

Preprint Manuscript:

Askarzadeh, T., Bridgelall, R. (2021). Micromobility Station Placement Optimization for a Rural Setting. *Journal of Advanced Transportation*, 2021(9808922).

[DOI](https://doi.org/10.1155/2021/9808922): 10.1155/2021/9808922, pp. 10.

Micromobility Station Placement Optimization for a Rural Setting

Taraneh Askarzadeh

Doctoral Graduate Research Assistant
Transportation, Logistics & Finance, College of Business
North Dakota State University
PO Box 6050, Fargo ND 58108-6050
Email: taraneh.askarzadeh@ndsu.edu
ORCID: 0000-0002-4301-8310

Raj Bridgelall (Corresponding Author)

Assistant Professor
Transportation, Logistics & Finance, College of Business
North Dakota State University
PO Box 6050, Fargo ND 58108-6050
Email: raj@bridgelall.com
ORCID: 0000-0003-3743-6652

Abstract

Micromobility is an evolving form of transportation modality that uses small human- or electric-powered vehicles to move people short distances. Planners expected that bike sharing, the first form of micromobility, would reduce traffic congestion, cut travel cost, reduce pollution, enable connectivity with other modes of transport, and promote public health. However, micromobility options also brought new challenges such as the difficulty of placement decisions to encourage adoption and to minimize conflict with other transport modes. Sound deployment decisions depend on the unique environmental characteristics and demographics of a location. Most studies analyzed deployments in high-density urban areas. This research determines the best locations for 5 new bike sharing stations in Fargo, North Dakota, a small urban area in the rural United States. The workflow combines a geographic information system (GIS), level of traffic stress (LTS) ratings, and location-allocation optimization models. The spatial analysis considered 18 candidate station locations and eliminated those that fell within the 700-meter isochrone walking distance of the 11 existing stations. This case study demonstrates a scalable workflow that planners can repeat to achieve sustainable micromobility deployments by considering the land-use, population density, activity points, and characteristics of the available pathways in their unique setting.

Keywords: Geographic information system (GIS); Level of Traffic Stress; Location-Allocation Model; Spatial Analysis; Spatial Optimization

41 **1 Introduction**

42 Transportation planners worldwide view new micromobility options such as bike sharing as
43 another important means towards achieving sustainable transportation (Midgley, 2009). A bike
44 sharing system (BSS) is a network of bicycles that enable short-distance, low-cost travel for the
45 public. Such services provide short-term rental between self-service stations distributed
46 throughout an area such as a city or suburb (NYC Department of City Planning, 2009).

47 Micromobility services have recently exploded across the world because they provide
48 low-cost, convenient, and accessible alternatives to public transportation. Some studies found
49 that in some cities, micromobility services can result in a mode shift from automobile trips
50 (Shaheen, Martin, Cohen, & Finson, 2012). Additional motivations for deployments include the
51 promotion of physical exercise, congestion reduction, pollution reduction, and support for
52 multimodal transportation connections. Organizations have also deployed dock-less BSSs but
53 issues such as sidewalk clutter, interference with pedestrian traffic, and increased coordination
54 costs hampered their adoption in many cities (Taleqani, Vogiatzis, & Hough, 2020). Even with
55 docked BSS, there are numerous challenges to integrating them into communities and the
56 transportation network.

57 The demand for a BSS can become induced based on the choice of station location.
58 Demand is also closely linked to weather (Godavarthy, Mattson, & Taleqani, 2017), season, and
59 working days. A BSS design scheme that focuses solely on reducing construction costs can lead
60 to unsatisfactory service and high operational costs. Planners also need to balance the important
61 relationship between design to satisfy dynamic demand and design to accommodate supply
62 rebalancing.

63 Design decisions for rural and small urban areas are different from those of densely
64 populated urban areas and large cities. Most studies previously focused on deployments in large
65 urban areas and large cities. In 2015, the city of Fargo, North Dakota, launched a bike-sharing
66 enterprise with only 11 stations. Expanding the system could increase accessibility and reduce
67 the demand for cars in the downtown, shopping, and university districts of this small urban
68 community.

69 The **goal** of this study is to identify the most appropriate locations to add new bike
70 sharing stations in Fargo, North Dakota. The **contribution** of this study is an analytical
71 workflow that combines level of traffic stress (LTS) network rating, demand location
72 assessment, and spatial optimization models within a geographic information system (GIS)
73 platform to solve the location optimization problem.

74 The remainder of this paper is organized as follows: Section 2 reviews the body of works
75 related to the case study, demand modeling, LTS formulation, and the spatial optimization
76 problem. Section 3 presents the methodology and further defines the location-allocation
77 optimization problem. Section 4 describes the results and discusses the implications. Section 5
78 concludes the study and hints as future work.

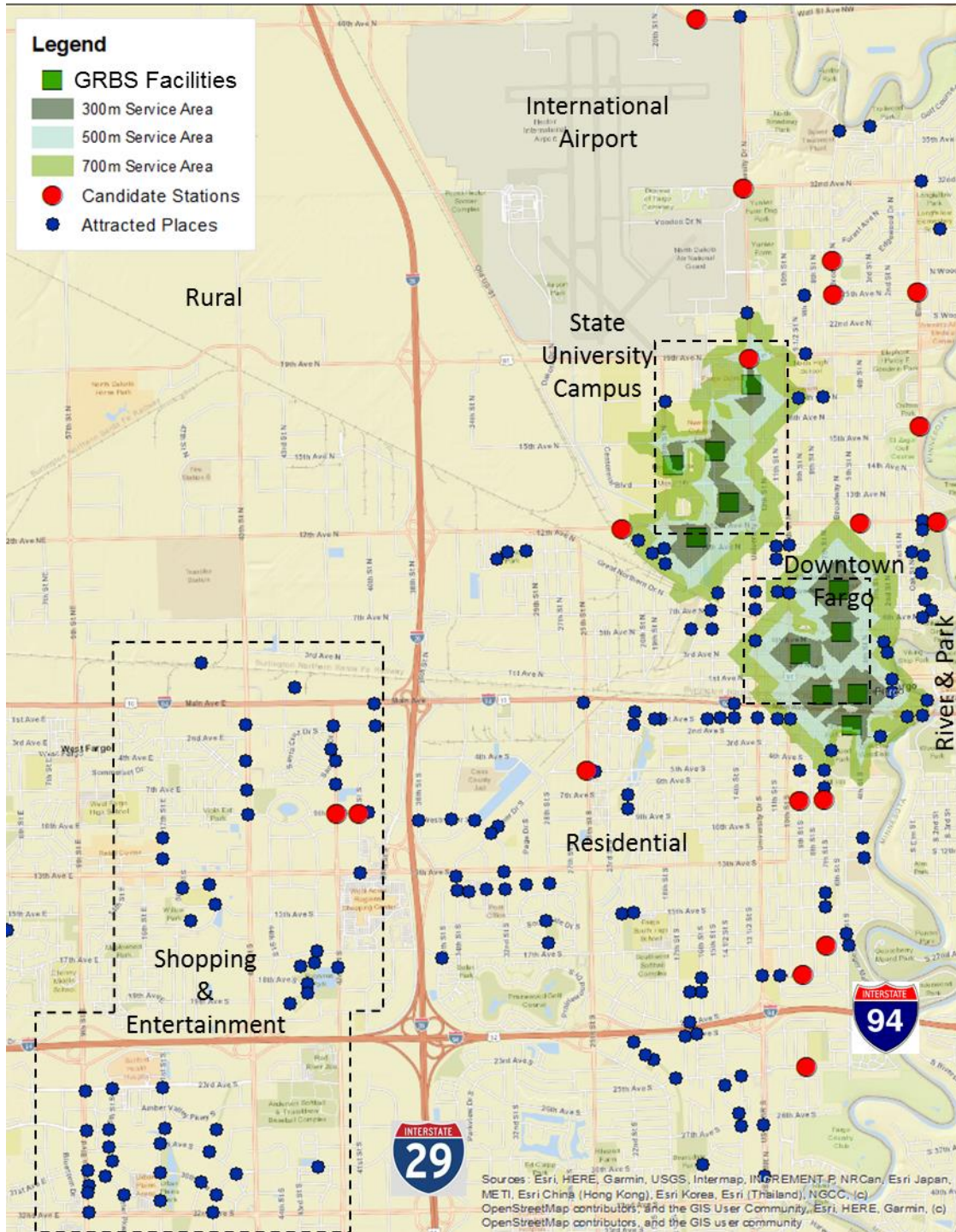
79 **2 Literature Review**

80 Since the introduction of a third generation BSS in the United States in 2010, the network grew
81 to 3,378 BSSs in 104 cities within six years (Firestine, 2016). Sponsorships and usage fees were
82 the primary sources of funding for BSS deployments in North America (Shaheen, Martin, Cohen,
83 & Finson, 2012). The next subsections describe the case history for the existing bikeshare
84 locations in Fargo, North Dakota, and review related work on general decision making for other
85 BSS deployments.

86 2.1 Case History

87 In March 2015, the Great Rides Bike Share (GRBS) company began operating the first BSS in

88 Fargo, North Dakota with 11 stations (Figure 1).



89

90

Figure 1: Service areas for the GRBS bike stations in Fargo, North Dakota.

91 After collaborating with North Dakota State University (NDSU) to produce contactless student
92 identification cards, the company distributed 101 bikes across the deployed stations.
93 Consequently, GRBS became the first company in the United States to integrate contactless
94 identification cards with the BSS rental system (Godavarthy & Taleqani, Winter bikesharing in
95 US: User willingness, and operator's challenges and best practices, 2017). As shown in Figure 1,
96 the 11 stations formed two clusters approximately two miles apart. One cluster was on or near
97 the NDSU campus and the other was in and around the Fargo downtown area. The deployment
98 induced a fast growing demand within months, with 79% and 19% of the users being students
99 and guests, respectively (Godavarthy & Taleqani, 2017).

100 **2.2 Demand Modeling**

101 The Latent Demand Score (LDS) is a commonly used method of demand analysis for locations
102 where bicycles are not yet a popular option (Landis, 1996). The LDS method is a probabilistic
103 gravity model that produces a measure of potential demand by considering trip production sites,
104 trip attraction sites, and the bikeable pathways between them. For example, the Portuguese city
105 of Coimbra used the LDS method by considering the number of trips between production and
106 attraction sites, and the shortest path between them (Frade & Ribeiro, 2014). The authors later
107 developed an optimization model to maximize demand coverage within a given budget constraint
108 (Frade & Ribeiro, 2015).

109 Market modeling based on other deployments is another method used to forecast demand.
110 For example, New York City identified the three user groups of cyclists based on trends from
111 deployments by Velib' (Paris, France), Velo'v (Grand Lyon, France), and Bicing (Barcelona,
112 Spain) (NYC Department of City Planning, 2009). The analysts then estimated the size of each
113 group (recreational, errand users, visitors) and their growth based on the adoption rates of 3%,

114 6%, and 9% determined from surveys conducted in London and Paris. Krykewycz et al. (2010)
115 identified two market areas in Philadelphia, Pennsylvania, by using a raster-based geographic
116 information system (GIS) method (Krykewycz, Puchalsky, Rocks, Bonnette, & Jaskiewicz,
117 2010). Based on low-, medium-, and high-demand scenarios from the Grand Lyon and Barcelona
118 surveys, they applied three trip diversion rates to estimate the mode shift for each market.

119 Gregerson (2011) applied the GIS approach used for Philadelphia and the adoption rates
120 observed in Paris and Barcelona to estimate bike sharing demand for Seattle, Washington, in the
121 United States. Their GIS raster dataset consisted of weighted sum indicators to predict usage.
122 The indicators were population density, non-institutionalized group quarter population density,
123 job density, retail job density, commute trip reduction, tourist attractions, parks, topography,
124 regional transit stations, local transit stops, and various characteristics of the bicycle
125 infrastructure (Gregerson, et al., 2011).

126 Daddio (2012) created a regression model for bikeshare station demand that was
127 dependent on the trip generation rate, trip attraction rate, and the transportation network
128 characteristics within 400 meters of each station (Daddio, 2012). The author trained the
129 regression model with data from the Capital Bikeshare network in Washington, DC. García-
130 Palomares (2012) also proposed a GIS-based method to calculate the spatial distribution of
131 potential trip demand and found that the method can be effectively combined with location-
132 allocation models (García-Palomares, Gutiérrez, & Latorre, 2012).

133 **2.3 Level of Traffic Stress**

134 The Geelong bike plan team first developed a bicycle tension rate in 1978 to guide deployments
135 in Australian cities (Scott, Hurnall, & Pattinson, 1978). The plan characterized roads based on
136 their difficulty of cycling and the stress of sharing them with other vehicles. Decades later,

137 Sorton and Walsh (1994) proposed five bicycle stress levels based on traffic volume, traffic
138 speed, and curb lane width (Sorton & Walsh, 1994). Mekuria et al. (2012) used four levels of
139 traffic stress (LTS) to characterize bikeable paths (Mekuria, Furth, & Nixon, 2012). The lower
140 stress levels of LTS 1 and LTS 2 were suitable for children and tolerable by most adults,
141 respectively. Murphy and Owen (2019) cautioned that restricting bicycles to only low LTS
142 networks can result in a universal reduction in accessibility, modulated by land use (Murphy &
143 Owen, 2019). Larsen and El-Geneidy (2011) surveyed 2917 cyclists in Montréal, Quebec,
144 Canada to determine spatial characteristics that affect route choice (Larsen & El-Geneidy, 2011).
145 They found that cyclists make longer trips on facilities that are separate from vehicle traffic.

146 Obtaining the street geometry and traffic data for all roads to classify their LTS can be a
147 significant challenge. However, some analysts discovered that OpenStreetMap (OSM) data can
148 provide a viable alternative. For example, Wasserman et al. (2019) compared ground-truth data
149 to the accuracy of LTS predictions based on OSM data and found that the results were
150 comparable, but very sensitive to incorrect classifications (Wasserman, Rixey, Zhou, Levitt, &
151 Benjamin, 2019). Similarly, Hochmair et al. (2015) examined the integrity of OSM tags and
152 Google Maps data for bicycle paths and found that the accuracy can surpass those of datasets
153 from local planning agencies (Hochmair, Zielstra, & Neis, 2015).

154 **2.4 Location-Allocation Optimization**

155 Common applications of the location-allocation optimization problem are the placement of
156 healthcare facilities (Murawski & Church, 2009), fire stations (Liu, Huang, & Chandramouli,
157 2006), police stations, and schools (Teixeira & Antunes, 2008). The optimization models can
158 define discrete or continuous locations but planners often use discrete locations in practice (Yeh
159 & Chow, 1996). The emergence of GIS presented enhanced options to combine spatial analysis

160 and optimization (Ribeiro & Antunes, 2002). Conrowa et al. (2018) utilized GIS to determine the
161 tradeoff between coverage and accessibility for Phoenix, Arizona (Conrowa, Murray, & Fischer,
162 2018). Their optimization model selected placements that maximized user coverage for a given
163 level of investment. Guo et al. (2020) used a branch and bound optimization algorithm to address
164 the bike-stowage problem for a university campus (Guo, Yang, He, & Tang, 2020). Their
165 optimization model solved an impedance minimization problem by considering all pair-wise
166 combinations of candidate locations and demand points. Banerjee et al. (2020) used a location-
167 allocation model to determine the locations for three new bike stations in Baltimore City,
168 Maryland, based on maximizing potential demand and weighing facility locations with a
169 suitability score (Banerjee, Kabir, Khadem, & Chavis, 2020). More recently, Pérez-Fernández
170 and García-Palomares (2021) used a GIS-based location-allocation model to reserve parking
171 spaces for moped-style scooters (Pérez-Fernández & García-Palomares, 2021).

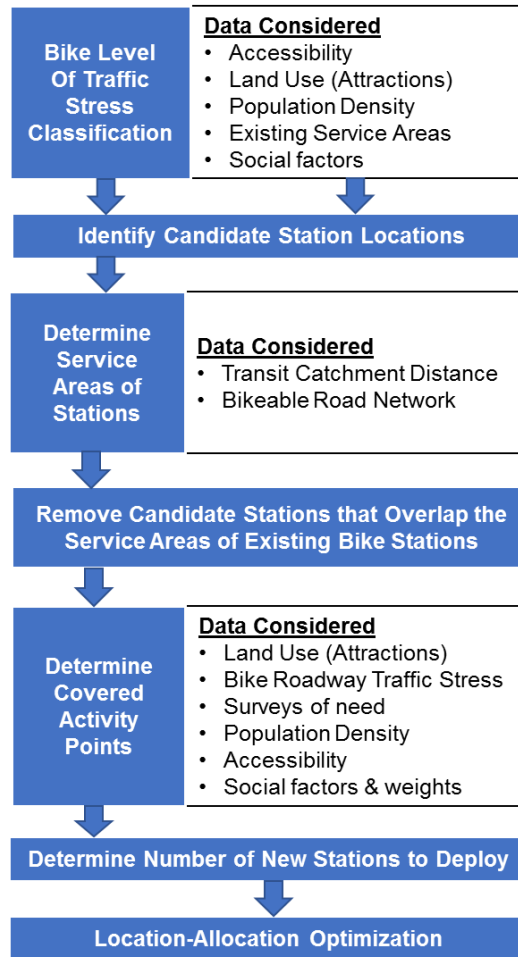
172 **3 Methodology**

173 The analysis evaluated the placement of five more bike-share stations in the Fargo small urban
174 area. Figure 2 shows the *workflow* to prepare the data for the location optimization model to
175 cover all the service points identified. The workflow is applicable to any populated place, but
176 planners must decide on the candidate station locations and covered activity points (CAPs) based
177 on the population density, land use, trip generation centers, and roadway network characteristics
178 that are unique to every place. The next subsections describe the data sources, service area
179 analysis, LTS formulation, identification of the CAPs, and the location-allocation optimization
180 problem.

181 **3.1 Data and Sources**

182 Table 1 summarizes all the datasets obtained to set up and solve the bikeshare station location

183 optimization problem. The description column identifies the data source.



184
185 Figure 2: Workflow for the location allocation optimization model.

186 Table 1: Dataset Used for the Location Optimization Problem

Dataset	Description
Bike-share Stations (Existing)	Shapefile from the Fargo-Moorhead Metropolitan Council of Governments (METROCOG) of North Dakota encoding the location of bike-sharing stations.
Population Density	2020 block group census data from the U.S. Census Bureau.
Road Centerline	Shapefiles for Fargo street segments from METROCOG including geographical coordinates, number of lanes, speed limit, functional class, and shape length.
Bikeways	Shapefiles for Fargo bikeway segments from METROCOG including geographical coordinates, type of bikeways, and shape length.
Shared-Use Paths	Shapefiles for Fargo shared use path segments from METROCOG including geographical coordinates, pavement type, pavement width, and shape length.
Traffic Signals	Shapefiles for Fargo signalized intersections from METROCOG.
Traffic Volume	METROCOG interactive map of the 2015 annual average daily traffic volume (AADT) for Fargo (METROCOG, 2021).
Right-Turn Lanes	Manual measurements of right-turn lane geometries from Google Earth® imagery.

187

188 **3.2 Service Area Analysis**

189 A GIS network analysis tool determined accessibility to a facility based on radial walking
190 distances within 700 meters. This distance threshold reflected the accepted transit industry
191 definition for service “catchment” based on a 5–10-minute walk (FTA, 2002). The service area
192 analysis computed the walking distances along all paths that can access a bike sharing station.
193 Figure 1 shows the spatial contours of accessibility to each of the 11 existing bike stations. The
194 three contours are the core, primary, and secondary catchment areas based on walking distances
195 of 300-, 500-, and 700-meters, respectively.

196 **3.3 Level of Traffic Stress**

197 A GIS tool divided the street and bike lane networks in Fargo into small segments for LTS
198 classification. The analysis used roadway geometry and traffic data from METROCOG as inputs
199 to the classification model. Factors included, if present, bike lane width, speed limit, parking
200 width, a residential area indicator, mid-block crossings, the geometry of right-turn lanes, bike
201 lane type, functional class, traffic volume, and the type of intersection signalization.
202 Consequently, a traffic-separated bike lane and a mixed pathway with high traffic volume or
203 high-speed limit had the lowest (LTS 1) and highest (LTS 4) stress levels, respectively. Figure 3
204 shows a map of the LTS classified roadways of the Fargo study area.

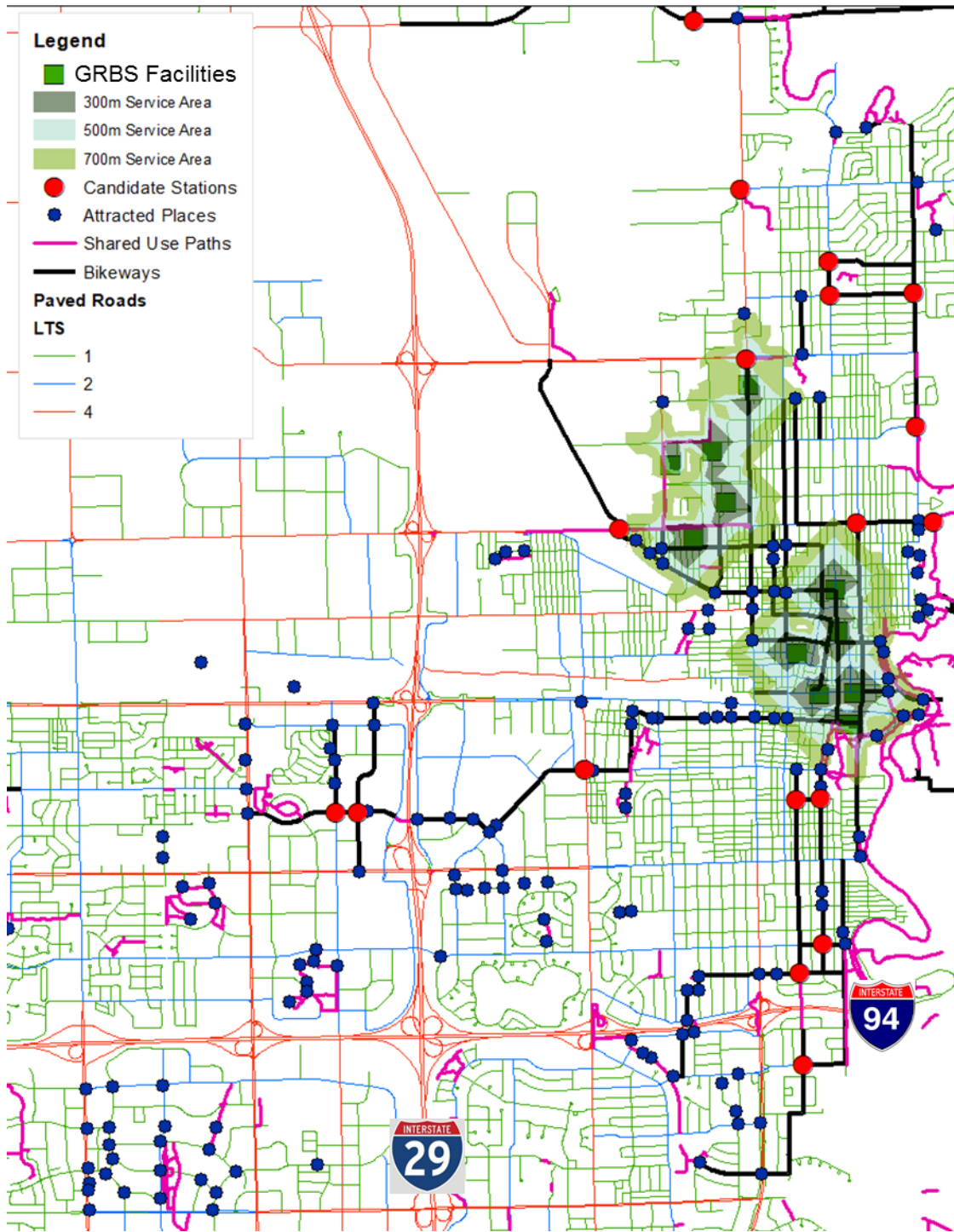
205 In general, the LTS classification model assigned LTS 1 to physically separated
206 bikeways, multi-use pathways, and walkways in parks and trails. A decision tree model used the
207 same traffic volume, functional class, number of traffic lanes, and speed limit thresholds of
208 Bearn (2018) to assign one of four LTS levels to each road segment (Bearn, Mingus, & Watkins,
209 2018). In particular, the speed limit thresholds for LTS 1 through LTS 4 were 25, 30, 35, and 50
210 mph, respectively. Bearn (2018) scaled down the tiered traffic volume thresholds when

211 considering bikeways that were alongside parking lanes. The model also included geometric
212 criteria used by Mekuria et al. (2012) for any auxiliary right lane along the path (Mekuria, Furth,
213 & Nixon, 2012). The model adopted the LTS level of the highest stress rating among all
214 segments that cross non-signalized intersections.

215 Figure 3 shows the LTS ratings derived for all bikeable pathways in Fargo. To simplify
216 the methodology and to reduce the scope, the model did not adjust thresholds for signalized
217 intersections to account for possible misalignments between green-time and slow riding speeds.
218 Figure 3 shows traffic separated bikeways (LTS 1) and shared-use pathways (LTS 1 or LTS 2) in
219 different colors to highlight their location and how the network spans the city.

220 **3.4 Candidate Locations**

221 An overlap of four GIS layers helped to identify the candidate locations for bikeshare stations.
222 One layer was the LTS classified network. A second layer was the population density derived
223 from the 2020 block group census data obtained from the U.S. Census Bureau. Selecting areas of
224 high population density assured the potential for demand. A third GIS layer was the land-use
225 classification. Selecting commercial, entertainment, and shopping areas with potentially high trip
226 generation and attraction rates assured potential adoption. A fourth GIS layer was the
227 aggregation of the 700-meter service areas for the existing bikeshare stations. The analyst then
228 identified all junctions with at least three intersecting paths of LTS rating at or below 2. Low-
229 level LTS junctions assured flexible accessibility and maximum safety. The analyst then
230 eliminated locations with low population density or poor access to CAPs such as parks,
231 restaurants, and commercial areas. This process resulted in the selection of 18 candidate
232 locations to deploy bikeshare facilities. Figure 3 shows the candidate locations.



233
234

Figure 3: LTS ratings for pathways in Fargo, North Dakota.

235 **3.5 Covered Activity Points**

236 The location-allocation optimization model utilized the METROCOG dataset of 200 covered
237 activity points (CAPs) for Fargo. METROCOG determined the CAPs based on the presence of

238 transit stops, parks, restaurants, bars, commercial areas, industrial centers, universities in high
239 density population areas, and surveys of needed coverage points. Planners used the 2020 block
240 group census data from the U.S. Census Bureau to determine the population density of an area
241 smaller than the traffic analysis zones that planners often use in travel demand analysis. Figure 3
242 shows the location distribution of CAPs across the city. As observed, CAP clusters form near
243 shopping, entertainment, university, park, and residential areas.

244 **3.6 Location-Allocation Optimization**

245 The *objective* of the location-allocation model was to identify the subset of facilities from among
246 the candidate locations to serve the CAPs with the least travel impedance. Given the multiplicity
247 of alternative routes to a CAP, the analysis simplified the travel impedance as the geodesic
248 distance. The *constraint* for the model was to select five locations from the 18 candidate sites.
249 The travel cost between a facility location and a CAP was the geodesic distance, with the
250 maximum distance set to 1,000 meters.

251 The optimization model allowed the same bike station location to service multiple CAPs
252 but restricted more than one station from serving the same CAP. The variables of the
253 optimization problem were:

254 I the set of N *demand* node locations indexed by i

255 J the set of M candidate station locations indexed by j

256 p the number of stations to deploy

257 w_i relative weight of CAP i (0 to 2)

258 d_{ij} the geodesic distance between CAP i and candidate station j .

259 The problem formulation is:

260 Minimize

$$D = \sum_{i=1}^N \sum_{j=1}^M w_i d_{ij} Y_{ij} \quad (1)$$

261 Subject to:

$$\sum_{j=1}^M Y_{ij} = 1, \quad \forall i \in I \quad (2)$$

262 and

$$\sum_{j=1}^M X_j = p \quad (3)$$

263 and

$$Y_{ij} \leq X_j, \quad \forall i \in I, \forall j \in J \quad (4)$$

264 where

$$Y_{ij} = \begin{cases} 1 & \text{location } i \text{ is served from location } j \\ 0 & \text{otherwise} \end{cases}, \quad \forall i \in I, \forall j \in J \quad (5)$$

265

$$X_j = \begin{cases} 1 & \text{if server is placed at location } j \\ 0 & \text{otherwise} \end{cases}, \quad \forall j \in J \quad (6)$$

266

267 The *objective* function selected candidate sites that minimized the overall weighted geodesic
268 distance in the network. The relative weight for each CAP reflects combined considerations that
269 are important to the planners, for example, social factors and environmental impacts. The
270 nominal weight is 1. A weight lower or higher than 1 reflects the relative importance level of that
271 CAP. A weight of zero means that the model will not consider service to that CAP. A weight of
272 2 means that a CAP is 100% more important than the nominal CAP. A high weight has the effect
273 of a pseudo increase in the distance to a candidate facility, hence the optimization for minimum

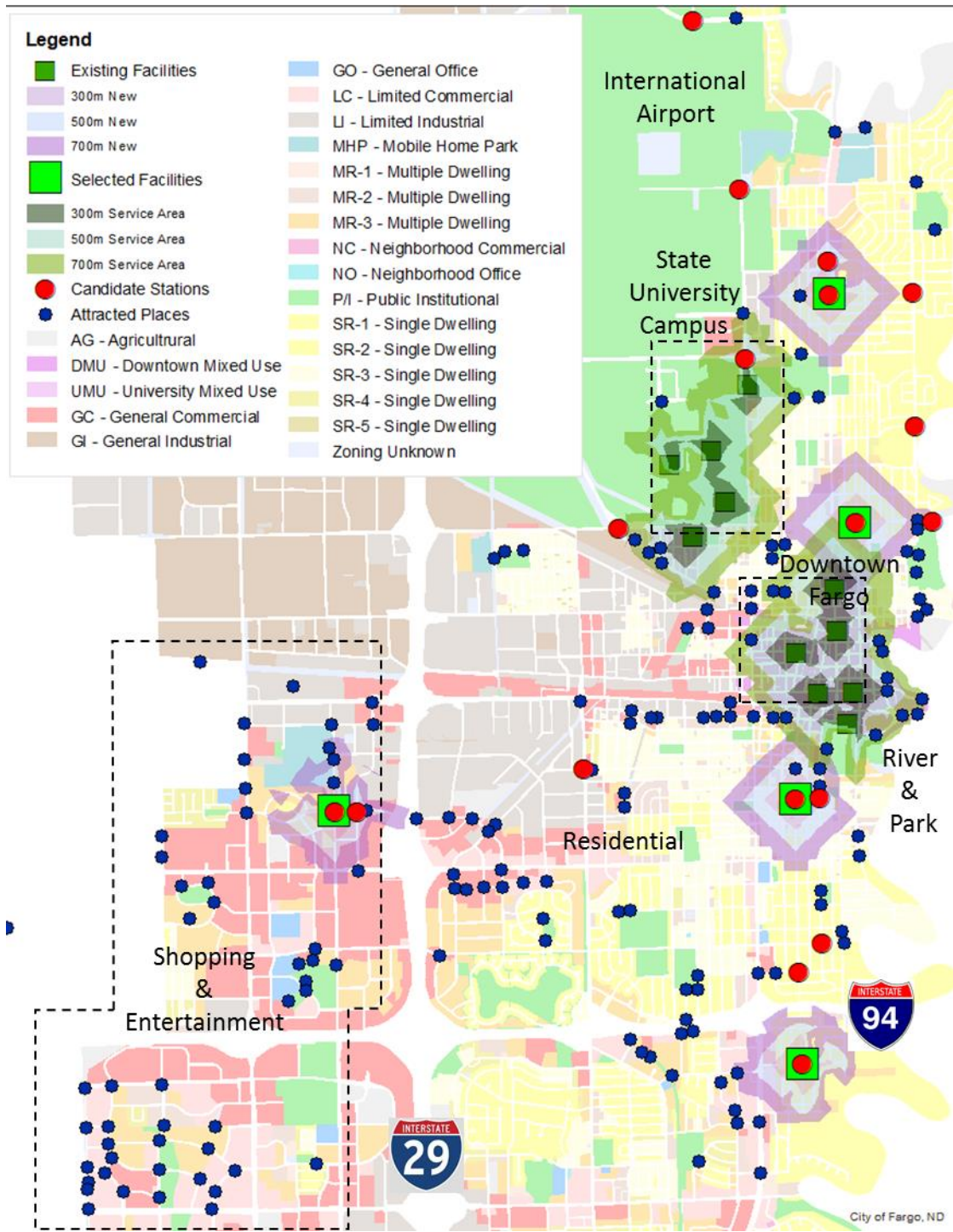
274 total distance will tend to select a candidate facility that is closer. The planners wanted identical
275 weight for all CAPS in this analysis. The first *constraint* assured that one and only one station
276 served a demand site. The second constraint assured that the number of stations selected was
277 exactly p . The third constraint assured that if the optimizer placed a station at location j to serve
278 location i then it must set station j location as assigned. All decision variables were binary.

279 **4 Results and Discussion**

280 Figure 1 shows that Interstates 29 and 94 are the main traffic conduits through Fargo. As
281 anticipated, the LTS model assigned those highways to level 4 as shown in Figure 3. The LTS
282 model also assigned level 4 to the major arterials that form a grid pattern throughout the city. As
283 observed, the LTS model classified local roads in residential areas as LTS 1. Assignments of
284 LTS 2 were mostly to the narrower avenues. The bikeways highlighted are roadways with bike
285 path designations, so the model classified them as LTS 1. Most of the shared use paths are along
286 the river park to the east of the city. Pedestrians, hikers, and cyclists use the shared-use paths, so
287 the model set their LTS ratings to level 1. All candidate bikeshare station locations were at the
288 intersections of traffic-separated bikeways and shared-use pathways, as Figure 3 shows.

289 The workflow selected the five locations for the new bike sharing stations as shown in
290 Figure 4. Three of the new stations fill gaps within the aggregate service area of the existing
291 stations. The other two extend the service areas towards the southwestern and southeastern
292 regions of the small urban area. The southwestern location serviced CAPs near shopping and
293 entertainment regions. The southeastern location covers residential, park, and golf course
294 regions. One can visually observe that the selected locations for new stations are distributed in a
295 manner that evenly covers all the CAPs. The coverage was highest in the eastern part of Fargo,
296 along the winding Red River that forms a border between the states of North Dakota and

297 Minnesota. All five of the selected locations are at the intersection of bikeways and shared-use
 298 paths, thus making them suitable even for beginners.



299
 300 Figure 4: Selected facilities and new service areas relative to land-use zoning in the City of Fargo, ND.

301 The 700-meter service areas of the selected locations cover LTS 1 and LTS 2 segments, thus

302 making them easily accessible from many points throughout the city.

303 **5 Conclusion**

304 Bike sharing is a popular form of micromobility that is rapidly expanding across many cities of
305 the world to fill mobility gaps and enhance accessibility at affordable prices while achieving
306 sustainable deployments. While there has been a lot of analysis about deployments in high-
307 density areas and cities, analysts have paid little attention to small urban and rural areas. This
308 study addressed the micromobility needs of Fargo, North Dakota, a small urban area in the rural
309 United States. The analysis accounted for the unique land-use settings, street geometry, and
310 traffic situations of the area. Applying the level of traffic stress (LTS) technique to all the
311 available pathways in the area helped identify accessible locations for 18 candidate stations at the
312 junction of low-stress pathways.

313 The spatial analysis of service areas for the existing bike stations produced isochrones of
314 walking distances based on accepted public transit catchment criteria. Subsequently, overlapping
315 layers in a geographic information system (GIS) helped to identify and eliminate from
316 consideration candidate stations that fell within the isochrone clusters of the existing bikeshare
317 stations. The analysis also determined covered activity points (CAPs) throughout the city based
318 on population density and land-use characteristics such as shopping, entertainment, university,
319 park, and residential areas.

320 The location-allocation optimization procedure selected the five bike station locations
321 that minimized the total geodesic distances to all the CAPs. Consequently, service area analysis
322 showed that three of the selected locations filled gaps around the existing deployment sites near
323 the state university campus and in the downtown areas. The other two selected locations

324 extended accessibility towards the shopping districts in the southwest and residential areas in the
325 southeast.

326 Analysts can benefit from this study by following the same workflow. The data obtained
327 for roadway, pathway, intersection, land-use, population, and traffic characteristics would be
328 unique to their study area. Analysts can use any suitable GIS tool to visualize the results of their
329 LTS classification and spatial optimization to refine the selection of deployment sites. However,
330 analysts should consider that deployments at the selected sites could lead to an induced demand
331 for bike sharing and other micromobility modes such as electric scooters, which can attract a
332 broader demographic of users. Future work will examine how induced demand would affect the
333 distribution of LTS segments from the current distribution in Fargo. That study will include a
334 traffic impact analysis after collecting data on bicycle volume and motorized traffic volume.

335 **6 Data Availability**

336 The shapefile data used to support the findings of this study were supplied by the Fargo-
337 Moorhead Metropolitan Council of Governments (METROCOG) of North Dakota under license
338 and so cannot be made freely available. Requests for access to these data should be made to Dan
339 Farnsworth at 701.532.5106 or farnsworth@fmmetrocog.org.

340 **7 References**

- 341 Banerjee, S., Kabir, M., Khadem, N., & Chavis, C. (2020). Optimal locations for bikeshare stations: A new GIS
342 based spatial approach. *Transportation Research Interdisciplinary Perspectives*, 4, 100101.
343 doi:10.1016/j.trip.2020.100101
- 344 Bearn, C., Mingus, C., & Watkins, K. (2018). An adaption of the level of traffic stress based on evidence from the
345 literature and widely available data. *Research in Transportation Business & Management*, 29, 50–62.
346 doi:10.1016/j.rtbm.2018.12.002
- 347 Conrowa, L., Murray, A. T., & Fischer, H. A. (2018). An optimization approach for equitable bicycle share station
348 siting. *Journal of Transport Geography*, 163-170. doi:10.1016/j.jtrangeo.2018.04.023
- 349 Daddio, D. (2012). *Maximizing bicycle sharing: an empirical analysis of capital bikeshare usage*. College of Arts
350 and Sciences. University of North Carolina at Chapel Hill. doi:doi.org/10.17615/qv32-b860
- 351 Firestine, T. (2016). Bike-Share Stations in the United States. *Technical Brief*. doi:10.21949/1502458
- 352 Frade, I., & Ribeiro, A. (2014). Bicycle sharing systems demand. *Procedia - Social and Behavioral Sciences*, 111,
353 518-527. doi:10.1016/J.SBSPRO.2014.01.085

354 Frade, I., & Ribeiro, A. (2015). Bike-sharing stations: A maximal covering location approach. *Transportation*
355 *Research Part A: Policy and Practice*, 216-227. Retrieved from 10.1016/j.tra.2015.09.014
356 FTA. (2002). *Transit-Oriented Development and Joint Development in the United States: A Literature Review*.
357 Washington, DC: Federal Transit Administration (FRA). Retrieved from
358 http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rrd_52.pdf
359 García-Palomares, J. C., Gutiérrez, J., & Latorre, M. (2012). Optimizing the location of stations in bike-sharing
360 programs: A GIS approach. *Applied Geography*, 235-246. Retrieved from 10.1016/j.apgeog.2012.07.002
361 Godavarthy, R., & Taleqani, A. (2017). Winter bikesharing in US: User willingness, and operator's challenges and
362 best practices. *Sustainable Cities and Society*, 30, 254-262. doi:10.1016/J.SCS.2017.02.006
363 Godavarthy, R., & Taleqani, A. (2017). Winter bikesharing in US: User willingness, and operator's challenges and
364 best practices. *Sustainable Cities and Society*, 30, 254-262. Retrieved from
365 <https://academic.microsoft.com/paper/2588229545>
366 Godavarthy, R., Mattson, J., & Taleqani, A. (2017). *Evaluation Study of the Bike Share Program in Fargo, North*
367 *Dakota*. Fargo, North Dakota: Upper Great Plains Transportation Institute. Retrieved from
368 <https://trid.trb.org/view/1473775>
369 Gregerson, J., Hepp-Buchanan, M., McCormack, E., Rowe, D., Vander Sluis, J., Erica, W., & Xenakis, M. (2011).
370 *Seattle Bicycle Share Feasibility Study*. College of Built Environments, Department of Urban Design &
371 Planning. Seattle, Washington: University of Washington. Retrieved from [https://nacto.org/wp-](https://nacto.org/wp-content/uploads/2015/07/2011_McCormack-et-al_Seattle-Bicycle-Share-Feasibility-Study.pdf)
372 [content/uploads/2015/07/2011_McCormack-et-al_Seattle-Bicycle-Share-Feasibility-Study.pdf](https://nacto.org/wp-content/uploads/2015/07/2011_McCormack-et-al_Seattle-Bicycle-Share-Feasibility-Study.pdf)
373 Guo, T., Yang, J., He, L., & Tang, K. (2020). Layout Optimization of Campus Bike-Sharing Parking Spots. *Journal*
374 *of Advanced Transportation*, 2020, 1-10. doi:10.1155/2020/8894119
375 Hochmair, H., Zielstra, D., & Neis, P. (2015). Assessing the Completeness of Bicycle Trail and Lane Features in
376 OpenStreetMap for the United States. *Transactions in GIS*, 19(1), 63-81. doi:10.1111/tgis.12081
377 Krykewycz, G., Puchalsky, C., Rocks, J., Bonnette, B., & Jaskiewicz, F. (2010). Defining a Primary Market and
378 Estimating Demand for Major Bicycle-Sharing Program in Philadelphia, Pennsylvania. *Transportation*
379 *Research Record*, 2143(2143), 117-124. doi:10.3141/2143-15
380 Landis, B. W. (1996). Bicycle System Performance Measures. *ITE Journal*, 66(2). Retrieved from
381 <https://trid.trb.org/view/459029>
382 Larsen, J., & El-Geneidy, A. (2011). A travel behavior analysis of urban cycling facilities in Montréal, Canada.
383 *Transportation Research Part D: Transport and Environment*, 172-177. doi:10.1016/j.trd.2010.07.011
384 Liu, N., Huang, B., & Chandramouli, M. (2006). Optimal Siting of Fire Stations using GIS and ANT Algorithm.
385 *Journal of Computing in Civil Engineering*, 20(5), 361-369. doi:10.1061/(ASCE)0887-
386 3801(2006)20:5(361)
387 Mekuria, M., Furth, P., & Nixon, H. (2012). Low-Stress Bicycling and Network Connectivity. *Mineta*
388 *Transportation Institute*. doi:<https://rosap.ntl.bts.gov/view/dot/24453>
389 METROCOG. (2021, July 1). *Traffic Counts*. Retrieved from Fargo-Moorhead Metropolitan Council of
390 Governments (METROCOG): <http://fmmetrocog.org/resources/traffic-counts>
391 Midgley, P. (2009). *The role of smart bike-sharing systems in urban mobility*. London: Global Transport Knowledge
392 Partnership. Retrieved from <https://trid.trb.org/view/1152301>
393 Murawski, L., & Church, R. (2009). Improving accessibility to rural health services: The maximal covering network
394 improvement problem. *Socio-economic Planning Sciences*, 43(2), 102-110.
395 doi:10.1016/J.SEPS.2008.02.012
396 Murphy, B., & Owen, A. (2019). Implementing Low-Stress Bicycle Routing in National Accessibility Evaluation.
397 *Transportation Research Record*, 2673(5), 240-249. doi:10.1177/0361198119837179
398 NYC Department of City Planning. (2009). *Bike-Share Opportunities in New York City*. New York: U.S.
399 Department of Transportation. Retrieved from
400 https://www1.nyc.gov/assets/planning/download/pdf/plans/transportation/bike_share_complete.pdf
401 Pérez-Fernández, O., & García-Palomares, J. C. (2021). Parking Places to Moped-Style Scooter Sharing Services
402 Using GIS Location-Allocation Models and GPS Data. *ISPRS International Journal*.
403 doi:10.3390/ijgi10040230
404 Ribeiro, A., & Antunes, A. (2002). A GIS-Based Decision-Support Tool for Public Facility Planning. *Environment*
405 *and Planning B: Planning & Design*, 29(4), 553-569. doi:10.1068/B1281
406 Scott, M., Hurnall, D. D., & Pattinson, W. H. (1978). *The Geelong Bikeplan: Practical Planning for Cyclists Real*
407 *Needs*. Perth, Western Australia: Western Australia Director General of Transport. Retrieved from
408 <https://trid.trb.org/view/79790>

409 Shaheen, S., Martin, E., Cohen, A., & Finson, R. (2012). *Public Bikesharing in North America: Early Operator and*
410 *User Understanding*. San Jose, California: Mineta Transportation Institute. Retrieved from
411 <https://rosap.ntl.bts.gov/view/dot/24566>
412 Sorton, A., & Walsh, T. (1994). Bicycle Stress Level as a Tool to Evaluate Urban and Suburban Bicycle
413 Compatibility. *Transportation Research Record*(1438), 17-24. Retrieved from
414 <https://trid.trb.org/view/413763>
415 Taleqani, A., Vogiatzis, C., & Hough, J. (2020). Maximum Closeness Centrality k -Clubs: A Study of Dock-Less
416 Bike Sharing. *Journal of Advanced Transportation*, 2020, 1275851. doi:10.1155/2020/1275851
417 Teixeira, J., & Antunes, A. (2008). A hierarchical location model for public facility planning. *European Journal of*
418 *Operational Research*, 185(1), 92-104. doi:10.1016/J.EJOR.2006.12.027
419 Wasserman, D., Rixey, A., Zhou, X., Levitt, D., & Benjamin, M. (2019). Evaluating OpenStreetMap's Performance
420 Potential for Level of Traffic Stress Analysis. *Transportation Research Record*, 2673(4), 284-294.
421 doi:10.1177/0361198119836772
422 Yeh, A.-O., & Chow, M. (1996). An integrated GIS and location-allocation approach to public facilities planning :
423 An example of open space planning. *Computers, Environment and Urban Systems*, 20, 339-350.
424 doi:10.1016/S0198-9715(97)00010-0
425