# Creating grocery delivery hubs for food deserts at local convenience stores via spatial and temporal consolidation

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A B S T R A C T

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 a 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 d i df dh model have a significant imp f c( eh

### 3.1. Set cover problem

A set cover model is solved to assign customer orders to neighborhood convenience stores, which are also referred to 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 a minimal number of stores. The walkable distance $\omega$ is varied as a model parameter. In our experiments, we use 300 m, 600 m and 1,000 m representing 3 min, 6 min and 10 min of walking distance, respectively. The walking distance catchment area of up to 10 min of walking is also used in other research [57]. For heavier items and bigger orders, regular customers can use wheeled bags or carts to lessen the physical effort. Customers without a convenience store within 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:

$$\text{SCP} \quad \min \sum_{z\in} y_q, \tag{1}$$

$$\text{s.t.} \sum_{z\in\Phi_o} x$$

MDCVRP-TW (6)–(17) is then to determine the set of minimal-cost 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 each delivery vertex must be visited exactC U U

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

The formulation for MDCVRP-TW is given as follows:

MDCVRP − TW

$$\min \sum_{k\in} \sum_{i,j\in} t_{ij}x_{ijk}, \tag{6}$$

$$\text{s.t.} \sum_{k\in} \sum_{j\in\delta\ i} x_{ijk} = 1,\quad i \in \ _c \tag{7}$$

$$\sum_{v\in\ _f} \sum_{j\in\delta\ _f} x_{vjk} \leq 1,\quad k \in \tag{8}$$

$$\sum_{v\in\ _f} \sum_{i\in\delta^-\ _f} x_{ivk} \leq 1,\quad k \in \tag{9}$$

$$\sum_{i\in\delta^-\ j} x_{ijk} - \sum_{i\in\delta\ j} x_{jik} = 0,\quad k \in \ ,\ j \in \tag{10}$$

$$x_{ijk}\left(\tau_{ik}\quad w_i \quad t_{ij} - \tau_{jk}\right) \leq 0,\quad k \in \ ,\quad i,j \in \tag{11}$$

$$e_i\left(\sum_{j\in\delta\ i} x_{ijk}\right) \leq \tau_{ik} \leq u_i\left(\sum_{j\in\delta\ i} x_{ijk}\right),\quad k \in \ ,\quad i \in \ _c \tag{12}$$

$$e_v \leq \tau_{ik} \leq u_v,\quad k \in \ ,\quad v \in \ _f, i \in \ _c \tag{13}$$

$$\sum_{i\in\ _c} d_i \sum_{j\in\delta\ i} x_{ijk} \leq P,\quad k \in \tag{14}$$

$$\sum_{i\in\ _c} x_{ivk}\ \tau_{ik} \quad w_i \quad t_{iv} \quad - \sum_{i\in\ _c} x_{vik}\ \tau_{ik} - t_{iv} \ \leq T,\quad k \in \ , v \in \ _f \tag{15}$$

$$x_{ijk} \geq 0,\quad k \in \ ,\quad i,j \in \tag{16}$$

$$x_{ijk} \in \ 0,1 \ ,\quad k \in \ ,\quad i,j \in \ . \tag{17}$$

$\omega$, 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 U.S. Department of Agriculture [11] consists of various measures of food access at the census tract level for the United States. For Hillsborough County in Florida, we use the USDA definition of 1 mile 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 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 [64] 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 includes 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 [65]. If no Walmart locations offer delivery in a county, we select locations that 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 the SNAP retailer database [66]. For instance, Hillsborough County has 1076 retailer ꞁ

## 5. Experimental results and managerial insights

Some important managerial insights for delivery services will derive from measuring the delivery costs (representing the benefits of spatial and temporal consolidation) 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 it is 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 , can also be an important determinant of the percentage of accepted orders and the extent of spatial consolidation. Similarly, the walkable distance parameter $\omega$ can impact the percentage of accepted orders and also the number of convenience stores available for delivery.

In our results, we have focused on transportation costs alone. For in-store delivery, the delivery service is responsible for renting the in-store refrigrated space incurring extra cost. At the same time, the in-store option uses lesser number of refrigrated vehicles for lesser time. Furthermore, due to relatively large delivery time windows, the in-store option also reduces the time groceries spend inside the depot location.

the capacity of the delivery vehicle and the walkable-distance parameter. This implies increased spatial consolidation when vehicles of larger capacity are used and the walking distance parameter is increased.

Similarly, we have used the number of orders delivered per hour as a measure of temporal consolidation. This measure can provide the extent of temporal consolidation achieved by eliminating the delivery time windows. A major issue with attended home delivery for groceries is relatively strict time windows which can be removed in case of store delivery. As shown in Table 8, the number of orders delivered per hour is very close for store delivery and home delivery when no home delivery time windows are considered, and the vehicle capacity is small. The ratio gradually increases as home delivery time windows become smaller, and vehicle capacity is increased.

## 5.2. Sensitivity to supply side parameters

In this section, we explore the sensitivity of our approach to the supply side parameters like the number and size of time windows, vehicle capacity, number of delivery locations or depots, and the number of pick-up point store locations.

### 5.2.1. Sensitivity to number and size of time windows

We vary the parameter $T$ representing the total time for delivery between 240 min (4 h) and 480 min (8 h). 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.

Fig. 4 gives the results for all three counties when $T = 240$ min 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 the 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 9. This represents the situation when only spatial consolidation can be achieved.

When considering only spatial consolidation, the average improvement across

142% versus 66%, while for Hillsborough they are 37% versus 12%, respectively, as shown in Table 9. Even for cases with temporal consolidation, i.e., when

lower than 50% when $\omega =$ -

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