

In Charge of Charging: Optimizing Overnight Orchestration for Electric Delivery Fleets

BUSINESS PROBLEM

As electric delivery fleets scale, overnight charging at distribution centers relies on manual first-come- first-served parking and reactive vehicle shuffling by overnight staff. With fewer chargers than vehicles, this approach leads to low charger utilization, excessive labor-intensive vehicle relocations, and vehicles departing below target state-of-charge. Potential transition to multi-nozzle chargers add combinatorial complexity that would exceed human capacity. The result: hundreds of millions in unnecessary capital expenditure and suboptimal fleet readiness at morning dispatch.

DATA SOURCES

Vehicle telemetry: arrival times, departure times, initial state-of-charge (SOC), route IDs, delivery company assignments per vehicle per night

Charger infrastructure specs: charger type (AC/DC/multi-nozzle), connection capacity (Hc), activation capacity (Ac), power rating, delivery company allocation

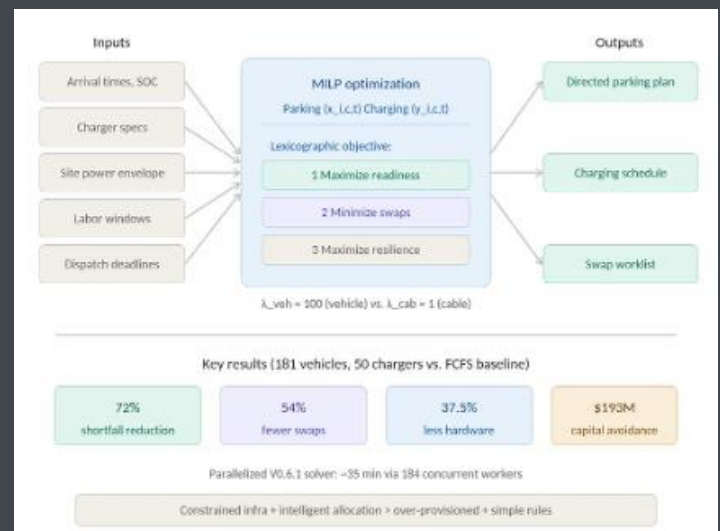
Site operational parameters: power envelope limits, labor shift windows, target SOC thresholds

Data Types and Format

Boolean, Categorical (nominal), Count (integer), Numeric, Relational Data, Text, Time series (Dynamic)

APPROACH

Developed a family of mixed-integer linear programming (MILP) models for overnight parking and charging orchestration. The formulation explicitly distinguishes cable swaps (<1 min) from vehicle swaps (>8 min), captures multi-nozzle charger topology (connection vs. activation capacity), and uses a lexicographic objective: readiness first, then swap minimization, then resilience. A parallelized two-stage decomposition solver (V0.6.1) achieves fleet-scale solutions (181 vehicles) in ~35 minutes using Gurobi.



IMPACT

Quantified results (constrained scenario: 181 vehicles, 50 DC chargers):

- Energy shortfall reduced by 72% (83 → 23.55 vehicle-equivalents) vs. FCFS heuristic baseline
- Vehicle swaps reduced by 54% (100 → 46 per night)
- Hardware utilization improved by 60%: optimizer at 50 chargers achieves readiness that FCFS requires 80 chargers to match -- 37.5% fewer chargers needed

Network-scale financial impact (from internal project documentation):

- \$XXM capital avoidance entitlement (charger deferral across constrained sites)
- \$XXM annual labor savings entitlement (reduced swap operations, ~7.2 labor-hours saved per site per night)

Upside estimates:

- up to \$XXM CapEx and \$XXM/year OpEx in favorable constrained scenarios

Operational impact:

- Would enable aggressive 2:1 vehicle-to-charger ratios that would be infeasible under manual heuristic operations
- Inverts traditional capacity planning: constrained infrastructure + intelligent allocation outperforms over-provisioned infrastructure + simple rules
- Converts costly vehicle relocations into low-cost cable swaps by co-locating compatible vehicles at multi-nozzle chargers
- Provides directed parking plans, charging activation schedules, and time-ordered swap worklists for overnight staff
- Broader significance: Framework generalizes to heavy-duty trucking, transit bus depots, and autonomous vehicle fleets. Demonstrates that optimization-based coordination is viable for any infrastructure-constrained electric fleet.

 DRIVERS	Rapid EV fleet scaling created infrastructure bottleneck: manual first-come-first-served operations could not efficiently share limited chargers across large fleets. Multi-nozzle charger consideration amplifies complexity beyond human cognitive capacity. Network-scale capital avoidance and labor savings created strong business case.
 BARRIERS	Computational complexity wall: monolithic MILP intractable beyond ~20 vehicles. Operator trust: charging associates and delivery drivers resistant to algorithm-driven direction. Data quality: SOC forecasts and arrival predictions have inherent uncertainty. Stakeholder alignment across operations, engineering, and delivery with competing priorities.
 ENABLERS	Access to real operational data and infrastructure specs. Field immersion: overnight site visits, ride-alongs, and interviews grounded model in reality and built stakeholder trust. Commercial solver with parallelization support. LGO dual-degree structure enabling OR + engineering + business integration. Faculty advisors spanning optimization.
 ACTIONS	Conducted extensive field immersion (overnight site visits, delivery ride-alongs, stakeholder interviews). Developed family of five MILP formulations spanning fidelity-tractability spectrum. Characterized computational complexity wall empirically. Built parallelized two-stage decomposition solver achieving scale. Translated optimization results into economic impact framework with parameterized CapEx/OpEx formulas. Designed phased deployment road
 INNOVATION	First MILP formulation in the EV charging scheduling literature to jointly model: (1) multi-nozzle chargers with connection capacity > activation capacity ($H_c > A_c$), (2) heterogeneous reconfiguration costs distinguishing cable swaps from vehicle swaps, and (3) labor windows gating manual swap actions. Parallelized decomposition enables fleet-scale operation.
 IMPROVEMENT	72% reduction in energy shortfall (83 → 23.55 vehicle-equivalents). 54% reduction in vehicle swaps (100 → 46 per night). 60% improvement in charger hardware utilization (50 chargers achieving what 80 achieved under FCFS). Network-scale: \$XXM capital avoidance, \$XXM/yr labor savings.
 BEST PRACTICES	Field immersion before modeling: overnight operations visits validated assumptions and built operator trust. Develop model family at multiple fidelity levels rather than one monolithic formulation. Decomposition is a design requirement for fleet-scale optimization. Lexicographic objectives cleanly separate non-negotiable constraints.
 OTHER APPLICATIONS	Heavy-duty electric trucking depots (longer dwell, higher power). Public transit electric bus depots (fixed routes, opportunity charging). Autonomous vehicle fleet parking and charging coordination. Shared mobility/ride-hail EV charging hubs.