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SHARED-TAXI OPERATIONS WITH ELECTRIC VEHICLES

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ABSTRACT

Electric Vehicles (EVs) are energy-efficient and often presented as a zero-emission transport mode to achieve longer-term decarbonization visions in the transport sector. The implementation of a sustainable transportation environment through EV utilization, however, requires the addressing of certain cost and environmental concerns, before its full potential can be realized. These include EVs' limited driving range and issues related to battery charging. Taxis are visible and thus EV use in taxi service can bring attention in urban life to a commitment towards sustainability in the public's opinion. For this reason, this study proposes an integrated approach incorporating EV operation and an appropriate shared-ride conceptual design for taxi service. Despite several obvious societal and environmental benefits, it is however true that EV use entails certain vehicle productivity loss due to the time lost in charging. As this could lead to a deterioration in system performance, and thus in demand as well, it is important to look at whether the expected performance loss from the passengers' and systems' standpoint can be offset with ingenuity in operational design. A combination of shared-taxi and EV fleet is proposed for this purpose, as it can be competitive in passenger travel and wait times with conventional non-EV taxis. Such systems are modeled and analyzed using simulation in this paper, under routing algorithms modified from previous research. More specifically, EV charging schemes for taxi service implementation were proposed and the effects of the limited driving range and battery charging details were examined from a system performance viewpoint. First, this study shows illustrative results on the impact of the EV taxi fleet's vehicle charging on system performance. Then, real-time shared-taxi operation schemes are developed and applied to maximize the system efficiency with such a fleet. Some limitations and future research agenda have also been discussed.

KEY WORDS: Electric Vehicles (EV), EV feet charging schemes, EV charging demands, real-time shared-ride, shared-taxi algorithms, insertion heuristics, taxi simulation.

1. INTRODUCTION

Reducing carbon-based vehicle emissions and greenhouse gases (GHG) has been a critical issue due to its serious impact on environment and human health in my urban areas. There have been two major approaches that emerged in sustainable transportation research, (1) developing energy efficient technologies and (2) adopting efficient transportation operations. As part of the energy strategy, auto manufacturers are producing Alternative-Fuel Vehicles (AFV) such as Hybrid Vehicles (HV), Plug-in Hybrid Electric Vehicles (PHEV), Electric Vehicles (EV), and Fuel Cell Vehicles (FCV) that have zero or significantly reduced vehicle emissions. There is growing interest in EVs because they are also considered to be Zero Emission Vehicles (ZEV) as they use no internal combustion engines (ICE), and are powered by electric motors from battery packs without any CO and NO_x emissions. Nevertheless, other concerns limit EV utilization due to the higher vehicle-prices and the cost for the charging infrastructure, along with the shorter driving range compared to gasoline vehicles and the lost productivity if vehicles are idle due to battery-charging. Even if EVs are not yet considered ready to replace ICE vehicles on a large scale, they can certainly be considered as a viable option for many fleet applications that envisage the use of energy-efficient vehicles and require fewer resources to operate than even personal automobiles (Barth and Todd 2001; Better Place™ 2011; Blosseville et al. 2000).

As the traditional transportation systems' designs may render the above limitations of EVs prohibitive, it becomes important to consider if newer paradigms of passenger transport can help offset it. For instance, newer designs of sustainable Demand Responsive Transit (DRT) have been introduced in recent years because the provision of traditional public transport services for medium or lower demands has always been criticized for its operational inefficiency (Dial 1995; Cortés and Jayakrishnan 2002; Quadrifoglio 2007). However, it has been known that the newer conceptual designs are not yet fully refined for practical service in the real world. At the same time there are also commercial enterprise proving that newer concepts can indeed be introduced. For instance, Zimride and Avego are services recently initiated in the U.S. in the private sector, which facilitate ridesharing by simply matching drivers and riders in real-time for passenger travel in urban areas. These services utilize vehicles operated by regular car owners and not commercial drivers. However, those private ridesharing services could raise potential concerns about passenger insurance and fare-collection systems since the services use private vehicles operated by private drivers. In addition, a shared ride on any given vehicle can be offered only when that private vehicle is moving, and not all the time, which raises operational issues about the nature and composition of available vehicles at any point in time. Real-time shared-taxi can be a good alternative that overcomes these issues and maximizes the efficiency of conventional taxi services by employing a shared-ride concept. Shared-taxi can be characterized as an on-demand ride-share service operated by an online dispatch center such that the system is capable of taking service requests from individual customers in real-time and establishing service vehicle schedules.

There have been studies in the recent past on EV deployment, with regard to environmental impacts, effects of driver behavior, site selection for charging stations, and smart grid solutions. Unfortunately, there has not been much focus on the potential impact of EV fleet characteristics on the performance of fleet operations and the charging infrastructure, and furthermore, there has been no consideration of flexible transportation solutions that may be particularly applicable for even larger use of EVs than the limited fleet contexts discussed so far. A simulation study conducted by Jung and Jayakrishnan (2012) is a good example of larger-scale EV fleet application for DRT. The study assumed an innovative transportation alternative called High Coverage Point-to-Point Transit (HCPPT), which involves a sufficient number of deployed small vehicles for point-to-point passenger travel services, with associated hub terminals for passenger transfers (Cortés and Jayakrishnan 2002). However, that study mainly focused on the HCPPT design and operation rather than on investigating the impact of vehicle-charging. In this study, we consider an EV charging scheme for taxi service and its impact on system performance of taxi services considered as a potential EV fleet application.

There are some reasons to study shared-taxis for EV use before other potential newer passenger transport concepts. First, taxi is certainly the most popular on-demand dial-a-ride system in many urban areas of the world. The next reason is that the typically-short taxi trips within smaller areas are particularly suitable when EV driving range is an issue. Finally, taxis are known to be no less polluting than private autos because of lesser average number of riders than even private vehicles, which in turn is caused by substantial driving without passengers. It is indeed easier, however, to improve this using better ridesharing, unlike with private auto use. Apart from the cost of initial investment, utilizing EVs for taxi may prove to be an ideal application in terms of reducing emissions and fuel costs.

This study first examines the expected inefficiency of EVs when introduced in conventional taxi services. The paper then proposes an EV-based shared-taxi strategy that allows ride-sharing to improve the system performance. The main objectives of this paper are to model a case of a large fleet of vehicles providing shared-ride in a real-time demand responsive manner, and to discuss the specific issues that affect the feasibility of the implementation of EV fleets for taxi service. The discussion is divided into two main topics: real-time shared-taxi service and EV taxi charge-replenishing schemes. For shared-taxi operation, a brief discussion of the background on the shared-ride concept is also given first. In the subsequent section, we propose an EV charging scheme for taxi service. Then, detailed simulation assumptions and scenarios are introduced. Finally, we discuss the simulation results in terms of system performance, quality of service and recharging demands.

2. THE EV SHARED-TAXI CONCEPT

2.1. Shared-taxi algorithm

In many urban areas, real-time taxi dispatching offers better services in terms of shorter wait times but it is possible to maximize its efficiency via the use of shared rides. There are recent successes in implementing real-time ridesharing as well, as mentioned above. These services are typically operated by online dispatch center algorithms with the help of communication technologies and geo-location services utilizing GPS (Global Positioning System) and digital maps. Developing advanced vehicle dispatch algorithms to maximize occupancy and minimize travel times in real-time then becomes important. An advanced shared-taxi service is capable of taking service requests from individual customers travel demands and establishing subsequent vehicle schedules that combine individual rides. Such services are differentiated from conventional carpooling services by Cervero (1997): (1) Vehicles are operated by taxi drivers; (2) Vehicle pickup schedules are assigned dynamically to minimize passenger waiting time and in-vehicle travel time; and (3) Vehicle operations are scheduled and controlled by the central dispatch system. In recent years, a few studies have addressed the design of dynamic taxi-dispatch scenarios (Seow et al. 2010; Tao 2007), and various real-time shared-taxi dispatch algorithms have been proposed based on advanced optimization techniques such as Insertion Heuristics, Genetic Network Programming, and Hybrid Simulated Annealing (Lee et al. 2005; Meng et al. 2010; Jung et al. 2013).

In a typical real-time taxi dispatch system, when a new request is identified by system operator, the service request is delivered to the system queue where each customer is labeled with time windows and locations of trip origin and destination. Meanwhile, the dispatch algorithm takes a service request from the queue based on a first-come-first-served (FCFS) policy and finds an available taxi for the pickup request within the time windows. If there is no available taxi to meet the pickup and delivery time windows, the dispatch system can reject the request. Once a vehicle is assigned with the updated schedule, the most natural scheme is for the vehicle to use the shortest (fastest) path to the pickup location or drop-off location based on the real-time traffic information provided by the dispatch system. Since customer requests are incoming in real-time, the dispatch algorithm should be able to optimize the system performance without incurring prohibitively high computation times.

For a shared-ride taxi service such as we propose here, the dispatch algorithm needs to find not only the best vehicle among candidates, but also the optimal route with the newly updated schedules that avoid the violation of time windows of previously-assigned and new passengers as well as the vehicle capacity constraints. This study involves two types of time windows, which are based on maximum waiting times and maximum detour times. Note that the first constraint is necessary because trip requests can be rejected by service provides due to the number of vehicles being limited. The constraint for maximum wait time prevents the indefinite deferment of unassigned passengers. In other words, once a trip request is accepted, the system guaranties vehicle arrival in a pre-set amount of time. The second constraint is self-explanatory, in that a maximum detour time prevents excessive detours caused by too many passengers being assigned on a vehicle trip.

The real-time shared-taxi problem in this study can be defined as a continuous many-to-many vehicle routing problem. An algorithm based on an Insertion Heuristic (IS) was recently proposed by Jung et al. (2013) for such a problem. The insertion heuristic starts comparing all vehicles to find a best vehicle to minimize both passenger travel time and waiting time. However, the algorithm results in computational inefficiency when both the service area and the fleet size are large. As a notable improvement, in this paper we propose a two-stage algorithm, which is shown in Figure 1. First, each passenger trip is identified by its origin and destination, and the available vehicles are identified in the corresponding geographical service area, to insert a new trip request. In this stage, available vehicles are filtered to prevent excessive computational burden. In the second stage, the algorithm selects the best vehicle by minimizing service waiting time and travel time of the new passengers as well as the existing passengers.

Stage 1: Prepare a vehicle set J based on z_i's trip points and time windows.

Stage 2: Find a best vehicle V_{min}, $V_{min} \in J$ satisfying the following objective function to insert new l-th and m-th stops in the vehicles schedule as pickup and drop-off for the new request z_i of passenger i from the set of passengers, $i \in I$.

$$min\ IC_j = C_j(E_j \cup z_i) - C_j(E_j) \tag{1}$$

$$C_j(E_j) = \sum_{k \in K} \left[WT(E_{j,k}) + TT(E_{j,k}) \right] \tag{2}$$

$$C_j(E_j \cup z_i) = min_{l,m} \sum_{k \in K+2} \left[WT(E_{j,k}) + TT(E_{j,k}) + WT(z_{i,l}) + TT(z_{i,m}) \right] \tag{3}$$

where

z_i = a new passenger request i, $i \in I$
IC_j = incremental cost of vehicle j for inserting a new request z_i
$C_j(E_j)$ = current total cost of vehicle j's with schedule E_j

$WT(E_{j,k})$ = waiting time (cost) associated with k-th event in E_j
$TT(E_{j,k})$ = in-vehicle time (cost) associated with k-th event in E_j
$C_j(E_j \cup z_i)$ = total cost of vehicle j when adding a new request z_i

In this formulation, when a new passenger request comes in, the dispatch system constructs a set of vehicles that are available to serve, based on the passenger's origin point and the minimum waiting time allowance. For example, if a vehicle is in a certain zone which is too far from the passenger's origin point within a waiting time window, the vehicle is excluded from the available vehicle set. Vehicles in the corresponding passenger zone would have higher priority to serve the passenger request. Once the vehicle set J is built, the algorithm goes over the vehicles in the set. For each vehicle j, it first confirms whether the constraints are satisfied for the new pair of pickup and drop-off events. If they are acceptable, the incremental cost IC_j over the cost of its current schedule E_j is calculated for the new events based on the expected waiting and in-vehicle travel times of the new passenger and the previously-assigned passengers. For vehicle j under consideration, an inner optimization is done for finding the best insertion position in the current schedule over alternate l-th positions for pickup and alternate m-th positions for drop-off (m being always greater than l). Once all vehicles in set J are examined, the best vehicle, with the minimum incremental cost is found and its schedule is updated with the optimal insertion positions l and m in its current schedule of vehicle stops. If no vehicle in the set satisfies the time window constraints, then the passenger request is rejected.

The insertion heuristic is fairly easy and straight-forward to implement, and shows computational efficiency, but it has limitations on large-scale dynamic pickup and delivery problems. Since the insertion heuristic based on an FCFS priority scheme does not consider all new requests at the same time, it may lead to a sub-optimal solution as well. In other words, there is no re-optimization by exchanging a passenger assigned to one vehicle's schedule to another vehicle's schedule later. As expected, such re-optimization causes significant combinatorial issues and is computationally prohibitive. It is also possible that such re-optimizations and exchange of passengers across vehicle schedules may cause operational difficulties, as the drivers may keep finding pickup locations to be disappearing from the schedule. The current algorithm can add additional locations by inserting a new passenger pickup, but does not remove an existing pickup. Thus, despite not having fully-optimal solutions, the algorithm is computationally and operationally practical, and our studies have found it to lead to reasonable solutions. Note that the FCFS priority is used only to give an earlier request a higher priority to be considered in vehicle schedules. It does not imply that the pickups will be according to that priority order. Requests that come in later will be considered later, but the pick-up time for that request can be earlier than for a previously-assigned passenger.

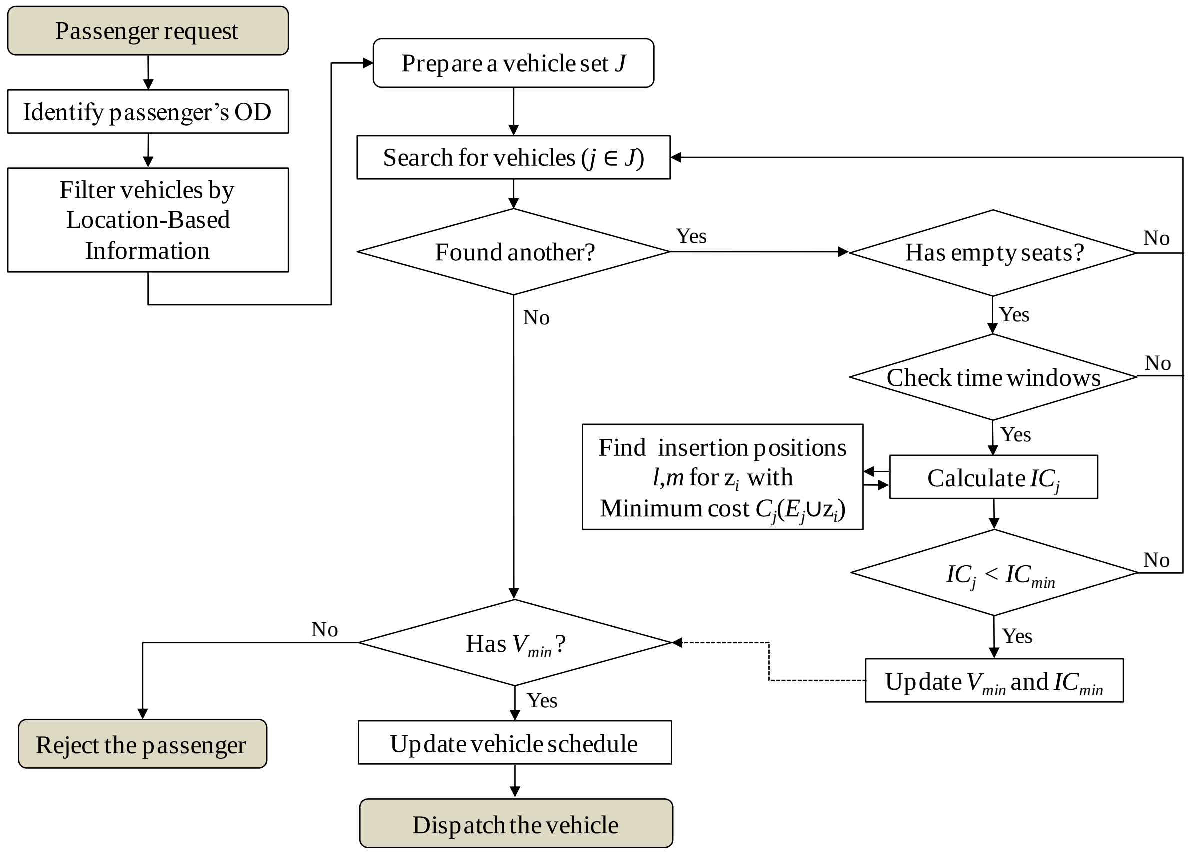


Figure 1. Insertion Heuristic for Shared-Taxi Dispatch

2.2. EV Taxi charging system

EV taxi service is an ideal application when speeds are lower and traveling distances are shorter, especially in several Asian and European contexts. An EV charging station is commonly called EVSE (Electric Vehicle Supply Equipment). The Society of Automotive Engineers (SAE) lists three classes of EV charging schemes: (1) Level 1 refers to a portable "plug" using a 120 volt outlet; (2) Level 2 refers to using 240 volts to deliver AC power to the on-board charger, usually over five to eight hours; and (3) Level 3 refers to fast charging with higher-voltage DC power, bypassing the on-board charger, and taking less than one hour. An alternative to quick recharging is battery swapping, i.e., replacing the depleted battery with a fully charged one, which takes only about five minutes. For example, Better Place™, an American-Israeli firm based in Palo Alto, California, is one of the companies offering a battery switch station for EV, and their pilot installations are already operating in Israel, Denmark and Hawaii, as we write this paper. A pilot project showed the feasibility of battery swapping as a means for EV taxi services in Tokyo in 2010. Considering that waiting five or six hours for charging is not a good option for fleet applications, EV taxi will require fast charging stations or instantaneous battery replacement services so as to maintain their services. However, it is still necessary for EV taxicabs to visit charging stations to replenish the batteries, and so taxicabs cannot be in service (with passengers) during the charging period. This indicates a direct impact on not only the revenue of taxi companies, but also the charging infrastructure. This motivates our investigation of charging issues in EV taxi service.

Since all vehicles are dynamically re-routed in response to real-time service requests, it is not a viable option to optimize battery charging schedules in terms of long-term vehicle routing plans. Thus in the cases we consider, vehicles build their own charging decisions based on their existing pickup and delivery schedules. Also, we hasten to note that we do not consider any optimality of charging control in vehicle-to-grid (V2G) schemes because the focus of this simulation study is on the taxi system performance rather than on the grid-scale power infrastructure.

2.3. EV Taxi Recharging Scheme

The proposed EV vehicle recharging schemes in general real-time routed transi and shuttle systems was previously studied by Jung and Jayakrishnan (2012) in an HCPPT context. However, the recharging scheme in the current study are significantly different in its basic characteristics. We assume here that an EV taxi can visit a charging station only after completion of passenger delivery whereas HCPPT vehicles can visit charging stations with passengers on board so that charging events can be treated similar to an ordinary vehicle schedule event, as could be done in our previous study. In the context of system efficiency, since hub terminals in HCPPT can be used both for passenger transferring and electric charging locations, the concept of hubs could not only yield infrastructure investment benefits for both systems, but also be a great advantage for vehicles to save on travel times when visiting charging stations. However in taxi service, visiting charging stations with passengers on board could result in noticeable deterioration of the service quality. It is also not reasonable to predict the travel distance to the next idling state using measures such as say the average busy period distances, because vehicle idling is a rarer event in fully-operational real-time demand-responsive shared taxi service, resulting in very high variance for the distances traveled between idle periods. Thus new schemes are necessary to incorporate charging events within EV taxi operations, as we develop here.

The new EV taxi dispatch algorithm consists of three types of vehicle events: passenger pickup, passenger delivery, and vehicle charging events. In the proposed charging scheme, a call request for inserting a new pickup and delivery in the schedule can be rejected due to the limited remaining range of EV. However, it is possible to insert a new pickup and delivery event even if a vehicle charging event is already scheduled as long as the vehicle has enough range to visit a charging station and the new passenger event can be added before the charging event.

Inserting pickup, delivery, and charging events proposed in this study is straightforward, but it has a few requirements: (1) When the current battery level (B_r) of a vehicle gets lower than the critical battery level (θ), the vehicle starts considering vehicle charging into current schedules; (2) A charging event (e_r) can be inserted only at the end of the vehicle's existing schedules (E_j) to prevent it from visiting charging stations with passengers on board; (3) new pickup and delivery events are prohibited if the vehicle is already headed to a charging station, which implies that it is the only event left in the schedule list (i.e., $e_r = E_j$), or if the vehicle has the potential to get discharged ($R > R_c$) when the new schedule is performed, given the remain range (D_r).

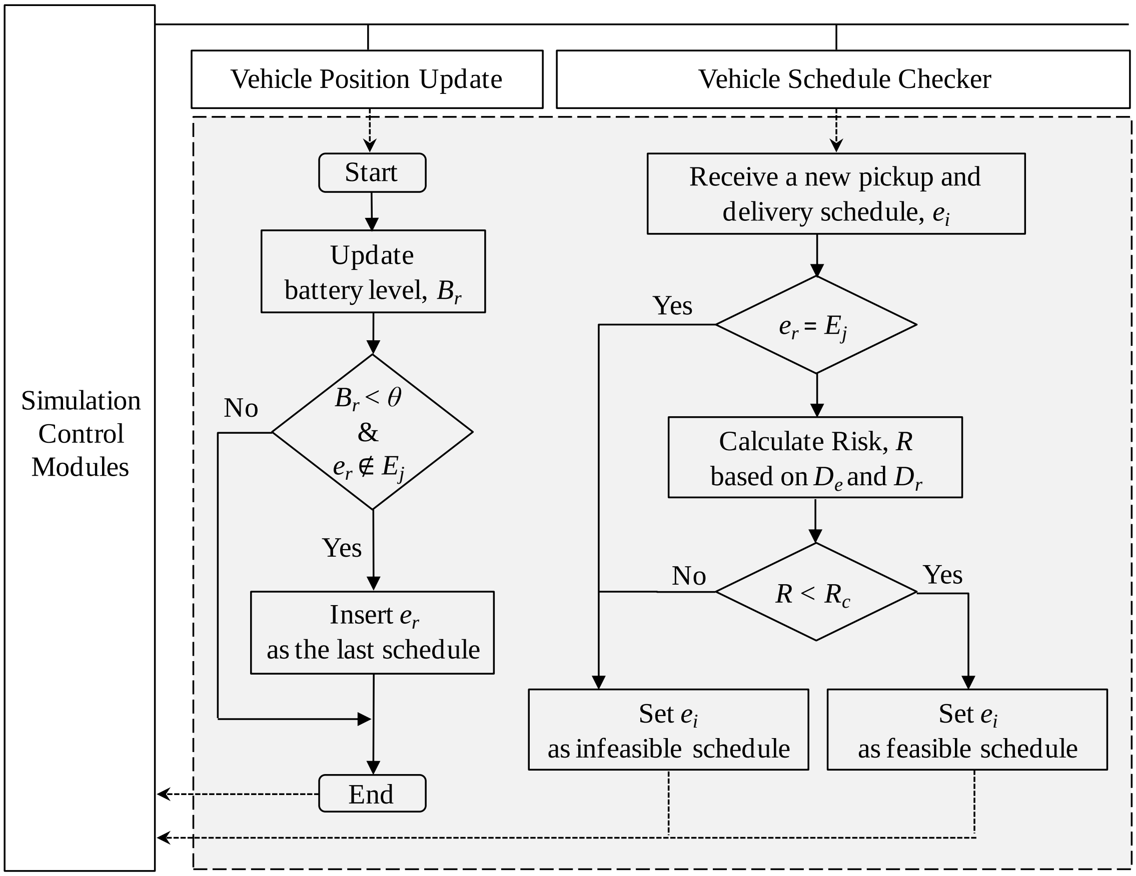


Figure 2. EV Taxi Charging Scheme

Figure 2 provides the proposed charging scheme for EV taxi. Inserting a charging event is primarily controlled by Vehicle Position Update module. Vehicle Schedule Checker is introduced to regulate newly incoming passenger events. The proposed insertion algorithm mainly checks against the drive range constraint while inserting a new passenger pickup and delivery event e_i. This is done by searching among the available vehicle's schedules for the best vehicle and its best insertion position so as to minimize the passenger waiting and travel times as well as the risk of the vehicles' battery getting discharged. Once a charging event e_r is inserted into a vehicle and the vehicle is already headed to a charging station, a new passenger request cannot be assigned to the vehicle.

A risk function is considered in the constraint preventing the battery discharge. As mentioned above, I is defined as a set of new passenger requests indexed by $i \in I$ waiting to be assigned to a vehicle V_j from a vehicle list J. For a passenger request, z_i, the possible insertion positions are l and m (for pickup and drop-off) in the schedule list for a vehicle V_j, $j \in J$. If the risk R associated with inserting new pickup and delivery events at positions l and m in the existing schedule of the vehicle V_j is higher than the critical level (R_c), then the new pickup and delivery request will not be considered.

$$R(z_i, V_j^{l,m}) = \begin{cases} e^{(D_e - D_r)/\beta} & \text{if } D_e < D_r \\ 1.0 & \text{otherwise} \end{cases} \tag{4}$$

z_i = Passenger request i
$V_j^{l,m}$ = Vehicle j with pickup and delivery in the l-th and m-th positions in its schedule list of events.
D_e = Travel distance to the charging station from current location
D_r = Remaining range (distance) based on the current battery level
β = Scale parameter

The risk function assumes a simple probability for the battery being discharged for a given schedule. D_e is calculated by summing up the event-to-event travel distances from the current vehicle position to the last drop-off location and then to the nearest recharging station. Combined EV ranges based on highway and city can be used for the scale parameter, β.

3. SIMULATION STUDY

3.1. EV Shared-Taxi Simulator

The current study requires the simulation of door-to-door passenger services with flexible routes and vehicle scheduling. As facilities for such modeling are not available in most commercial transportation simulation tools, an EV shared-taxi simulation framework was developed with Microsoft Visual C++, which offers great flexibility in implementing various types of algorithms and visualizing all relevant simulation elements (e.g., transportation network, vehicle operations, passenger requests, and charging locations), without any dependency on commercial simulators. The EV shared-taxi simulator imports digital maps designed for map display and geo-coding, and performs faster vehicle routing with realistic roadway attributes such as road categories, turning prohibition, one-way links, posted speed, number of lanes, link length, and link shapes. It also supports graphic user interfaces (GUI) that allow users to track simulation objects such as vehicles' schedules and locations of passenger requests during simulation runs. The statistics module in the simulator stores all system performance data, algorithm running time, and generated stochastic passenger demand data. It is noted that the simulation environment used in this study does not consider traffic dynamics, as predictive control based on changing travel times was not a focus, though the re-optimization schemes developed here are evidently faster and makes such real-time feedback control more practical. Elaborate microscopic simulation models have been developed for real-time routed fleet vehicle operations with real-time traffic feedback (see Cortes and Jayakrishnan, 2002), but the computational burden was considered too high, as the parametric study in this paper requires a fairly large number of simulations,

3.2. Simulation Assumptions

As the case study that is subsequently presented is based on a network in Korea, the simulation model that we developed includes modeling of recharging that is appropriate for a common vehicle model in Korea. The representative EV assumed is a Renault-Samsung SM3 Z.E., built in South Korea. Renault-Samsung claims that the SM3 Z.E. is outfitted with a 24 kWh lithium-ion battery with the maximum range of 184 km (115 mile) measured on the NEDC (New European Driving Cycle) combined cycle. A "QuickDrop" system (known as battery swapping) that allows the discharged battery to be replaced quickly with the fully charged one at a dedicated EV battery switch station is introduced, as well as a fast charging system using a 32A 400V 3-phase supply that completes battery charging in 30 minutes. Since an official range specification is not yet established in South Korea, we assume conservative average ranges of 113 km (70 miles) on highways and 145 km (80 miles) in city traffic with +/-16 km (10 miles) of uniform random variation across individual vehicles. The insertion heuristic algorithm described in the earlier section is adopted for both conventional taxi and shared-taxi algorithm. For conventional single customer group taxi service, the insertion heuristic algorithm assigns the new passenger to the nearest available vehicle.

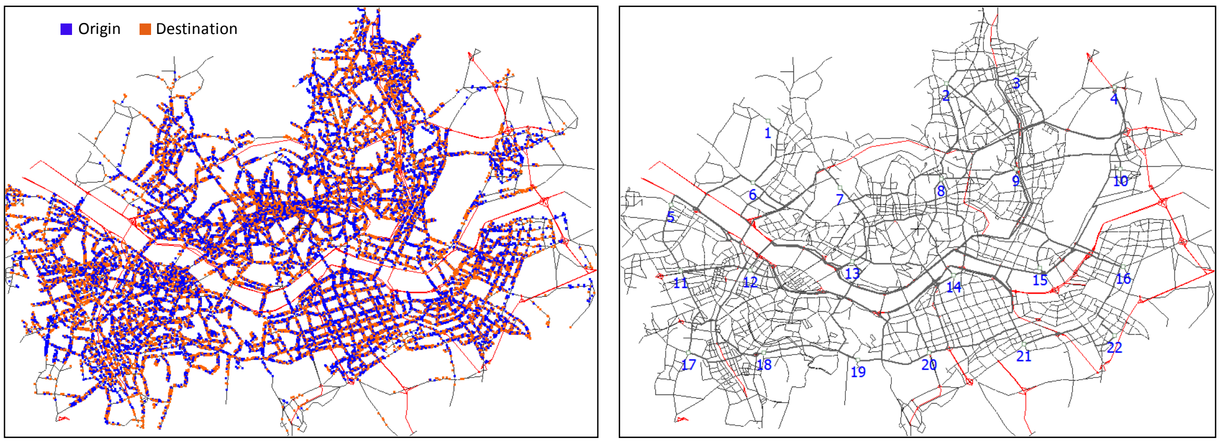


Figure 3. Passenger Requests Points and Charging Locations in EV Shared-taxi Simulator

For taxi demand generation, the demand data in the KOTI (The Korea Transportation Institute) regional transportation planning model based on the EMME/2 software is used. As of 2011, the trip demand files consists of auto, bus, subway, rail, taxi, and other types of demands, and the model covers the city of Seoul with a total of 560 zone centroids over and area of 605 km^2 (233 mi^2). Under the usual assumption of spatial uniformity of demand around a zone centroid, point-to-point taxi demands are randomly generated in accordance with destination probabilities of the taxi demand table in each centroid. The point-to-point demands are projected to the nearest directed road segment to model door-to-door services, except on limited-access roads. The real-time service requests arrive according to a temporal Poisson process with the locations being spatially uniformly distributed along the road segments in each zone. Figure 3 shows the network where 24,000 trip requests are generated for an 8-hour simulation based on the taxi demand table with the minimum trip length of 1.5 km for taxi service. A total of 22 charging stations on 5 km by 5 km reference grid cells are assumed over the road network. Figure 4 shows that a majority of generated trip demands are within 10 km. The average trip length is 6.4 km and the expected door-to-door travel time 13.4 min under the assumption that vehicles can travel at 60~90% of the posted speeds on the network.

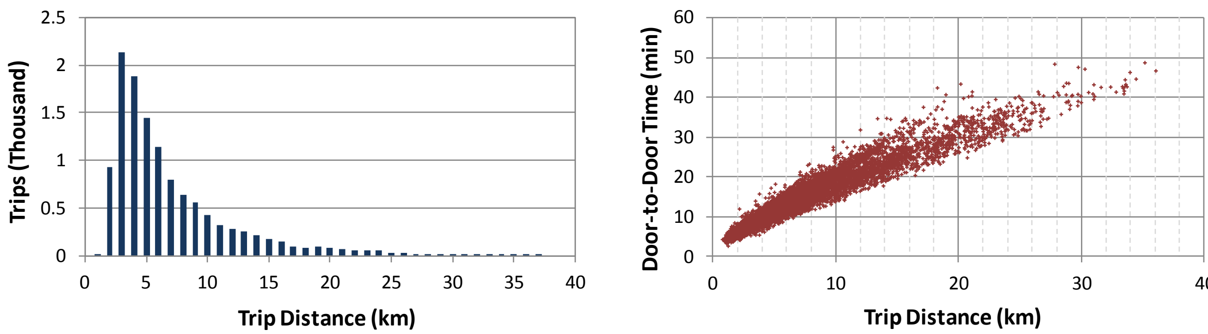


Figure 4. Distribution of Passenger Trip Requests

3.3. Simulation Scenarios

According to the statistics from the Seoul Taxi Association (2006), a taxi carries more than 30 passengers each day, on average. The average travel distance is over 235 km/day and 5 km/trip, with a significant portion of the travel distance being non-revenue segments when the taxis travel empty for the pickups. A total of 72,000 taxi licenses are registered including owner-driver taxis, and a total fleet of 40,000 vehicles operated as of 2011 under a taxi rotation system to restrict the number of operating taxicabs. Shared rides in taxis are prohibited by regulations in South Korea, but it is known publicly that many taxicabs carry multiple passenger groups at the same time if they are traveling to the same destination because there are higher passenger demands than taxicabs available during the peak hours.

In this study, 600 taxicabs are considered, which is equivalent to 1.5% of the total number of vehicles operating in Seoul. The initial positions of vehicles are randomly generated over the simulation area. The simulation time is set to 8 hours including 30 minutes as a warm-up period. An average of 1-min boarding and alighting times are assumed for each passenger, which is based on a normal distribution $N(1.0, 1.0)$. In the shared-taxi scenario, the time window constraints represent a maximum waiting time of 15 minutes, and the maximum detour lengths used are uniformly randomly distributed between 1.1 to 1.5 times the door-to-door travel distances. A taxicab can carry a maximum two passenger groups at the same time, which provides a realistic scenario rather than having three or more groups. Two charging times are assumed for fast charging (30 min) and battery replacement (5 min), both assuming standard 24 kWh batteries. Two different initial charging strategies were considered because it was found in our previous studies that charging demands tend to cause peaking of the grid power demand as well as poor system performance when the eight hour period started with all vehicles fully charged, as many vehicles go off service for charging at the same time later during the period. Thus we studied one case that involves fully charged EVs (FISOC: Full Initial Sates of Charge) and another case that involved randomly charged EVs (RISOC: Random Initial State of Charge) at the beginning of the simulation. Both cases are realistic, however, with the former case applying to the start of day and the latter situation perhaps applying to a later period in the day, in the regular operation of such systems.

Table 1. Simulation Scenarios

Simulation setup for Taxi service and EV charging	
Service area	605 km^2
Simulation time and warm up time (hours)	8 hours, 0.5 hour
Number of service vehicles	600 vehicles
Vehicle capacity (passenger groups/vehicles)	Maximum 2 groups with 4 seats
Vehicle types	ICE[1], EV
Service types	Non-Shared, Shared-Taxi
Number of EV charging locations	22 locations
Battery Capacity[2]	24 kWh
EV Range on Highway and City Traffic (km/charge)	113 km, 145 km
Charging time (minutes)	5 (battery replace), 30 (fast charge)
ISOC (Initial State of Charge)	Fully charged, Randomly charged

[1] ICE: Internal Combustion Engine Vehicle (Non-EV)

[2] Battery pack capacity (kWh): kilowatt-hour(s)

4. SIMULATION RESULTS

4.1. EV Non-Shared Taxi Service

Figure 5 shows (a) numbers of completed and rejected requests, (b) numbers of charging events with difference combinations of recharging times, (c) average vehicle load, and (d) average vehicle distance traveled for non-EV and ISOC scenarios. It is noted that refueling ICE vehicles is not considered in this simulation because regular taxi vehicles use engines powered by Liquefied Petroleum Gas (LPG) and there are more than 70 LPG charge locations distributed in Seoul as of 2011. This indicates that refueling of the LPG vehicles would not significantly impact the system performance.

Figure 5(a) clearly shows that employing EVs reduces the number of delivered passengers in comparison with ICE. Recharging time with 30 min significantly worsened the performance of taxi service. For example, the number of completed requests under RISOC 30 (Random Initial State of Charge with 30 min recharging time) decreased by 15% compared with ICE while it decreased by 5% under RISOC 5 (Random Initial State of Charge with 5 min battery replace time). It is reasonable that the number of rejected requests increased at the same time too, as vehicles spent more time to recharge. As for charging events in Figure 5 (b), FISOC 30 shows the lowest value among the scenarios and the overall numbers of charging events under FISOC are significantly lower than under RISOC. In the RISOC scenarios, the vehicles start with insufficiently charged batteries that vary from 20% to 100% of maximum charge, which results in more frequent visits to charging stations. Under FISOC 30, each vehicle has an average of 1.35 charging event while under RISOC 30, it is 1.86 during the simulation period.

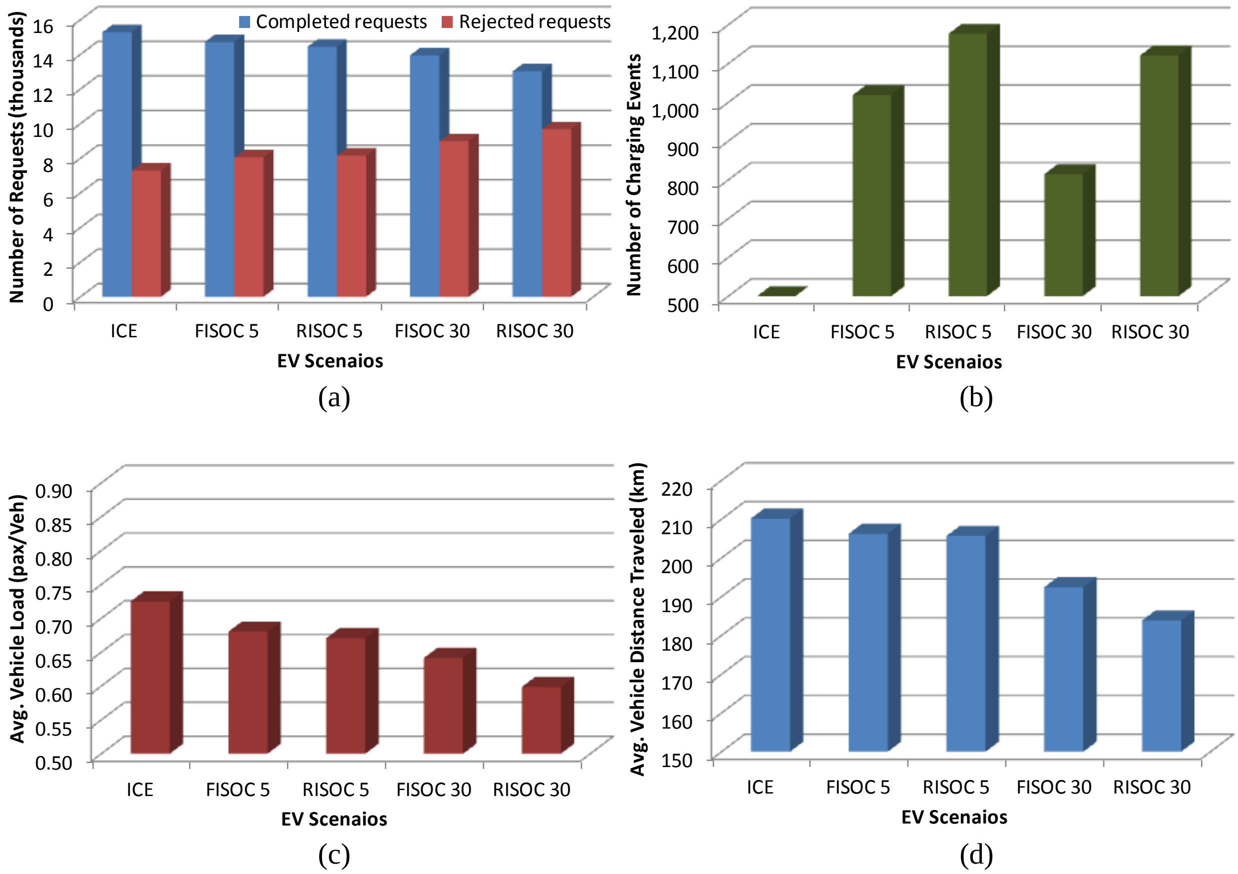


Figure 5. Non-shared EV Taxi System Performance: (a) Numbers of completed and rejected requests (b) Number of Charging Events (c) Average Vehicle Load (passengers/vehicle) (4) Average Vehicle Distance Traveled (km/vehicles).

Average vehicle distance traveled and vehicle load in Figure 5 (c) and (d) show the same pattern. Since vehicles with 30 min recharging time spend much more time at charging locations, they travel shorter distance with fewer passengers given the simulation time. It should be noted that the average vehicle loads are a direct reflection of the number of delivered passengers in non-shared taxi serve.

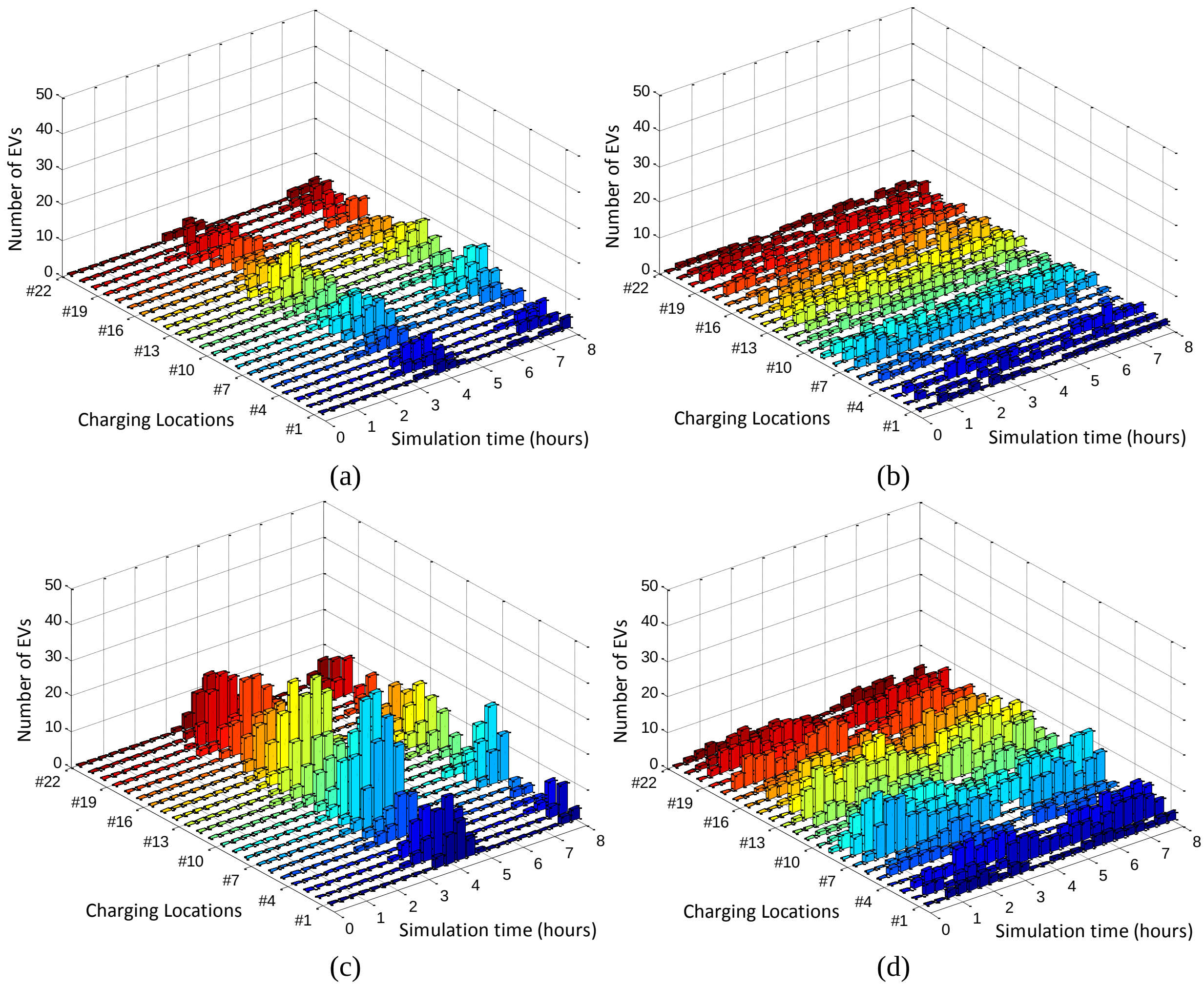


Figure 6. Charging Demand Profiles: (a) FISOC 5 min (b) RISCO 5 min (c) FISOC 30 min (d) RISOC 30 min

Figure 6 shows the number of vehicles at charging locations. Since a sufficient number of charging stations is assumed at each location, these numbers indicate the number of vehicles being charged, as no vehicle is assumed to have to wait at charging locations to get a charging station. As expected, during the first three hours of simulation, charging events can be hardly seen in Figure 6 (a) and (c) because the vehicles start with FISOC from the beginning of the simulation whereas randomly charged vehicles start visiting the charging stations earlier on in Figure 6 (b) and (d). It is also seen that EV charging demands are concentrated with FISOC because EV batteries on the vehicles tend to run out roughly around the same time and all those vehicles start visiting the charging stations. An average of under 10 vehicles are at each charging location under the 5 min battery-replacement scenario, as seen in Figure 6 (a) and (b). Obviously this shows much lower occupancy at charging stations than for the cases with 30 min charging time. It is apparent that the total numbers of charging events with 5 min replacing time are higher than the numbers with 30 min. The peak charging load of FISOC 30 shows 34 vehicles at the charging location #8 and a total of 307 vehicles over all charging locations. That means that more than a half of services vehicles could be in energy replenishing mode at a given time due to FISOC and 30 minutes of recharging time. In contrast, the peak demand is 6 vehicles under RISOC 5. Considering that we assumed enough number of charging stations at each location, the impact could be more significant on system performance under FISOC than RISOC. It can be concluded that the shorter recharging time shows not only better performance, but also less impacts on the charging infrastructure even though the total number of charging events are not different. It is conceivable that vehicle arrivals at the charging locations are correlated with peak charging load that could result in not only a shortage of service vehicles in term of system performance, but also a large coincident peak in the grid system. Perhaps uncontrolled charging might be the most serious concern of the grid system especially with larger fleet sizes of taxis. Note that FISOC 30 has lower number of charging events than FISOC 5 because of not only the shorter charging time but also the eight hours of simulation time.

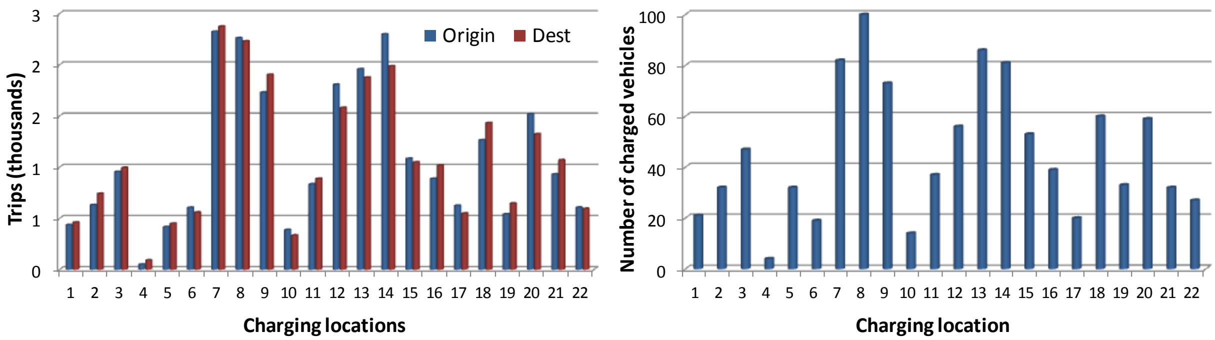


Figure 7. Trip demands and charging vehicles at charging locations

Figure 7 provides the OD distribution of trip requests corresponding to the nearest charging locations and the numbers of vehicles charged at each charging locations. Since the trip OD demand table used in this study is for daily demand, not for a peak time, there are no directional patterns in origins and destinations flows. However, it is apparent that the charging demands at charging locations are affected by the spatial distribution of trip data. It is expected that the EV charge load is affected by delivery points rather than pickup because the taxis visit the charging stations only after completing a final delivery in a sequence of pickups and deliveries.

While the above graphs bring out several illustrative details of relevance during the operation of EVs in shared-taxi operation, they are only illustrative in nature and quite context dependent in a given urban area. It is as important to also examine the system performance summaries to make judgments on how competitive EVs are, in comparison to conventional taxis, as we know that EVs will certainly lose some periods due to recharging. Of course, if the recharging locations are owned by the taxi companies and replacement vehicles are available immediately, then EVs will operate quite similar to conventional taxis except for the deadheading trips to the charging stations. Then the issues of concern are more related to the grid level energy demands, as we examined above, rather than the taxi system performance. Our interest here is however any potential performance loss due to charging needs, and thus our next summary results refer to the case when a fixed fleet of vehicles are in operation and some are lost from service during the charging time.

Table 2 (a) reports the detailed performance measures. The non-shared taxi service results include the conventional ICE taxi column, which can be used as the comparison to examine any potential deterioration of system performance. As can be seen in the different EV cases show certain loss of performance. This is primarily on the basis of the rejected customers. Between 10 and 20% more customers are rejected in the case of EV use. For those customers who were served, the average wait time home and average passenger travel time (in-vehicle) are constant over all the EV scenarios. This indicates that vehicles are fully utilized with generated demands in this simulation. It is noted that random passenger boarding and alighting times are included in passenger travel time, not in the wait time. The question arises on how the lost customers can also be served with EV taxis, and the next set of results, as in Table 2 (b) show that this is indeed possible.

Table 2. Detailed Performance Measures

(a) EV Non-shared Taxi Service with Different charging schemes					
Initial State of Charging (ISOC) Scheme	ICE taxi[1]	Full	Random	Full	Random
Charging time (min)	n/a	5	5	30	30
Number of delivered passengers	15,281	14,720	14,440	13,953	13,027
Number of rejected requests	7,294	8,058	8,156	8,991	9,678
Avg. wait time home (min)	14.03	13.80	13.83	13.81	13.92
Avg. passenger travel time (min)	12.78	12.52	12.52	12.49	12.42
Avg. vehicle load (passengers/vehicle)	0.73	0.68	0.67	0.64	0.60
Avg. vehicle distance traveled (km)	210.17	206.24	205.66	192.46	183.85
Number of charging events	n/a	1,019	1,177	815	1,121
Peak charging loads	n/a	65	29	307	109
(b) EV Shared Taxi Service with Different Detour Factors					
Initial State of Charging (ISOC) Scheme	Random	Random	Random	Random	Random
Charging time (min)	30	30	30	30	30
Detour factor for shared-ride	1.1	1.2	1.3	1.4	1.5
Number of delivered passengers	14,274	14,597	15,005	15,226	15,467
Number of rejected requests	8,348	8,023	7,556	7,328	7,075
Avg. wait time home (min)	13.07	12.79	12.48	12.34	12.32
Avg. passenger travel time (min)	13.85	15.02	16.57	17.85	18.67
Avg. vehicle load (passengers/vehicle)	0.75	0.85	0.96	1.06	1.13
Avg. vehicle distance Traveled (km)	180.00	179.24	176.85	176.78	176.17
Number of charging events	1,078	1,069	1,050	1,048	1,034

[1] ICE taxi: Conventional taxi powered by internal combustion engine (Non-EV taxi)

4.2. EV Shared-taxi Service

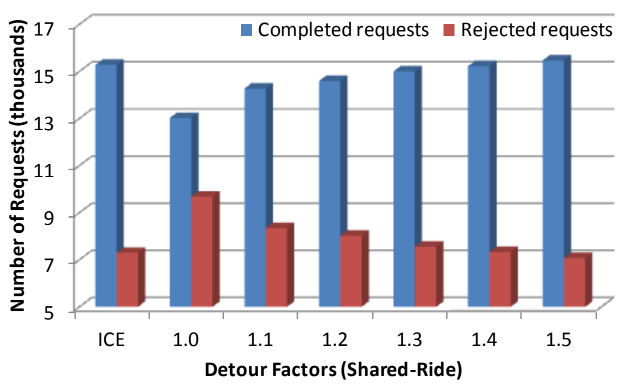
It would be expected that employing EVs in taxi would cause system inefficiency due to its inherent limitations in travel range and lost productivity while vehicles are idle for charge replenishment. The results on modeling the shared-ride concept to improve system performance in EV taxi service are reported in Table 2 (b), which immediately shows that even for the worst case EV operation with 30 minutes charging time, operational scenarios that serve the same number of customers as conventional taxi are possible.

We assumed that ride-sharing allowed with the maxim capacity of two passenger groups in RISOC 30, and then another constraint is employed with maximum detour factors from 1.1 to 1.5 in which the system can provide efficient service with less passenger inconvenience. The maximum detour factor is equivalent to the ride-time index when the system is fully operated. In this study, the maximum detour factor of 1.0 implies a single customer policy in which a taxi can carry only one passenger group at any time.

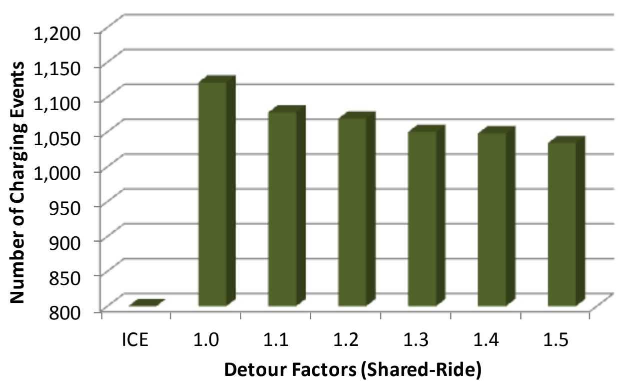
Figure 8 shows system performances with difference detour factors in comparison with single customer non-EV (ICE) and single customer EV (Detour factor 1.0) scenarios. As seen in the previous simulation, the number of delivered passengers decreases by 15% in RISOC 30 in comparison with ICE.

However it is seen that the number of completed requests increases as the maximum detour factor increases with shared-ride. RISOC 30 with the detour factor 1.5 shows even better system performance than single customer with ICE vehicles in terms of delivered passengers.

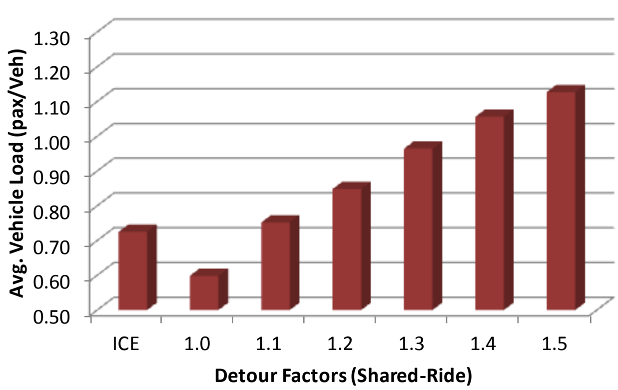
It is also important to note the vehicle load, as that indicates potential higher revenue for the same or lower miles traveled by vehicles, though a proper comparison is only possible with pricing of shared and non-shared services, which is beyond the scope of this study. Certainly the increased vehicle load indicates a significant increase in system efficiency with the shared EV taxi system. The vehicle distance traveled remains significantly at lower levels with shared-taxi scenarios. It means that the shared taxi system can deliver more passengers with less operational travel distance. The average vehicle distance traveled decreases as the detour factor increases, which could be a potential benefit for the vehicle operator to reduce the vehicle operating cost as well as the number of EVs in charge replenishing mode. The smaller numbers of charging events are expected with shared-ride taxi service due to the shorter distance traveled given the same ISOC and recharging time. In other words, higher efficiencies in both passenger delivery and power grids are expected with the share-ride in taxi system.



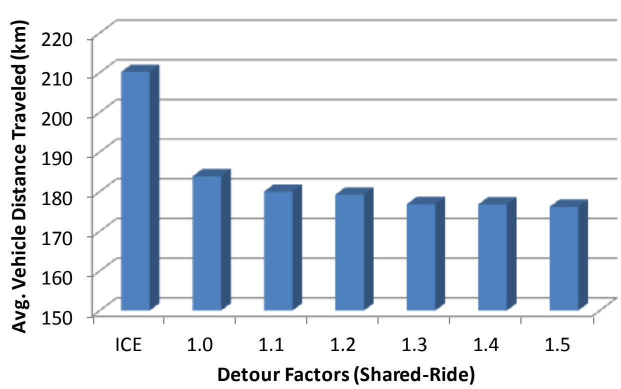
(a)



(b)



(a)



(b)

Figure 8. Shared EV Taxi System Performance (30 min recharging time) : (a) Numbers of completed and rejected requests (b) Number of Charging Events (c) Average Vehicle Load (passengers/vehicle) (4) Average Vehicle Distance Traveled (km/vehicles).

Further numbers, as reported in Table 2(b) in terms of the passenger times are also important, as they directly impact the demand for the service. In this study, no demand models can be incorporated for shared and non-shared services. Such a demand model would conceivably involve the travel and wait times, pricing and perceived disutility from shared rides and additional stops. As pilot systems have not been used for developing such models, this study does not delve into the demand aspects. It is however instructive to look at the indicative results in Table 2, under the assumption that demand stays at a certain level. It is reasonable that the values of average passenger travel time increase as the system allows longer detours with the detour factor. One interesting result is that the average wait times at home (12 - 13 min) with shared-taxi are lower than the values of single customer operations (14 min) because there are higher opportunities to pick up passenger requests when vehicles have available seats. Even in the worst case from the user perspective, i.e., with a detour factor of 1.5, the average total time spent is 30.99 minutes, as opposed to the best case (conventional taxis in Table 2(a)) of 26.81 minutes – and increase of about 15%. Considering that the average passenger load increases from 0.73 to 1.13, an increase of nearly 55%, even that scenario of shared-ride EV operation may prove to be beneficial from the operator's and society's viewpoint. Though this is at the expense of the passenger, note also that this seemingly worst scenario is able to serve as many passengers as the conventional taxis can, which indicates that the users are also served well in the final analysis.

Finally, Table 2 also shows summary results regarding the charging demand profiles, the effects of which on the energy grid was discussed in detail above. Once again, we see that the share-taxi operation could reduce the total number of charging events, without showing much noticeable difference in the peak charging demand during the simulation period. Thus shared-ride operations appear not to have significantly different impacts on the power grid in comparison with single ride EV taxis.

5. CONCLUSION

This study investigated the feasibility and the expected changes in system performance if EVs are used for taxi service. First set of studies dealt with conventional single-customer taxi operations. Those simulation results showed that system productivity decreases with respect to regular ICE taxis, especially when longer periods of charging are required, but the quicker battery replacement schemes shows similar system performance to ICE vehicles in terms of passenger delivery. The simulation result reveals that battery replenishing time and charging location are two important factors for EV fleet operation. In addition, starting fully charged batteries without any control scheme would cause the charging demands to concentrate at the same time.

As EVs are expected to cause productivity loss due to charging times, we proposed an alternative that could yield similar system performance as conventional taxi, and the simulation results showed that the shared-ride taxis can indeed result in comparable the system performance to conventional ICE taxis in terms of both passenger delivery and EV charging demands. The average passenger loads in vehicles were found to be improved significantly with the same fleet of vehicles and under the same passenger time window constraints, by up to 55% from conventional taxi service. Considering the environmental and societal benefits, shared-ride EV taxis should then be taken as a much better alternative for urban regions where significant taxi demands exist. Certain details were also brought out such as the need to properly design the EV charging schedules to prevent excessive demands on the power grid.

Much further work remains to study the performance of such EV-based shared-taxi systems for different urban contexts and under various fleet and passenger constraints. The results of this study are primarily to illustrate the impact of EV on taxi system by assuming predefined EV charging specifications and fixed locations. The design of optimal charging locations would be an interesting issue for further study. As a possibility, a simple non-parametric approach can be used to find the optimal charging locations for EV taxi operation via the consideration of alternative sites. It is also beneficial to develop demand models to incorporate in the simulation framework by studying the passenger response behavior to pricing as well as their discomfort in shared-rides, or undergoing significant rerouting, preferably from a real world implementation.

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