OPTIMIZING ALLOCATION OF SCOOTER BATTERY SWAPPING FACILITY IN MINNEAPOLIS

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ABSTRACT. Better battery swapping station (BSS) allocation helps improve operation and management of scooter sharing. Demand fulfilling and capacity constraint jointly determine the optimal location for BSS, and this consideration results in nonlinear constraints. To minimize the total cost, this project develops a modified facility location model based on optimization programming. The optimization model is demonstrated on a case study in Minneapolis including 2826 streets and 20 neighborhoods. The results reveal that performance of the model is different from clustering, and provide strong evidence to its feasibility.

Keywords: Dockless E-scooter; Battery Swapping Station; Optimization

1 Introduction

High auto dependency has encumbered many United States cities with congestion and sprawl for a long time. As a result, lacking infrastructural support for non-motorized modes of transport has shackled residents living in such cities with limited travel alternatives, leading to air pollution and unhealthy lifestyles. Shockingly, most of the daily trips in the US are short-distance trips, which could be replaced by walking, biking, transit, or other alternative transportation modes. In 2007, more than 50% of the total trips were 1 to 10 miles. 2009 National Household Travel Survey (NHTS) statistics showed that trips shorter than 3 miles accounted for 50% of total trips that year. Moreover, among all trips less than or equal to 1 mile, 60% of them were completed by personal vehicles such as cars, pick-up trucks, and sport utility vehicles. The most recent 2017 NHTS statistics provided a similar result by pointing out that over half of the total trips traveled were less than 4 miles.

As can be seen, the gap between the strong demand for short-distance travel and an insufficient number of short-distance travel alternatives have existed for over a decade. In recent years, following the contextualization of the sustainability-oriented principles of smart growth, transportation planning in the U.S. has been proactively investing vast human resources and capital in active transportation (AT) modes, such as public transit, cycling, and walking. Recently, dockless small vehicles, including (electric) bikes and electric scooters, have been receiving more attention as the primary short-distance travel option and connecting the first/last mile to transit (Lime, 2019). Fig. 1 shows the Lyft (Figure (a) on the left) and Lime (Figure (b) on the right) dockless electric scooters (e-scooter from here on out) parked on streets in Minneapolis.

The behavior of battery swapping could be deemed as the behavior of recharging. The BSS location could be considered as one of the recharge facility location problems. Usually, the contributing factors in the development of recharging facilities heavily rely on the local workplace, such as shopping malls, parking lots, and other similar things. In effect, the locations allotted for those electric facilities needed to build BSSs or recharge facilities for the uses of ESs can be a matter for debate because this can be associated with the interest of the classic chicken-and-egg problem. Regarding the problems of BSS or battery allocation, different decision/plan variables, such as BSS location, the number of batteries , or recharge strategy, were investigated for the purpose of optimization.

(a) Lyft scooter (b) Lime scooter

Figure 1: Scooters in Minneapolis

2 Methods and Data

2.1 Clustering

Clustering aims to discover latent knowledge from data. It is an unsupervised learning method, it is used in many fields such as data mining, pattern recognition, healthcare, document clustering, big data, image processing, bioinformatics, social networks, and outlier detection, and so on. Clustering is an unsupervised classification since there is no training dataset or predefined labels.

k-means, as one of the clustering methods, is a way to vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. k-means clustering minimizes within-cluster variances (squared Euclidean distances), but not regular Euclidean distances, which would be the more difficult Weber problem: the mean optimizes squared errors, whereas only the geometric median minimizes Euclidean distances.

2.2 Modified Facility Location Problem

The facility location problem (FLP) is an optimization problem that appears in many disciplines and whose methods of solution can be applied to a vast range of initial problems. The traditional FLP is based on linear program with objective function to minimum the total cost, when fulfilling all the demand. The modified facility location problem we build in the project includes more constraints and specifically divide the cost into fixed cost and variable cost. Moreover, the constraints of our model are nonlinear inequality instead of linear function, which is more close to the operation of battery swap in Minneapolis.

3 Battery Swapping Station(BSS) Allocation Model

3.1 List of Symbols

Table 1: Notations and Explanation

Notations	Type	Explanation
FC_i	constant	Fixed cost for building a BSS at i
VC_{ij}	constant	Variable cost when station i is responsible for region j
HC	constant	Holding cost for each battery
DIS_{ij}	constant	Distance between i and
URC_i	constant	Unit rental cost
UTC	constant	Unit travel cost

ASF	constant	Average Square Foot of BSS
AE	constant	Average Electricity usage per mile
CAP	constant	Capacity of battery reserve in each BSS
K	constant	Battery usage coefficient
d_j	constant	Battery demand at area j
x_{ij}	variable	fraction of the demand at j that is serviced by the facility at i
y_i	binary variable	equal 1 if build BSS at i, 0 otherwise
z_i	variable	Number of batteries BSS i reserve
TC	dependent var	Total Cost

3.2 Mathematical Model

$$
\begin{aligned}
\min \quad & TC = \sum_{i=1}^{n} FC_i y_i + \sum_{i=1}^{n}\sum_{j=1}^{n} VC_{ij} x_{ij} d_j + \sum_{i=1}^{n} HC y_i z_i && (1)\\
\text{s.t.} \quad & FC_i = URC_i * ASF, \quad \forall i \in V && (2)\\
& VC_{ij} = DIS_{ij} * UTC, \quad \forall i, j \in V && (3)\\
& z_i = K * \sum_{j=1}^{n} x_{ij} d_j, \quad \forall i \in V && (4)\\
& \sum_{i=1}^{n} x_{ij} = 1, \quad \forall j \in V && (5)\\
& (1 - y_i) z_i = 0, \quad \forall i \in V && (6)\\
& z_i \le CAP, \quad \forall i \in V && (7)\\
& x_{ij} \le y_i \quad \forall i, j \in V && (8)\\
& 0 \le x_{ij} \le 1, \quad \forall i, j \in V && (9)\\
& y_i \in \{0, 1\}, \quad \forall i \in V && (10)
\end{aligned}
$$

Here, i is the index for Battery Swap Station, j is the index for streets. The Eq (1) is the objective function, TC consists of the fixed cost, variable cost and holding cost. Specifically, in Eq (2), fixed cost refers to the product of unit rental cost and the average BSS area. In Eq (3), variable cost is calculated by distance between BSS i and street j times unit travel cost. After this, the reserved battery number z_i is determined through the demand of it's area of responsibility Eq (4). Eq (5) shows that all the demand should be fulfilled by one or several BSS. To make sure only reserve battery in the BSS chosen to built, Eq (6) set up an nonlinear feasible region. As given in Eq (7), Eq (9), they are the upper bounds and lower bounds of independent variables.

4 Case Study

4.1 Scooter in Minneapolis

The first scooters were deployed in Minneapolis and neighboring St. Paul on the morning of July 10th, 2018 by the company Bird Rides, Inc. The arrival of the scooters was unexpected and both cities rushed to put policies in place around their usage. The Minneapolis City Council approved a resolution on July 24th developing a pilot licensing program for shared scooter operators within the city. The pilot program ran for 144 days. The pilot program set the maximum number of scooters at 200 for the first two months of the program, after which it could be increased to 400 until the program ended on November 30th, 2018. The University of Minnesota held a concurrent pilot program with 200 scooters. The pilot program in Minneapolis also required operators to pay a fee of $20 per scooter and to share usage data with the city. The requirement that scooter operators share usage data with cities gave rise to the public dataset that this research is built on. However, the topic is subject to contentious debate in the industry.

4.2 Scooter Usage Analysis

The usage of dockless scooters, which describes the context and circumstances in which the scooters are used, is important to understand if the scooters are to become a part of the transportation fabric of the City of Minneapolis.

4.2.1 Total daily distance and duration

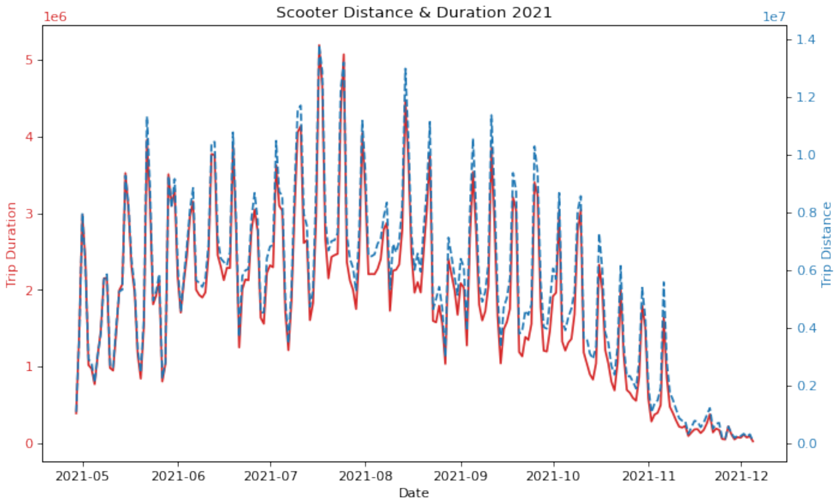
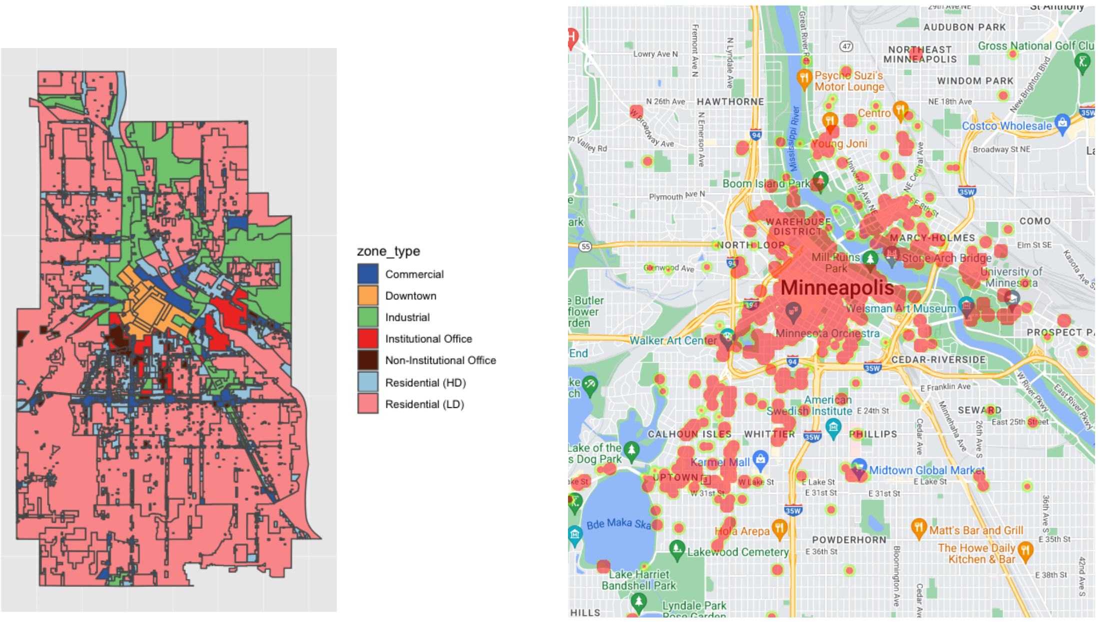


Figure 2: Total daily distance and duration

As shown in Figure 2, the daily usage depends on season and weather. The usage in 2021 goes up from May, reaching its peak in August and deeply falls down in November. Taking Covid-19 into consideration, Omicron blew up in December 2021, whcih means people's travel intentions heavily decrease.

4.2.2 Geographical distribution



(a) Zoning

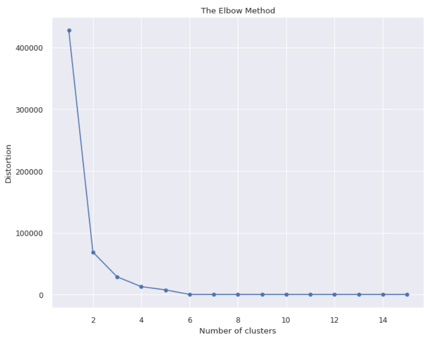
(b) Heatmap

Figure 3: Zoning and Heatmap

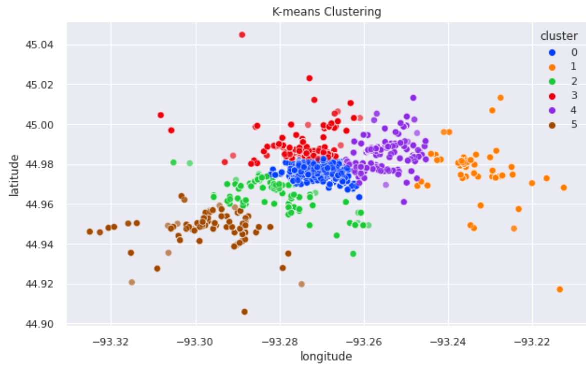
The left picture shows zoning information in Minneapolis, and the right picture is the heatmap of scooter sharing trip. The majority of scooter rides begins in downtown Minneapolis, followed by 19% in residential areas, and 17% in commercial areas, including university campuses.

4.3 Clustering

Initial cluster center significantly affect the results of clustering. In this project, we randomly select k points from the data points as the initial cluster center. As for the number of clusters, typically, we use elbow method to test the weighted sum of distance between the point and cluster center and then determine the k value according to the curve. Given by Fig 4 left, the best number of clusters suppose to be 6. In clustering, we mainly use Lloyd's algorithm, which calculating the distance between each point and cluster center, then assign it to the nearest cluster, repeating the process until all the points are assigned to a cluster.



(a) Elbow Method



(b) Clustering

Figure 4: Elbow method and Clustering

By using k-means clustering, historical scooter sharing rides are divided into 6 group, and the number of each group are 54016, 30051, 26889, 20862, 11496, 6433 separately. Based on the results, we can come up with a BSS allocation plan, which is to build the BSS at the center of each cluster. However, this method only concerns about the geographical distribution of the e-scooter usage, ignoring the BSS capacity, fixed cost and variable cost and travel cost. So in next session, we will introduce a more advanced optimization model to determine the allocation of BSS, taking cost into cosideration.

4.4 Optimization Model

The parameter setting for the case study are sated as follows. The Unit rental cost is obtained by zip code from Zillow and average squre foot is 2000 sf. The average electricity use is 0.1kwh/mile. Normally, the capacity for each BSS is 1000, because the cable can only charge about 50 battery at one time. The distance of each 2 street are calculated by Google Map Distance Matrix API, setting mode to driving. Assume travel cost to be $0.9 per mile. Then plug all the information to the Gurobi, and generate the nonlinear programming.

To simplify the problem, we rezone the area by zip code. The nonlinear optimization model has 440 variables and 460 constraint. After inputting all the variables and constraints and setting objective function to minimize the total cost including fixed cost, variable cost and holding cost, use Gurobi 9.5.0 to solve the program. and get the results as shown in table 2.

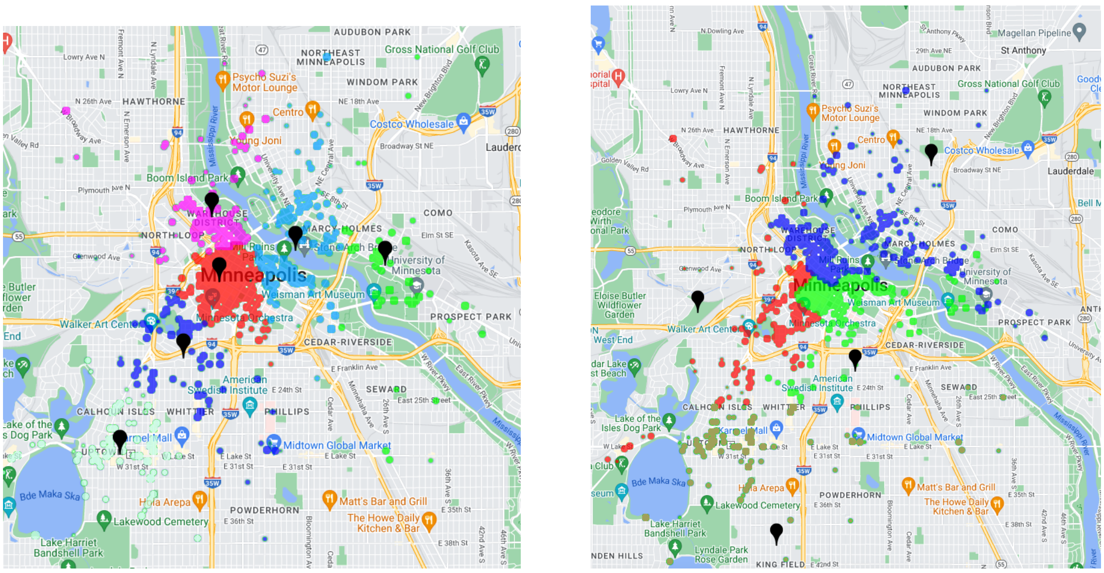
Each set BSS is responsible for several regions in the neighborhood except for Minneapolis (zip code: 55430). However, after displaying all the spot on the map, we find that the e-scooter sharing happened in some rural places, far away from downtown. So the BSS in that area only take care of small part of workload to the whole battery swapping.

Table 2: Optimization Results

Neighborhood	BSS Location Zip code	Serve Region
Lowry Hill	55405	Lowry Hill, Calhoun Isles, Near North, Minneapolis
Phillips	55404	Downtown West, Downtown East, University Of Mn, University
Beltrami	55413	University Of Mn, North Loop, Beltrami, Audubon Park
King Field	55409	King Field, Carag, Howe, Fulton, Powderhorn Park, Tangletown
Minneapolis	55430	Minneapolis

4.5 Results

Use Google Map API to visualize all the data as shown in Figure 5.



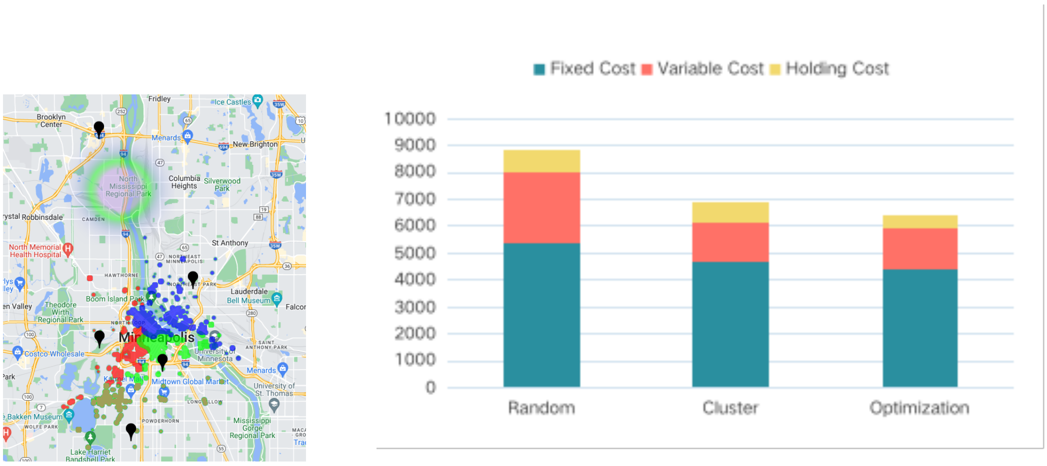
(a) Cluster

(b) Optimization

Figure 5: Cluster & Optimization

In the clustering, the allocation of BSS facility mostly locate at the center of each cluster, which means the BSS is very close to the busy area in the city. This is because in clustering, the only thing the Lloid's algorithm cares is the shortest distance, ignoring the rental cost, and etc. When consiering the rent difference among the regions, minimizing the total cost in optimization program, the locations of BSS are distributed at the rural area, balancing the travel cost and rental cost.

However, the optimization problem also has some cons, regarding some outliers. The optimal solution to the model is heavily affected by some usage outside downtown area. In Figure 6, there is a BSS especially built to fulfill the demand in the northeast area, while in clustering the result will not be influenced significantly.



(a) Outlier (b) Cost Comparison

Figure 6: Outlier and Cost comparison

5 Conclusion

This work, which is motivated by the advent of the e-scooter popularity, aims to solve the battery swapping station location and optimize total cost considering geographical distance and rental difference. A modified facility location problem is proposed in our study which aims to minimize the total operation cost. Plus, a real case in Minneapolis using clustering and optimization method verify the feasibility of the model. The results shows that optimal solution based on our model is significantly effective and reduce the total cost up to 43% compared with randomly choose the location.

However, a limitation of our study is we simplify the city zoning by zip code, which is not precise enough to be used in reality. What's more, small part of usage in remote area influence the optimal result considerably, the sub-optimal solution ignoring the outliers may be more acceptable.

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