Optimizing Electric Vehicle Charging: A Customer's Perspective

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***Abstract*—Electric vehicles (EVs) are considered to be a promising solution for current gas shortage and emission problems. To maximize the benefits of using EVs, regulated and optimized charging control needs to be provided by load aggregators for connected vehicles. An EV charging network is a typical cyber-physical system, which includes a power grid and a large number of EVs and aggregators that collect information and control the charging procedure. In this paper, we studied EV charging scheduling problems from a customer's perspective by jointly considering the aggregator's revenue and customers' demands and costs. We considered two charging scenarios: static and dynamic. In the static charging scenario, customers' charging demands are provided to the aggregator in advance; however, in the dynamic charging scenario, an EV may come and leave at any time, which is not known to the aggregator in advance. We present linear programming (LP)-based optimal schemes for the static problems and effective heuristic algorithms for the dynamic problems. The dynamic scenario is more realistic; however, the solutions to the static problems can be used to show potential revenue gains and cost savings that can be brought by regulated charging and, thus, can serve as a benchmark for performance evaluation. It has been shown by extensive simulation results based on real electricity price and load data that significant revenue gains and cost savings can be achieved by optimal charging scheduling compared with an unregulated baseline approach, and moreover, the proposed dynamic charging scheduling schemes provide close-to-optimal solutions.**

***Index Terms*—Charging regulation, electric vehicle (EV), optimization, smart grid.**

I. Introduction

As THE shortage of petroleum storage and the increase in CO_2, SO_2, and NO_x emissions receive increasing attention, policy makers, engineers, and business leaders are searching for alternative energy sources, which are both economically and environmentally friendly [23]. Using electric vehicles (EVs) instead of traditional internal combustion engine vehicles is considered as a promising solution. Compared with traditional vehicles, EVs can offer many benefits such as lower operational costs, lower gas emissions, and so on [6]. Renewable energy, such as solar and wind power, can be also utilized to charge EVs to further reduce costs. However, integrating EVs into the power grid is very challenging. Unregulated charging of EVs with fast charging speeds can result in a heavy load burden on the power grid system and may even cause the system to break down [33]. The high cost of initial investment on EV purchase is also a concern for consumers, although this can be compensated by government incentive funds and relatively lower power costs. To maximize the benefits of using EVs, we need regulated and optimized charging control strategies. Individual customers are usually not able to perform the charging regulation to their own cars in the most efficient way, although they have the motivation to save on charging costs. They can provide their needs for charging to load aggregators, which act as a control interface between consumers and the grid operator to provide regulated charging for connected vehicles with joint consideration for benefits of both consumers and the grid.

An EV charging network is a typical cyber-physical system, which includes a power grid and a large number of EVs and aggregators that collect information and control the charging procedure. The development of modern sensing and communication technologies enables the energy management system to obtain information from the power grid system and energy consumers efficiently. New algorithms and automatic operation strategies are needed for more precise and efficient control to enable intelligent load aggregation, reduce electricity costs, prevent the system from overloading, and satisfy customers' demands. An aggregator can perform centralized integration and control for EV charging. Usually, EVs can be charged at various charging rates. The aggregator automatically controls both the charging rate and the regulation capacity for the connected EVs through power electronics.

The revenue of aggregators consists of two parts: the mark over price for energy sold to customers and the regulation service provided to the power grid. EV charging optimization has been studied by a few recent works [18], [34], most of which, however, focused on maximizing the revenue of an aggregator without carefully addressing customers' needs. Specifically, the existing methods [18], [34] may not necessarily lead to the maximum benefit for consumers, i.e., the minimum charging cost. Moreover, at the end of charging, some EVs may not be fully charged or charged to desired states of charge (SOCs). In this paper, we consider EV charging from a customer's perspective and present optimal schemes to maximize the revenue of aggregators and minimize the total charging cost of customers, which allow customers to specify their charging demands (starting time, finishing time, desired SOC, etc.). Meanwhile, we also take into account the requirements of the grid system (such as the power delivery capacity requirement)

Manuscript received February 6, 2012; revised July 13, 2012 and October 16, 2012; accepted January 29, 2013. Date of publication March 7, 2013; date of current version September 11, 2013. This work was supported in part by the Department of Energy under Grant DE-OE0000495 and in part by the National Science Foundation under Grant CNS-1113398. The review of this paper was coordinated by Prof. J. Wang.

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Digital Object Identifier 10.1109/TVT.2013.2251023

to ensure that it operates normally. We consider two charging scenarios: static and dynamic. In the static charging scenario, customers' charging demands are provided to the aggregator in advance; however, in the dynamic charging scenario, an EV may come and leave at any time, which is not known to the aggregator in advance. The dynamic scenario is more realistic; however, the solutions to the static problems can be used to show potential revenue gains and cost savings that can be brought by regulated charging. Moreover, they can serve as a benchmark for performance evaluation. To the best of our knowledge, we are the first to conduct a comprehensive study for EV charging from a customer's perspective with emphases on different individual demands and a tradeoff between the aggregator's revenue and charging costs. We summarize our contributions as follows.

1) We present optimal schemes for the static charging scheduling problems and heuristic algorithms for the dynamic problems with considerations for both the aggregator's revenue and customers' demands and cost.
2) We present extensive simulation results based on real electricity price and load data to show the potential revenue gains and cost savings that can be brought by optimal charging scheduling and the performance of the proposed dynamic charging scheduling algorithms.

II. Related Work

EV charging has attracted substantial research attention due to its potential impact on the grid system. Experimental results from the Oak Ridge National Laboratory [17] and the National Renewable Energy Laboratory [13] showed that in most regions, additional generation capacities are needed to meet demands of EVs if they are charged with an uncontrolled charging strategy. Researchers from Virginia Tech, Blacksburg, VA, USA, pointed out in [31] that as EVs take a greater share in the fleet market, they may bring potential challenges to electric utilities, particularly at the distribution level. Their simulation results showed that at the EV penetration level of interest, new load peaks will be created, which, in some cases, may exceed the distribution transformers' capacities. EV stagger charge and household load control were exploited to solve this problem [31]. In [15], Green *et al.* concluded that the impact of EV charging on distribution networks can be determined by the following factors: driving patterns, charging characteristics, charging timing, and vehicle penetration. A dynamic programming model for assessing the impact of EVs on the distribution grid of Belgium was developed by Clement *et al.* [9].

The optimal operation of an aggregator for controlled EV charging has been studied by a few recent works. In [18], Han *et al.* designed an aggregator that makes efficient use of the distributed power of EVs to produce the desired grid-scale power. Both the cost arising from battery charging and the revenue obtained by providing the regulation service were considered. A dynamic programming algorithm was presented to compute the optimal charging control for each vehicle. Sortomme and El-Sharkawi [34] presented algorithms to find the optimal charging rates with the objective of maximizing the aggregator's profit. Pedrasa *et al.* [28] improved the basic formulation of cooperative particle swarm optimization by introducing stochastic repulsion among particles to investigate the potential consumer value added by coordinated distributed energy resource scheduling. Jang *et al.* [21] proposed a method for analytic estimation of the probability distribution of the procured power capacity to obtain an optimal contract size regarding the frequency of regulation. Deilami *et al.* [12] proposed a real-time smart load management control strategy to minimize the total cost of energy generation and associated grid energy losses, which utilizes the maximum sensitivities selection optimization technique. In a recent work [11], Dallinger *et al.* presented a new approach to analyze the economic impacts of vehicle-to-grid (V2G) regulation and performed a case study for Germany using average daily data.

In [27], Ma *et al.* developed a decentralized method to coordinate the charging of autonomous plug-in EVs using concepts from noncooperative games, for the case where central computing resources or communications infrastructure are not available or adequate. In [7] and [20], conceptual frameworks for actively involving highly distributed loads in system control actions are presented, and the communications infrastructure required to support such a load control scheme is discussed. In [8], Callaway developed new methods to model and control the aggregated power demand from a population of thermostatically controlled loads, with the goal of delivering services such as regulation and load following. In [22], Kempton and Tomic examined the systems and processes needed to tap energy in vehicles and implement V2G. In [29], an optimization algorithm was presented to manage a virtual power plant composed of a large number of customers with thermostatically controlled appliances.

The differences between our work and these related works are summarized as follows: 1) Unlike papers addressing only the aggregator's benefit [11], [18], [21], [34], we consider the charging problems from a customer's perspective and aim at satisfying customers' demands and reducing their costs. 2) We conduct a comprehensive study for the EV charging problems by considering both the static and dynamic cases. The methods proposed for the dynamic problems can be used in a real-time manner. However, algorithms in [9], [13], [15], [31], and [35] are not real-time algorithms. 3) Our schemes determine the charging rate for each individual EV, whereas in [31] and [35], the EV charging pool was treated as a whole operation unit, and the charging rate is assigned to the unit based on its statistical behavior. 4) Closely related works [11]–[13], [17], [28] presented heuristic algorithms that cannot provide any performance guarantees. However, we present schemes to produce optimal solutions for the static charging problems. 5) Regulation services provided by EV charging control have not been considered in [27]. In [20] and [22], the authors presented conceptual frameworks without presenting specific optimization algorithms, whereas in our work, we presented algorithms to optimize EV charging scheduling with consideration for customer demands. Both [8] and [29] studied thermostatically controlled loads instead of EV charging loads; thus, the problems in their works are mathematically different from ours.

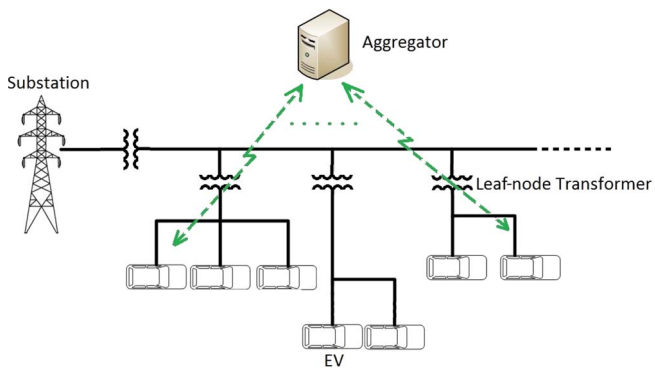

Fig. 1. EV charging network.

III. System Model

Here, we introduce the system model and necessary notations.

An EV charging network consists of a substation, transformers connected by transmission lines, EVs connected to the leaf-node transformers, and an aggregator, which is shown in Fig. 1. In such a network, the aggregator serves as a central control node that collects information from both the power grid and connected EVs and instructs the grid to charge each EV with a charging rate given by the charging scheduling algorithm in each hour. The efficient and safe delivery of power from the substation to EVs requires that, at any time, the power flow through each transformer or each branch does not exceed its delivery capacity. Usually, if the power flow through each leaf-node transformer does not exceed its delivery capacity, all the other devices and transmission lines will not be overloaded. This implies that the power delivery through one leaf-node transformer is independent from that through another leaf-node transformer. Therefore, we can divide EVs into multiple groups such that each group includes EVs associated with a leaf-node transformer and solve a charging scheduling problem independently for each group. This way, we can significantly reduce the computational complexity of the problem. In the following, we will focus on solving the charging scheduling problems for EVs in one group. In addition, in each transformer, in addition to power consumed by EVs, there are basic daily power loads contributed by all other electronic appliances (e.g., refrigerators, coffee makers, washing machines, etc.), which can be estimated from historical data and should be counted toward the total power load. This is referred to as *base load* in the following.

An EV can be connected to or disconnected from the charging network at any time according to the customer's needs. A customer will input his desired finishing time and final SOC of the battery for his car when it is connected to the network. Each *charging task* can be characterized by a 5-tuple (i, s_i, f_i, e_i, e_i'), where i is the vehicle ID, s_i is the starting time, f_i is the desired finishing time, e_i is the initial SOC of the battery, and e_i' is the desired SOC after charging. Since most charging tasks will be undertaken at night, we consider a charging scheduling period starting from 12:00 P.M. (noon) and ending at 12:00 P.M. (noon) on the next day. Moreover, for simplicity, we use a single decimal number between 0 and 24 to present a time, i.e., hour:minute. For example, suppose that an EV i is connected to the grid at 6:15 P.M. with an initial SOC of 0.6. It is scheduled to leave at 7:30 A.M. on the next day, with the battery fully charged. Then, the corresponding charging task can be presented as $(i, 6.25, 19.5, 0.6, 1)$.

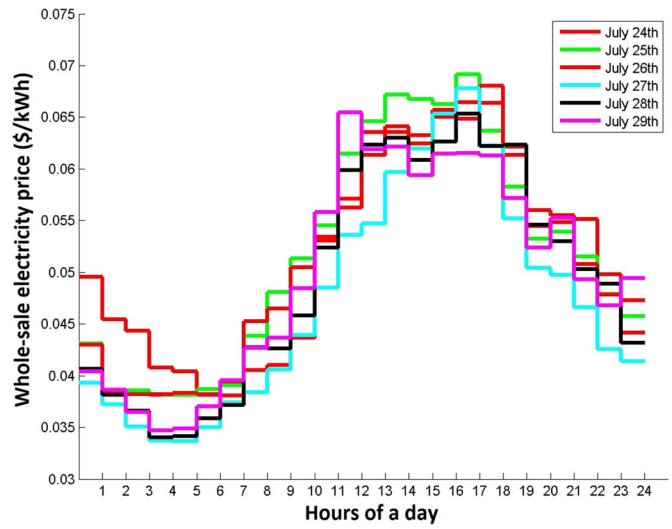

Fig. 2. Daily electricity wholesale prices in Central New York.

An aggregator is able to charge each EV at any charging rate, ranging from a minimum value to a maximum value, depending on the type and the condition of the EV's battery [22], [36]. When EVs are connected to the grid, the aggregator controls charging rates and makes sure that the total charging rate of EVs associated with each transformer does not exceed its delivery capacity. This is referred to as the power delivery capacity constraint.

In addition, the aggregator will also try to maximize its revenue. The aggregator buys electricity from the grid at a wholesale price, which usually varies on an hour-to-hour basis, as shown in Fig. 2. We plotted this figure based on real prices in Central New York during July 14–20, 2011, obtained from the New York Independent System Operator (NYISO), which is a regional transmission organization in North America [25]. In this figure, we can see that the daily wholesale electricity price follows a quite similar hourly change pattern on different days, i.e., higher values at peak hours (such as 3 P.M.–6 P.M.) and lower values at off-peak hours (such as 3 A.M.–5 A.M.). At a particular hour, the day-to-day price difference is not significant compared with the hourly difference. The aggregator will add a markup price to the wholesale price and sell electricity to customers for charging their vehicles. Note that we consider a widely used pricing model in which the power grid operator specifies electricity prices on an hourly basis, which do not change with vehicle charging and discharging policies.

The power grid operator prefers relatively even load distribution and stable frequency for the purpose of system stability and reliability. The aggregator can adjust charging rates of connected EVs to produce relatively even load distribution, i.e., charge EVs with higher rates when the base load is low, and *vice versa*. Moreover, when the grid calls for extra load or

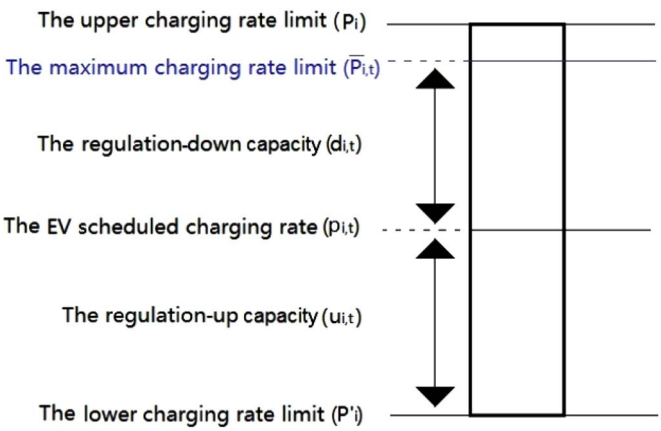

Fig. 3. Regulation capacities provided by a single EV.

additional power supply in case of emergency, the aggregator can respond with temporally increased or temporally decreased charging rates. This is referred to as *regulation service* in the electricity market. The amount of charging rate that an aggregator can increase or decrease as requested by the grid is referred to as *regulation capacity*. The aggregator determines the regulation capacity offered to the grid while performing charging services. The calculation of regulation capacity that one EV can provide to the grid is shown in Fig. 3. In the figure, the potential regulation capacity that can be provided by each EV is limited by the operational range of charging rates. The difference between the upper charging rate limit or the maximum charging rate limit (whichever is smaller) and the scheduled charging rate is the regulation-down capacity. The upper charging rate limit is given by the battery of the EV, which is the largest rate at which the battery can draw power. The maximum charging rate limit is the power needed to charge the EV to its desired SOC in one timeslot, which can be calculated using the following equation:

$$\bar{P}_{i,t} = \frac{(e'_i - x_{i,t}) \times C_i}{E_i} \qquad \forall i, t \tag{1}$$

where e'_i is the desired SOC of EV i, $x_{i,t}$ is the current SOC of EV i at the beginning of timeslot t, C_i is the battery capacity, and E_i is the battery charging efficiency of EV i (the ratio between the effectively stored energy and input energy). Obviously, the charging rate of each EV cannot exceed this value in every timeslot. In addition, when charging a group of EVs, the total regulation-down capacity should be further restricted by the delivery capacity of the transformer. Specifically, the aggregator determines charging rate $p_{i,t}$ for each connected EV to make sure that in each timeslot t, the total charging rate plus the regulation-down capacity is within its upper operational limit, i.e., $\sum_i p_{i,t} + \sum_i d_{i,t} \leq R$, where $d_{i,t}$ is the regulation-down capacity, and R is the transformer delivery capacity. This way, the aggregator can help keep the system frequency stable, which is why the power grid operator is willing to pay for the regulation service. The regulation-up capacity, on the contrary, is the ability that the EV can decrease its charging rate to help boost the system frequency and is given by the difference between the lower charging rate limit and the scheduled charging rate of the EV (as shown in Fig. 3). The regulation capacity is the sum of the regulation-up capacity and the regulation-down capacity. The aggregator will be paid by the power grid operator based on the regulation capacities. We use a model similar to that in [34] to calculate the aggregator's revenue. On one hand, an aggregator makes money from customers via the price difference between retail and wholesale. On the other hand, its revenue comes from the grid operator for its regulation service. Equation (2) is used to calculate the aggregator's revenue obtained from an EV in a timeslot, i.e.,

$$m_{i,t} = a_t r_{i,t} + M p_{i,t} h_{i,t} \tag{2}$$

where $m_{i,t}$ is the aggregator's revenue from EV i in timeslot t, a_t is the regulation price in timeslot t, $r_{i,t}$ is the regulation capacity from EV i in timeslot t, M is the markup price, $p_{i,t}$ is the charging rate for EV i in timeslot t, and $h_{i,t}$ specifies for how long EV i is connected to the grid during timeslot t. Note that the aggregator makes money from the grid operator only for EV charging but not for base loads.

From a customer's perspective, the cost of charging an EV in a timeslot is given as follows:

$$c_{i,t} = (M + g_t) p_{i,t} h_{i,t} \tag{3}$$

where $c_{i,t}$ is the charging cost for charging EV i in timeslot t, and g_t is the wholesale electricity price in timeslot t. Note that if an EV is connected to the charging network in the middle of a timeslot, it does not pay for the period during which it is not connected during that timeslot.

IV. Problem Definition

The electricity market operates on an hourly basis; therefore, we can naturally divide the time domain into timeslots with a duration of 1 h each and consider $T = 24$ h as a charging period, starting at 12:00 P.M. (noon). We define a charging schedule for a given charging task i as a vector $\mathbf{\Phi_i} = [p_{i,1}, \ldots, p_{i,t}, \ldots, p_{i,T}]$ in which each entry specifies the charging rate at hour t. We say that a charging schedule is *feasible* if both customers' demands (specified by charging tasks) and the system loading requirement are satisfied. In addition, we consider two objectives: maximizing the aggregator's revenue and minimizing the total electricity cost of customers. Moreover, we take account of customers' costs when maximizing the aggregator's revenue, i.e., for the revenue maximization problems; we also make sure that the cost of a charging task does not exceed a given *upper bound*. This way, we can achieve a tradeoff between the aggregator's revenue and the customers' costs. Accordingly, a charging schedule can be defined for a set of given tasks: $\mathbf{\Phi} = \{\mathbf{\Phi_i} : i \in \{1, \ldots, N\}\}$, where N is the number of charging tasks.

We study two charging scenarios: static and dynamic. In the static version, we assume that the aggregator knows all the scheduling tasks (starting time, finishing time, initial SOC, and

expected SOC) in a coming scheduling period beforehand. The aggregator calculates a charging schedule using an algorithm, and each vehicle will follow it for charging after its arrival. In reality, information on some charging tasks may not be available ahead of time. Therefore, we consider a more realistic dynamic scenario in which the aggregator is not assumed to know the charging tasks before EVs actually arrive. A charging scheduling algorithm will be used by the aggregator to calculate the charging schedule for each vehicle right after it is connected to the grid.

First, we define the static scheduling problems. Given a set of charging tasks $\mathbf{Q} = \{(1, s_1, f_1, e_1), \ldots, (i, s_i, f_i, e_i), \ldots, (N, s_N, f_N, e_N)\}$; base loads $\mathbf{l} = [l_1, \ldots, l_t, \ldots, l_T]$; electricity prices $\mathbf{g} = [g_1, \ldots, g_t, \ldots, g_T]$; regulation prices $\mathbf{a} = [a_1, \ldots, a_t, \ldots, a_T]$; transformer delivery capacity R; EV battery capacities $\mathbf{C} = [C_1, \ldots, C_i, \ldots, C_N]$; EV battery charging efficiency $\mathbf{E} = [E_1, \ldots, E_i, \ldots, E_N]$, which is the ratio between the effectively stored energy and input energy; and upper and lower charging rate limits $\mathbf{P} = [P_1, \ldots, P_i, \ldots, P_T]$ and $\mathbf{P}' = [P'_1, \ldots, P'_i, \ldots, P'_T]$, we define the following optimization problems.

Definition 1: The **Maximum Revenue Static Charging Scheduling Problem (R-SCSP)** seeks a feasible charging schedule $\mathbf{\Phi}$ for the set of given charging tasks $\mathbf{Q}$ such that the corresponding aggregator's revenue $\sum_{t=1}^{T}\sum_{i=1}^{N} m_{i,t}$ is maximum among all feasible charging schedules.

In addition, we also aimed at minimizing the total charging cost from a customer's perspective.

Definition 2: The **Minimum Cost Static Charging Scheduling Problem (C-SCSP)** seeks a feasible charging schedule $\mathbf{\Phi}$ for the set of given charging tasks $\mathbf{Q}$ such that the corresponding total electricity cost $\sum_{t=1}^{t=T}\sum_{t=1}^{i=N} c_{i,t}$ is minimum among all feasible charging schedules.

The dynamic charging scheduling problems are the same as their static counterparts except that the charging task sequence is not assumed to be known in advance. Correspondingly, we call the two problems as the **Maximum Revenue Dynamic Charging Scheduling Problem (R-DCSP)** and the **Minimum Cost Dynamic Charging Scheduling Problem (C-DCSP)**.

For easy reference, we summarize all major notations in Table I.

TABLE I
MAJOR NOTATIONS

	Notations
T	The total number of timeslots
N	The number of EVs
M	The mark-up price (\$/kWh)
g_t	The electricity price at timeslot t (\$/kWh)
a_t	The regulation price at timeslot t (\$/kWh)
l_t	The base load at timeslot t (kW)
P_i	The upper charging rate limit of EV i (kW)
P'_i	The lower charging rate limit of EV i (kW)
C_i	The battery capacity of EV i (kWh)
E_i	The battery charging efficiency of EV i
e_i	The initial SOC of EV i
e'_i	The desired SOC of EV i
s_i	The starting time of EV i
f_i	The finishing time of EV i
R	The transformer delivery capacity (kW)
B	The cost upper bound
$h_{i,t}$	The EV connection time of EV i during timeslot t (h)
	Unknown Variables
$x_{i,t}$	The SOC of EV i at timeslot t
$p_{i,t}$	The charging rate of EV i at timeslot t (kW)
$\bar{P}_{i,t}$	The maximum charging rate limit of EV i at timeslot t (kW)
$r_{i,t}$	The regulation capacity of EV i at timeslot t (kW)
$u_{i,t}$	The regulation-up capacity of EV i at timeslot t (kW)
$d_{i,t}$	The regulation-down capacity of EV i at timeslot t (kW)
$m_{i,t}$	The aggregator's revenue from EV i at timeslot t (\$)
$c_{i,t}$	The cost of charging EV i at timeslot t (\$)

V. PROPOSED ELECTRIC VEHICLE CHARGING SCHEMES

Here, we present optimal schemes for the problems defined in the last section. We find that the static problems can be formulated as linear programming (LP) problems, which are known to be solvable in polynomial time [4]. For the dynamic problems, we present polynomial-time heuristic algorithms.

A. Static Charging Scheduling

First, we present the LP formulation for the R-SCSP.LP-R-SCSP:

$$\max_{x_{i,t}, p_{i,t}, r_{i,t}} \quad \sum_{t=1}^{T} a_t \left(\sum_{i=1}^{N} r_{i,t}\right) + M \sum_{t=1}^{T}\sum_{i=1}^{N} p_{i,t} h_{i,t} \tag{4}$$

subject to

$$x_{i,t} = \begin{cases} e_i & \forall i, t = \lfloor s_i \rfloor \\ e'_i & \forall i, t = \lceil f_i \rceil \\ x_{i,t-1} + \frac{E_i h_{i,t-1} p_{i,t-1}}{C_i}, & \text{otherwise} \end{cases} \tag{5}$$

$$P'_i \le p_{i,t} \le P_i \qquad \forall i, t \tag{6}$$

$$\sum_{t=1}^{T} (M + g_t) \left(\sum_{i=1}^{N} p_{i,t} h_{i,t}\right) \le B \tag{7}$$

$$r_{i,t} = u_{i,t} + d_{i,t} \qquad \forall i, t \tag{8}$$

$$u_{i,t} = \begin{cases} p_{i,t} - P'_i & \forall i, t \text{ s.t. } h_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$d_{i,t} = \begin{cases} \min\{\bar{P}_{i,t}, P_i\} - p_{i,t} & \forall i, t \text{ s.t. } h_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$\sum_{i}^{N} p_{i,t} + l_t + \sum_{i}^{N} d_{i,t} \le R \qquad \forall t. \tag{11}$$

In this formulation, (5) assigns a value for the SOC of each connected EV in each hour properly. This way, each EV is guaranteed to be charged to the desired SOC when it is disconnected from the charging network. Note that in these equations, $h_{i,t}$ gives the actual connection time of each EV during each timeslot. An EV may not always arrive at the beginning of a timeslot and leave at the end of a timeslot. Therefore, in a timeslot, the connection time of an EV may be less than 1 h, and this would affect the calculation of regulation capacities, charging energy, and cost. Note that $h_{i,t}$ is NOT a decision variable, and its value can be precalculated using the following equation once a charging task is given:

$$h_{i,t} = \begin{cases} 1, & \lfloor s_i \rfloor < t < \lfloor f_i \rfloor \\ 1, & t = \lfloor s_i \rfloor, s_i = \lfloor s_i \rfloor \\ \lceil s_i \rceil - s_i, & t = \lfloor s_i \rfloor, s_i \neq \lfloor s_i \rfloor \\ f_i - \lfloor f_i \rfloor, & t = \lfloor f_i \rfloor, f_i \neq \lfloor f_i \rfloor \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

Constraint (6) ensures that in each timeslot, the charging rate of each EV is no smaller than its lower limit but no larger than its upper limit. In addition, the total charging cost of an EV should not exceed *cost upper bound B*, which is guaranteed by constraint (7). B is the maximum total cost that customers are willing to pay for charging their EVs, which is specified by customers based on their needs. We make these constraints general enough such that the cost upper bound can be set to any reasonable value based on various factors such as emergency level, the cost without regulation, the minimum possible total cost, etc. Constraints (8)–(11) use the model described in Section IV to calculate the regulation capacities and make sure that there is no violation on the transformer delivery capacity. Note that since the regulation service is provided on an hourly basis, the regulation capacity should be consistent during the whole timeslot. In the hours when the EV arrives or leaves in the middle, regulation service is not considered to be provided by the aggregator. Hence, (9) and (10) ensure that the regulation capacity will NOT be accounted for in those hours. ThusLP-C-SCSP:

$$\min_{x_{i,t}, p_{i,t}, r_{i,t}} \quad \sum_{t=1}^{T} (M + g_t) \left(\sum_{i=1}^{N} p_{i,t} h_{i,t} \right) \tag{13}$$

subject to constraints (5)–(6) and (8)–(11).

B. Dynamic Charging Scheduling

Either the R-DCSP or the C-DCSP cannot be solved by solving a single LP problem because the charging tasks are not known in advance. We propose two schemes to solve the dynamic scheduling problems. In the first scheme, we solve an LP problem to find charging schedule Φ_i every time charging task i arrives (i.e., an EV is connected to the charging network). Once the charging schedule for an EV is calculated, it will not be changed during the whole charging period. The LP problem is presented in the following, which has a much smaller size (the number of constraints and variables) than that previously presented since it is used for a single EV i. ThusLP-R-DCSP (i)

$$\max_{x_{i,t}, p_{i,t}, r_{i,t}} \quad \sum_{t=1}^{T} a_t r_{i,t} + M \sum_{t=1}^{T} p_{i,t} h_{i,t} \tag{14}$$

subject to

$$x_t = \begin{cases} e_i & \forall t = \lfloor s_i \rfloor \\ e_i' & \forall t = \lceil f_i \rceil \\ x_{i,t-1} + \frac{E_i h_{i,t-1} p_{i,t-1}}{C_i}, & \text{otherwise} \end{cases} \tag{15}$$

$$P_i' \leq p_{i,t} \leq P_i \qquad \forall t \tag{16}$$

$$\sum_{t=1}^{T} (M + g_t) p_{i,t} h_{i,t} \leq B \tag{17}$$

$$r_{i,t} = u_{i,t} + d_{i,t} \qquad \forall t \tag{18}$$

$$u_{i,t} = \begin{cases} p_{i,t} - P_i' & \forall t \text{ s.t. } h_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

$$d_{i,t} = \begin{cases} \min\{\bar{P}_{i,t}, P_i\} - p_t & \forall t \text{ s.t. } h_{i,t} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

$$\sum_{j=1}^{i} p_{j,t} + l_t + \sum_{j=1}^{i} d_{i,t} \leq R \qquad \forall t. \tag{21}$$

In this formulation, the objective function and constraints are similar to those in the R-SCSP. However, we only calculate the charging scheduling for the newly arriving EV i. Note that constraints (17) and (21) are different from (7) and (11) because we only consider this new EV i and all those EVs that were connected before EV i. Similarly, for the C-DCSP, we solve the following LP:LP-C-DCSP(i):

$$\min_{x_{i,t}, p_{i,t}, r_{i,t}} \quad \sum_{t=1}^{T} (M + g_t) p_{i,t} h_{i,t} \tag{22}$$

subject to constraints (15)–(21).

Although this approach can find a charging schedule with either the maximum incremental revenue (LP-R-DCSP) or the minimum incremental cost (LP-C-DCSP) every time an EV is connected to the network, it cannot guarantee that the solution is optimal for either the R-DCSP or C-DCSP. To improve its performance further, we come up with another scheme, namely, dynamic charging scheduling with updating, which adjusts the charging schedules for the connected EVs every time k more EVs arrive. This can be done by solving an LP problem that is the same as the LP-R-SCSP or LP-C-SCSP, except that the input only includes EVs that are currently connected to the network (instead of all EVs). The smaller the value of k, usually, the better the performance, but the higher the overhead.

VI. Simulation Results

We evaluated the performance of the proposed schemes using real electricity prices and real base load and battery data. Specifically, the hourly electricity prices and regulation prices in each day in Central New York were obtained from the NYISO [25]. Average electricity prices and regulation prices over 30 days (July 1–30, 2011) were used for simulation.

TABLE II
COMMON SIMULATION SETTINGS

Mean of s_i	6 pm;
Mean of f_i	7 am;
Standard deviation of s_i	2 h;
Standard deviation of f_i	2 h;
e'_i	0.9,
E_i	0.9;
C_i	16 kWh;
R	200 kW;
T	24;
M	\$0.05 [34]

The aggregator charges a markup price (M) of \$0.05 per kilowatthour from customers. We set EV-battery-related parameters, including the charging rate limit and battery capacity based on the specifications of the Chevy Volt Li-ion battery [3]. A typical summer base load profile for a 100-household residential community was generated using the demand profile generators from the University of Strathclyde, Glasgow, U.K. [26].

In the simulation, N charging tasks were generated for a scheduling period from 12 P.M. (noon) to 12 P.M. on the next day to simulate the overnight EV charging. According to the survey data in [14], we used Gaussian distributions to model vehicles' travel pattern and generate EV arrival (starting) and departure (finishing) times. Specifically, the starting times s_i follow a normal distribution with a mean of $\mu = 6$ P.M. and a standard deviation of $\sigma = 2$ h; the desired finishing times f_i follow a normal distribution with $\mu = 7$ A.M. and $\sigma = 2$ h; and the daily travel distances follow a lognormal distribution with $\mu = 3.22$ mi and $\sigma = 0.66$ mi. The initial SOCs e_i were set to be distributed in the range [0.3, 0.9], and the desired SOC e'_i was set to 0.9 for each EV. A total of ten seeds (from one to ten) were used to generate ten sets of random input data, and the average values over ten runs were presented as results in the following figures. The common simulation settings are summarized in Table II.

In the simulation, an unregulated charging scheme was used as a baseline solution for comparison, in which the aggregator serves EVs on a first-come first-serve basis and charge EVs with the maximal allowable charging rate. We used the aggregator's revenue, the total charging cost as the performance metrics. The following parameters may have a significant impact on system performance: the number of EVs (N), the total charging cost upper bound (B), and the upper charging rate limit (P_i). We first try to find out how they can affect the system performance using the optimal static charging scheduling schemes by setting them to different values. As previously mentioned, the optimal solutions given by the static charging scheduling schemes can be used to show the potential benefit that can be brought by regulated charging and serve as a benchmark for performance evaluation. We used the CPLEX [10] to solve all the LP problems.

A. Potential Benefits Given by Optimal Charging Scheduling

To show the potential benefits that can be brought by optimal charging scheduling, we compare the maximum aggregator's revenue (given by the R-SCSP scheme) and the minimum total charging cost (given by the C-SCSP scheme) with the baseline solutions. In the simulation, we fixed the EV battery upper charging rate limit P_i at 4.4 kW and the charging cost upper bound at the total cost of unregulated charging. Moreover, we perform simulation runs on networks with sizes of $N = \{10, 20, 50, 100, 200\}$, respectively.

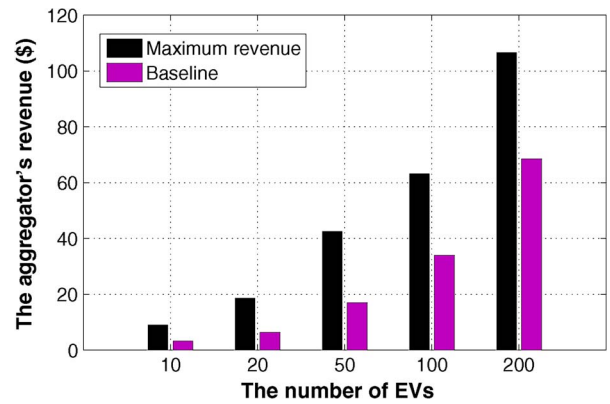

Fig. 4. Revenue gains given by optimal charging scheduling.

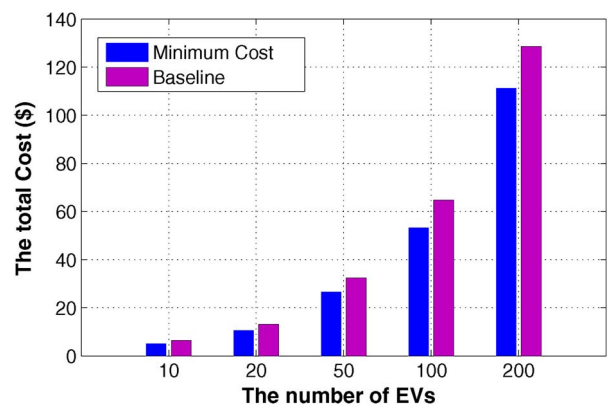

Fig. 5. Cost savings given by optimal charging scheduling.

In Figs. 4 and 5, we can see that significant revenue gains and cost savings can be brought by optimal charging scheduling. Specifically, on average, the aggregator's revenue can be improved by 132%, and the total charging cost can be reduced by 17.4%, compared with unregulated charging.

B. Performance of Dynamic Charging Scheduling Schemes

As previously mentioned, the dynamic charging scheduling schemes are more likely to be used in reality. To evaluate their performance, we used the maximum possible aggregator revenues given by the R-SCSP scheme, the minimum possible total charging costs given by the C-SCSP scheme, and the revenues and costs given by the baseline approach as benchmarks. The simulation settings in the scenario were the same as those in the first scenario previously described, except that the charging cost upper bound was set as the minimum possible total cost. The simulation results are presented in Figs. 6 and 7.

In Figs. 6 and 7, we can see that the dynamic charging scheduling schemes with updating (R-DCSP-updating and C-DCSP-updating) consistently perform better than the dynamic scheduling schemes without updating (R-DCSP and

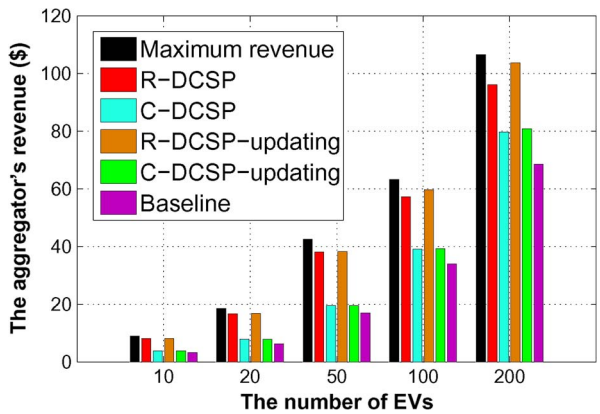

Fig. 6. Performance of dynamic charging scheduling schemes in terms of revenue.

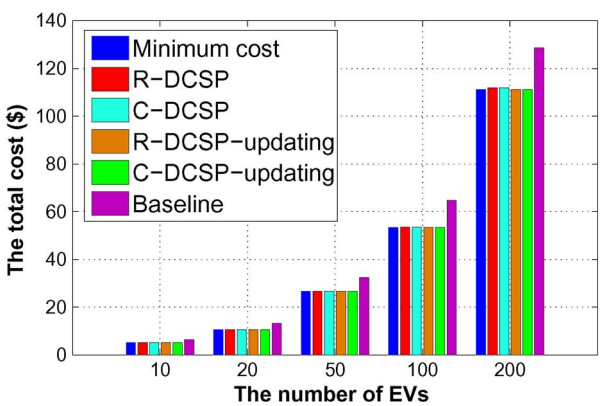

Fig. 7. Performance of dynamic charging scheduling schemes in terms of cost.

C-DCSP). Hence, the updating procedure can actually improve system performance. Moreover, on average, the aggregator's revenue given by the R-DCSP-updating scheme is only 7% away from the optimal values, and the total charging cost given by the C-DCSP-updating scheme is almost the same as the optimal values. Therefore, similar to the optimal charging scheduling scheme, the R-DCSP-updating scheme improves the aggregator's revenue by 113% and reduces the total charging cost by 17.4% on average, compared with the baseline approach. Therefore, we conclude that the R-DCSP-updating scheme provides close-to-optimal solutions and achieves a good tradeoff between revenue and cost.

C. Impact of the Upper Charging Rate Limit on System Performance

The impact of the upper charging rate limit on the maximum aggregator's revenue and the minimum total charging cost is shown in Figs. 8 and 9. We performed simulation runs on a network with $N = 200$ EVs by changing the upper charging rate limit from 3.3 to 8.8 kW with a step size of 1.1 kW. The cost upper bound was set to the total cost of unregulated charging. The maximum aggregator's revenues were computed by the R-SCSP scheme, and the minimum total charging costs were calculated by the C-SCSP scheme.

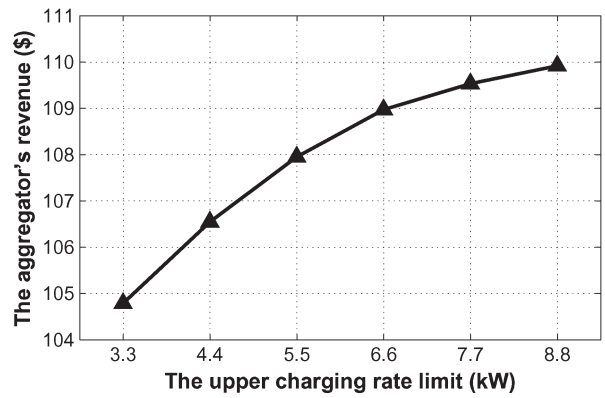

Fig. 8. Maximum aggregator's revenue versus the upper charging rate limit.

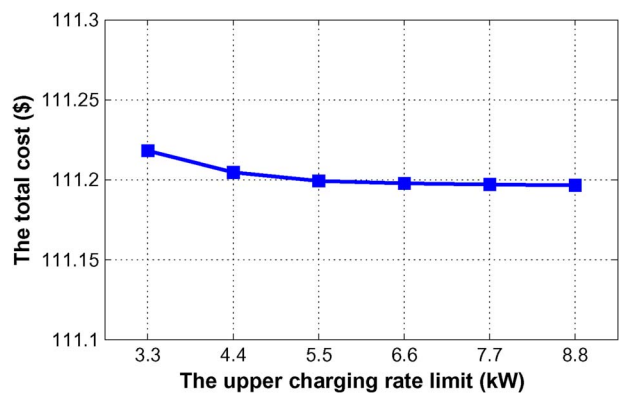

Fig. 9. Minimum total charging cost versus the upper charging rate limit.

We make the following observations from the simulation results: The upgrade of the upper charging rate limit does not benefit the customers much (i.e., does not significantly reduce the charging costs). However, the upper charging rate limit has a positive impact on the aggregator's revenue, i.e., the aggregator's revenue increases with the upper charging rate limit. This is because the upgrade of this limit improves the regulation capacity, which determines the revenue. However, this increase can only be achieved by upgrading the charging station hardware. In addition, when the upper limit becomes relatively large, the increase in revenue slows down, because there exists a fixed transformer delivery capacity R.

VII. Conclusion

In this paper, we have studied EV charging scheduling problems from a customer's perspective by jointly considering the aggregator's revenue and customers' demands and costs. We presented LP-based optimal schemes for the static charging scheduling problems and effective heuristic algorithms for the dynamic problems. It has been shown by extensive simulation results based on real electricity price and load data that, compared with an unregulated baseline approach, the aggregator's revenue can be improved by 113%, and the total charging cost can be reduced by 17.4% on average. Moreover, the proposed dynamic charging scheduling schemes provide solutions that are very close to optimal.

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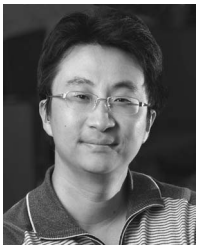

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