Selecting optimal locations of public charging stations for electric vehicles using the big data of driving behaviors: A case study of Seoul, Korea

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Abstract

Electric vehicles (EVs) have been recognized as a promising alternative of conventional internal combustion engine vehicle. As the global EV market is rapidly growing, the importance of charging infrastructure including public charging stations cannot be overstated. In the case of Seoul, since EV users cannot install private chargers easily due to the high population density, public charging stations should be located properly in order to cover all potential EV charging demand. In this study, we develop the time-dependent demand estimation model of EV based on purpose Origin-Destination (OD) data and hourly traffic flow. We assume that driving purpose has a significant impact on the propensity for charging type. So potential demands of slow and fast chargers are estimated by separating the total demand into two types, reflecting the driving purpose of EV drivers. Based on the estimated demand for each type of charger, cost minimization model is formulated to investigate the optimal location of charging stations designed to satisfy all potential demand. The locations of each type of chargers are revealed. The case study of Seoul is conducted by using our models. It is shown that the demand for slow charging is concentrated on the residential areas and workplaces. Meanwhile, commercial districts show a high level of fast charging demand. The optimal locations of slow chargers are concentrated on residential and workplaces, whereas fast chargers are quite evenly distributed in the study area, due to the effect of taxis. The study proposes the optimal location of public charging stations to cover EV demands and to minimize the installation cost of chargers at the same time in the perspective of the entire system.

Keywords: Electric vehicle, Charging station, Driving behaviors, Demand estimation, Optimization

1. Introduction

As the environmental pollution problem of conventional internal combustion engine vehicles (ICEVs) has been pointed out, EVs are regarded as a promising alternative worldwide. EVs use electricity as its main power source. This feature enables EVs to emit less GHGs than ICEVs, which combusts fossil fuel to get power, except for exceptional case (e.g., oil and coal are dominantly used to generate electric power.) (Elgowainy et al., 2009). Due to the eco-friendly nature of EVs, many countries, including the United States, China, and Korea, are planning and implementing various policies for the introduction and diffusion of EVs (OECD/IEA, 2018).

However, the limited battery capacity is the biggest factor in interrupting EV adoption. Compared to ICEVs, EVs have a shorter driving range and take a relatively long time to be fully charged. Also, the charging infrastructure has not yet been fully established. Several studies revealed that the driving range, charging time, and charging station accessibility is significantly influential on the consumer preference for EVs (Daziano and Chiew, 2012; Jensen et al., 2013; Huang and Qian, 2018). In Korea, as a part of overcoming such disadvantages, the government is trying to improve the accessibility of charging stations. The installation of public charging stations and the subsidy for home charging equipment are representative examples. Owing to these efforts, the EV penetration rate in Korea is rapidly growing, although the market share of EV is still around 1%. Accumulated registration number of EVs in Korea has more than doubled from 11,767 in 2016 to 25,593 in 2017 (Ministry of Environment, 2018). Given this tendency, the EV adoption rate is expected to increase further and charging demand for EVs is also expected to skyrocket. As a result, the importance of public charging stations is being reinforced to fully meet the soaring charging demand, and the charging infrastructure needs to be systemically designed through the optimal charging station location models.

Meanwhile, there are two types of chargers in public charging stations (Hardman et al., 2018). One is a slow charger, which is AC-based and takes 4 ~ 5 hours to charge an EV fully. The other is a fast charger, which is DC-based and takes 0.5 ~ 1 hours to charge an EV fully. In selecting the location of the charging stations, it is necessary to determine how many slow and fast chargers should be installed in the public charging point. In order to manage this issue, it is essential to know how much demand for a specific type of charger will be aggregated in a particular time interval in the unit area. This requires the Origin-Destination (OD) information and the driving purpose of drivers, and the amount of hourly traffic flow. The reasons are as follows. The total amount of driver’s charging demand is directly related to his driving distance, i.e., OD distance. Also, the type of charger driver wants to use may vary depending on his driving purpose. It is because of their parking time. For example, drivers may prefer slow charging if they are allowed to park their cars for a long period of time, such as after going to work and returning home, while they may prefer fast charging if they park a relatively short period of time, such as shopping or leisure (Xu et al., 2017). Finally, the peak time demand is revealed in detail when we consider the hourly traffic flow. Some previous studies on selecting optimal locations of charging stations developed the models using OD information of drivers (Cai et al., 2014; Dong et al., 2014; Shahraki et al., 2015) and the model assuming that demand for each type of charger is separated by driving purpose of drivers (Kleiner et al., 2018) for the estimation of potential charging demand. However, they didn’t estimate the demand for each type of charger by separating driving purposes. Also, previous studies have not yet taken into account OD information, driving purpose, and the amount of hourly traffic flow period simultaneously. It is a meaningful approach to estimate charging demand through purpose OD data in this context.

Seoul, the capital city Mof Korea, ranked the 1st place in population density among metropolitan cities of 2016 OECD members (OECD, 2016). 9.77 million people live in Seoul, and more than 25 million people, which is half of the Korean population, reside in the adjacent area of Seoul (KOSIS, 2019). It is not easy for the citizens living in Seoul to install home charging equipment when they purchase EVs since it is very difficult for them to secure the private parking space or garage. Therefore, the importance of public charging stations which can cover all demand becomes more significant. Due to the limited budget of the government for installing EV charging stations, optimization research is necessary from the perspective of the entire system, which aims to minimize installation cost and to cover potential demand at the same time. However, the study for selecting optimal locations of charging stations in Seoul has not yet been conducted. Therefore, the research which has an objective to optimize the locations of public charging stations considering the cost and the demand coverage in Seoul can have a great contribution.

The objective of this study is to construct an optimal charging station location model which minimizes the installation cost while perfectly satisfying potential demand, by estimating demand using purpose OD data of drivers in Seoul. To this end, we formulate the hourly demand estimation model for the slow and fast charger in the unit area. Also, based on this demand, cost minimization model is formulated to derive the optimal location of charging stations and the number of slow and fast chargers. We apply these models to actual data in Seoul and conduct a case study on Seoul.

The rest of the paper is organized as follows. In Section 2, we review the related work on demand estimation model and optimal charging facility location model. In Section 3, we describe the data and assumptions used to develop our model. In Section 4, we formulate a demand generating model, which combines OD distance, driving purpose, and the total movement in the unit time interval. Also, the mathematical formulation of our cost minimization model is revealed. In Section 5, we present the data of Seoul and the basic result of our model. In Section 6, we conclude the paper with political recommendations to locate charging stations in Seoul and with the suggestions for further study.

2. Literature Review

Much research has been conducted on selecting the optimal location of EV charging stations. The models formulated in the research can be divided into demand estimation model, which aims to figure out the potential charging demand in the unit area, and optimization model, which aims to find the optimal location of charging stations based on the estimated demand. The most of constructed models have been applied to the case study of a specific country or city, by using the real data of the region. Through the procedure, the location and the number of charging stations in a specific region are revealed.

2.1. Work on demand estimation

Demand estimation models presented so far can be divided into two types. The first type is a model which estimates potential charging demand by reflecting the social, and demographic characteristics of a study area. Frade et al. (2011) formulate a demand model for the Lisbon area, Portugal, assuming that the charging demand depends on the demographic features of workers during the daytime and depends on those of residents during the nighttime. Liu (2012) conduct a case study for Beijing, China, and separate unit demand areas, taking into account the distribution of residential areas, gas station locations, parking lot locations, and power station locations. Sathaye and Kelley (2013) estimate the potential charging demand of highway corridor as a function of population and the amount of traffic, making a study of the highway of Texas, the United States. Morrissey et al. (2016) forecast the future charging demand in the whole area of Ireland based on the real EV driver's data, such as charging location, charging time, and charging type. He et al. (2016) estimate the potential charging demand in a specific area through a weighted sum of six socio-demographic components, such as age, sex, income level, etc., in Beijing, China. Delphi technique is used to determine the weight of each component in the research. Kleiner et al. (2018) separate German area into metropolitan, urban, and rural area. The average distance traveled in each area is calculated by the features of the area. (e.g., vehicle type ratio, commute distance) and it becomes a potential demand. In this model, they assume that drivers use a slow charger when they commute and use fast charger during long journeys.

A second type is an approach to estimate demand based on measuring the traffic flow of real vehicles. Xi et al. (2013) estimate the number of EV in the study area through EV penetration rate. The potential charging demand is generated by assigning tour direction to each EV randomly, based on real tour record data of conventional cars. Riemann et al. (2015) set each OD pair as a flow pattern, and generate EV charging demand, reflecting the routing choice behaviors of EV drivers. A numerical study is conducted instead of a case study of the real world in the research. Meanwhile, several studies estimate EV demand by using GPS OD data of real vehicles. Dong et al. (2014) make the daily driving route of EV by using the tour record of conventional cars in Seattle, the United States. The potential demand occurs when drivers arrive at the destination and need to charge to finish the remaining route of the day. Cai et al. (2014) and Shahraki et al (2015) estimate the traffic flow in the city through the driving data of taxis in Beijing, China. Based on it, EV traffic flow and its charging demand are calculated.

In this study, the potential demand is estimated based on the driving distance of passenger cars, using purpose OD data. However, we consider not the route of the individual, but the total amount of vehicles which move from specific origin to a specific destination. Also, we distinguish the demand by its driving purpose. Therefore, the demographic information, such as whether an area is a workplace or a residential area, is implicitly reflected in our model.

2.2. Work on optimal location of charging stations

Optimization methodology is the most prevalent in the research related to selecting optimal locations of charging stations. Most research formulates models containing objective function and several constraints which represents the circumstances they want to analyze. Wang and Wang (2010) formulate the model to optimize the location of charging stations for alternative fuel vehicle (AFV). Mixed-integer program is used, whose objective function is composed of the weighted sum of cost minimization factor and demand coverage maximization factor. Frade et al. (2011) fix the number of charging stations, and formulate maximal coverage location problem (MCLP) is implemented as MIP, which select the location of potential charging stations that can cover the demand as possible. Sathaye and Kelley (2013) construct convex optimization model to minimize the total distance of deviation which occurs when drivers try to charge in their driving route. The constraints are a budget limit for installation and service level above a certain level. Dong et al. (2014) formulate the model which focus on the minimization of missing trips of drivers due to the lack of battery charging under the budget constraint.

Chung and Kwon (2015) present a multi-period optimization model, whose objective is coverage maximization of the flow in the planning horizon. The subject of the study is the highway in Korea. Riemann et al., (2015) and He et al. (2018) develop a network model to capture the maximum flow under a traffic network. Numerical studies are conducted to evaluate these network flow model. He et al. (2016) develop a set covering problem (SCP) to minimize the number of charging stations which guarantees to cover the potential demand. MCLP and P-median model are also formulated, which has an objective to maximize the demand coverage when the number of charging stations is fixed. They compare these 3 models in various viewpoint and show that P-median model is the most effective. Yang et al. (2017) analyze electric taxis in Changsha, China, by formulating the MIP model of cost minimization while ensuring service quality above a certain level.

In this study, we develop a MIP model which combines SCP and cost minimization model. We try to find the optimal location of charging stations which minimize the installation cost of slow and fast chargers while covering all potential demand. We focus on how charging stations should be located to relax battery anxiety of EV drivers and to make use of the minimum budget in the viewpoint of government.

3. Background

3.1. Data and assumptions

This study is conducted based on the OD data of "passenger transmission nationwide and future demand forecast" by Ministry of Land, Infrastructure, and Transport of Korea (Korea Transport Database, 2017). Two types of OD data are used in the study. The first is the purpose OD data. This data classified each OD data between administrative districts by travel purposes which includes going to work, returning home, shopping, etc. It indicates the number of people who move a particular OD for a particular purpose during the day. The second is transportation OD data, which classifies the OD data based on the means of transportation such as bus, car, taxi, etc. This data is required to estimate the amount of EV traffic flow since purpose OD data which we've obtained did not distinguish people by means of transportations. Transportation OD data also indicates the number of people who move a particular OD using particular transportation during the day. We also use the hourly traffic flow of Seoul grouped by travel purposes, since it is necessary to distribute the amount of daily travel into hourly travel, according to the purpose.

The OD data is divided into two parts: purpose and transportation. Since we need the number of EV with each purpose, we should combine these two data. So, it is assumed that those two data are independent. Also by assuming that hourly traffic flow data sorted by travel purposes is independent OD data, we can get hourly demand sorted by each travel purpose and transportation. For further simplification, we grouped travel 11 purposes into 3 groups (Going to work, Returning home, Others). The reason why we divide purposes into these 3 groups is that each group has a distinct difference in the degree of concentration in hourly traffic flow. Also, 21 transportations into 3 groups (Private car, Taxi, Others) from the OD data. This is because we only focus on EV charging stations for passenger cars. Due to economic reasons, taxis prefer fast charging in order to do more work and has no home charger. Therefore, we divide the passenger car type as private car and taxi. The details of the grouping are shown in **Table 1**.

Table 1 | Grouping details in purpose and transportation types

Purpose group	Transportation group
Purpose 1 (p1): Going to work	***Transportation 1 (v1): private car***
Going to work	Private car (self-drive)
Going to school	Private car (drive by others)
Purpose 2 (p2): Returning home	***Transportation 2 (v2): Taxi***
Returning home	Taxi
Purpose 3 (p3): Others	***Transportation 3 (v3): Others***
Send-off	Bus (city, town, wide area, intercity, express, others)
Going to academy	Rail (light, high speed, general, subway)
Business	Cargo (small, medium and large)
Shopping	Bicycle
Returning workplace	Motorcycle
Leisure	Air transportation
Dining	Ship
Visiting relatives	Walk
	Etc

Also, as mentioned earlier, purposes are grouped as 3 types. Hourly traffic flow of each travel purposes has significantly different characteristics. **Figure 1** depicts the hourly traffic flow of each purpose in a day. P1, which implies going to the workplace, has a quite high rate in the morning hours (6-9), while P2, which implies returning home, shows high rate in the evening time (18-21). At the same time, the rate of P3, which includes all other than commuting traffic, distribute relatively evenly in all time period except for late night hours.

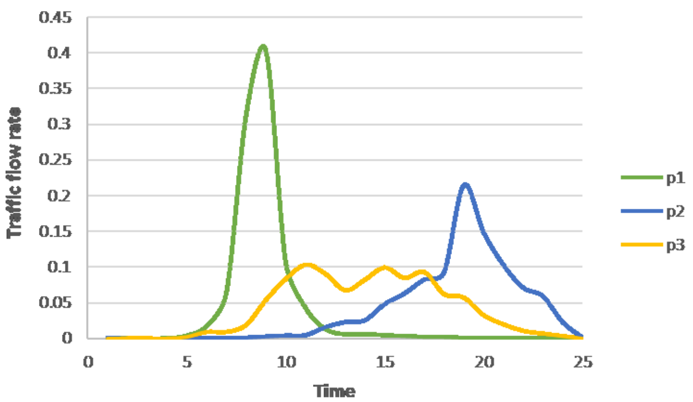

Figure 1 | Traffic flow ratio of each purpose in a day

3.2. Study area

The OD data represents the moving amount of people between *Dong* across Korea. *Dong* is the smallest administrative district of Korea. To reduce the complexity of the problem, we only focus on the traffic flow arriving in Seoul. It is assumed that all EVs are fully charged before entering Seoul, which allows us to focus on the public charging stations in Seoul. Therefore, OD data with a destination in Seoul are used only. Meanwhile, we consider data with the origin of Seoul and the adjacent areas, i.e., Incheon and Gyeonggi-do. This is because there is a huge traffic flow from these adjacent areas to Seoul for the commute or other purposes, and its scale is not ignorable. Also, it is assumed that demand is generated automatically at the end of the travel (destination) occurring hourly. In this study, we are interested in the demand from the perspective of the whole system, not each passage point of view. Thus, there is no need to consider the usage schedule of the charging station.

In more detail, there are 424 *Dong* in Seoul, which are the smallest administrative districts in Seoul. We assume that those are the unit area. It is assumed that all travels are to move between the centers of the unit areas. The distance between *Dong* is measured as the distance between their centers. For the distance parameter, we use the Manhattan distance system to measure the distance between the centers. The centers of unit regions are called as "demand point", which implies that all potential demand which occurs in the unit area is aggregated to the demand point. The 424 demand point of Seoul is pointed in **Figure 2**.

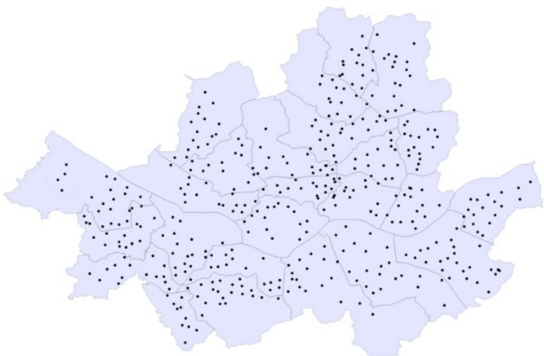

Figure 2 | Demand points of Seoul

For the location of potential public EV charging stations, we consider public parking lots in Seoul. Public parking lots are considered as candidates of EV charging stations in much research (Frade et al., 2011; Sadeghi-Barzani et al., 2014; He et al., 2016). The public car park is a good example of how charging stations should be distributed because it is highly accessible and evenly distributed in the study area. Each public car park has parking lots which have limited capacity and we assumed only 10% is available for EV charger installation. The 838 public parking lots, which has more than 10 parking lots in Seoul are considered as candidates of EV charging stations. The location of potential charging stations is depicted in **Figure 3**.

One traffic flow starts from the origin and ends in the destination. It then requests charging to potential EV charging stations nearby. During the process, we assume there will be a maximum desirable distance, which people will drive just for EV charging. To simplify the model, we also assumed that people with the home charger do not use the public charger and taxis only use the public charger.

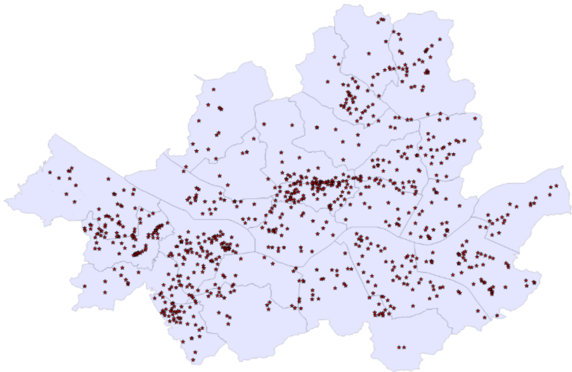

Figure 3 | Location of potential EV charging stations in Seoul

4. The models

In this section, we develop a model for demand estimation for each type of chargers based on the data and assumptions in Section 3. Furthermore, after estimating the demand for each charger at each demand point, we formulate cost minimization model to ensure for public charging stations to cover all potential demand which occurs hourly, considering the capacity of a parking lot.

4.1. Demand estimation model

The objective of this section is to get hourly demand for fast and slow EV public charger in each demand point. Set and parameter notations used for demand generating model is described in **Table 2** and **Table 3.**

Table 2 | Notation of sets

Notation	Description
O	set of all origins
D	set of all destinations
L	set of potential EV charging stations
P	set of all travel purposes
V	set of all travel transportations
T	24-hour time / $T = \{0, 1, 2, \cdots, 23\}$

Table 3 | Notation of parameters

Notation	Description
H_v	EV home charger adoption rate of transportation $v \in V$
$EVPR_v$	EV penetration rate of transportation v
$\delta^{p,v}$	percentage of people who want to use a slow charger after the travel by transportation $v \in V$ with purpose $p \in P$
n_{ij}^{p}	number of travels from origin $i \in O$ to destination $j \in D$ with purpose $p \in P$
n_{ij}^{v}	number of travels from origin $i \in O$ to destination $j \in D$ by transportation $v \in V$
n_j^t	number of travels to destination $j \in D$ at time $t \in T$
r_{ij}^{v}	ratio of the number of travels from origin i to destination j by trasportation $v \in V$ to the total number of travels from origin i to destination j, where $i \in O, j \in D$
d_{ij}	distance between district $i \in A$ and district $j \in S$
q_p^t	ratio of the demand with purpose p ∈ P at time $t \in T$ to the total demand with purpose p ∈ P
$N_{ij}^{p,v}$	number of travels from origin $i \in O$ to destination $j \in D$ taking EV transportation $v \in V$ with purpose $p \in P$
$D_{jt}^{p,v}$	demand in destination $j \in D$ at time $t \in T$, caused by transportation $v \in V$ with purpose $p \in P$
D_{jt}^{S}	demand for slow charger in destination $j \in D$ at time $t \in T$
D_{jt}^{F}	demand for fast charger in destination $j \in D$ at time $t \in T$

To estimate charging demand, the first mission is to know the number of EV of each transportation arrived in a certain hour, with a specific purpose. Two parameters n_{ij}^{p}, n_{ij}^{v} are used to represent each for the purpose, transportation OD data. Each parameter means the number of people whose origin is i and the destination is j, with the purpose p or with the transportation v. In order to know the number of each type of transportation moving from i to j with a certain purpose in a day, which is represented as $N_{ij}^{p,v}$, transportation usage rate is multiplied to purpose OD value as in (1). Then, the number of EV traveling specific OD in a day is revealed by multiplying EV penetration rate of each vehicle type ($EVPR_v$) as in (2).

$$r_{ij}^{v} = \frac{n_{ij}^{v}}{\sum_{x \in V} n_{ij}^{x}} \tag{1}$$

$$N_{ij}^{p,v} = EVPR_v \times n_{ij}^{p} \times r_{ij}^{v} \tag{2}$$

The second mission is to distribute daily traffic of EV to each time period and to calculate total demand in each demand point. As shown in **Figure 1**, the hourly demand rate generated by each purpose is calculated from purpose OD data as in (3). Lastly, charging demand in a certain time period t at the destination j is derived in the measure of distance as in (4). Since only the vehicles who don't have home charger request public charging, the home charging parameter is also multiplied.

$$q_p^t = \frac{n_p^t}{\sum_{x \in P} n_p^x} \tag{3}$$

$$D_{jt}^{p,v} = \sum_{i \in O} \left(N_{ij}^{p,v} \times d_{ij} \right) \times q_p^t \times \left(1 - H_v\right) \tag{4}$$

Now that we have hourly demand for each travel purpose and transportation used, we need to separate the demand with the choice between slow and fast charger as in (5) and (6). $\delta^{p,v}$ is a measure of the propensity to the slow charger of drivers traveling with a purpose p, whose vehicle time is v.

$$D_{jt}^{S} = \sum_{v \in V,\, p \in P} \left(\delta^{p,v} \times D_{jt}^{p,v} \right) \tag{5}$$

$$D_{jt}^{F} = \sum_{v \in V,\, p \in P} \left(\left(1 - \delta^{p,v}\right) \times D_{jt}^{p,v} \right) \tag{6}$$

From the model, the total potential demand for each type of charger in each demand point can be calculated in the hour unit. The unit of demand is represented as distance. Therefore, in this study, all units related to the amount of charging is converted into distance.

4.2. Optimization model

Additional notations used for the optimization model is described in **Table 4** and **Table 5**. The formulation of the optimization model is as follows. There exists a driver's maximum desirable charging distance, which means that if the charging station is away from this distance, drivers won't go to charge their EVs.

Table 4 | Notation of sets and parameters

Notation	Description
B_j	set of all potential charging stations whose distance is less than maximum desirable distance from destination $j \in D$
$COST_S$	cost of a slow EV charger
$COST_F$	cost of a fast EV charger
$CAPA_S$	capacity of a slow EV charger per hour
$CAPA_F$	capacity of a fast EV charger per hour
$SPACE_l$	number of available installation spaces in potential EV charging station $l \in L$

Table 5 | Notation of decision variables

Notation	Description
y_{jlt}^{S}	flow quantity for a slow charger from demand point $j \in S$ to charging station $l \in L$ at time $t \in T$
y_{jlt}^{F}	flow quantity for a fast charger from demand point $j \in S$ to charging station $l \in L$ at time $t \in T$
N_{l}^{S}	optimal number of slow chargers in location $l \in L$
N_{l}^{F}	optimal number of fast chargers in location $l \in L$

$$\min \sum_{l \in L} \left(COST_S \times \mathrm{N}_l^S + COST_F \times \mathrm{N}_l^F \right) \tag{7}$$

$$s.t. \sum_{l \in B_j} y_{jlt}^S = D_{jt}^S \quad \forall j \in J, t \in T \tag{8}$$

$$\sum_{l \in B_j} y_{jlt}^F = D_{jt}^F \qquad \forall j \in D, t \in T \tag{9}$$

$$\sum_{j \in D} y_{jlt}^S \le CAPA_S \times \mathrm{N}_l^S \qquad \forall l \in L, t \in T \tag{10}$$

$$\sum_{j \in D} y_{jlt}^F \le CAPA_F \times \mathrm{N}_l^F \qquad \forall l \in L, t \in T \tag{11}$$

$$\mathrm{N}_l^S + \mathrm{N}_l^F \le SPACE_l \qquad \forall l \in L \tag{12}$$

$$y_{jlt}^S, y_{jlt}^F \ge 0 \qquad \forall j \in D, l \in L, t \in T \tag{13}$$

$$\mathrm{N}_l^S, \mathrm{N}_l^F \in Z_+ \qquad \forall l \in L \tag{14}$$

The objective function (7) is minimizing the installation cost of the EV charging stations. Setting the installation cost of fast and slow EV chargers as constants ($COST_S$, $COST_F$), we made two decision variables (N_l^S , N_l^F) as numbers of EV chargers needed in each district so that the objective function can be linear. Two additional decision variables(y_{jlt}^S , y_{jlt}^F) are used to calculate the traffic flow between demand points and potential EV charging stations. (8) and (9) state that the sum of traffic flow which goes to charge EV from the demand point should be equal to the demand of each type of charger. Moreover, it states traffic flow is only made under the maximum desirable distance limit. (10) and (11) states that hourly traffic flow to charge aggregated at the potential EV charging station should not be larger than the capacity of EV chargers installed. Constraints (12) states that the number of the EV charging station cannot be installed above the possible parking lot of potential EV charging station. (13) states non-negativity condition of traffic flow. Finally, (14) states the number of EV chargers should be nonnegative integers, making this model MIP formulation.

5. Result and discussion

5.1. Demand estimation

There are several sets and parameters to be determined before starting the analysis. As mentioned earlier, the study focus on the installation of charging stations in Seoul. Also, the volume of traffic flow from the adjacent areas of Seoul cannot be ignorable. Therefore, the origin and destination set used in the study are determined as follows.

$$O = \{\text{centers of Dong in Seoul, Incheon, and Gyeonggi-do}\}, \quad D = \{\text{centers of Dong in Seoul}\}$$

Note that destination set represents demand point, since charging demand occurs in the destination. Further, the subjects of the study are passenger cars, not bus, cargo, rail, etc. Therefore, we set EV penetration of transportations other than passenger cars (private cars and taxis) as 0%, while setting the EV penetration rate of passenger cars at 1%. i.e.,

$$EVPR_v = \begin{cases} 0.01 & \text{if } v \in \{v_1, v_2\} \\ 0 & o.w. \end{cases}$$

Also, it is assumed that a taxi cannot use the home charger. We set 10% of EV users to have their own home charger, which means they don't use a public charging station, i.e.,

$$H_v = \begin{cases} 0.1 & \text{if } v = v_1 \\ 0 & o.w. \end{cases}$$

Lastly, the most critical issue is to determine the propensity to slow charger of each purpose, $\delta^{p,v}$. In terms of private car users whose driving purposes are going to work or returning home, EV drivers can park their cars relatively long time. They might prefer slow charging over fast charging. Meanwhile, private car users whose driving purposes are shopping, business, etc., they might prefer fast charging, since they cannot charge a long time. We set the propensity to slow charger when going to work and returning home as 0.8, and others as 0.2. Regarding taxis, they always request fast charging. It is not necessary to define the propensity of other transportations since there is no electric-based transportation except for passenger cars in our model. Then the propensity to the slow charger can be written as

$$\delta^{p,v_1} = \begin{cases} 0.8 & p = p_1, p_2 \\ 0.2 & p = p_3 \end{cases}, \qquad \delta^{p,v_2} = 1, \forall p \in P$$

The estimated time-dependent demand in each demand point is calculated through the model presented in Section 4.1. and the parameters determined above. **Figure 4** describes the time-dependent potential demand toward slow charger. To see the variance of time-dependent demand more simply, we separate time period in 4 sections: (1) morning (6~9), (2) afternoon (10~18), (3) evening (18~21), (4) night (22~5). It is easy to see that the areas where demand is high become different depending on time period. In the morning, the southern and central areas of Seoul show higher demand comparing to others. This is because workplaces are concentrated in these areas. At the same time, it is shown that demand in outer areas of Seoul rise sharply and demand in central areas drop significantly in the evening time, compared to morning. This trend can be interpreted as residential areas of Seoul are mainly distributed in outer regions. However, southern parts continue to show a high level of demand, since residential and workplace coexist in these parts.

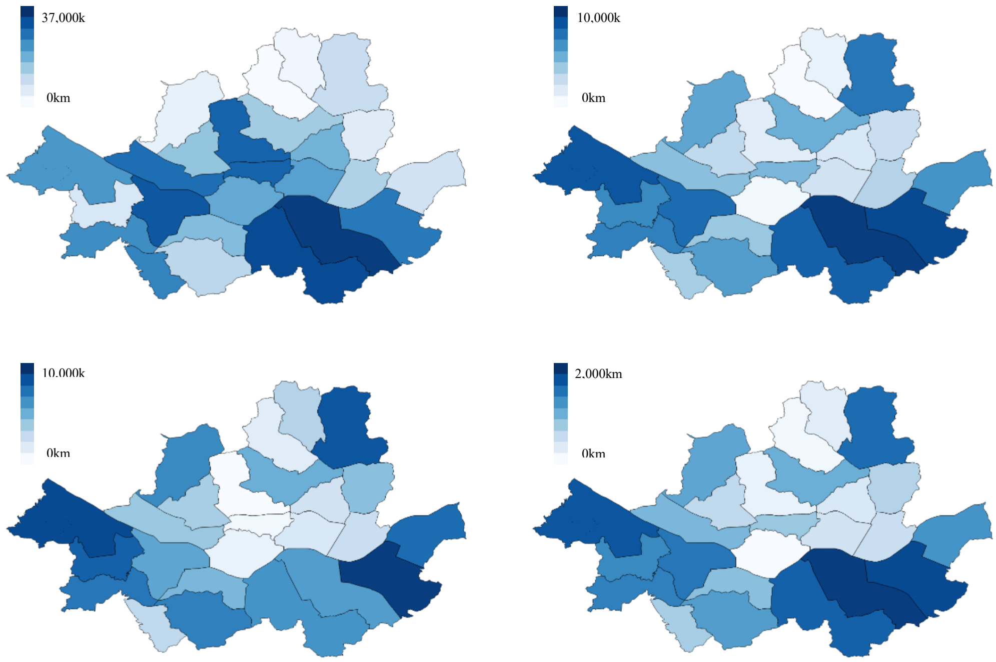

Figure 4 | Time-dependent demand for the slow charger
(Top-Left: 6~9, Top-Right:9~18, Bottom-Left:18~21, Bottom-Right: 21~5)

Figure 5 describes the time-dependent potential demand toward fast charger. Surprisingly, compared to the distribution of demand for the slow charger, it seems to show quite similar distribution regardless of time. Except for the central areas, whose demand is mainly concentrated in the morning time. The southern areas show a high level of fast charging demand in all time period since the areas are the center of the commercial district of Seoul. People travel these areas for many purposes, such as shopping or visiting, etc. However, the northern areas show a low level of demand. It is because these areas don't have many commercial places, and people reside there less than in other regions.

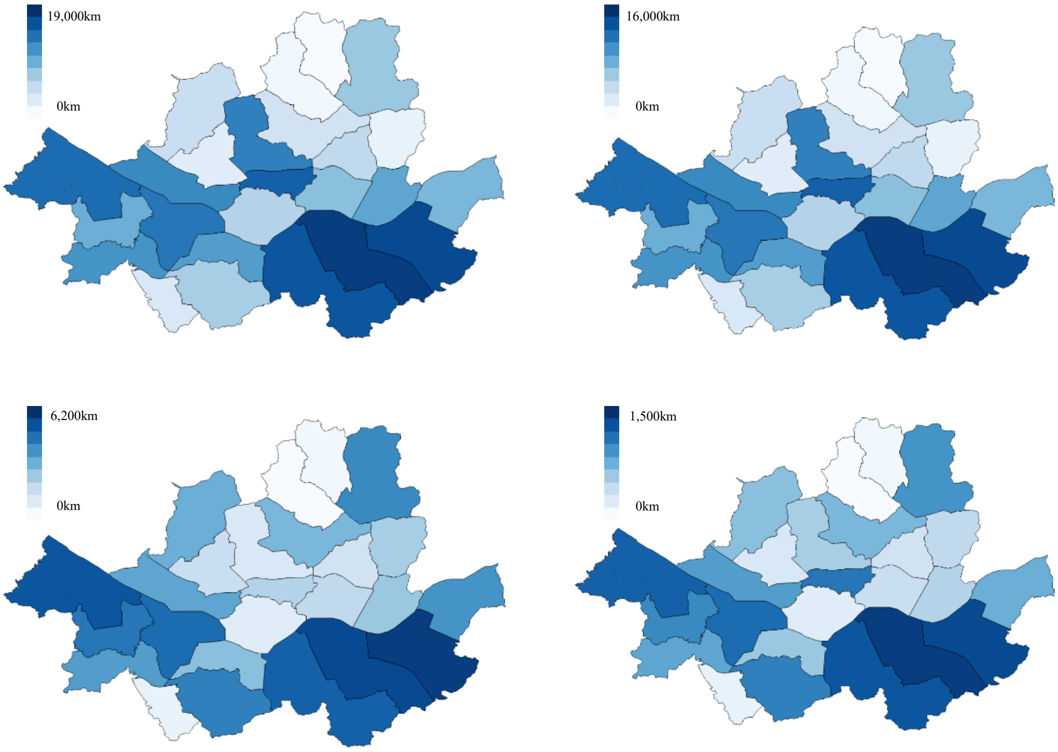

Figure 5 | Time-dependent demand for the fast charger
(Top-Left: 6~9, Top-Right:9~18, Bottom-Left:18~21, Bottom-Right: 21~5)

The totally estimated hourly charging demand for EV is shown in **Figure 6**. The peak time of both types of charging is 8 a.m. but demand for fast charging shows more flat shape. Commuting is the most influential in charging demand.

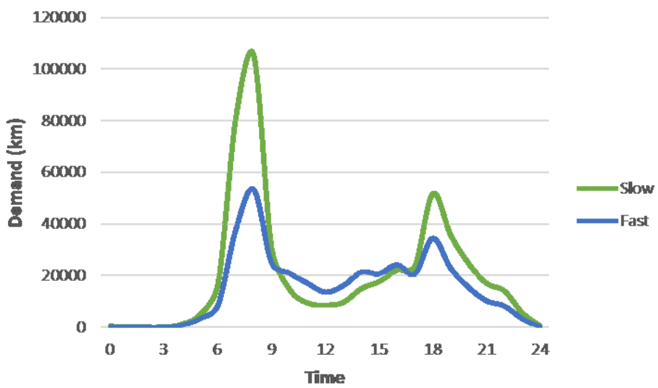

Figure 6 | Total estimated hourly demand

5.2. Optimal locations of charging stations

From the demand of each type of charger, which is estimated in the demand estimation model, the optimization model is applied to figure out the optimal number of chargers and their locations. We set the maximum desirable distance as 2km (He et al., 2016), which means the drivers in a certain demand point won't go to charging station far away more than 2km to charge their EVs. It is assumed that all of EVs have the same battery capacity, whose operation range is 300km if fully charged. Further, it is assumed that it takes 4h 30min for the slow charger to fully charge a perfectly discharged battery, and 30 min for the fast charger to charge a perfectly discharged battery to 80% level. Since we estimate demand unit as kilometers, the capacity of each type of charger calculated in the unit of kilometers per hour is

$$CAPA_S = \frac{200}{3}\text{km/hour}\,,\quad CAPA_F = 480\text{km/hour}$$

The unit cost of each type of charger is \$3,000 for a slow charger and \$40,000 for a fast charger. Also, only 10% of the total parking lot of potential charging stations can be used to install chargers. For the computational experiment, we used X-press of FICO® as a solver of our MIP model. Since the problem is NP-hard, we stopped the computation when the gap of LP bound and IP solution goes below 3%. The model is performed on the personal computer with Intel® Core™ i7-6700 3.40GHz CPU and 16.0GB of RAM.

From the model and parameters, the optimization results are obtained. A total of 1610 slow chargers and 113 fast chargers are needed to cover the estimated demand. The minimized cost is \$935,000. The optimal locations of each type of chargers are depicted in **Figure 7** and **Figure 8**.

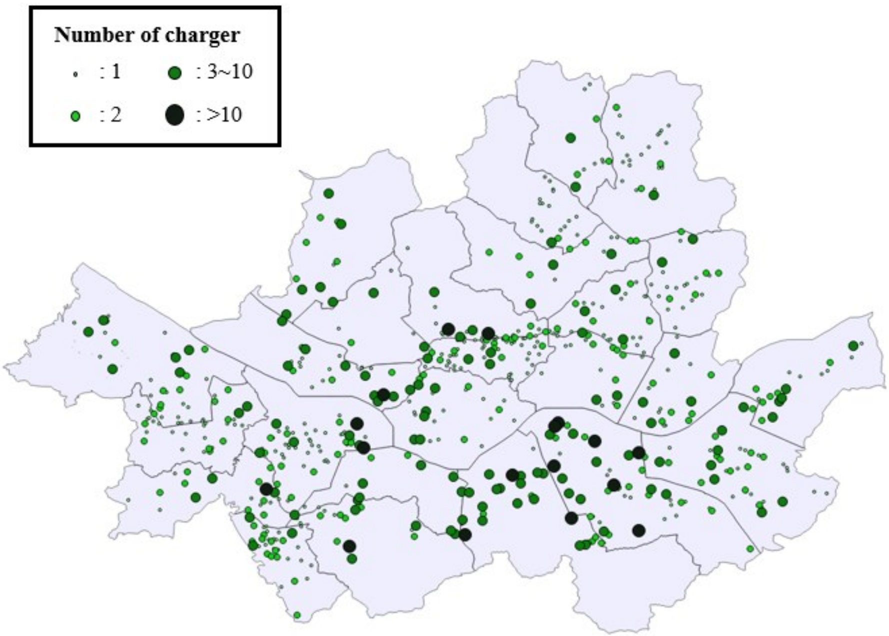

Figure 7 | Optimal location of slow chargers

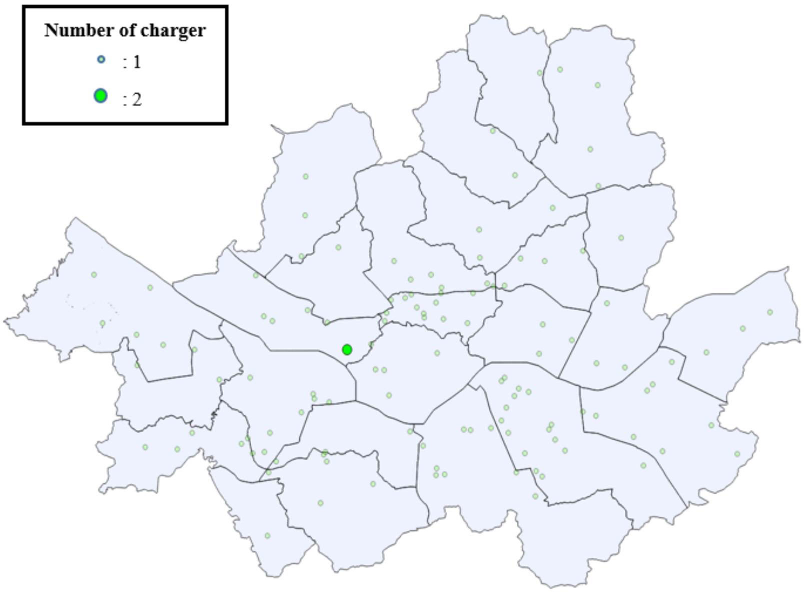

Figure 8 | Optimal location of fast chargers

The distributions of slow and fast chargers are quite different. In terms of slow chargers, due to EV users who travel with the purpose of going work, there is a tendency to be a considerable concentration of charging stations in the work areas, i.e., central and southern regions. Charging stations in the workplace are distributed evenly, and many chargers are installed at each charging station. Meanwhile, the outer region of Seoul has charging stations whose sizes are small compared to that of the work area, although the charging stations are highly distributed. This is because the outer regions are mostly residential areas, and people's time to get home are usually less crowded than the time to go to work. So, a small number of chargers can fully cover the hourly demand for slow charging in evening and night time.

In terms of fast chargers, not many of them are installed in one place. This is because that fast charger has a good capacity and peak time demand for fast chargers is not that big compared to slow chargers. So, it is not necessary to build expensive fast chargers in the same charging stations. Meanwhile, the locations of fast chargers are quite evenly distributed all over Seoul. The results appear to have been made by the traffic flow of electric taxis. Since taxis travel a wide range of Seoul and request fast charging demand at each destination.

6. Conclusion

In this study, we argued that the travel purposes matter in the hourly demand estimation for the two types of EV chargers, slow and fast. Our first objective was to construct a new demand model for the EV charging station by incorporating the OD data, travel purpose, and hourly traffic flow at the same time. Our second objective was to generate an optimization model which minimizes the installation cost of EV charging station while covering the total demand with consideration of travel purposes.

With the purpose-oriented demand and optimization model, we carried out a case study of Seoul, Korea. Dealing with particular characteristics of Seoul, such as high population density and spatial difficulty for home charger installation, we suggested an optimal plan for the EV charger distribution including charger types, locations, and number to install.

In the case of Seoul, hourly EV charging demand showed a certain proclivity depending on the characteristics of districts, such as residential areas, commercial areas, workplaces. In the morning time, slow charger demands at workplaces got higher compared to other areas. As time goes by, slow charger demands at night were concentrated on residential areas, which also includes some parts of workplaces. For the fast charger, the demand was quite time-independent with a slight peak on morning and evening periods. It has seemed as commercial areas have high needs for the fast charger due to the high traffic concentration caused by purposes such as shopping or visiting. From the optimization result of EV charging station distribution, we could see fast chargers are located evenly throughout Seoul. This is because of high capacity so that there is no need to install a large number of fast chargers. Accordingly, slow chargers should be located mainly on workplaces rather than residential areas which are less crowded.

This study can be further improved in many respects. By examining the utilization rate of installed chargers, we can suggest a policy-relevant EV charging station installation plan. Also, we can develop the study by executing propensity survey for a certain type of charger usage getting a more reliable result for the case study of Seoul. By carrying out a sensitivity test for parameters, we can check which parameter affects the installation plan the most. Furthermore, implementing various optimization models such as maximum coverage model can help optimization model be more practical.

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