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Stochastic Coordination of Aggregated Electric Vehicle Charging With On-Site Wind Power at Multiple Buildings*

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***Abstract*— The development of renewable energy has been recognized as a promising resolution to fuel depletion and excess carbon emission. However, the utilization of renewable energy is far less than satisfactory due to the inherent uncertainty. The rapid development of electric vehicles (EVs) provides new opportunities to balance volatile renewable generation. Nowadays, modern technology advances allow to mount on-site wind power generators on the buildings. Considering that EVs are usually parked in buildings, the problem to coordinate EV charging with locally generated wind power of buildings shows various significance. Therefore, we investigate this important problem and three contributions are made. First, we formulated it as an EV-based multiagent Markov decision process (MMDP), which incorporates the uncertain wind power supply at different buildings and the random driving requirements of EVs. Second, to alleviate curses of dimensionality associated with the number of EVs, we developed an EV aggregation framework, which dynamically groups EVs into EVAs (electric vehicle aggregator) based on their remaining parking time and locations. And an EVA-based MMDP is derived. Third, scenario-tree based dynamic programming (TSP) is introduced to incorporate the multiple uncertainties in the problem. And the performance of this method is demonstrated by a number of case studies.**

***Index Terms*— Electric vehicles (EVs), building mounted wind power, Multiagent Markov decision process, scenario tree**

I. INTRODUCTION

The development of renewable energy, such as wind power, has been recognized as a promising resolution to fuel depletion and excess carbon emission. However, the utilization of renewable energy is still far less than satisfactory due to the inherent uncertainty [1]. Over the decades, electric vehicles (EVs) have gained popularity worldwide due to economical and environmental concerns [2]. On one hand, the rapid growth of EVs will produce nonnegligible impacts on the electric grid if not properly controlled [3], on the other hand, it brings new opportunities to balance volatile renewable generation due to their charging flexibility. Nowadays, modern technology advances have created conditions to mount on-site wind power generators on the buildings. The huge number of high-rise buildings, especially in cities, reveals great potential to fully explore wind power in the built environment [4]. Considering that EVs are usually parked in the parking lots of buildings for long time periods, the issue to coordinate EV charging with the locally generated wind power of buildings shows various significance. On one hand, the variation of wind power can be regulated by shifting flexible EV charging demand to periods with sufficient wind power supply, on the other hand, the charging demand of EVs can be partially supported by wind power thus reducing the impacts on the electric grid.

However, there exists multiple difficulties. *First*, there exist multiple randomness due to the uncertain wind power supply at the buildings and the random driving behaviors of EVs. *Second*, the problem is a multi-stage decision problem. The charging demand of each EV should be accomplished during their parking duration to satisfying the travel requirements. *Third*, there exist multiple curses of dimensionality due to the potentially large number of vehicles.

In the literature, much endeavor has been made to investigate the coordination of EV charging with renewable energy. For example, Wu et at. [5] developed three heuristic dispatching approaches for EVs based on the prediction of wind generation to improve matching of energy consumption and wind supply. Besides, the technique of model predictive control (MPC) has been widely employed to deal with the uncertainties [6], [7]. The main idea of this approach is to make decisions at each stage based on prediction information over a predefined future horizon. The above approaches are advantageous in computation, however, their performance usually depends on the accuracy of predictions. Multistage stochastic programming (MSP), which makes use of scenarios to represent dynamics of stochastic variables is also common in tackling EV charging problems [8]. However, the number of scenarios usually increase exponentially with the number of EVs to capture the uncertainties. Markov decision process (MDP), which takes advantage of Markov property of system, is another approach adaptable for multistage stochastic problems like EV charging [9], [10]. However, it is usually intractable to find the optimal solution of large scale problems due to the curse of dimensionality.

In this paper, we follow up the existing researches and concentrate on the coordination of EV charging with the locally generated wind power of multiple buildings with the aim to reduce the impacts of EV charging on the power grid. The locally generated wind power at each building can be utilized to charge the vehicles parked there. If not sufficient

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to charge the vehicles in time, the additional electricity purchased from power grids supplements. The problem is discussed in a stochastic framework, which incorporates the stochastic wind generation of buildings and the random driving requirements of EVs. The main contributions of the paper are outlined. *First*, we investigate the problem and formulate it as an EV-based multiagent Markov decision process (MMDP). *Second*, to alleviate the curses of dimensionality associated with the number of EVs, we develop an EV aggregation framework, which dynamically groups EVs into EVAs (electric vehicle aggregator) based on their remaining parking time and locations. And an EVA-based MMDP is derived. *Third*, scenario-tree based dynamic programming (TSP) is introduced to tackle the uncertainties of the problem.

The remainders of this paper are as follows. In Section II, we formulate the problem as a two-layer MMDP. In Section III, TSP approach is introduced. In Section IV, the method is assessed by a number of case studies. In Section V, we briefly conclude this paper.

II. FORMULATION

A. System Descriptions

A typical microgrid [11] is shown in Fig. 1. There are multiple high-rise buildings, building-equipped wind generators and a number of EVs. The EVs are driven among the buildings or parked in the buildings during their idle time. For example, an office worker may drive to work in the morning from a residential building and park the EV in the parking lot of an office building till after work. The driving patterns of EVs are random, which depend on the owners' travel requirements. Considering that wind power has a negligible marginal cost, the on-site wind power of buildings is assumed free to charge EVs parked there. When it is not enough to support the EVs' charging demand in time, the electricity from the power grid can supplement but with cost. In the system, there is a local coordinator corresponding to each building. Besides, an envisioned smart charger, which possesses the ability of communication with the buildings is attached to each individual EV. The EVs are required to report their charging demand (next trip time) and parking duration to the building coordinator upon arrival.

Similar to [12], we assume the EV owners are motivated to register as dispatching load by providing some financial compensation. However, the buildings are contractually obligated to satisfy the travel requirements of the owners. In order to best utilize the local wind power harvested from the buildings to charge the EVs, we select the objective as the minimum of total EV charging cost.

The problem is formulated and discussed in a discrete time framework corresponding to a $\Delta_t = 1$ hour's interval over the optimization horizon T.

B. EV-Based MMDP

We first formulate the problem to coordinate EV charging with locally generated wind power at multiple buildings as a MMDP. MMDPs generalize MDPs to multiagents, which describe sequential decision tasks associated with multiagents

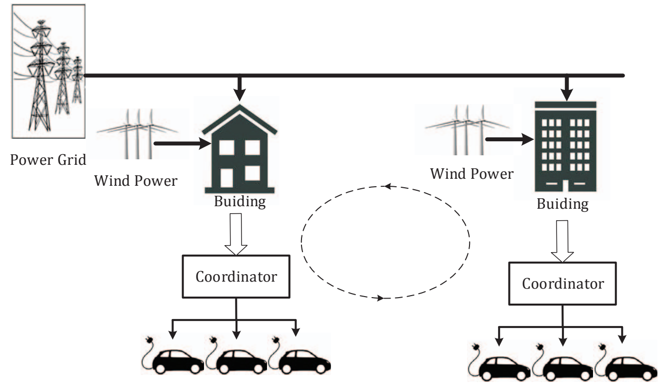

Fig. 1. System Architecture

to jointly achieve a common-owned objective [13]. In this problem, each EV acts as an agent and coordinate with each other to achieve the minimum of the total EV charging cost.

*1) **System States**:* we define the state component associated with EV n as $S_t^n = [L_t^n, E_t^n, D_t^n]$ $(n = 1, 2, ..., N)$, where N is the number of EVs, E_t^n denotes the remaining charging energy to support its next trip, D_t^n denotes its location. In the formulation, we define the location space as $D_t^n \in \mathcal{D} = \{0, 1, ..., M\}$, where $1 \sim M$ correspond to M buildings and $D_t^n = 0$ indicates that EV n is on travel at time t. L_t^n represents the remaining parking tine $(D_t^n > 0)$ or remaining trip time $(D_t^n = 0)$. Besides, we define the state component independent of EV agent as $S_t^0 = [W_t^j]$ $(j = 1, 2, ..., M)$, which represent the wind power generation of each building at time t. Intuitively, the system state for the EV-based MMDP can be described by $S_t = [S_t^0, S_t^n]$.

*2) **Action Space**:* we assume the charging rates of EVs are constant, therefore the problem to schedule EV charging is to decide when to charge the vehicles during their parking durations. A binary vector $A_t = [a_t^n]$ $(n = 1, 2, ..., N)$ can be used to denote the joint charging decisions for the EV agents at time t. We have $a_t^n = 1$, if EV n is selected to get charged at time t, otherwise $a_t^n = 0$.

*3) **System Dynamics**:* the dynamics of state component associated with EV agent n can be described as follows. The remaining parking time $(D_t^n > 0)$ or remaining trip time $(D_t^n = 0)$ for EV n is depicted as

$$L_{t+1}^n = \begin{cases} L_t^n - 1 & \text{if } L_t^n > 0 \\ \tau_{t+1}^n & \text{if } L_t^n = 0, D_t^n = 0 \\ \eta_{t+1}^n & \text{if } L_t^n = 0, D_t^n > 0 \end{cases} \tag{1}$$

where τ_{t+1}^n and η_{t+1}^n are random variables, τ_{t+1}^n represents the possible parking duration of EV n when it arrives at a building at time $t+1$, η_{t+1}^n denotes the trip time for its departure at time $t+1$.

The location transition of EV n is depicted as

$$D_{t+1}^n = \begin{cases} D_t^n & \text{if } L_t^n > 0 \\ R_{t+1}^n & \text{if } L_t^n = 0, D_t^n = 0 \\ 0 & \text{if } L_t^n = 0, D_t^n > 0 \end{cases} \tag{2}$$

where the random variable$R_{t+1}^n \in \{1, 2, ..., M\}$ denotes the building that EV n arrives at time $t+1$.

Accordingly, the dynamics of the remaining required charging energy for EV n are written as

$$E_{t+1}^n = \begin{cases} E_t^n - a_t^n \cdot P \cdot \Delta_t & \text{if } L_t^n \geq 0, D_t^n > 0 \\ E_t^n + f_n(\eta_{t+1}^n) & \text{if } L_t^n = 0, D_t^n = 0 \\ E_t^n & \text{if } L_t^n > 0, D_t^n = 0 \end{cases} \quad (3)$$

where P represents the constant charging rate for EVs. The function $f_n(\cdot)$ describes the relationship between energy consumption of EV n and its trip time. In the discussion, we assume the energy consumption rates of EVs are constant, therefore the required energy for EV n to support its next trip can be calculated as $f_n(\eta^{t+1}) = Q_n \cdot \eta^{t+1}$.

4) ***Constraints****:* as aforementioned, the buildings are obligated to satisfy the travel requirements of EVs, therefore the charging decisions are constrained by

$$E_t^n - a_t^n \cdot P \cdot \Delta_t \leq (L_t^n - 1) \cdot P \cdot \Delta_t, \quad \forall n = 1, 2, ..., N, t = 1, 2, ..., T \quad (4)$$

The constraint (4) implies that the remaining required charging energy can't exceed the maximum possible charging energy during the remaining parking time. This guarantees that the EVs will finish charging before their departure.

Besides, the remaining required charging energy can't exceed EV battery capacities, i.e.

$$E_t^n \leq E_{\text{cap}}, \forall n = 1, 2, ..., N, t = 1, 2, ..., T \quad (5)$$

where E_{cap} represents the battery capacity.

Additionally, the charging processes of EVs are constrained by their parking durations, i.e.

$$a_t^n \leq D_t^n, \forall n = 1, 2, ..., N, t = 1, 2, ..., T \quad (6)$$

The constraint (6) reveals that when EV n is on travel ($D^n = 0$), the EV is impossible to get charged ($a_t^n = 0$).

5) ***Objective Function****:* as aforementioned, the one-step cost for the buildings is to purchase electricity from power grid to supplement surplus EV charging demand, i.e.

$$C_t(S_t, A_t) = \sum_{j=1}^{M} c_t \cdot \max(P_t^j - W_t^j, 0) \cdot \Delta_t \quad (7)$$

where c_t denotes the TOU (Time-Of-Use) price of power grid at time t. $P_t^j = \sum_{n \in \{D_t^n = j\}} a_t^n \cdot P$ is the total charging power of EVs in building j at time t.

Therefore, the multistage stochastic problem to schedule EV charging can be described as

$$\min J(\pi, S_1) = \boldsymbol{E}\Big\{ \sum_{t=1}^{T} \sum_{j=1}^{M} c_t \cdot \max(P_t^j - W_t^j, 0) \cdot \Delta_t \Big\} \quad s.t. (1) - (6) \quad (8)$$

where $\pi = [A_1, A_2, ..., A_T]$ represents the charging policy over the optimization horizon T.

It is not difficult to note that the state and action are high-dimension vectors of size $(M + 3 \times N)$ and N. This implies that both the state and action space will increase exponentially with the number of EVs. To tackle this difficulty, an EV aggregation framework is developed.

C. EVA-Based MMDP

To alleviate the curse of dimensionality of problem (8), we first introduce a vehicle aggregation framework. Specifically, the EVs are dynamically aggregated into electric vehicle aggregators (EVAs) based on their remaining parking time and locations. In other words, at each stage the EVs of the same remaining parking time and location will be aggregated into an EVA. And an EVA-based MMDP is derived.

1) ***System state****:* at time t, the EVs parked in building j with remaining parking time i are aggregated into EVA (i, j) $(i = 1, 2, ..., T_p, j = 1, 2, ..., M)$, where T_p denotes the maximum parking intervals for the EVs. Similarly, we define the state component for EVA (i, j) as $S_t^{i,j} = [L_t^{i,j}, E_t^{i,j}, N_t^{i,j}]$, where $L_t^{i,j} = i$ denotes the remaining parking time, $E_t^{i,j} = \sum_{n \in \text{EVA}(i,j)} E_t^n$ denotes the total remaining charging energy, $N_t^{i,j}$ represents the number of EVs in the EVA.

Also, the EVs on travel are aggregated as EVA (i, j) $(i = 1, 2, ..., T_r, j = 0)$, where the index $j = 0$ denotes the EVs are on travel, T_r represents the maximum parking intervals. The state component for EVA (i, j) is described as $S_t^{i,j} = [L_t^{i,j}, E_t^{i,j}, N_t^{i,j}]$, where $L_t^{i,j} = i$ denotes the remaining trip time for the EVA and $E_t^{i,j} = i$. Besides, we define $S_t^{0,0} = [W_t^j]$ $(j = 1, 2, ..., M)$ (the same as S_t^0) as the EVA independent state component. Thus the system state for EVA-based MMDP is described as $S_t = [S_t^{i,j}]$ $(i = 0, 1, ..., \max(T_p, T_r), j = 0, 1, ..., M)$.

2) ***Action****:* the charging decision for EVA-based MMDP is to determine the number of EVs in each EVA to get charged at each stage. Therefore, the charging decision can be defined as $A_t = [a_t^{i,j}]$ $(i = 0, 1, ..., \max(T_p, T_r), j = 0, 1, ..., M)$, where $a_t^{i,j} = \sum_{n \in \text{EVA}(i,j)} a_t^n$ denotes the number of EVs selected to charge in EVA (i, j) at time t.

3) ***System Dynamics****:* the system dynamics of EVA-based MMDP can be derived from the EV-based MMDP. i.e., for the EVAs (i, j) $(i \geq 1, j = 1, 2, ..., M)$ that are parked in buildings at time $t+1$, we have

$$\begin{aligned} & L_{t+1}^{i,j} = i; \\ & E_{t+1}^{i,j} = E_t^{i+1,j} - a_t^{i+1,j} \cdot P \cdot \Delta_t + E_{t+1}^{i,j,\text{in}} \\ & N_{t+1}^{i,j} = N_t^{i+1,j} + N_{t+1}^{i,j,\text{in}} \end{aligned} \quad (9)$$

where $N_{t+1}^{i,j,\text{In}}$ and $E_{t+1}^{i,j,\text{In}}$ are random variables, $N_{t+1}^{i,j,\text{In}}$ represents the number of EVs that arrives at building j at time t with parking time i, $E_{t+1}^{i,j,\text{In}}$ denotes the remaining required charging energy for those new arrival EVs.

For the EVAs $(i \geq 1, j = 0)$ that will depart from the building at time $t+1$, we have

$$\begin{aligned} & L_{t+1}^{i,0} = i; \\ & E_{t+1}^{i,0} = E_t^{i+1,0} + \sum_{j=1}^{M} E_t^{1,j,\text{out}} \\ & N_{t+1}^{i,0} = N_t^{i+1,0} + \sum_{j=1}^{M} N_t^{1,j,\text{out}} \end{aligned} \quad (10)$$

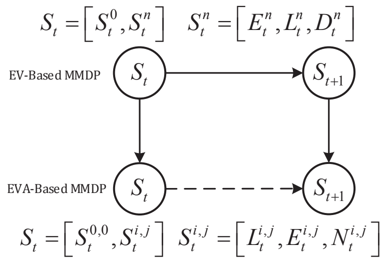

Fig. 2. The relationship of states in the two-layer MMDP

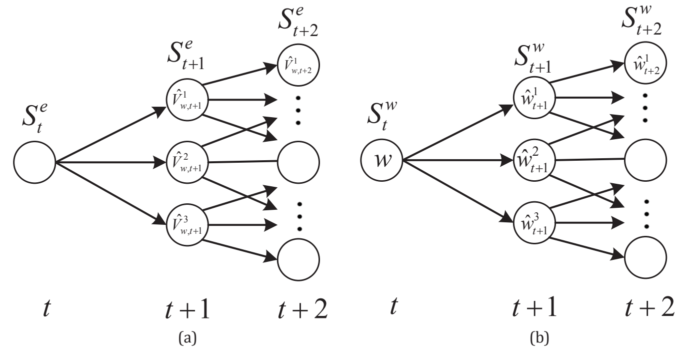

Fig. 3. (a) Scenario tree for EV dependent state components. (b) Scenario tree for wind power of buildings

where $E_t^{1,j,\text{out}}$ and $N_t^{1,j,\text{out}}$ are random variables, $N_t^{1,j,\text{out}}$ represents the number of EVs that departs from building j at time t with trip time i, $E_t^{1,j,\text{out}}$ represents the remaining charging energy for those new departure EVs.

In the literature, there exist a few works concerning the scheduling of EV aggregators [6], [14], however, statistical models are usually employed to describe the dynamics of EVAs. The travel requirements of each individual EV is not addressed. Different from the existed works, we present a two-layer MMDP to schedule EV charging, which can incorporate the random travel requirements for each individual EV. The relationship of the state dynamics in the two-layer MMDP are shown in Fig. 2. At each stage, the dynamics for the aggregated EV charging demand in EVAs can be derived from the EV-based MMDP.

4) ***Constraints****:* to satisfy the travel requirements of EVs, the charging decisions for EVAs should be constrained by

$$E_t^{i,j} - a_t^{i,j} \cdot P \cdot \Delta_t \le N_t^{i,j} \cdot (L_t^{i,j} - 1) \cdot P \cdot \Delta_t, \quad \forall i = 1, ..., T_p, j = 1, ..., M \tag{11}$$

$$N_t^{i,j,\min} \le a_t^{i,j} \le N_t^{i,j}, \forall i = 1, ..., T_p, j = 1, ..., M \tag{12}$$

$$a_t^{i,j} = 0, \forall i = 1, ..., T_r, j = 0 \tag{13}$$

It is easily noted that the constraint (11) is a relaxation of constraint (4), which alone is not enough to guarantee the travel requirements of the EVs. Therefore, another constraint (12) is added, where $N_t^{i,j,\min}$ denotes the minimum number of EVs of EVA (i,j) to get charged at time t, which can be derived from $N_t^{i,j\min} = \sum_{n \in \text{EVA}(i,j)} I(L_t^n \le E_t^n \cdot P \cdot \Delta_t)$, where $I(\cdot)$ is an indicator function, we have $I(A) = 1$ if the condition A is true, otherwise $I(A) = 0$. The constraint (13) implies that the EVs on travel are impossible to get charged.

Accordingly, the charging decisions of EVAs are limited by the battery capacity of EVs, i.e.

$$E_t^{i,j} \le N_t^{i,j} \cdot E_{\text{cap}} \tag{14}$$

5) ***Objective function****:* Similarly, the one-step cost for the buildings to support EV charging is calculated as (7) but with $P_t^j = \sum_{i=1}^{T_p} a_t^{i,j} \cdot P$ denoting the total charging power of EVs parked in building j at time t. Therefore, the problem to schedule charging of EVAs can be described as

$$\min J(\pi, S_1) = \boldsymbol{E}\Big\{ \sum_{t=1}^{T} \sum_{j=1}^{M} c_t \cdot \max(P_t^j - W_t^j, 0) \cdot \Delta_t \Big\} \quad s.t.\ (9) - (14) \tag{15}$$

In (15), the number of EVAs is usually much smaller than the size of EVs, therefore both the state and action space will be greatly reduced by introducing EVAs.

III. Tree-Based Dynamic Programming

It is well acknowledged that dynamic programming (DP) is one of the common approaches adaptable for multistage MDPs with different kinds of objective functions and constraints [15]. The main idea of DP is to find an optimal policy by minimizing the value function of each state, i.e.

$$V(S_t) = \min_{A_t \in \mathcal{A}_t} C_t(S_t, A_t) + \boldsymbol{E}[V_{t+1}(S_{t+1}|S_t)] \tag{16}$$

where $\mathcal{A}_t$ denotes the decision space at time t, which depends on the constraints of the problem, such as (9)-(14).

From (16), we note that the main computation of making decision at each stage based on DP is to enumerate the value functions for all possible states in the future stages. In terms of the EVA-based MMDP, the system space is composed of the random wind power of buildings and the random charging demand of the aggregators. Though the state space has been greatly reduced, it is still time-consuming to enumerate the state space of EVAs. The technique of scenario tree modeling for multistage stochastic problem [16] provides a new resolution to combine DP with scenario trees to explore an approximated optimal solution. Therefore, tree-based dynamic programming (TSP) proposed in [17] is introduced in this part.

The main idea of TSP is to approximate the value function of states based on a scenario tree, which is constructed from a number of scenarios. This approach is advantageous in incorporating the multiple randomness of the problem. Considering that the dynamics of EV charging demand is independent of the local wind power generation, two scenario trees for the EV charging demand and wind power of buildings can be constructed separately, thus reducing the total number of scenarios needed to capture the randomness. An example of scenario tree for wind power of buildings and the EVA charging demand is shown in Fig. 3. The value function based on scenario tree can be estimated as

$$\begin{aligned}\hat{V}_t(S_t) &= \min_{A_t \in \mathcal{A}_t} C_t(S_t, A_t) + \sum_{k=1}^{n_{t+1}} \hat{V}_{t+1}(\hat{S}^k_{t+1}|S_t) \\ &= \min_{A_t \in \mathcal{A}_t} C_t(S^e_t, S^w_t A_t) \\ &\quad + \sum_{l=1}^{l_{t+1}} p(\hat{w}^l_{t+1}) \sum_{k=1}^{n_{t+1}} p(\hat{S}^{e,k}_{t+1}) \hat{V}_{\hat{w}^l_{t+1}, t+1}(\hat{S}^{e,k}_{t+1})\end{aligned} \tag{17}$$

where we use $S^w_t = [S^{0,0}_t]$ and $S^e_t = [S^{i,j}_t]$ to represent wind power of buildings and EVA charging demand. l_{t+1} and n_{t+1} denote the number of nodes for the two scenario trees. The superscript k and l denotes the index of node in the constructed scenario tree and $p(\cdot)$ indicates the transition probability from one node to another.

The details of TSP to deal with the problem of this paper is in **Algorithm** 1. In Step 6, the scenario trees for wind power and the EVAs charging demand can be constructed using backward tree construction proposed in [17]. In Step 7-10, the optimal charging decision for EVAs is determined by TSP method. However, how to select EVs in each EVA to charge is also an important problem. In this paper, the less remaining time (LRT) rule developed in [10] can be employed to address this problem. The main ideas of LRT is that the optimal selection for a set of EVs with same remaining parking time is to choose the vehicles by the remaining required charging energy in the descent order. From Step 2-13, we note that the charging decision at stage t is determined by backward recursion the value functions for the future states in the scenario tree. After the decision at time t is taken, the system will evolve based on the action and exogenous dynamics meanwhile. An sequence of the charging decisions for EVs over the optimization horizon can be attained until the time horizon T is reached.

Algorithm 1 Tree-based Dynamic Programming

1: Initialize the states for EVs S^n_1 $(n = 1, 2, ..., N)$ and wind power of buildings S^0_1.
2: **for** $t = 1, 2, ..., T$ **do**
3: Generate M_w scenarios for wind power of buildings.
4: Generate M_e scenarios for N EVs
5: Aggregate the EVs into EVAs.
6: Construct Scenario trees for wind power and EVAs
7: Initialize $V_T(s) = 0$ $\forall s \in \mathcal{S}_T$
8: **for** $\tau = (T-1), ..., t$ **do**
Estimate $\hat{V}^k_t(\hat{S}^k_t), \ \forall k = 1, 2, ..., n_\tau$ using (17)
9: **end for**
10: Implement decision at time t based on LRT rule
11: Update State in EV-based MMDP at time t
12: **end for**

IV. Case Studies

In this section, a number of case studies are conducted to evaluate the performance of the approach. We consider a microgrid of $M = 2$ buildings with $N = 50$ EVs over the optimization horizon $T = 12$ hours. The probability distribution for EV parking time and trip time is listed in TABLE I. We assume the possible wind power generation of the buildings are the same as $W = [1, 2, ..., 18]$ kW with transition probability $\boldsymbol{P}_{i,i} = 0.167$, $\boldsymbol{P}_{i,j} = 0.049$ $(\forall i, j \in W, j \neq i)$. Though we consider a stationary wind power generation of buildings in the case studies, the approach is adaptable for time-dependent wind power generation. The charging power and energy consumption rate of EVs are set as $P = 1$ kW, $Q_n = 1$ kW/h. The TOU price are assumed as $c_t = 1$ $(t = 1, 2, ..., T)$.

TABLE I
The probability distribution of trip time and parking time

Trip time (hr)	1	2	-
$\boldsymbol{P}$	0.5	0.5	-
Parking time (hr)	4	5	6
$\boldsymbol{P}$	0.25	0.5	0.25

In the case studies, $M_w = 50$ and $M_e = 50$ randomly generated scenarios are used to construct the scenario trees for the local wind power and the EVA charging demand, respectively. To evaluate the performance of the approach, the tree-based dynamic programming is compared with (1) greedy charging policy and (2) MyOpic charging policy.

- Greedy policy: in non-control environment, the EVs are likely to get charged upon arrival until the required charging energy is reached.
- Myopic policy: a one-step stochastic optimization is conducted based on current state to minimize the one-step cost in (7) constrained by (4)-(6) .

The total charging cost of EVs under 50 cases studies (sample paths) are plotted in histograms as Fig. 4. From Fig. 4 (a) and (b), we note that the total charging cost of EVs using myopic policy is apparently reduced compared with greedy policy. The phenomenon result from that the information for the local wind power of buildings is incorporated in myopic policy at each stage. Additionally, from Fig. 4 (a)-(c), we note that the total EV charging cost using TSP are greatly reduced compared with the greedy charging policy and MyOpic policy. This implies that the TSP is effective in improving the coordination of EV charging with uncertain locally generated wind power of buildings.

It is easily noted that the number of scenarios that used to construct the scenario trees may affect the approximation accuracy of the random variables (i.e. wind power generation of buildings, EV charging demand). However, more scenarios will contribute to an increase of computation in estimating the value function. To address this problem, we conduct a number of case studies to generate different number of scenarios to construct scenario trees. The total EV charging cost with $M_e = 50, M_w = 50$ and $M_e = 80, M_w = 80$ scenarios in TSP under 50 cases studies are plotted in Fig. 5. From Fig. 5 (b) and (c), we conclude that the TSP approach

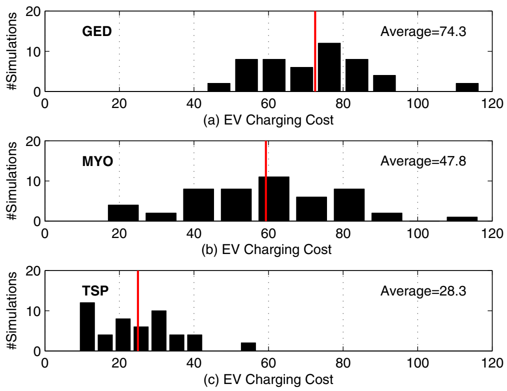

Fig. 4. (a) Greedy charging policy. (b) MyOpic charging policy. (c) Tree-based dynamic programming.

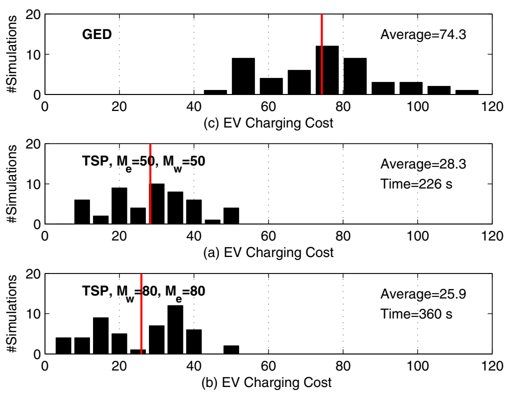

Fig. 5. (a) Greedy charging policy. (b) Tree-based dynamic programming with $M_e = 50$, $M_w = 50$. (c) Tree-based dynamic programming with $M_e = 80$, $M_w = 80$.

for the EV scheduling problem shows better performance with an increasing number of scenarios to construct the scenario tree. The total EV charging cost is reduced by about 8.5% with an increase by 30 scenarios. However, the average total simulation time to make decisions over $T = 12$ hrs is apparently increased by about 38.5%. Therefore, the problem how to choose a proper number of scenarios while ensure a good enough performance of TSP should be interesting problem. Besides, we note that the average simulation time at each stage is about 21.7 s for $N = 50$ EVs, which is much smaller than the 1 hour's interval. Therefore, the TSP method is time-efficient in making decisions and may be extended to a larger scale problem if possible.

V. CONCLUSIONS

In this paper, the problem to coordinate EV charging with locally generated wind power of buildings is investigated. We first formulate the problem as a Multiagent Markov decision process (MMDP), in which each EV acts as an agent and cooperate with each other to jointly minimize the total EV charging cost (therefore the charging cost for each individual EV owner will be reduced). Considering that this problem suffers from curse of dimensionality, an aggregation framework, which dynamically groups the EVs into EVAs (electric vehicle aggregator) based on their remaining parking time and location is developed to alleviate dimension explosion. And a EVA-based MMDP is derived to deal with the charging decisions for EVAs. Meanwhile, a scenario tree-based dynamic programming (TSP) method is introduce to tackle the EVA-based MMDP. And we conclude that the TSP method is efficient in improving the coordination of EV charging with uncertain wind power of buildings.

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