Robust Sizing of Solar-Powered Charging Station with Co-located Energy Storage

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***Abstract*—This paper studies optimal sizing of an electric vehicle charging station with multiple types of chargers. The station is coupled with a photovoltaic system and stationary battery to reduce the overall cost of delivering charging services. Our approach entails (a) generating sample paths from a stochastic process that represents the state of the charging station given the minimum number of chargers of each type needed to meet some quality of service requirements, (b) solving an optimization problem for each sample path to find the smallest battery capacity and number of solar panels that meet specific requirements, and (c) determining the robust size of co-located distributed energy systems by finding an upper envelope on the sizing curves obtained for different sample paths. Using real data, we find the least expensive size of the entire system that is robust to seasonality effects, travel patterns, and future increase in the penetration of electric vehicles.**

***Index Terms*—Electric vehicle charging station, distributed energy resources, capacity provisioning, Markov chain**

I. Introduction

The widespread introduction of passenger electric vehicles (EVs) in the mass market will increase the demand for charging points, especially fast chargers in public charging stations. As the levelized cost of solar energy continues to decline, electric vehicle charging stations (EVCSs) will increasingly be equipped with on-site distributed energy resources (DERs), such as solar photovoltaic (PV) panels, for maximum savings and efficiency [1]. The PV system can be paired with a stationary battery energy storage system (BESS) to shift PV generation for alignment with the charging station's busy hours [2–5]. The uptake of PV-powered charging stations with co-located energy storage poses an important research question: how to size a charging station with multiple supply sources to accommodate the expected growth of the EV charging demand and provide Quality of Service (QoS) guarantees to customers? Over-provisioning resources will be prohibitively expensive, hence not a viable solution.

Extensive research has been done on sizing PV and BESS jointly in smart homes [6] and microgrids [7, 8] to minimize the probability of requiring grid power to meet the charging load, or the total amount of energy that must be bought from the grid [9]. Similarly, there is a vast literature on sizing a charging station to meet various QoS requirements, such as keeping the average waiting time or blocking probability below some threshold [10–13]. Yet, to our knowledge, the related work does not address sizing of a charging station that contains multiple types of chargers and on-site distributed energy resources to satisfy QoS and grid power intake requirements simultaneously. This problem is nontrivial for several reasons. First, the uncertainty of EV mobility and PV generation makes it difficult to size the system by solving an optimization problem over a finite horizon and ensure that the constraints will not be violated in the long run. Second, modelling battery imperfections makes the optimization problem nonconvex. Third, minimizing the total installed cost of the EVCS and co-located DER requires searching the large space of feasible sizes, increasing the running time complexity of the algorithm.

To address this problem, in this paper, we introduce a queueing model for a charging station that contains both Level 2 (L_2) and Level 3 (L_3) chargers, where customers have a strong preference for L_3 chargers to reduce the charging time. Using historical charging data from a real charging station, we estimate the average arrival rate of EVs to the charging station and the average initial energy requirement of these EVs. These estimates are used to construct the transition rate matrix of a continuous-time Markov chain (CTMC), where the state represents the number of active chargers. Given this rate matrix, we compute the stationary probability distribution over different states and subsequently the probability that an arriving EV does not find any available charger, hence it is *blocked*. To attain our QoS target, we solve a feasibility problem to obtain the set of designs, in terms of the number of L_2 and L_3 chargers, that can keep the blocking probability below a certain threshold without straining the power grid.

Given a feasible design for the EVCS, we formulate a mixed integer linear program (MILP) to obtain the smallest BESS and PV system sizes that are necessary to keep the total amount of grid energy required to meet the EVCS demand over the optimization horizon below a threshold. To solve this optimization problem over an interval of 1 month, we use sample paths of the CTMC constructed for the EVCS and obtain real PV generation traces for the EVCS location. We pick this short interval because solving the optimization problem over a long time horizon requires a lot of data to capture non-stationarity of stochastic processes and takes a significant amount of time due to the large number of variables and constraints. The downside of solving the problem over a short interval is that the resulting optimally sized system may not be able to withstand multiple consecutive cloudy days or a growing EV population. To address this issue, we sample this interval from 4 years of data several times and solve the optimization problem for every sample. Lastly, we use the empirical Chebyshev inequality [14] to obtain a robust sizing for the BESS given the size of the PV system and vice versa.

The robust sizing method adopted in this work draws on the method proposed in [15] for sizing PV systems and BESS. We extend this work by (a) building a queueing model for the EVCS; (b) incorporating the QoS requirement and transformer capacity; (c) decomposing the sizing optimization problem. The extended method is applied to jointly size an EVCS and

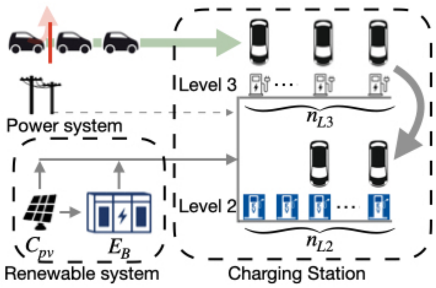

Fig. 1. Schematic of an EVCS equipped with storage with capacity E_B, a PV system with capacity C_{pv}, and n_{L_2} L_2 and n_{L_3} L_3 chargers.

co-located DER, the problem that is not studied in [15].

The rest of this paper is organized as follows. We state our assumptions and describe the queueing model in Section II. The robust sizing methodology is introduced in Section III. We describe the datasets, and present our sizing recommendations for the EVCS and co-located DER in Section IV.

II. Background

We consider a grid-tied EVCS that houses a mix of L_2 and L_3 chargers ($n_{\mathrm{L}2}$ and $n_{\mathrm{L}3}$ chargers specifically), coupled with a PV system with capacity C_{pv} kW and a BESS with capacity of E_B kWh. We refer to the combined PV and storage system as DER. Fig. 1 shows the entire system comprised of EVCS and co-located DERs. When EVs arrive at the EVCS, they first occupy parking stalls with L_3 chargers to take advantage of fast charging. Once these stalls are full, new arrivals will occupy parking stalls with L_2 chargers. When all stalls get full, newly arrived EVs cannot be admitted (they are blocked). To enhance customer comfort and satisfaction, it is important to keep this blocking probability below a threshold. This is viewed as the QoS requirement in this work.

We assume that EVs are charged immediately upon connecting to a charger and their battery is replenished primarily from on-site PV generation. When the available PV power exceeds the aggregate demand of all chargers, the surplus is stored in the stationary BESS. When BESS is full, PV power must be either exported to the grid or curtailed. When the available PV power is less than the aggregate EV demand, the BESS discharges to meet the difference. If the energy discharged from the BESS is not sufficient to fulfill the charging demand, the remainder must be imported from the grid. This specific order of using the supply sources guarantees the minimum cost operation of the EVCS.

We make the following assumptions about the chargers, EVCS and EVs that visit the station:

- The charge power of L_2 and L_3 chargers is constant, regardless of the state of charge (SOC) of the BESS[1]. The charge rate of L_3 chargers, denoted by $\overline{P}_{\mathrm{L}3}$, is higher than that of L_2 chargers, denoted by $\overline{P}_{\mathrm{L}2}$.
- EVCS consumes real power only. Hence, the loading of the transformer that supplies the EVCS demand equates the total real power consumed by the chargers, i.e., it has a unity power factor.
- The rate of EV arrivals to the EVCS is independent of the number of EVs that are being charged. The charging demand of every EV is known upon arrival.

The desired sizing of the EVCS and co-located DER satisfies the following four key requirements in the long-term operation of EVCS. First, the total charging demand of the EVCS cannot surpass the rated capacity of the distribution transformer as sustained overload can damage it. Second, the blocking probability must be kept below an acceptable threshold for the given EV traffic pattern. Third, the fraction of EV charging demand supplied from the conventional grid power must be minimal. The cap is defined by the EVCS operator to minimize the operation cost. We refer to this as the power import requirement. Fourth, the sizing must have the lowest cost among all feasible options.

To solve the optimal sizing problem, we first identify all sizing options that are feasible, i.e., they satisfy the first three requirements. They should also be robust to solar variability, random changes in traffic flow, and increased penetration of EVs. In the next step, we select the robust sizing option that has the minimum cost among the feasible options. We cast the robust sizing problem as an optimization problem where the design variables are the numbers of L_2 and L_3 chargers, the energy capacity of the stationary BESS, and the size of the PV system. The structure of this optimization problem, which follows directly from the operational logic that the stationary BESS is only charged from the surplus PV generation, allows for a straightforward decomposition into two subproblems that can be solved sequentially. The first one is an EVCS sizing problem which defines bounds on the number of chargers that can be installed. The upper bound, in the worst case, is the rated capacity of the transformer[2] and the lower bound stems from the QoS requirement. The second problem is a DER sizing problem subject to the power import requirement, given the EVCS charging demand, which depends on the EVCS sizing found in the previous step. Solving these two problems separately is more tractable than solving the original optimization problem. We present these problems in Section III.

A. *Proposed Queueing Model for EVCS:*

We use a Markovian model to characterize the demand of the EVCS and find the blocking probability. A reasonable choice of state space is the number of EVs being served at the station [10]. By analyzing the real data in Section IV, we show that Poisson process is an accurate model for EV arrival and that the exponential distribution is a good fit for EV charge requirements (energy demand). We model the EVCS as an $M/M/k/k$ queue with two types of servers (fast and slow) and determine the blocking probability by finding the steady state distribution of the corresponding Markov chain shown in Fig. 2. This *birth-death process* has $k = n_{\mathrm{L}_3} + n_{\mathrm{L}_2}$ states. The arrival rate is denoted by λ. We divide the charge requirement of each EV by the charge rate of the respective charger to get the service time distribution of L_2 and L_3 chargers. The

[1]This is a simplifying assumption that is only suitable for EVCS sizing and relaxing it should not change the robust sizing result. To simplify the derivation, we can assume that the constant power drawn by an active charger is the maximum charge power it supports.

[2]The available capacity for EV charging cannot be less than the transformer rating because the BESS can only be charged from on-site PV generation.

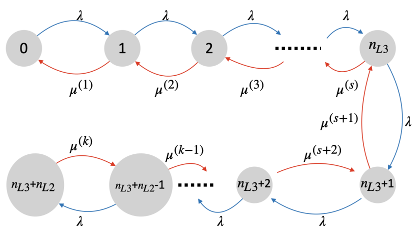

Fig. 2. State transition diagram for the proposed CTMC of EVCS constructed with n_{L_2} and n_{L_3} number of L_2 and L_3 chargers, respectively.

mean of these exponential distributions is denoted by $1/\mu_2$ and $1/\mu_3$, respectively. The service completion rate in state s, denoted by $\mu^{(s)}$, can be written as:

$$\mu^{(s)} = \begin{cases} s\mu_3 & 0 \le s \le n_{\mathrm{L3}}, \\ n_{\mathrm{L3}}\mu_3 + (s - n_{\mathrm{L3}})\mu_2 & n_{\mathrm{L3}} < s \le k. \end{cases} \tag{1}$$

To calculate the total amount of real power consumed by the EVCS in a state, we associate every state s with the total power delivered to EVs by the active chargers:

$$P_L(s) = \begin{cases} \frac{s \cdot \overline{P}_{\mathrm{L3}}}{\eta_3} & 0 \le s \le n_{\mathrm{L3}}, \\ \frac{n_{\mathrm{L3}} \cdot \overline{P}_{\mathrm{L3}}}{\eta_3} + \frac{(s - n_{\mathrm{L3}}) \cdot \overline{P}_{\mathrm{L2}}}{\eta_2} & n_{\mathrm{L3}} < s \le k, \end{cases} \tag{2}$$

where η_2 and η_3 are the charging efficiency of L_2 and L_3 chargers, respectively.

Since Poisson arrivals see time averages (a.k.a. the PASTA property), the probability that an EV finds no available charger upon arrival is the stationary probability of being in state $k = n_{\mathrm{L}_3} + n_{\mathrm{L}_2}$. It can be written as:

$$\pi_{blk} = \frac{\lambda^{(n_{\mathrm{L}_3} + n_{\mathrm{L}_2})}}{n_{\mathrm{L}_3}! \mu_3^{n_{\mathrm{L}_3}} \prod_{i=1}^{n_{\mathrm{L}_2}} (n_{\mathrm{L}_3}\mu_3 + i\mu_2)} \pi(0), \tag{3}$$

where $\pi(0)$ is the stationary probability that the EVCS is empty calculated from the normalizing equation that states the stationary probabilities must sum to 1:

$$\frac{1}{\pi(0)} = \sum_{i=0}^{n_{\mathrm{L}_3}-1} \frac{\lambda^i}{i! \mu_3^i} + \sum_{i=n_{\mathrm{L}_3}}^{k} \frac{\lambda^i}{n_{\mathrm{L}_3}! \mu_3^{n_{\mathrm{L}_3}} \prod_{j=1}^{i-n_{\mathrm{L}_3}} (n_{\mathrm{L}_3}\mu_3 + j\mu_2)}$$

Assuming that we have access to representative traffic data and historical charging demand data, we can estimate the arrival and service rates. The resulting transition rate matrix can be used to generate sample paths of a desired length. We can then calculate the net demand of the EVCS for each sample path from (2). The PV generation traces are based on publicly available solar radiation data collected at regular intervals (e.g., hourly) for the specific location of the EVCS from the Solcast API[3] and fed to PVWatts[4]. Once both traces are ready, they can be sampled from to create *scenarios* for the optimization problems defined in the next section.

III. Joint Sizing of EVCS and Co-located DER

We start off with solving the first problem that concerns finding all feasible $(n_{\mathrm{L}_3}, n_{\mathrm{L}_2})$ pairs. In the next step, given a feasible EVCS design and a fixed BESS size, we find the minimum size of the PV system such that the ratio of unmet load (RUL) by DER to total load is less than a threshold δ.

[3]https://solcast.com/solar-data-api/api/

[4]https://pvwatts.nrel.gov/pvwatts.php

To find all possible sizing options for the EVCS, we solve the following feasibility problem

$$\min_{n_{\mathrm{L}_3}, n_{\mathrm{L}_2}} \quad Z \tag{4a}$$

$$s.t. \quad \pi_{blk} \le \theta, \tag{4b}$$

$$\frac{n_{\mathrm{L}_3}\overline{P}_{\mathrm{L}_3}}{\eta_3} + \frac{n_{\mathrm{L}_2}\overline{P}_{\mathrm{L}_2}}{\eta_2} \le \overline{P}_G, \tag{4c}$$

where Z is an arbitrary constant, and $\overline{P}_G$ is a limit imposed by the power utility based on the rating of the transformer that feeds the EVCS. Constraint (4b) gives the lower bound on the required number of L_2 and L_3 chargers, while (4c) caps the number of chargers. This is a convex problem if we precalculate and cache the blocking probability for different $(n_{\mathrm{L}_3}, n_{\mathrm{L}_2})$ pairs. Solving (4) gives a set $\mathcal{H}$ that includes all tuples $(n^*_{\mathrm{L}_3}, n^*_{\mathrm{L}_2})$ that meet the QoS requirement and do not strain the power grid.

To size the co-located DERs, given a feasible EVCS sizing option ($\in \mathcal{H}$), we solve an optimization problem over T timesteps of equal length, T_u. We denote the power supplied to EVCS directly from PV panels in timestep i by P^i_{in} and the SOC of the stationary BESS by e^i_b. The charge (resp. discharge) rate, labeled P_c (resp. P_d), must be less than the BESS power capacity, which is assumed to be a multiple of the battery energy capacity ($\alpha_c E_B$ and $\alpha_d E_B$) because BESS are modular. P^i_{cs} is the ith element of a sample path generated from the CTMC as explained in Section II, and S^i is the ith element of the available solar power (as a percentage of the peak generation capacity) extracted from the data trace. Given P^i_{cs} and S^i, we solve the following optimization problem to minimize the capacity of the PV system such that DER's RUL is lower than a threshold δ.

$$\min_{C_{pv}, P_c, P_d, P_{in}, u, e_b} \quad C_{pv} \tag{5a}$$

$$s.t. \quad P^i_c + P^i_{in} \le S^i C_{pv} \tag{5b}$$

$$P^i_{in} + P^i_d = P^i_{cs} - e^i \tag{5c}$$

$$e^0_b = E_B \tag{5d}$$

$$e^{i+1}_b = e^i_b + P^i_c \eta_c T_u - P^i_d \eta_d T_u \tag{5e}$$

$$a_1 P^i_d + b_1 E_B \le e^i_b \le a_2 P^i_c + b_2 E_B \tag{5f}$$

$$0 \le P^i_c \le \alpha_c E_B u^i \tag{5g}$$

$$0 \le P^i_d \le \alpha_d E_B (1 - u^i) \tag{5h}$$

$$E_B, C_{pv}, P^i_{in}, e^i, e^i_b \ge 0 \quad \forall i \tag{5i}$$

$$u^i \in \{0, 1\} \quad \forall i \tag{5j}$$

$$\sum_{i=1}^{T} e^i \le \delta \sum_{i=1}^{T} P^i_{cs} \tag{5k}$$

The above problem is a MILP as u is a binary variable. Constraint (5b) ensures that the total PV power delivered is less than the PV system output; (5c) is the power balance equation that ensures grid power is used to supply the unmet charging demand denoted by e^i; (5d)-(5h) are related to the battery as discussed in [15]; and (5k) limits the ratio of the charging demand that must be supplied from grid power in T timesteps to the total charging demand. We solve this optimization problem over intervals of length T that are randomly sampled from the entire dataset. Each sample gives a sizing scenario. We solve the optimization problem for n scenarios, each time setting the BESS capacity to a fixed value.

A. Robust Sizing

Solving the two optimization problems introduced earlier in this section for each scenario yields a set $\mathcal{C}$ that contains PV system sizes for a fixed BESS capacity $E_B = B$ and an EVCS sizing option. The cardinality of this set is $N_{pv} \leq n$. Considering the elements of this set, we compute the empirical estimates of the mean $m_{C,N_{pv}}$ and standard deviation $\sigma_{C,N_{pv}}$, and write the Chebyshev inequality [14] as follows:

$$\mathbf{P}\{|C_{pv} - m_{C_{N_{pv}}}| \geq \beta\sigma_{C_{N_{pv}}}\} \leq \min(1, f(\beta)), \tag{6}$$

$$f(\beta) = (N_{pv}+1)^{-1}\left\lfloor \frac{(N_{pv}+1)(N_{pv}^2 - 1 + N_{pv}\beta^2)}{N_{pv}^2\beta^2} \right\rfloor \tag{7}$$

This gives an upper bound on the probability that the difference between a value of C_{pv} (for any, possibly unseen, scenario) obtained for a BESS of size B and the estimated mean $m_{C_{N_{pv}}}$ exceeds a factor β of the estimated standard deviation $\sigma_{C_{N_{pv}}}$. Note that β is the smallest number that satisfies $f(\beta) \leq \gamma$, where γ is our confidence measure. As γ approaches 1, the value of β that satisfies the confidence measure becomes larger. This will result in a more conservative sizing, i.e., a larger PV system. In other words, we tend to employ more DER capacity to be less dependent on the main grid. Given the value of β, we derive the optimal PV sizing from (6), that is $C^*_{pv} = m_{C_{N_{pv}}} + \beta\sigma_{C_{N_{pv}}}$. Similarly, we find a Chebyshev curve on E_B values and use both curves (from PV and BESS sizing) to calculate an upper envelope for DER sizing. We then employ a simple grid search to find the least expensive sizing tuple for C_{pv} and E_B among the points that lie on the upper envelope of the Chebyshev curves.

IV. Results

The proposed robust sizing methodology is evaluated using real data traces of PV generation from NREL's PVWatts and historical EV charging data from the adaptive charging network (ACN) [16] that contains more than 30,000 charging sessions since 2018. We collect the traces for a period of 4 years with hourly resolution. In the next step, we verify that the interarrival times and energy requirements follow exponential distributions (see Fig. 3), and estimate the parameter of each distribution to obtain the average arrival and service rates. These rates are used to construct the transition rate matrix and subsequently compute the blocking probability of the CTMC. To account for the future increase in EV penetration, we can multiply the birth rate of the CTMC found empirically by a factor that represents the annual growth in EV population.

The timestep is set to $T_u = 1$ hr (the temporal resolution of the solar irradiance data). The total length of EV charging P_{cs} and PV generation S traces are $4 \times 365 \times 24 = 35040$ hours. From the traces, we randomly select 100 scenarios, 720 hours each, solve the optimization problem for each scenario, and find the upper envelope of the empirical Chebychev sizing curves. For each scenario, we find the optimal C_{pv} for 30 values of E_B in the set $\mathcal{E_B} = [45, 700]$. The battery parameters are borrowed from the lithium-ion battery model used in [15]: $\eta_c = -0.99$, $\eta_d = 1.11$, $a_1 = 0.053$, $a_2 = -0.125$, $b_1 = 0$,

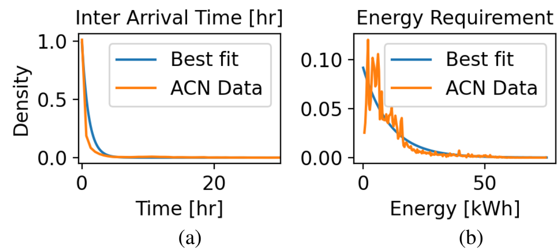

Fig. 3. Probability density function of (a) the time between two successive arrivals to the EVCS and (b) energy requirement of EVs upon arrival. The best fit is an exponential distribution. $\lambda = 0.98, \mu_2 = 0.98, \mu_3 = 4.44\ hr^{-1}$.

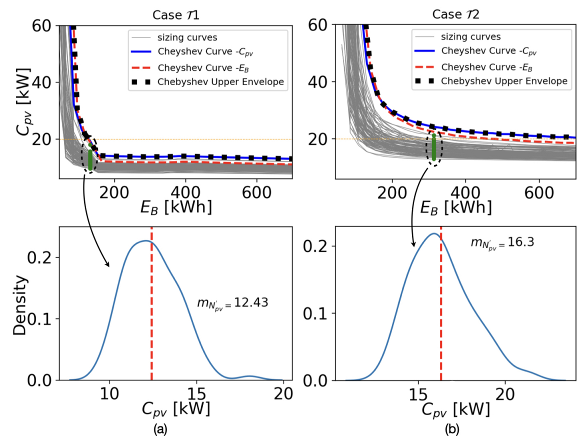

Fig. 4. Chebyshev bound curves for optimal sizing of C_{pv} for (a) $\mathcal{T}1$ and (b) $\mathcal{T}2$ sizing options with $\delta = 0.05$. Plots in the second row show the empirical distribution of C_{pv} for $E_B = 295kWh$.

$b_2 = 1$, $\alpha_c = \alpha_d = 1$. The initial SOC for BESS is set to $e_b^0 = B$. The charging station parameters and other parameters used for the simulations are $\overline{P}_{\mathrm{L}_2} = 11$ kW, $\overline{P}_{\mathrm{L}_3} = 50$ kW, $\eta_2 = 0.96$, $\eta_3 = 0.98$, $\delta = 0.05$, $\gamma = 0.95$.

A. EVCS Sizing

The total power consumed by the installed chargers cannot exceed the rated capacity of the transformer, which is assumed to be 250 kW. By solving the feasibility problem (4), we found 49 feasible tuples $(n_{\mathrm{L}_2}, n_{\mathrm{L}_3})$. The installed costs of L_2 and L_3 chargers are set to \$800 and \$16,500, respectively [13]. Due to the high computation overhead of the optimization, we only investigate two extreme sizing tuples, $\mathcal{T}1$) the least expensive option $(8, 0)$, and $\mathcal{T}2$) the most expensive option $(4, 4)$. Both options yield a blocking probability that is below $\theta = 10^{-6}$.

B. Solar and Storage Sizing

For each EVCS size, we size the PV system and BESS based on the mean and standard deviation of sizing curves obtained for a sample population of sizing scenarios. Specifically, for each value of E_B, we have 100 curves in the (E_B, C_{pv}) space. Similarly, for each value of C_{pv}, we have 100 curves in the (E_B, C_{pv}) space. We depict the optimal sizing curves and empirical Chebyshev bounds for two specific EVCS sizing options $\mathcal{T}1$ and $\mathcal{T}2$ in Fig. 4 for $\delta = 0.05$.

The recommended C_{pv} sizing, as shown in Fig. 4 for a randomly selected E_B value, is higher for $\mathcal{T}2$ than $\mathcal{T}1$. This shows that the EVCS equipped with 4 L_2 chargers and 4 L_3 chargers requires approximately 60% higher PV capacity than (8,0). The upper envelope of Chebyshev curves (shown as a dotted black curve in Fig. 4) shows our robust sizing

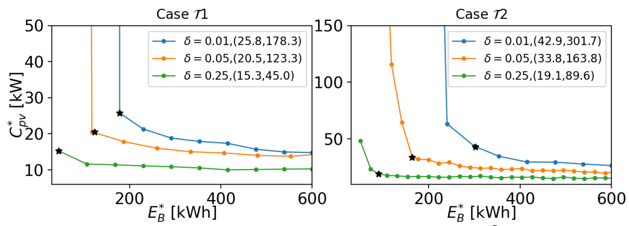

Fig. 5. Optimal robust sizing recommendation values of δ. In each case, the design with the lowest cost is suggested as (C^*_{pv}, E^*_B) in the legend.

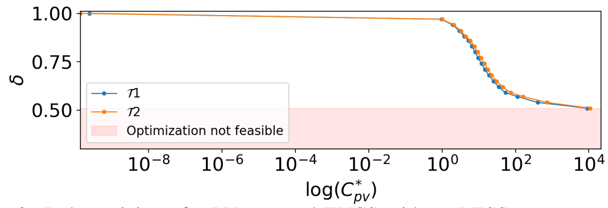

Fig. 6. Robust sizing of a PV-powered EVCS without BESS.

recommendation. Considering all (E_B, C_{pv}) points that lie on the upper envelope of Chebyshev curves, we find the least expensive sizing option (C^*_{pv}, E^*_B) assuming the installed cost of \$2,500/kW for PV and \$460/kWh for BESS.

Sensitivity to δ: We evaluate the proposed sizing method for PV and BESS by incorporating different values of δ in (5). We illustrate the sizing results for three sample values of δ in Fig 5. It can be readily seen that the minimum BESS size increases as the minimum PV system decreases and vice versa. For small values of δ, both PV system and BESS must be considerably larger to satisfy the RUL requirement for a fixed EVCS sizing. The BESS size is especially important for small δ values because it is impossible to meet the RUL requirement before sunrise or after sunset regardless of the PV system size.

Sizing PV-powered EVCS without BESS: We also investigate the case where BESS is not installed in the EVCS to shift PV generation. To solve the sizing problem in this case, we modify the optimization problem in (5) by removing the constraints and variables corresponding to BESS. The updated optimization problem is a linear program that can be solved efficiently. We find that the sizing problem has no feasible solution for $\delta \leq 0.46$, which is expected because without BESS it is impossible to meet the EVCS demand using PV generation without relying too much on grid power. Fig. 6 shows the minimum C^*_{pv} required to meet the grid import requirement for values of $\delta > 0.46$. One interesting observation is that a 10 MW PV system is required to meet the EVCS demand for a threshold of $\delta = 0.51$. Should we install a small 45 kWh BESS, the PV system size could be reduced to 15.25 kW for $\delta = 0.05$ which is 10 times lower than the previous delta value. This underscores the importance of installing a BESS for shifting PV generation.

V. Conclusion

With the falling costs of solar PV and battery technologies, it is anticipated that more EV charging stations will be equipped with DER. This paper proposes an optimal sizing methodology for an EVCS with two types of chargers and co-located DERs, given the constraints imposed by the power grid operator and customers. Our approach guarantees robustness of the resulting system size to non-stationarity of PV generation and EV traffic. Using real data, we provide robust sizing recommendations with minimum cost.

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