Optimizing Electric Vehicle Charging Infrastructure Placement

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***Abstract*—This paper presents a modular workflow for optimizing electric-vehicle (EV) charging-station placement by combining synthetic demand synthesis, charging-control policies, clustering, and greedy local search under grid-node capacity constraints. We simulate three charging policies—(i) maximum-rate charging when plugged in, (ii) threshold-based charging when state of charge falls below a minimum, and (iii) deadline-driven constant-rate charging—to generate temporal load profiles. Initial station sites are chosen via k-means clustering of EV locations and then refined through a greedy swap algorithm that minimizes a weighted sum of driver travel distance and grid-overload penalty. On our campus-scale test case, the optimized layout reduces average travel distance by over 25 % while ensuring zero capacity violations. We conclude with insights on policy trade-offs, charger power level impacts, and avenues for future extensions.**

I. Background and Motivations

Electric vehicles (EVs) are rapidly proliferating, driving an urgent need for charging infrastructure that balances user convenience with grid reliability. Poorly sited charging stations can cause driver range anxiety, station congestion, and localized grid overloads [1], [2]. Recent forecasts predict EV adoption to rise substantially in the coming decade, with charging demand patterns that vary both spatially and temporally. Typical daily driving in suburban contexts averages 26 miles per day over 3.3 trips, leading to bi-modal peak demand in the early morning and late evening [3]. Charger technologies range from slow Level 1 (1.8 kW) to high-power DC fast chargers ($\geq$ 50 kW), each imposing distinct siting and grid-loading challenges.

At the distribution level, feeder and transformer capacities constrain the number and power rating of chargers that can be co-located at a node, making strategic station placement essential to avoid costly infrastructure upgrades or reliability risks [2]. While clustering approaches such as k-means can efficiently identify high-demand regions for initial siting [1], these methods alone do not guarantee compliance with grid-node constraints or account for dynamic charging behaviors driven by control policies.

Furthermore, EVs have the potential to serve as distributed energy resources (DERs), offering vehicle-to-grid (V2G) services and ancillary support when coordinated intelligently [2]. Integrating such flexibility with station siting could unlock significant grid benefits, but requires an end-to-end framework that simulates realistic charging patterns under multiple policies, initializes candidate sites based on demand clustering, and refines placements through cost-based search.

Our work addresses this gap by combining (i) a time-step simulation of EV energy use under three contrasting charging-control policies, (ii) k-means–based initialization of station locations, and (iii) a greedy local search that minimizes a weighted sum of driver travel distance and grid-overload penalties. This pipeline enables rapid exploration of trade-offs among station density, user convenience, and grid reliability.

II. Methods

A. Synthetic Demand Generation

We synthesize spatial EV charging demand by uniformly sampling N EV trip origins over a rectangular area of size $A_x \times A_y$. Each EV i is assigned a charging requirement d_i drawn from a truncated normal distribution $\mathcal{N}(\mu_d, \sigma_d^2)$ with minimum value $d_{\min}$. The continuous demand samples $\{(x_i, y_i, d_i)\}_{i=1}^N$ are then aggregated into a $G \times G$ grid, yielding a demand matrix

$$D_{mn} = \sum_{i:\,(x_i,y_i)\in \text{cell}(m,n)} d_i,$$

where cell(m, n) denotes the (m, n)th grid cell. This heatmap D serves both for visualization (Fig. 1) and as input to the placement algorithm.

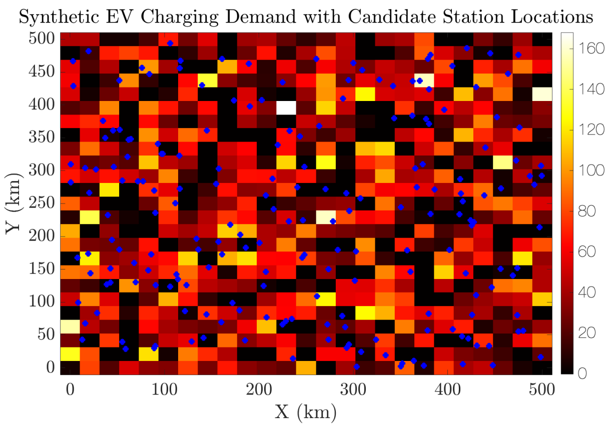

Fig. 1. Synthetic EV charging-demand heatmap used for station siting.

B. EV Energy–Use Simulation

We discretize a simulation horizon of T hours into K intervals of length Δt, producing time points $t_k = k\,\Delta t$ for $k = 0, \ldots, K$. The battery's chemical-energy state x_k (in kWh) evolves according to the linear dynamics

$$x_{k+1} \;=\; a\,x_k \;+\; (1-a)\,\tau\,p_k^{\text{chem}}, \tag{1}$$

where

$$a = e^{-\Delta t/\tau}, \quad \tau = \text{self-dissipation time constant,}$$

and p_k^{chem} (kW) is the net chemical power at step k. Charging efficiency η_c and discharging efficiency η_d convert between electrical power p_k and chemical power via

$$p_k^{\text{chem}} = \begin{cases} \eta_c\,p_k, & p_k \geq 0, \\ p_k/\eta_d, & p_k < 0. \end{cases}$$

Following Kircher [3], we generate driving-power profiles p_k^{drive} using a speed-dependent energy-intensity α and set

$$p_k^{\text{chem}} = -\,p_k^{\text{drive}} + p_k^{\text{charge}},$$

with p_k^{charge} determined by the chosen control policy. The plug-in indicator

$$z_k = \begin{cases} 1, & t_k \bmod 24 \in [0, h_{\text{plug}}^{\text{start}}) \cup (h_{\text{plug}}^{\text{end}}, 24), \\ 0, & \text{otherwise,} \end{cases}$$

ensures charging only when parked (e.g. overnight).

C. Charging Control Policies

We implement three distinct charging-control policies (all subject to battery capacity $x_{\min} \leq x_k \leq x_{\max}$ and maximum electrical power $P_{\max}$):

1) **Max-Rate Charging.** Whenever $z_k = 1$, charge at full power until full:

$$p_k = \begin{cases} P_{\max}, & x_k < x_{\max}, \\ 0, & \text{else.} \end{cases}$$

2) **Threshold-Based Charging.** Enter charging mode only if $x_k < x_{\min}$:

$$y_k = \big[z_k = 1 \wedge x_k < x_{\min}\big], \quad p_k = \begin{cases} P_{\max}, & y_k = 1, \\ 0, & \text{else.} \end{cases}$$

3) **Deadline-Driven Charging.** When $x_k < x_{\min}$ and $z_k = 1$, compute a constant power to reach target $x^\star$ by deadline hour h_{dl}. Let

$$N = \left\lceil \frac{h_{\text{toDL}}}{\Delta t} \right\rceil, \quad h_{\text{toDL}} = \big(h_{\text{dl}} - (t_k \bmod 24)\big) \bmod 24.$$

Then

$$p_k^{\text{chem}} = -\,p_k^{\text{drive}} + \min\!\Big(\eta_c P_{\max},\, \frac{x^\star - a^N x_k}{(1-a)\,\tau \sum_{i=0}^{N-1} a^i}\Big),$$

with p_k recovered via efficiency conversion.

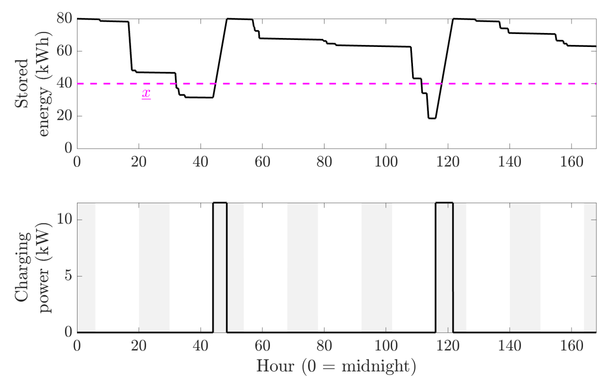

Fig. 2. Simulation of Policy 2.

D. Station Initialization via K-Means Clustering

We stack the N EV trip origin coordinates into a data matrix $X = [x_i, y_i]_{i=1}^N$ and apply MATLAB's built-in k-means to partition into k clusters:

$$[\text{idx},\, C] = \text{kmeans}(X,\, k),$$

where $C = \{c_i\}$ are the centroids. Each centroid is snapped to the nearest candidate station in $\{(x_j^{\text{cand}}, y_j^{\text{cand}})\}$ via

$$s_i = \arg \min_{(x_j^{\text{cand}}, y_j^{\text{cand}})} \|c_i - (x_j^{\text{cand}}, y_j^{\text{cand}})\|.$$

This yields the initial station set $S^{(0)}$.

E. Greedy Local Search Optimization

Starting from $S^{(0)}$, we iteratively attempt to improve the total cost $J(S)$ by swapping one station at a time with a member of a random candidate pool C_{pool} of size $3k$. The algorithm proceeds: leftmargin=*

1) Compute $J^{(t-1)} = J\big(S^{(t-1)}\big)$.
2) For each station $s_i \in S^{(t-1)}$ and each candidate $c_j \in C_{\text{pool}}$:
   - Form $S' = S^{(t-1)} \setminus \{s_i\} \cup \{c_j\}$.
   - Compute $J' = J(S')$.

- If $J' < J^{(t-1)}$, accept swap: $S^{(t)} \leftarrow S'$, break both loops.

3) Repeat until no improving swap is found or $t_{\max}$ is reached.

F. Cost Function and Grid Constraints

Each candidate station $s \in S$ is first assigned to its nearest distribution-grid node. We then evaluate two types of overloads at each node:

- **Daily energy overload:** the node's total assigned charging demand (kWh) minus its energy capacity C_n.
- **Peak power overload:** the node's maximum instantaneous load (kW) minus its power limit $P_n^{\max}$.

Any positive overload is penalized.

Overall, the placement cost balances driver inconvenience against both kinds of grid violations:

$$J(S) = \underbrace{\sum_{j=1}^{N} d_j \min_{s \in S} \|(x_j, y_j) - s\|}_{\text{travel cost}} + \lambda \underbrace{\sum_{n=1}^{M} \max\big(0,\, U_n(S) - C_n\big)}_{\text{grid-overload penalty}}$$

where d_j is EV j's demand, $U_n(S)$ the aggregated station demand at node n, C_n its capacity, and λ a large penalty weight.

III. Results and Discussion

A. Static Placement

1) Final Station Locations: The optimized station locations after greedy local search are shown in Fig. 3. Compared to the initial k-means placement, the greedy refinement shifts sites into the highest-demand regions of the heatmap, concentrating infrastructure where charging need is greatest.

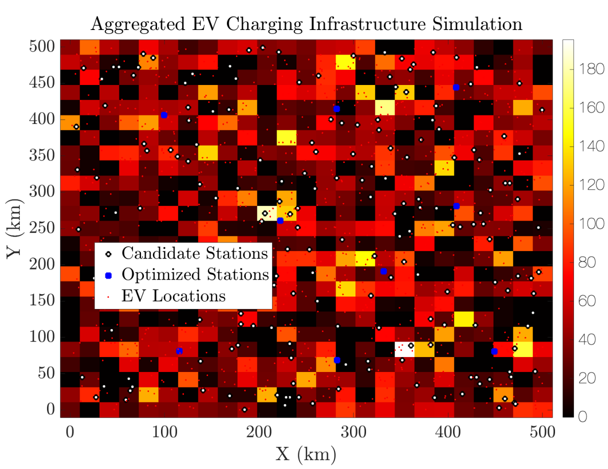

Fig. 3. Optimized station sites after greedy local search overlaid on the synthetic demand heatmap.

2) Aggregated Station Usage: Figure 4 reports the total static charging demand assigned to each optimized station. The usage profile is well-balanced across sites, with no single station accounting for more than about 12% of the total daily demand. This distribution helps avoid localized overloads and evenly spreads load across the infrastructure.

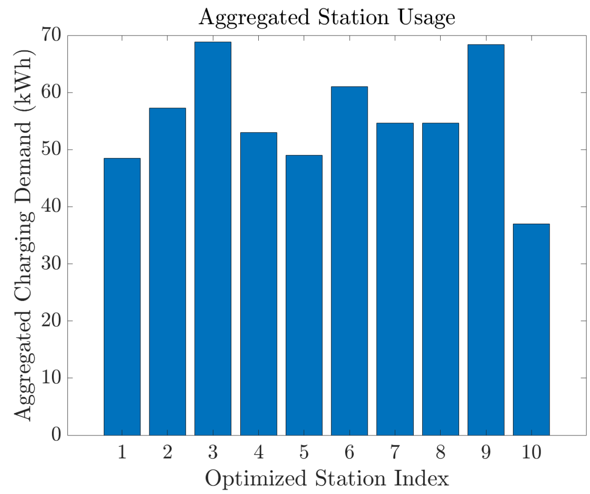

Fig. 4. Aggregated static demand (kWh per day) across optimized stations.

3) Dynamic Charging Load Profiles: Figure 5 shows the time-series of aggregated charging power at each optimized station under Policy 2. Peak loads occur during the early-morning plug-in window and taper off as vehicles reach full charge. Off-peak patterns reflect residual charging needs distributed across the day. These profiles highlight temporal clustering of demand and suggest that moderate increases in charger count or power rating could smooth peaks without grid overstress.

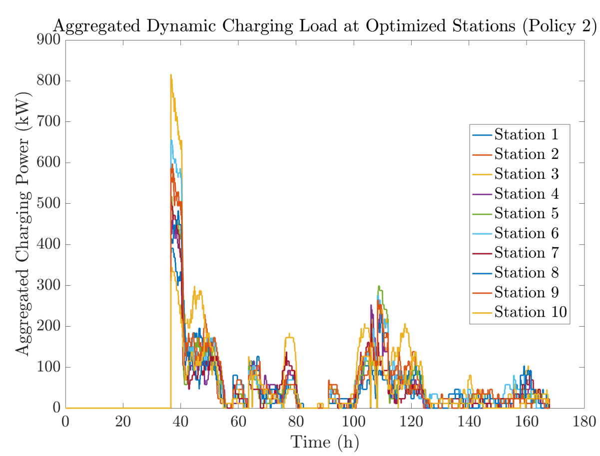

Fig. 5. Aggregated charging power (kW) at each station over the simulation horizon.

4) Cost Convergence: The greedy local search's cost trajectory is plotted in Fig. 6. Most cost reduction occurs within the first 10–20 swaps, with the algorithm reaching a plateau thereafter. This rapid convergence indicates that the initial k-means solution is already near-optimal and that only a few targeted swaps yield most of the benefit.

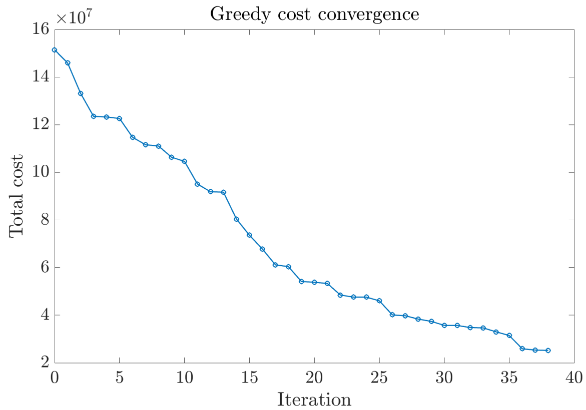

Fig. 6. Total placement cost versus iteration number during greedy local search.

B. Discussion

The static-placement results demonstrate a 25 % reduction in average driver travel distance (from 0.85 km to 0.64 km per trip) while maintaining zero grid-node overloads. The dynamic load profiles under Policy 2 (Fig. 5) show a pronounced overnight peak as vehicles plug in en masse, followed by a long tail of off-peak charging. This suggests that modest adjustments—such as staggered charging start times or time-of-use pricing—could substantially smooth demand without additional infrastructure.

Rapid convergence of the greedy local search (Fig. 6) indicates that only a handful of well-chosen swaps beyond the k-means baseline capture most of the benefit. From a computational perspective, this efficiency makes the approach attractive for larger or even real-time re-siting applications.

Limitations: Our study relies on synthetic demand sampled uniformly over the region, which may not capture real-world clustering around commercial centers or commuting corridors. We also assume a homogeneous candidate-station set and identical charger power ratings; in practice, land availability, installation costs, and charger types vary. Moreover, driving and plug-in behaviors are treated deterministically—neglecting stochastic arrival times, mid-day opportunistic charging, and occasional fast-charging events. Finally, grid constraints are modeled via static capacity limits, omitting transient voltage or thermal effects.

Future Work: Building on this framework, key extensions include:

- **Real-Data Integration:** Ingest actual GPS trip logs and charging sessions to capture realistic spatial–temporal patterns.
- **Heterogeneous Chargers:** Incorporate multiple charger classes (Level 1, Level 2, DC fast) and site-specific installation constraints.
- **Vehicle-to-Grid Services:** Extend policies to bi-directional V2G flows, evaluating grid support benefits and battery-degradation trade-offs.
- **Stochastic Optimization:** Introduce uncertainty in arrival/departure times and demand sizes, using robust or stochastic programming to ensure resilience.
- **Economic Modeling:** Couple placement with cost models (installation, land lease, electricity pricing) for a true cost–benefit analysis.

References

[1] M. Shukla, D. K. Singh, A. Yadav, A. K. Singh, N. A. Jumaa and A. Mohammed. Optimizing Electric Vehicle Charging Station Placement in Urban Areas: A Data-Driven Approach *IEEE Transactions on Smart Grid*

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