Optimal Planning of Renewable Generations for Electric Vehicle Charging Station

Conference Paper · March 2018

DOI: 10.1109/ICCNC.2018.8390352

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Optimal Planning of Renewable Generations for Electric Vehicle Charging Station

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***Abstract*—Driven by the recent innovation in battery technology and electric drivetrain, electric vehicles (EVs) have grown rapidly and are widely deployed to enable a sustainable transportation system. One of the key challenges is how to optimize the sizing and operation of the charging stations to meet the ever-increasing EV demands. In this paper, we develop a two-stage optimization framework to address this challenge. The proposed framework can determine the optimal capacity of renewable energy generation, and the optimal scheduling for power supply, in two stages, respectively. We reformulate a single-level stochastic programming problem to solve the two-stage optimization problem. In addition, we analyze the arrival patterns and demand profiles of EVs using real-world data to facilitate a practical EV request model. Numerical results demonstrate the optimal planning for a renewable-powered EV charging station. We show the optimal mix of solar and wind energy generations and the optimized power scheduling.**

***Index Terms*—Smart grid, renewable energy, solar, wind, energy storage, electric vehicle, charging station.**

I. Introduction

The transportation sector is one of the major contributors to air pollution and carbon dioxide emissions. Widespread adoption of electric vehicles (EVs) is a promising solution to address the environmental problems and decarbonize transportation sectors [1]. However, increasing penetration of EV load can result in negative impact on the operation of power systems, especially the distribution networks [2]. For example, remarkable EV charging load may lead to problems such as load spikes, voltage fluctuations, overload of circuits, and energy losses. Rather than upgrade the grid infrastructure, those impacts can be mitigated by investing in local generations. Moreover, renewable energy resources from solar and wind can provide clean power to meet the EV charging demand. Motivated by this, we aim to develop an optimization framework for determining the optimal planning for an EV charging station using realistic renewable data.

Many research efforts have been made in EV charging station planning. A few of them, e.g., [3], [4], [5], [6], [7], [8], [9], studied the placement and sizing of the EV charging stations, taking into consideration of the constraints in both transportation network and power grid. A number of heuristic solutions have been proposed to minimize the investment and operational costs. The authors in [10] proposed a capacity planning strategy aiming at maximizing social welfare while minimizing the grid cost. They considered multi-class clients and conducted experiments in both big and small cities. In [11], the authors proposed a coordinated charging solution that uses the valley-filling technique to optimize the capacity planning. They used a capacity margin index to select the best time for the grid to supply the charging station and a charging priority index to select the appropriate EV to charge. In [12], the authors proposed a two-stage solution where the first stage offers an offline optimal solution that can be used as a day-ahead strategy for the capacity sizing and the second stage provides a real-time charging plan for each EV based on their demands.

In this paper, we analyze the realistic data trace of EVs and derive the arrival patterns and demand profiles of EVs, which facilitate a practical EV request model. In addition, we develop a two-stage optimization framework to determine the optimal planning of an EV charging station, including the optimal capacities of renewable energy generations and optimal power scheduling. We reformulate a single-level stochastic programming problem to jointly optimize the planning and scheduling decisions. The main contributions of this work are as follows:

- *EV data analytics*: We analyze and discuss arrival patterns and demand profiles of EVs using realistic data.
- *Two-stage charging station optimization*: We develop a two-stage optimization framework for the optimal planning of an EV charging station. The framework jointly optimizes the capacity planning and power scheduling in the two stages.
- *Numerical results based on realistic data*: We demonstrate the optimal planning using realistic data of EV loads and renewable generations, showing the optimal capacities of solar/wind energy and optimal power scheduling.

The rest of this paper is organized as follows. In Section II, we present data analytics of EV arrival patterns and demand profiles. We present the system model and the two-stage optimization framework in Section III. In Section IV, we present the problem formulation and solution method. Section V shows the simulation results and Section VI concludes this paper.

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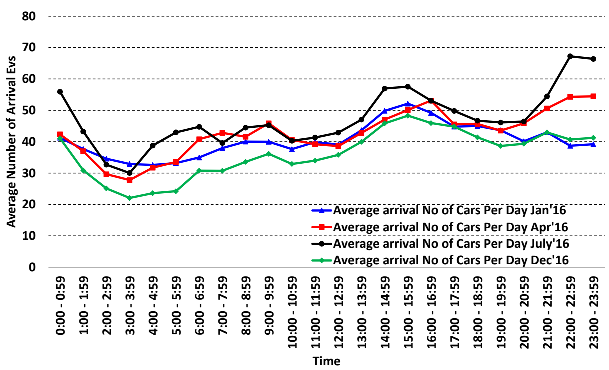
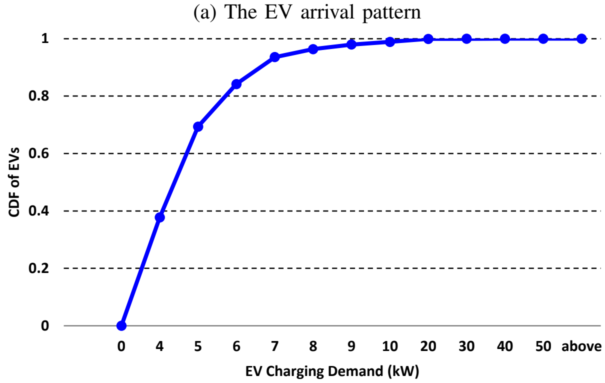
II. Data Analytics of EV Charging Profiles

To formulate a practical EV model, we need to answer the following questions: (1) When will an EV arrive? (2) How much is the charging demand of the EV? (3) How long will the EV stay in the station? We analyze a real-world EV data trace [13] to answer these questions, and obtain several insightful findings in terms of (1) the average number of EV arrivals per hour, (2) the cumulative distribution function (CDF) of EV charging demand, and (3) the average duration of EV. The detailed description of the EV model is as follows.

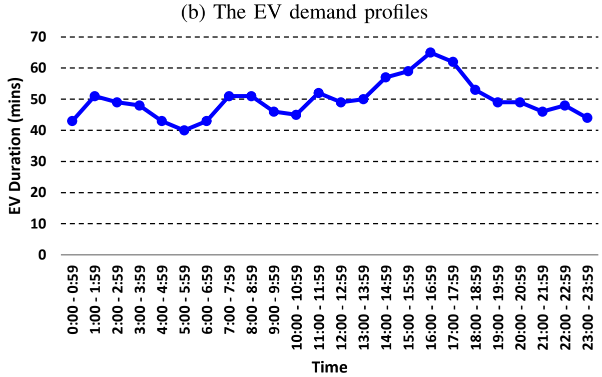
EV arrival pattern: We first analyze the average number of hourly arrival EVs in a day. Since the renewable energy source (e.g., solar or wind) and the EV's travel condition may vary in different seasons, we conduct comprehensive data analytics to produce four different arrival patterns in four seasons. In each season, we select a representative month (e.g., January, April, July, and December) and summarize the average results in each of those 30 days, as shown in Fig. 1 (a). We see that the four EV arrival curves follow a similar pattern that has a peak number of EV arrivals at 9am, 4pm and 10pm. This is reasonable since the pattern coincides with the human behaviors that people may drop their EVs at the station when they get to the office (e.g., 9am) or back home (4pm or 10pm). From Fig. 1 (a), we can also observe that there are slight differences between these four patterns, where the average number of arrival EVs in July is the highest and that in December is the lowest. The reason is that people may travel a lot or constantly use air conditioners in the vehicles in summer, while they travel less in winter.



(a) The EV arrival pattern



(b) The EV demand profiles



(c) The EV duration model

Fig. 1: Data analytics of a real-world EV data trace

EV charging demand profile: When an EV arrives, we need to know its charging demand before it departs from the charging station. To obtain the EV charging demand profile, we calculate the CDF of EVs' charging demand, as shown in Fig. 1 (b). We see that 99% of the EVs have a charging demand of less than 10kW, which indicates that EVs are mostly used for short distance commute. This finding holds true in practice because EV's battery may not be sufficient to support long distance travels. Another reason is that the charging stations are not widely distributed, which may limit the usage of EVs only in a small area, such as the downtown area of a city.

EV duration pattern: To satisfy the charging demand, the charging station operator can either choose to immediately fulfill the requirement using fast chargers or optimally schedule the charging tasks by flexibly allocating the charging time and adjusting the charging rate. For example, for the EVs having requirement of a short charging time, the expensive fast charger may be applied; while for the EVs that stay in the charging station for a long time, the operator may defer their demands to a later time or use a slow charger (which is less expensive), as long as the EVs can get their charging demand satisfied before their departures. In Fig. 1 (c), we plot the average charging duration of EVs over 24 hours. We see that the average duration is relatively stable, ranging between 40 and 65 minutes. Therefore, in our modeling and simulations (to be presented in Sections III and V), we assume that all EVs must have their charging demands satisfied within an hour upon their arrivals[1].

III. System Model

In this section, we present the system model for the EV charging station planning problem. We consider a typical EV charging station that receives supply from the power grid and local renewable generations to serve the EV charging demand. We assume that the charging station has been equipped with superchargers, and thus focus on the investment in renewable energy generation. We consider both solar and wind generations as candidate renewable energy technologies[2]. The demand side consists of a set of EVs denoted by $\mathcal{N} = \{1, ..., N\}$.

[1]We will consider the flexibility of charging demand in our future work.

[2]We did not present the results when an energy storage unit is co-located with renewable generations, due to page limit.

The operator of the charging station determines the optimal capacities of renewable energy for the entire planning phase and the optimal power scheduling in each day.

Note that the optimization problem is challenging due to the fact that (1) the operator needs to jointly optimize both planning and operation in two different time scales, and (2) the capacity investment and operational decisions are highly coupled. We denote the planning phase as $\mathcal{D} = \{1, ..., D\}$, which includes D days in total. For each day $d \in \mathcal{D}$, we further divide it into $T = 24$ hours and denote the daily operational horizon as $\mathcal{T}_d = \{1, ..., T\}$. To model the decision process of planning and operation, we formulate a two-stage stochastic program. Specifically, the operator determines the capacities of solar and wind energy generations in the first stage. Once the capacities are installed, in the second stage, the operator schedules the power supply from renewable generations and the grid to serve the aggregated EV charging demand.

A. EV Charging Demand

Since the charging station serves many EVs at the same time, the operator is interested in characterizing the aggregated behaviors of EVs. Based on the data analytics in Section II, we see that the EV behaviors exhibit periodic patterns on a daily basis. To capture the EV patterns on different days, we call each daily EV pattern (e.g., EV arrival rate) as an *EV scenario*, denoted by ω_e. Each EV scenario is associated with a realization probability π_{ω_e}. All the EV scenarios form an EV scenario set Ω_e.

We denote the number of arrival EVs over a day as $\boldsymbol{n}^{\omega_e} = \{n^{\omega_e,t},\ \forall \omega_e, t\}$. The number of arrival EVs varies over a day as shown in Fig. 1 (a). We assume that the charging demand of EVs satisfies the same distribution, as depicted in Fig. 1 (b). We denote l_i as the demand of EV i and the associated probability density function is $p(l_i)$. As shown in Fig. 1 (c), EVs will depart in an hour and thus the charging station needs to charge the arrival EVs in current time slots. Therefore, we can calculate the aggregated EV charging demand in time slot t and scenario ω_e by:

$$L^{\omega_e,t} = n^{\omega_e,t} \sum_{i \in \mathcal{N}} p(l_i) l_i,\ \forall \omega_e \in \Omega_e,\ \forall t \in \mathcal{T}_d,$$

and we denote the demand vector $\boldsymbol{L}^{\omega_e} = \{L^{\omega_e,t},\ \forall t \in \mathcal{T}_d\}$.

B. Power Supply in the EV Charging Station

To meet the EV charging demand, the charging station can use its local renewable generations and the grid power. In this paper, we consider both solar and wind energy generations. We calculate the energy generations based on realistic meteorologic data [14], [15], since solar energy generation and wind energy generation heavily depend on the solar radiation and wind speed, respectively.

We call each daily renewable energy generation (consisting of both solar energy generation and wind energy generation) as a *renewable energy scenario*, denoted by ω_r. Each renewable energy scenario is associated with a realization probability π_{ω_r}. All the renewable energy scenarios form a scenario set denoted by Ω_r. We use realistic data from [14], [15] to numerically model the distribution of renewable energy generation. Specifically, we denote $\boldsymbol{P}_s^{\omega_r} = \{P_s^{\omega_r,t},\ \forall t \in \mathcal{T}_d\}$ and $\boldsymbol{P}_w^{\omega_r} = \{P_w^{\omega_r,t},\ \forall t \in \mathcal{T}_d\}$ as solar and wind generations per kWh capacity of installed solar panel and wind turbine in scenario $\omega_r \in \Omega_r$. Given the solar energy capacity α_s and wind energy capacity α_w, the total renewable energy generation in the charging station is

$$P_s^{\omega_r,t}\alpha_s + P_w^{\omega_r,t}\alpha_w.$$

In each scenario ω_r and time slot t, the charging station needs to schedule the renewable power supply, grid power procurement to meet the aggregated EV charging demand. The renewable power supply $\boldsymbol{p}_r^{\omega_r} = \{p_r^{\omega,t},\ \forall t \in \mathcal{T}_d\}$ and grid power procurement $\boldsymbol{p}_g^{\omega r} = \{p_g^{\omega,t},\ \forall t \in \mathcal{T}_d\}$ satisfy the following constraints:

$$0 \le p_r^{\omega_r,t} \le P_s^{\omega_r,t}\alpha_s + P_w^{\omega_r,t}\alpha_w, \forall t \in \mathcal{T}_d, \tag{1}$$

$$0 \le p_g^{\omega_r,t} \le P_g, \forall t \in \mathcal{T}_d, \tag{2}$$

where constraint (1) restricts the renewable power supply but allows the charging station to curtail renewable generation. Constraint (2) specifies that the charging station can purchase power from the grid to meet the EV charging demand but is upper-bounded by the line capacity P_g.

IV. Problem Formulation and Solution Method

After modeling the EV charging demand and power supply, we formulate a two-stage stochastic programming problem for the optimal planning for the charge station. We first present the problem formulation in the second stage.

A. Daily Operation in the Second Stage

We define a joint scenario set over EV scenarios and renewable generation scenarios, i.e., $\Omega = \{\omega = \omega_e \times \omega_r,\ \forall \omega_e \in \Omega_e,\ \omega_r \in \Omega_r\}$. In each joint scenario $\omega \in \Omega$ and time slot t, the charging station needs to balance the power supply and EV charging demand as follows:

$$p_r^{\omega,t} + p_g^{\omega,t} = L^{\omega,t},\ \forall t \in \mathcal{T}_d. \tag{3}$$

The cost of grid power production is modeled as a quadratic function [16]:

$$C_g(\boldsymbol{p}_g^{\omega}) = \beta_g \sum_{t \in \mathcal{T}_d} \left(p_g^{\omega,t}\right)^2,$$

where β_g is the coefficient of the production cost.

We assume that the marginal operational cost of producing renewable energy is zero. Therefore, the charging station will utilize renewable energy generation as much as possible. If the total renewable generation can meet the EV charging demand, i.e., $P_s^{\omega,t}\alpha_s + P_w^{\omega,t}\alpha_w \ge L^{\omega,t}$, then the charging station does not need to purchase grid power, i.e., $p_g^{\omega,t} = 0$. Otherwise, the charging station will use up all the renewable generation, and purchase grid power to compensate the local power deficit.

The charging station operator coordinates power supplies $\boldsymbol{p}_r^{\omega}$ and $\boldsymbol{p}_g^{\omega}$ to minimize the daily operational cost in the second stage. We state the operational cost minimization problem in scenario ω:

P2: Operation Cost Minimization in the Second Stage

$$\begin{aligned} \min_{\boldsymbol{p}_r^\omega, \boldsymbol{p}_g^\omega} \quad & C_g(\boldsymbol{p}_g^\omega) \\ \text{subject to} \quad & \text{Constraints (1)-(3).} \end{aligned}$$

Note that the minimized operational cost depends on the capacities of solar energy and wind energy generations and thus we denote the minimized operational cost as a function of α_s and α_w in scenario ω:

$$f(\alpha_s, \alpha_w, \omega) = \min_{\boldsymbol{p}_r^\omega, \boldsymbol{p}_g^\omega} C_g(\boldsymbol{p}_g^\omega). \tag{4}$$

B. Capacity Planning in the First Stage

In the first stage, the charging station operator needs to decide the capacities of solar energy and wind energy for the planning phase. The planning decision in the first stage will determine the operational cost in each day of the second stage, and the charging station must incorporate the impact on operational cost in the planning decision.

Denote c_s and c_w as the unit investment costs for solar energy and wind energy, respectively. Therefore, we have the total investment cost as

$$C_I(\alpha_s, \alpha_w) = c_s\alpha_s + c_w\alpha_w. \tag{5}$$

The minimized daily operational cost is a function of the invested capacities as shown in (4). The expected daily operational cost over all scenarios can be written as

$$\mathbb{E}_{\omega\in\Omega}\left[f(\alpha_s, \alpha_w, \omega)\right] = \sum_{\omega\in\Omega} \pi_\omega f(\alpha_s, \alpha_w, \omega), \tag{6}$$

where π_ω is the realization probability of scenario ω.

Usually, the charging station has set a budget for the planning, and thus we model the budget constraints as:

$$c_s\alpha_s + c_w\alpha_w \le B, \tag{7}$$
$$\alpha_s \ge 0, \;\; \alpha_w \ge 0, \tag{8}$$

where (7) ensures that the total investment cost is no larger than the budget B.

The objective of planning is to minimize the overall cost, inclucing both instant investment cost (5) and accumulative expected operational cost (6) over all the entire planning phase. Hence, we formulate the overall cost minimization problem in the first stage as:

P1: Overall Cost Minimization in the First Stage

$$\begin{aligned} \min_{\alpha_s, \alpha_w} \quad & C_I(\alpha_s, \alpha_w) + \sum_{d\in\mathcal{D}} \mathbb{E}_{\omega\in\Omega}\left[f(\alpha_s, \alpha_w, \omega)\right] \\ \text{subject to} \quad & \text{Constraints (7) and (8),} \end{aligned}$$

where $\sum_{d\in\mathcal{D}} \mathbb{E}_{\omega\in\Omega}\left[f(\alpha_s, \alpha_w, \alpha_e, \omega)\right]$ denotes the total expected operational cost under all scenarios $\omega \in \Omega$ over the entire planning phase $\mathcal{D}$.

C. Problem Reformulation and Solution

To solve the two-stage optimization problem for the charging station planning, we can reformulate the two-stage optimization problem into a single-level overall cost minimization problem. Specifically, the two-stage optimization problem in **P1** and **P2** is equivalent to the following single-level optimization problem **EP1**:

$$\begin{aligned} \min \quad & (c_s\alpha_s + c_w\alpha_w) + \sum_{d\in\mathcal{D}}\sum_{\omega\in\Omega} \pi_\omega C_g(\boldsymbol{p}_g^\omega) \\ \text{subject to} \quad & \text{Constraints (1)-(3), (7) and (8),} \\ \text{Varaibles:} \quad & \alpha_s, \;\alpha_w, \;\{\boldsymbol{p}_r^\omega, \boldsymbol{p}_g^\omega, \forall\omega\in\Omega\}. \end{aligned}$$

Since the charging station knows the scenarios of EV charging demand and its local renewable generations, it can solve the equivalent problem **EP1** in a centralized manner. The problem **EP1** is a convex quadratic program and can be solved by standard convex optimization techniques [17].

V. Simulation Results

A. Simulation Setup

In the simulation, we consider a 10-year planning phase and use the realistic date of renewable energy scenarios and realization probabilities from [15]. We set $\beta_g = 0.01$ and budget B from 0.1 to 0.8 million dollars. The unit costs for solar energy and wind energy are set as $c_s = \$3000$ per kW and $c_w = \$2000$ per kW, respectively.

B. Simulation Results

We first study the optimal planning strategy under different budgets. The optimal mixed investment in solar energy and wind energy is depicted in Fig. 2. When the budget is 0.1 million dollars, the optimal investment portfolio only consists of solar energy. This is because the solar energy profiles fit the EV charging demand better than the wind energy. When the budget increases to 0.4 million dollars, the investment in wind energy becomes greater than the investment in solar energy. This is because the wind energy is complementary with solar energy and the cost of wind energy is lower. When the budget increases to 0.7 million dollars, the investment cost remains the same, since the capacity investment has achieved the optimal value.

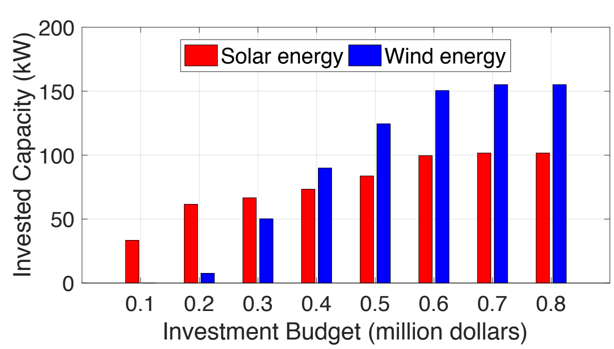


Fig. 2: Optimal planning under different budgets.

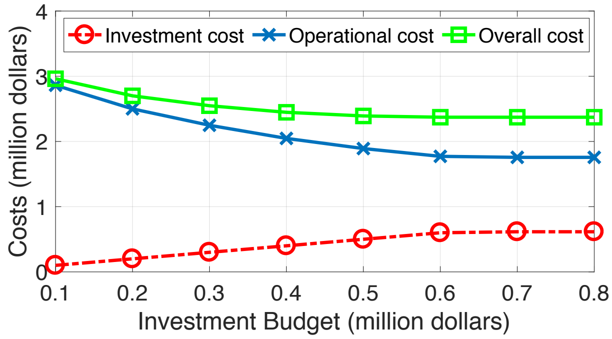


Fig. 3: Minimized costs under different budgets.

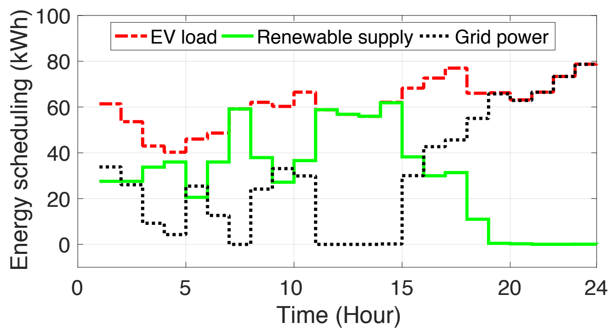


Fig. 4: Optimal power scheduling.

We also show the minimized costs under different budgets in Fig. 3. We can see that investment cost increases steadily with increasing budgets. When the budget is larger than 0.7 million dollars, the system already achieves the best performance and thus the overall cost does not decrease. Compared with the benchmark case without investment in renewable energy and energy storage, our planning strategy can reduce the operatonal cost and overall cost by 49.1% and 31.2%, respectively.

Finally, we take a deeper look and study the optimal operational strategy in one specific scenario. As shown in Fig. 4, the charging station utilizes renewable energy (from mixed solar and wind energy) in most of the time slots (during hours 1-18). In the showed scenario, there is no renewable generation at night. Therefore, the operator purchases grid power at night to meet the EV charging demand.

VI. Conclusion

Given the ever-increasing number of EVs, it is essential to effectively plan the capacity and schedule the power supply for the EV charging stations. In this paper, we developed a holistic framework for the planning and operation of an EV charging station, taking into consideration the supply of both the grid and local renewable energy. To capture the coupled decisions in two phases (i.e., investment and daily operation), we formulated a two-stage stochastic programming problem to jointly optimize the capacities of solar energy and wind energy, as well as the optimal daily power scheduling. Using realistic EV and renewable energy generation traces, we demonstrated the optimal planning strategy and showed the optimal capacities and optimized costs with respect to budgets. We also showed the optimal energy scheduling of renewable energy and grid power in one scenario.

Due to the page limit, we present the results with fixed EV charging demand and only consider solar and wind energy. In our extended study, we explore the flexibility of EV charging demand and develop a smart charging strategy. We also consider energy storage in the charging station to improve the utilization of renewable generation and reduce the system cost.

Acknowledgment

This work was in part supported by the University of Washington Clean Energy Institute.

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