Research Article

Integrating a Connected Micromobility Infrastructure to the Existing Public Transport

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Abstract: This paper presents the integration of connected micromobility infrastructure into the existing public transport system. The integration purpose is to help organize the public space in the urban environment, lower operation costs for micromobility operators, and create a better Mobility-as-a-Service (MaaS) experience for citizens with the connected and universal micromobility charging infrastructure solution. Our goal is to efficiently consolidate electric-powered shared micromobility vehicles such as e-scooters and e-bikes into hubs to manage their charging and maintenance operations efficiently. Therefore, determining the locations of these e-hubs and the required charging infrastructure is paramount for satisfying the commuters' needs. We address this problem using an optimization approach and develop a model for siting and sizing micromobility e-hubs within an urban context. We formulate the problem as a mixed-integer linear programming (MILP) and develop a Variable Neighbourhood Search (VNS) metaheuristic algorithm to solve the problem. The evaluation of the performance of the solution methodology is applied using real data from Ankara Metropolitan Municipality (AMM).

Keywords: Micromobility vehicles, e-hub, electric-powered shared micromobility vehicles, charging, urban mobility, e-scooters, e-bikes, variable neighborhood search

Bağlantılı Mikromobilite Altyapısını Mevcut Toplu Taşıma Sistemine Entegrasyonu

Özet: Bu çalışma, bağlantılı mikromobilite altyapısının mevcut toplu taşıma sistemine entegrasyonunu ele almaktadır. Entegrasyonun amacı, kentsel ortamda kamusal alanın düzenlenmesine yardımcı olmak, mikromobilite operatörleri için işletme maliyetlerini düşürmek, bağlantılı ve evrensel mikromobilite şarj altyapısı çözümüyle vatandaşlar için daha iyi bir Hizmet Olarak Mobilite (MaaS) deneyimi sağlamaktır. Amacımız, şarj ve bakım işlemlerini verimli bir şekilde yönetmek için elektrikli skuter ve elektrikli bisiklet gibi elektrikle çalışan paylaşılan mikromobilite araçlarını istasyonlarda verimli bir şekilde birleştirilmesidir. Bu bağlamda, istasyonların konumlarının ve gerekli şarj altyapısının belirlenmesi, vatandaşların yolculuk ihtiyaçlarının karşılanması açısından büyük önem taşımaktadır. Çalışmada bu problemi eniyileme yaklaşımı kullanarak ele alıyoruz ve kent içindeki mikromobilite istasyonlarının konumlarının ve gereken şarj altyapısının belirlenmesi için bir karma tamsayılı doğrusal programlama modeli sunuyoruz. Daha sonra, problemin etkin çözümü için bir Değişken Komşuluk Araması yöntemi geliştiriyoruz. Geliştirilen yöntemi Ankara'ya ait veriler üzerinde uygulayarak performansını sınıyor ve elde edilen sonuçları sunuyoruz.

Anahtar Kelimeler: Paylaşımlı mikromobilite, kentsel mobilite, elektrikli skuter, elektrikli bisiklet, şarj istasyonu, değişken komşuluk araması.

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1. Introduction

Using road-based (diesel) vehicles that produce CO_2 emissions have caused severe environmental pollution and, consequently, is harmful to human health. Nowadays, many people use internal combustion engine vehicles (ICEVs) in their transportation. However, increasing concerns about climate change have forced many countries to impose stricter emission reduction targets and tighter environmental regulations to restrict the use of ICEVs (Pan et al, 2021). These motivations have accelerated the change toward low-emission and battery electric bikes (e-bikes) and electric scooters (e-scooter) in the mobility transport sector (Figure 1). E-bikes/ e-scooters are fully powered with rechargeable batteries. The E-bikes/ e-scooters with zero tailpipe emissions are classified as clean passenger transportation modes (Jaller et al, 2018). In addition, their maintenance cost is low as they have fewer parts, and they do not need oil changes or air-filter replacements. On the contrary, long recharging times, limited driving range, and limited recharging facility infrastructure restrain their broader adoption in the sector (Giordano et al, 2017).

Figure 1. e-bike and e-scooter (Source: https://elektriklimotor.com.tr)

Electric-powered shared micromobility vehicles have offered a favorable resolution to diminish the greenhouse gas effect of a territory's passenger transportation design. It was anticipated that using e-bikes could decrease the usage of ICEV from 84.7% to 74.8%. Similarly, carbon dioxide (CO2) emissions could decrease by 12%. An individual e-bike could lessen 225 kg of CO2 per year on average. These analyses reveal that e-bikes have the prospect of aiding municipalities and areas to acquire their environmental objectives. E-bikes/ e-scooters are newly instructed methods rapidly earning attention throughout the U.S. E-bikes can propose a more affordable option instead of using a car for journeys (Popovich et al, 2014). Furthermore, e-bike can give users a satisfactory level of physical exercise intensity required to improve health (Fishman & Cherry, 2016). Using an e-bike/e-scooters is rewarding and entertaining for numerous users, is released for users with limited ability and mobility, and can direct to a car-free household (Popovich et al, 2014).

This paper aims to efficiently consolidate electric-powered shared micromobility vehicles such as e-bikes and e-scooters into hubs to manage their charging and maintenance operations. Therefore, determining the locations of these e-hubs and the required charging infrastructure is of paramount importance for satisfying the needs of the commuters. Using an optimization approach, we address this problem as an e-Hub Location Problem (eHLP) and develop a model for siting and sizing micromobility e-hubs within an urban context. In this problem, we find the optimal sites to build the e-hubs and determine the quantity of charging units at each site to maximize the utilization of the fleet. We first define the notation employed in the optimization model, present the formulation and describe it. Then, we develop Variable Neighborhood Search (VNS) as an alternative solution methodology. Finally, we implement the model and VNS to determine e-hub locations using the commuter data provided by the Ankara Metropolitan Municipality (AMM) transport authorities. The data includes the home and work locations of 120 citizens selected for the pilot implementation.

An optimization solver was employed to solve the formulated mathematical model based on the criteria and parameters set by the AMM authorities. According to the optimal solution obtained, six metro stations were selected as e-hub locations, and 58 chargers were distributed optimally to these e-hubs according to the expected demand of potential e-bike users. In addition, two chargers were installed at the "Bicycle Campus" of AMM for testing a non-metro station e-hub. Ride data was collected for two weeks to investigate the commuter behavior and effectiveness of the selected locations. Despite the unfavorable winter conditions, the results were promising and supported the e-hub location decisions; however, the collected data reveals that some charging units may be repositioned to enhance service levels.

2. Problem description and formulation

The mathematical notation employed in the formulation of the eHLP is as follows:

Sets:

V	Set of all commuters
S	Set of metro stations

Parameters:

d_{ij}	Distance between commuter $i \in V$ and commuter $j \in V$
D_{max}	Maximum distance between a commuter and hub
a_{ij}	Binary (0-1) coverage parameter (i.e. $a_{ij} = 1$ if $d_{ij} \leq D_{max}$)
b_{sj}	Binary (0-1) parameter represents that the metro station $s \in S$ is the nearest station to the commuter hub $j \in V$
P_h	Maximum number of hubs in districts
P_e	Maximum number of e-hubs in metro stations
P_s	Maximum number of chargers in an e-hub
K	Number of total commuters per charger installed
Q	Maximum number of total available chargers
ε	A sufficiently small constant

Decision variables:

x_j	1 if a commuter hub is located at commuter $j \in V$; 0 otherwise
z_i	1 if commuter $i \in V$ is covered; 0 otherwise
w_s	1 if an e-hub is located in metro station $s \in S$; 0 otherwise
q_s	Number of chargers in metro station $s \in S$
y_{ij}	1 if commuter $i \in V$ is assigned to hub $j \in V$; 0 otherwise
T	Maximum walking distance between a commuter and a hub

The mathematical programming (mixed-integer linear programming) model can be formulated as follows:

$$\max \ \sum_{i \in V} z_i - \varepsilon \sum_{s \in V} q_s \tag{1}$$

subject to:

$$\sum_{j \in V} a_{ij} x_j \geq z_i \qquad i \in V \qquad (1)$$

$$\sum_{j \in V} y_{ij} \leq z_i \qquad i \in V \qquad (2)$$

$$y_{ij} \leq x_j \qquad i, j \in V \qquad (3)$$

$$w_s \geq b_{sj} x_j \qquad j \in V, s \in S \qquad (4)$$

$$T \geq \sum_{j \in V} d_{ij} y_{ij} \qquad i \in V \qquad (5)$$

$$\sum_{j \in V} x_j \leq P_h \qquad (6)$$

$$\sum_s w_s \leq P_e \qquad (7)$$

$\sum_{i\in V, j\in V} b_{sj} y_{ij} \leq K \times q_s \quad s \in S \quad (8)$

$w_s \leq q_s \leq P_s \quad s \in S \quad (9)$

$\sum_{s\in S} q_s \leq Q \quad (10)$

$x_i, z_i \in \{0,1\} \quad i \in V \quad (12)$

$y_{ij} \in \{0,1\} \quad i, j \in V \quad (13)$

The objective function (1) maximizes the total number of covered commuters. Constraints (2) is a covering constraint that makes sure the commuter i will be covered by commuter j if $a_{ij} = 1$. Constraints (3) guarantee that if commuter i is assigned to commuter j, then the commuter i must be covered. Constraints (4) make sure that if commuter i is assigned to commuter j, then commuter j will be a commuter hub. Constraints (5) show that if a commuter hub is located at commuter $j \in V$, then an eHub must be located in commuter $j \in V$ nearest metro station $s \in S$. Constraints (6) satisfy the maximum walking distance between a commuter and a hub. Constraints (7) and (8) control the maximum number of hubs in districts and the maximum number of e-hubs in metro stations, respectively. Constraints (9) guarantee that if commuter $i \in V$ is assigned to hub $j \in V$, then at most K chargers can be installed in metro station $s \in S$. Constraints (10) show that if an e-hub is located in a metro station $s \in S$, at least one charger must be installed in the associated metro station. Constraints (11) provide the upper bound on a maximum number of available chargers. Finally, constraints (12)-(13) define the domain of the binary decision variables.

3. Solution methodology

As a solution methodology for solving the eHLP, we use the Variable Neighborhood Search (VNS) of Mladenović and Hansen, 1997. The VNS is used for solving many combinatorial optimization problems (Rincon-Garcia et al, 2017; Affi et al, 2018; Özger, 2022; Sadati et al, 2021; Sadati et al, 2022). The algorithm starts with an initial solution S_0. Initially, the current solution S' and the incumbent solution S^* are set to $S' = S^* = S_0$. Then, the shaking phase is started using a set of neighborhood structures N_k $(k = 1, \ldots, k_{max})$. In this phase, a random solution $\overline{S}$ is generated by implementing the first neighborhood N_1 of S'. Next, the local search phase is applied to obtain a new solution S'. If S' is feasible and improves the incumbent solution S^*, then S^* is replaced with S' and the neighborhood counter k is reset to 1 (i.e., we return to the first shaking neighborhood structure). Otherwise, k is increased by 1 ($k = k + 1$) and the algorithm continues by applying another shaking move on S'. If all neighborhood structures are explored ($k = k_{max}$), the algorithm restarts from the best solution found so far S^* and neighborhood structure index k is re-initialized to 1. This procedure is repeated until a termination condition is satisfied.

3.1. Initial solution construction

We represent the solution with a matrix of different row lengths. In this matrix, the first column shows the ID of the selected hub, and the following columns will show the assigned commuters to the hub. The number of the row will be set to P_h (i.e., the maximum number of hubs in districts) Moreover, depending on those commuters assigned to the associated hub, each row will have a different length. To construct an initial feasible solution S_0, we initially created a list of assigned commuters for each hub. To do this, we generate another similar matrix M_{cover} with $|V|$ (number of commuters) rows (the first column shows the ID of commuters), and for each row, the ID of other commuters that can be covered is inserted. Note that the ID of inserted commuters at each row will be determined using the coverage parameter a_{ij} $(i, j \in V)$. Then we sort the M_{cover} in descending order of rows length (i.e., in the sorted M_{cover} The first row has the highest number of assigned commuters). From the sorted M_{cover} matrix, we select the first P_h rows and insert them into S_0 (since our objective is to maximize the number of coverage commuters). Two or more hubs can cover some commuters, and if such conditions hold, we remove the same ID from S_0. Note that it is possible that by removing the same ID, the number of rows in S_0 can be decreased due to the empty ID in some hubs. After generating the initial solution, we can extract the opened stations and the number of installed charges using the $b_{sj\ (s\in S, j\in V)}$.

Table 1. coordinates of 47 metro stations in AMM

Metro Station Name	X-coordinate	Y-coordinate
Akköprü	39.9515847010483	32.8341795243818
AKM	39.9443795162620	32.8439087810831
Anadolu	39.9347858951204	32.8369747514223
ASKİ	39.9474217591986	32.8502967868702
AŞTİ	39.9182626438759	32.8143773153182
Bahçelievler	39.9311253339485	32.8201135202388
Batı Merkez	39.9677779745099	32.7154040086390
Batıkent	39.9686637727400	32.7269929199242
Beşevler	39.9323883009931	32.8286182623825
Beytepe	39.9063852532501	32.7333680475345
Bilkent	39.9078366805602	32.7639437564344
Botanik	39.9809540847158	32.6947608271056
Çayyolu	39.8967996302740	32.6915482899637
Demetevler	39.9654526466281	32.7939524664253
Demirtepe	39.9249069837490	32.8482662806608
Dikimevi	39.9323772150356	32.8776683230518
Dutluk	39.9994460923559	32.8706762907213
Emek	39.9230562325935	32.8148175562953
Eryaman 1-2	39.9805249449850	32.6479294929466
Eryaman 5	39.9810459707558	32.6274123399772
Fatih	39.9840807419541	32.5853408380043
Harikalar Diyarı	39.9824908586034	32.5982955507296
Hastane	39.9690627048819	32.7836334840208
İstanbul Yolu	39.9796510179896	32.6625997900486
İvedik	39.9572393334365	32.8170395394222
Kızılay	39.9205573326480	32.8532866498255
Kolej	39.9237378422280	32.8617998007825
Koru	39.8875524691288	32.6869668515318
Kurtuluş	39.9287430485953	32.8696629264171
Macunköy	39.9719016693441	32.7664946547301
Maltepe	39.9319618065686	32.8429415289544
Mecidiye	39.9839457267553	32.8754203880277
Mesa	39.9718396828269	32.7030747030507
Meteoroloji	39.9663328568328	32.8639081878403
Milli Kütüphane	39.9157437767599	32.8270941634899
MTA	39.9090486996796	32.7962690115671
Necatibey	39.9152066084294	32.8437950428813
ODTÜ	39.9080134213928	32.7840959236438
OSB- Törekent	39.9877471686397	32.5586545550208
OSTİM	39.9704130087718	32.7449577876105
Sıhhiye	39.9276909068732	32.8548496799674
Söğütözü	39.9109593942524	32.8077190051603
Şehitler	39.9964196335417	32.8612046321450
Tarım Bakanlığı - Danıştay	39.9072302285182	32.7499858449839
Ulus	39.9396177180966	32.8509547144680
Ümitköy	39.9053448044684	32.7086148273902
Yenimahalle	39.9618983785488	32.8043395557967

3.1. Shaking

In the shaking phase of the proposed algorithm, a random solution is constructed using two types of problem-specific neighborhood structures: γ-*AddHub* and λ-*SwapHub*.

The γ-*AddHub* neighborhood operator is applied when the number of rows in a given solution is less than P_h. To this end, we randomly select γ unused hubs and insert them into the solution by adding their covered commuters. We use three types of γ-*AddHub* moves and refer to them as 1-*AddHub*, 2-*AddHub*, and 3-*AddHub*.

The λ-*SwapHub* neighborhood operator is applied for swapping the current hubs in the solution with unused hubs. To this end, randomly λ hubs and their associated covered commuters from the solutions are swapped by randomly unused λ hubs and their associated covered customers. We employ 1-*SwapHub*, 2-*SwapHub*, and 3-*SwapHub*.

3.2. Local search and detecting infeasible solutions

The feasibility of a given solution is measured by considering the maximum number of e-hubs in metro stations (P_e), the maximum number of chargers in an e-hub (P_s), and the maximum number of total available chargers (Q). If a solution is infeasible, we apply the MakingFeasible procedure to make the solution feasible concerning infeasibility terms. The MakingFeasible procedure is called local search in our implementation. It is possible that by applying shaking operators, the generated solution becomes infeasible, and this approach helps to make the solution feasible.

4. Implementation and Results

In this section, we implement the model and VNS to determine e-hub locations using the commuter data provided by the Ankara Metropolitan Municipality (AMM) transport authorities. The data includes the home and work locations of 120 citizens selected for the pilot implementation. An optimization solver (CPLEX Optimization Studio 20.1) was employed to solve the formulated mathematical model based on the criteria and parameters set by the AMM authorities. All experiments were conducted on a computer with Intel Core i7-8700 3.2 GHz CPU and 32 GB RAM. VNS was coded in C# in Microsoft® Visual Studio 2019. The geographical locations of the Home and work selected 120 citizen and metro stations are illustrated in Figure 2. The coordinates of 47 metro stations are provided in Table 1.

The parameters set by the AMM authorities are provided in Table 2.

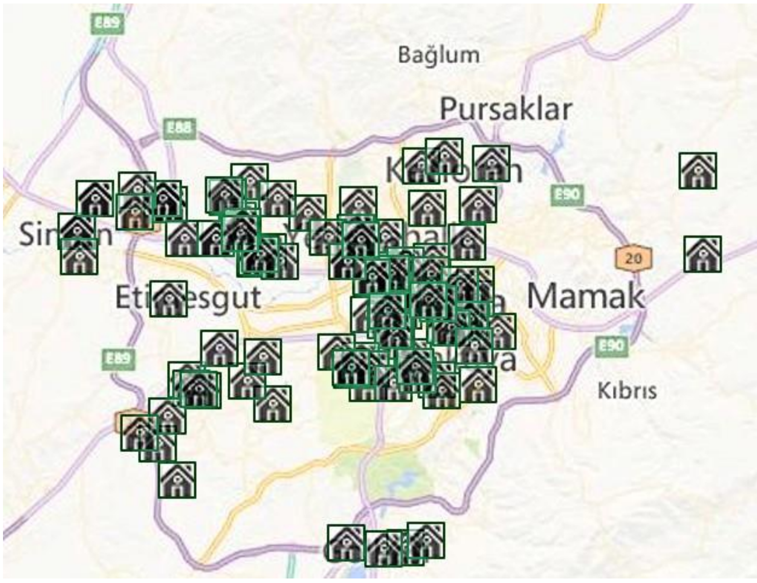
Table 2. Parameters set by the AMM

Walking distance threshold to the station	500 m
Maximum distance between a commuter and hub	500 m
Maximum number of hubs in districts	10
Maximum number of e-hubs in metro stations	10
Number of total commuters per charger installed	10
Maximum number of total available chargers	30

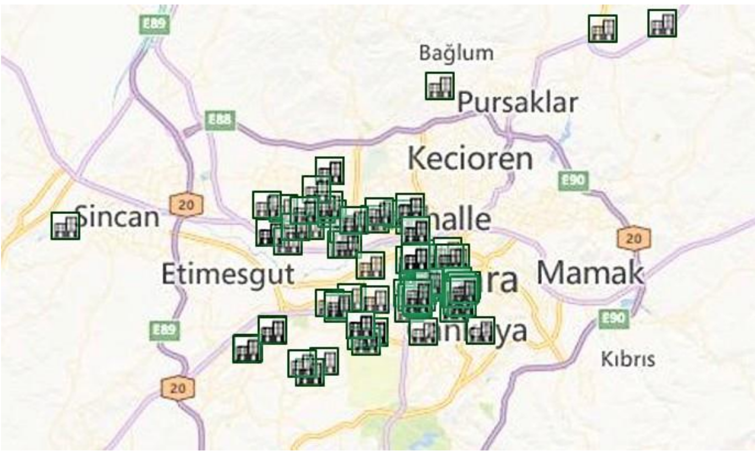
The field trials were performed for three weeks spanning the end of January and the beginning of February 2022, and ride data were collected from seven e-hubs given in Table 3.

Table 3. E-hub locations and numbers of installed chargers

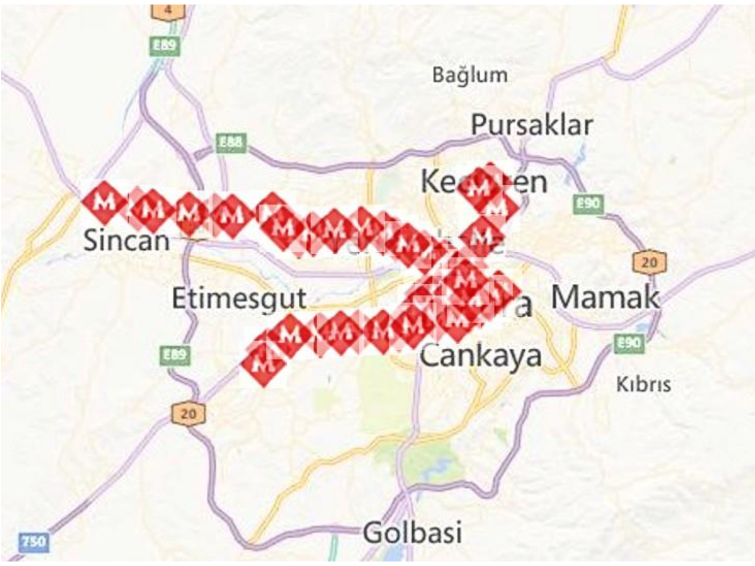
e-Hub Location	Abbr.	No. Charging
Bahçelievler Metro Station	BAH	12
Batıkent Metro Station	BAT	8
Bilkent Metro Station	BIL	14
Bicycle Campus	BIS	2
Kızılay Metro Station	KIZ	8
Koru Metro Station	KOR	8
National Library Metro Station	MIL	8



Home Locations



Work Locations



Metro Station Locations

Figure 2. The geographical locations of the Home and work and metro stations

An interruption during five consecutive days occurred because of harsh weather conditions and below 0 ºC ambient temperature levels. Therefore, the data belongs to the net two weeks. Forty-five users performed a total of 230 rides using the magnetic cards provided. We excluded the rides with more than one-minute duration, assuming they do not correspond to actual micromobility trips. The data is summarized in Table 4.

Table 4. Ride data*

	To:								Unidentified
From:	BAH	BAT	BIL	BIS	KIZ	KOR	MIL	Total	Attempts
BAH	19			1	2		10	32	61
BAT		20		4			1	25	8
BIL	2		14	1	3	4	1	25	20
BIS		5		23	3	2	2	35	-
KIZ	3		1	3	32	2	7	48	114
KOR			7	1	1	17		26	24
MIL	8		2	3	10		16	39	44
Total	32	25	24	36	51	25	37	230	271

* Excluding trips < 1 min

Almost 40% of the trips correspond to the Kızılay metro station and Bicycle Campus, whereas only 17% (ten out of 60) chargers were installed in those two e-hubs. Although the trials took place with only 25 e-bikes, the ride data points out a need for repositioning existing chargers and/or installing additional chargers at Kızılay metro station, which is located at the heart of Ankara city center and also at Bicycle Campus, which is a central attraction point for bike commuters. On the other hand, the data shows that the demand at Bahçelievler and Bilkent metro stations was overestimated as 43% of the charging units were installed at these two locations while 25% of the rides took place. The last column in

Table *4* reports the number of attempts to unlock the e-bikes using unidentified magnetic cards and AMM public transportation cards. This data shows the interest of the citizens in this new e-bike sharing system, with 42% occurring in Kızılay, a significant business and entertainment district. The collected ride data is also visualized in Figure 3. In this Figure, the sizes of the circles representing the e-hubs and the widths of the connecting arcs are proportional to the number of trips.

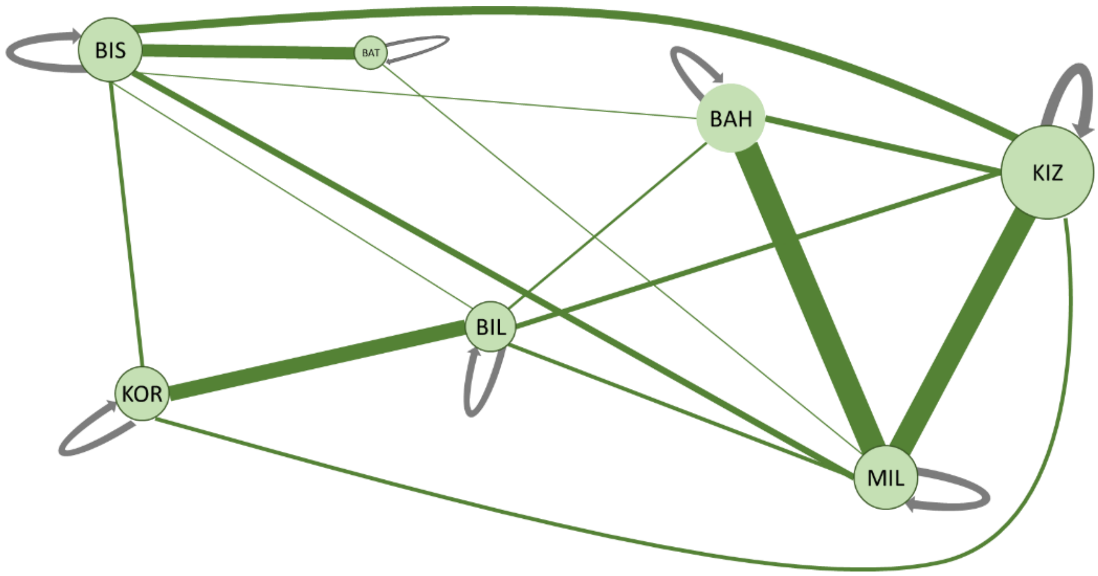


Figure 3. Ride volumes

The number of installed chargers in metro stations is illustrated in Figure 4.

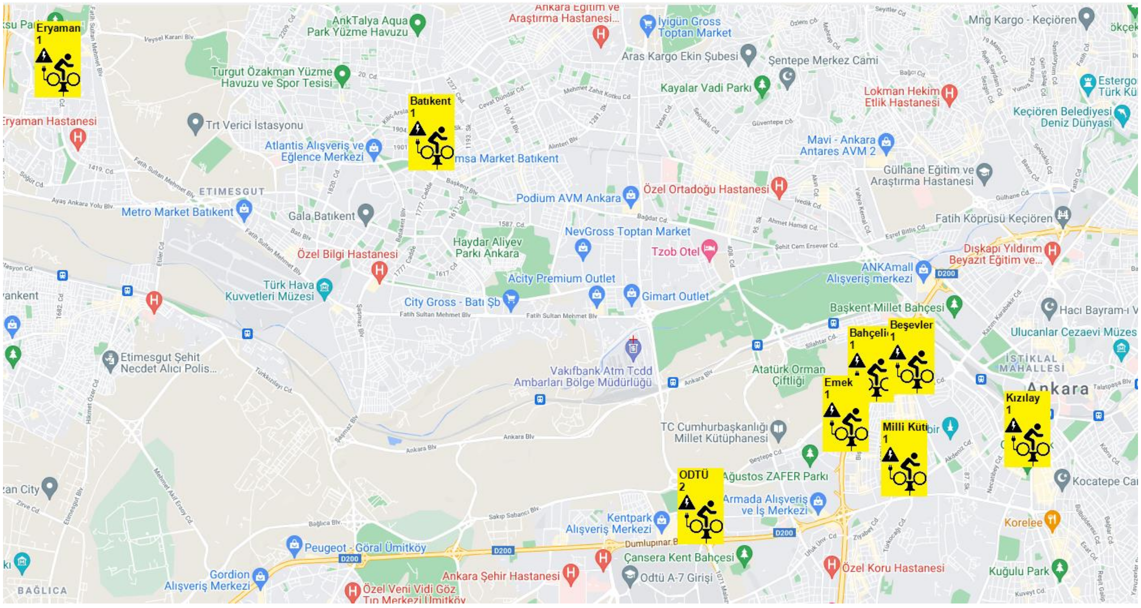


Figure 4. The number of installed chargers in seven metro stations

5. Conclusion

This paper presents the integration of connected micromobility infrastructure into the existing public transport system. The integration purpose was to help organize the public space in the urban environment, lower operation costs for micromobility operators, and create a better Mobility-as-a-Service (MaaS) experience for citizens with the connected and universal Micormobility charging infrastructure solution. Our goal was to efficiently consolidate the electric-powered shared micromobility vehicles into hubs to manage their charging and maintenance operations efficiently. Therefore, determining the locations of these e-hubs and the required charging infrastructure is of paramount importance for satisfying the needs of the commuters. We formulated the problem as a mixed-integer linear programming (MILP) and developed a Variable Neighborhood Search (VNS) metaheuristic algorithm to solve the problem. The evaluation of the performance of the solution methodology was applied using real data from Ankara Metropolitan Municipality (AMM) and comparing our solution with the optimal solution. The pilot trials took place in a short time frame and under unfavorable weather conditions that adversely affected the utilization of the e-bikes. More meaningful and insightful data could have been collected in warm and mild conditions. The collected data support the location decisions. Installation of e-hubs near metro stations and at the Bicycle Campus provided visibility to both users and citizens. It promoted the utilization of e-bikes as an alternative transportation mode to the metro and public road transport. On the other hand, the sizing decisions, i.e., determining the number of charging units at each location, may be revised to enhance the employment of the bike-sharing system. The performance of ehubs near metro stations and at Bicycle Campus facilitated using e-bikes to replace public transportation and metro transport. On the other side, the sizing options, i.e., calculating how many charging units are located at each location, may be varied to enhance the utilization of the bike-sharing system.

Researchers' Contribution Rate Statement

All research and writing steps belong to the corresponding author.

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Conflict of Interest Statement, if any

There is no conflict of interest with any institution or person within the scope of the study.

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