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A Grid-Edge Intelligence Architecture for Distributed EV Charging Control Using Local Forecasting, Federated Updates, and Resilience-Aware Coordination

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Abstract

Electric vehicle charging imposes new operational stress on distribution grids, especially where local transformer capacity and feeder voltage margins are limited. Grid-edge intelligence could enable charging decisions to be made closer to the physical constraints that shape those impacts. Existing EV charging control architectures often depend on centralized optimization, cloud-side visibility, or stable communication paths. Such designs can create privacy, latency, and resilience gaps when local operating conditions change rapidly. This article proposes a layered grid-edge intelligence architecture for distributed EV charging control. The architecture integrates local forecasting, federated model updates, and resilience-aware coordination into a unified system design. The architecture is developed conceptually through functional layers, interfaces, data flows, and operational workflows. Implementation scenarios and validation stages are outlined to guide future simulation, hardware-in-the-loop testing, and field deployment. The proposed architecture defines local forecasting nodes, a federated update layer, and resilience coordination functions that interact through structured protocols. Five tables are specified across the full manuscript to summarize model roles, coordination strategies, resilience mechanisms, deployment scenarios, and validation procedures. The architecture offers a blueprint for grid-edge EV charging management that balances intelligence, privacy, and resilience. It is intended to support future practical implementation rather than report experimental results.

Keywords Federated learning, Grid-edge intelligence, EV charging control, Local forecasting, Resilience coordination

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Introduction

Electric vehicle charging introduces controllable but highly variable demand into distribution networks, and smart charging has therefore become a critical function for managing local grid constraints. Safe reinforcement learning for constrained charging illustrates how charging decisions can be shaped by operational limits rather than energy demand alone [1]. Fleet-level smart charging research further shows that charging behavior can be coordinated to reduce stress on local infrastructure while preserving mobility needs [2]. This article treats EV charging not only as an optimization problem, but as an architectural problem requiring distributed intelligence at the grid edge.

A grid-edge intelligence architecture would place forecasting, control, communication, and resilience functions near transformers, feeders, or community energy nodes rather than concentrating all intelligence in a remote platform. Hierarchical EV charging station operation has already demonstrated the value of layered control structures that connect

local charging actions with broader grid objectives [3]. Reviews of smart charging strategies emphasize that practical deployment must integrate control algorithms, communication technologies, and operational constraints rather than treat them separately [4]. The proposed architecture builds on that insight by defining interoperable layers for local forecasting, federated learning, and resilience coordination.

Local forecasting is essential because charging demand varies by user behavior, location, time of day, electricity price, and feeder context. Forecasting studies for EV charging stations show that probabilistic and hierarchical methods can support local planning where uncertainty is unavoidable [5]. Spatial-temporal EV load prediction further suggests that charging behavior and grid topology should be jointly considered when designing local decision systems [6]. In the architecture proposed here, each grid-edge node would maintain a local forecast of EV demand and flexibility that directly informs charging control.

Federated learning is relevant because EV charging data can be sensitive, locally fragmented, and difficult to centralize without privacy and communication burdens. Federated short-term load forecasting has shown how residential load models can be improved without exposing raw customer-level measurements [7]. Federated approaches for smart-grid consumer characterization similarly indicate that distributed learning can support system-wide intelligence while limiting raw-data exchange [8]. This article contributes an original system architecture that combines those learning principles with resilience-aware EV charging coordination at the grid edge.

EV Charging Control Problem

Grid impact of uncoordinated charging

Uncoordinated EV charging can concentrate demand during evening peaks, overload distribution transformers, and aggravate voltage deviations on feeders with limited hosting capacity. Reviews of smart charging highlight that uncontrolled charging may undermine the operational flexibility that EVs could otherwise provide to power systems [4]. EV charging station planning studies also show that infrastructure placement and charging behavior must be considered together because local grid impacts are spatially uneven [9]. A grid-edge controller should therefore be designed to translate local measurements and forecasts into charging limits, deferral decisions, or flexibility requests.

Requirements for distributed control

Distributed EV charging control must respond to local constraints while maintaining compatibility with feeder-level and system-level objectives. Online charging control based on multi-agent learning illustrates how distributed charging agents could react to local states without requiring a single centralized decision point [10]. Distribution-grid-constrained scheduling research further emphasizes that charging operations should respect network constraints rather than optimize station performance in isolation [11]. The architecture proposed here therefore assigns each grid-edge node responsibility for local feasibility while allowing higher-level coordination through federated updates and resilience signals.

Role of forecasting and learning

Forecasting and learning are central because EV load is behavior-driven, temporally clustered, and sensitive to location-specific travel and charging patterns. Transformer-based and deep learning approaches for EV charging demand prediction show that model selection can affect how well short-term charging needs are anticipated [12]. Comparative forecasting across spatial levels also indicates that prediction tasks differ when applied to stations, neighborhoods, feeders, or broader zones [13]. A grid-edge architecture should therefore support local model adaptation while using federated exchange to improve generalization across many nodes.

Architecture Requirements

Functional requirements

The architecture requires functions for data acquisition, local preprocessing, short-term forecasting, charging decision support, model update generation, federated aggregation, resilience monitoring, and operator supervision. EV load forecasting for centralized charging stations demonstrates that predictive information can guide operational planning when linked to charging decisions [14]. Smart charging with photovoltaic generation and local consumption further shows that charging control should account for nearby distributed energy resources and household or feeder demand patterns [15]. These requirements imply that the architecture should expose clear interfaces between sensors, forecasts, controllers, learning services, and resilience logic.

Non-functional requirements: latency, privacy, resilience

The architecture should satisfy latency, privacy, and resilience requirements because charging decisions are time-sensitive, user data can be sensitive, and communications may degrade during grid stress. Edge-cloud federated learning for smart grids shows how local computation and remote aggregation could reduce raw-data exposure while supporting collaborative learning [16]. Secure federated deep learning for false-data-injection detection further illustrates that privacy and cybersecurity concerns must be considered together in smart-grid intelligence systems [17]. For EV charging control, this means that raw charging sessions, user schedules, and local measurements should remain at the edge whenever possible.

Design principles

The design should follow modularity, local autonomy, graceful degradation, interoperability, and explainable operator oversight. A hierarchical local electricity market for a DER-rich grid edge illustrates how local coordination structures can connect distributed assets with broader grid objectives [18]. Edge-computing surveys for IoT-enabled smart grids also emphasize that distributed intelligence depends on modular sensing, communication, computation, and control resources [19]. In the proposed architecture, each layer should be independently deployable while still participating in a shared workflow for forecasting, federated updating, and resilience response.

Figure 1 presents the proposed layered grid-edge intelligence architecture, showing how local EV charging data, feeder measurements, edge forecasting, federated model exchange, resilience coordination, and operator oversight interact to support distributed charging control.

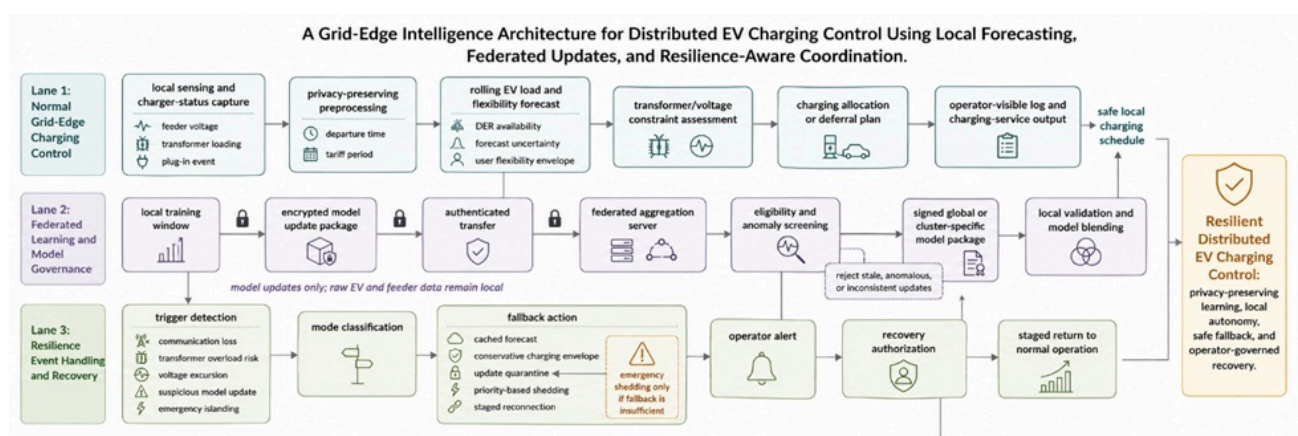


Figure 1. Grid-Edge Intelligence Architecture for Privacy-Preserving and Resilient Distributed EV Charging Control

Local Forecasting Layer

Data inputs and preprocessing

The local forecasting layer would collect transformer loading, feeder voltage, charging-session status, plug-in events, historical EV demand, weather signals, tariff information, and available distributed energy resource data. Statistical characterization of real EV charging transactions shows that charging data contain temporal patterns that should be cleaned, aligned, and contextualized before operational use [20]. Spatial-temporal prediction research further indicates that charging behavior should be linked with local grid context rather than treated as an isolated customer-data stream [6]. The preprocessing block should therefore perform timestamp alignment, anomaly screening, missing-data handling, feature extraction, and privacy-preserving aggregation at the node.

Forecasting models for EV load and flexibility

The layer could host multiple forecasting models, including baseline statistical predictors, machine learning models, deep temporal models, and hybrid models for uncertainty-aware forecasting. Ensemble hierarchical EV load forecasting demonstrates that probabilistic forecasts can support operational decisions when charging demand is uncertain [5]. Short-term EV load forecasting comparisons also suggest that time-series, machine learning, and deep learning methods can serve different operational contexts depending on data availability and computational capacity [21]. The architecture should therefore support model plurality, allowing each grid-edge node to select or receive a model suited to its feeder type.

Real-time update cycle

The real-time update cycle would refresh local forecasts whenever new charging sessions begin, local grid states change, or scheduled control intervals are reached. EV charging demand prediction based on human decision-making behavior indicates that forecasts should adapt to behavioral dynamics rather than rely only on fixed load curves [22]. Prediction models using deep temporal architectures also support the idea that recent charging sequences can refine near-term demand expectations [12]. In the proposed architecture, the local controller would consume these rolling forecasts to update charging limits, flexibility estimates, and risk indicators.

Outputs to control

The forecasting layer would output expected EV load, forecast uncertainty, available deferrable demand, user flexibility envelopes, transformer loading risk, and feeder voltage risk indicators. Forecasting across spatial levels shows that outputs should be tailored to the control boundary, because station-level, feeder-level, and area-level forecasts support different decisions [13]. Real-time EV charging control research further implies that local forecasts should feed directly into charging actions rather than remain as passive analytics [10]. **Table 1** summarizes how the proposed architecture maps forecasting models to operational inputs, outputs, and update frequencies.

Table 1. Local Forecasting Models and Operational Parameters

Forecasting function	Typical inputs at grid-edge node	Primary outputs to controller	Suggested update frequency	Architectural role
Baseline temporal forecast	Historical charging demand, calendar variables, tariff periods	Expected EV load profile	Scheduled control interval	Provides stable default prediction for normal operation
Event-driven session forecast	Plug-in events, state of charge, requested departure time, charger rating	Session-level energy need and urgency	On every new plug-in event	Supports immediate charging admission and prioritization

Feeder-aware load forecast	Transformer load, feeder voltage, non-EV load estimate, local DER output	Constraint-risk-adjusted EV demand	Rolling short-term cycle	Links EV charging demand to local grid feasibility
Flexibility forecast	User preferences, charging deadline, minimum energy requirement, historical flexibility	Deferrable power and time-shift window	At admission and after user update	Enables local charging rescheduling without violating service expectations
Uncertainty-aware forecast	Forecast residuals, weather variability, charging-event volatility	Confidence band and stress probability	Periodic recalibration	Supports resilience thresholds and conservative fallback decisions

Federated Update Layer

Federated learning rationale

The federated update layer would allow edge nodes to improve forecasting models collaboratively while keeping raw charging and feeder data local. Privacy-preserving federated learning for residential short-term load forecasting demonstrates the relevance of distributed model training for energy time-series data [7]. Electricity consumer identification through federated learning further shows that smart-grid models can benefit from learning across distributed clients without centralizing customer measurements [8]. In the proposed architecture, this layer would periodically collect encrypted model parameters or gradients from grid-edge nodes rather than raw EV charging records.

Client-server architecture

Each transformer or feeder controller would act as a federated client, while a utility, aggregator, or distribution system platform would host the federated server. Secure and efficient edge-cloud federated learning illustrates how smart-grid clients can collaborate through an aggregation layer while retaining local data ownership [16]. Federated benchmarking for smart energy forecasting also suggests that communication constraints should be treated as an architectural design issue rather than a secondary implementation detail [23]. The client-server interface should therefore define model versioning, update eligibility, authentication, encryption, and rollback procedures.

Aggregation algorithm and privacy

The aggregation block could use federated averaging, weighted aggregation, clustered aggregation, or robustness-aware aggregation depending on feeder diversity and data quality. Adaptive federated learning for EV charging-station occupancy prediction indicates that charging-related prediction tasks may benefit from adaptation across heterogeneous sites [24]. Privacy-aware EV load forecasting using blockchain and federated learning also reinforces the need for trustworthy update exchange when charging information is operationally and commercially sensitive [25]. In the proposed design, privacy guarantees would be supported through local training, encrypted update transfer, secure aggregation, and audit logs rather than through central raw-data storage.

Update frequency and communication efficiency

Federated updates should occur at a slower rhythm than local control actions, because charging control may require near-real-time decisions while model aggregation can tolerate scheduled or event-triggered exchange. Federated learning benchmarks for smart energy forecasting show that communication limits can shape model performance and update design [23]. Edge-cloud collaboration studies further suggest that communication-efficient protocols are important when many clients participate in a smart-grid learning system [16]. **Table 2** describes the proposed federated learning configuration, aggregation strategy, communication protocol, and privacy mechanisms.

Table 2. Federated Learning Configuration and Protocols

Federated component	Architectural configuration	Aggregation strategy	Communication protocol expectation	Privacy and integrity guarantee
Edge forecasting client	Local model hosted at transformer, feeder, or charging cluster controller	Sends encrypted weights or gradients	Authenticated publish–subscribe or utility message broker	Raw charging and feeder data remain local
Federated server	Utility, aggregator, or distribution management platform	Federated averaging with eligibility filters	Scheduled secure transport session	Central node receives model updates, not source datasets
Heterogeneity manager	Groups nodes by feeder class, charger density, or behavior pattern	Cluster-aware aggregation	Metadata-limited coordination channel	Reduces negative transfer across dissimilar nodes
Communication optimizer	Compresses or sparsifies updates before transmission	Communication-efficient weighted update	Bandwidth-aware reporting interval	Limits network burden during grid or telecom stress
Audit and rollback module	Maintains model version history and validation checks	Rejects anomalous or stale updates	Signed model package exchange	Supports traceability, rollback, and resilience coordination

Resilience Coordination Layer

Resilience threats and failure modes

The resilience coordination layer would monitor threats that could disrupt distributed EV charging control, including communication outages, abnormal feeder loading, transformer thermal stress, voltage excursions, cyber anomalies, and inconsistent model updates. Distributed anomaly detection based on federated learning shows that smart-grid resilience should include detection capabilities distributed across local nodes rather than depend only on central supervision [26]. Public EV grid data have also been identified as a potential cyberattack vector, indicating that EV charging coordination must account for malicious data use and adversarial manipulation [27]. In the proposed architecture, each grid-edge node would classify failure modes according to whether local control, federated exchange, or emergency intervention remains available.

Fallback control strategies

Fallback control should allow grid-edge nodes to continue safe operation when federated updates, cloud connectivity, or upstream optimization signals are unavailable. Safe constrained EV charging control demonstrates that charging policies can be designed around operating limits, which is important when fallback decisions must preserve transformer and voltage security [1]. Hierarchical EV charging station operation also supports the use of layered autonomy, where local controllers retain operational responsibility even when higher-level coordination is degraded [3]. The proposed fallback mode would therefore use cached forecasts, conservative charging envelopes, and locally stored constraint rules until normal coordination is restored.

Emergency load shedding and prioritization

Emergency load shedding would be reserved for severe stress states where local flexibility, charging deferral, and fallback control are insufficient to maintain feeder security. Distribution-grid-constrained EV scheduling indicates that charging operations should explicitly respect network constraints, which supports prioritizing curtailment when the network approaches unsafe conditions [11]. Optimal planning of EV charging facilities further shows that charging infrastructure interacts with local capacity limits, making emergency prioritization dependent on feeder topology and charger concentration [9]. The architecture should prioritize essential mobility needs, minimum committed energy, public-service charging, and user-declared departure constraints before shedding lower-priority flexible demand.

Coordination with federated and local layers

The resilience layer would coordinate with the local forecasting layer by adjusting uncertainty margins and with the federated update layer by pausing, delaying, or filtering updates during abnormal conditions. Privacy-preserving regulation capacity evaluation through federated and transfer learning shows that distributed flexibility estimation can be combined with privacy-aware learning, which is relevant when resilience actions depend on local available flexibility [28]. Federated EV charging load prediction also indicates that distributed learning can support charging-related forecasts while avoiding centralized raw-data pooling [29]. **Table 3** summarizes the proposed resilience mechanisms, triggering conditions, fallback actions, and recovery procedures.

Table 3. Resilience Mechanisms, Triggers, and Recovery Actions

Resilience mechanism	Trigger condition	Fallback action	Recovery procedure	Layer interaction
Communication-loss mode	Missing server heartbeat, failed update exchange, or degraded link quality	Switch to local-only charging control using cached model and conservative limits	Resume federated synchronization after authenticated reconnection	Pauses federated updates while preserving local control
Transformer-stress protection	Thermal margin breach or forecast overload risk	Reduce flexible charging power and defer non-urgent sessions	Gradually restore charging after forecasted margin stabilizes	Uses local forecasts to set temporary charging envelopes
Voltage-security response	Feeder voltage approaches operational limit	Shift charging away from affected phases or nodes where controllable	Return to normal scheduling after voltage risk clears	Couples feeder measurements with charging decisions
Cyber-anomaly containment	Suspicious model update, abnormal data pattern, or inconsistent command	Quarantine update source and use last verified model version	Validate logs, restore trusted model, and reauthorize client	Links anomaly detection with federated audit controls
Emergency shedding mode	Local fallback cannot satisfy safety constraints	Shed lowest-priority flexible charging according to declared service class	Reconnect loads in staged order after grid condition recovers	Coordinates resilience logic with user-priority rules

Control Workflow

Normal operation sequence

During normal operation, the grid-edge node would collect feeder measurements, charging-session states, and local context data before generating an updated forecast and charging plan. Smart charging strategies that incorporate photovoltaic generation and local consumption show that local energy context can materially affect charging decisions [15]. Real-time online charging control research further supports a workflow in which local decision agents repeatedly update charging actions from current system states [10]. The proposed sequence would therefore move from sensing to preprocessing, forecasting, constraint assessment, charging allocation, and operator logging within each control interval.

Federated update cycle

The federated update cycle would begin after the local node completes a training window using its private charging and feeder data. Secure edge-cloud federated learning suggests that the client would transmit protected model updates to a server that aggregates contributions from multiple nodes [16]. Federated learning benchmarks for smart energy forecasting show that this process should account for communication constraints and heterogeneous client performance [23]. After aggregation, the server would distribute a signed global or cluster-specific model package, which each node would validate before replacing or blending with its local model.

Resilience event handling

When a resilience event occurs, the control workflow would shift from optimization-oriented charging to safety-oriented operation. Secure federated detection of false-data-injection attacks shows that abnormal data conditions can require defensive smart-grid responses before normal control resumes [17]. Federated anomaly detection similarly indicates that distributed nodes can participate in recognizing local or system-wide irregularities [26]. In this architecture, the resilience event handler would freeze risky model updates, tighten charging limits, invoke local fallback schedules, and escalate to emergency shedding only when softer measures are insufficient.

Human operator interface

The human operator interface would present feeder status, forecast confidence, charging flexibility, model version, communication health, and active resilience mode in a concise supervisory view. Edge computing for IoT-enabled smart grids emphasizes the need to connect distributed sensing and control assets with higher-level operational visibility [19]. A hierarchical local electricity market for DER-rich grid-edge operation also suggests that operators may need visibility into local flexibility and coordination states rather than only raw device telemetry [18]. The interface should therefore support explainable alerts, manual override permissions, audit trails, and post-event review without requiring operators to micromanage individual chargers.

Figure 2 illustrates the proposed control workflow across normal operation, federated update exchange, degraded communication, cyber-anomaly containment, and emergency fallback states.

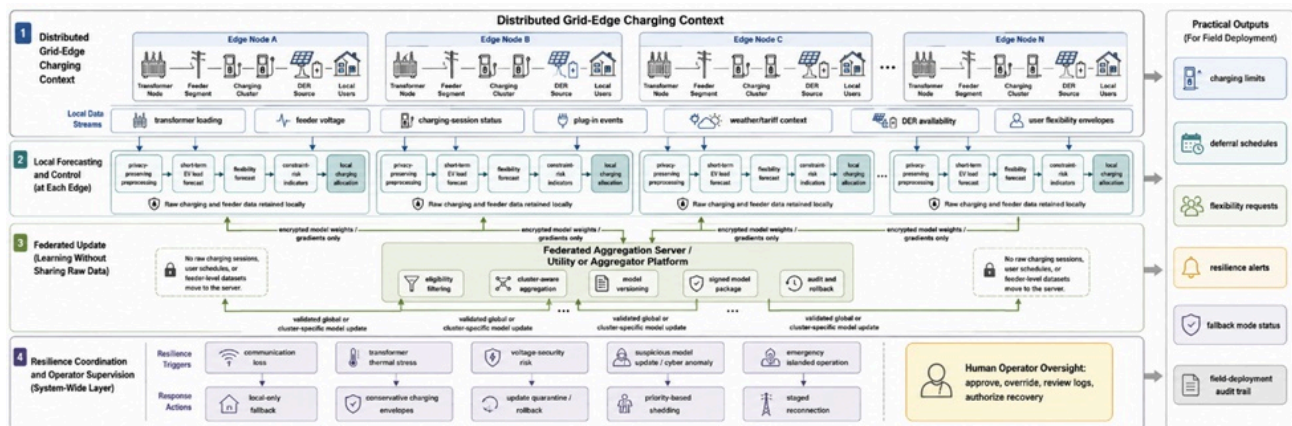


Figure 2. Resilience-Aware Control Workflow for Distributed EV Charging Under Normal, Degraded, and Emergency Operating Conditions

Implementation Scenarios

Urban high-density feeder

In an urban high-density feeder, the architecture would manage large numbers of chargers connected near constrained transformers, shared parking facilities, or mixed-use buildings. Charging demand forecasting with behavioral decision modeling shows that user arrival, departure, and charging choices can strongly shape urban station demand [22]. Statistical analysis of transaction data further indicates that real charging behavior contains repeatable but variable temporal patterns that can support local forecasting [20]. The urban scenario would therefore emphasize fast local preprocessing, uncertainty-aware forecasts, congestion-sensitive charging allocation, and frequent resilience checks.

Suburban distributed feeder

In a suburban distributed feeder, EV charging may be spatially dispersed across homes, workplaces, and community charging points, with stronger interaction between rooftop photovoltaic generation, household load, and evening charging demand. Smart charging research that considers photovoltaic production and electricity consumption shows that residential and feeder-level charging decisions should be coordinated with local energy availability [15]. Solar-powered EV charging station placement studies also highlight that distributed generation and charging infrastructure planning can affect distribution-network performance [30]. The suburban scenario would therefore prioritize feeder-aware flexibility estimation, local voltage support, and federated learning across similar residential nodes.

Emergency islanded operation

In emergency islanded operation, a feeder or microgrid segment would operate with limited upstream support and constrained local supply, requiring the EV charging controller to preserve essential loads and critical mobility services. Resilience-aware coordination can draw on hierarchical charging operation concepts because local charging decisions must remain feasible even when broader system coordination is unavailable [3]. Privacy-preserving flexibility evaluation also supports the idea that local estimates of controllable demand could help determine how much EV charging can remain connected during constrained operation [28]. Table 4 describes the proposed implementation scenarios and key architectural parameters.

Table 4. Implementation Scenarios and Key Parameters

Scenario	Deployment context	Dominant control concern	Forecasting emphasis	Federated update behavior	Resilience posture
Urban high-density feeder	Apartment clusters, public garages, commercial charging hubs	Transformer congestion and coincident peak charging	High-resolution session and feeder-load forecasting	Frequent participation in cluster-specific model updates	Rapid fallback and congestion-triggered charging limits
Suburban distributed feeder	Residential chargers, community chargers, rooftop photovoltaic systems	Voltage variation and evening charging concentration	Household, DER, and feeder-aware flexibility forecasting	Periodic updates across similar suburban nodes	Conservative local mode during communication loss

Workplace charging district	Office parks and daytime destination charging	Departure-time satisfaction and parking-duration uncertainty	Event-driven flexibility and occupancy forecasting	Scheduled updates aligned with business-day charging patterns	Priority preservation for declared departure constraints
Mixed DER-EV feeder	EV chargers co-located with storage and distributed generation	Coordination between charging, local generation, and feeder loading	Net-load and controllable-demand forecasting	Aggregation grouped by DER and charger configuration	Adaptive fallback using local energy availability
Emergency islanded feeder	Feeder segment operating under abnormal supply or restoration condition	Supply adequacy and essential-service prioritization	Short-horizon demand and flexibility-risk forecasting	Federated updates paused or restricted until stable operation	Emergency shedding and staged reconnection procedures

Validation Strategy

Simulation testbed

The first validation stage would use a simulation testbed that represents distribution feeders, transformer constraints, EV arrival behavior, charger ratings, communication delays, and local control intervals. EV charging control based on safe deep reinforcement learning provides a precedent for evaluating control policies under constrained operating conditions without assuming unconstrained charging freedom [1]. Charging station planning and grid-constrained scheduling studies also indicate that simulation should represent network limits and charger placement effects rather than treat EV demand as a single aggregate load [11]. The simulation stage would not be used here to report results, but to define whether the architecture can be tested under realistic operating conditions.

Hardware-in-the-loop integration

The second validation stage would connect grid-edge controllers, charger communication interfaces, and simulated feeder states in a hardware-in-the-loop environment. Edge computing for IoT-enabled smart grids supports this step because the architecture depends on physical or near-physical interactions among sensors, computation, communication, and control [19]. EV charging station hierarchy studies also imply that device-level control and supervisory coordination should be validated together before field deployment [3]. This stage would check message timing, controller failover behavior, model-package handling, operator interface functions, and resilience-state transitions.

Field trial roadmap

The field trial roadmap would begin with passive monitoring, proceed to advisory control, and then gradually enable closed-loop charging control under utility supervision. Statistical charging-transaction analysis shows that real operational data are necessary for understanding actual charging behavior and validating assumptions about temporal patterns [20]. Federated EV load forecasting studies further suggest that field trials should assess whether local clients can participate in collaborative learning while keeping raw charging data private [29]. The roadmap should therefore include stakeholder onboarding, privacy review, communication testing, emergency fallback drills, and staged authorization of control actions.

Performance metrics and success criteria

The validation strategy should assess architectural performance through operational feasibility, interoperability, privacy preservation, resilience behavior, forecast usability, and operator acceptance rather than through a single quantitative optimization outcome. Adaptive federated learning for charging-station occupancy prediction indicates that model

usefulness may depend on heterogeneity, participation, and update timing [24]. Privacy-aware blockchain and federated EV load forecasting further suggests that integrity, traceability, and privacy should be included as validation concerns when learning is distributed across charging nodes [25]. **Table 5** summarizes the proposed validation stages, environments, metrics, and success criteria.

Table 5. Validation Stages, Environments, and Metrics

Validation stage	Test environment	Primary architectural focus	Representative metrics	Success criteria
Conceptual design review	Architecture workshop with utility, aggregator, and operator stakeholders	Completeness of layers, interfaces, and responsibility boundaries	Requirement coverage, interface clarity, failure-mode coverage	Stakeholders confirm that functional and non-functional requirements are represented
Software simulation	Distribution feeder simulator with EV behavior and communication models	Local forecasting, charging control, and federated update logic	Forecast usability, control feasibility, communication burden, constraint handling	Architecture can be exercised across normal and stressed operating states
Hardware-in-the-loop test	Edge controller, charger interface, real-time feeder simulator, operator display	Device integration and timing of control workflows	Message latency, failover response, model-package validation, command traceability	Controllers execute workflows without unsafe state transitions
Cyber-resilience drill	Emulated abnormal data, communication loss, and suspicious update scenarios	Resilience coordination and fallback behavior	Detection consistency, rollback execution, isolation of suspect update, operator alert clarity	Local control remains safe while compromised coordination paths are contained
Field pilot	Selected urban, suburban, or mixed DER-EV feeder	Operational readiness under supervised deployment	Operator acceptance, privacy compliance, charging-service continuity, resilience drill completion	Architecture is ready for expanded deployment after staged control authorization

Conclusion

This article proposed a grid-edge intelligence architecture for distributed EV charging control that combines local forecasting, federated model updates, and resilience-aware coordination. The design places operational intelligence near transformers, feeders, and charging clusters so that decisions can reflect local constraints and user flexibility. Rather than framing EV charging management as a purely centralized optimization problem, the architecture treats it as a layered control and information system.

The local forecasting layer is intended to convert charging sessions, feeder measurements, and contextual data into actionable predictions of demand, flexibility, and constraint risk. The federated update layer is intended to improve model quality across many nodes while reducing the need to expose raw charging and customer data. The resilience coordination layer is intended to preserve safe operation when communications degrade, model updates become suspect, or the grid enters an emergency state.

The proposed control workflow links sensing, forecasting, charging allocation, federated exchange, resilience response, and operator supervision into a coherent operational sequence. The implementation scenarios show how the same

architecture could be adapted to urban high-density feeders, suburban distributed feeders, mixed DER-EV settings, and emergency islanded operation. The validation strategy outlines how the architecture could move from conceptual review to simulation, hardware-in-the-loop testing, cyber-resilience drills, and field pilots.

Future work should refine interoperable message formats, cybersecurity assumptions, operator-interface requirements, and governance models for federated EV charging intelligence. Standardization will be important because grid-edge nodes, chargers, utilities, aggregators, and customer platforms must exchange information reliably without weakening privacy or resilience. The architecture offers a practical blueprint for next-generation EV charging management systems that are distributed, adaptive, privacy-aware, and resilient by design.

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