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Authors

Jung, Jaeyoung, PhD
Chow, Joseph Y.J., PhD
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16 **Jaeyoung Jung, Ph.D.**
17 **Joseph Y.J. Chow, Ph.D.**
18 **R. Jayakrishnan, Ph.D.**
19 **Ji Young Park, Ph.D.**
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21

22
23 **Institute of Transportation Studies**
24 **University of California, Irvine; Irvine, CA 92697-3600, U.S.A.**
25

26 **jaeyounj@uci.edu, joseph.chow@ryerson.ca, rjayakri@uci.edu, parkjy@koti.re.kr**
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34 **Institute of Transportation Studies**
35 **University of California, Irvine**
36 **Irvine, CA 92697-3600, U.S.A.**
37 **<http://www.its.uci.edu>**

Stochastic dynamic itinerary interception refueling location with queue delay for electric taxi charging stations

Jaeyoung Jung^{1*}, Joseph Y.J. Chow², R. Jayakrishnan¹, and Ji Young Park³

¹*Institute of Transportation Studies, Department of Civil and Environmental Engineering,
University of California, Irvine, California, United States*

²*Department of Civil Engineering, Ryerson University, Toronto, Ontario, Canada*

³*Department of National Transport Strategy Planning, The Korea Transport Institute, Gyeonggi-do,
Korea*

ABSTRACT

A new facility location model and a solution algorithm are proposed that feature 1) itinerary-interception instead of flow-interception; 2) stochastic demand as dynamic service requests; and 3) queueing delay. These features are essential to analyze battery-powered electric shared-ride taxis operating in a connected, centralized dispatch manner. The model and solution method are based on a bi-level, simulation-optimization framework that combines an upper level multiple-server allocation model with queueing delay and a lower level dispatch simulation based on earlier work by Jung and Jayakrishnan. The solution algorithm is tested on a fleet of 600 shared-taxis in Seoul, Korea, spanning 603 km², a budget of 100 charging stations, and up to 22 candidate charging locations, against a benchmark “naïve” genetic algorithm that does not consider cyclic interactions between the taxi charging demand and the charger allocations with queue delay. Results show not only that the proposed model is capable of locating charging stations with stochastic dynamic itinerary-interception and queue delay, but that the bi-level solution method improves upon the benchmark algorithm in terms of realized queue delay, total time of operation of taxi service, and service request rejections. Furthermore, we show how much additional benefit in level of service is possible in the upper-bound scenario when the number of charging stations approaches infinity.

KEYWORDS: Electric Vehicle, Shared-Taxi, EV charging, Bi-Level Optimization, Facility Location, Stochastic Demand, Simulation, Refueling

1. INTRODUCTION

Carbon-based emissions and greenhouse gases (GHG) are critical issues that policy-makers have sought to address in a generally global effort since the Kyoto Protocol in 1998. The transportation sector is a major culprit, contributing approximately 30 percent of the GHG emissions in the United States (U.S. EPA, 2006). One technology-oriented solution is to switch vehicle fuels to alternative, sustainable sources and wean consumers off their oil dependency. To that end, automobile manufacturers produced a range of different types of alternative-fuel vehicles (AFVs) including hybrid vehicles (HVs), plug-in hybrid electric vehicles (PHEVs), electric vehicles (EVs), and fuel cell vehicles (FCVs). It has been shown that EVs can cost as little as 1.2 to 1.9 cents per km (2 to 3 cents per mile) compared to 8 cents per km (13

* Corresponding Author. Tel.: +1 949-824-5989
E-mail address: jaeyoung@uci.edu

cents per mile) for vehicles powered by Internal Combustion Engines (ICE), and EVs cause 50 percent less CO₂ emissions per mile traveled compared to ICE (Mak *et al.*, 2012).

Nevertheless, there are several obstacles to EV adoption; the most important being the chicken-and-egg problem related to the electric charging infrastructure. The lack of penetration in the EV market (and other AFVs as well) limits the value of fuel infrastructure investments, which increases the “range anxiety” and reduces consumer demand. As a result, much of the recent research in AFVs has placed optimal location and allocation of refueling infrastructure at the forefront (e.g. Kuby and Lim, 2005; Lin *et al.*, 2008; Wang and Lin, 2009; Nourbakhsh and Ouyang, 2010; Kameda and Mukai, 2011; Kang and Recker, 2012; MirHassani and Ebrazi, 2012; Chung and Kwon, 2012, Jiang *et al.*, 2012; He *et al.*, 2013; Xi *et al.*, 2013). This problem is particularly relevant to EVs because the vehicles tend to have limited ranges, and recharging can take on the order of an hour or more.

One implementation strategy is to invest in EV flexible transit services (FTS) (Koffman, 2004) and taxi fleets. FTS encapsulate a wide range of transit and taxi services that include demand responsive transit (DRT), flexi-route transit, car-sharing systems, and ride-sharing. There are several advantages to implementing EV FTS for initial EV adoption: 1) it takes the individual consumer behavior out of the picture since the decision would be based on fleet managers and/or public agencies; 2) “range anxiety” is less of an issue because transit fleets operate in the same urban region; 3) the reduction in energy consumption would be most realized by transit vehicles operating in a congestion-heavy region (Tong *et al.*, 2000) as opposed to long distance rural trips; and 4) specific to FTS, the vehicles can be passenger cars so that the same infrastructure can also serve the consumer market. Even if EVs are not considered ready to replace private ICE vehicles for the general public, they may be viable options for these fleet applications (Barth and Todd, 2001; Better Place, 2012; FedEx, 2012). The Seoul Metropolitan Government in Korea unveiled its “2014 Master Plan for Electric Vehicle” in 2011, which will commercialize 30,000 units of EVs on the road by 2014 with buses and taxicabs (eGlobal Travel Media, 2011). One of the key goals in the plan is to deploy 1,000 EV taxicabs by 2014. The EV taxis will be able to operate over a distance of 200 km to 400 km a day and will require battery charging stations or battery replacing facilities.

The proliferation of computing and mobile technologies for connected vehicles has made it easier to operate FTS (Lau *et al.*, 2011), resulting in a growing literature in that area: Cortés and Jayakrishnan (2002), Zhao and Dessouky (2008), Hadas and Ceder (2008), Quadrioglio and Li (2009), Mulley and Nelson (2009), Crainic *et al.* (2010), Alshalalfah and Shalaby (2012), Nourbakhsh and Ouyang (2012), Kim and Schonfeld (2012), Jung (2012), Jung and Jayakrishnan (2012), and Jung *et al.* (2013). Surprisingly, there has not been much research in the facility location problem specifically for EV taxi and FTS fleets.

Facility location problems for EV transit and taxi fleets have a set of unique characteristics that cannot be addressed by the solutions developed thus far in the literature. First, EV taxis, as service vehicles, need to place much more weight on the cost of the recharging time. Whereas consumers can recharge when they return home for the night, a taxi may need to be out of commission for a significant period of time during the day if it runs out of charge. With limited infrastructure, queue delay is an important problem that has been largely neglected in the AFV facility location literature to date. Second, many of the AFV location problems focused on fuel stations covering paths formed by origin-destination (OD) pairs in a network. However, connected taxis operate with a central dispatch as a dynamic vehicle routing system. In other words, each taxi follows an itinerary that is determined dynamically. Trip-based demand, even modeled with methods such as path flow-interception as described in the next section, cannot capture this dynamic itinerary. Lastly, passenger demand is stochastic, which results in a *stochastic dynamic itinerary* for each taxi. The AFV location literature has generally ignored such stochastic elements with a few exceptions.

A new model is proposed for locating infrastructure for electric taxis: the stochastic dynamic itinerary-interception refueling location problem with queue delay (SDIRQ). The model can also be applied to many other problems in urban logistics. The problem is presented as a bi-level simulation-optimization model, and tested on a network in Seoul, Korea spanning 603 km² (233 mi²) with 600

1 taxicabs, a budget of 100 charging stations, and 22 candidate refueling locations. Section 2 provides a
 2 more in-depth literature review to show the motivation. Section 3 presents the bi-level SDIRQ model and
 3 two solution methods. A numerical study is provided in Section 4, followed by a conclusion in Section 5.
 4

5 **2. LITERATURE REVIEW**

6 **2.1. Refueling Location Problems**

7 Facility location problems are optimization models used to determine a set of locations to serve
 8 neighboring demand in a network at a minimum or constrained cost. The cost is usually defined by the
 9 distances between the demand nodes and the server nodes. These problems have a long history and
 10 extensive literature spanning many different fields. Comprehensive reviews and introductions to the
 11 subject are available from Owen and Daskin (1998), Drezner and Hamacker (2002), and Snyder (2006).

12 In the studies on conventional-fuel vehicles, it is well recognized that conventional models with
 13 node-based demand do not handle the refueling station siting problem very well. This is because people
 14 generally will not make a trip from their home to the station solely for refueling. Both Upchurch and
 15 Kuby (2010) and Kang and Recker (2012) have convincingly demonstrated this point by comparing
 16 against the conventional models. Instead, three alternative approaches have been considered.

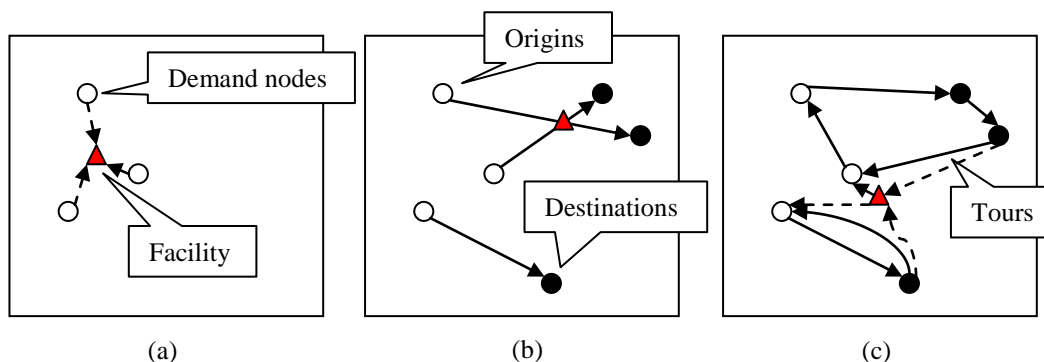
17 The first, and the more popular approach, has been the flow-capture or flow-interception location
 18 problem (Hodgson, 1990; Berman *et al.*, 1992). The problem is designed as a path-based version of
 19 Church and ReVelle's (1974) conventional maximal covering location problem. The shortest path
 20 between each OD pair is considered covered if it passes through at least one node that contains a server.
 21 The ij notation is switched to p path notation over the set of all shortest paths between each OD pair.
 22 Kuby and Lim (2005) extended the model to a flow-refueling location problem (FRLP), which serves
 23 demand from origin-destination flows along their shortest paths rather than demand at their end points.
 24 FRLP selects optimal refueling locations to maximize coverage of these flows by considering vehicles
 25 traveling the full round trip path with a range constraint not present in the prior formulation. Kuby and
 26 Lim (2007) further extended the problem to allow solutions on arcs because the optimality condition of
 27 being on nodes was only true for the flow-interception problem, not the range-constrained flow-refueling
 28 location problem. Upchurch *et al.* (2009) added capacity constraints to the problem. Kim and Kuby (2012)
 29 relaxed the FRLP to allow penalized or maximum deviations from the shortest paths to get to fuel stations.
 30 Jiang *et al.* (2012) proposed a flow-based model that combined capacity as well as deviation flow.

31 Because of the need to enumerate facility combinations, the FRLP was not very tractable. Wang and
 32 Lin (2009) proposed a variant path-based set covering model that avoided the combination enumeration
 33 by using variables to track remaining fuel and range. Wang and Wang (2010) further combined path and
 34 node-based passenger demand as a multiobjective problem. Capar and Kuby (2012) reformulated their
 35 model in an effort to make it more efficient, also resorting to constraints based on range variables.
 36 MirHassani and Ebrazi (2012) proposed a new model based on both Kuby's and Wang's models that was
 37 more computationally efficient. Their model was extended by Chung and Kwon (2012) to handle multi-
 38 period staging of investment strategies.

39 A second approach is to ignore ODs altogether and just relate the value of a location based on
 40 vehicle-miles traveled (VMT) indicators (Lin *et al.*, 2008). While this simplifies the problem somewhat, it
 41 ignores the range from a given location to a fuel station and simplifies assumptions about the probability
 42 of a particular vehicle's location.

43 The third and most recent approach is to locate based on an itinerary, or trip chain of multiple ODs,
 44 instead of just a trip OD. Nourbakhsh and Ouyang (2010) integrated the path-based refueling location
 45 problem with the fuel scheduling problem for freight locomotives, which was an initial step in this
 46 direction in the refueling literature. Kang and Recker (2012) introduced a model to locate hydrogen
 47 stations where households respond to location decisions by rescheduling their daily itineraries using an
 48 activity-based variant of the pickup and delivery problem (Recker, 1995). This approach is more high

1 resolution than the trip-based location solutions because it includes departure and arrival times throughout
 2 the day and maintains trip chains for each household member. It is the first study of an *itinerary-*
 3 *interception* refueling location model. The model is based on the location-routing problem (Perl and
 4 Daskin, 1985; Laporte *et al.*, 1988), and has been generalized to an activity-based network design
 5 problem (Kang *et al.*, 2013). The differences between these classes of models and their hypothetical
 6 solutions are shown in Figure 1.



10 **Fig 1.** (a) Node-based, (b) flow-intercept, and (c) itinerary-intercept.

11 Figure 1(a) shows conventional node-based models, such as the maximal cover location problem.
 12 Figure 1(b) shows the flow interception models that try to cover as many OD flows as possible,
 13 acknowledging that travelers tend to refuel as part of a trip. In this second scenario, it would make more
 14 sense to have the single facility located further to the right where two out of three paths can be
 15 “intercepted”. Figure 1(c) shows the itinerary-interception models where refueling is scheduled into the
 16 trip chains. The proposed SDIRQ is a new itinerary-interception location problem for refueling FTS and
 17 taxis in particular considering two added complexities not currently in this literature: 1) stochastic
 18 demand from customers that occur dynamically over time; and 2) queuing due to daytime charging for
 19 the service fleet.

20

21 2.2. Uncertainty

22 There have not been many attempts at stochastic variations of the FRLP, perhaps due to its complexity
 23 and also the belief that it is sufficient to assume routine consumer demands. Berman *et al.* (1995)
 24 extended their flow-interception model to include flows that are not known with certainty, using Dial’s
 25 algorithm to help solve the Markov Decision Process at each node. Mak *et al.* (2012) was one of the few
 26 to consider demand uncertainty in a flow-interception location model for EV battery swapping stations.
 27 They used a robust optimization approach to address uncertainty in demand.

28

29 2.3. Queueing

30 Stochastic queueing has not been considered at all in the AFV refueling station location literature. Most
 31 refueling location problems have not considered stochastic demand, which explains why there have not
 32 been any efforts to evaluate stochastic models of standard queues such as the well-known Kendall-
 33 notation queues (e.g. M/M/c). Facility location problems that feature queueing are defined such that
 34 optimal locations do not just minimize or constrain distances from a demand node to a server node; they
 35 also include the delay caused by a queue at the server node. This is an important issue to include for
 36 limited infrastructure and long recharging times, especially in a much more stochastic environment such
 37 as in the fleet context with real-time dispatch that we focus on.

1 One of the earliest efforts to incorporate queues in a location model is Larson's (1974) hypercube
 2 queueing model. More recently, Boyaci and Geroliminis (2011) extended the model to handle large scale
 3 spatial queueing. Spatial queueing treats the whole coverage of demand as a service, and are more
 4 appropriate for mobile servers that relocate from one node to another.

5 For stationary location siting that covers a large neighborhood of nodes, the challenge is to find some
 6 way to quantify the steady state delay at a server node to include in the objective function. This is trivial
 7 for single server nodes that assume Markov arrivals and service times, but becomes cumbersome for
 8 multiple co-located servers. In AFV refueling location problems, there is usually a set number of
 9 refueling or charging stations at a given server node. It becomes a highly nonlinear function of the
 10 demand arriving at the server node, which leads to an intractable facility location problem if it is included
 11 in the objective function. In a special context of emergency vehicles' dispatch, Marianov and ReVelle
 12 (1996) linearized this expression by moving it to the constraint of a maximal availability location problem
 13 (MALP) and showing how an equivalent linear form relative to a reliability measure can be obtained.
 14 Marianov and Serra (1998) further extended the linearized queueing constraint to other location models.
 15 To date, there has not been such an extension to the path-based FRLP, much less to itinerary-based
 16 demand.

17 A similar area of research is on an allocation problem that considers queueing. In this problem, the
 18 locations are already set and the problem is to allocate the demand to the server nodes (or to allocate
 19 servers to given demand) in an optimal manner. For example, Xi *et al.* (2013) proposed an allocation
 20 model with exogenous deterministic demand using simulation to evaluate the deterministic multiple-
 21 server delay and level of service. The allocation problem with stochastic queueing is even more
 22 challenging and has its roots in queueing networks, where researchers sought to determine the optimal
 23 allocations of servers in a network to minimize total network cost. Approximations for the multiple server
 24 delay evaluation were considered very early on. Iglehart (1965) presented a proof of an approximation for
 25 an M/M/c model. Rolfe (1971) extended the approximation to M/D/c queues with deterministic service
 26 times. Kimura (1983) generalized the approximation to M/G/c queues. Lovell *et al.* (2012) introduced a
 27 continuum approximation approach to approximate M/M/1 queues.

28 Berman and Drezner (2007) proposed a multiple server allocation model that accounted for queues at
 29 the server nodes, assuming demand is allocated to the closest server node. The multiple server allocation
 30 problem can be solved exactly using a greedy algorithm to incrementally assign servers, as has been
 31 demonstrated in the queueing network literature (e.g. Rolfe, 1971).
 32

33 **2.4. Shared-Taxi Operations**

34 In short, the literature on AFV refueling stations has been growing in recent years but they have dealt
 35 primarily with *consumer passenger vehicles*, using deterministic approaches that do not account for
 36 queueing. Furthermore, one investment strategy that may help overcome the chicken-and-egg problem—
 37 investing in publicly operated or regulated AFV fleets and infrastructure to primarily support them—has
 38 been largely disregarded. Investing in infrastructure for public fleets can reduce the risk of lack of
 39 demand. At the same time, the infrastructure would provide a positive feedback force that could drive the
 40 demand for the consumer AFV market.

41 Jung and Jayakrishnan (2012) showed that the shared-ride taxi (or shared-taxi) is a less constrained,
 42 and hence more generalized, operation than the standard taxi. A shared-taxi allows different groups of
 43 passengers to share a taxi ride. This trend is gaining traction in many countries in Asia. In China, the
 44 Beijing government recently allowed taxi-sharing due to the shortage of taxicabs during rush hours
 45 (China.org, 2012). In Singapore, Taiwan, and Japan, dynamic shared-taxi services are provided to link
 46 passengers who travel to the same area (Asiaone, 2012; Tao, 2007; Tsukuda and Takada, 2005).

47 Jung and Jayakrishnan (2012) proposed a real-time shared-taxi system operated by an online
 48 dispatch center with the help of communication technologies and geo-location services. The advanced
 49 shared-taxi service is capable of taking random service requests and updating vehicle schedules. Further

1 details of the shared-taxi concept and simulation procedure, as well as a more in-depth review of the
 2 shared-taxi literature, are given by Jung and Jayakrishnan (2012).
 3

4 **2.5. BEV Taxi Charging**

5 Unlike HEVs or PHEVs, BEVs are powered exclusively by the electricity from its battery pack. Most
 6 prevailing 5-seater vehicles produced by major automobile manufacturers are equipped with up to 24
 7 kWh battery types that allow up to a maximum of 100 miles per charge depending on driving conditions.
 8 The EV charging station is commonly called EVSE (Electric Vehicle Supply Equipment), which has three
 9 levels of SAE (Society of Automotive Engineers) classification: (1) Level 1 with 120 volt outlet; (2)
 10 Level 2 with 240 volts; and (3) Level 3 with higher voltage DC power for fast charging, which takes less
 11 than one hour. These considerations are made in the computational study in Section 4.
 12

13 **3. PROPOSED MODEL**

14 The SDIRQ model simultaneously seeks a set of locations and number of co-located servers at each of
 15 those locations to minimize the average delay—defined as the sum of travel to a facility, wait time at the
 16 facility to be served, and service time—for a set of random demand itineraries. This type of problem has
 17 many applications where demand can be characterized as an itinerary of trip chains that occur with a
 18 degree of uncertainty, including taxi fleets, activity based land use planning, military logistics, supply
 19 chain logistics, humanitarian logistics, among others. The specific application addressed in this study is
 20 the location of charging stations to minimize the delay to taxi fleets' itineraries, which are dependent on
 21 random customer arrivals over time. A simulation-based optimization problem formulation is presented to
 22 characterize this problem.
 23

24 **3.1. SDIRQ Model Formulation**

25 Given the complexity of the shared-taxi operations, the location model is formulated as a bi-level problem.
 26 Bi-level programming problems split the decisions of the system planner (leader) and the system users
 27 (followers) into two levels so that the sub-problems are solvable and an iterative approach can be used to
 28 arrive at a local optimum. The upper-level problem is defined by
 29

$$\min_u F[u, v(u)]$$

30
 31 Subject to

$$G[u, v(u)] \leq 0$$

32
 33 Where $v(u)$ is implicitly determined in the lower-level problem
 34
 35

$$\min_v f[u, v]$$

36
 37 Subject to

$$g[u, v] \leq 0$$

38
 39
 40 where F and G are the objective function and constraint set of the upper-level; f and g are for the lower-
 41 level problem. The decision variables u and v are defined for the upper level and lower level, respectively.

1 In the case of the stochastic dynamic itinerary-interception refueling location problem with queue
 2 delay (SDIRQ), the master problem is split into an 1) upper level server allocation problem with queue
 3 delay, and a 2) lower level stochastic dynamic itinerary simulation.
 4

5 **3.1.1. Upper Level Formulation**

6 The upper level problem is based on Berman and Drezner's (2007) multiple server allocation problem.
 7 The objective is to minimize the sum of the travel times and the average queue delays at each server node
 8 for all taxis. A complete graph $G(N, L)$ with a set N of n nodes and a set L of $m = n(n - 1)$ links is
 9 considered. At each node $i \in N$, demand is generated at a rate of λ_i per time unit (e.g., an hour). This
 10 demand is obtained from the output of the lower level problem. The service rate of each server is μ
 11 customers per time unit with a maximum of p servers on the network. The set S of nodes which are
 12 assigned servers (server nodes) has a cardinality of $q \ll p$, which means that some of the nodes may not
 13 have servers. $C_i(S)$ is defined as the set of closest nodes in N to a node i in S , resulting in Equation (1) to
 14 determine the arrival rate at a service node $i \in S$.
 15

$$16 \quad \lambda_i(S) = \sum_{j \in C_i(S)} \lambda_j \quad (1)$$

17
 18 The total travel times from demand nodes to all server nodes are modeled as a p -median objective.
 19 $W_k(\lambda, \mu)$ is defined as the expected time spent at a server node with k servers when the arrival rate is λ
 20 and the service rate is μ , where k is greater than or equal to one. The vector $K = \{k_1, \dots, k_q\}$ is the
 21 assignment of servers to the set S . The queue delay at each location can be represented as an $M/M/k_i$
 22 queueing system. The upper level objective function is then expressed as Equation (2), as shown in
 23 Berman and Drezner (2007).
 24

$$25 \quad \min_{S, K} \{F(S, K) = \sum_{i \in S} [\sum_{j \in C_i(S)} \lambda_j d_{ij} + \lambda_j(S) W_{k_i}(\lambda_i(S), \mu)]\} \quad (2)$$

26
 27 subject to

$$28 \quad \sum_{i \in S} k_i = p \quad (3)$$

29
 30 Unlike Berman and Drezner's study, we assume that all demand nodes can be server nodes. Since $C_i(S)$ is
 31 not predefined in our study, the solution algorithm shown in Section 3.2 includes a consolidation process
 32 in which servers at a lower demand node can be consolidated with another node if it reduces the total
 33 queue delay. We set up an additional constraint for the maximum number of servers, $p_{i,max}$, at node i due
 34 to the geographical limitations of EV charging locations in an urban area.
 35
 36

$$37 \quad 0 \leq k_i \leq p_{i,max} \quad (4)$$

38
 39 As pointed out by Pasternack and Drezner (1998), higher values of utilization ($\rho = \lambda/k\mu$) may cause
 40 small P_0 (the probability of no customers in the system) when calculating W (the average waiting time) in
 41 the standard way. Lower values of P_0 can cause computational overflows for subsequent calculations of
 42 L_q (the average queue length) and W . The same recursive method is used for the queue delay. For a given
 43 λ , μ , and k_i , the queue delay time can be obtained in a recursive manner shown in Equations (5) and (6).
 44

$$45 \quad a_1 = 1; a_i = 1 + \frac{\mu}{\lambda}(i - 1)a_{i-1} \quad (5)$$

46
 47 and
 48

$$W_k(\lambda, \mu) = \frac{\lambda}{(k\mu - \lambda)^2 \left(a_k + \frac{\lambda}{(k\mu - \lambda)}\right)} + \frac{1}{\mu} \quad (6)$$

3.1.2. Lower Level Problem

The lower level problem, $v(u)$ is replaced with a simulation similar to the recharging schemes previously designed for HCPPT by Jung and Jayakrishnan (2012). Because this problem requires great flexibility of implementing various types of vehicle routing algorithms and vehicle controls for door-to-door passenger services, which are not available in most commercial transportation simulation tools. However, there is a significant difference that needs to be considered. An EV taxi is assumed to visit a charging station only after completion of passenger delivery (similar to the assumption made by Kameda and Mukai (2011) for shared-buses in Tokyo). EV taxi charging is added as event at the end of vehicle schedule within the current driving range, but the event can be considered at any time step in the vehicle's movement. We assume that the dispatch algorithm is provided with the locations of charging stations so that it can determine when a connected taxi should be replenished and which station the taxi should visit. New pickup and delivery events are prohibited if the vehicle is already headed to a charging station or if the vehicle has higher risk of being discharged when the new schedule is performed given the remaining range. Further details can be found in Jung *et al.* (2013).

A simulation rule is used to insert a charging station visit when a taxi reaches a threshold and no passenger is being served. For battery charging, a vehicle tries to find the closest charging locations to minimize the travel distance and risk of being discharged after finishing its final delivery. The lower-level simulation generates a unique charging profile and queue delay at each charging location as well as a system performance for shard-taxi operation. The simulation time is set to be long enough so that vehicles need to visit charging stations multiple times. Since the stochastic taxi demand is determined by a simulation seed number, multiple sets of simulations are conducted for each iteration to minimize the random effect.

The simulation framework is depicted in Figure 2. The simulation container reads the configuration file and then creates the data access library to import maps, taxi service requests, and EV charging locations including charger allocations. The simulation time is synchronized by a timer that controls passenger request generation, real-time vehicle controls, and vehicle queue at charging locations.

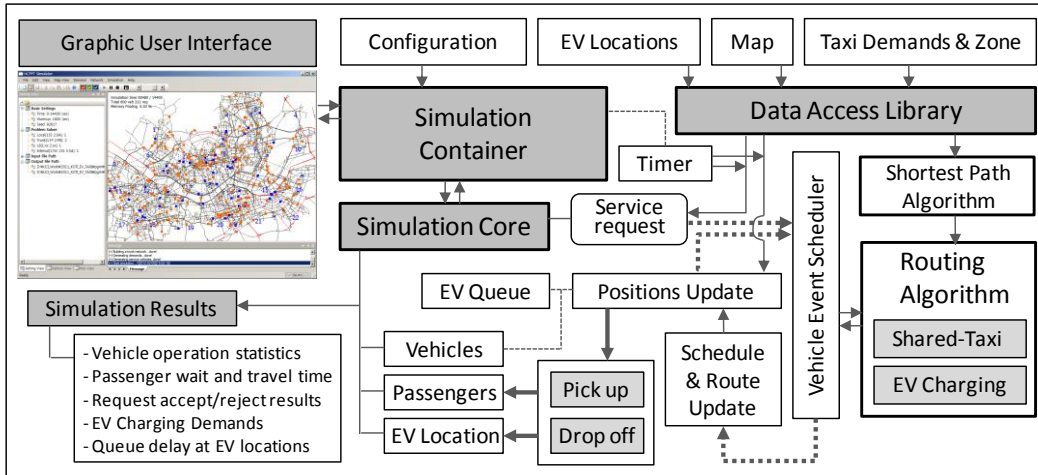


Fig. 2. Lower Level Simulation Framework.

In the preliminary simulation, we found that the arrivals at a majority of charging stations follow a Poisson process. However, some locations have lower sample sizes, depending on EV location allocations.

1 The lower samples are not enough to estimate the arrival rates because they can produce very noisy
 2 estimates. Second, the translated demand rate should always be less than the service rate according to the
 3 assumption made in the upper level (steady state intensity less than one). In other words, the basic inverse
 4 function shown in Equation (7) can fail in the upper level problem.

$$6 \quad \lambda_i = W_{k_i}^{-1}(\mu, D_{q,i}) \quad (7)$$

7
 8 The lower level simulation provides the number of servers k , service rate μ , and queue delay time D_q for
 9 each location. To address the intensity issue, an inverse interpolation method is used to approximate the
 10 corresponding demand rate so that the queue delay function in Equation (6) is continuously and
 11 monotonically increasing within an interval $\rho \in [0.0, 1.0]$ in which there is a single-valued inverse. A
 12 bisection method is applied to compute the inverse given the stable utilization interval.

14 **3.1.3. Bi-Level Interactions**

15 The iteration between the upper and lower level problems captures the cyclic effect that queue delay has
 16 on the dispatch of the taxi fleet, which in turn determine the demand patterns for the charging stations,
 17 resulting in the allocation of chargers that impact that queue delay. Figure 3 describes the iterative
 18 procedure for the simulation-optimization-based EV charger location problem. First, servers are evenly
 19 distributed over the candidate charging locations, and then the lower level simulation is called. The lower
 20 level simulation tracks all vehicle pickups, dropoffs, queueing, and charging events including which
 21 charging location is used. After the first run of lower level simulation, the charging profiles and queue
 22 delay are collected and transferred to the upper level problem. The upper level problem assigns servers
 23 optimally to minimize queue delay and travel time. Once the upper level problem is solved, the optimal
 24 allocation of chargers is compared with the previous allocation status. If there is no change, the procedure
 25 ends with the current charger allocation on candidate locations; otherwise, the lower level simulation is
 26 called with the updated charger allocation.

27

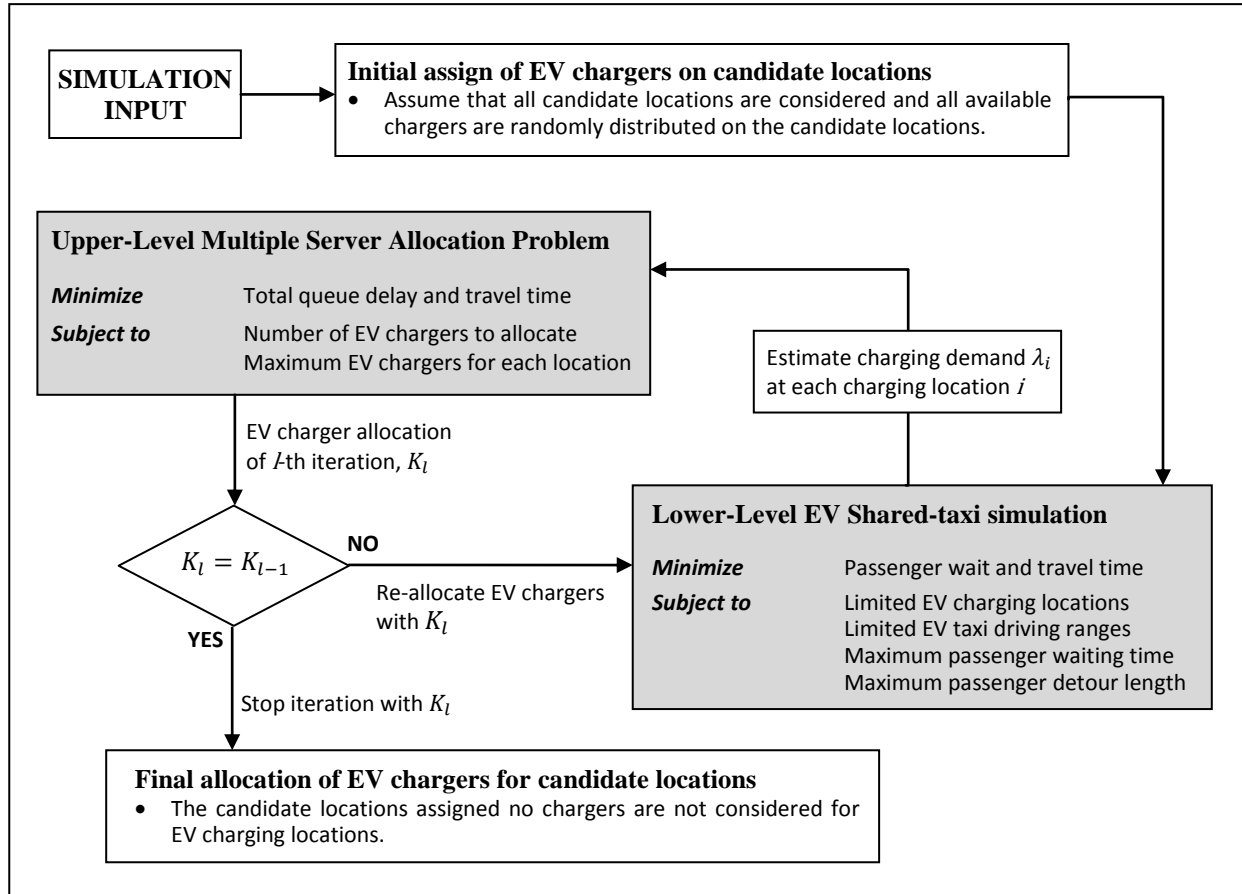


Fig. 3. Bi-Level Procedure for EV charger allocation.

A solution method is presented to solve this bi-level problem in Section 3.2. The method is based on a modification of Berman and Drezner's (2007) allocation algorithm. This solution method is compared to a benchmark single level solution method presented in Section 3.3. The benchmark method uses a genetic algorithm to assign chargers without considering any iterative interaction of queue delays in the upper level with the demand assignment in the lower level. It is used to validate the benefit of considering queue delay in the SDIRQ.

3.2. Proposed Solution Method – Bi-level

The solution of the upper level uses a modification of Berman and Drezner's (2007) Algorithm 1 that includes a consolidation procedure discussed in Section 3.1. At this level, the demand obtained directly from the lower level is assumed constant.

Proposed Upper Level Algorithm: (steps 1-4 are from Berman and Drezner (2007))

1. For each node $i \in S$, find the minimum number of servers necessary to service the demand. This minimum number is $l_i = \text{int}[\lambda_j(S)/\mu] + 1$.
2. If $\sum_{i=1}^q l_i > p$, then there is no feasible solution.
3. If $\sum_{i=1}^q l_i < p$, check the decrease in queue delay by changing l_i to $l_i + 1$. If $l_i < p_{i,max}$, increase the number of servers by one at the node with the maximum time decrease.
4. Repeat until $\sum_{i=1}^q l_i = p$.

- 1 5. For each node i , find the closest server node j with 1 or more servers, and compare the current
- 2 objective value with relocating demand λ_i and servers l_i to the adjacent node j with $\lambda_j + \lambda_i$ and $l_j + l_i$
- 3 and considering travel cost d_{ij} . If $l_j + l_i \leq p_{j,max}$ and the objective value of relocating decreases, set
- 4 node i and j as a candidate node pair.
- 5 6. Find a best node pair among the candidate node pairs to minimize the objective function, then
- 6 consolidate node i to node j .
- 7 7. Repeat the step 5 and 6 until there is no improvement in the objective value.

8

9 We also propose an improvement to the dispatch algorithm from Jung and Jayakrishnan (2012). The
 10 original insertion heuristic starts by comparing all vehicles to find a best vehicle to minimize both
 11 passenger travel time and waiting time. However, the algorithm is computationally inefficient when both
 12 service area and fleet size are large.

13 The proposed algorithm consists of two steps. First, once a new passenger request, z_i ($i \in I$) comes in,
 14 the system selects available vehicles in the corresponding geographical zonal area to insert a new trip
 15 request. Each passenger trip is identified by its origin and destination. In this stage, available vehicles are
 16 filtered to prevent excessive computational burdens. At the second stage, the algorithm seeks the best
 17 vehicle to minimize service wait time and travel time of the new passengers as well as the previously
 18 assigned passengers. In this lower level simulation, the allocation of charging stations is obtained directly
 19 from the upper level and assumed fixed.

20

21 ***Proposed Lower Level Dispatch Algorithm***

22 *Stage 1:* Identify the zonal area of the new passenger request, z_i , then prepare a vehicle set J based on z_i 's
 23 trip points and time windows.

24

25 *Stage 2:* Find the best vehicle V_{min} , $V_{min} \in J$ satisfying the following objective function to insert l -th and
 26 m -th for the new request z_i in equation (5).

27

$$28 \quad \min IC_j = C_j(E_j \cup z_i) - C_j(E_j) \quad (5)$$

29

$$30 \quad C_j(E_j) = \sum_{k \in K} [\text{WT}(E_{j,k}) + \text{TT}(E_{j,k})] \quad (6)$$

31

$$32 \quad C_j(E_j \cup z_i) = \min_{l,m} \sum_{k \in K+2} [\text{WT}(E_{j,k}) + \text{TT}(E_{j,k}) + \text{WT}(z_{i,l}) + \text{TT}(z_{i,m})] \quad (7)$$

33

34 where

35

36 z_i = new request from passenger i , $i \in I$

37 E_j = set of pickup and dropoff events in vehicle j 's schedule

38 IC_j = incremental cost of vehicle j for inserting a new request z_i

39 $C_j(E_j)$ = current total cost of vehicle j 's with schedule E_j

40 $\text{WT}(E_{j,k})$ = waiting time (cost) associated with k -th event in E_j

41 $\text{TT}(E_{j,k})$ = in-vehicle time (cost) associated with k -th event in E_j

42 $C_j(E_j \cup z_i)$ = total cost of vehicle j when adding a new request z_i

43 $l, m = l$ -th pickup and m -th dropoff insertion positions for vehicle j 's minimum cost with z_i

44

45 In stage 2, equations (6) and (7) denote the travel cost based on vehicle j 's current itinerary and the
 46 updated cost by assuming that the new request is inserted into an optimal position among the existing
 47 pickup and dropoff events. When inserting a new request, all previously assigned events should be kept

1 within the constrained time windows. If there are no more available vehicles to consider, the dispatch
 2 algorithm assigns the new request to the vehicle with minimum incremental cost, IC_j . Otherwise, the
 3 passenger request is rejected due to the constraint. The dispatch algorithm is then combined with the
 4 recharging scheme by Jung *et al.* (2013).
 5

6 **3.3. Single-level Solution Method**

7 The single-level procedure is proposed as a baseline algorithm without the cyclic interaction of queue
 8 delay and demand between the upper and lower level. This method consists of simply evaluating
 9 simulation outputs of different EV charger allocation schemes and using Genetic Algorithm (GA) to
 10 improve the fitness of the population of solutions. Unlike the bi-level method, the direction finding is
 11 based purely on fitness function that includes queue delay, but no update of that cost is present in the
 12 simulation. This baseline algorithm is designed to show what happens if no queueing is considered by the
 13 taxi fleet dispatch even though the cost exists.
 14

15 **Single-level procedure**

16
 17 *Step 1:* EV charging demand allocation for each location is achieved from the lower level simulation by
 18 relaxing the queue delay constraint.
 19

20 *Step 2:* The multiple server allocation problem is applied to allocate EV chargers.
 21

22 In Step 1, it is assumed that enough chargers are installed at each location so that vehicles start battery
 23 charging without the queue delay effect when they visit charging locations. This approach provides a
 24 viable option in the sense that one can estimate the upper bound of potential EV charging demands when
 25 the deployment size is not determined yet (Jung and Jayakrishnan, 2011). However, such an upper bound
 26 can be seriously overestimated especially when the charging frequency of EV fleet operation is higher. As
 27 a result, the server allocation problem in Step 2 might end up with an infeasible solution that has a higher
 28 demand rate than the service rate.

29 GAs have great flexibility to solve the combinatorial optimization problem with complex
 30 contraints. Although GAs do not guarantee optimal solutions, they are efficient in seeking approximate
 31 solutions in NP -hard problem. The solution procedure employs an initial population, selection, elitism,
 32 crossover, and mutation. Figure 4 provides an illustrative example of chromosome encoding and genetic
 33 operators designed for the single level procedure with five candidate locations. In figure 4(b), as the
 34 crossover operation may produce an infeasible solution – having more or less chargers in total, an
 35 additional modification procedure is required to keep the same total number of chargers. The modification
 36 procedure adds or subtracts additional chargers on a random position to keep the total number of chargers
 37 the same.

38 The EV charging demands from simulation results are translated into the demand rates because there
 39 is no queue delay measured in the simulation results with infinite numbers of servers. Instead, a finite
 40 number of servers are assumed to consider queue delay at each charging location. If the demand rate goes
 41 over the service rate given by the number of servers at a location, a penalty value, W_p , is applied with a
 42 linear relationship of queue utilization, ρ , as shown in Equations (8) and (9).
 43

$$44 \quad W_{k_i} = \begin{cases} W_k(\lambda_i(S), \mu \cdot k_i) & \text{if } \rho_i < 1.0 \\ W_p \cdot \rho_i & \text{otherwise} \end{cases} \quad (8)$$

45 where
 46

$$47 \quad \rho_i = \lambda_i(S) / \mu \cdot k_i \quad (9)$$

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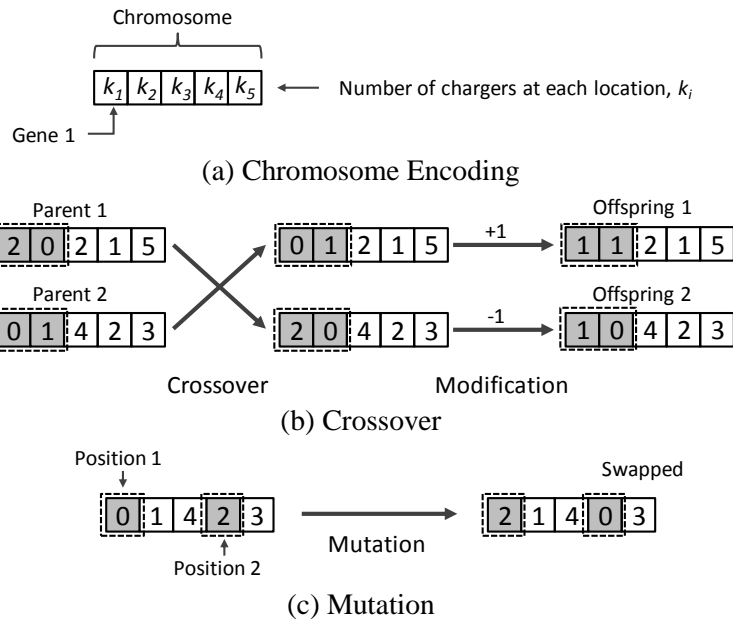


Fig. 4. Chromosome Encoding and Genetic Operators in GA.

4. COMPUTATIONAL STUDY

The goal of the computational study is to compare the performance of the proposed bi-level solution algorithm against the benchmark “naïve” single-level GA approach. Because stochastic dynamic shared-taxi dispatch can only be evaluated as an itinerary, the earlier models of flow-interception or even node-based location models cannot be run without making crippling assumptions. In addition, the improvement of deterministic itinerary-interception models against node-based models has already been documented in Kang and Recker (2012). This comparison was to demonstrate the feasibility and the performance of the bi-level algorithm with and without the cyclic interaction between the demand and the allocation with queue delay that is present in the method.

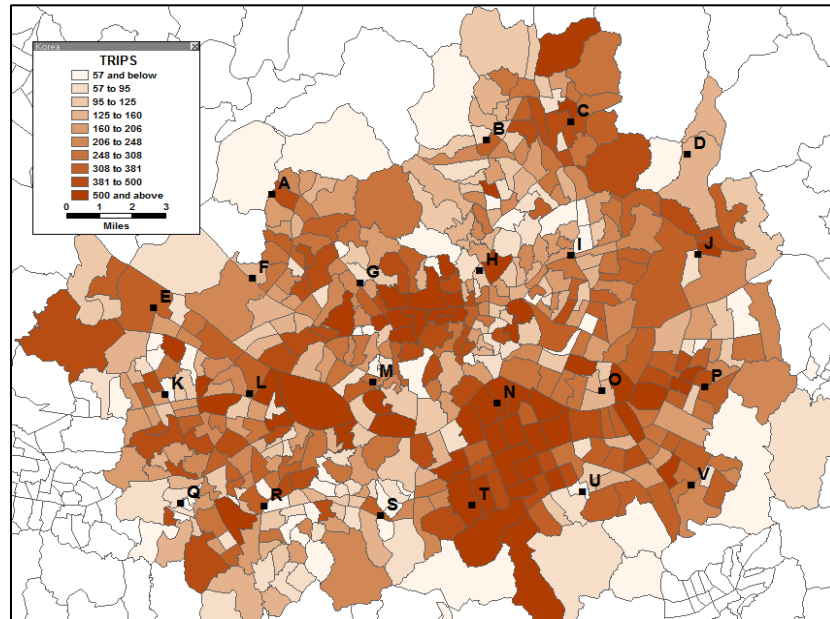
4.1. Study Setting and Parameters

In this study, the Renault-Samsung SM3 Z.E. is assumed, which is a model built by Renault-Samsung Motors for South Korea, based on the Renault Fluence Z.E. Renault-Samsung claims that the SM3 Z.E. is outfitted with a 24 kWh lithium-ion battery with a maximum range of 115 mile (184 km) measured on the NEDC (New European Driving Cycle) combined cycle, which is similar to Nissan LEAF. A “QuickDrop” system (known as battery swapping) allows the discharged battery to be replaced quickly with a fully charged one at a dedicated EV battery switch station. In addition, a fast charging system using a 32A 400V 3-phase supply enables the battery to be charged in 45 minutes. Since an official Korean range specification is not yet established, we assume conservative average ranges of 112 km (70 miles) on highways and 128 km (80 miles) on city traffic with a 16-km range of random variation for each individual vehicle.

Stochastic taxi demand is obtained from an EMME/2 transportation planning model developed at the Korea Transportation Institute (KOTI). As of 2011, trip demand consists of automobile, bus, subway, rail, taxi, and other types of demand, which cover Seoul with a total of 560 centroids over 603 km² (233 mi²). Under the usual assumption of spatial uniformity of demand around a zone centroid, point-to-point taxi

1 demands are randomly generated in accordance with destination probabilities of the taxi demand table in
 2 each centroid. The point-to-point demands are projected to the nearest road segment with its direction for
 3 door-to-door services except on limited-access roads. Real-time service requests arrive according to a
 4 Poisson process in a temporal manner. Figure 5(a) presents the spatial distribution of taxi demands
 5 including both origins and destinations used for stochastic trip requests for an 8-hour simulation with the
 6 minimum trip length of 1.0 km for taxi service. In figure 5(b), a total of 22 candidate charging stations on
 7 5 km by 5 km reference grid cells are assumed over the road network in the EV taxi simulator. One
 8 hundred chargers are evenly distributed over the 22 candidate locations in the initial simulation setup.

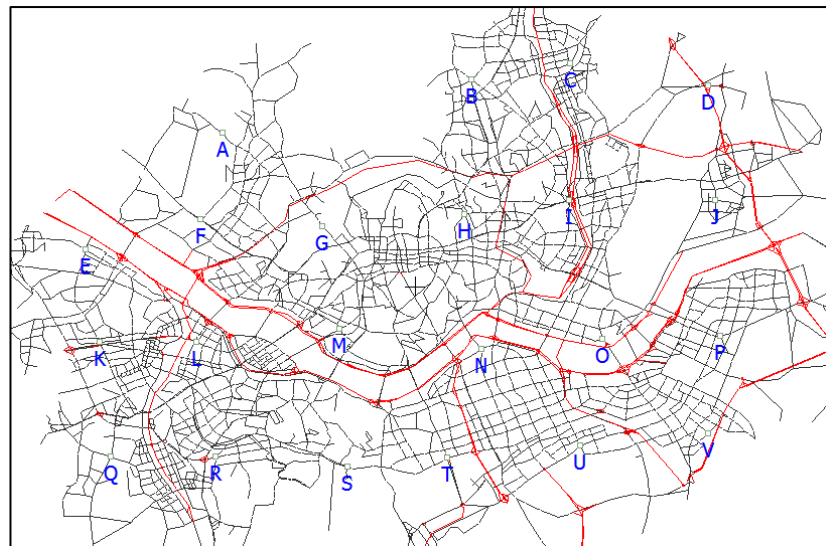
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(a) Distribution of Stochastic Taxi Demand



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(b) EV Charging Locations and Transportation Network in Seoul

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Fig. 5. Taxi Demands, EV Charging Locations on Transportation Network.

1
2 According to the statistics from Seoul Taxi Association, a taxi carries more than 35 passengers each day
3 on average. The average travel distance is over 250 km/day and 5 km/trip, with a significant portion of the
4 travel distance being non-revenue segments when the taxis travel empty for the pickups. A total of 72,000
5 taxi licenses are registered including owner-driver taxi and a total fleet of 40,000 vehicles due to the taxi
6 rotation system to restrict the number of operating taxicabs operating as of 2011. Shared-taxis are
7 prohibited by regulations in Korea, but it is publicly known that many taxicabs carry multiple passenger
8 groups at the same time if they are traveling to the same destination because of limited supply. It is
9 assumed that EV taxi service offers dynamic shared-ride for passengers in order to increase its system
10 performance. According to 2014 Master Plan for Electric Vehicle by Seoul, Korea, the city plans to
11 deploy around 30,000 commercial EVs including buses, taxis, and private vehicles. Since it is expected
12 that EV taxi will be able to operate over a distance of 200 km to 400 km a day, Seoul seeks to initially
13 establish replenishing stations with high-speed charging (SAE Level 3) or battery replace facilities.

14 In this study, 600 taxicabs are initially considered for electrification, which is equivalent to 1.5% of
15 the total number of vehicles operated in Seoul. The initial positions of vehicles are randomly generated
16 over the simulation area. The simulation time is set to 8 hours including 30-min as a warm-up period,
17 which is assumed to include peak operating hours. An average of 1-min boarding and alighting times are
18 assumed for each passenger, which is based on a random uniform distribution $U(0.5, 1.5)$. At each lower
19 level simulation step, ten simulation sets are conducted by choosing ten different seed values.

20 In the shared-taxi scenario, we set maximum waiting time (900 sec) and maximum detour length
21 (maximum 1.2 times of door-to-door travel distance) for passenger time windows. A taxicab can carry a
22 maximum of four passenger groups at the same time, which provides a realistic scenario rather than
23 having three or more groups. The charging time is assumed to be exponentially distributed with an
24 average of 45 minutes. From our preliminary simulation, the majority of generated trip demands are
25 within 10 km. The average trip length is 6.4 km and the expected door-to-door travel time 13.4 min under
26 the assumption that vehicles can travel at 60~90% of the posted speeds on the network.

27 Two initial charging strategies are possible, one starting with fully charged EVs (FISOC: Full Initial
28 States of Charge) and the other with randomly charged EVs (RISOC: Random Initial State of Charge) at
29 the beginning of the simulation. Jung (2012) found that charging demands tend to be concentrated at
30 certain times during the simulation when the eight hour period started with fully charged vehicles, so
31 RISOC is assumed in this study. This study provides four different scenarios: (1) Single-level approach;
32 (2) Bi-level approach; (3) Infinite chargers intended to relax charging delay factors; and (4) Non-EV
33 operation with conventional ICE taxicabs.

34
35 **Table 1**
36 **Scenarios for computational study.**

EV Shared-taxi simulation	
Shared-taxi settings	
Service area (km ²)	605
Simulation time (hours) / Warm up (hours)	8.0 / 0.5
Number of service vehicles	600
Vehicle capacity (seats/vehicle)	4
Number of centroids (zonal areas)	560
Max. wait time (min) / Max. detour factor	15 / 1.2
Vehicle types	EV / ICE
EV settings	
Battery Capacity ¹ (kWh) / Battery Charging Time (average min)	24 / 45
Ranges (km)	112 (Highway) / 128 (City Traffic)
Number of charging stations (/each candidate location)	Min. 0 – Max. 20 chargers
Charging schemes	Random Initial State of Charge (RISOC)
Candidate EV locations / Max. available chargers	22 / 100
EV Charging Operations	Single-level, Bi-level, Infinite Chargers, Non-EV

37 ¹ Battery pack capacity (kWh): kilowatt-hour(s)

1

2 **4.2. Results**

3 The system performance of the lower level simulation is calculated with passenger delivery and its
 4 associate wait and travel time. Since each simulation could have different number of delivered passengers
 5 and dropped requests, the total cost is proposed as the lower level objective value based on the number of
 6 delivered and rejected requests, average waiting time, and average travel time. A penalty value is applied
 7 for dropped passenger requests. When the cost is found this way, a lower value indicates better
 8 performance in Equation (10).

9

$$10 \quad \text{Total Cost } (C_t) = T_p \cdot P^r + \sum_{i \in I} TT(P_i^c) + \sum_{i \in I} WT(P_i^c) \quad (10)$$

11

12 T_p : Penalty value for a dropped request, assumed to be 7200 sec

13 P^r : A set of rejected requests during the simulation

14 P^c : A set of completed requests during the simulation

15 $TT(P_i^c)$: Travel time of passenger $P_i^c \in P^c$

16 $WT(P_i^c)$: Waiting time of passenger $P_i^c \in P^c$

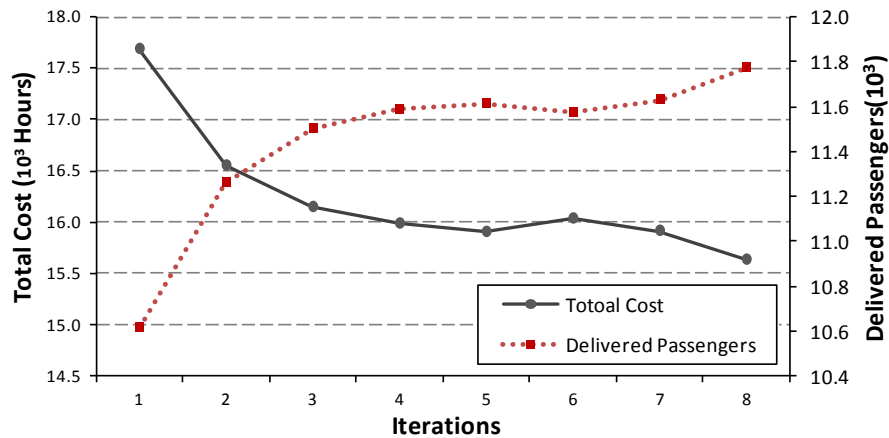
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18 The number of charging events and queueing delay (D_q) at each charging location is measured as
 19 charging system performance since the upper level allocates EV chargers to minimize the queue delay.
 20 The lower level simulation model includes a queueing model for each charging location so that it creates
 21 a simulated queue delay given the charger allocations and the candidate location.

22 Figure 6 shows the overall SDIRQ performance by bi-level iterations in which the procedure
 23 converges at the eighth iteration. The total cost of lower level simulation significantly decreases during
 24 the first three iterations in figure 6(a). The minimum cost is achieved with 15,632 hours at the eighth
 25 iteration. At the same time, it shows that the number of delivered passengers increases from 10,615 to
 26 11,773 passengers, which is consistent with the objective function to minimize passenger wait and travel
 27 time.

28

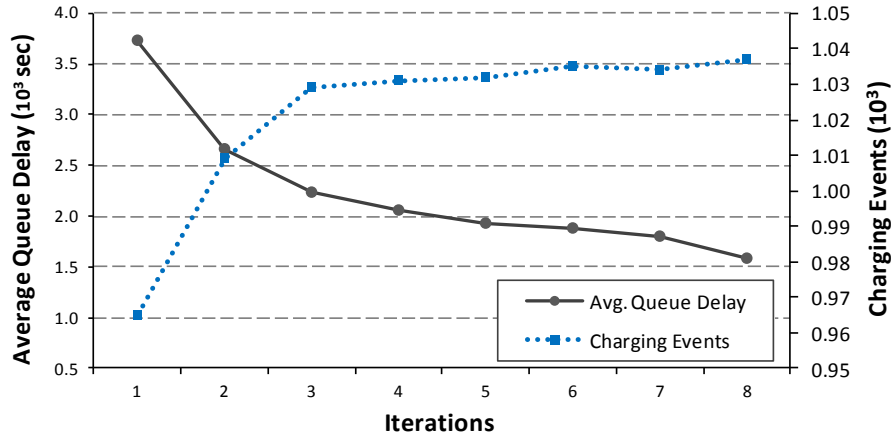
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(a) Total cost and number of delivered passengers



(b) Average queue delay and number of charging events

Fig. 6. Overall SDIRQ Performance by Bi-level Iterations.

When comparing the average queue delay and the number of charging events in Figure 6(b), the proposed procedure not only decreases the average queue delay at charging locations, but also increases the number of charging events at the same time. With the initial setting, each EV taxicab spends an average queue delay of 3,730 sec/visit (62.2 min/visit) excluding battery replenishing time, which could be a significant loss of service time when considering a vehicle might visit charging stations with an average of 1.75 times during the 8-hour operation. As the iteration increases, the average queue delay drops to 1,580 sec/visit (26.3 min/visit), which enables vehicles travel longer distance for its operation. The average vehicle traveled distance increases from 130 km to 148.3 km as the procedure converges. In other words, given the same size of fleet, the decreased queue delay at charging locations can improve the EV fleet utilization, which causes more frequent charging behavior.

Table 2
System Performance.

System Performance	EV Operations			Non-EV
	Single-level	Bi-level	Infinite Chargers	
Total delivered passengers	11,273	11,773	12,940	15,738
Avg. wait time home (min)	12.71	12.63	12.47	11.76
Avg. passenger travel time (min)	14.73	14.77	14.77	14.75
Rejected passenger requests	5,700	5,128	3,872	947
Avg. vehicle load (pax/vehicle)	0.63	0.66	0.73	0.88
Avg. vehicle traveled distance (km)	140.05	148.29	166.47	204.71
Avg. operating hours except charging time (hour)	5.25	5.62	6.16	8.00
Total cost (hours)	16,557.66	15,632.20	13,621.81	8,849.24
Number of vehicle visits at EV locations, E_d	1,013	1,037	1,142	n/a
Number of charging events completed, E_c	875	971	1,142	n/a
Number of selected EV locations	18	12	22	n/a
Avg. queue delay at charging locations (sec)	2,509	1,580	0	n/a
Total queue length at charging locations (veh)	98.0	62.8	0.0	n/a
Avg. queue length at each location (veh)	5.4	5.2	0.0	n/a
Avg. distance to charging locations (km)	2.53	2.83	2.39	n/a

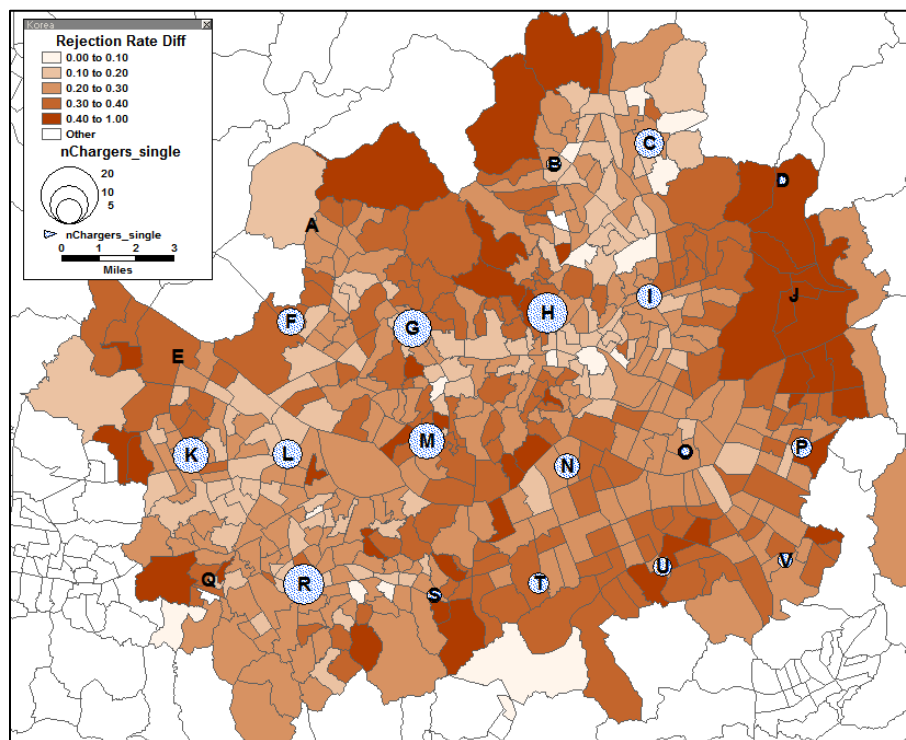
Table 2 reports the detailed simulation results comparing single-level, bi-level, infinite chargers, and non-EV. For non-EV condition, it is assumed that refueling ICE taxicabs is not considered in this condition because regular taxicabs in Korea use engines powered by Liquefied Petroleum Gas (LPG). Their refueling time is not considered in this simulation since there are more than 70 LPG refueling

1 locations in that area. Note that the non-EV condition causes additional financial and environmental costs
2 from EV taxi operations which are not considered in this study.

3 A higher average vehicle load indicates greater efficiency in taxi operation. Since the same vehicle
4 routing algorithm is applied to all scenarios, the average vehicle load gets worse as vehicles stay longer at
5 the charging locations. The single-level procedure ends up with a total of 18 locations selected for
6 allocating 100 chargers while the bi-level result shows 12 locations with the same total number of
7 chargers. A significant difference in the queue delays is measured between single-level and bi-level. The
8 single-level result reports an average 2,509 sec/visit (41.8 min/visit) of queue delay at each location,
9 which is about 15.5 min/visit more than the bi-level result. An average distance to charging location is
10 defined as a weighted distance by the number of charging events representing from a vehicle's last
11 delivery position to the charging location where the vehicle is headed. If all candidate locations are used,
12 the average distance is 2.39 km. The bi-level result shows the 0.3 km higher distance due to the smaller
13 number of charging locations selected. Average actual taxi service hours with EV operations show less
14 than 77% of Non-EV even without queue delay impact. Single-level shows 5.25 hours of service
15 operation, which indicates average 2.75 hours are spent on moving to charging locations, queueing, and
16 refueling.

17 Figure 7 reports the distribution of EV chargers on the geographical area. The colored polygons
18 show the spatial distribution of increase in request rejection rate compared with non-EV scenario. The
19 thicker color means there is a greater increase in passenger pickup request rejections in a zone. The size
20 of circles represents the number of chargers allocated at each candidate location. The rejection rate
21 increases around the EV charger allocated areas are less than the other areas. For example, the zonal areas
22 around locations D, J, and Q show higher rejection rates in both Figure 7(a) and 7(b). This is because
23 vehicles would choose nearby pickup requests when they finish EV charging. The bi-level solution
24 clearly shows lower rejection rate than the single-level solution. Both solutions try to place more chargers
25 in the center of Seoul. The spatial distribution of chargers in Figure 7(b) shows a similar pattern in
26 comparison with the distribution of stochastic taxi demand in Figure 5(a).
27

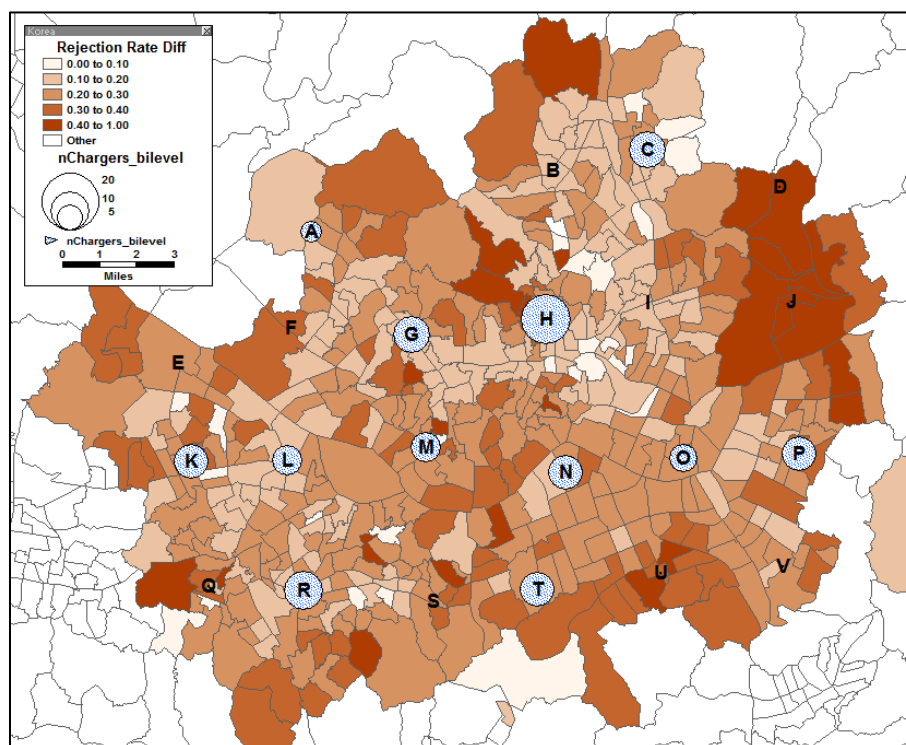
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(a) Single-level



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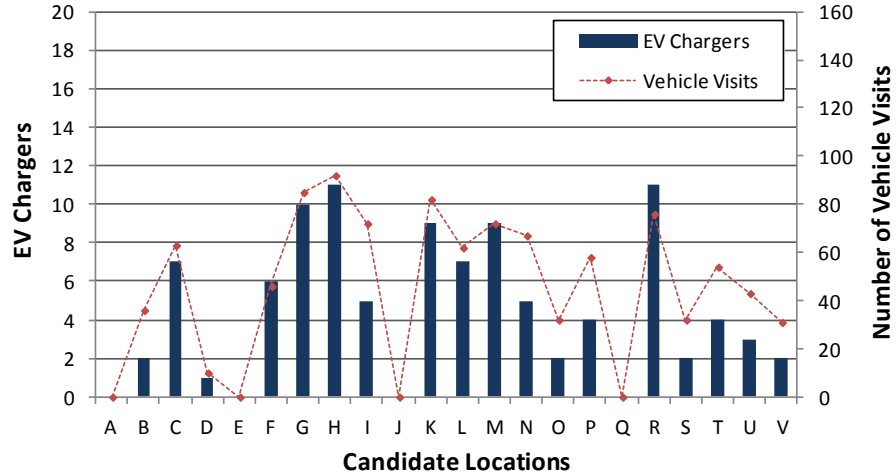
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(b) Bi-level

Fig. 7. Changes in Passenger Rejection Rate of EV Taxi Operation.

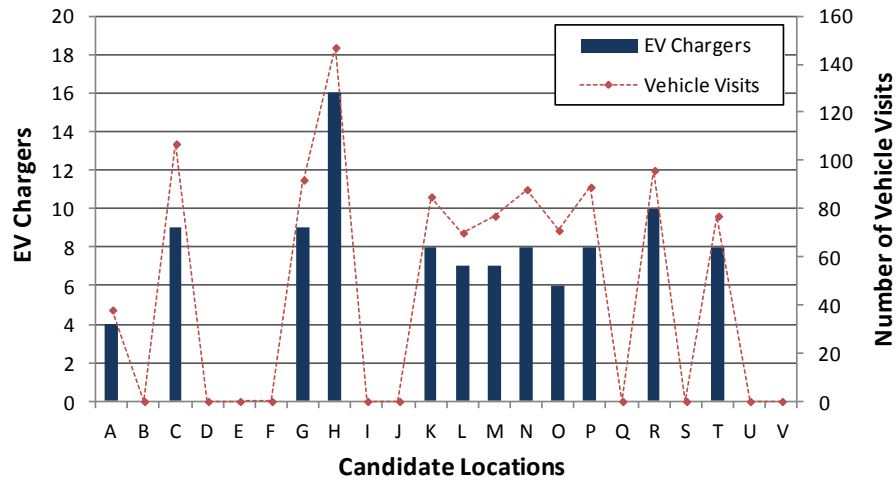
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Figure 8 shows the comparison between the number of vehicle visits and the number of chargers allocated at each location. The EV charger utilization (vehicle visits / charger) shows higher values with the bi-level results.



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(a) Single-level



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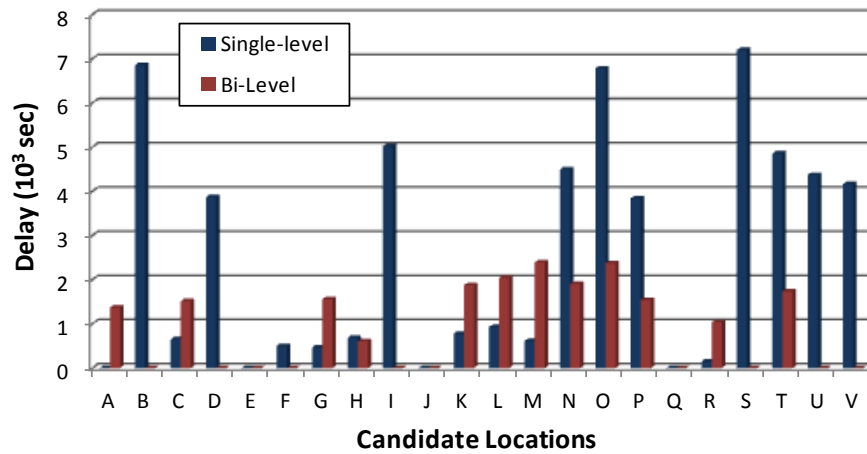
(b) Bi-level

10 **Fig. 8.** EV Charger Allocation and Simulated Charging Demands.

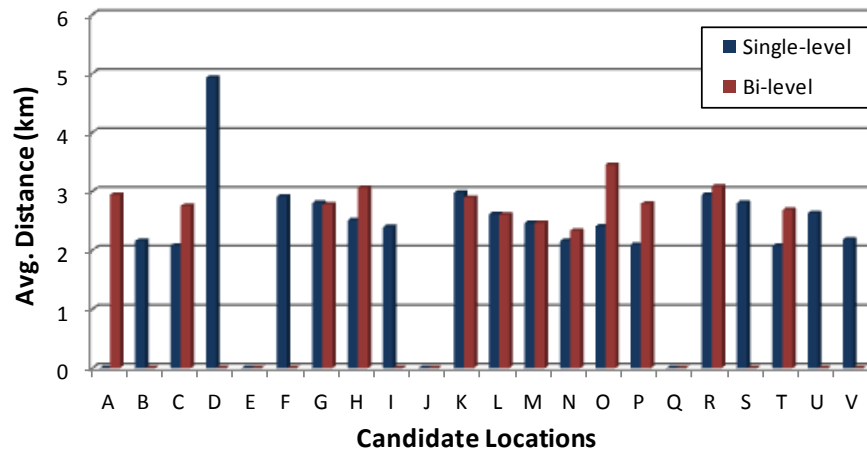
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Figure 9 provides a side-by-side comparison for average queue delay at charging locations and average distance to charging locations. The average delays show significant difference between single-level and bi-level results. Locations such as C, G, K, L, and M in Figure 9(a) show lower average queue delays with single-level, but they also show extremely higher queue delays at locations with a fewer numbers of chargers. In contrast, the bi-level results show lower deviation in average queue delays on all selected locations. Figure 9(b) reports the average distance to charging locations. Most of them remain less than 3 km except the location D in single-level. These values can be used for re-calibration of the critical battery level considered in the recharging scheme. Note that these distances to charging locations

1 are affected by the location distribution itself, in which vehicles tend to reject passengers whose
 2 destinations are far from any of charging locations when the battery level gets critical.
 3



4 (a) Average Queue Delay at Charging Locations

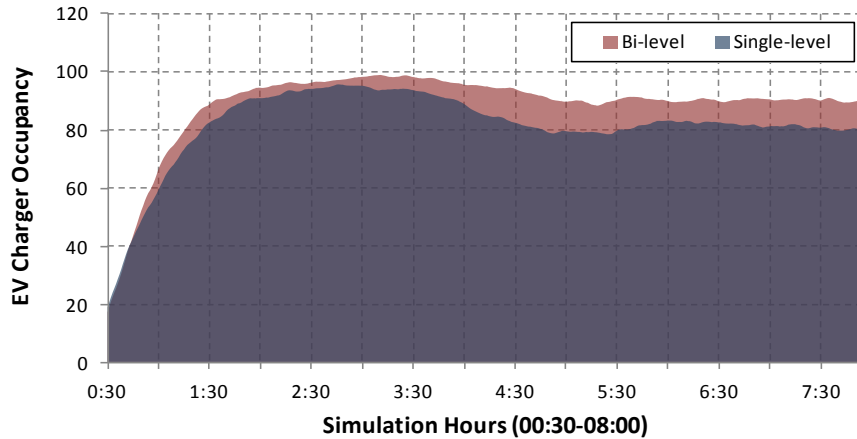


5 (b) Average Distance to Charging Locations

6 **Fig. 9.** Queue Delay at Locations and Average Distance to Charging Locations.

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 9
 10 The temporal distribution of the aggregated EV charger occupancy and total queue length at
 11 charging locations are provided in Figure 10. The warm-up time period is not included. As the simulation
 12 starts, vehicles are visiting charging stations and saturate them after two hours in Figure 10(a). The bi-
 13 level solution shows an 8.2% higher occupancy level of EV chargers than the single-level. That indicates
 14 higher utilization of charging system with the bi-level solution given the same refueling time. Once the
 15 occupancy of chargers is saturated, the queue length starts decreasing in both solutions. Indeed, it is
 16 conceivable that the charging demands of EV fleet operations are not constant, but the demand itself can
 17 be influenced by the charging system performance. In other words, as charging locations hold more
 18 vehicles for longer in the queue, the subsequent charging demands decrease as well as the system delivery
 19 performance due to the changes in vehicle itinerary. This will be an important problem to be considered
 20 when available chargers are not enough to support a deployed fleet size.
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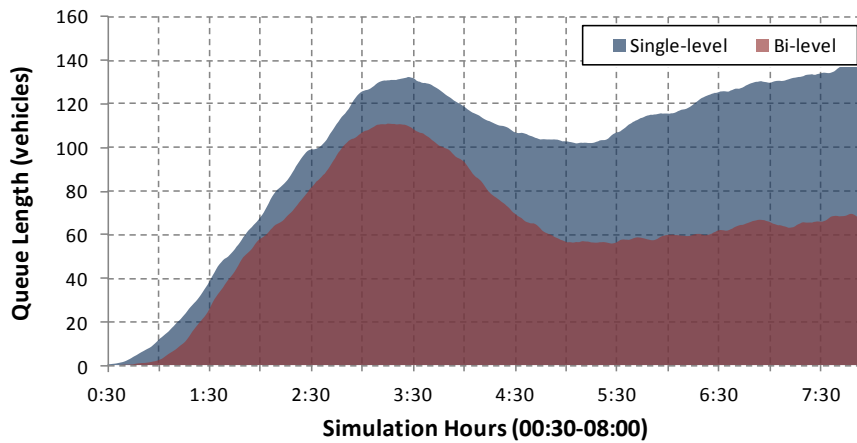


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(a) EV Charger Occupancy (chargers)

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(b) Total Queue Length (vehicles)

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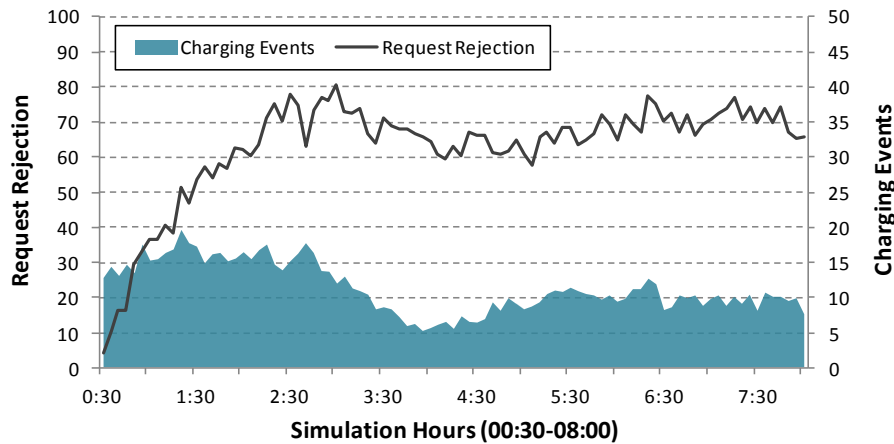
Fig. 10. EV charger Occupancy and Total Queue Length at Charging Locations

8

9 Regarding the queue length, both solutions reach their maximums around 3:30, and then start
 10 decreasing. The peak charging demand combined with the occupancy and the queue length is estimated
 11 around up to 3:00 after warm-up. The queue length of the single-level solution keeps increasing after 5:00.
 12 The overall average queue length of the single-level solution is 55% higher than the bi-level. Considering
 13 the bi-level solution generates more charging events than the single-level, the EV charger distribution and
 14 the location selection of the single-level is clearly worse than the bi-level solution.

15 Figure 11 compares the temporal relationship between the charging events generated and the
 16 passenger pickup request rejections. The request rejection curves are aggregated every 5 min. As
 17 mentioned, the peak charging demand is shown during the first three hours, and then the charging demand
 18 decreases. The passenger request rejection peaks around 3:00, which is consistent with holding more
 19 vehicles at charging locations as shown in Figure 10. The EV charging demands are derived from the taxi
 20 operation caused by passenger requests. The spatial and temporal characteristics of charging demand can
 21 be significantly influenced by the taxi demand, and neither of these characteristics can be analyzed using
 22 node-based or flow-based model location models.

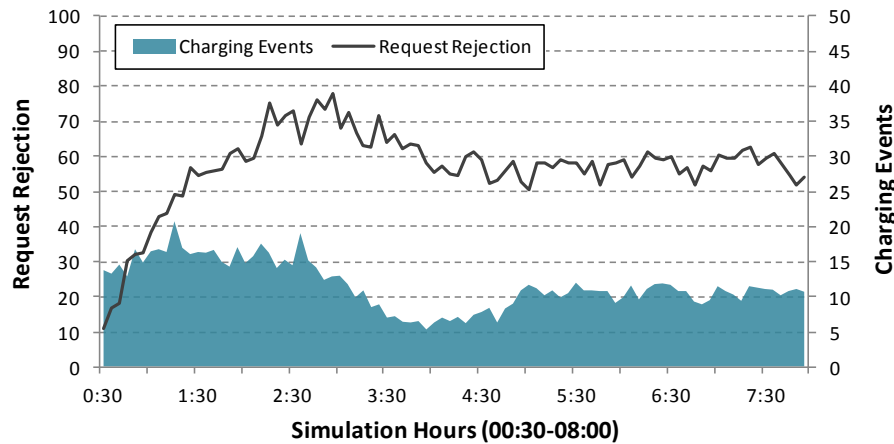
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(a) Single-level



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(b) Bi-level

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Fig. 11. Passenger Request Rejection and Charging Events

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In summary, these results show that the proposed model is capable of locating charging stations with stochastic dynamic itinerary-interception and queue delay. The proposed bi-level solution method improves upon the benchmark algorithm without the interaction effects (allocation of fixed demand and demand realization with fixed allocation, but no feedback mechanism) in terms of realized queue delay (37%), total taxi service operating hours (6.7%), and reduced service request rejections (10%). Furthermore, we show how much additional benefit in level of service (17.7%) can be achieved if the current budget of 100 charging stations approaches infinity.

Obviously, having longer charging times will reduce the number of passengers served on average. Compared to the non-EV scenario for the 600 shared-taxis, having infinite number of chargers (queueing no longer becomes an issue), the reduction in number of delivered passengers is 17.8%. With only 100 charging stations, the number of delivered passengers is 25.2% of the non-EV scenario. These results, along with the others presented in Table 2, give decision-makers trade-off values to consider in their planning. For example, it is possible to evaluate the change in queue delay, allocation of charging stations, and number of passengers served if the charging time can be technologically improved by 50%. It is also possible to modify the simulation so to evaluate the presence of charging station queue informatics to the central dispatch. Currently the simulation considers taxicabs going to the closest server node, but a more

1 efficient solution may be achieved if the dispatch is informed on average wait times at each node in real
2 time. The difference in objective value would be the value of investing in that information. These trade-
3 off values will be crucial for justifying the research and development investments in the battery
4 technology, in equipping the charging stations and fleet with proper information flow, and in convincing
5 taxi companies to switch to electric vehicles.
6

7 **5. CONCLUSION**

8 Implementation of EV FTS has received growing attention from policy-makers because mobile
9 technologies make it easier to operate FTS and the clean energy technologies produce less GHG
10 emissions in urban areas. This study focuses on the EV facility location problem for EV taxi service with
11 FTS fleets in which vehicles operate with a stochastic dynamic itinerary. As opposed to the conventional
12 refueling station problems with node-based static charging demands, the proposed SDIRQ is a simulation
13 based bi-level optimization model in which EV refueling events are dynamically derived from the spatial
14 and temporal passenger demand levels. The lower-level problem involves an EV shared-taxi simulation
15 model to minimize both pickup requests and passenger travel times, while the upper-level objective offers
16 the optimal refueling locations and the allocation of chargers.

17 For the baseline comparison, a single-level approach is introduced by relaxing the charging
18 constraints to collect static charging demands in a conventional manner. Due to the complexity of
19 involving the queueing model in the objective functions, a bi-level solution approach is proposed. The
20 computational results report that SDIRQ with the bi-level approach shows a promising solution approach
21 given the demonstrated EV FTS.

22 It is worthwhile to mention the lack of spatial-equity in the proposed solution. For example, it only
23 takes into account the benefit distribution of EV locations and distributions for EV FTS operations. As
24 mentioned in the simulation results, customers in the zones that are far from the EV locations may have
25 lower chances to be served by EV taxicabs, in which case those customers are significantly worse off. On
26 the other hand, the customers near charging stations will have much higher chance to be picked up. This
27 might be a practical issue when determining the optimal EV charging facility locations. The spatial-equity
28 issue will be studied further.

29 Another area of future research is the integration of the loading on the power grid or incorporating
30 smart grid features, perhaps similar to He *et al.*'s (2013) study. Having an integrated approach can allow
31 scheduling both the charging location and time to minimize delay on the fleet and temporal loading
32 constraints on the grid. Time-of-day pricing should be considered in this case.

33 The location problem may also be viewed as a sequential, dynamic decision under uncertainty to
34 introduce flexibility to adapt the investment strategy over time, similar to the forecast horizon introduced
35 in the dynamic server relocation problem by Chow and Regan (2011). The recent work by Chung and
36 Kwon (2012) shows a promising effort in that direction, introducing a multi-period aspect to the refueling
37 location problem, although demand is kept deterministic.
38

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