Extending Energy Storage Lifetime of Autonomous Robot-Like Mobile Charger for Electric Vehicles

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ABSTRACT At public parking facility, electric vehicles (EVs) restore their depleted batteries at dedicated parking lots with charging points. An EV that has been charged may continue to occupy the parking lot and thus, blocking other EVs from using the limited number of charging points. We propose to decouple the parking need from charging need through the use of an autonomous robot-like mobile charger, which can roam freely in the parking area to reach each EV location for charging. Such mobile charger has an energy storage to temporarily hold energy from power grid before using it to charge EVs. The energy storage lifetime can be affected by frequent charging and discharging cycles. This paper proposes a scheme called demand dependent mobile charger configuration (DDMCC) to dynamically control the mobile charger operation parameters to extend the energy storage lifetime. Specifically, DDMCC determines the depth of discharge (DOD) for each service cycle and the charging rate for each EV, depending on the instantaneous charging demand. By using the smallest DOD and the lowest charging rate, we show that DDMCC can achieve a significantly longer storage lifetime compared to a baseline greedy scheme. Specifically, for a 50% EV penetration level, DDMCC can extend the storage lifetime to more than 7 years.

INDEX TERMS Electric vehicle, autonomous charger, robot-like charger, mobile charger, energy storage.

I. INTRODUCTION Transportation sector is one of the largest contributors to greenhouse gas emissions. According to the United State Environmental Protection Agency, cars, trucks, commercial aircraft and railroads have collectively contributed 27% of the total greenhouse gas emissions [1]. Within this aggregate emissions, passenger cars and trucks are responsible for a major share of 83%. The carbon emissions can be drastically reduced by replacing internal combustion engine in traditional vehicles with electric motors. In electric vehicles (EVs), motive power is provided completely or partially by an onboard battery. The battery must be charged from time to time to replenish its energy after trips. Large-scale uncoordinated EV charging can threaten stability of power grid [2]. Charging coordination is essential in facilitating a rapid growth of EV population.

In addition to the coordination of EV charging, there is another problem called range anxiety, which highlights the driver’s fear of emptying the battery before reaching a location that has charging facility. Range anxiety is a major obstacle in persuading people to switch from traditional vehicles to EVs. One way to deal with range anxiety is to provide prevalent publicly accessible charging facilities outside residential premises, so that EVs can be charged in transit. Charging points can be installed at shared parking areas in large business buildings, university campuses and shopping malls. Providing these public charging points can be an effective way in encouraging a broader EV acceptance and a higher EV penetration.

Planning and deploying public charging points and stations constitute a major challenge, which requires an intensive assessment in terms of power grid loading, capital investment and operation issues. In this aspect, [3] has used weighted Voronoi diagram to partition a road network into multiple cells, where the centroid of each Voronoi cell is the location of a charging station. This method aims to minimize the battery energy loss and travel cost of a vehicle in reaching a charging station. In a separate work, [4] has considered the effects of uncertainties in vehicle behaviors on the capacities and profits from the construction of parking lots with charging facility. Here, the uncertainties appear in vehicle arrival times and
parking durations. Similarly, [5] has accounted for randomness in EV arrival patterns but with the use of Poisson process. In [5], the parking lots are located in commercial buildings. Compared to residential charging, this parking lot charging is more challenging because it is performed during day-time, when electricity tariff can change more dynamically and EV arrival pattern is more uncertain. A two-stage approximate dynamic programming framework has been proposed in [5] to determine the optimal charging schedule to minimize cost.

Both parking lot planning and operation problems are considered in [6]. As a planning problem, [6] allocates electrical feeders to parking lots to minimize power loss and expected energy not supplied. For the operation problem, [6] manages the charging time of EVs to defer the more expensive and polluting energy sources, so that daily profit can be maximized. In both the planning and operation problems, EV owner behaviors are modeled with respect to their response to charging price and distance from parking lots. The EV parking lot operation can be affected by road traffic flow because charging load may be transferred from one location to another location following vehicle movements. Such movement has an influence on the power flow in distribution network. This issue is studied in [7], where traffic flow is modeled by taking into account the travel purposes, zonal traffic patterns, and parking durations.

In all the existing works presented above, each charging point is permanently installed at a parking lot. Specifically, EVs must be parked in some dedicated parking lots with charging points installed for them to be charged. This type of charging point deployment is not cost efficient because an EV may have been fully charged but continue to occupy a parking lot until it is driven away. As such, a fully charged EV may block another EV from accessing a charging point. This inefficiency is caused by a fixed association between a parking facility and a charging facility, although not all vehicles that want a parking lot also need a charging point. To ensure each parked EV can be charged, all parking lots must be installed with charging points. However, this can be too costly. In view of the problem, this paper proposes to decouple charging facility from parking facility by using robot-like mobile chargers which can roam around autonomously within a parking area and move to charge EVs at their respective parking lots. Through decoupling of charging need from parking need, the autonomous robot-like mobile chargers can solve the dilemma between investing significantly in charging facilities to drive EV adoption and waiting for significant EV adoption to drive charging facility investment.

The work [8] has proposed an idea of keeping a group of portable charging stations which can be transported using a separate vehicle. These portable charging stations can be dropped at specific location as need arises. There are limited existing works on autonomous robot-like mobile chargers for EVs. A Markov chain model has been developed in [9] for mobile charger operation in a parking facility, which is shared by EVs and non-EVs with stochastic arrivals and departures. The model is used to study performance of the charger, in terms of system throughput, charging delay and blocking probability. Accuracy of the proposed model has been verified through simulations. In [10], the authors have proposed an idea of dispatching mobile chargers to temporarily increase the number of charging points at some charging stations when all the existing charging points are occupied. The mobile charger in [10] is a truck loaded with a hybrid energy storage, which combines battery and ultracapacitor, similar to that in [11] and [12]. The truck-based mobile charger aims to reduce EV waiting time before reaching an available charging point at congested charging stations. The main contribution is in developing an operation procedure which governs the process of locating charging stations and dispatching mobile chargers. A separate work [13] has also aimed to reduce EV waiting time at a charging station by deploying mobile chargers. In [13], the mobile charger does not carry its own energy storage but functions as physical charging ports which draw electricity from its deployed location.

The same idea of deploying mobile chargers to dynamically increase the number of charging points has been studied in [14] and [15]. For the similar idea, [16] has formulated an optimization problem using graph theory to identify which fixed charging stations are the best locations to accept the deployment of a set of mobile chargers. Uniquely, the mobile charger in [16] has only one charging port and thus, can charge only one EV. Taking into account vehicle traffic flow pattern, [17] has proposed a method to identify the optimal location to deploy a mobile charging station to capture the most amount of EV traffic. The work [18] has considered the communication requirements between EVs and mobile chargers. In the work, some EVs can act as communication relays for other neighboring EVs, in transmitting charging requests to mobile chargers at some remote locations. The effects of communication impairments on energy storage operation has been studied in [19] in a general context of smart grid.

In our vision, each mobile charger has an energy storage to provide off-grid charging by temporarily holding the energy before transferring it to EVs. The energy storage is technically the same as EV’s battery. However, in order to avoid confusion, we use the term “energy storage” for mobile charger and the term “battery” for EVs, hereafter. In a mobile charger, the energy storage is charged and discharged frequently when it transfers energy from power grid to the parked EVs. Each charging or discharging process degrades the energy storage in the form of reducing its energy holding capacity [20]–[22]. As such, more frequent charging and discharging can shorten the energy storage lifetime, where lifetime is defined as the time taken for the remaining capacity to drop below a threshold. Energy storage is a major component of a mobile charger, and a shorter lifetime means more frequent replacement. Ideally, we want the energy storage to last for at least a number of years before replacement so that its cost can be spread over a sufficiently long asset depreciation duration. In this paper, we propose a scheme to
tune the mobile charger operation parameters to extend its energy storage lifetime.

For ease of reference, we summarize the novelties and contributions of this paper as follows:

- Propose to decouple EV charging need from parking need by using autonomous robot-like mobile chargers. The mobile charger can move to the parking lot of an EV for charging and thus, eliminate the need of installing a charging point at each parking lot.
- Propose a scheme to extend the lifetime of mobile charger energy storage. The scheme is novel as it uses a pair of demand curve and service curve to dynamically determine the smallest amount of charging service required. Given the service requirement, the mobile charger operation parameters are configured accordingly.
- Provide extensive evaluation results based on a real-world parking facility model and a realistic energy storage capacity degradation model.

II. SYSTEM MODEL

In this section, we present the mobile charger system model which consists of four main parts. There is a model describing the geometry of the parking area, a model describing the vehicle arrival and departure behaviors, a model describing the mobile charger operation, and a model describing the capacity degradation process in energy storage.

A. PARKING AREA MODEL

We consider a surface parking area of an office building. Fig. 1 shows the layout of the parking area with 100 parking lots. All lots are equally accessible by EVs and non-EVs because none of the lots is reserved only for a specific type of vehicles. Each parking lot dimension is 2.4 m \( \times \) 4.8 m. Within the parking area, the traffic lane has a width of 3.7 m in each direction. As illustrated in the figure, a mobile charger base station is located at the lower left corner of the parking area. This base station is the location for mobile charger to restore its energy storage. It is also the resting place for the mobile charger when it is not performing charging service. The base station also houses the control center for mobile charger operation. The scheme proposed in this paper is implemented at the control center.

B. VEHICLE ARRIVAL AND DEPARTURE MODEL

The parking area is used by workers of the adjacent office building. On a weekday, workers arrive in the morning and depart in the afternoon after working hours. On each of the 5 working days in a week, we assume vehicles arrive to the parking area following a Poisson process with rate \( \lambda_i \) vehicles per hour within the \( i \)-th hour of the day [5]. The first hour is from 00:00AM to 00:59AM. The profile of these arrival rates is as follows:

- \( \lambda_7 = 30 \),
- \( \lambda_8 = 40 \),
- \( \lambda_9 = 5 \), and
- \( \lambda_i = 0 \) for \( i \notin \{7, 8, 9\} \).

After arrival, a vehicle is parked for a duration \( \mu \) hours. Here, \( \mu \) is randomly distributed within 7 and 10 hours, representing the duration of a typical working day.

Not all workers drive an EV. The fraction of all vehicles that are EVs is called the EV penetration, \( p \). Therefore, in the \( i \)-th hour, the EV and non-EV arrival rates are \( p\lambda_i \) and \( (1 - p)\lambda_i \), respectively. EVs and non-EVs entering the parking area can be freely parked in any available lot. We assume each newly arrived vehicle picks a parking lot randomly from all the available lots. Upon parking, an EV sends a charging request to the controller. Each charging request indicates the EV’s parking lot, battery capacity, current state of charge (SOC) and target SOC. Here, SOC is the energy level indicator with a value between 0 and 1, representing the remaining energy as a fraction of the battery capacity. Given the three battery related values, the control center can determine the corresponding demand size, which is the amount of energy required to satisfy the request. Each charging request also indicates its demand deadline, which is the latest moment...
by when the EV is expected to be charged. In this context, the deadline is the current time plus parking duration \( \mu \). At the controller, the received request is inserted into a service queue and waits for its turn for charging. In the queue, all requests are sorted in an increasing order of their deadlines, such that the one with the smallest deadline is at the head of the queue. A completed request is removed from the queue.

An EV that has been charged may continue to occupy its parking lot. In view of this phenomena, we use the term “customer” to represent an EV, which is waiting for its turn for charging service. On the other hand, the term “non-customer” refers to an EV that has been charged, an EV that has not requested for charging service or a non-EV.

C. MOBILE CHARGER OPERATION MODEL

The mobile charger can move autonomously within the parking area to reach any EV for charging. This autonomous movement is facilitated by establishing pre-planed way-points within the parking area, where these way-points are the only locations where the mobile charger can make a stop and change movement direction. These way-points are marked as black dots on the traffic lane in Fig. 1. There are 125 way-points, with a way-point at the entrance to each parking lot.

In Fig. 1, the dash line connecting two adjacent way-points are the trajectory that must be followed by the mobile charger when moving between the way-points. To move between two locations that are separated by multiple way-points, the route is represented by a sequence of way-points. When there are multiple candidate routes between two locations, the mobile charger will choose the route with the shortest distance using the Dijkstra’s algorithm. The distance between two locations is not symmetric, because the mobile charger movement must follow the direction of traffic lanes and other traffic rules, just like a typical vehicle.

The mobile charger carries an energy storage, which is separated from the motive battery that powers the movement of the charger. The energy storage is used solely to charge the batteries of EVs. When the mobile charger is not providing service, it is docked at a base station, where the charger can restore its energy storage while waiting for customers. The mobile charger can only leave the base station after restoring its energy storage to the target SOC, \( \sigma_{max} \). Right before departing from the base station, the mobile charger asks the controller for the next job from the service queue, indicating which EV to charge. Then, the charger moves directly to the EV and starts charging immediately. After completing the job at current EV, the charger asks the controller for the next EV to charge and repeats the same process until its SOC drops to \( \sigma_{min} \), before returning to the base station. The charger may return to the base station with SOC above \( \sigma_{min} \) only if there is no remaining request in the service queue. Upon returning to the base station, the actual difference between the departing SOC and returning SOC is called the depth of discharge (DOD), and it must not exceed \( (\sigma_{max} - \sigma_{min}) \).

The returning charger must restore its energy storage to \( \sigma_{max} \) before departing again to provide charging service.

D. ENERGY STORAGE DEGRADATION MODEL

We assume the use of lithium-ion cells for the energy storage because of their higher power density, lower discharge rate and longer lifetime compared to other cell types. Also, the manufacturing cost of lithium-ion cells is expected to continue to decrease. A model that accurately formulates the degradation process of an lithium-ion energy storage as a function of mobile charger operation is critical in estimating its expected lifetime. We adopt the semi-empirical degradation model proposed in [23].

According to the adopted model, degradation rate of energy storage cells depends not only on external stress factors such as charging, discharging, time and temperature, but also on its current state of life. Specifically, the degradation rate is significantly higher during the early stage than during the later part of a lifespan. This faster rate of early degradation is mainly caused by the formation of the solid electrolyte interphase (SEI) film on the electrodes. When a new battery starts to operate, a certain amount of active lithium ions are irreversibly consumed to form this SEI film. The rate at which this film is formed depends on the composition of the electrolyte, cell temperature and battery operation reactions such as the interactions between the positive and negative electrodes. Such SEI film formation rate decreases when a stable film has already been formed.

We define \( C(t_c) \) as the normalized capacity at time \( t_c \), such that \( C(0) = 1 \) for a new energy storage which starts running its time from \( t_c = 0 \). The more rapid early stage degradation has been seen when \( C(t_c) \) is higher than 0.9. At any time \( t_c, t_c' \leq t_c \) is defined as the previous time when the capacity has been most recently recorded. Then, the normalized remaining capacity as a result of cell degradation has been formulated in [23] as follows:

\[
C(t_c) = \begin{cases} 
\alpha e^{-f_d} + (1 - \alpha) e^{-f_d} & \text{if } C(t_c') > 0.9 \\
C(t_c') e^{-f_c} & \text{otherwise.} 
\end{cases}
\]  

(1)

In (1), \( \alpha \) is the portion of charge capacity consumed by the SEI film formation with its value ranges from 0.03 to 0.08, and \( \beta \) is the factor that takes into account the effects of usage and temperature on SEI formation. Here, \( f_c \) is the degradation caused by non-SEI effects in the most recent time interval \( (t_c', t_c) \), and \( f_d \) is the accumulated non-SEI degradation since the beginning of a new energy storage usage at \( t_c = 0 \). As such, \( f_d = f_d' + f_c \), where \( f_d' \) is the most recent \( f_d \) determined previously at time \( t_c' \). We will next describe a few component formulas before presenting the calculation of \( f_c \).

The capacity reduction \( f_c \) caused by non-SEI effects depends on time duration, SOC, DOD and temperature. The energy storage cell may continue to degrade over time accounting for its calendar life, even when it is not in use. This non-SEI degradation due to time duration is determined at time \( t_c \) as follows:

\[
S(t_c) = k(t_c - t_c'),
\]  

(2)
where \( k_t \) is the time degradation coefficient. Let \( S_\sigma(t_c) \) be the non-SEI capacity degradation due to SOC at time \( t_c \). Then, the amount of this degradation is determined as follows:

\[
S_\sigma(t_c) = \exp \left( k_\sigma (\sigma(t_c) - \sigma_r) \right),
\]

where \( k_\sigma \) is the SOC stress coefficient and \( \sigma_r \) is the reference SOC level which is usually selected around 0.4 to 0.5. In (3), \( \sigma(t_c) \) is the SOC at time \( t_c \) and it is bounded by the target SOC such that \( \sigma_{\text{min}} \leq \sigma(t_c) \leq \sigma_{\text{max}} \).

The actual DOD of a mobile charger at time \( t_c \) can be determined as \( \delta(t_c) = \sigma_{\text{max}} - \sigma(t_c) \). This is because the charger is dispatched only after it is restored to the target SOC. Then, the non-SEI degradation due to DOD at time \( t_c \) is determined as follows:

\[
S_\delta(t_c) = \frac{1}{(k_{\delta,1}(\delta(t_c)+k_{\delta,2})+k_{\delta,3})},
\]

where \( k_{\delta,1}, k_{\delta,2} \) and \( k_{\delta,3} \) are empirical coefficients.

Let \( k_T \) denote the temperature stress coefficient, and \( T_r \) denote the reference temperature. A reasonable value for the reference temperature is 298 K. Then, the non-SEI degradation due to temperature \( T(t_c) \) at time \( t_c \) is determined as follows:

\[
S_T(t_c) = \exp \left( k_T \frac{(T(t_c) - T_r) T_r}{T(t_c)} \right),
\]

where the energy storage cell temperature is measured in Kelvin. The cell temperature is linked to charging current through thermodynamic energy balance. Let the current \( I \) be a positive value when the mobile charger is charging an EV and be a negative value when the energy storage is being restored at the base station. Then, according to [24],

\[
mc_p \frac{\partial T(t_c)}{\partial t_c} + hA(T(t_c) - T_a) = I(U - V),
\]

where \( m \) is the cell mass, \( c_p \) is the cell heat capacity, \( h \) is the cell heat transfer coefficient, \( A \) is the cell surface area, \( T_a \) is the ambient temperature, \( U \) is the open-circuit potential and \( V \) is the cell operating voltage. The right hand side of (6) ignores the heat generation due to entropy changes, and focuses only on the heat generation due to Joule heating.

Combining the four types of degradation formulated by (2)-(5), the current non-SEI degradation \( f_c \) is determined as follows:

\[
f_c = (S_\delta(t_c) + S_\sigma(t_c))S_\delta(t_c)S_T(t_c).
\]

In order to compute the degraded capacity using (1) as time progresses, we need the exact values for the various model coefficients. Obtained from [23], Table 1 shows a set of the model coefficients that are tuned using LiMn_2O_4 cells degradation test data.

As an industrial practice, an EV battery is considered has reached its end-of-life at the point at which the battery capacity falls below 75% of its original value. Compared to an EV, the proposed mobile charger has a much smaller mobility area, which is limited to the parking facility. Hence, for cost efficiency, we consider the energy storage reaches its end-of-life when the normalized capacity drops to 0.5. Since the focus is on the lifetime of mobile charger energy storage, we assume each EV has a battery capacity of 22.5 kWh, implying a compact sedan with an all-electric-range of about 145 km. Based on this assumption, we consider a new energy storage has a capacity of 225 kWh so that one round of fully charged energy storage will allow the mobile charger to serve multiple EVs. The energy storage is constructed using a total of 18750 LiMn_2O_4 cells. Each cell has a capacity throughput of 3.33 Ah and the fully charged open-circuit potential is 3.6 V. The mobile charger energy storage is restored at rate \( p_c = 135 \text{ kW} \) at the base station, and it charges an EV at a rate \( p_v \) which depends on charging current \( I \). When \( I \) is equal to the C-Rate \( I_c \) of the EV’s battery, the charging rate \( p_v = 22.5 \text{ kW} \). At a fixed voltage \( V \), a higher charging current \( I \) leads to a higher charging rate \( p_v = IV \).

### III. Extending Storage Lifetime

From the system model, we know that energy storage lifetime depends on calendar time, SOC, DOD and charging rate which affects the temperature. We cannot stop time from passing, and thus we can only influence the lifetime through SOC, DOD and charging rate. We want to extend the mobile charger’s energy storage lifetime by controlling the operation parameters \( \sigma_{\text{max}}, \sigma_{\text{min}} \) and \( p_v \). For this purpose, our strategy is to first define a demand curve which tracks the total charging demand as a function of time. Then, we further define a service curve to track the effective charging rate offered by the mobile charger. Since a higher charging rate can decrease the energy storage lifetime, we extend the lifetime by dynamically adjusting the three parameters so that the effective charging rate is merely sufficient to meet the requirement of instantaneous charging demand. We call the proposed scheme the demand dependent mobile charger configuration (DDMCC).

In developing DDMCC, we assume a continuous time system with a virtual clock which ticks at the same speed of real world time. The virtual clock time \( t \) is reset to zero as long as the service queue which holds charging requests at the control center is empty. Therefore, time \( t \) can start to increase in its value from zero only when the service queue starts to backlog. Backlog interval is a time duration within which the service queue is never empty. At current time \( t \), the current backlog interval \( (0, t] \) may continue to extend beyond \( t \) as long as new customer arrivals continue to result in non-empty service queue.

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| \( k_\sigma \) | 1.04  | \( \sigma_r \) | 0.50  |
| \( \alpha \) | 5.75 \times 10^{-2} | \( \beta \) | 121   |
| \( k_{\delta,1} \) | 1.40 \times 10^{-5} | \( k_T \) | 4.14 \times 10^{-10} s^{-1} |
| \( k_{\delta,2} \) | -5.01 \times 10^{-1} | \( k_{\delta,3} \) | 6.93 \times 10^{-2} |
| \( k_T \) | -1.23 \times 10^{-5} | \( T_r \) | 298 K |
FIGURE 2. An illustration of the demand curve and service. Notice that two consecutive backlog intervals are separated by a waiting period. There are multiple service cycles within a backlog interval, and each cycle consists of a working period and a restoring period.

Following the model described in Section II, each charging request can be specified by two parameters, namely demand deadline and demand size. These requests are sorted in an increasing order of their demand deadlines, such that the request that starts the current backlog interval is indexed as the first request. Let $\mathcal{R}$ be the set of all requests within the current backlog interval which includes request that has yet to arrive at the current moment, and $\mathcal{R}_i \in \mathcal{R}$ is the $i$-th request. For the $i$-th request, $r_i'$ and $r_i''$ denote its deadline and size, respectively. Also, $\mathcal{R}(t) \subseteq \mathcal{R}$ is the subset of requests with deadlines up to time $t$, as determined by $\mathcal{R}(t) = \{\mathcal{R}_i | 0 < r_i' \leq t\}$. Then, we define a demand curve $X(t)$ as a function which tracks the total size of demand accumulated up to time $t$ within the current backlog interval as calculated below:

$$X(t) = \sum_{i=1}^{\mathcal{R}(t)} r_i''.$$

From (8), $X(t)$ is a non-negative and non-decreasing function. As illustrated in Fig. 2, $X(t)$ is indeed a step function that changes value only at each demand deadline.

Following the same idea of demand curve, we define a service curve $Y(t)$ as a function which records the total amount of energy consumed in charging EVs as accumulated up to time $t$ within the current backlog interval. Mathematically similar to $X(t)$, $Y(t)$ is also non-negative and non-decreasing; and it begins with value zero at time zero. As illustrated in Fig. 2, the proposed DDMCC scheme increases the value of $Y(t)$ by as much as $r_i''$ only when the $i$-th request is completed at time $t \leq r_i'$. At any time $t$, it is necessary that $Y(t) \geq X(t)$ to ensure all charging requests are completed before their respective deadlines. The demand curve $X(t)$ is an outcome of EV driver’s behaviors and it is not controllable. In order to satisfy all charging requests, we are left with no choice but to control the service curve $Y(t)$. We formulate the control of service curve in the rest of this section.

According to our system model, the operation of a mobile charger can be divided in time domain into three types of period, namely working period, restoring period and waiting period. As illustrated in Fig. 2, working period is a time interval, within which the mobile charger is dispatched to the parking area to charge EVs. A working period may cover multiple charging jobs where each job is to charge an EV. Different EVs may be charged at different rates, and we use the term $p_{v,i}$ to denote the charging rate applied to complete the $i$-th charging request $\mathcal{R}_i$. By taking on a new job immediately after completing an existing job, the mobile charger continues a working period until its energy storage SOC drops to $\sigma_{\text{min}}$. Restoring period is a time interval which is required.
by the mobile charger to restore its energy storage back to the target SOC $\sigma_{\text{max}}$. Waiting period is a time interval which elapses after the energy storage has been restored to $\sigma_{\text{max}}$ but there is no EV to charge. A waiting period is ended by the arrival of a new customer, which starts a new working period that is also the beginning of a new backlog interval. Within a backlog interval, there is no waiting period while working period and restoring period take turn to occur alternatively in sequence.

We define a service cycle as the combination of a working period and the restoring period that follows it immediately. As illustrated in Fig. 2, there can be multiple service cycles within a backlog interval. The proposed DDMCC scheme controls the service curve by configuring the mobile charger parameters for a desired target SOC and DOD for each service cycle. To facilitate the DDMCC description, we use $\sigma_{\text{max}}[n]$ and $\sigma_{\text{min}}[n]$ to denote their respective values for the $n$-th service cycle. In the scheme, the decision epoch is at the end of each working period, right before the start of a restoring period. More specifically, at the end of the $n$-th working period, the scheme decides on the values of $\sigma_{\text{max}}[n+1]$ and $\sigma_{\text{min}}[n+1]$. Here, $\sigma_{\text{max}}[n+1]$ is the target SOC for energy storage restoration in the $n$-th restoring period, and $\sigma_{\text{max}}[n+1] - \sigma_{\text{min}}[n+1]$ is the target DOD for the EV charging operation during the $(n+1)$-th working period. Logically, we should find $\sigma_{\text{max}}[n+1]$ and $\sigma_{\text{min}}[n+1]$ to lower the target SOC and DOD because both are important factors in extending energy storage lifetime, as presented earlier in Section II.

Algorithm 1 shows the DDMCC execution at each $n$-th decision epoch to configure $\sigma_{\text{max}}[n+1]$ and $\sigma_{\text{min}}[n+1]$ for the next restoring period and the subsequent working period. Let $t_n$ be the time at the $n$-th decision epoch. At this time, the scheme first determines the total size $X'(t_n)$ of all remaining charging requests that have yet to be completed in the current backlog interval, as follows:

$$X'(t_n) = X(t') - Y(t_n),$$

where $t'$ is the largest demand deadline among all charging requests. The value $t'$ is determined below:

$$t' = \max_{1 \leq i \leq |\mathcal{R}|} \{r'_i\}.\tag{10}$$

With an evenly distributed charging demand and a continuous charging operation, all the remaining requests can be completed by their respective deadlines at the latest time $t'$, if the charging rate is fixed at $p'_v(t_n)$ which is determined at time $t_n$ as follows:

$$p'_v(t_n) = \frac{X'(t_n)}{t' - t_n}.$$

Unfortunately, fixing charging rate at $p'_v(t_n)$ will not work in practice, because demand sizes and deadlines are not evenly distributed over time. Also, the charging process is not continuous, since the mobile charger needs to suspend its service from time to time to restore its energy storage at the base station. Nevertheless, $p'_v(t_n)$ is an important value, because it is the minimum average charging rate that is necessary to complete all requests by their respective deadlines.

Given $p'_v(t_n)$, the scheme wants to find the smallest fraction of $X'(t_n)$ to be completed in the next service cycle.

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**Algorithm 1** DDMCC Execution at Each Decision Epoch

1. Start of the $n$-th decision epoch.
2. Determine the time $t_n$ of the current decision epoch.
3. Find the values of $C(t_n), X'(t_n)$ and $t'$.
4. Set the minimum average charging rate:

$$p'_v(t_n) = \frac{X'(t_n)}{t' - t_n}.$$

5. Initialize $\delta(t_n) = 0, \Delta(t_n) = \Delta_n$, and $B(t_n) = 0$.
6. if $X'(t_n) > 0$ then
7. Find next unscheduled request with smallest deadline:

$$\mathcal{R}_{t'} = [r'_1, r'_n].$$

8. if $\delta(t_n) + r''_n \leq C(t_n)$ then
9. Schedule $\mathcal{R}_{t'}$ and update demand curve:

$$X'(t_n) = X'(t_n) - r''_n.$$

10. Update scheduled service for next working period:

$$\delta(t_n) = \delta(t_n) + r''_n.$$

11. Update duration of unproductive restoring period:

$$W(t_n) = \frac{\delta(t_n)}{p_c}.$$

12. Update charger travel distance:

$$\Delta(t_n) = \Delta(t_n) + \Delta_r.$$

13. Update unproductive charger travel time:

$$W(t_n) = \frac{\Delta(t_n)}{v_r}.$$

14. Find allowable charging time for request $\mathcal{R}_{t'}$:

$$b_{t'} = \min\left(\frac{\delta(t_n)}{p'_v(t_n) - t' - t_n}, W(t_n) - B(t_n)\right).$$

15. Find actual charging rate for request $\mathcal{R}_{t'}$:

$$p_{v, t'} = \frac{r''_n}{b_{t'}}.$$

16. Update cumulative productive time:

$$B(t_n) = B(t_n) + b_{t'}.$$

17. if $\frac{X'(t_n)}{t' - t_n - W(t_n) - B(t_n)} \geq p'_v(t_n)$ then
18. Goto line 6.
19. else
20. Goto line 26.
21. end if
22. else
23. Goto line 26.
24. end if
25. end if
26. Report a set of charging rate $p_{v, t'}$.
27. Determine $\sigma_{\text{max}}[n+1]$ and $\sigma_{\text{min}}[n+1]$ using $\delta(t_n)$.
28. End of the $n$-th decision epoch.
Identifying the smallest amount of demand is necessary because it results in a smaller DOD and a lower charging rate. Let $\delta(\tau_n)$ be the amount of charging demand to be completed in the next service cycle. Then, at the $n$-th decision epoch, we want to find the smallest value of $\delta(\tau_n) \leq X'(\tau_n)$ to be completed in the $(n+1)$-th working period, using $p'_{i}(\tau_n)$ as the guideline.

Conceptually, DDMCC iteratively schedules the next charging request with smallest deadline, to be completed in the next working period, if doing so does not exceed the energy storage capacity, and the iteration will continue if the newly scheduled request does not result in a lower average charging rate for the next decision epoch. This iterative process is presented in Algorithm 1. Let $R_{p'}$ be the next uncompleted and unscheduled request with the smallest deadline. The request does not exceed storage capacity if the following condition is satisfied:

$$\delta(\tau_n) + r''_{p'} \leq C(\tau_n).$$

(12)

The size of the acceptable request is then added to the scheduled service such that $\delta(\tau_n) = \delta(\tau_n) + r''_{p'}$, and the amount of unscheduled request is also reduced accordingly as $X'(\tau_n) = X'(\tau_n) - r''_{p'}$. For the newly scheduled request $R_{p'}$, deciding its effective charging rate such that $p'_{i}(\tau_n)$ is met, requires practical considerations of the unproductive restoring period and charger’s travel time. Recall that the duration of restoring period depends on the charger’s target SOC, which in turn affects the number of EVs that can be charged in the next service cycle. Thus, the amount of unproductive time due to energy storage restoration is calculated as follows:

$$W_c(\tau_n) = \frac{\delta(\tau_n)}{p_c}.$$ 

(13)

Similarly, the unproductive travel time is computed as follows:

$$W_t(\tau_n) = \frac{\Delta(\tau_n)}{v},$$

(14)

where $v = 0.5$ m/s is the slow moving speed of the mobile charger, and $\Delta(\tau_n)$ is the aggregate charger travel distance at the $n$-th decision epoch. At the start of a decision epoch, $\Delta(\tau_n) = \Delta_0$, where $\Delta_0$ is the distance from the charger’s current position to the base station that is determined using the way-points introduced earlier in Section II. This travel is necessary for charger to return to the base station after completing the $n$-th working period. For each newly scheduled request $R_{p'}$, the aggregate distance is updated as follows:

$$\Delta(\tau_n) = \Delta(\tau_n) + \Delta_r,$$

(15)

where $\Delta_r$ is the distance to reach the EV location of request $R_{p'}$, from wherever the charger’s current location. As an example, for the first job in each working period, the charger’s current location must be the base station.

Due to the unproductive times, the charger must complete request $R_{p'}$ in a shorter than that is allowed assuming an all-productive process, in achieving charging rate $p'_{i}(\tau_n)$.

shorter charging time $b_{p'}$ for request $R_{p'}$ is determined as follows:

$$b_{p'} = \min \bigg( \frac{\delta(\tau_n)}{p'_{i}(\tau_n)}, r'_{p'} - \tau_n \bigg) - W_c(\tau_n) - W_t(\tau_n) - B(\tau_n),$$

(16)

where the min($\cdot$) term is necessary to ensure that the request is completed before its deadline $r_{p'}$. Notice that in min($\cdot$), $r_{p'} - \tau_n$ is the remaining physical time duration that can be used to serve all scheduled requests in the next service cycle. However, the actual remaining time duration is shorter than the physical remaining time because a part of the physical time is used to restore the energy storage, and to move mobile charger from its current location to the next service location. In the equation, $B(\tau_n)$ is the cumulative productive charging time allocated at the $n$-th decision epoch, so far without including the current $b_{p'}$. Given the shorter charging time $b_{p'}$, the effective charging rate $p_{v,i,p'}$ needed to complete request $R_{p'}$ is computed as follows:

$$p_{v,i,p'} = \frac{r'_{p'}}{b_{p'}}.$$ 

(17)

With the actual charging rate $p_{v,i,p'}$ determined for the newly scheduled request $R_{p'}$, this iteration is considered complete. A new iteration will start only if the following condition is satisfied:

$$X'(\tau_n) \frac{t_{i,n} - W_c(\tau_n) - W_t(\tau_n) - B(\tau_n)}{t_{i,n} - \tau_n} \geq p'_{i}(\tau_n).$$

(18)

The left hand side of this equation is the estimated minimum average charging rate given that no additional request is scheduled for the next service cycle. This condition is to check if serving the remaining unscheduled requests after the next service cycle, requires a lower average charging rate than $p'_{i}(\tau_n)$. If this is true, there is no need to schedule more request at the current decision epoch and the algorithm terminates. Otherwise, a new iteration starts by identifying the next awaiting request $R_{p'}$ with the smallest deadline.

At each decision epoch, the process in Algorithm 1 will eventually terminates after some iterations. The outcomes is a set of charging rates $p_{v,i,p'}$, one for each charging request $R_{p'}$, which are identified to be served in the $(n+1)$-th working period. Also, the total amount of energy required to complete the identified set of requests is given by $\delta(\tau_n)$. Then, given the current energy storage capacity $C(\tau_n)$,

$$\sigma_{\max}[n + 1] = \frac{(C(\tau_n) + \delta(\tau_n))}{2},$$

(19)

$$\sigma_{\min}[n + 1] = \frac{(C(\tau_n) - \delta(\tau_n))}{2}.$$ 

(20)

The process described above is repeatedly performed at each decision epoch until the service queue becomes empty and the current backlog interval ends.

IV. PERFORMANCE EVALUATIONS

We have evaluated performance of the proposed DDMCC through extensive random event driven simulations using program written in MATLAB. For these simulations, the model
parameters presented in Section II are used. Also, the charging demand for each EV depends on its initial SOC at arrival, which is a random variable uniformly distributed within the range [0.1, 0.9] of the vehicle’s battery capacity. For the purpose of performance comparison, we have defined a baseline scheme that does not consider extending energy storage lifetime. This baseline is greedy in the sense that it wants to complete all charging requests as soon as possible, by using the biggest DOD and the highest charging rate. Specifically, for this greedy scheme, \( \sigma_{\text{max}} = 1 \) and \( \sigma_{\text{min}} = 0 \) are fixed in each service cycle. Also, \( p_{v,i} = 3 I_C V \) for all charging requests \( R_i \). As we can see from literature survey in Section I, there is very limited existing work regarding mobile chargers. Almost all these related existing works have dealt with the problem of placing mobile chargers at some fixed charging stations for a temporary increase in the number of charging ports. There is no existing scheme that we can compare with. More importantly, we believe that comparing the proposed DDMCC against a baseline greedy scheme is fair.

Fig. 3 shows a sample of demand curve and service curve extracted from a simulation run. In the figure, service curve is always ahead of the demand curve. As such, the figure confirms that DDMCC can indeed charge all EVs before their respective deadlines.

Fig. 4 shows the degradation of energy storage capacity as time progresses. In the figure, the greedy scheme experiences a significantly faster deterioration as compared to the proposed DDMCC scheme. This is a clear evidence of the superiority of DDMCC. In Fig. 4, the graph is obtained from a single simulation run. For more statistically meaning results, Fig. 5 shows the probability distribution of energy storage lifetimes collected from 1,000 simulation runs on the greedy scheme. In these results, each run lasts for as long as it takes for the energy storage to reach its end-of-life. The figure shows that the energy storage can last for an average of 2.07 years with EV penetration \( p = 0.75 \). Comparing Fig. 5 to Fig. 6(a), we notice that DDMCC can indeed extend the energy storage lifetime to an average of 6.73 years for 0.75 EV penetration, and this result has again confirmed the
The ability to keep charging throughput stable while waiting time increases, indicates the efficiency of DDMCC.

V. CONCLUSION AND FUTURE WORK

We propose to use autonomous robot-like mobile charger for EV charging at public parking slots, to decouple charging need from parking need so that charging infrastructure can be used in a more efficient manner. The lifetime of a mobile charger energy storage can be greatly affected by frequent charging and discharging, while transferring energy from power grid to the EVs. We have developed a scheme, called DDMCC to dynamically configure the mobile charger operation parameters, namely SOC, DOD and charging rate, to extend the energy storage lifetime. Simulation result comparisons with a greedy scheme have confirmed that DDMCC can indeed extend the energy storage lifetime to more than 6, 7 and 9 years for a moderate EV penetration level of 75%, 50% and 25%, respectively.

Despite the merits as stated above, DDMCC has not considered the effects of charging efficiency. Practically, less than ideal charging efficiency will prolong the energy storage restoration time at the base station and reduce the number of EVs that can be charged in a service cycle. In our future work, we would like to analyze the impacts of non-ideal charging efficiency and develop a method to account for such impacts without compromising charging service quality as well as energy storage lifetime. The parking area model described in Section II.A is a real-world model with accurate parking slot sizes and traffic lane dimensions, and it closely represents an actual facility in which we can run a prototype test. Nevertheless, there is no need to confine the proposed DDMCC to only a single parking facility. In our future work, we plan to study the impact of a change in parking facility layout on the DDMCC performance. In [25], an idea has been proposed to offload computation and sensors to roadside infrastructure in lowering the cost of an autonomous vehicle. As a potential future work, we may consider the same idea of computation offload for the proposed autonomous mobile charger for cost efficiency, when multiple chargers are needed in serving a parking facility.

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