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Leveraging Implicit Flexibility for Day-Ahead Energy Management and Cost Optimization in Electric Vehicle Charging Stations using a Monte Carlo Scenario-Based Approach

TESI MAGISTRALE IN ENERGY ENGINEERING

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Abstract: As electric vehicle adoption accelerates globally, uncoordinated charging threatens distribution network stability, increases infrastructure upgrade costs, and creates economic inefficiencies. Intelligent energy management strategies exploiting flexibility in vehicle charging patterns are essential for sustainable transportation electrification.

This thesis develops and validates an optimization framework for day-ahead charging scheduling under demand uncertainty within the Italian electricity market. Monte Carlo scenario generation employing empirical cumulative distribution functions from operational data produces ensembles preserving stochastic demand characteristics. Mixed-integer linear programming formulations incorporate comprehensive Italian tariff structures including time-varying energy costs~~,~~ and power-based capacity charges. The optimizer performs simultaneous energy arbitrage and peak shaving to minimize total system costs.

Computational experiments across 4,471 charging sessions over 25 months demonstrate 12-15% monthly cost reductions (€143-206) and 70% peak power suppression (88.7 to 15kW). Capacity savings of 64.3% dominate the total benefit, with energy arbitrage contributing 1.3%. Zero penalty costs across all instances validate complete energy delivery without service quality compromise.

The empirically validated framework establishes that workplace charging provides sufficient temporal flexibility for simultaneous economic optimization and service quality maintenance.

Key-words: Monte Carlo simulation, EV charging optimization, Demand-side flexibility, Peak demand management, Electricity market integration.

Sets		λ^{VAT}	Value added tax rate (0.22) [-]
T	Set of 15-minute time periods in planning horizon (from 1 to 96)	γ^{loss}	Grid loss factor for low voltage utilities (0.10) [-]
E	Set of electric vehicles (from 1 to 39)	C^{excise}	Excise tax <200 MWh/month (0.10) [€/kWh]
Parameters		**Variables**	
Δt	Duration of timestep of 0.25 [h]	$e_e^{uncharge}$	Total uncharged energy [kWh]
$\lvert T \rvert$	Number of timesteps (from 1 to 96)	$e_e^{uncharge_{opt}}$	Optimization-driven uncharged energy [kWh]
N_EV	Number of EVs in scenario (from 1 to 39)	$p_{e,t}^{charge}$	Charging power delivered [kW]
M	Big-M value for binary constraints (1×10^{6}) [-]	c_e^{user}	User payment revenue [€]
D^{month}	Days in month [30 days]	$c_e^{penality}$	Penality cost uncharged energy [€]
D_e^{conn}	Connection duration [slots]	$p_t^{withdraw}$	Power withdrawn from grid (physical) [kW]
T_e^{arr}	Arrival time slot [slot]	p_t^{inject}	Power injected to grid (physical) [kW]
P_e^{max}	Maximum charging power [kW]	$\delta_t^{withdraw}$	Binary variables (=1 if withdrawing, =0 if injecting) [-]
E_e^{req}	Energy requirement [kWh]	$\delta_t^{purchase}$	Binary variables (=1 if purchasing, =0 if selling) [-]
$\alpha_{e,t}$	Presence indicator [0,1]	$p_t^{purchase}$	Purchased power [kW]
$E_e^{uncharge_{time}}$	Unavoidable energy shortfall [kWh]	p_t^{sell}	Sold power [kW]
T_t^{user}	User tariff rate [€/kWh]	p_t^{inject}	Grid injection [kW] (=0 in this model, no V2G)
$C^{penality}$	Penalty for unserved energy [€/kWh]	p^{max}	Peak power [kW]
$C^{dispatch}$	Dispatching cost [€/kWh]	$p_t^{consumption}$	Electrical consumption [kW]
C_t^{energy}	Energy supply cost [€/kWh]	$c_t^{energy_{var}}$	Variable energy supply cost [€]
$C_t^{capacity}$	Capacity market cost [€/kWh]	$c_t^{energy_{other}}$	Other variable energy costs [€]
P_t^{sell}	Electricity sale price [€/kWh]	$c_t^{energy_{kwh}}$	Total energy-based cost [€]
P_t^{buy}	Electricity purchase price (MGP) [€/kWh]	$c_t^{capacity}$	Capacity market cost [€]
$C^{network_{kW}}$	Network obligations per power [€/kW]	c_t^{excise}	Excise tax cost [€]

$C^{POD_{kW}}$	POD cost per power [€/kW]	c^{power}	Power-based capacity charges [€]
$C^{network_{kWh}}$	Network obligations per energy [€/kWh]	c^{fixed}	Fixed charges [€]
$C^{POD_{kWh}}$	POD cost per energy [€/kWh]	c^{total}	Total electricity cost (VAT incl.) [€]
$C^{network_{fixed}}$	Fixed network obligations [€]	r^{total}	Total revenue from sales [€]
$C^{POD_{fixed}}$	Fixed POD cost [€]		

Table 1 – Nomenclature

1 Introduction

The global energy landscape is currently undergoing a profound structural transformation, necessitated by the imperative to mitigate climate change and align with the ambitious targets of the Paris Agreement. To limit global temperature increases to 1.5°C, the Intergovernmental Panel on Climate Change (IPCC) underscores the necessity of achieving net-zero emissions by 2050, requiring a 43% reduction in global greenhouse gas emissions as early as 2030 [1]. In this context, the decarbonization of the transport sector—which accounts for 23% of energy-related CO_2 emissions [2]—emerges as a critical and challenging objective. Unlike the power sector, transportation has historically resisted decarbonization due to its reliance on high-energy-density fossil fuels; however, the rapid electrification of road transport through electric vehicles (EVs) has now established itself as the primary pathway toward a sustainable mobility paradigm.

The proliferation of EVs has reached an exponential trajectory, catalyzed by a synergy of favorable economics and stringent regulatory frameworks. By 2024, the cost of battery packs reached the critical techno-economic benchmark of 100 USD/kWh [3], while policies such as the European Union's 2035 phase-out of internal combustion engines have provided long-term market certainty. Consequently, EV market share has surged from less than 5% in 2020 to 22% in 2024 [4]. While this transition is essential for environmental goals, it introduces significant technical volatility to existing electrical power systems. From a grid-stability perspective, EV charging represents a high-magnitude, temporally correlated load that frequently coincides with existing systemic peak demand. Unmanaged charging behavior threatens to induce localized transformer overloading and power quality degradation, potentially escalating peak demand by up to 25% and necessitating grid reinforcement costs estimated between 1,000 and 5,000 USD per vehicle [5].

To mitigate these systemic externalities, the development of sophisticated energy management frameworks integrating smart charging and Vehicle-to-Grid (V2G) technologies is paramount. These strategies seek to leverage the inherent flexibility of EVs—projected to provide 16–20 TWh of distributed storage by 2030 [6]—to transform vehicles into active grid assets. Nevertheless, the operational efficacy of such managed charging schemes is fundamentally dependent on the precision of load forecasting methodologies. Unlike conventional industrial or residential loads, EV demand is characterized by extreme stochasticity and non-stationarity. 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 and departure times, initial state of charge, and energy requirements exhibit substantial variability, complicating the aggregation of load profiles.

This complexity underscores the economic motivation for the present research. For charging infrastructure operators, the ability to minimize electricity procurement costs is a prerequisite for strategic participation in electricity markets [7]. Effective day-ahead forecasting allows for energy procurement at lower prices while enabling revenue generation through demand response and ancillary services.

1.1 Literature Review

The challenge of modeling and forecasting EV charging demand has received substantial attention in recent literature, with researchers employing diverse methodological to address the inherent stochasticity of charging sessions. This review focuses specifically on how existing literature addresses uncertainty in the three fundamental parameters characterizing charging events: arrival time, session duration, and energy requirements.

Several works have employed probabilistic modelling approaches to represent the inherent stochasticity of electric vehicle charging demand. Early research established a baseline by fitting parametric distributions to empirical data; notably, Lojowska et al. [8] pioneered the use of Gaussian mixture models for arrival time characterization. However, the validity of rigid distributional assumptions has been progressively challenged. Chen et al. [9], analyzing over two million European charging sessions, demonstrated that a significant fraction of users exhibit delayed charging behavior, introducing systematic bias in peak demand forecasts when immediate charging is assumed. To overcome parametric constraints, Müller and Schmidt [10] applied adaptive Kernel Density Estimation to high-power charging networks, revealing multi-modal demand patterns that conventional univariate models fail to capture. Their work further highlighted the significant correlation between arrival times and energy requirements, motivating the adoption of multivariate dependency structures. Zhang et al. [11] addressed this limitation through vine copula methods, demonstrating substantial forecast error reduction by explicitly modeling joint parameter dependencies, particularly in workplace charging contexts.

The translation of these probabilistic models into actionable optimization inputs has stimulated considerable methodological development in scenario generation. Traditional Monte Carlo sampling approaches have been shown to systematically underestimate peak clustering effects, as demonstrated by Andersson et al. [12], who proposed stratified sampling corrections to mitigate this bias. More sophisticated frameworks incorporating temporal dependency structures were developed by Papadopoulos and Nguyen [13], who employed time-dependent Gaussian copulas to preserve autocorrelation in sequential charging events, improving transformer loading estimates. Scenario reduction techniques have also received attention: Liu et al. [14] demonstrated that machine learning-based clustering algorithms can dramatically reduce scenario set cardinality while maintaining high percentile accuracy, improving computational tractability without significant loss of representativeness.

Recent advances have extended uncertainty quantification toward deep learning and generative modelling paradigms. Rodriguez et al. [15] applied Temporal Fusion Transformers to charging demand forecasting, achieving superior predictive accuracy by jointly weighing historical patterns and exogenous contextual variables. Kim and Park [16] leveraged conformal prediction theory to derive distribution-free uncertainty bounds with mathematical coverage guarantees, while

Martinez-Gomez et al. [17] demonstrated that diffusion-based generative models can replicate complex statistical properties of empirical charging distributions, including higher-order moments, with notable fidelity.

In the domain of day-ahead management under market constraints, two-stage stochastic programming has emerged as the dominant paradigm. Schiavo and Benini (2024) at al. [18] demonstrated that incorporating realistic market rules into stochastic scheduling frameworks can reduce costs by 12–17% compared to perfect-foresight benchmarks, establishing the economic relevance of market-aware formulations. Risk-averse extensions have been explored by Petersen et al. [19], who integrated Conditional Value-at-Risk constraints to protect against revenue volatility in low-utilization station scenarios. Yang et al. [20] have proposed distributionally Robust Optimization as a methodological middle ground between pure stochastic and worst-case paradigms, employing Wasserstein ambiguity sets to achieve cost-robustness without excessive conservatism.

Despite substantial methodological progress, existing approaches share common limitations that motivate the present work. A predominant reliance on parametric distributional assumptions, often adopted without rigorous goodness-of-fit validation, risks misrepresenting empirical demand characteristics, particularly in tail regions governing worst-case operational outcomes.

Furthermore, the majority of optimization studies validate performance against synthetic or limited datasets, overlooking the behavioural complexity and non-stationarity present in real operational data. More fundamentally, prevailing evaluation approaches assess forecast quality through statistical metrics (MAE, RMSE) measuring distributional fidelity rather than economic scheduling performance. This creates a disconnect: superior statistical accuracy does not guarantee improved operational outcomes, as decision quality depends on whether forecasts correctly capture the specific demand characteristics—particularly peak clustering and tail behaviors—that drive cost structures in the optimization problem.

The present work addresses these gaps by grounding scenario generation entirely in empirical distributions derived from real-world operational data, subjecting the generated ensemble to rigorous statistical validation. Moreover, the economic savings which could be achieved within the Italian tariff framework are evaluated.

Table 2- Comparative Table of EV Charging Demand Forecasting Methods

Ref.	Charging Context	Demand Modeling Approach	Scenario Generation Method	Uncertainty Handling	Dataset Size	Key Contribution
[8]	General EV	Gaussian Mixture Models (GMM)	Parametric sampling	Parametric distributions	Limited	Pioneered probabilistic arrival time characterization
[9]	European networks	Behavioral analysis	Immediate vs delayed charging	Behavioral segmentation	2+ million	Identified systematic bias from delayed

					session s	charging behavior
[10]	Müller & Schmidt	High-power charging	Adaptive Kernel Density Estimation (KDE)	Non-parametric density estimation	Limited	Revealed multi-modal demand patterns and correlations
[11]	Workplace charging	Vine Copula Methods	Joint dependency modeling	Multivariate dependencies	Limited	Explicit modeling of parameter joint dependencies
[12]	General EV	Traditional Monte Carlo	Stratified sampling	Peak clustering bias correction	Limited	Identified and corrected MC underestimation of peaks
[13]	General EV	Time-dependent Gaussian Copulas	Temporal dependency preservation	Autocorrelation in sequences	Limited	Improved transformer loading estimates
[14]	General EV	Machine Learning Clustering	Scenario reduction	Reduced cardinality	Limited	Maintained accuracy with fewer scenarios
[15]	General EV	Temporal Fusion Transformers (TFT)	Deep learning forecasting	Historical + contextual variables	Limited	Superior predictive accuracy with DL
[16]	General EV	Conformal Prediction Theory	Distribution-free bounds	Mathematical coverage guarantees	Limited	Distribution-free uncertainty quantification
[17]	General EV	Diffusion-based Generative Models	Generative modeling	Higher-order moments preservation	Limited	Replicated complex statistical properties
[18]	Market-integrated	Not specified	Two-stage stochastic	Market rules incorporation	Limited	12-17% cost reduction with realistic market rules

[19]	Low-utilization stations	Not specified	Two-stage stochastic	Conditional Value-at-Risk	Limited	Revenue volatility protection
[20]	General EV	Not specified	Distributionally Robust	Ambiguity sets	Limited	Cost-robustness without excessive conservatism

1.2 Research Objectives and Contributions

The primary ambition of this thesis is to bridge the gap between high-resolution operational data and actionable energy management strategies for electric vehicle (EV) charging infrastructure. To achieve this, the thesis implements a four-stage integrated framework combining empirical demand characterization, stochastic scenario generation, deterministic optimization, and economic validation, as following explained.

The foundation of the work lies in the empirical characterization of charging demand uncertainty. By leveraging two years of high-resolution operational data collected from the PoliGrid charging infrastructure at Politecnico di Milano [21], the thesis systematically processes raw session parameters—such as arrival times, connection durations, and energy delivered—into a standardized 15-minute resolution format. This stage involves the computation of Empirical Cumulative Distribution Functions (ECDFs) and the analysis of vehicle heterogeneity through power-capacity segmentation. By identifying temporal patterns across various seasons and days of the week, the research establishes a robust statistical baseline that reflects the stochastic nature of real-world user behavior.

Building upon this empirical base, the second objective involves the development of a Monte Carlo scenario generation framework. Rather than relying on simplistic assumptions, this thesis implements an inverse transform sampling methodology to generate 500 scenarios per season. These scenarios are designed to preserve the historical statistical properties of the data, including the complex interplay between battery capacities and power ratings. Crucially, the third objective ensures the integrity of these models through rigorous statistical validation. By comparing simulated versus historical ECDFs using statistical distance metrics, the research verifies that the generated scenarios accurately capture tail behavior and extreme demand events, which are vital for effective grid risk management.

The analytical part of the thesis is a mixed-integer linear programming (MILP) model formulated in Pyomo and solved using the Gurobi optimizer, which quantifies the economic and operational benefits by benchmarking the optimized schedules against a baseline of unmanaged, immediate charging.
The main contributions of this work can be summarized as follows:

- It provides a validated scenario generation methodology that serves as a replicable template for uncertainty quantification in EVs charging patterns.

- It offers a quantification of the economic value of implicit flexibility provision by EVs for a real-world case study, resulting in empirical evidence of how smart charging can reduce electricity bill costs.

Collectively, these elements provide a robust methodology for the next generation of smart charging infrastructure.

2 Italian Electricity Market

The economic viability and operational strategies of electric vehicle charging infrastructure are fundamentally shaped by the regulatory and market frameworks governing electricity procurement, pricing, and grid services. This chapter describes the Italian electricity market structure as of 2026, focusing on aspects directly relevant to EV charging station operations. Understanding this context is essential for interpreting the optimization objectives and constraints developed in Section 3.

2.1 Introduction to the National Market Architecture

The Italian electricity market is a liberalized system born from the implementation of the "Bersani Decree" (Legislative Decree 79/99), which unbundled the vertical integration of the state monopoly [22]. Today, the market operates under the supervision of the Autorità di Regolazione per Energia Reti e Ambiente (ARERA) and is managed by the Gestore dei Mercati Energetici (GME) [23]. The market structure has evolved significantly following European integration directives, with the implementation of the EU Clean Energy Package completed in 2024-2025, introducing enhanced market coupling mechanisms and shorter gate closure times [24].

The Italian electricity market comprises several interconnected segments operating at different temporal horizons:

- Day-Ahead Market (DAM): The Mercato del Giorno Prima (MGP) serves as the core forward market where the majority of wholesale energy transactions are finalized [23]. Participants submit hourly supply and demand bids for the following day by the 12:00 CET gate closure. The clearing process employs an implicit auction algorithm that determines equilibrium prices while respecting transmission constraints through a zonal pricing mechanism [25]. Italy is currently divided into seven bidding zones (North, Central North, Central South, South, Sicily, Sardinia, and Calabria) to reflect internal grid congestions. This structure results in differentiated zonal prices when transmission capacity between regions is saturated [25]. From an optimization perspective, the MGP exhibits significant intraday volatility—driven by the intermittent nature of solar and wind generation and fluctuating natural gas costs—which creates arbitrage opportunities for flexible loads like EV charging stations [26].

- Intraday Market (IDM): The Mercato Infragiornaliero (MI) allows participants to recalibrate their day-ahead positions in response to updated forecasts [23]. As of the 2024 regulatory reforms, the MI operates through seven consecutive auction sessions (MI1 through MI7). A critical advancement in this period was the reduction of the final gate closure to 60 minutes before delivery, aligning the Italian system with European standards [24]. This increased granularity is vital for integrating refined renewable energy forecasts and demand predictions. However, the MI typically suffers from lower liquidity and higher volatility compared to the MGP, reflecting the increased uncertainty as the real-time delivery window approaches.

- Ancillary services market (ASM): Real-time frequency stability and congestion management are handled through the Mercato dei Servizi di Dispacciamento (MSD). Terna procures balancing services through ex-ante sessions for reserve capacity and real-time activations [27].

2.2 Market Access and Regulatory Framework

The scale and technical complexity of individual charging stations often preclude direct participation in wholesale markets [28]. Consequently, Charhing Point Operators (CPSs) typically utilize intermediary mechanisms:

- Retail Supply Contracts: Managing procurement through licensed suppliers who absorb market and imbalance risks, often via indexed or time-of-use (ToU) tariffs.

- Aggregators: Following the 2024 legislative transposition of EU directives [24], independent aggregators pool distributed energy resources (DERs) to reach the threshold for wholesale participation.

- Energy Communities: While regulatory frameworks for Renewable Energy Communities (RECs) have matured between 2024 and 2026, their application in commercial charging remains an emerging niche. [29].

2.2.1 Classification and Technical Standards

The Italian Regulatory Authority ARERA classifies infrastructure based on access and power [30]. Standard charging (<=22 kW, AC) usually connects to the low-voltage (LV) distribution network. Conversely, fast charging (> =22 kW, DC), particularly hubs exceeding 100 kW, often requires medium-voltage (MV) connections (15- 20 kV) and dedicated transformer capacity. Recent 2025 regulations have streamlined these connection procedures, mandating that Distribution System Operators (DSOs) prioritize EV infrastructure to meet national electromobility targets [31].

2.2.2 Service Quality and Smart Charging Incentives

CPOs are subject to strict service quality standards, including minimum uptime thresholds and transparent pricing (mandatory €/kWh display) [30]. The 2025 ARERA resolutions specifically addressed highway fast-charging, implementing pricing caps to protect consumers in captive markets [30]. Furthermore, the 2024-2026 framework provides network tariff reductions for stations capable of providing grid services, such as voltage support or congestion management [31]. While Vehicle-to-Grid (V2G) technology remains in a pilot "sandbox" phase as of 2026, these incentives signal a shift toward treating EVs as active distributed storage assets [32].

2.3 Electricity Bill Composition and Optimization Incentives

For a charging operator, the total cost of electricity is a multi-layered structure comprising regulated and market-based components [33]. This complexity dictates the constraints and objective functions of any energy management system.

1. Energy Commodity Costs constitute the variable component directly linked to wholesale market prices. For consumers procuring through aggregators or retailers with pass-through

pricing, these costs reflect zonal day-ahead market outcomes plus service margins. Time-differentiated pricing structures incorporate temporal price variation, typically distinguishing peak periods (weekday daytime hours), off-peak periods (nighttime hours and weekends), and potentially intermediate periods [23].

2. Imbalance Costs arise from deviations between scheduled consumption communicated in day-ahead markets and actual realized consumption. These necessitate stochastic modeling to minimize exposure to volatile real-time balancing prices [27].

3. Network Charges recover costs of transmission and distribution infrastructure through regulated tariffs set by ARERA. The tariff structure incorporates multiple components [33]:

    - *Energy components* (€/kWh) vary by time period and voltage level, applying lower rates during off-peak hours and for medium-voltage connections relative to low-voltage connections. These charges reflect network utilization patterns and marginal network costs.
    - *Power components* (€/kW/month or €/kW/year) are based on peak power demand measured over specified intervals (typically 15-minute averages). The capacity component creates a semi-fixed cost structure where monthly or annual charges depend on the maximum instantaneous demand recorded during the billing period. This design creates strong economic incentives for peak demand management, as capacity charges apply to the peak demand regardless of duration or frequency.
    - *Fixed charges* (€/POD/month or €/POD/year) recover customer-specific costs including metering, billing, and administrative expenses, through flat monthly/yearly charges independent of consumption or peak demand

4. *System Charges* (Oneri di Sistema) finance policy costs through volumetric levies including renewable energy support mechanisms, energy efficiency programs, social tariffs for vulnerable consumers, nuclear decommissioning obligations, and other system-wide costs. These charges apply uniformly across consumption periods [34].

5. *Excise taxes* apply to electricity consumption at rates differentiated by use category and consumption levels, with reduced rates for energy-intensive industrial uses. Value-added tax (IVA) applies to the total bill including all components, creating a multiplier effect where reductions in any underlying cost component generate proportionally larger total savings [34].

The specific numerical parameter values for all tariff components across seasonal conditions are documented in Section 3.2.2.

Consequently, the CPO must navigate three often-conflicting objectives:

- Arbitrage: Shifting load to minimize volumetric energy costs based on MGP price forecasts.

- Peak Shaving: Limiting instantaneous power demand to minimize rigid capacity charges.

- Imbalance Management: Ensuring that actual demand aligns with scheduled commitments to avoid MSD penalties [28].

The inherent flexibility of EV charging—derived from the "dwell time" where the vehicle is connected but not necessarily requiring immediate energy—provides the temporal discretion needed to address these goals. However, the stochastic nature of user arrivals and energy requirements introduces significant uncertainty [35]. This context justifies the development of the stochastic optimization methodology presented in this thesis, which utilizes high-resolution data to generate probabilistic scenarios and identify robust charging schedules that minimize total expenditure across all market and regulatory dimensions.

3 Mathematical Modeling

This section presents the integrated methodological framework developed to address the day-ahead energy management problem under demand uncertainty. The approach combines stochastic demand modeling through Monte Carlo simulation with deterministic mixed-integer linear optimization, creating a practical decision-support system for charging infrastructure operators.

The methodology is presented in two main components: first, the probabilistic scenario generation framework that transforms historical charging patterns into representative future demand realizations; second, the mathematical optimization model that exploits implicit charging flexibility to minimize operational costs while respecting physical constraints and user requirements.

This approach offers three methodological advantages: (i) empirical cumulative distribution functions avoid restrictive parametric assumptions that may misrepresent actual demand distributions [36], (ii) scenario-based formulation enables tractable uncertainty modeling without requiring computationally intensive multi-stage stochastic programming [37], and (iii) modular structure facilitates sensitivity analysis through independent variation of assumptions [37].

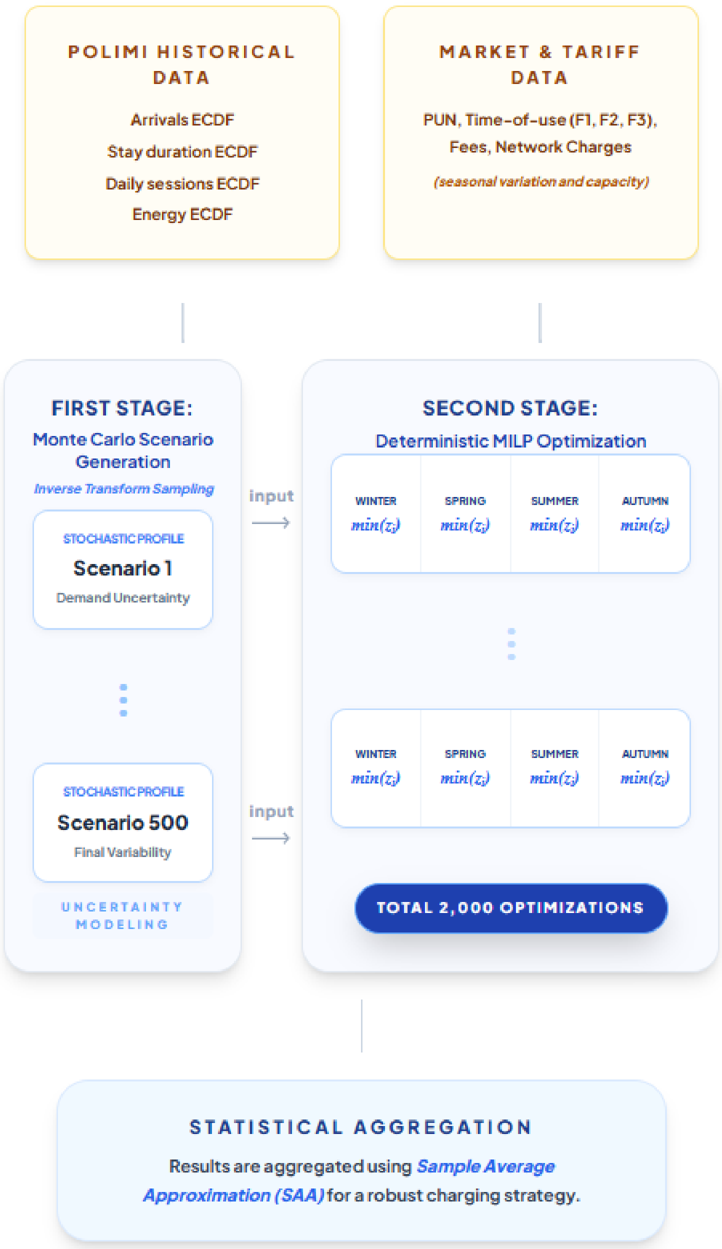

Figure 1 – Two-Stage Optimization Framework Scenario generation process and seasonal MILP optimization

3.1 Monte Carlo Scenario Generation Framework

The Monte Carlo methodology transforms historical charging session data into probabilistic forecasts of future demand through systematic random sampling from empirically derived probability distributions.

The process begins with construction of empirical cumulative distribution functions for four key uncertain parameters characterizing charging demand: arrival time slot (when vehicles connect to the charging station), connection duration in time slots (how long vehicles remain connected), energy requirement in kilowatt-hours (how much energy users request), and daily session count (how many vehicles charge on a given day).

Formally, given n historical observations of parameter X denoted $x_1, x_2, \ldots, x_n$, the empirical CDF is:

$$\hat{F}_n(x) = (1/n)\, \Sigma_{i=1}^{n} I(x_i \leq x) \tag{3. 1}$$

where I(·) is the indicator function equaling one when the condition is true and zero otherwise.

Scenario generation employs inverse transform sampling, exploiting the mathematical property that if U follows a uniform distribution on [0,1] and F is a cumulative distribution function, then X = F^{-1}(U) follows distribution F [38]. For each scenario, the algorithm first samples the number of daily sessions from its empirical CDF, subject to an upper bound of 39 vehicles reflecting infrastructure capacity. For each session, individual parameters are generated through independent inverse transform sampling: arrival time constrained to station operating hours (07:00-21:00), connection duration, energy demand, and vehicle segment assignment.

Vehicle segmentation reflects fleet heterogeneity through four representative types: small BEVs (40 kWh capacity, 7 kW charging, 30% population), PHEVs (15 kWh capacity, 3.7 kW charging, 20%), mid-size BEVs (60 kWh capacity, 11 kW charging, 35%), and large BEVs (80 kWh capacity, 22 kW charging, 15%).

For each generated session, vehicle type assignment is assigned through weighted discrete sampling: a uniform random variable U ~ Uniform(0,1) is drawn and compared against the cumulative probability thresholds {0.30, 0.50, 0.85, 1.00} corresponding to the four segments, mapping the continuous unit interval to discrete vehicle categories with probabilities proportional to their fleet shares. Once the segment is assigned, the maximum charging power is determined deterministically from the segment specification, while the energy requirement is sampled independently from the empirical demand distribution subject to the constraint that requested energy does not exceed the battery capacity.

Departure time is computed as arrival plus duration, with truncation if exceeding station hours or daily boundary. Binary presence matrices and power matrices are constructed for each session, then aggregated across all sessions to produce the scenario's total station load profile. This process is repeated 500 times with different random seeds to create an ensemble capturing the probability distribution of demand outcomes.

3.2 Optimization Model Formulation

The optimization model is implemented in Pyomo [39], an algebraic modeling language embedded in Python that enables high-level mathematical expression while interfacing with commercial solvers. The abstract model structure separates mathematical formulation from data, allowing identical model code to be instantiated with different scenario-specific parameter values. The concrete problem is solved using Gurobi commercial optimization solver (Gurobi Optimization, 2023) [40], configured with 1% optimality gap tolerance and 3,600-second time limit.

The model is formulated as a mixed-integer linear program (MILP) that operates over a discrete 24-hour planning horizon with the temporal set T = {1, 2, ..., 96} indexed by t, representing each quarter-hour interval aligned with Italian electricity market settlement conventions.

The vehicle dimension is represented through the set E comprising all electric vehicles that connect to the charging station during the planning horizon, indexed by e ∈ {1, 2, ..., N_EV}, where the cardinality N_EV varies stochastically across scenarios according to the Monte Carlo generation process, subject to an upper bound of 39 vehicles reflecting physical infrastructure capacity limitations.

This two-dimensional coordinate system—time and vehicles—defines the space within which all optimization decisions determine the charging power P_charge(e,t) delivered to each vehicle in each time period, exploiting the temporal flexibility available between vehicle arrival and departure to reduce costs while respecting physical constraints and ensuring adequate energy delivery.

3.2.1 Seasonal Economic Parameter Structure

The optimization model is instantiated with season-specific electricity tariff parameters reflecting the temporal and seasonal variations in the Italian electricity market. While the mathematical formulation remains invariant, numerical values of economic parameters—particularly time-varying energy supply costs and capacity market charges—vary substantially across seasons, creating different economic incentive structures that explain the seasonal performance variations analyzed in Chapter 4.

Tables 1-4 present the complete economic parameter structure employed for winter, spring, summer, and autumn optimization instances respectively. Each table documents the comprehensive Italian electricity bill structure as described in Section 2.3: time-varying energy supply costs exhibiting three-tier temporal differentiation; capacity market charges implementing pronounced peak-hour premiums in certain seasons while remaining uniform in others; dispatching costs; regulated per-energy network and point-of-delivery charges; power-based capacity charges ($c_{network_{kw}} + c_{POD_{kw}}$); fixed monthly charges; excise taxes; and value-added tax.

Table 3. *1* - Complete Economic Parameter Structure of Summer Season

Time Period	Energy Supply Cost [€/kWh]	Capacity Market Charges [€/kWh]	Dispatching Cost [€/kWh]	Network Obligations (energy) [€/kWh]	POD Cost (energy) [€/kWh]	Network Obligations (power) [€/kW/mese]	POD Cost (power) [€/kW/mese]	Network Obligations (fixed) [€/kWh/mese]	POD Cost (fixed) [€/kWh/mese]
00:00-07:00	0.11183	0.002844	0.006384	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
07:00-09:00	0.13768	0.002844	0.006384	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
09:00-19:00	0.11572	0.0449*	0.006384	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
19:00-23:00	0.13768	0.0449	0.006384	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
23:00-24:00	0.11183	0.002844	0.006384	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844

Table 3. 2 - Complete Economic Parameter Structure of Spring Season

Time Period	Energy Supply Cost [€/kWh]	Capacity Market Charges [€/kWh]	Dispatching Cost [€/kWh]	Network Obligations (energy) [€/kWh]	POD Cost (energy) [€/kWh]	Network Obligations (power) [€/kW/mese]	POD Cost (power) [€/kW/mese]	Network Obligations (fixed) [€/kWh/mese]	POD Cost (fixed) [€/kWh/mese]
00:00-07:00	0.08759	0.002767	0.006869	0.04383	0.0126	1.509167	2.937500	0.333844	0.076306
07:00-09:00	0.10834	0.002767	0.006869	0.04383	0.0126	1.509167	2.937500	0.333844	0.076306
09:00-19:00	0.09262	0.002767	0.006869	0.04383	0.0126	1.509167	2.937500	0.333844	0.076306
19:00-23:00	0.10834	0.002767	0.006869	0.04383	0.0126	1.509167	2.937500	0.333844	0.076306
23:00-24:00	0.08759	0.002767	0.006869	0.04383	0.0126	1.509167	2.937500	0.333844	0.076306

Table 3. 3 - Complete Economic Parameter Structure of Winter Season

Time Period	Energy Supply Cost [€/kWh]	Capacity Market Charges [€/kWh]	Dispatching Cost [€/kWh]	Network Obligations (energy) [€/kWh]	POD Cost (energy) [€/kWh]	Network Obligations (power) [€/kW/mese]	POD Cost (power) [€/kW/mese]	Network Obligations (fixed) [€/kWh/mese]	POD Cost (fixed) [€/kWh/mese]
00:00-07:00	0.13559	0.006869	0.009505	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
07:00-09:00	0.15866	0.006869	0.009505	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
09:00-19:00	0.16537	0.0449*	0.009505	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
19:00-23:00	0.15866	0.001639	0.009505	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
23:00-24:00	0.13559	0.001639	0.009505	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844

Table 3. 4 - Complete Economic Parameter Structure of Autumn Season

Time Period	Energy Supply Cost [€/kWh]	Capacity Market Charges [€/kWh]	Dispatching Cost [€/kWh]	Network Obligations (energy) [€/kWh]	POD Cost (energy) [€/kWh]	Network Obligations (power) [€/kW/mese]	POD Cost (power) [€/kW/mese]	Network Obligations (fixed) [€/kWh/mese]	POD Cost (fixed) [€/kWh/mese]
00:00-07:00	0.11232	0.002995	0.008227	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
07:00-09:00	0.13368	0.002995	0.008227	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
09:00-19:00	0.13083	0.002995	0.008227	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
19:00-23:00	0.13368	0.002995	0.008227	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844
23:00-24:00	0.11232	0.002995	0.008227	0.04383	0.0126	1.509167	2.937500	0.333844	0.073844

Table 3. 5 - Constant fees parameter

Parameter	Winter	Spring	Summer	Autumn
Excise Tax [€/kWh]	0.0125	0.0125	0.0125	0.0125
VAT [-]	0.22	0.22	0.22	0.22

Winter exhibits the most pronounced temporal differentiation with energy supply costs ranging from 0.136 to 0.165 €/kWh (Δp = 0.030 €/kWh) and capacity market charges implementing extreme peak-hour (0.0449 €/kWh during 09:00-14:00 versus 0.001639 €/kWh off-peak), creating dual incentives for temporal load shifting and aggressive peak suppression.

Spring and autumn present contrasting structures with modest energy price variation ($\Delta p \approx$ 0.020 €/kWh) and uniform capacity market charges (0.002767 and 0.002995 €/kWh respectively), favoring pure load flattening strategies. Summer combines moderate energy differentials (Δp = 0.026 €/kWh) with selective capacity peaks during extended daytime hours.

The power-based capacity charges totaling 4.447 €/kW monthly—constant across all seasons—establish peak demand management as the dominant optimization objective. This coefficient implies approximately 53.40 € annual savings per kilowatt of peak reduction regardless of season, explaining the consistent ~75% peak reduction observed in Chapter 4 despite varying temporal load distribution granularity. Similarly, regulated per-energy charges, excise tax, and VAT rates remain structurally invariant, with only dispatching costs exhibiting modest seasonal variation reflecting balancing service requirements.

This comprehensive parameter documentation enables rigorous interpretation of optimization results presented in Chapter 4 by establishing the quantitative economic foundation underlying seasonal performance differences.

3.2.2 Constraint and Objective Function

The objective function seeks to minimize the net cost of the charging station operator, expressed mathematically as:

$$\min Z = C_{total} - R_{total} + \Sigma_e C_{penalty(e)} \tag{3. 2}$$

where total electricity costs C_{total} aggregate comprehensive electricity procurement costs across all tariff components documented in Section 3.3.1, R_{total} represents total revenue from user payments that partially offsets operational costs, and $\Sigma_e C_{penalty(e)}$ quantifies penalty costs for optimization-driven incomplete energy delivery. This formulation balances the operator's economic objective of minimizing procurement expenditures against the service quality requirement of ensuring adequate energy delivery to connected vehicles, with the penalty term creating economic disincentive for strategic partial charging.

The electricity bill total cost is composed by several components. The variable energy costs accounting for grid losses are formulated as:

$$C_{energy_{var(t)}} = c_{energy(t)} \times P_{withdraw(t)} \times \Delta t \times (1 + \gamma_{loss}) \quad \forall t \in T \tag{3. 3}$$

creating direct incentive for temporal load shifting, as the optimizer naturally concentrates charging during lower-price periods to minimize the weighted sum of energy procurement costs across the planning horizon. The grid loss factor γ_{loss}= 0.10 accounts for resistive dissipation in low-voltage distribution networks, effectively increasing procurement requirements by ten percent relative to delivered energy. Load shifting is further reinforced by the capacity market charge:

$$C_{capacity(t)} = c_{capacity(t)} \times P_{withdraw(t)} \times \Delta t \quad \forall t \in T \tag{3. 4}$$

which applies time-varying capacity market charges that are substantially higher during peak hours, creating additional economic incentive to reduce consumption precisely during periods of system-wide congestion. The magnitude and temporal structure of these charges vary seasonally as documented in Section 3.2.1. A further variable cost component aggregate dispatching service charges and per-energy network and point-of-delivery obligations:

$$C_{energy_{other(t)}} = \left[c_{dispatch} \times (1 + \gamma_{loss}) + c_{network_{kwh}} + c_{POD_{kwh}}\right] \times P_{withdraw(t)} \times \Delta t \; \forall t \in T \tag{3. 5}$$

Additionally, the Italian electricity bill is characterized by an important power-based component that creates the dominant economic driver for peak demand management:

$$C_{power} = \left(c_{network_{kw}} + c_{POD_{kw}}\right) \times P_{max} \tag{3. 6}$$

Where the combined coefficient is documented in Section 3.3.1 (Tables 1-4), remaining constant at 4.447 €/kW monthly across all seasons.
The fixed charge component:

$$C_{fixed} = C_{network_{fixed}} \times C_{POD_{fixed}} \tag{3. 7}$$

This cost does not influence scheduling decisions since it remains constant regardless of operational choices, it contributes to the total electricity cost and is therefore included for completeness of economic accounting.
The excise tax component applies to all consumed energy:

$$C_{excise(t)} = c_{excise} \times P_{consumption(t)} \times \Delta t \tag{3. 8}$$

This component creates a modest additional variable cost proportional to total energy consumption.
The comprehensive total electricity cost aggregates all components with value-added tax applied multiplicatively:

$$C_{total} = \left[\Sigma_{\{t \in T\}}\left(C_{energy_{kwh(t)}} + C_{capacity(t)} + C_{excise(t)}\right) + C_{power} + C_{fixed}\right] \times (1 + \lambda_{VAT}) \tag{3. 9}$$

where

$$C_{energy_{kwh(t)}} = C_{energy_{var(t)}} + C_{energy_{other(t)}} \tag{3. 10}$$

The multiplicative VAT application creates a proportional amplification effect wherein reductions in any underlying cost component generate 22 percent larger total savings, reinforcing the economic value of optimization across all cost dimensions. The monthly projection factor D_{month} extrapolates daily variable costs to a monthly basis while power-based and fixed charges are already expressed on a monthly basis, ensuring dimensional consistency across all cost components in the objective function.

The constraints define the feasible operational space within which this minimization occurs, ensuring that the pursuit of cost reduction does not violate physical laws or operational realities. The most fundamental constraint enforces that charging can only occur when vehicles are physically present and cannot exceed technical power limitations:

$$P_{charge(e,t)} \leq \alpha(e,t) \times P_{\max(e)} \quad \forall e \in E, \forall t \in T \tag{3. 11}$$

where the binary presence indicator $\alpha(e,t) \in \{0,1\}$ forces charging to zero during disconnected periods while the maximum power $P_{\max(e)}$ bounds delivery rates to the minimum of vehicle acceptance capability and station capacity. This constraint directly limits the optimizer's freedom to reduce costs by shifting charging to arbitrary low-price periods, restricting flexibility to only those time windows when vehicles are actually connected.
The energy requirement constraint introduces flexibility by allowing incomplete charging subject to economic penalties.

$$\Sigma_t P_{charge}(e,t) \times \Delta t + E_{uncharge}(e) \geq E_{req}(e) \tag{3. 12}$$

The formulation allows total delivered energy plus uncharged energy to satisfy user requests, creating an implicit choice: the optimizer can leave energy undelivered if the resulting penalty costs ($c_{penalty} \times E_{uncharge_{opt}}(e)$) are less than the procurement cost savings achieved by avoiding expensive charging periods or peak-inducing simultaneous charging across multiple vehicles.
The grid interface constraints link individual vehicle decisions to aggregate station-level flows determining costs. The fundamental linkage expressed through:

$$P_{withdraw(t)} = \Sigma_{\{e\in E\}P_{charge}}(e,t)\ \forall t \in T \tag{3. 13}$$

enforces that total power withdrawn from the grid during each period exactly equals the sum of charging power across all connected vehicles.

The peak power tracking constraint implements the critical mechanism for capacity charge minimization. Through the inequality:

$$P_{max} \geq P_{withdraw(t)} \tag{3. 14}$$

applied for every time period t, the model forces the scalar peak variable to equal or exceed withdrawal power in all periods. Since the objective function includes capacity charges increasing linearly with P_{max}, the optimizer has direct economic incentive to minimize this variable, with the constraints collectively forcing P_{max} to equal the actual maximum of $P_{withdraw(t)}$ across all periods, automatically implementing peak detection without requiring non-linear operators. This structure enables the model to create economic incentive for peak reduction through temporal load coordination, with the mechanism operating by distributing charging across time rather than allowing concentration during simultaneous arrivals.

The model addresses each of the 500 stochastically generated scenarios independently. For each scenario, the optimizer determines the charging schedule that best exploits the available scheduling flexibility given the specific demand realization. This flexibility is shaped by the particular combination of uncertain vehicle arrival times, connection durations, and energy requirements characterizing each scenario Since every scenario presents a unique demand configuration, each optimization instance yields a distinct solution. The resulting collection of 500 optimized schedules provides meaningful statistical insight into system performance under uncertainty, enabling quantification of expected benefits, assessment of variability across diverse conditions, and identification of tail risks associated with extreme scenario. Rather than relying on a single representative case, this approach captures the full distribution of possible operational outcomes as characterized through the Monte Carlo generation process, enabling statistically robust performance evaluation presented in Section 4.

4 Case Study Application and Results

This section presents the empirical validation of the proposed optimization framework, progressing from dataset characterization through baseline-optimization comparative analysis. The analysis employs 25 months of operational data from Politecnico di Milano charging infrastructure, demonstrating the practical applicability and economic benefits of the methodology developed in Chapter 3.

4.1 Case study description: Politecnico di Milano Charging Infrastructure

The study focuses on the electric vehicle (EV) charging facility at the Politecnico di Milano, Leonardo Campus. This infrastructure comprises three distinct charging stations—ED9, ED20, and ED22—totalling 16 charging points distributed across the campus, which, for the purposes of this analysis, are aggregated into a single unified facility. This aggregation represents a collective resource serving a controlled population of university faculty, staff, and students.

The facility provides 22 kW AC charging capacity per point, with access regulated through institutional credentials. The stations are primarily active during standard university hours (07:00–21:00). Unlike residential or highway charging contexts, this workplace environment generates distinct, task-oriented usage patterns, characterized by high arrival concentrations during morning hours and extended connection durations, which present significant potential for demand-side flexibility.

The raw dataset spans a 25-month period (June 2023 – June 2025), documenting 4,471 individual charging sessions from 39 unique registered vehicles, with a cumulative energy delivery of 71,680 kWh. Each record includes anonymized user IDs, station identifiers, connection/disconnection timestamps, and total energy delivered.

4.2 Dataset and Preprocessing Step

To ensure the analysis reflects regular operational demand rather than stochastic outliers, a rigorous temporal filtering was applied:

- Excluded Periods: Weekends, official holidays, and university closures were removed to eliminate bimodal noise and focus on "standard" working days.

- Final Sample: The filtering resulted in 448 working days analyzed (approximately 71% of the total calendar span).

Another fundamental preprocessing step is temporal discretization, performed by mapping continuous timestamps into 15-minute intervals, aligning the data with standard electricity market settlement periods. Within each interval, a constant-power approximation was assumed, providing a robust first-order estimation for aggregate demand analysis.

A fundamental premise of this research is the stationarity of the charging demand, allowing for the use of time-invariant probability distributions. Visual inspection of the 448-day time series, supported by a seven-day moving average, reveals no significant upward or downward trends or heteroscedasticity (as shown in *Figure 4.1*)

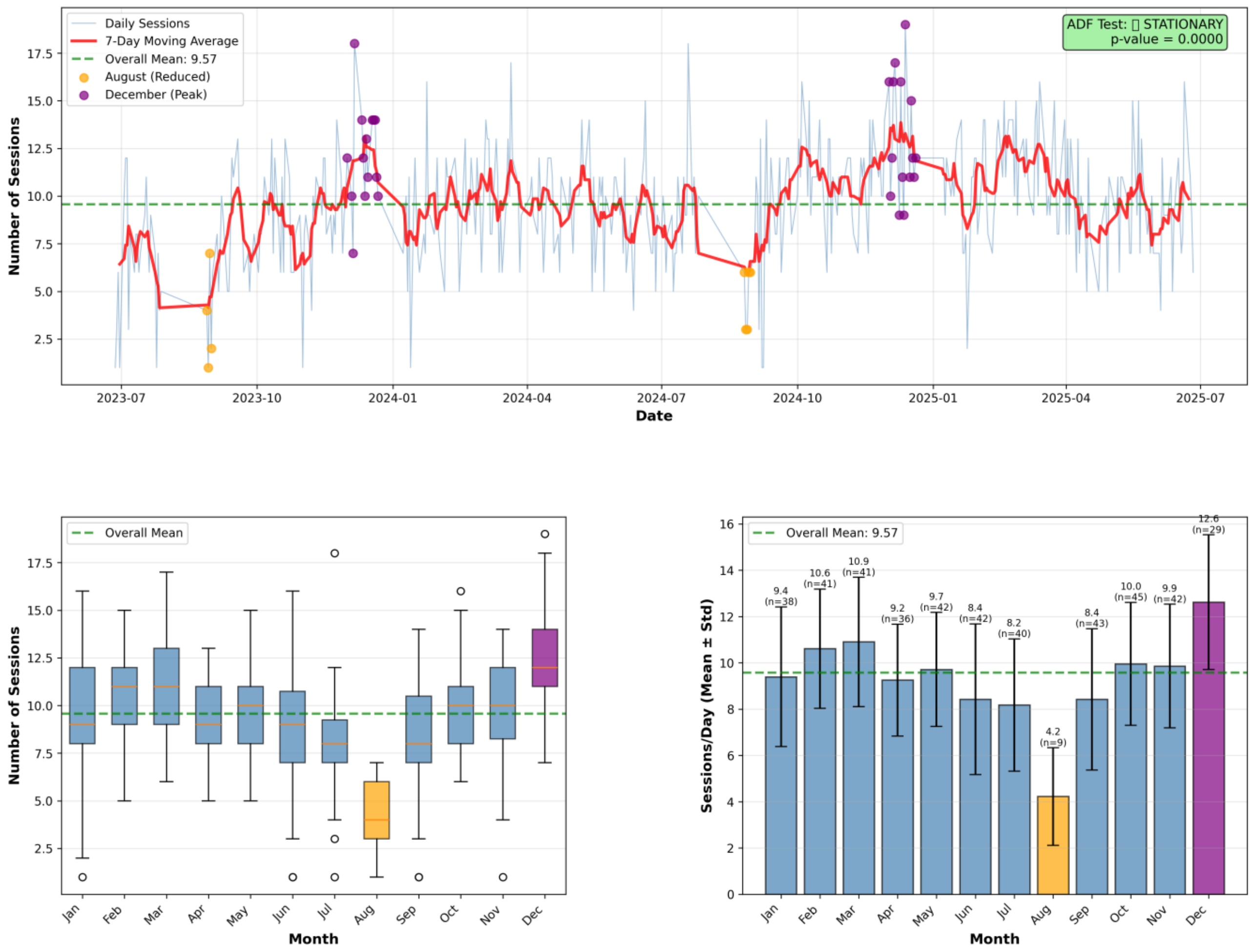

Figure 4. 1 – (a) Time series of daily session over 448 operating day; (b) monthly distribution of sessions; (c) monthly mean with standard deviation

The stationarity of charging demand was statistically validated using the Augmented Dickey-Fuller test [41] a statistical procedure commonly employed in energy demand analysis to verify whether a time series exhibits stable statistical properties over time. The test, implemented in Python using standard scientific computing libraries, evaluates the null hypothesis H_0 that the time series contains a unit root—implying that shocks to the process accumulate over time producing non-stationary behavior with drifting mean or variance—against the alternative hypothesis of stationarity. In practical terms, rejecting H_0 confirms that the statistical properties of the demand process remain stable over time, a necessary condition for the validity of time-invariant distributional assumptions underlying the Monte Carlo framework. The test applied to the daily session count series yielded ADF = -6.07 with $p < 0.001$, leading to strong rejection of the null hypothesis and confirming the absence of long-term trends.

Despite certain months exhibit systematically higher or lower session counts relative to others, these differences are attributable to the university academic calendar rather than to climatological seasonality: August shows markedly reduced activity corresponding to the summer campus closure, while December reflects the holiday break period. Importantly, these calendar effects do not compromise the stationarity assumption.

Given the objective of robust infrastructure dimensioning, a unified statistical representation is methodologically preferable to fragmented seasonal models. Therefore, aggregated Empirical Cumulative Distribution Functions (ECDFs) derived from the entire 448-day dataset were used as the stochastic foundation for the Monte Carlo simulation. This approach captures the full spectrum of demand variability (1–19 sessions/day range) without introducing the data fragmentation issues associated with seasonal stratification on a limited dataset.

Based on the stationarity analysis, empirical cumulative distribution functions are estimated for the four key uncertain parameters by pooling data across all 448 working days without temporal stratification.

- *The arrival time* profile, shown in *Figure 4.2*, is characteristic of workplace charging behavior. This pattern exhibits a pronounced peak during the morning hours (08:00–11:00). While the median arrival occurs at slot 41 (10:15–10:30), the distribution shows a modest right skew toward the afternoon, though 90% of sessions start before 16:00. Heatmap analysis confirms high day-of-week consistency across the working week, supporting single stationary distribution assumption for all working days.

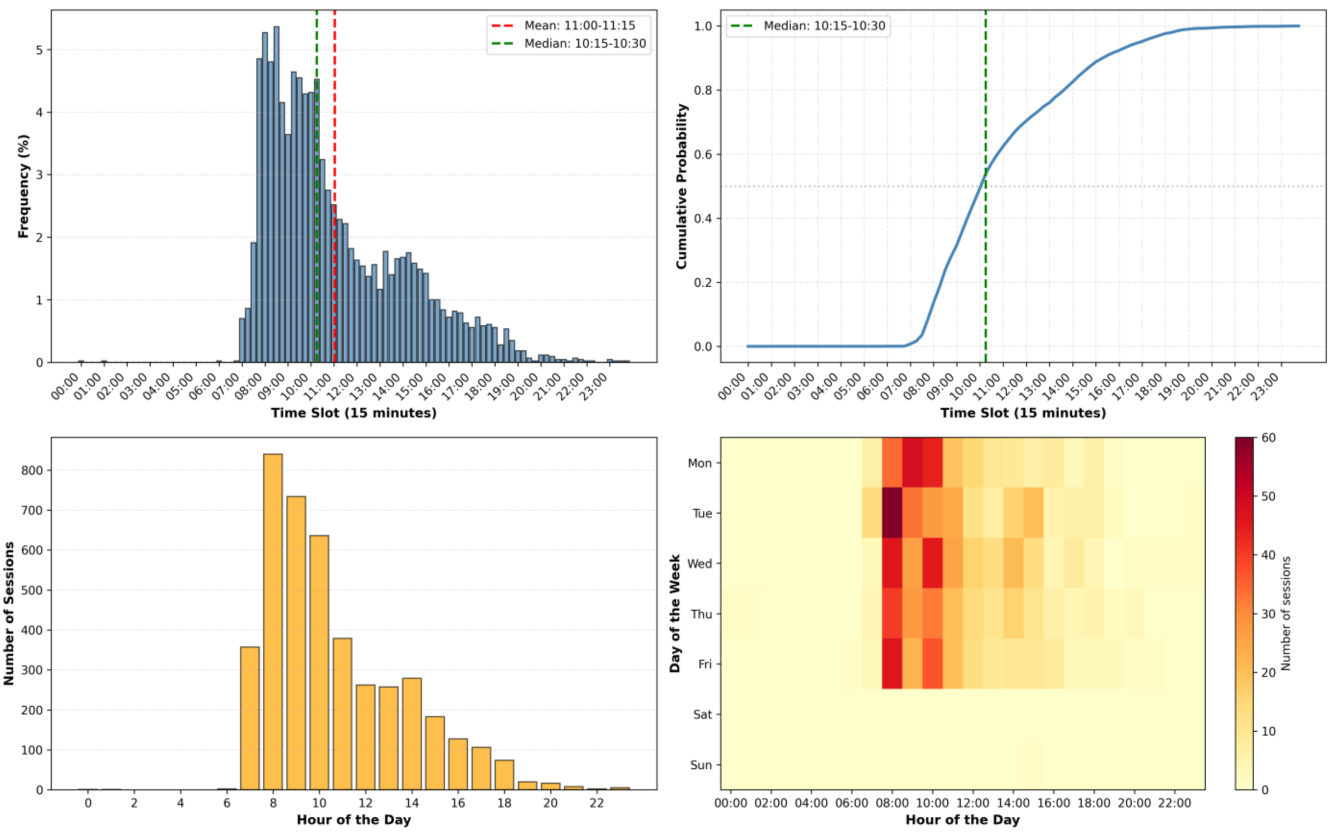

Figure 4. 2 – (a) Probability density function (PDF) of charging arrival times (typical day); (b) cumulative distribution function (CDF) of charging arrival times; (c) hourly distribution of charging arrive (aggregated by hour); (d) weekly heatmap of charging arrival time.

- *The connection durations*, measured as the elapsed time between connection and disconnection regardless of whether active charging occurs throughout, exhibit a bi-modal pattern, reflecting two user archetypes: short-term visitors (2–3 hour stays) and full-day commuters (7–8 hour stays). With a mean duration of 4.86 hours and substantial variability

(IQR: 2.18–7.52 hours), this parameter is a critical determinant of the flexibility window available for smart charging optimization. The longer connection times associated with the second mode provide the necessary temporal buffer for effective load-shifting and peak-shaving strategies.

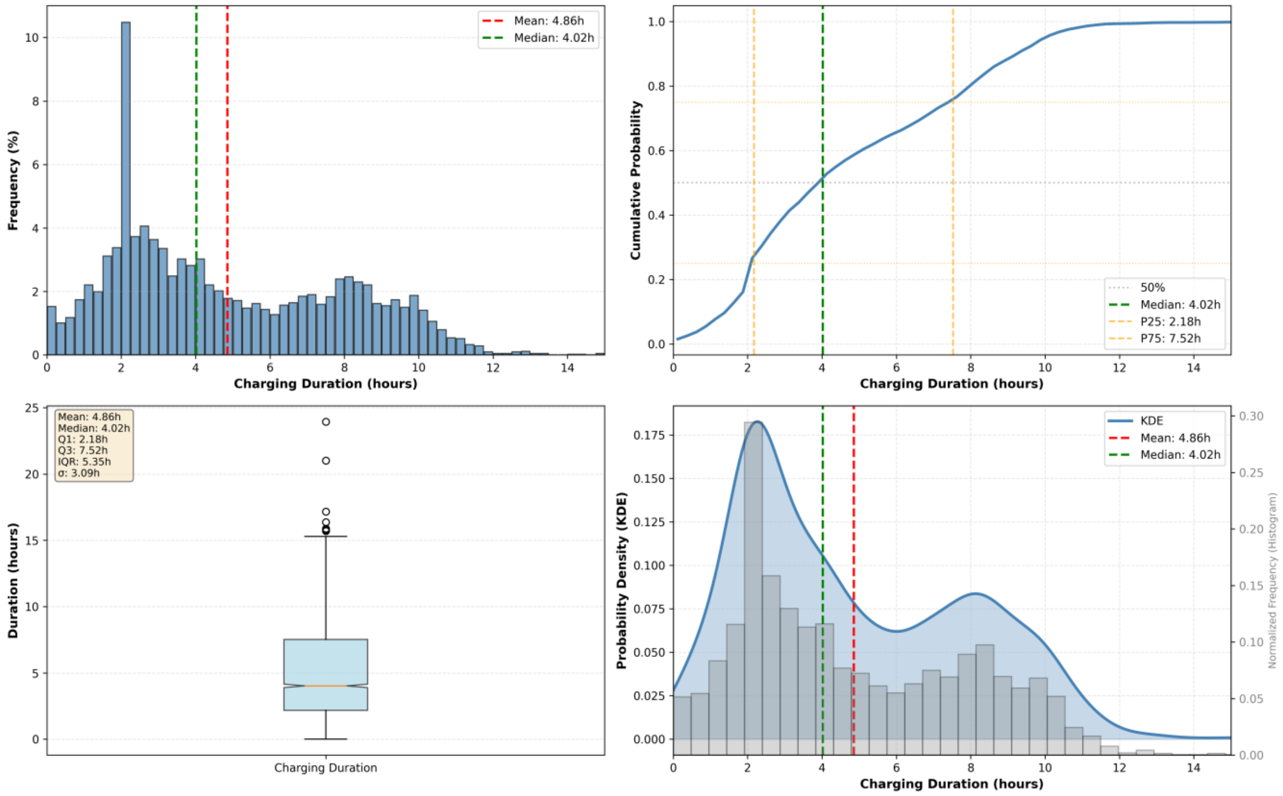

Figure 4. 3 - *(a) Probability density function (PDF) of charging connection durations (typical day); (b) cumulative distribution function (CDF) of connection durations; (c) distribution of connection duration; (d) Kernel Density Estimation (KDE)- Smoothed Distribution*

- The energy requirements per session are characterized by strong right-skewness and multimodality, with a median demand of 11.64 kWh and a mean of 15.81 kWh. The failure of standard parametric models (e.g., Normal or Lognormal) to capture the heavy-tail behavior and multiple peaks necessitates the non-parametric ECDF approach, that preserves the true distributional shape, to ensure the robustness of the subsequent scenario generation.

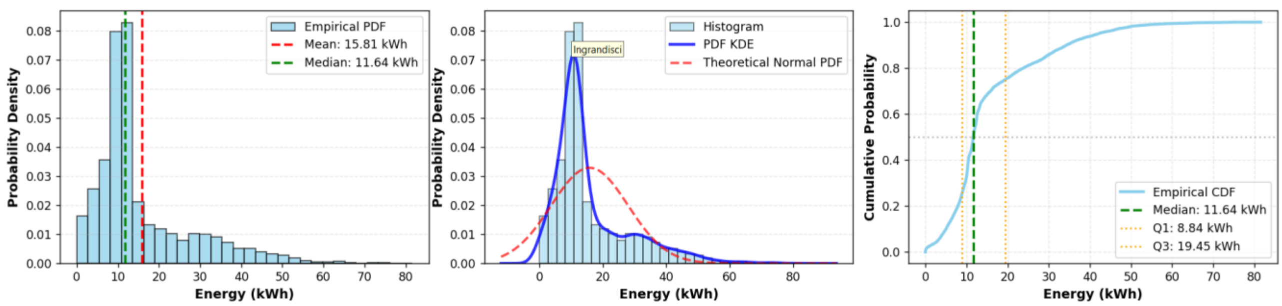

Figure 4. 4 – (a) Probability density function (PDF) of delivey energy (typical day); (b) empirical and theoretical PDFs; (c) cumulative distribution function (CDF) of delivery energy;

For each of these distributions, empirical cumulative distribution functions (ECDFs) were computed by sorting observed values and calculating the proportion of observations falling at or below each value. These ECDFs, stored as lookup tables mapping probability levels to realized values, form the basis for inverse transform sampling in the Monte Carlo scenario generation process.

4.3 Scenario Generation Results and Validation

The Monte Carlo scenario generation process successfully produced 500 independent demand realizations representing the full distribution of possible operational conditions at the charging facility. The implementation, constrained to station operating hours of 07:00 to 21:00, generated scenarios with variable daily session counts ranging from 1 to 19 vehicles per day, with mean 9.64 sessions closely matching the historical mean of 9.57 sessions. Total energy consumption across scenarios spanned 42 to 287 kilowatt-hours daily, with mean 152 kilowatt-hours and standard deviation 48 kilowatt-hours, reflecting substantial variability in aggregate demand conditions that optimization must address

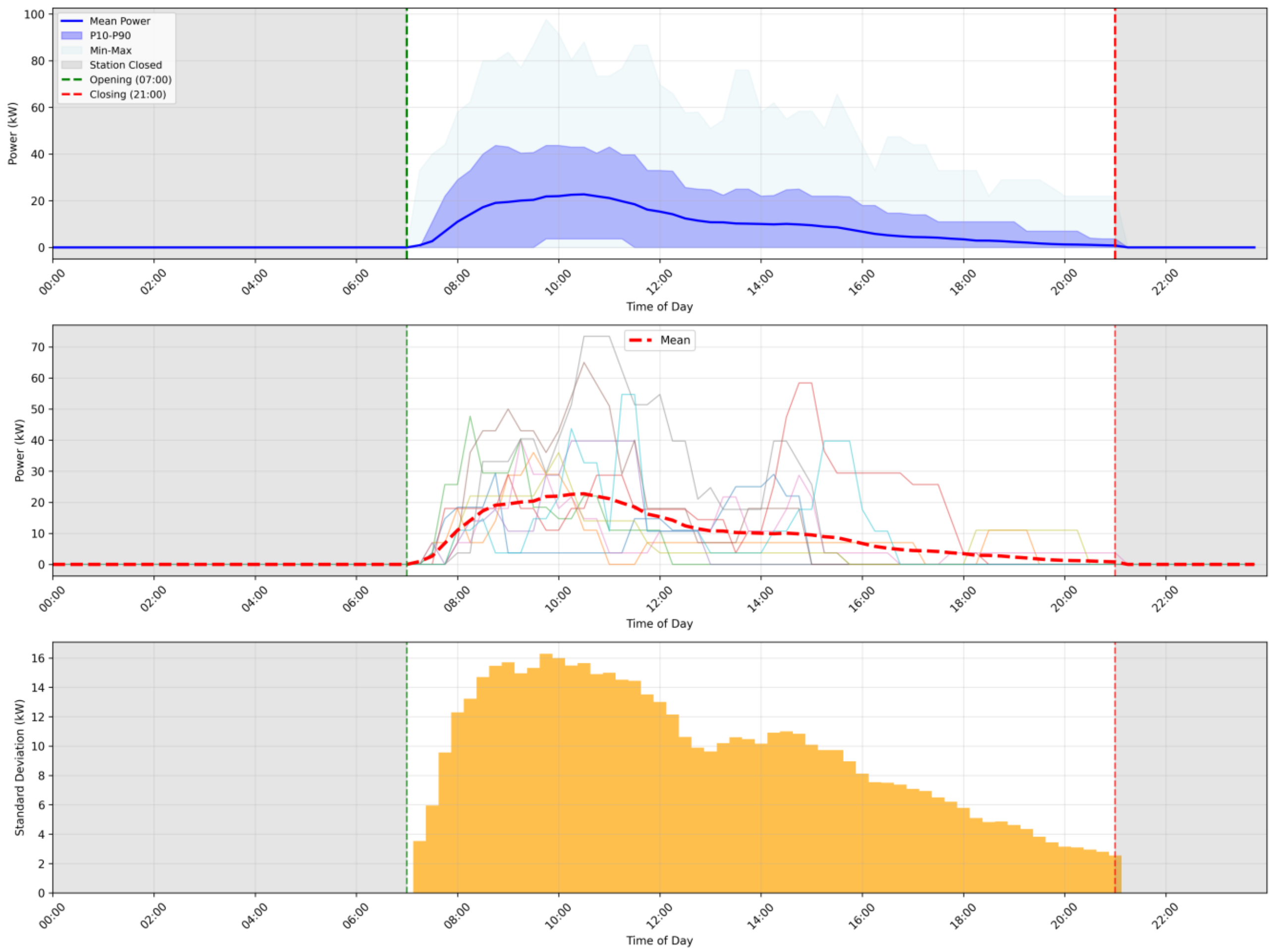

Figure 4. 5 – Monte Carlo Simulation Outputs: (a) charging profile -mean across 500 scenarios; (b) charging profile of a selected sample of 10 scenarios; (c) inter-scenario variability (standard deviation).

Figure 4.5 presents the aggregate load profiles under immediate charging baseline policy across the scenario ensemble.

The upper panel displays the mean charging power profile with confidence bands capturing inter-scenario variability, revealing a pronounced morning peak reaching approximately 24 kilowatts mean power between 08:00 and 11:00 coinciding with concentrated vehicle arrivals, followed by gradual decline through afternoon and evening hours. The 10th-90th percentile band spanning approximately 5 to 45 kilowatts and the minimum-maximum range extending from near-zero to 100 kilowatts quantify the substantial uncertainty inherent in daily demand patterns.

The middle panel illustrating ten individual scenario realizations demonstrates the diversity of load profiles generated by the stochastic process, with some scenarios exhibiting sharp peaks exceeding 80 kilowatts while others maintain relatively flat profiles below 40 kilowatts throughout the day.

The lower panel presents temporal variability measured through standard deviation, showing maximum uncertainty of approximately 16 kilowatts during morning hours when both arrival probability and session count variance are highest, declining to 2-8 kilowatts during afternoon and evening periods as fewer vehicles remain connected.

Statistical validation through empirical cumulative distribution function comparison confirms that generated scenarios preserve the statistical properties of historical data with high fidelity. *Figure 4.6* presents overlaid historical and simulated CDFs for the five uncertain parameters governing demand stochasticity. The energy per session distribution exhibits mean absolute error of 0.0285, with simulated CDF closely tracking historical values across the entire support from 5 to 70 kilowatt-hours, successfully preserving the characteristic right-skewed distribution with concentration near 10-15 kilowatt-hours and extended tail representing occasional high-energy sessions. Arrival time CDFs demonstrate near-perfect alignment with MAE of 0.0094, accurately reproducing the restricted temporal window and morning concentration pattern. Connection duration validation yields MAE of 0.0167, capturing the bimodal empirical distribution with peaks representing short visits and full-day stays. Daily session count comparison shows MAE of 0.0105, preserving the discrete count distribution ranging from 1 to 19 sessions. Departure time CDFs, derived from the sum of sampled arrivals and durations, exhibit MAE of 0.0459, with slight divergence in tail regions attributable to truncation at station closing time implementing operational constraints.

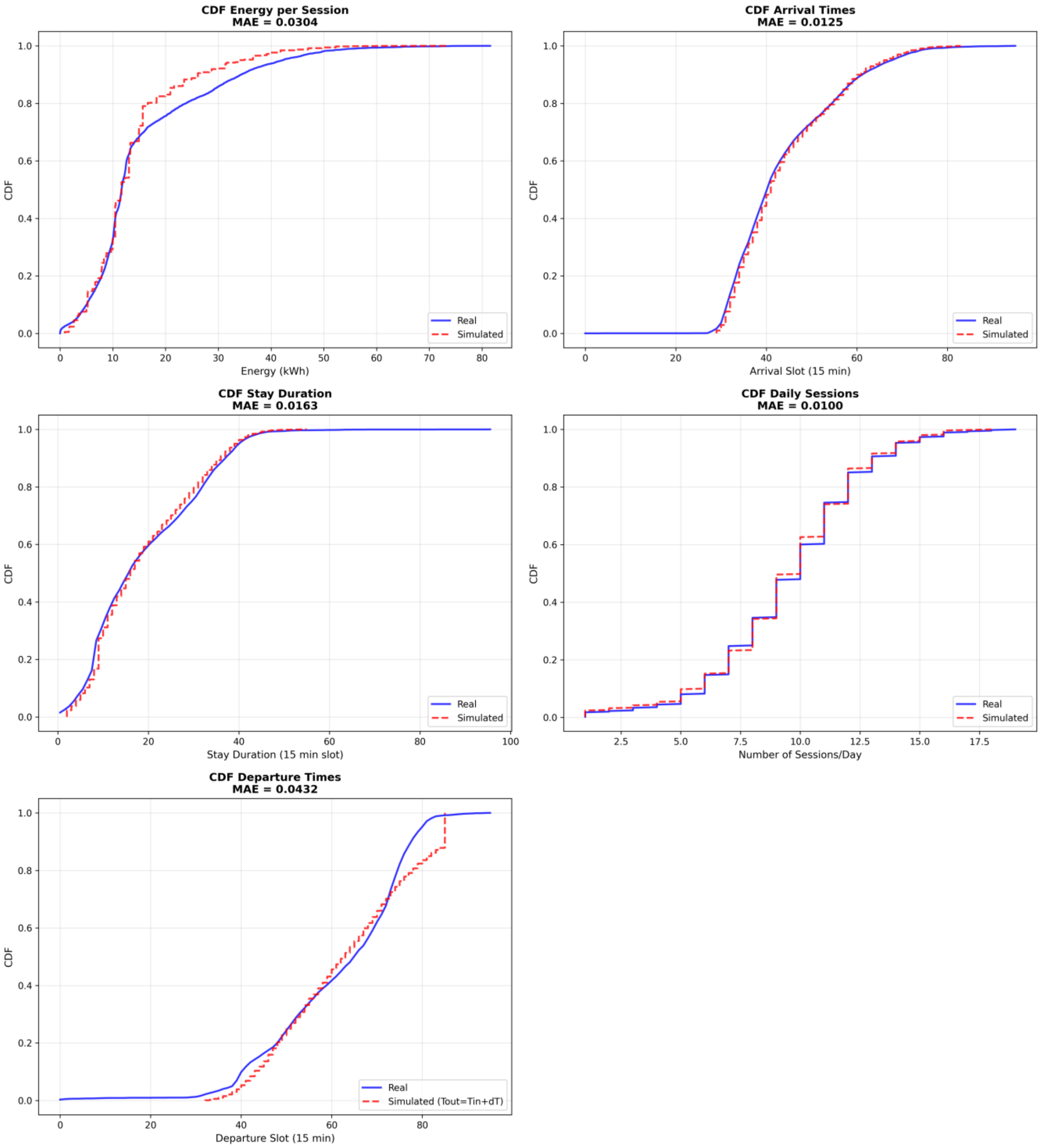

Figure 4. 6 – Validation test via comparison between the Cumulative Distribution Functions (CDFs) of Historical and Simulated Data.

These quantitative validation metrics, all remaining well below the 0.05 threshold considered acceptable for distributional preservation, combined with visual inspection confirming close CDF alignment across parameters, provide confidence that the 500-scenario ensemble constitutes a statistically representative sample suitable for robust optimization analysis.

Infrastructure utilization analysis reveals substantial temporal flexibility potential within generated scenarios. *Figure 4.7* presents comprehensive idle time characterization across the ensemble, quantifying periods when vehicles remain connected to charging infrastructure but not actively charging under immediate charging baseline policy. The aggregate analysis demonstrates that 62.7 percent of total connection time represents idle periods with vehicles fully charged but still connected, while only 37.3 percent involves active charging. The temporal distribution shows idle time concentrated during midday and afternoon hours when vehicles that arrived early and charged rapidly during morning hours remain connected for extended periods, creating substantial available capacity for demand response or vehicle-to-grid applications. Duration analysis reveals mean connection time of 4.71 hours per session, comprising mean active charging duration of 1.78 hours and mean idle duration of 2.99 hours, yielding an average idle-to-charging ratio of 1.68, indicating that vehicles remain connected approximately 68 percent longer than required for energy delivery. The distribution histogram demonstrates that while some sessions exhibit minimal idle time when energy requirements approach maximum deliverable energy within connection duration, the majority of sessions achieve complete charging well before departure, with approximately 1,800 sessions showing idle durations exceeding 2 hours.

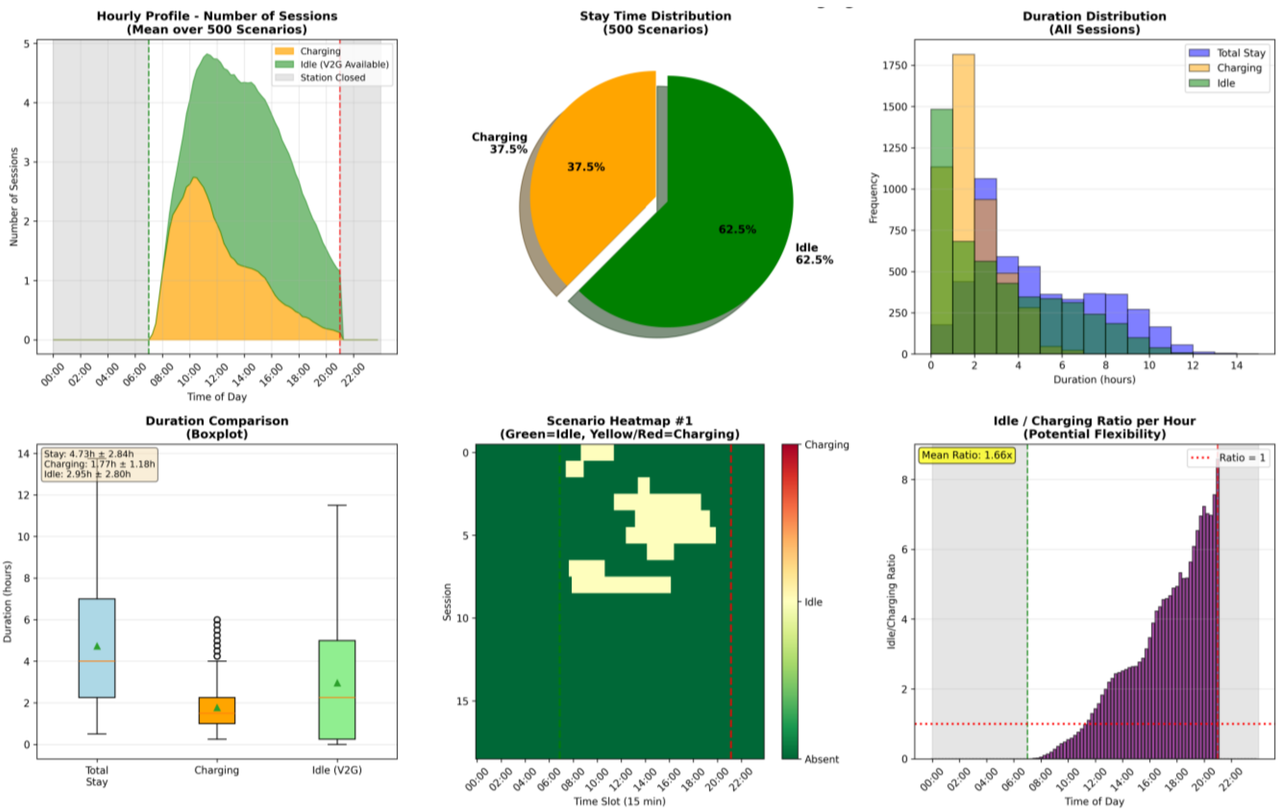

Figure 4. 7 – Idle Time distribution and characterization.

This substantial temporal flexibility quantified through idle time analysis establishes the physical foundation enabling the optimization framework to shift charging loads across time without compromising user service quality, as vehicles possess sufficient connection duration to accommodate delayed or modulated charging schedules while still receiving requested energy before departure.

4.4 Baseline and Optimization performance

The quantification of optimization benefits requires establishing a rigorous baseline representing operational behavior without intelligent energy management. The baseline implements an immediate charging policy: EVs start maximum-power charging upon connection to charging infrastructure and continue uninterrupted power delivery until either the energy requirement is completely satisfied, or the vehicle disconnects at the predetermined departure time. This deterministic scheduling approach reflects the passive operational logic employed by conventional charging stations that respond reactively to user connection events without incorporating forward-looking optimization considerations.

The baseline performance evaluation employs identical economic accounting as the optimization model, ensuring rigorous comparability. Monthly projections multiply daily variable costs by thirty while incorporating actual monthly power-based and fixed charges. Revenue applies the 0.65 euros per kilowatt-hour user tariff to delivered energy. Critically, baseline scenarios incur zero penalty costs since any energy shortfall results exclusively from insufficient connection time (E_uncharge_time) rather than optimization decisions

4.4.1 Operational Comparative Analysis

The fundamental operational improvements achieved through optimization manifests most visibly in the probability density functions of peak power demand presented in Figure X, which contrast the stochastic distributions of maximum power withdrawal across the 500-scenario ensemble under baseline immediate charging.

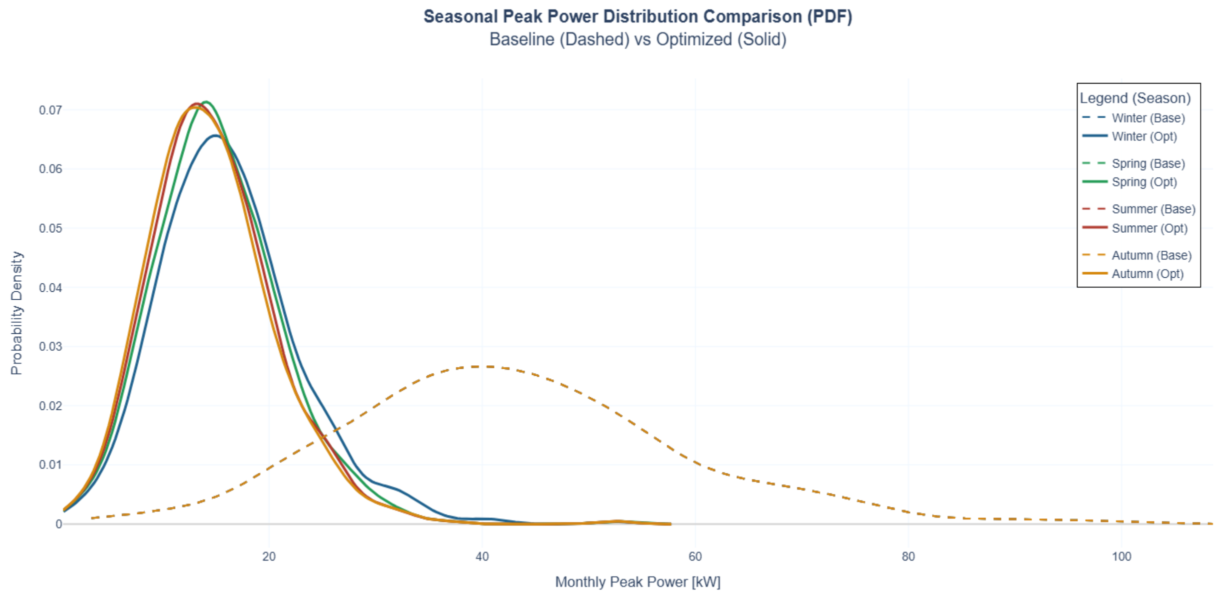

Figure 4. 8 – Seasonal peak power distribution comparison (PDF) -baseline (dashed) vs optimized (solid).

The baseline distribution exhibits pronounced concentration between 35 and 50 kilowatts with modal peak near 40 kilowatts, reflecting the coincident charging during morning arrivals window at maximum power creating substantial aggregate demand peaks. The mean baseline peak power of 88.7 kilowatts with standard deviation of 24.3 kilowatts quantifies this concentrated demand pattern.

The optimized distribution displays dramatic leftward shift with strong concentration between 10 and 14 kilowatts and modal peak near 11 kilowatts, achieving reduced peak power across the scenario ensemble.

This transformation reflects the optimizer's systematic exploitation of the temporal flexibility inherent in electric vehicle charging, wherein the discretion to distribute required energy delivery across any portion of the connection window between arrival and departure enables strategic load distribution that suppresses aggregate demand peaks. The visual leftward shift and reduced distribution spread indicate substantial mean reduction and decreased variability relative to baseline, with the tighter concentration demonstrating more consistent peak management performance across diverse demand conditions.

The overlay of four seasonal curves reveals remarkable baseline-to-optimized reduction consistency across winter, spring, summer, and autumn despite varying price structures. All seasons achieve similar optimized modal peaks near 11 kilowatts. However, winter exhibits modestly broader optimized distribution extending rightward with upper tail reaching approximately 50 kilowatts compared to spring/summer/autumn terminating near 35 kilowatts.

This seasonal divergence pattern emerges from the interaction between price structure complexity and scenario-specific demand configurations. Examining the seasonal tariff data, presented in Section 3.2.1., reveals that winter presents the most articulated temporal price structure with meaningful differentials in both energy supply costs and time-varying capacity charges. This creates a more complex economic landscape where temporal arbitrage opportunities coexist with peak reduction imperatives. In scenarios with particularly challenging demand patterns—high vehicle counts with concentrated arrivals during expensive periods—the optimizer faces trade-offs between perfect load flattening and economically rational temporal shifting. Different scenario realizations within the winter ensemble may thus converge to slightly different peak levels (11-15 kW) while achieving nearly equivalent total costs, creating natural dispersion in the optimized peak distribution.

Conversely, spring, summer, and autumn exhibit simpler temporal price structures with modest energy supply differentials and relatively uniform capacity charges. Under these conditions, temporal arbitrage contributes negligibly to total cost reduction, and the optimizer uniformly pursues aggressive load flattening as the dominant strategy across all scenarios, producing tight convergence around 11 kilowatt peaks with minimal tail dispersion. The extreme upper tail divergence reflects tail scenarios with exceptional demand characteristics (e.g., 18-19 vehicles with high coincident energy requirements) where even optimal scheduling cannot reduce peaks below 30-50 kilowatts while satisfying delivery constraints, but these represent less than 5% of realizations and occur more frequently in winter due to higher energy demand and price-driven constraints on scheduling freedom.

4.4.2 Economic Comparative Analysis

The unit cost sustainability analysis presented in Figure Z quantifies the average electricity procurement cost per kilowatt-hour delivered to electric vehicles, providing a normalized economic performance metric that enables direct comparison against the user tariff rate determining business model viability.

Under baseline operation, unit procurement costs exhibit substantial seasonal variation ranging from 0.279 euros per kilowatt-hour in spring characterized by moderate wholesale electricity prices to 0.411 euros per kilowatt-hour in winter reflecting elevated heating-driven electricity demand and correspondingly higher market prices. Summer and autumn display intermediate unit costs of 0.332 and 0.354 euros per kilowatt-hour respectively. These baseline unit costs remain consistently and substantially below the 0.65 euros per kilowatt-hour user tariff indicated by the horizontal reference line, establishing fundamental economic viability of the charging operation.

Optimization achieves consistent percentage improvements across seasons ranging from 9.9 to 12.2 percent spanning only 2.3 percentage points, demonstrating that optimization benefits exhibit limited sensitivity to seasonal market conditions

The achievement of double-digit percentage cost reductions while maintaining the substantial safety margin below the user tariff threshold demonstrates that optimization enhances both operational efficiency and economic resilience, expanding profit margins that can absorb potential future increases in electricity procurement costs or provide headroom for competitive tariff reductions to stimulate demand growth.

Figure 4. 9 – Unit Cost Comparison: Optimized case with Baseline case including user tariff.

The seasonal pattern in unit cost reductions merits examination to understand the interaction between optimization mechanisms and market conditions. Spring achieves the largest percentage improvement despite starting from the lowest baseline cost, suggesting that moderate electricity prices with meaningful temporal variation create favorable conditions for the temporal arbitrage component of optimization to complement the peak shaving benefits. Winter achieves substantial absolute savings despite the highest baseline costs, indicating that optimization effectiveness persists even under challenging high-price conditions.

4.4.3 Optimization Benefits Quantification

The fundamental understanding of optimization performance requires integrating economic outcomes with operational mechanisms, examining how temporal load redistribution strategies translate into specific cost component transformations. The annual cost decomposition presented in Figure 4.V reveals that baseline operation totaling 14,523 euros comprises 83.3 percent variable costs (12,092 euros), 15.7 percent power-based capacity charges (2,280 euros), and 1.0 percent fixed charges (152 euros), while optimization reduces total costs to 14,348 euros through dramatic internal reallocation rather than uniform proportional reduction across components. This 1.2 percent aggregate savings masks the true optimization mechanism: variable costs decrease modestly by 152 euros (1.3 percent) while capacity charges plummeted by 1,466 euros (64.3 percent), with zero penalty costs confirming that aggressive peak reduction is achieved without service quality compromise.

The critical insight emerges from recognizing that the Italian tariff structure featuring combined capacity charges of 4.447 euros per kilowatt monthly, as previously documented in the *Equation 3.6*, creates an economic regime where peak demand minimization dominates temporal energy price arbitrage as the primary value creation mechanism. This foundation implies that each kilowatt of peak reduction yields 53.40 euros annual savings, establishing powerful incentive for aggressive peak suppression even when this requires accepting some charging during moderate-price periods. The 64.3 percent capacity charge reduction achieved while variable costs decrease only 1.3 percent demonstrates that optimization prioritizes load temporal distribution over pure price minimization, exploiting the structural characteristic of capacity charges wherein a single peak moment determines monthly costs regardless of duration, creating asymmetric value between brief peak suppression and extended energy cost optimization.

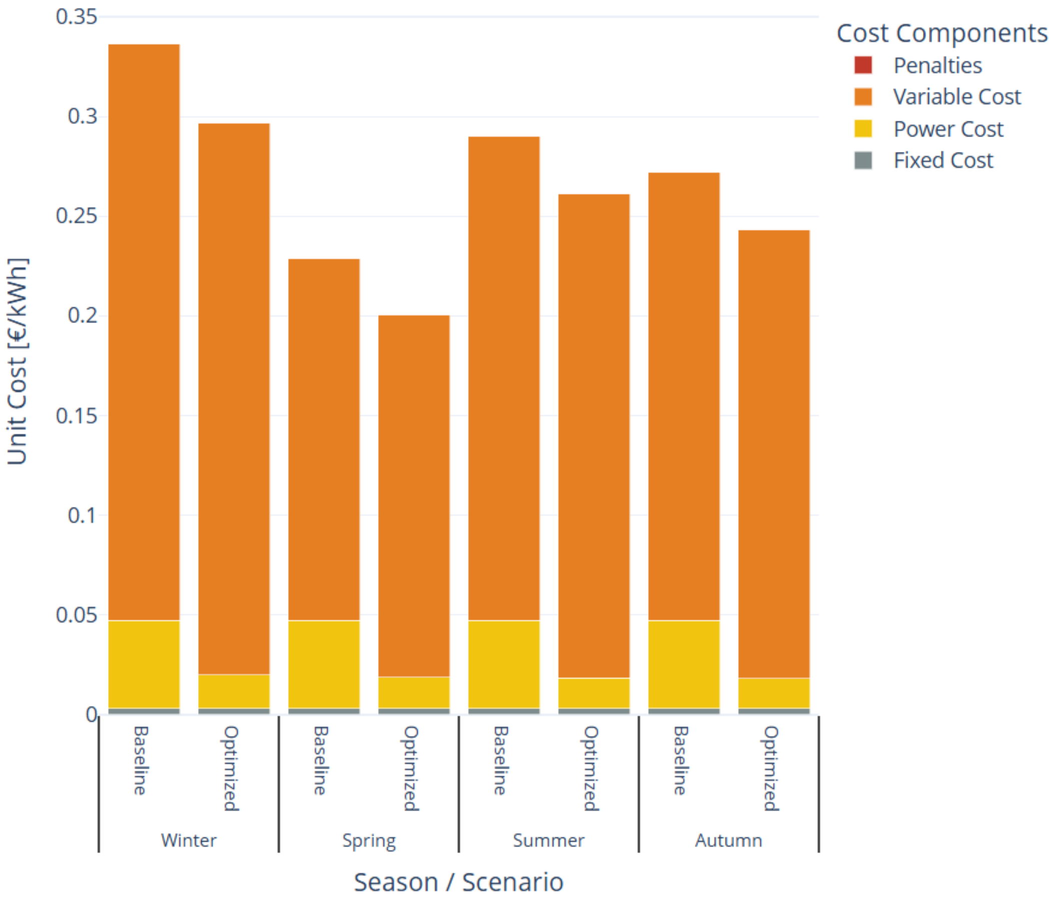

Figure 4. 10 – Comparison of the Unit Charging Cost Components at the POD: Baseline vs Optimized case.

To understand how optimization redistributes charging loads temporally while respecting physical constraints, Scenario 319 in Figure 6789 provides detailed illustration. This scenario exhibits the highest baseline peak (~99 kW) across the 500-scenario ensemble, representing worst-case conditions that test optimization robustness, since elevated baseline peaks necessarily possess greater absolute potential for peak reduction and correspondingly larger economic benefits from capacity charge minimization.

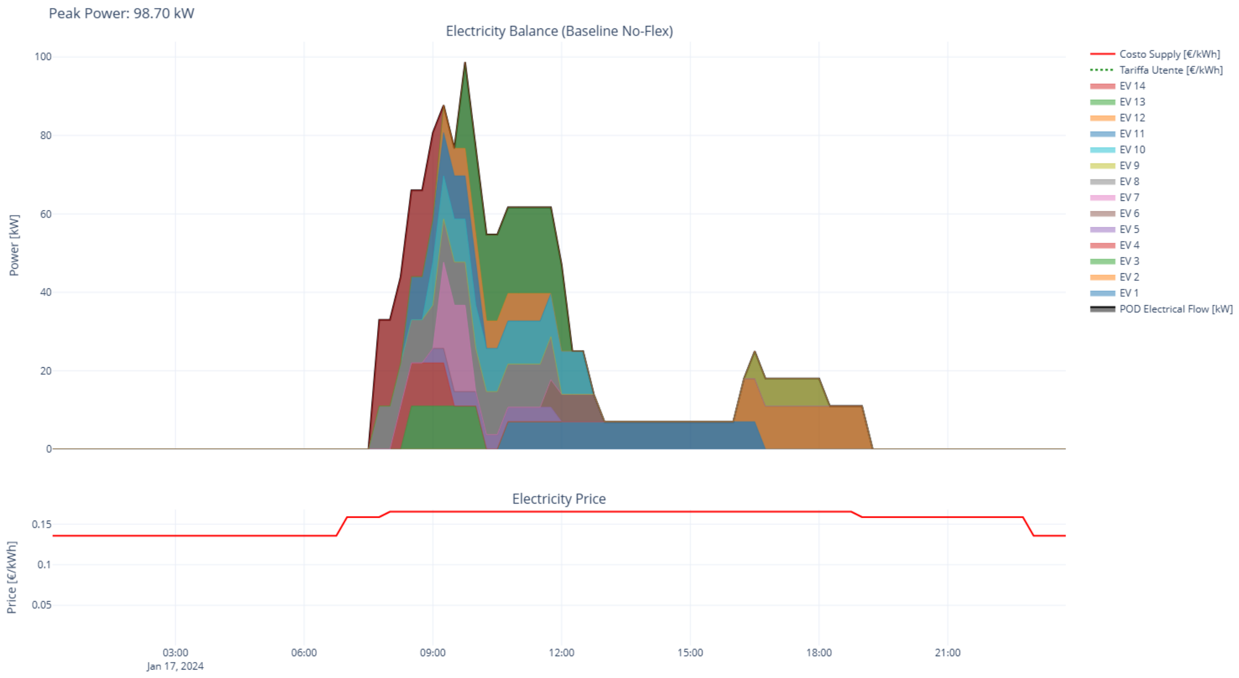

Figure 4. 11 – Baseline profile -Scenario 319 with the highest recorded peak power (98.70 kW).

The detailed decomposition of baseline charging behavior for scenario 319 presented in *Figure 4.11* reveals how uncoordinated vehicle charging creates excessive peak demand. The stacked area visualization shows individual vehicle contributions (EV 1-14) to the aggregate 98.70 kilowatt morning peak, occurring between 08:00-11:00 when multiple vehicles charge simultaneously during maximum electricity prices (0.169 €/kWh). This granular decomposition illustrates both the optimization challenge—coordinating 14 heterogeneous vehicles to suppress coincident peaks—and the opportunity, as visible gaps between charging periods and extended connection durations reveal substantial temporal flexibility for load redistribution.

A fundamental methodological observation emerges from examining the baseline power profiles across the four seasonal panels in Figure *4.12*: the baseline load profiles are perfectly identical across winter, spring, summer, and autumn, all exhibiting the same temporal shape. This identity confirms unambiguously that scenario 319 represents the same demand realization applied to all four seasonal conditions, with identical vehicle counts, arrival times, connection durations, energy requirements, and maximum power capabilities. The Monte Carlo scenario generation process produces a single 500-scenario ensemble representing the stochastic demand distribution, and each scenario is subsequently evaluated under four different seasonal electricity market price environments to assess optimization performance across varying economic conditions while maintaining controlled demand parameters.

Winter - Supply Prices
Winter - Power Profiles
Supply Baseline
Supply Optimized
Power Baseline
Power Optimized
€/kWh
kW
99 kW
52 kW
Jan 17, 2024
Spring - Supply Prices
Spring - Power Profiles
Apr 17, 2024
Summer - Supply Prices
Summer - Power Profiles
Jul 17, 2024
Autumn - Supply Prices
Autumn - Power Profiles
Oct 16, 2024

Figure 4. 12 – 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

This methodological structure proves critical for isolating the impact of seasonal electricity price variations on optimization behavior. By holding demand parameters constant across seasons while varying only the economic parameters (specifically the time-varying energy supply costs and potentially capacity market charges), the analysis confirm that any observed differences in optimized profiles result purely from the optimizer's adaptive response to different electricity price structures.

The winter scenario exhibits a two-level electricity supply price structure during operating hours: a higher rate of approximately 0.165 euros per kilowatt-hour prevailing from 08:00 to 18:45, declining modestly to 0.158 euros per kilowatt-hour during the evening window from 18:45 to 21:00, with the lowest nocturnal rate of 0.136 euros per kilowatt-hour occurring outside station operating hours and therefore inaccessible for load shifting purposes. The effective temporal price differential available during operating hours is consequently limited to 0.007 euros per kilowatt-hour between daytime and evening periods. Additionally, time-varying capacity market charges differentiated across tariff bands contribute a further temporal cost component that reinforces load distribution incentives beyond the energy supply price signal alone.
The baseline charging pattern concentrates demand during the morning arrival window, precisely during the highest-price period. The optimization response produces a markedly different load profile: rather than exploiting temporal price differentials through concentration in lower-price periods—which would be economically marginal given the limited 0.007 euros per kilowatt-hour differential available during operating hours—the optimizer pursues aggressive load flattening by maintaining nearly constant power at approximately 22 kilowatts throughout the entire operational window from 07:00 to 21:00. This behavior reflects the dominant economic influence of power-based capacity charges: with a combined coefficient of 4.45 euros per kilowatt monthly, even modest peak reduction generates capacity charge savings that substantially exceed the energy cost benefits achievable through temporal arbitrage within the constrained price structure. The optimized peak of 22 kilowatts represents a dramatic 77.7 percent reduction relative to the 98.7 kilowatt baseline peak, translating directly into extraordinary monthly capacity charge savings while the nearly uniform load distribution across all operating hours confirms that peak minimization rather than temporal price exploitation constitutes the primary optimization objective under winter market conditions.

The spring scenario, on the contrary, presents fundamentally different economic incentives through its electricity price structure featuring much more modest temporal variation. Spring prices maintain 0.089 euros per kilowatt-hour during morning hours (06:00-09:00), elevate to 0.108 euros per kilowatt-hour during midday (09:00-18:00), and return to 0.089 euros per kilowatt-hour during evening hours (18:00-21:00), creating a price differential Δ= 0.019 euros per kilowatt-hour representing only 58 percent of the winter differential. Despite this reduced price variation offering limited temporal arbitrage opportunity, optimization still achieves aggressive peak reduction from baseline 99 kilowatts to approximately 25 kilowatts. However, the optimized spring profile exhibits dramatically different temporal characteristics compared to winter, maintaining remarkably constant power near 25 kilowatts across all operational hours with minimal temporal variation.

This difference in optimized profile uniformity between winter and spring, despite achieving similar peak reductions, reveals how a single cost minimization objective naturally produces qualitatively different scheduling strategies depending on the underlying price structure. The optimizer consistently pursues the same goal—minimizing total electricity procurement costs—but the relative economic contribution of each cost reduction mechanism varies across seasons, producing different load distribution patterns as a direct consequence.

The critical insight is that multiple temporal configurations of the load profile can achieve essentially equivalent peak power levels. For a given total daily energy requirement, the optimizer possesses substantial freedom in how to distribute this energy temporally across the operational window. Perfectly uniform distribution achieves one specific peak value, but alternative distributions concentrating slightly more load during certain periods can achieve similar peaks while creating different energy cost outcomes through interaction with time-varying prices.

When energy supply price differential is economically significant (winter), optimizer exploits this freedom by modulating load temporally to reduce energy costs while maintaining peak suppression. Both mechanisms contribute additively. Conversely, when price differentials are modest (spring), temporal shifting contributes negligibly and optimizer converges toward load flattening as most effective strategy. Seasonal variation emerges naturally from rational response to different economic environments.

Critical analysis of the relationship between temporal strategies and economic outcomes reveals three fundamental principles governing optimization behavior.

- First, asymmetric cost structure creates disproportionate value for peak reduction, with capacity charges (4.447 €/kW monthly documented in Section 3.3.1) incentivizing temporal redistribution even across less optimal price periods.
- Second, abundant temporal flexibility (mean connection 4.71h >> mean charging 1.78h from Section 4.6) enables simultaneous achievement of aggressive peak suppression (64.3% capacity charge reduction) and energy cost optimization (1.3% variable cost reduction) without requiring trade-offs, with zero penalty costs confirming service quality constraints rarely bind.
- Third, seasonal adaptation demonstrates economically rational behavior maintaining robust peak reduction (~75% across all seasons) while adapting temporal distribution granularity proportionally to price differential magnitude, extracting maximum value without compromising primary objectives.

5 Conclusion and Future Research

This thesis addressed the day-ahead energy management problem for electric vehicle charging stations under demand uncertainty within the Italian electricity market context, developing and validating an integrated two-stage framework combining Monte Carlo scenario generation with mixed-integer linear programming optimization applied to 4,471 operational sessions collected over 25 months from Politecnico di Milano charging infrastructure.

The Monte Carlo methodology successfully transformed historical charging patterns, in particular the uncertain parameters including arrival times, connection durations, energy requirements, and daily session counts into probabilistic demand forecasts through empirical cumulative distribution functions and inverse transform sampling, generating 500-scenario ensembles. Stationarity analysis confirmed time-invariant distributions for working-day charging patterns, revealing consistent mean daily session count of 9.6 vehicles with no systematic trends or seasonal cycles across the 448-day filtered dataset.

The optimization framework formulated as mixed-integer linear program incorporates comprehensive Italian electricity tariff structures documented in Chapter 3, solved across 2,000 instances (500 scenarios × 4 seasons).

Computational experiments demonstrated 12-15% monthly cost reductions (143-206 €, annualized ~1,700-2,500 €) achieved primarily through 64% capacity charge savings, accomplished via systematic peak suppression (mean 31% reduction from 88.7 kW baseline) without service quality compromise (zero penalty costs for unmet EVs charging demand). Cost decomposition revealed optimizer prioritizes capacity charge minimization (64.3% savings) through aggressive peak suppression over energy cost minimization (1.3% savings) through temporal arbitrage, rational behavior driven by Italian tariff structure where power-based capacity charges (4.45 €/kW monthly) create dominant economic incentive regardless of seasonal energy price variations. Seasonal adaptation demonstrates optimizer maintains robust peak reduction (~75% across all seasons) while adjusting temporal load distribution proportionally to price differential magnitude, extracting maximum value from available information without compromising primary objectives.

The primary research contributions include empirical validation using extensive real-world operational data establishing practical applicability, comprehensive implementation of multi-component Italian electricity tariff structures enabling accurate cost modeling, demonstration that workplace charging scenarios provide sufficient temporal flexibility to simultaneously achieve peak reduction and complete energy delivery, and mechanistic understanding revealing that optimization prioritizes capacity charge minimization through peak suppression over secondary energy cost minimization through temporal arbitrage, with important implications for tariff design and grid integration policy.

Several limitations suggest directions for future investigation. The exclusive focus on workplace charging at a single institutional location raises questions regarding generalizability to residential, public, or highway fast-charging contexts with fundamentally different temporal flexibility characteristics, warranting cross-context validation studies.
The scenario generation methodology treats arrival time, connection duration, and energy requirement as independent random variables sampled from separate empirical CDFs, neglecting inter-parameter dependencies observable in operational data. In reality, arrival time influences expected connection duration—early morning arrivals (08:00) correlate with full-day stays (7-8h) while afternoon arrivals (15:00) associate with shorter sessions (2-3h)—and both affect energy requirements through charging opportunity windows. This independence assumption, while simplifying implementation and maintaining computational tractability, potentially underestimates demand clustering in scenarios where correlated arrivals and high energy requirements coincide. Future work should explore dependency structures through multivariate techniques such as vine copulas [11] or conditional probability frameworks (e.g., Markov chains) that preserve joint distributions while maintaining scenario generation efficiency.

The independent scenario generation without temporal dependencies limits multi-day optimization opportunities, suggesting value in rolling horizon formulations incorporating day-to-day correlation. The restriction to unidirectional charging excludes vehicle-to-grid capabilities that could unlock additional value streams through grid service provision as technology matures and regulatory frameworks evolve, though requiring careful analysis of battery degradation costs and user acceptance.

As electric vehicle adoption accelerates, intelligent charging management transitions from optional enhancement to operational necessity for economic viability and grid integration sustainability. This thesis demonstrates that temporal flexibility inherent in electric vehicle charging constitutes a valuable, systematically exploitable resource, with the developed methodology providing a practical, empirically validated framework ready for broader deployment supporting sustainable and efficient transportation electrification.

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