This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

Optimized Electric Vehicle Charging with Intermittent Renewable Energy Sources

Chenrui Jin, Xiang Sheng and Prasanta Ghosh

***Abstract*—Renewable energy and Electric Vehicles (EVs) are promising solutions for energy cost savings and emission reduction. However, integration of renewable energy sources into the electric grid could be a difficult task, because of the generation source intermittency and inconsistency with energy usage. In this paper, we present results of our study on the problem of allocating energy from renewable sources to EVs in a cost efficient manner. We have assumed that the renewable energy supply is time variant and in many ways unpredictable. EVs' charging requests should be satisfied within a specified time frame, which may incur a cost of drawing additional energy (possibly non-renewable energy) from the power grid if the renewable energy supply is not sufficient to meet the deadlines and may also reduce energy efficiency. We have formulated a stochastic optimization problem based on queuing model to minimize the time average cost of using non-renewable energy sources. The proposed approach fully considers the individual charging rate limit and deadline of each EV. The Lyapunov optimization technique is used to solve the problem. The developed dynamic control algorithm does not require knowledge of the statistical distribution of the time-varying renewable energy generation, EV charging demand, or extra energy pricing. Simulation results using different wind power generation profiles were performed and analyzed in the study. The results show that our EV charging scheduling method based on Lyapunov optimization can reduce both charging cost and mean delay time of fulfilling EV charging requests.**

***Index Terms*—energy efficiency, electric vehicle, renewable energy, Lyapunov optimization**

I. Introduction

The shortage of petroleum storage and the increase of gas emissions (CO_2, SO_2 and NO_x) have become worldwide concerns at economic, environmental, industrial and social levels [22]. Electric power generation and transportation sectors are considered as main reasons for petroleum shortage and gas emission. Policy makers, engineers and business leaders are searching for alternative energy sources, which are both economically and environmentally friendly [20]. The use of renewable energy sources for the production of electric energy can significantly reduce gas emissions (CO_2, SO_2 and NO_x) and protect the environment from further degradation. Using Electric Vehicles (EVs) instead of traditional Internal Combustion Engine (ICE) vehicles is also a promising solution. Compared to traditional vehicles, EVs can offer many benefits such as lower operational costs and lower gas emissions, and so on [6], [15], [16]. In addition, charging EV from renewable energy will become a popular approach for green and efficient energy usage [19]. The authors in [34] illustrated that charging 50,000 EVs by renewable energy sources can reduce gas emission by 409,493.865 tons per year. Furthermore, since the charging rate of EV can be controlled, EVs can be considered as controllable loads in grid systems or even distributed energy storage units when vehicle-to-grid (V2G) is available [13], which can further benefit the grid system with demand response or load following [1], [2], [9].

However, there are also challenges with renewable energy supplying EV charging. The productions of renewable energy, strongly influenced by weather conditions, are intermittent and cannot be forecasted accurately [40], which results in difficulties in power system planning and scheduling [41]. Stand-by generators or other backup energy supplies are necessary to offset the variability of renewable energy generation, which may lead to additional cost for purchasing extra energy from other sources. Therefore, in order to minimize the cost of purchasing extra energy and to increase energy efficiency, the stochastic characteristics and the dynamic cooperation between renewable energy generation and load demand should be carefully studied.

The goal of our work is to design a methodology for efficient EV charging with renewable energy supply. A stochastic optimal charging scheduling is required to achieve that goal, which involves regulating the input power of distribution networks (power coming from the grid), the input power of renewable energy sources, and the charging rates of EVs, while at the same time satisfying the grid system constraints such as: the energy balance, the limits of charging rate of each EV and charging requests specified by EV customers.

In this study, we have used Lyapunov optimization for those above mentioned approaches. The technique of Lyapunov optimization is initially developed for dynamic control of queuing systems for wireless networks [12], [25], [28]. In [28], researchers utilize the Lyapunov optimization technique to show that the queuing model naturally fits in the scheduling problem for renewable energy supply and present a simple energy allocation algorithm that does not require prior statistical information and is provably close to optimal. In our work, we have extended that approach to include individual charging request constraints, such as charging rate limits and different deadlines of different EVs. The constraints regarding EV charging rate limits are addressed by calculating arriving charging demand in each timeslot using information packaging technique. The constraints regarding various charging deadlines for EVs are addressed by grouping EVs into multiple queues according to their tolerable delay times. The problem is now more complete and practical while still providing a

Chenrui Jin, Xiang Sheng and Prasanta Ghosh are with the Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY, 13244, USA (e-mail: {cjin01,xsheng,pkghosh}@syr.edu).

This research is funded by a DOE grant DE-OE0000495.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

uncomplicated approach for real-time operation. The objective function of the optimization is to minimize the total cost of charging EVs, considering real-time electricity price of the grid, along with the renewable energy generation and EV charging characteristics. We believe we are the first to apply Lyapunov optimization to study stochastic energy efficient scheduling of EV charging by renewable energy sources without prior information of system unknown variables, while at the same time satisfying the charging constraints such as the EV charging rate limits and deadlines. Our main contributions are as follows:

1) We present a queuing model for EV charging scheduling problem considering the variance and randomness in renewable energy generation and individual EV charging requests.

2) We perform extensive simulations using real electricity prices and renewable energy generation data to show the cost savings that can be achieved by the energy efficient scheduling algorithm compared to two greedy scheduling algorithms.

The rest of this paper is organized as follows: Section II discusses related work. Section III introduces EV charging queuing model; In Section IV we present the problem formulation for energy efficient charging scheduling; Section V discusses numerical results and is followed by Section VI the conclusion.

II. Related Work

Recently, research is quickly moving towards renewable energy based systems interaction with transportation and residential/commercial buildings. Researchers of Virginia Polytech. presented in [7] the structure and capabilities of a small, grid-interactive distributed energy resource (DER) system comprised of a photovoltaic source, plug-in hybrid electric vehicle, and various local loads and implemented the system at the residential level. Researchers in [23] studied the interaction of PHEV with the power grid and the energy market. Their simulation results showed potential benefits, such as energy cost and pollutant reduction, and less dependency on the grid. In [34], the authors presented cost and emission reduction in a smart grid by maximum utilization of gridable-vehicles (GVs) and renewable energy sources (RESs). The intelligent scheduling and control of GVs, which was calculated by particle-swarm-optimization (PSO) showed potential as solutions for evolving a sustainable integrated electricity and transportation infrastructure. The authors in [21] proposed the integration of PHEVs as an energy efficient solution to address the problem of the inter-temporal variation and limited predictability of the renewable energy, using stochastic optimization methods. Their methods showed that the integration of PHEVs could reduce the energy generation of the conventional thermal power plants apparently. In [33], the author reviewed the current literature on EVs, the electric grid, and renewable energy integration, which indicated that EVs can significantly reduce the amount of excess renewable energy produced in an electric system. In another review, [8], the authors used the German 2030 scenario as an example of RES generation profile, to show how PEVs can contribute to improve the integration of intermittent renewable power generation into the grid. Similarly, in [5], the authors used the case of wind generation in northeastern Brazil to evaluate the possibility of using a fleet of PHEVs to regularize possible energy imbalances and also demonstrate the advantages of optimizing simultaneously the power and transport sectors.

Controlling and scheduling algorithms, which have been widely applied in areas such as wireless communication and distributed computing, are now providing energy efficient solutions in smart grid technologies. Papavasiliou and Oren [32] introduced the problem when renewable energy supplier cannot match a deadline commitment and have to purchase the extra energy from the energy spot market or maintain a costly energy backup unit, and proposed an exact backward dynamic programming algorithm and an efficient approximate dynamic programming algorithm for renewable energy scheduling. In [38], the authors presented in their work ways to minimize the user inconvenience caused by demand scheduling. While in [24], the authors' objective is to minimize the overall energy cost by optimal energy consumption scheduling. Several ideas from the distributed computing area such as makespan were introduced to solve energy consumption scheduling problem in [38]. Resource allocation method, which is typically used in wireless network technology, is applied in [24]. In both works, the user demands are known beforehand and the optimization problem is solved in numerical iterations. In [4], the authors proposed a PHEV charging station architecture and a quantitative stochastic model using queuing theory, that can sustain grid stability while providing a required level of quality of service (QoS). In [37], two solutions for PHEV charging were proposed: a multi-agent systems (MAS) solution and an optimal quadratic (QP) programming scheduler solution. It was shown in their work that though QP scheduler is able to optimally flatten peak loads and sufficiently charge PHEVs, it is not scalable, while the MAS solution is both scalable and adaptable to incomplete and unpredictable information. Researchers in [36] modeled their EV charging system as a $M/M/\infty$ queuing system and used one-way broadcasting for EV charging control. In the work of [11], the authors proposed to apply the principle of congestion pricing in IP networks to PHEV charging in the smart grid and deal with various EV charging requests using a willingness to pay parameter that models the differential quality of QoS aspect of charging.

The differences between our work and these related works are summarized as follows:

1) The work in [7], [8] and [33] reviewed the capability of the interaction of EVs and renewable energy based system, without specifically designing or implementing optimal EV charging strategies. The work in this paper, however, focuses on designing and implementing novel energy efficient EV charging scheduling methods that supports renewable energy generation.

2) The optimization problems considered in related works [21], [23], [24], and [38] are based on stochastic optimization, which requires the prior knowledge of the probabilistic characteristics of energy demand. The Lyapunov optimization method used in this paper does not require the EV charging scheduler to know the probabilistic information of unknown events. So our methodology is capable of broader application.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

3) In addition to the work presented in [5] and [34], which focus mainly on maximizing renewable energy utilization, we also considered reducing EV charging cost and delay in serving EVs' charging demand.

4) Renewable energy supplied EV charging was not considered in [4], [11], [32], [36] and [37]. While in our work, we presented algorithms to optimize EV charging scheduling with consideration for improving renewable energy efficiency and satisfying customer demands. Thus conditions in their works are mathematically different from ours.

III. EV Charging Queuing Model

A. Aggregated EV Charging Control

In order to fully regulate the charging rates of flexible EV loads, in smart grid system, we assume that the charging of a fleet of EVs is controlled by an aggregator, which could be distribution system operators or other third party entities [19], [20], [35]. EV can communicate with aggregator in real time and can be charged at various charging rates. During the charging scheduling period, the aggregator collects information from both the renewable energy sources and connected EVs and instructs the renewable energy and other additional energy sources to charge each EV with a charging rate given by charging scheduling algorithm. For situations when the renewable power is more than needed for EV charging, the surplus renewable power will not be saved for future use or sold to the grid. Also, the renewable power sources are located close to the charging facilities, so congestions in the power transmission are not considered.

An EV can be connected to or disconnected from the distribution network at any time according to the EV customer's need. We have no prior information about a charging request of an EV until it is connected to the network. As stated in a cutting edge framework [18], an EV customer will inform the aggregator with his/her desired finishing time and final State of Charge (SOC) of the battery for his/her EV through a user interface, when connected to the network. The charging request of an EV is regarded as a *charging task*. Each charging task can be characterized by a 5-tuple (i, d_i, f_i, b_i, b_i'), where i is the index for EV, d_i is the starting time, f_i is the desired finishing time, b_i is the initial SOC of the battery and b_i' is the desired SOC after charging [15], [16]. The maximum allowed charging time is then $R_i = f_i - d_i$ for EV i. Any delay in charging should not exceed this limit, which we define as the *charging deadline*.

B. Queuing Model

For system facilitated with renewable energy supply, aggregator is responsible to efficiently allocate the renewable energy to each EV so that the total cost of purchasing additional energy is minimized, which involves optimal scheduling of EV charging and importing additional energy (from the grid or other non-renewable energy sources). Inspired by the model in Neely's work [28], we formulated our problem based on a queuing model and propose an energy allocation and scheduling algorithm that does not require prior knowledge of the statistical distribution of the renewable energy generation, EV charging requests or prices of addtional energy.

In this work, we consider a fleet of EVs charged by a single renewable energy generation plant with the grid as an additional energy source within charging period T. T has a unit of time, which can be second, minute or hour. We make the statement general enough such that the exact unit can be determined based on the specifications of problems. Within charging period T, at timeslot t, $t \in \{0, 1, 2, \cdots, T\}$, the renewable energy output is $s(t)$. $s(t)$ is a random process corresponding to the maximum energy that the energy plant can provide to charge the EVs, which is time variant and unpredictable. In timeslot t, when the renewable energy is not enouth to charge EVs before their deadlines, an amount of addtional energy $x(t) - s(t)$ will be purchased from the grid at an electricity price $e(t)$, where $x(t)$ is the total energy consumption by EVs during timeslot t. We also have no information on the distribution of future electricity price.

Each EV arrives with a charging task. The charging tasks are stored in a queue and served on a First-In-First-Out (FIFO) basis. Letting $Q(t)$ denote the total charging tasks in timeslot t in a single queue, then we have the following equation for the queue backlog growth, Eqn. (1).

$$Q(t+1) = \max[Q(t) - x(t), 0] + a(t) \tag{1}$$

where $x(t)$ is a decision variable. $a(t)$ is the arrival rate of EV charging tasks, which is the sum of arriving energy demand of all EVs arriving during timeslot t, Eqn. (2), where N is the number of EVs; $a_i(t)$ is the arriving energy demand of EV i during timeslot t.

$$a(t) = \sum_{i=1}^{N} a_i(t) \tag{2}$$

The value of $a_i(t)$ is determined by both the EV charging request and EV charging rate limit. Because of the charging rate limit, a single EV can at most add a energy demand of $P_{max}\Delta t$ to a queue during a single timeslot, where P_{max} is EV's maximum charging rate limit; Δt is the duration of one timeslot. If an EV needs more than one timeslot to fully charge, then it adds energy demand to more than one timeslot, which is similar to information packaging in wireless communication. For example, if an EV needs 7 kWh to fully charge, while P_{max} is 4kW and Δt is one hour, the EV needs at least two timeslots to fully charge. The EV adds an energy demand of 4kWh to the timeslot when it connects to the grid and 3kWh to the following time slot. Thus for a single EV i, it generates the energy demand $a_i(t)$ as shown in (3), where C_i is the energy capacity of EV i; $\beta = \dfrac{(b_i' - b_i)C_i}{P_{max}}$.

$$a_i(t) = \begin{cases} P_{max}, & d_i \le t < \lfloor \beta \rfloor + d_i; \\ (b_i' - b_i)C_i - \lfloor \beta \rfloor P_{max}, & t = \lfloor \beta \rfloor + d_i; \\ 0, & \text{otherwise}; \end{cases} \tag{3}$$

Since EV users choose different charging deadlines to fulfill their charging tasks, which results in different acceptable delay times R_is, we need to use multiple queues for different R_is. We assume there are G values of R_is, in other words,

G queues, each of which corresponds to a delay time R_g, $g \in \{1, 2, \cdots, G\}$. For example, EV user can choose R_i from $\{4$ timeslots, 5 timeslots, $\cdots$, 12 timeslots$\}$. Then there are 9 queues with R_g ranging from 4 to 12. We modify our single-queue evolving equation into multi-queue evolving equations, Eqn. (4).

$$Q_g(t+1) = \max[Q_g(t) - x_g(t), 0] + a_g(t); \forall g \quad (4)$$

where $Q_g(t)$, $x_g(t)$ and $a_g(t)$ correspond to the queue backlog, energy consumption and energy demand arrival rate in timeslot t of queue g, Eqn. (5) [17].

$$Q(t) = \sum_{g=1}^{G} Q_g(t), x(t) = \sum_{g=1}^{G} x_g(t), a(t) = \sum_{g=1}^{G} a_g(t). \quad (5)$$

IV. Energy Efficient Charging Scheduling

The following assumptions are made to make sure the values of $s(t)$, $a(t)$ and $e(t)$ are bounded, Eqn. (6):

$$0 \le s(t) \le s_{max}, 0 \le a(t) \le a_{max}, 0 \le e(t) \le e_{max}, \forall t \quad (6)$$

where s_{max} is the maximum renewable energy generation; a_{max} is the maximum charging demand arrival rate; e_{max} is the maximum electricity price, which are all finite values.

We further assume that the charging facility is designed such that $x_{max} \ge a_{max}$, where x_{max} is power delivery capacity from the grid, so the charging queue can always be stabilized. Our objective is to minimize the time average charging cost for the fleet of EVs:

$$\min_{x_g(t)} \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{e(\tau)\{\max[x(\tau) - s(\tau), 0]\}\}, \quad (7)$$

subject to:

$$\overline{Q_g} < \infty; \quad \forall g \quad (8)$$

$$0 \le x(\tau) \le x_{max}; \quad \forall \tau \quad (9)$$

$$\overline{\frac{Q_g(\tau)}{R_g} + a_g(\tau) - x_g(\tau)} \le 0; \quad \forall g, \tau \quad (10)$$

where constraints (8) guarantee that all the queues are stable; $\overline{Q_g}$ denotes the time average value of Q_g, defined as: $\overline{Q_g} \triangleq \limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{Q_g(\tau)\}$; constraint (9) sets a limit on the maximum energy consumption.

We can rewrite (10) to the following inequality:

$$\frac{\overline{Q_g(\tau)}}{\overline{x_g(\tau) - a_g(\tau)}} \le R_g; \forall g, \tau \quad (11)$$

Since $\overline{Q_g(\tau)}$ is the average queue length and $\overline{x_g(\tau) - a_g(\tau)}$ is the average queue length decreasing rate, Inequality (10) impose limits on the average charging delay times.

The cost function (7) is a relaxed objective function for our problem of EV charging scheduling with renewable energy sources. If there exists no individual delay constraint for each EV, the minimum charging cost can be obtained by solving cost function (7) with constraints (8), (9) and (10), which only satisfy the queue stability constraint, maximum energy consumption constraint and average charging delay constraint. Obviously, by solving (7) we only obtain an ambitious target since it does not include the delay constraint for each individual EV. While in the following content of the paper, we modify the problem formulation and obtain a solution which satisfies the delay constraints and in the meantime provides a charging cost close to the result of cost function (7).

A. Delay-aware virtual queue

Note that (7) does not include the terms accounting for delay constraints. In order to make the function delay-aware, we introduce the virtual queues [17], which are defined as: $Z_g(0) = 0$, $\forall g$ and:

$$Z_g(t+1) = \max\{Z_g(t) + \frac{\eta}{R_g} 1_{Q_g(t)>0} - x_g(t), 0\}; \forall g, t. \quad (12)$$

We can see from (12), $\frac{\eta}{R_g} 1_{Q_g(t)>0}$ imposes a penalty to the virtual queue backlog when there is unserved charging task in the actual queue by ensuring that $Z_g(t)$ grows whenever the actual queue backlog is not empty. $1_{Q_g(t)>0}$ is an indicator function that equals to 1 if $Q_g(t) > 0$ and 0 else. The constant η can adjust the growth rate of the virtual queue, which guarantees that queue g has a finite worst case delay for any buffered EV charging requests in queue g, given $Q_g(t)$ and $Z_g(t)$ with finite upper bounds.

Lemma 1: Assume we have the system controlled to guarantee that the queue $Q_g(t)$ and queue $Z_g(t)$ have finite upper bounds, e.g. $Z_g(t) \le Z_{g,max}$ and $Q_g(t) \le Q_{g,max}$, then the worst case (longest) delay of all buffered EV charging requests in queue g is finitely upper bounded by $\delta_{g,max}$ timeslots, which is defined as:

$$\delta_{g,max} \triangleq \lceil \frac{(Q_{g,max} + Z_{g,max})R_g}{\eta} \rceil \quad (13)$$

Proof 1: The proof of Lemma. 1 follows the approach of Lyapunov optimization in [14], [28]. To prove the worst delay time is less than $\delta_{g,max}$, we use contradiction. Suppose at timeslot t, queue g has buffered charging task $a_g(t)$. The following shows that the charging task $a_g(t)$ will be fullfiled on or before timeslot $t+\delta_{g,max}$. If not, then the queue backlog $Q_g(\tau)$ will be non-empty for timeslots $\tau \in \{t+1, \cdots, t+\delta_{g,max}\}$. In that case, for all $\tau \in \{t+1, \cdots, t+\delta_{g,max}\}$, we have $I_{Q_g(t)>0} = 1$, and

$$Z_g(\tau+1) - Z_g(\tau) \ge -x_g(\tau) + \frac{\eta}{R_g} \quad (14)$$

Summing (14) from timeslot $t+1$ to $t+\delta_{g,max}$ gives

$$Z_g(t+\delta_{g,max}+1) - Z_g(t+1) \ge \sum_{\tau=t+1}^{t+\delta_{g,max}} [-x_g(\tau)] + \frac{\eta}{R_g}\delta_{g,max} \quad (15)$$

Since we have $Z_g(t+1) \ge 0$ and $Z_g(t+\delta_{g,max}+1) \le Z_{g,max}$, (15) can be further relaxed to

$$Z_{g,max} \ge \sum_{\tau=t+1}^{t+\delta_{g,max}} [-x_g(\tau)] + \frac{\eta}{R_g}\delta_{g,max} \quad (16)$$

Since the charging requests $a_g(t)$ are served in a FIFO manner and at timeslot t, $Q_g(t) \le Q_{g,max}$, if the charging requests are not fullfilled before $t+\delta_{g,max}$, the total served energy

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

in queue g should be less than the upper bound of queue length $Q_{g,max}$; otherwise the charging requests $a_g(t)$ should be served at some timeslot within $\{t+1,\cdots,t+\delta_{g,max}\}$. Thus, we have $\sum_{\tau=t+1}^{t+\delta_{g,max}}[x_g(\tau)] < Q_{g,max}$ and

$$Z_{g,max} > -Q_{g,max} + \frac{\eta}{R_g}\delta_{g,max} \tag{17}$$

which indicates that

$$\delta_{g,max} < \frac{(Q_{g,max}+Z_{g,max})R_g}{\eta}. \tag{18}$$

However (18) is in contradiction with the definition of $\delta_{g,max}$. So the worst case delay of queue g should be less or equal to $\delta_{g,max}$ as defined in (13).

B. Lyapunov Optimization

Following the approach in [28], we define the Lyapunov function as the scalar measurement of the queue length of both the $Z_g(t)$ and $Q_g(t)$ queues: $L(\Theta(t)) \triangleq \frac{1}{2}\sum_{g=1}^{G}[(Z_g(t)^2 + Q_g(t)^2]$ and the conditional Lyapunov drift as $\Delta(\Theta(t)) \triangleq \mathbb{E}\{L(\Theta(t+1)) - L(\Theta(t))|\Theta(t)\}$, where $\Theta(t)$ is defined as a concatenated vector of $Z(t)$ and $Q(t)$ queues: $\Theta(t) \triangleq (Z(t), Q(t))$. Considering both the charging cost (7) and queue backlog growth (12), our objective is then to minimize the following function in each timeslot t, Eqn. (19).

$$\min_{x_g(t)}\{\Delta(\Theta(t)) + V\,\mathbb{E}\{g(t)\{\max[x(t)-s(t),0]\}|\Theta(t)\} \tag{19}$$

Note that the left part is the growth of the queue and the right part is the expected cost for charging. V is a parameter that is used to tune the tradeoff between cost and queue backlog growth. The objective is to minimize the weighted sum of drift and penalty (cost), which can be proven bounded.

Lemma 2: The following inequality holds.

$$\begin{aligned}\Delta(\Theta(t)) &+ V\,\mathbb{E}\{e(t)\{\max[x(t)-s_t,0]\}|\Theta_t\}\\ &\le B + V\,\mathbb{E}\{e(t)\{\max[x(t)-s(t),0]\}|\Theta_t\}\\ &+ \sum_{g=1}^{G} Q_g(t)\,\mathbb{E}\{[a_g(t)-x_g(t)]|\Theta_t\}\\ &+ \sum_{g=1}^{G} Z_g(t)\,\mathbb{E}\{\frac{\eta}{R_g} - x_g(t)|\Theta_t\}\end{aligned} \tag{20}$$

where the constant B is defined as:

$$B \triangleq \frac{\sum_{g=1}^{G}[x_{g,max}^2 + a_{g,max}^2]}{2} + \frac{\sum_{g=1}^{G}\max[(\eta/R_g)^2, a_{g,max}^2]}{2} \tag{21}$$

Proof 2: The proof follows the drift-plus-penalty framework presented in [14], [28], [29]. The control algorithm is to determine the control variables $x_g(t)$, $g \in \{1,\cdots,G\}$ according to observed variables $Z_g(t)$, $Q_g(t)$, $a_g(t)$, $s_g(t)$,$g(t)$ of the current timeslot t. We show the proof starting with an individual queue g.

For queue backlog,

$$Q_g^2(t+1) = \{\max[Q_g(t)-x_g(t),0] + a_g(t)\}^2 \tag{22}$$

using the following inequality:

$$[\max(b-\mu,0)+a]^2 \le b^2+\mu^2+a^2+2b(a-\mu) \tag{23}$$

which holds for any $b \ge 0$, $a \ge 0$, and $\mu \ge 0$ and we have

$$Q_g^2(t+1) \le Q_g^2(t) + x_{g,max}^2 + a_{g,max}^2 + 2Q_g(t)[a_g(t)-x_g(t)] \tag{24}$$

and therefore:

$$\frac{Q_g^2(t+1)-Q_g^2(t)}{2} \le \frac{1}{2}(a_{g,max}^2 + x_{g,max}^2) + Q_g(t)[a_g(t)-x_g(t)]. \tag{25}$$

Similar for the virtual queue,

$$\begin{aligned}Z_g^2(t+1) &\le [Z_g(t)-x_g(t)+\frac{\eta}{R_g}1_{Q_g(t)>0}]^2\\ &= 2Z_g(t)[\frac{\eta}{R_g}1_{Q_g(t)>0} - x_g(t)] + Z_g^2(t)\\ &\quad +[\frac{\eta}{R_g} - x_g(t)]^2\\ &\le 2Z_g(t)[\frac{\eta}{R_g}1_{Q_g(t)>0} - x_g(t)] + Z_g^2(t)\\ &\quad +\max[(\frac{\eta}{R_g})^2, x_{g,max}^2(t)].\end{aligned}$$

Thus we have

$$\begin{aligned}\frac{Z_g^2(t+1)-Z_g^2(t)}{2} &\le Z_g(t)[\frac{\eta}{R_g} - x_g(t)]\\ &\quad + \frac{1}{2}\max[(\frac{\eta}{R_g})^2, x_{g,max}^2(t)].\end{aligned}$$

By summing all the G queues, we have Inequality (20).

C. Real-time Optimization Algorithm

The left-hand side of (20) is tightly bounded by the right-hand side of (20). Since B is a constant, trying to minimize the left-hand side of (20) leads to minimizing the right-hand side of (20), wihch can be solved in real time during each timeslot t with the following dynamic optimization algorithm:

Step 1, optimization:

$$\begin{aligned}\min_{x_g(t)} \quad & V e(t)\{\max[x(t)-s(t),0]\}\\ & + \sum_{g=1}^{G} Q_g(t)[a_g(t)-x_g(t)]\\ & + \sum_{g=1}^{G} Z_g(t)[\frac{\eta}{R_g} - x_g(t)]\\ \text{subject to:} \quad & x_{g,max} \ge x_g(t) \ge 0, \forall g,\end{aligned} \tag{26}$$

where $Z(t), Q(t), s(t), a(t), e(t)$ are inputs observed in timeslot t; $x_g(t)$ are decision variables.

Step 2, update:

$$\begin{aligned}Q_g(t+1) &= \max[Q_g(t)-x_g(t),0] + a_g(t), \forall g;\\ Z_g(t+1) &= Z_g(t) + \frac{\eta}{R_g}1_{Q_g(t)>0} - x_g(t), \forall g.\end{aligned}$$

D. Dynamic Algorithm Solutions

Since $Z(t), Q(t), s(t), a(t), g(t)$ are all observed values, problem formulation (26) can be converted to an easier form to solve, where auxiliary decision variable $s_g(t)$ is the renewable energy consumed by EVs in group g:

$$\begin{aligned} \min_{x_g(t), s_g(t)} \quad & Ve(t)\sum_{g=1}^{G}[x_g(t)-s_g(t)] - \sum_{g=1}^{G}[Q_g(t)+Z_g(t)]x_g(t) \\ \text{subject to} \quad & x_g(t) \geq 0, \forall g; \\ & s_g(t) \geq 0, \forall g; \\ & x_g(t) \leq x_{g,max}, \forall g; \\ & \sum_{g=1}^{G} s_g(t) \leq s(t); \\ & s_g(t) \leq x_g(t), \forall g. \end{aligned} \tag{27}$$

Function (27) can be rewritten into the following form:

$$\min_{x_g(t), s_g(t)} \quad \sum_{g=1}^{G}[Ve(t)-Q_g(t)-Z_g(t)]x_g(t) - Ve(t)\sum_{g=1}^{G} s_g(t) \tag{28}$$

Function (28) is a linear optimization problem, whose optimum solution can be solved by examing each vertex formed by the solution space. In order to achieve the optimum value of the objective function, for $\forall g, Q_g(t)+Z_g(t)-Ve(t) > 0$, we should assign the maximum possible charging rate to $x_g(t)$; for $\forall g, Q_g(t)+Z_g(t)-Ve(t) \leq 0$, we should allocate the available renewable energy to $x_g(t)$ without purchasing electricity from the grid; and we should have $\sum_{g=1}^{G} s_g(t) = \min\{\sum_{g=1}^{G} x_g(t), s(t)\}$.

The solution for (26) can be obtained by the following steps:

1) Sort the queues based on $Q_g(t)+Z_g(t)-Ve(t)$ in descending order.
2) $\forall g, Q_g(t)+Z_g(t)-Ve(t) > 0$, assign the maximum possible charging rate to $x_g(t)$.
3) $\forall g, Q_g(t)+Z_g(t)-Ve(t) \leq 0$, allocate the available renewable energy to $x_g(t)$ based on the queue order.
4) Update SOC of all EVs and acquire new information in timeslot $t+1$.

Theorem 1: Assume that $x_{g,max} \geq a_{g,max}, \forall g \in \{1,\cdots,G\}, t \in \{0,\cdots,T\}$, $Q_g(0) = 0$ *and* $Z_g(0) = 0$, $\forall g \in \{1,\cdots,G\}$, *then for any fixed parameter* $\eta, 0 \leq \eta \leq a_{g,max}R_g$ *and a parameter* V, *the proposed algorithm has the following properties for each queue* g:

1) *In all timeslots, for all queues,* $Q_g(t)$ *and* $Z_g(t)$ *are upper bounded by* $Q_{g,max}$ *and* $Z_{g,max}$, *where* $Q_{g,max}$ *and* $Z_{g,max}$ *are defined as following:*

$$\begin{aligned} Q_{g,max} &\triangleq Ve_{max} + a_{g,max}, \\ Z_{g,max} &\triangleq Ve_{max} + \frac{\eta}{R_g}. \end{aligned} \tag{29}$$

Meanwhile, $Q_g(t)+Z_g(t)$ *are upper bounded by* $\Theta_{g,max}$ *where* $\Theta_{g,max}$ *is defined as following:*

$$\Theta_{g,max} \triangleq Ve_{max} + a_{g,max} + \frac{\eta}{R_g}. \tag{30}$$

2) *The maximum delay of queue* $g, \forall g \in \{1,\cdots,G\}$ *can be calculated by*

$$\delta_{g,max} = \lceil \frac{2VR_g e_{max} + R_g a_{g,max} + \eta}{\eta} \rceil. \tag{31}$$

3) *Given that* $\eta/R_g \leq \mathbb{E}\{a_g\}$, *the time-average expected electricity cost provided by the proposed algorithm is upper bounded within* B/V *of the optimal value* C_{opt}, *i.e.,*

$$\lim_{t\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{e(t)[x(t)-s(t)]\} \leq C_{opt} + B/V, \tag{32}$$

where B *is given by (21).*

Proof 3:

1) In order to prove $Q_g(t) \leq Q_{g,max}$, we use induction method. It is obvious that $Q_g(0) \leq Q_{g,max}$. Thus we need to prove $Q_g(t+1) \leq Q_{g,max}$, given $Q_g(t) \leq Q_{g,max}$. If $Q_g(t) \leq Ve_{max}$, then the maximum queue backlog growth is $a_{g,max}$.

$$Q_g(t+1) \leq Q_g(t) + a_{g,max} \leq Ve_{max} + a_{g,max} \tag{33}$$

If $Q_g(t) > Ve_{max}$, since $Z_g(t) \geq 0$ we have $Q_g(t) + Z_g(t) - Ve(t) > 0$. According to the algorithm proposed above, we will assign the maximum possible charging rate to $x_g(t)$, which is larger than the maximum charging request arrives during timeslot t. Thus $Q_g(t)$ will not grow, i.e.,

$$Q_g(t+1) \leq Q_g(t) \leq Ve_{max} + a_{g,max}. \tag{34}$$

Therefore, we have

$$\begin{aligned} Q_g(t) \leq Ve_{max} + a_{g,max}, \\ \forall t \in \{0,\cdots,T\}, g \in \{1,\cdots,G\}. \end{aligned} \tag{35}$$

Similarly, for the virtual queue, we have $Z_g(0) \leq Ve_{max} + \frac{\eta}{R_g}$. Assuming that $Z_g(t) \leq Ve_{max} + \frac{\eta}{R_g}$. If $Z_g(t) > Ve_{max}$, then $Q_g(t) + Z_g(t) - Vg(t) > 0$, and the maximum possible charging rate will be assigned to $x_g(t)$, which is larger than the maximum amount of energy request during the timeslot t. The virtual queue will not grow, i.e.,

$$Z_g(t+1) \leq Ve_{max} + \frac{\eta}{R_g}. \tag{36}$$

If $Z_g(t) \leq Ve_{max}$, the maximum queue growth is $\frac{\eta}{R_g}$, which leads to

$$Z_g(t+1) \leq \quad Z_g(t) + \frac{\eta}{R_g} \leq Ve_{max} + \frac{\eta}{R_g} \tag{37}$$

Therefore, we have

$$Z_g(t) \leq Ve_{max} + \frac{\eta}{R_g}, \forall t \in \{0,\cdots,T\}, g \in \{1,\cdots,G\}. \tag{38}$$

In the following, we prove that $Q_g(t)+Z_g(t) \leq \Theta_{g,max}$. We start with the obvious, $Q_g(0)+Z_g(0) \leq \Theta_{g,max}$. Suppose $Q_g(t)+Z_g(t) \leq \Theta_{g,max}$. If $Q_g(t)+Z_g(t) > Ve_{max}$, then $Q_g(t)+Z_g(t)-Ve(t) > 0$. The maximum

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

possible amount of charging rate will be assigned to queue g, thus $Q_g(t)$ and $Z_g(t)$ will not grow, i.e.,

$$Q_g(t+1) + Z_g(t+1) \leq \Theta_{g,max}. \tag{39}$$

Else if $Q_g(t) + Z_g(t) \leq Ve_{max}$, the maximum growth of $Q_g(t)$ is $a_{g,max}$ and the maximum growth of $Z_g(t)$ is $\frac{\eta}{R_g}$. Therefore, we have

$$Q_g(t+1)+Z_g(t+1) \leq Ve_{max} + \frac{\eta}{R_g} + a_{g,max}. \tag{40}$$

Thus, we have

$$Q_g(t)+Z_g(t) \leq \Theta_{g,max}, \forall t \in \{0,\cdots,T\}, g \in \{1,\cdots,G\}. \tag{41}$$

2) From the definition of $\delta_{g,max}$, Eqn. (13), and applying the conclusion from Theorem 1. 1, we can have

$$\begin{aligned} \delta_{g,max} &= \lceil \frac{R_g}{\eta}(Q_{g,max} + Z_{g,max}) \rceil; \\ Q_{g,max} &= Ve_{max} + a_{g,max}; \\ Z_{g,max} &= \eta/R_g + Ve_{max}. \end{aligned}$$

Thus the value of $\delta_{g,max}$ can be calculated as

$$\begin{aligned} \delta_{g,max} = &\lceil \frac{2Ve_{max} + a_{g,max} + \eta/R_g}{\eta/R_g} \rceil \\ = &\lceil \frac{2VR_g e_{max} + R_g a_{g,max} + \eta}{\eta} \rceil. \end{aligned} \tag{42}$$

This bound shows by properly choosing the values of V and η, the charging scheduling algorithm can satisfiy the individual delay constraint for each EV.

3) Since the proposed method will always try to minimize the right handside part of the Inequality (20) among all feasible solutions, even the optimal solution, suppose the solution given by the proposed algorithm and optimal solution are $\{x_{g,pro}(t)\}$ and $\{x_{g,opt}(t)\}$ respectively, and the optimal result for minimizing average cost is C_{opt}, then by plugging the solution into the Inequality (20), we can have the following:

$$\begin{aligned} &\Delta(\Theta(t)) + V\,\mathbb{E}\{e(t)\{\max[x_{pro}(t) - s_t, 0]\}|\Theta_t\} \\ &\quad \leq B + V\,\mathbb{E}\{e(t)\{\max[x_{opt}(t) - s(t), 0]\}|\Theta_t\} \\ &\qquad + \sum_{g=1}^{G} Q_g(t)\,\mathbb{E}\{[a_g(t) - x_{g,opt}(t)]|\Theta_t\} \\ &\qquad + \sum_{g=1}^{G} Z_g(t)\,\mathbb{E}\{[\eta/R_g - x_{g,opt}(t)]|\Theta_t\} \\ &\quad \leq B + VC_{opt}. \end{aligned} \tag{43}$$

The result of (43) is based on the fact that

$$\lim_{t\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{a_g(t) - x_g(t)|\Theta_t\} \quad \leq 0; \tag{44}$$

$$\lim_{t\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}\{\eta/R_g - a_g(t)|\Theta_t\} \quad \leq 0. \tag{45}$$

Summing Inequality (43) over timeslots $t \in \{0,\cdots,T\}$, we can have:

$$\begin{aligned} &\Theta(T) - \Theta(0) + V\sum_{t=0}^{T} e(t)\max[x_{pro}(t) - s_t, 0] \\ &\quad \leq BT + VTC_{opt}. \end{aligned} \tag{46}$$

Using the fact that $\Theta(T) \geq 0$ and $\Theta(0) = 0$, dividing both sides of (46) by VT and letting $T \to \infty$ results in:

$$\lim_{t\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} e(t)\max[x_{pro}(t) - s_t, 0] \leq \frac{B}{V} + C_{opt}. \tag{47}$$

From the expression of B/V, Eqn. (48), and the expression of $Q_{g,max}$ and $Z_{g,max}$, Eqns. (29), we can see that V and η are control parameters that affect the growth rate of $Z_g(t)$, Eqn. (12), the upper bounds for the queue and virtual queue length, and the upper bound for the average charging cost.

$$\frac{B}{V} = \frac{\sum_{g=1}^{G}\{x_{g,max}^2 + a_{g,max}^2 + \max[(\frac{\eta}{R_g})^2, a_{g,max}^2]\}}{2V}. \tag{48}$$

The aggregator can increase V and decrease η to deduce the charging cost for EVs; however, this may increase the value of maximum charging delay $\delta_{g,max}$. Bounds in Theorem 1 provide the aggregator references to balance between service delay and energy cost.

V. Simulation Results

We have performed simulations on data sets with 10-minute timeslot interval and use wind energy as renewable energy source. 10-minute interval is a reasonable response time for EV batteries to receive charging command signals, since it is significantly long time for EV batteries to adjust charging rate while short enough to reflect the rapid change in renewable resource generation. The charging period is 24 hours, which means 144 timeslots. Real wind speed data are taken from [39] and converted to wind energy generation with 10-minute granularity, based on the specifications of the Vestas V800 2000 kW offshore wind turbine (Fig. 1). Three wind energy generation samples are used to evaluate the algorithm performance on different wind generation patterns. Additional energy from the grid is purchased at 10-minute average real-time market prices $g(t)$ for the Capital area from New York Independent System Operator (NYISO) [31].

The 200 charging tasks were generated for a scheduling period from 12pm (noon) to 12pm in the next day to simulate the overnight EV charging [15], [16]. To reflect the real-life commute pattern [10], we used Gaussian distributions to model vehicles' travel pattern, and generate the EV arrival (starting) and departure (finishing) times. Specifically, the starting times d_i follow a normal distribution with a mean of $\mu = $ 6pm and a standard deviation of $\sigma = 2$ hours; the desired finishing times f_i follow a normal distribution with $\mu = $ 7am and $\sigma = 2$ hours; and the daily travel distances follow a lognormal

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

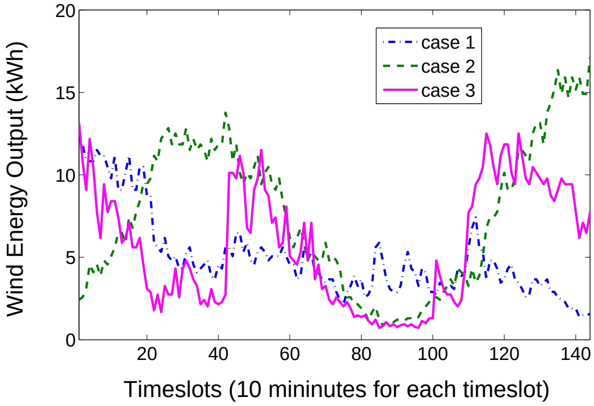


Fig. 1. Wind turbine energy generations

distribution with $\mu = 3.22$ miles and $\sigma = 0.66$ mile. We set EV battery related parameters, including the charging rate limit and battery capacity based on the specification of the Li-ion battery of a modern EV model [3]. The initial SOCs b_i were set to be distributed in the range $[0.3, 0.9]$, and the desired SOC b'_i was set to 0.9 for each EV. The charging efficiency is 0.9 for all EVs. The related simulation settings are summarized in Table I:

TABLE I
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
Mean trip length	3.22 miles
Standard deviation of trip length	0.66 mile
EV battery state of charge range	[0.3, 0.9]
EV battery charging efficiency E_i	0.9
EV battery maximum charging rate P_{max}	4.4 kW
EV all electricity operation range	40 miles
EV battery capacity C_i	16 kWh
Total number of timeslots T	144

To better evaluate the performance of our proposed algorithm, three scenarios are considered for simulations, each tested with three wind power profiles. The first two scenarios use simple greedy algorithms. In the first scenario, the aggregator deploys a “charge-upon-arrival” strategy. The aggregator charges each connected EV with maximum possible charging rate as soon as the EV arrives, which results in the least delay time, but possibly higher charging cost. In the second scenario, the aggregator deploys the strategy “purchase-at-deadline”. The strategy “purchase-at-deadline” means the aggregator starts to charge an EV with energy from electricity market at a timepoint when if no renewable energy is available after the timepoint, the time left till the deadline is just enough to finish charging the EV to its desired SOC. Before that timepoint, the aggregator only charges the EV with renewable energy. Lyapunov optimization algorithm is used in the third scenario with a balance between delay time and charging cost, where η is set to 44, and V is set to 500.

A. Performance on charging cost

Fig. 2 shows the charging costs of different scenarios for each cases. From the results, we can see Lyapunov optimization achieves the minimum charging cost among the three scenarios: the average charging cost reduces by 76% compared to scenario 1 and 33% to scenario 2. Lyapunov optimization enables the aggregator to purchase additional energy at relatively lower prices, while “charge-upon-arrival” and “purchase-at-deadline” may result in purchasing additional energy at times when electricity prices are high. The reason case 2 gives lower charging costs than the other two cases is that more renewable energy is available in case 2 during the charging period than the other two cases (Fig. 1).

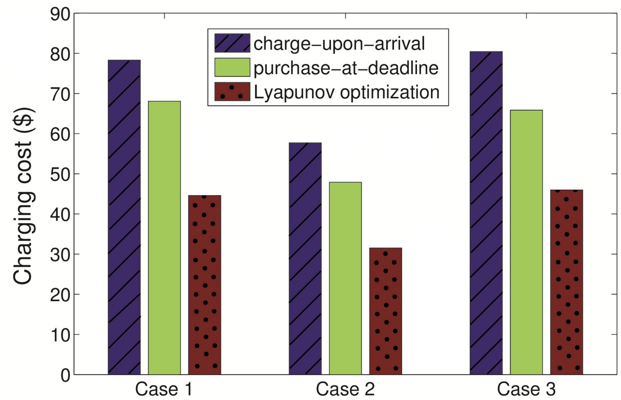


Fig. 2. Comparison of charging cost in different scenarios.

B. Performance on delay time

From the simulation results (Tab. II), we can see that compared to “purchase-at-deadline”, Lyapunov optimization can reduce the mean delay time for charging tasks by 63% on average. To have a better insight of the impact of delay-time reduction, we have shown simulation results on the fraction of waiting customers in Fig. 3, taking case 1 as an example. The fraction of waiting customers is defined as the percentage of charging tasks in the queue. Fig. 3 clearly shows that Lyapunov optimization can serve customers in a more timely manner.

TABLE II
MEAN DELAY TIME (TIMESLOTS) IN DIFFERENT SCENARIOS

Case number	purchase-at-deadline	Lyapunov optimization
1	48.99	15.93
2	38.47	16.40
3	52.32	19.21

C. Balance between charging cost and delay time

In order to study the impact of parameter η on the total charging cost and mean delay time, we have plotted figures showing the relationship between the total charging cost and the value of η and the relationship between the mean delay

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

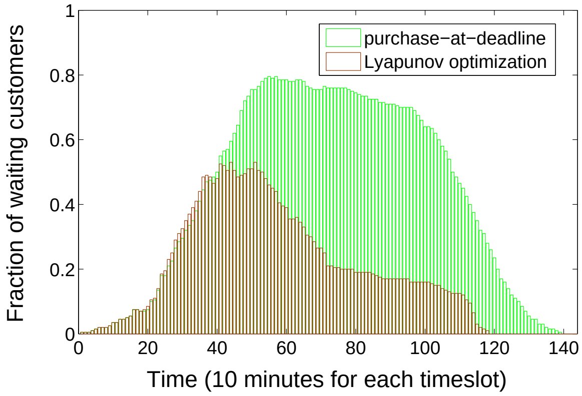


Fig. 3. Histogram of fraction of customers waiting in the service queues in different scenarios.

time and the value of η (Fig. 4), taking case 1 as an example. From the result we can see that as we expected, the charging cost increases non-linearly with the value of η, while the mean delay time decreases with the value of η. The total charging cost and mean delay time reach saturation when the value of η is larger than a certain value, which illustrates that when the value of η is large enough, the mean delay time will reach its minimum and the total charging cost is close to the value obtained by the "charge-upon-arrival" strategy.

Similarly, We can observe increase of charging cost and reduction of mean delay time as V increases (Fig. 5).

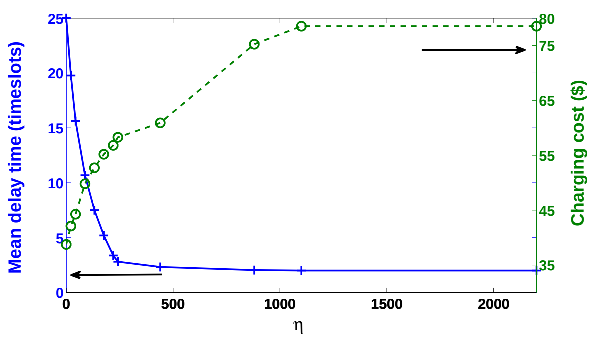


Fig. 4. Total charging cost and mean delay time vs. the value of η in case 1. The value of V is set to 500.

VI. Conclusion and Discussion

In this study, we focus on the future electricity grid where EVs, renewable energy and electricity grid are integrated together to form a green and efficient energy hub. EVs act as controllable loads to support the generation of renewable energy, improving energy efficiency and reducing energy cost. To address the uncertainties inherent with renewable energy generation, electricity pricing and EV charging requests, we present Lyapunov optimization for EV charging scheduling problems, with the goal of efficient utilization of renewable energy and reducing charging cost. Multi-queue model is used to incorporate different EV charging deadlines and packaging

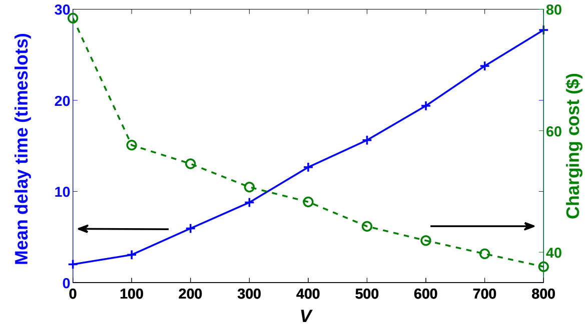


Fig. 5. Total charging cost and mean delay time vs. the value of V in case 1. The value of η is set to 44.

technique is used to address the constraint of EV charging rate limit.

Simulations with different wind profiles are performed and analyzed. Two other EV control strategies are presented, for comparison with the proposed Lyapunov optimization approach, namely "charge-upon-arrival", which charges EV with all available power as soon as the EV is connected to the grid and "purchase-at-deadline", which charges EV with renewable energy only except when the deadline approaches. Simulation results show that based on real electricity price and renewable energy data, the charging cost can be reduced by 76% and 33% on average compared to two greedy approaches: "charge-upon-arrival" and "purchase-at-deadline" respectively. In addition, the mean delay time can be reduced by 63% as compared to the "purchase-at-deadline" approach. Moreover, since the proposed charging scheduling scheme based on Lyapunov optimization does not require the statistics of underlying processes, such as the distribution of future renewable energy generation, real-time electricity prices and charging demands, it can be applied when the aggregator has no such prior knowledge, while other optimization methods, such as dynamic programming or robust optimization, are unable to do the calculation without the information.

References

[1] S. L. Andersson, A. K. Elofsson, M. D. Galus, *et al.*, Plug-in hybrid electric vehicles as regulating power providers: Case studies of Sweden and Germany, *Energy Policy*, vol. 38, no. 6, 2010, pp. 2751–2762.

[2] P. H. Andersen, J. A. Mathews, and M. Raska, Integrating private transport into renewable energy policy: The strategy of creating intelligent recharging grids for electric vehicles, *Energy Policy*, vol. 37, no. 7, 2009, pp. 2481–2486.

[3] Chevy Volt Specifications, online. Available: http://www.chevrolet.com/volt/

[4] I. S. Bayram, G. Michailidis, M. Devetsikiotis, and *et al*, "Local energy storage sizing in plug-in hybrid electric vehicle charging stations under blocking probability constraints," *IEEE SmartGridComm*, 2011, pp. 78–83.

[5] B. S. M.C. Borba, , A. Szklo and R. Schaeffer, "Plug-in hybrid electric vehicles as a way to maximize the integration of variable renewable energy in power systems: The case of wind generation in northeastern Brazil," *Energy*, vol. 36, no.1, 2012, pp. 469–481.

[6] Vehicle-to-Grid Demonstration Project: Grid Regulation Ancillary Service with a Battery Electric Vehicle, California environmental protection agency, *Air Resources Board, Research Division, Regulation*, 2010, pp. 1–61.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSTSP.2014.2336624, IEEE Journal of Selected Topics in Signal Processing

[7] I. Cvetkovic, T. Thacker, D. Dong, *et al.*, "Future home uninterruptible renewable energy system with vehicle-to-grid technology," *Energy Conversion Congress and Exposition*, 2009.

[8] D. Dallinger and M. Wietschel, "Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, 2012, pp. 3370-3382.

[9] P. Denholm and W. Short, An evaluation of utility system impacts and benefits of optimally dispatched plug-in hybrid electric vehicles, *Technical report. National Renewable Energy Laboratory*, 2006.

[10] Summary of Travel Trends, 2009 National Household Travel Survey, *U.S. Department of Transportation*, 2009.

[11] Z. Fan, "Distributed charging of PHEVs in a smart grid," *IEEE SmartGridComm*, 2010, pp. 255–260.

[12] L. Georgiadis, M. J. Neely, and L. Tassiulas, Resource allocation and cross-layer control in wireless networks. *Foundations and Trends in Networking*, vol. 1, no. 1, 2006, pp. 1–149.

[13] C. Guille and G. Gross, A conceptual framework for the vehicle-to-grid (V2G) implementation, *Energy Policy*, vol. 37, no. 11, 2009, pp. 4379 – 4390.

[14] Y. Guo, M. Pan and Y. Fang, Optimal Power Management of Residential Customers in the Smart Grid *IEEE Trans. on Parallel and Distributed Systems*, vol. 23, no. 9, 2012, pp. 1593–1606.

[15] C. Jin, J. Tang, P. K. Ghosh, Optimizing Electric Vehicle Charging with Energy Storage in the Electricity Market, *IEEE Trans. on Smart Grid*, vol. 4, no. 1, 2013, pp. 311–320

[16] C. Jin, J. Tang, P. K. Ghosh, Optimizing Electric Vehicle Charging: A Customer's Perspective, *IEEE Trans. on Vehicular Technology*, 2013.

[17] C. Jin, X. Sheng, P. K. Ghosh, "Energy efficient Algorithms for Electric Vehicle Charging with Intermittent Renewable Energy Sources," *Power & Energy Society General Meeting*, 2013.

[18] S. Kabisch, A. Schmitt, M. Winter, *et al.*, Interconnections and communications of electric vehicles and smart grids, *Smart Grid Communications*, 2010, pp. 161–166.

[19] W. Kempton and J. Tomic, Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy, *Journal of Power Sources*, vol. 144, no. 1, 2005, pp. 280–294.

[20] W. Kempton, V. Udo, K. Huber, *et al.*, A test of vehicle-to-grid (V2G) for energy storage and frequency regulation in the PJM system, *Univ. Delaware, Newark, DE*, 2008.

[21] Y. Li, R. Kaewpuang, P. Wang, *et al.*, "An energy efficient solution: integrating plug-in hybrid electric vehicle in smart grid with renewable energy," *IEEE Conference on Computer Communications Workshops*, 2012.

[22] U. K. Madawala, P. Schweizer, and V. V. Haerri, Living and mobility- A novel multipurpose in-house grid interface with plug-in hybrid BlueAngle, *IEEE International Conference on Sustainable Energy Technologies*, 2008, pp.531–536.

[23] V. Marano, G. Rizzoni, "Energy and economic evaluation of PHEVs and their interaction with renewable energy sources and the power grid," *IEEE International Conference on Vehicular Electronics and Safety*, 2008.

[24] A. Mohsenian-Rad, V. Wong, J. Jatskevich, and R. Schober, "Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid," *IEEE Innovative Smart Grid Technologies Conference*, 2010.

[25] M. J. Neely, Energy optimal control for time varying wireless networks. *IEEE Transactions on Information Theory*, vol. 52, no. 7, 2006, pp. 2915-2934.

[26] M. J. Neely, Dynamic power allocation and routing for satellite and wireless networks with time varying channels, PhD thesis, Massachusetts Institute of Technology, LIDS, 2003.

[27] M. J. Neely, Stock market trading via stochastic network optimization, ArXiv Technical Report, arXiv:0909.3891v1, 2009.

[28] M. J. Neely, A.S. Tehrani and A. G. Dimakis, Efficient algorithms for renewable energy allocation to delay tolerant consumers, *IEEE International Conference on Smart Grid Communications*, 2010, pp. 549– 554.

[29] M. J. Neely. Universal scheduling for networks with arbitrary traffic, channels, and mobility. *IEEE*, 2010, pp. 1822– 1829.

[30] M. J. Neely, Stochastic network optimization with application to communication and queueing systems. Morgan Claypool, 2010.

[31] NYISO: Market and Pricing Data, online. Available: http://www.nyiso.com/public/markets_operations/market_data/pricing_data/index.jsp

[32] A. Papavasiliou and S. S. Oren, "Supplying renewable energy to deferrable loads: Algorithms and economic analysis," *IEEE PES General Meeting*, 2010.

[33] D. B. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration," *Renewable and Sustainable Energy Reviews*, vol. 19, 2013, pp. 247-254.

[34] A. Y. Saber and G. K. Venayagamoorthy, Plug-in vehicles and renewable energy sources for cost and emission reductions, *IEEE Transactions on Industrial Electronics*, vol. 58, no. 4, 2011, pp. 186–193.

[35] E. Sortomme and M. A. El-Sharkawi, Optimal charging strategies for unidirectional vehicle-to-grid, *IEEE Transactions on Smart Grid*, vol. 2, no. 1, 2011, pp. 131–138.

[36] K. Turitsyn, N. Sinitsyn, S. Backhaus, *et al.*, "Robust broadcast-communication control of electric vehicle charging," *IEEE SmartGridComm*, 2010, pp. 203–207.

[37] S. Vandael, N. Boucke, T. Holvoet, and G. Deconinck, "Decentralized demand side management of plug-in hybrid vehicles in a smart grid," *AAMAS ATES Workshop*, 2010.

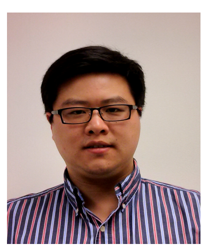
[38] C. Wang and M. Groot, "Managing end-user preferences in the smart grid," *International Conference on Energy-Efficient Computing and Networking*, 2010.

[39] Wind speed data, online. Available: http://www.windenergy.org/datasites/0000-aeiwtc/.

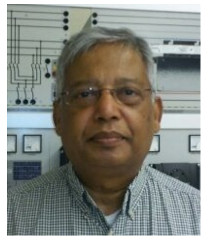
[40] R. Zavadil, 2006 Minessota Wind Integration Study, *The Minnesota Public Utilities Commission Technical report*, vol. 1, 2006.

[41] C. Loutan and D. Hawkins, Integration of renewable resources. Transmission and operating issues and recommendations for integrating renewable resources on the California ISO-controlled Grid, *California Independent System Operator technical report*, 2007.

Chenrui Jin (M'11) is a Ph.D candidate in the Department of Electrical Engineering and Computer Science at Syracuse University. She earned her BS degree in physics and mathematics from Tsinghua University, Beijing, China in 2007 and MSEE degree from Syracuse University in 2010. Her research interests include power system optimization, vehicle to grid technologies, distributed energy sources and energy management system.



Xiang Sheng (M'11) is currently pursuing the Ph.D. degree at the Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY, USA. He received the B.E. degree in electrical engineering from the Nanjing University of Science and Technology, Nanjing, China, in 2008, and the M.S. degree in electrical engineering from Syracuse University in 2010. His current research interests include mobile sensing, mobile computing, and green communications.



Prasanta Ghosh is a Professor in the department of Electrical Engineering and Computer Science at Syracuse University. He has been conducting research in the area of microelectronics and power engineering. He has authored or co-authored many journal articles and conference papers in the area of thin films, solid state devices, and power engineering. His current research focus includes smart grid, sensors, and optimization of distribution system with distributed sources. He is a senior member of IEEE.