State-of-Charge Aware EV Charging

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Abstract—Recent proliferation in electric vehicles (EVs) are posing profound impacts over the operation of electrical grids. In particular, due to the physical constraints on charging stations’ capacity and uncertainty in charging demand, it becomes an emerging challenge to design high performance scheduling algorithms to better serve charging sessions. In this paper, we design a predictive charging controller by actively incorporating each EV’s state-of-charge (SOC) information, which has strong effects on the utilization of dispatchable power during peak hours. Simulation results on both synthetic and real-world EV session and charging demand data demonstrate the proposed algorithm’s benefits on maximizing charging throughput and achieving higher rate of feasible charging sessions while satisfying battery and station physical constraints at the same time.

I. INTRODUCTION

EV proliferation is just unfolding worldwide. In the United States, a recent report predicts under medium scenario, EV consumption will increase 30-fold from 2020 to 2050 [1]. However, such rapid electrification of transportation sector presents unprecedented challenge to the charging infrastructure. For uncontrolled EV charging system, the unplanned charging sessions may lead to transformer overloading, reduced equipment lifetime, low charging capacity utilization ratio, and even bring distribution grid operational challenges [2]. Compared to unmanaged charging, recent report found specifically designed smart charging EVs could not only maximize the usage of charging facilities, but also further reduce greenhouse gas emissions by additional 32% [3]. By properly controlling the charging rate for individual EV, system operator can achieve the operational goals such as alleviating over-capacity demand during peak hours, fulfilling more charging requests, or participating in demand-side management and other utility services.

In order to realize highly flexible and reliable charging support for EVs, researchers have looked into the scheduling and operation problem of a charging station. [4] focused on earliest-deadline-first charging scheme, and proved the average-cost optimality of such policy. If the full information regarding each charging session is beforehand revealed to the charging station operator, the offline optimal charging strategy can be derived by solving an optimization problem [5], [6]. Online formulation and hardware interface were introduced in [7], [8], [9] designed pricing schemes to either optimize social welfare or minimize system costs. There are also learning-based algorithms to tackle the problem of charging session uncertainty and associated resource allocation under congestion [10], [11]. For a survey of EV charging algorithms, we refer readers to [12].

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that for different setups on peak rate - SOC curve and charging demand, the proposed SOC-aware EV charging scheduler can always accommodate more feasible charging tasks when charging capacity is limited.

II. EV CHARGING MODEL

In this section we describe charging system model, and illustrates how to model both the EV level and station level constraints. Along with the operator’s objective, we formulate the optimization problem for scheduling charging sessions, and illustrate the importance of procuring charging flexibility during peak hours.

A. Charging Station Model

We consider a single charging station which can provide simultaneous charging services for multiple EVs. Let \( \mathcal{V} := \{1, 2, 3, \ldots \} \) be the set of all EVs over an optimization horizon \( \mathcal{T} := 1, \ldots, T \). For each EV charging session \( i \), it is represented by a 5-element tuple \( (x_{i,\text{initial}}, x_{i,\text{final}}, t_{i,\text{arrival}}, t_{i,\text{depart}}, \bar{u}_i) \), where \( x_{i,\text{initial}} \) is the initial state of the battery when arriving at the station, and \( x_{i,\text{final}} \) is user-specified required SOC before departure. \( t_{i,\text{arrival}} \) and \( t_{i,\text{depart}} \) denote the arrival and departure time for vehicle \( i \) respectively. For each EV, there is also a hard constraint \( \bar{u}_i \) on the EV’s peak charging rate, which is a unique value for each battery and can be time-varying. We will detail the modeling of such peak charging rate in Section III.

The system operator of the EV charging station is interested in finding a feasible schedule of charging rate \( u_i(t) \), \( i \in \mathcal{V} \), \( t \in \mathcal{T} \) which can satisfy each customer’s charging needs. There are a set of operational constraints which have to be satisfied considering both the charging station and charging sessions physical limits:

1) Charging session temporal constraints: For each EV \( i \), the charging power is only available when the charging session is live:

\[
u_i(t) = 0, \quad t \notin [t_{i,\text{arrival}}, t_{i,\text{depart}}], \quad i \in \mathcal{V}.
\] (1)

2) Available charging power: At each timestep, there is a limit on the total power drawn from the charging station:

\[
\sum_{i \in \mathcal{V}} u_i(t) \leq P(t), \quad t \in \mathcal{T}.
\] (2)

We note that \( P(t) \) can be a limit imposed by the parking garage infrastructure such as transformer capacity or available renewable generations. In this work, we assume there are adequate chargers for onsite EVs.

3) Valid charging rate: For each EV \( i \), the charging power is nonnegative and always limited by the maximum acceptable charging rate \( \bar{u}_i \):

\[
0 \leq u_i(t) \leq \bar{u}_i(t), \quad i \in \mathcal{V}.
\] (3)

4) EV battery state: For each EV with a live charging session, the battery state is initiated with EV’s arrival state, and is updated based upon the current charging rate \( u_i(t) \):

\[
x_i(0) = x_{i,\text{initial}},
\]
\[
x_i(t) = x_i(t-1) + \delta u_i(t), \quad t \geq 1
\] (4a)

where \( \delta \) is a constant with unit of hours of sampling time intervals.

B. Scheduling Objective

There are several different objectives possibly achieved by the charging facility operator. In this work, we encourage maximizing the sum of each customer’s utility throughout \( \mathcal{T} \). Other possible choices include following pre-defined load profile \( [7] \), reducing load variance with demand response goals \( [5], [13] \), or minimizing system cost considering variable price \( [6] \), while such objectives can be flexibly integrated into our scheduling framework. The utility maximization problem (MPC) can be formulated as follows:

\[
\max_{\mathbf{u}} \sum_{i \in \mathcal{T}} \sum_{t \in \mathcal{T}} \log u_i(t) \quad \text{s.t. } (1), (2), (3), \text{ and } (4).
\] (5a)

where \( \mathbf{u} \) denotes the collection of \( u_i(t) \), \( i \in \mathcal{V}, t \in \mathcal{T} \) and \( \lambda \) is a weighting parameter.

The objective (5a) is a strictly concave function, and it will incur a proportionally fair vector for each timestep, which maximizes the sum of all vehicle’s logarithmic utility functions. We choose the objective function to motivate fair sharing of available \( P(t) \) and meeting the terminal energy demand at the same time. By solving (5) based on current availability of charging power and connected EVs, we can find optimal charging action which satisfy all operating constraints.

III. SOC AWARE CHARGING SCHEDULING

In this section, we describe how to integrate each vehicle’s SOC-dependent peak charging rate into the design of charging sessions scheduling. We would like to emphasize that by leveraging the SOC and peak charging rate information, the proposed algorithm can manage to serve more EVs with higher throughput.

A. Modeling of Peak Charging Rate Under Variable SOC

One intrinsic limitation of previous work is treating the peak charging rate \( \bar{u}_i(t) \) as a time-invariant variable. Under such assumption, solving the ordinary MPC problem \( [5] \) leads to inefficient use of charging capacity especially when battery is approaching fully charged states, as the dispatched \( u_i(t) \) may exceed the actual peak charging rate. These unutilized energy during congested hours can alternatively meet greater charging demands. To overcome such limitation, we propose to model \( \bar{u}_i(t) \)’s dependency on SOC using the following function:

\[
\bar{u}_i(t) = \bar{u}_i^* - \alpha_i \cdot x_i(t-1), \quad i \in \mathcal{V}
\] (6)

where we term \( \alpha_i \) as a “decaying factor” to model the peak charging rate decrease with respect to battery SOC. And \( \bar{u}_i^* \) is the nominal value for the maximum charging rate. Adding such evolution of \( \bar{u}_i(t) \) results to the following optimization problem (SOC_MPC):
When an EV plugs in, the vehicle sends information about its current SOC, so that information with both hardware and software infrastructure [14]. Current charging station design realizes the practical and can be easily integrated into real-world EV charging stations. The implementation, the proposed SOC-aware charging scheme resolves the problem every time when there is a new EV coming/leaving, or the terminal states for required energy resolves the problem every time when there is a new EV coming/leaving, or the terminal states for required energy changing, yet the optimality and solution feasibility are not guaranteed. We will illustrate our solution procedure to the exact solution in the next subsection.

B. SOC Aware Adaptive Charging

For each vehicle $i$, to resolve the dependence between optimization variables and time-varying $\bar{u}_i(t)$, optimization problem (7) can not be solved directly using off-the-shelf solvers due to the nested nature of constraints and time-varying bounds in inequality constraints. In [15], the authors proposed a heuristic based method to solve the optimization problem involving time-changing $\bar{u}_i(t)$, yet the optimality and solution feasibility are not guaranteed. We will illustrate our solution procedure to find the exact solution in the next subsection.

\[
\max_{\bar{u} \in [\bar{u}_1, \bar{u}_2, \ldots, \bar{u}_N]} \sum_{i=1}^{N} \sum_{t=0}^{T} \log u_i(t) - \lambda \sum_{i=1}^{N} \|x_i(T) - x_i,depart\|_2^2
\]

s.t. (1), (2), (3), (4), and (5).

We also note that such modeling assumption on SOC is practical and can be easily integrated into real-world EV charging stations. When an EV plugs in, the vehicle sends information about its current SOC, so that $\bar{u}_i(t)$ can be adjusted in real time for both operator’s and EV owner’s benefits.

However, as $\bar{u}_i(t)$ is a function of $x_i(t)$, while $u_i(t)$ is further constrained by $\bar{u}_i(t)$, optimization problem (7) can not be solved directly using off-the-shelf solvers due to the nested nature of constraints and time-varying bounds in inequality constraints. In [15], the authors proposed a heuristic based method to solve the optimization problem involving time-changing $\bar{u}_i(t)$, yet the optimality and solution feasibility are not guaranteed. We will illustrate our solution procedure to find the exact solution in the next subsection.

\[
\begin{bmatrix}
   x_i(1) \\
   x_i(2) \\
   \vdots \\
   x_i(T)
\end{bmatrix} = \begin{bmatrix}
   x_i(0) \\
   x_i(1) \\
   \vdots \\
   x_i(T-1)
\end{bmatrix} + \begin{bmatrix}
   u_i(1) \\
   u_i(2) \\
   \vdots \\
   u_i(T)
\end{bmatrix}
\]

In this way, we can explicitly model all the constraints on EV peak charging rate, EV charging capacity and charging states, and thus we can find the optimal solution for the SOC_MPC problem with low computation complexity.

**Algorithm 1: SOC Aware EV Charging**

**Input:** Charging session information

**Output:** Charging actions $u(1),...,u(T)$

**Parameters:** Charging station capacity $P(t)$

1. for $t=0,..., T$ do
2. $\hat{V}_t := \{i \in \mathcal{V} | t_i,arrival \leq t \text{ AND } t_i,depart > t\}$;
3. $\{u_i(t)\} = \text{SOC}_\text{MPC}(x_i(t-1), P(t), t)$
4. Validate feasibility of $u_i(t)$;
5. $x_i(t) = x_i(t-1) + \delta u_i(t)$;
6. Check terminal constraint based on $x_i(t)$ and $x_i,depart$
7. Check EV departure and arrival information.

The detailed algorithm is listed in Algorithm 1. In our implementation, the proposed SOC-aware charging scheme resolves the problem every time when there is a new EV coming/leaving, or the terminal states for required energy are met so that the list of active sessions $\hat{V}_t := \{i \in \mathcal{V} | t_i,arrival \leq t \text{ AND } t_i,depart > t\}$ needs to be updated. At time $t$, the predictive controller receive last step’s EV states and final required energy $x_i,depart$, and implements the action $u(t)$. We note that the EV’s state evolution is always based on actual $\bar{u}_i(t)$, so that over-the-limit charging power will not be used. We will show in the next section such SOC information is valuable especially when there is a congestion...
IV. SIMULATIONS

In this section, we will evaluate the performance of proposed SOC-aware EV charging mechanism (SOC_MPC), and compare it against other algorithms such as equal share (ES) [16], earliest-deadline-first (EDF) [4], [17], and model predictive control (MPC) [7] (without considering SOC information). We make the code for EV station modeling and proposed algorithm publicly available\footnote{github.com/chennnnnyize/State-Demand_Aware_EV_Charging}.  

A. Test Cases and Simulation Setup

We use both synthetic dataset and real-world EV charging station data from ACN-Data [18]. In the synthetic data, we model the commuting pattern for a workspace charging station using a Poisson process, and randomly sample the initial SOC and required energy for each individual EV. For the ACN-Data, we process the EV data in the week of September 5th to September 11th in 2021 for the Caltech site. The charging session temporal distribution is illustrated in Fig. 2. For the

in the charging station (e.g., the total available charging power $P(t)$ can not meet all EVs to charge at their full capacity), and can allocate limited power more efficiently.

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\begin{itemize}
    \item The ES algorithm allocates available charging power supply equally to all active EV charging sessions at each timestep while satisfying each EV's minimum and maximum charging rate.
    \item The EDF algorithm assigns $\bar{u}_i$ to EVs with earliest deadlines while keeping the sum of charging power less or equal to $P(t)$.
    \item The ordinary MPC algorithm iteratively solves (5) with a fixed $\bar{u}_i$, and other settings are kept the same as SOC_MPC.
\end{itemize}

For all tested cases and implemented algorithms, we update the charging status when either an EV connects, departs or the charging session terminal constraints have been met. Without loss of generality, we choose simulation interval as 15 minutes, and set $\delta = 1$ in all our simulation cases. We look into three different settings on the peak charging rate-SOC parameter $\alpha$\footnote{The choice of $\alpha$ is based on the battery capacity, and thus we choose different set of values for the two datasets.} and illustrate the value of including SOC information into efficient EV charging algorithm design. We use CVXPY [19] to solve the optimization problem and find MPC solutions.

B. Performance Evaluation

We first compare the amount of delivered energy using all four algorithms. In all settings with different $\alpha$ for both datasets, we find proposed algorithm can always deliver the most energy to EVs, and the average performance gain with respect to ordinary MPC is 10.27\%. ES and EDF algorithms are not performing stably when faced with different settings.
of EV arrival process and peak charging rate decay. The EDF algorithm are performing well when the charging demand is low, such that charging sessions with earliest deadline can be always satisfied. Once the charging demand are high while EDF is dispatching too much power based on schedule priority, a portion of the power is not fully utilized on the EVs with high SOC. The ES algorithm is performing more evenly under different setting of $\alpha$, but can not produce many feasible charging sessions with regard to the final energy requests $x_{\text{req},t}$, since many sessions requesting higher quantity of energy during peak hours are only allocated small amount of power. This illustrates that when there are limited charging power capacity, EDF and ES are not ideal policies in terms of maximizing the usage of charging power or satisfying individual EV charging needs.

Performance gain achieved by SOC_MPC majorly comes from better utilization of total available power $P(t)$ during peak hours. The awareness of SOC lets the algorithm distributes the charging power to more EVs rather than allocating large amount of power to single EV. This is further illustrated in Fig. 4, where during peak hours with multiple simultaneous charging sessions, SOC_MPC is able to make use of almost all of the available charging power. On the other hand, MPC finds charging actions that are over the charging limit $u(t)$. Similar deficiencies are observed for ES and EDF algorithm, as EDF and ES often allocate more-than-allowed power to batteries which are almost fully charged.

We also compare the final states of batteries in Fig. 5 between the MPC and SOC_MPC algorithm. We can observe that for almost all vehicles, the final battery states by using the proposed algorithm are higher than using standard MPC controller. This also shows the promise that SOC information can help design algorithm that brings benefits for EV customers.

V. CONCLUSION AND DISCUSSION

In this work, we show that state-of-charge information for EV batteries are valuable for designing charging station algorithms in terms of maximizing energy usage and meeting more charging session requests. By explicitly considering the EV peak charging rates with respect to SOC as time-varying constraints, we design an EV charging controller to better allocate limited charging power particularly during peak hours. This calls for a more accurate modeling of the battery characteristics especially the peak charging rate given different SOC values. In the future work, we will investigate the predictive model for the future uncertain charging demand, and also analyze how to harness flexibility as grid resources via smart charging interfaces.

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