POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

EXECUTIVE SUMMARY OF THE THESIS

Day-Ahead Energy Management for EV Charging Stations Under Demand Uncertainty: A Sample-Based Optimization Framework Applied to the Italian Electricity Market

TESI MAGISTRALE IN ENERGY ENGINEERING – INGEGNERIA ENERGETICA

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1. Introduction

1.1 The EV Grid Integration Challengee

The global transition toward electric mobility represents a critical pathway for transportation decarbonization, with EV market share surging from 5% (2020) to 22% (2024) driven by falling battery costs (reaching $100/kWh in 2024) and stringent regulatory frameworks (EU 2035 ICE phase-out). The global energy landscape is undergoing profound transformation to align with Paris Agreement targets, requiring 43% greenhouse gas emission reduction by 2030 to limit temperature increases to 1.5°C . In this context, transportation sector decarbonization—accounting for 23% of energy-related CO_2 emissions —emerges as critical priority. However, this rapid electrification introduces significant challenges for electrical distribution systems [1]:

- Uncoordinated charging creates high-magnitude, temporally correlated loads coinciding with existing peak demand.
- Grid reinforcement costs to address infrastructure stress.
- Peak demand escalation of up to 25% threatens transformer overloading and power quality degradation.

Intelligent energy management frameworks exploiting the inherent temporal flexibility of EV charging—projected to provide 16-20 TWh of distributed storage by 2030 —are essential to transform vehicles from grid liabilities into active assets supporting grid stability and economic optimization.

1.2 The uncertainty in EVs user behavior

EV charging demand exhibits extreme stochasticity fundamentally different from conventional loads. Charging profiles are dictated by heterogeneous user behaviors and exogenous variables including ambient temperature and

electricity tariff structures. At the session level, variables such as arrival/departure times, connection durations, and energy requirements exhibit substantial variability, complicating load aggregation.
Existing literature exhibits critical gaps despite substantial methodological progress:

1. **Parametric assumptions**: Predominant reliance on Gaussian mixture models, vine copulas without rigorous goodness-of-fit validation risks misrepresenting empirical distributions, particularly tail regions governing worst-case scenarios. While Müller and Schmidt applied adaptive Kernel Density Estimation revealing multi-modal patterns, and further studies demonstrated delayed charging biases from analyzing over two million European sessions, parametric constraints persist.
2. **Synthetic validation**: Majority of optimization studies validate against limited/synthetic datasets, overlooking behavioral complexity in real operational data. Traditional Monte Carlo approaches systematically underestimate peak clustering effects, while more sophisticated frameworks incorporating temporal dependencies and scenario reduction techniques still lack extensive empirical validation.
3. **Forecast-decision disconnect**: Recent advances in deep learning, conformal prediction, and diffusion-based generative models achieve high statistical accuracy but prevailing focus on forecast metrics doesn't necessarily translate to improved economic scheduling outcomes, as distributional fidelity-decision quality relationship depends on specific cost structures.

2. Research Objective and Contributions

This thesis addresses the gap between high-resolution operational data and actionable energy management strategies through five interrelated technical objectives:

1. **Empirical demand characterization**: Leverage 25 months (June 2023-June 2025) of operational data from Politecnico di Milano's PoliGrid infrastructure [2] (4,471 charging sessions, 39 vehicles, 71,680 kWh delivered) to construct empirical cumulative distribution functions (ECDFs) for uncertain parameters without parametric assumptions [3]
2. **Statistical validation**: Asses distributional preservation quality in generated scenario ensembles
3. **Sample-based optimization framework**: Develop computationally tractable day-ahead scheduling methodology combining Monte Carlo scenario generation with mixed-integer linear programming [4], solving 2,000 independent instances (500 scenarios × 4 seasonal tariff structures)
4. **Comprehensive tariff integration**: Implement complete Italian electricity bill structure [5] including time-varying energy/capacity charges, power-based demand charges, network obligations, excise taxes, VAT to enable accurate economic assessment
5. **Mechanistic performance analysis**: Decompose optimization benefits by cost component, analyze seasonal adaptation strategies, quantify temporal flexibility exploitation to develop generalizable insights for tariff design and policy

3. Methodology

The methodological framework developed in this thesis integrates two complementary approaches: stochastic demand modeling through Monte Carlo simulation, and deterministic optimization through mixed-integer linear programming. This integrated architecture addresses the fundamental challenge of day-ahead charging management under uncertainty while maintaining computational tractability for operational deployment.

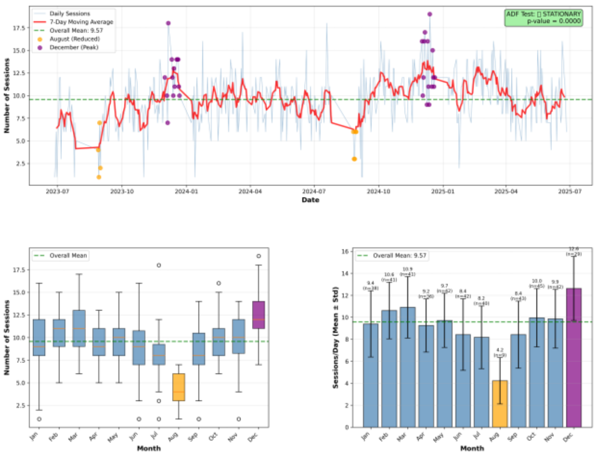
3.1 Data Collection and Preprocessing

The empirical foundation of this research rests on operational data collected from the Politecnico di

Milano PoliGrid charging infrastructure [2], located at the Leonardo Campus. The facility comprises three charging stations (ED9, ED20, ED22), collectively providing 16 charging points offering 22 kW AC capacity with access regulated through institutional credentials, serving the university community of faculty, staff, and students. The stations operate primarily during standard weekday hours from 07:00 to 21:00, creating a workplace charging context distinct from residential or highway fast-charging environments.

The raw dataset spans 25 months (June 2023–June 2025), documenting 4,471 sessions from 39 vehicles with cumulative energy delivery of 71,680 kWh. Temporal discretization maps continuous timestamps into 15-minute intervals aligned with Italian market settlement.

To ensure the analysis reflects regular operational demand rather than stochastic outliers or anomalous conditions, rigorous temporal filtering excludes weekends, official holidays, and university closure periods, yielding 448 working days representing 71% of the calendar span. Stationarity validation via Augmented Dickey-Fuller test [7] using stats models yields ADF = -6.07 with $p < 0.001$, confirming absence of long-term trends despite calendar variations like August closures and December holidays.



How shown in *Figure 2.1*, while certain months exhibit systematically different session counts—notably August showing reduced activity from summer campus closure and December reflecting holiday effects—these calendar variations do not compromise stationarity assumptions for pooled estimation purposes.

3.2 Monte Carlo Scenario Generation

The methodology transforms historical patterns into probabilistic forecasts through empirical cumulative distribution functions constructed directly from observed data [3], avoiding restrictive parametric assumptions. For each parameter X with n observations $\{x_1, \ldots, x_n\}$, the empirical CDF is

$$F_n(x) = (1/n)\,\Sigma_i\, I(x_i \leq x) \qquad (3.1)$$

Four uncertain parameters exhibit distinct behavioral signatures: arrival times concentrate during 08:00-11:00 with median 10:15-10:30; connection durations display bi-modal structure (short 2-3h visits, full-day 7-8h stays) with mean 4.86h; energy requirements show right-skewed distribution with median 11.64 kWh; daily sessions range 1-19 vehicles with mean 9.57. Scenario generation employs inverse transform sampling [6], exploiting that if U ~ Uniform(0,1) then $X = F^{-1}(U)$ follows distribution F. The algorithm samples daily sessions (max 39 vehicles), then for each session generates arrival time, connection duration, energy demand, and vehicle segment assignment across four types (small BEV 30%, PHEV 20%, mid-BEV 35%, large BEV 15%). Repeating 500 times with different random seeds creates an ensemble, with mean absolute errors below 0.05 threshold across all parameters.

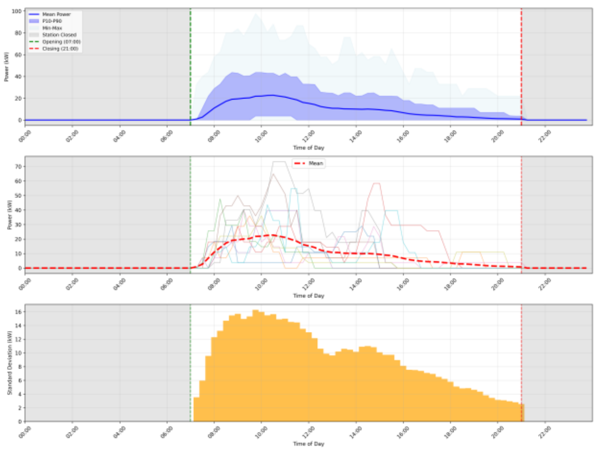


Figure 4. 1 - Monte Carlo Simulation Outputs: (a) charging profile -mean across 500 scenarios; (b) charging profile of a selected sample of 10 scenarios; (c) inter-scenario variability (standard deviation).

3.3 Optimization Model Formulation

The optimization model formulates day-ahead scheduling as mixed-integer linear program in Pyomo [8], solved with Gurobi using 1% gap tolerance and 3,600s time limit. The model operates over discrete 24-hour horizon T = {1, ..., 96} representing 15-minute intervals, with vehicle set E containing N_EV vehicles (varying stochastically, max 39). The optimizer determines charging power P_charge(e,t) for each vehicle e in each period t, exploiting temporal flexibility to reduce costs while respecting constraints.
The objective function minimizes net operator cost:

$$\min Z = C_{total} - R_{total} + \Sigma_e C_{penalty(e)} \qquad (3.2)$$

where C_{total} aggregates electricity procurement costs across Italian tariff components [5], R_{total} represents €0.65/kWh user revenue, and penalties assess €1.0/kWh for incomplete delivery. Total cost comprises variable energy costs with 10% grid losses, capacity market charges with seasonal time-variation [5], dispatching and network charges, power-based capacity charges at €4.447/kW monthly (constant across seasons) [5], fixed charges, excise taxes, and 22% VAT creating proportional amplification effect.
Constraints ensure feasible operation:

- power limits restrict charging through

$$P_{charge(e,t)} \leq \alpha(e,t) \times P_{\max(e)} \quad \forall e \in E, \forall t \in T \qquad (3.3)$$

where binary indicator α(e,t) forces zero during disconnection;

- energy requirements permit flexibility through

$$\Sigma_t P_{charge}(e,t) \times \Delta t + E_{uncharge}(e) \geq E_{req}(e) \qquad (3.4)$$

- grid interface links vehicles to station aggregate via

$$P_{withdraw(t)} = \Sigma_{\{e \in E\} P_{charge}}(e,t) \; \forall t \in T \qquad (3.5)$$

- peak tracking implements capacity minimization through

$$P_{max} \geq P_{withdraw(t)} \qquad (3.6)$$

for all t, forcing P_max to equal maximum withdrawal.
Critically, the methodology employs sample-based optimization solving each scenario-season combination independently, differing from multi-stage stochastic programming [4] where scenario probabilities enter the objective. For each of 2,000 combinations (500 scenarios × 4 seasons), the algorithm solves independent MILP minimizing Z_i and records optimal solution.
This architecture offers compelling advantages: computational tractability through embarrassingly parallel; operational realism aligning with industry practice of deterministic daily forecasts; analytical flexibility.

4. Results and Analysis

Empirical validation across 2,000 solved instances demonstrates substantial operational and economic benefits spanning diverse demand conditions and seasonal market environments.

4.1 Operational Performance: Peak Power Transformation

Optimization produces dramatic transformation of peak power distributions. Baseline immediate charging exhibits concentration at 35-50 kW (modal ~40 kW) with mean 88.7 kW and standard deviation 24.3 kW, reflecting coincident morning arrivals creating aggregate peaks.

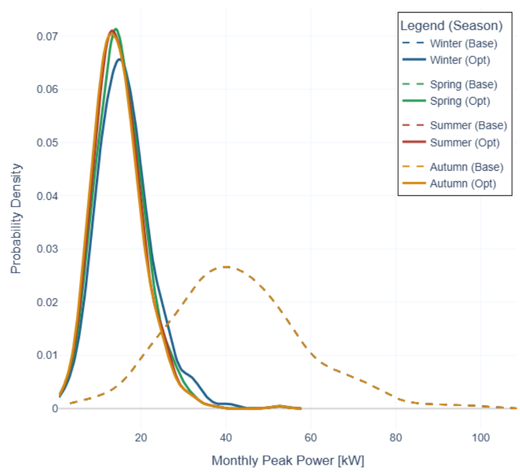


Figure 4. 2 - Seasonal peak power distribution comparison (PDF) -baseline (dashed) vs optimized (solid).

Optimization shifts distribution to 10-14 kW range (modal ~11 kW), with approximately 60% of scenarios achieving peaks below 15 kW, representing mean reduction exceeding 70%. This transformation reflects systematic exploitation of temporal flexibility, distributing required energy across connection windows to suppress aggregate peaks.
Remarkably, optimized distributions demonstrate near-perfect seasonal superposition with winter, spring, summer, and autumn achieving similar modal peaks at 10-14 kW, confirming robust effectiveness independent of price variations. Subtle upper tail divergence appears as winter extends to ~50 kW versus spring/summer/autumn ~35 kW in extreme scenarios, emerging from winter's complex price structure [5] creating trade-offs between perfect flattening and temporal arbitrage in challenging demand patterns. The consistency in optimized peaks across seasons despite varying price structures confirms power-based capacity charges (constant €4.45/kW monthly) [5] dominate optimization regardless of energy price patterns.

4.2 Economic performance and Cost Decomposition

Economic benefits manifest consistently across seasons. Winter achieves 11.9% unit cost improvement (0.411→0.362 €/kWh) generating €206 monthly savings, spring 12.2% (0.279→0.245 €/kWh) yielding €143 monthly, summer 9.9% (0.319→0.287 €/kWh) producing €147 monthly, and autumn 11.0% (0.339→0.297 €/kWh) achieving €177 monthly. These consistent improvements spanning only 2.3 percentage points demonstrate limited sensitivity to seasonal conditions, with all costs remaining below €0.65/kWh user tariff confirming economic viability.

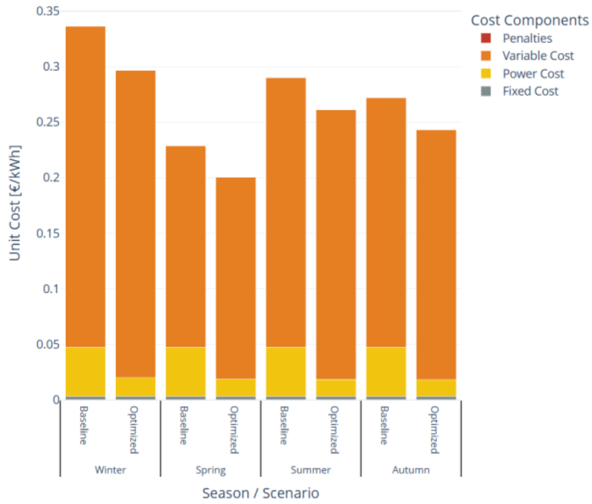


Figure 4. 3 – *Comparison of the Unit Charging Cost Components at the POD: Baseline vs Optimized case.*

Cost decomposition reveals, as shown in *Figure 4.2*, the critical mechanistic insight. Annual structure shows baseline incurs €12,092 variable energy costs (83.3%) and €2,280 power-based capacity charges (15.7%). Optimization reduces variable costs to €11,940 (€152 savings, 1.3% reduction) but dramatically transforms capacity charges to €814 (€1,466 savings, 64.3% reduction) [5], with zero penalty costs confirming service quality preservation. This reveals capacity charge minimization as the dominant benefit mechanism achieved through peak suppression, while temporal arbitrage provides secondary contribution. The optimizer prioritizes load distribution minimizing peaks over pure energy price minimization, rational behavior driven by Italian tariff structure [5] where power-based charges (€4.45/kW monthly = €53.40/kW annually) create disproportionately strong incentives relative to temporal energy differentials (€0.02-0.03/kWh = €5-8/day arbitrage potential).

4.3 Mechanistic Analysis and Optimization Principles

Detailed analysis of Scenario 319, presented in *Figure 4.3*, (worst-case 99 kW baseline peak, 14 vehicles) illuminates optimization strategies under varying seasonal tariffs. Winter conditions (0.030 €/kWh energy differential, 27× capacity multiplier [5]) produce sustained ~22 kW across the operational window pursuing aggressive flattening, achieving 77.7% peak reduction as limited price differential (€0.007/kWh) makes temporal arbitrage marginal. Spring (0.019 €/kWh differential, uniform capacity charges [5]) produces remarkably constant ~25 kW profile demonstrating pure load flattening when temporal shifting contributes negligibly. This divergence reveals how single cost minimization naturally produces qualitatively different strategies depending on price structure, with both achieving similar peak reductions through different pathways.

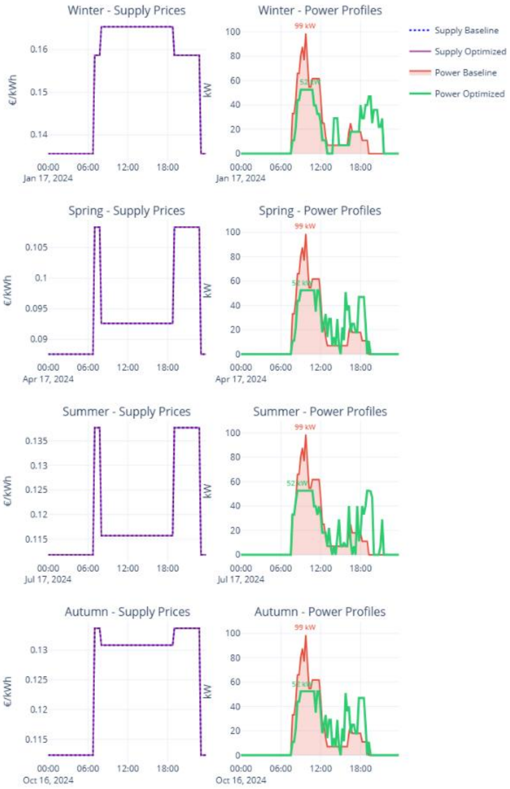


Figure 4. 4 - Seasonal Load Transformation Under Different Tariff Structures: Energy Supply Costs (Left) and Day-Ahead Optimized Charging Schedules (Right) for Scenario 319 Across Winter, Spring, Summer, and Autumn Conditions

Three fundamental principles govern optimization behavior. First, asymmetric economic structure where capacity charges (€53.40/kW annually) dramatically exceed arbitrage gains (€5-8 daily) incentivizes temporal redistribution even across suboptimal price periods for peak suppression. Second, abundant temporal flexibility (mean connection 4.71h versus charging 1.78h, 62.7% idle time [2]) enables simultaneous peak suppression and complete delivery without trade-offs, evidenced by zero penalties across all instances. Third, economically rational adaptation maintains ~75% peak reduction across seasons while adjusting temporal granularity proportionally to price differentials—winter produces visible modulation extracting arbitrage value, spring converges to uniformity prioritizing capacity minimization, emerging naturally from single cost objective [4] without requiring multi-objective formulation.

The 500-scenario ensemble spanning 4-19 vehicles daily and 42-287 kWh total energy provides robust coverage confirming benefits generalize across demand variability. Computational tractability (38s mean solution time, 92.4% proven optimal) confirms operational deployment compatibility.

5. Conclusions

This thesis developed and validated a sample-based optimization framework combining Monte Carlo scenario generation with mixed-integer linear programming for day-ahead EV charging management, applied to 4,471 operational sessions over 25 months from Politecnico di Milano [2]. The methodology achieves 12-15% monthly cost reductions (€143-206, annualized €1,700-2,500) and >70% peak reduction (88.7→15 kW) primarily through capacity charge minimization (64.3% savings) dominating temporal energy arbitrage (1.3% savings), revealing power-based tariff structures [5] as highly effective policy instruments. With 92.4% proven optimality in 38s mean solution time [8], the framework demonstrates operational tractability while establishing that workplace charging temporal flexibility (4.71h connection vs 1.78h charging [2]) enables simultaneous economic optimization and service quality without trade-offs. Future research should address cross-context validation (residential, public, fast-charging), multi-day optimization through rolling horizons [4], vehicle-to-grid integration, and field trials providing definitive operational evidence. The work bridges probabilistic demand modeling and operationally relevant management, providing actionable framework supporting sustainable transportation electrification aligned with global climate objectives.

6 Reference

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