Creating Grocery Delivery Hubs for Food Deserts at Local Convenience Stores via Spatial and Temporal Consolidation

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Abstract

For many socioeconomically disadvantaged customers living in food deserts, the high costs and minimum order size requirements make attended grocery deliveries financially non-viable, although it has potential to provide healthy foods to the food insecure population. This paper proposes consolidating customer orders and delivering to a neighborhood convenience store instead of home delivery. We employ an optimization framework involving the minimum cost set covering and the capacitated vehicle routing problems. Our experimental studies in three counties in the U.S. suggest that by spatial and temporal consolidation of orders, the deliverer can remove minimum order-size requirements and reduce the delivery costs, depending on various factors, compared to attended home-delivery. We find the number and size of time windows for home delivery to be the most important factor in achieving temporal consolidation benefits. Other significant factors in achieving spatial consolidation include the capacity of delivery vehicles, the number of depots, and the number of customer orders. We also find that the number of partner convenience stores and the walkable distance parameter of the model, have a significant impact on the number of accepted orders, i.e., the service level provided by the deliverer. The findings of this study imply consolidated grocery delivery as a viable solution to improve fresh food access in food deserts. In light of the recent global pandemic, and its exacerbating effects on food insecurity, the innovative solution proposed in this paper is even more relevant and timely.

Keywords: Food deserts; last-mile delivery; spatial consolidation; temporal consolidation; vehicle routing

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1 Introduction

The term food deserts is used to describe neighborhoods and communities where access to affordable and nutritious foods is limited due to issues of income and access [11]. Various qualitative and quantitative definitions have been proposed and used to categorize certain neighborhoods as food deserts. The United States Department of Agriculture (USDA) uses locations of supermarkets and grocery stores and the census tract level demographic, income and vehicle access data to classify census tracts as food deserts. Different criteria are used for rural and urban census tracts [51]. A tract is designated as a food desert if the tract's poverty rate is 20 percent or greater and a significant number (at least 500 people) or share (at least 33 percent) of the population is greater than 0.5 miles (alternately 1 mile) from the nearest supermarket, supercenter, or large grocery store for an urban area or greater than 10 miles (alternately, 20 miles) for a rural area [51]. Food deserts are neighborhoods marked by lack of access to affordable, nutritious and healthy foods with measurably adverse impacts on individual and community health. Food insecurity as a health risk is linked to costly and preventable chronic diseases, including high blood pressure, coronary heart disease, hepatitis and arthritis. On one hand, the distance to supermarket and food prices is positively correlated with obesity [22] and lack of access to supermarkets is associated with lower expenditures on healthy foods [54]. On the other hand, better access to convenience stores, often the only available food location, causes an increased risk of obesity [54]. Convenience stores offer food choices with the lowest nutritional value among all store types [7].

Food insecurity has a close, intuitive link to not only poverty and food prices, but also spatial access to healthy foods, which is the focus of this paper. The lack of healthy food options in many neighborhoods represents a market failure. Supermarkets are unwilling to locate in such neighborhoods, while the small convenience stores either do not offer healthy food options or offer them at higher cost and low quality. The efforts for incentivizing supermarkets to relocate through tax rebates and rezoning have not worked. Many households in these neighborhoods also lack access to personal or public means of transportation. Public transit in many cities is perennially under-resourced and even modern shared mobility mechanisms like car-sharing and bike-sharing disproportionately serve advantaged neighborhoods. This paper quantifies the potential of consolidated last-mile food delivery for converting convenience stores within food deserts from sources of unhealthy food to hubs of healthy foods. This research ultimately aims to contribute to improve the quality of foods accessible to people living in food deserts and promote food security.

The proposed solution involves modern last-mile delivery services specialized in food, such as Instacart and Walmart Same-Day Grocery Delivery, and Amazon Prime Now. The grocery delivery orders are usually in small quantities and deliverers need to make multiple stops. Since the delivery vehicle is not equipped with refrigeration, there is a limit on the amount of fresh produce that can be delivered at once. The attended home delivery requirements for fresh produce can also cause missed deliveries, and narrow delivery time windows. While last-mile delivery options can certainly provide access to healthy foods to people in food deserts, the aforementioned factors pose a significant challenge of high delivery cost. For many socioeconomically disadvantaged customers living in food deserts, the costs associated with attended home delivery of groceries and the minimum order size requirements make grocery deliveries financially non-viable. To reduce the delivery cost, this paper proposes consolidating customer orders and delivering to a neighborhood convenience store, instead of delivering directly to the customer's home. The convenience store will serve as a pickup point. Similar location-routing models have also been proposed for various other problems [32]

This proposed solution has several advantages. First, by consolidating orders, the deliverer can enjoy the economy of scale to not only lower the delivery cost but also enable small-quantity orders from customers in food deserts. For store delivery, fewer delivery points are visited by delivery vehicles. We call this *spatial consolidation*, i.e., when there are no time windows on both store delivery and home delivery. Second, the deliverer does not need to deliver to attended homes, and therefore they need not consider time windows to ensure customers are present at home. Moreover, since most convenience stores are equipped with refrigerated spaces, the delivery of fresh produce can occur at any time within a day. Therefore, delivering to convenience stores not only achieves spatial consolidation but also *temporal consolidation*. Third, this proposal significantly improves the access to healthy foods for customers living in food deserts. The total delivery costs are reduced and customers can walk within a reasonable distance to obtain healthy foods. The improved access can in turn lead to better health outcomes for people utilizing the delivery service. This approach can also moderate the adverse impacts of disruptions caused by COVID-19 pandemic on grocery access, which predominantly affects food deserts, by delivering healthy foods directly to the most affected neighborhoods.

This paper also makes a crucial contribution to the literature of last mile urban delivery, beyond the current application for food insecurity problem. No other study has quantified both spatial and temporal aspects of consolidation at neighborhood pickup points for last mile urban delivery. Achieving such consolidation for grocery delivery requires special arrangement with attended convenience stores because of refrigeration requirements. For package delivery, however, a larger number of locations can be selected as pickup points. In fact, such partnerships between shipping companies and partner locations to install lockers are already in practice in North America and in Europe where kiosks, florists, subway stations and all manner of small retail locations can serve as pickup points.

In this paper, we focus on quantifying the consolidation benefits, both spatial and temporal, from delivery of fresh foods and groceries at convenience stores closest to the underserved customers. The following specific research aims can help fill crucial parts of this puzzle:

- To quantify the consolidation benefits to grocery delivery services achieved by delivering groceries to neighborhood convenience stores compared with direct-to-home delivery;
- To identify the ideal number, density, and location of partner convenience stores to achieve "sufficient" consolidation and service level; and
- To evaluate how urban form and certain model parameters, including size of delivery time-windows, delivery vehicle capacity, number of depots, and number of customers affect the extent of consolidation and the service level.

To address the first research question, we employ an optimization framework involving the minimum cost set covering problem [21] and a customized version of the capacitated vehicle routing problem (CVRP) [49] with multiple depots and time-windows, which we call MDCVRP-TW. The customer orders are randomly generated and only orders within a walkable distance to one of the convenience stores are accepted for fulfillment. The set cover problem minimizes the number of convenience stores that can service (cover) the accepted customers. To quantify the impact of consolidation on order delivery costs, MDCVRP-TW is run twice; first time to fulfill the orders without consolidation at each customer's location and second time to fulfill the orders at consolidation points selected by the set cover model. The second research question is addressed by varying the number of available convenience store locations as a model sensitivity parameter in the optimization framework. We are interested in determining the number of locations necessary to achieve sufficient levels of consolidation as well as accepted customer orders (service level) to justify the deliverer-store partnership. The final research question involves determining the circumstances, including urban form and other model parameters, which impact the extent of consolidation and the service level.

Our experimental set up consists of data from three counties with marked differences in urban form and population densities. For each county, we create eight instances of varying sizes, depending on the number of depot locations (low, high), number of partner convenience stores (low, high) and number of customer orders (low, high). For comparison across instances, we calculate delivery cost per order and the percentage of accepted orders (service level). Following are the key findings of experimental studies in this paper:

- The results show that only spatial consolidation, measured in terms of reduction in delivery costs per order, although substantial, is not sufficient to justify the store delivery;

- Our results also show that benefits of temporal consolidation in terms of total delivery cost far outweigh those of only spatial consolidation. For our instances, temporal consolidation due to store delivery can accrue delivery cost benefits of ten times and more when narrow customer time windows are considered.

- The capacity of delivery vehicles is an important factor in determining the extent of consolidation. The larger the vehicle capacity is, the more delivery cost savings are, due to in-vehicle pooling.

- The number of available partner stores positively impacts the service level, while a higher number of depot locations and customer orders reduce the cost of delivery.

- The consolidated delivery is not worthwhile for rural and less dense urban neighborhoods due to insufficient service level.

The rest of the paper is organized as follows. In Section 2, we present an extensive literature review of food desert related transportation problems and the last mile of grocery logistics. We also review work related to benefits of consolidation in urban logistics. In Section 3, we present mixed integer programming models for the underlying set cover and routing problems and the algorithms used to solve these models. Section 4 details the experimental setup, including data collection and the case studies used in the paper. Section 5 summarizes the key findings and results of the model including sensitivity analysis of key model parameters. Finally, Section 6 summarizes the key takeaways and findings of the paper.

2 Literature Review

We identify two research streams relevant to our study: research at the confluence of transportation and food insecurity and online grocery delivery research. Each stream is discussed in turn.

2.1 Food Deserts

The term food deserts is used to describe neighborhoods and communities where access to affordable and nutritious foods is limited due to issues of income and access [11]. USDA uses a poverty level of more than 20 percent and a distance to the closest supermarket of 0.5 miles (alternately 1 mile) for urban areas and 10 miles (alternately, 20 miles) for rural areas, to designate a tract as food desert [51]. Others have suggested the inclusion of non spatial characteristics like income, time use and household characteristics. Efforts have been made to use localized studies to collect data on a neighborhood food environment including details about local households and available food options. However, the extensive data collection effort and budget constraints make it difficult to replicate such studies on national level. Following USDA's definition, Figure 1 shows the food desert tracts in continental US, using low income and a distance to supermarket of 1 mile and 10 miles for urban and rural areas, respectively.

The current efforts to combat food insecurity have addressed the three dimensions of 1) income, 2) location, 3) and mobility using various non-governmental and governmental policy interventions. There is a large body of evidence supporting an inverse causal link between low income and food insecurity; and consequent nutritional deprivation; in disadvantaged households [35]. There are also federal and state run programs to promote consumption of healthy foods through grants and tax breaks [3, 39]. These initiatives, along with community kitchens, community farms, food pantries, food banks, fruit and vegetable box delivery schemes, and other community initiatives, although structurally inadequate, serve to moderate the effect of low income on food insecurity [48, 2, 13].

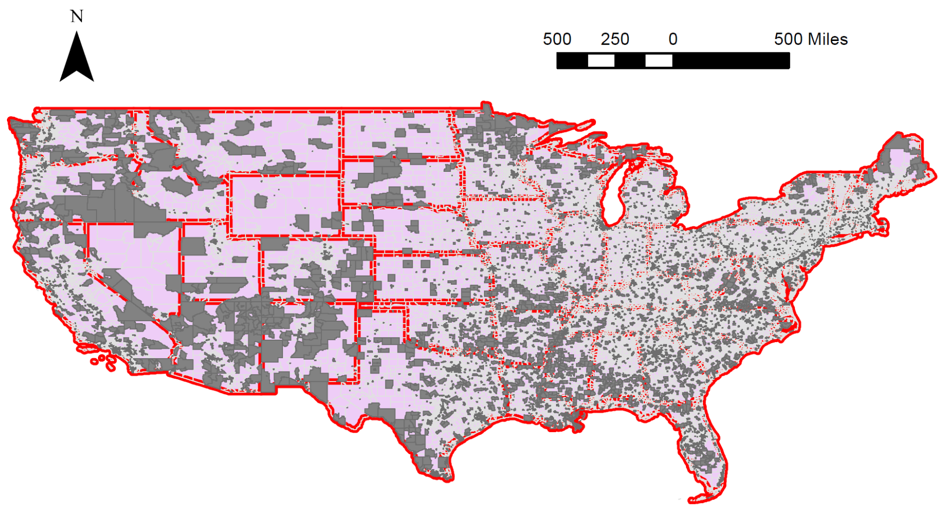


Figure 1: Tracts Designated as Food Deserts in the Continental US shown in Grey

The location dimension explores the proximity of households to supermarkets, grocery stores and other sources of healthful foods. Lack of access to supermarkets causes greater prevalence of health challenges, like diabetes, heart disease and cancer, with diet as a major risk factor [56]. The disparities in access to supermarkets overwhelmingly affect low-income and minority communities [56]. The *Let's Move!* program launched in 2010 by the then first lady, Michelle Obama, envisaged building or expanding 1,500 stores to sell fresh food in underserved communities across the United States [41]. Bastian et al. [4] propose using an incentive contract design to calculate optimal subsidies offered by not-for-profit agencies to incentivise food retailers' operation in certain counties. Despite efforts made by all levels of government, and by some industry organizations [26], it is impracticle to locate supermarkets in all low-income neighborhoods.Moreover, building more supermarkets is hardly a panacea for food insecurity and their impact on dietary habits is unclear [23, 12]. Because online grocery delivery services provide access to a wider variety of foods and do so digitally, their offerings and suggestions can be tailored to increase positive behaviors [17] and promote the consumption of healthy foods.

Efforts to combat the mobility dimension of food insecurity have taken a variety of forms. For many residing in socioeconomically disadvantaged neighborhoods, lack of mobility can hamper access to healthy foods, education, healthcare and employment opportunities [24, 29]. Modern mobility options, like bike-sharing and car-sharing can complement the under-resourced public transit systems and improve urban mobility and help households overcome the 'tyranny of distance.' However many social, financial, and cultural barriers to their widespread use remain in place [29], and mobility benefits of these systems appear to accrue disproportionately to advantaged populations [50, 43]. Moreover, apart from some small-scale pilots using carshare for grocery delivery [33], their potential for improving access to healthy foods remains unexplored.

Our proposed solution to use consolidated delivery services makes fresh food accessible to underserved communities by addressing all three dimensions of food insecurity. For socioeconomically disadvantaged communities, the proposal reduces the cost of delivery and makes it easier for deliverers to deliver small quantity orders. From location perspective, the proposal seeks to convert convenience stores, which are sources of unhealthy food in the communities, to hubs of healthy food. In terms of mobility, the solution removes the need for grocery trips by providing customers access to fresh food within their communities. Initial research on grocery-delivery solutions has found that an affordable online grocery delivery model could serve as a feasible solution for improving access to healthy foods in transportation-scarce and low-income contexts [17]. However, there is currently no research on how an "affordable" grocery-delivery transportation model could work in practice in low-income contexts. This research is also timely because of the unprecedented strains imposed on all three dimensions of food insecurity by the COVID-19 pandemic [44], and the growing popularity of food delivery as a cheaper, healthier and safer method of accessing fresh food [25].

2.2 Logistics of Food Recycling

Most operations research literature for addressing food insecurity have focused on the problem of food recycling. There is a rich literature on using vehicle routing problems to collect and distribute food through food banks or pantries. The food is picked up from pickup nodes (providers) and dropped at one or multiple delivery nodes. The problem is defined as an unpaired pickup and delivery vehicle routing problem [38]. What makes food recycling problems unique is their focus on fairness and equity considerations where unsatisfied demand for all food recipients, the latest arrival time and the total response time is minimized [38]. The perishability of food items, however, makes time of service completion a critical factor to consider. Various exact and heuristic approaches have been proposed to solve the single period vs multi period, and capacitated vs uncapacitated versions of the problem [37]. Davis et al. [14] propose a solution similar to this paper for food banks to deliver food to satellite locations called food delivery points (FDPs) rather than directly to charitable agencies. They solve a set covering model to determine the assignment of food receiving agencies to FDPs, and a periodic vehicle pick-up and delivery model with backhauls for delivering food to FDPs.

2.3 Last Mile Grocery Logistics

Research in last mile logistics has focused in most part on solving vehicle routing problems with or without time windows [55, 20]. More recently, the advent of modern delivery options, such as cargo-bikes, tricycles, electric vehicles, autonomous vehicles, drones and crowd-sourced delivery has initiated research on these new models and systems of delivery [15, 9]. The last mile of grocery supply chain is a complex but important problem area with research work needed to understand the connections between conventional supply chain solutions, like consolidation, and last-mile realities [47].

Current research in same day delivery (SDD) space is focused on optimizing order acceptance and order fulfillment to address the high degree of information dynamism arising in SDD [27]. An important problem in SDD is designing mechanisms for accepting or rejecting arriving customer orders [19]. One stream of research focuses on approximation of delivery costs and their incorporation into booking process for acceptance of arriving orders [31]. Another stream focuses on evaluating arriving customer requests to create optimal or maximal time window offer sets [1, 30]. Another well-studied problem involves design of pricing mechanisms including differentiated slot pricing [28], incentive schemes [6], and dynamic pricing for time slots for management of arriving demand [59].

This paper proposes to use the well-established last mile logistics channel to address the access and mobility dimensions of food insecurity. This solution is made possible by confluence of a variety of enabling factors. The direct-to-consumer delivery market, driven by rapid growth in e-commerce, has seen an annual growth of 7–10 % in mature markets like the United States [15]. The value of the US online grocery market, led by Walmart, Instacart, and Amazon Prime Now, has grown from $12 billion in 2016 to a projected $47 billion in 2020, which is 7 % of the total grocery market [34]. Recently, USDA launched an online purchasing pilot in many US states, allowing Supplemental Nutritional Assistance Program (SNAP) dollars to be spent on online food purchases [52]. Last-mile logistics driven by the instant meal delivery and the same-day grocery delivery has seen huge investment from major competitors in capacity expansion, technology, and delivery systems. Recently, the COVID-19 pandemic has created a sudden expansion in online grocery orders, as more consumers comply with stay-at-home and social distancing orders [25].

Despite these positive developments, the 'last mile' of grocery logistics can be costly and ineffective due to the lack of economies of scale and issues of attended home delivery, like difficult to find addresses, narrow time windows and missed deliveries [16]. For groceries, especially fresh produce, the need for refrigerated storage further complicates the last-mile logistics. The resulting high cost of delivery has been a major impediment in market growth and customers have shown resistance to delivery charges [40]. Most delivery services charge \$6–\$9 per order for delivering orders including fresh produce. However, some deliverers have started offering annual subscription based services including for fresh produce and other similar items. This cost is a big barrier for residents in food insecure neighborhoods. Furthermore, due to very thin margins in grocery retailing, demand side factors like number of expected customers and supply side factors like location of delivery depots can bypass low income localities with predominantly minority populations [8]. The solution we propose consolidates delivery at neighborhood pickup points, therefore eliminating most cost-inducing factors mentioned above.

Recently, major e-commerce players have explored the concepts of locker-boxes to allay some issues in attended home delivery. Although popular in Europe, these intermediate consolidation points have only recently gained traction in the US. Online retailers like Walmart and Amazon have started pilot partnerships with convenience stores and apartment complexes to install lockers for unattended parcel delivery. However, no such partnership currently exists for grocery deliveries. Very little research in the US is focused on design of network of alternate delivery points as a means for consolidation in the last-mile of grocery logistics.

2.4 Benefits of Consolidation

Many parcel delivery services have recently experimented with a network of hyper-local pickup points to achieve last mile consolidation [16]. Pickup points are locations where customers can pick up their orders. They can be either unattended, e.g. locker boxes, or attended, e.g. fuel stations and local convenience stores. Pickup point networks also have economic benefits as they increase the number of successful first-time deliveries and allow more effective optimization of delivery routes (due to reduced location and time uncertainty) [45].Such networks have recently proliferated in

Europe with large number of pickup locations in France, UK, Germany and other countries. Most research on pickup points has focused on the network design problem and location problem for pickup points [16, 36, 58]. Most systems use current locations like convenience stores, commuter stations or other attended locations like florists or kiosks as potential locations in the network [36]. The current models do not take into account walkable-distance considerations when designing the pickup point networks.

The benefits of freight consolidation in long haul transportation and global supply chains are well-known. In the context of urban logistics, researchers have studied urban consolidation centers (UCC) as terminals outside urban centers where incoming urban freight from multiple carriers could be consolidated and dispatched for delivery on smaller, energy efficient vehicles [46]. In the US, Conway et al. [10] study the design and impacts of urban micro-consolidation centers (UMC) aided by last-mile tricycle deliveries in New York City. However, there is little work, if any, on small scale consolidation in the context of urban last-mile delivery services. Moreover, very few studies quantify the cost-benefits from spatial consolidation achieved by the delivery services due to pickup points and no other study explores the temporal dimension of consolidation. Durand et al. [18] quantify the benefits from spatial logistic pooling but only for non-food items.

3 Methodology

We envisage spatial and temporal consolidation of order delivery at pickup points or neighborhood convenience stores. The stores work as pooling locations for multiple customers (orders). Information about all customer orders is assumed to be available at the beginning of planning horizon and the orders must be delivered on the same day. A coalition of customers is assigned to each pick up store. Pick up points can have limited capacity, especially if they are a standalone kiosk. However, we assume these points to have unlimited capacity to serve customer orders since we only consider convenience stores with refrigerated storage. A customer is assigned a pick up store which is within walkable distance to their home. Our model therefore cannot service all customers and only those within a walkable distance are accepted for service. We also assume the depot locations to have unlimited capacity. Similarly, the delivery routes available are also assumed to be unlimited in number since we must deliver all the accepted orders. The delivery vehicles are assumed to be homogenous and are assumed not to have a refrigerated compartment for delivery of refrigerated/frozen groceries. The size of delivery time windows is also assumed to be the same for all customers.

This scheme helps achieve aggregation, removes last mile delivery costs for the retailer, and helps in order consolidation. Most retailers currently require a minimum order of \$30–\$35 to deliver at homes. Order consolidation can help retailers waive the minimum cost requirements and deliver smaller orders to the pickup points. The customers end up paying smaller delivery costs and get the flexibility of making smaller orders. Our proposed methodology involves solving a minimum set cover problem and a multi depot capacitated vehicle routing problem with time windows. In this section, we describe the two problems and the solution methods employed for solving them.

3.1 Set Cover Problem

A set cover model is solved to assign customer orders to neighborhood convenience stores, which are also referred as 'stores' for simplicity. All stores within a walkable distance can serve the customer orders. The set cover model minimizes the number of stores required to serve the customer orders by aggregating the orders in minimal number of stores. The walkable distance ω is varied as a model parameter. In our experiments, we use 600 meters and 1,000 meters. Customers without a convenience store within the walkable distance are not served. Although stores may have limited storage capacity or refrigerated space, we do not put any upper limit on the number of customers which can be served by a single store. However, due to limits on vehicle capacity, we allow multiple vehicle visits to a store.

Given the notation in Table 1, we write the minimum cost set cover problem (SCP) as follows:

$$\text{(SCP)} \quad \min \quad \sum_{q \in \mathcal{Q}} y_q, \tag{1}$$

$$\text{s.t.} \sum_{q \in \Phi(o)} x_{oq} = 1 \qquad \forall o \in \mathcal{O}, \tag{2}$$

$$x_{oq} \leq y_q \qquad \forall a = (o, q) \in \mathcal{A}, \tag{3}$$

$$x_{cq}, y_q \in \{0, 1\} \qquad \forall c \in \mathcal{C}, \forall q \in \mathcal{Q}. \tag{4}$$

In the set cover problem described above, the objective is to find the minimum number of stores

Table 1: Mathematical Notation for SCP

Sets	
$\mathcal{C}$	Set of all customer orders in a planning period indexed by $c \in \mathcal{C}$
$\mathcal{Q}$	Set of neighborhood convenience stores (stores) within 1 mile of food desert tracts indexed by $q \in \mathcal{Q}$
$\Phi(c)$	Set of stores q within walkable distance ω to a customer c, i.e., $\{q \in \mathcal{Q} : d_{cq} \leq \omega\}$
$\mathcal{R}$	Set of stores which are within walkable distance to one or more customer orders and can service one or more customer orders, i.e., $\mathcal{R} = \bigcap_{c \in \mathcal{C}} \Phi(c)$
$\mathcal{O}$	Set of accepted customer orders indexed by $o \in \mathcal{O}$, where $\mathcal{O} = \{c \in \mathcal{C} : \Phi(c) \neq \emptyset\}$
$\mathcal{A}$	Set of all possible arcs indexed by $a \in \mathcal{A}$ where each arc $\mathcal{A} = \{(o, q) : q \in \Phi(o), \forall o \in \mathcal{O}\}$
$\mathcal{S}$	Optimal set of stores selected by the set cover model, i.e., $\mathcal{S} = \{q \in \mathcal{Q} : y_q = 1\}$
$\bar{\mathcal{S}}$	Set of all store vertices to be visited to deliver customer orders. The set includes the set of original store nodes $\mathcal{S}$ and the dummy nodes, created to allow multiple vehicle visits to a single store due to capacity limitations
Variables	
x_{oq}	Binary variable; 1 when a a customer order o is assigned for delivery at store location q, 0 otherwise
y_q	Binary variable; 1 when a store location q is selected as a pickup point, 0 otherwise
Parameters	
d_{oq}	travel distance alongside a travel arc (o, q)
P	capacity of delivery vehicles in terms of number of orders
ω	Parameter representing walkable distance

required to service all the customers. Constraint (2) makes sure that each accepted order is covered by (assigned to) a neighborhood store q. Constraint (3) ensures that customers can only be serviced by a store q if the store is selected as a pickup point. The output of the set cover model is the set of stores selected ($y_q = 1$) and the respective customers serviced by each store ($x_{oq} = 1$). The total demand at a store vertex q, denoted as d_q is given as $d_q = \sum_{o \in \mathcal{O}} x_{oq}$ for each $q \in \mathcal{S}$. Since vehicles have limited capacity P, a store location may need multiple vehicle visits if $d_q > P$. Therefore, we create dummy store locations for each subsequent vehicle visit. Let β_q be the number of such dummy nodes created for each store q, given as:

$$\beta_q = \left\lfloor \frac{\sum_{o \in \mathcal{O}} x_{oq}}{P} \right\rfloor, \qquad \forall q \in \mathcal{S}. \tag{5}$$

Given P and β_q, the updated demand value at each original and dummy node can also be calculated. For example, let us consider three stores with demands $d_1 = 12, d_2 = 4, d_3 = 8$, and the vehicle capacity limited to 5. The number of dummy nodes created to accommodate the extra trips to the stores can be given as $\beta_1 = 2, \beta_2 = 0$ and $\beta_3 = 1$. Accordingly, for store 1, the demand for original node is updated from 12 to 5 while the demands for two dummy trips are 5 and 2, respectively. The outputs of set cover model, after the post processing, include the set of all store vertices ($\bar{\mathcal{S}}$), demand at all store vertices (d_i, $\forall i \in \bar{\mathcal{S}}$) and set of accepted orders ($\mathcal{O}$). These serve as inputs for the subsequent vehicle routing problem.

3.2 Multi Depot Capacitated Vehicle Routing Problem with Time Windows

The second part of our methodological framework is a multi-depot capacitated vehicle routing problem with time windows (MDCVRP-TW). MDCVRP-TW can be formally described as follows. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ be a graph, where $\mathcal{V}$ is the set of vertices and $\mathcal{E}$ is the set of eges or arcs connecting each pair of vertices. The set $\mathcal{V}$ consists of delivery locations and depot locations. The two subsets are described as: $\mathcal{V}_c = \{v_1, v_2, \ldots, v_N\}$ which is the set of delivery locations to be served; and $\mathcal{V}_d = \{v_{N+1}, v_{N+2}, \ldots, v_M\}$ which is the set of depots. Each vertex $v_i \in \mathcal{V}$ has several non-negative weights associated with it. These include a nonnegative demand d_i representing the number of orders to be delivered at the vertex, a nonnegative waiting time w_i and a delivery time window $[e_i, l_i]$, where, e_i is an earliest start time and l_i is a latest start time for the delivery. Let $r_i = l_i - e_i$ br the size of the time window for delivery vertex i. If T is the total time available for delivery, let $q = \frac{T}{r}$ be the number of equally sized, non-overlapping, time windows available for delivery. In this paper, we choose T and r such that T is divisible by r and q is an integer. Further, for the depot vertices $v_i \in \mathcal{V}_d$, there is no demand and wait times, i.e. $d_i = w_i = 0$. The set of edges $\mathcal{E} = \{(v_i, v_j) | v_i, v_j \in \mathcal{V}, i \neq j\}$ is defined for all vertex pairs. Each arc belonging to the set $\mathcal{E}$ has an associated cost, given by the travel time t_{ij}. A total of K homogenous vehicles are available. Each vehicle has the capacity P. Feasible solutions exist only if

$$e_d = E_d \leq \min_{i \in \mathcal{V}_c}\{l_i - t_{di}\}, \qquad \forall d \in \mathcal{V}_d,$$

$$l_d = L_d \geq \min_{i \in \mathcal{V}_c}\{e_i + w_i + t_{id}\}, \qquad \forall d \in \mathcal{V}_d.$$

Note also that an arc $(i, j) \in \mathcal{E}$ can be eliminated due to temporal considerations, if $e_i + w_i + t_{ij} > l_j$, or capacity limitations, if $d_i + d_j > P$, or by other factors.

With the notation in Table 2, MDCVRP-TW consists of determining a set of vehicle routes in such a way that:

Table 2: Mathematical Notation for MDCVRP-TW

Sets	
$\mathcal{V}$	Set of vertices consisting of two subsets: a set of delivery locations $\mathcal{V}_c$ and depot locations $\mathcal{V}_d$
$\mathcal{E}$	Set of edges or arcs connecting each pair of vertices, i.e., $\mathcal{E} = \{(v_i, v_j) \vert v_i, v_j \in \mathcal{V}, i \neq j\}$
$\mathcal{K}$	Set of vehicles available for order delivery at all depots. For each depot, set $\mathcal{K}_d$ of vehicles is available
Variables	
x_{ijk}	Binary variable; 1 when a vehicle k traverses arc $(i, j) \in \mathcal{E}$, 0 otherwise
τ_{ik}	Integer time variables specifying the arrival of vehicle k at vertex i
Parameters	
d_i	Demand at vertex $i \in \mathcal{V}$ representing the number of orders to be delivered at that vertex
w_i	A nonnegative waiting time w_i at vertex $i \in \mathcal{V}$
$[e_i, l_i]$	Delivery time window for vertex $i \in \mathcal{V}$ where e_i is an earliest start time and l_i is a latest start time for the delivery
t_{ij}	The travel time for arc $(i, j) \in \mathcal{E}$ representing the traversal cost
T	Total time available for delivery
q	The number of equally sized (with size r in minutes), non-overlapping, time windows available for delivery given as $q = \frac{T}{r}$
P	capacity of delivery vehicles in terms of number of orders

- Each vehicle route starts at a depot and ends at the same depot.
- The number of vehicles used at each depot cannot exceed the fleet size.
- Each delivery vertex is serviced exactly once by a vehicle route.
- The total demand (number of orders) served by each vehicle route is bounded by the vehicle capacity P while the total route duration (the sum of travel time and wait time) must not exceed maximum route length T.
- Orders must be delivered during the delivery time window $[e_i, l_i]$ for each delivery vertex. If a vehicle arrives at a vertex i earlier than time e_i, it must wait.
- The objective is to minimize the total cost of delivery.

The mathematical formulation for MDCVRP-TW can be defined using two types of decision variables: binary decision variables related to flow, notated as $x_{ijk}, (i, j) \in \mathcal{E}, k \in \mathcal{K}$, equal to 1 if the pair of vertices i and j are in the route of vehicle k, and 0 otherwise; and time variables $\tau_{ik}, i \in \mathcal{V}, k \in \mathcal{K}$, specifying the arrival of vehicle k at vertex i.

The formulation for MDCVRP-TW is given as follows:

(MDCVRP-TW)

$$\min \sum_{\substack{k\in\mathcal{K}\\(i,j)\in\mathcal{E}}} t_{ij}x_{ijk}, \tag{6}$$

$$\text{s.t.} \sum_{k\in\mathcal{K}}\sum_{j\in\delta^+(d)} x_{djk} \le |\mathcal{K}_d|, \qquad \forall d\in\mathcal{V}_d, \tag{7}$$

$$\sum_{k\in\mathcal{K}}\sum_{j\in\delta^+(i)} x_{ijk} = 1, \qquad \forall i\in\mathcal{V}_c \tag{8}$$

$$\sum_{d\in\mathcal{V}_d}\sum_{j\in\delta^+(d)} x_{djk} \le 1, \qquad \forall k\in\mathcal{K} \tag{9}$$

$$\sum_{d\in\mathcal{V}_d}\sum_{i\in\delta^-(d)} x_{idk} \le 1, \qquad \forall k\in\mathcal{K} \tag{10}$$

$$\sum_{i\in\delta^-(j)} x_{ijk} - \sum_{i\in\delta^+(j)} x_{jik} = 0, \qquad \forall k\in\mathcal{K}, \forall j\in\mathcal{V} \tag{11}$$

$$x_{ijk}\left(\tau_{ik}+w_i+t_{ij}-\tau_{jk}\right) \le 0, \qquad \forall k\in\mathcal{K}, \forall\,(i,j)\in\mathcal{E} \tag{12}$$

$$e_i\left(\sum_{j\in\delta^+(i)} x_{ijk}\right) \le \tau_{ik} \le l_i\left(\sum_{j\in\delta^+(i)} x_{ijk}\right), \qquad \forall k\in\mathcal{K}, \forall i\in\mathcal{V}_c \tag{13}$$

$$E_d \le \tau_{ik} \le L_d, \qquad \forall k\in\mathcal{K}, \forall d\in\mathcal{V}_d \tag{14}$$

$$\sum_{i\in\mathcal{V}_c} d_i \sum_{j\in\delta^+(i)} x_{ijk} \le P, \qquad \forall k\in\mathcal{K} \tag{15}$$

$$\sum_{i\in\mathcal{V}_c} x_{idk}\left(\tau_{ik}+w_i+t_{id}\right) - \sum_{i\in\mathcal{V}_c} x_{dik}\left(\tau_{ik}-t_{id}\right) \le T, \qquad \forall k\in\mathcal{K}, d\in\mathcal{V}_d \tag{16}$$

$$x_{ijk} \ge 0, \qquad \forall k\in\mathcal{K}, \forall\,(i,j)\in\mathcal{E} \tag{17}$$

$$x_{ijk} \in \{0,1\}, \qquad \forall k\in\mathcal{K}, \forall\,(i,j)\in\mathcal{E}. \tag{18}$$

MDCVRP-TW (6)–(18) is then to determine a minimal cost set of routes required to complete all deliveries while fulfilling constraints related to capacity, total time and delivery time windows. All routes must originate at one of the depots, and end at the same depot. Constraint (7) ensures that the number of vehicle routes originating at a depot is not more than total number of vehicles available at the depot. Constraint (8) ensures that each delivery vertex must be visited exactly once by exactly one vehicle. Constraints (9)–(10) represent that each vehicle route used in the model

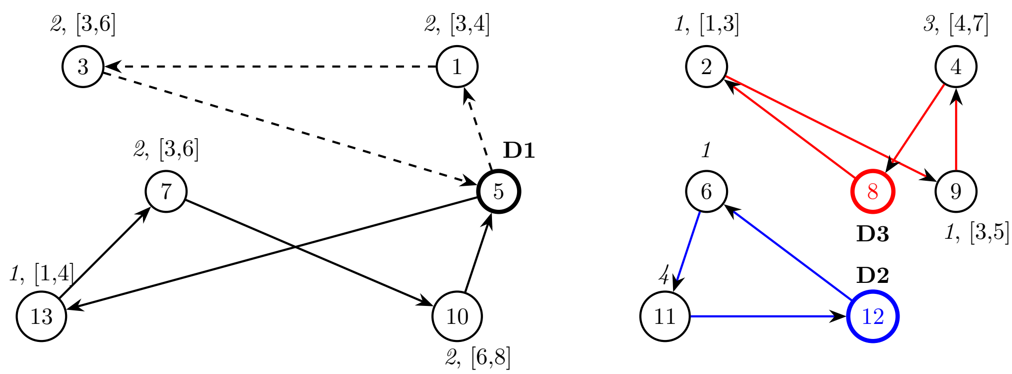


Figure 2: A Small Example of a Multi-depot Capacitated Vehicle Routing Problem with Time Windows (MDCVRP-TW)

must start from a depot, and end at a depot, respectively. Constraint (11) is flow conservation constraint. Constraint (12) updates the arrival time of a vehicle at a vertex j when it visits arc (i, j). Additionally, constraints (13)–(16) guarantee schedule feasibility with respect to time windows, capacity and total route time aspects, respectively. Note that for a given k, constraints (13) force $\tau_{ik} = 0$ whenever vertex i is not visited by vehicle k. Constraints (17) denote the range of flow decision variable.

A small example of the aforementioned routing problem is shown in Figure 2. The problem determines the optimal routes for delivery of all orders while satisfying the delivery time windows. The optimal origin depot for all orders is also determined. The number of available vehicles (or routes) is assumed to be unlimited.

To evaluate the benefits of consolidation in store delivery, we compare the routing costs of the two scenarios by running the vehicle routing problem twice: once for store deliveries and once for direct to customer deliveries. In the former instance of the problem, $\mathcal{V} = \overline{\mathcal{S}}$ while for the latter case, $\mathcal{V} = \mathcal{O}$. For store deliveries, the set cover problem furnishes the demand at each vertex while for direct-to-home delivery, we assume unit demand. Total available time, length and number of time windows, and vehicle capacity are varied as model parameters in our experiments.

All the experiments were done on a machine with 3.6 GHz CPU clock speed, 16 GB RAM and 64-bit Windows 8 operating system. To solve the set cover problem, we used Python API of CPLEX 12.9.0. The routing problem for our model can involve multiple depots, hundreds of customers, time windows and scores of vehicles. Therefore, to solve MDCVRP-TW instances, we use vehicle routing library of Google OR-Tools 7.5 which is Google's software suite for combinatorial optimization [42]. The library provides good solutions fast using a combination of metaheuristics. We use default routing search parameters for our model which lets the software choose among many metaheuristics based on guided local search, simulated annealing and tabu search. The total time limit for solving all instances of the problem is set at 1200 seconds.

4 Numerical Experiments and Case Studies

We conduct extensive numerical analysis to gain crucial insights about the consolidated delivery proposal analyzed in this paper. To account for different urban form, we build three separate case studies with data from three counties with varied population densities. For all three counties, the data about food desert tracts, grocery depots, convenience stores and customers is collected from various governmental and non-governmental sources. For each county, we create eight separate instances to evaluate the sensitivity of our model to densities of depot locations, store locations and the number of customers (orders). All the data instances are run with different values of model parameters for total delivery time T, delivery vehicle capacity P, walkable distance ω and the number of customer time windows q_c.

4.1 Data Collection

We limit the scope of our case study to three counties of varying population densities and sizes. We collect data for Hillsborough County in Florida, Hudson County in New Jersey and Henderson County in North Carolina. Hudson County and Henderson County have predominantly urban and rural characteristics, respectively, while Hillsborough has mixed urban rural characteristics.

We collect the data from four major sources. The Food Access Research Atlas Data by Economic Research Service at US Department of Agriculture [51] consists of various measures of food access at census tract level for the United States. For Hillsborough County in Florida, we use the USDA definition of 1 miles from the nearest grocery store for urban areas and 10 miles for rural areas. For Hudson and Henderson counties, we use a relatively liberal definition with distance measures of 0.5 miles for urban areas and 10 miles for rural areas to get enough number of representative food insecure tracts. Hillsborough County, for instance, has 43 food insecure census tracts out of a total

Table 3: Salient Data Features for Hillsborough, Hudson and Henderson Counties

County	Pop. Density (per sq. mi.)	# of Census Tracts	Food Desert Tracts	# of Delivery Points	# of Chain Stores	# of Total Customers
Hillsborough	702	320	43	7	217	1,619
Hudson	14,973	166	17	7	70	1,758
Henderson	286	27	6	5	48	372

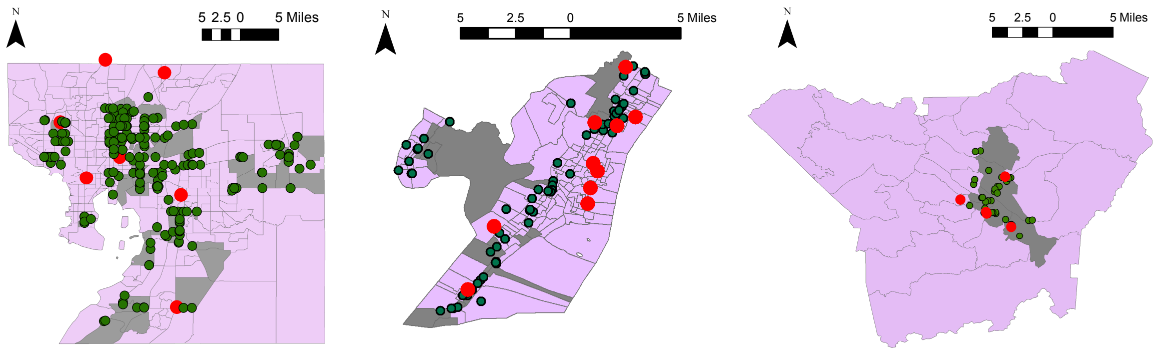
of 320 tracts.

The second source of data is related to the cartographic boundary lines for various census tracts in our study areas. We use the 2015 TIGER data accessed from United States Census Bureau [5] to get shapefiles for statewide census tracts. We then trim the data to our areas of study for respective counties.

The third source of data include the locations of depots, convenience stores, and potential customers. We consider Walmart and other large locations providing grocery delivery services. For instance, for Hillsborough County, 7 Walmart locations provide home delivery service [57]. If no Walmart locations offer delivery in a county, we select locations which offer their own delivery services or Instacart delivery. The model chooses the optimal depot location for each order.

In order to identify the locations of convenience stores, we use SNAP retailer database [53]. For instance, Hillsborough County has 1076 retailers in the database. Since we envisage business partnership involving deliverers and convenience stores, and also require refrigerated storage, independently owned convenience stores and chains with less than 3 stores are not considered in the current analysis. For Hillsborough County, for instance, we limit our selection to 13 largest chains of pharmacies, dollar stores and gas stations (stores). This reduces the number of stores to 442. Finally, only stores within 1 mile distance of a ‘food desert’ census tract are included in the analysis. We consider 217 convenience stores within 1-mile distance of a food desert in Hillsborough County. Stores are assumed to have refrigerated space for carrying groceries. There is no capacity limit for stores. The key data features for the three counties are given in Table 3. Figure 3 shows the census tracts designated as food deserts, the grocery depots (red) and the neighborhood store locations (green) considered for consolidation for the three counties.

The customers within the food insecure census tracts are created at random locations on the road



(a) Hillsborough, Florida (b) Hudson, New Jersey (c) Henderson, North Carolina

Figure 3: Food Desert Tracts, Depot Locations and Neighborhood Stores for Hillsborough, Hudson and Henderson Counties

Table 4: Eight Instances with Different Densities for Depot Locations, Stores, and Customers for the Three Case Studies

	Hillsborough			Hudson			Henderson		
Instance	$\|\mathcal{V}_d\|$	$\|\mathcal{Q}\|$	$\|\mathcal{C}\|$	$\|\mathcal{V}_d\|$	$\|\mathcal{Q}\|$	$\|\mathcal{C}\|$	$\|\mathcal{V}_d\|$	$\|\mathcal{Q}\|$	$\|\mathcal{C}\|$
Instance 1	1	108	801	5	39	823	2	5	170
Instance 2	1	108	1619	5	39	1758	2	5	372
Instance 3	1	217	801	5	70	823	2	5	170
Instance 4	1	217	1619	5	70	1758	2	5	372
Instance 5	7	108	801	10	39	823	5	5	170
Instance 6	7	108	1619	10	39	1758	5	5	372
Instance 7	7	217	801	10	70	823	5	5	170
Instance 8	7	217	1619	10	70	1758	5	5	372

network. The number of customers in each tract is proportional to the number of households without access to vehicles. We choose 30 % of the number of such households as our potential customers. For food desert census tracts in Hillsborough County for instance, the number of 'potential' customers is 1619. The travel distances between road networks between points of interest including depots, stores, and customers are obtained using ArcGIS. The experimental setup consists of various instance sizes for each county. To understand the sensitivity of our model to the number of depot locations, number of convenience stores and number of customer orders, we vary these parameters to create different instances for all three case studies.

Customer orders are supposed to arrive at the beginning of the time horizon and the number of customer orders per planning period is varied as a model parameter. The total time limit for making

Table 5: Experimental Setup for the Study Involving Instances of Various Sizes and Sensitivity Analysis for Number and Size of Time Windows and other Parameters

Instances	County	Hillsborough, Hudson, Henderson
	# of Depots	{1,7}, {5,10}, {2, 5}
	# of Store Chains	{6,13}, {6,13}, {4, 8}
	Order Proportion	0.5, 1
Time Windows (TW)	Total Time	240 min, 480 min
	# of TWs (customers)	{6, 3, 2, 1}, {12, 6, 3, 2, 1}
	Size of TWs (customers)	{40, 80, 120, 240} , {40, 80, 120, 240, 480}
	# of TWs (stores)	{2, 1} , {2,1}
	Size of TWs (stores)	{120, 240} , {240, 480}
Parameters	Walkable Distance	600 m, 1,000 m
	Vehicle Capacity	5, 10, 20

deliveries is set to 4 hours (240 minutes) or 8 hours (480 minutes). The delivery time windows for customers and stores are also a model parameter. The time windows are evenly sized, e.g., if the total time $T = 240$, and $r = 40$ minutes, then $q = 4$ time windows of equal size are created. Customer orders are randomly assigned the delivery time window. Since time windows impact the total delivery time, this randomness translates into slightly different values of total travel time for every run of the instances. However, the difference does not considerably alter the fundamental insights of the model. For customers, we consider the following time windows sizes: 40 minutes, 80 minutes, 120 minutes, 240 minutes, and 480 minutes (only when $T = 480$ minutes). For stores, we consider the following time window size: 120 minutes (only when $T = 240$ minutes), 240 minutes and 480 minutes (only when $T = 480$ minutes). The capacity of delivery vehicles is measured in number of orders which can be delivered in a single run. We test the sensitivity of our model with capacity parameter of 5, 10, and 20 orders. Table 5 gives the details of experimental analysis and parameters for all three case studies.

5 Experimental Results

Some important managerial insights for delivery services will derive from measuring the extent of spatial and temporal consolidation (representing the delivery costs) and the percentage of accepted orders (representing the service level), under various operational circumstances. A delivery service may be interested in evaluating how different time window sizes r, representing relatively strict or loose attended home delivery requirements, may impact the temporal consolidation. This may help determine the circumstances under which is it worthwhile to use neighborhood convenience stores for consolidated delivery. The extent of spatial consolidation is also impacted by various factors. The capacity of the delivery vehicle P may allow for in-vehicle pooling whereby using larger vehicles may reduce the delivery costs. The total number of stores a deliverer partners with, denoted as $\mathcal{Q}$, can also be an important determinant of percentage of accepted orders and the extent of spatial consolidation. Similarly, the walkable distance parameter ω can impact the percentage of accepted orders and also the number of convenience stores available for delivery.

In this section, we study the relationship between the total cost of delivery and all the aforementioned parameters of our model. Specifically, using our computational methods and the data from three counties representing different urban forms, we conduct an extensive numerical experiment by calculating the total delivery cost for a large number of instances for each county. We find that the biggest impact on delivery costs is due to time window requirements of attended home delivery. Besides the time windows, the vehicle capacity P, walkable distance parameter ω and, and number of partner convenience stores are important determining factors for the extent of spatial consolidation achieved and the service level provided.

A template of results for a single instance of the model for Hudson County is provided in Table 6. For this instance, the number of orders served in a day is 1324. When served through the convenience stores, 57 store locations are utilized while 76 visits are made to the stores. Vehicle capacity is assumed to be 20 orders per trip. The table clearly shows the impact of spatial and temporal consolidation for the instance. If customer delivery time-windows are narrow, and there are no time-windows for store delivery, maximum improvement of more than 1,800 % can be achieved through a combination of spatial and temporal consolidation. On the other hand, only spatial consolidation achieves an improvement of 234 % for total delivery time. These results underscore the importance of convenience stores as points of temporal consolidation since store-delivery removes the time-window constraints imposed by attended home delivery.

5.1 Sensitivity to Number and Size of Time Windows

A major issue with attended home delivery for groceries is relatively strict time windows. Due to threat of pilferage, and refrigeration requirements for fresh produce, customers do not prefer

Table 6: Experimental Results for a Single Instance (Instance 8) of the Problem for Hudson County when $\omega = 1{,}000$ meters. For this Instance, $|\mathcal{O}| = 1{,}324$, $|\mathcal{N}_S| = 76$, and $P = 20$

Total Time	(# of TWs, TW size) (customer)	(# of TWs, TW size) (store)	Delivery Time (customers)	Delivery Time (stores)	Percentage Improvement
240 min	(6, 40)	(1, 240)	7,035	500	1,307 %
	(6, 40)	(2, 120)	7,577	899	743 %
	(3, 80)	(1, 240)	6,343	500	1,168 %
	(3, 80)	(2, 120)	6,616	999	562 %
	(2, 120)	(1, 240)	4,859	500	872 %
	(2, 120)	(2, 120)	5,451	902	504 %
	(1, 240)	(1, 240)	1,670	500	234 %
	(1, 240)	(2, 120)	1,670	860	94 %
480 min	(12, 40)	(1, 480)	9,777	500	1,855 %
	(12, 40)	(2, 240)	9,577	881	987 %
	(6, 80)	(1, 480)	8,461	500	1,592 %
	(6, 80)	(2, 240)	7,512	959	683 %
	(4, 120)	(1, 480)	7,530	500	1,406 %
	(4, 120)	(2, 240)	7,866	799	884 %
	(2, 240)	(1, 480)	6,667	500	1,233 %
	(2, 240)	(2, 240)	6,782	940	621 %
	(1, 480)	(1, 480)	1,670	500	234 %
	(1, 480)	(2, 240)	1,670	861	94 %

Table 7: The Percentage Difference between Delivery Costs for Store Delivery and Home Delivery for Different Values of Number of Customer Time Windows and Vehicle Capacity for the Three Case Studies when $T = 240$ and $q_s = 1$. The Percentage Difference is Averaged across the Eight Instances.

	Hillsborough			Hudson			Henderson		
# of TWs (q_c)	$P = 5$	$P = 10$	$P = 20$	$P = 5$	$P = 10$	$P = 20$	$P = 5$	$P = 10$	$P = 20$
1	12 %	23 %	37 %	48 %	104 %	198 %	66 %	92 %	142 %
2	112 %	179 %	210 %	269 %	587 %	855 %	511 %	657 %	825 %
3	122 %	207 %	288 %	336 %	627 %	976 %	539 %	819 %	1,073 %
6	153 %	272 %	382 %	428 %	829 %	1,291 %	722 %	1,023 %	1,377 %
Aggregate	100 %	170 %	229 %	270 %	536 %	830 %	460%	648 %	854 %

groceries to be left out in the open unattended. Therefore, the deliverers must adhere to strict time windows when making deliveries. We vary the parameter T representing the total time for delivery between 240 minutes (4 hours) and 480 minutes (8 hours). For each of these values, the number and size of time windows, denoted by q and r, respectively, are varied as a model parameter as given in Table 5. Since the experiments involve three separate case studies, and also eight instances for each case study, the total number of accepted (delivered) orders is different for all instances. Therefore, we calculate delivery time per order to normalize the total delivery time across instances.

Figure 4 gives the results for all three counties when $T = 240$ minutes and only one time window is considered for store delivery, i.e., $q_s = 1$. The thick black vertical lines separate the results for different P values representing vehicle capacity while green vertical lines separate the results for different number of customer time windows q_c. As the number of time windows increases, so does the difference between delivery costs for attended home delivery (blue) and store delivery (red) across all instances. When there is only one time window for customer delivery, i.e., $q_c = 1$, the difference in delivery costs is relatively insubstantial as shown in Table 7. This represents the situation when only spatial consolidation can be achieved.

When considering only spatial consolidation, the average improvement across all instances and vehicle capacity values for Hillsborough County is 24 %. For Hudson and Henderson counties the average improvement is 116 % and 100 %, respectively. While the improvement is substantial, these averages are not commensurate with the number of vertices visited for store and home deliveries. For Hudson, the average number of vertices visited is 7 times less for store delivery compared to home

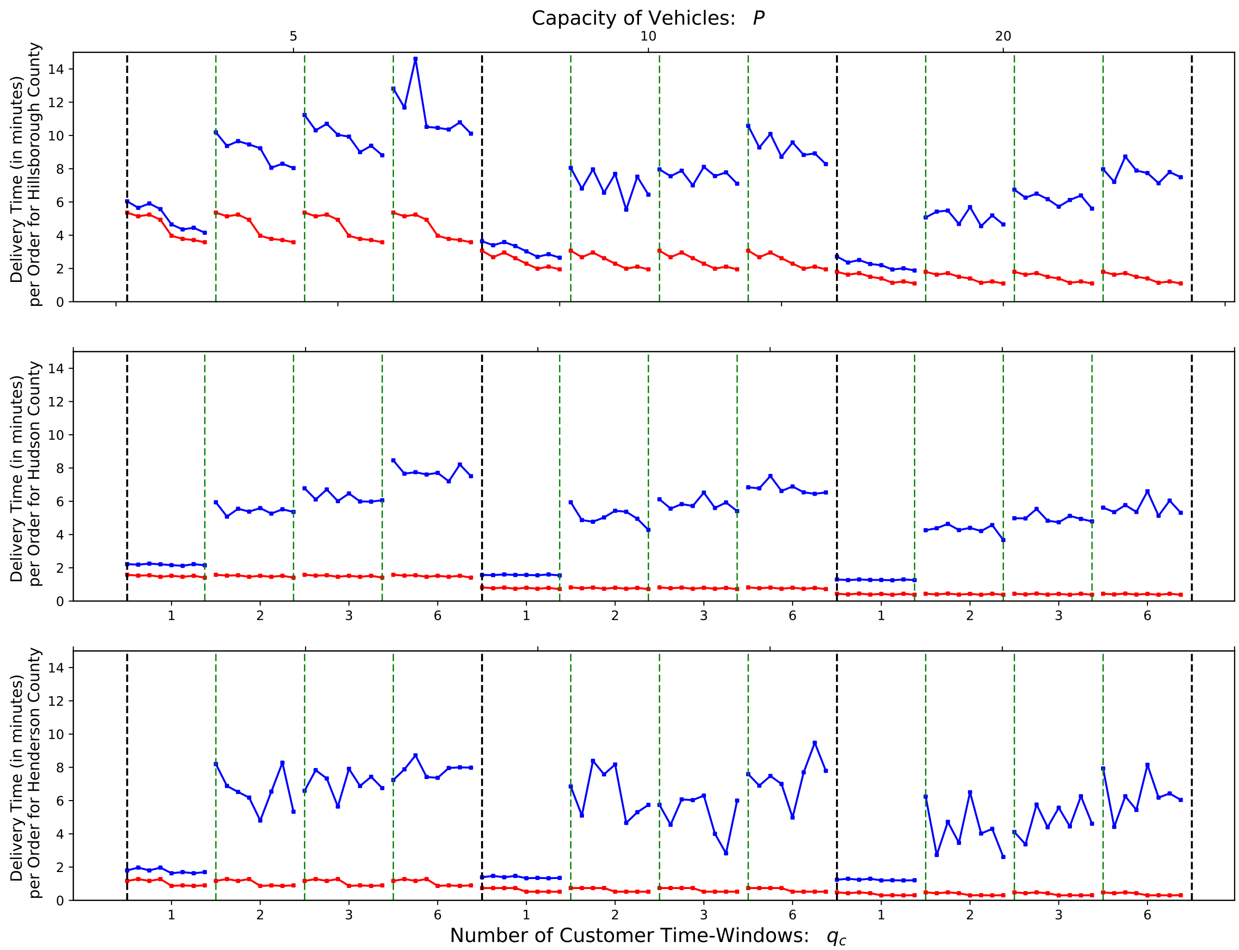


Figure 4: Comparison of Travel Time per Order for Customers (blue) and Stores (red) as a Function of Vehicle Capacity and Number of Customer Time Windows when ω = 1,000 m, T = 240 mins, and $q_s = 1$

delivery. Similarly for Hillsborough and Henderson counties, despite lesser number of vertices being visited, 4 times less on average, the delivery costs for store delivery do not improve proportional to the decrease in number of vertices visited. This is primarily due to stores being farther away from each other compared to homes. Besides, due to capacity limitations, the number of vehicle visits (trips) to deliver accepted orders is the same for both types of delivery.

5.2 Sensitivity to Vehicle Capacity

We also see that vehicle capacity plays an important role in determining the extent of consolidation. As shown in Figure 4, delivery costs per order decrease as vehicle capacity increases for both store and home delivery. When only spatial consolidation is considered, i.e, $q_s = q_c = 1$, increasing vehicle capacity brings substantial improvement to delivery costs. For Hudson County, on average, the costs for store delivery across instances, are 198 % less than home delivery when $P = 20$ while the difference is only 48 % when $P = 5$. For Henderson, the numbers are 142 % versus 66 %, while for Hillsborough they are 37 % versus 12 %, respectively, as shown in Table 7. Even for cases with temporal consolidation, i.e., when $q_s = 1$ and $q_c > 1$, larger vehicle capacity substantially improves the extent of consolidation and the total delivery costs for all three counties as evidenced by aggregate improvement values in Table 7.

5.3 Sensitivity to Walkable Distance and Urban Form

In addition to the cost of delivery, another important factor to consider for last mile consolidation is the service level the deliverer can provide to the customers. We define the ratio of accepted orders $|\mathcal{O}|$ and total customers $|\mathcal{C}|$, i.e., $|\mathcal{O}|/|\mathcal{C}|$ as the service level. Since we envisage last mile consolidation of grocery deliveries at neighborhood convenience stores, the number of stores available for delivery, denoted by $|\mathcal{R}|$, is an important determinant of number of accepted orders $|\mathcal{O}|$. In turn, the number of walkable stores $|\mathcal{R}|$, depends on total number of stores $|\mathcal{Q}|$ and the walkable distance parameter ω. As shown in Figure 5, the service level improves significantly when ω is increased to 1000 meters (orange) from 600 meters (blue).

Another important factor is the urban form and built environment of the delivery neighborhood. Rural areas where customers and convenience stores are spread out may not provide sufficient service level to offer consolidated delivery. As can be seen in Figure 5, the service level for Henderson County is substantially lower than the other two case studies considered. This is because there are lesser number of possible convenience stores available for partnering and they are farther than walkable distance from most customers. In such cases, it is better to consider home delivery, and despite the cost advantages accrued due to store delivery, it may not be worthwhile due to very low service levels. Even for urban counties of Hillsborough and Hudson, the service level is lower than 50 % when $\omega = 600$ meters. Service level for Hudson County, the most urban of the three case studies considered, has the highest value across instances. This is despite the relatively lower number of available stores $|\mathcal{Q}|$ for Hudson County compared with Hillsborough County.

In this section, the service level is calculated considering all food desert neighborhoods in a county. However, not all food insecure neighborhoods have the same level of access to neighborhood

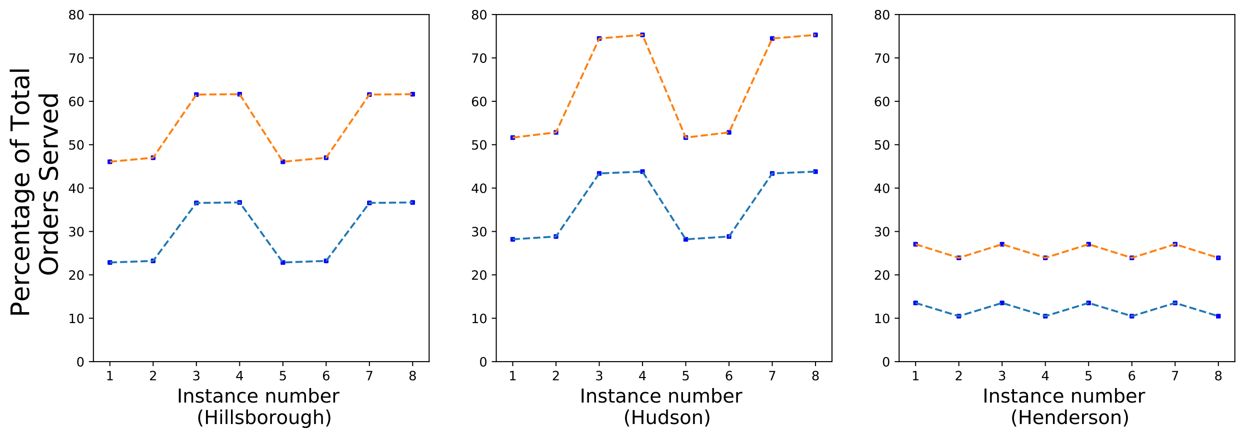


Figure 5: Percentage of Orders Accepted for the Three Case Studies when Walkable Distance (ω) = 1000 m (orange) and 600 m (blue)

convenience stores. For instance, as can be seen for Hillsborough County in Figure 3, the food desert tracts in the Southern (lower) and Western (right) half of the county have a relatively lower access to convenience stores. Similarly, for Hudson County, a large food insecure tract at the Western end, which is an industrial area, does not have any neighborhood convenience stores available. In such cases, it may be worthwhile for deliverer to evaluate the service level on tract by tract basis and serve the neighborhoods where most orders can be delivered to consolidated locations within a walkable distance. Attended home delivery can still be an option for tracts and neighborhoods without any convenience stores.

5.4 Sensitivity to Number of Depot Locations, Number of Stores, and Number of Orders

The eight instances considered in our experiments for each of the three case studies signify different densities for depot locations, number of stores and the number of total customers as shown in Table 4. Having a larger number of depots (red bars) improves the delivery costs per order as shown in 6. The improvement is especially significant for Hillsborough and Henderson counties. This is expected since Hillsborough county is the largest in area while Henderson county is most rural. Having lesser number of depots increases the length of first and last legs of vehicle routes, therefore increasing the overall delivery costs.

We also evaluate the sensitivity of our model to the density of partner convenience stores by

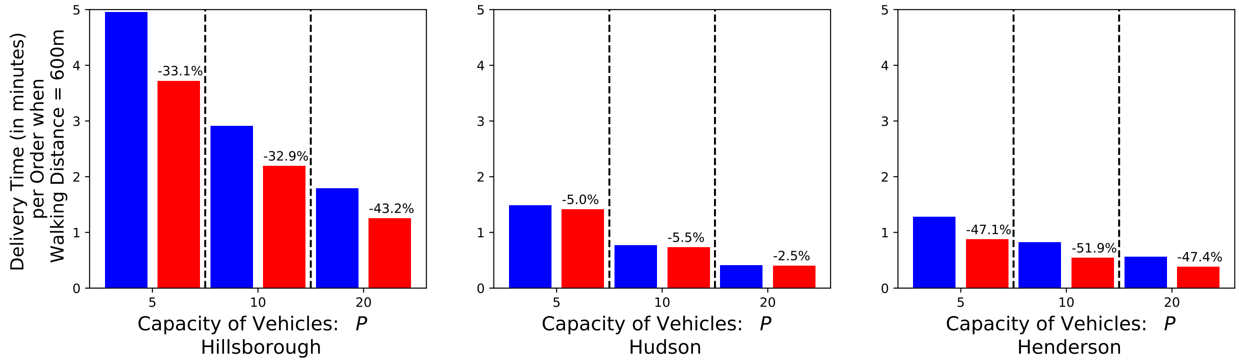


Figure 6: Comparison of Travel Time per Order for Stores when the Number of Depots is less (blue) and more (red) for the Three Case Studies

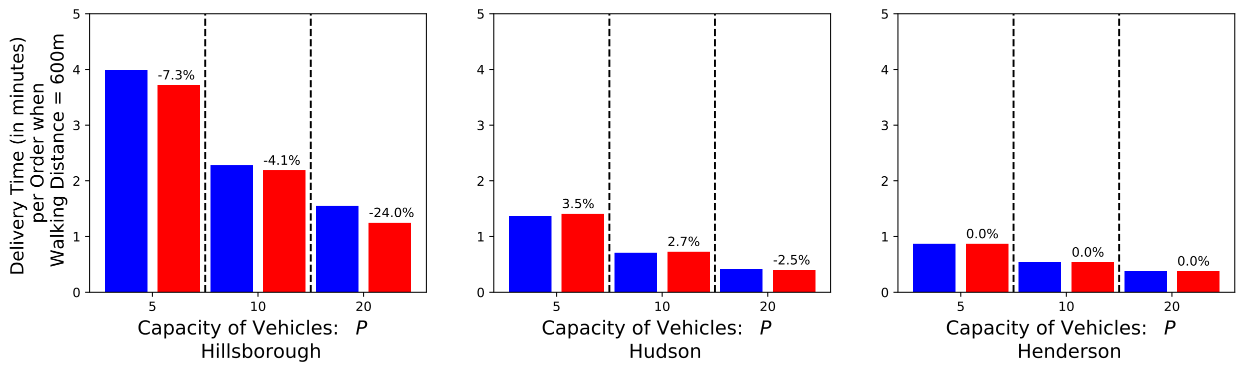


Figure 7: Comparison of Travel Time per Order for Stores when Store Density = 0.5 (blue) and when Store Density = 1 (red) for the Three Case Studies

varying the number of store chains considered in our model as shown in Table 5. We find that although the number of partner stores significantly impacts the service level and the orders served (see Figure 5, instances 3, 4, 7, 8), it does not significantly improve the cost of delivery per order as can be seen in Figure 7. In this study, we only consider store chains in our analysis. For rural and less dense urban neighborhoods, partnerships with family owned corner stores can also be a viable option to increase the service level of store delivery.

Finally, we also alter customer density as a model parameter. It is of interest to deliverers to achieve scale in the delivery operations by having a larger customer base. Figure 8 shows the improvement in delivery cost per order when larger number of total customers $|\mathcal{Q}|$ or orders is available. This essentially signifies the scaling up of delivery operations. The results for all three case studies suggest a larger improvement in per unit delivery costs when vehicles of large capacity, $P = 20$, are utilized. This suggests that not only do large vehicles improve delivery costs significantly,

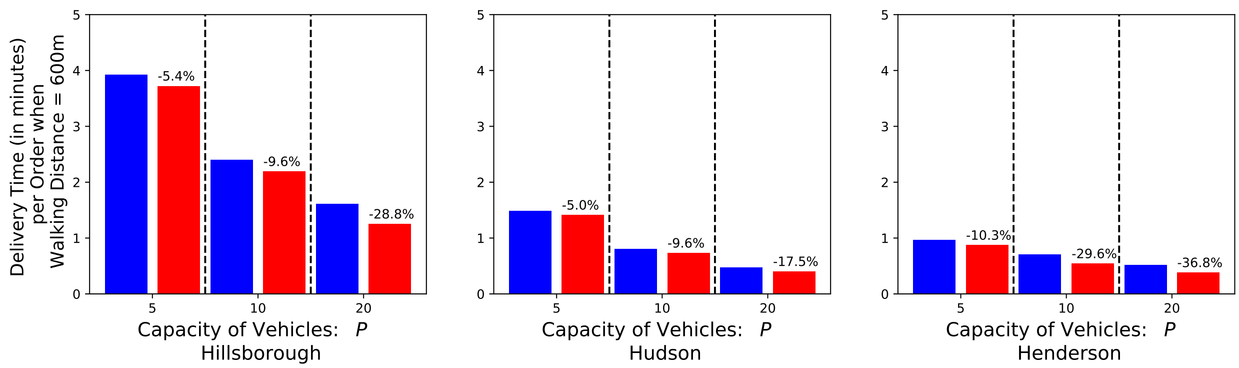


Figure 8: Comparison of Travel Time per Order for Stores when Customer Density = 0.5 (blue) and when Customer Density = 1 (red) for the Three Case Studies

the benefits of in-vehicle pooling especially accrue when larger number of orders are to be delivered.

6 Conclusion

Low income, lack of viable transportation options and unavailability of proximate supermarkets make access to fresh and healthy food an urgent issue in many neighborhoods. This paper proposes using last mile grocery delivery services as a solution to the food insecurity problem for these low income and low access neighborhoods, the so called food deserts.' Due to various issues with attended home delivery and the minimum order size requirements, the cost of home delivery for groceries can be prohibitively expensive for low income households. To resolve these problems, we propose using the neighborhood convenience stores as consolidation pickup points where the grocery delivery services can deliver orders and the customers can pick them up. Oftentimes, these neighborhood stores are the only source of food but carry more expensive and unhealthy food items. The solution we propose converts these locations to hubs of healthy food.

The main focus of this research is to quantify the consolidation benefits achieved due to this arrangement. To this end, we compare the cost of delivering customer orders to customer homes with store delivery. A set cover problem is solved to find the minimal number of stores required to serve all customers within a predefined walkable distance to one of the stores. Subsequently, we solve customized vehicle routing problem with time windows twice: first to deliver the accepted orders direct to customers and second to deliver the same orders through pick up convenience stores. The time windows of customer delivery are changed as a model parameter to see how the narrowness of delivery windows impacts the temporal aspect of consolidation. The total cost of delivery for the two situations is compared to answer the main research question. We also evaluate the operational circumstances under which this solution may or may not be worthwhile in real neighborhoods by comparing the service level, i.e., the percentage of accepted orders for store delivery, across many operational situations. Our experimental analysis uses real life data from three counties with different urban forms. We also evaluate the sensitivity of our model to capacity of delivery vehicles, the number of partner convenience stores, number of depot locations, and number of orders.

The results suggest that consolidation benefits of store delivery across instances are substantial. In the best case instance (with narrowest customer time windows considered), the delivery cost reduction of up to 1,800 % can be achieved compared to home delivery. However, spatial consolidation alone does not reduce the delivery costs sufficiently to justify store delivery. We find that most of improvement in delivery costs comes from temporal consolidation which is higher when customer time windows are narrow. The capacity of delivery vehicles is an important factor in determining the extent of consolidation. The difference in delivery costs between two schemes is larger for larger capacity vehicles due to in-vehicle pooling. Number of available partner stores positively impacts the service level, while higher number of depot locations, and customer orders reduces the cost of delivery. We also find that the consolidated delivery may not be worthwhile for rural and less dense urban neighborhoods due to insufficient service level.

This paper is an important step in enabling the use of consolidated grocery delivery to substantially address the problem of food insecurity in socioeconomically disadvantaged neighborhoods. In light of the recent global pandemic, and its exacerbating effects on food insecurity, the innovative solution proposed in this paper is even more relevant and timely. Further research, both qualitative and quantitative, is required and in depth field research based on interviews and focus groups can engage the stakeholders, including conveniece stores and neighborhood residents, to enable the proposed solution. Further research can be conducted in designing a market to enable the consolidated delivery operations. A market design approach (e.g., see [4]) can further inform how the costs and benefits of the consolidated delivery can be divided between stakeholders, and how targeted government subsidies, if required, can make this model financially viable for all parties including food delivery service, convenience stores and customers.

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