SUBSCRIPTION & PER-DAY PRICING VS SAME-DAY SERVICE: A SIMULATION OF TEMPORALLY CONSOLIDATED DELIVERY SYSTEMS

WON MO JEOUNG

A THESIS SUBMITTED TO THE FACULTY OF GRADUATE STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF APPLIED SCIENCE

GRADUATE PROGRAM IN CIVIL ENGINEERING
YORK UNIVERSITY
TORONTO, ONTARIO

SEPT 2025

Abstract

Same day delivery is often viewed as the benchmark for last mile logistics because of its convenience and time savings, but its adoption as a wide spread service is limited by high costs. Orders vary between time and location, restricting economies of scale and often resulting in inefficient routes where multiple vehicles serve the same neighborhood within short intervals. To address these issues, this thesis introduces temporal consolidation, where deliveries are grouped and scheduled for specific days of the week or month. Using simulations of customers with different order behaviors and locations, we evaluate delivery scenarios that include grouping requests, optimizing travel routes, and adjusting delivery frequencies. Results show that consolidated deliveries reduce total travel distance compared with same day service. Customers are generally willing to accept longer consolidation periods when paired with cost savings, while higher delivery prices increase demand for faster service.

Dedication

This appreciation goes to everyone who has been part of this journey and contributed to its completion. I would like to dedicate my thesis to my family, whose support and encouragement has helped me in the success of my career and the start of my career in engineering.. I would also like to give appreciation to everyone who has been a part of the team and I have spent time with in the lab. Their presence has provided constant strength and motivation. To all of them, I extend my sincere thanks.

Acknowledgements

I want to thank my supervisors, Dr. Mehdi Nourinejad, Dr. Kevin Gingerich, and Dr. Peter Park, for their support and guidance throughout my research and MASc program. Providing valuable insights throughout my research and progress throughout my degree. This achievement would not have been possible without the guidance and support of my supervisor and professors.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Convenience vs. Cost in Delivery

The market for online grocery delivery has shown substantial growth in the last decade, which can be attributed to the growing demand for prompt services and desired convenience of avoiding storefronts. According to Morganosky and Cude [1], the convenience and time savings of online deliveries serve as primary motivators for consumers to engage in online shopping. The ability of leisurely shopping transforms how consumers interact with online stores and purchasing decisions, no longer being restricted by the physical boundaries of conventional in-person shopping. In addition, the ease of comparing prices, accessing a broader range of products, and avoiding crowded stores enhances the appeal of online delivery.

One example of swift online delivery is Amazon Prime, a premium service which allows consumers to receive their package on the same day or one day after placing an order on certain items, having over 200 million global subscribers who pay a premium for faster shipping. A consumer's willingness to pay a premium for the convenience of fast shipping is also exemplified by companies such as Uber and its UberEats

service, which prioritizes same-day delivery and has accumulated over 88 million users. While initially focused on quickly delivering ready-made food, UberEats has recently expanded its offerings to include same-day grocery delivery services. Other companies in the market of online grocery delivery have also adapted to this demand for speed and convenience. Instacart is an example of this as well, an online delivery company that focuses on delivering groceries. Similar to Uber, Instacart hires personal shoppers and drivers to deliver groceries directly to consumers' homes, providing a convenient solution for those who prefer grocery delivery over going in-person to the store themselves. Another company known as HelloFresh, have chosen to focus more on convenience by delivering preportioned ingredients along with easy-to-follow instructions. HelloFresh gives consumers a more convenient method of have home-cooked meals delivered straight to their front door without the requirements of getting their own groceries and having to meal prep by planning multiple meals ahead of time.

The rapid growth of same-day delivery underlines a broader transformation in consumer expectations and retail logistics. However, the pursuit of same-day delivery includes both challenges and drawbacks. Looking through the lens of the retailer, the service requires high operation costs and negatively impacts the environment. The approach requires additional resources, such as additional drivers and vehicles, with the frequent trips necessitated by rapid delivery schedules contribute to increased carbon emissions and urban congestion [2].

Distributors face additional difficulties in providing convenient fast deliveries,

which raises transportation costs, mostly as a result of erratic order timing and location. Same-day delivery demands that all orders be completed quickly within the available delivery area, in contrast to standard delivery schedules that allow for deliveries and routes to be optimized with larger lead times.

The timing and location of customer orders are highly variable, further complicating logistics, requiring deliveries to be made within tight delivery windows and making it difficult to complete multiple orders simultaneously. Consequently, same-day delivery vehicles often experience a low deliveries-per-vehicle ratio, which does not fulfill their cargo-carrying capacity. This challenge stands in contrast to the method of delivering orders, where multiple orders are grouped and shipped together in order to optimize efficiency. The lower ratio of deliveries to vehicles increases both the labor and vehicle requirements per order, leading to higher operational costs and reduced productivity.

Sporadic delivery patterns and short lead times require a larger fleet to meet the high demands. Unpredictable order schedules mean that delivery drivers often have minimal time between receiving an order and needing to depart, requiring quick dispatch to ensure timely completion. This urgency can lead to missed opportunities for optimizing parcel loads and routes with an increased need for drivers and vehicles, resulting in higher fleet activity between depots and residential areas. Consequently, vehicles may frequently travel similar routes or operate in close proximity, completing fewer orders per trip and often revisiting the same areas, leading to inefficiencies and redundant trips. These factors collectively contribute to increased operational costs

and reduced efficiency in the delivery process.

From the consumers side, While consumers enjoy the benefits of rapid delivery and convenience, they often pay a premium due to the resource-intensive nature of the system. Same-day delivery consumers are confronted with steep prices as the transportation costs of time-sensitive operations are typically reflected in higher delivery fees. These fees are usually priced at a premium, making the service limited to those who can afford to pay the price of quick delivery or an occasional purchase out of necessity in an urgent situation, rather than serving as a regular alternative to grocery shopping.

The trade-off between convenience and cost may be acceptable to some customers, but the high costs of same-day delivery limit its appeal to a broader consumer base. As found in Morganosky and Cude [1], 15% of users rely on online grocery shopping out of necessity rather than convenience. This limitation is challenging for individuals who rely online grocery shopping out of necessity, rather than convenience. For customers such as the elderly, disabled, or those living in areas with limited access to physical stores, the inflated prices of these same-day delivery services create a barrier to essential goods and services. Even certain consumers aware of the benefits of online grocery shopping often struggle to justify the high costs associated with delivery [1]. The authors raise concerns about orders being fulfilled correctly and the quality of goods received from the service and highlight the decision-making process involved in selecting online grocery services beyond pricing.

The cost of same-day delivery is twofold, influencing both the distributor and

consumer. From the distributor's side, the need for rapid fulfillment increases transportation costs, and from the consumer's side, the high prices limit accessibility. These challenges form the basis of this research, which examines the effects consolidation can have on transportation outcomes and consumer appeal.

1.2 Methodology

The increasing demand for same-day delivery in online shopping continues to grow, as consumers search for the fastest and most convenient delivery options. However, this rapid delivery model comes with significant drawbacks. Inefficiencies inherent in rapid, time-sensitive delivery systems have resulted in higher resource consumption, increased costs, and greater environmental impact.

This study introduces an approach of consolidating orders and delivery dates to reduce the price and total driving distance of the same-day delivery model while providing at-home convenience for the user. Instead of the more traditional delivery system of having same-day delivery, Figure 1.1 illustrates how temporal consolidation optimizes delivery schedules by allowing orders placed on different days to be combined and delivered together on a single date. By separating the scheduling and delivery dates, multiple orders can be fulfilled in a single delivery trip.

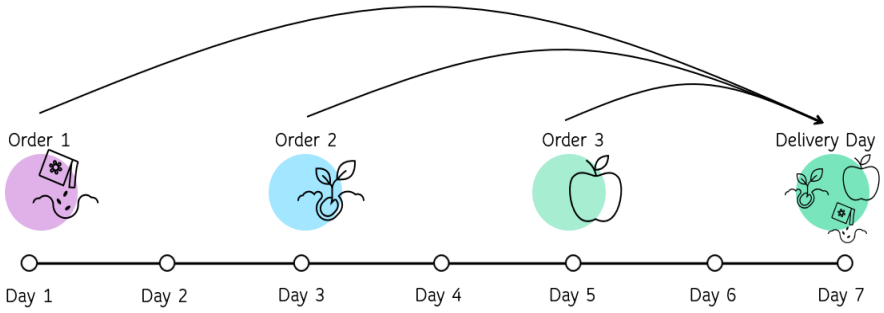


Figure 1.1: A diagram showing a method of temporally consolidating orders

Introducing a consolidated delivery system brings a variety of benefits and helps address many challenges associated with same-day delivery. By consolidating orders into selected delivery days, vehicles have the ability to fulfill higher capacity delivery routes. This approach addresses the issues of low capacity dispatches on delivery vehicles, able to reduce the number of trips and fleets required to meet the same demand in orders.

The implementation of temporal consolidation in online delivery addresses the challenges associated with short lead times and reduces the requirements for additional storage facilities. Lead time refers to the interval between when a customer places an order and when that order is delivered. Traditional rapid delivery services often promise same-day or next-day delivery, resulting in short lead times and tight delivery schedules. The strategic use of well positioned warehouses is one method for meeting these tight timelines, located in and around urban areas, allowing for prompt response times to consumer demand. In contrast, temporal consolidation extends lead times by temporally grouping orders placed on different dates. This approach allows for

more efficient use of resources, minimizing the use of additional storage facilities and vehicles to complete the same volume of deliveries.

The consolidation of orders addresses several concerns associated with same-day delivery. With consolidation able to optimize delivery routes by increasing the number of orders carried per vehicle and reducing redundant and overlapping routes that often occur with instantaneous delivery. By grouping orders, the challenges of unpredictable timing and spatial distribution in same-day delivery are alleviated. Instead of responding to each order individually as it arrives, a consolidated delivery model sorts the orders based on geography and time, allowing for more efficient routing. For example, instead of dispatching multiple vehicles in making separate trips to the same neighborhood within a short period, a single vehicle can deliver all of the consolidated orders in that area in one trip. This strategy is illustrated in Figure 1.2, which results in fewer delivery vehicles and reduces the number of vehicles needed to complete the orders.

Temporal consolidation also offers benefits to the consumers, as with more optimized trips and improved vehicle load efficiency, the cost of transportation and delivery can be reduced. With same-day delivery, an order is quickly processed and shipped directly to the consumer, making the consumer pay the price for the entire trip. However, when delivering orders using the consolidation process the optimization of orders and delivery routing, the cost of transportation is split costs across consumers.

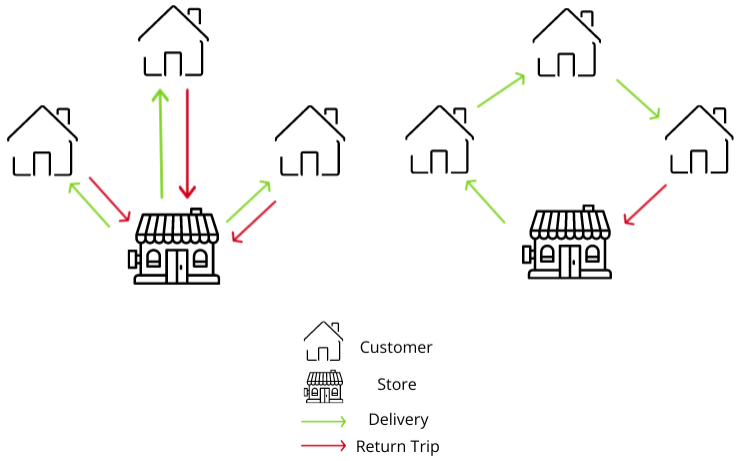


Figure 1.2: Representation of reducing travel distance through the use of consolidation

1.3 Application

When examining the practicality and feasibility of consolidated orders and deliveries, parallels can be drawn to established systems with similar characteristics, such as garbage collection and traditional milkman delivery services. Both of these systems highlight the efficiency that is gained with the consolidation of predetermined routes with multiple spots. In garbage collection, vehicles follow preset routes with multiple scheduled stops at designated locations, optimizing the sequence of stops to minimize travel distance and time. This approach optimizes travel efficiency, reducing the necessity for multiple trips and decreasing the travel distance along with the number of required vehicles. The milkman delivery service historically operated on a model of

regular, predetermined deliveries, where milk was distributed to multiple households in a single trip as efficiently as possible. This system allowed for efficient use of time and resources, as the delivery route was carefully planned to cover a specific area with minimal backtracking ensuring the timely delivery of fresh milk.

The concept of consolidating online grocery orders draws parallels to these traditional systems by emphasizing efficiency and sustainability. This approach groups orders and schedules deliveries on specific days, in order to efficiently carry out deliveries. This approach benefits delivery providers by reducing the distance vehicles have to travel while offering environmental advantages by decreasing the required number of vehicles, compared to frequent individual deliveries. Both systems involve vehicles following predetermined routes with multiple scheduled stops at designated locations, typically grouping deliveries to homes in relatively close neighborhoods. Groceries are recurring purchases for many households. This makes them well suited for consolidated delivery, similar to scheduled garbage collection or milk delivery. Such services, like garbage collection and milk delivery, were traditionally scheduled to align with when consumers were most likely to need them. Grocery shopping aligns with this pattern, as many households consistently shop for groceries on a recurring schedule multiple times a month. This consolidation approach as the potential to optimize vehicles and drivers and reduce environmental impact, while still meeting the regular needs of customers.

The implementation of a consolidated delivery system can be enhanced through the utilization of existing infrastructure and technologies in modern grocery stores.

Services such as grocery store lockers and parking lot pickup points provide efficient intermediary steps between order placement and final delivery. These systems enable orders to be prepared and stored securely by store employees who are familiar with inventory and layout, rather than relying on delivery drivers to shop for items. Grocery store lockers, where orders are placed in temperature-controlled compartments accessible via unique codes, offer a flexible and very compatible pickup option that can be integrated into a consolidated delivery route.

Figure 1.3: Example of a storage locker for online order pickup

Similarly, designated parking slots for order pickup may be used as efficient collection points for delivery drivers allows retailers of al sizes to implement this delivery method. This approach differs from delivery methods that require drivers to perform in-store shopping, select items, and deliver directly to households. Having drivers perform in-store shopping and item selection can be time-consuming and less efficient, potentially creating more points of friction and reducing user satisfaction

when orders are not completed to their standards. Using these existing pickup methods, the consolidated delivery system is able to streamline the process, reducing time spent at each stop and allowing for faster pickups and drop-offs. This integration of store-based preparation with consolidated delivery routes combines the efficiency of bulk order processing with the precision of professional in-store fulfillment. Allowing partnership between small and larger retailers and delivery services with the added benefit of fresher produce, fewer errors, and the improvement overall customer satisfaction.

1.4 Framework

This research aims to gather empirical data on how temporal consolidation affects online delivery. A delivery system was modeled for a specific area with a diverse group of customers, each with unique preferences for order frequency and location. Orders are collected in advance of the delivery date and combined into fewer shipments. Grouping orders this way makes the delivery process more efficient by reducing the number of trips and using resources more effectively.

Customers are assumed to choose from three distinct payment plans to receive their orders. The first option is a one-time subscription plan that uses consolidation, allowing customers to pay a fixed fee for a set period and benefit fully from grouped deliveries. This option can reduce overall costs but demands the highest level of commitment from customers, which may act as a barrier to entry. The second option

is a pay-per-use model, where customers pay per order placed while still benefiting from delivery consolidation. This offers more flexibility but can result in higher costs per delivery compared to the subscription plan. The third option is a traditional same-day delivery approach, where customers pay per order and receive their items that day. While this provides the fastest service, it comes with the highest cost and less efficient use of delivery resources.

Once customers select their preferred payment models, their orders are grouped based on their proximity to one another and their time to delivery. Delivery planning must account for multiple factors, including minimizing travel distances, coordinating vehicle capacity, and adhering to specific delivery time windows.

A key challenge in implementing the consolidation process is balancing the trade-offs between customer convenience and transpiration efficiency. Longer consolidation periods lower operational costs for the service provider, but adds inconvenience to the consumer, who must wait longer for their orders. To satisfy consumers, the retailer could provide faster service at the cost of needing to make more frequent trips and use more vehicles. In addition, efficient routing methods are used to reduce operational costs, reduce environmental impact, and maintain affordable prices for customers. By efficiently grouping and scheduling deliveries, the system is able to strike the right balance between meeting customer expectations and optimizing delivery.

The delivery system scenarios are tested under various conditions, including different delivery days, vehicle counts, and customer types. Important results like travel distances, delivery costs, and customer participation are recorded and analyzed.

This analysis offers insights to the advantages and challenges involved in adopting a successful consolidated delivery approach.

Offering a competitive service that prioritizes cost savings over the fastest delivery times, this thesis provides a practical and cost-effective solution that retains the convenience of online delivery without the associated high costs. Aiming to enhance efficiency and reduce environmental impact while making online grocery delivery more accessible and affordable for a wider range of consumers.

1.5 Implementation

The city of Hamilton, Ontario, with its urban landscape and population exceeding 569,000, presents a suitable setting for examining the potential implementation of consolidated delivery services. This case study explores the integration of a system in a specific area of Hamilton, focusing on a grocery store located at the intersection of Ogilvie St, Hamilton, ON, and Governors Rd, Hamilton, ON, which is an area with a large grocery store surrounded by residential areas.

This case study examines the potential implementation of a consolidated delivery system in the city, taking into account the city's urban landscape, population demographics, and age distribution. The research aims to evaluate the receptiveness of a consolidated delivery system within Hamilton by assessing its potential demographic and quantifying the benefits for its users. By comparing this model to the standard same day delivery service, the study seeks to measure the reductions in both costs

and emissions, thereby assessing the overall efficiency and environmental impact of consolidated delivery services.

The main objective of this case study aims to assist and assess the implementation of a consolidated sustainable delivery system in an urban area. Through the analysis and simulation of the selected area and Hamilton's population, The results could be a useful model for putting into practice effective, cost-effective, and environmentally sustainable delivery systems in Hamilton or other urban cities with similar characteristics.

1.6 Objectives

The objectives of this research are to develop a model that demonstrates the benefits of implementing a consolidation approach within an online delivery systems. This will be achieved by first establishing a base scenario utilizing same-day delivery, and subsequently presenting an example that incorporates consolidation. Through this comparative analysis, the study aims to illustrate the potential advantages of implementing a consolidated delivery model.

First, what effects will delivery consolidation have on the overall delivery system? This question explores the impact consolidation has on delivery, looking into consolidation's impacts on aspects such as travel distance, number of trips, and fleet size. By grouping orders and strategically planning delivery schedules, we seek to demonstrate that consolidation can lead to substantial cost savings and reduced environmental

impact.

Second, what effects consolidation will have on customers? This inquiry focuses on understanding the customer's perception of delivery resulting from a shift to a consolidated delivery model. Assessing customer engagement in a consolidated program and examining how factors such as price or time between order and delivery influence decision making.

The thesis presents a holistic view of the benefits and challenges associated with implementing a consolidated delivery approach. This approach has the potential to make delivery systems more sustainable and improve accessibility for consumers who rely on online grocery shopping out of necessity. The goal is to find the right balance between meeting consumer expectations for a reliable delivery service, creating a more affordable and efficient delivery system, and optimizing routing and order consolidation to minimize customer costs and delivery wait times.

1.7 Outline

This paper is organized into the following sections to comprehensively address the research question of how to develop and optimize temporally consolidated deliveries. Following this introduction, Section 2 presents a literature review examining relevant research on consolidation.Exploring the benefits of consolidation for delivery services and investigating different forms of consolidation. This section also discusses vehicle routing and appropriate methods that would complement consolidation strategies.

Section 3 details the methodology, outlining the algorithms used in building the system for the simulation, the rationale behind the chosen model, and its suitability for the current applications. It discusses the parameters chosen for the K-means algorithm and Vehicle Routing Problem (VRP), concluding with a breakdown of the simulation that was created to gather synthetic data. This section elaborates on the practicality and feasibility of the proposed system, detailing the individual steps that the model takes to produce results, including components such as plotting and generating customers. Section 4 presents the simulation results, followed by an analysis that discusses the findings and highlights various connections revealed by the simulated scenarios. Section 5 presents a case study applying the simulation to the city of Hamilton, exploring potential outcomes if the system were implemented there. Finally, Section 6 concludes with a summary of the research, closing with some final remarks and potential next steps for future research.

Chapter 2

Literature review

2.1 Spatial Consolidation

2.1.1 Spatial Consolidation

Delivery consolidation has long been a focal point of logistics research, particularly in populated urban centers where congestion and environmental concerns necessitate more efficient delivery systems. Urban consolidation has traditionally focused on spatial optimization, particularly by improving truck capacity and delivery times through the use of designated centers. These centers, known as Urban Consolidation Centers (UCCs), are strategically located to facilitate efficient deliveries in urban areas. By providing a shared space for consolidating deliveries from multiple suppliers, UCCs aim to reduce the number of vehicles entering cities. This helps lower congestion and improves overall delivery efficiency. UCCs provide a shared space where multiple suppliers can access a single outpost, reducing the extra trips trucks might need to make to collect all necessary packages for delivery. By simplifying the consolidation of goods to single building, UCCs enable more effective and efficient deliveries.

Urban consolidation centers have emerged as a promising solution for tackling the growing challenges associated with urban logistics and last-mile delivery. As Browne et al. [2] highlights, UCCs offer several significant advantages that can transform urban freight distribution, including their capability to enable better resource allocation across the supply chain. UCCs can substantially reduce the number of freight vehicles entering cities, allowing for the combination of multiple shipments into fewer, more efficiently loaded vehicles. This form of consolidation decreases traffic congestion and reduces emissions in urban areas. The implementation of UCCs can also lead to more streamlined delivery routes, reducing the total distance traveled by delivery vehicles. This efficiency gain translates to lower fuel consumption, decreased wear and tear on vehicles, and potentially lower operational costs for logistics companies.

Similar to UCCs, Naccache and Montreuil [3] writes about the consolidation and use case of online vendors using a shared space to further improve delivery efficiency. Naccache and Montreuil [3] conducted a case study in South Shore that demonstrated the potential benefits of providing a shared space for online vendors, particularly in managing high order demand. However, while the concept of integrating multiple online retailers overcomes the challenges of previously mentioned companies having already established real estate for their depots, this use case still involves the complexity of consolidation optimization between various companies and retailers. While showing improvements in transportation costs, there is the added complexity and computational challenge of managing all of the various inventories, dramatically increasing in complexity with each additional vendor.

While UCCs have the potential to bring significant improvements to urban delivery, they do not guarantee solutions to urban logistics challenges. Although they can offer significant benefits to communities and urban delivery systems, their implementation is not always straightforward or universally beneficial. The success of a UCC depends on various factors, including local regulations, urban layout, existing infrastructure, and the willingness of stakeholders to collaborate.

As discussed in Searle [4], the critique of urban consolidation centers highlights the limitations of their potential benefits when applied in real-life scenarios. While each city faces its own unique challenges, this study focuses on Sydney, where several key obstacles impact UCC implementation. One major issue is the limited availability of suitable urban real estate for developing UCCs. Additionally, the evolving nature of urban development—particularly in high-density residential areas—adds uncertainty and complexity. For the case of Sydney, although market demand for high-density living initially appeared promising, past trends show fluctuations that could affect UCC viability. These constraints reveal the gap between the theoretical advantages of UCCs and the practical difficulties posed by real-world urban dynamics.

Another notable limitation of UCCs, as discussed by Browne et al. [2], is the significant cost involved in operating and managing these centers. Although the idea of multiple companies sharing a single depot for product consolidation is attractive in theory, coordinating different supply chains in one location introduces added complexity and expense. Managing the logistics for various suppliers demands substantial resources, which can lead to higher operational costs and reduce the

overall economic feasibility of UCCs. Additionally, onboarding multiple companies to work together presents further challenges, as UCCs depend on the cooperation of various suppliers to share space in strategically located urban environments for maximum efficiency. However, initiating this process is difficult, as many companies are hesitant to participate. Established businesses often have their own depots and pre-planned delivery routes, making the need to overhaul infrastructure, relocate inventory, and revise existing logistics a costly and unappealing prospect. As a result, the reluctance of companies to make these adjustments poses a major barrier to the widespread adoption and success of UCCs.

2.1.2 Temporal Consolidation

For this thesis, we are taking a step away from urban consolidation's focus on UCCs and spatial systems for consolidation. Instead, we are examining temporal consolidation, which involves consolidating orders and delivery days throughout the week. This approach involves consolidating orders and delivery days throughout a set length of time. Temporal consolidation offers benefits similar to spatial consolidation, such as lowering travel distances and operational costs, but differs in how they are achieved. While spatial consolidation depends on physical locations like depots or urban consolidation centers to group deliveries within a certain area, temporal consolidation instead relies on coordinating the scheduling of orders and deliveries. Unlike spatial methods, temporal strategies do not require additional real estate, making them more flexible to implement within existing networks and still achieving

efficiency goals.

The potential of temporal consolidation in delivery systems was investigated by Alnahhal et al. [5], highlighting its capacity to reduce transportation costs and CO2 emissions, particularly in make-to-order industries with long lead times. The researchers developed a simulation model using Arena Software to simulate the supply chain of a furniture company conducting shipments across Europe. Their findings indicated that the use of temporal consolidation was most effective when applied to an environment with high-frequency orders with variable preparation times. The study observed improvements of up to a 30% reduction in shipments through effective temporal consolidation, highlighting how temporal consolidation can enhance sustainability in the supply chain without necessitating additional infrastructure or real estate investments.

The benefits of temporal consolidation in delivery systems are further substantiated by the research of Zhang et al. [6]. Which directly compares a consolidated delivery approach to instantaneous delivery, which they term the First-In-First-Out (FIFO) approach. Through simulated testing, the researchers found that the consolidated delivery method yielded a significant 5.09% reduction in total delivery costs compared to the FIFO method. This comprehensive analysis considered the direct costs associated with the deliveries as well as the inventory costs incurred from both methods. The findings highlight the potential of consolidated delivery systems to achieve substantial cost savings while maintaining service efficiency.

Another example of consolidated delivery is considered in Peng et al. [7], which

discusses a method of a three-phase heuristic model which solves complex delivery routes through the use of a hybrid spatial-temporal system. The model first establishes a distribution schedule, then creates options, optimizes vehicle routing through a series of traveling salesman problems, and finally improves the initial solution with a general improvement routing procedure. This approach breaks down the problem by addressing different in each phase to achieve an optimized solution. Their strategy consolidates parcels based on their delivery due dates and spatial distributions to minimize redundant trips by allowing parcels arriving at different times for the same recipient to be delivered together, which in turn enhances operational efficiency and customer satisfaction while reducing costs.

Consolidation can also be applied collaboratively between existing companies to help reduce costs across shared supply chains. Nguyen et al. [8] discusses this approach through a case study in California focused on the cut flower delivery sector. By consolidating shipments from multiple agricultural suppliers, the study develops a look-ahead heuristic that aims to maximize capacity, ship in larger quantities, and reduce transportation costs while maintaining shelf life. Finding many benefits that come along with the consolidation between companies, such as cost savings, reduced transportation complexity, and and improved competitive advantage. Additionally, the paper discusses a proportional cost allocation rule to encourage supplier cooperation, emphasizing the significance of consolidation and the potential collaborative strategies it brings in reducing overall transportation costs and enhancing supply chain efficiency

2.2 Vehicle Routing Problem Variations

When considering the practicality of order consolidation for delivery, it is also important to understand how the end user ultimately receives these consolidated deliveries. To address this, we can refer to a standard problem often discussed in logistics, the Traveling Salesman Problem (TSP), which is a popular optimization problem that determines the shortest possible route for a "single salesman" to visit a set number of deliveries and return to their initial position while meeting the requirement of delivering to each destination exactly once. This problem parallels delivery logistics, where the objective is to minimize travel distance and time while servicing multiple delivery locations. An extension of the TSP is the VRP, where the same conditions apply, but we are now solving for multiple vehicles at once carrying out multiple delivery routes simultaneously, instead of a singular salesman. By applying VRP algorithms to online grocery deliveries, we could reduce fuel consumption, lower operational costs, and mitigate environmental impacts. This foundational understanding of VRP sets the stage for exploring how consolidated delivery approaches can use these optimization techniques to improve logistics in various delivery scenarios.

We review existing examples such as garbage collection and the milk run. Both involve predetermined routes with multiple scheduled stops, optimizing the sequence of stops in order to minimize travel distance and time, equivalent to the proposed consolidated delivery systems. The consolidation of orders improves the likelihood of a single delivery vehicle making multiple deliveries in a general residential area, again

sharing parallels with how garbage collection and the milk run routes work. Multiple vehicles make multiple stops on a predetermined route efficiently to residents. Brar and Saini [9] mentions the traveling benefits that come from the use of such a system. Reducing the number of vehicles needed for delivery, along with reducing the travel costs of said vehicles, while also being able to lighten the load of traffic. Bae et al. [10] found that utilization of the milk run method from supply trains showed nearly a 4% improvement when evaluating the system using two separate supply trains and theorized potentially larger benefits in scenarios of using a single train. Looking at garbage collection, it shares even more similarities with the proposed consolidated delivery systems due to there being a vehicle that must optimally route to different locations along a route, while also being time-sensitive. Nambiar and Idicula [11] discusses the benefits gained from adding a dynamic aspect to the standard VRP. Seeing an improvement from anywhere from 10-25% for various DVRP scenarios and better reflecting the dynamic process of receiving orders for the consolidated delivery systems.

In exploring various VRP approaches, Ombuki et al. [12] discusses a branch of VRP problems that introduce new variables to the base VRP, one which introduced time-sensitive windows for when deliveries are accepted. The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the original VRP problem, with the introduction of time-sensitive windows where each customer must be served their order within a specific timeframe. Ombuki et al. [12] discusses the vRPTW problem using a multi-objective genetic algorithm, meaning instead of trying to find one absolute solution, the algorithm searches for a set of feasible solutions and then balances the

different solutions into a final complete one. Finding that their algorithm provided better results than the usual singular computation of the determined final best route, the study highlights the effectiveness of treating VRPTW as a multi-objective problem, providing flexibility in decision-making and final route solutions.

A separate branch of the VRP is explored by Archetti and Speranza [13], who investigates the split vehicle routing problem methodology. This approach lifts the single-visit restrictions on customers, allowing a single customer to receive their order through multiple deliveries. This method is particularly useful in situations where customer orders exceed the capacity of a single delivery vehicle or when it can enhance logistics by enabling more efficiently packed vehicles. Gulczynski et al. [14] provides a comparative analysis of this split method against various other VRPs, considering that split deliveries may inconvenience customers who might prefer to have their orders completed in a single delivery. Their study examines a VRP where split deliveries are permitted if they complete a certain percentage of the customer's order. The results were favorable, for the split VRP methods when compared to other VRPs, in some cases, even outperforming other VRP approaches.

Another variation that builds upon the VRP system is the Robust Vehicle Routing Problem, which adds the complexity of uncertain delivery times and routes to the system. Unlike the traditional VRP system where the timing of the delivery routes and points of pickup and drop off are all established before the vehicle sets off to complete the deliveries, the RVRP algorithm accounts for variation in delivery times by incorporating measures to handle any variations that may come from travel times

or additional customer demands. Hu et al. [15] presents a study on the Robust Vehicle Routing Problem (RVRP) with time constraints and limited vehicle availability. The research explores time windows with a restricted fleet size under RVRP conditions, resulting in routes that either exclude customer orders that cannot fit within the allocated time windows or expand the time windows to accommodate additional orders. The paper employs a tabu search method that incrementally introduces new vehicles into the system, aiming to maximize the number of customers added to existing robust routes. This approach focuses on grouping customers within existing routes to optimize for density, utilizing a queue system for customer additions to each of the routes. When compared to solutions using widened time window constraints for route optimization, this tabu method yielded more favorable results in certain scenarios. The study found that a combined approach, which first solves the VRP without widened time windows and then uses this solution as the initial scenario for further optimization, demonstrated the most significant improvements in results.

An alternative approach to solving VRP involves integrating clustering algorithms to enhance solution quality and efficiency. A study on solving pickup-and-delivery time windows is done by Ioachim et al. [16] focus on request clustering as a foundational step before solving the routing procedure. The clustering process turns neighborhoods into mini clusters for the routing algorithm, which are then routed using a vehicle routing subroutine. Their method introduces specialized heuristics to manage cluster sizes and ensure scalability, proving effective in large-scale instances by reducing the travel time within clusters by 10% compared to parallel insertion heuristics.

Another implementation of the cluster-and-routing method is presented by Lou [17], who created an intelligent tourism route planner using an improved k-means clustering algorithm combined with a VRP algorithm. The initial clustering step divides the VRP into smaller, more manageable subproblems, which allows for focused route optimization within each cluster. The paper implements user preferences through additional steps that calculate specific point values, consider maximum and minimum distances, and include visitor interests, resulting in routes optimized not only for distance but also better aligned with individual preferences. Compared to traditional clustering and VRP methods, this hierarchical approach achieves better outcomes by producing travel routes that are more practical and coherent.

The K-means sorting algorithm is a popular choice in grouping together large spatial datasets. Kanungo et al. [18] describes the algorithm that assigns n data points in a real space to center points denoted by K, minimizing the mean squared distance from each data point to its nearest center point. Although easy to implement, the K-means algorithm has its limitations, having difficulties with the initialization of initial center points, as well as having troubles with managing multiple data sets [19]. Ahmed et al. [19] compares five different variations of the K-means algorithm and concludes there is no universal answer for a solved K-means algorithm. Instead, the various algorithms shine best with their appropriate applications and data sets.

To deepen the understanding of clustering methods further, Zhao et al. [20] compares partitional algorithms and agglomerative algorithms, with partitional algorithms using all data points in a single cluster and dividing the cluster into a predefined

number of clusters similar to the K-means algorithm. Agglomerative algorithms take an inside-out approach by starting with single data points and iteratively merging them with each other. Their study found that partitional algorithms are more suitable for hierarchical clustering due to their lower computational requirements and higher clustering quality. The researchers conducted additional experiments on joining the two algorithms to yield the best results. Using the partitional algorithms as a constraint on the agglomeration algorithm, this third option of combining the two systems yielded the best results.

Further the discussion on clustering algorithms, Bhattacharjee and Mitra [21] examines comparisons of various density clustering algorithms, first by grouping the different density algorithms into four characteristic categories such as whether the algorithms are serial or parallel, or if they use a point or grid based system. The paper compares the different algorithms and identifies which algorithms work best together while also discussing the fields where the algorithms may be best applied.

Regarding optimization of the K-means algorithm, [22] discusses methods for reducing the sorting time of the algorithm by having the centroids retain data of their previous closest n points. This optimization significantly reduces the execution time, especially for large-capacity databases, by minimizing redundant distance calculations with each iteration, thus speeding up the sorting process. This system would prove useful for sorting through customers who use delivery services, as they vary geographically and exhibit different ordering habits, with the timing and frequency of their orders differing from customer to customer.

Continuing the exploration of potential ways to improve the K-means algorithm, another promising approach is the constrained K-means algorithm evaluated by Bradley et al. [23], a version of K-means that assigns the number of data points to its closest centroid, it requires each centroid to take a minimal number of nodes to satisfy the sorting algorithm. The constrained K-means algorithm is well-suited for online delivery applications, as each centroid paired with a surrounding number of data points can be compared to a delivery route. For example, replacing the centroid as the center of a general neighborhood and each data point being a customer who has placed an order, with the constrained centroid and its limited number of grouped nodes being comparable to the limited number of deliveries a single vehicle could make on a round trip.

Interestingly, the application of K-means for online grocery delivery has the potential to bypass one of K-means' limitations. The K-means algorithm tends to form circular clusters and has trouble clustering areas with uniformly spread out nodes [21][19]. However, in the case of online grocery delivery, most of the deliveries will take place in residential neighborhoods, meaning when orders are placed and then delivered, most orders will already be partially grouped together due to the nature of where the delivery spots are located.

2.3 Environmental Impact of Last-Mile Deliveries

A topic discussed earlier in the literature review Section 2.1 was the consolidation of orders allowing for vehicles to operate more efficiently. In contrast to instantaneous

or same-day delivery models, where vehicles often operate at partial capacity to meet tight delivery windows, consolidated delivery systems can offer environmental benefits. By implementing order consolidation, vehicles can be used to their maximum capacity, combining multiple deliveries into a single trip rather than making separate journeys for each individual order. This approach optimizes resource utilization and significantly reduces the number of vehicles needed on the road, leading to a decrease in overall fuel consumption and carbon emissions. The environmental impact of consolidated deliveries extends beyond reducing the number of vehicles on the road, further optimizing the delivery routes taken by each vehicle, and reducing the overall carbon footprint of the delivery process. This study addresses both the economic benefits associated with consolidated delivery systems and the environmental advantages that arise from this method of delivery.

Evaluating Urban Consolidation Centers (UCCs) involves navigating various implementation processes which all have influences on their effectiveness. Gillström and Björklund [24] examines Urban Consolidation Centers (UCCs) and their implementation in various environments, offering insights into the contrasting perspectives on their success or failure. Through a literature review and case study analysis, the paper explores the diverse methodologies used in UCC evaluations and highlights the critical factors influencing their perceived effectiveness. The research emphasizes the importance of considering multiple variables when assessing UCC performance, including the geographical scope of implementation, ranging from small towns to large metropolitan areas. Additionally, the study underscores the significance of clearly defining the scope of deliveries covered by the UCC, as this can significantly

impact the observed outcomes. The paper also draws attention to the variability in performance metrics used across different studies, such as vehicle kilometers traveled or environmental impact indicators. Furthermore, the research highlights the role of vehicle types and sizes in UCC evaluations, noting that comparisons between different vehicle configurations can yield varying results. Importantly, Gillström and Björklund [24] argues that the baseline scenario used for comparison is a key determinant in UCC assessment, suggesting that an inefficient starting point without a UCC can artificially inflate the perceived benefits of UCC implementation. This comprehensive analysis provides valuable insights into the complexities of evaluating UCC effectiveness and the need for standardized assessment methodologies in future research.

Expanding on the environmental evaluation of UCCs, Lin et al. [25] finds that the use of UCCs does not always lead to a lower impact, and the use of UCCs does not always directly reduce truck trips, congestion, and emissions. They found that achieving the highest return on monetary and environmental benefits was from maximizing vehicle capacity through consolidation and providing cheaper UCC space. Having UCCs receive cheaper storage space allows them to be in more centralized areas, aiding in reducing the environmental impact and having a bigger influence on trip optimization due to them being able to be placed in their ideal locations. Efficient maximization of vehicle capacity and their potential to complete the most orders had the largest impact on reducing environmental impact.

To address the negative environmental impact of same-day delivery services,

Dayarian and Savelsbergh [26] introduces a crowd-sourcing concept where in-store customers assist in fulfilling online orders. The study proposes a concept where in-store customers supplement company drivers in fulfilling online orders. This method diverges from the traditional optimization of delivery schedules and routes, instead leveraging existing trips to and from retail locations. The core idea involves in-store customers delivering online orders on their way home, effectively sharing their spare time and vehicle capacity. This approach offers potential advantages over conventional delivery methods. It may provide faster and more cost-effective delivery services while reducing compensation costs compared to outsourcing to independent drivers, as in-store customers are already making the trip and may accept smaller incentives. By utilizing the spare capacity of customers' vehicles and their planned journeys, this crowd-sourcing model presents a strategy for improving the efficiency and sustainability of last-mile delivery operations.

While Urban Consolidation Centers (UCCs) focus on spatial consolidation, Ülkü [27] examines a temporal approach through a Discrete-Time Based Shipment Consolidation (DTB-SCL) strategy. Unlike the UCCs where the consolidation is spatial, the use of the DTB-SCL policy is a temporal form of consolidation. Instead of consolidating the inventory into the same locations for easy access like the UCCs, the consolidation is done on the timing of when vehicles are sent out to fulfill orders. The research aimed to find the optimal length between consolidated deliveries, reducing the cost of deliveries, the impact on the environment, and CO2 emissions.

By consolidating orders, the DTB-SCL policy can reduce the number of truck

dispatches, leading to a higher average vehicle capacity when compared to immediate shipping schedules and leading to less traffic congestion, further lowering CO2 emissions per dispatched vehicle. Ülkü [27] found that the policy is most effective in reducing the number of dispatched vehicles carrying a low capacity, through the use of consolidation by having more strategic dispatching times.

In researching the consolidation process, Berling and Eng-Larsson [28] explores the different variations of consolidating orders. Finding that in order to reach the highest amount of improvement on environmental impacts for consolidated orders, an important aspect is catering the system to consumer's needs to achieve best results. Dealing with consumer characteristics such as the ordering frequency and location, prioritizing the number of consumers being delivered to at once showed the highest impact when many customers were ordering. Consolidating time intervals, with longer shipment intervals between shipments, had the highest impact with fewer consumers. The environmental benefits of shipment consolidation are not always clear-cut: Inventory build-up or higher-than-optimal dispatch frequency may lead to adverse effects and is affected by the mode of transportation or the item being transported, highlighting the importance of having an appropriate schedule catered to the consumer base.

In conclusion, the environmental benefits of order consolidation in e-commerce and last-mile delivery are substantial and multifaceted. By reducing vehicle miles traveled, improving capacity utilization, enhancing energy efficiency, reducing packaging waste, optimizing routes, and enabling the adoption of green technologies, consolidation

offers a tool for mitigating the environmental impact of the growing e-commerce sector. As consumers become more environmentally conscious, businesses that effectively implement consolidation strategies can reduce their ecological footprint and also gain a competitive advantage in the marketplace.

2.4 Subscription Planning Strategies

Subscription-based business models have become a significant trend in online services, transforming how companies deliver products and services to consumers. A subscription model is a payment system where customers pay a recurring fee, typically monthly or annually, to continuously access a product or service. This approach differs from the pay-per-use model, where customers are charged only for individual transactions or instances of service use. The shift from traditional one-time payment structures to recurring billing strategies has been adopted by many large companies such as Microsoft, AutoDesk, and Adobe. These companies transitioned from selling bundled programs for one-time purchases to offering software as a service through subscription plans for access to their online program libraries. Similarly, newer companies such as Netflix and Spotify have transformed previously one-time-purchase markets for purchasing movies and music into media service hubs, allowing access to those who purchase a subscription plan. The success of subscription models across various industries highlights their potential to drive growth and innovation in online services. In the context of an online consolidated grocery delivery system, a subscription model could be particularly well-suited.

There are several aspects that make subscription models appealing to both consumers and retailers. One of the advantages for consumers is the convenience and predictability they offer when managing expenses. Customers often prefer subscription services over one-time purchases, as subscriptions provide a hassle-free payment option without additional fees for each use of the service. Kodali [29] found that nearly 70% of consumers preferred subscription models because they allowed for easier budgeting and greater flexibility in managing expenses. The ability to accurately manage monthly spending is a benefit valued by consumers who find the unpredictability of pay-per-use fees challenging. This predictability in monthly expenses has become increasingly valuable to consumers, particularly given recent trends in the service industry. For example, service companies like Uber and Lyft have introduced "surge pricing," allowing service providers to adjust prices based on real-time demand and supply conditions. When demand for services exceeds the available supply, prices are scaled and increased to incentivize more drivers to provide services while discouraging some users from requesting rides. This can result in a negative user experience due to the significant price fluctuations with little advance notice.

The benefits of subscription models extend beyond consumers, offering not only convenience and budgeting ease but also advantages for retailers. Retailers also gain a benefit from subscription models by having a reliable, constant stream of revenue from the subscription fee of onboarding consumers, unlike the sporadic and unpredictable revenue generated by pay-per-use models. Randhawa and Kumar [30] discusses how this predictable financial model enables companies to better optimize pricing strategies and service offerings. The stable revenue stream allows retailers to

cater more effectively to their customers while ensuring continued use of the service through the subscription model.

Personalization also plays a crucial role in the success of subscription-based services. Companies can leverage subscription data to provide tailored recommendations and experiences, enhancing the overall value proposition for customers [31] [32][33]. While many consumers initially adopt subscription services for financial benefits, personalization is key for customer retention. Li et al. [33] They found that both tangible financial benefits and perceived social benefits influence user satisfaction. Moreover, a system that caters to the user is just as important, if not more so, than the financial advantages gained from the model. Finding consumers valued the perceived social benefits of subscription models nearly twice as much as financial benefits. The ability to offer personalized content or product selections based on individual preferences plays a key role in customer retention.

To address these challenges, companies must focus on enhancing the perceived value of their subscriptions. che [32] notes that monetary value is not the sole factor influencing consumer decisions about subscriptions. Other aspects such as convenience, content importance, and service quality are also significant considerations. To achieve high perceived value and trust from consumers, subscription models can adopt various strategies. For instance, offering tailored subscription plans specifically designed for individual customer needs is often recommended for retaining customer attention [34][31][33]. Another approach is providing multiple subscription options at different price points, allowing consumers to select a plan that best suits their preferences [35].

Trust is another critical factor influencing the perceived value of subscription models. Many consumers express concerns about the risks associated with receiving poor service when using online platforms [1] [36]. Retailers can address these concerns and foster long-term relationships with their consumers by improving the ease of access to information and offering straightforward cancellation processes [29] [35] [33]. Enhancing the transparency and accessibility of service details, builds trust with consumers, enabling them to make more informed decisions about their subscriptions. This approach not only alleviates concerns about potential service quality issues but also demonstrates a company's commitment to customer satisfaction. When customers feel secure and valued, they are more likely to remain loyal to the subscription service, benefiting both consumers and retailers in the long term.

In terms of implementing a subscription model to a consolidation delivery service, a subscription model, when paired with a consolidated grocery delivery system, acts synergistically to enhance its benefits while mitigating its drawbacks. For example, Iyengar et al. [37] researched subscription-based users and their spending habits, finding that many customers tend to spend more money when faced with a subscription cost due to a sunk cost fallacy. Consumers already feel invested in having paid the subscription fee and have the impulse to buy more things to make up for the initial deposit of money. While this benefits retailers by aiding profits from customers who have paid for these programs, it is seen as a negative by consumers. It puts additional pressure on users who have opted into the program. However, when paired with online grocery shopping, there is relief from this sunk cost fallacy as consumers have a reliable projected timeline for when they need to buy groceries.

With most households buying groceries at least once to twice a week [38] [39], the added pressure of sunk cost is not as prevalent in grocery shopping.

The recurring nature of grocery purchases complements subscription services and enhances the appeal of online grocery shopping, creating a synergistic relationship between the two systems. This synergy is particularly noteworthy in the context of customer retention, as mentioned prior, one of the key elements of customer retention is the perceived value of the subscription.

One of the main ways consumers gauge the value of a subscription plan is by how much use they get out of paying the subscription fee. One of the issues with subscription services is the loss of consumers due to infrequent usage of the service. As customers have less need for the service or use it infrequently, they will leave and seek different alternatives. According to Scheff [40], the influence of subscription models in the performing arts industry has been studied comparing the sale of tickets through one-time purchases or a subscription-based model in symphonies, theatres, operas, and ballets. Consumers who attended fewer showings or canceled their subscription service were asked their reason for their loss of interest in the program, with dissatisfaction with the programs offered ranging from 17-36% as the reason for their loss of interest across the four arts. Many single-ticket customers were ex-subscription users (25-78%), their main concern was over the potential value of their subscription. They stated that with the difficulty of scheduling a viewing, there was a fear of not using the program versus the use of a single ticket. Interestingly, Scheff [40] found that factors unrelated to the model itself contributed to the loss and

gain of subscription users. Many consumers cited difficulty in timing their visits/use of the program as a major reason for no longer using it and having less time to schedule recreational activities. Many left the program not out of pricing or dissatisfaction but found that it no longer suited their lifestyle.

The synergy between online grocery shopping and subscription services addresses these challenges of perceived value by providing a required and repetitive aspect to the service. Unlike the subscription models of activities like theatres and operas, where program or service dissatisfaction, and a loss of interest in the performing arts led to subscription cancellations, online grocery subscriptions benefit from the consistent and essential need for purchasing food. The recurring need for groceries ensures that subscribers maintain a high perceived value of the service, mitigating the risk of customer churn due to infrequent usage.

The convenience of online grocery shopping coupled with a subscription model alleviates many of the scheduling concerns observed in other industries. Unlike concert subscriptions, which require scheduling and physical attendance, online grocery subscriptions offer flexibility in ordering times and delivery options, often saving consumers time by eliminating the need for in-person grocery shopping. This adaptability better integrates with the varied lifestyles of consumers, addressing the issue of finding additional recreational time for activities. The essential and repetitive nature of grocery shopping presents a unique opportunity to mitigate this challenge. The consistent demand for groceries ensures a steady perceived value of the subscription service, as consumers can rely on its regular utilization.

In conclusion, subscription-based models present beneficial opportunities for companies across diverse sectors, yet their effectiveness relies on a multitude of factors, including consumer behavior, effective value propositions, and strategic catered pricing. The integration of online delivery services with subscription models enhances the strengths of these approaches while addressing inherent weaknesses. Specifically, online grocery subscriptions capitalize on the essential and recurring nature of food purchases, ensuring that subscribers perceive consistent value from their service. This predictability not only mitigates the risk of customer churn associated with infrequent usage but also fosters a sense of reliability among consumers under the guarantee of its continued usage. Ultimately, the success of subscription models in the online delivery context hinges on the ability to continually deliver value to the customer, adapting to the consumer needs, and maintaining a high level of service quality.

Chapter 3

Methodology

In this section, we will discuss the simulation model used to generate synthetic data. We begin by examining the model itself, detailing the various steps involved in its operation and the model's capabilities. This will be followed by an overview of the selected models used to simulate clustering and routing in the generation of delivery data.

3.1 Simulation Optimization Model

The proposed model aims to assess simulated scenarios for a consolidated delivery service offered to customers. The service has two specific features: the frequency of delivery service days and the pricing for subscription and per-order plans. The simulation generates customers and considers their engagement based on their desired delivery frequency and pricing. The proposed measures travel distances to obtain the cost based on customer decisions, focusing on delivery distances and customer engagement.

To replicate specific details and route properties, the simulation model iterates 10

times for each scenario, simulating 150 customers with varying ordering behaviors. The simulated time frame for each data sample was six weeks, with data from the last four weeks used for analysis, allowing for an ample warm-up period to ensure accurate results. Below is a detailed breakdown of the procedural steps undertaken in the simulation:

1. **Initialization**: The simulation begins by placing the initial input parameters, including the delivery frequency, the total number of customers to be generated, the pricing levels for each delivery option, and the available fleet size. These initial variables form the foundation for all following steps in the model.

2. **Customer Placement**: A blank two-dimensional coordinate system is created with a single depot positioned at its center. Within this plane, customer locations are randomly distributed to simulate an arrangement of households within a delivery area.

3. **Order Behavior Assignment**: Each generated customer is then assigned an individual ordering behavior. This is expressed as the number of orders per month, which varies across the customer base and follows a Poisson distribution to realistically capture differences in consumer purchasing frequency.

4. **Utility Calculation**: Customers are assigned to one of three delivery plans based on which plan better suits their needs. The three available plans are same-day delivery, the subscription plan, and the per-order plan. Same-day

delivery provides maximum convenience by delivering orders the same day they are placed, making it ideal for customers who value immediate access to goods and are willing to pay a higher margin. The other two plans follow a consolidated delivery schedule, with the subscription plan offering deliveries for a fixed monthly fee and the per-order plan operating on a pay-per-delivery basis. Both the subscription plan and the per-order plan allow customers to reduce delivery costs by accepting scheduled delivery days on a later date from when they have placed their order.

5. **Customer Grouping**: After assigning each customer their utility value, customers are categorized into two main groups: those who use either of the the temporally consolidated delivery service (subscription and per-order plans) and those who opt for the same-day delivery option, treated as an outside service. This distinction influences how orders are scheduled and routed in the subsequent steps.

6. **Order Consolidation**: For customers using the consolidated service, individual orders are organized so that each is assigned to the nearest available delivery day within the delivery schedule. This reflects real-life behaviors where individuals wait for the first upcoming delivery day.

7. **Delivery Scheduling**: The model then groups customers into delivery groups for each delivery day according to the available fleet size. This clustering is performed using the K-means algorithm, which assigns customers to specific vehicles based on their proximity to one another.

8. **Travel Distance Calculation**: For each cluster that needs a delivery, a VRP solver is used to generate the shortest possible routes that meet delivery constraints. The routing process is applied to each delivery vehicle and day to calculate travel distances, which are then used to determine the travel distances for each delivery month across all trips.

9. **Results Compilation**: Finally, the simulation compiles all outputs, including the number of canceled orders, calculated utilities, daily ordering patterns, delivery locations, trip details, shortest possible routes, and the number of customers served per trip. The results are then averaged across all ten iterations to ensure accuracy and to mitigate any outliers in customer placement and behavior.

When recording the information from the simulations, the data from the 10 iterations are averaged for higher accuracy. With the output of the simulation providing a summary of the final results for each simulated scenario, including the number of canceled orders, customer order frequency, delivery days, number of customers per delivery, customer utilities, delivery destinations, and trip distances.

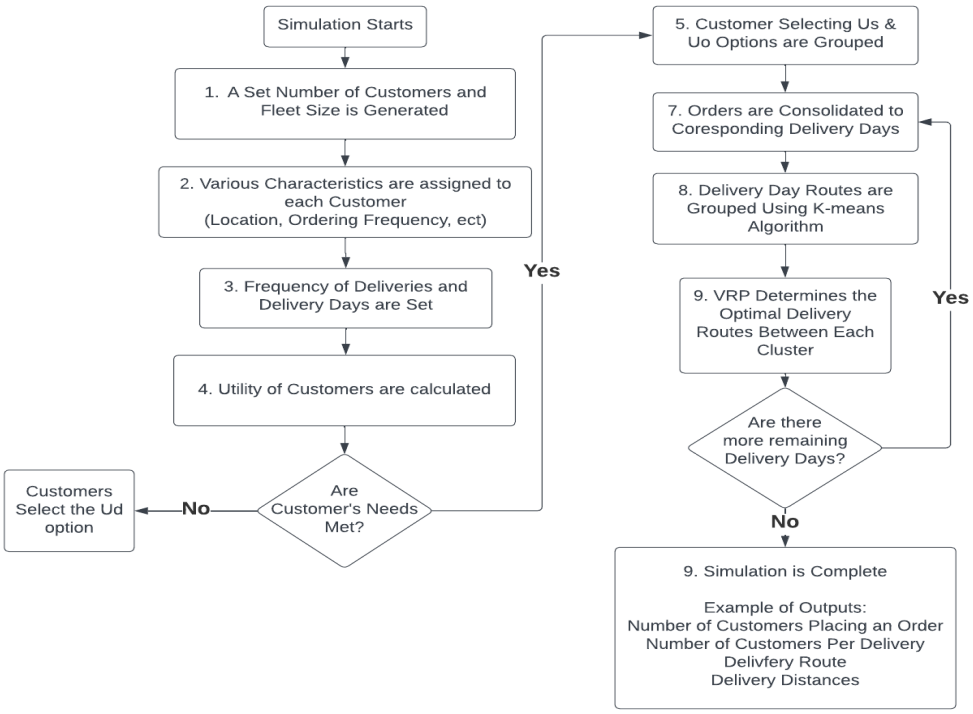


Figure 3.1: A flow chart of the simulation for the temporally consolidated orders

3.2 Utility Functions Breakdown

Customer utilities are evaluated for three delivery options: the Temporally Consolidated (TC) service with subscription-based and per-order pricing, and the same-day delivery service, also referred to as the outside option. We denote these options using the subscripts s for subscription, o for per-order, and d for same-day delivery.

3.2.1 Same-Day Delivery

The same-day delivery option offers maximum convenience as customers receive their orders they day they are placed. The utility for same-day delivery, $U_d(x)$, is

$$U_d(x) = x(v - p_d) \geq 0, \quad \forall x \geq 0 \tag{1}$$

The utility function (1) reflects this higher level of convenience by incorporating the full value of convenience v for each order, where x is the number of orders placed by the customer, v represents the value of convenience that customers experience by having their orders delivered on the same day they are placed, rather than having to visit the store in person. p_d is the price per delivery for using the same-day delivery service. However, the cost associated with this option is reflected in the price p_d charged per delivery, which reduces the overall utility. This option is particularly appealing to customers who prioritize immediate delivery and are willing to pay a premium for the upmost convenience.

3.2.2 Subscription Plan

The subscription plan provides cost savings by allowing customers to pay a fixed fee for the available deliveries for the month. This model is advantageous for customers who are looking for a cheaper alternative to delivery, and won't mind having to wait

for their deliveries for the right price. The utility for the subscription plan, $U_s(x)$, takes into account the delivery frequency f and is given by:

$$U_s(x) = \begin{cases} xkv - p_s & \text{if } x \leq f \\ fkv - p_s - \beta kv(x - f) & \text{if } x > f, \end{cases} \tag{2}$$

In the subscription plan (2) function k is a discount factor representing the reduced value of convenience due to scheduled delivery days rather than on-demand service. The term p_s is the subscription fee, which is a fixed cost regardless of the number of deliveries made. f is the frequency of delivery service days available in a month. β is a penalty factor applied when the number of orders x exceeds the delivery frequency f. The utility decreases for $x > f$ because the customer must either forego some orders or pay additional costs (penalty) for extra deliveries, reducing the overall convenience and utility. This option appeals to customers who regularly order groceries but can tolerate some scheduling flexibility for a reduced cost.

3.2.3 Per-Order Plan

The per-order plan provides flexibility without a commitment to a subscription, appealing to customers with varying order frequencies and still wish to minimize the upfront costs of delivery. The utility for the per-order plan (3), $U_o(x)$, is also influenced by the delivery frequency f:

$$U_o(x) = \begin{cases} x(kv - p_o) & \text{if } x \leq f \\ f(kv - p_o) - \beta kv(x - f) & \text{if } x > f, \end{cases} \tag{3}$$

where p_o is the per-order price, offering a pay-as-you-go model for delivery services. Customers pay for each delivery, which allows them to manage their expenses based on actual usage. As with the subscription plan, ordering beyond the delivery frequency f incurs additional costs, thereby reducing the utility when compared to ordering within the plan limits.

3.3 Summary of Variables

The variables used in the utility functions introduced represent key factors that influence customer decisions. Here are the definitions and assumptions for each variable:

x: Represents the number of orders placed by the customer,

v: the perceived value of convenience for receiving orders without going to a physical store. In our model, this value is assumed to be 2, indicating a strong preference for home delivery over store visits.

f: Is the frequency of delivery days per month. In our model, various scenarios are simulated to illustrate different delivery frequencies, ranging from 2 to 8 deliveries made within a month.

k: The discount factor representing the reduced convenience value in consolidated deliveries. It is set to 0.9, implying that customers perceive consolidated deliveries as 90% as valuable as same-day delivery due to the waiting time involved.

β: The penalty factor for orders exceeding the delivery frequency. It is assumed to be 1, meaning the penalty cost equals the perceived convenience lost by having to wait.

p_d: The price per delivery for same-day delivery services. The service which offers the highest level of convenience, receiving orders on the same day but has the highest pricing point

p_s: The price per delivery for the subscription plan services. A consolidated delivery service plan where consumers pay a flat fee per month.

p_o: The price per delivery for the per-order plan services. A consolidated delivery service plan where consumers pay a delivery raet based off how frequently they place orders.

Using these variables and functions, customer choices and preferences for each delivery option can be modeled, creating unique customers with individual delivery habits and standards.

3.4 Vehicle Routing Problem Algorithms

In this section, we delve into one of the main algorithms used in the model, using a VRP algorithm, we plan multiple delivery routes for each scheduled delivery day. For the routing section of the simulation, the python_tsp library developed by Goulart [41] was used to generate the distances of orders for the delivery routes based on their geographic locations. The VRP portion is used to simultaneously determine the shortest path for each delivery route. Ensuring that each route is efficiently optimized for distance, and meets the requirements for the delivery process. Each delivery vehicle must begin its route at the depot, serve every customer exactly once, and return to the depot at the end of the delivery.

The objective of the VRP is

$$\min \quad Z = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} c_{ij} x_{ijk}, \tag{4}$$

which minimizes the total travel distance across all vehicles. It does so by reducing the cumulative distance required to serve customers. Specifically, c_{ij} denotes the distance between nodes i and j, and x_{ijk} is a binary decision variable equal to 1 if vehicle k travels from node i to node j, and 0 otherwise.

The mathematical model is subjecto to the following constraints:

$$\sum_{j=1}^{n} x_{0jk} = 1 \qquad \forall k \in K \tag{5}$$

$$\sum_{i=1}^{n} x_{i0k} = 1 \qquad \forall k \in K \tag{6}$$

$$\sum_{i=0, i\neq h}^{n} x_{ihk} = \sum_{j=0, j\neq h}^{n} x_{hjk} \qquad \forall h \in N, \forall k \in K \tag{7}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{K} x_{ijk} = 1 \qquad \forall j \in N \tag{8}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} d_j x_{ijk} \leq Q \qquad \forall k \in K \tag{9}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i, j \in N \cup \{0\}, \forall k \in K \tag{10}$$

Variable	**Description**
n	Number of customers
K	Set of vehicles
c_{ij}	Distance between nodes i and j
x_{ijk}	1 if vehicle k travels from node i to j, 0 otherwise
N	Set of customers
d_j	Demand of customer j
Q	Vehicle capacity

Table 3.1: Variables used in the Vehicle Routing Problem

Constraint (5) ensures that each vehicle k departs from the depot (node 0) exactly once, by summing over all possible destination nodes j. This guarantees that every vehicle initiates its route from the central depot. Constraint (6) similarly enforces that each vehicle returns to the depot exactly once after completing its delivery route. Constraint (7) maintains route continuity: for any customer node h visited by vehicle k, the number of incoming arcs must equal the number of outgoing arcs. This prevents infeasible routing behaviors such as a vehicle arriving at a customer without subsequently departing. Constraint (8) ensures that each customer j is

visited exactly once by exactly one vehicle, thereby avoiding both missed deliveries and repeated visits. Constraint (9) enforces vehicle capacity limitations by ensuring that the total demand d_j served by any vehicle k does not exceed its capacity Q. Finally, Constraint (10) defines the binary decision variable x_{ijk}, which equals 1 if vehicle k travels from node i to node j, and 0 otherwise.

The VRP is an optimization problem classified as NP-hard, meaning that its computational complexity increases exponentially with the number of customers and vehicles involved in the deliveries. As a result, finding the optimal delivery route becomes extremely challenging as the problem size grows. To address these complexities, heuristic algorithms can be used to find acceptable solutions for delivery routes within a reasonable computation time. In the next section, we present a cluster-then-route algorithm, which first divides all assignments and assigns each customer to a vehicle (i.e., cluster), then solves a routing problem from each cluster individually, which is a much easier problem to solve than the original VRP. The single vehicle routing model is called the Traveling Salesman Problem (TSP), which is a special case of VRP but with one vehicle.

3.5 A Standard Cluster-and-Route Algorithm for the Vehicle Routing Problem

We present a standard cluster-and-route algorithm to simplify the VRP. In the clustering phase, we use the K-means algorithm to group geographically close customers

into k clusters based on its euclidean distance to each centroid. Note that k is the number of vehicles in the problem. In the routing phase, we solve a TSP tour, a simplified version of the VRP with one vehicle within each cluster, reducing overall problem complexity.

The k-means clustering can be presented as the following mathematical model with the objective of:

$$\min \quad J = \sum_{i=1}^{n} \sum_{k=1}^{K} r_{ik} \|x_i - \mu_k\|^2 \tag{11}$$

which seeks to minimize the squared distances withing the sum of the cluster. With x_i represents ith data point, μ_k is the centroid of the cluster, and r_{ik} is a binary variable which determines if the assigned point i is assigned to the corresponding cluster k, if the statement is true, r_{ik} is set to 1, if i is not assigned to that node, it is instead 0.

The constraints are:

$$\sum_{k=1}^{K} r_{ik} = 1 \qquad \forall i \in \{1, \ldots, n\} \tag{12}$$

$$r_{ik} \in \{0, 1\} \qquad \forall i \in \{1, \ldots, n\}, \forall k \in \{1, \ldots, K\} \tag{13}$$

$$\mu_k = \frac{\sum_{i=1}^{n} r_{ik} x_i}{\sum_{i=1}^{n} r_{ik}} \qquad \forall k \in \{1, \ldots, K\} \tag{14}$$

Constraints (12)–(14) ensure that the cluster assignments in the K-means algorithm are properly defined. They guarantee that each data point is assigned to exactly one cluster, that each point is assigned to a cluster and there are no partial

Symbol	Description
n	Total number of data points
K	Number of clusters
x_i	The i-th data point
μ_k	The center (mean) of the k-th cluster
r_{ik}	Binary variable, 1 if point i is assigned to cluster k, 0 otherwise
$\|x_i - \mu_k\|^2$	Squared distance between point x_i and cluster center μ_k

Table 3.2: Variables and parameters for K-means algorithm

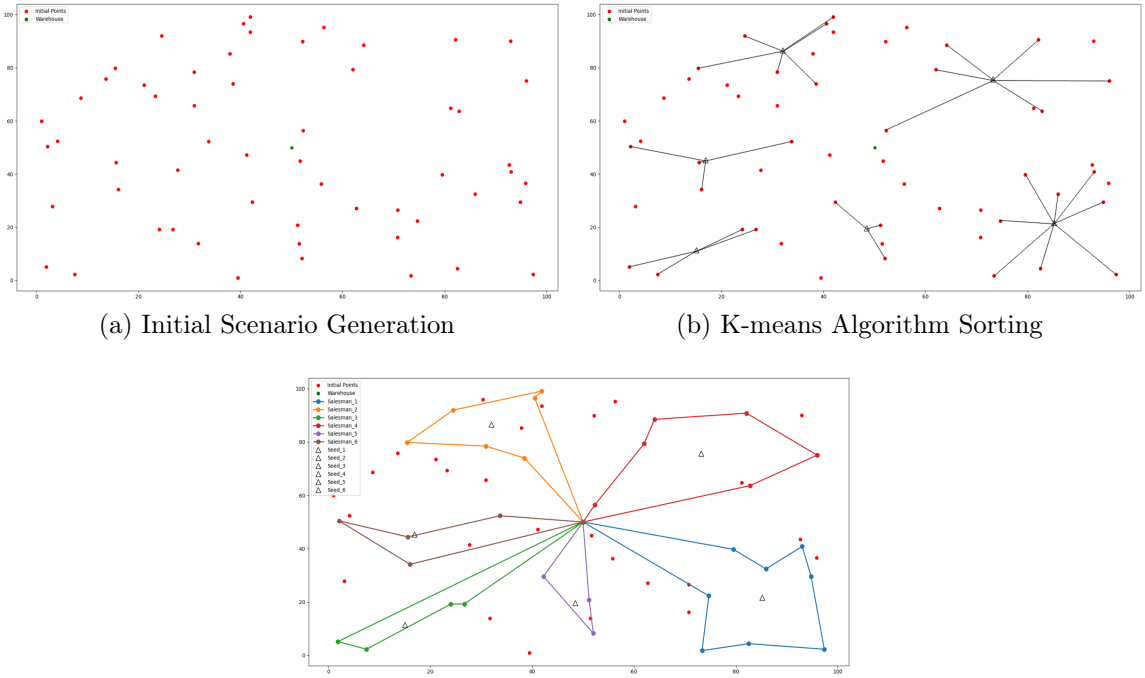
or shared assignments, and require that each cluster center be computed as the mean of its assigned points. Together, these constraints ensure proper partitioning of the data into distinct clusters. Constraints (12) states that each data point x_i must be assigned to exactly one cluster, for every i, the sum of r_{ik} over all k clusters is 1, ensuring a unique assignment to every point. Constraints (13) denotes that variable r_{ik} can only be 1 or 0. For each data point x_i, and each cluster k, r_{ik} either equals 1 or 0, if $r_{ik} = 1$ the point x_i belongs to the cluster k, if not $r_{ik=0}$. This constraint ensures that that every point is either assigned to a cluster or not, with no partial or shared assignments between the different clusters. Constraint (14) enforces that the centroid μ_k of cluster k is computed as the mean of all data points assigned to that cluster. Only those x_i with $r_{ik} = 1$ contribute to the mean, and the denominator counts the number of points assigned to cluster k. Ensures that the cluster center accurately represents the average position of all its assigned points.

In this scenario, each point represents a customer placing an order, with a specific location for order delivery. The K-means algorithm enables us to position the specified number of centroids among these customers and group them by their closest distances.

Each cluster is assigned to a delivery driver, who starts their route from the depot in the center of the plane and completes x orders before returning to the depot. However, we account for the fact that a driver cannot carry an unlimited number of orders; there is a capacity limit on the number of orders per trip. In addition, it is important to prevent clusters with overlapping from one another when grouping customers. To address this constraint, we implemented an adjusted K-means clustering algorithm that incorporates these considerations, allowing for a constrained number of customers per centroid. The primary feature of this constrained K-means clustering algorithm is its ability to limit the number of customers grouped in each cluster, effectively defining the vehicle capacity for each route. We chose the constrained K-means algorithm as described by Levy-Kramer [42] because of the ability to implement new restrictions and parameters and supports the function of running multiple iterations of the same layout in a Python coding format.

Once the clusters are defined using the K-means algorithm, each group of geographically proximate customers is treated as a separate routing problem. To determine the delivery sequence within each cluster, we apply the nearest neighbor algorithm using euclidean distances, a simple yet effective heuristic for the TSP. The use of euclidean distances was chosen as a control factor in requiring flexibility in testing multiple delivery scenarios, ensuring better control over the simulated scenarios vs any interference a real road network calibration may bring into the system. Starting from the depot, the algorithm repeatedly selects the nearest unvisited customer until all have been served, then returns to the depot. Although it does not guarantee an optimal route, the nearest neighbor method alongside euclidean distances offer fast

and scalable results which perform well in practice when testing for various delivery scenarios. By decoupling the VRP into clustering and routing phases, this approach significantly reduces computational complexity and enables efficient, parallel route generation across clusters.



(a) Initial Scenario Generation

(b) K-means Algorithm Sorting

(c) Completed Determined Routes for Delivery Day

Figure 3.2: Simulation mapping & routing examples

Figure 3.2 presents three figures representing the different steps of the simulation, showcasing how the VRP and K-means algorithms are applied to generate various case scenarios. Figure 3.2a illustrates the initial step of the simulation which a plane is created with a supply depot marked in green placed in the center of the generated area, afterwords loading of the randomly generated customer locations

shown in red, with each customer having their own unique starting day for placing orders and ordering frequency. Figure 3.2b displays the K-means sorting algorithm aspect for a singular day of delivery within the month time span, and shows where the centroids of each group is placed for the corresponding day of delivery. Figure 3.2c shows the final simulation process, where the pre-formed groups of customers creating by the K-means algorithm are now able to forming trips and complete their corresponding deliveries. Each of the groups formed the K-means algorithm are then put through many iterations of various routes, until the VRP algorithm finds their most optimal delivery path. Finally, each of the optimal routes are represented in the multiple colored lines, connecting the depot to the customers and showing the route that is taken by the delivery vehicle. Notably, Figure 3.2d, does not display every customer being apart of a generated, as these images only shows the delivery routes for one particular day of delivery in the simulated month. The customers that are not included in the delivery routes shown in the figure are customers who have chosen one of the subscription models and have placed orders to be delivered later in the month on another delivery day.

Chapter 4

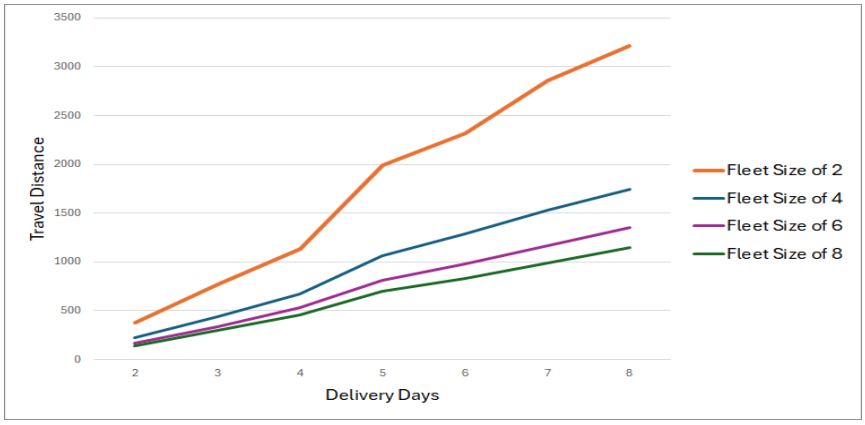
Results and Discussion

This section presents and discusses the key findings obtained from the simulation experiments. This section covers how travel distance varies with delivery frequency, fleet size, and vehicle capacity, as well as the impact of these factors on operational efficiency. Additionally, the section explores customer behavior and preferences by evaluating utility and engagement across different pricing schemes, including day to day delivery, subscription and pay-per-use models. The following results present sensitivity analyses exploring how key parameters such as delivery frequency, fleet size, and vehicle capacity influence travel distances and overall system performance. These analyses show the trade-offs and effects of different delivery strategies and consolidation methods on efficiency, customer behavior, and environmental outcomes.

4.1 Travel Distance vs Delivery Day Analysis

This section examines the relationship between travel distance and delivery day frequency within a consolidated delivery system. Figure 4.1a illustrates how the

average travel distance per vehicle varies with the number of delivery service days, ranging from 2 to 8. This analysis was conducted with various fleet sizes: 2, 4, 6, and 8. As the frequency of deliveries increases, the average travel distance of the vehicles also sees an increase This occurs because there are fewer opportunities to consolidate orders within the delivery time frame. Deliveries that would normally be grouped and dispatched altogether are instead spread further and between multiple days, resulting in less efficient and routing overlap, increasing overall travel distances.



(a) Average Travel Distance vs Delivery Day Graphs

(b) Total Travel Distance vs Delivery Day Graphs

Figure 4.1: Travel Distance vs Delivery Day Graphs

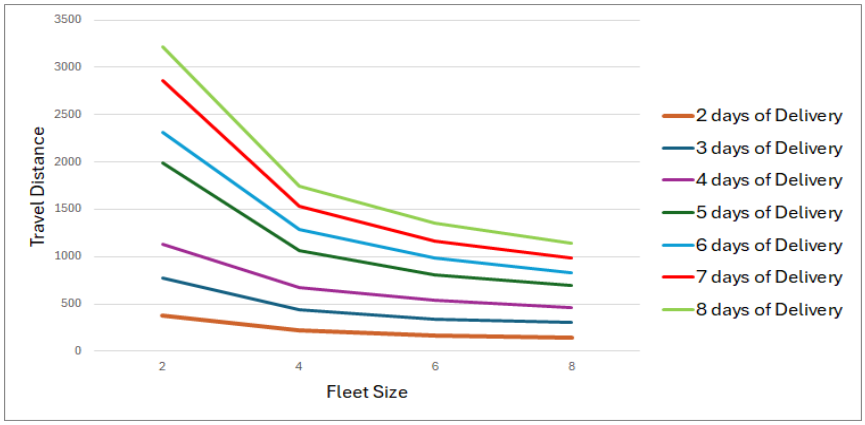
As the number of delivery days increases, customers tend to prefer consolidated delivery options (U_s and U_o, as they experience less inconvenience due to shorter time frames between orders and deliveries. This results in an increase in customers joining the consolidated delivery system, further increasing the average travel distance. Figure 4.1a also highlights how the addition of more delivery vehicles reduces the average travel distance per vehicle, as each vehicle completes a smaller batch of deliveries when more vehicles are added to the system to fulfill the same number of deliveries. The reduction in average travel distance for each vehicle is comparable to a decrease in delivery time, suggesting that with the inclusion of more vehicles, each individual trip could theoretically be completed faster. This is particularly significant for grocery delivery, as certain orders may contain perishable goods that may not stay fresh during long delivery routes.

Analyzing how delivery frequency, fleet size, and total travel distance interact is necessary for understanding how they are able to affect one another. Balancing these factors together play a key roll in the performance of the system, helping to reveal how adjustments to one can influence the others and how examining different delivery frequencies and fleet sizes affect total travel distance in a consolidated delivery system, Figure 4.1b displays the total travel distance for various delivery frequencies and fleet sizes. There is a correlation between the increase in total travel distance and the increase in delivery frequency. This trend is attributed to more deliveries being made with the availability of more delivery days, as more customers join the system and place orders. The rise in customers results from higher delivery frequency, providing a stronger incentive for previous customers who were unwilling to use the

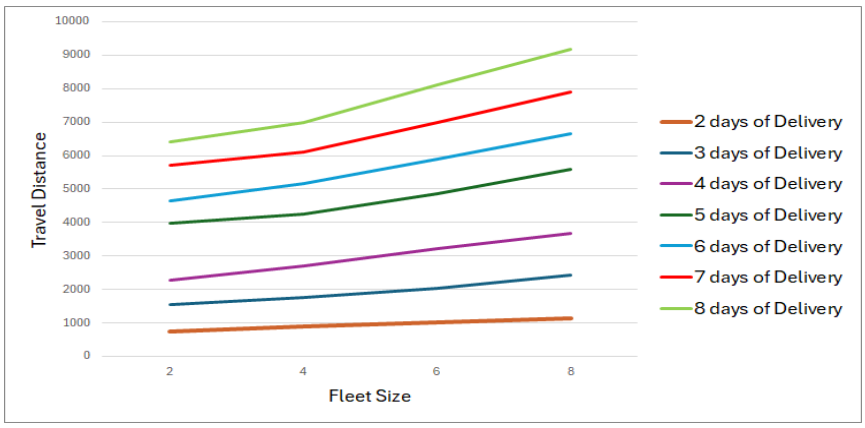
consolidated programs to join the system and place orders due to reduced wait times between placing and receiving orders. Regarding fleet size, an increase in total travel distance occurs as the number of delivery vehicles increases. This increase is due to the addition of more repeated distances to and from the store for each vehicle introduced into the system. For example, if the fleet size were increased to match the number of available customers, the travel distance would peak and be comparable to same-day delivery, with each customer being assigned a dedicated vehicle for their order.

4.2 Travel Distance vs Fleet Size Analysis

Fleet size plays a key role in delivery efficiency, being able to influence how many vehicles are available for deliveries and how trips each delivery vehicle will make. Figure 4.2 analyzes how travel distance changes with fleet size according to the different frequencies of delivery dates available per month. Each graph depicts 8 different delivery day scenarios between delivering once to eight times in the span of a month. The Y-axis depicts the travel distance traveled by the vehicles while the X-axis representing the increase of fleet size for each scenario.



(a) Average Travel Distance vs Fleet Size



(b) Total Travel Distance vs Fleet Size

Figure 4.2: Travel Distance vs Fleet Size

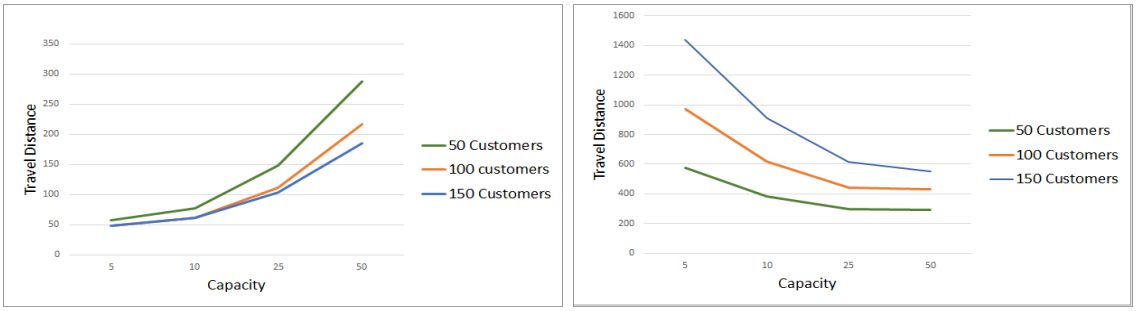
Figure 4.2a depicts an inverse relationship between average travel distance and fleet size. As the number of vehicles increases, each vehicle has fewer deliveries to complete, resulting in shorter average travel distances per vehicle. We can also see trends which show that there are diminishing returns when adding addition vehicles, with the curve appearing to flatten as more vehicles are added to each delivery route. As fleet size increases, the reduction to the average travel distance per vehicle becomes

less significant, as routes become similar to one another and to an extreme, revert back to the standard business practice of one delivery per vehicle.

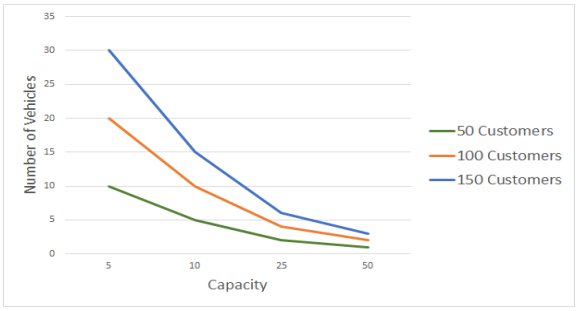
The analysis highlights the direct relationship between total travel distance and fleet size, as shown in Figure 4.2b. As more vehicles are added to the system, the total travel distance increases because each additional vehicle must make repeated trips to and from the depot. This highlights the importance of optimizing fleet size in order to minimize unnecessary travel distance. Effective management of both fleet size and delivery routes decrease travel distance due to inefficient routing and underused vehicles.

4.3 Influence of Capacity on Travel Distance and Fleet Size

The relationship between vehicle capacity and its effect on travel distance and fleet size can be seen in Figure 4.3. This analysis examines how adjusting vehicle capacity can have an affect on travel efficiency. The graph displays three lines, each corresponding to a different customer group: green for 50 customers, orange for 100 customers, and blue for 150 customers. For each scenario, simulations were conducted with capacity constraints ranging from 5 to 50 orders per vehicle. These delivery scenarios assume that all orders must be fulfilled across four delivery days within a one-month period.



(a) Average Travel Distance vs Fleet Capacity (b) Total Travel Distance vs Fleet Capacity



(c) Fleet Size vs Fleet Capacity

Figure 4.3: Travel distance and Number of Vehicles vs Capacity

Starting with an analysis on capacities influence on the average travel distance, Figure 4.3a shows the correlation between the average travel distance of the individual vehicles vs the capacity. Depicting all three scenarios following the similar trend of an increase in capacity leading to an increase of the average distance per vehicle. This is caused from a total save in travel distance, shown in Figure 4.3b, but comes at a trade off of each individual vehicle needing to complete longer trips in order to fulfill all orders. Next, analyzing the effects capacity has on the total travel distance, Figure 4.3b depicts the decrease in total travel distance when capacity increases. The trends are also reflected similarly in the change of Figure 4.2b. As the capacity of a

vehicle increases, each individual vehicle is able to complete more orders, resulting in a decrease in the total fleet size required in order to complete the set of deliveries. With the decrease in fleet size, the travel distance produced for each vehicle is reduced due to the fact that each vehicle must repeat the same first and last process of each trip. The instance of going from the grocery store to the first customer and the instance of returning from the last customer is an unavoidable repeated trip that must be included for each additional vehicle.

Lastly, Figure 4.3c shows the effect of capacity on fleet size, showing an inverse relationship between the two: as capacity increases, fleet size decreases. Increasing vehicle capacity allows for more orders per trip, decreasing the number of vehicles needed to complete the deliveries. These findings highlight the benefits of optimizing vehicle capacity to reduce fleet size and improve delivery efficiency.

4.4 Total Travel Distance With Various Levels of Consolidation

Comparing the travel distance of consolidated delivery to same-day delivery highlights the advantages of consolidated delivery schedules, providing evidence that consolidating deliveries rather than distributing them on the same day, leads to considerable savings in travel distance.

A comparison of various delivery frequencies within a month to an everyday delivery schedule was created to illustrate how consolidation can have a positive

impact on total travel distance. Figure 4.4 compares the total travel distances in consolidated delivery scenarios depicted in orange to an everyday delivery schedule shown in green. For the consolidated delivery scenario, orders were consolidated to deliver groceries from 2 to 8 times a month, while the everyday delivery scenario sent out a delivery every day. The total number of customers served and their locations relative to each other are kept the same between each delivery scenario.

Figure 4.4: Total Travel Distance With Various Levels of Consolidation

Figure 4.4 shows that consolidation reduces travel distance across all scenarios. The temporal consolidation of orders optimizes delivery routes and reduces unnecessary travel, leading to significant savings in travel distance and operational costs. The graphs show that as the number of delivery days increases, the gap between the travel distance in consolidated and everyday deliveries grows larger. Convenience factors for customers contribute to the number of participants added to the system on subsequent delivery days. As more delivery days are available and delivery becomes

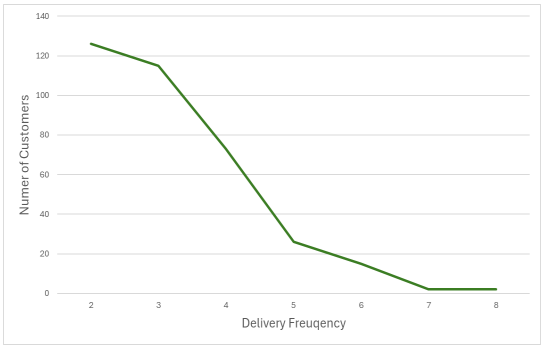
more frequent in the consolidated delivery scenarios more customers are added to place more orders. With a larger set of individual orders being placed, the overlapping trips that are being made increase in frequency and add more towards the total travel distance. Even with every delivery case scenario, the gap in travel distance from the comparison still does not fully reflect the potential savings that are gained from consolidation and has room to grow. The routing for the everyday delivery scenario is still routed throughout and optimized through the VRP algorithm. Therefore, when comparing the gap in travel distance between the two methods, theoretically there should be an even greater gap due to modern delivery systems forming each of the single-day deliveries one at a time.

4.5 Delivery Frequency and Customer Preferences

Exploring the relationship between delivery frequency and customer interest in various pricing plans provides insight into how customer preferences vary between pricing options. This analysis illustrates the shifts in customer interest for each respective payment plan based on the number of available delivery days in a month. This information can help inform decisions about which pricing strategies are most effective for each respective delivery schedule. Figure 4.5 illustrates three graphs based on customer preferences towards each subscription and per-order plan offered by consolidated delivery and everyday delivery. The trends reflect how these preferences change alongside the available amount of delivery days.

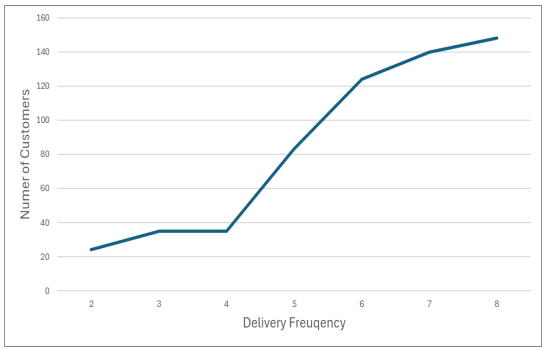
With respect to U_d Everyday Delivery, Figure 4.5a shows that as delivery frequency increases, fewer customers choose same-day delivery. When deliveries are infrequent, consumers experience a high level of inconvenience due to long times between placing and receiving their orders. However, as the frequency of deliveries increases, the time between a customer order and delivery lessens, resulting in a higher level of convenience. When there is minimal inconvenience, customers are more likely to choose U_s or U_o as options, favoring cheaper delivery price points.

Examining U_s Subscription Model, Figure 4.5b depicts that as delivery frequency increases, more customers initially join the subscription plan. However, after a certain point, the trend reverses. This trend is due to the higher likelihood that customers place four to five orders a month. As Us is a one-subscription payment plan, it



(a) Customers Choosing Ud

(b) Customers Choosing Us



(c) Customers Choosing Uo

Figure 4.5: Delivery Frequencies Affect on Customers' Payment

charges a single fee based on the number of delivery days provided. As customers' order frequency aligns with the number of available delivery days, the customer will choose the Us option as being the most cost-effective for them. The downward trend is due to the same reason. As the frequency of offered delivery days increases, not many customers will need to order as often as the days being provided. This leads to the price of p_s becoming too high for customers as a majority won't be ordering 8 times a month. With the price of p_s being too high, customers will seek the other two options.

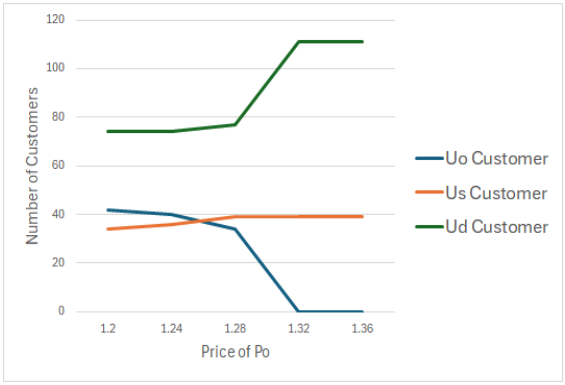
For the U_o Pay-Per-Use Model, Figure 4.5c demonstrates that as delivery frequency increases, more customers choose the pay-per-use model. This option becomes increasingly attractive due to its flexibility and lower cost for those who order less frequently than the provided delivery days of the model. As the frequency of deliveries increases, fewer customers are inconvenienced by the consolidated system. With enough high delivery days, the wait between orders and deliveries becomes short enough to where the cheaper price point of the U_o option becomes the most favorable. We can see a spike in the trend of users joining the U_o system midway through the different delivery frequencies due to many users who used the Us option moving over to joining U_o, as well as the number of delivery days being high enough to where customers receive low levels of inconvenience.

4.6 Influence of Pricing on Customer Engagement

Assessing how customer engagement changes relative to the pricing of payment plans in relation to one another is shown in Figure 4.6. Exploring the impact of pricing on customer engagement for each delivery plan as prices fluctuate for the three available services in this scenario. The base scenario used is 150 customers with four days of delivery, with adjustments being made to the pricing for each plan by increasing and decreasing the price for each available service.

(a) Price Change in Pd

(b) Price Change in Ps



(c) Price Change in Po

Figure 4.6: Price vs Customer Engagement

First, looking at the Everyday Delivery Price P_d, Figure 4.6a shows that as the price of P_d decreases, more customers are drawn to everyday delivery. A lower Pd makes this option more attractive as customers will be receiving the highest level of convenience for a cheaper price. As the price of Pd increases, we can see some customers start to move over to the P_s and P_o plans as the steep price of P_d starts to outweigh the convenience factor.

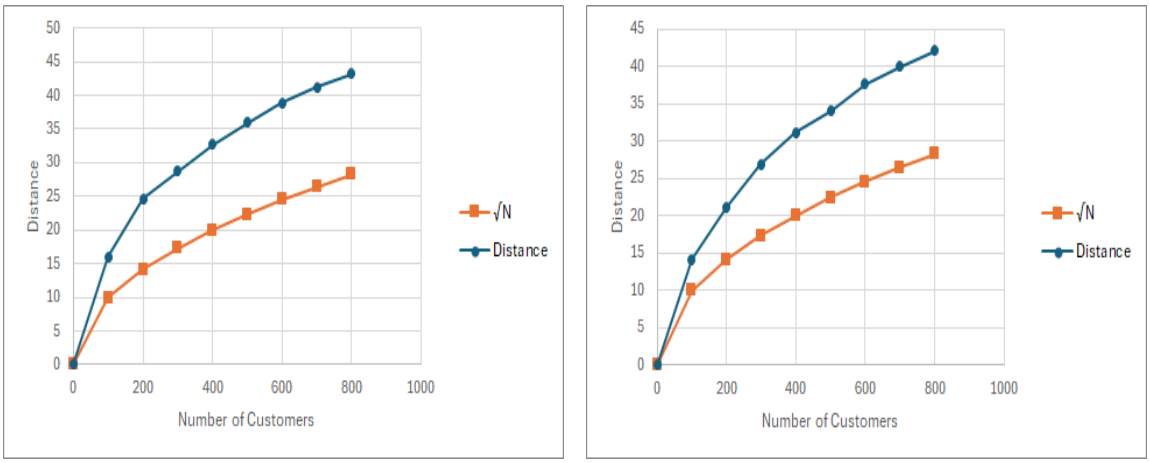
Next, the analysis of the Subscription Price P_s, show in Figure 4.6b we observe similar trends in customer behavior in response to pricing changes of P_s. However, when the price of P_s increases, we see that most subscription customers are shifting towards the per-order pricing plan, which offers a better balance between cost and convenience.

Finally, Figure 4.6c illustrates the Pay-Per-Use Price P_o. Depicting that when the price of P_o changes, customers often switch to everyday delivery rather than subscription plans. This is because many customers order infrequently enough that the everyday delivery option becomes more convenient and cost-effective.

Across all three pricing plans, similar trends are observed, where the increase in the price of one plan influence customers to shifts toward the other options based on which other plan best meets their needs. When the price of a plan decreases, it attracts more customers as the delivery schedule is now deemed to be worth the wait. As the price increases for each respective plan, customers tend to move to one of the alternative plans that offer a more favorable balance between cost and convenience. An important distinction can be made when looking at Figure 4.6a and the price of P_d, with the first point on the graph illustrating that all customers will choose this delivery plan if it is priced very low. At this point, the price of P_d simultaneously offers the highest level of convenience at the lowest cost, making it the dominant choice between the three pricing options.

4.7 Relations in Customer Size and Travel Distance

This set of data explores how the expected distance based off of customer density align with expected values, as well as an analysis on if the dimensions of the simulated area can affect travel distance. Figure 4.7 illustrates the relationship between customer size and travel distance for two different map geometries, a square map and a circle map.



(a) Distance vs Customer Size, Square map (b) Distance vs Customer Size, Circle map

Figure 4.7: Simulation Mapping & Routing Examples

The graph showing two different lines representing travel distance, with the blue line indicating the simulated distance, and the orange line representing the theoretical distance in relation to the number of customers. In both 4.7a and 4.7b the graphs show that as the number of customers increases, the total travel distance also rises, with the relationship between the two being nonlinear. This is because as the number of customers increases within the delivery area, the total travel distance required to

reach all customers does not continue to rise at the same rate. As more customers are added, they become more densely packed within the same space, reducing the average distance between each customer. As a result, the additional distance needed to serve each additional customer becomes smaller, highlighting once again the increase in efficiency of serving a larger customer base. We can see that both curves follow a similar pattern with the simulated distance always being above the $\sqrt{N}$ line, this trend can be explained and correspond with previously shown graphs. Due to limitations in fleet size and the additional travel distance that is not directly related to the number of customers, delivery routes are not perfectly optimized for a single vehicle to serve all customers in one trip. Instead, deliveries are divided among multiple vehicles, with each vehicle assigned a portion of the total customer base. This segmentation requires each vehicle to start and end its route at the depot, which introduces additional travel distances that are independent of customer count but closely tied to fleet size. Consequently, the need for vehicles to return to the depot after completing their deliveries contributes to the overall travel distance, once again highlighting the operational impact of fleet size on route efficiency. Comparing the two graphs with one another, we can also draw the conclusion of the shape of the simulated area, having very little impact on the total travel distance.

Chapter 5

Case Study

5.1 Background and Methodology

The area selected for the study was Hamilton, Ontario, where a hypothetical implementation of the consolidated delivery system was analyzed to assess its potential benefits within a specific urban context. The selected area features ideal conditions for the simulation, a major grocery store major grocery store located within residential neighborhoods.

According to the 2021 Census, Hamilton has a population of 569,350 residents and spans 1,373.15 square kilometers. The city exhibits a balanced age distribution: 16% of residents are youth aged 0 to 14, 65.7% are between 15 and 64, and 18.3% are aged 65 and older. The average age of citizens was around 41.5 years with the median age of the population being 40.8 years. Hamilton provides an ideal setting for evaluating the potential of consolidated grocery delivery services, particularly given research by Morganosky and Cude [1] indicating that the majority of online grocery shoppers are under the age of 55. Consequently, this case study simulation focuses on people aged 20 to 54. According to the 2021 Census data, this demographic constitutes

approximately 45% of Hamilton's population, this age group is particularly relevant for online grocery delivery services, as they are more likely to engage with digital platforms for their shopping needs. a

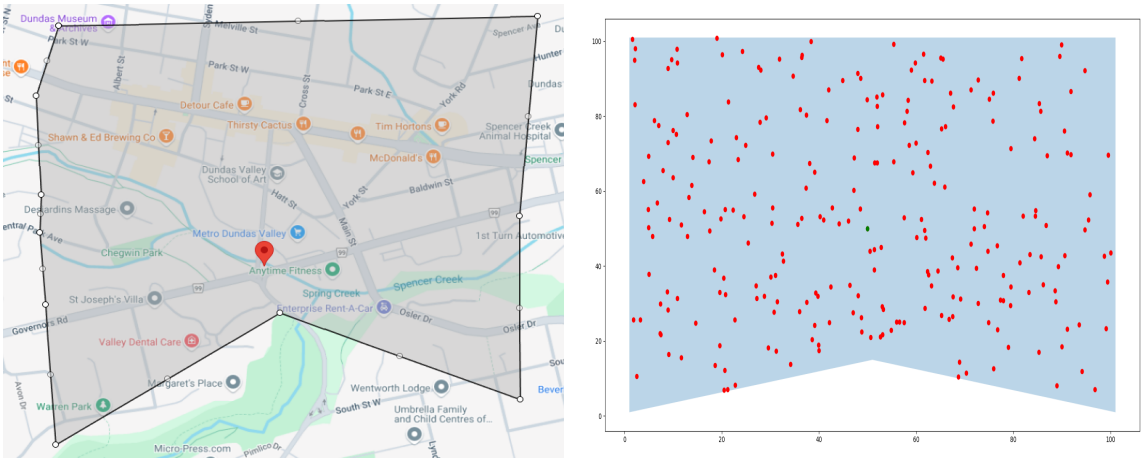
Age Group	**Population**	**Age Group**	**Population**
0 to 14 years	91,240 (16.0%)	45 to 49 years	34,155
0 to 4 years	29,100	50 to 54 years	36,665
5 to 9 years	30,695	55 to 59 years	40,930
10 to 14 years	31,450	60 to 64 years	38,045
15 to 64 years	373,820 (65.7%)	65 years and over	104,290 (18.3%)
15 to 19 years	31,795	65 to 69 years	31,630
20 to 24 years	36,405	70 to 74 years	26,700
25 to 29 years	40,525	75 to 79 years	18,290
30 to 34 years	41,330	80 to 84 years	12,990
35 to 39 years	38,940	85 and over	14,685
40 to 44 years	35,025		

Table 5.1: Hamilton Population by Age Group (2021 Census)

Hamilton's estimated population density is approximately 571.8 people per square kilometer. By integrating these demographic and density insights, we hypothesize that within a square kilometer in Hamilton, there are approximately 257 individuals aged 20 to 54 who are likely to engage in online grocery shopping. This hypothesis establishes a foundational basis for evaluating the feasibility and efficiency of implementing consolidated delivery services in urban environments.

We next identified an area in Hamilton with a major grocery store surrounded by residential neighborhoods. The selected area was a grocery store located at the intersection of Ogilvie St and Governors Rd in Hamilton, ON. Using Google Maps, we isolated a square kilometer surrounding the grocery store and plotted an approximate

area using Python, as shown in Figure 5.1



(a) Map1 (b) Map2

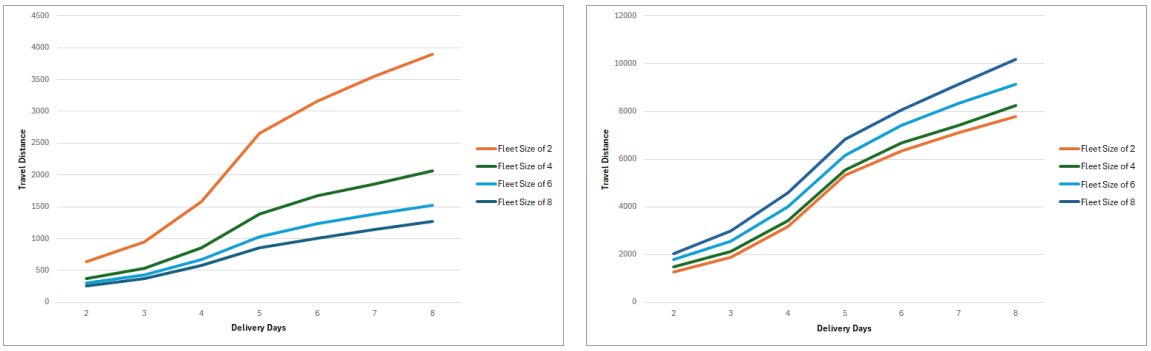
Figure 5.1: Simulation Mapping

With the number of customers and are now accounted for, we can begin simulating the order and delivery process for this section of Hamilton. The simulation for the selected area was carried out over a one-month period, evaluating eight different levels of consolidation. The first scenario simulated grocery deliveries without consolidation, where orders were delivered on the same day they were placed. The other seven scenarios represented consolidated delivery approaches, with consolidation levels ranging from 2 to 8 days within the simulated time span. For each of the different simulated consolidated delivery scenarios, each scenario was run with four different cases of various fleet sizes, ranging from 2 to 8 vehicles completing orders on a given delivery date. Multiple iterations of each scenario were run to ensure precision and consistency in the results. Each simulated scenario encompassed a six-week period of orders, with data from the final four weeks constituting the analyzed "month" of

deliveries. This approach allowed for an initial warm-up period in the simulated order and delivery process, ensuring precise and consistent results.

5.2 Case Study Results

Looking into the relationships between travel distance and the frequency of delivery days for the city of Hamilton, Figures 5.2 demonstrates seven scenarios from 2 to 8 delivery days between 4 varying fleet sizes. A fleet of 2,4,6, and 8 were all assigned to the same location and customers while recording their travel data.



(a) Average Travel Distance vs Delivery Day Graphs (b) Total Travel Distance vs Delivery Day Graphs

Figure 5.2: Travel Distance vs Fleet Size

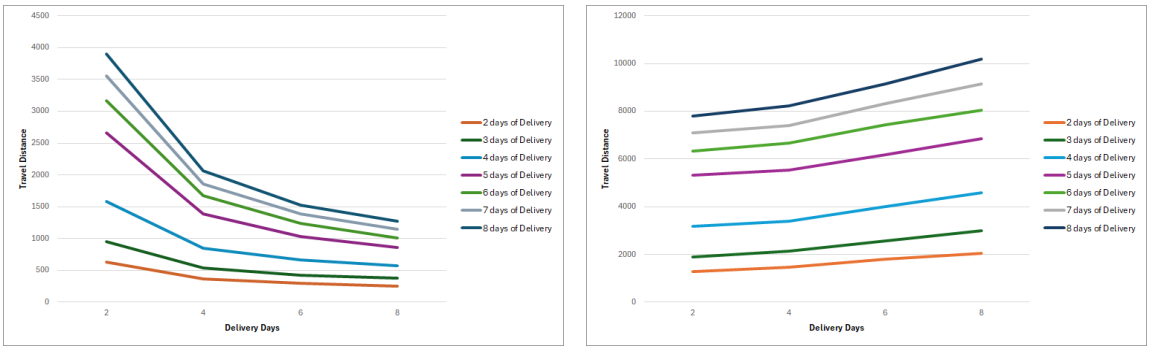
Figures 5.2 demonstrates seven scenarios from 2 to 8 delivery days between 4 varying fleet sizes. A fleet of 2,4,6, and 8 were all assigned to the same location and customers while recording their travel data. Figure 5.2a illustrates how the average travel distance per vehicle varies with the number of delivery service days. As the frequency of deliveries increases, the average travel distance of the vehicles also

increases. Each of the different delivery day scenarios was conducted with various fleet sizes ranging from 2 to 8 vehicles.

The increasing trend in the graphs can be explained by two factors. As the number of consolidated delivery days increases, orders become more divided between these increasing dates, creating routes where some deliveries are spatially closed but temporally grouped on different delivery days. Additionally, with more frequent and available delivery days, customers are more inclined to use the consolidated delivery options (U_s and U_o. As the time frame between placing orders and the day they receive their delivery decreases, customers are more compelled to select a consolidated delivery plan as the price justifies the now smaller inconvenience. The resulting increase in vehicle usage affects the average travel distance by decreasing the distance traveled by each individual vehicle. As the number of fleet size increases, the distance each individual vehicle needs to travel to complete the total number of orders is reduced.

Figure 4.1b shows the total travel distance with changing frequency for different fleet sizes. We observe a correlation between the increase in total travel distance and the increase in delivery frequency. This trend is attributed to the fact that more deliveries are made with the availability of more delivery days, as more customers join the system and place more orders. The rise in customers results from having a higher delivery frequency, providing a stronger incentive for previous customers unwilling to use the consolidated programs to join the system and place orders due to the reduction in wait time between placing and receiving orders as more delivery days

become available. The increased vehicle usage also adds more repeated distances to and from the store. For instance, one vehicle making all deliveries in a day travels to and from the store once, but additional routes require repeating the initial steps of visiting the grocery store, increasing the overall distance.



(a) Average Travel Distance vs Fleet Size (b) Total Travel Distance vs Fleet Size

Figure 5.3: Travel Distance vs Fleet Size

The graphs depicting travel distance versus fleet size for the case study seen in Figure 5.3 shows that the average travel distance per vehicle decreases as fleet size increases, while the total travel distance rises. While the total travel distance increases with the increase in fleet size. The trend seen in Figure 5.3a the average travel distance occurs with the increase of fleet size due to the total amount of orders becoming more spread out among the larger fleet of vehicles, with each individual vehicle having to complete a smaller route in order to complete the same total amount of orders. For Figure 5.3b we can see once again there is an increase in distance from the increase in fleet size for the total travel distance. This increase is explained once again by the repeated mandatory step of each travel route that comes with each

additional vehicle. Highlighting the importance of optimizing fleet size in order to balance delivery time, efficiency, and cost.

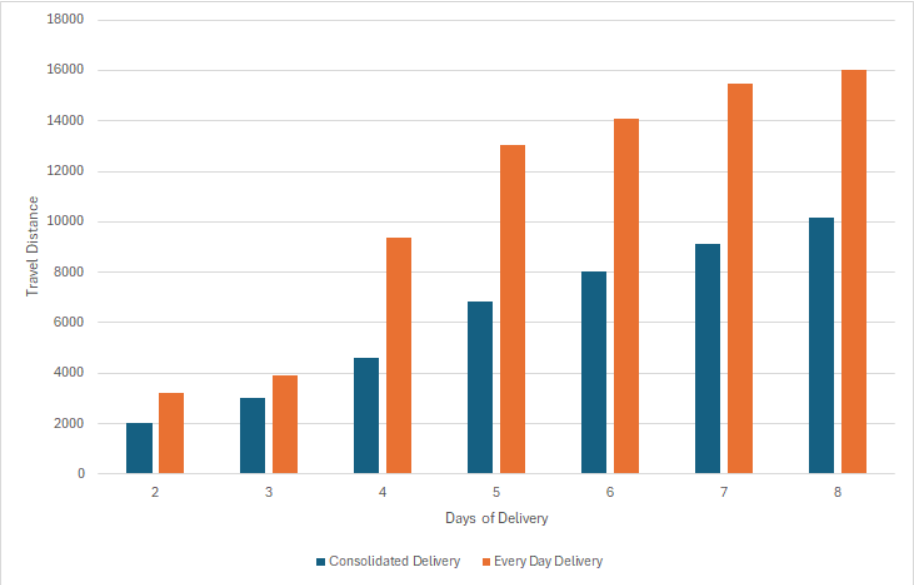


Figure 5.4: Total Travel Distance With Various Levels of Consolidation

To further demonstrate the efficiency gained through the use of consolidated delivery when compared to same-day delivery Figure 5.4 illustrates the difference in potential delivery scenarios between consolidated and non-consolidated orders and delivery days. Each pair of scenarios uses identical parameters, including the number of customers, customer locations, number of delivery vehicles, and the placement of orders each day. The results cover between the seven delivery scenarios with the frequency of delivery per month ranging from 2 to 8 days. The consolidated delivery scenarios, represented in orange, and the non-consolidated delivery scenarios, represented in green, show the difference in total travel distance betweem the different delivery day scenarios ranging from 2 to 8 days. The figure demonstrates the contrast

in potential cost savings and reduction in environmental impact between consolidating and same-day delivery, with a greater impact observed when there are more customers. It should be noted that the same-day delivery scenarios highlighted in green still group orders into a single delivery and do not deliver instantaneously when orders are placed. Therefore, when comparing consolidation to delivery methods used by companies such as Uber, where deliveries happen instantaneously, the gap between the two methods of delivery would further increase.

5.3 Case Study Analysis

The simulated data for the Hamilton region indicates that the city is well-suited for the adoption of consolidated delivery systems, given its population size and diverse age demographics. As a well-populated urban area, Hamilton offers an ideal setting for implementing such services. Consolidated delivery systems may have a large impact on operational efficiency while simultaneously reducing fuel consumption and emissions. By introducing various payment plans, these systems can cater to a wide range of customers, further optimizing cost savings. As more individuals participate in the service, the potential for additional savings on fuel and emissions increases, while also reducing the cost of delivery for each subsequent customer, reinforcing the economic and environmental benefits of this approach.

The implementation of consolidated delivery services presents some challenges that need to be addressed before implementation, particularly when compared to traditional delivery models that prioritize speedy delivery times. Unlike these rapid

delivery systems, consolidated delivery focuses on improving cost savings. This approach necessitates a shift in consumer expectations, emphasizing efficiency over immediacy, as it is a service with consistent and repetitive use that aligns with the user's budget.

To further enhance the effectiveness of the case study, integrating a Geographic Information System (GIS) could provide valuable insights into local road networks and neighborhood layouts. The integration of a GIS system would supply much more accurate data on travel distance, routing, and emissions savings, allowing for the simulated data to better reflect real world scenarios and really highlighting its environmental benefits.

For easier implementation, the delivery service can be simplified by tapping into different existing systems and infrastructure that are already in place. For instance, using the already implemented grocery store order lockers or designated parking lot pickup points at certain locations already support this faster logistics. These systems allow for quick pick-up and drop-off times at the store, without any of the hassles associated with existing systems.

Bypassing the need for drivers to enter stores and manually select items contrasts sharply with many instant delivery services where drivers must navigate store aisles, often leading to inefficiencies and delays. By leveraging existing systems like order lockers or parking pickups, the process of order fulfillment becomes more efficient. Store employees, familiar with the layout and inventory, can quickly assemble orders. This speeds up the pickup process and allows for immediate feedback on item

availability or necessary substitutions at the time of order placement, rather than during delivery. Such a system ensures a smoother transition from ordering to receiving groceries, enhancing customer satisfaction and operational efficiency.

In summary, while consolidated delivery services offer significant advantages in terms of cost reduction and environmental impact mitigation, their successful implementation necessitates careful consideration of existing logistical frameworks and consumer expectations. As evidenced by the graphs presented in the case study, consolidation can indeed yield benefits in both economic and environmental domains. However, poor implementation may result in marginal or negligible benefits.

The efficacy of consolidated delivery systems depends on several factors. Firstly, a low and infrequent customer base will result in minimal savings, as the economies of scale that drive efficiency in the consolidated delivery system cannot reach their full potential. Secondly, the optimization of the delivery fleet is crucial. An insufficient number of vehicles can lead to excessively long delivery routes, potentially compromising food quality or failing to meet daily delivery quotas. Conversely, an overly generous fleet size, when not optimally used, may not yield significant benefits compared to traditional delivery methods. In extreme cases, if the number of vehicles approaches the number of orders, the system essentially devolves into an instantaneous delivery model, negating the intended benefits of consolidation. This scenario underscores the importance of a well-managed delivery system. Without proper optimization, the system may significantly inconvenience customers or fail to differentiate itself from instantaneous delivery models, which would negate its

intended benefits.

By addressing these challenges through strategic use of technology and infrastructure, businesses can optimize their delivery models to better serve their communities. This section provides a comprehensive overview of the challenges and potential solutions associated with implementing consolidated delivery services.

Chapter 6

Conclusion

6.1 Summary of Contributions and Findings

This research challenges the prevalent approach in modern online grocery delivery systems, which prioritizes immediate order placement and delivery. Instead, it explores a delivery system that applies consolidation to online grocery deliveries, demonstrating the advantages of order consolidation. This approach provides benefits not only to end users through cost savings but also to companies and industries seeking to reduce travel distances and fleet sizes, ultimately offering an appealing benefit to both parties.

The thesis aims to develop a model that demonstrates the benefits of consolidation in online delivery systems, addressing two key questions: the overarching effects consolidation has on delivery systems and its impact on customers. Through the development of the model, our findings reveal that consolidating deliveries significantly impacts the operational aspects of the delivery system, leading to substantial reductions in delivery travel distances, the number of trips made for each delivery, and the required fleet size. By grouping orders and strategically planning delivery schedules, we also obtain the benefits of cost savings and the reduction of environmental impact.

The study demonstrates that many factors contribute to the feasibility of implementing a consolidated system. Factors such as how many customers are joining the system, their availability, preferences, pricing, and the scheduling of orders and delivery dates all play a role in determining the success of a delivery system. We observed these relationships and their various effects on each other, noting that factors such as travel distance, number of customers, customer availability, fleet size, and capacity, along with the degree to which they all affect one another. We found that the consolidated delivery systems reduce the total travel costs in all scenarios when compared to same-day delivery, along with various trends such as fleet size having greater importance with less frequent delivery times. This highlights the importance of optimizing the number of vehicles and their capacities. We also gained insights into customer preferences in a consolidated system, noting that aspects such as user behavior, pricing, and the time between the consolidation of orders and delivery all have a positive or negative impact on a customer's impression of using the system. It was determined that many customers appreciate the balance between cost savings and service efficiency offered by the consolidated model when compared to the prices and service of instantaneous delivery.

The study provides a holistic view of the benefits and challenges associated with implementing a consolidated delivery approach, highlighting its potential to make delivery systems more sustainable and improve accessibility for consumers who rely on online grocery shopping out of necessity. Ultimately, our research demonstrates that it is possible to strike a balance between meeting consumer expectations for prompt service and creating a more efficient and affordable delivery system through

the implementation of order consolidation.

The study provides a holistic view of the benefits and challenges associated with implementing a consolidated delivery approach, highlighting its potential to make delivery systems more sustainable and improve accessibility for consumers who rely on online grocery shopping out of necessity. Ultimately, our research demonstrates that it is possible to strike a balance between meeting consumer expectations for prompt service and creating a more efficient and affordable delivery system through the implementation of order consolidation.

6.2 Future Research

While our research provides insights into the benefits of implementing consolidated delivery systems for online grocery shopping, it's important to acknowledge certain limitations of our study. Firstly, our simulation model, although comprehensive, use's euclidean distances when calculating travel distance between the different nodes of delivery. This method does not fully capture the complexities of real-world delivery scenarios. For instance, we did not account for existing roads or traffic conditions, including unpredictable events such as traffic congestion and road closures, which could significantly impact delivery times, costs, and environmental benefits in practice. This limitation may lead to an overestimation of efficiency gains in our results. Additionally, our study focused on testing and generalizing an urban environment, such as a region where a grocery center is located relatively close to multiple neighboring residential areas. However, our findings have not yet been

extended to regions with varying population densities or geographical layouts, such as sparsely populated areas or highly urbanized locations where multiple deliveries may be made to a single address, such as several individuals placing orders within the same apartment building). Lastly, our customer preference data was based on synthetic simulated behavior patterns rather than real-world surveys or trials. While we attempted to model these preferences as accurately as possible, actual consumer responses to a consolidated delivery system might differ, potentially affecting adoption rates and overall system success. These limitations suggest that while our results provide a strong indication of the potential benefits of consolidated delivery systems, real-world implementation may face additional challenges not captured in our study. Future research should address these limitations to provide a more comprehensive understanding of the feasibility and impact of consolidated delivery systems in diverse settings.

For future research, the models could significantly benefit from the integration of more sophisticated tools and methodologies for measuring and mapping out travel distance, for example, through the use of a Geographic Information System (GIS). With the inclusion of a GIS system, details such as parking lots, road networks, street lights, and traffic interactions, would all be accessible and benefit the system by allowing for more realistic and nuanced models. Such an approach could provide more accurate estimations of travel times and distances, leading to more precise and accurate information on delivery routes.

Additionally, implementing real customer data could significantly enhance the

accuracy and relevance of our findings. While our current study uses synthetic data derived from online sources, incorporating real-world customer information gathered through surveys in specific areas could provide more reliable and realistic data on the potential adaptation of a consolidated delivery system. This approach would be especially valuable when paired with the previously mentioned improvements of adding a GIS system to our simulations. Real customer data would capture authentic preferences, shopping habits, and delivery expectations specific to the local population, allowing for more precise modeling of user behavior and the performance of introducing the consolidated system into the area. This approach could reveal unique patterns or preferences that may not be apparent in synthetic data, such as neighborhood-specific delivery preferences or local factors influencing shopping frequency. Furthermore, real data could help validate or refine our assumptions about customer behavior, leading to more accurate predictions of system performance and customer satisfaction.

6.3 Implications for Practice and Policy

As the delivery industry rapidly evolves, balancing convenience and cost remains a critical challenge. Our research demonstrates that integrating consolidated delivery models can achieve significant cost savings for both customers and organizers while enhancing operational efficiency and customer satisfaction. Companies in the delivery sector should consider implementing consolidated delivery systems by investing in route optimization technologies, creating tiered consolidated pricing models, and

educating customers about the benefits, as the ease of integration is made possible by the existing infrastructure. In today's fast-paced world with growing consumer expectations, optimizing delivery logistics is more crucial than ever. Embracing innovative, consolidated delivery systems offers a promising path to meet these demands sustainably and effectively, balancing the pressure for faster deliveries with the need for sustainability and cost-effectiveness.

By adopting these approaches, new or existing companies can position themselves at the forefront of a more sustainable and efficient delivery service. This approach addresses current challenges and prepares businesses for future developments in urban logistics and changing consumer behaviors. As the industry continues to grow and evolve, those who can successfully balance convenience, cost, and sustainability will likely emerge as leaders in the competitive landscape of delivery services.

Bibliography

[1] Michelle Morganosky and Brenda Cude. Consumer response to online grocery shopping. *International Journal of Retail Distribution Management*, 28:17–26, 02 2000. doi: 10.1108/09590550010306737.

[2] Michael Browne, Michael Sweet, Allan Woodburn, and Julian Allen. Urban freight consolidation centres final report. *Transport Studies Group, University of Westminster*, 10, 2005.

[3] Salma Naccache and Benoit Montreuil. Optimizing consumer order delivery consolidation in drop-ship based b2c distribution. *IFAC-PapersOnLine*, 48(3): 1996–2001, 2015. ISSN 2405-8963. doi: https://doi.org/10.1016/j.ifacol.2015.06.381. URL `https://www.sciencedirect.com/science/article/pii/S2405896315006205`. 15th IFAC Symposium onInformation Control Problems inManufacturing.

[4] Glen Searle. The limits to urban consolidation. *Australian Planner*, 41(1):42–48, 2004. doi: 10.1080/07293682.2004.9982332. URL `https://doi.org/10.1080/07293682.2004.9982332`.

[5] Mohammed Alnahhal, Diane Ahrens, and Bashir Salah. Modeling freight consolidation in a make-to-order supply chain: A simulation approach. *Processes*, 9(9), 2021. ISSN 2227-9717. doi: 10.3390/pr9091554. URL `https://www.mdpi.com/2227-9717/9/9/1554`.

[6] Yuankai Zhang, Lijun Sun, Xiangpei Hu, and Chen Zhao. Order consolidation for the last-mile split delivery in online retailing. *Transportation Research Part E: Logistics and Transportation Review*, 122:309–327, 2019. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2018.12.011. URL `https://www.sciencedirect.com/science/article/pii/S1366554518304046`.

[7] Xiaoshuai Peng, Lele Zhang, Russell G. Thompson, and Kangzhou Wang. A three-phase heuristic for last-mile delivery with spatial-temporal consolidation and delivery options. *International Journal of Production Economics*, 266: 109044, 2023. ISSN 0925-5273. doi: https://doi.org/10.1016/j.ijpe.2023.109044. URL `https://www.sciencedirect.com/science/article/pii/S0925527323002761`.

[8] Christine Nguyen, Maged Dessouky, and Alejandro Toriello. Consolidation strategies for the delivery of perishable products. *Transportation Research Part E: Logistics and Transportation Review*, 69:108–121, 2014. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2014.05.018. URL `https://www.sciencedirect.com/science/article/pii/S1366554514000957`.

[9] Gurinder Brar and Gagan Saini. Milk run logistics: Literature review and directions. *Lecture Notes in Engineering and Computer Science*, 1:797–801, 07 2011.

[10] Ki-Hwan G. Bae, Lee A. Evans, and Alan Summers. Lean design and analysis of a milk-run delivery system: Case study. In *2016 Winter Simulation Conference (WSC)*, pages 2855–2866, 2016. doi: 10.1109/WSC.2016.7822321.

[11] Sindhya K. Nambiar and Sumam Mary Idicula. A multi-agent vehicle routing system for garbage collection. In *2013 Fifth International Conference on Advanced Computing (ICoAC)*, pages 72–76, 2013. doi: 10.1109/ICoAC.2013.6921930.

[12] Beatrice Ombuki, Brian J Ross, and Franklin Hanshar. Multi-objective genetic algorithms for vehicle routing problem with time windows. *Appl. Intell.*, 24(1): 17–30, February 2006.

[13] Claudia Archetti and Maria Grazia Speranza. *The Split Delivery Vehicle Routing Problem: A Survey*, pages 103–122. Springer US, Boston, MA, 2008. ISBN 978-0-387-77778-8. doi: 10.1007/978-0-387-77778-8_5. URL `https://doi.org/10.1007/978-0-387-77778-8_5`.

[14] Damon Gulczynski, Bruce Golden, and Edward Wasil. The split delivery vehicle routing problem with minimum delivery amounts. *Transportation Research Part E: Logistics and Transportation Review*, 46(5):612–626, 2010. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2009.12.007. URL `https://www.sciencedirect.com/science/article/pii/S1366554509001574`.

[15] C. Hu, J. Lu, X. Liu, and G. Zhang. Robust vehicle routing problem with hard time windows under demand and travel time uncertainty. *Computers Operations Research*, 94:139–153, 2018. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2018.02.006. URL `https://www.sciencedirect.com/science/article/pii/S0305054818300376`.

[16] IRINA Ioachim, JACQUES DESROSIERS, YVAN DUMAS, MARIUS M. SOLOMON, and DANIEL VILLENEUVE. A request clustering algorithm for door-to-door handicapped transportation. *Transportation Science*, 29(1):63–78, 1995. ISSN 00411655, 15265447. URL http://www.jstor.org/stable/25768670.

[17] Na Lou. Analysis of the intelligent tourism route planning scheme based on the cluster analysis algorithm. *Computational Intelligence and Neuroscience*, 2022, 06 2022. doi: 10.1155/2022/3310676.

[18] Tapas Kanungo, David M. Mount, Nathan S. Netanyahu, Christine Piatko, Ruth Silverman, and Angela Y. Wu. The analysis of a simple k-means clustering algorithm. In *Proceedings of the Sixteenth Annual Symposium on Computational Geometry*, SCG '00, page 100–109, New York, NY, USA, 2000. Association for Computing Machinery. ISBN 1581132247. doi: 10.1145/336154.336189. URL https://doi.org/10.1145/336154.336189.

[19] Mohiuddin Ahmed, Raihan Seraj, and Syed Mohammed Shamsul Islam. The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 9(8), 2020. ISSN 2079-9292. URL https://www.mdpi.com/2079-9292/9/8/1295.

[20] Ying Zhao, George Karypis, and Usama Fayyad. Hierarchical clustering algorithms for document datasets. *Data Mining and Knowledge Discovery*, 10 (2):141–168, March 2005.

[21] Panthadeep Bhattacharjee and Pinaki Mitra. A survey of density based clustering algorithms. *Frontiers of Computer Science*, 15(1):151308, September 2020.

[22] Shi Na, Liu Xumin, and Guan Yong. Research on k-means clustering algorithm: An improved k-means clustering algorithm. In *2010 Third International Symposium on Intelligent Information Technology and Security Informatics*, pages 63–67, 2010. doi: 10.1109/IITSI.2010.74.

[23] Paul S Bradley, Kristin P Bennett, and Ayhan Demiriz. Constrained k-means clustering. *Microsoft Research, Redmond*, 20(0):0, 2000.

[24] Henrik Gillström and Maria Björklund. Assessing the benefits of urban consolidation centres: an overview based on a systematic literature review. *Transport Reviews*, 44(5):972–991, 2024. doi: 10.1080/01441647.2024.2348639. URL `https://doi.org/10.1080/01441647.2024.2348639`.

[25] Jane Lin, Qin Chen, and Kazuya Kawamura. Sustainability SI: Logistics cost and environmental impact analyses of urban delivery consolidation strategies. *Netw. Spat. Econ.*, 16(1):227–253, March 2016.

[26] Iman Dayarian and Martin Savelsbergh. Crowdshipping and same-day delivery: Employing in-store customers to deliver online orders. *Production and Operations Management*, 29(9):2153–2174, 2020. doi: 10.1111/poms.13219. URL `https://doi.org/10.1111/poms.13219`.

[27] M. Ali Ülkü. Dare to care: Shipment consolidation reduces not only costs, but

also environmental damage. *International Journal of Production Economics*, 139 (2):438–446, 2012. ISSN 0925-5273. doi: https://doi.org/10.1016/j.ijpe.2011.09.015. URL https://www.sciencedirect.com/science/article/pii/S0925527311004014. Compassionate Operations.

[28] Peter Berling and Fredrik Eng-Larsson. Pricing and timing of consolidated deliveries in the presence of an express alternative: Financial and environmental analysis. *European Journal of Operational Research*, 250(2):590–601, 2016. ISSN 0377-2217. doi: https://doi.org/10.1016/j.ejor.2015.09.041. URL https://www.sciencedirect.com/science/article/pii/S0377221715008838.

[29] Sucharita Kodali. What consumers like - and detest - about subscriptions, Feb 2023. URL https://www.forrester.com/blogs/what-consumers-like-and-detest-about-subscriptions/.

[30] Ramandeep S Randhawa and Sunil Kumar. Usage restriction and subscription services: Operational benefits with rational users. *Manuf. Serv. Oper. Manag.*, 10(3):429–447, July 2008.

[31] Christoffer Weland Johannes Lindström, Behzad Maleki Vishkaei, and Pietro De Giovanni. Subscription-based business models in the context of tech firms: theory and applications. *International Journal of Industrial Engineering and Operations Management*, 6(3):256–274, July 2024.

[32]

[33] Zhuo Li, Xuefeng Zhao, and Grace Ou. Understanding customer satisfaction in curated subscription services: Moderating roles of subscription time and information disclosure. *Information Management*, 60(6):103834, 2023. ISSN 0378-7206. doi: https://doi.org/10.1016/j.im.2023.103834. URL `https://www.sciencedirect.com/science/article/pii/S0378720623000824`.

[34] Dipti Bhatt, Hye-Shin Kim, and Siddharth Bhatt. Shopping motivations of fashion subscription service consumers. *Int. Rev. Retail Distrib. Consum. Res.*, 31(5):549–565, October 2021.

[35] Laura Wagner, Catarina Pinto, and Pedro Amorim. On the value of subscription models for online grocery retail. *European Journal of Operational Research*, 294(3):874–894, 2021. ISSN 0377-2217. doi: https://doi.org/10.1016/j.ejor.2020.05.011. URL `https://www.sciencedirect.com/science/article/pii/S0377221720304392`.

[36] Kim Ramus and Niels Asger Nielsen. Online grocery retailing: what do consumers think? *Internet Res.*, 15(3):335–352, July 2005.

[37] Raghuram Iyengar, Young-Hoon Park, and Qi Yu. The impact of subscription programs on customer purchases. *Journal of Marketing Research*, 59(6): 1101–1119, 2022. doi: 10.1177/00222437221080163. URL `https://doi.org/10.1177/00222437221080163`.

[38] Sylvain Charlebois and Janet Music. Grocery experience survey: A canadian perspective on service, product and management specifies. *Journal of Food Research*, 8:15, 01 2019. doi: 10.5539/jfr.v8n2p15.

[39] Dalhousie University. fgrocery experience national survey report. https://www.foodincanada.com/wp-content/uploads/2018/11/Independant-Grocer-Study-November-14-2018.pdf, Fall 2018. [Accessed 08-09-2024].

[40] Joanne Scheff. Factors influencing subscription and single-ticket purchases at performing arts organizations. *International Journal of Arts Management*, 1(2): 16–27, 1999. ISSN 14808986. URL http://www.jstor.org/stable/41064647.

[41] Fillipe Goulart. Python$_t sp, Aug2023.URL.$

Josh Levy-Kramer. k-means-constrained, apr 2018. URL magentahttps://github.com/joshlk/k-means-constrained.