Electric Vehicle Charging Station Placement

State of the Art Studies

Decision Science Course - 2025

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Abstract

Electric Vehicle (EV) charging station placement is a critical planning problem that can be addressed by Integer Linear Programming (ILP) models. These models enable planners to optimize infrastructure deployment with objectives such as cost minimization and reducing the number of required chargers while ensuring adequate coverage based on vehicle location. In this document, we review a range of ILP formulations—including those solved with the CPLEX Python library employing branch-and-cut algorithms—and provide a comprehensive discussion of different approaches from peer-reviewed journals, conference papers, theses, and institutional reports. The report details classical set covering models, cost minimization formulations, multi-objective extensions, and solution techniques alongside practical case studies.

1 Introduction

The deployment of EV charging infrastructure is a complex decision-making problem due to the combinatorial nature of selecting optimal locations. ILP models are particularly well-suited for this purpose since they allow the incorporation of multiple objectives (e.g., cost minimization, facility count minimization) and constraints (e.g., spatial coverage, service level requirements). Many models in the literature are inspired by classical facility location problems, with recent work focusing on minimizing both the total installation cost and the number of chargers required based on vehicle location data. Commercial solvers such as IBM CPLEX, which implement branch-and-cut algorithms, are widely used to solve these ILP formulations efficiently [1, 4].

2 ILP Models for EV Charging Station Placement

2.1 Coverage and Facility Count Minimization Models

One common ILP approach ensures that every EV has access to a charging station while keeping the number of stations as low as possible. In this method, potential charging locations are modeled as nodes in a network, and a binary decision variable determines whether a station is built at each node. The model includes constraints to guarantee that every demand point or road segment is within the acceptable range of at least one station. The overall goal is to cover all demand while minimizing the number of charging facilities.

2.2 Cost Minimization and Profit-Based Models

Another major group of ILP models focuses on directly minimizing costs, such as installation, operational, and user-related costs. In these models, charging station placement is treated as a fixed-charge facility location problem. That is, building a station incurs a fixed cost plus additional variable costs (for example, for each charger or per usage). One approach minimizes the total investment cost for deploying fast-chargers by choosing both the station locations and the number of chargers at each location, while considering land expenses and power infrastructure limits. Another approach minimizes the access cost for EV users—reducing the distance or time it takes to reach a station—by selecting the minimum number of stations needed so that most demand is covered within a target range. Some models even shift the focus to maximizing net profit by balancing revenues from charging sessions against both investment and operational costs through a penalty-reward mechanism in the objective function.

2.3 Multi-Objective and Multi-Stage Extensions

In practical EV charging station planning, decision-makers often need to balance several objectives at once or plan deployments over multiple time periods. For example, some models aim to reduce both investment costs and user travel distances simultaneously, yielding a range of optimal trade-offs. Other approaches incorporate uncertainty—such as varying EV adoption rates or travel demand—by using multi-stage planning techniques that adjust the deployment over time. These strategies, sometimes combined with heuristic methods to manage large problems, show that ILP models can be flexibly adapted to meet both short-term and long-term planning goals.

2.4 Solution Techniques and Solver Usage

Exact ILP formulations for EV charging station placement are typically solved using commercial solvers like IBM CPLEX or Gurobi. These solvers use branch-and-cut algorithms along with MILP heuristics to quickly find optimal solutions for moderate-sized problems. However, as the problem grows—for instance, when planning at a national level or over multiple time periods—even branch-and-cut methods can have difficulties. Researchers address this by breaking the problem into smaller parts using techniques like Benders decomposition, or by applying heuristics and metaheuristics, such as greedy algorithms or rolling-horizon approaches, to obtain near-optimal solutions more quickly. Some studies even combine ILP with simulation models in a two-step process where the ILP selects candidate locations and simulation assesses operational performance, refining the solution iteratively. For those using the CPLEX Python API, these techniques provide practical ways to formulate constraints efficiently and incorporate valid inequalities or decompositions to accelerate the MILP process.

3 Comparison of Representative ILP Models

The following table summarizes key ILP-based EV charging station placement studies, highlighting their objectives, data sources, and solution methodologies.

Table 1: Comparison of ILP Models for EV Charging Station Placement

Study (Year) Solution Method	Objective/Model	Case Study/Data
Frade *et al.* (2011) [2] ILP solved with CPLEX	Maximal covering; minimize stations for demand coverage	Lisbon, Portugal (neighborhood-level demand)
Chen *et al.* (2013) [3] MILP via CPLEX (branch-and-cut)	Minimize user access cost with penalty for unmet demand	Seattle, USA (30k trip records)
Lam *et al.* (2014) [4] Exact ILP versus heuristic comparisons	Ensure city-wide coverage with minimal stations; NP-hard formulation	Hong Kong road network; artificial grid cases
Sadeghi-Barzani *et al.* (2014) [6] MILP solved via CPLEX with iterative techniques	Minimize total cost for fast-charger placement and sizing	Tehran, Iran (traffic flows on major roads)
Shahraki *et al.* (2015) [5] MILP in GAMS solved with CPLEX	Maximize electrified VMT by optimal station placement	Beijing, China (11,880 taxi trajectories)
Asamer *et al.* (2016) [7] Bi-objective ILP (cost vs. travel distance) solved with CPLEX	Optimize station locations for urban taxi fleet minimizing detour distances	Vienna, Austria (taxi operation data)
He *et al.* (2018) [8] Reformulated to single-level MILP solved with custom heuristics + CPLEX	Bi-level model: maximize flow coverage with driving range constraints	Abstract small-scale networks
Miljanić *et al.* (2018) [1] ILP (covering model) solved with integer programming	Minimize number of stations to ensure network connectivity	Montenegro road network (nodes and distances)
Bian *et al.* (2019) [9] MILP solved with CPLEX integrating GIS data	Maximize profit from station deployment (revenue vs. cost)	Västerås, Sweden (GIS-based demand data)
Kadri *et al.* (2020) [10] Benders decomposition + heuristic approaches	Multi-stage stochastic ILP to maximize expected demand satisfaction	Hypothetical inter-city network with EV adoption scenarios
Anjos *et al.* (2020) [11] Rolling-horizon heuristic for large-scale MILP	Multi-period MILP integrating urban and highway demand to boost EV adoption	Quebec and California case studies

4 Conclusion and Further Resources

Over the past decade, numerous studies have employed ILP to address the EV charging station placement problem. The reviewed literature demonstrates that while pure coverage models aim to minimize the number of stations, cost-based models integrate fixed and variable cost components to optimize overall investment. Multi-objective and multi-stage extensions further address uncertainties in EV adoption and user behavior, often necessitating decomposition techniques or heuristics to manage computational complexity.

For practitioners implementing ILP via the CPLEX Python API, these studies offer valuable insights into model formulation, constraint design, and solver strategies. It is essential to consider scalability issues by using data clustering, valid inequalities, or hybrid approaches (combining ILP with simulation) to improve performance. Comprehensive reviews, such as those by Kchaou-Boujelben (2021) [13] and Putra *et al.* (2024) [14], provide further bibliographic resources and comparative analyses of the various methodologies in this domain.

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