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Optimization of Shared Electric Scooter Deployment Stations Based on Distance Tolerance

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Abstract: The proliferation of shared electric scooters (E-scooters) has brought convenience to urban transportation but has also introduced challenges such as disorderly parking and an imbalance between supply and demand. Given the current inconsistent quantity and spatial distribution of shared E-scooters, coupled with inadequate research on deployment stations selection, we propose a novel maximal covering location problem (MCLP) based on distance tolerance. The model aims to maximize the coverage of user demand while minimizing the sum of distances from users to deployment stations. A deep reinforcement learning (DRL) was devised to address this optimization model. An experiment was conducted focusing on areas with high concentrations of shared E-scooter trips in Chicago. The solutions of location selection were obtained by DRL, the Gurobi solver, and the genetic algorithm (GA). The experimental results demonstrated the effectiveness of the proposed model in optimizing the layout of shared E-scooter deployment stations. This study provides valuable insights into facility location selection for urban shared transportation tools, and showcases the efficiency of DRL in addressing facility location problems (FLPs).

Keywords: shared electric scooters; multi-criteria decision making; maximal covering location problem; distance tolerance; deep reinforcement learning

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1. Introduction

In recent years, the flourishing micro-mobility market has provided a new solution to urban transportation issues [1–5]. Shared E-scooters, as representative micro-mobility vehicles, have been widely used in cities around the world for their compactness, mobility, easy maneuverability, and adaptability to urban environments [6], which can bring convenience and efficiency to urban travel by saving travel time and reducing traffic congestion [7–9]. This trend is expected to continue growing, driven by increasing demand in urban areas [10,11].

However, the widespread adoption of shared E-scooters comes with a series of problems. The use of dockless operating systems for shared E-scooters services leads to irregular parking, occupying urban space, hindering the normal use of public facilities [12], and seriously affecting the safety and comfort of pedestrians [13]. This not only disrupts urban order and negatively impacts traffic fluency but also increases the management difficulty for shared E-scooter providers. In addition, in areas with high population density, higher education levels [14], and diverse entertainment needs [15], a large number of shared E-scooters have been deployed, with some vehicles having relatively low usage rates or being idle on the streets. In contrast, in areas with lower socioeconomic levels but with demand for shared E-scooters, there may be a lack of corresponding shared E-scooter deployment stations [16]. The unreasonable quantity and spatial layout of shared E-scooter deployments make it challenging for users to access shared E-scooters, thus reducing the quality of the travelling experience.

To better meet the travel demand of users in different regions, increase the utilization rate of shared E-scooters, reduce improper parking behavior, and improve the travel experience of urban residents, it is crucial to research the travel demand for shared E-scooters and deployment stations selection. In previous studies, the analysis of potential demand for shared E-scooters often considered the demand within a certain distance range as the same, without considering the potential impact of distance on the intensity of demand. Therefore, we propose a Distance Tolerance MCLP, which fully considers users' acceptance of walking distance to shared E-scooter deployment stations. In our study, Chicago serves as the study area. By analyzing shared E-scooter travel patterns, target users, traffic conditions, and points of interest (POIs) within Chicago, we utilize DRL to ascertain the optimal layout for deploying shared E-scooter stations in the study area, thus validating the efficacy of our model. Our study provides decision support for optimizing the urban micro-mobility layout for the Chicago city government and vehicle dispatching for shared E-scooter providers. Additionally, it offers an efficient solution for FLPs.

The main contribution of our study is as follows:

- Introduces a novel MCLP based on distance tolerance for shared E-scooter deployment.
- Introduces a novel algorithm based on DRL to optimize location.
- Evaluates the effectiveness of the model and algorithm through experimentation.
- Provides decision support for optimizing urban micro-mobility layout and vehicle dispatching.

The subsequent sections of the paper unfold as follows. Section 2 scrutinizes relevant studies, highlighting disparities with the current research. Section 3 introduces the model, elucidating the Distance Tolerance MCLP and the DRL. In Section 4, an empirical experiment is executed in Chicago. Section 5 discusses and interprets the results derived from the experiment. Finally, Section 6 concludes the study, summarizing key insights and suggesting future research directions.

2. Related Works

2.1. Factors Influencing E-Scooter Travel

Shared E-scooters and shared bicycles have garnered widespread attention, as emblematic of dockless shared micro-mobility. By reviewing the existing literature, we can identify some factors influencing the use of shared E-scooters and bicycles, which provides a direction for determining the indicator of our study.

Demographic factors play a crucial role in shaping the demand for shared E-scooters. Research by Bai and Jiao [14,15] illustrated that areas characterized by higher population density, a more educated populace, proximity to the city center, convenient transportation options, and diverse land use exhibit increased shared E-scooter usage. Hosseinzadeh et al. [17] found that land usage, age distribution, gender distribution, walking scores, and park scores influence the travel density of shared E-scooters in Louisville, Kentucky. Additionally, studies by Cao et al. [18] and Laa et al. [19] found that shared E-scooter users are more likely to be young, male, with a higher income, and educated.

Furthermore, weather conditions significantly influence the use of shared E-scooters and bicycles. Hosseinzadeh et al. [20] demonstrated the impact of factors like weather, day of the week, holidays, and special events on travel frequency in Louisville, Kentucky. Hamed et al. [21] identified the intensity and duration of rainfall as critical factors influencing the variation in demand for shared bicycles. Abouelela et al. [22] found that external factors such as weather, day of the week, infrastructure, socio-demographic, land use, and traffic accessibility all significantly influence shared E-scooter demand by comparative analysis of shared E-scooter trip characteristics in five cities in North American. Moreover, Kimpton et al. [23] revealed that shared E-scooter usage increases with warmer weather but decreases with rainfall, and the distance travelled is shortened during periods of inclement weather. In contrast, Noland's studies indicated that shared E-scooters are less affected by rainy weather compared to other micro-mobility [24], that there was a significant correlation between rain and snow and a reduction in travel frequency, while wind speed and average temperature showed negligible impacts [25].

Several studies have explored the influence of the built environment on shared E-scooters and bikes, encompassing land use characteristics such as transportation facilities, road network, residential and population distributions, commercial, industrial, educational, and cultural facilities [26–31]. Yu et al. [32] investigated the associations between shared bicycle activities and four categories of urban facilities. Bieliński et al. [33] and McKenzie [34] compared the use patterns of shared E-scooters and bicycles and found that shared E-scooters are mainly used for leisure travel. Jin et al. [35] investigated the non-linear relationship between the built environment and shared E-scooter link flows, highlighting variables like distance to the city center, types of bike facilities, slope, speed limits, and street trees as crucial determinants of shared E-scooter travel behavior. Additionally, Huo et al. [36] found that shared E-scooter ridership decreases with distance to the city center.

Travel time also influences the use of shared micro-mobility. Guevara et al. [37] delineated three components of travel time: waiting time, walking time, and trip time. Shared micro-mobility is typically utilized to conveniently and quickly address the need to travel short distances, so users may be less willing to walk longer distances to access vehicles as they use themselves as a reference point [38,39]. In North America, a 5 min walking distance to bus stations and shared bicycle stations is generally deemed acceptable, equivalent to approximately 400 m [40,41]. For shared bicycles or electric bicycles, the acceptable walking distance for users typically falls within the range of 200–500 m [42–44], whereas for shared E-scooters, users' tolerance for walking distances is even shorter, usually not exceeding 300 m [44–49]. Additionally, as trip time increases, users prefer to use electric bicycles [50–52].

In summary, a multitude of factors profoundly influence the usage dynamics of shared E-scooters, encompassing demographic characteristics, weather conditions, the built environment, and travel time. In light of data availability, we delineated 13 key influencing factors from three perspectives: transportation accessibility, population density, and land use, such as fundamental transport stations, sidewalks, population density, land use types such as shopping malls, parks and attractions, hospitals, schools, etc.

2.2. Facility Location Problems

FLPs have garnered significant attention from researchers, encompassing various variants such as the p-Median problem, which aims to minimize the weighted distance between demand points and facilities [53]; the p-Center problem, which aims to minimize the maximum distance from facilities to demand points [53]; the location set coverage problem, targeting the minimization of facility location costs while achieving specified coverage levels [54]; and the maximal covering location problem (MCLP) aiming to maximize the demand within the coverage radius for a fixed number of facilities [55]. Some of the comparative studies of the p-Median problem and the MCLP [56–58] showed that the p-Median problem has advantages in spatial fairness, while the MCLP excels in efficiency [58]. When the coverage threshold is low, the MCLP has advantages in maximizing demand, while for larger coverage ranges, p-Median is the preferred choice [57].

The MCLP has demonstrated outstanding performance in coverage efficiency [31,56,59,60] and has been widely applied in the location selection of shared economy facilities. Some studies focused on accessibility factors to evaluate the accessibility of residential areas to shared bike and public transportation networks. Ebrahimi et al. [61] employed the Maximize Coverage and Minimize Facility method, optimizing the facility count while maximizing service coverage, to identify shared bike potential docking stations. Additionally, based on building environments and accessibility, optimal locations for stations in bike sharing systems were modeled [62]. The determination of new bike station locations considers demand and spatial fairness [63], and the potential spatial distribution of travel demand was taken into account to determine docking station locations for docked shared bikes [64]. Moreover, a study explored the optimal location of shared bike stations considering budget constraints [59].

Improving the MCLP is also a research focus. To model certain dynamic features of the problem, Gunawardane [65] proposed a dynamic variant or multi-period MCLP, aiming to maximize coverage over all time periods. Yang et al. [66] established a spatial-temporal coverage optimization model based on the space–time demand cube, finely characterizing the spatiotemporal dynamics of user demands. Li et al. [60] introduced the Balanced MCLP, considering the resultant quality lower bound and balanced service level, etc.

2.3. Location Selection Optimization Algorithms

FLP is an NP-Hard combinatorial optimization problem, and as the problem scale increases, the solution time increases exponentially. Researchers have proposed approximate solutions, exact solutions, and heuristic algorithms, such as GA, ant colony algorithms, particle swarm algorithms, and greedy randomized adaptive search procedures. The application of heuristic algorithms in FLPs has matured relatively.

With the rapid development of machine learning, innovations have emerged in FLPs. Some researchers have applied machine learning and deep learning to predict demand and solve FLPs. For instance, the suitability index for optimal astronomical observatory sites was obtained through the integration of random forest and gradient tree boost [67], GIS and support vector machines were used to predict potential locations of convenience stores [68], the Markov chain was used to predict the demand for shared bicycle stations [69], deep learning was used to predict the demand for shared E-scooters [70], neural networks were used for business location selection [71,72], graph convolutional networks and greedy algorithms were combined to solve the p-Center problem [73], and Gaussian processes and machine learning were used to find electric vehicle charging stations [74].

Compared to traditional heuristic algorithms, machine learning optimizes decision models for location selection and integrates multi-source geospatial big data, enabling spatial analysis, prediction of urban spatial morphology, and real-time updates. And in this field, DRL has demonstrated unique advantages.

DRL combines the technologies of deep learning and reinforcement learning, effectively handling large-scale and high-dimensional geographic big data and extracting critical features. Through the trial-and-error learning process of reinforcement learning, it can seek optimal solutions in complex environments. Researchers have introduced DRL into FLPs, such as Wang et al., who applied DRL to solve the p-Median problem [75], the MCLP problem [76], and the location-routing problem [77], obtaining feasible solutions. Liang et al. [78] designed a unified framework, SpoNet, combining the characteristics of location problems with a deep learning to solve the p-Median problem, p-Center problem, and MCLP. Zhong et al. [79] proposed a ReCovNet for reinforcement learning using covering information to solve the maximal coverage billboards location problem.

Shared E-scooters, as an emerging mode of shared mobility, have had relatively limited research on location selection. Some studies use data-driven clustering algorithms to identify high-demand parking locations for shared E-scooters in the case of user demand only and both user demand and built environment factors [80]. And the rest mainly focus on multi-criteria decision-making based on fuzzy logic for location selection [30,81,82], such as the integrated Interval 2-Type Fuzzy BWM-MARCOS model [82] and the Pythagorean fuzzy-SWARA and Pythagorean fuzzy-CODAS frameworks [83]. These models consider multiple factors, including land use, traffic networks, POIs, and socioeconomic information to determine the optimal locations for shared E-scooter deployment stations or charging stations.

Overall, significant progress has been made in the FLPs of shared transportation facilities, but there is relatively less research on the location selection of shared E-scooters. Most studies in this field employ evaluation methods for location selection, with fewer studies applying optimization models, and the majority are simple extensions of basic models, lacking innovative research on optimization models. Therefore, we propose to establish a maximal coverage location problem model with the optimization objective of maximizing coverage of user demand and minimizing the sum of distances from users to deployment stations, and use DRL to solve the model. An experiment is conducted in a region of Chicago with high travel intensity of shared E-scooters to validate the effectiveness of the model and algorithm.

3. Methodology

3.1. Formulation of the Problem

To address the current issue of mismatched distribution of deployment stations and demand for shared E-scooters, it is necessary to establish a rational location selection model to achieve the optimal allocation of shared E-scooters with the constraint of satisfying user demand. For dockless shared mobility, the parking locations of shared E-scooters exhibit high variability, dispersing and aggregating based on user usage in residential, commercial, and business areas. Therefore, the distribution range of deployment stations should be as extensive as possible, with a sufficient quantity to ensure the fulfillment of user demands for pick-up and drop-off at various locations. Considering the cost of operation and construction, as well as traffic circulation, the number of deployment stations should not be excessive. We introduce MCLP [55], aiming to maximize user demand through a certain number of deployment stations and enhance the utilization efficiency of the stations.

The MCLP makes a group of facilities maximize the coverage of the target area by cleverly setting the number of facilities and coverage radius. However, nearly all MCLPs assume a binary perspective regarding coverage, whereby if the distance between demand points and service facilities is less than the coverage radius, it is considered completely covered; otherwise, it is not covered [84]. This simplistic treatment of distance fails to account for users' tolerance thresholds regarding facility proximity, resulting in instances where certain facilities, although capable of covering a substantial user base, exceed users' travel tolerances, consequently leading to low actual utilization rates and suboptimal user experiences. In contrast to public transportation, users are more sensitive to the distance of dockless shared E-scooter deployment stations, with an accepted threshold typically not exceeding 300 m. Thus, in the process of optimizing layout decisions, it is imperative to ensure the distance acceptance of users for shared E-scooter deployment stations.

The traditional MCLP predominantly focuses on meeting the travel demand of shared E-scooters quantitatively while disregarding users' perceptions of the convenience of deployment stations. Therefore, we propose a Distance Tolerance MCLP, which comprehensively considers users' tolerance for deployment station distances, taking maximizing coverage of user demand and minimizing the sum of distances between users and deployment stations as the optimization objectives, so that the accessibility and convenience of users to shared E-scooter deployment stations are perceived as the best.

3.2. Distance Tolerance MCLP

To formulate shared E-scooter deployment stations covering location model, the parameters and symbols involved in the model are defined as follows:

- Sets:

  I: the set of demand points for shared E-scooters.
  J: the set of candidate points for deploying shared E-scooters.
  N_i: the set of candidate points covering demand point i.

- Parameters:

  i: a demand point for shared E-scooters.
  j: a candidate point for shared E-scooters.
  d_{ij}: the walking distance from demand point i to candidate point j.
  D_{max}: the maximum covering distance from any demand point to a shared E-scooter deployment station.
  $F(d_{ij})$: the distance tolerance function.
  p: the number of candidate points to be established.

S: the maximum covering distance for candidate point j.
w_i: the demand intensity for demand point i.
Y_{ij}: the coverage status of whether demand point i is covered by candidate point j.
The distance tolerance function is defined as follows:

When the distance from the user to the deployment stations is within d_a meters, the user's acceptance of that deployment station is optimal. When the distance exceeds d_a meters but is within d_b meters, the user acceptance decreases with increasing distance. When the distance surpasses d_b meters, the user's acceptance of that deployment station is 0.

$$F(d_{ij}) = \begin{cases} 1 & d_{ij} \le d_a \\ \frac{1}{2} + \frac{1}{2}cos\left[\frac{\pi}{d_b - d_a}\left[d_{ij} - \frac{d_b + d_a}{2}\right] + \frac{\pi}{2}\right] & d_a < d_{ij} \le d_b \\ 0 & d_{ij} > d_b \end{cases} \tag{1}$$

The following mathematical model is formulated:

$$Max \sum_{i \in I} \sum_{j \in J} w_i F(d_{ij}) Y_{ij} \tag{2}$$

$$Min \sum_{i \in I} \sum_{j \in J} d_{ij} Y_{ij} \tag{3}$$

$$Y_{ij} \le \sum_{j \in N_i} X_j \quad \forall i \in I \tag{4}$$

$$\sum_{j \in J} X_j = p \tag{5}$$

$$\sum_{j \in J} d_{ij} Y_{ij} - D_{max} \le 0, \forall i \in I \tag{6}$$

$$\sum_{j \in J} Y_{ij} = 1 \tag{7}$$

$$X_j,\ Y_{ij} \in \{0, 1\} \quad \forall i \in I, \forall j \in J \tag{8}$$

Constraint (4) ensures that each demand point is covered by at least one candidate point. Constraint (5) limits the number of deployment stations to p. Constraint (6) ensures that the distance from any demand point to a candidate point is less than the maximum covering distance. Constraint (7) specifies that each demand point must be covered by at least one candidate point.

$$X_j = \begin{cases} 1 & if\ a\ station\ is\ located\ at\ j \\ 0 & otherwise \end{cases} \tag{9}$$

$$Y_{ij} = \begin{cases} 1 & if\ demand\ point\ i\ is\ covered\ by\ j \\ 0 & otherwise \end{cases} \tag{10}$$

$$N_i = \{\, j \in J \mid d_{ij} \le S \} \tag{11}$$

In this model, the first objective is to maximize the coverage of demand points by maximizing the total weight of demand. The second objective is to minimize the distances between users and deployment stations, including the pick-up and drop-off distances. To unify these objectives, a linear weighted approach [85] is employed:

$$Max \quad w_1 \sum_{i \in I} \sum_{j \in J} w_i F(d_{ij}) Y_{ij} - w_2 \sum_{i \in I} \sum_{j \in J} d_{ij} Y_{ij} \tag{12}$$

where w_1 and w_2 are weight coefficients, and $w_1 + w_2 = 1$. The values of w_1 and w_2 are set to 0.6 and 0.4.

3.3. Deep Reinforcement Learning

In the realm of DRL, an intelligent agent engages with its environment, employing a trial-and-error methodology to learn decision-making strategies aimed at maximizing cumulative rewards. This iterative process involves five essential components: the Agent, the Environment, the State, Action, and Reward. We adopted the Attention Model proposed by Kool et al. [86] and employed the REINFORE algorithm with a greedy rollout baseline for model training.

The algorithm's design unfolds as follows:

Objective: Maximize the coverage of demand points while minimizing the distance between users and shared E-scooter deployment stations.

States: Represent the environment's state, including the locations of potential deployment stations, demand points, and their respective weights.

Actions: Define possible actions as the selection of locations to establish shared E-scooter deployment stations.

Rewards: Design a reward function according to Formula (12) that integrates travel demand and distance tolerance.

Model: Utilize the Attention Model to estimate the policy $p_\theta(\pi|s)$, where θ represents model parameters, π is the action sequence, and s is the current state. Incorporate problem-specific features (e.g., locations, demand, distances) into the model's encoder to generate node embeddings. Sequentially select deployment station locations based on the decoder's output, ensuring that the action choices align with the problem's constraints.

Baseline: Utilize the deterministic greedy rollout of the policy to estimate the baseline, reducing the variance of the reward.

Reinforce: Compute the policy gradient using the difference between obtained reward and baseline, adjusting the model parameters to maximize expected rewards. Use Adam optimizer [87] to update the model parameters based on the computed gradients.

Training Loop: For each epoch, sample a set of instances, perform action selection, calculate rewards, and update the model using the REINFORE algorithm. Stop training when there is minimal change in the reward function value or when the maximum number of epochs is reached.

Validation: Periodically validate the model against a separate set of instances to ensure generalization and avoid overfitting.

4. Experiment

4.1. Study Area

Chicago is one of the largest cities in the state of Illinois, USA, with a large population, a developed economy, and busy traffic. It serves as a pivotal hub for commerce and transit in the northeastern USA. In 2019, Chicago launched a shared E-scooter pilot program [88]. We utilized the entire trip dataset provided by three operating companies, Lime, Bird, and Spin, during the pilot program period from 12 August 2020 to 10 December 2020 [89]. This dataset comprises a total of 630,816 trips. To ensure data reliability and accuracy, trips with missing start or/and end location data, zero total mileage within two minutes, durations of less than one minute, and those exceeding two hours were excluded [13,34,90]. The final dataset retained 596,504 trips, accounting for 94.56% of the total trips.

To safeguard user privacy, the start and end locations of the trips were processed to correspond to the centroid positions of census tracts [91]. Thus, we investigated the spatial distribution and clustering patterns of shared E-scooters in Chicago by quantifying the count of shared E-scooter trips within each census tract. The results indicated that shared E-scooter trips were predominantly clustered in the northern and eastern parts of the city, including areas such as West Town, Lincoln Park, Lake View, and surrounding census tracts like Logan Square, West Town, and Near North Side. These areas are close to the Chicago Loop, featuring large shopping centers, numerous headquarters of well-known companies, high-quality schools, hubs of public transportation systems, and famous landmarks. The diverse land use types and dense population movements in these areas contribute to a significant demand for shared E-scooters. Therefore, we selected the areas with clustered shared E-scooter trips as the focus of the experiment, as shown in Figure 1.

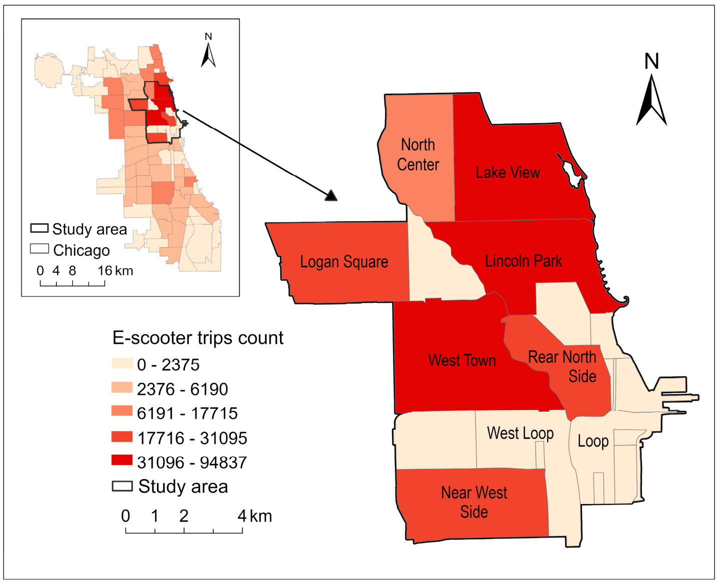


Figure 1. The count of shared E-scooter trips and the census tracts of the study area. Darker colors correspond to a greater number of trips.

4.2. Extract Potential Demand Points

4.2.1. Divide Study Units

The road network is an essential component of urban transportation, influencing urban spatial structure, functionality, and socio-demographic diversity [92,93]. In urban planning and design, different road types typically serve distinct functional zones, so it is reasonable and effective to consider parcels based on the distribution of the road network as study units [94–97].

In our study, guided by the street division regulations of the Illinois Department of Transportation (IDOT) [98] and the Chicago Metropolitan Agency for Planning (CMAP) [99], and considering the actual situation of the study area, the road network was classified into three levels, generating buffers with widths of 40 m, 20 m, and 10 m. The combination of these three buffer zones forms a complete spatial road network. Through erasure, splitting processes, and result cleaning, a total of 2370 study units were obtained.

4.2.2. Evaluate Study Unit Demand

To assess the intensity of users' demand for travelling with shared E-scooters, it is necessary to comprehensively consider the influence of the surrounding environment. We took into account POIs, including public transportation, education and culture, business and shopping, national landmarks, and healthcare. These data were provided by the Chicago Data Portal [89]. In addition, population data were derived from the World Pop website [100], providing population weighted-density grid data with a resolution of 100 m.

The Analytic Hierarchy Process (AHP) was employed to evaluate the demand, with the optimal location selection as the goal level, factors such as transportation convenience, population density, and land use as the criteria level, and 13 influencing factors (Table 1) as the sub-criteria level. The relative importance of these factors was determined by expert subjective judgments and quantitative comparisons, and the final evaluation results were obtained through mathematical calculations.

Firstly, standardization was applied to public transportation stations, POIs, and different land use data. According to the law that similar things are more relevant, linear fuzzy membership functions for Euclidean distance grids were determined, with the minimum and maximum parameters for each sub-criterion shown in Table 1. The minimum value of the distance parameter was defined as 1, and spatial membership gradually decreased with increasing distance. For instance, the spatial membership of a train station is 1, gradually decreasing as the distance from the train station increased, reaching 0 when the distance exceeded 500 m. The maximum distance for sidewalks and bike lanes was limited to 100 m [101], and the distance between public transportation stations and POIs was restricted to within 500 m [102]. Regarding population density data, the membership of the maximum population density was defined as 1, and the minimum value was defined as 0, as population scale correlates positively with travel demand.

Table 1. The influencing factors, minimum and maximum parameters of linear fuzzy membership functions, and AHP weights.

Base Data	Derived Criteria	Min (m)	Max (m)	Weight
Railway stations	Distance to railway stations	500	0	0.0675
Metro stations	Distance to metro stations	500	0	0.1722
Bus stations	Distance to bus stations	500	0	0.1722
Bicycle stations	Distance to bicycle stations	100	0	0.0285
Sidewalks	Distance to sidewalks	100	0	0.0317
Population	Density population	min	max	0.0828
Shopping mall	Distance to shopping mall	1000	0	0.1468
Pedestrian streets	Distance to pedestrian streets	500	0	0.0372
Parks	Distance to parks	1000	0	0.0575
National landmarks	Distance to national landmarks	1000	0	0.0654
Hospitals	Distance to hospitals	1000	0	0.0255
Schools	Distance to schools	500	0	0.0917
Industries	Distance to industries	500	0	0.0210

The AHP judgment matrix was presented to five experts for scoring. The average score for each influencing factor was calculated and rounded to obtain the scoring matrix. Subsequently, the AHP weights were calculated by the SPSS PRO, and the results underwent consistency checks. Table 1 presents the influence weights of each factor. Employing a raster calculator, the spatial membership grids of sub-criteria were overlaid with corresponding AHP weights to generate a land suitability map (Figure 2). A suitability index of 1 indicates an ideal location for shared E-scooter deployment, while a suitability index of 0 indicates an unsuitable location. With the centroid of the study unit as the demand point, a total of 2370 demand points was identified, and their demand intensities were assigned based on the suitability index values.

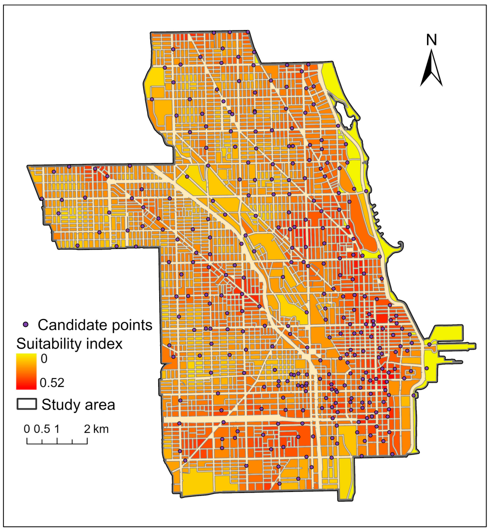


Figure 2. The suitability map of study units. The study area is divided into several units based on different levels of road network buffers.

4.3. Selecting Candidate Points

Due to the privacy measures applied to shared E-scooter trip data, we utilized shared bicycle trip data, which exhibit similar travel patterns to shared E-scooters, to identify candidate points. The shared bicycle trip data provided by the Divvy company includes geographic coordinates of user origin and destination points. For the purpose of this study, all shared bicycle trips from September 2020 were selected as the dataset. After cleaning the data for anomalies, the trip frequency for each station was calculated. Stations with a frequency exceeding 10 were selected as candidate points for shared E-scooters, resulting in 313 candidate points (Figure 2). These candidate points were utilized in the subsequent study to determine the optimal locations for deploying shared E-scooters.

4.4. Select Locations for E-Scooters Deployment

4.4.1. Set Parameter

We set the maximum walking distance for shared E-scooter users at 300 m based on previous research, and the distribution of candidate points in the area and the coverage of demand points within various radius buffer zones are outlined in Table 2. Therefore, the distance tolerance function $F(d_{ij})$ was set with d_a = 50 m and d_b = 300 m. The maximum service distance for facility points was set as D_{max} = 300 m. The number of facility points was set as p = 50.

Table 2. The coverage rates of demand points for different coverage radius.

Radius (m)	200	250	300
Coverage rate (%)	32.98	46.71	59.45

4.4.2. Train the Reinforce Algorithm

We imported the demand points and candidate points data, generating 12,800 training samples and 2000 validation samples, set the epoch size to 12,800, configured 1000 training epochs, and trained 50 steps in each epoch. The convergence results of the algorithm are shown in Figure 3, illustrating the average reward–return curve across training epochs. As the number of training epochs increases, experience accumulates gradually, and the algorithm converges. By the 800th training epoch, the reward–return curve shows no significant changes, indicating convergence of the algorithm.

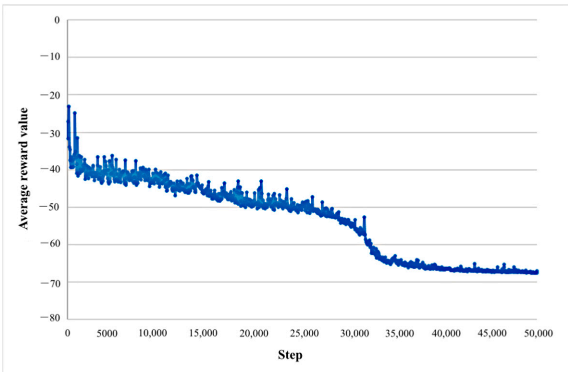


Figure 3. The curve of average reward returns across training epochs. The horizontal axis represents the training steps, corresponding to training epochs multiplied by 50. As the number of steps approaches approximately 40,000, the reward function gradually converges.

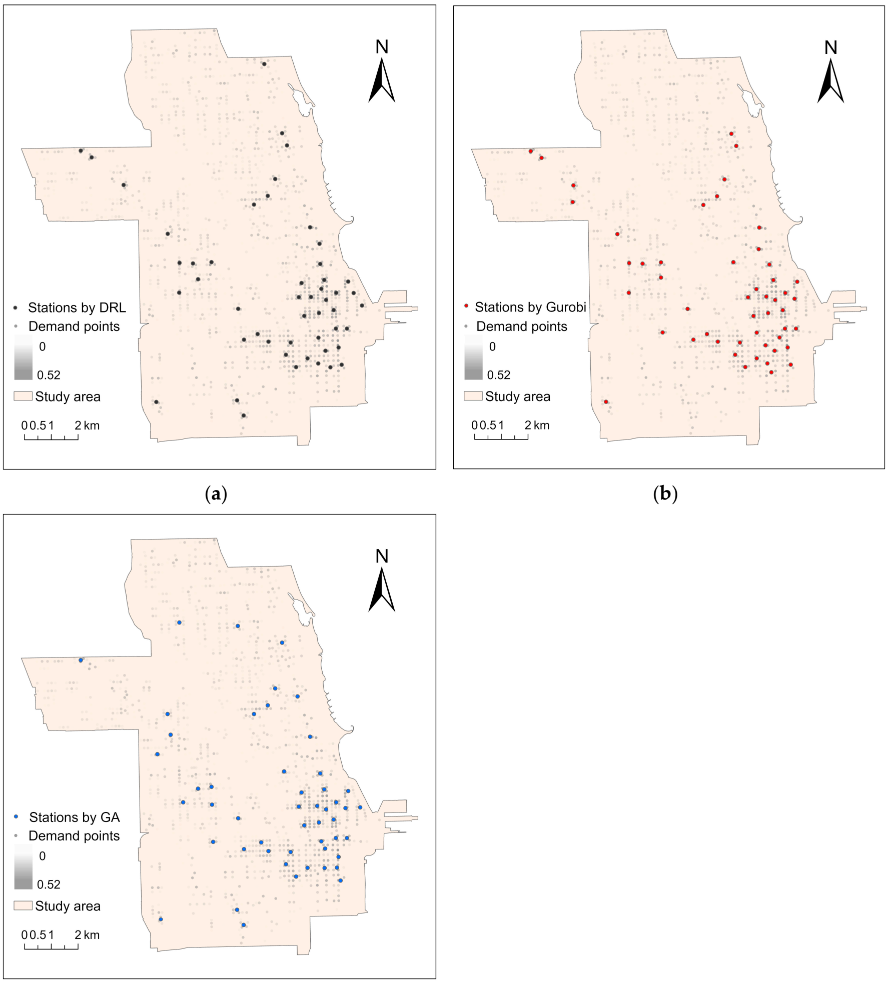
4.4.3. Results and Validation

The 992nd training epoch with the largest reward return value was selected for solving the Distance Tolerance MCLP. The results of shared E-scooter deployment stations aligned with the spatial characteristics of travel patterns, mainly distributed in the densely populated Loop and River North census tracts, exhibiting a uniform distribution pattern and avoiding excessive clustering. These points adequately covered demand points, achieving a coverage rate of 16.58%. The model's objective function value stood at 73.06, meeting the optimization requirements for deployment station selection.

To validate the effectiveness and feasibility of the DRL in FLPs, we compared and analyzed the results obtained by the Gurobi solver and the GA under the same conditions of scale and model parameters. The comparative analysis included the solving time, objective function value, demand points coverage rate (Table 3), and spatial distribution of deployment stations (Figure 4). The results of the Gurobi solver provided the best performance in terms of both objective function value and demand points coverage. The results of the DRL were slightly inferior to the Gurobi solver in terms of objective function value and demand point coverage, but were superior to the GA. This suggests that the DRL is able to provide a superior solution in FLPs.

Table 3. The comparative results of different solving methods.

Solving Method	Solving Time (s)	Objective Value	Coverage Rate (%)
DRL	0.47	73.10	16.58
Gurobi	13.50	74.21	16.88
GA	2.83	71.12	16.50



(**a**)

(**b**)

(**c**)

Figure 4. The results of different solving methods: (**a**) results of DRL; (**b**) results of Gurobi solver; (**c**) results of GA. Demand points are color-coded based on their demand intensity, with darker colors indicating higher demand.

5. Discussion

Shared E-scooters, as a mode of short-distance transportation, effectively bridge the first and last miles of public transportation, enhancing urban accessibility. However, for shared E-scooter users, accessibility refers to the convenience of obtaining shared E-scooters within their daily travel range. The perceived accessibility directly impacts their satisfaction and willingness to use shared E-scooters as a mode of transportation. Users typically choose shared E-scooters to reduce travel time, and if the walking distance is too long, it may decrease their satisfaction and even lead to abandonment. Therefore, based on the traditional MCLP, we considered the distance from the user's location to the shared E-scooter deployment stations, arguing that different walking distances lead to differences in user satisfaction, and employed the cosine function to quantify the complex non-linear relationship between walking distance and user satisfaction.

We employed the AHP to evaluate the user demand in the study area and found that users in the east and the south had a higher travelling demand (Figure 2), both of which are suitable regions for the location of shared E-scooter deployment. However, comparing the results of the three methods, we found that most deployment stations were concentrated in the eastern region, with only a few in the southern region. Due to the sparse distribution of shared E-scooter candidate points in the southern region, the accessibility of shared E-scooters is lower, and users need to spend more time walking to the nearest shared E-scooter deployment stations. Therefore, after considering the impact of walking distance, the actual demand for users in the southern region decreased, making it unsuitable for constructing a large number of deployment stations.

In FLPs, the selection of an appropriate coverage radius plays a crucial role in determining the quality of location results, especially when both demand points and facilities are limited. Based on the investigation conducted by Reck et al. [44–49], we set the maximum walking tolerance distance for users to shared E-scooters at 300 m. Although the results in Table 3 indicate a coverage rate of demand points below 17%, they represent the optimum solution for coverage found in this scenario. If the maximum walking distance is increased or the number of facilities is increased, our study would achieve a more considerable coverage rate.

Additionally, we introduced DRL into FLPs and compared the results of DRL, the Gurobi solver and GA. The results showed that in terms of objective function value and coverage, the gap between the results of DRL and Gurobi solver was smaller and they outperformed the GA. In terms of solution time, DRL showed a clear advantage, being more than 5 times faster than the GA and more than 20 times faster than the Gurobi solver, demonstrating its ability to solve quickly. Comparing the spatial distribution of the stations obtained by the three methods, we found that the overlap between the DRL results and the Gurobi solver results was high, but DRL selected one or two stations in the Lake View and Near West Side census tracts, which did not exist in the Gurobi solver results. Further analysis revealed that the Lake View and Near West census tracts had a very large count of trips, which indicates that the DRL results were more in line with the actual situation of users using shared E-scooters. Although its results were not as good as those of the Gurobi solver in terms of objective function value and coverage, it was better than the Gurobi solver in terms of spatial distribution uniformity. Of course, it is important to note the training time for deep learning. The rapid solution of DRL is based on long-term training. The results of the training significantly influence the effectiveness of the final solution. To promote the idea of DRL, further optimization of the algorithm, improvement of training efficiency, and refinement of training actions and reward algorithms are needed to achieve location results superior to other solving methods.

6. Conclusions

Aiming to improve the current distribution of shared E-scooter deployment stations and demand in Chicago, we proposed a maximal covering location problem model based on distance tolerance. This model considers the distance from the user's location to the shared E-scooter deployment stations, introducing a distance tolerance function to enhance the MCLP. By accurately reflecting the change of user demand with distance, it addresses a limitation of traditional coverage models, which prioritize quantity while overlooking the distance factor.

To validate the feasibility of the model, we designed a DRL based on the attention mechanism for our experiment. Our study focused on a high-usage area of shared E-scooters in Chicago. To accurately assess user demand, we comprehensively considered 13 key influencing factors, such as accessibility, population density, and land use, and used the AHP to determine the relative importance of each factor, which in turn led to the demand intensity of each demand point.

We chose Divvy shared bicycle stations as the candidate points for shared E-scooters, and used DRL to obtain the results of the shared E-scooter deployment stations, which coincided with the travelling spatial characteristics, and showed a uniform distribution characteristic. By comparing and analyzing the results with those of the Gurobi solver and the GA, we found that the results of DRL were better in terms of spatial distribution, which verified the efficiency of DRL in the field of FLPs.

Based on the results of the experiment, we suggest that the Chicago city government or shared E-scooter providers should consider user accessibility when designing shared E-scooter deployment, especially in areas close to the city center, with a variety of land use and high user demand, and design densely populated stations to reduce the user walking time. For the outskirts of the city, the deployment should be evenly spread to ensure equitable access to shared E-scooter services across Chicago's diverse districts. This strategy will enhance service coverage and cater to the varying needs of users throughout the city. In addition, predictive analytics can be used to predict the demand for different stations based on user travel patterns and demand to further optimize the deployment of vehicle resources and improve the station service level.

In summary, our study provides a practical and feasible model for shared E-scooter deployment stations selection and a solving method. It considered the impact of user demand and walking distance tolerance, offering a reliable basis for actual location selection decisions. However, there are some shortcomings in the study, such as the lack of actual geographic coordinates in the shared E-scooter trip data used, preventing a comparative analysis of the location optimization before and after deployment. The subjectivity inherent in the AHP scoring model hindered genuine result evaluation. Future studies can focus on collecting more detailed shared E-scooter trip data, utilizing objective evaluation models, optimizing the DRL, and comparing various location models and methods to validate the effectiveness of the Distance Tolerance MCLP and DRL, thus obtaining more efficient location optimization solutions.

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