City Logistics*, Dubrovnik, Croatia, June 12-14, 2019.

(c) with abstract submission only

1. **Ballare, S.**, Lin, J. (2017) Case Study of a Crowdsourced Parcel Delivery System. *58th Transportation Research Forum Annual Conference*, Chicago, IL, April 20-21, 2017.
2. Lin, J., **Ballare, S.** (2018) A Last Mile Delivery Paradigm Using Microhubs with Crowdshipping, the *EURO (The European Operational Research) 2018*, Valencia, Spain, July 8-11, 2018.
3. Sonntag, D., Brakora, J., Fulper, C., Brzezinski, D., Verma, A., **Ballare, S.**, Kotz, A., Kelly, K., Boriboonsomsin, K., Scora, G., Johnson, K., Durbin, T. (2019) Updating MOVES with Instrumented Heavy-duty Truck Activity Data. *29th CRC Real World Emissions Workshop*. March 10-13, 2018, Long Beach, CA.
4. Lin, J., **Ballare, S.** (2019) Many to Many Split Pickup and Deliveries, *ISMT 2019*, Singapore, Dec. 6-7, 2019.
5. Sonntag, D., Brakora, J., Fulper, C., Brzezinski, D., Verma, A., **Ballare, S.**, Kotz, A., Kelly, K., Boriboonsomsin, K., Scora, G., Johnson, K., Durbin, T. (2020) MOVES activity updates using Fleet DNA and CE-CERT data. *29th CRC Real World Emissions Workshop*. March 15-18, 2020, San Diego, CA.

6. Poster Presentations

1. **Ballare, S.** and Lin, J. (2017) Case study of crowdsourcing parcel delivery service. *97th Transport Chicago*, June 9, 2017, Chicago, IL.
2. Kotz, A., Sonntag, D., and **Ballare S.** (2019) MOVES activity updates using fleet DNA: vehicle speed distributions. *29th CRC Real World Emissions Workshop*. March 10-13, 2018, Long Beach, CA.
3. **Ballare, S.**, Sonntag, D., and Warila, J. (2019) Evaluation of Light -Duty Emission Rates in MOVES Using Real World Measurements. *29th CRC Real World Emissions Workshop*. March 10-13, 2019, Long Beach, CA.
4. **Ballare, S.** and Lin, J. (2019) Many to Many Split Pickup and Deliveries, *INFORMS 2019*, Seattle, Oct. 20-23, 2019.
5. **Ballare, S.**, Sonntag, D., and Warila, J. (2020) Evaluation of Light -Duty Emission Rates in MOVES Using Real World Measurements: An Update. *29th CRC Real World Emissions Workshop*. March 15-18, 2020, San Diego, CA.

7. Published Technical Reports

1. **Ballare, S.**, Chandel, M. and Rohit (2016). Assessment of the Current Situation in each Case Cities -Delhi, Bangalore, Mumbai. (Available at https://www.toi.no/getfile.php/1348381/Publikasjoner/WP%202%20Report.pdf)
2. Kotz, Andrew J, and Kelly, Kenneth J. MOVES Activity Updates Using Fleet DNA Data: Interim Report. United States: N. p., 2019. (Available at https://afdc.energy.gov/files/u/publication/moves_activity_interim_rpt.pdf)

8. Teaching Experience

Undergraduate courses (India) – Teaching Assistant

- 171CE16 Construction Materials
- 171CE25 Building Construction
- 171CE36 Building Design and Drawing

Graduate courses (India) – Laboratory Assistant

- CE0404 Water Resources engineering
- CCE1401 Environmental Engineering Laboratory

Undergraduate required course – Teaching Assistant

- CME 302 Introduction to Transportation Engineering

9. Professional Service

Journal paper reviewer:

1. Case Studies on Transport Policy
2. Transportation Research Record: Journal of the Transportation Research Board
3. Atmospheric Environment
4. Environmental Science & Technology
5. Journal of the Air & Waste Management Association
6. Transportation Research Part D: Transportation and the Environment
7. Transportation Research Part E: Transportation Review and Logistics

Conference paper reviewer:

1. Transportation Research Board (TRB) annual meetings
2. World Conference on Transportation Research (WCTR)

10. University Activities

1. Secretary of the UIC Institute of Transportation Engineers (ITE) Chapter, August 2016 – February 2020.
2. Member of the UIC Sustainability Fee Advisory Board, August 2016 – May 2019.
3. Member of the Graduate Student Council Executive Committee, August 2017 – May 2019.
4. Member of the UIC Eco Campus Club, August 2015 – May 2018.
5. Member of the UIC Toastmasters Club, August 2015 – February 2019.