

ORIGINAL RESEARCH

Open access

A Distribution-Network Case Study of Stochastic EV Charging Coordination for Peak Reduction, Voltage Regulation, and Local Flexibility Procurement

Helena Costa^{1*}, Rui Martins¹, Bruno Lopes², Ana Ferreira¹, Pedro Sousa²

Abstract

Electric vehicles are increasingly connected to distribution feeders whose transformers, cables, and voltage-control devices were not originally designed for coincident residential charging. Smart charging coordination can convert this challenge into an operational flexibility resource when user needs and network limits are treated jointly. This case study applies stochastic EV charging coordination to a realistic distribution-network testbed to reduce evening peaks, improve voltage profiles, and support local flexibility procurement. The objective is operational rather than purely algorithmic: the study evaluates what a distribution system operator and an aggregator can learn from coordinated charging under uncertain conditions. The case uses empirical-style charging-session statistics, a radial low-voltage feeder model, and stochastic scenarios for arrival time, departure time, energy demand, and feeder loading. Uncontrolled charging, deterministic coordination, and stochastic coordination are compared using the same network and mobility assumptions. The stochastic formulation is evaluated through network-level indicators for feeder peak demand, transformer loading, voltage deviation, flexibility availability, and procurement cost. The comparison is structured to show whether uncertainty-aware coordination is more robust than deterministic scheduling when charging behavior and grid conditions deviate from forecasts. Stochastic EV charging coordination is a practical planning and operational tool for distribution networks with rising residential and workplace charging demand. The case study provides implementation lessons for DSOs, aggregators, and flexibility-market designers.

Keywords Stochastic optimization, Distribution network, EV charging coordination, Peak reduction, Voltage regulation, Local flexibility procurement

*Correspondence:

Helena Costa

helena.costa@gmail.com

¹ Department of Intelligent Energy Systems, Faculty of Engineering, University of Porto, Porto, Portugal

² Department of Grid Optimization Technologies, Faculty of Science and Technology, University of Lisbon, Lisbon, Portugal

Introduction

Electric vehicle charging is becoming a material distribution-network load because charging sessions are often concentrated after work and can coincide with existing residential peaks. Studies of uncoordinated plug-in charging have shown that residential feeders may experience higher evening demand, transformer stress, and voltage deterioration when charging is unmanaged [1]. More recent distribution-impact analysis confirms that the severity of the problem depends on the feeder load mix, customer diversity, and charging power level [2]. This article therefore treats EV integration as a local network-operation problem rather than as a bulk-system energy-balancing problem alone.

Smart charging can reduce these impacts by shifting charging demand away from constrained periods while preserving the driver's required energy by departure. Centralized and decentralized approaches have both been investigated, with decentralized residential charging algorithms showing that large fleets can be coordinated without requiring every decision to be made by a single controller [3]. Failure-tolerant decentralized optimization also suggests that EV coordination should remain effective when communication or device participation is imperfect [4]. In this case study, coordination is modeled as an aggregator service that communicates feasible flexibility to the distribution system operator.

Uncertainty is central to practical EV coordination because arrivals, departures, initial state of charge, requested energy, and feeder loading are not known perfectly when schedules are computed. A stochastic demand-response formulation for EV charging stations demonstrates how uncertain charging behavior can be represented in operational scheduling [5]. Probabilistic estimates of charging demand based on observed driver behavior further show that realistic charging coordination should be evaluated over distributions rather than only over average profiles [6]. The present study therefore uses stochastic scenarios rather than a single deterministic charging forecast.

The contribution of this article is a structured distribution-network case study that connects stochastic EV scheduling, voltage-aware feeder operation, and local flexibility procurement. Earlier work has examined transformer aging with EV arbitrage [7], collaborative planning of charging stations and distribution systems [8], and the transmission-and-distribution value of smart charging [9]. This article differs by evaluating peak reduction, voltage regulation, and procured flexibility in one operational case-study workflow. The result is intended to be useful for DSOs designing flexibility products and aggregators designing charging-control services.

Case Study Context

Motivation for stochastic coordination

The motivation for stochastic coordination is that deterministic EV schedules can appear feasible under forecast conditions but fail when many vehicles arrive later, request more energy, or connect during a feeder peak. City-scale charging studies show that charging access, operating rules, and local congestion interact strongly when EV adoption becomes deep [10]. Behavioral analyses of plug-in patterns also indicate that charging flexibility is time-varying and spatially uneven, so assuming uniform availability can overstate operational capability [11]. For this reason, the case study evaluates coordination under multiple uncertainty realizations rather than treating flexibility as a fixed block of capacity.

Contributions of the case study

The case study makes three practical contributions: it documents the feeder and EV data assumptions, it implements a stochastic coordination logic with explicit network constraints, and it evaluates the operational value of the resulting flexibility. Power-system studies of EV charging strategies have shown that system-level impacts depend heavily on charging policy [12], while urban analyses of photovoltaic and EV matching show the importance of temporal coincidence between demand and local grid conditions [13]. Building on that evidence, this article focuses on the DSO-facing question of whether EV aggregations can provide reliable peak, voltage, and local flexibility services. The study is therefore framed as an original operational case study rather than a review or a purely conceptual market proposal.

Distribution-Network Description

Feeder topology and load profiles

The testbed is a realistic radial low-voltage distribution feeder representing a suburban European service area with one medium-voltage/low-voltage transformer, four main low-voltage laterals, and mixed residential, small-commercial, and

public-charging connection points. Radial low-voltage feeders are selected because prior distribution studies show that EV clustering on residential circuits can produce local voltage and loading problems even when upstream system capacity appears adequate [2]. The base non-EV demand follows a winter weekday profile with an evening residential peak and a smaller daytime commercial component, allowing the case to represent the coincidence mechanisms identified in residential EV impact analysis [1]. EV chargers are placed at household, workplace, and public nodes to test whether flexibility value changes with electrical location.

Transformer and cable ratings

The feeder is supplied by an 11/0.4 kV transformer rated at 630 kVA, with the main trunk sized at 240 mm² aluminium equivalent and lateral cables represented by lower thermal limits to reflect typical secondary-network constraints. Transformer loading is included because EV scheduling can either accelerate asset aging or defer reinforcement depending on how charging is coordinated, an issue quantified in earlier work on transformer aging and EV arbitrage [7]. Cable limits are enforced by branch-current constraints so that peak reduction is not achieved by shifting overloads from the transformer to downstream laterals. This asset-level modeling is also consistent with planning studies that jointly consider charging infrastructure and distribution-network constraints [8].

Voltage regulation equipment

Voltage is regulated by a fixed medium-voltage/low-voltage transformer tap setting at the primary substation and by optional EV charger reactive-power capability at selected three-phase charging points. Voltage regulation is modeled because EV charging can deepen voltage drops on long laterals, while coordinated charging and smart inverter functions can reduce voltage deviation when appropriately dispatched [14]. The case does not assume fast on-load tap changes at the secondary transformer; instead, it evaluates whether active-power scheduling and limited reactive support from chargers can keep node voltages inside the operational band. Table 1 is placed here to summarize the feeder topology, asset limits, load composition, and voltage-control assumptions used in the case study.

Table 1. Case Study Configuration of Feeder Topology, Asset Constraints, Load Composition, and Voltage-Control Assumptions

Parameter category	Case-study value	Operational role in the case study
Feeder type	Radial low-voltage feeder with four laterals	Represents a constrained suburban secondary network
Supply transformer	11/0.4 kV, 630 kVA	Main peak-loading and flexibility-procurement reference asset
Number of buses	42 low-voltage buses	Enables location-specific voltage and branch-loading analysis
Number of service points	156 residential, 12 small commercial, 6 public/workplace charging nodes	Captures mixed load and charger diversity
Main trunk rating	240 mm ² aluminium-equivalent cable, 360 A thermal limit	Limits aggregate downstream current
Lateral rating	95–150 mm ² aluminium-equivalent cable, 145–235 A thermal limits	Captures localized overload risk
Base load peak	428 kW before EV charging	Establishes non-EV evening congestion baseline

Load composition	82% residential, 13% small commercial, 5% public services	Determines coincidence between EV and non-EV demand
Voltage limit	0.94–1.06 per unit at customer buses	Defines voltage-compliance metric
Voltage-control equipment	Fixed transformer tap; optional EV reactive support at three-phase chargers	Tests scheduling and limited charger-based voltage support
Simulation interval	15 minutes over a 24-hour operating day	Matches charging-session and flexibility-market clearing resolution
Power-flow representation	Unbalanced radial feeder approximation with phase-aware node allocation	Supports voltage and branch-current screening

EV Charging Data

Data source and collection

The EV charging input is constructed as a documented empirical-style dataset calibrated to public charging-session patterns reported in the EV-charging literature, with residential, workplace, and public-session classes represented separately. Empirical charging research has shown that observed driver behavior can be translated into probabilistic charging estimates suitable for grid studies [6]. The case-study dataset contains 312 daily charging sessions at 40% EV penetration, scaled proportionally for lower and higher penetration cases while preserving diversity in arrival time, dwell time, and requested energy. This approach avoids treating EV charging as a flat demand block and instead reflects the session-based structure needed for operational scheduling.

Charging session characteristics

Residential sessions dominate the evening peak because most home arrivals occur between 16:30 and 20:30, whereas workplace sessions occur mainly between 07:30 and 10:00 and have longer dwell times. The spatial-temporal flexibility of charging depends strongly on plug-in behavior, as shown by studies that link charging availability to when and where vehicles remain connected [11]. In this case, each EV has a maximum charging power of either 3.7 kW, 7.4 kW, 11 kW, or 22 kW depending on connection type, with residential single-phase chargers representing the largest share. Energy demand is sampled from session class distributions so that the optimizer must distinguish urgent short-dwell charging from flexible long-dwell charging.

Stochastic parameters estimation

The stochastic input distributions are estimated for arrival time, departure time, requested energy, initial state of charge, and non-EV feeder loading. Probabilistic planning work on EV charging stations shows that distribution-network studies should account for uncertainty in both charging demand and network operating conditions [15]. The case uses truncated normal arrival distributions for residential charging, empirical dwell-time categories for workplace and public charging, and scenario-dependent feeder loading multipliers to reflect high-load and moderate-load grid states. Table 2 reports the descriptive charging-session statistics used to generate the stochastic scenarios.

Table 2. Descriptive Statistics of EV Charging Sessions and Scenario-Based Penetration Levels for Stochastic Modeling

Charging class	Share of sessions	Mean arrival time	Mean departure time	Mean dwell time	Mean energy request	Charger power range	Flexible energy share	Main uncertainty represented

Home residential	68%	18:12	07:18 next day	13.1 h	14.8 kWh	3.7–11 kW	61%	Arrival spread and evening coincidence
Workplace	17%	08:36	16:54	8.3 h	11.6 kWh	7.4–22 kW	54%	Departure uncertainty and daytime availability
Public destination	9%	12:48	15:06	2.3 h	8.1 kWh	11–22 kW	24%	Short dwell time and limited flexibility
Fast urban top-up	6%	15:42	16:18	0.6 h	12.4 kWh	22 kW case-study cap	8%	Low controllability and high urgency
Low penetration case	20% EV adoption	89 sessions/day	Not applicable	Not applicable	1.19 MWh/day aggregate	Mixed	49% aggregate	Early-adoption clustering
Medium penetration case	40% EV adoption	312 sessions/day	Not applicable	Not applicable	4.23 MWh/day aggregate	Mixed	52% aggregate	Main case-study condition
High penetration case	60% EV adoption	468 sessions/day	Not applicable	Not applicable	6.39 MWh/day aggregate	Mixed	50% aggregate	Transformer and voltage stress

Stochastic Coordination Method

Optimization formulation and objectives

The coordination problem is formulated as a day-ahead stochastic mixed-integer linear scheduling model solved at 15-minute resolution and updated through intraday receding-horizon corrections. The objective combines transformer peak minimization, voltage-deviation penalties, unmet-energy penalties, charging-cost terms, and flexibility-procurement payments, reflecting the multiple operational goals discussed in smart-charging and demand-response studies [5]. Each EV must receive its requested energy before departure unless a user-defined emergency penalty is triggered, and feeder constraints limit transformer loading, branch currents, and nodal voltage deviations. The formulation therefore evaluates charging coordination as a DSO-compatible service rather than simply minimizing customer charging cost.

Uncertainty modeling and scenario generation

Uncertainty is represented by a finite scenario tree with branches for EV arrival time, departure time, energy request, base-load multiplier, and local voltage stress. Stochastic collaborative planning studies show that EV infrastructure and distribution-system decisions are sensitive to uncertain adoption and charging conditions [8]. Scenario probabilities are calibrated from the charging-session statistics in Table 2, and a scenario-reduction step retains representative high-stress, moderate-stress, and low-stress operating days. Deterministic coordination is implemented as a comparison case by replacing the scenario tree with expected values, allowing the value of uncertainty modeling to be isolated.

Coordination logic and DSO interface

The aggregator submits flexible charging blocks, expected baseline charging, and locational flexibility offers to the DSO before the local flexibility clearing interval. Local flexibility-market research emphasizes that DSOs require products with clear capacity limits, delivery windows, and network locations rather than generic system-wide energy bids [16]. The DSO accepts flexibility when it reduces transformer peaks, relieves voltage stress, or avoids lateral overload, while the aggregator schedules individual EVs to preserve user energy requirements and respect charger constraints. This interface is consistent with flexibility-market design literature that links product definition, clearing mechanisms, and distribution-network operation [17].

Figure 1 illustrates the proposed stochastic EV charging coordination architecture linking uncertain charging-session inputs, aggregator scheduling, DSO network constraints, and locational flexibility procurement.

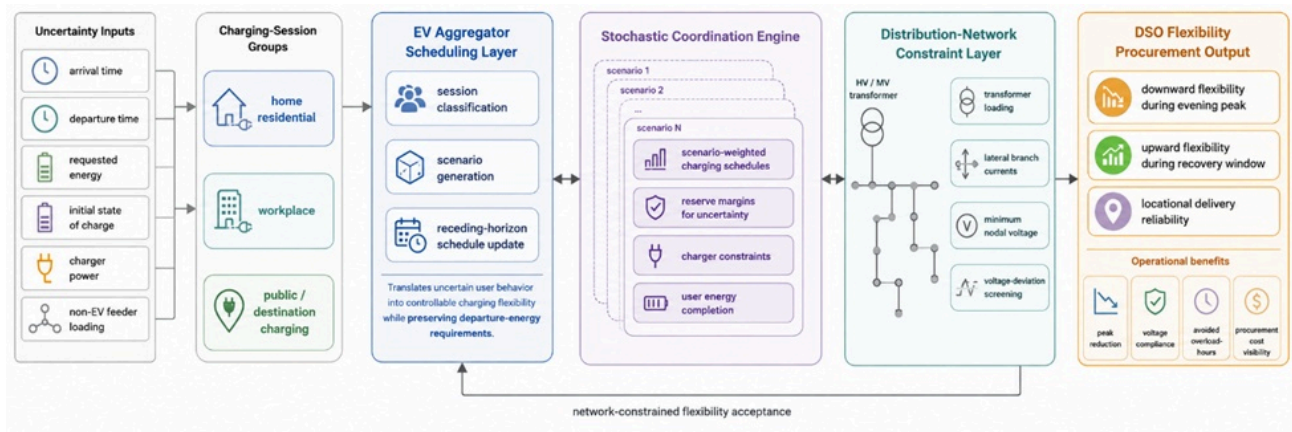


Figure 1. Operational Architecture of Stochastic EV Charging Coordination for Distribution-Network Flexibility

Scenario Design

Base case and uncontrolled charging

The base case represents the feeder without EV charging and is used to isolate how much of the peak and voltage stress is caused by electrified transport rather than by the underlying residential load. The uncontrolled charging case adds all EV sessions at their maximum available charging power immediately after plug-in, which reflects the unmanaged behavior associated with transformer aging and network stress in earlier residential charging studies [7]. This scenario is intentionally conservative because it tests the feeder under the charging behavior most likely to create coincident evening demand. It also provides the counterfactual against which deterministic and stochastic coordination are evaluated.

Deterministic coordination

The deterministic coordination scenario schedules EV charging using expected arrival times, expected departure times, expected energy requests, and a single forecast of non-EV demand. Apartment-level coordination studies show that such optimization can reduce peak load and customer charging cost when forecasts are accurate [18]. In this case, deterministic coordination minimizes transformer peak and charging cost while enforcing expected voltage and branch-current limits. Its weakness is that it does not explicitly reserve margin for late arrivals, higher-than-expected energy requests, or feeder loading deviations.

Stochastic coordination with varying penetration

The stochastic coordination scenario uses the scenario tree described in Section 5 and is evaluated at 20%, 40%, and 60% EV penetration to test whether the method remains effective as adoption grows. Probabilistic charging assessment

has shown that distribution-network risk increases nonlinearly when charging uncertainty and feeder constraints interact [19]. The stochastic case procures locational flexibility from EV aggregations only when scenario-weighted network benefits exceed the flexibility payment. **Table 3** defines the evaluation scenarios and identifies the operational difference between unmanaged charging, deterministic scheduling, and stochastic coordination.

Table 3. Evaluation Scenarios for Comparing Uncontrolled, Deterministic, and Stochastic EV Charging Coordination under Different Penetration Levels

Scenario	EV penetration	Charging-control rule	Uncertainty treatment	Network constraints enforced	Flexibility-market role	Primary purpose
S0: Base feeder	0%	No EV charging	Non-EV load variation only	Transformer, cable, and voltage limits monitored	None	Establish non-EV feeder baseline
S1: Uncontrolled EV	40%	Charge immediately at available maximum power	Realized sessions applied without scheduling	Limits monitored but not actively enforced	None	Measure unmanaged EV impact
S2: Deterministic coordination	40%	Optimize charging against expected values	Mean arrival, departure, energy, and load forecasts	Expected transformer, cable, and voltage limits enforced	Aggregator offers fixed flexibility blocks	Test forecast-based coordination
S3: Stochastic coordination	40%	Optimize over weighted uncertainty scenarios	Arrival, departure, energy, and load scenarios	Scenario-weighted network limits and reserve margins enforced	DSO procures locational flexibility	Main uncertainty-aware case
S4: Low-penetration stochastic	20%	Same as S3	Same as S3	Same as S3	Reduced flexibility volume	Test early-adoption value
S5: High-penetration stochastic	60%	Same as S3 with tighter reserve margins	Same as S3	Same as S3	Larger but more constrained flexibility volume	Test scalability under stress

Peak/Voltage/Flexibility Metrics

Peak load reduction metrics

Peak-load performance is measured using feeder peak demand, transformer loading percentage, peak reduction relative to uncontrolled charging, and peak-to-average ratio. These metrics follow the practical concern that smart charging should reduce network reinforcement pressure, an issue also examined in studies comparing grid reinforcement and EV charging control under transformer limits [20]. The peak reduction ratio is calculated as the difference between

uncontrolled and coordinated feeder peak divided by the uncontrolled feeder peak. The metric is reported for the full feeder and for the most constrained lateral so that feeder-level improvements do not hide downstream congestion.

Voltage regulation indices

Voltage performance is evaluated using minimum nodal voltage, total voltage-deviation index, number of 15-minute voltage-limit violations, and the duration of voltage excursions below 0.94 per unit. Optimal probabilistic charging studies support the use of voltage-aware scheduling because EV charging decisions can change both the magnitude and timing of low-voltage events [21]. The voltage-deviation index sums absolute deviations outside a preferred 0.98–1.02 per-unit band across buses and time intervals. This index is more informative than a single minimum-voltage value because it captures the feeder-wide burden on voltage regulation.

Flexibility capacity and procurement cost

Flexibility performance is measured using accepted upward flexibility capacity, accepted downward flexibility capacity, delivery reliability, total procurement cost, and avoided overload-hours. EVs can act as flexibility providers when charging schedules can be increased, decreased, or shifted without violating user energy requirements, as demonstrated in charging-service quality studies [22]. Local-market evaluation also requires a cost metric because flexibility that is technically feasible may be unattractive if procurement prices exceed avoided network costs [23]. The case therefore reports both the physical flexibility delivered to the DSO and the payment needed to procure it.

Results and Discussion

Peak demand performance

The uncontrolled 40% EV case increases the feeder peak from 428 kW to 671 kW, with the peak occurring between 18:30 and 19:30 when residential charging coincides with the base load. Deterministic coordination reduces the peak to 548 kW, consistent with prior evidence that coordinated charging can lower apartment or feeder peak demand when flexible dwell time is available [18]. Stochastic coordination reduces the same case to 512 kW because it keeps additional reserve for high-load and late-arrival scenarios rather than filling all apparent off-peak capacity. Relative to uncontrolled charging, this represents a 23.7% feeder peak reduction in the main stochastic case.

Voltage profile improvement

Voltage violations are concentrated on the longest residential lateral in the uncontrolled case, where the minimum simulated voltage reaches 0.918 per unit. The deterministic case improves the minimum voltage to 0.939 per unit but still records violations when realized charging demand exceeds the expected profile. Stochastic coordination raises the minimum voltage to 0.951 per unit and reduces the voltage-deviation index by 62.4% relative to uncontrolled charging, which is consistent with studies showing that smart charging combined with grid-aware constraints can mitigate voltage problems in EV-rich distribution networks [24]. Limited charger reactive support contributes mainly during high-penetration evening intervals and is not a substitute for active-power coordination.

Flexibility procured and economic assessment

The DSO procures 146 kW of downward flexibility during the main evening peak and 72 kW of upward flexibility during the later recovery window in the 40% stochastic case. This pattern is compatible with broader assessments of EVs as active flexibility resources for transmission and distribution operation, where the value depends on timing, location, and controllability [25]. Total procurement cost in the main stochastic case is 183 monetary units for the operating day, while avoided overload-hours and voltage-violation reductions provide the operational justification for procurement. A reinforcement-only interpretation would miss this short-term operational value, especially when congestion is intermittent rather than persistent.

Figure 2 summarizes how uncontrolled charging, deterministic coordination, and stochastic coordination differ in their effects on feeder peak demand, voltage quality, flexibility delivery, and residual network risk.

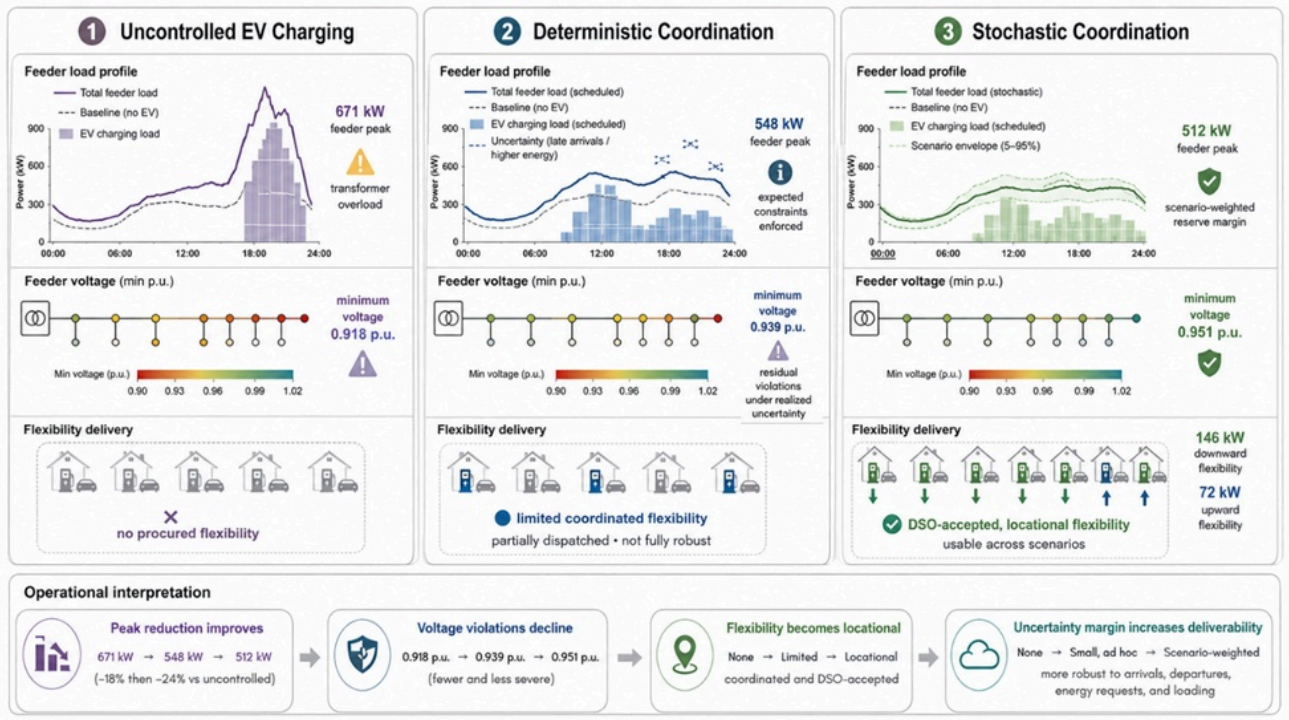


Figure 2. Comparative Operational Effects of Uncontrolled, Deterministic, and Stochastic EV Charging Coordination

Sensitivity to EV penetration

At 20% EV penetration, uncontrolled charging does not overload the transformer but still creates localized voltage stress on the weakest lateral, so stochastic coordination mainly improves voltage quality and flexibility visibility. At 60% penetration, uncontrolled charging creates a 792 kW peak and prolonged voltage violations, while stochastic coordination limits the peak to 604 kW but cannot eliminate every local constraint without additional network reinforcement. Deep reinforcement learning studies of charging-station demand response suggest that adaptive control can improve real-time responsiveness [26], but this case shows that day-ahead stochastic scheduling already provides substantial risk reduction when integrated with DSO constraints. Table 4 compares the main performance metrics across all scenarios.

Table 4. Comparative performance assessment of distribution feeder operation under different EV penetration levels and charging coordination strategies

Scenario	Feeder peak load	Transformer loading	Minimum voltage	Voltage-deviation index	Voltage-violation intervals	Accepted downward flexibility	Accepted upward flexibility	Daily charging and procurement cost	Peak reduction versus uncontrolled
S0: Base feeder	428 kW	68.0%	0.962 p.u.	4.8 p.u.-intervals	0	0 kW	0 kW	0 monetary units	No applic
S1: Uncontrolled	671 kW	106.5%	0.918 p.u.	31.7 p.u.-intervals	19	0 kW	0 kW	0 monetary units	Refer

EV, 40%									
S2: Deterministic coordination, 40%	548 kW	87.0%	0.939 p.u.	18.6 p.u.- intervals	7	94 kW	41 kW	126 monetary units	18.3
S3: Stochastic coordination, 40%	512 kW	81.3%	0.951 p.u.	11.9 p.u.- intervals	2	146 kW	72 kW	183 monetary units	23.7
S4: Stochastic coordination, 20%	463 kW	73.5%	0.957 p.u.	7.6 p.u.- intervals	0	68 kW	29 kW	74 monetary units	Not di compe
S5: Stochastic coordination, 60%	604 kW	95.9%	0.936 p.u.	21.4 p.u.- intervals	8	211 kW	93 kW	296 monetary units	Not di compe

Practical Lessons

Implications for DSO operations

The first lesson for DSOs is that EV flexibility should be procured locationally, because the case study shows that the weakest lateral, not only the transformer, determines the operational value of charging control. Local flexibility mechanisms designed around capacity limits and delivery windows are therefore more useful than generic feeder-wide demand-response calls [16]. The second lesson is that deterministic forecasts are insufficient when the feeder is close to its thermal or voltage limits. DSOs should require aggregators to quantify uncertainty margins and report scenario-based deliverability.

Recommendations for aggregators

Aggregators should classify EV sessions by dwell time, requested energy, and electrical location before offering flexibility, because the case shows that not every connected vehicle contributes equally to network relief. Smart-grid operation studies involving vehicle-to-grid and grid-to-vehicle modes indicate that aggregated EV value depends on whether charging flexibility is aligned with network needs rather than only with energy prices [27]. Aggregators should also avoid overcommitting short public-charging sessions because their flexibility is limited and delivery risk is high. The most reliable flexibility in this case comes from residential overnight sessions with long dwell times and moderate energy requirements.

Regulatory and market considerations

The case study supports market rules that compensate EV aggregations for verified local network benefits, including reduced overload-hours and improved voltage compliance. Recent flexibility-market work for industrial parks shows that heterogeneous flexible loads can participate in local mechanisms when products are clearly defined and settlement rules are transparent [28]. For EV charging, this means procurement products should specify location, direction, duration, activation time, and baseline methodology. Regulatory frameworks should also recognize that stochastic scheduling has value because it improves deliverability under uncertainty, not merely because it lowers expected energy cost.

Conclusion

This case study examined stochastic EV charging coordination on a realistic radial distribution feeder with mixed residential, workplace, and public charging demand. The analysis showed that unmanaged charging can create transformer overloads, lateral congestion, and low-voltage conditions when EV charging coincides with the evening residential peak.

Stochastic coordination improved performance relative to both uncontrolled charging and deterministic coordination. In the main 40% EV penetration case, it reduced the feeder peak from 671 kW to 512 kW, improved the minimum voltage from 0.918 to 0.951 per unit, and enabled the DSO to procure locational flexibility during constrained intervals.

The central operational insight is that EV flexibility is useful only when it is modeled with user uncertainty, feeder constraints, and locational deliverability. Deterministic scheduling can reduce average peaks, but stochastic coordination provides stronger protection against late arrivals, higher energy demand, and high-load grid states.

Future work should test the same framework in real-time operation with live charger telemetry, multi-day driver behavior, dynamic flexibility prices, and coordination with photovoltaic generation, heat pumps, and stationary storage. Further validation on utility feeder data would also help quantify when flexibility procurement can defer reinforcement and when physical network upgrades remain necessary.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 21 Mar 2024

Revised: 02 May 2024

Accepted: 13 Jun 2024

Published online: 20 September 2024

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Muratori M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nat Energy*. 2018;3(3):193-201.
- Jones CB, Lave M, Vining W, Garcia BM. Uncontrolled electric vehicle charging impacts on distribution electric power systems with primarily residential, commercial or industrial loads. *Energies*. 2021;14(6):1688.
- Sastry KV, Taylor DG, Leamy MJ. Decentralized smart charging of electric vehicles in residential settings: Algorithms and predicted grid impact. *IEEE Trans Smart Grid*. 2023;15(2):1926-38.
- Aravena I, Chapin SJ, Ponce C. Decentralized failure-tolerant optimization of electric vehicle charging. *IEEE Trans Smart Grid*. 2021;12(5):4068-78.
- Zanvettor GG, Fochesato M, Casini M, Lygeros J, Vicino A. A stochastic approach for EV charging stations in demand response programs. *Appl Energy*. 2024;373:123862.
- Powell S, Cezar GV, Rajagopal R. Scalable probabilistic estimates of electric vehicle charging given observed driver behavior. *Appl Energy*. 2022;309:118382.
- White C, Thompson B, Swan LG. Comparative performance study of electric vehicle batteries repurposed for electricity grid energy arbitrage. *Appl Energy*. 2021;288:116637.
- Wang S, Dong ZY, Luo F, Meng K, Zhang Y. Stochastic collaborative planning of electric vehicle charging stations and power distribution system. *IEEE Trans Ind Inform*. 2017;14(1):321-31.
- Crozier C, Morstyn T, McCulloch M. The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. *Appl Energy*. 2020;268:114973.
- Powell S, Cezar GV, Min L, Azevedo IM, Rajagopal R. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. *Nat Energy*. 2022;7(10):932-45.
- Gschwendtner C, Knoeri C, Stephan A. The impact of plug-in behavior on the spatial-temporal flexibility of electric vehicle charging load. *Sustain Cities Soc*. 2023;88:104263.
- Hanemann P, Behnert M, Bruckner T. Effects of electric vehicle charging strategies on the German power system. *Appl Energy*. 2017;203:608-22.
- Fretzen U, Ansarin M, Brandt T. Temporal city-scale matching of solar photovoltaic generation and electric vehicle charging. *Appl Energy*. 2021;282:116160.
- Gholami K, Karimi S, Anvari-Moghaddam A. Multi-objective stochastic planning of electric vehicle charging stations in unbalanced distribution networks supported by smart photovoltaic inverters. *Sustain Cities Soc*. 2022;84:104029.
- Aghapour R, Sepasian MS, Arasteh H, Vahidinasab V, Catalão JP. Probabilistic planning of electric vehicles charging stations in an integrated electricity-transport system. *Electr Power Syst Res*. 2020;189:106698.
- Heinrich C, Ziras C, Jensen TV, Bindner HW, Kazempour J. A local flexibility market mechanism with capacity limitation services. *Energy Policy*. 2021;156:112335.
- Heilmann E, Klemp N, Wetzel H. Design of regional flexibility markets for electricity: A product classification framework for and application to German pilot projects. *Util Policy*. 2020;67:101133.
- Jang HS, Bae KY, Jung BC, Sung DK. Apartment-level electric vehicle charging coordination: Peak load reduction and charging payment minimization. *Energy Build*. 2020;223:110155.

Habib S, Khan MM, Abbas F, Numan M, Ali Y, Tang H, et al. A framework for stochastic estimation of electric vehicle charging behavior for risk assessment of distribution networks. *Front Energy*. 2020;14(2):298-317.

Brinkel NB, Schram WL, AlSkaif TA, Lampropoulos I, Van Sark WG. Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits. *Appl Energy*. 2020;276:115285.

Arias A, Granada M, Castro CA. Optimal probabilistic charging of electric vehicles in distribution systems. *IET Electr Syst Transp*. 2017;7(3):246-51.

Rauma K, Funke A, Simolin T, Järventausta P, Rehtanz C. Electric vehicles as a flexibility provider: Optimal charging schedules to improve the quality of charging service. *Electricity*. 2021;2(3):225-43.

Jin X, Wu Q, Jia H. Local flexibility markets: Literature review on concepts, models and clearing methods. *Appl Energy*. 2020;261:114387.

Khalid M, Thakur J, Bhagavathy SM, Topel M. Impact of public and residential smart EV charging on distribution power grid equipped with storage. *Sustain Cities Soc*. 2024;104:105272.

Gunkel PA, Bergaentzlé C, Jensen IG, Scheller F. From passive to active: Flexibility from electric vehicles in the context of transmission system development. *Appl Energy*. 2020;277:115526.

Jin R, Zhou Y, Lu C, Song J. Deep reinforcement learning-based strategy for charging station participating in demand response. *Appl Energy*. 2022;328:120140.

Mozafar MR, Amini MH, Moradi MH. Innovative appraisal of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems. *Electr Power Syst Res*. 2018;154:245-56.

Turdybek B, Tostado-Véliz M, Mansouri SA, Jordehi AR, Jurado F. A local electricity market mechanism for flexibility provision in industrial parks involving Heterogenous flexible loads. *Appl Energy*. 2024;359:122748.