Optimal Charging Control for Electric Vehicles in Smart Microgrids with Renewable Energy Sources

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***Abstract*—There is growing interest in plug-in electric vehicles (EVs). Charging EVs from smart microgrids fueled by renewable energy resources is becoming a popular green approach. Although some works have been done about renewable energy sources and EVs in smart microgrids, the stochastic characteristics and the dynamic interplay between these two important green solutions should be carefully considered. In this paper, we study the charging policies in smart microgrids with EVs and renewable energy sources. Based on the renewable energy sources states, battery states, and the number of charging EVs, an optimal charging policy is obtained to maximize the energy utilization with service availability constraints. We formulate the optimal charging problem as a stochastic decision process. Simulation results are presented to show that the proposed scheme can improve the service availability for EVs in microgrids fueled by renewable energy sources.**

I. Introduction

The use of renewable energy sources for the production of electric energy can contribute significantly to the reduction of GHG emissions [1]. Therefore, to achieve the goal of GHG emission reductions, it is highly desirable for the plug-in electric vehicles (EVs) to use the electric energy from renewable energy sources.

Since most renewable energy sources are scattered in different locations and intermittent in nature, it is a challenging task to integrate a significant portion of renewable energy recourses into the power grid infrastructure, which needs to have means of effectively coordinating energy demand and generation [2]. Although there are some recent developments in *smart grid* to facilitate the integration of renewable energy sources into the grid [3], such integration could take many years to fully implement, and could inevitably result in a new electric supply risk on a significantly large scale associated with the security of the supply infrastructure [4].

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Alternatively, *smart microgrids* fueled by renewable energy resources are becoming a popular green approach [5]. Like the bulk power grid, smart microgrids generate, distribute, and regulate the flow of electricity to consumers, but do so locally. For example, photovoltaic (PV) panels can be easily deployed on the roof top and facades of buildings.

Although some works have been done about renewable energy sources and EVs [6]–[8], the dynamic inter-play between these two important green solutions merits further research, especially in a microgrid. Particularly, most existing works assume that either the supply (from the renewable energy sources) or the demand (from the EVs) is random and another one is constant. However, renewable energy sources are highly intermittent in nature, and EVs arrive at the microgrid randomly. Therefore, the stochastic characteristics of both renewable energy sources and EVs should be carefully considered. Furthermore, one of the important performance metrics, service availability for EVs, is largely ignored in the existing models. Given the fact that there is limited energy produced by the intermittent renewable energy sources at a specific time, guaranteeing service availability for arriving vehicles is one of the most important issues for the EVs power supply system with renewable energy sources.

In this paper, we study the charging policies in smart microgrids with EVs and renewable energy sources. Based on the renewable energy sources states, battery states, and the number of charging EVs, an optimal charing policy is obtained to maximize the energy utilization with service availability constraints. We formulate the optimal charging problem as a stochastic semi-Markov decision process (SMDP) [9], which has been successfully used to solve admission control [10] and routing [11] problems, among others. Simulation results illustrate that the proposed scheme can significantly improve the service availability for EVs in microgrids fueled by renewable energy sources.

The rest of this paper is organized as follows. Section II presents the smart microgrid fueled by renewable energy sources. Section III presents the proposed optimal charging policy. Numerical results are presented and discussed in Section IV. Finally, we conclude this study in Section V.

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II. A Smart Microgrid Fueled by Renewable Energy Sources for Charging Plug-in Electric Vehicles

For simplicity of presentation, we only consider a photovoltaic panel as the renewable source in our model. It is straightforward to extend our model with other renewable sources, such as wind, and hydro. Moreover, we assume that no electricity from traditional power grid is connected to this microgrid to achieve zero GHG emission target. In this system, the randomly arrived EVs can be charged by the photovoltaic panel or the battery bank. The total number of vehicles that can be charged by the photovoltaic panel is limited by the solar radiation conditions. When the power produced at the current solar radiation condition is more than the power needed to charge the arrived vehicles connected to photovoltaic panel, the remaining power will be put into the battery bank, which can be used to charge EVs when the solar radiation condition is not good enough. There are several classes of EVs in the system, each class with different charing capacity and quality of service requirements (e.g., emergency vehicles will need higher service availability). When a vehicle arrives at the charging spot, it will communicate with the control center and report its vehicle class. Then, the control center decides which source will be used to charge the vehicle based on the current solar radiation and battery conditions.

Markovian models for solar radiation have been successfully used in climatology. In this paper, we adopt the continuous-time Markov chain model described in [12] for solar radiation. The intensity of solar power is affected by the thickness of the clouds and wind speed S_w. The cloud size is assumed to be exponentially distributed with mean c_r, and it results in the solar radiation state e_r. The solar radiation state is partitioned into V discrete levels, $R_0, R_1, R_2, ..., R_{V-1}$. State $e_r = R_0$ corresponds to the case that clouds block sunlight, and the photovoltaic panel has no energy output. State $e_r = R_{V-1}$ corresponds to the case that there is no cloud blocking sunlight, and the photovoltaic panel has the maximum energy output. Given that the transitions among the solar radiation states are sequential and circular, the infinitesimal generator matrix corresponding to the continuous-time Markov chain representing the evolution of solar radiation states can be expressed as

$$\begin{pmatrix} -\frac{S_w}{c_1} & \frac{S_w}{c_1} & & & \\ & -\frac{S_w}{c_2} & \frac{S_w}{c_2} & & \\ & \cdots & \cdots & & \\ & & -\frac{S_w}{c_{R-1}} & \frac{S_w}{c_{R-1}} & \\ \frac{S_w}{c_R} & & & -\frac{S_w}{c_R} & \end{pmatrix}, \tag{1}$$

where $\nu_r = \frac{S_w}{c_r}$ is the variation rate between solar radiation states. The current power generated from the photovoltaic panel is p_s, which is directly related to the current solar radiation state e_r.

The battery state is partitioned into L discrete levels, $E_0, E_2, ..., E_{L-1}$. The battery state at a specific time is $e_b \in \{E_0, E_2, ..., E_{L-1}\}$. When $e_b = E_0$, the battery is completely depleted and needs recharging. When $e_b = E_{L-1}$, the battery is fully charged.

We consider a lithium battery in which a linear battery model is assumed. In the model, the remaining battery capacity is expressed as follows.

$$e_b^{'} = e_b - \int_{t_0}^{t_0+t} I(t_0)dt, \tag{2}$$

where $e_b^{'}$ is the next capacity after time t, and $I(t_0)$ is the instantaneous current consumed by the circuit at time t_0. $I(t_0) > 0$ when the battery is discharging, and $I(t_0) < 0$ when the battery is charging.

Due to the *relaxation effect*, when the battery is discharged, the active material is replaced at the electrode-electrolyte interface by new material that moves from the electrolyte to electrode through diffusion effect. Without any current discharge, the probability of recovery of battery capacity depends on the remaining capacity and can be approximated as follows [13],

$$P_{rx}(e_b) = \begin{cases} e^{-g(E_{L-1}-e_b)-\beta(e_b)}, & e_b < E_{L-1}, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

where $\beta(e_b)$ is a staircase function that decreases as the remaining capacity of the battery increases, g is a constant that depends on the battery discharge process.

Based on the linear battery model and relaxation effect, the transition probability that the battery state transitions from e_b to $e_b^{'}$, $P_{e_b,e_b^{'}}$, can be derived as follows.

When $I(t_0) > 0$, i.e., the battery is discharging,

$$\begin{cases} P_{E_l,E_{l+1}} = 0, \\ P_{E_l,E_{l-1}} = \frac{I(t_0)*t}{\Delta(E_l,E_{l-1})} + P_{rx}(E_l), \\ P_{E_l,E_l} = 1 - P_{E_l,E_{l-1}}. \end{cases} \tag{4}$$

When $I(t_0) \leq 0$, i.e., the battery is charging,

$$\begin{cases} P_{E_l,E_{l+1}} = \frac{-I(t_0)*t}{\Delta(E_l,E_{l+1})} + P_{rx}(E_{l+1}), \\ P_{E_l,E_{l-1}} = 0, \\ P_{E_l,E_l} = 1 - P_{E_l,E_{l+1}}. \end{cases} \tag{5}$$

In the above equations, t is the mean time between two state transitions, and $\Delta()$ is the battery capacity difference between two battery states.

III. The Optimal Charging Policy

We assume there are J classes of vehicles in the system. Class $j, j = 1, 2, ..., J$, vehicles arrive at the charging spot according to a Poisson distribution with the rate of λ_j. The charging time for class j vehicles is exponentially distributed with the mean $1/\mu_j$. The probability that the class j vehicles cannot be charged is taken as the metric for service availability. It shall be kept as low as possible.

A. System States

We define the system state as

$$x = [p_s, e_b, n_s, n_b], \tag{6}$$

where p_s is the current power from the photovoltaic panel, e_b is the current remaining battery energy, n_s and n_b are the current numbers of vehicles being charged by the photovoltaic panel and battery, respectively. n_s and n_b are defined as follows.

$$n_s = \left\{[n_{js}] \in Z_+^J, j \in \{1, ..., J\}\right\}, \tag{7}$$

$$n_b = \left\{[n_{jb}] \in Z_+^J, j \in \{1, ..., J\}\right\}, \tag{8}$$

where n_{js} and n_{jb} denote the numbers of class j vehicles that are currently being charged by the photovoltaic panel and battery, respectively.

B. Decision Epochs and Actions

The natural decision epochs are the arrival instances of the vehicles. However, each time when a vehicle departure occurs, or the solar radiation state and battery state changes, the state of the system also changes. Therefore, we choose the decision epochs as the set of all the vehicle arrival and departure instances, as well as the instance that the solar radiation state and battery state change. Let $t_0 = 0$, the decision epochs are taken to be the instances $t_n, (n = 1, 2, ...)$. At each decision epoch t_n, the control center makes a decision for each vehicle arrival that may occur during the time interval $(t_n, t_{n+1}]$, which is defined in (**??**).

For a given state in the state space, $x \in X$, a selected action should not result in a transition to a state that is not in X. In addition, action $[0]$ should not be the only possible action when there is no vehicle in the system. Otherwise, no vehicle will be charged, and the system cannot evolve. Therefore, the feasible action space of a given state $x = (p_s, e_b, n_s, n_b) \in X$ is defined as:

$$\begin{aligned} A_x = \{[a_1, a_2, ..., a_J] \in A :& \\ a_j \neq -1 \text{ if } (p_s, e_b, n_s + \theta_j, n_b) \notin X,& \\ a_j \neq 1 \text{ if } (p_s, e_b, n_s, n_b + \theta_j) \notin X,& \\ a_j \neq 0, \text{ if } n_s = \{0\}^J \text{ and } n_b = \{0\}^J, j = 1, ..., J\},& \end{aligned} \tag{9}$$

where $\theta_j \in \{0, 1\}^J$ denotes a vector containing only zeros except for the j component, which is 1. $n_s + \theta_j$ corresponds to an increase of the number of class j vehicles being charged from the photovoltaic panel. $n_b + \theta_j$ corresponds to an increase of the number of class j vehicles being charged from the battery by 1.

C. State Dynamics and Reward

The state dynamics of this system can be characterized by the state transition probabilities of the embedded chain $P_{xy}(a)$ and the expected sojourn time $\tau_x(a)$ for each state-action pair. $P_{xy}(a)$ can be defined as the probability that at the next decision epoch the system will be in state y if action a is selected at the current state x, while $\tau_x(a)$ is the expected time until the next decision epoch after action a is chosen at the present state x.

According to the solar radiation model, the solar radiation process can be modeled as a continuous time Markov chain. Given the current state $x = (p_s, e_b, n_s, n_b)$, the time the solar radiation state stays in a specific state is exponentially distributed with a mean of $1/\nu_{p_s}$, where ν_{p_s} is the solar radiation state variation rate that depends on the current clouds thickness and wind speed. For the battery model, we assume that battery state stays in a specific state is exponentially distributed with a mean of $1/\kappa_{p_s,e_b,n_s,n_b}$, which is dependent on the current sub-state p_s, e_b, n_s, and n_b.

We assume the vehicle arrivals and departures are mutually independent Poisson processes, the cumulative event rate is the sum of the rates for all constitution processes, i.e., the resulting process consists of a vehicle arrival process with rate $\sum_{j=1}^{J} \lambda_j$, a vehicle departure process with rate $\sum_{j=1}^{J} \mu_j(n_{js} + n_{jb})$, a solar radiation process with rate ν_{p_s}, and a battery state variation process with rate κ_{p_s,e_b,n_s,n_b}. The expected sojourn time is the inverse of the event rate.

$$\tau_x(a) = \left[\sum_{j=1}^{J} \lambda_j |a_j| + \sum_{j=1}^{J} \mu_j(n_{js} + n_{jb}) + \nu_{p_s} + \kappa_{p_s,e_b,n_s,n_b}\right]^{-1} \tag{10}$$

We can use the decomposition property of a Poisson process to derive the transition probabilities: an event of certain type occurs (e.g., class j vehicle arrival) with a probability equal to the ratio between the rate of that particular type of event and the total cumulative event rate $1/\tau_x(a)$. Therefore, the state transition probability of the embedded chain from $x = (p_s, e_b, n_s, n_b)$ to $y = (p_s^{'}, e_b^{'}, n_s^{'}, n_b^{'})$, $P_{xy}(a)$, is shown as $P_{xy}(a) =$

$$\begin{cases} \lambda_j \delta(a_j) \tau_x(a), & \text{if } n_s^{'} = n_s + e_{js}, \\ \lambda_j \delta(-a_j) \tau_x(a), & \text{if } n_b^{'} = n_b + e_{jb}, \\ \mu_j n_{js} \tau_x(a), & \text{if } n_s^{'} = n_s - e_{jk}, \\ \mu_j n_{jb} \tau_x(a), & \text{if } n_b^{'} = n_b - e_{jb}, \\ \nu_{p_s} \tau_x(a), & \text{if } p_s^{'} \text{ and } p_s \text{ are neighboring states}, \\ \kappa_{p_s,e_b,n_s,n_b} \tau_x(a), & \text{if } e_b^{'} \text{ and } e_b \text{ are neighboring states}, \\ 0, & \text{otherwise}, \end{cases} \tag{11}$$

where $\delta(x)$ is defined as follows.

$$\delta(x) = \begin{cases} 0, & \text{if } x \leq 0, \\ 1, & \text{if } x > 0. \end{cases} \tag{12}$$

The expressions (10) and (11) can be explained as follows: if $x(t_n) = x$ and $a(t_n) = a$, the new state $x(t_{n+1})$ and sojourn time in the current state, i.e., $t_{n+1} - t_n$, are determined by a composition of independent Poisson processes. The resulting process consists of one departure process with rate μ_j for each vehicle class j, an arrival process with rate λ_j if action a charge a class j vehicle, a solar radiation process with a radiation state variation rate ν_{p_s}, and a battery state variation process with state variation rate κ_{p_s,e_b,n_s,n_b}.

D. Policy

Let U denote the charing policy, which is defined as follows:

$$U = \{\widetilde{u} : X \to A | \widetilde{u}(x) \in A_x, \forall x \in X\}. \tag{13}$$

Given any $\widetilde{u} \in U$, the vehicle charging process is performed as follows: For interval $(t_n, t_{n+1}]$, the action is chosen as $a(t_n) = \widetilde{u}(x(t_n))$.

E. Performance Criterion

We consider the average reward criterion in our study. Given a reward function

$$r : X \times A \longrightarrow R. \tag{14}$$

The performance criterion is given as follows: For any $\widetilde{u} \in U$ and $x_0 \in X$, define

$$J_{\widetilde{u}}(x_0) = \lim_{T\to\infty} \frac{1}{T} E\left\{\int_0^T r(x(t), a(t))dt\right\}, \tag{15}$$

where $a(t) = \widetilde{u}(x(t_n))$ for $t \in [t_n, t_{n+1})$, and $x(0) = x_0$. The aim is to compute the optimal policy $\widetilde{u}^* \in U$ which satisfies

$$J_{\widetilde{u}^*}(x_0) = \max_{\widetilde{u}\in U} J_{\widetilde{u}}(x_0), \tag{16}$$

for all $x_0 \in X$, i.e., $\widetilde{u}^*$ has the maximum reward for all initial states.

We now state the form of the function $r(x(t), a(t))$ corresponding to the charing policy $\widetilde{u}$ given by $J_{\widetilde{u}}(x_0)$ in (15). The objective is to construct an optimal charging policy that minimizes the probability that vehicles cannot be charged.

Singh et al. [12] show that the blocking probability can be expressed as an average cost criterion in the CAC setting. Similarly, Authors of [10] show that the admission probability (1-blocking probability) can be expressed as the average reward criteria to maximize the network utilization of wireless cellular networks. Here, we use the vehicle admission probability as the average reward. Based on the action $a(t)$ taken in a state $x(t)$, a reward $r(x(t), a(t))$ occurs in the system. The reward related to $a(t)$ can be expressed as $w_j^s\delta(a_j) + w_j^b\delta(-a_j)$, where w_j^s is the weight associated with class j vehicles charged by the photovoltaic panel, and w_j^b is the weight associated with class j vehicles charged by the battery. The objective is to construct a charging control policy that maximizes the long-run average energy utilization. Therefore, the reward for state-action pair $r(x(t), a(t))$ can be expressed as follows.

$$r(x(t), a(t)) = \sum_{j=1}^{J}(w_j^s\delta(a_j) + w_j^b\delta(-a_j)). \tag{17}$$

An SMDP can be solved using algorithms such as policy iteration, value iteration, and linear programming. Similar to [10], we choose to use the linear programming techniques because linear programming formulation has a nice feature (which is not available with policy iteration or value iteration) for solving an SMDP problem.

IV. Numerical Results and Discussions

In this section, numerical examples are used to illustrate the performance of the proposed charing policy. We compare the proposed policy with the other two heuristic policies. In addition, the obtained optimal policy is presented in this section. For simplicity of simulations and presentation, we consider 2 battery states and 2 solar radiation states in the smart microgrids, and there are two classes of vehicles in the system, among which 40% of the vehicles belong to class I. Following [14], we consider that these two classes of vehicles are designed to achieve a range of 120km and 160km, and the corresponding required energy for the two classes of vehicles are 15kwh and 20kwh, respectively.

We specify two metrics to evaluate the performance of our proposed charing policy. The first metric is the probability P_j^b that the newly arrived class j vehicles cannot be charged due to the lack of enough energy, which is also the metric that we take as service availability in Section III. We denote it as vehicle charging blocking probability. The second metric is the average reward, which is defined in (17).

Fig. 1 gives the system average reward under different reward ratios between charging by the battery and charging by the photovoltaic panel. We assign different reward weights to charging sources. This is because some energy will be lost when the vehicles are charged by batteries due to battery efficiency. Therefore, the reward ratio between charging by the battery and charging by the photovoltaic panel can be approximately considered as the battery efficiency. SMDP policy gives the highest average reward under all different reward ratios. In addition, it can be seen that the lower the reward ratio, the higher the reward gain obtained in the SMDP policy. This is because the SMDP policy can optimally admit more vehicles to the photovoltaic panel when the reward provides by the photovoltaic panel is higher.

In order to make it clear what the optimal policy looks like, next we will give an example to illustrate the obtained optimal policy. The SMDP optimal policy is numerically computed by implementing the linear programming algorithm. In our optimal charging policy, the state space S has 6 dimensions. To present the optimal policy clearly, four

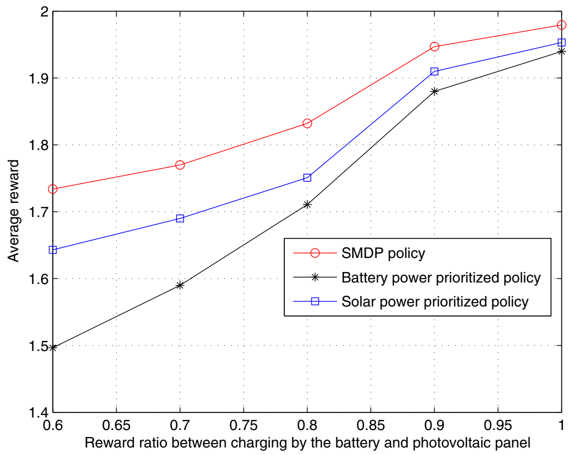

Fig. 1. The effect of the reward ratio between charging by the battery and charging by the photovoltaic panel on average reward.

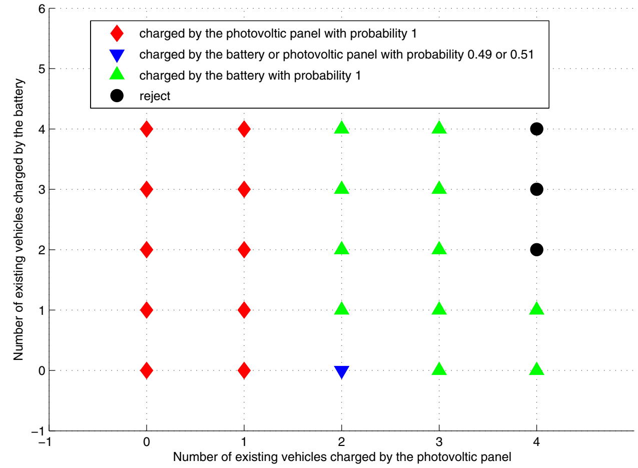

Fig. 2. Optimal policy for class I vehicles. (The solar radiation and battery state are fixed in state 2; There are no class II charging vehicles.)

dimensions need to be fixed to specific values. We fix the solar radiation and battery states in our example, and they are both considered to be in state 2. The number of existing class II vehicles being charged is considered to be zero. Fig. 2 illustrates the obtained policy for class I vehicles. The service availability ($P_j^b \leq 3\%$) constraint is set for class I vehicles. We can see that, when there are two vehicles being charged by the photovoltaic panel and no vehicles are being charged by the battery, the optimal policy is a randomized policy, which means that a newly arrived class I vehicle will be charged by the photovoltaic panel or the battery, with probabilities 0.49 and 0.51, respectively. This randomized policy is due to the service availability constraint. By contrast, in other states, a newly arrived vehicle will be rejected or charged by different sources with probability one.

V. Conclusions

In this paper, we have studied the charging policies in smart microgrids with electric vehicles (EVs) and renewable energy sources. We considered the stochastic characteristics of both intermittent renewable energy sources and EVs. The system is modeled as a continuous time Markov Chain. We have formulated the optimal charging problem as a stochastic semi-Markov decision process with the objective of maximizing the energy utilization with service availability constraints. Linear programming is used to obtain the optimal charging policy.

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