Analyzing EV Charging Infrastructure with DER Integration for Economic Viability

Abstract

Enabling nationwide electrification of vehicles, is key to transportation sector decarbonization and greenhouse gas emissions reduction. The limited availability of fast chargers for electric vehicles has posed a significant obstacle to widespread EV adoption. Therefore, the National Electric Vehicle Infrastructure Formula Program has allocated funding resources to accelerate the deployment of fast charging infrastructure throughout the United States. The charging stations are subject to demand charges from the utility and to power outages due to severe weather conditions, transformer overloading, etc. Leveraging Distributed Energy Resources (DERs) reduces demand costs and ensures self-sustainability for charging stations. This work introduces DERs, such as onsite battery energy storage systems and solar photovoltaic, to address both the economic viability and resiliency of fast charging stations. We forecast electric vehicle charging events and optimize the operation of onsite battery and solar energy, thus minimizing demand charges and energy costs.

I. Introduction

Transportation electrification entails transitioning from conventional fossil fuel-powered vehicles to electric vehicles (EVs). Despite the numerous benefits, several challenges remain on the path to widespread transportation electrification. The limited driving range and longer charging times of electric vehicles compared to traditional vehicles are factors that need to be addressed. However, continuous advancements in battery technology, increased charging infrastructure, and the development of fast-charging solutions, such as direct current fast charging (DCFC) stations, are rapidly improving these aspects. The United States introduced the National Electric Vehicle Infrastructure (NEVI) formula program [1] that aims to facilitate the installation of electric vehicle fast charging stations and the development of a cohesive network to improve data collection, accessibility, and reliability.

Currently, studies in the literature mainly focus on control strategies with the objective of minimizing the investment costs for adding distributed energy resources (DERs) at a charging station and maximizing the return on investment of the charging station during their life cycles. For example, Li et al. [2] propose an energy management strategy for a large charging station with solar photovoltaic energy generation and energy storage system. Their results indicate that the cost of electric vehicle charging can be decreased almost by 50% in a certain confidence level of photovoltaic forecasting compared to uncoordinated charging [2]. Similarly, Mehrjerdi and Hemmati present a model for designing a charging station integrated with a diesel generator, PV generation, and energy storage system to minimize the investment cost, operational cost, peak load cutting, and drivers' comfort at the same time [3]. Additionally, they consider multilevel charging by including DCFC scenarios. Lastly, Jain et al. [4] studied an implementation of charging electric vehicle stations along with a battery and solar. Their simulation and experimental results reveal improved power quality operation under various system dynamic conditions, such as intermittent solar, etc. Results reveal that, from the grid perspective, charging stations with DERs can reduce grid power losses, delay the capacity expansion of the network, and reduce power generation costs. From the consumer and societal perspective, charging stations with DER can reduce costs related to environmental degradation and allow for energy savings for EV owners. Additional literature survey will be provided in the final manuscript.

The main contributions of the paper are summarized below:

1) Integration of distributed energy resources such as onsite battery storage and photovoltaic solar to reduce operational costs and strain on the grid.
2) Demonstration on how different traffic prices affect the energy and demand costs of various configurations of DERs.
3) Break-even cost for optimal sizing of DER (battery and solar) based on location-specific fast charging stations. This part of the work will be presented in the final version of the paper.

II. Integration of DER with EV

Integrating DERs with DCFC stations is expected to lower the overall cost of providing DCFC services. Solar photovoltaic (PV) systems aim to reduce energy costs, while battery energy storage systems (BESS) help minimize demand charges during peak hours or times of low utilization.

A. EV Load forecast

For a given site, expected charging sessions are obtained using a combination of regional EV ownership (local commuters seeking public charging) and national (long-distance travelers seeking opportunistic charging) EV adoption forecasts. Expected daily load profiles (with a 5-minute time granularity) over the planning horizon were projected using a stochastic vehicle arrival fed into Caldera_Grid, an EV charging simulation platform developed by Idaho National Laboratory [7]. The projected schedules were generated incorporating seasonal driving patterns, varying vehicle battery sizes, and state of charge. Formulation of the projected schedule will be provided in the final manuscript. As per the NEVI guidelines, which specify a minimum requirement of four connectors per DCFC station. Each connector should be capable of providing a continuous 150 kW power supply, resulting in a combined power demand of 600 kW for a 4-connector station.

B. Photovoltaic (PV) generation forecast

PV generation workflow presented in Fig. 1, where the pvlib python library [6], in conjunction with the NSRDB [5], is used to generate hourly PV electricity profiles. The NSRDB database provides key parameters, including direct normal irradiance, global horizontal irradiance, and diffuse horizontal irradiance, along with meteorological variables like temperature, wind speed, and humidity. The NSRDB helps assess the solar energy potential of diverse geographic locations. Additionally, system configuration encompasses the design and components of the PV system, including solar panel type and efficiency, inverters, and other relevant components.

C. Battery energy storage system (BESS)

The battery energy storage system (BESS) shifts energy consumption from peak to off-peak hours. During off-peak times when demand charge costs are lower, the battery system charges and stores excess electricity from the

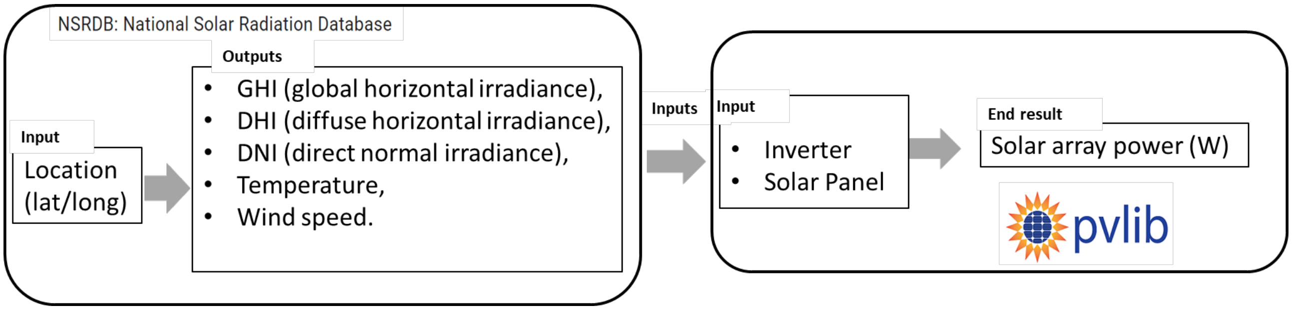

Fig. 1. Workflow to generate location-specific solar array power output.

grid and/or from on-site renewable sources, such as photovoltaic solar. DCFC stations are billed based on both their total energy consumption and peak demand. The peak demand in a billing cycle can significantly impact the demand charges on the electricity bill. Using the battery to reduce the peak demand during these periods can lead to substantial cost savings.

The BESS is modeled using state of charge (SOC) linear approximation as shown in (1). SOC is a measure of the remaining available capacity within a battery, expressed as a percentage of the total capacity. The remaining available capacity is calculated by dividing the amount of stored energy by the total capacity.

$$\text{SOC}_{\text{bess}}(t) = \text{SOC}_{\text{bess}}(t-1) - \frac{(P_{\text{bess\_chg}}(t-1) \times n_c - \frac{P_{\text{bess\_dis}}(t-1)}{n_d}}{E_{\text{max}}} \times T \tag{1}$$

The equation (2) represents the power of a Battery Energy Storage System (BESS) at a given time t. Where, $\text{I}_{\text{bess\_chg}}$ (1 for charging, 0 otherwise) represents the charging state, with associated power $P_{\text{bess\_chg}}(t)$ contributing negatively. $I_{\text{bess\_dis}}$ (1 for discharging, 0 otherwise) represents the discharging state, with associated power $P_{\text{bess\_dis}}(t)$ contributing positively.

$$P_{\text{BESS}}(t) = -I_{\text{bess\_chg}} \cdot P_{\text{bess\_chg}}(t) + I_{\text{bess\_dis}} \cdot P_{\text{bess\_dis}}(t) \tag{2}$$

D. Price-based system optimization

The flow chart in Fig. 2 illustrates the optimization of the charging and discharging operations of the battery to minimize costs, considering a specific electricity tariff. For optimal scheduling, the algorithm requires the EV load (kW) and the price ($/kWh) profiles as inputs, the energy storage models, the pv generation model, and the formulation of constraints with respect to the interconnected system. The total power consumption at the distributed node can be formulated (3):

$$P_{\text{Total}}(t) = -P_{\text{BESS}}(t) + P_{\text{EV}}(t) - P_{\text{PV}}(t) \tag{3}$$

The objective function of the optimization of the storage system is to minimize the total electricity cost, which includes energy and demand cost as shown in (4).

$$\text{Objective Function} = \text{Minimum}(\text{cost} = \sum_{t=0}^{24} (\lambda(t) \times P_{\text{Total}}(t) \times 1\text{hr}) + D \tag{4}$$

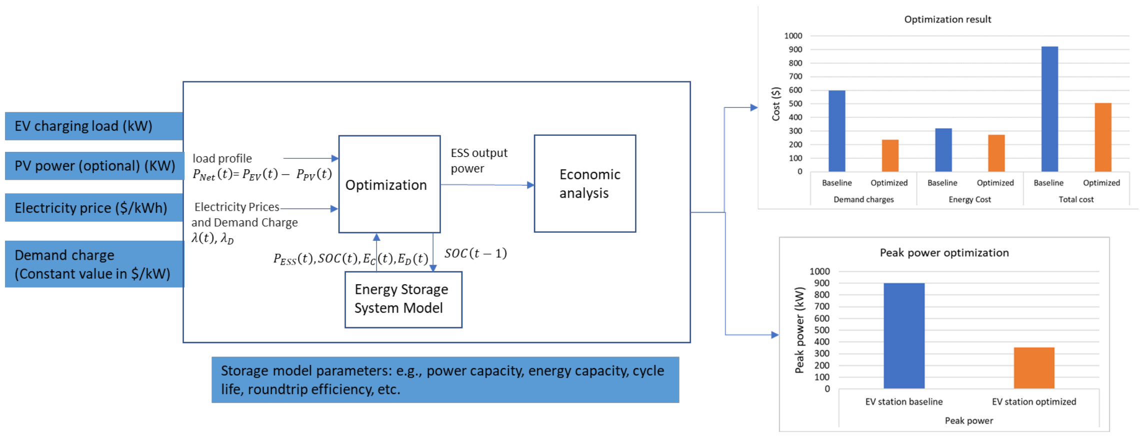

Fig. 2. Workflow to generate location-specific solar array power output.

Where $E(t)$ is the total energy consumption, and D is the daily demand cost, which is calculated as:

$$D = (\max(P_{\text{Total}}(t)|_{15\text{min}})) \times \lambda_D \tag{5}$$

The method of calculating the demand charge λ_D will vary from one utility to another. In this test setup, the demand charge is estimated for a month, where the demand cost is calculated for the maximum demand that occurs in a month for 15-minute average consumption. From (6) to (9) equations represent a list of constraints developed for optimal scheduling:

$$\text{BESS power limit -:} \quad I_{\text{bess}} \cdot P_{\text{BESS\_max}} \geq P_{\text{BESS}} > P_{\text{BESS\_min}} \cdot (1 - I_{\text{bess}}) \tag{6}$$

$$\text{SOC limit -:} \quad \text{SOC\_bess\_max} \geq \text{SOC\_bess} > \text{SOC\_bess\_min} \tag{7}$$

$$\text{Desire final SOC at the end of the day} \quad SOC(N) = SOC_{\text{ref}} \tag{8}$$

Restriction on total power to prevent the feeding of power back to the grid is shown in 9:

$$P_{\text{Total}}(t) > 0 \quad \text{or} \quad P_{\text{Total}}(t) > P_{\min} \tag{9}$$

We consider a flat tariff, a time-of-use (TOU) tariff, and an electric vehicle supply equipment (evse) tariff. The EVSE tariff generally features lower demand charges compared to flat or time-of-use (TOU) tariffsI.

TABLE I

ELECTRICITY TARIFFS USED IN ANALYSIS

Tariff	**Demand charge ($/kW)**	**Energy charge ($/kWh)**	
		on-peak	**off-peak**
Flat	11.86	0.082	0.082
TOU	11.86	0.220 (2-8pm)	0.078
EVSE	3.07	0.179 (2-8pm)	0.082

III. USE CASE

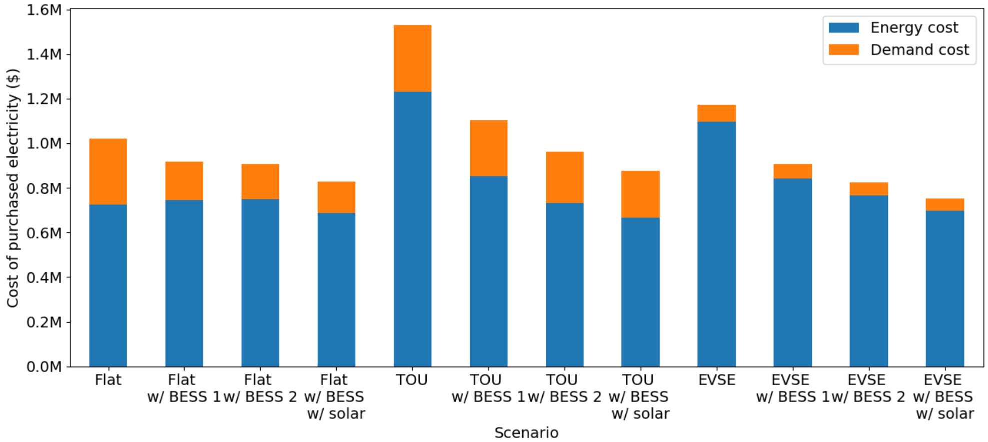

Fig. 3. Energy and demand costs for different electricity tariffs (i.e., Flat, TOU, and EVSE rate). The configurations are a) baseline (without DERs), b) with a BESS sized at 50% of rated load (e.g., 300 kW), c) with a BESS sized at 100% of rated load (e.g., 600 kW), d) with a BESS sized at 100% of rated load and a solar photovoltaic system of 40 kW.

In this section, we present preliminary results of energy and demand costs for the electricity tariffs described in Table I. The simulations are performed for a hypothetical DCFC station in Garden City, Kansas, covering a planning horizon of 10 years, spanning from 2025 to 2034. In the final version of the paper, additional locations along with their respective price tariffs, as well as the break-even costs of DCFC stations, will be presented.

IV. CONCLUSION

In this paper, we have showcased the impact of varying electricity tariffs and DERs on the operational expenses of a 600 kW DCFC station equipped with four ports, each rated at 150 kW. Introducing a BESS sized at 50% of the station's capacity results in cost reductions of 10%, 37%, and 22% under flat, TOU, EVSE electricity tariffs, respectively. Alternatively, sizing the battery at 100% of the station's capacity leads to additional savings of 1%, 5%, and 6% for the same tariffs. Furthermore, incorporating a 40 kW solar array alongside the BESS system results in a combined additional cost savings of 7%, 5%, and 6%. The findings highlight the importance of optimizing DER infrastructure sizing, as installing larger and more expensive systems tends to yield diminishing marginal energy savings. These considerations and their implications will be further addressed and discussed in the final version of the paper.

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