# Optimizing Satellite Locations for a Multi-Echelon Last Mile Distribution Network to utilize Alternative Delivery Vehicles for Last Mile Delivery

by

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ABSTRACT

The growing urban population over the past few years has created many challenges for last mile distribution, such as traffic congestion, pollution, and lack of parking space availability. With the advent of e-commerce industry, the volumes for last mile delivery are growing consistently. As firms struggle to provide competitive delivery commitments to the end customers, they are exploring alternative delivery methods, such as drones and e-cargo bikes to navigate urban areas efficiently while addressing pollution and traffic concerns. However, range and capacity constraints associated with such alternative delivery modes restrict the operations that can be carried out with such vehicles. Hence, firms are re-designing their last mile distribution strategies to adapt to the constraints posed by these delivery modes. One such strategy is to deploy a multi-echelon distribution network, using satellite nodes near customer locations that allow for transshipment. The large conventional trucks deliver parcels to a satellite, from whereon the parcels are cross-docked into lighter vehicles (such as e-cargo bikes) which perform the final delivery. This project introduces a mixed integer linear programming model for a two-echelon delivery network, to determine the optimal count and locations of satellites for a large parcel company. The transactional data for deliveries and pickups associated with one parcel center has been used to develop and test the model. The first-tier transportation, that is from parcel center to satellites, has been designed as a location routing problem. The second-tier transportation, that is from satellites to customer delivery points, has been designed as an allocation problem. The model tries to minimize the associated costs with the satellite operation, optimizing the fixed cost of establishing a satellite against the cost of distance travelled and transit time. Traffic considerations and road network distances have been accounted for by using real road network data for distance calculations, and transit times adjusted for traffic conditions across multiple hours during the day. The model returns the count of satellites to be established, along with their respective locations and vehicle routes for first tier transportation. Finally, the model maps all the customers to their respective satellites to achieve an optimum distribution cost.

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# 1. INTRODUCTION

### 1.1 Impact of Urban Population Growth & E-commerce on Last Mile Delivery

According to a report released by Center for Sustainable Systems at University of Michigan in 2019, the urban population in the US has gone up to 84% of the overall population in 2019 from 64% in 1950, with 300 urban areas having a population higher than 100,000. By 2050, the urban population is expected to go up to 89%.

The growing population density in urban areas poses multiple challenges for last mile distribution:

- Increasing traffic congestion on road, leading to increase in transit times
- Increasing congestion causing higher levels of pollution
- Lack of parking space availability, making it difficult large trucks to make deliveries in residential as well as commercial areas

Over the last few years, e-commerce sector has experienced significant growth. Revenue generated from global online sales is expected to reach USD 4.5 trillion by 2021, almost two times the estimated sales in 2017 (eMarketer, 2017). A large share of the overall e-commerce sales is driven by the urban population (Janjevic et al., 2019). With the development of e-commerce industry, customer preferences have evolved as higher service levels are expected from e-commerce retailers. In order to maintain a competitive edge, companies are constantly trying to reduce the time to deliver orders to customers, and achieve higher service levels (Allen et al., 2017). At the same time, the funds to spend on logistics costs have become quite small (Veldman, 2019), owing to the decreasing margins in a competitive market.

In response to the advancement in this consumer driven market, the demand for city logistics has increased, with a significant rise in deliveries of smaller sized parcels using light commercial vehicles (LCV) (Balm et al., 2018). The surge in the usage of LCVs for delivery of small sized parcels has led to a high level of traffic congestion. Pollution levels are heightening due to the emission of greenhouse gases.

Parking spaces in urban areas have become extremely limited, and accessibility to major urban environments has become a challenge.

The urgency to reduce the transit time from fulfilment centers to customer locations -- while operating within the constraints of costs, traffic congestions, sustainability and accessibility limitations in urban areas -- has led parcel delivery companies to innovate alternate last-mile delivery methods. Ride sharing-based business models have been emerging recently such as Zipcar and Uber in attempts to find alternate uses for passenger vehicles (Fatnassi et al., 2016). Other solutions proposed by companies are cargo-bicycles to perform the last-mile delivery, package pickup lockers and, personal vehicle deliveries. Among these solutions, usage of light electric freight vehicles (LEFV) is emerging as a feasible alternative to conventional vehicles (Veldman, 2019).

The sponsoring company for the project is a global industry leader in parcel delivery and specialized logistics services, operating in over 200 countries and territories worldwide. In an effort to improve the operations in response to the aforementioned concerns, along with the ever-increasing consumer demand, the sponsoring company is exploring alternative delivery methods to complement current operations, leveraging the latest and emerging technology trends (such as electric cargo bikes and drones), while maintaining their service level commitments to their customers.

### 1.2 Alternative Delivery Methods and Multi-Echelon Networks

Giuliano et al. highlighted the usage of light electric freight vehicles (LEFV) for urban freight as a sustainable and efficient method for last-mile delivery (Giuliano et al., 2013). While such alternative delivery methods can be effective at addressing the aforementioned concerns, they have certain limitations:

- Carrying capacity of vehicles such as electric cargo bikes and drones can be fairly limited, and needs to consider the weight of the bike itself, as well as the weight of the rider
- Due to limited power output of the motor, it is difficult for electric bikes to access delivery points located on high elevation slopes

- Limited battery capacity and high re-charging times limits the distance that an electric bike can travel

Thus, it is essential to design a last mile distribution network that can leverage these alternate delivery methods while operating within the constraints highlighted above. One such strategy involves leveraging a multi-echelon network design, that utilizes intermediate transshipment nodes in the existing delivery network called satellite facilities. Satellite facilities are essentially small locations (such as parking lots, departmental stores etc.) that can be used for cross docking shipments from larger vehicles into smaller ones (like electric cargo bikes). These smaller vehicles can then be sent out for final parcel deliveries. The multi-echelon network design leads to shorter distance of travel between the satellite and the customers, allowing to overcome the range problem associated with alternative delivery vehicles. The usage of satellites allows for deconsolidation of delivery volumes based on customers allocated to each satellite before final delivery. This reduces the volume handled by each satellite in comparison to the larger parcel center, thus facilitating the usage of smaller capacity vehicles for final deliveries.

Currently, the sponsor company has a fleet of large vehicles that make deliveries directly from their package centers to customers. The company is looking to implement a revised multi-echelon network design, in order to utilize alternative delivery vehicles to carry out final deliveries to the customers. According to the revised network flow, large trucks (first-tier vehicles) carrying shipments from the parcel center would reach the satellites that are located in vicinity of the customer. The shipments from the first-tier vehicles will be transferred to smaller sized electric cargo bikes (second-tier vehicles). These cargo bikes will then go to various customer locations to make final deliveries.

### 1.3 Report Outline

This project proposes a mathematical optimization model that can act as a decision support system for the sponsor company to help plan for future satellite locations that can be incorporated in their existing distribution network. In order to design and test the model, a masked version of delivery and pickup transaction data has been provided by the sponsor company, for shipments handled by one parcel center across five days in July 2018. The proposed model is based on various factors such as:

- Geo-spatial spread of customer demand
- Road network
- Traffic conditions
- First and second tier vehicle capacities
- Average transit time from package center to satellite locations

This report has been structured as follows: Section 2 reviews the research conducted in multi-echelon network design. Section 3 proposes the mathematical model for solving the problem, outlining the assumptions made while developing the model. Section 4 exhibits the results of executing the model using the dataset provided by the sponsor company. Section 5 presents the conclusions derived from this project and establishes the scope of future work on this project.

# 2. LITERATURE REVIEW

The previous chapter highlights the emerging challenges in last mile distribution, and introduces the concept of utilizing multi-echelon networks in order to leverage the advantages alternative delivery vehicles for last mile delivery. This chapter reviews the research work that has been carried out in multi-echelon distribution networks. Section 2.1 introduces the concept of Multi-Echelon Distribution systems and establishes its relevance with urban last mile distribution networks. Section 2.2 highlights the importance of adopting a combinatorial approach to location and routing decisions while formulating a multi-echelon distribution system, and examines the various frameworks proposed by researchers over the years to formulate and optimize the mathematical models for multi-echelon distribution networks. Finally, Section 2.3 highlights the impacts associated with making large scale changes in a distribution network, when transitioning to a multi-echelon distribution strategy.

## 2.1 Multi-Echelon Last Mile Distribution Networks

A multi-echelon distribution system typically consists of logistics facilities such as parcel centers and satellites across multiple tiers, connected to each other and to the customer locations through delivery vehicle routes. Multi echelon systems are commonly used in development of traffic planning strategies, modelling distribution networks etc. (Perboli et al., 2011). Many parcel service companies and online retailers across the world, such as Amazon and Jingdong have incorporated multi-echelon network design strategy in their last mile delivery systems (Janjevic et al., 2019).

Over the last two decades, significant research has been carried out on optimization of multi-echelon distribution networks. Early research includes the work of Taniguchi et al. (Taniguchi et al., 1999), who explore the formulation and optimization of two-echelon distribution systems. Crainic et al. (2004) stipulate the importance of rationalizing distribution activities through consolidation of freight and coordination of city levels operations, in order to achieve higher levels of efficiency in urban distribution networks. Addressing freight consolidation activities, they analyze the usage of satellites for transshipment of freight from large conventional trucks to smaller, environment friendly vehicles (which they refer to as city-freighters) in order to carry out forward and reverse leg movement of parcels within urban areas (Crainic et al., 2004).

### 2.1.1 Single-Echelon vs Multi-Echelon Last Mile Distribution

Many researchers (Merchan et al., 2016; Savelsbergh & Van Woensel, 2016; Winkenbach et al., 2016; Snoeck & Winkenbach, 2020; Winkenbach, 2016) have studied and recognized the usage of multi-echelon networks in order to enhance the efficiency of last mile distribution. Operating a single echelon delivery system in an urban environment can be an inefficient strategy (Janjevic et al., 2019). Typically, distribution centers that consolidate, sort and ship out parcels tend to be large facilities generally located outside the city limits. Consolidating parcels for every delivery point in the city area for direct doorstep delivery from the distribution center leads to higher levels of truck traffic (Crainic et al., 2004). Along with traffic congestion, this also adds a significant transit time for line haul travel from the distribution center to the point of delivery. These extended transit times lead to a reduction in vehicle utilization (Janjevic et al., 2019). In contrast, in a multi-echelon network design approach, companies establish large distribution centers in the periphery of the urban territory, and a second echelon of satellite facilities closer to high demand customers for final deliveries (Snoeck et al., 2018). These satellite facilities enable shorter lead times from the satellite node to the customer, leading to a quicker turnaround and a higher utilization of delivery vehicles.

### 2.1.2 Usage of Alternative Delivery Vehicles

As discussed in Chapter 1, parcel distribution companies are exploring the usage of alternative delivery methods such as cargo bikes, drones and LEFVs to overcome the constraints of pollution, traffic congestion and lack of parking space availability in densely populated urban areas. Multi-echelon networks support the usage of different types of vehicles across the different hierarchies of the network, thus allowing companies to utilize alternative delivery vehicles such as LEFVs (Veldman, 2019; Zhou et al., 2018). Allowing for intermediate satellite facilities to carry out the transshipment of freight, companies can get much closer to the end customers, thus reducing the distance of the final leg of transportation. This enables companies to overcome the range and capacity limitations of LEFVs.

It is important to investigate all modes of transportation when assessing which modes are best suited for a specific leg of the distribution network. There are traditional operators such as trucks and vans that use fossil fuel, and there are green operators such as electric vehicles and cargo bicycles (Perboli & Rosano, 2019). The perfect combination of these vehicles can be used to optimize the overall system. The first layer of the delivery network would consist of large capacity vehicles traveling from distribution centers to transshipment nodes or satellites. The second layer of the multi-echelon network would consist of light vehicles collecting packages from the satellite and transporting them to their final customer. Deciding on the most suitable locations for satellites is key to a successful delivery network.

## 2.2 Modeling and Optimization of Multi-Echelon Distribution Networks

The decision of locating satellites in a multi-echelon network is inherently connected with the vehicle routing problem (VRP). The ability to serve multiple customers on a single route from a satellite, while operating within the vehicle and satellites capacity constraints, necessitates a combined approach to location and routing problems (Wu et al., 2002). Salhi and Rand analyze the difference in optimality of solutions derived by considering location and routing decisions separately, and by considering them together as interdependent. The results conclusively prove that considering location optimization problem in connection with VRP produces more optimal results overall rather than when considering the two problems separately (Salhi & Rand, 1989).

Over the years, researchers have proposed various ways to structure a multi-echelon VRP or ME-VRP. A commonly researched version of ME-VRP is the two-echelon vehicle routing problem, or 2E-VRP. A 2E-VRP usually consists of a distribution center that acts as a consolidation point for customer parcels. These parcels are delivered to multiple intermediate satellite locations in large first tier vehicles, for delivery to customers. The connection to satellites is modeled as a vehicle routing problem, consisting of multiple routes that start from and end at the distribution center, covering all the satellite nodes. Once the parcels are received at the satellite nodes, smaller sized second tier vehicles make final deliveries to the end customers (Zhou et al., 2018). Researchers have adopted different techniques and studied various factors that impact 2E-VRP. Early research by Jacobsen and Madsen (1980) introduces the concept of two echelon location routing problem or 2E-LRP in the context of newspaper distribution system (Jacobsen & Madsen, 1980). The model proposes the optimal locations for satellites, and routing decisions across the two echelons of the network. However, capacity constraints and establishment costs for satellites have not been considered in the model.

Capacity considerations in a 2E-VRP are commonly formulated in Two-Echelon Capacitated Vehicle Routing Problem or 2E-CVRP, that optimizes the total delivery cost while considering vehicle and satellite capacity constraints (Gonzalez-Feliu et al., 2013). Perboli et al. propose a mathematical model for two-echelon capacitated vehicle routing problem, and present two math-heuristics based on the model to solve the problem for fifty customers over four satellites (Perboli et al., 2011).

Other extensions include VRP with delivery and pickups, 2E-VRP with time windows (2E-VRP-TW) and multi depot VRP (MDVRP). A 2E-VRP-TW enforces pre-defined time windows for making deliveries to customers, by either restricting or penalizing the violation of delivery time window constraints (Gonzalez-Feliu et al., 2013). Govindan et al. propose a multi-objective optimization model for a Two-Echelon Location Routing Problem with Time Windows or 2E-LRPTW for a perishable food supply chain network. The model facilitates the decision for the number and locations of satellites, and product quantity and routing decisions at each level (Govindan et al., 2014).

A 2E-VRP with Satellite Synchronization (2E-VRP-SS) constrains the time windows for arrival and departure of vehicles at the satellites, thus allowing for a realistic modeling of delivery operations at the satellite. The MD-VRP formulation allows for multiple depots to connect parcels to a single satellite (Gonzalez-Feliu et al., 2013). Crainic et al. (2009) propose a time dependent formulation of two echelon vehicle routing problem, with fleet synchronization and consumer time windows (Crainic et al., 2009).

## 2.3 Challenges Associated with Changing Network Design

As discussed in Section 1.3, this project proposes a mathematical model that can act as a support system for satellite location and routing decisions, in order to transition from a single echelon design to a multi-echelon network design that can support the efficient usage of alternative delivery vehicles.

While migrating from a single-echelon strategy to a multi-echelon one can have major gains in efficiency, it is important to understand that drastically changing a supply chain network design could have potential impacts affecting inventories, transportation, facilities and handling, and flow of information (Chopra, 2003). Pipeline inventory costs tend to increase as a greater number of nodes are introduced in a network (Perboli & Rosano, 2019). Crainic et al. analyze the impact of relevant parameters such as customer distribution, satellite-location rules, existing facility locations, transportation costs etc. on the total overall distribution cost of a two echelon distribution network (Crainic et al., 2010). Migrating to a multi-echelon strategy could lead to operational and technical issues, as well as concerns regarding sustainability potential environmental impacts (Perboli & Rosano, 2019). These operational and environmental impacts should be considered when making decisions to adopt a multi-echelon last mile distribution network. Hence, the decision-making process for establishing satellites should consider these aspects along with inputs from the model proposed in this research.

# 3. METHODOLOGY

As discussed in Chapter 1, this project proposes a mathematical model that would act as a decision support system to determine the most suitable locations for opening satellite locations within the existing delivery network, in order for the sponsoring company to transition to a multi echelon network design strategy. For the purpose of developing the model, the company has provided masked delivery and pickup data for one parcel center in a metro city. The data depicts the delivery and pickup transactions corresponding to the parcel center. While the data has been sufficiently modified for the purpose of privacy, it still adequately represents the geo-spatial distribution of demand across the territory. The project methodology involves the following steps:

- Generating an initial set of feasible candidates based on pre-defined parameters
- Formulating a mathematical model to determine the best locations to open Satellite Locations, using a two-echelon location routing problem framework
- Determining the road distance (based on road network) and transit times (based on traffic data) for First and Second Tier transportation using OSM
- Solving the model using Python

This chapter has been structured as follows: Section 3.1 discusses the assumptions considered in this project. Section 3.2 describes the approach adopted to generate the initial set of candidates for satellites. Section 3.3 covers the calculation of distance and time matrices, using GIS and OSM. Finally, Section 3.4 describes the formulation of the mathematical model to determine the final locations for opening satellites.

## 3.1 Assumptions

Following are the assumptions that have been considered in this work:

- The function considered in the model is a proxy for determining the optimal allocations, and does not reflect the true cost of the operations based on the found solution. The costs considered in this model are modelled such that they capture the tradeoff between satellite location decisions and the resulting transportation cost.

- All customer points are assumed to be allocated to a satellite, and no customer will be served directly by the package center.
- Each customer will be served from one satellite only.
- First tier transportation (DC to Satellite) has been modeled as a Vehicle Routing Problem.
- Second tier transportation (Satellite to Customer) has been modeled as an allocation problem, and for the sake of simplicity of solving the model, vehicle routing for second tier transportation has not been considered.
- Since second tier transportation is an allocation problem and not a VRP, no constraint for second tier vehicle count or capacity has been considered.
- For the purpose of solving the model, fixed cost and capacity of operating a satellite has been considered to be the same for all satellites. However, this constraint can be relaxed easily by inputting individual parameters for all satellite candidates.
- Within each tier, a homogenous vehicle fleet has been assumed. That is, within each of the two tiers, all vehicles are considered to have the same characteristics such as capacity, cost per mile, cost per hour etc.

### 3.2 Generating Feasible Candidates

In order to generate a list of feasible candidates for establishing satellites, a set of favorable delivery/pickup locations from the available dataset have been shortlisted, based on the following parameters:

- Total weight of shipments delivered /picked up
- Total weight of shipments delivered /picked up
- Average size of shipments delivered /picked up

- Average volume of the shipments delivered /picked up
- Time window of delivery

A user-controlled threshold value for each of the parameters has been defined in consultation with the sponsoring company. All delivery points fulfilling the criteria for threshold values have been shortlisted as feasible candidates for satellite locations.

## 3.3 Calculation of Distance and Time Matrices

As mention in Chapter 1, the proposed model utilizes road network distances and considers traffic density for the calculation of transit times between the satellites, the parcel center and the delivery/pickup locations.

### 3.3.1 Distance Calculation

For the purpose of this project, the road distance has been calculated using the OpenStreetMap (OSM) database. OSM is an open source, digital database of road networks around the world. A Python package (OSM NetworkX or OSMNx) that allows for accessing the OSM database, and projection and visualization of complex street networks, has been used for carrying out the distance calculations. The following steps define the logic employed for distance calculation:

- A digital roadmap of the service area under investigation is queried from the OSM database. The digital roadmap is essentially a collection of nodes, connected by a set of arcs that mimic the road network of the area under consideration.
- For each node in the input dataset, the node ID for the closest digital node on the OSM dataset was determined.
- Once the node ID for each delivery point was determined, the distance between any two points is calculated using an inbuilt shortest path function in OSMNx that calculates the shortest distance of travel between the corresponding closest node IDs of the origin and destination.

- The shortest path function is used to determine the distance matrices for all possible origins and destinations, for first-tier transportation between parcel center and satellites, and the second-tier transportation between satellites and customers.

### 3.3.2 Transit Time Calculation

In order to take traffic density into consideration, the transit time calculation in the model has been carried out using Uber Movement data. Uber Movement is an open source dataset provided by the ride sharing company Uber, that provides traffic related datasets such as average transit times and average speeds of vehicles, spread out geographically and across multiple time slots. In order to calculate these for any city, Uber has divided each city into small, unique sections called Zones. While the area of each Zone is different, these Zones are small enough to provide an adequate estimation of transit time between any two points that are located in their respective Zones. The transit time values are derived from anonymized and aggregated trip location data from the ride sharing company's daily trips across the Zones. The following steps describe the methodology used for the calculation of a transit time matrix for first and second tier transportation:

- A digital record of each Zone boundary mapped across the service area under investigation is obtained from Uber Movement portal.
- Using an open source GIS, the locations from the input dataset are mapped onto the layer of Zone boundaries.
- Through the mapping of layers, the GIS returns the Zone ID for each delivery point in the dataset.
- A transit time master dataset for the service area under investigation is obtained from the Uber Movement portal.
- For each origin and destination, the transit time is queried from the Uber Movement dataset using the corresponding Zone IDs, averaged over the delivery/pickup time window for each customer.

Since the Uber Movement dataset derives transit times from actual trips carried out by Uber drivers, it provides a fairly accurate estimation of traffic conditions.

### 3.4 Formulation of Mathematical Model

The mathematical model in this project tries to minimize the cost of operating the satellites, while connecting to all the customers that need to be served by a package center. As mentioned previously in Section 3.1, the first tier of the model has been modeled using a location routing framework. While modeling a vehicle routing problem, various factors such as geospatial spread of demand, fixed and variable costs, distance, and capacity constraints have to be considered. Wu et al. propose a mathematical model to solve a multi-depot location routing problem or MD-LRP (Wu et al., 2002). The model proposed by them determines the number of locations, assignment of delivery points to depots, and routing decisions. They consider parameters such as fixed cost of establishing a depot, fixed cost of each vehicle, and distance between each node in the network. These parameters have a direct impact on the location of the satellites. Tables 3.1, 3.2 and 3.3 list out all the sets, decision variables and relevant parameters of the model proposed in this project.

**Table 3.1: Sets and indices**

| | |
|---|---|
| I | {0, …, i}: Set of all DC sites (in this case, only 1) |
| J | {0, 1, …, j}: Set of all satellites |
| R | {0, 1, …, r}: Set of all routes |
| K | {0, 1, …, k}: Set of all customers |

**Table 3.2: Decision Variables**

| | |
|---|---|
| $Y_j^S$ | 1, if satellite j is established, 0 otherwise |
| $Y_{j,k}^C$ | 1, if customer k is mapped to satellite j, 0 otherwise |
| $X_{i,j,r}^D$ | 1, if point i immediately precedes j, 0 otherwise, for delivery run of vehicle r |
| $X_{i,j,r}^P$ | 1, if point i immediately precedes j, 0 otherwise, for pickup run of vehicle r |
| $h_{j,r}^d$ | delivery volume at satellite j to be carried by vehicle r |
| $h_{j,r}^p$ | pickup volume at satellite j to be carried by vehicle r |
| $Z_{i,j,r}^D$ | auxiliary variable for first tier delivery vehicle capacity constraints |
| $Z_{i,j,r}^P$ | auxiliary variable for first tier pickup vehicle capacity constraints |
| $U_i^D$ | auxiliary variable to eliminate sub-tours in delivery run |
| $U_i^P$ | auxiliary variable to eliminate sub-tours in delivery run |

**Table 3.3: General Parameters**

| | |
|---|---|
| $F_j^S$ | Fixed cost of operating satellite j |
| $d_{i,j}$ | Distance between node i and node j |
| $t_{i,j}$ | Time taken to travel from node i to node j |
| $C_{mile}^{FT}$ | Cost per mile for first tier transportation |
| $C_{hour}^{FT}$ | Cost per hour for first tier transportation |
| $C_{hour}^{ST}$ | Cost per hour for second tier transportation |
| $C_{mile}^{ST}$ | Cost per mile for second tier transportation |
| $F^{FT}$ | Fixed cost associated with first tier transportation |
| $F^{ST}$ | Fixed cost associated with second tier transportation |
| $D_k$ | Delivery volume for customer k |
| $P_k$ | Pickup volume for customer k |
| S | Capacity for satellite j |
| $Q_r^{FT}$ | Capacity for First Tier vehicle |
| $Q^{ST}$ | Capacity for Second Tier vehicle |
| M | A very large number |
| N | Total number of parcel centers (=1 in this case) |

Building on the formulation of Wu et al. (2002), the following formulation of the mathematical optimization model is used for the analysis:

$$\text{MIN} \sum_{j\in J} F_j^S * Y_j^S + \sum_{i\in I\cup J}\sum_{j\in I\cup J}\sum_{r\in R}\left(d_{i,j} * C_{mile}^{FT} + t_{i,j} * C_{hour}^{FT}\right) * (X_{i,j,r}^D + X_{i,j,r}^P) +$$
$$\sum_{r\in R} F^{FT}\sum_{i\in I}\sum_{j\in J}(X_{i,j,r}^D + X_{i,j,r}^P) + \sum_{j\in J}\sum_{k\in K}\frac{(D_k * Y_{j,k}^C)}{Q^{ST}} * (F^{ST} + d_{j,k} * C_{mile}^{ST} + t_{j,k} * C_{hour}^{ST}) +$$
$$\sum_{j\in J}\sum_{k\in K}\frac{(P_k * Y_{j,k}^C)}{Q^{ST}} * (F^{ST} + d_{j,k} * C_{mile}^{ST} + t_{j,k} * C_{hour}^{ST}) \quad (1)$$

subject to

$$\sum_{j\in J} Y_j^S \geq \left(\frac{\max(\sum_{k\in K} D_k, \sum_{k\in K} P_k)}{S}\right), \quad (2)$$

$$Y_{j,k}^C \leq Y_j^S, \forall\, j \in J, k \in K, \quad (3)$$

$$\sum_{j\in J} Y_{j,k}^C = 1, \forall\, k \in K, \quad (4)$$

$$h_{j,r}^D \leq \sum_{k\in K} D_k * Y_{j,k}^C, \forall\, j \in J, r \in R, \quad (5)$$

$$h_{j,r}^P \leq \sum_{k\in K} P_k * Y_{j,k}^C, \forall\, j \in J, r \in R, \quad (6)$$

$$\sum_{r\in R} h_{j,r}^D = \sum_{k\in K} D_k * Y_{j,k}^C, \forall\, j \in J, \quad (7)$$

$$\sum_{r\in R} h_{j,r}^P = \sum_{k\in K} P_k * Y_{j,k}^C, \forall\, j \in J, \quad (8)$$

$$X_{i,j,r}^D \leq Y_j^S, \forall\, i \in I \cup J, j \in J, r \in R, \quad (9)$$

$$X_{j,i,r}^D \leq Y_j^S, \forall\, i \in I \cup J, j \in J, r \in R, \quad (10)$$

$$X_{i,j,r}^P \leq Y_j^S, \forall\, i \in I \cup J, j \in J, r \in R, \quad (11)$$

$$X_{j,i,r}^P \leq Y_j^S, \forall\, i \in I \cup J, j \in J, r \in R, \quad (12)$$

$$\sum_{i\in I}\sum_{j\in I\cup J} X_{i,j,r}^D \leq 1, \forall\, r \in R, \quad (13)$$

$$\sum_{i\in I}\sum_{j\in I\cup J} X_{i,j,r}^P \leq 1, \forall\, r \in R, \quad (14)$$

$$\sum_{j\in I\cup J} X_{i,j,r}^D = \sum_{j\in I\cup J} X_{j,i,r}^D, \forall\, i \in J, r \in R, \quad (15)$$

$$\sum_{j\in I\cup J} X^{P}_{i,j,r} = \sum_{j\in I\cup J} X^{P}_{j,i,r}, \forall\, i \in J, r \in R, \quad (16)$$

$$h^{D}_{j,r} \leq Q^{FT}_{r} * \sum_{i\in I\cup J} X^{D}_{i,j,r}, \forall\, j \in J, r \in R, \quad (17)$$

$$h^{P}_{j,r} \leq Q^{FT}_{r} * \sum_{i\in I\cup J} X^{P}_{i,j,r}, \forall\, j \in J, r \in R, \quad (18)$$

$$\sum_{i\in I\cup J} X^{D}_{i,j,r} \leq Y^{S}_{j}, \forall\, j \in J, r \in R, \quad (19)$$

$$\sum_{i\in I\cup J} X^{P}_{i,j,r} \leq Y^{S}_{j}, \forall\, j \in J, r \in R, \quad (20)$$

$$X^{D}_{j,l,r} \leq \sum_{i\in I\cup J} X^{D}_{i,j,r}, \forall\, j \in J, l \in I \cup J, r \in R, \quad (21)$$

$$X^{P}_{j,l,r} \leq \sum_{i\in I\cup J} X^{P}_{i,j,r}, \forall\, j \in J, l \in I \cup J, r \in R, \quad (22)$$

$$X^{D}_{i,j,r} \leq h^{D}_{j,r}, i \in I \cup J, j \in J, r \in R, \quad (23)$$

$$X^{P}_{i,j,r} \leq h^{P}_{j,r}, i \in I \cup J, j \in J, r \in R, \quad (24)$$

$$\sum_{i\in I\cup J} X^{D}_{i,j,r} - \sum_{i\in I\cup J} X^{D}_{j,i,r} = 0, \forall\, r \in R, j \in J, \quad (25)$$

$$\sum_{i\in I\cup J} X^{P}_{i,j,r} - \sum_{i\in I\cup J} X^{P}_{j,i,r} = 0, \forall\, r \in R, j \in J, \quad (26)$$

$$X^{D}_{i,i,r} = 0, \forall\, i \in I \cup J, r \in R, \quad (27)$$

$$X^{P}_{i,i,r} = 0, \forall\, i \in I \cup J, r \in R, \quad (28)$$

$$U^{D}_{i} - U^{D}_{l} + Z^{D}_{i,l,r} + N * X^{D}_{i,l,r} \leq \sum_{j\in J} Y^{s}_{j} + N - 1, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (29)$$

$$Z^{D}_{i,l,r} \leq M * X^{D}_{i,l,r}, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (30)$$

$$Z^{D}_{i,l,r} \leq \sum_{j\in J} Y^{s}_{j}, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (31)$$

$$Z^{D}_{i,l,r} \geq \sum_{j\in J} Y^{s}_{j} - \left(1 - X^{D}_{i,l,r}\right) * M, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (32)$$

$$Z^{D}_{i,l,r} \geq 0, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (33)$$

$$U^{P}_{i} - U^{P}_{l} + Z^{P}_{i,l,r} + N * X^{P}_{i,l,r} \leq \sum_{j\in J} Y^{s}_{j} + N - 1, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (34)$$

$$Z^{P}_{i,l,r} \leq M * X^{P}_{i,l,r}, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (35)$$

$$Z^{P}_{i,l,r} \leq \sum_{j\in J} Y^{s}_{j}, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \quad (36)$$

$$Z^{P}_{i,l,r} \geq \sum_{j\in J} Y^{s}_{j} - \left(1 - X^{P}_{i,l,r}\right) * M, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \tag{37}$$

$$Z^{P}_{i,l,r} \geq 0, \forall\, i \in I \cup J, l \in J, r \in R, i \neq l, \tag{38}$$

$$\sum_{r\in R} h^{D}_{j,r} \leq S * Y^{S}_{j}, \forall\, j \in J, \tag{39}$$

$$\sum_{r\in R} h^{P}_{j,r} \leq S * Y^{S}_{j}, \forall\, j \in J, \tag{40}$$

$$\sum_{j\in J} h^{D}_{j,r} \leq Q^{FT}_{r}, \forall\, r \in R, \tag{41}$$

$$\sum_{j\in J} h^{P}_{j,r} \leq Q^{FT}_{r}, \forall\, r \in R, \tag{42}$$

$$h^{D}_{j,r} \leq \min(S, Q^{FT}_{r}), \forall\, j \in J, r \in R, \tag{43}$$

$$h^{D}_{j,r} \geq 0, \forall\, j \in J, r \in R, \tag{44}$$

$$h^{P}_{j,r} \leq \min(S, Q^{FT}_{r}), \forall\, j \in J, r \in R, \tag{45}$$

$$h^{P}_{j,r} \geq 0, \forall\, j \in J, r \in R. \tag{46}$$

Equation (1) is the objective function that considers the cost of the overall solution, as explained earlier in this section. The objective function of the model proposed in this project consists of four major components. First component of the objective function comprises of the fixed cost of operating a satellite, along with a binary decision variable that indicates whether the satellite is operational or not. Second and third term calculate the cost associated with transporting packages from package center to the satellite (first-tier transportation). The first-tier transportation has been modeled as a Vehicle Routing Problem (VRP). The fourth term and fifth term consider the cost of transporting packages from the satellite to customers, formulated as an allocation problem.

Constraint (2) defines the minimum number of satellites required for the operation, based on the total volume and the capacity of satellites. Constraint (3) ensures that customers are allocated to active satellites only. Constraint (4) constrains each customer's allocation to a single satellite only. Constraints (5) and (6) ensure that a vehicle r is allocated to visit a satellite j only if the satellite has demand for delivery and/or pickup. Constraints (7) and (8) ensure fulfilment of all demand for delivery and pickup respectively.

Constraints (9) to (12) ensure that routes can only enter and leave a satellite only if the satellite is active. Constraints (13) and (14) ensure that every vehicle leaves the depot at most once. Constraints (15) and (16) ensure that the vehicles return to the depot they left from, if they ever left the depot. Constraints (17) and (18) enforce that if a satellite j has been allocated to vehicle r, then that vehicle must visit the satellite, for delivery and pickup runs respectively. Constraints (19) and (20) ensure that a vehicle visits a satellite only once. Constraints (21) and (22) ensure that vehicle can only go from node j to node i, if it previously visits node j first. Constraints (23) and (24) ensure that a satellite is visited by a vehicle only if there is any demand associated with the satellite. Constraints (25) and (26) enforce conservation of flow at all satellites, ensuring that no parcels are generated from or consumed at any of the satellites. Constraints (27) and (28) ensure that a vehicle does not visit the same node after leaving that node (i.e., these constraints ensure removal of single node loops). Constraints (29) to (38) ensure elimination of subtours across the networks during the first-tier delivery and pickup runs. Constraints (39) and (40) ensure that satellite capacity is not exceeded. Constraints (41) and (42) enforce the capacity constraints for first tier vehicles for delivery as well as pickup runs. Finally, Constraints (43) to (46) set the bounds on the decision flow variables for delivery and pickup runs.

# 4. ANALYSIS

The previous chapter proposes a mathematical model to determine the optimal locations for satellites in a multi-echelon last mile delivery network for the sponsoring company. This chapter analyzes the results obtained by executing that model on a sample dataset. This chapter is structured as follows: Section 4.1 describes the different datasets used and various relevant parameters associated with each of them. Section 4.2 describes the tools used for solving the model. Section 4.3 describes the scenarios of analyses that have been conducted to test the robustness of the model to changes in various parameters, and presents the final results of the model for each scenario. Section 4.4 interprets the results obtained from the model and makes corresponding recommendations for deployment.

## 4.1 Data

As discussed in Chapter 1, the sponsoring company has provided a masked version of the transactions for 5 days in July 2018. This dataset consists of the following attributes:

- **Date:** The date of transaction
- **Center number:** ID of the parcel center from where the parcel was delivered from, or where the picked-up parcel was brought into
- **Package ID:** Unique parcel identifier, used for tracking purposes
- **Customer ID:** unique customer identifier
- **Stop Type:** Binary identifier defining if the transaction was a delivery or pickup. Equal to zero if delivery, equal to 1 if pickup
- **Stop Commercial/Residence:** A binary identifier, defining if the location of customer is a commercial or a residential location. Equal to 0 if residential, 1 if commercial
- **Latitude:** Latitude coordinate of the location of customer
- **Longitude:** Longitude coordinate of the location of customer
- **Commitment Window:** Requested time window of customer delivery/pickup

- **Max Side Length:** Length of the largest side of the customer parcel, in inches
- **Volume:** Net volume of the customer parcel, in cubic inches
- **Weight:** Weight of the customer parcel, in pounds

### 4.2 Model Implementation

The model was implemented in Python 3.6, in Jupyter Notebook environment, using Gurobi Optimizer version 9.0.1, on a Dell XPS 15 laptop with 9th Generation Intel® Core™ i7-9750H processor and 16 GB RAM, running on Windows 10.

### 4.3 Scenarios of Analysis

As discussed in Section 4.1, the sponsoring company has provided masked data for delivery and pickup transactions from one parcel center for 5 days (from 16th July 2018 to 20th July 2018). The base case analysis has been carried out by solving the model individually for each of the five days in the dataset. The sensitivity analysis (as discussed in further sections) has been carried out by testing the model for varying values of input parameters. For the sake of analyses, a set of 20 satellite candidates has been generated (using the methodology described in Section 3.2).

#### 4.3.1 Base Case Analysis

The model has been executed for 5 different scenarios, with each scenario pertaining to one of the 5 days in the dataset, to understand how the count of required satellites varies from day to day. For the purpose of solving the model, the following values for the input parameters have been used, based on the inputs received from the sponsor company (Table 4.1)[1]:

[1] The dollar values among the input parameters have not been shown, for the purposes of confidentiality

**Table 4.1: Input parameter values**

| Parameter | Base Case Value |
|---|---|
| $F_j^S$ | *concealed* |
| $C_{mile}^{FT}$ | *concealed* |
| $C_{hour}^{FT}$ | *concealed* |
| $C_{hour}^{ST}$ | *concealed* |
| $C_{mile}^{ST}$ | *concealed* |
| $F^{FT}$ | *concealed* |
| $F^{ST}$ | *concealed* |
| $Q_r^{FT}$ | 1000 parcels |
| $Q_r^{ST}$ | 35 parcels |
| S | 3000 parcels |

Table 4.2 tabulates the results obtained by executing the model for each of the 5 days. For the purpose of confidentiality, the values for delivery/pickup/total customers and volumes have been normalized against the actual values of Day 1.

**Table 4.2: Results for each scenario**

| | **Day 1** | **Day 2** | **Day 3** | **Day 4** | **Day 5** |
|---|---|---|---|---|---|
| Count of total customers | 100.0 | 102.4 | 105.3 | 115.9 | 111.0 |
| Count of delivery customers | 97.2 | 100.0 | 102.6 | 112.9 | 107.9 |
| Count of pickup customers | 8.5 | 8.9 | 9.3 | 10.6 | 9.9 |
| Total Volume | 100.0 | 103.0 | 105.9 | 117.7 | 111.8 |
| Delivery Volume | 95.0 | 97.7 | 100.4 | 111.5 | 106.0 |
| Pickup Volume | 5.0 | 5.2 | 5.5 | 6.2 | 5.8 |
| Count of active satellites | 9 | 8 | 10 | 11 | 9 |
| Count of 1st tier delivery vehicles | 17 | 17 | 18 | 19 | 20 |
| Count of 1st tier pickup vehicles | 2 | 1 | 2 | 2 | 3 |
| Total Vehicles | 19 | 18 | 20 | 21 | 23 |

Table 4.3 shows the various satellite candidates proposed by model for activation on each day (value is 1 if satellite is activated, 0 otherwise).

**Table 4.3: Proposed activation of satellites for each scenario**

| Satellite ID | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 |
|---|---|---|---|---|---|
| Sat_318 | 1 | 0 | 1 | 1 | 1 |
| Sat_422 | 1 | 1 | 1 | 1 | 1 |
| Sat_507 | 1 | 1 | 1 | 1 | 1 |
| Sat_667 | 0 | 0 | 0 | 0 | 0 |
| Sat_880 | 1 | 1 | 1 | 1 | 1 |
| Sat_1320 | 1 | 1 | 1 | 1 | 1 |
| Sat_2101 | 0 | 0 | 0 | 1 | 0 |
| Sat_2733 | 0 | 0 | 0 | 0 | 0 |
| Sat_3364 | 1 | 1 | 1 | 1 | 1 |
| Sat_4036 | 1 | 1 | 1 | 1 | 1 |
| Sat_5116 | 0 | 0 | 0 | 0 | 0 |
| Sat_5493 | 1 | 1 | 1 | 1 | 1 |
| Sat_5638 | 0 | 0 | 0 | 0 | 0 |
| Sat_6022 | 0 | 0 | 0 | 0 | 0 |
| Sat_6207 | 0 | 0 | 1 | 1 | 0 |
| Sat_6424 | 0 | 0 | 0 | 0 | 0 |
| Sat_6527 | 0 | 0 | 0 | 0 | 0 |
| Sat_7274 | 0 | 1 | 0 | 1 | 0 |
| Sat_7496 | 1 | 0 | 1 | 0 | 1 |

Figure 4.1 depicts the variation of the total count of satellites proposed by the model, against the total volume (delivery and pickup volumes combined):

**Figure 4.1: Total Volume v/s Active Satellites**

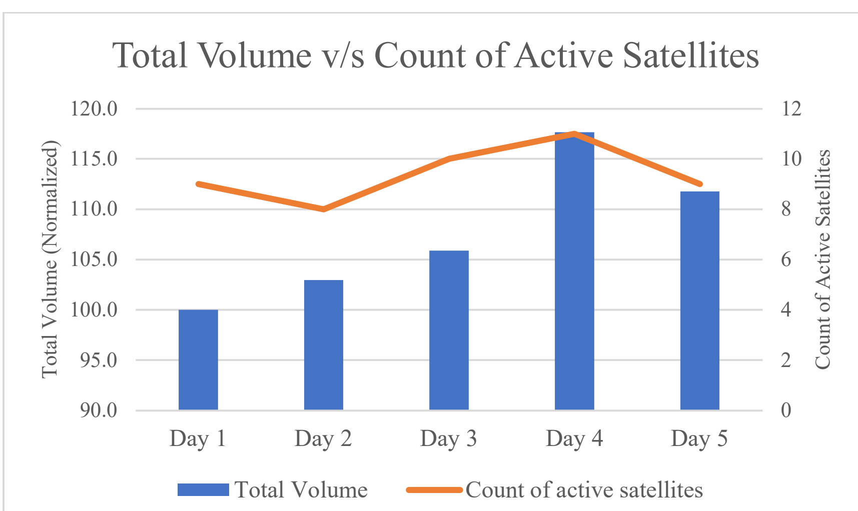

Figure 4.2 shows the variation in count of satellites activated against the total number of first tier vehicles used for delivery and pickup, across each scenario:

**Figure 4.2: Count of satellites v/s count of first tier vehicles**

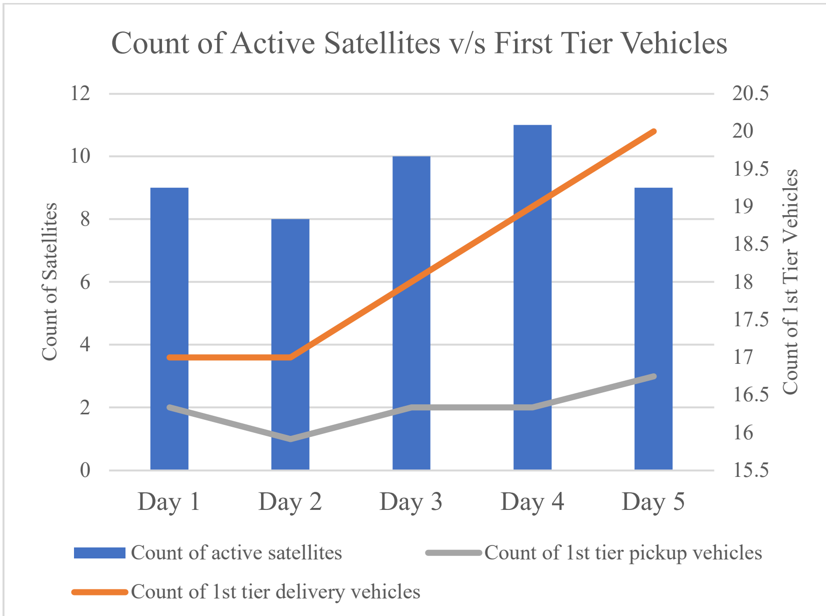


Table 4.4 shows the breakdown of various components of the objective function of the model, for each day in the base case analysis. The values in the table have been normalized on a scale of 0 to 100, for the sake of confidentiality.

**Table 4.4: Breakdown of individual costs in the objective function for each day of base case analysis**

| | **Day 1** | **Day 2** | **Day 3** | **Day 4** | **Day 5** |
|---|---|---|---|---|---|
| Satellite Fixed Cost | 18.51 | 16.18 | 19.30 | 19.41 | 16.61 |
| First Tier Travel Cost | 1.27 | 1.08 | 1.21 | 1.26 | 1.31 |
| First Tier Fixed Cost per route | 0.98 | 0.91 | 0.96 | 0.93 | 1.06 |
| Second-tier fixed and travel cost of routes | 79.24 | 81.84 | 78.52 | 78.40 | 81.01 |

### 4.3.2 Sensitivity Analysis

To test the robustness of the model to changes in various input parameters, multiple sensitivity analyses have been conducted, varying parameters such as vehicle capacity, satellite capacity etc. The sensitivity analyses have been conducted for the day with the highest overall volume (delivery and pickup combined), i.e., Day 4 in the dataset provided by the sponsoring company. Other than the parameter being tested for sensitivity analysis, all other input parameters for used for the test are the same as mentioned in Table 4.1.

- **First tier vehicle capacity:** The model has been tested for first tier vehicle capacities of 1000 parcels, 1500 parcels, and 2000 parcels. Table 4.5 shows the results of the sensitivity analysis. As observed from the results, the count of active satellites remains constant for vehicle capacities of 1000 and 1500 parcels, but reduce by one for a vehicle capacity of 2000 parcels, as the model tries to optimize the vehicle cost against the cost of operating satellites. As expected, the count of first tier vehicles reduces consistently as the capacity increases.

**Table 4.5: Results for sensitivity analysis for variation in $\mathbf{Q_r^{FT}}$**

| | $\mathbf{Q_r^{FT} = 1000}$ | $\mathbf{Q_r^{FT} = 1500}$ | $\mathbf{Q_r^{FT} = 2000}$ |
|---|---|---|---|
| Count of active satellites | 11 | 11 | 10 |
| Count of 1st tier delivery vehicles | 19 | 13 | 10 |
| Count of 1st tier pickup vehicles | 2 | 1 | 2 |

- **Satellite capacity:** The model has been tested for satellite capacities of 2000 parcels, 3000 parcels and 4000 parcels. As evident from results tabulated in Table 4.6, the total number of satellites activated reduces consistently from 11 to 9, as the capacity for each satellite increases. It is also observed that the total number of pickup vehicles utilized increases to 4 when satellite capacity increases to 4000 parcels. This can be attributed to the model's attempt to optimize the cost of deploying newer vehicles rather than having same vehicles doing longer trips. This also indicates the interconnection between the routing problem and the facility location problem.

**Table 4.6: Results for sensitivity analysis for variation in S**

| | **S = 2000** | **S = 3000** | **S = 4000** |
|---|---|---|---|
| Count of active satellites | 12 | 11 | 9 |
| Count of 1st tier delivery vehicles | 19 | 19 | 19 |
| Count of 1st tier pickup vehicles | 2 | 2 | 4 |

- **Second tier vehicle capacity:** The model has been tested for two types of second tier vehicle capacity. The first is bike delivery, with a capacity of 35 parcels, and second is truck delivery, with a capacity of 350 parcels. As observed in Table 4.7, the count of active satellites reduces significantly, as the second-tier vehicle capacity increases.

**Table 4.7: Results for sensitivity analysis for variation in $Q^{ST}$**

| | $Q^{ST} = 35$ | $Q^{ST} = 350$ |
|---|---|---|
| Count of active satellites | 11 | 7 |
| Count of 1st tier delivery vehicles | 19 | 19 |
| Count of 1st tier pickup vehicles | 2 | 2 |

- **Satellite fixed cost:** The model has been tested for satellite fixed cost of x, 1.25*x and 1.5*x (the actual dollar values of the costs have been concealed for the purpose of confidentiality). As observed in Table 4.8, the count of satellite sharply decreases as the fixed cost of satellite increases by 25%. Since the minimum count of satellites required is 7 (based on the capacity of satellites and number of parcels), the count does not change at 1.5*x.

**Table 4.8: Results for sensitivity analysis for variation in $F_j^S$**

| Parameter | $F_j^S = x$ | $F_j^S = 1.25*x$ | $F_j^S = 1.5*x$ |
|---|---|---|---|
| Count of active satellites | 11 | 7 | 7 |
| Count of 1st tier delivery vehicles | 19 | 19 | 19 |
| Count of 1st tier pickup vehicles | 2 | 2 | 2 |

### 4.4 Discussion

As discussed in Section 1.3, the model proposed in this project has been developed as a decision support system for the sponsoring company to determine the best locations for satellites, based on the geo-spatial distribution of customer demand volume. As the model is executed for each of the five days in the dataset, it is observed that some of the satellite candidates (for example, Sat_422, Sat_507 etc.) are activated consistently by the model (as evident in Table 4.3). As the volume increases, some additional satellites (for example, Sat_7274) are proposed by the model for activation to handle the higher capacity requirements. As observed in Figures 4.1 and 4.2, the count of satellites proposed by the model varies in line with the overall demand volume and the total number of customers.

The sensitivity analyses described in Section 4.3.2 show the robustness of the model to changes in various input parameters. It has been observed that as the capacity of the first-tier vehicles varies, the count of satellites remains constant (the count of satellite reduces by 1 when the capacity of first tier vehicles increases two-fold). This shows that the model is fairly robust to fluctuations in first-tier vehicle capacities. With variations in satellite capacities, as expected, the count of satellites activated changes significantly. Accordingly, the satellite capacity is identified as a major driving factor in the decision-making process for satellite operations. The variation in second tier vehicle capacity seems to have a significant impact on the count of satellites. As the vehicle type is changed from bikes to trucks (hence increasing the capacity from 35 parcels to 350 parcels), it is observed that the count of satellites reduces by 36%. Hence, it is essential to consider second tier vehicle types and their corresponding capacities when determining the count and locations for satellites. Finally, with an increase in the fixed cost of operating a satellite, the count of satellites activated decreases, as the model optimizes the routing of vehicles against the total number of sites activated and corresponding cost incurred.

Based on the observations from the execution of the model, it can be concluded that the model provides fairly robust results for activation of satellites. The model can be solved for a larger time horizon (a greater number of days) with further variations in volumes and locations of customers, in order to estimate the best locations for the satellites based on the results from each execution. Hence, the results from the model can support the strategic and tactical level decisions related to the establishment and operation satellites.

# 5. CONCLUSION AND FUTURE WORK

The model developed in this project determines the optimal count and locations of satellites for a large-scale parcel distribution company, in order to transition from a single-echelon to a multi-echelon last mile distribution network design strategy. The model has been structured as a combination of a vehicle routing problem (considered for the first-tier transportation) and an allocation problem (considered for the second-tier transportation). While the overall design of the model has been largely adopted from a classic 2E-LRP framework, the research leverages the usage of tools like OSMNx and GIS in order to incorporate additional features such as traffic density considerations (by the virtue of transit times derived from the Uber Movement data), and distances along actual road networks between any two points. These additional factors enable the model to mimic reality of a typical last mile distribution operation, which in turn returns a solution which is closer to optimality than a classic 2E-LRP framework.

The sponsor company for this project is an industry leader in parcel delivery and specialized logistics services. A multi-echelon network design approach can enable the company to overcome the range and capacity constraints associated with the usage of alternative delivery vehicles (such as e-carts, electric cargo bikes, drones etc.) in last mile distribution. This model can support system the company to successfully design a multi-echelon last mile distribution network, while considering the existing facilities and network design, thus allowing for the revised design to be incorporated within the company's current network.

The model proposed in this research can be extended in many ways. First, the model can incorporate the usage of a heterogenous fleet within a tier for the transportation of shipments. This would allow the model to further mimic the real operations. Second, the constraints in the model can be modified to consider limits on the total distance travelled and transit time for each trip within the first-tier transportation. This would allow the model to propose solutions that are in line with the vehicle range and maximum allowable time over a single trip. Third, while the model uses time window information to calculate the expected transit time to each customer, the deliveries and pickups are not constrained to the time windows expected by the customers. The model can be modified further to incorporate time window bound deliveries and pickups. Finally, the model can be modified to consider vehicle routing logic for second tier transportation of parcels as well, in order to improve the optimality of the solution.

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