Undergraduate Research Toward a Linear Programming–Based Method for Estimating Feeder-Level EV Charging Hosting Capacity Using Simulated Demand Data

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***Abstract*—Electric vehicle (EV) charging can impose significant stress on distribution feeders, whose thermal and operational limits vary across space and time. This paper presents a linear programming (LP) method for estimating feeder-level EV hosting capacity using simulated demand data and publicly accessible feeder geometry and loading profiles. EV charging sites are geospatially mapped to feeders, baseline loading and hourly headroom are constructed, and a constrained 24-hour charging schedule is solved for each node subject to feeder, substation, hardware, and availability limits. LP is selected for its convexity, guaranteed optimality, and scalability to thousands of independent node-level problems.**

In contrast to approaches requiring detailed proprietary distribution system models, the proposed workflow uses only publicly accessible data sources, making it suitable for undergraduate-led research and reproducible by the broader community. Case studies on California feeders demonstrate how headroom patterns influence achievable charging, reveal binding constraints, and highlight sensitivity to charging efficiency and maximum power.

***Index Terms*—Electric vehicles, distribution feeders, hosting capacity, optimization, ArcGIS, linear programming, undergraduate research**

I. Introduction

Transportation electrification is increasing demand on distribution grids, particularly at the feeder level where thermal and operational constraints are most sensitive. Although EV charging is flexible in time, its spatial distribution is heterogeneous, and feeders serving dense charging clusters may experience localized stress not visible in system-wide aggregates. Existing methods often require proprietary distribution models [1], limiting their accessibility for academic research and third-party analysis.

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Accurately quantifying feeder-level EV hosting capacity requires understanding where charging occurs, how much energy is required, and how these needs align with feeder headroom. "Hosting capacity" refers to the amount of EV charging that can be added without violating existing feeder and substation limits, assuming EV charging power can be scheduled within availability windows.

Simulated charging demand data provided by ElectroTempo [2] offers large-scale EV charging simulations with geographic identifiers, daily energy requirements, and hourly charging profiles. Combined with feeder topology and loading information from public utility ArcGIS services [3], these data enable feeder-level hosting capacity analysis without requiring access to internal utility planning models.

A. Motivation and Challenges

Several practical challenges motivate this work. First, hourly loading on distribution feeders is highly time-varying and often correlated across feeders sharing a substation. Second, EV charging sites have heterogeneous characteristics: different power ratings, daily energy requirements, and arrival or departure times. Third, there is tension between model fidelity and computational tractability. High-fidelity mixed-integer formulations with detailed network constraints quickly become difficult to scale to thousands of nodes, whereas overly simplified heuristics may obscure key limiting factors.

The goal is to create a transparent, reproducible pipeline that reveals how much simulated demand can be accommodated on real feeders given their published capacities and hourly loading profiles.

B. Contributions

This work provides several contributions relevant to both EV hosting capacity analysis and undergraduate research. It establishes a reproducible workflow that integrates simulated charging demand data with publicly available ArcGIS feeder information to construct EV node datasets, feeder assignments, and hourly headroom profiles. It develops a linear programming formulation capable of computing node-level charging schedules that reflect feeder, substation, hardware, and availability limits while remaining computationally scalable to thousands of nodes.

The case studies on California feeders illustrate how feeder headroom patterns shape feasible charging schedules and influence hosting capacity outcomes, including situations resulting in binding constraints or infeasible schedules. Finally, the project documents the undergraduate research process, emphasizing the data engineering, software tooling, and methodological decisions required to conduct hosting-capacity studies with publicly accessible resources.

C. Related Work

Optimal decentralized protocols using convex optimization for valley-filling objectives were developed in [4]. Coordinated charging algorithms to minimize distribution system losses while maintaining voltage constraints were presented in [5]. A mixed-integer linear programming model for EV charging coordination in unbalanced distribution systems was proposed in [6]. A comprehensive assessment of PV hosting capacity using Monte Carlo methods on 50,000 real low-voltage systems was provided in [1]. A comprehensive review of renewables and EV hosting capacity in active distribution networks was presented in [7], surveying limiting factors, assessment methods, and enhancement techniques across 1,400 publications.

Most hosting capacity studies rely on detailed utility models and proprietary data, limiting reproducibility. This work differs by: (1) using only publicly accessible data sources, (2) focusing on LP formulations for guaranteed optimality and computational tractability, and (3) providing a workflow specifically designed for undergraduate-led research without access to internal utility planning models.

II. Data Sources and Preprocessing

The workflow requires EV charging demand data, feeder geometry, and feeder loading profiles.

A. Simulated Daily and Hourly Data

Simulated site-level charging demand provides geographic coordinates as WKT "POINT(lon lat)" objects, daily energy requirements, and hourly load profiles. Preprocessing parses coordinates, filters invalid entries, groups repeated observations, and produces `csv/ev_nodes.csv` containing:

$$\{\text{node_id}, \text{lat}, \text{lon}, P_{\max}, E_{\text{req}}, \text{avail_start}, \text{avail_end}\} \quad (1)$$

Typical maximum charging powers fall between 7.2 and 50 kW (Level 2 and DC fast-charging), with daily energy requirements of 10–40 kWh. Sites with missing or invalid geometries are discarded, and duplicates are aggregated by averaging. The hourly dataset is aggregated into a 24-hour baseline:

$$\text{baseline}(h) = \text{mean of all hourly observations at hour } h \quad (2)$$

B. Feeder Geometry and Loading Profiles

Feeder traces and hourly loading data are obtained from ArcGIS services such as PG&E's LineDetail and FeederLoadProfile layers, providing polyline geometries, thermal ratings (*LoadCapacity_kW*), and monthly-hourly loading values.

ArcGIS queries are limited to a bounding box defined by node coordinates. The feeder loading profile layer provides hourly *high* and *low* loading estimates. High values are averaged by hour to obtain conservative baseline feeder loading L_h^{feeder}.

C. Node-to-Feeder Mapping

Each EV node is assigned to a feeder by computing shortest distance to feeder polylines. When GeoPandas and Shapely are available, nodes are represented as buffered points and spatially joined with feeder lines in projected coordinates. Without geospatial libraries, the workflow uses explicit feeder identifiers from the EV dataset when available.

D. Feeder and Substation Headroom

Feeder headroom is computed at each hour:

$$H_h^{\text{feeder}} = C_{\text{thermal}} - L_h \quad (3)$$

where C_{thermal} is feeder ampacity and L_h is hourly baseline load. Substation headroom:

$$H_h^{\text{sub}} = C_{\text{sub}} - L_h^{\text{substation}} \quad (4)$$

When thermal capacity values are unavailable, or when feeders have zero kW hosting capacity for all line segments, those feeders are excluded from the analysis. For feeders with partial data (e.g., missing substation capacity), only feeder-level constraints are applied. This conservative approach ensures that hosting capacity estimates do not overestimate available headroom.

It is important to note that the feeder headroom values obtained from public ArcGIS services represent a proxy for actual network constraints rather than results from detailed power flow analysis. The published thermal ratings and loading profiles do not capture voltage constraints, line impedances, or reactive power flows that would be modeled in a full distribution system study. Additionally, the data represents aggregated feeder-level thermal limits rather than segment-by-segment conductor ratings, meaning that localized bottlenecks within a feeder may not be visible. Power factor variations and their effects on apparent power limits are also not explicitly represented. These simplifications are appropriate for screening-level analysis and early-stage planning comparisons, but detailed distribution planning studies would require validation against utility-grade power flow models with complete network topology and impedance data.

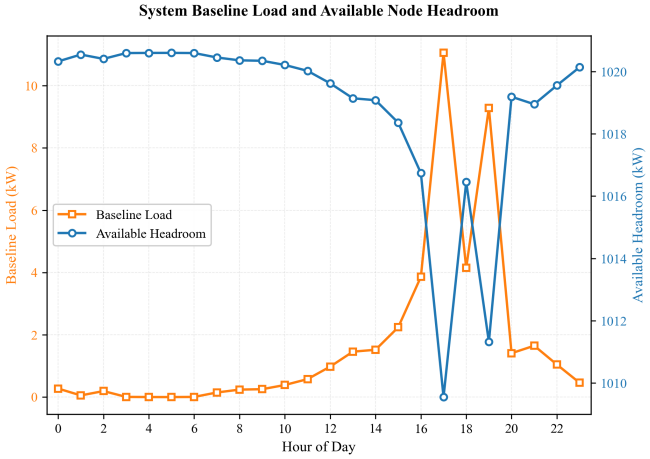

Fig. 1. System baseline load and available system headroom over a representative 24-hour period.

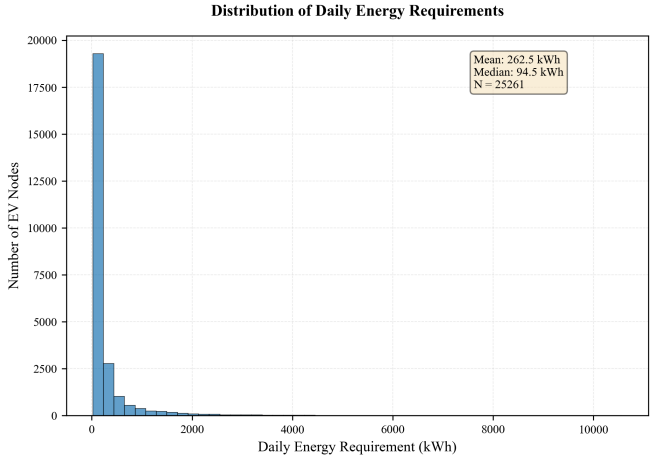

Fig. 2. Distribution of daily energy requirements across all EV nodes.

Fig. 1 shows diurnal headroom patterns with tight evening constraints and overnight flexibility.

E. Availability Windows

Optimization incorporates availability windows representing hours vehicles are connected to chargers. The availability set $\mathcal{A}$ contains all hours h during which the vehicle is connected and available for charging. For many sites, this is approximated as 18:00 to 08:00, refinable with more detailed behavioral models.

III. Optimization Model and Solution Method

A. Linear Programming Motivation

The simulated data models charging as continuous power, and constraints (thermal ratings, availability, energy requirements) are linear. This approach follows the convex optimization framework established for EV charging coordination [4], adapted here for hosting capacity estimation with explicit feeder constraints. LP guarantees global optimality, preserves flexible charging physics, and scales to tens of thousands of independent node-level problems. Open-source LP solvers make the method accessible for undergraduate research.

B. Mathematical Formulation

Decision variables represent hourly charging power p_h for $h = 0, \ldots, 23$, where η is charging efficiency and E_{req} is daily energy requirement.

For hosting capacity analysis, the objective maximizes total delivered energy:

$$\max \sum_h \eta p_h \tag{5}$$

Charging and availability constraints:

$$0 \le p_h \le P_{\max} \tag{6}$$

$$p_h = 0 \quad h \notin \mathcal{A} \tag{7}$$

$$p_h \le H_h^{\text{feeder}} \tag{8}$$

$$p_h \le H_h^{\text{sub}} \tag{9}$$

Energy requirement (for feasible nodes):

$$\sum_h \eta p_h = E_{\text{req}} \tag{10}$$

When the energy requirement can be met, this equality constraint is active and the objective value equals E_{req}. Each node's problem is independent, enabling parallel solution.

C. Solver and Computational Complexity

Each LP has 24 variables and approximately 50–80 constraints. The open-source CBC solver via PuLP requires milliseconds per node. Even for several thousand nodes, computation completes in minutes.

D. Infeasibility Handling

When the energy equality constraint cannot be satisfied, the LP is solved without it, maximizing deliverable energy subject only to hourly constraints. The delivered-to-target ratio indicates whether nodes require infrastructure upgrades or additional flexibility.

E. Software Implementation

Python implementation uses `pandas` for CSV handling, `requests` for ArcGIS queries, `geopandas` and `shapely` for geospatial operations, and PuLP for optimization. Modular design separates data ingestion, headroom construction, and LP solving.

IV. Case Study and Results

A. EV Node Dataset

The dataset contains approximately 25,000 EV nodes with average energy requirements near 18–20 kWh per day. The distribution of $P_{\max}$ reflects Level 2 chargers (7.2 kW) and DC fast chargers (up to 50 kW). Fig. 2 shows the distribution of daily energy requirements across all nodes, demonstrating significant heterogeneity in charging demand.

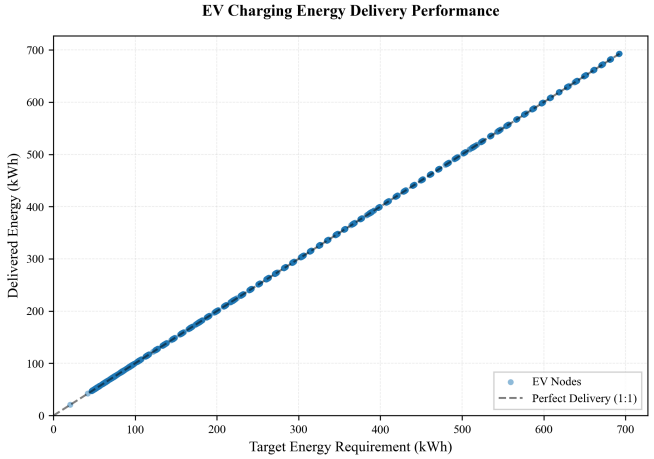

Fig. 3. Relationship between target energy requirements and delivered energy for nodes with optimal schedules.

TABLE I
SOLVER STATUS DISTRIBUTION ACROSS ALL EV NODES

Solver Status	Number of Nodes	Percentage
Optimal	23,197	91.8%
Infeasible (Binding Constraints)	2,064	8.2%

TABLE II
EXAMPLE FEEDER HOSTING CAPACITY RESULTS

Feeder ID	Daily EV Energy Delivered (kWh)	Limiting Constraint
389	939	Feeder Thermal
2911	2,265	Feeder Thermal
3022	2,442	Feeder Thermal

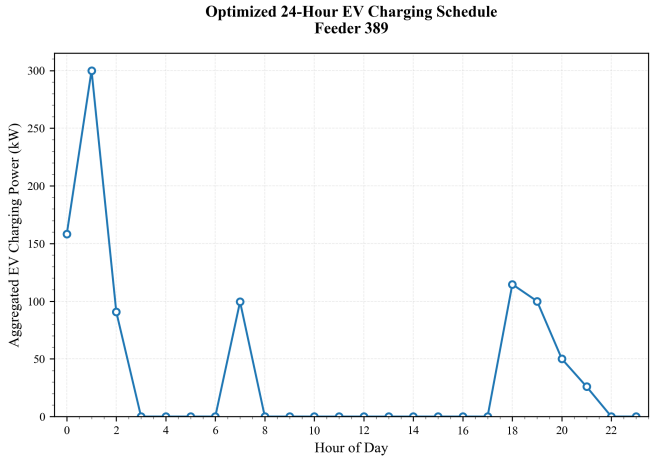

Fig. 4. Optimized 24-hour charging schedule for nodes assigned to Feeder 389.

B. Feeder Mapping Results

Feeder mapping reveals high variability. Some urban feeders serve more than 40 EV nodes, while rural feeders serve few. Some feeders have high thermal capacities but few nodes, suggesting expansion potential. This heterogeneity underscores the need for feeder-specific optimization.

C. Baseline Loading and Headroom Patterns

Headroom is smallest during evening peak hours (17:00–21:00) and largest primarily between 01:00 and 05:00 during low load periods. Nodes with long availability windows can shift charging to early morning, while nodes with short windows may struggle to meet energy requirements.

D. Optimized Charging Schedules

The LP shifts charging to high-headroom hours (01:00–05:00). Tight feeder constraints spread charging across multiple low-load hours. Some nodes are limited by $P_{\max}$, others by feeder headroom or availability windows.

The equality constraint enforces exact delivery for feasible nodes, yielding delivered-to-target ratios near unity (Fig. 3).

E. Solver Status Distribution and Causes of Infeasibility

Table I shows the distribution of solver outcomes across all EV nodes. Although most nodes are feasible due to generous overnight headroom, clusters of constrained nodes emerge on heavily loaded feeders, late-arrival schedules, or locations with high daily energy requirements.

Infeasibility most often occurs when a node's availability window is too short relative to its required energy and maximum charging power. Because system and feeder headroom are most constrained between 17:00 and 21:00, as shown in Fig. 1, nodes arriving during this interval often cannot begin charging until later at night. If the remaining overnight hours do not provide sufficient time, either due to low $P_{\max}$ values or high E_{req}, the LP cannot satisfy the energy equality constraint.

Feeder-specific congestion also contributes to infeasibility. Some feeders exhibit consistently low thermal headroom throughout the day, imposing strict hourly charging caps that limit nodes to only a few kilowatts. Even when availability windows are long, nodes mapped to such feeders may be unable to accumulate enough energy to satisfy the requirement. In other cases, a combination of moderate availability, intermediate energy requirements, and simultaneous reductions in both feeder and substation headroom produces conditions under which the schedule cannot meet the daily energy requirement. Here, the equality constraint is relaxed and the model maximizes deliverable energy, resulting in delivered-to-target ratios below unity.

F. Feeder Hosting Capacity

Three representative feeders illustrate hosting capacity outcomes and limiting constraints, as summarized in Table II. Detailed 24-hour charging schedules for these feeders are presented in Figs. 4–6, where the aggregate schedules illustrate how EV charging shifts toward off-peak hours under feeder headroom constraints.

Fig. 7 summarizes peak capacity utilization for the 15 feeders with the largest number of EV nodes. Feeders with utilization exceeding 80% (shown in red) represent locations where thermal constraints significantly limit additional EV

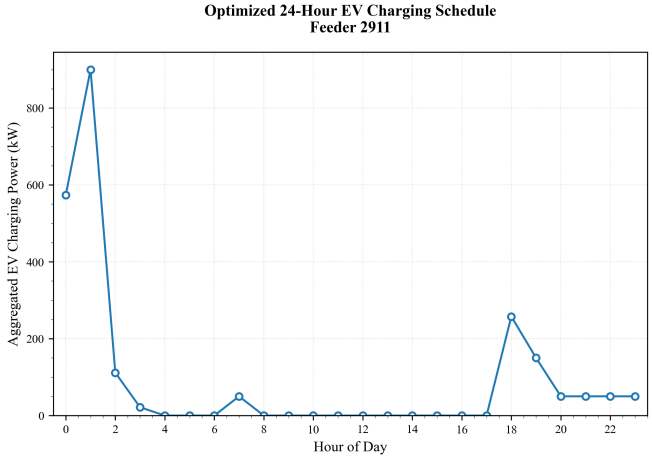

Fig. 5. Optimized 24-hour charging schedule for nodes assigned to Feeder 2911.

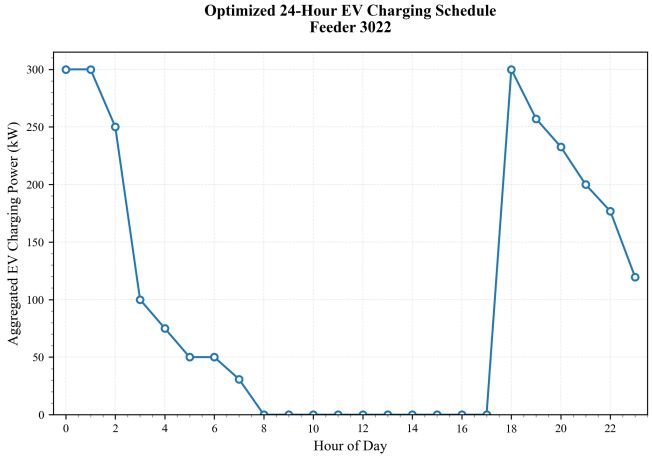

Fig. 6. Optimized 24-hour charging schedule for nodes assigned to Feeder 3022.

charging capacity, while feeders with lower utilization indicate potential for expansion under the 2045 CEC load-hosting-capacity assumptions.

G. Educational Perspective and Lessons Learned

This project highlighted several important lessons from an undergraduate research standpoint. A substantial portion of the effort focused on data cleaning and preprocessing, as handling missing values, inconsistent formats, and large datasets proved just as essential as developing the optimization model itself. Working with public web services such as ArcGIS required careful attention to query parameters, API rate limits, and data format inconsistencies, providing valuable experience with real-world data sources that do not always behave predictably. Additionally, the project demonstrated how relatively simple optimization models, when paired with a carefully designed data pipeline, can yield meaningful insights into EV integration and feeder-level hosting capacity. These experiences

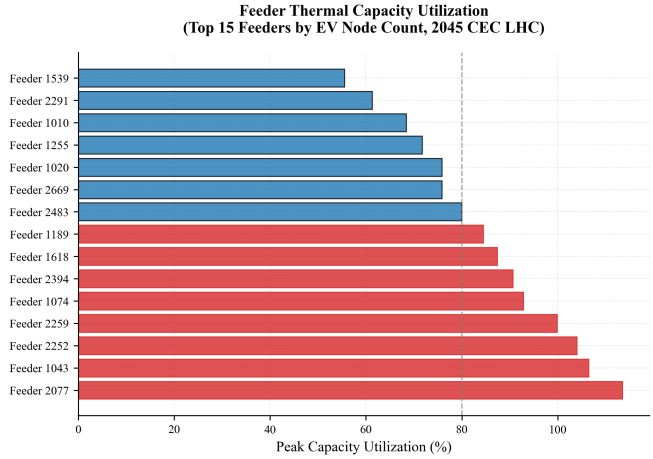

Fig. 7. Peak thermal capacity utilization for top 15 feeders by EV node count under the 2045 CEC load-hosting-capacity assumptions. Red indicates feeders with utilization exceeding 80%.

collectively provided a strong introduction to both power systems analysis and hands-on research workflows.

V. Conclusion

A linear programming workflow was developed to compute feeder-level EV hosting capacity using simulated demand data and public feeder loading profiles. The approach builds on established convex optimization methods for EV charging [4], [5] while addressing the practical challenge of limited data access in hosting capacity analysis. The approach integrates geospatial mapping, baseline load construction, and constrained optimization in a form accessible to undergraduate researchers.

Results highlight the dependence of hosting capacity on headroom patterns and sensitivity to charging efficiency and maximum power. They reveal the importance of feeder-specific analysis: some feeders have abundant headroom while others are constrained by thermal limits or availability windows even when system-level headroom appears sufficient. The computational efficiency of the LP formulation, combined with its reliance on publicly accessible data, makes the approach suitable as a screening tool for identifying constrained feeders prior to detailed engineering studies.

VI. Future Work

Future extensions include incorporating voltage constraints via linearized DistFlow equations, modeling time-varying feeder topology, integrating distributed energy resources, adding transformer thermal constraints, scaling analysis to statewide datasets, and introducing robust or chance-constrained formulations. Refining behavioral assumptions with stochastic arrival times or different user segments could improve realism. Future teams could extend the implementation into an interactive visualization tool for exploring hosting capacity under alternative scenarios.

From a practical standpoint, the proposed method is well-suited as a screening tool for utility distribution planners. Its

computational efficiency enables rapid evaluation of thousands of candidate charging locations, allowing planners to identify feeders likely to face hosting capacity constraints before committing resources to detailed engineering studies. The approach can support scenario comparisons, such as evaluating the impact of different EV adoption rates or charging power levels, at a fraction of the computational cost of full power flow simulations. However, feeders flagged as constrained through this screening process should be validated using detailed distribution system models with complete network topology, impedance data, and voltage regulation controls before final planning decisions are made. Integration with utility planning workflows could involve using the LP-based screening results to prioritize which feeders warrant detailed study, thereby improving the efficiency of the overall planning process.

ACKNOWLEDGMENT

The authors thank the Texas A&M Energy & Power Research Group. This work was supported by ElectroTempo. The authors also acknowledge the use of AI-assisted tools during algorithm development and manuscript preparation. All methodological decisions and conclusions were independently validated by the authors.

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