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# Trajectory-interception based method for electric vehicle taxi charging station problem with real taxi data

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**ABSTRACT**

Taxi fleets are suitable for the first stage of deployment of electric vehicles (EV) because EV taxis can provide chances for more people to experience EV. However, the lack of charging facilities and limited operation range are barriers to the adoption of EV taxis. As EV taxis can charge when there is no passenger in the vehicle, the conventional origin-destination (OD)-based flow-interception method for the charging station problem is not appropriate. In this study, we present a new EV taxi charging facility planning model that uses the trajectory-interception method with real taxi trajectory data and electric vehicle operation data. Global positioning system (GPS) data from 1,000 vehicles (taxis) and taxi battery performance data from three EVs are used. We developed an optimization algorithm to find optimal charger distribution considering charger installation cost and waiting delay simultaneously based on the evolution algorithm. The results show that the maintenance cost of the chargers and the charging stations is more sensitive than the opportunity cost of taxis, including additional travel distance and time to minimize the total cost. The methodology proposed in this study provides a robust result for the charging station location problem and can be widely applied to other cities with similar situations.

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**KEYWORDS**
Charger allocation; charging station; EV taxi; trajectory-interception method

## 1. Introduction

Greenhouse gas (GHG) is an imminent global issue threatening the sustainability of human civilization. The field of transportation is one of the highest contributing sectors to GHG emissions and consumes a major portion of the world's energy. Moreover, the transportation sector is heavily dependent on petroleum as an energy source, and petroleum has high GHG emission. The transportation sector accounts for about 30% of the total GHG emissions in the United States (US EPA, 2006). One prominent way to reduce GHG emissions in the transportation sector is to promote the use of public transportation and to replace internal combustion engine (ICE) vehicles with more environmentally friendly vehicles with low emissions, such as electric vehicles (EV) and hybrid vehicles. Switching from ICE vehicles to alternative-fuel vehicles (AFV) is a technology-based GHG emission reduction policy. As EVs do not emit GHG during operation, except for electricity production, EVs are getting more attention as an alternative for ICE vehicles. To spread EVs, we need a successful model through which the general public can participate in and experience EV technology. In that sense, as a taxi drives 200–400 km per day and many passengers can experience taxi rides firsthand, EV taxis are thought to be the most suitable mode for triggering the spread of EVs. In Korea, the purchasing price of an EV taxi is not much higher than that of the general liquified petroleum gas (LPG) taxi because of the high government subsidy. (The LPG taxi price is approximately $20,000, EV taxi price is approximately $42,000, and the subsidy is about $20,000 shared between the Ministry of Environment, $15,000, and local government, $5,000. When purchasing an EV, acquisition taxes and bonds are free.) So, the EV taxi price is approximately $2,000 higher than the general LPG taxi in Korea. To improve the taxi industry, diverse feasibility studies of adopting EV taxis have been conducted in Korea. The lack of charging facilities and limited operation range are barriers to the adoption of EV taxis.

Among previous research studies on optimal allocation of AFV refueling stations, the *p*-median method and the flow interception refueling model (FIRM) are two of the more popular models (Upchurch & Kuby, 2010). However, we cannot utilize the previous research results because taxis have different than normal EVs in terms of input OD pair data used to find the optimal EV taxi charging facility location. Generally, taxis operate more than 12 h a day serving customer requests. EV taxis usually recharge after dropping off customers due to long charging time (normal charging, 4 h; quick charging, 30 min). Therefore, EV taxi charging is considered to occur when there is no passenger. The existing flow-based methods based on OD do not consider passenger presence, and this is not appropriate for the charging station problem for EV taxis. Also, EV taxis are different from other EV vehicles that can be charged once a

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day during the nighttime at home because EV taxi drivers usually run a long distance and operate during the nighttime as well as the daytime. In particular, real battery performance counts in determining the optimal locations of charging stations.

In this study we present a new charging facility planning method for EV taxis, which optimizes the location of chargers based on real taxi trajectory data and EV operation data. For this study, we used multiday taxi global positioning system (GPS) data that collected from 1,000 taxis and battery performance monitoring data of three EV taxis in Daejeon metropolitan city of South Korea. The approach of this article includes the following:

1. EV charging station allocation research with realistic charging scenarios from real taxi trajectory data, including passenger presence data, is used.
2. EV taxi battery SOC data acquired from real operation are used for simulation to determine charging demand locations.
3. Evolutionary algorithm (EA) is used to find the optimal deployment of chargers at candidate charging locations with realistic taxi operation cost estimation.

## 2. Literature review

The traditional location problem is to find the best location that gives the minimum cost for a new facility. Travel distance or incurred cost related to location (e.g., travel time or cost, demand satisfaction) is the basic criteria for evaluating the solution to the problem. Naturally, location problems are classified according to the types of distance evaluation. The set covering, maximal covering, *p*-center, and *p*-dispersion models are based on the maximum distance, and the *p*-median, fixed charge, hub, and maximum models are based on the total (or average) distance (Current, Daskin, & Schilling, 2002). Among these, the *p*-median and flow refueling model, which is an extension of the maximal set covering model, are the more popular models for optimal location determination for AFV stations (Upchurch & Kuby, 2010). In recent years, agent-based model or trajectory-interception methodology has been researched for the location problem.

The *p*-median method is basically an optimization model that locates *p* facilities and allocates demand from node *i* to facility *j* to minimize the total traveled distance (Hakimi, 1964; Revelle & Swain, 1970). Goodchild and Noronha (1987) applied the *p*-median model to the fuel station location problem. They used it as part of a multiobjective model for optimizing station location. Recently, as alternative fuels have entered into development, other researchers have reapplied the *p*-median model to locate hydrogen stations using a heuristic method (Nicholas, Handy, & Sperling, 2004; Nicholas & Ogden, 2006; Greene et al., 2008). Lin, Ogden, Fan, and Chen, (2008) also used the *p*-median model to develop the fuel travel-back approach, which computes fuel consumption from demand node *i* (instead of population) to candidate facility location *j*. This model uses vehicle miles traveled (VMT) data to minimize the total travel time to access a station.

The flow-interception location model (FILM) is an extension of the set covering methodology, developed by Church and Revelle (1974). It is used to find the minimum cost set of facilities from a finite set of candidate facilities; it is the most widely used model in the alternative vehicle refueling station problem. The FILM can be implemented as a path-based or a flow-based demand model as shown by Hodgson (1990) and Berman (1992). Kuby and Lim (2005) extended the flow-capture model to the flow-refueling model by considering the limited range of AFV for long-distance trips using multistop refueling. They pointed out that the FILP is not applicable if an AFV's range is shorter than their trip length. They introduced the flow-refueling location problem (FRLP), which explicitly considers the range of a vehicle and locates *p* facilities to maximize the captured traffic. Later, Kuby and Lim (2007) extended the FRLP problem and proposed a method to efficiently add candidate sites on the links to improve the quality of the solution model. Upchurch, Kuby, and Lim (2009) considered capacity constraints in their optimization. Kim and Kuby (2012) relaxed the FRLP to allow deviations from the shortest paths. An exhaustive search enumerating all facility combinations is not possible for computation limitations. Thus, more efficient computation algorithms were studied by many researchers (Wang & Lin, 2009; Wang & Wang, 2010; Capar & Kuby, 2012; MirHassini & Ebrazi, 2013; Capar, Kuby, Leon, & Tsai, 2013). These methods are based on the OD pair and on flow or path interception.

Most existing refueling models have ignored the constraints imposed by the driver's activities (Dong, Lie, & Lin, 2014). Therefore, the agent-based model (ABM) (Sweda & Klabjan, 2011; Dong et al., 2014) has come to be used in recent years because of its ability to capture both spatial and temporal patterns. Sweda and Klabjan (2011) presented an ABM method to identify patterns in residential EV ownership and driving activities for strategic deployment of new charging infrastructure. Later, Dong et al. (2014) proposed an activity-based approach using GPS-based multiday travel data for charging infrastructure planning. They used ABM to evaluate battery electric vehicle (BEV) feasibility for a heterogeneous traveling population in a real-world driving context. Acquired GPS data were used to capture driver activities such as origin, destination, dwell time, travel distance, etc.

There is also an approach using trajectory data for identifying the locations of charging demand. Jung, Chow, Jayakrishnan, and Park (2014) proposed a trajectory-interception refueling problem as an alternative to flow interception for the electric taxi charging problem based on a bilevel simulation–optimization. They generated a trajectory using a stochastic model based on the destination distribution ratio from the origin zone, and the trajectory was assigned along a minimum path. The passenger presence data were also simulated using the average travel time drawn from taxi operation statistics of Seoul city.

Unlike normal auto vehicles that usually have short travel times and long parking durations, due to commuting, taxis are moving continually inside cities without parking. EV taxis have to be charged multiple times a day because of their short operation rage. Even the express chargers need 1 h for full charging. Thus an EV taxi has to be charged when it is out of service. To analyze the locations for charging stations, we need trajectory data including taxi coordinates with passenger presence information. Among the previous research, *p*-median method is not appropriate because it only uses population data as input data, not OD data. FIRM and FILM use OD data as the input data, but those data do not contain passenger presence data, and they are not also appropriate for the EV taxi charging station location problem. Notably, Jung et al. (2014) intercepted the charging demand locations from the generated multiple trajectories from zone-to-zone OD data. However, that study has some limitations that are overcome in this research. Trajectories built from an OD matrix, which is based on zone-to-zone travel, contain a lot of errors, while taxi OD trajectories contains exact origin and destination locations of passenger travel. Therefore, the taxi OD trajectories are preferred for a more accurate solution for the charging station location problem. Previous research used assumed operation range of EVs, not real operation range. However, lithium-ion batteries show different performance according to different conditions of weather and roadways. Therefore, there is seriously need for research on EVs with real experimental data.

## 3. Methodology

### 3.1 *Model framework*

The purpose of this research is to develop a methodology for determining the locations of charging stations using real taxi GPS data and EV taxi battery performance data. It is a disaggregated model to set up the strategy for distributing charging stations over the city area, combining the trajectories extracted from taxi GPS data and real EV observed range to find the charging demand.

We used two datasets: (1) Real operation data obtained from 1,000 general LPG taxis operated in Daejeon city, Korea, in September 2013. (2) Real operation data from three EV taxis from 6 September 2013 to 13 January 2014. Figure 1 shows the EV taxis used for the experiment project.

The procedure for allocation of charging stations for EV taxis is composed of two steps, shown in Figure 2. The first step is an uncapacitated problem of finding the number of chargers needed for serving charging demand without constraining the maximum number of the chargers for each station. The result is used as the input for the second step of the capacitated problem. In the analysis, we first intercept the charging locations from the real LPG taxi trajectory data and actual battery performance data of EV taxis on the taxi trajectory. Then, the acquired charging demand locations for each time period are mapped to the nearest charging stations, giving the required number of chargers for each candidate charging station. This result provides an initial solution for the next step of the optimization for fast solution convergence. The initial solution is actually the solution for an uncapacitated problem when there is no limit on the number of installable chargers for each station. However, the capacity of each station, the number of installed chargers for each station, must be constrained in order to obtain a result similar to the actual situation.

The second step takes the initial solution as input data and solves for the optimal charging station locations and the number of the chargers for each station while the constraining the number of the maximum chargers. This is a capacitated problem and can be solved by combinatorial optimization. The number of chargers can be constrained for individual stations according to the area of the site or other considerations. The capacitated problem can be formulated as a constrained combinatorial optimization problem that finds the best combination of chargers giving the minimum total cost. Because this class of problem belongs to the group of nondeterministic polynomial time-hard (NP) problems, we adopted a metaheuristic approach. We used the evolution algorithm (EA) as a solution algorithm. In this algorithm, we first generate the random population of the solution from the parent solution. Then, the solution is improved by selecting the best child solution based on cost evaluation and constraints. By repeating this process, we can finally find the best near-optimal solution.

### 3.2 *Uncapacitated problem*

The first step for allocation of EV taxi charging stations is to find taxi *k*'s charging demand location $D_{k,i}$. In this procedure, we find the location of subject taxi *k* when there is no passenger and the calculated battery level from the taxi trajectory drops below the minimum threshold value of the state of charge (SOC), $SOC_{min}$. We used GPS data acquired by the taxi dispatching center of Daejeon city to generate the trajectory data and used battery monitoring data obtained from the


Figure 1. Experimental EV taxi, Renault SM3.Z.E model.

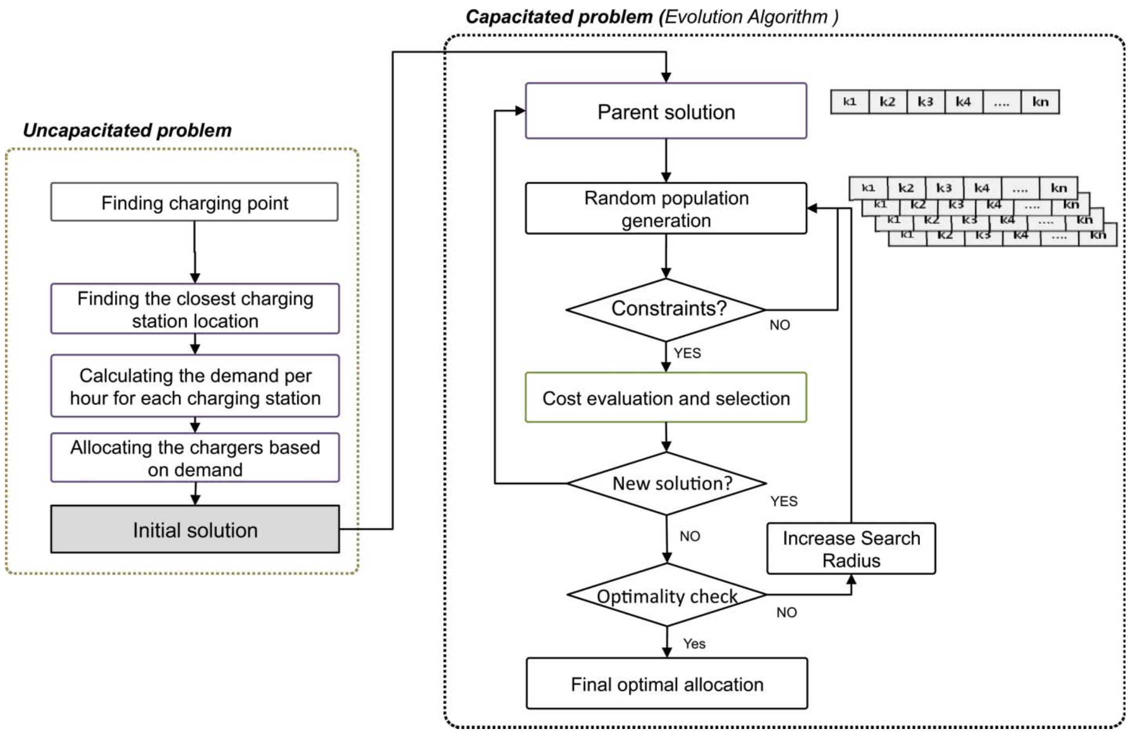


Figure 2. Framework of EV taxi charging station location problem.

experimental EV taxi deployment project:

$$D_{k,i,} = \text{Charging demand location i of taxi } k$$
$$\text{such that Battery level} \le \text{SOC}_{\min}, \text{ Passenger } = 0 \text{ (vacant)} \quad (1)$$

For the realistic optimal charging station location problem for EV taxis, we must consider the performance of the EV taxi battery. Figure 3 shows the relationship between the SOC of the battery and the charging time. Range is defined as the maximum operable travel distance when battery SOC drops from 100% to 0%. Operating range gives a more practical distance for taxi operation, measured when SOC drops from 100% to 15%. The adopted EV taxi model, Renault SM3 Z.E., gives a warning for recharging when SOC is less than 15%. We assume that when SOC is 15% without any passenger in the taxi, the subject EV taxi directly moves to the nearest charging station. In a service case with passengers, the EV taxi is assumed to move to the nearest charging station after finishing the current service to the passenger's destination.

The charging demand of taxi $k$ ($D_{k,i}$) intercepted from the trajectory is assigned to the nearest candidate charging station $j$. The access distance ($d_{i,j}$) from the taxi demand location ($D_{k,i}$) to the nearest candidate site is obtained by calculating the taxi distance [Manhattan distance, not Euclidean distance; see Eq. (3)], representing the approximate travel distance in the grid network:

$$\textit{Access distance}: \quad D_{k,i} \rightarrow \text{candidate site } j, \quad j \in J$$
$$\{j = 1, 2, 3, \ldots, J\} \quad (2)$$

$$d_{i,j} = |x_i - x_j| + |y_i - y_j| \quad (3)$$

where $(x_{i,} \ y_i)$ are coordinates of location $i$.

The total charging demand of candidate site $j$, $D_j$, can be obtained by the sum of the individual intercepted demand as follows:

$$D_j = \sum_{k \in K} D_{k,i,j} \quad (4)$$

The number of chargers ($N_j$), based on the charging demand of facility $j$ and the service rate of the chargers, is obtained by Eq. (5):

$$N_j = \frac{\sum_j D_j}{\mu} \quad (5)$$

where $D_j$ is charging demand at candidate site $j$ and $\mu$ is service rate (vehicle/h) of charger.

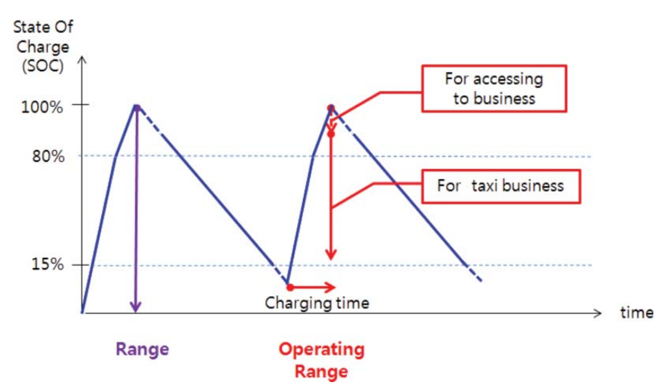


Figure 3. Simplified battery performance profile.

## 3.3 *Capacitated problem*

### 3.3.1 *Objective function*

The charger deployment model minimizes the total daily cost, which is the sum of the fixed facility cost, access cost to the station, operating cost, and charging delay cost. The formulation of the EV taxi charge facility location is as follows:

$$\text{Minimize} \quad \alpha \sum_j f_j X_j + \beta \sum_j X_j + \varphi \sum_k \sum_i \sum_j 2D_{k,i} d_{i,j} Y_{k,i,j} + \omega \sum_j (C_j + Dl_j) \tag{6}$$

$$\text{subject to} \quad \sum_j Y_{kij} = 1, \quad \forall_i \tag{7}$$

$$Y_{kij} \le X_j, \quad \forall_{i,j} \tag{8}$$

$$X_j = 0, 1, \quad \forall_j \tag{9}$$

$$Y_{k,i,j} = 0, 1, \quad \forall_{i,j} \tag{10}$$

$$O.R. \le \text{Range} \tag{11}$$

$$d_{i,j} < d_{\text{threshold value}} \tag{12}$$

$$Dl_j \le \text{delay}_{\max} \tag{13}$$

Decision variables are as follows:

$X_j = 1$ (if a facility is located at candidate site $j$)
0 (if not)
$Y_{k,i,j} = 1$ (if EV taxikis served at charging demand *candidate site j*)
0 (if not)

where $Y_{k,I,j}$ is 1 if EV taxi $k$ point $i$ is served by facility $j$, and $Y_{k,I,j}$ is 0 if not. $X_j$ is 1 if charging facility is located at candidate site $J$, and $X_j$ is 0 if not. Other variables are defined in Table 1.

The objective function, Eq. (6), minimizes the total cost, which is composed of the facility installation cost and the opportunity cost due to charging. The first constraint, Eq. (7), is to ensure that each demand location $i$ is allocated to only one facility $j$. The second constraint, Eq. (8), implies that demand at location $i$ cannot be allocated to a facility at candidate site $j$ if the facility is not located at location $j$. The constraints (9) and (10) deal with the assignment of the variable in Boolean numbers of 0 or 1. The constraint in Eq. (11) means that taxi's operating range is smaller than the maximum range. By constraint (12), the accessing distance is smaller than the distance from the SOC threshold level to 0%. Constraint (13) is used to set the maximum waiting time for charging.

**Table 1.** Variables for objective function.

| Variable | Description |
|---|---|
| $\alpha$ | Charger installation cost (USD/EA) |
| $f_j$ | Number of chargers (EA) |
| $\beta$ | Operating cost of location *j* (personnel expenses for charger maintenance) |
| $\varphi$ | Value of distance (cost per unit distance per unit demand) |
| $D_{k,i}$ | Charge demand of taxi *k*, at location *i* (*x*,*y*-coordinate), at time *t* |
| $d_{i,j}$ | Distance from recharge demand point *i* to candidate site *j* |
| $d_{threshold}$ | Distance that can travel from threshold level of battery to 0% |
| $\omega$ | Value of time (cost per unit time per unit demand) |
| $C_j$ | Charging time at location *j* |
| $Dl_j$ | Delay time at charging location *j* |
| $R$ | Total travel distance (range) from battery level 100% to 0% |
| $O.R.$ | Operating distance from battery level 100% to 15% |

### 3.3.2 *Evolution algorithm solution procedure*

In Figure 2, the solution obtained, $N_j$, is used as an initial solution for the following capacitated problem. It is used as the first parent solution for the evolution algorithm, from which the new population is randomly generated. Generated child solutions are checked for constraints; this process is followed by an evaluation procedure to determine the new solution. The new improved solution is then working as a new parent solution for next population generation. This procedure repeats until the solution is thought to be the most optimal solution. Note that the most optimal solution does not necessarily mean the real global optimal solution, as the metaheuristic method cannot guarantee global optimality. When the algorithm cannot find a better solution than the current parent solution, it increases the search radius by generating populations with higher values of randomness in an attempt to find a better solution in a wider area. If this fails for a certain number of iterations, we have no other choice but to accept the current solution as the best one.

## 4. Simulation

### 4.1 *Simulation rule*

The main purpose of this study is to develop a methodology to allocate charging stations and determine the number of chargers for charging stations based on taxi GPS data and EV taxi operation data. In this research, the individual taxi's operation patterns were considered. The basic premises are as follows: (1) Real taxi trajectory data from 1,000 taxis are assumed to represent the passenger loading and unloading locations. (2) EV taxi starts operation with SOC level of 100% after charging during the night. Taxi moves to charging station when the SOC level is less than 15%. (3) After charging, the EV taxi returns to the original trajectory location and continues operation. (4) EV taxi uses fast charger systems installed on candidate charging stations that are shared among all taxis.

Taxi trajectory database includes GPS location data recorded in 1-s intervals and passenger presence information. We selected typical weekday data (Tuesday, 24 September 2013; Wednesday, 11 September 2013; Thursday, 5 September 2013). From the GPS database, we extracted 1,000 samples out of 2,300 taxies for each day. Recorded charging time and energy consumption rate from EV taxis, model Renault SM3 Z.E., are used for following steps.Table 2 provides the description on the detailed input data used for the simulation. Earning per distance of taxi is used to determine the unit access cost for lost business. The locations of 76 taxi companies in Daejeon city are used as candidate charging station sites.

**Table 2.** Input data for simulation study.

| Variable | Value |
|---|---|
| Battery capacity | 22 kwh |
| Energy consumption rate | 6.52 km/kwh |
| Electric vehicle taxi range | 143.5 km |
| Average accessing distance from demand point *i* to candidate site *j* | 1.045764858 km, SOC 0.7% |
| Electric vehicle taxi operating range (travel distance from SOC 99.3% to SOC 15%) | 120.9 km |
| Charging time (14.3% to 100% full charge) | 63.5 min |
| Charger installing cost | USD $23,960/EA (assumed that life cycle is 6 years) = $12/day |
| Personal expense for charger maintenance | $57/day/facility |
| Earning per distance of taxi ($\varphi$) | $0.54/km |
| Value of time per taxi ($\omega$) | $0.27/min |
| Number of vehicles | 1,000 |
| Number of candidate sites | 76 |
| Number of maximum chargers | 200 |

*Note.* $1 = 1,114.36 won (13 April 2015).

## 4.2 *Uncapacitated problem*

### 4.2.1 *Finding charging points*

The taxi trajectory data contains vehicle identification number, event occurrence time, coordinates in WGS84 format, and passenger presence (Table 3). To calculate the accumulated travel distance, the location of the taxi has to be tracked along the real road network. In this research, for simplicity, we assumed a grid-type road network in which the taxi is moving. Therefore, we calculated taxi distance as the sum of the absolute value of the difference of two $x$ coordinates and two $y$ coordinates; this method of calculation is usually used in urban networks.

This study assumes that a subject taxi starts its operation with 100% SOC level. Then, when it drops to 15% and no passenger is in the taxi, it starts to move to the nearest charging station. When there is a passenger, the taxi will finish the service to the passenger first; then, it will move to the nearest station from the unloading location. As we actually considered the real trajectories of Daejeon taxis in September 2013 (normal weather condition), we were able to find the charging demand point on the trajectories of a subject taxi identifying the location of 85% of the maximum travel distance. Table 4 shows the average maximum running distance from the EV taxi operation experiments. The experimental data were gathered from three EV taxis in September 2013 (average temperature was 21.4°C). The average maximum travel distance (143.5 km) was found by multiplying the average distance per power consumption (6.52 km/kWh) measured by the battery capacity (22 kWh). The charging demand points found are illustrated in Figure 4.

**Table 3.** GPS data description.

| Data field | Contents |
|---|---|
| Vehicle ID | Unique ID of taxi |
| Event time (YYYY/MM/DD/HH/MM/SS) | Time when the event happened |
| Longitude | *x* coordinate of GPS / WGS84 format |
| Latitude | *y* coordinate of GPS / WGS84 format |
| Passenger | 1: occupied / 0: vacant |

**Table 4.** Range and operating range based on real EV taxi (SM3 Z.E. in Daejeon city).

| September 2013 | Travel distance (km/day) | Electricity consumption (kWh) | Energy consumption efficiency (km/kWh) | Available range (km) |
|---|---|---|---|---|
| Week 1 | 85.84 | 12.66 | 6.78 | 149.2 |
| Week 2 | 138.92 | 21.22 | 6.55 | 144.1 |
| Week 3 | 97.70 | 15.24 | 6.41 | 141.0 |
| Week 4 | 133.14 | 20.97 | 6.35 | 139.7 |
| Average | 113.90 | 17.52 | 6.52 | 143.5 |

### 4.2.2 *Finding the closest charging station*

Because one of the purposes of the EV taxi project of Daejeon is to find a way to secure financial feasibility of participating taxi companies, we only considered the parking lots of taxi companies as the candidate charging station locations in order to minimize the installation cost for chargers, and we assumed that the taxi companies would share the charging locations. This saves the high rental costs and land prices; fortunately, we have 76 taxi companies widely spread over the city. Figure 5 shows the mapped locations of the 76 candidate sites, which are the taxi companies in Daejeon. Although the sites are not evenly distributed across the city, many of them are located near the downtown area at the center; others are located near the old towns and in areas outside the city.

Charging demand for each charging station ($D_j$) is obtained by assigning charging points to the nearest charging station. Here we excluded the charging points of intercity travel, for which the distance to the charging station is greater than 10 km. Figure 6 shows aggregated charging demand on 24 September 2013. We intercept 949 charging points from the data from 1,000 taxi itineraries.

Figure 7 shows that the assigned charging demand for the candidate charging stations, which is also the result of an uncapacitated problem, has a pattern that is almost identical for different days. This means that, every day, taxi patterns are similar and a solution based on these demand data can be further used as a general solution.

### 4.2.3 *Finding the highest demand per hour: Initial solution*

We identify charging demand for each time period (1 h); the number of required chargers is calculated for the stations. This calculated number of chargers can be used as a solution for the uncapacitated problem, in which each station can have an unlimited number of chargers for the peak time period. This solution is considered as a worst-case solution, without consideration of waiting delay at the stations. However, in a real situation, we have to set a limit on the number of chargers for each station according to the limits of the budget. Figure 8 shows the charging demand for peak hours on 24 September 2013; this demand information is used as the input for the solution algorithm.

To verify the stability of the allocation model, Figure 9 compares the highest demand patterns for 3 days (5, 11, and 24 September). As can be seen, the 3 days show very similar patterns for each time period.

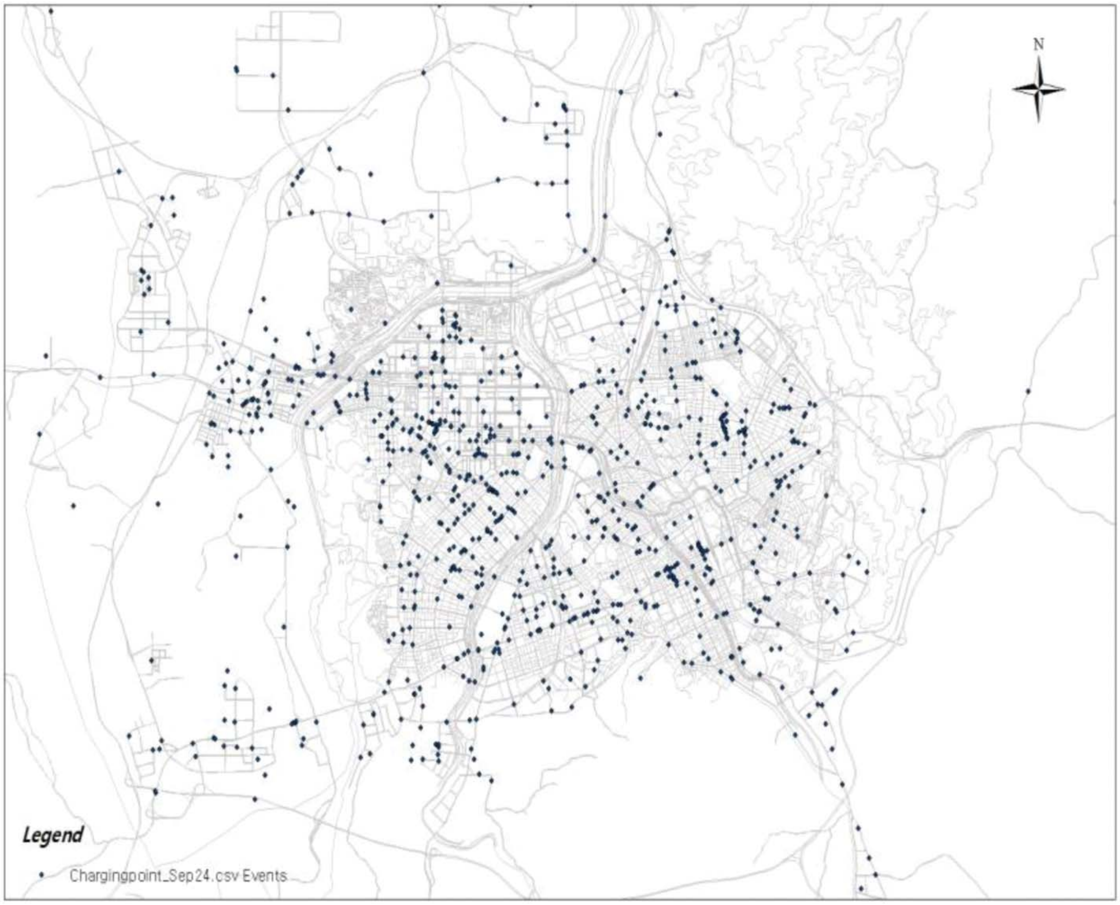


Figure 4. Map of charging demand points.

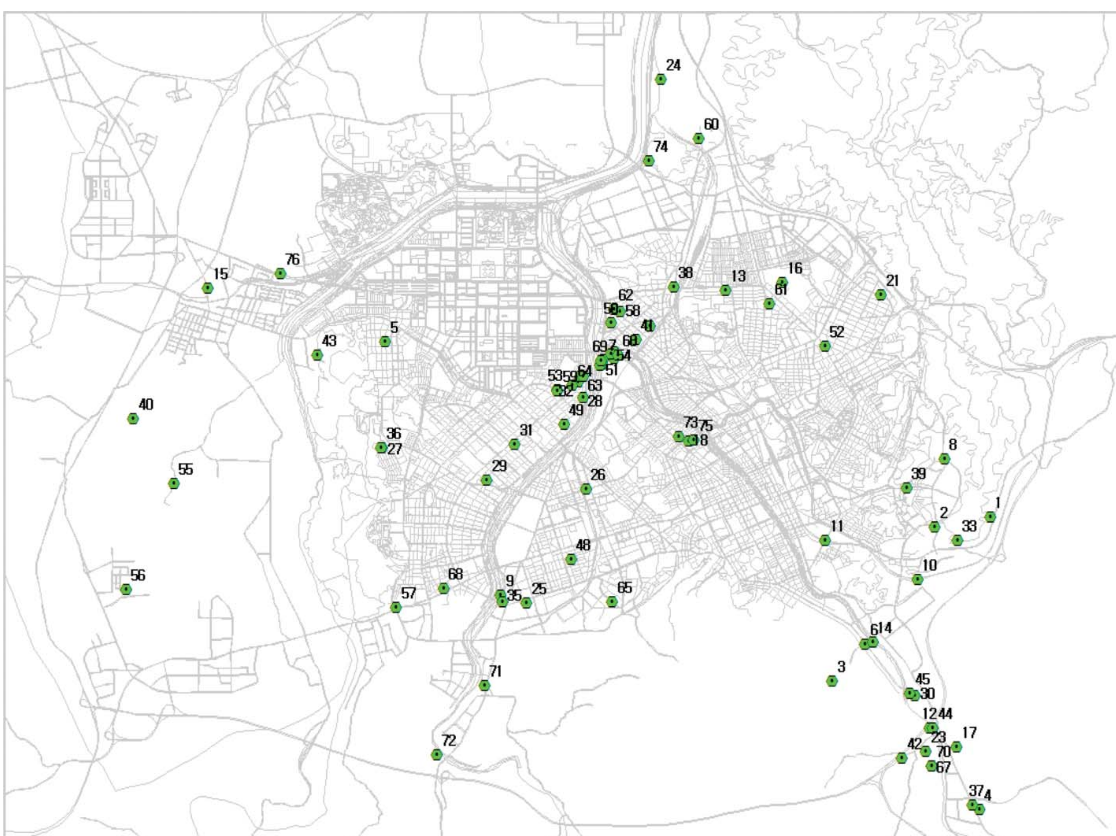


Figure 5. Mapping of candidate sites.

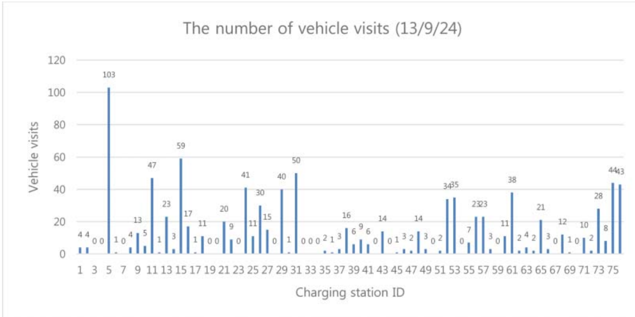


Figure 6. Daily charging demand of candidate site.

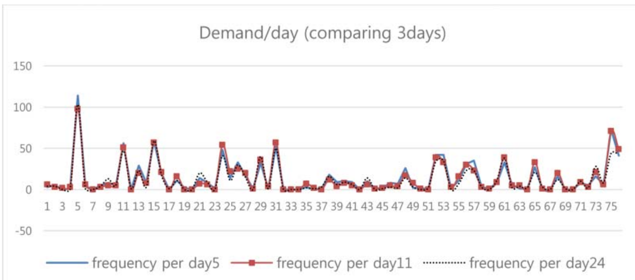


Figure 7. Verification by daily demands on 3 days.

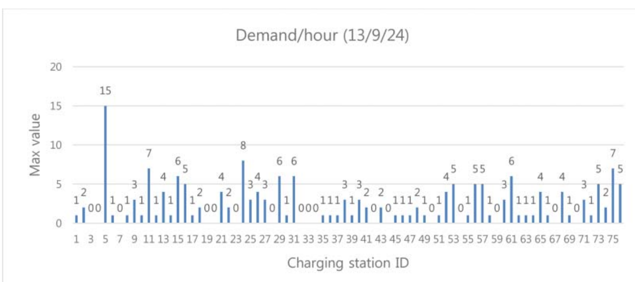


Figure 8. Highest demand (24 September 2013).

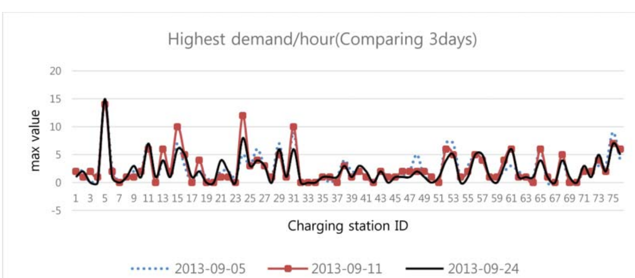


Figure 9. Verification by 3-day highest demands.

### 4.3 Capacitated problem: Evolution algorithm

From the input of highest demand, we can add the limit on the number of the chargers for each station. The maximum number of chargers for the stations is set to 10, and the maximum total number of chargers is set to 200. With these added constraints, waiting delay at the charging stations occurs. We also added the maximum waiting delay constraint $delay_{max}$. In the evolution algorithm solution framework, we first generate candidate charging locations

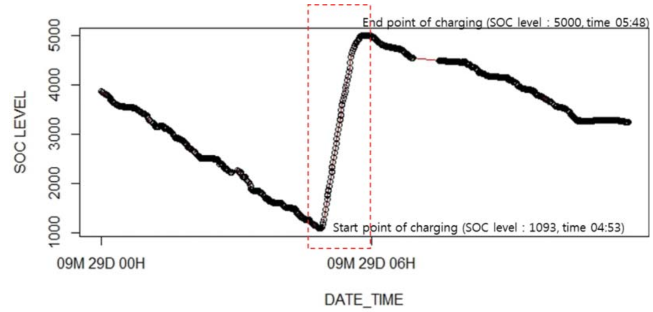


Figure 10. Electric taxi battery profile based on field data (case of 29 September 2013).

and number of chargers at the same time; taxis are assigned to the nearest charging stations and the total cost, including delay, is calculated and compared in order to find a better solution within the constraints.

#### 4.3.1 Accessing cost to charging station

During the accessing time to the charging station, which is significant in EV cases, taxi drivers lose business opportunities. This influence must be considered in the charging location problem. If a city installed more charging stations, it would decrease this access cost. The opportunity cost can be obtained by multiplying the taxi value per operation distance by the taxi distance to the station, as in Eq. (14):

$$\text{Facility accessing of taxi } k = \text{opportunity cost of taxi } \varphi \times 2\ d_{i,j}. \tag{14}$$

where $\varphi$ opportunity cost parameter for accessing charging station and $d_{i,j}$ taxi distance (m).

#### 4.3.2 Charging time

Refueling time for internal combustion engine based vehicles is less than 5 min. However, EV recharging time is about 1 h with a fast charger. In this research, we used measured charging time data from the experiments of Daejeon city demonstration project instead of using the data provided by the automaker. Figure 10 and Table 5 show the results from the SOC monitoring of EV taxis in September 2013. It took 58 min for taxi 1 to recover to 69.01% SOC level; it took 72 min to go from 14.3% to 100% SOC level. In the case of taxi 2, it took 48 min to achieve a 70.86% SOC level and 58 min to achieve an 85% SOC level. For taxi 3, it took 55 min to reach 78.14% and 60 min to reach an 85% SOC level. The differences of the charging time come from the battery temperature differences at charging time and from the quality of the

Table 5. Range and operation range based on real EV taxi (SM3 Z.E.) data in Daejeon city.

| Time | | SOC level | | Charging rate | | Generalization | |
|---|---|---|---|---|---|---|---|
| Start | End | Start | End | Rate (%) | Duration (min) | Rate (%) | Duration (min) |
| 4:26 | 5:24 | 1,549 | 5,000 | 69.02 | 58 | 85.72876 | 72.04097 |
| 1:53 | 2:41 | 1,457 | 5,000 | 70.86 | 48 | 85.72876 | 58.07198 |
| 4:53 | 5:48 | 1,093 | 5,000 | 78.14 | 55 | 85.72876 | 60.34146 |
| | | | | | | Average | 63.5 |

**Table 6.** Factors for computational study.

| Factor | Cost |
|---|---|
| Charger installing cost ($\alpha$) | \$23,960/EA (assumed that life cycle is 6 years) =\$12/day |
| Charging station operating cost ($\beta$) | \$57/day |
| Charging time ($Cj$) | 63.5 min |
| Value of distance per taxi ($\varphi$) | \$0.54/km |
| Value of time per taxi ($\omega$) | \$0.27/min |

**Table 7.** Value of distance and time in Daejeon metropolitan city.

| Income per day per taxi (\$/day) | Average travel distance of taxi per day (km/day) | Value of distance per taxi (\$/km) | Value of time per taxi (\$/min) |
|---|---|---|---|
| 170.49 | 330.89 | 0.54 | 0.27 |

*Source.* Daejon Metropolitan City 2012.

electric power delivered to the chargers. The average charging time of EV taxis from 14.3% (15%–0.7% buffer distance) of SOC level to 100% was found to be 63.5 min in September.

### 4.3.3 *Delay time*

Delay time for charging at charging station is calculated by dividing the total demand by the service rate. The calculation of delay time is done in a macro-level approach:

$$\text{Delay time } = D_j/\mu\text{–recharging time (63.5 min)} \quad (15)$$

where $D_j$ is charging demand at candidate site $j$ and $\mu$ is service rate [the number of chargers / recharging time (63.5 min)].

If $D/\mu \leq 1$, then delay time is set to 0.

The maximum delay time allowed is set as follows:

$$Delay_{max} = \text{recharging time}$$

**Table 8.** EA parameters.

| Parameter | Value |
|---|---|
| Initial population | Solution from uncapacitated problem |
| Iterated generations | 2,000 |
| Number of generated population at each iteration | 50 |
| Variation of generating offspring | [−1,1] with uniform probability |

### 4.3.4 *Charging cost*

The cost for charging EV taxies includes installation cost, operating cost, and opportunity cost for business loss during the time used for charging. This time includes the access time to the charging station and charging time. In this research, we used the installation cost from 2013 Daejeon EV taxi project, real management cost of taxi companies, and real operation range and income from taxi operation. Table 6 gives the detailed cost items used in calculating the total cost. These items are extracted from the Daejeon city report (Daejon Metropolitan City 2012; Daejeon Techno Park 2014).

The value of time for taxi operation is evaluated using the Daejeon taxi operation data as shown in Table 7.

### 4.3.5 *Simulation results*

EA-based simulation first generates the improved solution as the generation progresses. Table 8 reports the EA parameters used in this study.

Figure 11 shows the solution progression for the case of 24 September 2013. The total cost of the improved solution first decreases rapidly and becomes slow, converging to a certain value that is thought to be the most optimal value. Without any improvement for several generations, the determined solution is decided on as the final solution.

Table 9 reports the detailed simulation results. When comparing the simulation results based on EA and the results from

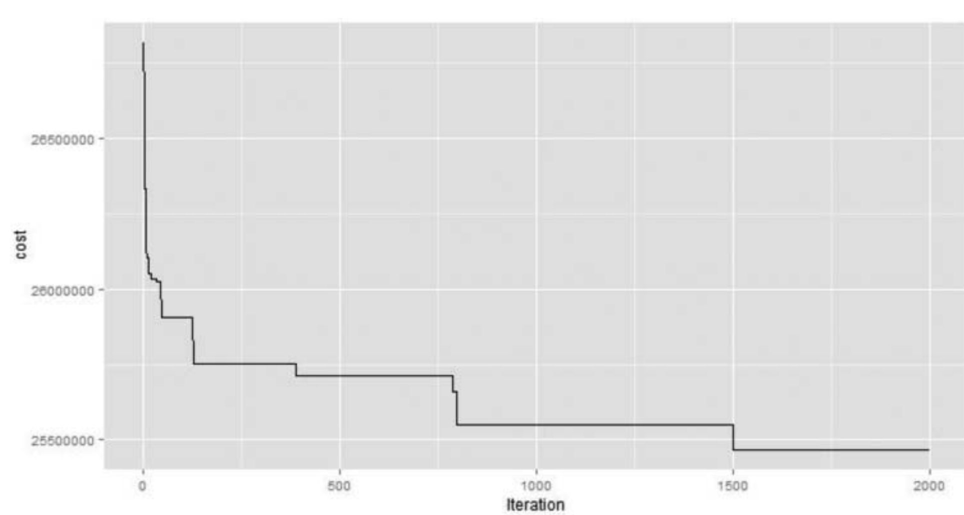


**Figure 11.** Solution progress.

Table 9. Summary of results.

| Simulation parameters | Value | |
|---|---|---|
| | Uncapacitated problem | Capacitated problem (EA) |
| Total distance from charging points to stations | 934.8 km | 1,018.6 km |
| Charging point (events) | 949 | 949 |
| Total number of EV chargers | 175 | 146 |
| Total number of charging stations | 59 | 34 |
| Total delay time | 0 min | 189.1 min |
| Total cost | $24,460/day | $22,836/day |

the uncapacitated problem, the EA method reduces not only the total number of chargers but also the total number of charging stations. The total number of chargers decreases from 175 to 146 units. At the same time, the total number of charging stations decreases from 59 to 34. The total distance from charging points to charging stations increases from 934.8 to 1,018.6 km. The initial solution (uncapacitated problem) is calculated with the charging demand so that the delay time for charging is zero. In contrast, the simulation based on EA should consider the delay time due to the limited number of installable chargers at each charging station. In the simulation, 949 charging events in total led to a delay time of 189.1 min,

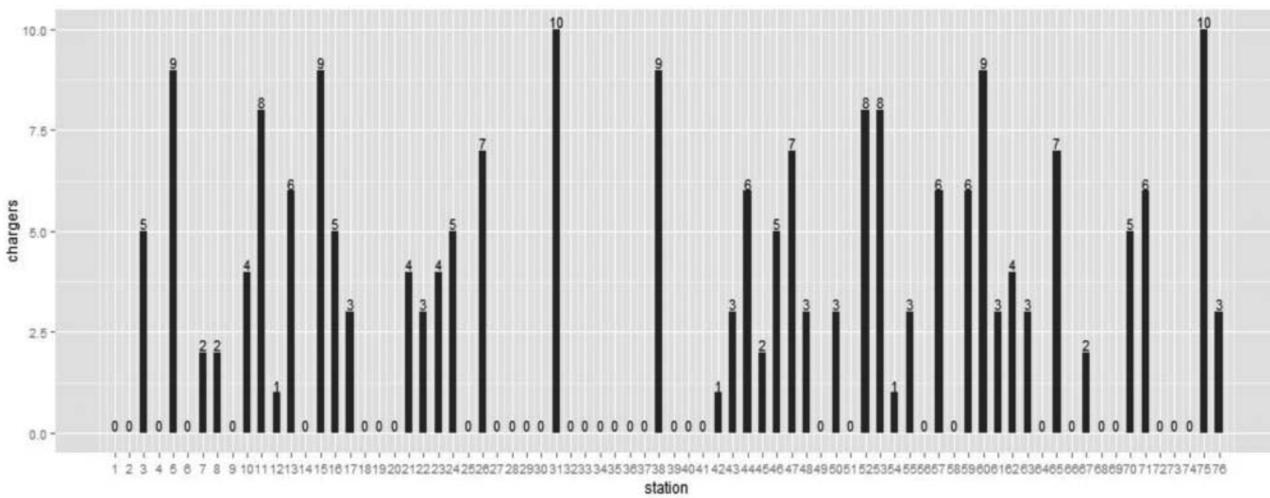


Figure 12. Optimal charger deployment results.

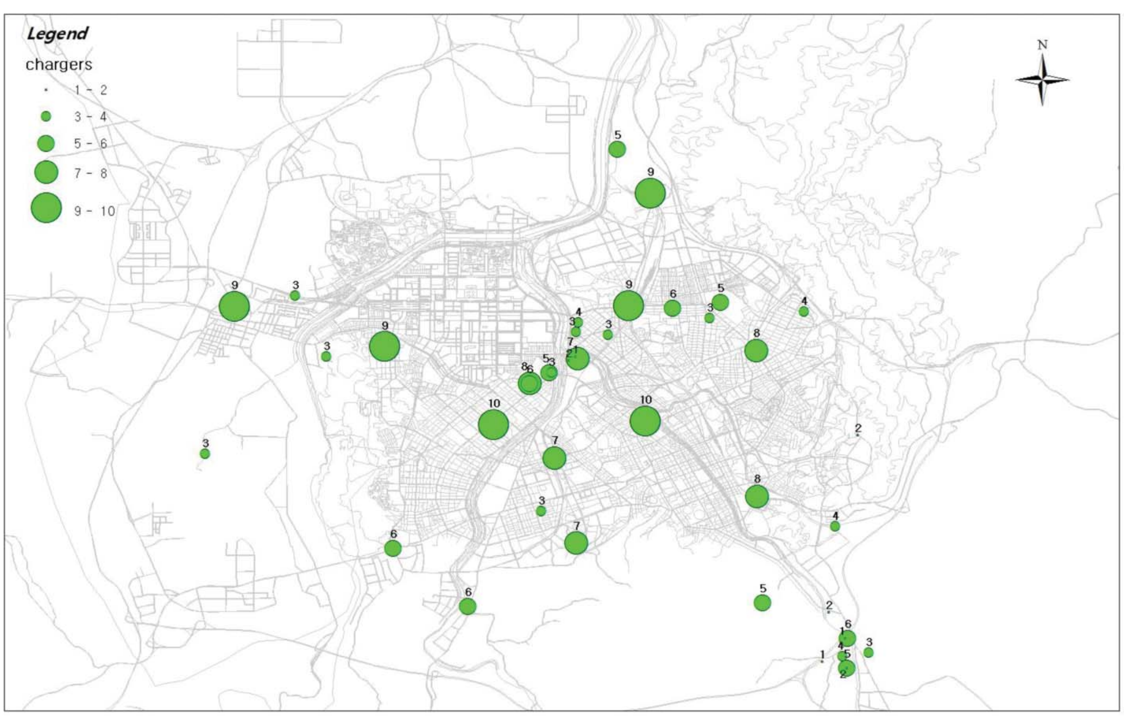


Figure 13. Optimal charger deployment map.

which is an average delay time of 0.2 min for each charging event. The average delay time had a small value because most solutions were rejected due to constraints in the delay max time. This means that delays at each location did not happen during most charging events. The minimum cost decreases 6.6%, from $24,460 to $22,836/day.

Figure 12 reports the allocated number of chargers for each charging station. Figure 13 shows the distribution of chargers on a geographical map. The size of the circles represents the number of chargers at each charging station.

## 5. Conclusions

This study focuses on developing a methodology for the location problem for optimal EV charging stations. As opposed to the flow-based conventional refueling station problem or the simulation model based on EV taxis with OD pair data, this study uses real trajectory data of general LPG taxis and real battery performance data of EV taxis to generate a more realistic solution than has previously been possible. The main conclusions from the research are as follows:

First, the numbers of chargers and locations are more sensitive in the minimization of the total cost. When comparing the results of the uncapacitated problem with those of the capacitated problem, it was found that the total distance to charging stations and the delay time increase; however, the total cost, the number of chargers, and the number of charging locations all decrease.

The number of the chargers in uncapacitated problem is calculated from the total charging demand for each candidate locations and capacity of the express charger. However, in the capacitated problem we set the limit of the maximum number of the chargers as 10 for each location. Then we calculated the opportunity that is the total charging cost including installation cost, operation cost, access time cost, and charging time cost.

Second, chargers for EV taxies have to be installed intensively in specific regions, for example, when we install 10 chargers. Some alternatives for installation are possible. The first alternative is five sites installed with two chargers, and the second alternative is to install one site with 10 chargers. If the real estate cost is neglected, the second alternative is more preferable. Therefore, to neglect the rent cost in this study, all candidate sites belong to the taxi companies. Under this condition, the daily opportunity costs are as follows: USD$12 from chargers, $57 for management, $17 for 63.5 min charging time, and $4.34 for 8-km average round trip to charging station. If the charging stations are concentrated in one location, installation cost and management cost decreases while opportunity cost for access time increases.

Third, the result of this study provides a robust result for charging station location problem. Because the research used individual trajectories data, which treats the individual vehicle activity and interactions, the research treats the subject system as a nonequilibrium system, which is different from the existing research assuming equilibrium system using OD and traffic assignment. As shown in Figures 7 and 9, the traffic pattern over the 3 days is stabilized, which implies that the result is robust.

Because this article focuses on the planning model, there exist some limitations in the methodology. The proposed methodology is not able to simulate real driving or charging behaviors. For example, taxi drivers usually want to charge when they have no passenger or when vehicle is close to a charging station regardless of SOC level. In this article, we could not reflect those diverse behaviors because of the limitations of data (only GPS data), so we made a simplified behavior for charging events (occurring when SOC level is less than 15%). Another limitation is in the assumption of constant traffic pattern (trajectory). When EV taxis are deployed, though there will not be significant change of passengers' OD, taxi behavior and operation might change in reality due to charging station locations and queue delay. This study has used the data from normal temperature condition during the study period, in order to obtain the best battery performance. Future research will have to consider low-temperature situations, in which battery performance is worse. Another consideration is delay maximum time. Instead of assuming delay maximum time, it is necessary to reflect on the proper delay maximum time based on driver behavior or opinions as determined by survey. Another area of future research related with this study is to develop an operating tool for informing drivers of the nearest charging stations and predicting delay time for EV taxi drivers.

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