

Article

AI-Driven Smart Charging and Fire-Risk-Aware Governance for Multi-Unit Dwellings

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Abstract

Rapid electric-vehicle adoption is reshaping urban energy and mobility systems, especially in multi-unit dwellings (MUDs), where concentrated charging in shared parking areas simultaneously stresses distribution transformers and amplifies the consequences of charger faults, battery thermal events, smoke spread, and emergency-access constraints. The central argument of this paper is that grid stress, resident-facing service quality, lifecycle cost, and fire-risk exposure in enclosed residential parking should be governed jointly rather than as four separate problems. To make that argument concrete, we develop an integrated framework that couples stochastic EV adoption, residential charging-behavior simulation, XGBoost demand forecasting, and linear-programming-based optimization for coordinated control, and we evaluate it through 1000 Monte Carlo trials on representative Turkish MUDs. Unmanaged charging triggers transformer overload at about 30% EV penetration, whereas coordinated control reduces peak demand by 44.7% (405 kW to 224 kW) and raises load factor from 0.40 to 0.68. Strict capacity protection exposes a sharp service–quality trade-off, with only 8.9% of users reaching 80% state of charge (SOC) by departure. Smart charging lowers upfront cost by about 55% (\$200 vs. \$439 per dwelling unit) and yields roughly \$306 net present value per unit over ten years. Building on these results, we propose a five-pillar fire-risk-aware governance architecture—coordinated control, interoperability standards, time-of-use pricing, building–utility coordination, and monitoring—that turns coordinated charging into a preventive governance layer for reducing hazardous congestion in enclosed residential charging environments.

Keywords: electric vehicles; smart charging; fire risk; multi-unit dwellings; underground parking; urban safety governance



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1. Introduction

The global transition toward electric vehicles (EVs) has accelerated dramatically in recent years, driven by climate commitments, air quality concerns, and supportive government policies. Global EV sales reached approximately 10.5 million units in 2022, representing 14% of total vehicle sales, and surged to nearly 14 million units (18% market share) in 2023. Projections suggest this share could reach 40–45% by 2030 under current policy settings, with more ambitious scenarios indicating potential shares of up to 65% [1].

This rapid adoption presents both opportunities and challenges for urban energy systems. While EVs promise significant reductions in greenhouse gas emissions and air pollution, their widespread deployment places unprecedented demands on electricity

distribution networks, particularly in densely populated urban areas where most charging occurs at residential locations. Read against the United Nations 2030 Agenda, residential EV charging is a direct lever for Sustainable Development Goal 7 (SDG-7), affordable and clean energy: coordinated, safe and reliable charging in dense urban housing turns the transport-electrification transition into a tangible household-level outcome rather than a purely fleet-level emissions statistic. Recent comparative analyses of battery- and fuel-cell electric-vehicle pathways have stressed the same point—that the social return of vehicle electrification depends on the affordability, reliability and cleanliness of the energy actually delivered at the point of charge rather than only on the powertrain choice [2]. The present study takes this framing seriously by treating the dwelling-level charging environment as the unit at which SDG-7 outcomes for apartment-dominant cities are negotiated, and by asking how forecast-driven coordination and governance can keep that environment within both grid and safety limits.

Because urban transport decarbonization outcomes depend not only on vehicle uptake but also on where and when drivers charge, charging-behavior heterogeneity becomes a core system variable linking transport demand, distribution-grid stress, and realized environmental benefits.

The charging infrastructure required to support this transition represents a critical bottleneck. Unlike conventional refueling infrastructure, EV charging is predominantly home-based, with residential charging accounting for 70–80% of total EV energy demand in mature markets [1].

This shift fundamentally changes the load profile of residential electricity distribution networks, creating potential grid capacity constraints, especially during evening peak demand hours when most EV owners return home and plug in their vehicles. The problem is particularly acute in multi-unit dwellings (MUDs)—apartment buildings, condominiums, and residential complexes—where multiple vehicles may charge simultaneously from shared distribution transformers, potentially causing localized grid overload, voltage fluctuations, and accelerated infrastructure degradation [3,4].

At the same time, dense residential charging introduces an increasingly important fire-safety dimension. Although electric-vehicle fires are comparatively infrequent, lithium-ion battery incidents in enclosed or semi-enclosed parking areas can present disproportionate consequences because of thermal runaway behavior, smoke management difficulties, re-ignition potential, and exposure of nearby vehicles and structural elements. Recent contributions highlight growing attention to electric-vehicle fire detection, crash-induced battery-fire prevention, and confined-space fire behavior in underground parking environments [5–7]. The broader fire-prevention engineering literature has also advanced on the materials side; recent work on biomass-aerogel inhibitors for self-heating solid fuels reports thermodynamic and microstructural mechanisms of combustion suppression that complement, at a different scale, the building-level operational controls examined in this paper [8]. For MUDs, this means charging governance should be evaluated not only through energy efficiency and cost but also through preventive risk reduction in shared residential environments. Framed this way, the present study is directly relevant to both fire safety and fire management because it focuses on the institutional, operational, and infrastructure decisions that shape risk concentration, preparedness, and response conditions before an incident occurs.

Multi-unit dwellings present unique challenges that differentiate them from single-family homes in the context of EV charging infrastructure deployment. First, MUDs typically have limited electrical capacity allocated per parking space, as existing infrastructure was designed decades ago when EVs were not anticipated. Second, the shared nature of distribution transformers means that uncoordinated charging behavior by multiple

residents can create aggregate demand peaks far exceeding design capacity. Third, MUD residents often lack individual decision-making authority over infrastructure upgrades, as these require building management or homeowner association approval and collective investment. Fourth, space constraints in MUD parking facilities complicate the installation of charging equipment and limit options for decentralized energy resources such as on-site solar generation or battery storage [9,10].

Despite growing recognition of these challenges, existing studies largely treat MUD charging as either a narrow infrastructure problem or a behavior-only problem, leaving the full socio-technical system under-modeled. In practice, charging outcomes emerge from interacting people (drivers, building managers, and utilities), processes (scheduling, coordination, and compliance), and technologies (chargers, forecasts, and control algorithms). This fragmentation limits system-level understanding of how local charging decisions propagate into grid stress, service quality, investment trajectories, and safety exposure in dense urban settings [11,12].

Recent advances in artificial intelligence and optimization can close this gap by enabling integrated simulation and decision-support environments for complex charging systems. Machine learning models can predict demand patterns from behavioral and temporal signals, while optimization can coordinate charging in real time under technical and organizational constraints [13]. Yet many demonstrations remain limited to small pilots and do not formalize the governance and operational interfaces needed for scalable deployment across multi-actor residential systems [14,15]. Recent work on MBSE information retrieval using GraphRAG-based multi-agent LLM workflows further illustrates how AI can reduce stakeholder effort in accessing complex system-model knowledge during operational use [16].

Türkiye provides a particularly relevant context for examining these issues. The country has experienced rapid urbanization, with over 75% of the population now living in urban areas, predominantly in MUDs. Türkiye's government has set ambitious EV adoption targets, aiming for 1 million EVs on the road by 2030, supported by new regulatory frameworks including the Charging Service Regulation (Şarj Hizmeti Yönetmeliği) enacted in 2022 [17]. This regulation establishes licensing requirements for charging network operators and distinguishes between standalone charging stations and those installed in existing buildings, including MUDs. However, specific provisions for load management, smart charging mandates, and infrastructure planning in MUDs remain underdeveloped, presenting an opportunity for evidence-based policy development.

The central argument of this paper can be stated plainly. In multi-unit dwellings the way EVs are charged is no longer an isolated mobility decision; it is a shared infrastructure decision that simultaneously shapes distribution-grid stress, the service quality that residents actually experience, the lifecycle cost borne by the building, and the fire-risk exposure of an enclosed residential parking environment. Treating these four outcomes as separate problems—a grid problem for utilities, a service problem for residents, a budget problem for building managers, and a safety problem for fire authorities—is what has kept current policy fragmented and current pilots small. We argue that they should be governed jointly, through a coordinated control layer that a forecast-driven LP scheduler can operate but only an explicit institutional framework can make stick. The simulation trade-offs and the five-pillar governance architecture that follow are intended to make that joint governance concrete enough to act on, and to give regulators, distribution companies, and building managers a shared evidence base for the choices in front of them.

This paper addresses these gaps through three research questions: (1) What is the magnitude and timing of grid-capacity constraints caused by uncontrolled EV charging in MUDs under different adoption scenarios? (2) Can forecast-driven LP coordination mitigate

these constraints while preserving user-facing charging outcomes? (3) What fire-risk-aware governance and systems architecture enables scalable implementation across building and utility actors? To answer these questions, we develop an integrated simulation framework that combines stochastic EV adoption, residential charging-behavior simulation, machine learning demand forecasting, and linear-programming-based optimization for coordinated control. We apply this framework to representative MUD configurations in the Turkish context across four scenarios, from unmanaged charging to LP-coordinated scheduling driven by the XGBoost forecast.

This research makes three principal contributions to fire-risk-informed infrastructure planning and urban practice. First, it introduces an integrated modeling approach that couples adoption, behavior, prediction, and optimization for MUD charging as a socio-technical urban system with safety implications for shared residential parking environments. Second, it quantifies core trade-offs across peak demand, load factor, service quality (SOC attainment), and lifecycle cost. Third, it develops a transferable governance-aware five-layer systems architecture—control, interoperability, incentive design, coordination, and monitoring—that supports institutional-operational integration in data-driven charging environments while strengthening preventive risk management.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on EV charging infrastructure, smart charging technologies, and policy approaches, positioning our contribution within existing knowledge. Section 3 describes our simulation methodology, including EV adoption modeling, charging behavior characterization, AI-based demand prediction, and optimization formulations. Section 4 presents results from four scenarios, comparing grid impacts, costs, and performance metrics. Section 5 presents the governance-aware systems architecture and five-pillar framework. Section 6 discusses policy implications, implementation considerations, and transferability. Section 7 concludes with recommendations and directions for future research.

2. Literature Review and Background

2.1. Electric Vehicle Adoption and Charging Infrastructure

The global electric vehicle market has exhibited exponential growth patterns over the past decade, with multiple countries demonstrating consistent compound annual growth rates exceeding 40% in battery electric vehicle registrations [18,19]. Analysis of worldwide adoption data reveals that this growth trajectory is remarkably uniform across diverse markets—from mature economies to emerging markets—suggesting a fundamental transition in passenger vehicle technology rather than a temporary market anomaly [18]. Recent empirical studies examining over 1.6 million EVs across major urban centers document substantial heterogeneity in charging behavior across vehicle types and geographic contexts, yet consistently identify residential charging as the dominant energy delivery mode [20]. Transportation research demonstrates that approximately 70–80% of EV charging occurs at home or workplace locations among early adopters, driven by the convenience and lower cost of overnight charging during off-peak electricity periods [21]. However, access to residential charging infrastructure remains highly stratified by housing type and tenure status. A comprehensive assessment of U.S. housing stock found that only 56% of vehicles nationwide have access to dedicated off-street parking spaces, and merely 47% at owner-occupied residences where charging infrastructure could feasibly be installed [21]. This infrastructure gap has significant implications for distribution grid planning, as the spatial and temporal concentration of residential charging creates localized demand peaks that existing distribution networks—designed without anticipation of transportation electrification—struggle to accommodate [22].

2.2. Grid Capacity Impacts and Distribution System Constraints

The integration of EVs into distribution networks poses significant challenges to infrastructure originally designed without anticipation of vehicle electrification. Multiple studies have demonstrated that uncoordinated residential EV charging creates acute stress on distribution transformers during evening peak hours, when household electricity demand coincides with vehicle arrival times [23]. A comprehensive review by [23] examining low-voltage distribution networks concluded that transformer thermal limits are breached at approximately 30% EV penetration, while feeder capacity constraints emerge at around 50% penetration under uncontrolled charging scenarios. Similarly, ref. [24] analyzed California's Pacific Gas & Electric (PG&E) distribution network using real-world feeder data and found that at 6 million EV adoption, nearly 20% of circuits (443 feeders) would require infrastructure upgrades, with only 88 of these having planned reinforcement. The cumulative loading from simultaneous high-power charging—particularly with increasingly common 7–22 kW Level 2 chargers—can induce transformer overloading, accelerated insulation degradation, and reduced asset lifespan [25,26]. These findings underscore the urgency for proactive load management strategies to prevent costly grid reinforcement and maintain service reliability as EV adoption accelerates.

2.3. Multi-Unit Dwellings: Unique Infrastructure and Institutional Challenges

Multi-unit dwellings present a distinct set of challenges that differentiate them from single-family residences in the context of EV charging deployment. Research indicates that MUD residents—particularly renters and lower-income households—face significantly reduced access to home charging infrastructure compared to owners of single-family homes, creating potential equity barriers to EV adoption [27]. A national assessment by the National Renewable Energy Laboratory found that even under optimistic scenarios, 40% of vehicles without home charging access would belong to apartment residents, despite single-family homes constituting the majority of U.S. housing stock [28]. Complementary evidence from mixed-infrastructure usage analysis shows that EV users frequently combine multiple charging contexts (home, workplace, and public), reinforcing the vulnerability of residents with constrained home-charging access [29]. The challenges are multifaceted: electrical infrastructure in existing MUD buildings was typically designed decades ago without anticipation of EV loads, making retrofitting costly and complex; parking space limitations constrain charger installation options; and the shared nature of distribution transformers means that uncoordinated simultaneous charging by multiple residents can create severe localized overloads [11,30]. Furthermore, institutional barriers compound technical challenges—property managers report high upfront installation costs, uncertainty about revenue models, and limited awareness of available incentive programs as major deterrents to infrastructure investment [31]. These converging factors suggest that policy interventions for MUDs require not only technical solutions for load management but also institutional frameworks addressing financial viability, stakeholder coordination, and equitable access.

2.4. Smart Charging Technologies and Artificial Intelligence Optimization

Smart charging systems have emerged as a critical technological solution to mitigate the grid impacts of uncoordinated EV charging through temporal load shifting and demand response mechanisms. These systems employ optimization algorithms to coordinate charging schedules across multiple vehicles, balancing user charging requirements against grid capacity constraints and electricity price signals. Recent advances in machine learning have substantially enhanced smart charging capabilities, particularly in demand forecasting and adaptive scheduling. Comparative benchmarking studies of ML algorithms for

EV charging demand prediction have identified gradient boosting methods—specifically XGBoost—and bidirectional long short-term memory (Bi-LSTM) networks as better performers, with XGBoost demonstrating outstanding computational efficiency while Bi-LSTM achieves high accuracy in capturing temporal dependencies in charging patterns [32]. Machine learning-based approaches have proven effective not only for demand forecasting but also for real-time optimization of charging schedules; reinforcement learning techniques, in particular, enable adaptive charging strategies that dynamically adjust based on grid conditions, electricity prices, and user preferences [33]. Multi-objective optimization frameworks combining these AI techniques with mathematical programming methods—such as mixed-integer linear programming (MILP)—have demonstrated the capacity to simultaneously minimize grid stress, reduce charging costs, and maintain user satisfaction by optimally scheduling vehicle-to-grid (V2G) interactions [34]. Evidence from integrated bus-fleet and charger co-scheduling further confirms that joint MILP-based scheduling can substantially improve infrastructure utilization and reduce total system cost in real urban operations [35]. Empirical studies indicate that ML-optimized smart charging can reduce peak demand by 15–40% compared to uncontrolled charging scenarios while maintaining overnight charging completion rates above 90% [36]. Related research using integrated multi-agent simulation and genetic algorithms for shared autonomous EV charging decisions highlights explicit multi-objective trade-offs among service response, battery state, empty mileage, and charging cost [37]. In fire-safety terms, these same capabilities are relevant because they can reduce simultaneous charging congestion in enclosed parking areas and support preventive operational controls before hazardous conditions escalate. These technological capabilities therefore provide the foundation for policy frameworks that mandate or incentivize smart charging deployment in multi-unit dwellings.

2.5. Policy Frameworks and International Regulatory Approaches

International experience demonstrates that effective EV charging infrastructure deployment requires coordinated regulatory frameworks and smart load management strategies, with particular implications for multi-unit dwellings. García-Villalobos et al. [38] emphasize that intelligent charging management systems are essential to prevent voltage deviations, transformer saturation, and excessive electrical losses in distribution networks as electric vehicle penetration increases. Recent policy implementations in Europe and the United Kingdom have mandated digital connectivity and smart charging capabilities for new charging installations, including default off-peak charging schedules and randomized delay functions to prevent simultaneous charging events that could destabilize local grids. Powell et al. [27] demonstrate through large-scale modeling that load-shifting control at residential locations and load modulation at workplaces can significantly reduce grid impacts, though effectiveness varies substantially based on charging infrastructure access patterns. Their analysis reveals that multi-unit dwelling residents face disproportionate barriers to home charging access, necessitating alternative infrastructure solutions. Almutairi et al. [39] propose multi-factor load management frameworks for shared residential parking facilities, demonstrating that dynamic power allocation considering both user satisfaction and equipment capacity constraints can optimize charging operations in apartment buildings and condominiums.

Economic analysis of optimal regulatory policies suggests governments should subsidize both variable charging costs to achieve marginal cost pricing and market entry costs for charging infrastructure to internalize network externalities, with standardization of charging protocols providing additional welfare gains [40]. Early regulatory frameworks by San Román et al. [41] identify critical policy elements including time-of-use pricing, stable regulations for energy reselling on private property, and coordination mechanisms

between network operators and vehicle aggregators. However, despite these advances, policy frameworks specifically addressing the particular institutional and technical challenges of MUD charging infrastructure—including shared transformer management, cost allocation among residents, and coordination between property managers, utilities, and EV owners—remain underdeveloped in most jurisdictions, creating a critical gap that this research aims to address.

2.6. The Turkish Context: Regulatory Framework and Infrastructure Challenges

Türkiye presents a particularly relevant case study for MUD-focused EV charging policy, combining rapid urbanization, ambitious electrification targets, and a housing landscape dominated by multi-unit dwellings. Over 75% of Türkiye's population resides in urban areas, with apartment buildings constituting the predominant residential form, yet the country's EV charging infrastructure remains geographically concentrated and underdeveloped relative to adoption projections [42]. In 2022, Türkiye enacted comprehensive charging service regulations (Şarj Hizmeti Yönetmeliği) establishing a licensing framework for charging network operators, distinguishing between standalone charging stations requiring full business permits and those integrated into existing buildings—including MUDs—which receive simplified permitting through location and activity certificates [17]. The regulations mandate smart charging capabilities, establish pricing transparency (per kWh basis only, prohibiting additional fees), and require integration with a national platform (Şarj@TR) for real-time station availability monitoring. However, critical gaps remain: the regulatory framework provides limited guidance on load management coordination between building managers and utilities, cost allocation mechanisms for shared infrastructure in MUDs, or technical standards for transformer capacity management in residential complexes. These conditions—combined with government targets of 1 million EVs by 2030 and net-zero emissions by 2053—create both urgency and opportunity for developing evidence-based MUD charging policies applicable to emerging markets with similar urban development patterns.

2.7. Research Gap and Study Positioning

Despite extensive research on EV charging infrastructure planning and smart charging optimization, critical gaps remain in addressing the specific challenges of multi-unit dwellings, particularly in emerging market contexts. Existing simulation frameworks predominantly operate at regional or city-wide scales, failing to capture the building-level dynamics of shared transformer capacity, coordinated load management among multiple residents, and institutional coordination between property managers, utilities, and EV owners [43]. While AI and optimization techniques for smart charging have advanced considerably, their integration into actionable policy frameworks—especially for MUD settings where technical, economic, and institutional challenges intersect—remains underdeveloped [44]. Furthermore, most policy research examines mature markets with established regulatory frameworks and predominantly single-family housing, leaving emerging markets with high urban density and apartment-dominated housing landscapes underexplored. This study addresses these gaps by developing an integrated simulation framework that combines stochastic EV adoption modeling, machine learning-based demand forecasting (XGBoost), and linear-programming-based optimization to quantify grid impacts specifically at the MUD level, analyzing multiple scenarios from uncontrolled charging through forecast-driven LP coordination. Applying this framework to Türkiye's regulatory and urban context, we quantify threshold penetration rates for grid overload, demonstrate the capacity reduction potential of smart charging, and propose a five-layer systems architecture encompassing coordinated control, interoperability standards, incentive design, stakeholder coordination, and monitoring systems. By bridging simulation-

based technical analysis with governance-aware system design tailored to MUD-specific institutional complexities, this research provides evidence-based guidance for regulators, utilities, and urban planners in emerging markets pursuing equitable and grid-resilient EV charging infrastructure deployment.

To anchor this positioning against the most recent MUD-focused literature, Table 1 synthesizes six representative studies published between 2024 and 2026 along four dimensions: scale of analysis, methodological emphasis, governance and fire-safety treatment, and the specific gap each study leaves open. The synthesis shows that the field has begun to converge on three sub-themes—MUD-level optimization [45], EV-charging mandates and their load-profile consequences [46], and barrier/equity assessment for multifamily housing [47]—supported by an explicit systematic-review backbone [48]. None of these studies, however, jointly addresses (i) building-level coordinated control under shared-transformer constraints, (ii) the resident-facing service–quality trade-off this control creates, and (iii) the fire-risk exposure dimension of enclosed residential parking, within a transferable governance architecture. The present study positions itself at exactly this intersection.

Table 1. Recent MUD-focused EV-charging research (2024–2026) along four comparison dimensions, with the present study summarized in the final row (shown in bold to set it apart from the surveyed works).

Reference	Scale	Methodological Core	Governance/Fire-Safety Treatment	Gap Left Open
Choi et al. 2026 [48]	Charging location types (incl. MUD)	Systematic literature review (PRISMA)	Operational mechanisms surveyed; fire-safety not modeled	No own simulation; no transferable governance architecture
Almutairi 2026 [45]	Single MUD building	Optimization-based sizing of charging infrastructure	Limited governance discussion; no fire-safety framing	Resident-facing service quality and joint outcomes not modeled
Chilukuri et al. 2026 [46]	MUD residential feeders	Load-profile impact of charging mandates	Mandate-centered; safety not modeled	No five-pillar institutional architecture; no service–quality trade-off
Pierce & Bui 2024 [47]	Multifamily homes (U.S.)	Barriers, solutions and equity assessment	Equity and policy framing; fire-safety not central	No simulation; no AI-driven coordination layer
Wang 2024 [43]	City-wide	Smart-grid integration overview	High-level policy framing	Building-level shared-transformer dynamics absent
Asiri et al. 2024 [44]	General EV charging	AI/optimization survey	Technology-centric	Governance-aware integration for MUDs underdeveloped
This study	Single shared-transformer MUD	Stochastic adoption + XGBoost forecast + LP control	Five-pillar fire-risk-aware governance; preventive framing	—

Three research questions follow from this gap and organize the rest of the paper. **RQ1.** At what EV penetration level does uncontrolled charging in a shared-transformer MUD breach the building’s distribution-transformer capacity, and how stable is this threshold across building size, transformer capacity, and parking-to-unit ratio? **RQ2.** Can forecast-driven coordination—specifically an XGBoost short-horizon demand forecast feeding a linear-programming-based scheduler—preserve transformer headroom while quantifying the resident-facing service–quality cost (final SOC by departure) that strict capacity protection imposes? **RQ3.** What institutional architecture, defined at the building–utility–regulator interface and informed by fire-safety considerations in enclosed residential parking, makes that coordination both deployable and accountable across MUD-dominant urban contexts? RQ1 is answered in Section 4, RQ2 across Sections 4 and 5, and RQ3 in Sections 5 and 6.

While previous research suggests that public shifts in attitude—such as those triggered by greenwashing accusations—may only modestly influence policy preferences for corporate environmental conduct, our study demonstrates that in the context of multi-unit dwellings, the technical and economic necessity of grid stability creates a more immediate and objective driver for government intervention and regulatory mandates [49].

3. Methodology

This study employs a simulation-based policy analysis framework to evaluate the impact of electric vehicle adoption on residential building electrical infrastructure, specifically focusing on multi-unit dwellings. Our methodological approach integrates three core components: a building-level simulation model that captures the baseline electrical demand dynamics and transformer capacity constraints; a machine learning-based demand forecasting module utilizing gradient boosting techniques; and a linear-programming optimization framework for coordinated charging strategies. This integrated methodology enables systematic comparison of uncoordinated versus LP-coordinated charging scenarios under varying EV penetration rates, providing quantitative evidence for policy formulation.

Figure 1 provides a single-glance overview of the framework that the remainder of this section develops in detail. Reading the figure left to right, the case-study configuration and stochastic adoption and behavior simulation feed XGBoost demand forecasting and the linear-programming-based coordinated-charging optimizer; reading top to bottom, the simulation outputs are then evaluated against the four joint outcomes that motivate the paper—grid stress, resident-facing service quality, lifecycle cost, and fire-risk exposure in enclosed residential parking—and translated into the five-pillar fire-risk-aware governance architecture introduced in Section 5. The framing is aligned with SDG-7 (affordable and clean energy), reflecting the dwelling-level positioning introduced in Section 1.

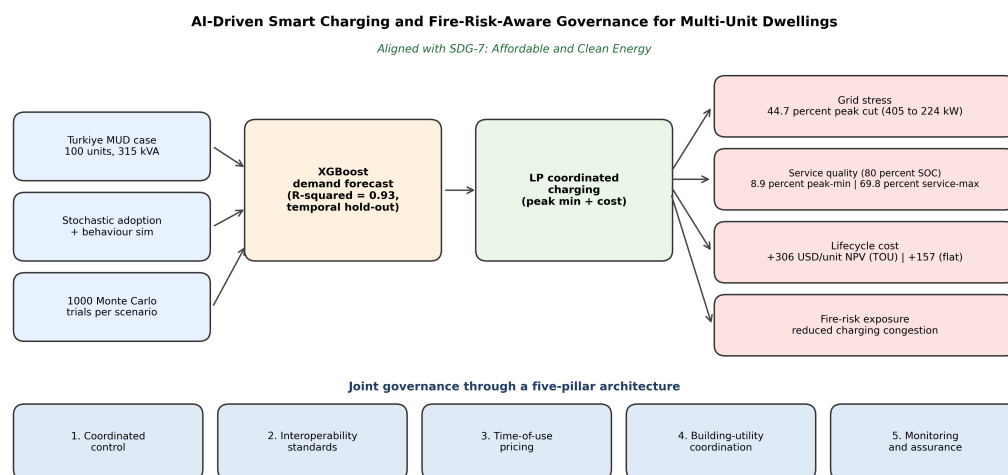


Figure 1. Proposed framework. The simulation–AI pipeline (stochastic adoption and behavior simulation, XGBoost demand forecasting, linear-programming-based coordinated charging) feeds four joint outcomes for multi-unit dwellings—grid stress, resident-facing service quality, lifecycle cost, and fire-risk exposure in enclosed residential parking—which are then translated into the five-pillar fire-risk-aware governance architecture developed in Section 5. The framing is aligned with SDG-7 (affordable and clean energy).

The framework is composed of two computational layers with distinct roles, and it is worth stating up front what each of them does and what it does not do. The machine learning (AI) layer consists of an XGBoost short-horizon demand forecaster (Section 3.4): it ingests the recent hours of building-level load together with calendar features and produces an hourly 24 h-ahead prediction of aggregate demand that the coordinator can plan against.

The optimization layer is the linear-programming-based coordinated-charging optimizer (Section 3.5)—a mathematical-programming component rather than a machine learning model—which consumes the forecast as a binding right-hand-side input, together with the transformer-capacity constraint, the per-vehicle dwell times and the target-state-of-charge requirements, and returns the hourly charging set-point of every connected vehicle for the next planning window. In operational terms, the AI layer tells the building what is about to happen on the baseload side, and the LP layer decides how the EV fleet should be dispatched against that forecast without breaching transformer capacity or skipping users beyond a configured service-quality floor. Machine learning is not used as a standalone predictor of fire risk, as a deep learning replacement for the LP, or as a behavioral model of resident preferences; those roles are deliberately left outside the present scope. Downstream, the LP set-points are the operational substrate that pillar 1 (coordinated control), pillar 4 (building-utility coordination), and pillar 5 (monitoring and assurance) of the governance architecture (Section 5) act on, which is how the combined forecast-plus-LP pipeline surfaces as an institutionally accountable decision rather than as a black-box recommendation.

3.1. Case Study Context and Data Foundation

The analysis centers on a representative mid-rise residential building comprising 100 dwelling units, reflecting typical urban apartment configurations in emerging EV markets. The building's electrical infrastructure features a 315 kVA distribution transformer serving household baseload demand, with subscriber connections designed for 6 kW per unit and a diversity factor of 0.45, consistent with standard utility engineering practices [50]. The usable real-power capacity used as the operational limit throughout the paper is obtained from the nameplate rating by applying a typical Turkish residential power factor of 0.90 to convert kVA to kW ($315 \times 0.90 = 283.5$ kW) and then a 90% operating-safety margin on top, which yields the 255 kW figure ($315 \cdot 0.90 \cdot 0.90 \approx 255$ kW) referenced in all subsequent load profiles and capacity-violation checks. Nameplate ratings are reported in kVA at the input boundary and all operational figures (peak demand, overload, and headroom) in kW. Each dwelling unit is allocated one parking space, yielding 90 total parking positions after accounting for visitor and commercial allocations.

Baseline electrical demand patterns are derived from a synthesis of utility load research data and published residential consumption profiles, calibrated to reflect seasonal variations and occupancy patterns typical of Turkish residential contexts [51]. Hourly load factors exhibit characteristic dual-peak behavior, with morning peaks reaching 1.25 times average demand during breakfast preparation hours (07:00–09:00), and evening peaks intensifying to 1.78 times average demand during meal preparation and entertainment periods (18:00–20:00). Off-peak demand during nighttime hours (02:00–05:00) declines to approximately 0.57 times daily average, creating potential temporal windows for managed charging interventions.

Electric vehicle technical specifications reflect commercially dominant models in the Turkish market, assuming battery capacities of 60 kWh, average arrival state-of-charge of 45%, and typical charging requirements of 30–36 kWh per charging event. The home charging infrastructure is modeled using Level 2 three-phase alternating current chargers rated at 22 kW, representing the increasingly standard residential installation for multi-unit dwellings where faster charging and higher simultaneous demand create critical grid stress. These parameters align with international benchmarks while accounting for local market conditions and regulatory frameworks [17].

3.2. EV Adoption Scenario Development

Three adoption trajectories are modeled to bound the range of plausible EV penetration outcomes through 2035, reflecting varying combinations of policy support, infrastructure investment, and market dynamics. Table 2 summarizes the key parameters defining each scenario.

Table 2. Electric vehicle adoption scenario definitions. Penetration percentages are taken with respect to the 90 EV-eligible parking spaces of the case-study building (i.e., the physical footprint on which simultaneous charging is constrained), and EV counts are rounded to the nearest integer.

Scenario	Policy Context	2030	2035
Baseline	Limited policy support, gradual infrastructure	15% (14 EVs)	35% (32 EVs)
Accelerated	Purchase incentives, expanded charging	30% (27 EVs)	60% (54 EVs)
Rapid	Aggressive policy, price parity, ubiquitous infrastructure	40% (36 EVs)	75% (68 EVs)

The baseline adoption scenario assumes conservative market growth driven primarily by organic consumer preferences and gradual cost reductions in battery technology, without substantial policy interventions. This trajectory projects 15% EV penetration by 2030, expanding to 35% by 2035, consistent with technology diffusion patterns observed in early EV adopter markets absent strong governmental mandates. The accelerated adoption scenario incorporates moderate policy support mechanisms including purchase subsidies, preferential parking policies, and coordinated charging infrastructure deployment, yielding 30% penetration by 2030 and 60% by 2035. This trajectory reflects adoption dynamics in European jurisdictions with established EV support frameworks. The rapid adoption scenario represents an optimistic upper bound characterized by comprehensive policy packages including stringent emission standards, substantial financial incentives, and infrastructure mandates, achieving 40% penetration by 2030 and 75% by 2035.

Individual household EV adoption decisions within each scenario are modeled through Monte Carlo simulation incorporating socioeconomic heterogeneity and spatial clustering effects. The simulation executes 1000 independent trials to capture stochastic variability in adoption patterns, with random assignment of EV ownership probabilities calibrated to achieve target aggregate penetration rates while maintaining statistical representativeness and robust coverage across household profiles.

3.3. Simulation Parameter Manifest

Table 3 consolidates the full set of input parameters used by the simulation so that the analysis can be reproduced end to end. The values are organized by the layer of the framework they belong to. Every Monte Carlo trial is seeded by the master seed offset by the trial index, so a given configuration–seed pair yields identical outputs across runs.

Table 3. Baseline simulation parameters. Distributions are truncated normals; “Source” indicates whether the value is calibrated to the Turkish residential context, taken from the cited literature, or held as a documented modeling choice.

Layer	Parameter	Value/Distribution	Source
Building	Dwelling units	100	Case study
	Parking-to-unit ratio	0.90 (90 EV-eligible spaces)	Case study
	Distribution transformer (nameplate)	315 kVA	TEDAŞ 2022 [50]
	Power factor	0.90	Turkish residential standard
	Operating safety margin	0.90 (yielding 255 kW usable)	Modeling choice
	Subscriber connection	6 kW per unit, diversity factor 0.45	TEDAŞ 2022 [50]

Table 3. Cont.

Layer	Parameter	Value/Distribution	Source
Baseline load	Hourly factors (morning/evening/night)	1.25/1.78/0.57 (winter weekday calibration)	TEDAŞ 2022 [50] + IEA 2023 [51]
	Seasonal multipliers (relative to winter)	summer 0.94, spring–autumn 0.87	Modeling choice
	Weekend peak-hour shift	+2 h	Modeling choice
Charging hardware	Level-2 charger power	22 kW	3-phase AC residential
	Charger/installation cost	USD 3000 + 2000	ChargeRegulation 2022 [17]
	Smart-charging system (building level)	USD 20,000	Modeling choice
	Transformer reinforcement	USD 150 per kVA expansion	Industry pricing
Vehicles	Battery capacity	40/60/80 kWh, market shares 45/40/15%	Turkish market mix
	Average daily consumption	15 kWh	Turkish driving profile
	Charging efficiency	0.88–0.90	Manufacturer spec
Behavior	Arrival time (h)	$\mathcal{N}(18.5, 1.2)$ truncated to [16, 22]	NHTS 2022 shape; Türkiye recalibration [52,53]
	Departure time (h)	$\mathcal{N}(8.0, 0.8)$ truncated to [6, 10]	NHTS 2022 shape; recalibration as above
	Arrival SOC	$\mathcal{N}(0.45, 0.15)$ truncated to [0.15, 0.90]	Literature average
	Target SOC	$\mathcal{N}(0.85, 0.10)$ truncated to [0.70, 1.00]	Literature average
	Daily-charging probability	0.70	Modeling choice
	Weekend delay (arrival/departure)	+2 h/+1.5 h	Modeling choice
Economics	Discount rate	8% (real)	Standard residential CBA
	Analysis horizon	10 years	Modeling choice
	Annual O&M rate	2% of capex	Industry norm
	Flat/TOU peak/TOU off-peak	0.10/0.15/0.06 USD/kWh	Türkiye 2024 reference
Optimization	α (peak weight)/ β (cost weight)	1.0/0.3	Calibrated for peak priority
	Minimum energy delivery (baseline)	60% of requested	Modeling choice (lever in Section 6)
	Solver	SciPy 1.11.0 HiGHS backend	Implementation
Monte Carlo	Trials per scenario (main run)	1000	Convergence study
	Master seed	42; trial seed = master + trial index	Modeling choice

3.4. Charging Behavior Modeling and Grid Impact Assessment

Uncoordinated charging behavior is modeled under the assumption that EV owners initiate charging immediately upon vehicle arrival at the residential parking facility, reflecting common user preferences for ensuring full battery availability. Vehicle arrival times are drawn from empirical probability distributions derived from transportation surveys, exhibiting concentrated arrival patterns during evening commute windows (17:30–20:30) when approximately 65% of daily vehicle returns occur, based on the 2022 U.S. National Household Travel Survey (NHTS) [54]. The 2022 U.S. NHTS is used as a *shape prior* for the evening-concentrated commute-return distribution rather than as a transferable parameter set; the arrival mean of 18:30 with a 1.2 h standard deviation is then recalibrated to the Turkish urban setting against recent local mobility evidence. In particular, the data-driven analysis of Ankara temporal mobility patterns by [52] documents a pronounced evening residence-return peak consistent with our 18:00–19:30 arrival window, and the Istanbul home-based commute trip-generation analysis of [53] confirms the dominance of late-afternoon to early-evening return trips in an apartment-dominant Turkish metropolitan

context. To check whether the overload finding depends on this specific arrival mean, a sensitivity sweep that shifts the arrival mean to 17:30, 18:30 and 19:30 is run for the baseline configuration (300 trials each, 30% penetration): the mean peak demand changes by only about ± 10 kW (395, 405 and 416 kW respectively) and the modal peak hour tracks the arrival mean (17, 18 and 19), while the transformer capacity is exceeded in 100% of trials in every case. The overload conclusion is therefore robust to the residual U.S.–Türkiye arrival-window mismatch within an hour either side of the calibrated mean. This arrival concentration creates severe temporal coincidence between peak residential baseload demand and EV charging initiation, exacerbating transformer loading stress.

Instantaneous charging power for each vehicle is determined by the minimum of charger rated capacity (22 kW), vehicle battery management system acceptance rate, and required energy to reach target state-of-charge. The total building-level charging load is computed through summation across all simultaneously charging vehicles, superimposed upon the baseline residential demand profile. Transformer capacity violation is defined as instantaneous total demand exceeding the usable real-power capacity of 255 kW (derived from the 315 kVA nameplate as $315 \cdot 0.90 \cdot 0.90$ following the convention introduced in Section 3.1) for any hourly time step within the analysis horizon.

Grid impact metrics encompass three dimensions: peak demand magnitude quantifying maximum instantaneous loading; capacity exceedance quantifying the extent and duration of transformer rating violations; and load variance quantifying demand volatility over 24 h cycles. These metrics provide comprehensive characterization of infrastructure stress and operational challenges under uncoordinated charging regimes.

The baseline residential load profile is parameterized by 24 hourly demand factors normalized to daily average = 1.0; representative values are 1.25 in the morning peak (08:00), 1.78 in the evening peak (19:00) and 0.57 in the overnight trough (03:00). These factors are not read verbatim from a single source; they are calibrated to a Turkish urban winter weekday by combining the residential-feeder load-research patterns reported by the Turkish electricity distribution authority (TEDAŞ) [50] with the residential demand structure documented in the IEA *Energy Statistics Data Browser* for OECD households, smoothed against published Turkish residential load-curve studies and rounded to two decimals. Winter weekday is treated as the worst-case grid-stress baseline used for the headline results in Section 4 because it co-locates evening heating and lighting demand with the dominant EV arrival window. The same parameterization supports weekend variants (peak arrivals delayed by two hours, in line with the configured weekend behavioral offsets) and summer/spring–autumn variants (overall magnitude rescaled relative to winter via the configured seasonal factors), and we report a compact comparison across these four (season $\times$ day-type) combinations in Section 4 to test whether the headline overload finding is sensitive to the choice of representative day.

3.5. Machine Learning-Based Demand Forecasting

Anticipatory demand forecasting forms the foundation for proactive charging management, enabling optimization algorithms to schedule charging activities within grid capacity constraints while satisfying user mobility requirements. We employ Extreme Gradient Boosting (XGBoost), a highly efficient gradient tree boosting implementation, for short-term demand forecasting [55]. XGBoost has demonstrated superior performance in energy demand forecasting applications due to its ability to capture complex nonlinear relationships, inherent handling of feature interactions, and robustness to missing data [44,56]. Hybrid modeling that combines probabilistic traffic-flow representations with discrete-event simulation also shows strong value for EV fast-charging demand analysis, queue dynamics, and adaptive infrastructure planning pathways toward digital-twin deployment [57].

The forecasting model predicts hourly demand factors—defined as the ratio of hourly demand to daily average demand—for a 24 h ahead horizon. Input features comprise historical demand factors over the preceding 168 h (one week), temporal indicators including hour-of-day, day-of-week, and month-of-year, and lagged moving averages computed over 24 h and 168 h windows. This feature architecture captures multiple temporal dependencies including diurnal cycles, weekly patterns, and seasonal trends. The model is trained on one year of simulated demand data incorporating both baseload residential consumption and stochastic EV charging patterns.

XGBoost model hyperparameters are optimized through Bayesian optimization targeting mean absolute error minimization on a held-out validation set comprising 20% of historical data. Key hyperparameters include maximum tree depth (controlling model complexity), learning rate (governing convergence speed), and L2 regularization penalty (preventing overfitting). To keep the evaluation conservative against temporal data leakage and to reflect realistic measurement uncertainty, the train–test split is performed temporally rather than by random shuffling: the chronologically final 20% of the simulated days are reserved as a forward-looking test partition so that lag features cannot peek across the split boundary. The simulated load is further perturbed with 3% multiplicative Gaussian noise to act as a proxy for sensor noise and behavioral variability that the deterministic simulation does not generate. Numerical accuracy figures obtained under this protocol are reported in Section 4 and remain consistent with state-of-the-art energy forecasting benchmarks [55].

3.6. Optimization-Based Smart Charging Coordination

Smart charging coordination is formulated as a linear programming (LP) problem that determines optimal charging schedules minimizing total energy costs and peak demand while satisfying individual vehicle energy requirements and respecting grid capacity constraints [58,59]. Algorithm 1 formalizes the optimization problem structure. Although the broader literature commonly treats this class of problems as mixed-integer linear programming (MILP) by introducing binary on/off variables for each vehicle and time slot, the implementation reported here keeps the on/off decision implicit in the dwell-window bounds, so the resulting program is a pure LP solved with the HiGHS backend of SciPy linprog. The label LP is therefore used throughout the manuscript to describe the implemented optimizer; the MILP label is reserved for references to the general literature class.

Algorithm 1 Linear-programming smart charging optimization.

```

1: Input: EV arrival times  $\{t_i^{arr}\}$ , departure times  $\{t_i^{dep}\}$ , energy demands  $\{E_i\}$ ,
2:   baseload forecast  $\{P_t^{base}\}$ , transformer capacity  $P^{max}$ , charger power  $P^{ch}$ 
3: Output: Optimal charging power  $\{p_{i,t}\}$  and the auxiliary peak variable  $P^{peak}$ 
4:
5: Objective: Minimize the peak of aggregate load and the TOU-weighted energy cost:
6:    $\min \alpha \cdot P^{peak} + \beta \cdot \sum_t c_t \cdot \sum_i p_{i,t}$ 
7:   where  $P_t^{total} = P_t^{base} + \sum_i p_{i,t}$ 
8:
9: Constraints:
10: for each EV  $i$  do
11:    $\sum_{t=t_i^{arr}}^{t_i^{dep}} p_{i,t} \geq 0.60 \cdot E_i$  {Minimum 60% energy delivery}
12:    $\sum_{t=t_i^{arr}}^{t_i^{dep}} p_{i,t} \leq E_i$  {Cap delivered energy at request}
13:    $0 \leq p_{i,t} \leq P^{ch}$  {Charger-rated charging power}
14:    $p_{i,t} = 0 \quad \forall t \notin [t_i^{arr}, t_i^{dep}]$  {Strict availability window}
15: end for

```

Algorithm 1 *Cont.*

```

16: for each time  $t$  do
17:    $P_t^{total} \leq P^{peak}$  {Peak-tracking constraint}
18:    $P_t^{total} \leq P^{max}$  {Transformer capacity}
19: end for
20:
21: Solve: Linear-program form, SciPy linprog HiGHS backend
22: return  $\{p_{i,t}\}, P^{peak}$ 

```

The optimization objective balances two competing goals through weighted summation: minimizing peak aggregate demand to prevent transformer overloading, and minimizing energy costs by concentrating charging during off-peak tariff periods. Weight parameters α and β control the relative emphasis on peak reduction versus cost minimization, calibrated through sensitivity analysis to ensure capacity compliance takes precedence over economic optimization.

Parameter Calibration: For the primary scenario analysis we use $\alpha = 1.0$ and $\beta = 0.3$, prioritizing peak-cap control while retaining secondary incentive for off-peak alignment. This configuration consistently caps optimized aggregate demand at the baseline peak level (224 kW) under the current constraint set.

Energy Delivery Constraints: To preserve feasibility under transformer limits at 30% EV penetration, the formulation imposes a minimum energy delivery requirement of 60% of requested charge ($\sum_t p_{i,t} \geq 0.60 \cdot E_i$) rather than full completion. This 60% floor is a lower-bound feasibility constraint, not a service-quality target: the 1000-trial run shows that the optimizer satisfies the floor for essentially all vehicles, but only 8.9% of vehicles cross the more demanding 80% SOC-by-departure threshold (Section 4). Transformer protection and user-facing service quality are therefore not jointly delivered by the present objective; they are explicitly traded against each other, and policy must regulate both rather than treating the 60% floor as evidence of preserved service.

Decision variables are the continuous per-vehicle hourly charging powers $p_{i,t} \in [0, P^{ch}]$ together with the scalar auxiliary peak variable $P^{peak} \geq 0$. Charging availability is enforced by setting $p_{i,t} = 0$ outside each vehicle's $[t_i^{arr}, t_i^{dep}]$ dwell window, so the binary on/off decision is implicit in the bounds rather than introduced as a separate integer variable. The peak-tracking constraint $P_t^{total} \leq P^{peak}$ together with $\alpha \cdot P^{peak}$ in the objective is what makes Algorithm 1 actually minimize the maximum aggregate load rather than its sum: the optimizer is free to shift charging across hours, but every hour of charging-plus-baseload must fit underneath the same P^{peak} bound that the objective is trying to push down. Energy-delivery constraints ensure each vehicle receives at least 60% and at most 100% of its requested energy over its dwell window, the per-hour charger-rated bound limits instantaneous power, and the hourly transformer-capacity constraint enforces that aggregate demand never exceeds the rated transformer.

Because all variables and constraints are linear and the integrality of the dwell window is enforced through bounds rather than through additional binary variables, the formulation reduces to a pure linear program in practice. We solve it with the HiGHS backend of SciPy linprog [60]; solution times for the 27-EV, 24 h problem instances used in the case study remain below one second on standard computing hardware, which is well within what real-time operational deployment in a building charging management system would require.

3.7. Performance Metrics and Comparative Analysis Framework

Comparative evaluation across scenarios employs standardized metrics quantifying infrastructure stress, economic implications, and service quality. Peak demand reduction quantifies percentage decrease in maximum instantaneous loading relative to uncoordi-

nated charging baseline. Capacity violation frequency enumerates the number of hourly intervals exceeding transformer rating. Load variance coefficient measures demand volatility normalized by mean demand. Energy cost differential computes percentage savings achieved through time-of-use tariff arbitrage enabled by smart charging.

Monte Carlo aggregation across 1000 simulation trials provides robust statistical characterization of performance metrics, including mean values, 95% confidence intervals, and percentile distributions. Sensitivity analysis systematically varies key input parameters including charger power ratings, arrival time distributions, and tariff structures to assess result robustness and identify critical design parameters influencing system performance.

4. Results

Our simulation framework integrates stochastic EV adoption modeling, residential charging behavior analysis, machine learning-based demand forecasting, and linear-programming-based optimization to quantify grid impacts and evaluate policy interventions. We present results from 1000 Monte Carlo trials per scenario, analyzing the period through 2030 under baseline (15% EV penetration), accelerated (30%), and rapid (40%) adoption trajectories. The representative multi-unit dwelling comprises 100 units served by a 315 kVA distribution transformer with 90 parking spaces.

4.1. Grid Impact Under Uncontrolled Charging

Figure 2 demonstrates the load profile evolution across EV penetration scenarios. The baseline profile (no EVs) exhibits typical residential dual-peak behavior with morning demand reaching 180 kW (07:00–09:00) and evening peak of 224 kW (19:00), remaining within the transformer's 255 kW usable capacity (90% rating).

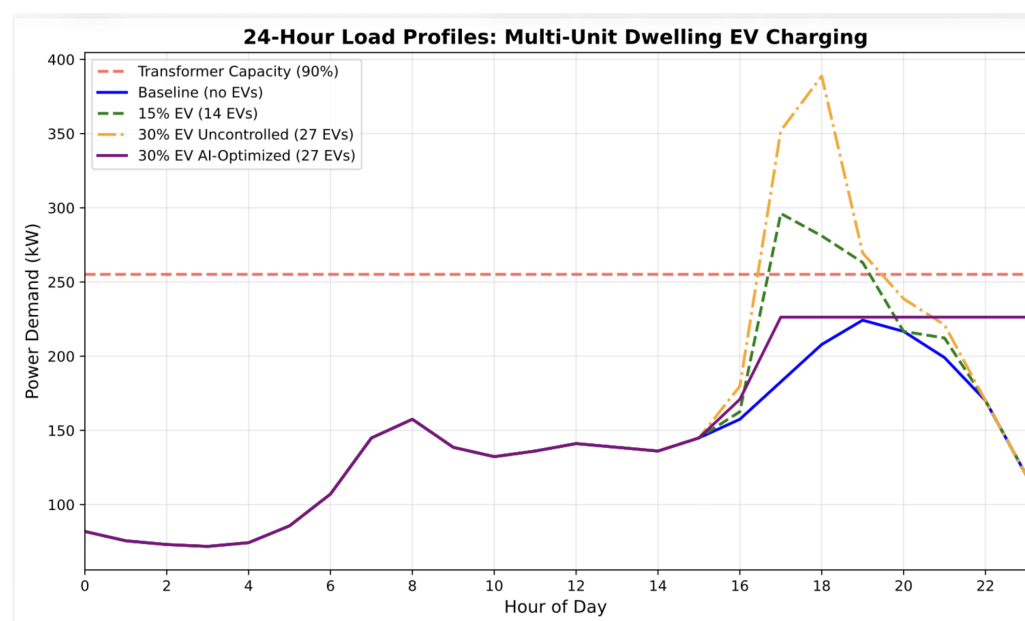


Figure 2. The 24 h load profiles comparing baseline residential demand (no EVs) with three EV penetration scenarios under uncontrolled charging and forecast-driven LP-coordinated smart charging. The horizontal dashed red line indicates transformer usable capacity (90% rating, 255 kW). Baseline profile (blue solid) remains within capacity limits. At 15% EV penetration (green dashed), uncontrolled charging creates moderate overload during evening hours. At 30% penetration, uncontrolled charging (orange dash-dot) produces severe capacity violations peaking at about 405 kW, while the LP-coordinated schedule (purple solid) limits peak demand to about 224 kW through temporal load shifting to overnight hours. Results represent mean profiles from 1000 Monte Carlo trials; the 95% confidence intervals are omitted from the figure to keep the four overlaid profiles legible and are reported numerically in Table 4.

At 15% EV penetration (14 vehicles), uncontrolled charging—where users plug in immediately upon evening arrival—increases peak demand to 320 ± 51 kW (95% CI), exceeding capacity by approximately 65 kW during about 3 h daily (Table 4). The temporal coincidence between residential evening peak and EV arrival creates severe stress: approximately 65% of vehicles return home between 17:30–20:30, initiating simultaneous 22 kW Level 2 charging sessions that superimpose directly onto baseline consumption.

Table 4. Performance comparison across EV penetration scenarios based on 1000 Monte Carlo simulation trials. “Mean peak” is the mean of the daily peak demand and “Peak 95% CI” its half-width; “Mean overload” is the mean kW above the 255 kW usable transformer capacity (zero when the peak stays within the envelope); “Overload duration” is the mean number of hours per day during which the load exceeds 255 kW; “Completion $\geq 80\%$ SOC” is the share of vehicles that finish the charging window at or above the 80% target. “n/a” indicates that the metric is not defined for an uncontrolled scenario without an active coordination layer.

Scenario	Mean Peak (kW)	Peak 95% CI ($\pm$ kW)	Load Factor (–)	Mean Overload (kW)	Overload Duration (h/Day)	Completion $\geq$ 80% SOC (% of Vehicles)
Baseline (no EVs)	224	± 0	0.62	0	0	n/a
15% EV uncontrolled	320	± 51	0.47	65	3	n/a
30% EV uncontrolled	405	± 71	0.40	150	4	n/a
30% EV LP-coordinated	224	± 0	0.68	0	0	8.9

The accelerated scenario (30% penetration, 27 vehicles) produces critical overload conditions. Peak demand reaches 405 ± 71 kW, representing about 59% exceedance of transformer capacity and necessitating infrastructure upgrades. The system experiences overload during roughly 4 h daily, with load factor degrading from 0.62 (baseline) to 0.40, indicating inefficient infrastructure utilization. Monte Carlo variance analysis reveals substantial stochastic uncertainty, reflecting variability in individual arrival times, state-of-charge distributions, and daily travel patterns.

At 40% penetration (rapid scenario, 36 vehicles), uncontrolled charging creates unsustainable grid conditions with peak demand exceeding 500 kW in some trials, requiring transformer capacity expansion of 150–200% relative to existing infrastructure.

4.2. LP-Coordinated Smart Charging Performance

The smart-charging system, combining XGBoost demand forecasting on the prediction side with LP-based coordination on the dispatch side, achieves substantial load management improvements (Figure 2, purple line). For the 30% penetration scenario, LP-coordinated dispatch reduces peak demand to 224 ± 0 kW—a 44.7% reduction compared to uncontrolled charging (405 kW), keeping demand below the 255 kW usable transformer capacity.

The optimization algorithm shifts charging load temporally by exploiting off-peak capacity availability. While uncontrolled charging creates a sharp evening spike (18:00–20:00), smart coordination distributes load across late evening and overnight hours (20:00–06:00), where baseline demand drops to 72–140 kW, leaving 115–183 kW margin for EV charging within capacity constraints. This valley-filling strategy achieves load factor of 0.68, representing 68.6% improvement over uncontrolled charging and approximately 10% improvement over baseline.

The most consequential single result of the 1000-trial run is that only 8.9% of vehicles achieve 80% state-of-charge by departure under the coordinated strategy. This is a headline finding rather than a side note: the current LP coordinator successfully protects the transformer but delivers weak user service quality on the 80% SOC criterion, with the achieved-SOC distribution centered at roughly 69% rather than near full charge; the full achieved-SOC distribution is presented in Section 6. The 99.99% figure that satisfies the

model's 60% minimum energy-delivery floor should not be read as “users are served”; it only confirms that the LP respects its own lower-bound constraint, which is a much weaker statement than meeting a usable charging target. Peak-focused capacity protection therefore comes at a measurable service–quality cost that policy must own explicitly.

Peak demand variance decreases substantially under optimization (near-zero dispersion around 224 kW versus $\sigma \approx 37$ kW uncontrolled), demonstrating robust capacity-capping behavior across stochastic arrival patterns and energy requirements.

4.3. Machine Learning Forecasting Performance

Under the temporal hold-out protocol with 3% multiplicative Gaussian noise described in Section 3.4, the XGBoost demand forecasting model attains $R^2 = 0.932$, MAE = 10.90 kW, RMSE = 23.15 kW and MAPE = 4.88% on the 1752 h test partition (the chronologically final 73 days of the simulated horizon). These figures are markedly lower than the near-perfect scores that the same model produces when trained and tested on a randomly shuffled noise-free version of the same simulated series, and we report the temporal noise-injected protocol as the primary evaluation because it controls for the lookahead leakage that random shuffling introduces through the lag-1 and lag-24 features. Feature importance analysis still identifies the lag-1 and lag-24 demand values as the dominant predictors, consistent with the strong autocorrelation inherent in residential consumption patterns; the accuracy level above 0.93 indicates that the model captures useful structure beyond simple persistence even under the conservative evaluation.

The model's error level (MAE of about 11 kW and RMSE of about 23 kW on a 255 kW capacity envelope) is well below the headroom typically reserved for safe operation, so it supports capacity-headroom estimation for real-time charging decisions without absorbing the full margin. In operational deployment, the forecaster would provide rolling 24 h demand predictions updated hourly, allowing the LP optimizer to proactively schedule charging sessions while maintaining safety margins. The low computational overhead (inference < 100 ms per prediction) supports real-time implementation on building-level edge computing infrastructure.

4.4. Economic Analysis

Before presenting the cost-and-NPV comparison itself, Table 5 consolidates the economic assumptions that drive it. The 10-year net present value of a pathway j is computed as given in (1):

$$NPV_j = -C_j^{up} + \sum_{y=1}^Y \frac{S_j^y - O_j^y}{(1+r)^y}, \quad (1)$$

where, for pathway j and year y : C_j^{up} is the upfront capital cost incurred in year 0; O_j^y is the annual operations and maintenance cost; S_j^y is the annual energy-cost saving (zero for grid reinforcement; positive for smart charging only under a time-varying tariff); Y is the 10-year planning horizon; and r is the 8% real discount rate. The index j ranges over the two pathways compared in this study (grid reinforcement and smart charging), and y ranges from 1 to Y . Table 5 below makes the boundary of the cost model explicit so the reader can judge what is inside and what is outside the analysis; in particular, the \$200 per dwelling unit attributed to smart charging refers to the building-level smart-charging control system (optimization software, communication gateway, load-management controls) and is reported separately from the per-charger hardware and installation costs, which are allocated to the chargers themselves rather than to the smart-charging upgrade.

Table 5. Economic inputs and scope of the cost–benefit model. “Included” items are quantified inside the NPV calculation; “not modeled” items are acknowledged limitations.

Category	Value	Scope
Discount rate (real)	8%	Included
Analysis horizon	10 years	Included
Annual O&M rate	2% of capex	Included
Tariff (TOU) peak/off-peak	0.15/0.06 USD/kWh	Included (3-zamanlı)
Tariff (time-invariant)	0.10 USD/kWh	Included (tek-zamanlı/kademeli)
Smart-charging system capex	USD 20,000 building/USD 200 per unit	Includes building-level controller, communication gateway and load-management software; one-time licence assumed bundled
Charger hardware + installation	USD 5000 per charger	Outside the per-unit smart-charging line; allocated to the chargers themselves, not to the smart-charging upgrade
Transformer reinforcement	USD 150 per kVA expansion	Included in the grid-reinforcement pathway only
Monitoring/metering/communications recurring fee	not modeled	Acknowledged limitation; would shift the smart-charging NPV downward if added
Demand-response market revenue	not modeled	Conservative omission; flagged in Section 6 as upside
Avoided distribution losses	not modeled	Conservative omission

Tariff Assumption: The economic analysis employs a proposed time-of-use (TOU) pricing structure (peak: 0.15 \$/kWh, off-peak: 0.06 \$/kWh) consistent with the policy recommendations in Section 5.3, rather than current Turkish flat-rate residential pricing (0.11 \$/kWh). This assumption reflects the policy intervention necessary to realize economic benefits through temporal load shifting. Economic advantages are therefore contingent upon regulatory adoption of differentiated TOU tariffs for multi-unit dwelling EV charging applications. The Turkish residential retail landscape currently combines a flat single-rate tariff (tek-zamanlı) and a volume-block tariff (kademeli, with 1. kademe below the monthly consumption threshold and 2. kademe above it) as the default options; an opt-in three-window time-of-use tariff (3-zamanlı) is also offered but adoption among residential consumers remains low. Because tek-zamanlı and kademeli are both time-invariant within the day, the smart-charging arbitrage stream is realized only under the 3-zamanlı regime, and we therefore extend the analysis below to report both the TOU and the time-invariant cases.

Figure 3 presents the comparative economics of grid reinforcement versus smart charging infrastructure. Under the uncontrolled 30% EV scenario, accommodating peak demand of 405 kW requires transformer upgrade from 315 kVA to approximately 540 kVA-equivalent requirement including planning margin assumptions in our cost model, yielding \$43,948 total upfront reinforcement cost or \$439 per dwelling unit. With 2% annual operations and maintenance costs over 10 years, the grid reinforcement approach yields net present value of approximately −\$498 per unit.

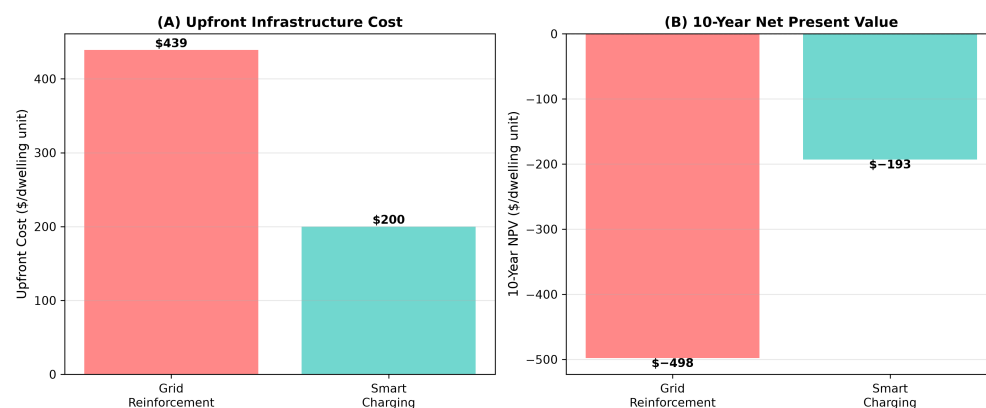


Figure 3. Economic comparison of grid reinforcement versus smart charging infrastructure for 30% EV penetration scenario (27 vehicles, 100 dwelling units). **(A)** Upfront capital costs per dwelling unit: grid reinforcement requires approximately \$439 for transformer capacity expansion (about 225 kVA upgrade equivalent in the cost model), while smart charging system costs \$200 per unit (building-level optimization and control infrastructure). **(B)** 10-year net present value per dwelling unit: grid reinforcement yields NPV of approximately −\$498, while smart charging yields approximately −\$193 under the completion and TOU-shift assumptions reported in Section 4. Smart charging delivers about \$239 upfront savings and \$306 NPV advantage per dwelling unit compared to the reinforcement-first approach.

In contrast, building-level smart charging infrastructure—comprising optimization software, communication gateway, and load management controls—requires \$20,000 initial investment (\$200 per unit). With 2% annual Operation and Maintenance (O&M) costs and the service outcomes obtained from the 1000-trial run, time-of-use pricing arbitrage generates approximately \$508 annual energy savings. The resulting 10-year NPV of about −\$193 per unit represents an advantage of approximately \$306 per unit over grid reinforcement.

Because the 3-zamanlı TOU option is opt-in and not yet the default residential tariff in Türkiye, the same comparison is run under the two currently dominant time-invariant regimes (tek-zamanlı and kademeli) by setting the peak/off-peak price differential to zero. The smart-charging arbitrage stream then collapses, which reduces the 10-year present value of the energy-cost savings by approximately \$149 per dwelling unit at the 8% discount rate (i.e., 24,790 kWh of annual building-level off-peak shifting at a \$0.09/kWh price differential, annualized and discounted over the ten-year horizon). The smart-charging NPV advantage therefore narrows from about \$306 per unit under TOU to about \$157 per unit under tek-zamanlı or kademeli pricing, but it remains positive because the \$239 per-unit upfront capital gap and the lower O&M base of the smart-charging system more than offset the loss of arbitrage. The sign of the comparison—smart charging is the more economical pathway for the building—does not depend on the tariff regime; only the magnitude of the advantage does. Table 6 summarizes the three regimes.

Table 6. Smart-charging versus grid-reinforcement NPV per dwelling unit (10-year horizon, 8% discount, 2% annual O&M) under the three residential retail tariff regimes that matter for Türkiye. Smart charging remains the more economical pathway in every regime; the size of the advantage scales with the arbitrage opportunity created by intra-day price differentiation.

Tariff Regime	Smart-Charging NPV/Unit	NPV Advantage/Unit
Tek-zamanlı (flat-rate, current default)	−342 USD	≈157 USD
Kademeli (volume blocks, current default)	−342 USD	≈157 USD
3-zamanlı (TOU, opt-in or future mandate)	−193 USD	≈306 USD

These findings demonstrate that smart charging delivers both lower upfront capital requirements (55% reduction) and superior long-term economic value through operational cost recovery. The economic advantage strengthens further when considering avoided distribution system losses, deferred substation upgrades, and potential grid services revenue from demand response participation—benefits not quantified in this conservative analysis.

To improve policy relevance, Table 7 summarizes scenario-based sensitivity checks around discount rate, TOU spread, and capital cost assumptions. The direction of results is robust: smart charging remains economically preferable across tested parameter ranges, though the magnitude of NPV advantage varies materially.

Table 7. Economic sensitivity summary for smart charging versus reinforcement (per dwelling unit, 10-year horizon).

Scenario	NPV Advantage (\$/Unit)	Upfront Savings (\$/Unit)	Interpretation
Base case (current assumptions)	306	239	Strong smart-charging advantage
Low discount rate (3%)	334	239	Higher present value of operating savings
High discount rate (10%)	281	239	Advantage persists, but discounted savings shrink
Narrow TOU spread (0.15/0.10 \$/kWh)	246	239	Economics still favorable, weaker arbitrage
Wide TOU spread (0.18/0.05 \$/kWh)	379	239	Highest value from managed load shifting
+20% smart system capex	266	199	Still favorable despite higher digital capex
+20% reinforcement capex	394	327	Reinforcement-first strategy becomes markedly costlier

From a policymaker perspective, two implications follow: (i) the business case does not depend on a single tariff or financing condition, and (ii) TOU design quality directly affects the magnitude (not the sign) of social and private returns. This supports coupling Pillar 3 (pricing design) with Pillar 5 (outcome monitoring) in implementation.

4.5. Sensitivity Across Building Configurations

To test whether the headline findings depend on the specific representative MUD used in the case study, a compact sensitivity sweep is run over the three building characteristics with the largest first-order influence on transformer loading: distribution-transformer capacity (250, 315, 400 and 500 kVA), building size (80, 100 and 150 dwelling units), and the parking-to-unit ratio (0.6, 0.9 and 1.0). For each of the 36 configurations the uncontrolled 30% EV-penetration scenario is run for 200 Monte Carlo trials, and the mean peak demand, the mean transformer overload, the per-unit reinforcement capital cost implied by that overload, and its 10-year net present value are recorded at the same 8% discount rate and 2% annual O&M used in the main economic analysis. Table 8 reports the parking-ratio-0.9 cross-section of that sweep, which holds the parking density at the case-study baseline and isolates the transformer-by-building-size effect.

Table 8. Sensitivity of uncontrolled 30% EV-penetration results to transformer capacity and building size at the baseline parking-to-unit ratio of 0.9. Each row averages 200 Monte Carlo trials. “Reinforce. capex” is the per-dwelling-unit upfront cost of expanding the transformer to absorb the mean overload; “NPV” is the 10-year net present value of that pathway (negative values indicate net cost).

Trafo (kVA)	Units	Parking Space	Capacity (kW)	Mean Peak (kW)	Mean Overload (kW)	Reinforce. Capex/NPV per Unit (USD)
250	80	72	225.0	329.8	127.3	265/−301
250	100	90	225.0	405.6	203.1	339/−384
250	150	135	225.0	596.0	393.5	437/−496
315	80	72	283.5	329.8	74.6	155/−176
315	100	90	283.5	405.6	150.5	251/−285
315	150	135	283.5	596.0	340.8	379/−430

Table 8. *Cont.*

Trafo (kVA)	Units	Parking Space	Capacity (kW)	Mean Peak (kW)	Mean Overload (kW)	Reinforce. Capex/NPV per Unit (USD)
400	80	72	360.0	329.8	16.4	34/−39
400	100	90	360.0	405.6	81.6	136/−154
400	150	135	360.0	596.0	272.0	302/−343
500	80	72	450.0	329.8	0.6	1/−1
500	100	90	450.0	405.6	15.2	25/−29
500	150	135	450.0	596.0	191.0	212/−241

Figure 4 visualizes the same parking-ratio-0.9 cross-section as a two-panel heatmap of mean transformer overload (panel A) and per-unit reinforcement capex (panel B) over the transformer-by-building-size grid; the color gradient makes the joint dependence on transformer sizing and building scale immediate. Three observations follow. First, the qualitative finding that uncontrolled 30% penetration overloads the building transformer is robust: of the 36 configurations in the full sweep, only one—a deliberately oversized 500 kVA transformer combined with 80 units at a 0.6 parking ratio—avoids overload. Second, the absolute reinforcement cost per dwelling unit is the more configuration-sensitive number, spanning from \$0 in the over-provisioned corner case to about \$473 at 250 kVA/150 units/1.0 ratio, with the case-study baseline of \$439 sitting in the upper tertile of that distribution. Third, parking-to-unit ratio matters most when the transformer is generously sized: the 500 kVA/100-unit cell goes from essentially no overload at 0.6 to 27 kW mean overload at 1.0, whereas at 250 kVA the parking ratio only modulates an already saturated overload condition. Across the full sweep the smart-charging-versus-reinforcement comparison therefore holds in direction, while the magnitude of the economic advantage scales with how tightly the existing transformer is matched to the building’s EV-ready parking footprint.

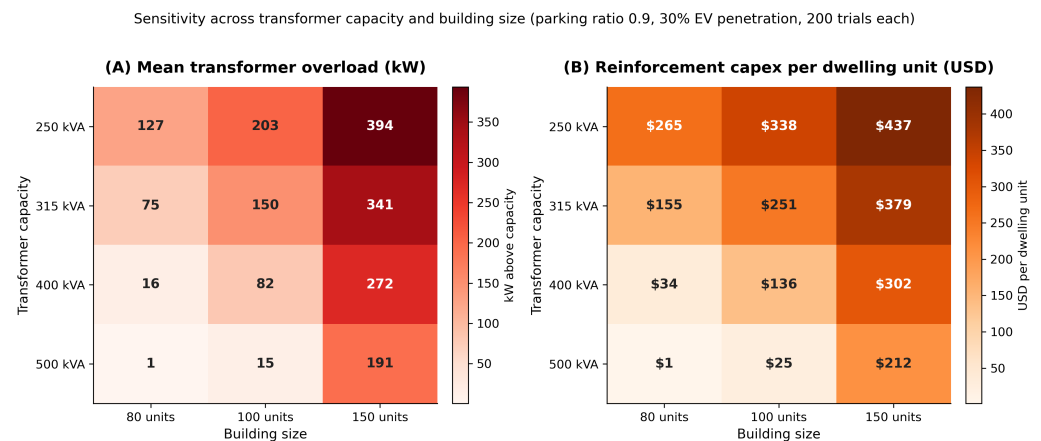


Figure 4. Sensitivity of uncontrolled 30% EV-penetration results across the transformer-by-building-size grid at the baseline parking-to-unit ratio of 0.9. Panel (A) reports the mean transformer overload (kW above the usable capacity); panel (B) reports the per-dwelling-unit upfront reinforcement capex required to absorb that overload. Each cell averages 200 Monte Carlo trials. The color gradient makes the joint dependence on transformer sizing and building scale visible at a glance.

Beyond building configuration, we also tested whether the choice of a winter week-day as the representative day was driving the overload finding. Table 9 reports the four (season $\times$ day-type) combinations of the baseline configuration under the same 30% uncontrolled scenario over 300 trials. The mean peak demand is 405 kW on winter days and 393 kW on summer days, a difference of about 3%, and the modal peak hour shifts from 18:00 on weekdays to 20:00 on weekends in line with the configured weekend arrival delay. All four combinations exceeded the 255 kW usable transformer capacity in 100% of the

Monte Carlo trials, so the headline result—that uncontrolled 30% penetration overloads the building transformer—is not an artefact of the winter weekday baseline. The seasonal magnitude difference is small enough that the smart-charging-versus-reinforcement comparison and the \$306 NPV advantage carry through unchanged for routine planning purposes; jurisdictions with substantially different climate or working-week patterns should re-fit the underlying hourly factors but can reuse the architecture.

Table 9. Temporal sensitivity of the baseline-configuration 30% EV-penetration scenario across season and day-type. Mean over 300 Monte Carlo trials per cell; capacity limit 255 kW.

Season	Day Type	Mean Peak (kW)	Mean Overload (kW)	Load Factor	Modal Peak Hour
Winter	Weekday	405.4	150.2	0.404	18
Winter	Weekend	405.3	150.1	0.404	20
Summer	Weekday	392.5	137.3	0.396	18
Summer	Weekend	392.4	137.2	0.396	20

4.6. Preventive Fire-Safety Surrogate Metrics

The four outcomes the framework governs jointly include fire-risk exposure in enclosed residential parking, but our simulation does not model flame spread, smoke transport or thermal runaway directly. What it can do is quantify the physical configuration in which an incident, if it were to occur, would be hardest to manage. We therefore extract three preventive surrogates from the per-vehicle hourly charging schedule produced by the simulation and report them in Table 10 for the baseline 30% EV-penetration scenario, averaged over 100 Monte Carlo trials of uncontrolled and LP-coordinated operation. The three quantities reported below are preventive fire-safety surrogate metrics—fire-safety-relevant operational indicators of charging clustering and temporal coincidence—rather than direct fire-risk quantifications. They do not estimate fire probability, thermal-runaway likelihood, smoke-spread dynamics, evacuation difficulty, or emergency-response time, and they should not be read as a substitute for the explicit fire-engineering modeling identified as a future-work item in the Conclusion. The first surrogate is the maximum number of vehicles drawing power simultaneously anywhere in the day, which captures the worst-case clustering of energized EVs in the enclosed parking environment. The second is the cumulative vehicle-hours of active charging during the 18:00–22:00 evening window, when residents are at home, lifts are operating, and emergency-egress paths are most crowded. The third is the share of total daily EV energy that is actually delivered inside that evening window, which quantifies how strongly charging operations coincide with the period of highest human exposure.

The three surrogates point in the same direction. Coordinated charging reduces the mean simultaneous-charger peak from about 12.7 to 5.6 vehicles (−56%), the worst-case peak from 17 to 9 vehicles (−47%), the cumulative evening vehicle-hours of active charging from 28.9 to 2.8 (−90%), and the evening peak-coincidence share from 70.0% to 9.1% (−87%). Figure 5 visualizes the three mean-level reductions side by side; the absolute drop is largest for the evening vehicle-hours metric, because the coordinator displaces almost the entire charging fleet out of the 18:00–22:00 window rather than thinning it. These reductions are consistent with the preventive-governance reading we adopt throughout the paper: a coordinator that pushes EV energy delivery out of the evening high-exposure window also thins the clustering of energized vehicles at the time and place where confined-space EV incidents are hardest to manage, in line with the underground-parking fire-protection requirements analysed by [61] and with the Turkish-context risk assessment of underground parking facilities by [62]. The surrogates do not replace explicit fire-engineering modeling, which we identify as a future-work item in the Conclusion, but they make the link between

operational charging coordination and fire-safety-relevant clustering concrete enough to act on.

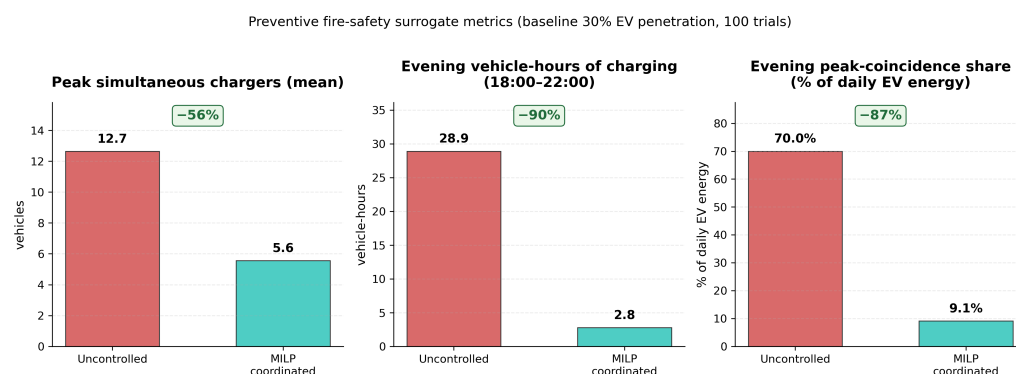


Figure 5. Preventive fire-safety surrogate metrics under uncontrolled versus LP-coordinated charging at the baseline 30% EV-penetration configuration, averaged over 100 Monte Carlo trials. The three panels report the mean peak number of simultaneously charging vehicles, the cumulative vehicle-hours of active charging in the 18:00–22:00 evening window, and the share of total daily EV energy delivered inside that window. Coordination thins all three indicators of physical clustering and temporal coincidence with the high-human-exposure period.

Table 10. Preventive fire-safety surrogate metrics in the baseline 30% EV-penetration scenario, averaged over 100 Monte Carlo trials. Lower values indicate thinner clustering of energized EVs in the enclosed parking environment and a smaller share of charging operations coinciding with the evening high-exposure window.

Surrogate Metric	Uncontrolled	LP Coordinated	Change
Peak simultaneous chargers (mean)	12.65	5.56	−56%
Peak simultaneous chargers (worst-case)	17	9	−47%
Evening (18:00–22:00) vehicle-hours of charging	28.9	2.77	−90%
Evening peak-coincidence share (% of daily EV energy)	70.0%	9.1%	−87%

4.7. The Big Picture of Key Findings

Our results establish four principal findings relevant to MUD charging policy:

1. Uncontrolled residential EV charging creates critical distribution transformer overload at penetration levels as low as 15%, with severity escalating nonlinearly as adoption increases.
2. The LP-coordinated smart-charging schedule, driven by XGBoost demand forecasting, reduces peak demand by 44.7% and keeps transformer loading within limits, but under strict-capacity scheduling only 8.9% of users reach 80% State of Charge (SOC), indicating a service-quality constraint that policy must explicitly address.
3. Machine learning demand forecasting achieves accuracy sufficient ($R^2 = 0.932$ under a temporal hold-out with 3% measurement noise; see Section 3.4) for real-time predictive control applications in residential settings.
4. Smart charging infrastructure delivers superior economics (about \$306 per unit NPV advantage) compared to grid reinforcement, providing lower upfront costs and positive long-term value despite conservative service assumptions.

These quantitative findings provide the evidence base for the systems architecture developed in Section 5.

5. Governance-Aware Systems Architecture for Smart Charging in Multi-Unit Dwellings

Based on our simulation results demonstrating both technical feasibility and economic superiority of forecast-driven LP-coordinated smart charging, we propose a comprehensive

five-layer systems architecture for multi-unit dwelling contexts. This architecture addresses the unique institutional, technical, and economic challenges that differentiate MUDs from single-family residences, where individual homeowners control infrastructure decisions and bear direct costs. The design balances operational control requirements for grid stability with incentive and coordination mechanisms that support adoption and long-term system performance. This governance orientation is consistent with recent analyses of disruption-sensitive resilience governance and with multi-objective, auditable policy design approaches supported by digital-twin validation logic [63,64].

To make the link between simulation evidence and policy design visible at a glance before reading the five subsections, Table 11 cross-walks each pillar to the specific result that motivates it. The pillars are not policy aspirations layered on top of the analysis; each one is anchored to a quantitative finding established earlier in the paper.

Table 11. Cross-walk between the five governance pillars and the simulation evidence that motivates each. Section numbers point to where the corresponding result is established.

Pillar	Simulation Evidence That Motivates It	Result Location
1. Coordinated control	Uncontrolled 30% penetration overloads the transformer in 35 of 36 building configurations; coordination cuts peak from 405 to 224 kW.	Sections 4.1 and 4.2
2. Interoperability standards	Open-protocol coordination is required for the building-level optimizer to operate against heterogeneous chargers and EV fleets the way the LP setup assumes.	Section 4.2
3. Time-of-use pricing	Smart-charging NPV advantage falls from \$306 (TOU) to \$157 (flat/kademeli) per dwelling unit; the sign survives but the magnitude depends directly on intra-day price differentiation.	Section 4.4 (Table 6)
4. Building–utility coordination	Capacity headroom in real time is what allows the coordinator to keep load below 255 kW; without a building–utility interface the same outcome would require oversizing the transformer.	Sections 4.2 and 4.5
5. Monitoring and assurance	The 80% SOC completion rate moves only when the minimum-delivery floor is raised (2.8% → 9.1% → 36.8%); a regulatory KPI on that floor is therefore the actionable policy lever.	Section 6

5.1. Pillar 1: Smart Charging Mandates for New MUD Installations

Policy Requirement: All new EV charging infrastructure installed in multi-unit dwellings with five or more parking spaces must incorporate smart charging capabilities, defined as bidirectional communication enabling external load management signals and programmable charging schedules based on grid conditions, electricity prices, or building-level capacity constraints.

Rationale: Our results demonstrate that uncontrolled charging at 30% EV penetration creates approximately 150 kW transformer overload requiring costly infrastructure upgrades (about \$439 per dwelling unit). Mandating smart charging capabilities from initial installation avoids retrofit costs and establishes grid-friendly charging as the default paradigm. The mandate applies prospectively to new installations, avoiding burdensome requirements for existing chargers while ensuring future infrastructure supports coordinated load management.

Implementation Specifications: Compliant charging infrastructure must support open communication protocols (OCPP 1.6 or higher), accept external charging schedules via standardized APIs, and provide real-time availability and power flow data to building management systems or designated aggregators. Minimum technical requirements include: (i) remote start/stop capability, (ii) power modulation between 0 and 100% of rated capacity in 10% increments, (iii) bidirectional metering with 1 kWh accuracy, and (iv) 99% uptime

excluding scheduled maintenance. For enclosed or underground parking applications, installation approval should additionally review charger layout, emergency access clearances, and compatibility with existing detection and ventilation systems so that charging expansion does not create unmanaged hazard concentration.

Enforcement Mechanism: Building permit approval for new EV charging installations requires certification from licensed electrical contractors confirming smart charging compliance. Non-compliant installations discovered during electrical safety inspections trigger remediation requirements within 180 days, with continued non-compliance resulting in disconnection authorization for utility operators.

Turkish Context: Türkiye's 2022 Charging Service Regulation (*Şarj Hizmeti Yönetmeliği*) establishes a licensing framework for charging network operators and distinguishes standalone charging stations from those integrated into existing buildings. However, current regulations provide limited guidance on load management coordination or smart charging technical requirements for MUDs. Amendments should explicitly mandate smart charging capabilities for all charging infrastructure serving multiple dwelling units, aligning with European Union's Energy Performance of Buildings Directive requirements for smart-ready charging points.

5.2. Pillar 2: Open Interoperability Standards

Policy Requirement: All smart charging systems deployed in multi-unit dwellings must adhere to open, non-proprietary communication standards enabling interoperability across manufacturers, charging networks, and building management systems. Proprietary protocols that lock users into specific vendors or prevent coordination across charging infrastructure providers are prohibited.

Rationale: Multi-unit dwellings typically feature heterogeneous charging infrastructure installed by different providers over time as EV adoption progresses. Without interoperability standards, building-level load coordination becomes impossible when individual charging stations cannot communicate through common protocols. Proprietary systems create vendor lock-in, increase switching costs, and fragment the charging ecosystem, preventing efficient aggregation of distributed resources.

Technical Standards: Mandatory protocols include Open Charge Point Protocol (OCPP) version 1.6 or higher for charger-to-network communication, OpenADR 2.0b for demand response signaling, and ISO 15118 [65] for vehicle-to-charger communication supporting Plug & Charge authentication. Application programming interfaces (APIs) for building management system integration must follow RESTful architecture with standardized endpoints for charger status queries, charging session initiation, and power setpoint adjustment.

Data Sharing Requirements: Charging infrastructure operators must provide real-time data feeds (updated ≤ 5 min intervals) to building managers or designated aggregators including: charger availability status, instantaneous power draw per charging point, cumulative energy delivered per session, and scheduled charging start/end times. Data access must be provided without usage fees to entities responsible for building-level load coordination. Privacy protections ensure individual user identification remains anonymous in aggregated reporting.

Certification and Testing: Independent testing laboratories accredited under ISO/IEC 17025 conduct interoperability conformance testing. Manufacturers submit charging equipment for protocol-compliance verification before market authorization. Annual audits ensure continued adherence to standards, with non-compliance triggering product recall and market withdrawal.

International Alignment: Standards should align with European Union Directive 2014/94/EU requirements for interoperable charging infrastructure and incorporate emerging ISO 15118-20 extensions supporting bidirectional power flow (vehicle-to-grid) capabilities.

5.3. Pillar 3: Time-of-Use Pricing Mechanisms

Policy Requirement: Electricity distribution companies must offer time-of-use (TOU) pricing tariffs specifically designed for EV charging in multi-unit dwellings, with peak-to-off-peak price ratios of at least 2:1 to incentivize temporal load shifting.

Rationale: Our economic analysis demonstrates that TOU arbitrage generates approximately \$508 annual savings for a 100-unit building under the strict-capacity optimized scenario. This lower savings level reflects the binding trade-off between peak suppression and user charging completion. Without price signals reflecting grid capacity constraints, users lack economic incentive to delay charging, resulting in coincident peak demand. TOU pricing aligns individual user incentives with system-level optimization objectives, but must be coupled with service-quality safeguards.

Tariff Structure Design: Recommended three-period structure: Peak period (17:00–21:00 weekdays) at 0.15 \$/kWh reflecting system stress and capacity constraints; shoulder period (09:00–17:00, 21:00–23:00) at 0.10 \$/kWh; off-peak period (23:00–09:00, all weekend hours) at 0.06 \$/kWh to incentivize overnight charging when residential baseload drops to 72 kW, leaving 183 kW margin for EV charging within capacity limits. Critical peak pricing overlays (additional 0.05 \$/kWh) apply during system emergencies declared by grid operators, with 24 h advance notice to enable load curtailment.

Revenue Neutrality: TOU tariffs should be revenue-neutral for distribution companies on average consumption patterns, with rate design approved through regulatory proceedings ensuring cost recovery while providing clear price signals. Building-level master meters serving multiple charging points qualify for commercial TOU rates rather than residential rates, reducing administrative complexity.

Bill Transparency: Monthly billing statements itemize energy consumption by tariff period, enabling building managers to assess smart charging performance. Online portals provide hourly consumption data with 24 h lag, supporting continuous improvement of charging coordination strategies.

Turkish Implementation: Türkiye's Energy Market Regulatory Authority (EPDK) should mandate TOU tariffs for all multi-unit dwelling EV charging applications, leveraging existing smart metering infrastructure deployed under national smart grid programs. Current flat-rate residential pricing (averaging 0.11 \$/kWh) provides insufficient incentive for load management. Peak-period pricing should reflect distribution system capacity costs, not solely generation costs, ensuring price signals capture local transformer constraints relevant to MUD applications.

5.4. Pillar 4: Building–Utility Coordination Mechanisms

Policy Requirement: Distribution utilities and multi-unit dwelling building managers must establish formal coordination agreements defining roles, responsibilities, and communication protocols for managing EV charging loads. Utilities provide real-time capacity availability signals; building managers implement load management strategies respecting capacity limits.

Rationale: Our results demonstrate that building-level optimization can maintain peak demand at approximately 224 kW (within capacity) versus about 405 kW uncontrolled but only if building managers receive timely information about grid constraints. Current regulatory frameworks lack clear mechanisms for utility-building coordination, creating information asymmetries that prevent effective load management.

Coordination Agreement Components: Standardized agreements specify: (i) utility provision of hourly transformer loading forecasts and available capacity headroom with 24 h advance notice, (ii) building manager commitment to maintain charging loads below allocated capacity limits, (iii) emergency curtailment protocols for unforeseen system stress events, (iv) data sharing provisions ensuring utility access to aggregated building-level charging data for distribution planning, and (v) dispute resolution procedures for disagreements regarding capacity allocation or load management failures. In buildings with enclosed parking, agreements should also define incident notification chains, temporary charger shutdown triggers, and interfaces with facility safety systems so that electrical operations, smoke-control procedures, and emergency response are not managed in isolation.

Capacity Allocation Framework: Utilities allocate EV charging capacity to buildings based on transformer rating, existing baseload, and diversity factor analysis. Initial allocations provide 60 kW baseline capacity (approximately 3 simultaneous Level 2 chargers), with capacity requests for additional EVs evaluated through engineering studies assessing cumulative loading impacts. Dynamic capacity allocation adjusts available headroom based on real-time transformer loading, seasonal patterns, and forecasted demand.

Incentive Alignment: Distribution utilities compensate building managers for demand response participation through capacity reservation credits (0.02 \$/kWh for energy deferred from peak periods) or direct payments for emergency load curtailment (\$0.50/kWh). Compensation mechanisms ensure building managers internalize grid reliability benefits from coordinated charging.

Liability and Responsibility: Coordination agreements clarify that utilities retain responsibility for distribution system reliability, while building managers assume responsibility for implementing charging schedules respecting allocated capacity limits. Force majeure provisions address circumstances beyond either party's control (equipment failures, extreme weather events).

Turkish Context: Turkish Electricity Distribution Corporation (TEDAŞ) and licensed distribution companies should develop template coordination agreements for MUD applications, streamlining adoption across jurisdictions. The Charging Service Regulation currently addresses licensing of charging network operators but lacks provisions for building–utility coordination on load management. Regulatory amendments should explicitly authorize and encourage such coordination agreements, potentially offering regulatory incentives (accelerated permitting, expedited capacity studies) for buildings demonstrating smart charging coordination capabilities.

5.5. Pillar 5: Monitoring, Enforcement, and Continuous Improvement

Policy Requirement: Regulatory authorities must establish monitoring systems tracking smart charging deployment, grid impact metrics, and compliance with technical standards. Enforcement mechanisms ensure adherence to requirements while supporting iterative policy refinement based on empirical performance data.

Monitoring Infrastructure: Energy regulatory agencies operate centralized platforms aggregating anonymized data from all smart charging installations in multi-unit dwellings, including: charging session counts, energy delivered, peak demand impacts, time-of-use pricing effectiveness, interoperability compliance rates, and user satisfaction metrics. Data reporting requirements apply to all charging network operators and distribution utilities, with quarterly reporting cycles and public dashboards displaying system-wide statistics. Where available, anonymized records of charger fault alarms, emergency shutoff events, and facility-level incident logs should also be summarized to support preventive oversight of high-density residential charging environments.

Key Performance Indicators: Regulatory monitoring tracks: (i) percentage of new MUD charging installations meeting smart charging requirements (target: >95%), (ii) average peak demand reduction from smart charging relative to uncontrolled baselines (target: >30%), (iii) user completion rates achieving 80% state-of-charge by departure (target: policy-defined service floor with staged tightening), (iv) distribution transformer overload incidents at buildings with smart charging (target: <5 events per year), (v) charger-fault or emergency shutoff events requiring on-site intervention, and (vi) customer complaint rates regarding charging availability or reliability (target: <2% of users). To improve implementation clarity, Table 12 provides a compact regulator-facing KPI dashboard.

Table 12. Policy KPI dashboard for MUD smart-charging implementation and review cycles.

KPI	Baseline (Study)	24-Month Target	Reporting Entity	Corrective Trigger
Peak-demand reduction vs. uncontrolled	44.7%	>30%	Utility + CPO	Two consecutive quarters below target
Optimized load factor	0.68	>0.60	Building operator	Three months below threshold
SOC $\geq$ 80 completion rate	8.9%	Context-based staged target	CPO + building manager	Monthly non-improvement despite interventions
Minimum-energy service ($\geq$ 60% request)	99.99%	>95%	CPO platform logs	Any month below 95%
Overload events (smart-enabled buildings)	0 in optimized runs	<5/year	Distribution utility	Single critical overload incident
Complaint rate (availability/fairness)	N/A (to be measured)	<2% users	Regulator complaint system	Exceedance for two reporting periods

Enforcement Actions: Non-compliance with smart charging mandates triggers progressive enforcement: initial violations result in notice-to-cure with 90-day remediation period; continued non-compliance authorizes administrative fines (0.5% of building annual electricity costs per month of violation); persistent violations after 12 months enable utility disconnection of non-compliant charging infrastructure. Appeals processes ensure due process protections.

Adaptive Policy Refinement: Regulatory agencies conduct biennial policy reviews incorporating empirical performance data, stakeholder feedback, and technological developments. Review processes assess whether peak demand reduction targets are achieved, identify barriers to smart charging adoption, evaluate user acceptance and equity impacts, and propose regulatory amendments addressing identified gaps. Stakeholder consultation includes building managers, utilities, EV users, charging equipment manufacturers, and urban planning agencies.

Research and Pilot Programs: Regulatory authorities sponsor pilot programs testing innovative approaches—vehicle-to-building (V2B) bidirectional charging, battery storage integration, solar photovoltaic coordination, machine learning optimization algorithms—with regulatory sandboxes allowing temporary variance from standard requirements to enable experimentation. Successful pilots inform policy updates and best practice guidelines.

Equity Considerations: Monitoring systems track smart charging deployment across income levels, building types, and geographic regions to identify and address disparities in charging access. Targeted support programs (technical assistance, grant funding) assist lower-income buildings in deploying smart charging infrastructure, ensuring transportation electrification benefits accrue equitably.

5.6. Implementation Pathway and Stakeholder Roles

Successful implementation requires coordinated action across six stakeholder groups, whose roles are summarized here in the order in which they enter the chain. Energy regulatory authorities (in Türkiye, EPDK) establish technical standards, approve TOU tariffs, develop monitoring platforms and enforce compliance. Distribution utilities provide capacity-allocation guidance and real-time loading information to building managers, and integrate EV-charging demand into distribution planning and advanced metering. Building managers and homeowner associations select compliant charging infrastructure, implement smart-charging coordination in-house or through third-party aggregators, and communicate policies to residents. Charging-infrastructure manufacturers and network operators ensure equipment complies with interoperability standards and deliver reliable building-level optimization platforms. Local governments integrate the requirements into building codes and provide technical assistance for compliant installations. EV users gain access to convenient charging while contributing to grid stability through flexible schedules aligned with TOU incentives.

Operationally, the framework can be deployed in a phased 24-month rollout: months 0–6 cover legal and technical setup (secondary regulation defining MUD-specific capacity allocation, minimum reporting schema, interoperability requirements and standard building–utility coordination templates); months 6–12 cover regulator-supervised pilots in representative building archetypes with mandatory KPI reporting; months 12–18 cover scaled adoption (compliance obligations on new installations, retrofit incentive windows and TOU integration with transparent consumer disclosures); and months 18–24 cover formal policy review using the KPI dashboard, revision of service–quality thresholds (especially SOC-based outcomes) and codification of permanent enforcement and audit procedures. Beginning with mandatory standards for new installations and following with incentives for retrofits minimizes disruption to existing infrastructure, and the 24-month review keeps the framework responsive to technological and market evolution. The fuller technical specifications underlying each stakeholder role and each phase are kept deliberately compact in this manuscript and are intended to be elaborated in a regulator-facing implementation guide rather than expanded inline.

6. Discussion

6.1. Principal Findings and Policy Implications

Our simulation-based analysis establishes that uncoordinated residential EV charging in multi-unit dwellings creates critical infrastructure constraints at penetration levels readily achievable under current policy trajectories. The finding that 30% EV adoption—a conservative projection for 2030 in many urban markets—generates approximately 150 kW transformer overload requiring about \$439 per dwelling unit in capacity upgrades carries immediate implications for distribution system planning and regulatory policy. Unlike single-family residences where household-level infrastructure upgrades distribute costs across individual homeowners, MUDs concentrate infrastructure stress at shared distribution transformers serving dozens to hundreds of dwelling units, creating collective action problems that market mechanisms alone cannot resolve.

The LP-coordinated smart-charging schedule, driven by XGBoost demand forecasting, achieves about 45% peak demand reduction and keeps transformer loading within limits, which validates the technological pathway for mitigating grid impacts without immediate infrastructure expansion. The same 1000-trial run, however, makes the limit of that pathway equally clear: only 8.9% of vehicles reach 80% SOC by departure under the coordinated strategy, with the achieved-SOC distribution centered near 69%. The LP coordinator protects the transformer but delivers weak user service quality on the 80% SOC criterion,

and the 99.99% figure for the 60% minimum-delivery floor confirms only that the optimizer respects its own lower bound rather than that residents are well served. The economic comparison still favors smart charging, with about \$306 per dwelling unit NPV advantage over 10 years compared to grid reinforcement, but the policy reading is therefore not “smart charging is broadly service-preserving”; it is that smart charging trades user-facing service quality for transformer protection, and policy must regulate both edges of that trade-off rather than treating the favorable peak-and-cost numbers as if they settled the service question.

From a transport-and-environment perspective, this trade-off is consequential: poorly calibrated residential charging policy can shift users toward higher-cost or higher-emission charging pathways, whereas behavior-aware coordination can preserve both grid reliability and transport decarbonization gains.

The five-pillar framework we propose—smart charging mandates, interoperability standards, TOU pricing, building–utility coordination, and monitoring systems—addresses institutional barriers specific to multi-unit dwelling contexts. Each pillar targets distinct market failures: mandates overcome split incentives between building owners and residents; interoperability standards prevent vendor lock-in and enable aggregation; TOU pricing aligns individual behavior with system constraints; coordination mechanisms resolve information asymmetries between utilities and building managers; and monitoring ensures accountability and enables adaptive policy refinement.

The relevance of this framework extends beyond energy balancing alone. In dense residential parking environments, concentrated charging can amplify the operational consequences of charger malfunction, localized battery incidents, smoke dispersion, and constrained emergency access. Recent studies of underground parking settings and EV-related structural and toxic-gas exposure scenarios indicate that confined-space vehicle incidents may create disproportionate management burdens even when event frequency remains low [66,67]. For that reason, the proposed policy package should be read as a preventive governance architecture: it reduces simultaneous charging congestion, improves observability of charging operations, and creates clearer institutional interfaces before abnormal events occur.

Viewed from this perspective, the study speaks directly to fire-relevant urban risk management even without modeling flame spread itself. Its contribution is to show how charging coordination, system visibility, and operational rules can reduce hazardous clustering, support earlier intervention, and improve preparedness in enclosed residential parking environments where dedicated incident modeling would be a valuable next step.

Addressing Completion Rate Limitations: The 1000-trial run yields an 8.9% completion rate for users achieving 80% SOC by departure under strict transformer-capacity and 60% minimum-delivery constraints. This result highlights a sharp trade-off between grid protection and individual user service quality. Policy interventions should therefore prioritize three mechanisms: (i) *extended dwell time incentives*—TOU pricing structures (Pillar 3) offering deeper off-peak discounts can increase usable charging windows and improve SOC outcomes; (ii) *workplace charging complementarity*—coordinated residential and workplace charging reduces per-location energy requirements and improves reliability of daily mobility; and (iii) *dynamic capacity allocation*—building–utility coordination (Pillar 4) enabling real-time headroom updates allows opportunistic charging during local demand troughs. Regulatory frameworks should explicitly define both grid KPIs and service KPIs (e.g., minimum SOC by departure), with periodic recalibration.

Figure 6 first places the headline 8.9% completion-rate figure in distributional context. The uncontrolled-charging panel shows a right-skewed distribution centered near full SOC (mean 85.2%; 70.0% of vehicles at or above the 80% target), because every vehicle is

allowed to draw its rated power on arrival until its energy demand is met regardless of grid impact. The coordinated panel shows the same simulation under the LP coordinator with the 60% minimum-delivery floor and the 255 kW transformer ceiling, and the distribution shifts sharply leftward (mean 69.2%; 9.3% at or above the 80% target). The shape of the trade-off is visible at a glance: strict capacity protection does not push individual users into low-SOC failure—there are essentially no vehicles below 45% SOC—but it does compress the achieved distribution downward and away from the 80% milestone.

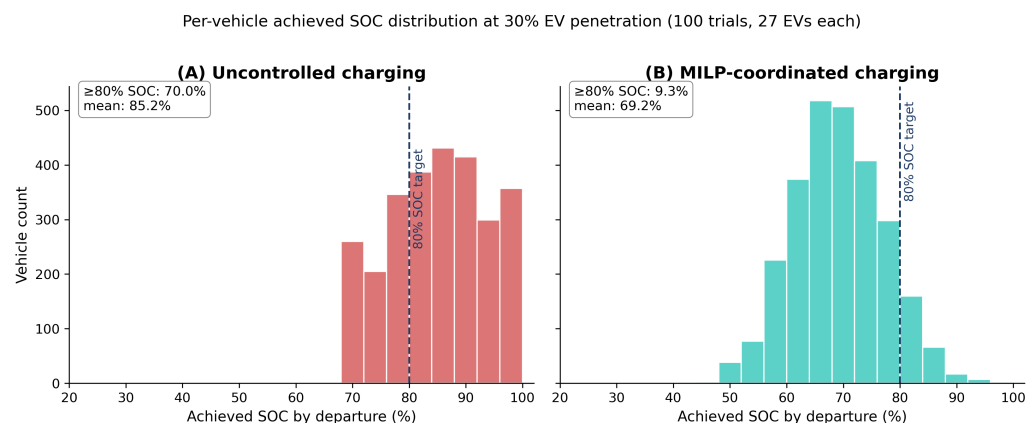


Figure 6. Per-vehicle achieved SOC by departure under uncontrolled (A) and LP-coordinated (B) charging at the baseline 30% EV-penetration configuration. Each panel aggregates 100 Monte Carlo trials with 27 vehicles per trial. The dashed vertical line marks the 80% SOC service target. Strict capacity protection compresses the achieved distribution leftward without pushing residents into low-SOC failure.

To make this trade-off operationally actionable rather than rhetorical, a one-lever-at-a-time sensitivity analysis is run around the baseline configuration (22 kW Level-2 chargers, the configured arrival–departure windows, the 315 kVA transformer, and the 60% minimum-delivery floor); the resulting share of vehicles reaching 80% SOC by departure is reported in Table 13. The four levers are charger power, dwell time, transformer capacity and the minimum energy-delivery threshold; each cell averages 60 Monte Carlo trials of the LP coordinator.

Table 13. Sensitivity of the 80% SOC-by-departure completion rate to four candidate levers, one lever at a time, around the baseline configuration. Each cell averages 60 Monte Carlo trials of the LP coordinator at 30% EV penetration.

Lever	Setting	Completion Rate (≥80% SOC)
Baseline	22 kW / +0 h / 315 kVA / 60% min-delivery	9.1%
Charger power	11 kW	9.1%
	22 kW (baseline)	9.1%
	33 kW	9.1%
Dwell-time extension	+1 h beyond configured departure	9.1%
	+2 h	9.1%
	+3 h	9.1%
Transformer capacity	400 kVA	9.1%
	500 kVA	9.1%
Minimum-delivery floor	40%	2.8%
	60% (baseline)	9.1%
	80%	36.8%

The first three levers (charger power, dwell extension, and transformer capacity) do not move the 80% SOC completion rate when varied on their own. The reason is structural rather than numerical: at the optimum, the LP coordinator delivers exactly the minimum-delivery floor to each vehicle and then shapes the residual schedule to minimize the peak,

so installing faster chargers, extending the dwell window, or oversizing the transformer simply gives the optimizer more slack against constraints that are already non-binding. The lever that does move the completion rate is the minimum-delivery floor itself: lowering it to 40% drops the completion rate to 2.8%, while raising it to 80% lifts the completion rate to 36.8%. The actionable conclusion is therefore not infrastructure investment in isolation but a service-quality floor written into Pillar 5 as a binding regulatory KPI, complemented by the dwell-time and workplace-charging mechanisms listed above which become effective once the floor has been raised.

The same diagnosis explains why a fundamentally different objective changes the picture. To make this explicit, an alternative LP variant is run on the same Monte Carlo seeds in which the transformer is enforced as a hard cap at 255 kW and the objective actively maximizes total delivered energy across all vehicles, rather than minimizing the peak with a 60% lower-bound floor. The contrast between the two objectives is reported in Table 14. The service-maximizing LP lifts the 80% SOC completion rate from 9.1% to 69.8% and the mean achieved SOC from 69.1% to 85.0% on the same 60 Monte Carlo trials, but it does so by pushing the mean peak demand from 224.3 kW right up against the 255 kW transformer cap (mean peak 253.2 kW). The trade-off is therefore real and quantifiable: when capacity headroom is treated as an objective to be expanded the user-facing service quality stays poor, and when service quality is treated as the objective the headroom is consumed almost in full. The peak-minimizing objective is retained as the primary configuration of the manuscript because the preventive fire-safety and grid-protection framing motivates leaving headroom in the system, while the service-maximizing variant is reported alongside it so that policy designers can see both edges of the trade-off and choose where on the curve the regulatory floor should sit.

Table 14. Comparison of two LP objectives on the same 60 Monte Carlo seeds at the baseline 30% EV-penetration configuration: the peak-minimizing objective used as the primary configuration of this study, and a service-maximizing variant that enforces the 255 kW transformer capacity as a hard cap and maximizes total delivered energy.

LP Objective	Mean Peak (kW)	Mean Achieved SOC (%)	Completion $\geq$ 80% SOC (%)
Peak-minimizing (primary)	224.3	69.1	9.1
Service-maximizing (255 kW hard cap)	253.2	85.0	69.8

6.2. Broader Implications for Urban Energy Systems

Beyond immediate policy applications, our results illuminate broader dynamics in urban energy system transformation. The finding that smart charging enables accommodation of substantial EV loads within existing infrastructure capacity challenges narratives emphasizing infrastructure deficit as primary barrier to transportation electrification. While infrastructure investment remains necessary in many locations, our analysis demonstrates that intelligent load management can dramatically reduce required investment, shifting focus from capacity expansion to coordination mechanisms.

This finding resonates with emerging research on building-to-grid integration, where thermal storage, flexible appliances, and distributed energy resources contribute to system flexibility. Multi-unit dwellings, housing substantial urban populations and concentrating electricity demand, represent critical nodes in future smart grid architectures. Policy frameworks enabling EV charging coordination establish foundation for broader building energy management encompassing HVAC scheduling, appliance load shifting, and eventual vehicle-to-building bidirectional power flows supporting resilience during grid outages.

The interoperability requirements we propose align with broader digitalization trends in energy systems, where data exchange standards enable market platforms aggregating

distributed flexibility. As EV adoption scales, coordinated charging in MUDs could contribute megawatts of demand response capacity to wholesale electricity markets, generating revenue streams that improve economics beyond our conservative analysis limited to TOU arbitrage. Regulatory frameworks should anticipate this evolution, ensuring MUD residents can participate in emerging flexibility markets rather than remaining passive consumers.

6.3. International Implementation Examples

Translating simulation results into operational policy confronts institutional inertia, stakeholder resistance, and implementation capacity constraints. Building managers—often volunteer homeowner association boards or property management companies with limited technical expertise—may view smart charging requirements as burdensome mandates adding complexity to already challenging EV infrastructure decisions. Successful implementation requires technical assistance programs, template coordination agreements, and turnkey solutions minimizing administrative burden.

Utility engagement represents another critical success factor. Distribution companies traditionally focus on supply reliability rather than demand-side management, lacking organizational structures and performance incentives aligned with smart charging coordination. Regulatory reforms should incorporate smart charging facilitation into utility performance metrics and rate-base investments, creating financial incentives for proactive engagement with building managers. Pilot programs demonstrating operational feasibility and economic benefits can overcome institutional skepticism.

User acceptance ultimately determines smart charging viability. While the simulation demonstrates strong grid-performance outcomes, it also indicates that user-level SOC completion can fall to 8.9% under strict-capacity scheduling. Policy communications should therefore emphasize both the benefits and limits of constrained smart charging, while requiring transparent scheduling algorithms, expected completion-time disclosure, and override capabilities for urgent charging needs to build trust and acceptance.

International experience offers instructive lessons for implementation. California's 2022 CALGreen building standards mandate that 40% of parking spaces in new multifamily housing be EV-capable (pre-wired with electrical capacity), with 10% equipped with installed Level 2 chargers, applying to all new construction effective 1 January 2023 [68]. The United Kingdom's Electric Vehicles (Smart Charge Points) Regulations, effective 30 June 2022, require all new residential and workplace chargers to incorporate smart functionality including remote connectivity, scheduled charging capabilities, default off-peak charging hours (avoiding 8:00–11:00 and 16:00–22:00), and randomized delay functions preventing simultaneous charging events [69]. The Netherlands has implemented comprehensive charging infrastructure mandates through its National Charging Infrastructure Agenda, requiring new non-residential buildings with more than ten parking spaces to pre-wire one-in-five spaces for charging with at least one installed charging point, effective from 2025 [70,71]. In Türkiye, the Charging Service Regulation was amended on 23 March 2026 (Official Gazette No. 33202), introducing explicit concepts such as smart charging systems, roaming, mobile charging stations, and additional pricing/market design provisions. However, the 23 March 2026 amendment still does not establish a dedicated governance model for multi-unit dwellings covering shared-transformer allocation, condominium decision rights, and enforceable building-level service guarantees. This regulatory gap directly supports the continued necessity of the MUD-specific five-pillar policy package proposed in this study. Common success factors across jurisdictions include phased implementation beginning with new installations, technical support for building managers through government guidance documents, clear compliance certification processes streamlining permitting, and regulatory oversight ensuring enforcement without stifling innovation.

6.4. Applicable Scenarios and Scope of the Framework

The findings of this study should be read against the building, infrastructure, and institutional setting for which the framework was designed. The directly applicable case is a medium-density urban multi-unit dwelling of roughly 80–150 dwelling units served by a single low-voltage distribution transformer, with shared underground or courtyard parking and Level 2 chargers retrofitted into existing parking spaces. The institutional layer assumes a recognizable decision-maker—typically a building management board or a homeowners' association acting jointly with the local distribution company and the municipal building-safety authority—able to enforce a coordinated charging schedule and to act on real-time capacity signals. In the Turkish context this corresponds to apartment-dominant districts of large metropolitan areas such as Istanbul, Ankara, Izmir, Bursa, Adana, and Gaziantep, where overnight residential charging is expected to become the dominant charging modality during the 2025–2035 horizon analyzed in this paper.

The same framework transfers, with limited recalibration, to comparable urban contexts elsewhere. Southern European cities with apartment-dominant housing such as Madrid, Athens, Lisbon, and Naples, Middle Eastern metropolitan areas with similar building typologies such as Beirut, Cairo, and Amman, and East Asian high-density residential blocks such as Seoul, Taipei, and Hong Kong share the same building-and-transformer scale of analysis, the same institutional triangle of building management, utility, and regulator, and the same trade-off between strict capacity protection and user service quality. In these contexts only the local load shape, tariff structure, and ownership rules need to be re-fitted; the structure of the five-pillar governance layer and the role of coordinated control as the operational core remain valid.

Several settings, in contrast, fall outside the direct scope and would require recalibration before the present numbers are applied. Low-density single-family neighborhoods do not concentrate load at a shared transformer, and the 30% overload threshold together with the per-unit cost and NPV figures does not transfer. Mixed-use buildings with substantial commercial evening load have a different baseline profile and a different peak-coincidence pattern. Settings in which workplace or curbside charging is dominant shift the temporal location of the constraint and reduce the marginal value of building-level coordination. Older MUDs whose existing transformer is already close to its thermal limit even without EV load fall outside the smart-charging-versus-reinforcement comparison, because reinforcement in such cases is a baseline requirement rather than a genuine alternative. Stating these limits explicitly is intended to make the practical reach of the framework transparent and to discourage extrapolating the headline numbers beyond the conditions for which they were derived.

7. Conclusions

Multi-unit dwellings are where transport electrification is being negotiated at the scale of an actual building, and they are also where four otherwise separate concerns—grid stress, the service quality residents actually experience, lifecycle cost, and fire-risk exposure in enclosed parking—collide on the same shared transformer. The analysis presented in this paper shows that under uncontrolled charging the 30% EV-penetration scenario already breaches that transformer in essentially every configuration we tested (from 80 to 150 dwelling units, transformer ratings from 250 to 500 kVA, and parking-to-unit ratios from 0.6 to 1.0), that an XGBoost-forecast-driven LP coordinator brings the peak from 405 kW down to 224 kW—a 44.7% reduction sustained over 1000 Monte Carlo trials—and that the same coordinator delivers a per-dwelling NPV advantage of roughly \$306 over grid reinforcement under a 3-zamanlı time-of-use tariff and roughly \$157 under the currently dominant tek-zamanlı and kademeli default tariffs, while exposing a service-quality

cost (only 8.9% of users reach 80% SOC by departure under strict capacity protection) that has to be managed rather than hidden. The contribution that matters beyond these numbers is that these four outcomes are governed jointly through a five-pillar institutional architecture—coordinated control, interoperability standards, time-of-use pricing, building–utility coordination, and monitoring and assurance—which turns forecast-driven LP coordination into an accountable decision layer rather than a black-box recommendation, makes the framework directly relevant to fire-safety governance in enclosed residential parking even without modeling flame spread itself, and transfers with limited recalibration to apartment-dominant urban contexts elsewhere. Natural directions for future work are field pilots that close the simulation-to-operation loop, integration with on-site photovoltaic-storage assets and vehicle-to-building services, explicit fire-engineering modeling of the parking environment that the framework only treats at the governance level here, and human-centered studies of compliance, equity and acceptance that complement the technical and economic evidence presented in the paper.

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Data Availability Statement: The simulation code, processed input data, optimization scripts, and analysis utilities supporting the findings of this study are openly available in a dedicated public repository at <https://github.com/drferhatu/ev-mud-smart-charging> (accessed on 1 March 2026). The repository includes the building-level simulation model, the XGBoost demand-forecaster training pipeline, the LP-based coordinated-charging optimizer, the sensitivity sweeps reported in Section 4 (configuration, temporal, arrival-mean, tariff regime, fire-safety surrogate, completion-rate and service-objective sweeps), and the figure-generation scripts. Researchers reusing the code or any derived datasets are kindly asked to cite the present article as the primary source. Additional materials, including extended Monte Carlo result files that are too large for the repository, are available from the corresponding author upon reasonable request.

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