An Equity-based Maximum Covering Location Model for Siting Mobility Hubs in Tempe, AZ

by

Hejun Quan

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Michael Kuby, Co-Chair
Amy Frazier, Co-Chair
Daoqin Tong, Member

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ABSTRACT

With the acceleration of urbanization in many parts of the world, transportation challenges such as traffic congestion, increasing carbon emissions, and the “first/last-mile” connectivity problems for commuter travel have arisen. Transport experts and policymakers have proposed shared transportation, such as dockless e-scooters and bike sharing programs, to solve some of these urban transportation issues. In cities with high population densities, multimodal mobility hubs designed to integrate shared and public transportation can be implemented to achieve faster public connections and thus increase access to public transportation on both access and egress sides. Haphazard drop-offs of these dockless vehicles, however, have led to complaints from community members and motivate the need for neighborhood-level parking areas (NLPAs). Simultaneously, concerns about the equitable distribution of transportation infrastructure have been growing and have led to the Biden Administration announcing the Justice40 Initiative that requires 40% of certain federal investments benefit disadvantaged communities. To plan a system of NLPAs to address not only the transportation shortcomings while elevating these recent equity goals, this thesis develops a multi-objective optimal facility location model that maximizes coverage of both residential areas and transit stations while including a novel constraint to satisfy the requirements of Justice40.

The model is applied to the City of Tempe, Arizona and uses GIS data and spatial analyses of the existing public transportation stops, estimates of transit station boardings,

population by census block, and locations of disadvantaged communities to optimize NLPA location. The model generates Pareto optimal tradeoff curves for different numbers of NLPAs to find the non-dominated solutions for the coverage of population nodes and boardings. The analysis solves the multi-objective model with and without the equity constraint, showing the effect of considering equity in developing a multimodal hub system, especially for disadvantaged communities. The proposed model can provide a decision support tool for transport and public authorities to plan future investments and facilitate multimodal transport.

ACKNOWLEDGEMENTS

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TABLE OF CONTENTS

1. Introduction

Shared transportation is a transportation strategy that allows users to access modes of transportation for short periods as needed, including scooter sharing and bike sharing, among others. Shared transportation was expected to solve urban transportation issues such as traffic congestion, emission and noise pollution, and the first/last-mile problem, as a complement to the public transport system. Shared transportation provides alternatives to driving for the public under the circumstances of rising fuel prices and extensive parking needs. However, despite its massive potential to create environmental and economic benefits, shared transportation is not currently widely applied in the U.S. One of the main reasons is high vehicle ownership. According to the Federal Highway Administration, over 93% of U.S. households owned at least one car in 2019. Combined with research from the U.S. Census Bureau in 2019 (Burrow et al., 2019), only 5% of U.S. workers chose shared/public transportation to commute to work, in contrast to 75.9% of workers who drove alone. High vehicle ownership has affected the promotion of shared transportation to a certain extent.

It is difficult to support a healthy infrastructure for shared transportation with limited customers and low market demands. Insufficient numbers of stations, as well as uneven distribution, also limit adoption of shared transportation. In addition to centralized distribution in the city center for profit, shared transportation programs need to be designed to provide affordable travel options for residents, especially low-accessibility populations, while maintaining profitability. At its peak, there were 112 bikeshare systems and 7,469 bikeshare stations across the United States (BTS, 2021). However, even with numerous sites, inequality still exists in how to balance the network coverage and spatial equity (Conrow et al., 2018). Therefore, a reasonable selection of site location and coverage within the budget is necessary in order to achieve the desired effect.

Furthermore, for those cities that promote shared transportation, lack of proper management can cause public issues. For example, due to the growing popularity of e-scooters (Fig. 1, Fig. 2), some cities are facing problems such as illegal dumping, abandonment, right-of-way obstruction, and even safety concerns, all of which lead to complaints by residents (Reinberg, 2022; Kelly, 2022). Following a number of high-profile accidents, legislation around e-scooters is likely to tighten. Cities such as San Francisco and Nashville have introduced laws to limit the number of e-scooter companies and regulate the market (Timms, 2019; Shouse Injury Law Group, 2021).

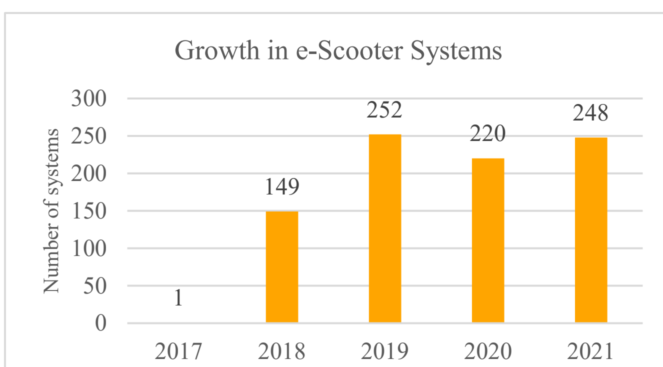


Fig. 1. Growth of e-scooter systems in the United States. Data courtesy of the Bureau of Transportation Statistics (BTS).

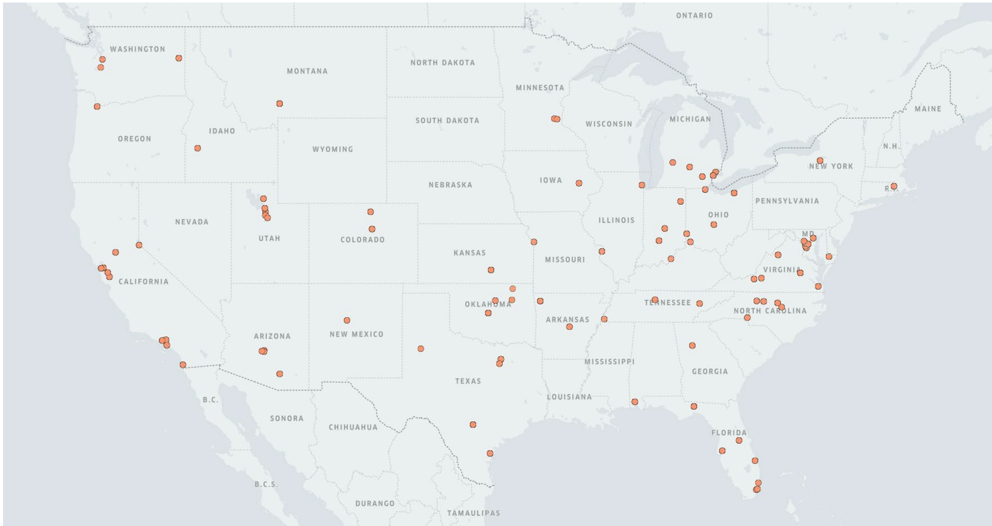


Fig. 2. Locations of e-scooter systems in the United States, 2020. Data courtesy of BTS.

Despite those social issues and concerns, in cities with well-developed public transit systems (i.e., Boston, Los Angeles) or with an extensive user community (university towns such as Tempe, Arizona), shared transportation has broad market prospects and great potential demand. Many cities are researching the feasibility of mobility hubs that lead to sustainable solutions for the city’s transportation network. A mobility hub is a facility designed to combine the resources of multiple modes of transportation in one physical location (DeRosa et al., 2021). As a type of Transportation Demand Management (TDM) strategy, the concept of mobility hubs has been proposed for decades and put into practice in many countries, especially in Europe. The idea is to provide a joint in the transportation network to improve the connectivity and accessibility of different transport modes, thus reducing the occupation space of stations and improving transport efficiency. According to the National Commission on Intermodal Transportation (NCIT, 1994), public intermodal transportation is limited by gaps in the connectivity of transport modes. The defect of any links may result in poor connectivity of transport. Intermodal travel itineraries with transfers at intermodal mobility hubs are seen as beneficial to provide higher accessibility and faster public connections (Frank et al., 2021).

Mobility hubs can be built in different levels based on the connection demand, from bike connections and bus infrastructure (bus ridership and bikeability) to an intermodal transportation center. To balance the needs of public transport users and the realities of the existing built environment reasonably and efficiently, mobility hubs are divided into three main categories: neighborhood, central, and regional according to scale, amenities, and environment (LADOT, 2016). Neighborhood mobility hubs are smaller, ancillary station areas generally found in lower-density neighborhoods. They offer a few basic amenities essential to every transit area including wayfinding, bike share, and bike parking. Central mobility hubs are typically located in more urbanized areas and encompass one or more stations/bus stops. They offer many amenities in addition to the baseline features including car share, bus shelter, and next bus information. Regional mobility hubs are the largest stations, usually located in dense urban areas or end-of-line stations, where they connect to other regional transit providers. Regional mobility hubs offer the most amenities including secured bike parking and a bus layover zone along with important amenities and infrastructure built into the station itself. The fusion of transport "integrates public transport services with walking, cycling, and micro-mobility to make it easier for people to travel seamlessly" (Arup et al., 2020, p. 4). In many cities, the train station and its surrounding area are broadly considered as appropriate locations to locate mobility hubs because of the well-established rail infrastructure and supporting facilities, which make adding other modes of public transportation relatively simple.

Against this background, I developed a decision support tool to help understand public transit system distribution and apply optimization modeling in finding feasible solutions to build NLPAs. The model is then applied to the City of Tempe, Arizona, which is working on strategies for transport demand management and 20-minute city goals (King et al., 2019). One of the options is to build a system of mobility hubs to coordinate with existing public transportation throughout the region. Regulation for shared scooters and bikes are necessary. As a part of parking regulation, it would be helpful if they are integrated into mobility hubs for unified management. This not only reduces the difficulty of supervision and law enforcement but also effectively increases the walkability, connectivity, and accessibility of the area around mobility hubs. Culdesac Tempe, a car-free apartment complex, is also set to open at the end of 2022, which is expected to bring considerable users of public and shared transportation to the Tempe area. It can be seen that the development of the shared transport network in Tempe has good prospects. This research will effectively inform the early development stage of mobility hub infrastructure planning in Tempe.

2. Literature review

In this section, I present some literature works to describe the framework in which my proposed model is positioned. In Subsection 2.1, the works related to the design of the mobility hub system are presented. Since my work focuses on equity in location optimization models, in Subsection 2.2, the literature proposing the use of widely used methods to address equity is described.

2.1. Optimal facility location models for Mobility hub systems

The goal of optimization is finding the maxima (or minima) of an objective function for efficient use of resources. It maximizes or minimizes one thing above all else. Optimization strategies have been applied broadly in network hub locations (see Alumur and Kara, 2008). Choosing a suitable model for optimizing a set of mobility hubs depends on many factors: accessibility, the type of transportation, the geographic scale of the region, the service range, population/household density, among others. According to the literature, two of the most widely used optimization models in the network design problem of mobility hub systems are the maximum covering location model and the p-median model. Church and Revelle (1974) presented the first maximum covering location model to solve the maximal service distance issue in the location set covering problem.

Campbell (1994) proposed the first integer programming formulations for different types of hub-covering models. As an important component of shared mobility, bike-sharing network analysis often applies the maximum covering model (Frade and Ribeiro, 2015; Park and Sohn, 2017; Conrow et al., 2018; Hu et al., 2019). For instance, Ciancio et al. (2017) proposed a maximal covering approach for bike sharing systems under deterministic and stochastic demand. In studying multimodal hub location problems, Mohammadi et al. (2013) developed a novel stochastic multi-objective multimodal transportation model to address multimodal hub location problems under uncertainty. Frank et al. (2021) presented two separate mixed integer maximum covering models, aiming at increasing the accessibility to POIs and workplaces, respectively, for locating mobility hubs in Heinsberg, Germany. As far as concerns the p- median model Alumur et al. (2012) jointly considered transportation costs and travel times based on the observations from hub networks in the real world. Cintrano et al. (2018) solved a p-median model with a variable neighborhood search algorithm. Real et al. (2021) introduced a multimodal hub network design problem with flexible routes.

2.2. Equity in location optimization models

Equity involves the fairness of the distribution (Adams, 1965). In theory, it is a function of both the project itself and how it is paid for. Equity focuses on past underserved communities during the planning process to create solutions to improve real, everyday transportation challenges. In optimal facility location modeling, achieving fairness in the distribution of public infrastructure has been a concern since the 1970s (see McAllister, 1976; Drezner et al., 1986; Maimon, 1986). Erkut and Neuman (1989) studied previous works of maximization location models by two main categories: maximin objective and maxisum objective in single/multiple facility problems. They then proposed a multi-objective model for locating obnoxious facilities, which identified the future research direction in this area (1992). More recently, the measures of equity in location optimization models are usually achieved through two methods: (1) adding priority weights on objectives (i.e., coverage, demand, travel times, costs); or (2) using the weighted coefficients of variation or spatial measures. Conrow et al. (2018) proposed a bi-objective optimization model with adding objective priority weights in to estimate the impact of the model on the coverage of bicycle networks and population demand under different weights. Qian et al. (2022) built a genetic algorithm, including a weight associated with each opportunity, to evaluate the user demand and site distribution for a bike-share system in Chicago.

The Theil index is one of the indices often used in equity research. Caggiani et al. (2020) incorporated a variant of the Theil index into the objective function and optimized it to minimize the difference in public multimodal mobility between population groups. Goodman and Cheshire (2014) also applied the location quotient to evaluate the equalities in the London bicycle-sharing system, including service coverage and pricing.

In 2021, President Biden signed Executive Order 14008, making it a goal to "withstand the devastating effects of climate change and promote environmental justice" (The White House, 2021). Justice40, a government-wide initiative, stemmed from this Executive Order. According to the Justice40 Initiative, "at least 40 percent of the overall benefits of certain Federal investments flow to disadvantaged communities that are marginalized, underserved, and overburdened by pollution" (Young et al., 2021). If designed and implemented properly, the implications of the Justice40 Initiative's commitment to environmental justice (disadvantaged) communities could be enormous. In addition to the potential benefits to the environment and community development, Justice40 may lead to new directions for research on the equitable distribution of public infrastructure.

2.3. Literature gap

Mobility hub systems are a complex network, providing alternative forms of transportation instead of driving alone. Many different methods have been proposed for planning a system of public transportation. Research by Frank et al. (2021) concludes that the relevant literature in transportation research includes two research directions: accessibility measure methods and optimization-based planning models for mobility hubs: "Approaches that are based on accessibility measures focus on the detailed analysis and evaluation of transportation systems with regard to the access to Point of Interests

(POI) or workplaces. In contrast, optimization-based planning models focus on providing decision support for mobility hubs, e.g., regarding their locations" (p.3). Combining the above analyses, there have been few case studies to include accessibility, equity, and external factors, such as ridership. The study of neighborhood-level mobility hubs is also limited in the open literature. Considering that buses and light rails make up the major public transportation system in the City of Tempe, neighborhood-level mobility hubs (e.g., buses, light rails, e-scooters) are feasible under the budget and current circumstances.

Since Justice40 Initiative came out in 2021, few articles in the field of location analysis have mentioned it. To the best of my knowledge, this is the first time to be done. In addition, adding an equity constraint generated from Justice40 may cause other constraints in the model to be contradictory, therefore creating the need for relaxation and conflicts. I added a mandatory constraint to avoid errors in optimal site selection. The literature search did not identify any other publications that considered this situation. This study will address both the inclusion of Justice40 goals into network optimization as well as model contradictions to avoid errors in optimal site selection, which will help apply the Justice40 Initiative to the optimal facility location model.

3. Mathematical model

A two-objective maximum covering optimization model for siting NLPAs was structured on the basis of previous research from Church and ReVelle (1974). The first objective is to maximize the residential coverage. The second objective is to maximize the coverage of public transportation boardings. In addition, the model introduces an equity constraint based on the specific requirements of Justice 40. Since the objective of the model is to site parking areas in census blocks, I will use the name "neighborhood-level parking area" (NLPA) uniformly in the following. Model notation is as follows:

Indices and Sets

i = index of population nodes

j = index of NLPA candidate sites

s = index of existing stops of public transportation

R = set of population nodes

Q = set of NLPA candidate sites

S = set of existing transit stops (e.g., bus, light rail)

N_i = set of NLPA candidate sites, j, capable of covering population node i

N_s = set of NLPA candidate sites, j, capable of covering existing transit stop s

Parameters

a_i = population size at population node i

b_s = demand weight of transit station s (boardings by station/stop)

p = total number of NLPAs to be established

w = importance weight for population coverage, $[0 \leq w \leq 1]$

M = ratio of total population to total boarding passengers

$$DC_i = \begin{cases} 1, \text{if census block } i \text{ is a disadvantaged community} \\ 0, \text{otherwise} \end{cases}$$

Decision Variables

$$X_j = \begin{cases} 1, \text{if a NLPA is sited at location } j \\ 0, \text{otherwise} \end{cases}$$

$$Y_i = \begin{cases} 1, \text{if population node } i \text{ is covered by a sited NLPA} \\ 0, \text{otherwise} \end{cases}$$

$$Z_s = \begin{cases} 1, \text{if transit station } s \text{ is covered by a sited NLPA} \\ 0, \text{otherwise} \end{cases}$$

In the model, population nodes and NLPA candidate sites are the centroids of census blocks. The set of NLPA candidate sites, Q, and the set of population nodes, R, were roughly similar, except that the census blocks with zero population were removed from the set R. It was assumed that each population node could install a NLPA in order to maximize the connections between residential areas and NLPAs, while no user demand would occur in census blocks with no population. Binary decision variable X_j indicates whether a NLPA is installed at location $j \in Q$. The installed NLPAs are able to improve the accessibility to population nodes or to transit stations.

This notation is now used to construct the equity-based coverage model. The formulation is as follows:

$$Maximize \ \sum_i a_i Y_i \tag{1}$$

$$Maximize \ \sum_s b_s Z_s \tag{2}$$

Accordingly, Objective (1) maximizes the potential user coverage, while Objective (2) maximizes the coverage of passenger of public transportation.

Constraints. Objectives (1) and (2) are maximized subject to Constraints (3)-(9). The constraints ensure the suitable coverage of population and of transit stops given the locations of NLPAs, as well as the bound with travel distance thresholds and the overall budget.

$$\sum_{j \in N_i} X_j - Y_i \geq 0 \quad \forall i \tag{3}$$

$$\sum_{j \in N_s} X_j - Z_s \geq 0 \quad \forall s \tag{4}$$

$$\sum_i DC_i a_i Y_i \geq 0.4 \sum_i a_i Y_i \tag{5}$$

$$X_j \leq Y_i \quad \forall i, j \in N_i \tag{6}$$

$$X_j \leq Z_s \quad \forall s, j \in N_s \tag{7}$$

$$\sum_j X_j = p \tag{8}$$

$$X_j, Y_i, Z_s = \{0,1\} \quad \forall i, j, s \tag{9}$$

Constraint (3) ensures that the population node i is not counted as covered unless an opened NLPA is located within the service distance. Similar to (3), Constraint (4) ensures that the transit stop s is considered to be covered only if an opened NLPA is located within the service distance. Constraint (5) stipulates that the covered population of those living in disadvantaged communities needs to be at least 40 percent of the total covered population. This constraint can be seen as a Justice40 constraint, which meets the requirement that at least 40 percent of the overall benefits of investments flowing to disadvantaged communities.

Constraint (6) forces a population node i to be covered ($Y_i = 1$) if there are any NLPA sited within the service distance. The reason Y_i must be forced to be a 1 once it is covered is because under some circumstances, Constraint (5) may force population node i to be uncovered ($Y_i = 0$), even when node i is within the service distance of at least one NLPA, in order for the equity constraint to hold. For example, if the covered population of disadvantaged communities is less than 40 percent of the total covered population, then Y_i is forced to be 0 to make Constraint (5) hold. By adding Constraint (6), Constraint (3) and (6) can avoid this situation. Similar to (6), Constraint (7) ensures that transit stop s is covered ($Z_s = 1$) if there is at least one NLPA sited within the service distance. In some situations, the use of Constraint (7) or not can affect the results. This happens when the importance weight $w = 1$. In this case, the number of boardings ($Z_s = 0$ or 1) has no effect on the model results. Constraint (8) requires locating exactly p facilities due to budgetary reasons. Constraint (9) accounts for integer requirements.

The two objectives complicate application and solution of this maximum covering location model, as the decision to locate a NLPA may not be equally beneficial for population coverage and public transport network coverage. In fact, they may conflict with each other. A common approach to integrating dual objectives is giving functions a priority weight, w (see Cohon, 1978). The value of this weight is usually between 0 and 1. The two sets of objectives can then be made into one weighted objective, as follows:

$$Maximize \;\; w \sum_i a_i Y_i + (1 - w) M \sum_s b_s Z_s \qquad (10)$$

By adding the constant M, the model can evaluate a large number and a relatively small number at the same order of magnitude, in order to prevent the impact of a large numerical gap on the fairness of the model. The demand weight w reflects the decision makers' preference among multiple objectives. In practice, a range of weights are often considered, therefore generating tradeoff curves to find the Pareto-optimal (non-dominated) solutions for decision making and analysis purposes.

4. Study area and usage data

Tempe is located in Maricopa County, Arizona. As of 2020, the residential population in Tempe was 180,587. As part of the Phoenix metropolitan area and the home of Arizona

State University's main campus, Tempe has a dense pattern of urbanized development in the northern part of the city, particularly as it relates to the Valley Metro light rail line. Toward the south, the urban layout becomes progressively more dispersed, including single-family homes, strip malls, and lower-density office parks ("Tempe, Arizona," 2022), as shown in Fig. 3. Tempe's urban geography significantly impacts the distribution of shared transportation, which is concentrated in northern Tempe, especially in the downtown area (Fig. 4). Currently, the major shared transportation systems in Tempe are composed of scooters from different companies (e.g., Bird, Spin, Razor). The bike share program, GRID Bike, exited the Tempe market in 2020. The City of Tempe declares that they will come out with a plan to search for new operators.

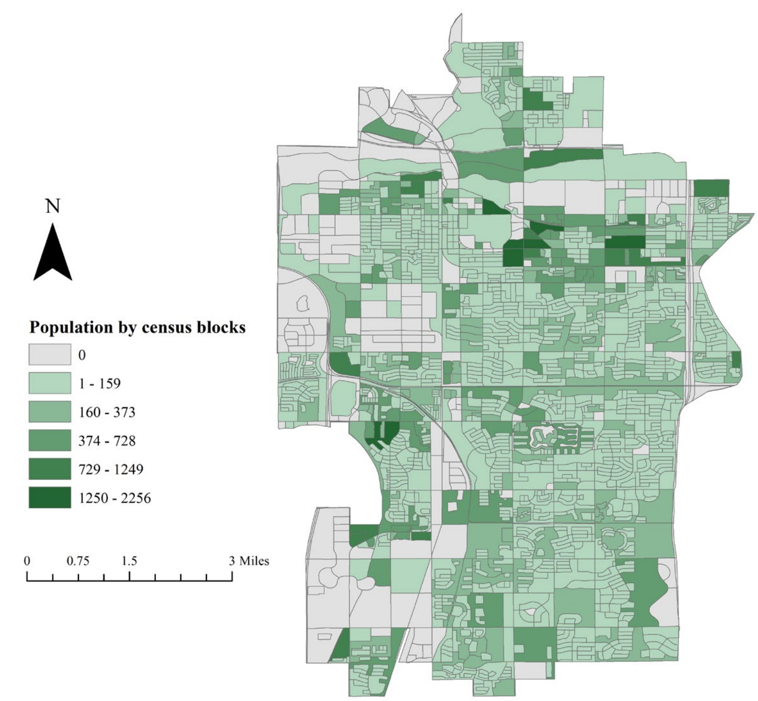


Fig. 3. Tempe population distribution in 2021, which are used in the first objective function.

I used the road network of Tempe, downloaded from the U.S. Census Bureau (2021), in the model. Besides the bike lanes, bike routes, and multi-use paths, the whole street network, especially sidewalks, was used for traversing between origins, NLPAs, and destinations. Of these, I removed all highway, freeway, and expressway segments from the road dataset because scooters or bikes are not permitted on those roads. Considering that the parking areas need to be settled at the neighborhood level, I chose 0.3 miles (483 meters) as the threshold of NLPA service distance to households, which represents a short enough distance for people reaching a nearby parking area by walking. This service distance prevents people from being reluctant to use shared scooters or bikes due to the difficulty of finding parking areas during the process of renting and returning. Given that the speed limit in alleys is 15 mph under Arizona law and the expected five-minute transit time from home to a transit stop, the service distance from an NLPA to transit stations was set as 1 mile (1609 meters).

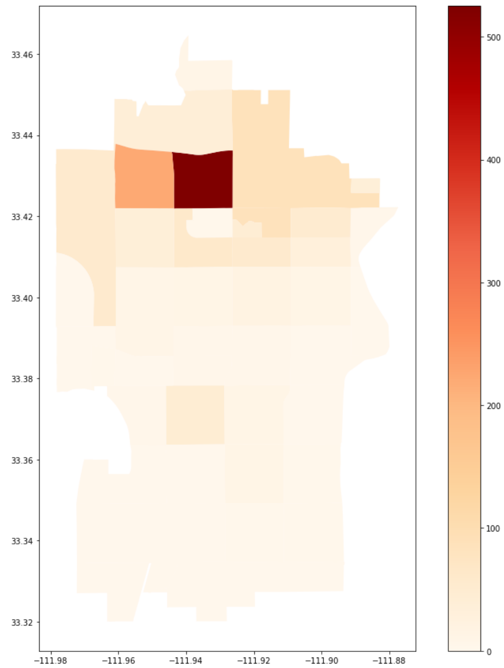


Fig. 4. The distribution of Bird e-scooters in Tempe, 2020. Data source: Tempe Data Catalog.

In order to better understand the distribution and interaction of shared transportation and public transportation, Tempe traffic data need to be analyzed. Considering the urban features of Tempe and that buses and light rails make up the major public transportation system (Fig. 5), neighborhood-level mobility hubs are feasible under the current circumstances.

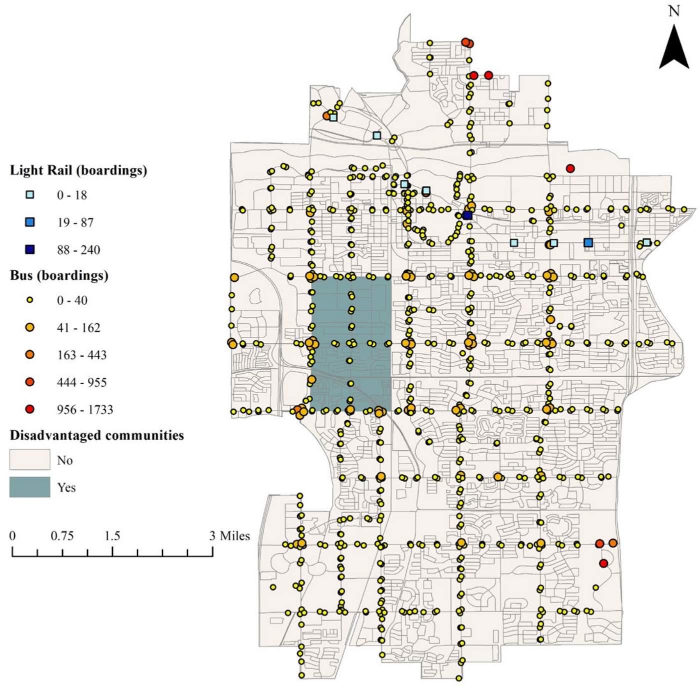


Fig. 5. Tempe public transit rail and bus station location and weekday boardings used in the second objective function.

The ridership (boarding) data for light rail and bus stations were downloaded from the Valley Metro GeoCenter (2021). Due to the impact of COVID-19 on public transportation, the light rail and bus ridership data were last updated in 2020 and 2019 respectively at the time of this writing. Both the light rail and bus ridership data were collected quarterly and include categories of boardings/departures and weekday/weekend separately. For the convenience of analysis, the annual averages of these data were taken. The Tempe Streetcar, an expansion to the Valley Metro transit network, was in operation in 2022, but ridership data were not publicly available at the time of this writing and have therefore not been included in this study.

Census blocks with population data were downloaded from AZGeo Open Data (2021). The data was last updated in 2020. The disadvantaged community data was obtained from the Climate and Economic Justice Screening Tool (CEJST), developed by Council of Environmental Quality. According to their statistics, two census tracts in the City of Tempe are identified as disadvantaged (environmental justice) with a total permanent population of 9,527, as shown in Fig. 6.

Data processing and service coverage determinations were performed in ArcMap Desktop 10.8, mainly using the Network Analyst extension. There are 1936 census blocks in the City of Tempe, 1581 of which are inhabited. Therefore, there were 1581 demand nodes and 1936 NLPA candidate sites. By using the walking distance cutoff of 0.3 miles (483 meters), 11283 trips from inhabited blocks to NLPA candidate sites were generated. Using the riding distance cutoff of 1 mile (1609 meters), 60741 trips were generated from 761 transit stops to 1936 NLPA candidate sites.

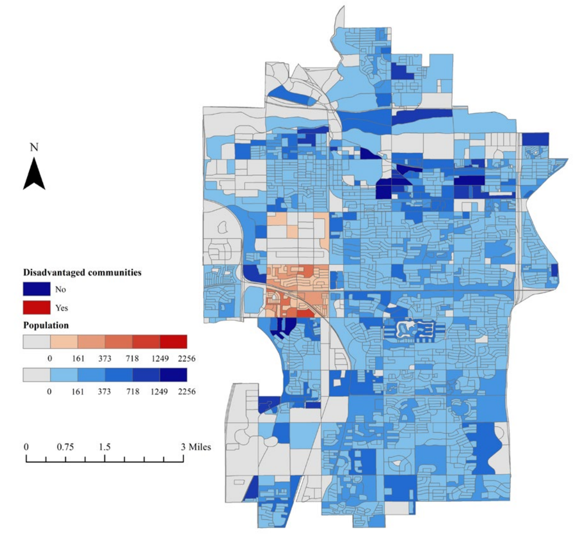


Fig. 6. Disadvantaged communities in Tempe. Transparency is based on the total population of each census block within the tracts.

5. Findings

The two-objective optimization model was solved using CPLEX Studio IDE 12.8.0. All data processing and analysis was done on a personal laptop (AMD Ryzen 7 4800H, 2.90 GHz with 16 GB RAM). In total, there were 3738 binary variables and 74366 constraints. The average computing time per problem was 25 seconds. Fig. 7 zooms in on one neighborhood to illustrate how the population nodes and transit stops covered by a particular NLPA more clearly. The small buffer contains six census block centroids that are covered because they fall within the 0.3-mile walking distance of this NLPA. Likewise, the larger buffer contains about 40 bus stops and one light rail station that are covered by this NLPA because they can be reached within 1 mile of biking or scootering from this NLPA.

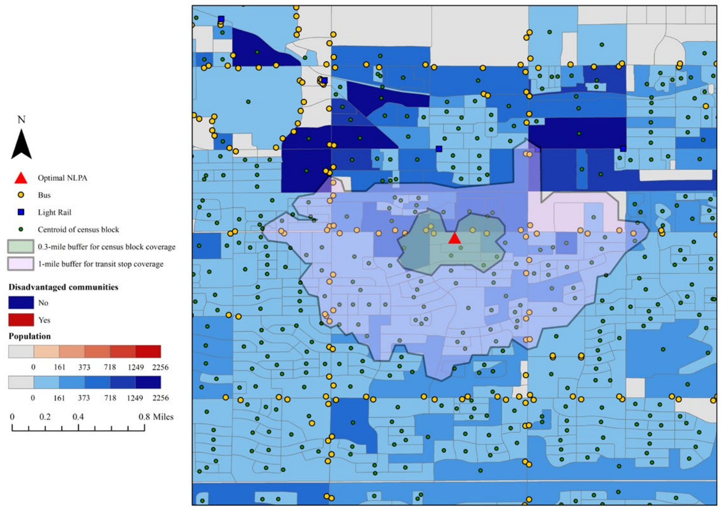
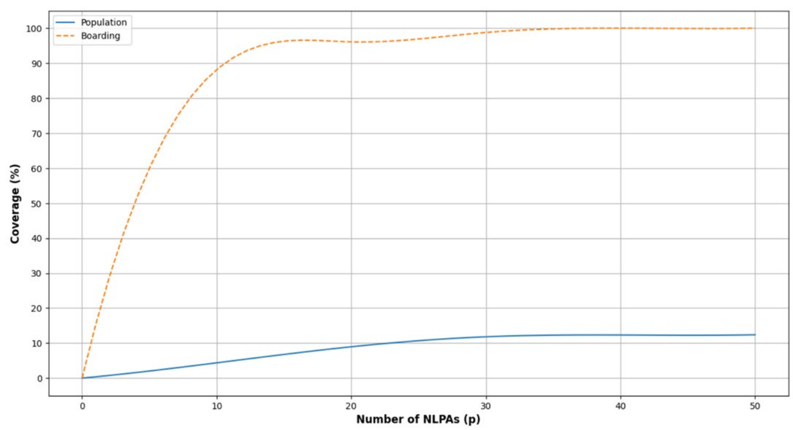


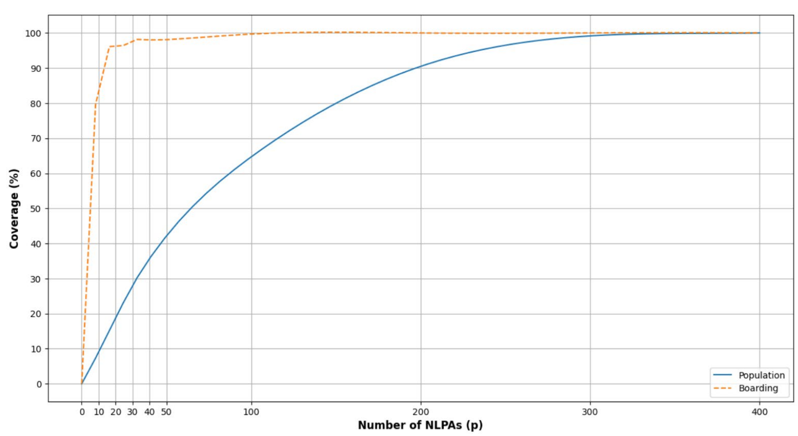
Fig. 7. An example of NLPA coverages of population nodes and transit stops. This NLPA is close to E Broadway Rd, halfway between S Rural Rd and S McClintock Dr.

By changing the investment level p and the objective demand weights w, the multi-objective model generates a range of decision options. Values of p ranged from 10 to 50 by increments of 10. When testing the effect of without Justice40 constraint on the model, the values of p ranged from 10 to 400 (10, 20, 30, 40, 50, 100, 200, 300, 400). Seven different importance weights were tested (1, 0.9, 0.7, 0.5, 0.3, 0.1, 0).

The effects of running the model with and without the Justice40 constraint on the coverage for boarding and population for a variation of investment level when the demand weight $w = 0.5$ is shown in Fig. 8. The x-axis indicates the number of NLPAs to install. The percentage of coverage related to the number of installed NLPAs is given along the y-axis. The coverage for boarding reaches over 80% with a steep rise in both graph a and b when locating 10 NLPAs but levels off thereafter. The Justice40 constraint limits the total covered population to no larger than 2.5 times the total disadvantaged population, thus the maximum population coverage is only around 12.4% of the total population in Tempe with the Justice40 constraint. After removing the Justice40 constraint, the population coverage rises steadily as the number of NLPAs increases and reaches full coverage when locating 400 NLPAs.



a.



b.

Fig. 8. Coverage for boarding and population for a given p ($w = 0.5$): a, (with Justice40 constraint); b, (without Justice40 constraint).

Fig. 9 shows the non-dominated tradeoff curve between the two objectives. Each line was generated by keeping a fixed value of *p* while changing *w*. Population coverage is favored when $w = 1$, whereas boarding coverage is favored when $w = 0$. Values in between represent a tradeoff between the preferences for these two extremes. As the value of *p* increases, the tradeoff curve gradually shifts up towards the upper right corner and gradually becomes a polyline with a right angle. The vertex at the elbow of certain curves, such as the p = 30 curve, is a promising win-win solution. For p = 50 and w = 0.9, there is only one point that is non-dominated, covering a boardings of 20,738 and a population of 22,352. Due to the Justice40 constraint, the maximum covered population is 22,352. The tradeoff solutions may vary if the Justice40 constraint is removed.

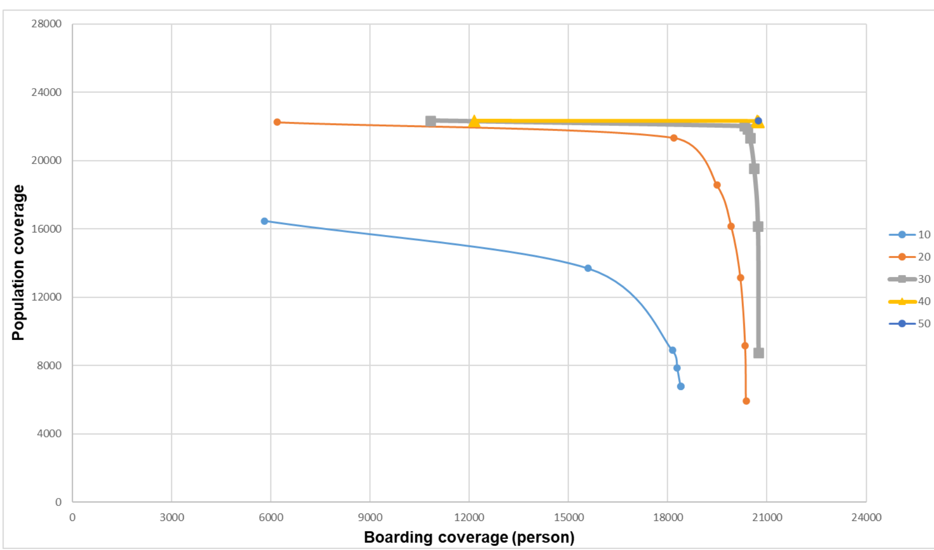


Fig. 9. Tradeoff solutions for a given *w* (1, 0.9, 0.7, 0.5, 0.3, 0.1, 0).

The optimal NLPA locations are affected by the Justice40 constraint. This is illustrated in Figs. 10 and 11 using equal weights of 0.5 on each objective. With the Justice40 constraint (Fig. 10), the optimal NLPAs are more evenly distributed, although sites in disadvantaged communities are clustered to some extent. Without the Justive40 constraint (Fig. 11), the optimal NLPAs tends to cluster in northern Tempe. By comparing Figs. 10a with 11a, Figs. 10b with 11b, and Figs. 10c with 11c, it is clear that fewer NLPAs are sited in or near disadvantaged communities when the Justice40 constraint is removed because these areas have a relatively lower population, which will not be chosen as optimal sites to provide coverage.

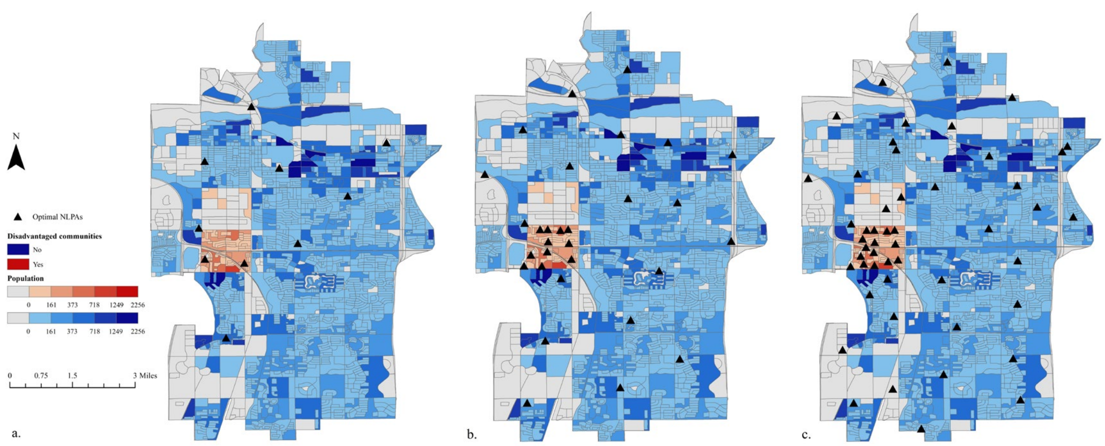


Fig. 10. Optimal with-Justice40 NLPA configuration a, (p=10 & w=0.5); b, (p=30 & w=0.5); c, (p=50 & w=0.5).

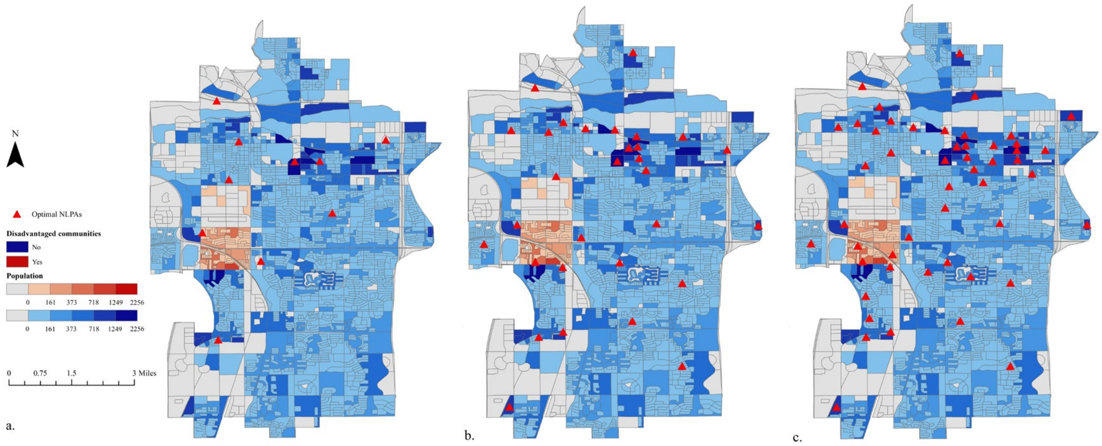


Fig. 11. Optimal without-Justice40 NLPA configuration a, (p=10 & w=0.5); b, (p=30 & w=0.5); c, (p=50 & w=0.5).

6. Conclusions and discussion

In this paper, I presented an equity-based maximum covering location model that introduces a novel constraint to satisfy the requirements of Justice40. It also introduces a double determination for the coverage of the population (Y_i) and boardings (Z_s). The model aims to increase accessibility from residential areas to transit stops by maximizing the coverage for population and boardings within a certain travel distance threshold. Based on the findings, I have come up with the following insights: (1) NLPAs can increase the accessibility from residential areas to transit stops, (2) the locations of optimal NLPAs are different with/without Justice40 constraint, (3) after a certain value of p, Justice40 constraint may limit the continued growth of coverage.

Several areas of this analysis could be improved in future research. At the theoretical level, although more disadvantaged communities can be covered with the Justice40 constraint, the total covered population is limited. Therefore, the Justice40 constraint is more appropriate as an early-stage threshold for the initial rollout of hubs. After the coverage for disadvantaged communities reaches the target, the Justice40 constraint can be removed, and the model can be modified as needed.

A limitation of the current analysis in practical application is that the tool developed by the Council on Environment Quality that is used here to identify disadvantaged communities does so at the census tract level of aggregation. In fact, some census blocks other than these may also meet the criteria of disadvantaged communities. However, because their nearby blocks may not meet the criteria, the entire census tract does not qualify as a disadvantaged community. The results would likely be different if the model can be rerun based on the identification of disadvantaged communities at the census block level.

Importantly, this model focused on locations in residential areas and does not consider where users would park after biking or scootering to transit stations. It is assumed that shared mobility parking areas will be located at every bus stop and light rail station. In fact, some bus stops and light rail stations already have designated parking areas, such as those near Dorsey & Apache Park and Ride, which is a free parking lot by Valley Metro. However, some stops and stations are not able to have parking areas nearby easily due to location or other reasons (e.g., not enough open space around), such as McClintock/Apache Blvd Station and Price-101 Fwy/Apache Blvd Station. It is important and necessary to provide parking areas for NLPA systems because it can enhance users' confidence in using shared transportation and lay a solid foundation for its popularity.

In addition, the COVID-19 pandemic has a huge impact on public transportation, which has still not been restored (BTS, 2022). Valley Metro has not updated their bus or light rail ridership data for the last two to three years. The actual ridership data may now be relatively small, which may also affect the selection of NLPAs.

Along with physical and socioeconomic factors, building NLPAs in residential areas also involves political factors. Since NLPAs are to be built in census blocks, stakeholders may have opinions and therefore lobby their political representatives for or against it. If stakeholders favor shared transportation development and are eager to cooperate, it can save legal and regulatory expenses. However, if stakeholders hold a "Not In My Back Yard" (NIMBY) view, it will be difficult for the project to proceed in these areas, which will lead to higher legal and regulatory costs. It is understandable why some residents would be opposed, as some people perceive public and/or shared transportation as reducing the level of security in the vicinity of the station. The increase in the floating population could cause some increase in the difficulty of policing. Building NLPAs also means occupying a certain amount of public space. Whether converting the original public space into parking areas will create new issues deserves further study.

Another concern that may affect people choosing shared transportation is the price.

Take Bird Scooter as an example. The user needs to pay an “unlocking fee” before using a Bird scooter, which is approximately $1.00 in most cities. After that, the per-minute fee is the only cost unless the user violates the Bird User Agreement. This rate varies by city and is currently $0.15 per minute in Tempe. If the user wants to travel one mile to reach a transit station, it will take about 5 minutes under the 15-mph speed limit, which is a cost of $0.75. After adding the unlock fee, the total trip cost comes to $1.75. Assuming this user chooses to rent a scooter for both his commute to and from the transit station, his total cost for the day would be around $3.50. If the user travels 25 days a month, his monthly scooter rental cost would be $90 to $100, which is relatively high even in the context of rising fuel prices. With the even distribution of shared scooters and the increase of potential users after building NLPAs, these commercial companies may lower the per-minute rate or offer monthly pass to attract more users. If commercial companies cooperate to build a transportation network, this will help to better understand how the way people travel is changing and how it is being changed. With the transformation of vague policy into detailed analysis, the City of Tempe can have a more precise understanding of how cooperation can have positive effects.

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