

Design of a Mobile Charging Service for Electric Vehicles in an Urban Environment

Shisheng Huang, *Member, IEEE*, Liang He, *Member, IEEE*, Yu Gu, *Member, IEEE*, Kristin Wood, and Saif Benjaafar

Abstract—This paper presents a novel approach to providing a service for electric-vehicle (EV) battery charge replenishment. This is an alternate system in which the charge replenishment is provided by mobile chargers (MCs). These chargers could have two possible configurations: a mobile plug-in charger (MP) or a mobile battery-swapping station (MS). A queuing-based analytical approach is used to determine the appropriate range of design parameters for such a mobile charging system. An analytical analysis is first developed for an idealized system with a nearest-job-next (N-JN) service strategy explored for such a system. In a N-JN service strategy, the MC services the next spatially closest EV when it is finished with its current request. An urban environment approximated by Singapore is then analyzed through simulation. Charging requests are simulated through a trip generation model based on Singapore. In such a realistic environment, an updated practical N-JN service strategy is proposed. For an MP system in an urban environment such as Singapore, there exists an optimal battery capacity with a threshold battery charge rate. Similarly, the battery swap capacity of an MS system does not need to be large for the system to perform.

Index Terms—Battery charging, battery swapping, electric vehicles (EVs), queuing theory, trip generation.

I. INTRODUCTION

ENERGY security is one of the biggest issues in the global political climate. Instability in global oil producing nations and the dwindling of relatively easily extractable oil reserves have driven the need for major energy importing nations to be less reliant on foreign sources of energy. The transportation sector, which accounts for the majority of oil consumption around the world, is one such sector that has seen a major impetus to transform. To help alleviate this dependence on limited resources, there have been tremendous development in electricity-propulsion-based vehicles. These include the pure electric vehicles (EVs), such as Nissan Leaf, Think City, and Tesla Roadster, and the hybrid plug-in hybrid EVs (PHEV),

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such as the GM Volt. The most significant difference between these two configurations of EVs is the ability of the PHEV to fall back on an alternative power source when its battery is depleted. In most configurations, the alternative power source is an internal combustion (IC) engine. An EV, by comparison, is reliant solely on the energy available in its battery for propulsion and, when the energy is depleted, it has to replenish its energy through a variety of options. Most of these options require a significant amount of time to execute, during which the vehicle is rendered immobile; hence, it creates a significant barrier to adoption among consumers known as *range anxiety*.

There are several options available that can recharge the EV and PHEV, and the most prevalent technologies can broadly be classified under two broad arms: plug-in chargers and battery swaps. Plug-in chargers can further be classified into three levels: levels 1, 2, and 3. A level-1 charger represents a charger that is typically installed into a household plug. The power output of these chargers vary across the world depending on the prevalent voltage and current levels of the socket installed and, in the United States, the charger will typically deliver about 1.6 kW of power. Level-2 chargers can deliver at higher power levels, typically more than twice that of a level-1 charger. These chargers are expected to be the most common of chargers available to EVs as they require minimal capital investment and installation. However, with these specifications, an EV could take about 8 h to fully charge its battery; hence, they are useful mainly for the recharging of EVs for instances where the vehicle is expected to be stationary for a significant amount of time.

Level-3 chargers, or quick chargers as they are also known, are high-voltage dc chargers that can deliver electricity at a high power and thus can potentially reduce charging times to about half an hour. These chargers are expensive and require the appropriate electricity distribution infrastructure to support them. However, since they substantially reduce charging times, they do help to alleviate range anxiety. The last popular option in literature is the concept of battery swapping. In these stations, depleted battery packs of EVs are swapped out for charged battery packs in specialized stations, which allows for service times that are competitive with gas stations for IC vehicles. A major player in the domain of battery swapping was Better Place with relatively large battery-swapping station installations in Denmark and Israel [1]. However, a battery-swapping station costs around \$500 000, representing a significant capital investment for EV companies [2]. This has severely hampered the success and deployment of swapping technology. Tesla has also announced plans for swapping stations for its own line of EVs [3]. Another possible alternative to these energy replenishment technologies could be wireless chargers such as the

Korean Advanced Institute of Science and Technology Online EV Project, which proposes for the installation of charging lines laid under roads [4]. Similar to the high-voltage chargers, these require extensive infrastructure investments.

These limitations in battery capacity and recharge time represent significant barriers to the adoption of EVs by consumers [5]. While there are solutions that can help alleviate these concerns, level-3 chargers and battery swap stations represent big investment decisions by the firms or government authorities. These could require a certain level of EV penetration before becoming financially viable.

In this paper, we are proposing a mobile charging platform as an alternative implementation of these battery recharge options. This option could initially be an interim measure to fulfill energy demand before infrastructure investment catches up or complement existing services to cover deficient coverage. The implementation could either be in the form of a mobile plug-in charger (MP) or a mobile battery-swapping station (MS). To evaluate the feasibility of the envisioned mobile charging service, we propose a queue-based framework to analytically capture the mobile charging process and use an example where a single mobile charger (MC) is employed to demonstrate its value. We then examine the implementation of such a system in an urban environment through a scenario based on the city-state of Singapore.

II. BACKGROUND

The library of work of EVs is increasing rapidly. Most have been focused on operational aspects assuming a certain level of EV adoption. A large body of work has looked at the impact of EVs on the electricity system, specifically on how EVs would affect the temporal usage pattern of electricity. One of the earlier and more influential studies examines the potential adoption limit of EVs in current electricity grids and concluded that, if we could fill in the valleys of off-peak periods with EV charging, the current system could absorb a high level of these vehicles [6]. Other studies have looked at more realistic charging patterns, simulating how actual usage would affect the electricity system [7]–[11].

Adoption rate studies, mostly based on agent-based simulation diffusion models, have looked at the effects of these vehicles at different penetration rates. In [12], Yabe *et al.* looked at different adoption rates and, coupled with how the electricity generation sector develops, determined the effects of CO₂ emissions for Japan. There needs to be a long-term incentive policy in order for EVs/PHEVs to achieve significant levels of penetration. Eppstein *et al.* [13] develop an agent-based framework that incorporates demographic and spatial considerations to investigate complex interactions that affect PHEV adoption rates. Their analyses suggest that the all-electric range of PHEVs was a significant factor in making PHEVs more cost competitive.

All of these studies assume that the EVs do most of their charging at home and overnight. However, in practical implementations, public charging options would need to be provided to help alleviate concerns of range anxiety among EV owners [14], [15].

A. Fixed Charging Stations

The predominant paradigm in EV energy replenishment is a static-location charging station. This system requires that the EVs drive to a predefined location where they can replenish their energy sources. The key considerations then include charging location sites and, correspondingly, how many stations to construct. Shukla *et al.* adopted a vehicle flow-interception model and looked at the optimal number of battery-swapping stations considering existing petrol station retrofits, specifically looking at a case study in Alexandria, USA [16]. Wang and Lin have also looked at the siting of a mixed composition of charging stations to achieve objectives of both minimal costs and maximal coverage, using a case study of Penghu in Taiwan [17].

Studies that look at the operational aspects of fixed charging stations have also started to appear in literature. Avci *et al.* have looked at the operational characteristics and parameters of a single charging station [18], and Andrews *et al.* concluded that a mixed ownership model for EV batteries with additional charging infrastructure is conducive for EV adoption [19]. However, a recent study concluded that investments in public fast chargers for EVs are hardly profitable at low EV adoption rates [20].

B. Mobile Service Systems

Mobile rescue systems possess certain similar properties to mobile charging systems. These systems are also concerned about the minimization of response times and key indicators such as latencies and miss rates. However, a key differentiating factor is the service capacity of the server. In rescue services such as an ambulance, the service capacity per vehicle is fixed. Instead, the design parameters used to influence the key parameters are usually the location of ambulance bases and coverage areas [21]–[24].

In contrast, the energy capacity of the MC is a key design parameter in the system. A large energy capacity allows for the MC to stay out of the depot for a longer period and hence affect service rates. Moreover, the rate of service is generally determined by the requestor and not affected by the design of the server. The rate of service of the server can be more easily determined in a mobile charging system through different charging rates. Both these factors, i.e., capacity and charging rate, also significantly affect the capital cost of such a system.

There has been previous work that has determined the feasibility and accuracy of queue-based models of mobile servers [25]–[30]. These studies focus on the analysis of data collection in wireless sensor networks with mobile data collectors. The most basic service discipline of first-come-first-serve (FCFS) is explored in [25]–[27], and the condition for a stable system has been identified [29]. Furthermore, the nearest-job-next (NPN) discipline is explored in [28], [30] and is shown to be able to achieve much more competitive performance. It is clear that the MCs in our EV domain can be viewed as a special type of mobile servers; hence, we can adopt a similar queue-based approach to analytically capture the mobile charging process for EVs.

III. METHODOLOGY

A. Overview

In this paper, an MC is proposed as a possible complementary alternative for public charging services. This charger may take either of two forms: an MP or an MS. In its first form, the MP acts like a conventional fixed plug-in charger with the ability to travel to the EV requesting for a charge. A possible scenario could be as follows: An EV drives to work, and realizing that it needs to make an additional trip, determines that it needs additional charging when it is parked at work. The workplace may not have a public charging station installed; hence, the MC can fulfill the need. The MC drives to where the EV is parked, starts charging the vehicle to a predetermined charge level, and leaves to fulfill its next request. In this capacity, the charger could also fulfill the role as the primary charger for the vehicle if the EV does not have access to a charging station at its residence. This is possible, particularly for high-density urban environments where the parking space for the residence is not owned by the EV owner and the owner may not have the access to install a charger at home. In the second MS derivative, it is assumed that the underlying assumptions dictating MC use are similar; however, the MS in this configuration swaps the depleted battery of the EV with a fully charged battery. In this scenario, the EV faces a constant and probably short turnaround time. Throughout this paper, MC refers to an MC in general, whereas MP and MS refer to specific configurations of this charger.

The MC system is approximated by a queuing model. The requests for MCs are generated through a stochastic trip generation model that assumes a vehicle use profile similar to conventional vehicles. These requests are then used in the queuing model, allowing us to examine critical design parameters that would govern the feasibility of the mobile charging system. The system operations in an urban environment such as Singapore are then examined to better illustrate the system implications. The approach and methods of the study can be applied to most urban environments.

In the following, we will first examine the queuing model framework used to analyze the operational performance of the chargers for an idealized system, followed by discussion of the scenario development for our case study. We will then present a study of the MC system in the urban environment, followed by a concluding section.

B. Queue-Based Analytical Framework

Here, we first present our queue-based analytical framework; this would be used to establish analytical reference points for the performance of the proposed system.

1) *General Framework*: The general charging process is easily translatable to queuing models, where the MC acts as the server and the requesting EVs are treated as the clients. The event of an EV requesting a charge is modeled as the client arrival. To charge an EV, the MC needs to drive to its parking location and replenish its energy supply. This process is modeled as a service process of the queuing model. Once the EV is finished charging, the event is treated as a client departure. Fig. 1 presents an overview of the queuing model.

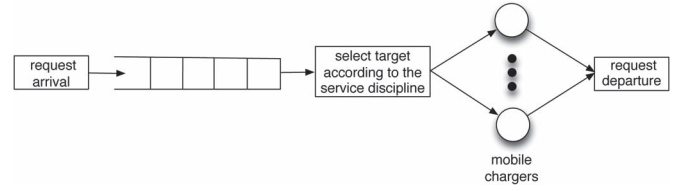


Fig. 1. Overview of the queuing model.

Based on this framework, there are several submodules that need to be specified to determine a representative model. Once specified, the model can allow us to analytically evaluate the resultant operation metrics. In this paper, we base our analysis on a single MC servicing multiple EV requests for energy replenishment.

- *Client Arrival Process*: This module describes the arrival process of the EVs' charging requests at the service provider. For example, a common practice is to assume the charging requests arrive according to a Poisson process, i.e., the interarrival time of requests is exponentially distributed. In this paper, we define the arrival of EV charging requests at the service provider as a Poisson process with intensity. This assumption not only allows for analysis of the system based on the queuing model but also matches reality in many cases. This is due to the following two reasons. First, in a mobile charging scenario, we expect the total number of EVs in the service coverage area, e.g., the city where the service is provided, to be relatively large, and the probability for a given EV to request charging at a specific time instance is relatively low. Second, the utilization of individual EVs is normally independent to each other, which indicates their charging requests are sent to the service provider independently. Hence, if the pool of potential clients is large and the probability for individual clients to arrive is low and independent, we can assume a Poisson process to capture the clients' arrival [31].
- *Service Discipline*: This module determines the order by which requesting EVs will be served. In this context, it would refer to the next EV to charge. The disciplines can include: FCFS (select EVs according to the order of their charge request times), NJN (select the EV that is spatially closest to the current location of the MC), earliest-deadline-first (select the EV whose charging process has to be accomplished the earliest), etc.

From previous work [28] and in a later section, we show that an NJN discipline gives competitive overall performance for the MC system. Hence, we will define our basic system as a single MC employed to carry out the charging process with the NJN discipline. This means that when the MC finishes the charge replenishment task of the current EV, it selects the requesting EV that is spatially closest to its current location as the next to charge. The advantage of NJN is that it greedily minimizes the driving distance for the MC to reach the target EV and thus reduces the time required to accomplish that charging task.

- *Client Departure*: This module describes how the charging of requesting EVs is carried out. Two factors determine the departure process: the service time of individual clients

(EVs) and the number of servers (MCs). The former consists of two parts: the driving time the MC takes to reach the parking location of the target EV, and then the charging time to replenish the energy supply of the EV.

The driving time is determined by the distance between the current location of the MC and that of the target EV and the driving speed of the MC, which is assumed constant. Note that the MCs location upon the accomplishment of the current charging task then becomes the parking location of a requesting EV (the one whose charging has been just accomplished). The distance between random locations is a well-studied problem in geometric probability, and results on the distribution of the distances in different area shapes exist. Without loss of generality, we assume a unit square area in this example, in which case the probability distribution of the distance d between two random locations conforms to

$$f_D(d) = \begin{cases} 2d(\pi - 4d + d^2), & d \in [0, 1] \\ 2d \left[2 \sin^{-1} \left(\frac{1}{d} \right) - 2 \sin^{-1} \sqrt{1 - \frac{1}{d^2}} \right. \\ \quad \left. + 4\sqrt{d^2 - 1} - d^2 - 2 \right], & d \in (1, \sqrt{2}] \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

and $f_D(d) = F'_D(d)$.

We then consider the case that l requests are waiting to be served when the MC just accomplishes the charging of the current EV (or a new request is just received by the MC). We can approximately treat the distances from the l requesting EVs to the MC as l independent and identically distributed (i.i.d.) random variables conforming to (1). Finding the smallest one of l i.i.d. variables is a first-order statistic. Hence, the distribution of the shortest distance to these l EVs can be calculated by

$$F_D(d, l) = 1 - (1 - F_D(d))^l. \quad (2)$$

With a constant speed, we can derive the driving time distribution as

$$F_T(t, l) = F_D(vt, l) \quad (0 \leq t \leq \sqrt{2}/v). \quad (3)$$

In this basic case, we assume that the EV user will request for a charging service when the remaining energy level of their EVs falls below a threshold; thus, we simplify our investigation in this formulation by assuming a homogeneous constant charging time T_c for all requesting EVs. Note that this homogeneous constant charging time is not required in the queue-based framework, which can be built based on the convolution theorem with any charging time distributions. With a given driving and charging time, and based on the fact that these two time periods are independent to each other, we can derive the service time distribution (i.e., the distribution of the time for the MC to accomplish a charging task) by

$$f_{s_l}(t) = f_{s'_l}(t - T_c)(T_c \leq t \leq T_c + \sqrt{2}/v). \quad (4)$$

Now that we have finished the construction of the queuing model for our example scenario, we can analytically evaluate performance measures such as the latency of service of the mobile charging process. The detailed steps for these analyses

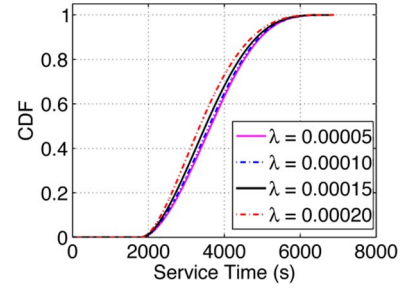


Fig. 2. Service time distribution with respect to charge request rate.

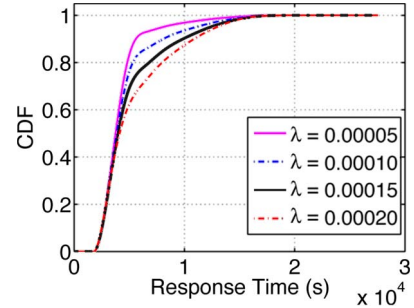


Fig. 3. Response time distribution with respect to charge request rate.

follow a classical queue analysis approach, which is detailed for a similar system in another publication [28] and will not be presented here. Figs. 2 and 3 below show service time distribution and response time distribution with respect to charge request rates.

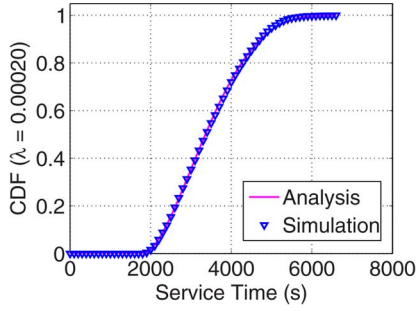
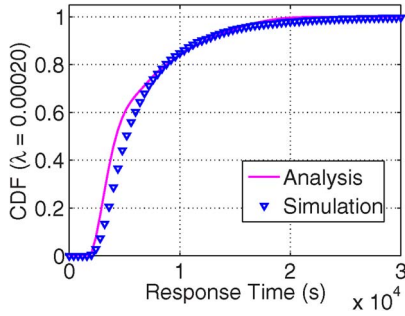
One immediate observation from Fig. 2 is that service times are reduced with a larger λ , i.e., a higher rate of charge service request. This is due to the greedy nature of NJN when selecting the next to-be-charged EV: A larger λ indicates a heavier load for the MC, resulting in more pending to-be-charged EVs. As a result, it is more likely for the charger to find an EV that is spatially closer as the next target, as shown in (2), reducing the driving time to reach the target.

In Fig. 3, we can see that a larger λ significantly increases the response time of the MC, particularly for the worst cases. The response time distribution with a λ of 0.0002 demonstrates much more obvious long-tail properties when compared with the case when $\lambda = 0.00005$. The significantly increased response time indicates that multiple MCs are needed to maintain performance metrics, defined in a later section, of the mobile charging process.

In this paper, this analytical analysis provides a theoretical reference for the performance metrics. In order to further analyze the mobile charging system, a simulation model needs to be developed that allows for more realistic and operating parameters to be examined.

C. Simulation Model

In the analytical model presented in the earlier section, the model makes several assumptions that allow for an analytical solution to be obtained. However, in practical implementations, these assumptions are not always valid. In order to examine these implementations, we build a simulation that allows for

Fig. 4. Service time distribution with $\lambda = 0.0002$.Fig. 5. Response time distribution with $\lambda = 0.0002$.

more varied and realistic assumptions to be examined. The analytical solutions obtained prior would serve as theoretical references for the performances for these systems.

1) *Basic Simulation Model and Validation:* We build the MC simulation in MATLAB. In this model, we assume a system with only one MC that moves around a predetermined service area to fulfill charging requests by EVs. As a first validation step, we build a model that incorporates the ideal assumptions of the analytical model following the NJN service discipline. We define a square service area of 100 km². The MC driving speed is assumed a constant 10 km/h. The charging requests arrive at random time instances at random locations, following a Poisson process with intensity λ . The battery charge capacity of the EVs is assumed as 54 kWh with a charger charging rate of 10 kW. An amount of 5-kW energy has to be charged to each requesting EV. A total number of 1000 charging requests are generated and served during the simulation.

2) *Service Time and Response Time Distribution:* We verify the results of the simulation against analytical results that were obtained in the earlier section. Figs. 4 and 5 show analytical results compared with simulation results for both service time and response time, respectively. Both figures show the simulation results that track well with analytical findings.

D. Urban Environment Analysis

Here, we will consider the implementation of the mobile charging system in an urban environment. As an illustrative scenario, we use the city-state of Singapore as a case study.

1) *Mobile Charger Model:* One significant difference of the analytical model from a realistic urban environment scenario is the energy replenishment rate of the MC. In the earlier section, we assumed a constant charging rate for all requests. However,

this assumption does not hold in a realistic scenario particularly when the MC can be of difference characteristics.

- *Charger Characteristics:* The MC system proposed in this paper can take two different forms. The first resembles a more conventional EV charger that plugs into the EV and transfers energy from the onboard battery to the EV battery. The second takes the form of a mobile battery swap station, which may require a technician to manually replace a depleted battery from the EV with a fully charged battery from the MC. They have slightly different operating characteristics and limitations.

In the first MP form, the charger carries around a large capacity battery bank that depletes as a whole throughout its operation. When the battery capacity is depleted and the MP is unable to continue its operation, the MP returns to a central depot to swap out its battery bank for a charged bank. In our assumptions, the central depot is assumed located in the center of the service area. For this paper, it is also assumed that the chemistry of these batteries are similar to the batteries found in EVs; however, in actual implementation schemes, the batteries can be chosen from all available technologies.

In the second MS permutation, the MS serves as a transport of individual battery packs that can be swapped in for depleted cells in EVs. However, since the battery packs that are swapped out would have varying degrees of charge left in them, they cannot be reused as battery recharge packs for other vehicles. Since the MS would have a limited carrying capacity, they can only serve a fixed number of vehicles before having to return to the central depot to swap out the depleted battery packs.

- *Specifications:* As a first iteration, we assume a conventional van as the vehicle type for the model of an MC. It is assumed that the vehicle is retrofitted to carry the equipment needed for performing its energy replenishment duties. Typically, these vehicles have a payload of about 1000 kg. A good example of such a vehicle is the Ford Transit. This represents a carrying limit to the amount of batteries that these vehicles can carry. In this paper, we assume a battery pack with similar chemistries to current EVs; a charge density of 7 kg/kWh for Lithium-ion batteries is assumed [25]. This charge density restricts the upper allowable limit of an MC to be up to 140 kWh. Another factor that could be a constraint for the MC is the operational range of the MC. As a first design assumption, we assume that the MC uses a conventional IC engine with an average of 20 mi/gal, giving an operational range of about 170 km.
- *Trip Generation:* The city-state of Singapore is used as a representative case study for analysis on the feasibility of such a system in urban environments. As a general case, we look at the feasibility of EVs in replacing a conventional vehicle used as the main mode of transportation daily for work commute. The EV is used as the primary mode of transport to work, with occasional uses for commuting to lunch and other destinations during the day. We assume a conventional work profile where the EV is used to commute to work in the morning and is back at the residence at night.

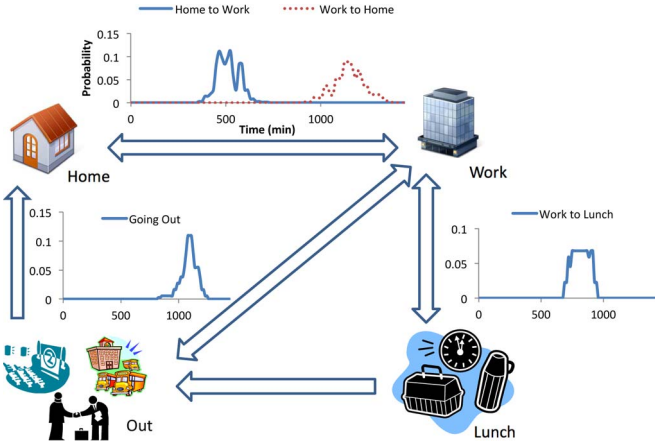


Fig. 6. Diurnal flow of trip generation model for vehicles.

We modified a trip generation framework used in a previous study [7] to generate a series of possible EV usage profiles and feed them into a mobile charging model to determine operational parameters for the MC. In this discrete-event-based model, it is assumed that there are four possible locations or states that an EV can be in. *Home* defines the initial and final state of an EV during a day. *Work* defines the primary destination of the EV during the day. *Lunch* represents a state where the EV is used to commute to a location for a meal during the day, and *out* would represent all other trips not represented by the other states. These trips could be off-site work-related trips, after work trips, or trips for leisure activities. Fig. 6 shows a general flow of this model.

The EV starts a work day at *home*. In this state, the EV determines the departure time and return time for the day from associated temporal distributions shown in Fig. 6. These temporal distributions have been inferred from the associated Electronic Road Prices (ERPs) on major expressways in Singapore [32]. These prices are analogous to road conditions in Singapore and represent the flow of traffic during peak commute hours for work-related activities [33], [34].

Once the EV is at *work*, there are three possible states that the EV can transition to, *home*, *lunch*, and *out*. The transition to *home* is governed by the predetermined return time determined at the start of the day; when the predetermined time is reached, the EV transitions to the home state. Lunch and out states have different temporal probability density functions that are also given in Fig. 6. Unlike the transition to *work*, the EV is not required to transition to these states. The determination of these transitions is similar to the model framework for appliance usage given in previous works [8], [35]. The temporal probability density functions are obtained from a combination of using ERPs [32], [34] and assumed profiles [7]. A previous study [7], provided basic temporal functions that are associated with the city of Indianapolis. These usage characteristics are different from a dense urban environment such as Singapore; hence, the temporal patterns are modified through the matching of peak timings determined through the ERPs of Singapore.

The distribution of travel distances to work is also another important input that affects the amount of electricity that is needed for a recharge. To approximate these distances, we assume that the distribution of EVs around Singapore is

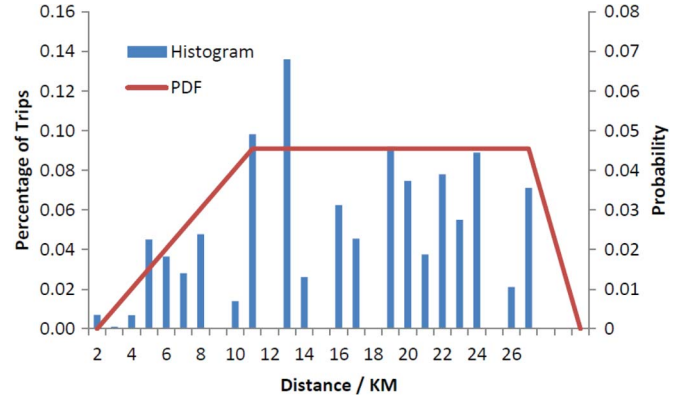


Fig. 7. Trip distribution for vehicles traveling to work.

TABLE I
CHARACTERISTICS OF NISSAN LEAF WITH 24-kWh BATTERY

	Highway, Summer	Start/Stop, Summer
Range	110 km / 70 miles	76 km / 47 miles
Consumption	0.218 kWh / km	0.315 kWh / km

proportional to the population densities of residential estates around Singapore. If it is determined that the distributions are not uniform in the urban area examined, these districts could be examined in isolation, similar to the approach taken in a previous study [7].

Population density numbers are obtained from census statistics obtained from the Department of Statistics of Singapore [36]. The average travel distance from these residential districts to the central business district are calculated and then assigned to these districts. The distribution of assumed travel distances can then be determined and is given in Fig. 7. A trapezoidal distribution is then fitted to the data to allow for ease of simulation and analysis. The probability density function for the trapezoidal distribution is given by

$$\begin{cases} (x-2)/(9 \times 22), & x \in [2, 11) \\ 1/22, & x \in [11, 27) \\ (30-x)/(3 \times 22), & x \in [27, 30). \end{cases} \quad (5)$$

2) *System Parameters*: The parameters for the EV used in this paper are based on the Nissan Leaf, the best-selling EV currently [37]. The range of an EV varies significantly according to the driving conditions on the roads. The dominant factors are traffic conditions and weather conditions. Traffic conditions determine how fast the car is driven and how often starts and stops are made. Weather conditions predominantly affect the energy demand for air conditioning in the vehicle. Nissan has established certain expected ranges based on these parameters, and based on these estimates, the expected range for an EV in Singapore can range from 47 to 70 mi [38]. Based on these two bounds, we construct a triangle distribution with a mean of 58.5 mi for the estimation of the energy consumed per mile assuming a linear relationship between battery capacity and EV range. The associated bounds are also shown in Table I.

The representative scenario in this paper is based on the city-state of Singapore with the rate tariff of electricity being a flat-rate electricity tariff. The most recent residential electricity tariff rate of \$0.026 per kilowatthour is used as the electricity

rate faced by the MC [39]. As this rate is constant throughout the day, this removes the complexity of scheduling recharge schedules of the battery packs of the MC. Incorporating a time-varying electricity tariff poses other design considerations that is not discussed in this paper but could be examined in detail in a separate study.

3) *Service Discipline Adjustments*: In the following, we adjust the ideal NJN discipline with a few practical considerations.

- *MC Charge Replenishment*: In the previous analytical example, we implicitly assume that the energy supply of the MC is high enough for completion of all charging requests under consideration. This assumption is obviously not practical under realistic scenarios. In actual operations, the energy supply is constrained by the battery capacity of the MC, which in turn is constrained by the carrying capacity and cost of the MC. Hence, it is critical to consider the decision factors of when the MC returns to the service depot for energy replenishment. We define a simple modification for the service discipline and name it as practical-NJN. In such a scheme, the MC returns to its service depot whenever it detects that its remaining energy level is not enough to accomplish the next charging task for the EVs. Once the MC replenishes its energy supply, the MC then selects a new energy replenishment task based on its current location through NJN. Similarly, practical implementations of other service disciplines also follow the same adjustment.
- *Idle Time Utilization*: Another special case to consider is that, upon the accomplishment of the current charging task, if there is no pending vehicle to be charged, should the MC stay at its current location or should it try to return to the service depot? In this paper, the default location of the MC is assumed the service depot, and the MC would always return to it when idle. This is because: 1) the service depot is assumed at the center of the service area and hence the MC expected distance to the next job requests would be shortest at that location; and 2) the MC can replenish its own energy supply during this idle period.

IV. RESULTS AND DISCUSSION

Here, we present a case study of MCs in an urban environment approximated by Singapore. The driving traces produced in Section III-D are used in the service simulation model detailed in Section III-C. The service depot where the power supply of the chargers can be replenished is assumed in the center of the service area. The arrival rate of the charge requests for this section is fixed at $\lambda = 0.0001$. Here, we look at two critical design specification for the MC, i.e., the battery capacity and the charging rate; this could serve as a design guide for the eventual implementation of such a system.

A. Operational Metrics

In the design of a mobile charging system, there are certain parameters that need to be determined that will greatly affect the performance of the system in general. We look at the system

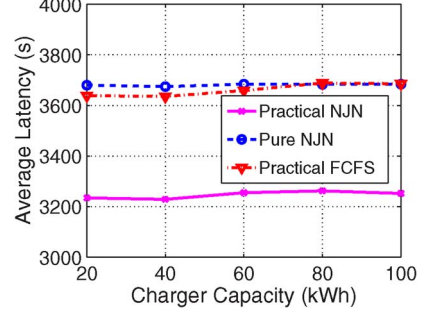


Fig. 8. Average latency with MP capacity.

design through two metrics that represent how well this system is operating. The first metric that we consider is the miss ratio r_{miss} , which considers the number of requests that do not finish by the required charge finish time of the EV. Specifically, we denote N as the total number of requests served during the mobile charging process, and N' as the number of requests that fail to be completed before their respective required finish time. r_{miss} is calculated as

$$r_{\text{miss}} = N'/N. \quad (6)$$

The second metric is the response time that the system requires to finish each request, which is defined as the time taken from when the EV sends out its charge request to the time the request is completed, i.e., the charging latency of charge requests. We evaluate the design parameters and compare between three different service disciplines: a practical FCFS strategy, a practical NJN strategy, and a pure NJN strategy (with assumptions used in the analytical base case).

B. MP System

1) *MP Battery Capacity*: The battery capacity determines the number of EV recharge requests that the MP can service before it needs to return to the central depot to replenish its energy supply. There is also the added consideration that the energy density of batteries is relatively lower than fossil fuels; hence, there is a practical upper bound that can be loaded onto mobile charging systems. As a result, there is a need to determine the impact of varying battery storage capacity on an MP. The figures in the following show the effect of increasing battery capacity on the performance metrics.

We can see that the practical NJN discipline significantly outperforms both the pure NJN and another intuitive strategy FCFS. More importantly, it is shown in Fig. 8 that, although increasing the battery capacity from 20 to 40 kWh can reduce the average charging latency, further increment of the MP capacity from 40 to 100 kWh does not significantly reduce the charging latency. This nonintuitive observation becomes even more obvious from the corresponding miss ratio, which increases noticeably when the charger capacity increases from 40 to 100 kWh, as shown in Fig. 9.

This is due to the fact that the service depot is located in the center of the service area. This position results in the shortest average distance to all charge request locations within the service area. Hence, when the MP returns to the center for

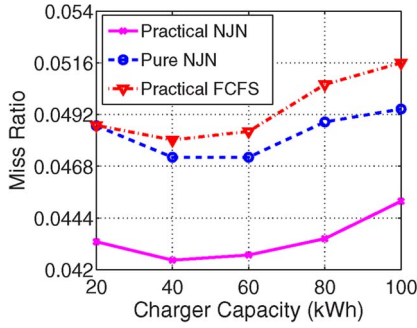


Fig. 9. Miss ratio with MP capacity.

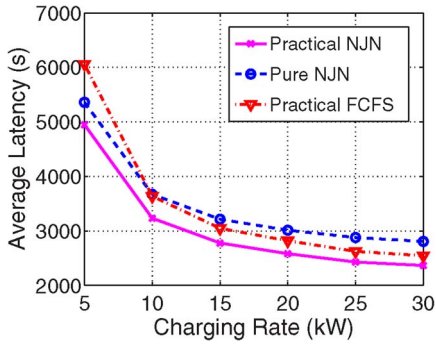


Fig. 10. Average latency with MP charging rate.

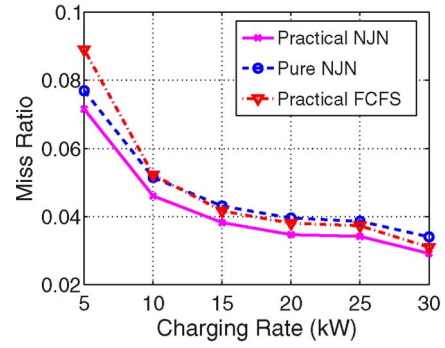


Fig. 11. Miss ratio with MP charging rate.

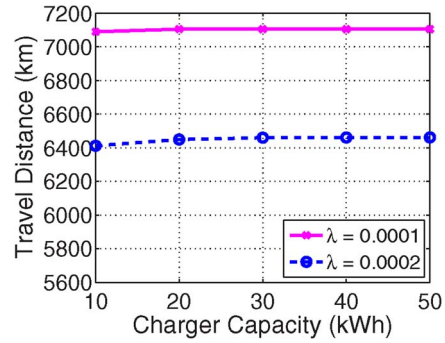


Fig. 12. Travel distance with charger capacity.

energy replenishment, it can usually find a charge request that is near to its current location. However, when its capacity is too small, i.e., 20 kWh in the simulation, the MP is forced to return to the depot too often, and this reduces the system performance. Conversely, a capacity that is too big would reduce the return of the MP to the center of the service area and reduce the performance of system. These observations point to an optimal MP battery capacity that is around 40 kWh for an urban environment based on Singapore and would differ for different systems. This observation is of significant practical value since it indicates that installing a high capacity and thus costly battery in an MC may not be necessary for a mobile charging service.

2) *MP Charging Rate*: The other important factor for an MP is the rate at which it can recharge the EV battery. We assume that the range of charging rates that the MP can operate at is similar to the range of rates that level-2 chargers can operate at. The typical charging rate for a level-2 charger is around 6.6 kW; however, level-2 chargers are rated up to handle up to 80 A at 240 V, allowing for charge rates over 10 kW [34]. Recently, the standards for dc chargers have been released, allowing level-1 dc chargers to support 36 kW and up to 90 kW for level-2 chargers [40]. Similar to the discussion in the earlier section, this charging rate is also an important design parameter that governs how well the MP system can operate.

Figs. 10 and 11 show the effect of increasing battery charging rate on the performance metrics, given for charging rates of 5–30 kW. It can be seen from the figures that, by increasing the battery charging rate of the MP, the performance metrics improve. It can be seen that the marginal benefit of increasing the charging rate for the MP decreases past a critical value. While there is a significant gain in performance from increasing the

range from 5 to 15 kW, any increase in recharge rate beyond that does not significantly increase the performance of the system.

3) *Systems Costs With Respect to Design Parameters*: The major costs associated with an MC system can be broken into two categories: capital costs and operating costs. The two major capital items are the cost of the vehicle and the cost of the battery pack. The major operating costs would include the fuel consumed by the MC and the electricity costs needed to recharge the depleted batteries. The purchase cost of the vehicle would be the same across all design parameters, whereas we can assume that the electricity costs are approximately constant across the scenarios considered.

Therefore, the consideration then is to determine if the fuel costs change across the design parameters. Fig. 12 shows the travel distance of an MC against its battery pack capacity, and it can be seen that the travel distance remains approximately constant across the battery capacities modeled. Hence, the most significant factor affecting the cost of the MC is the battery capital cost. Taken in context with results from Section IV-B1, the battery capacity should be sized according to the quality of service that is needed and, from the results, should not be sized with too much redundancy.

4) *Cost Effectiveness of an MP System*: From the analysis conducted throughout this paper, it would be interesting to determine the costs that would be associated with each charge fulfillment request of the MP. In order to do so, we do a ten-year net present value (NPV) analysis and determine the real price that each request would need to be charged in order for the system to have a zero NPV, i.e., a breakeven price. In such a scenario, we assume that the EVs would request for the MP service on an on-demand basis and the MP would charge the EV on a per-request served basis.

Price of Electricity (\$/kWh)	0.20
Price of Gasoline (\$/Gal)	6.00
Charger Capacity (kWh)	40
Battery Buffer Capacity	20%
Charger Capital Cost (\$)	40,000.00

Fig. 13. Parameter settings for cost analysis.

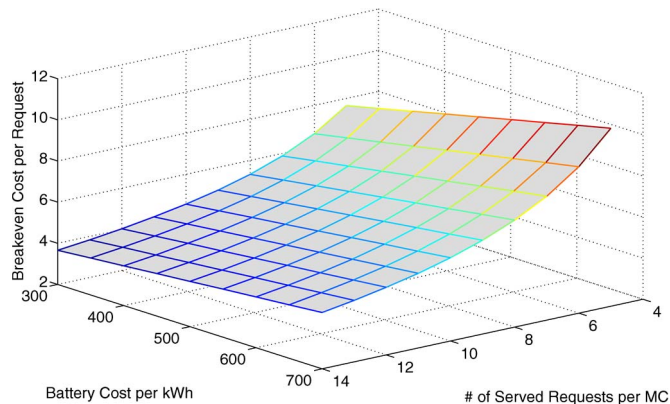


Fig. 14. Breakeven cost per charged request with regard to the battery cost and the total number of served requests.

For consistency, all dollar values in analysis are in 2014 U.S. dollars, and the parameters that are considered in this analysis are shown in Fig. 13.

We consider an operational battery capacity of 40 kWh as obtained from the earlier section. It is further assumed that the dominant variable cost in this system is the battery capacity; hence, the cost of configuring the battery system for various charge rates is constant. For NPVs, we consider a discount rate of the system of 6% and assume that the real price of gasoline increases at 3% per annum, whereas electricity prices would remain constant in real terms. These parameters are similar to values considered in a prior study [7].

Since the battery cost is dominant, we examine the required prices against different values of unit battery capacities. We also look at the system across different numbers of served charge requests per unit charger per day. Intuitively, a lower per unit cost of battery would result in a lower per charge price. Moreover, the higher the number of charge fulfillment, the lower per unit cost.

Fig. 14 shows a combined plot of the per unit charge price when compared with battery unit costs and charge request fulfillment. At the lowest end of the spectrum, when per unit battery costs are \$300/kWh with a charge fulfillment of 14 requests per day, the MP needs to charge at least \$3.66 per request to breakeven at a 6% real discount rate.

If we consider an EV that may require 20 charges a month, which translates to a monthly spend of about \$73.20, this would be comparable to a monthly spend by conventional IC vehicles. A more realistic ball park would be in the region of SGD180, which translates to about \$144; this is the current subscription fee for the Singapore EV Test Bed [41]. At this price point, this could correspond to a wide spectrum of design choice options, one of which would be a battery unit cost of \$550/kWh fulfilling an average of seven requests per charger per day.

5) *Consolidated Plots for an MP System*: The availability of two parameters allows for an optimal combination of the

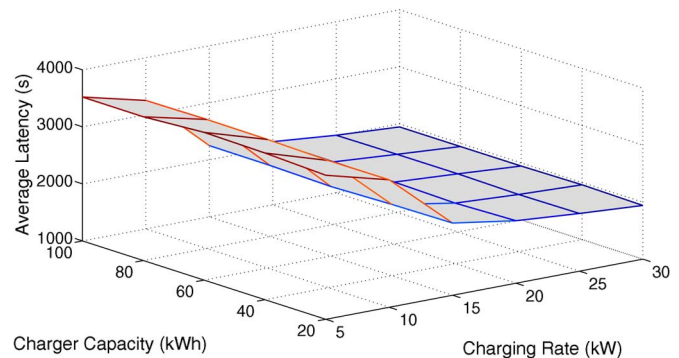


Fig. 15. Average latency with respect to MP battery capacity and charging rate.

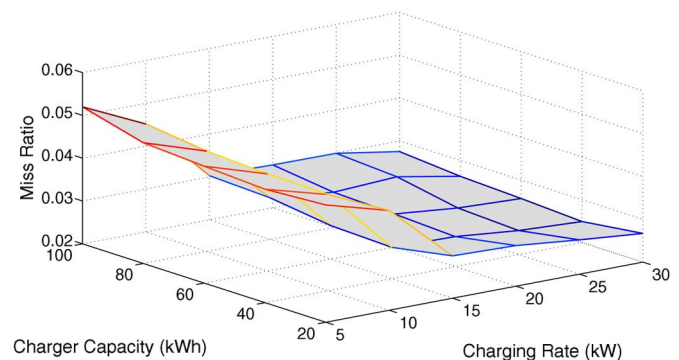


Fig. 16. Miss ratio with respect to MP battery capacity and charging rate.

two parameters for the MP system. Figs. 15 and 16 represent 3-D plots for the performance metrics against both MP battery capacity and charging rate. In an urban environment approximated by Singapore, depending on acceptable service quality levels, a possible optimal combination of the design parameters could be a battery capacity of around 40 kWh and a charging rate within a range of 15 kW to 30 kW.

6) *MS System*: An alternative configuration to the above MP system is the MS model. In this paper, this system is modeled as a mobile charging system with a fixed charging time, which represents the amount of time needed to do a full swap of battery packs of the EV. The whole battery pack of the EV is assumed switched out regardless of the amount of charge left in the battery. The MS is also assumed limited to a maximum number of swaps per trip out of the central depot. The central design parameters of this particular design can then be considered the time needed for the battery swap to occur and the number of battery packs that it carries. Figs. 17 and 18 present their impact on the mobile swapping process with a request arrival rate of 0.0002, examining a battery swap time of 10–40 min with swap capacities of one to five swaps.

The first observation is that a faster swapping time improves the performance in terms of both the average latency and the miss ratio, which is intuitive. As a frame of reference, current automated systems can do battery swaps that are comparable to filling a tank of gasoline [3]. Another important observation is that a large number of battery packs cannot really improve the performance metrics, particularly when the swapping time is short. This is again due to the centrally located service depot. With a small number of available battery packs, the MS needs to

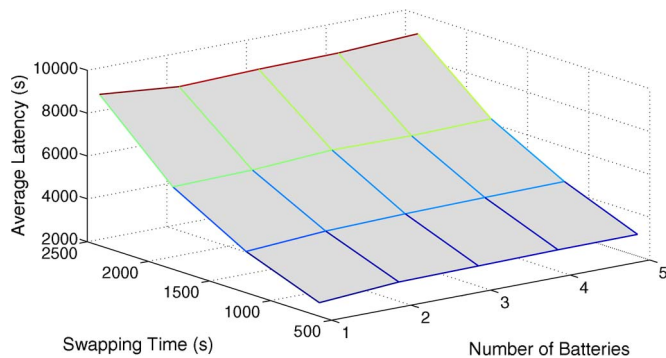


Fig. 17. Average latency with respect to MS swapping time and battery swap capacity.

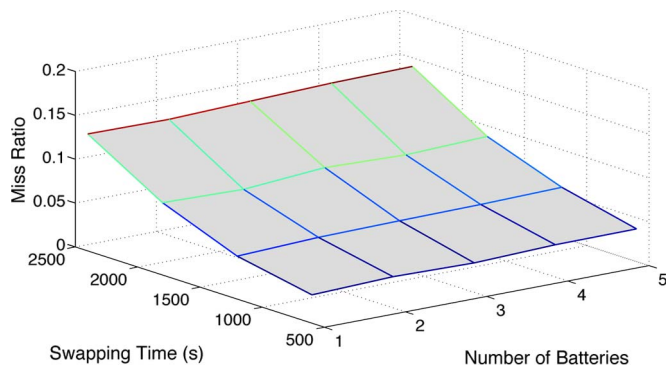


Fig. 18. Miss ratio with respect to MS swapping time and battery swap capacity.

return to the service center relatively frequently, which in turn reduces the service time (and thus the charging latency) of each requesting EV.

C. Study Limitations

There are several considerations between the alternative of an MP system versus a MS system. One of the more practical considerations would be the adoption rate of each alternative among EVs. Currently, the dominant paradigm is that of a plug-in charger for EVs. Battery-swapping support among current generation EVs is much lower, although support for swapping stations could increase [3]. There could be a design possibility for a hybrid mobile charging system that can support both paradigms, but this will not be examined in this paper.

Another consideration could be the costs involved in maintaining an inventory of charged batteries in the central service depot. The amount of battery packs that need to be maintained at the depot could be significantly different between the two configurations. This would require a more detailed examination that could encompass more dynamic electricity prices with different battery stock charging strategies.

In this paper, it is assumed that the MCs are able to carry out the requests for EV energy replenishment at any location that is required by the EV. Practically, this may not be feasible as there could be parking or space restrictions, particularly within the business districts. However, there could be avenues for operators to negotiate deals with the major parking operators in the areas that are serviced by the chargers. The exact implementation of these details will not be discussed in this paper.

Another factor that is not examined in this paper is the penetration rate of EVs in the service area. In essence, this is tied to the charging request rate λ of the EVs. A higher EV penetration can be directly correlated to a higher charge request rate. The analysis presented earlier assume a fixed request rate that then ties to an associated performance level that can be decided from the design parameters. A similar study can also be performed for different request rates with other factors being kept constant. Since that analysis will be largely similar to the results presented in this paper, the analysis is not presented here.

This paper proposes alternative solutions to EV battery energy replenishment. Although the technologies for such systems do exist, the adoption of such systems onto mobile platforms will be a significant engineering challenge. As such, the specific implementations of such systems will not be examined in this paper, but it is hoped that the analysis presented here could help influence design decisions for these systems.

V. CONCLUSION

This paper has present a novel approach to providing a service for EV battery charge replenishment. Instead of a system of fixed charging stations scattered around a service area, this paper has proposed an alternate system where the charge replenishment is provided by MCs. These chargers could have two possible configurations: an MP charger or an MS. A queuing-based analytical approach is used to determine the appropriate range of design parameters for such a mobile charging system. An analytical analysis is first developed for an idealized system. An NJN service strategy is explored for such a mobile charging system. In such a system, the charging requests from EVs are modeled through a Poisson distribution and are spatially distributed equally through the service area. In an NJN service strategy, the MC services the next spatially closest EV when it is finished with its current request. An urban environment approximated by Singapore is then analyzed through simulation. Charging requests are simulated through a trip generation model based on Singapore. In a realistic environment, an updated practical NJN service strategy is proposed. Depending on service quality preferences, for an MP MC system in an urban environment such as Singapore, there exists an optimal battery capacity with a threshold battery charge rate. Similarly, the battery swap capacity of a MS system does not need to be large for the system to perform. Although the exact specifications of implementation are not detailed in this paper, the approach detailed in this paper allows for certain design parameters to be examined carefully and used as reference points for a future system.

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the smart grid.



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