Title

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Journal

2025 IEEE Power & Energy Society General Meeting (PESGM), 00

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Publication Date

2025-07-31

DOI

10.1109/pesgm52009.2025.11225191

Economic Storage Size Optimization for Electric Vehicle Extreme-Fast Charging Stations

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2025 IEEE Power & Energy Society General Meeting (PESGM) | USGov | DOI: 10.1109/PESGM52009.2025.11225191

***Abstract*—En-route charging infrastructure for electric vehicles is critical to support transportation needs. These charging stations are likely to have high loads and especially sharp peak loads given fast charging capabilities needed to meet transportation schedules. In order to reduce both strain on distribution grid infrastructure and charging station operational costs, many stations are likely to employ behind the meter storage. This paper demonstrates a behind the meter storage sizing optimization that employs an open-source agent-based vehicle behavior model (BEAM) to determine the best sizing across many scenarios. This optimization and analysis is novel in that it examines how storage size impacts not only charging station cost and peak load, but also vehicle queue times. The optimization is also applied across a wide analysis region with sufficient diversity and numbers to provide novel statistical analysis of optimal sizes.**

***Index Terms*—Electric Vehicle Charging, Energy storage, Load management, Optimization Methods, Power distribution networks, System analysis and design, BEAM**

I. Introduction

Supporting vehicle charging loads on the electrical distribution grid will become challenging as the share of Electric Vehicles (EVs) and vehicle charging power ratings continues to rise. One way to tackle this is costly grid upgrades. A technically and economically sound alternative for many use cases is managed charging in combination with co-located energy storage at charging stations [1]. Appropriately sizing co-located storage is critical, as neither exceedingly large or small storage sizes would be reasonable or economical. For Behind the Meter Storage (BTMS), the inter-dependencies between the economic impacts of the metering and pricing scheme, the installed technology itself and a properly designed Energy Management System (EMS) with optimization techniques, enables beneficial (economic) use for the storage owner [2]. A process to determine storage capacities that is founded in economics, the physics of a charging station, energy storage price forecasts, and high fidelity vehicle charging simulation is necessary to maximize the potential of BTMS. This paper demonstrates a methodology for BTMS sizing optimization of BTMS-applications for grid impact reduction for Extreme-Fast-Charging (XFC) Depots of Ride-Hailing Fleets based on high-fidelity transportation simulation results generated by the *Behavior, Energy, Autonomy and Mobility model* [3] within the Co-Simulation project GEMINI-XFC [4].

This work was funded by the U.S. Department of Energy

A. Behind-The-Meter Storage (BTMS)

Energy storage installed on customers' premises and not controlled by the utility is called behind-the-meter storage (BTMS).
Peak-shaving with BTMS for demand charge reduction often discussed in economics and literature. [5] concludes that the necessary storage capacity (and therefore cost) increases over-proportionally with the desired peak-shaving magnitude. Therefore, small, short-duration batteries are most cost-effective for peak-shaving [5]. This work does not consider aggregated customer coincidence factors and instead focuses on economics for the site owner.

In another work, BTMS with a capacity equal to $30\,\%$ of the maximum power of the site in kW lead to a $55\,\%$ peak load reduction. [1] BTMS optimization has been conducted using linear programming with predetermined load profiles and time of use rates [6], optimizations have included demand charges and other site considerations [7], and they have leveraged site analysis software such as Hybrid Optimization Models for Energy Resources (HOMER) [8]. This work builds upon previous work by exploring different size BTMS at a larger scale for thousands of charging stations across the San Francisco bay area in a simulated high adoption scenario. The simulated high adoption scenario and large-scale analysis region allows for statistical analysis of optimized results for a wide variety of profiles and cites, as well as realistic future adoption scenarios.

II. Methods

The cost optimization of storage sizing for thousands of charging stations is performed for a high adoption scenario across the San Francisco Bay area and analyzed statistically. Vehicle motion and charging station use and queue times are created using the open-source agent-based regional transportation model for Behavior, Energy, Autonomy and Mobility (BEAM) [9]. Results from BEAM provide insights into charging station use patterns and potential peak loads, which are then used as inputs to the storage sizing optimization problem.

A. Optimization Problem

The power balance at the charging station can be summarized in the following way: Electrical power flowing from the grid into the station P_{Grid}, power to/from the BTMS P_{Θ} and the sum of all individual charging powers distributed to connected vehicles P_{Charge}. If $P_{\Theta} < 0$, the grid load is reduced by discharging the BTMS. Considering that $P_{\Theta} = \frac{\delta E_{\Theta}}{\delta t}$, where E_{Θ} is the energy stored in the BTMS, we can write the energy conservation equation as:

$$P_{\text{Grid}} = \frac{\delta E_{\Theta}}{\delta t} + P_{\text{Charge}} \tag{1}$$

From the Co-Simulation results here, we can derive load profiles at each site $P_{\text{Charge}}(k)$ for uncontrolled charging. These load profiles can be used in an optimization problem to determine the best storage size for each location. We choose the objective function to be

$$\begin{aligned} \min \quad & a \max P_{\text{Grid}} + b_{\text{sys}} \max |P_{\Theta}| + b_{\text{loan}} \max E_{\Theta} \\ & + (b_{\text{cap}} + c(1-\eta)) \sum_{k=0}^{T} P_{\Theta,\text{Ch}}(k) \Delta t \end{aligned} \tag{2}$$

This function considers demand charges (a), BTMS cost (b_i) and charging losses electricity cost (η, c), all amortized to one day of operation.

Monthly demand charges are amortized to the simulation period of one day and included with $a \max P_{\text{Grid}}$ (a in $\$/\text{kW}$). The cost of the storage is included in system cost b_{sys}, capacity degradation cost b_{cap} and loan cost of the capacity components b_{loan}. The system cost scales with the power rating of the BTMS (of e.g. the inverters) with $b_{\text{sys}} \max |P_{\Theta}|$ (b_{sys} in $\$/\text{kW}$). The system cost is increased by the interest on a loan that would be taken to finance the storage. We consider the BTMS capacity degradation cost $b_{\text{cap}} \sum_{k=0}^{T} P_{\Theta,\text{Ch}}(k) \Delta t$ (b_{cap} in $\$/\text{kWh}$) amortized to one cycle of operation, i.e. the projected cost of degradation that is induced by the process of storing the energy. We furthermore add the interest paid for the capacity component of the BTMS price with the term $b_{\text{loan}} \max E_{\Theta}$ (b_{loan} in $\$/\text{kWh}$).

Finally, the cost of charging losses is included in the term $c(1-\eta) \sum_{k=0}^{T} P_{\Theta,\text{Ch}}(k) \Delta t$ (c in $\$/\text{kWh}$). The charging losses are identified by using the first law of thermodynamics $E_{\Theta\text{Ch}} = E_{\Theta\text{DCh}} + E_{\text{loss}}$ for the case of the same state of its instationary term (the storage, $E_{\Theta}(0) = E_{\Theta}(T)$), the definition of the round-trip efficiency $\eta = \frac{E_{\Theta\text{DCh}}}{E_{\Theta\text{Ch}}}$ We assume that all losses occur during storage charging (see 3).

This objective is constrained by:

$$\begin{aligned} E_{\Theta}(k+1) &= E_{\Theta}(k) + \Delta t \cdot (\eta \cdot P_{\Theta,Ch}(k) \\ &\quad + P_{\Theta,DCh}(k)) && \forall k \in [0,T] \quad (3) \\ P_{\text{Grid}}(k) &= P_{\text{Charge}}(k) + P_{\Theta}(k) && \forall k \in [0,T] \quad (4) \\ P_{\Theta}(k) &= P_{\Theta,\text{Ch}}(k) + P_{\Theta,\text{DCh}}(k) && \forall k \in [0,T] \quad (5) \\ E_{\Theta}(0) &= E_{\Theta}(T+1) && (6) \end{aligned}$$

Equation 3 implements the physics of the charging station, i.e. the first law of thermodynamics as described in (1). Variables $P_{\Theta,\text{Ch}}$, P_{Grid}, and E_{Θ} are all always positive, while $P_{\Theta,\text{DCh}}$ is always negative. Furthermore, (6) ensures cyclic operation over the simulation horizon and prevents the optimization from completely emptying the storage at the end of the day to reduce the sample day's cost.

This optimization problem is implemented by using the Python-package CVXPY[1]. [10].

The resulting linear program from equations 2-6 is a convex problem.

After solving, the resulting BTMS storage size can be taken as:

$$\Delta E_{\Theta} = \max(E_{\Theta})$$

B. Modifications

Enforcing a specific C-Rate can be applied by adding the term

$$\max P_{\Theta} \leq C_{\max} \max E_{\Theta} \tag{7}$$

In the standard case, this constraint is not applied as we would like to see what storage C-Rates would be required for an economical case. Furthermore, the term b_{loan} is small compared to the other terms of the objective function, such that the influence of enforcing a specific C-Rate on the characteristic grid impact is small, while leading to considerably larger storage sizes.

For incorporating a Time-of-Use (ToU) price scheme, the parameter c becomes a vector $c(k)$ and the term $\sum c(k) P_{\text{Grid}}(k)$ is added to the objective 2 while removing the charging loss term. Likewise, time-varying demand charges are implemented with slack variables $P_{\text{Grid,max,i}}$ for each demand charge period. We furthermore introduce the option to include wait times of vehicles whose charging is delayed by adapting the objective to include the monetized cost $d(k)$ in $\$/\text{h}$ of waiting:

$$\begin{aligned} \min \quad & a \max P_{\text{Grid}} + b_{\text{sys}} \max |P_{\Theta}| + b_{\text{loan}} \max E_{\Theta} \\ & + (b_{\text{cap}} + c(1-\eta)) \sum_{k=0}^{T} P_{\Theta,\text{Ch}}(k) \Delta t && (8) \\ & + \sum_{k=0}^{T} d(k) \cdot \Delta t \cdot n_{\text{Veh., wait}}(k) && (9) \end{aligned}$$

C. Performance Metrics

For further analysis of the sizing results, we introduce rating measures:

The C-Rate is calculated as

$$\text{C-Rate} = \frac{\max P_{\Theta} \cdot 1\,\text{h}}{\Delta E_{\Theta}} \tag{10}$$

We calculate the number of cycles per day as

$$\text{Cycles} = \frac{|\int P_{\text{DCh}} dt|}{\Delta E_{\Theta}} \tag{11}$$

We define the BTMS-Ratio as ratio of total energy provided by the BTMS to total energy for EV charging

$$\text{BTMS-Ratio} = \frac{|\int P_{\text{DCh}} dt|}{\int P_{\text{Charge}} dt} = \frac{|\int P_{\text{DCh}} dt|}{E_{\text{Charge}}} \tag{12}$$

[1]CVXPY: https://www.cvxpy.org/

The load factor f_{load} is energy-based and defined as

$$f_{\text{load}} = \frac{\frac{\int P_{\text{Grid}} dt}{\Delta t}}{\max P_{Grid}} \tag{13}$$

We define the Peak-Ratio as the ratio of the maximum grid power draw compared to the maximum charging power (power-based)

$$\text{Peak-Ratio} = \frac{\max P_{\text{Grid}}}{\max P_{\text{Charge}}} \tag{14}$$

III. Application and Analysis

A. Charging Demand Predictions

The Behavior, Energy, Autonomy, and Mobility (BEAM) modeling framework [9, 11], built atop the MATSim platform [12], serves as an agent-based, multi-modal travel demand simulator offering a wide array of travel choices including ridehailing (both single-occupant and pooled), driving alone, walking, biking, and a variety of public transit routes. It features dynamic within-day mode choice adjustments, providing simulated travelers with up-to-the-minute ridehail pricing and waiting times.

Utilizing a utility-maximizing evolutionary algorithm, BEAM models individual preferences to optimize for cost and travel time across various modes, factoring in constraints like available vehicle seating, parking, and refueling options. It accurately simulates a dynamic transport ecosystem, blending land use, a synthetic population with distinct activities and preferences, and infrastructure elements such as parking, refueling stations, transit networks, and ridehail fleet operations. This comprehensive method allows for a nuanced representation of the complexities and interactions within contemporary transportation systems. The charging demand as simulated in BEAM is a representation of a typical working day, which is then used by BTMS as a data source for prediction.

B. Objective Function Parameterization

As described by [13], energy and power component costs of BTMS scale differently. Energy storage component costs are assumed to scale with capacity and power electronics costs are assumed to scale with power rating. The assumed costs in Table I are estimated for C-Rates between 0.1–0.5 [13], while we experience higher C-Rates of > 2 in this project. [14] cite numbers from "Bloomberg New Energy Finance" which indicate that higher C-Rate storage costs are higher, but only by a magnitude of $20\,\%$ from C-Rate 0.5 to 2. Therefore, we assume that extrapolation from the [13]-data is acceptable for our purposes.

The second major influencing factor of the objective-function is the demand-charge in $\frac{\$}{\text{kW}}$. Demand Charges in the US vary significantly by region. In California, the average commercial customer demand charge is $11\frac{\$}{\text{kW}}$, whereas the maximum demand charge is $47\frac{\$}{\text{kW}}$[15]. We therefore choose to vary the demand charge throughout our analysis to determine its impact on BTMS application.

Further parameterization of the optimization problem is given in Table I.

TABLE I
Parameterization Assumptions

Round-Trip Efficiency $85\,\%$ [13]	Lifetime 15 years [13] (1 cycle/day)	Cycles ca. 5400 [13]
BTMS Energy Cost $125\ \frac{\$_{2020}}{\text{kWh}}$ [13]	BTMS Power Cost $186\ \frac{\$_{2020}}{\text{kW}}$ [13]	Electricity Price $0.12\frac{\$}{\text{kWh}}$
Loan Payback Time 10 years	Interest Rate $5\,\%$p.a.	$P_{\text{Ch,Avg.}}$ $300\,\text{kW}$

IV. Results

The results of the BTMS-size optimization are analyzed statistically to capture a wide range of EV charging station scenarios possible by the year 2040.

A. Use Case

This BTMS-size optimization was applied to realistic but not real charging stations across the San Francisco Bay Area as simulated in the GEMINI-XFC project [16]. The charging profiles were created based on charging demand from high fidelity travel simulations for the same area conducted in BEAM. The Bay Area distribution grid was taken from SMART-DS, vetted synthetic distribution system available at: https://www.nrel.gov/grid/smart-ds.html. The stations were sited according to a combination of travel demand from the BEAM simulation, parcel land use data, expected adoption as simulated in TEMPO [17], and distribution system connection availability from the SMART-DS system configuration. The load profiles at each charging station were then created by re-running BEAM to simulate travel with the given station locations, allocating each vehicles' charging sessions to the appropriate charging stations for the vehicles' trip needs. Given the wide variety in charging stations and their charging demands a statistical approach was taken to analyze the BTMS sizing optimization results.

B. Statistical Sensitivity Analysis

We assume b_i, c to be fixed and vary a between 0–20 $\frac{\$}{\text{kW}}$ to determine the impact of different demand charges on the system performance and which prices for a produce more dynamic behavior at the grid connection. The results of this parameter sweep are depicted in Figure 1 and 2.

The physical property results of the sizing optimization in Figure 1 show that with no demand charges applied ($a = 0\frac{\$}{\text{kW}}$) the impact on the grid is highest. Without demand charges the grid must support unmitigated sharp charging demand peaks (Peak-Ratio $= 0$). A dynamic change in all measures occurs when demand charges are added, especially around $a = 5\frac{\$}{\text{kW}}$). When demand charges reach $a > 10\frac{\$}{\text{kW}}$, there are no longer notable changes. The control-function of demand charges diminishes as the system comes to the physical boundaries of charging and discharging the BTMS.

We see that the load-factors increase with a delayed increase in peak-ratio. This means that with increasing demand charges first the maximum values at the grid connection are decreased

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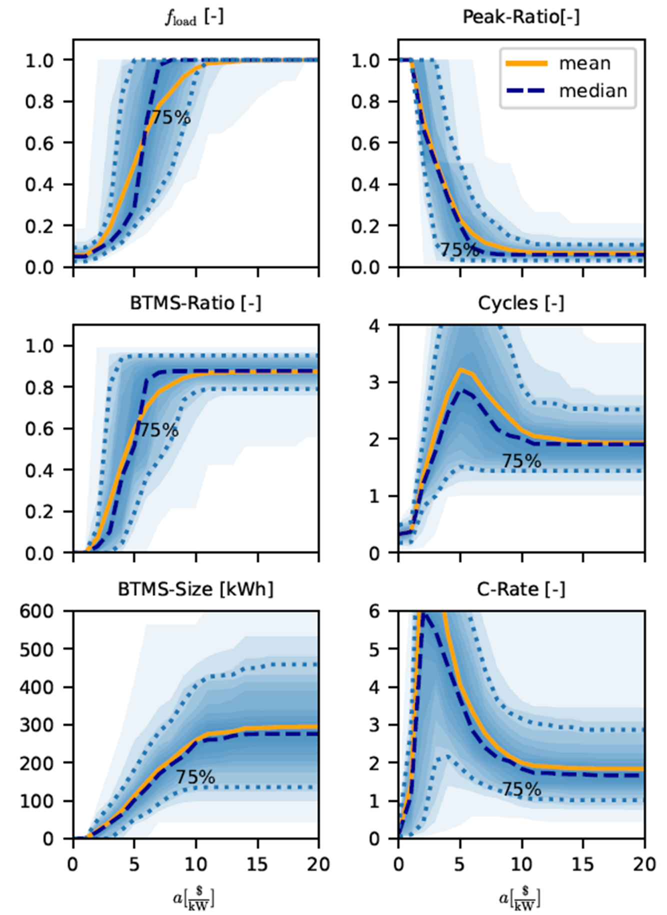

Fig. 1. Statistical Distribution of Sizing Results Physical Properties over a-values between 0–20$\frac{\$}{\text{kW}}$

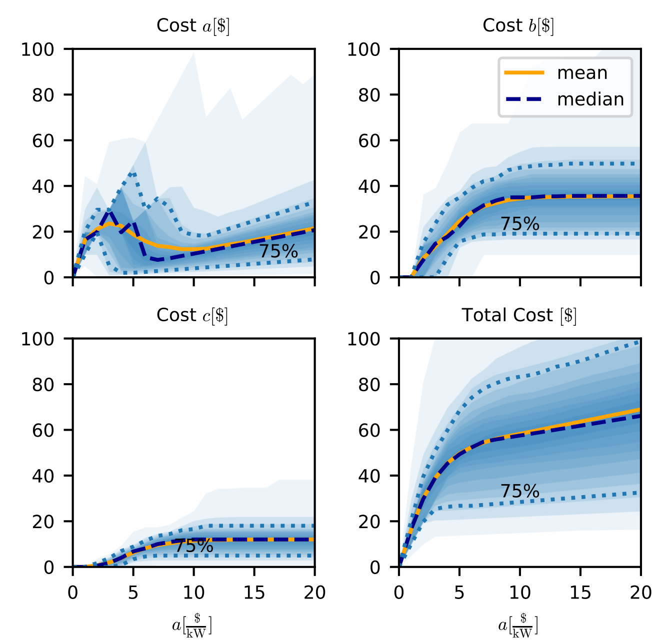

Fig. 2. Statistical Distribution of Sizing Results Costs of one day over a-values between 0–20$\frac{\$}{\text{kW}}$. The brighter the area is colored, the more depots lie in that range.

(starting at $a = 0\frac{\$}{\text{kW}}$), but smoothing the overall average load occurs at demand charges $2.5\frac{\$}{\text{kW}}$ and higher. At a demand charge of $a = 5\frac{\$}{\text{kW}}$, the mean BTMS-Size is around $100\,\text{kWh}$ while the mean peak reduction is about $80\,\%$ and the load factor is at $40\,\%$. A doubling of the mean storage size to $200\,\text{kWh}$ occurs at $a = 8\frac{\$}{\text{kW}}$. We can see a diminishing effect on the peak-ratio (further reduction by only around $15\,\%$) but still a sharp increase of the load-factor to a mean of $80\,\%$ and a median of $100\,\%$.

When the BTMS-cost is high compared to the demand charge, the optimization dispatches the storage aggressively, resulting in high C-Rates (Peak of the mean at $a = 2\frac{\$}{\text{kW}}$ with a value of 8.5 ± 12.3) and high number of charge and discharge cycles (mean of 3.2 ± 1.7 at $a = 5\frac{\$}{\text{kW}}$)). Both metrics show high variability. Especially for lower demand charges, we can conclude that under our assumptions, a wide range of BTMS-characteristics would be most economically appropriate depending on other characteristics of the site such as vehicle charging demand as simulated in BEAM. With higher demand charges, the storage system requirements tend to be more uniform.

C-Rates of 8 and higher will probably be infeasible in terms of technological development (full discharge in $< 10\,\text{min}$), at least under our price assumptions. Therefore, results are given for applying an enforced C-Rate of 2 by using constraint (7). There are no major differences to the net demand seen by the distribution grid when applying the enforced C-Rate. However when applying the C-Rate constraint, BTMS sizes double or triple at low demand charges ($a < 5\frac{\$}{\text{kW}}$)) compared to the non-C-Rate constrained case. The reason for this is the chosen parameterization of the objective function, specifically the term $b_{\text{loan}} \max E_{\Theta}$. For the assumed loan conditions in Table I, this term is several times smaller than the other factors in the objective function, therefore its influence on the optimization outcome, specifically the characteristics at the grid connection, is not large. We also tested a higher interest rate of $15\,\%$ p.a, but this does not significantly change the results.

In the unconstrained C-Rate case, the total cost and its components for one day of operation are depicted in Figure 2. Up to a value of $a = 5\frac{\$}{\text{kW}}$, the total cost increases steeply, followed by a slower increase for higher C-Rates. The BTMS-cost b and the charging-losses cost c stop increasing at a demand charge value of $a = 10\frac{\$}{\text{kW}}$, such that the increase of the total cost is then only caused by increasing demand charges. This is because the system reaches the physical limit of a perfectly flat power profile. A further increase of demand charges does not impact BTMS-size once a perfectly flat power profile is reached.

Future work will further statistically analyze these results to determine influences on BTMS-size at an individual site level. These results combined with the statistical analysis here can be leveraged by utilities and site owner stakeholders to create rules of thumb on storage sizing and demand charge policies.

V. Conclusion

This work used simulated travel patterns from a high EV adoption future scenario in the San Francisco Bay Area to determine optimal BTMS charging sizes at a wide range of fast charging stations. A novel statistical analysis of the size optimization was conducted and consideration of vehicle queue time was incorporated within the simulation framework. The BTMS size was greatly impacted by demand charge and station traffic, with total costs increasing most steeply until demand charges reached ($a = 5\frac{\$}{\mathrm{kW}}$) followed by a wider spread and more gradual increase in costs. This work demonstrates the necessity of simulations of future high adoption scenarios with charging queues and widespread en-route charging use for analysis of long term investment in charging station BTMS.

Acknowledgment

J.A. thanks Arne Speerforck and the GEMINI team for supporting this project during his exchange year at UC Berkeley.

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Vehicles Technology Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

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