Energy efficient Algorithms for Electric Vehicle Charging with Intermittent Renewable Energy Sources

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***Abstract*—Renewable energy and Electric Vehicles (EV) show potential to be promising solutions for energy cost saving and emission reduction. However, the integration of renewable energy generation into the electric grid can be difficult, because of the source intermittency and inconsistency with energy usage. In this paper, we study the problem of allocating energy from renewable sources to EVs in an energy efficient manner. We assume that the renewable energy supply is time variant and possibly unpredictable. EVs' charging requests should be satisfied within a specified time frame, which may incur a cost of drawing extra energy (possibly non-renewable energy) if the renewable energy supply is not sufficent to meet the deadlines and may also reduce energy efficiency. We formulate a stochastic optimization problem based on queueing model to minimize the time average cost of using other energy sources (and hence make most usage of the renewable energy source). 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 statistics of the time-varying renewable energy generation, EV charging demand process, or extra energy pricing.**

***Key Words:* energy efficiency, electric vehicle, renewable energy, Lyapunov optimization**

I. INTRODUCTION

Electric power generation and transportation sectors are considered as main sources of petroleum shortage and gas (CO_2, SO_2 and NO_x) emissions, which have become worldwide concerns at economic, environmental, industrial and social levels [12]. Policy makers, engineers and business leaders are searching for alternative energy sources, that are more economically and environmentally friendly [17]. Using renewable energy sources for electric energy production can significantly reduce energy cost and gas emissions, compared to non-renewable energy sources. Using Electric Vehicles (EVs) instead of traditional Internal Combustion Engine (ICE) vehicles is also a promising solution for lower operational costs and gas emissions [4]. In addition, renewable energy supplied EV charging is becoming a popular approach for green and efficient energy usage [10]. Since EVs have controllable charging rate, they can be considered as controllable loads in grid system or even distributed energy storage units when vehicle-to-grid (V2G) is available [8], which can further benefit the grid system with demand response or load following [1], [2], [5].

However, there are also challenges with renewable energy supplied EV charging. The productions of renewable energy, strongly influenced by weather conditions, are intermittent and cannot be forecasted accurately [20], which results in difficulties in power system planning and scheduling [21]. Stand-by generators or other backup energy suppliers are necessary to offset the variability of renewable energy generation, which results in the cost for purchasing extra energy from other sources. In order to minimize the cost for purchasing extra energy and increase energy efficiency, the stochastic characteristics and the dynamic cooperation between renewable energy generation and load demand should be carefully studied.

In this paper, we use Lyapunov optimization for efficient EV charging with renewable energy supply. The technique of Lyapunov optimization is initially developed for dynamic control of queueing systems for wireless networks [7], [13], [14]. In [15], the 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 extend that approach to include the charging request of each individual EV, such as the charging rate limit and different deadlines, using information packaging technique for charging rate limit and multi-queue model for different deadlines. The problem is now more complete and practical while still provides a simple approach for real-time operation.

This paper presents a queuing model based on Lyapunov optimization to solve the stochastic energy efficient scheduling problem. The objective function of the optimization is to minimize 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 supplied 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 limit and deadline. Our main contributions are as following:

1) We present a queuing model for EV charging scheduling problem considering stochastic characteristics of renewable energy generation and individual EV charging requests.

2) We perform extensive simulation using real electricity price and renewable energy generation data to show the cost

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savings that can be brought by the energy efficient scheduling compared to two simple greedy scheduling algorithms.

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

II. EV Charging Queuing Model

A. Aggregated EV Charging Control

In order to fully regulate the charging rate of flexible EV loads, in smart grid system, we assume the charging of a fleet of EVs is controlled by an aggregator, which can be distributed system operators or other third part entity [10], [11], [18]. EV can communicate with aggregator in real time and can be charged at various charging rates. During the charging scheduling period, aggregator collects information from both the renewable energy sources and connected EVs and instructs the renewable energy or the extra energy source to charge each EV with a charging rate given by charging scheduling algorithm.

An EV can be connected to or disconnected from the distribution network at any time according to the EV user's need. We have no priori information about a charging request of an EV until its connection. As stated in cutting edge framework [9], an EV user will inform the aggregator with his desired finishing time and final State of Charge (SOC) of the battery for his/her EV through user interface, when the EV is 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 (l, s_l, f_l, e_l, e_l'), where l is the index for EV, s_l is the starting time, f_l is the desired finishing time, e_l is the initial SOC of the battery and e_l' is the desired SOC after charging. The maximum allowed charging time is then $R_l = f_l - s_l$ for EV l, any delay in charging should not exceed this limit, which we define as the *charging deadline*.

B. Queuing Model

For system faciliated with renewable energy supply, aggregator is responsible to efficiently allocate the renewable energy to each EV so that the total cost for purchasing extra energy is minimized, which involves optimal scheduling of EV charging and importing extra energy (from the grid or other non-renewable energy sources). Inspired by the model in Neely's work [15], we formulate our problem based on a queuing model and propose an energy allocation and scheduling algorithm that does not require priori knowledge of the statistical behavior of the renewable energy generation, EV charging request or prices of extra energy.

In this work, we consider a fleet of EVs charged by a single renewable energy generation plant with the grid as an extra energy source. 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. We assume no energy storage in the system, so the renewable energy output will either be utilized or dumped (when there are no sufficient charging demand). In timeslot t, when the renewable energy is not sufficient to charge EVs before their deadlines, an amount of extra energy $x(t) - s(t)$ from the grid will be purchased at an electricity price $\gamma(t)$, where $x(t)$ is the energy consumption by EVs during timeslot t. We also have no information on the 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, 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 during timeslot t, Eqn. (2), where N is the number of EVs; $a_l(t)$ is the arriving energy demand of EV l during timeslot t.

$$a(t) = \sum_{l=1}^{N} a_l(t) \tag{2}$$

The value of $a_l(t)$ 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 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 communicaiton. For example, if an EV needs 7 kWh to fully charge, while the charging rate limit is 4kWh/timeslot, the EV needs at leat 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 l, it generates the energy demand $a_l(t)$ as shown in Eqn. (3).

$$a_l(t) = \begin{cases} P_{max}, & s_l \le t < \left\lfloor \dfrac{e_l' - e_l}{P_{max}} \right\rfloor + s_l; \\ \mathrm{mod}(\dfrac{\mathrm{e_l' - e_l}}{\mathrm{P_{max}}}), & t = \left\lfloor \dfrac{e_l' - e_l}{P_{max}} \right\rfloor + s_l; \\ 0, & \text{otherwise}; \end{cases} \tag{3}$$

Since EV users choose different charging deadlines to fulfill their charging tasks, which results in different acceptable delay times R_l, we need to use multiple queues for different R_ls. We assume there are G values of R_ls, 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_l from $\{$4 timeslots, 5 timeslots, $\cdots$, 12 timeslots $\}$. Then there are 9 queues with R_g ranging from 4 to 12. We modify our queue envolving equation into mult-queue envolving equations, Eqn. (4).

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

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

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

III. Energy Efficient Charging Scheduling

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

$$0 \leq s(t) \leq s_{max}, 0 \leq a(t) \leq a_{max}, 0 \leq \gamma(t) \leq \gamma_{max}, \forall t \quad (6)$$

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

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

subject to:

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

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

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

where constraints (8) guarantee that all the queues are stable, where $\overline{Q_g}$ denotes the average value of Q_g; constraint (9) sets a limit on the maximum energy consumption; constaints (10) impose limit on the average charging task delay times.

A. Delay-aware virtual queue

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

$$Z_g(t+1) = Z_g(t) + \eta \frac{Q_g(t)}{R_g} + a_g(t) - x_g(t); \forall g, t. \quad (11)$$

We can see from (11), $Q_g(t)/R_g$ imposes a penalty to the virtual queue backlog whenever the queue backlog is non empty, which ensures that $Z_g(t)$ grows whenever there are unserved charging tasks in the actual queue. The constant η can adjust the growth rate of the virtual queue, which guarantees queue g has a average delay: $\overline{D_g} \leq R_g/\eta$.

B. Lyapunov Optimization

We define the Lyapunov function as the scalar measue of the congestion in both the $Z_g(t)$ and $Q_g(t)$ queues: $L(\Theta(t)) = \frac{1}{2}\sum_{g=1}^{G}[(Z_g(t)^2 + Q_g(t)^2]$ and the conditional Lyapunov drift as $\Delta(\Theta(t)) = \mathbb{E}\{L(\Theta(t+1)) - L(\Theta(t))|\Theta(t)\}$. Considering both the charging cost (7) and queue backlog growth, our objective is then to minimize the following function in each timeslot t, (12).

$$\min_{x_g(t)} \{\Delta(\Theta(t)) + V\,\mathbb{E}\{\gamma(t)\{\max[x(t) - s(t), 0]\}|\Theta(t)\} \quad (12)$$

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:

$$\begin{aligned}
&\Delta(\Theta(t)) + V\,\mathbb{E}\{\gamma(t)\{\max[x(t) - s(t), 0]\}|\Theta(t)\} \\
&\leq B + V\,\mathbb{E}\{\gamma(t)\{\max[x(t) - s(t), 0]\}|\Theta(t)\} + \sum_{g=1}^{G}[\eta \frac{Q_g(t)}{R_g}]^2 \\
&+ \sum_{g=1}^{G} Q_g(t)[1 + \eta \frac{Q_g(t)}{R_g}]\,\mathbb{E}\{a_g(t) - x_g(t)|\Theta(t)\} \\
&+ \sum_{g=1}^{G} Z_g(t)\,\mathbb{E}\{\eta \frac{Q_g(t)}{R_g} + a_g(t) - x_g(t)|\Theta(t)\}
\end{aligned} \quad (13)$$

where the constant B is defined as:

$$B = \frac{x_{max}^2 + a_{max}^2}{2} + \frac{\max[x_{max}^2, a_{max}^2]}{2} \quad (14)$$

C. Real-time Optimization Algorithm

Using the Basic Property discussed in [7] we conclude that in order to minimize (12) in each timeslot, the bound in the right-hand side of drift-plus-penalty bound (13) should be minimized, leading to the following real-time dynamic optimization algorithm, which can be solved iteratively during each timeslot t:

Step 1, optimization:

$$\begin{aligned}
\min_{x_g(t)} \quad & V\gamma(t)\{\max[x(t) - s(t), 0]\} \\
& + \sum_{g=1}^{G}(1 + \frac{\eta}{R_g})Q_g(t)[a_g(t) - x_g(t)] \\
& + \sum_{g=1}^{G} Z_g(t)[\eta \frac{Q_g(t)}{R_g} + a_g(t) - x_g(t)] \\
\text{subject to} \quad & x_g(t) \geq 0, \forall g.
\end{aligned} \quad (15)$$

Since $Z(t), Q(t), s(t), a(t), \gamma(t)$ are all observed values, the above problem formulation can be converted to a easier to solve form, with $y(t)$ as the auxilary variable:

$$\begin{aligned}
\min_{x_g(t)} \quad & V\gamma(t)y(t) - \sum_{g=1}^{G}[Q_g(t)(1 + \frac{\eta}{R_g}) + Z_g(t)]x_g(t) \\
\text{subject to} \quad & x_g(t) \geq 0, \forall g; \\
& y(t) \geq x(t) - s(t); \\
& y(t) \geq 0.
\end{aligned}$$

Step 2, update:

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

D. Dynamic Algorithm Solutions

The solution for (15) at timeslot t can be obtained by the following steps:

1) Sort the queues based on $Q_g(t)(1+\frac{\eta}{R_g})+Z_g(t)-V\gamma(t)$ in descending order.
2) $\forall g, Q_g(t)(1+\frac{\eta}{R_g})+Z_g(t)-V\gamma(t) > 0$, assign the maximum possible charging rate to $x_g(t)$.
3) $\forall g, Q_g(t)(1+\frac{\eta}{R_g})+Z_g(t)-V\gamma(t) \leq 0$, 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 $t+1$.

IV. Simulation Results

In the simulation, we simulate on data sets with 10-mininute timeslot interval and use wind energy as renewable energy source. The charging period is 24 hours, which means 144 timeslots. Real wind speed data are taken from [19] and are converted to wind energy generation with 10-mininute 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. Extra energy from the grid is purchased at 10-minute average real-time market prices $\gamma(t)$ for the Capital area from New York Independent System Operator (NYISO) [16].

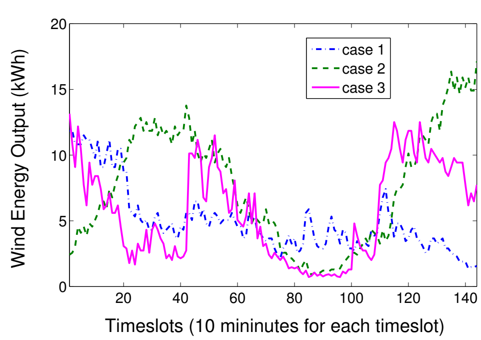

Fig. 1. The wind turbine energy generation

200 charging tasks were generated for a scheduling period from 12pm (noon) to 12pm in the next day to simulate the overnight EV charging. To reflect the real-life commute pattern [6], we used Gaussian distributions to model vehicles' travel pattern, and generate the EV arrival (starting) and departure (finishing) times. Specifically, the starting times s_i follow a normal distribution with a mean of μ = 6pm and a standard deviation of σ = 2 hours; the desired finishing times f_i follow a normal distribution with μ = 7am and σ = 2 hours; and the daily travel distances follow a lognormal distribution with μ = 3.22 miles and σ = 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 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. 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 algorithms, three scenarios are considered for simulations, each tested with three cases. The first two scenarios use simple greedy algorithms. In the first scenario, the aggregator deploys a "charge-upon-arrival" strategy. The aggregator charges each connnected 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", which tries to use all the available wind energy $s(t)$ at timeslot t and only buys from the real-time electricity market when the deadline approaches. Lyapunov optimization algorithm is used in the third senario with a balance between delay time and charging cost, where η is set to 2, V set to 1000.

A. Performance on charging cost

Fig. 2 shows the charging cost of different scenarios for each cases. From the results, we can see Lyapunov optimization achieve the minimum charging cost among the three scenarios, the average charging cost reduces by 78% compared with scenario 1 and 33% with scenario 2. Lyapunov optimization enables the aggregator to purchase extra energy at relative lower price, while "charge-upon-arrival" and "purchase-at-deadline" may result in purchasing extra energy at times when electricity price is high. The reason case 2 gives lower charging costs than the other two cases is that the renewable energy is more sufficient in case 2 during the charging period than the other two cases (Fig. 1).

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 65% on average. To have a better insight about the impact of

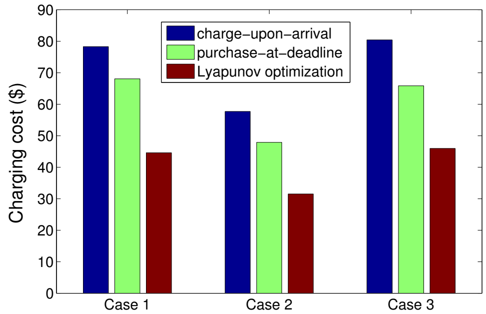

Fig. 2. Comparison of charging cost in different scenarios

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	14.22
2	38.47	15.61
3	52.32	18.75

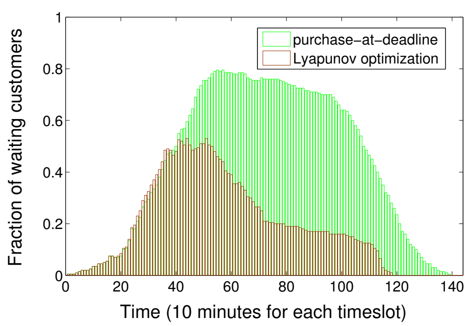

Fig. 3. Histogram of fraction of customers waiting in the service queues in different scenarios

V. CONCLUSION

In this paper, we present Lyapunov optimization for EV charging scheduling problems, with the objective of efficient utilization of renewable energy and reducing charging cost. Multi-queue model is used to cooperate different deadlines and packaging technique for charging rate limit. It is shown by simulation results, based on real electricity price and renewable energy data, that the charging cost can be reduced by 78% and 33% on average compared to two greedy approaches: "charge-upon-arrival" and "purchase-at-deadline" respectivley, and the mean delay time can be reduced by 65% as compared to the "purchase-at-deadline" approach. Moreover, since the proposed charging scheduling schemes based on Lyapunov optimization does not require the statistics of underlying processes, such as future renewable energy generation, real-time electricity price and charging demand, it can be applied when the aggregator has no such prior knowledge, while other optimization methods which require those pieces of information, such as dynamic programming or robust optimization, will be unable to do the calculation.

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