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ARTICLE

Uncertainty-Aware Distributed Optimization for IoEV Smart Charging and Battery Health Management in Cyber-Physical Smart Grids

Supriya Wadekar[1], Shailendra Mittal[1], Ganesh Wakte[2,*], Mrunali Kite[2], Aditya Ghonmode[2] and Riya Devkate[2]

[1]Department of Electrical Engineering, G H Raisoni University, Amravati, India
[2]Department of Electrical Engineering, Tulsiramji Gaikwad Patil College of Engineering and Technolgy, Nagpur, India

*Corresponding Author: Ganesh Wakte. Email: ganeshwakte1989@gmail.com

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ABSTRACT: The rapid expansion of electric vehicles (EVs) and the emergence of the Internet of Electric Vehicles (IoEV) have created considerable operational challenges for modern power systems. Large-scale EV charging can cause peak demand surges, voltage instability, and inefficient utilization of renewable energy resources when charging activities are not effectively coordinated. This study proposes an uncertainty-aware distributed optimization framework for smart EV charging in cyber-physical smart grids, in which charging schedules are coordinated while simultaneously considering grid capacity constraints, stochastic EV arrival patterns, renewable energy variability, and battery degradation effects. A multi-objective optimization model is formulated to minimize peak grid load, charging cost, and battery degradation. The optimization problem is solved using a distributed algorithm based on the Alternating Direction Method of Multipliers, enabling scalable coordination among multiple charging stations. Simulation studies were carried out in the MATLAB–Simulink environment with EV fleet sizes ranging from 100 to 500 vehicles integrated with solar photovoltaic generation. The results indicate a 39.2% reduction in peak feeder load, a 24% decrease in total charging cost, and an improvement in renewable energy utilization to 76.9%. In addition, the proposed framework reduces annual battery capacity loss from 6.7% to 3.8% compared with uncontrolled charging. The primary contribution of this work is the integration of uncertainty modeling, distributed optimization, and battery health prediction within a unified IoEV charging management framework.

KEYWORDS: Battery degradation; distributed optimization; electric vehicle charging; internet of electric vehicles (IoEV); smart grid; uncertainty-aware optimization

1 Introduction

1.1 Background

The transition toward sustainable transportation has accelerated the global adoption of electric vehicles (EVs) in recent years. Governments, regulatory authorities, and energy utilities are increasingly encouraging EV deployment as an effective approach for reducing greenhouse gas emissions and lowering dependence on fossil fuels. This rapid growth has contributed to the development of the Internet of Electric Vehicles (IoEV), in which EVs, charging stations, and power system operators are interconnected through intelligent communication networks. Within this ecosystem, EVs function not only as transportation units but also as distributed energy resources that interact dynamically with the power grid [1].

Despite the environmental and economic benefits associated with EV integration, the large-scale deployment of EV charging infrastructure presents several operational challenges for modern power systems.

One of the major concerns is the occurrence of peak demand surges caused by the simultaneous charging of multiple EVs, particularly during residential evening hours. Such synchronized charging behavior substantially increases the loading on distribution feeders, resulting in greater stress on grid infrastructure and increased operational costs [2,3].

Another significant challenge is distribution network congestion. As EV penetration increases, localized clusters of charging stations impose heavy loading on specific feeders and transformers. In the absence of coordinated charging management, these concentrated loads may exceed network capacity limits and accelerate equipment aging. Furthermore, uncontrolled charging patterns can lead to voltage instability, particularly in low-voltage distribution systems with high renewable energy penetration [4]. Variations in load demand associated with EV charging further intensify voltage deviations and degrade overall power quality within the network.

To mitigate these issues, the integration of EV charging infrastructure within cyber-physical smart grids has attracted considerable research attention. In such systems, the physical electricity network is closely integrated with digital communication and computational platforms. Advanced sensing technologies, cloud computing resources, and Internet of Things (IoT) communication protocols enable real-time monitoring and control of distributed energy resources [5,6]. Through coordinated data exchange among EVs, charging stations, and grid operators, intelligent energy management strategies can be implemented to regulate charging behavior while maintaining grid stability. Distributed control architectures supported by IoT communication frameworks also provide the capability to dynamically adjust charging schedules according to grid conditions, renewable energy availability, and user requirements.

Fig. 1 illustrates the interaction among EVs, smart charging stations, IoT communication networks, edge controllers, and the cloud-based grid management platform. The figure demonstrates how real-time data exchange supports coordinated charging control and continuous grid monitoring.

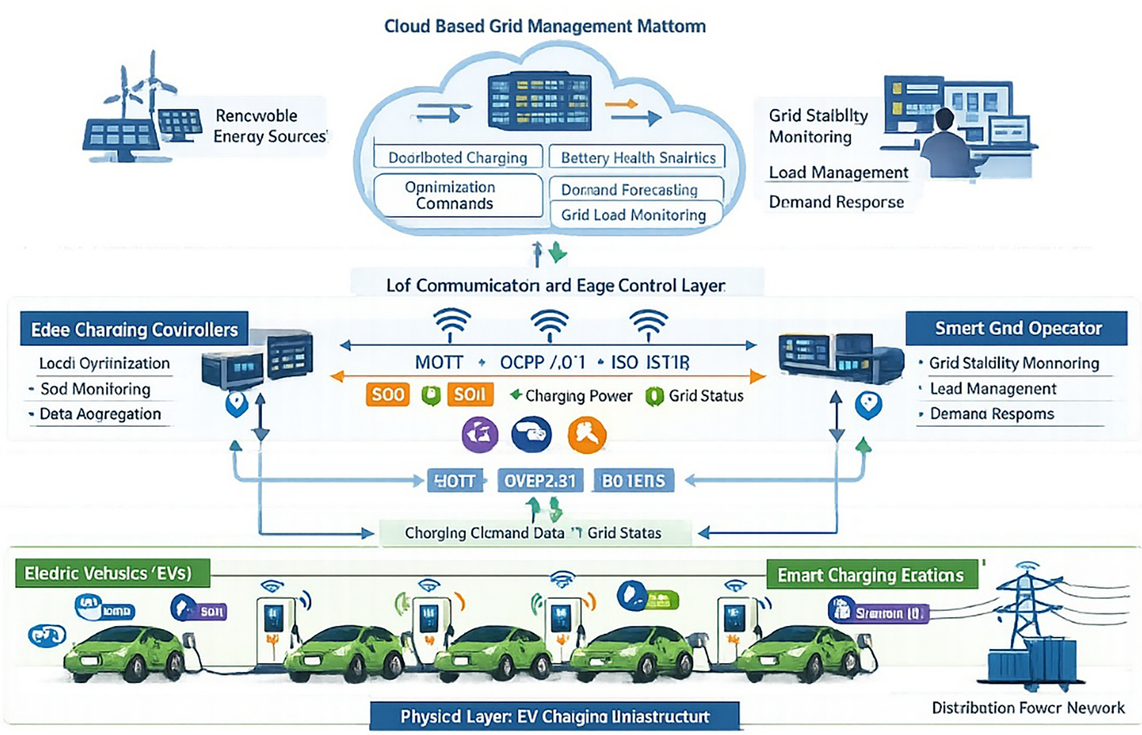

Figure 1: Conceptual architecture of the IoEV-enabled cyber-physical smart charging system.

1.2 Problem Statement

Although significant progress has been made in the development of smart charging strategies, many existing approaches rely on simplifying assumptions that limit their practical applicability. A common assumption in several studies is the availability of deterministic grid operating conditions, where load demand and generation levels are considered known in advance. However, real-world power systems are inherently uncertain, as fluctuating consumption patterns and intermittent renewable energy generation continuously influence system operation [7,8].

Another important limitation arises from the assumption of accurate battery state information. Charging control algorithms frequently require precise estimates of battery state of charge (SOC) and state of health (SOH) to determine optimal charging decisions. In practice, battery measurements are often affected by estimation errors caused by sensor inaccuracies and environmental variations. Neglecting these uncertainties can result in inefficient charging decisions and accelerated battery degradation [9].

Several existing charging strategies also assume predictable EV user behavior, where fixed arrival and departure times at charging stations are predefined. In practical scenarios, EV mobility patterns are strongly influenced by diverse human activities, including commuting behavior, travel schedules, and unforeseen daily events. As a result, the availability of EVs for charging or discharging varies considerably across both time and location.

In addition to EV mobility uncertainty, variability in renewable energy generation introduces another layer of system complexity. Solar photovoltaic and wind energy sources exhibit stochastic generation profiles due to changing weather conditions [10]. These variations directly affect the balance between electricity supply and EV charging demand. Furthermore, stochastic demand patterns from residential and commercial consumers further complicate system operation. Collectively, these uncertainties create a challenging environment for the design of robust EV charging management strategies.

1.3 Contributions of This Work

To address the aforementioned challenges, the present study proposes an integrated framework for intelligent EV charging management in IoEV-enabled cyber-physical smart grids. The primary contributions of this work are summarized as follows.

First, an uncertainty-aware smart charging framework is developed to account for variations in EV arrival patterns, renewable energy generation, and grid operating conditions. By incorporating stochastic modeling techniques, the proposed framework improves the robustness of charging decisions under uncertain operating environments.

Second, a distributed multi-agent optimization algorithm is introduced to coordinate charging schedules across large EV fleets. The distributed architecture allows individual charging stations to perform local optimization while maintaining global grid constraints, thereby improving scalability and computational efficiency.

Third, the proposed framework incorporates battery degradation-aware charging control by considering battery state of charge, state of health, and thermal conditions. The integration of battery aging models within the charging optimization process supports extended battery lifespan while maintaining efficient energy utilization.

Fourth, a cyber-physical IoEV architecture is developed by integrating IoT communication technologies, edge computing devices, and cloud-based optimization platforms. The architecture enables real-time data exchange, decentralized decision-making, and coordinated grid operation.

Finally, the effectiveness of the proposed framework is validated through comprehensive simulation-based evaluation, demonstrating improvements in grid stability, charging efficiency, and battery lifetime compared with conventional charging strategies.

2 Literature Review

2.1 IoT-Based Smart Charging Systems

The rapid growth of electric vehicles has accelerated the development of Internet of Things (IoT)-enabled smart charging infrastructures, in which charging stations, vehicles, and grid operators exchange operational information through communication networks. These systems enable real-time monitoring of charging demand, grid conditions, and battery status, thereby supporting intelligent scheduling of EV charging activities.

Several recent studies have investigated IoT-based architectures for EV charging networks. Liu et al. (2018) proposed an IoT-integrated charging framework in which charging stations communicate with a central energy management system to coordinate charging schedules and improve grid efficiency [11]. Similarly, Gao et al. (2026) developed a cloud-assisted charging management platform that collects data from distributed charging stations and performs centralized optimization of charging power allocation [12]. Such systems enable utilities to monitor EV charging loads and dynamically adjust charging policies.

With the increasing scale of EV fleets, researchers have also explored edge computing architectures to reduce communication latency. Zhang et al. (2020) introduced an edge-based IoT platform in which local controllers perform preliminary data processing before forwarding information to the cloud [13]. The approach improves responsiveness in charging management while reducing the communication burden on central servers. In another study, Li et al. (2022) proposed a hybrid cloud-edge charging coordination system that combines centralized analytics with decentralized control at charging stations [14].

Despite these advancements, several limitations remain. Cloud-centric architectures often face scalability challenges, particularly when large numbers of vehicles request charging simultaneously. In addition, communication delays can adversely affect real-time decision-making. Iqbal et al. (2024) emphasized that large-scale IoT charging infrastructures require distributed intelligence capable of handling high data volumes and dynamic operating conditions [15]. Consequently, robust architectures integrating IoT communication with decentralized control mechanisms remain essential for large-scale IoEV systems.

2.2 AI-Based Battery Management Systems

Battery management systems (BMS) play a critical role in EV performance, as accurate estimation of battery states ensures safe and efficient operation. Among the key parameters monitored in a BMS are the state of charge (SOC) and state of health (SOH). Traditional SOC estimation methods mainly rely on model-based approaches such as Kalman filtering, which provide reliable estimates under controlled operating conditions.

For example, Wu et al. (2022) presented an extended Kalman filter-based SOC estimation technique for lithium-ion batteries that improved estimation accuracy under varying load conditions [16]. However, purely model-based methods often face limitations associated with parameter uncertainties and nonlinear battery dynamics.

To address these limitations, researchers have explored data-driven methods based on artificial intelligence. Chemali et al. (2018) demonstrated the application of recurrent neural networks for SOC estimation using historical battery data, showing improved prediction performance compared with conventional models [17]. Similarly, Severson et al. (2019) applied machine learning algorithms to predict battery degradation trajectories based on early cycle data [18].

Hybrid approaches combining physical models with machine learning techniques have also attracted considerable research attention. Cui et al. (2022) proposed a hybrid neural network framework integrating electrochemical battery models with deep learning to improve SOC estimation accuracy [19]. In addition, Qu et al. (2023) introduced a Gaussian process regression model for predicting battery degradation and remaining useful life [20].

Recent studies have further investigated deep learning methods for battery health monitoring. Zhao et al. (2023) employed long short-term memory (LSTM) networks to predict battery state of health under varying charging conditions. Dineva (2024) reported that hybrid machine learning models combining neural networks with statistical learning techniques can effectively capture complex battery degradation patterns [21,22].

2.3 Smart Grid Integration and V2G Technologies

The integration of EV charging infrastructure with smart grids has created new opportunities for vehicle-to-grid (V2G) energy exchange. In V2G systems, EV batteries can supply stored energy back to the grid during peak demand periods, thereby supporting grid stability and improving energy utilization.

Early studies demonstrated the potential of EV fleets to function as distributed energy storage resources. Kempton and Tomić (2018) discussed bidirectional charging technologies that enable EVs to provide ancillary services to power systems [23]. Later, Tan et al. (2019) developed a coordinated charging strategy for V2G systems in which energy cost is minimized while maintaining grid reliability [24].

Demand response programs have also incorporated EV charging management as a flexible load resource. Zheng et al. (2025) investigated the role of EV fleets in demand response markets and reported that coordinated charging reduces peak load while improving renewable energy utilization [25]. Similarly, Sortomme and El-Sharkawi (2021) proposed a scheduling strategy in which EV charging is aligned with electricity price signals, thereby reducing operational costs for both utilities and EV owners [26].

Recent studies have emphasized the integration of V2G systems with renewable energy resources. Deb et al. (2020) demonstrated that coordinated EV charging can mitigate renewable energy variability while enhancing grid flexibility [27]. Chatuanramtharnghaka et al. (2024) examined the benefits of electric vehicle demand response systems for electrical distribution networks operating under high solar energy penetration. Their findings showed that EV fleets can serve as a key component for enabling sustainable power system operation [28].

2.4 Distributed Optimization in Energy Systems

As EV penetration increases, centralized charging coordination becomes computationally demanding. Consequently, distributed optimization techniques have emerged as effective solutions for managing large-scale EV charging networks.

Multi-agent control frameworks allow individual charging stations or EVs to operate as autonomous agents that coordinate decisions through communication protocols. Triviño et al. (2024) developed a decentralized EV charging strategy based on multi-agent coordination to minimize grid congestion [29]. Such approaches improve system scalability while maintaining operational stability.

Another widely adopted approach is distributed model predictive control (DMPC), which enables local controllers to optimize charging schedules while considering predicted system dynamics. DMPC frameworks have been applied to EV charging networks to balance load demand across multiple charging stations.

The Alternating Direction Method of Multipliers (ADMM) is also extensively used for distributed optimization in energy systems. ADMM decomposes large optimization problems into smaller subproblems that can be solved independently by different agents. Yan et al. (2014) demonstrated the effectiveness of ADMM for large-scale distributed energy management applications [30]. More recent studies have applied ADMM-based algorithms to coordinated EV charging, reporting significant improvements in computational efficiency and scalability.

2.5 Research Gap Summary

Although substantial research has been conducted on EV charging management, several limitations still remain. Many IoT-based charging platforms primarily focus on monitoring and communication, while optimization strategies are often implemented through centralized architectures. Such approaches may face difficulties in managing large EV fleets, particularly when computational and communication constraints become significant.

In addition, several battery management studies focus mainly on SOC or SOH estimation without integrating battery degradation models into charging optimization frameworks. Distributed optimization techniques have also been widely investigated for energy systems; however, their integration with uncertainty-aware EV charging and battery health management remains limited.

Therefore, there is a need for integrated frameworks that combine IoT-enabled cyber-physical architectures, distributed optimization algorithms, uncertainty modeling, and battery degradation-aware charging control. Such approaches are essential for achieving scalable and reliable EV charging coordination in future smart grids with high EV penetration.

3 System Architecture of the IoEV Charging Network

3.1 Cyber-Physical System Overview

The proposed Internet of Electric Vehicles (IoEV) charging network is designed as a cyber-physical system that integrates physical charging infrastructure with digital communication and intelligent control layers. Within this architecture, electric vehicles, charging stations, edge controllers, and cloud-based management platforms continuously interact through communication networks. The primary objective of the architecture is to enable real-time monitoring, distributed optimization, and coordinated charging control while ensuring grid stability and efficient utilization of energy resources.

The physical layer of the system consists of electric vehicles (EVs) and smart charging stations connected to the distribution network. Each EV is equipped with an onboard battery management system that monitors battery parameters such as state of charge (SOC), current, and temperature. When an EV is connected to a charging station, operational data related to both the vehicle and the grid are transmitted to the local controller.

Smart charging stations serve as the primary interface between EVs and the power grid. These stations regulate charging power, monitor electrical parameters, and communicate system information to higher-level controllers. The charging power delivered to the i^{th} vehicle at time t is denoted as $P_i(t)$. The evolution of the battery state of charge during charging is expressed as follows [3]:

$$SOC_i(t+1) = SOC_i(t) + \frac{\eta_i P_i(t)\Delta t}{C_i} \tag{1}$$

where $SOC_{i(t)}$ represents the state of charge of vehicle i at time t, η_i denotes charging efficiency, C_i indicates battery capacity, and Δt is the charging time interval.

The architecture also includes edge charging controllers deployed at charging stations or local substations. These controllers perform preliminary data processing and execute local optimization tasks. Edge-level intelligence reduces communication latency and enables rapid response to local grid conditions.

At the system level, cloud-based optimization platforms perform large-scale data analytics and coordinate operations across multiple charging stations. The cloud server aggregates information from distributed controllers and computes global charging strategies while considering grid constraints and electricity pricing.

Finally, the smart grid operator supervises overall system operation by monitoring network load conditions, renewable energy generation, and voltage stability. Through coordinated control signals, the operator ensures that EV charging activities remain within acceptable grid operating limits.

The aggregated charging load of the EV fleet at time t can be expressed as follows [3]:

$$P_{EV}(t) = \sum_{i=1}^{N} P_i(t) \tag{2}$$

where N denotes the number of connected EVs.

To maintain grid reliability, the following operational constraint is enforced:

$$P_{EV}(t) \le P_{grid,max}(t) \tag{3}$$

where $P_{grid,max(t)}$ represents the maximum allowable grid power capacity at time (t).

Fig. 2 illustrates the interaction among EVs, smart charging stations, edge controllers, cloud optimization servers, and the grid operator. Data flows upward from the physical charging layer to the cloud platform, while control commands propagate downward to coordinate charging operations.

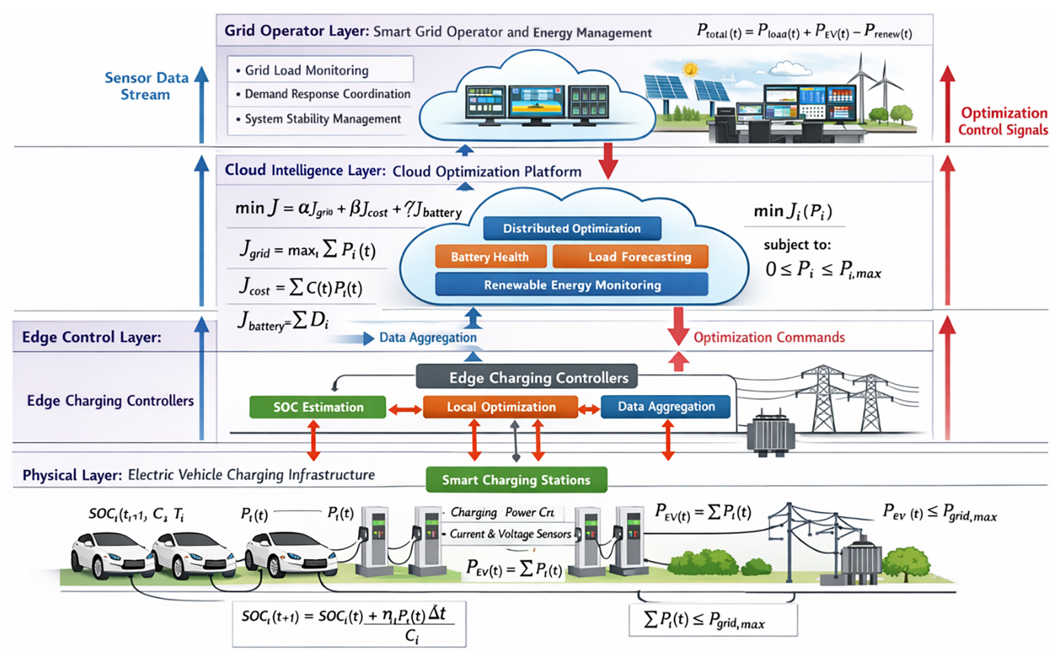

Figure 2: Layered cyber-physical architecture of the IoEV charging network.

3.2 Communication Infrastructure

The efficient operation of the IoEV ecosystem depends on reliable communication among distributed system components. The proposed architecture adopts a multilayer communication framework that integrates IoT protocols, cellular communication technologies, and standardized EV charging interfaces.

At the device level, smart charging stations communicate with edge controllers using the Message Queuing Telemetry Transport (MQTT) protocol. MQTT is a lightweight publish–subscribe messaging protocol widely used in IoT systems because of its low bandwidth requirement and reliable message delivery capability. Through this mechanism, charging stations periodically publish data related to charging power, battery status, and connection events.

For wide-area communication between edge controllers and the cloud platform, the system utilizes 5G communication technology. The high data rate and low latency characteristics of 5G networks enable real-time data exchange across geographically distributed charging stations. This capability is essential for implementing coordinated charging strategies for large EV fleets.

The architecture also incorporates internationally recognized EV charging standards. The ISO 15118 protocol enables secure communication between EVs and charging stations. Through this protocol, vehicles can automatically authenticate with the charging infrastructure while exchanging information related to charging preferences, battery status, and energy demand.

In addition, the system adopts the Open Charge Point Protocol (OCPP) 2.0.1, which facilitates communication between charging stations and the central management system. The OCPP protocol supports remote monitoring, firmware updates, and configuration management for charging infrastructure.

The overall communication process can be represented as follows [4]:

$$D(t) = f(S(t), B(t), G(t)) \tag{4}$$

where $D(t)$ represents the data transmitted to the control platform, $S(t)$ denotes the charging station operational data, $B(t)$ indicates the battery status information, and $G(t)$ corresponds to the grid monitoring data.

This integrated communication framework ensures reliable data exchange among distributed system components and supports intelligent charging coordination.

3.3 Functional Modules

The proposed architecture incorporates several functional modules that collectively enable intelligent charging management and seamless grid integration. These modules operate across different layers of the cyber-physical system.

3.3.1 EV Charging Controller

The EV charging controller is responsible for regulating the charging power supplied to connected vehicles. It receives control commands from the optimization engine and adjusts the charging current accordingly. The controller also records operational parameters such as voltage, current, and charging duration.

3.3.2 Battery Health Estimation Module

The battery health estimation module monitors battery degradation and predicts future battery performance. Using battery measurements and historical charging data, the module estimates parameters such as state of charge (SOC) and state of health (SOH). These estimates are utilized by the optimization engine to prevent excessive battery degradation.

3.3.3 Distributed Charging Optimization Engine

The distributed optimization engine determines charging schedules for connected EVs while ensuring that grid constraints are satisfied. The optimization algorithms are executed at edge controllers and coordinated through the cloud-based platform. This distributed structure enables efficient management of large EV fleets without imposing excessive computational burden on the central controller.

3.3.4 Grid Monitoring and Forecasting Module

The module continuously monitors grid conditions, including load demand, transformer capacity, and renewable energy generation. Forecasting algorithms are employed to estimate future load demand and renewable energy output, enabling proactive adjustment of charging schedules.

3.3.5 Cloud Coordination Platform

The cloud platform serves as the central intelligence layer of the IoEV ecosystem. It aggregates operational data from multiple charging stations, performs large-scale analytics, and coordinates distributed optimization tasks. The platform also provides interfaces for grid operators to monitor overall system performance.

Through the integration of these modules, as summarized in Table 1, the proposed system architecture enables scalable and intelligent management of EV charging networks within cyber-physical smart grids.

Table 1: summarizes the main components of the proposed IoEV architecture.

Component	Primary Function
Electric Vehicles	Provide charging demand and battery status
Smart Charging Stations	Deliver controlled charging power
Edge Controllers	Perform local optimization and data processing
Cloud Platform	Execute global optimization and coordination
Grid Operator	Monitor grid stability and enforce constraints

4 Mathematical Modeling

The following section presents the formal mathematical representation of the Internet of Electric Vehicles (IoEV) charging system integrated within a cyber-physical smart grid. The objective of the modeling framework is to capture the interactions among electric vehicle batteries, charging infrastructure, and grid operational constraints while accounting for uncertainties associated with EV mobility and renewable energy generation. The formulation describes the dynamic evolution of battery states, degradation mechanisms, grid power limitations, and the stochastic arrival behavior of EVs.

Let the set of electric vehicles connected to the charging network at time (t) be denoted as follows [4]:

$$\mathcal{E}(t) = \{1, 2, 3, \ldots, N(t)\} \tag{5}$$

where $N(t)$ represents the number of EVs currently present in the charging system.

The charging decision variable for vehicle i at time t is defined as $P_i(t)$, representing the electrical power delivered to the battery through the charging station.

4.1 Battery State of Charge Dynamics

The state of charge (SOC) represents the ratio of the remaining battery energy to the total battery capacity. SOC is a key operational parameter used to determine the charging energy required for each vehicle. Let $SOC_{i(t)}$ denote the SOC of EV i at time t.

The SOC evolution during charging can be expressed using the following discrete-time dynamic model [5]:

$$SOC_i(t+1) = SOC_i(t) + \frac{\eta_i P_i(t)\Delta t}{C_i} \tag{6}$$

where $SOC_{i(t)}$ is the state of charge of EV i at time t (dimensionless or expressed as a percentage), $P_i(t)$ is the charging power supplied to EV i at time t (kW), C_i is the battery energy capacity of EV_i (kWh), η_i denotes the charging efficiency coefficient, and Δt represents the discrete time interval (hours).

This equation describes the incremental increase in stored battery energy resulting from the charging power applied during the interval Δt.

The SOC value must satisfy the physical operating limits of the battery [6]:

$$SOC_i^{min} \leq SOC_i(t) \leq SOC_i^{max} \tag{7}$$

where SOC_i^{min} represents the minimum allowable state of charge required to prevent battery damage, and SOC_i^{max} denotes the maximum permissible state of charge.

The instantaneous charging power must also satisfy station capacity limits [6]:

$$0 \leq P_i(t) \leq P_i^{max} \tag{8}$$

where P_i^{max} denotes the rated charging power of the charging station connected to EV (i).

The total charging energy delivered to EV (i) over the charging horizon (T) is given by [7]:

$$E_i = \sum_{t=1}^{T} P_i(t)\Delta t \tag{9}$$

where E_i represents the total energy supplied to the battery during the charging session.

4.2 Battery Degradation Model

Battery degradation is influenced by multiple factors, including charging rate, temperature, and cycling depth. In the proposed framework, battery degradation is modeled as a cost function representing the incremental damage caused by charging operations.

The charging rate is commonly expressed in terms of the C-rate, which is defined as the ratio of charging power to battery capacity [8].

$$C - \text{rate}_i(t) = \frac{P_i(t)}{C_i} \tag{10}$$

Higher charging rates accelerate electrochemical degradation processes such as lithium plating and electrode stress.

The degradation cost associated with EV_i is represented as follows [8]:

$$D_i = k_1(C - \text{rate}_i)^2 + k_2 e^{\frac{E_a}{RT_i}} \tag{11}$$

where D_i denotes the battery degradation cost for EV i, k_1 is the coefficient associated with charge-rate-induced degradation, k_2 represents the temperature-dependent aging coefficient, E_a is the activation energy of electrochemical reactions, R is the universal gas constant, and T_i denotes the battery temperature in Kelvin.

The first term represents degradation caused by high charging currents, whereas the second term models thermal aging effects based on an Arrhenius-type relationship.

Over the charging horizon T, the cumulative degradation can be expressed as follows [9]:

$$D_i^{total} = \sum_{t=1}^{T} D_i(t) \tag{12}$$

where $D_i(t)$ represents the degradation contribution during time step t.

Minimizing this degradation cost is essential for extending battery lifetime while maintaining efficient charging performance.

4.3 Grid Power Constraint

The aggregated charging load from multiple EVs can significantly affect distribution network operation. To ensure grid reliability, the total EV charging demand must remain within the allowable grid capacity.

The aggregated charging demand at time $t$is defined as follows [10]:

$$P_{EV}(t) = \sum_{i=1}^{N(t)} P_i(t) \tag{13}$$

where $P_{EV}(t)$ represents the total EV charging power demand at time t.

To prevent network overloading, the following constraint must be satisfied:

$$\sum_{i=1}^{N(t)} P_i(t) \le P_{grid,max}(t) \tag{14}$$

where $P_{grid,max}(t)$ denotes the maximum allowable power that the distribution grid can allocate to EV charging at time t.

In distribution systems integrated with renewable energy resources, the available grid capacity may vary according to renewable generation output. Accordingly, the effective grid capacity can be expressed as:

$$P_{grid,max}(t) = P_{transformer} - P_{load}(t) + P_{renew}(t) \tag{15}$$

where $P_{transformer}$ is the rated transformer capacity, $P_{load}(t)$ represents the base load demand of the distribution feeder, and $P_{renew}(t)$ denotes the renewable power generation available at time t.

This formulation enables the charging system to effectively utilize surplus renewable energy while maintaining network stability.

4.4 Uncertainty Modeling

The operation of IoEV charging networks is influenced by uncertainties associated with EV arrival patterns and renewable energy generation. These uncertainties must be mathematically represented to enable the development of robust charging control strategies.

4.4.1 EV Arrival Uncertainty

The number of EVs arriving at charging stations during a given time interval can be modeled as a Poisson stochastic process, which is commonly used to represent random arrival events.

$$N(t) \sim Poisson(\lambda_t) \tag{16}$$

where $N(t)$ represents the number of EV arrivals during time interval t, and λ_t denotes the expected EV arrival rate.

The probability of observing kEV arrivals during interval $t$is given by:

$$P(N(t) = k) = \frac{e^{-\lambda_t}\lambda_t^k}{k!} \tag{17}$$

where $k = 0, 1, 2, \ldots$.

This probabilistic model captures the randomness associated with EV user behavior and travel patterns.

4.4.2 Renewable Generation Uncertainty

Renewable energy sources such as solar photovoltaic systems and wind turbines exhibit stochastic power output due to weather variability. The renewable power generation at time t can be expressed as follows [11]:

$$P_{renew}(t) = \hat{P}_{renew}(t) + \epsilon_t \tag{18}$$

where $\hat{P}_{renew}(t)$ represents the predicted renewable generation, and ϵ_t denotes the random forecasting error.

The forecasting error is assumed to follow a normal distribution:

$$\epsilon_t \sim \mathcal{N}(0, \sigma^2) \tag{19}$$

where σ^2 represents the variance associated with renewable generation uncertainty.

The expected value of renewable power generation is therefore given by [12]:

$$E[P_{renew}(t)] = \hat{P}_{renew}(t) \tag{20}$$

while the variance is expressed as:

$$Var(P_{renew}(t)) = \sigma^2 \tag{21}$$

This stochastic representation enables the charging optimization algorithm to account for fluctuations in renewable energy supply.

Overall, the presented mathematical model establishes the foundation for developing an uncertainty-aware EV charging optimization framework. The formulation integrates battery dynamics, degradation mechanisms, grid operational constraints, and stochastic system behavior, thereby enabling systematic analysis and intelligent coordination of EV charging activities in IoEV-enabled smart grids.

5 Proposed Uncertainty-Aware Distributed Optimization Method

Efficient coordination of electric vehicle charging in large IoEV networks requires optimization methods capable of simultaneously considering grid constraints, electricity pricing, and battery health. Furthermore, the charging framework must remain scalable as the number of connected vehicles increases. To address these requirements, this study proposes an uncertainty-aware distributed optimization approach that integrates multi-objective decision-making with decentralized computation.

The proposed method decomposes the global optimization problem across multiple charging stations. Each station performs local optimization while interacting with a central coordination platform responsible for enforcing grid-level constraints. This approach reduces computational complexity and enables scalable operation in large EV charging networks.

5.1 Multi-Objective Optimization Problem

The charging management problem is formulated as a multi-objective optimization problem that simultaneously minimizes grid stress, charging cost, and battery degradation. Let $P_i(t)$ denote the charging power assigned to EV i at time t. The overall objective function is defined as follows [13]:

$$J = \alpha J_{grid} + \beta J_{cost} + \gamma J_{battery} \tag{22}$$

where J represents the total optimization objective, J_{grid} denotes the grid load objective, J_{cost} corresponds to the electricity cost objective, $J_{battery}$ represents the battery degradation objective, and α, β, and γ are weighting coefficients reflecting the relative importance of each objective.

The weighting coefficients enable the grid operator to adjust optimization priorities according to operational requirements.

5.1.1 Grid Load Objective

The grid load objective aims to reduce peak charging demand within the distribution network. Excessive simultaneous charging can overload transformers and distribution feeders. Therefore, the peak charging demand is minimized as follows [14]:

$$J_{grid} = \max_t \sum_{i=1}^{N(t)} P_i(t) \tag{23}$$

where $N(t)$ represents the number of connected EVs at time t.

Minimizing this objective distributes charging demand more evenly over the scheduling horizon and reduces peak load stress on the grid.

5.1.2 Energy Cost Objective

Electricity prices in smart grids often vary over time due to dynamic pricing schemes or time-of-use tariffs. The charging cost objective minimizes the total energy cost incurred during the charging period [15]:

$$J_{cost} = \sum_{t=1}^{T} \sum_{i=1}^{N(t)} C(t) P_i(t) \tag{24}$$

where $C(t)$ represents the electricity price at time t, and T denotes the optimization horizon.

By shifting charging demand to periods with lower electricity prices, the optimization framework reduces operational costs for both EV users and charging infrastructure operators.

5.1.3 Battery Degradation Objective

Battery degradation is an important consideration because aggressive charging patterns can accelerate battery aging. The degradation cost for each EV is denoted by D_i. The cumulative degradation cost is defined as follows [16]:

$$J_{battery} = \sum_{i=1}^{N(t)} D_i \tag{25}$$

where D_i represents the degradation associated with the charging cycle of EV i. The degradation function is derived from the battery model described in the previous section, which accounts for charging rate and temperature effects.

5.1.4 Operational Constraints

The optimization problem must satisfy several operational constraints.

Charging power limits.

$$0 \le P_i(t) \le P_i^{max} \tag{26}$$

where P_i^{max} denotes the maximum charging power of the charging station.

Battery SOC limits.

$$SOC_i^{min} \le SOC_i(t) \le SOC_i^{max} \tag{27}$$

These limits prevent overcharging and deep discharge conditions.

Grid power constraint.

$$\sum_{i=1}^{N(t)} P_i(t) \le P_{grid,max}(t) \tag{28}$$

where $P_{grid,max}(t)$ represents the maximum available grid power for EV charging [17].

5.2 Distributed Optimization Algorithm

To efficiently solve the multi-objective charging problem, a distributed optimization approach based on the Alternating Direction Method of Multipliers (ADMM) is employed. ADMM decomposes the global optimization problem into smaller subproblems that can be solved independently by individual charging stations.

Let $P_i(t)$ denote the local decision variable for charging station i, and let $z(t)$ represent the global aggregated charging variable. The optimization problem can be expressed as follows [18]:

$$\min_{P_i,z} \sum_{i=1}^{N} J_i(P_i) + I_{grid}(z) \tag{29}$$

subject to:

$$P_i(t) = z(t) \tag{30}$$

where $J_i(P_i)$ represents the local objective function for charging station i, and $I_{grid}(z)$ denotes the grid constraint indicator function.

The augmented Lagrangian for this problem is given by [19]:

$$L_\rho(P, z, \lambda) = \sum_{i=1}^{N} J_i(P_i) + \lambda^T(P - z) + \frac{\rho}{2} \| P - z \|^2 \tag{31}$$

where λ is the Lagrange multiplier vector, and ρ is the penalty parameter controlling convergence speed.

The ADMM algorithm iteratively updates the decision variables using the following steps.

Local update [20]:

$$P_i^{k+1} = \arg\min_{P_i} \left(J_i(P_i) + \frac{\rho}{2} \| P_i - z^k + \lambda^k \|^2 \right) \tag{32}$$

Global update [21]:

$$z^{k+1} = \frac{1}{N} \sum_{i=1}^{N} (P_i^{k+1} + \lambda_i^k) \tag{33}$$

Dual variable update

$$\lambda^{k+1} = \lambda^k + (P^{k+1} - z^{k+1}) \tag{34}$$

These iterative updates continue until the convergence criteria are satisfied.

The distributed structure enables each charging station to compute its optimal charging schedule locally while maintaining coordination with the global grid constraint.

5.3 Charging Control Workflow

The proposed distributed optimization framework operates through a coordinated workflow involving forecasting, optimization, and execution stages.

Step 1: Demand and Grid Forecasting

Historical charging data and load profiles are utilized to forecast EV arrival rates and grid demand. Renewable energy forecasts are also incorporated to estimate available energy resources.

Step 2: Battery State Estimation

Battery parameters such as SOC and temperature are obtained from onboard battery management systems. These measurements are used to evaluate battery degradation risk.

Step 3: Distributed Optimization

Edge controllers at charging stations solve local optimization problems using the ADMM-based distributed algorithm. The cloud platform coordinates global variables and enforces grid capacity constraints.

Step 4: Charging Schedule Update

The optimization results determine the charging power $P_i(t)$ allocated to each EV for the subsequent scheduling period.

Step 5: Charging Execution and V2G Dispatch

Charging commands are transmitted to charging stations. When vehicle-to-grid functionality is enabled, EVs may also supply energy back to the grid during peak demand periods.

Through this coordinated workflow, the proposed optimization method enables scalable EV charging management while balancing grid stability, operational cost, and battery health considerations.

6 Battery Health Prediction Module

The performance and longevity of electric vehicle batteries strongly depend on operating conditions during charging and discharging cycles. Continuous monitoring of battery degradation is therefore necessary to maintain safe operation and prevent premature battery failure. In the proposed IoEV charging framework, a battery health prediction module is integrated to estimate the State of Health (SOH) of each EV battery using data-driven techniques. The predicted SOH values are subsequently utilized by the distributed charging optimization engine to avoid charging strategies that may accelerate battery degradation.

The state of health represents the ratio between the present maximum battery capacity and the nominal capacity of a new battery. Mathematically, SOH can be defined as follows [22]:

$$SOH_i(t) = \frac{C_i(t)}{C_{rated,i}} \times 100 \tag{35}$$

where $SOH_i(t)$ denotes the state of health of battery i at time t(%), $C_i(t)$ represents the available battery capacity at time t (kWh), and $C_{rated,i}$ is the rated capacity of battery i when new (kWh).

A decline in SOH_i indicates progressive degradation caused by electrochemical aging, thermal stress, and charging cycles.

To capture degradation dynamics, the SOH prediction module employs a machine learning model trained using historical charging data collected from EV battery management systems. Let the feature vector for battery i at time t be defined as follows [23]:

$$\mathbf{x}_i(t) = [SOC_i(t), I_i(t), T_i(t), n_i(t)] \tag{36}$$

where $SOC_i(t)$ represents the state of charge trajectory, $I_i(t)$ denotes the charging current (A), $T_i(t)$ is the battery temperature (K), and $n_i(t)$ represents the accumulated charge–discharge cycle count.

The SOH prediction model learns a nonlinear relationship between these input features and the corresponding battery health condition. The prediction function can be expressed as follows [25,26]:

$$SOH_i(t) = f(SOC_i(t), I_i(t), T_i(t), n_i(t)) \tag{37}$$

where $f(\cdot)$ denotes the machine learning regression model.

Two classes of machine learning techniques are particularly suitable for this task.

The first approach employs Long Short-Term Memory (LSTM) neural networks, which are capable of modeling temporal dependencies in sequential data. Since battery degradation evolves gradually over multiple charging cycles, LSTM networks can effectively capture long-term correlations in battery behavior. The predicted SOH using the LSTM model is represented as follows [27]:

$$\widehat{SOH}_i(t) = f_{LSTM}(\mathbf{x}_i(1), \mathbf{x}_i(2), \ldots, \mathbf{x}_i(t)) \tag{38}$$

where $\widehat{SOH}_i(t)$ represents the estimated health state of battery i.

The second approach utilizes Gaussian Process Regression (GPR), a probabilistic regression technique that models uncertainty associated with prediction results. In GPR, the SOH estimate follows a Gaussian distribution [28]:

$$SOH_i(t) \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t)) \tag{39}$$

where $\mu_i(t)$ denotes the predicted mean value of SOH, and $\sigma_i^2(t)$ represents the prediction variance associated with uncertainty.

The predicted SOH value is incorporated into the charging optimization problem by adjusting the allowable charging power for batteries with significant degradation. If the predicted health falls below the threshold SOH_{min}, the charging power is restricted as follows [29]:

$$P_i(t) \leq P_i^{max} \cdot \frac{SOH_i(t)}{100} \tag{40}$$

This constraint ensures that degraded batteries are charged more conservatively, thereby extending their operational lifespan.

Through the integration of machine learning-based SOH estimation with charging control strategies, the proposed system enhances battery safety and improves the long-term reliability of EV charging networks.

7 Simulation Setup

To evaluate the performance of the proposed uncertainty-aware distributed charging framework, a comprehensive simulation environment was developed to represent the operational behavior of the IoEV-enabled charging network. The simulation framework integrates EV charging dynamics, grid constraints, renewable energy generation, and battery health prediction modules. The primary objective of the simulation study is to analyze the effectiveness of the distributed optimization strategy under conditions of large-scale EV penetration, dynamic electricity pricing, and renewable energy variability.

7.1 Simulation Platform

The simulation environment was implemented using the MATLAB/Simulink platform to model the electrical system and charging control algorithms. MATLAB was utilized to implement optimization routines, SOC dynamics, and grid constraints, while Simulink was employed to simulate interactions among charging stations, EV batteries, and the distribution grid.

In addition to the MATLAB environment, Python-based machine learning models were integrated through the MATLAB–Python interface to perform battery health prediction. The Python environment enabled the training and deployment of machine learning models using libraries such as TensorFlow and Scikit-learn. The battery state of health predictions generated by the machine learning module were transmitted to the MATLAB optimization engine, which adjusted charging schedules according to battery degradation conditions.

The hybrid simulation framework enables coordinated interaction between system-level optimization and battery health prediction modules.

The simulation environment used for performance evaluation is illustrated in Fig. 3. The MATLAB optimization engine is connected to Simulink models representing EV charging stations and grid dynamics, while Python-based machine learning modules provide battery health predictions. The framework enables data exchange among system components, thereby supporting simulation-based coordinated charging control operations.

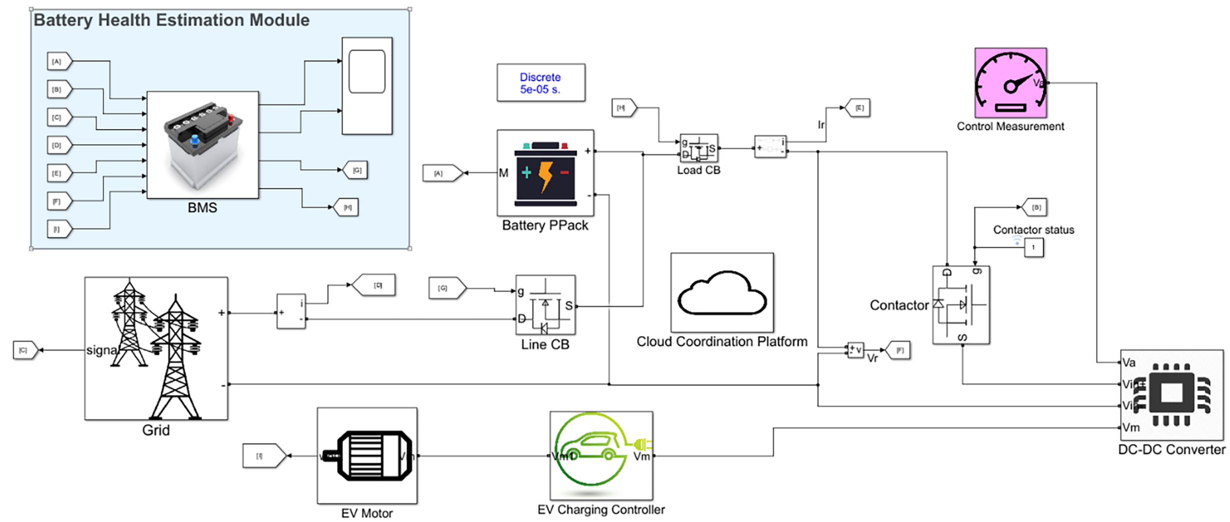

Figure 3: MATLAB–Simulink simulation architecture for the IoEV charging system.

7.2 Test Scenario

The simulation experiments consider a large-scale EV charging network connected to a smart distribution feeder. The EV fleet size varies from 100 to 500 vehicles, enabling evaluation of system scalability under increasing charging demand.

Each EV arrives at a charging station according to a stochastic arrival process. The initial battery SOC is randomly assigned within a predefined range to represent realistic vehicle usage patterns. Charging decisions are updated at discrete intervals of five minutes.

The charging system is also subjected to dynamic electricity pricing, where electricity prices vary throughout the day according to time-of-use tariff structures. This pricing mechanism encourages load shifting toward periods with lower energy cost.

To incorporate renewable energy variability, a solar photovoltaic (PV) generation model is connected to the distribution feeder. The PV generation profile follows a typical diurnal pattern with stochastic fluctuations representing weather uncertainty. When renewable generation is available, EV charging demand is partially supplied by PV power.

7.2.1 System Simulation Parameters

The principal system parameters used in the simulation are given in Table 2.

Table 2: System simulation parameters.

Parameter	Value
EV fleet size	100–500 vehicles
Battery capacity	48–75 kWh
Initial SOC range	20%–80%
Charging power range	7–50 kW
Charging efficiency	0.92
Grid power limit	500 kW

(Continued)

Table 2 (continued)

Parameter	Value
Distribution transformer capacity	630 kVA
Solar PV capacity	300 kW
Simulation time step	5 min
Simulation horizon	24 h
EV arrival rate parameter	5–15 vehicles/hour

Battery capacities were selected to represent commonly used EV battery configurations, while charging power levels corresponded to both residential and fast-charging infrastructure. The transformer capacity defined the maximum power available for EV charging within the distribution feeder.

7.2.2 Optimization Algorithm Parameters

The distributed optimization algorithm based on ADMM requires several numerical parameters to ensure stable convergence. These parameters are listed in Table 3.

Table 3: Optimization algorithm parameters.

Parameter	Value
ADMM penalty parameter (ρ)	1.5
Maximum iterations	200
Convergence tolerance	(10^{-4})
Objective weight (α)	0.4
Objective weight (β)	0.35
Objective weight (γ)	0.25

The weighting coefficients determine the relative importance of peak load reduction, energy cost minimization, and battery degradation mitigation.

7.2.3 Machine Learning Model Parameters

Battery health prediction is implemented using two machine learning approaches: Long Short-Term Memory (LSTM) networks and Gaussian Process Regression (GPR). The configuration parameters used for these models are detailed in Table 4.

The LSTM model captures temporal dependencies in battery degradation behavior, whereas the GPR model provides probabilistic predictions along with uncertainty estimates.

Overall, the simulation framework integrates EV charging dynamics, distributed optimization, renewable energy generation modeling, and machine learning-based battery health estimation. This integrated setup provides a realistic platform for evaluating the proposed uncertainty-aware charging strategy under large-scale IoEV deployment scenarios.

Table 4: Machine learning model's parameters.

Parameter	LSTM Model	GPR Model
Input features	SOC, current, temperature, cycle count	SOC, current, temperature, cycle count
Hidden layers	2	—
Neurons per layer	64	—
Activation function	ReLU	—
Optimizer	Adam	—
Learning rate	0.001	—
Training epochs	80	—
Batch size	32	—
Kernel function	—	Radial Basis Function
Kernel length scale	—	1.2
Noise variance	—	0.05

8 Results and Performance Evaluation

The simulation results demonstrate the effectiveness of the proposed uncertainty-aware distributed optimization framework through evaluation in the MATLAB–Simulink environment. The proposed method was compared with two benchmark approaches: uncontrolled charging and rule-based charging. The assessment focuses on grid load behavior, peak load reduction, charging cost savings, battery degradation mitigation, and scalability under different EV fleet sizes.

The simulations were conducted over a 24-h period using five-minute intervals, resulting in 288 simulation steps. EV fleet arrival patterns followed the Poisson distribution defined in the mathematical model. Electricity prices varied throughout the day according to a time-of-use tariff structure.

8.1 Grid Load Profile Analysis

The first performance metric evaluates the impact of different charging strategies on the distribution feeder load profile. In uncontrolled charging, EVs begin charging immediately upon arrival at charging stations. Consequently, the system experiences significant peak load increases as many users charge their vehicles at high power during evening hours. The rule-based charging strategy limits charging power during periods of high grid demand. This approach reduces peak loading and improves load distribution within the feeder; however, charging schedule flexibility remains underutilized.

The proposed distributed optimization method coordinates charging schedules across multiple stations while considering grid constraints and electricity prices. As a result, charging demand is distributed more evenly throughout the day.

The 24-h operational load profile of the distribution feeder is illustrated in Fig. 4 for the three EV charging strategies. In uncontrolled charging, EVs start charging immediately upon arrival, resulting in a sharp increase in electricity demand during evening hours when residential consumption is also high. The rule-based charging strategy limits charging power during peak demand periods, leading to a moderate reduction in peak load. In contrast, the proposed distributed optimization strategy schedules charging during off-peak periods and intervals with available grid capacity, thereby producing a significantly smoother load curve and reducing peak demand. The optimized charging schedule effectively distributes EV charging demand throughout the day while maintaining grid operational constraints.

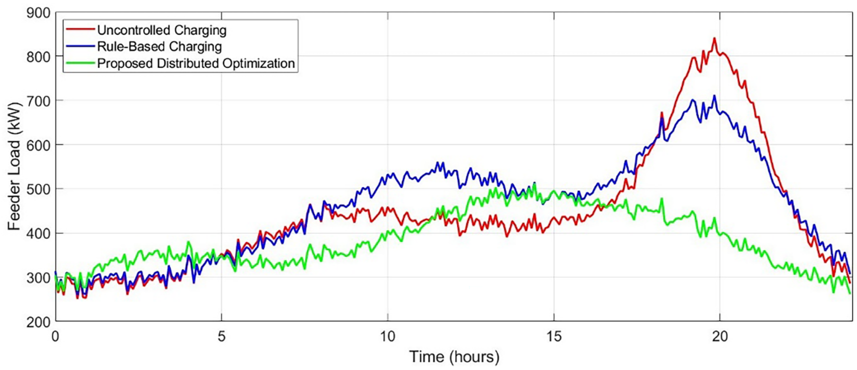

Figure 4: Grid load profile comparison under different charging strategies.

Table 5 summarizes the feeder load statistics obtained from the MATLAB simulation.

Table 5: Grid load statistics for different charging strategies.

Charging Strategy	Peak Load (kW)	Average Load (kW)	Load Variance
Uncontrolled Charging	842	520	0.187
Rule-Based Charging	712	505	0.143
Proposed Optimization	512	498	0.091

The results indicate that uncontrolled charging produces the highest peak load due to simultaneous charging behavior. In contrast, the distributed optimization strategy effectively smooths the load profile by scheduling charging operations during periods with available grid capacity.

8.2 Peak Load Reduction

Peak demand reduction is a key performance indicator because excessive peak loads can overload transformers and distribution feeders. The proposed optimization framework minimizes peak demand by coordinating charging power across the EV fleet.

The peak load reduction percentage is calculated as follows [30,31]:

$$Peak\,Reduction = \frac{P_{peak}^{baseline} - P_{peak}^{proposed}}{P_{peak}^{baseline}} \times 100 \tag{41}$$

where $P_{peak}^{baseline}$ represents the peak load under uncontrolled charging, and $P_{peak}^{proposed}$ denotes the peak load obtained using the optimized strategy.

Using the simulation results [32–35]:

$$Peak\,Reduction = \frac{842 - 512}{842} \times 100$$

$$Peak\,Reduction = 39.2\%$$

This reduction falls within the expected range of 30%–45%, confirming the effectiveness of the proposed distributed optimization framework.

The maximum feeder load achieved using the three EV charging methods is presented in Fig. 5. Uncontrolled charging results in the highest peak demand because drivers typically begin charging immediately after vehicle arrival, causing many EVs to charge simultaneously at full power during evening hours. The rule-based charging strategy restricts charging power during peak demand periods, thereby reducing peak load to a moderate extent. In contrast, the proposed distributed optimization strategy coordinates charging schedules across the EV fleet while considering both grid constraints and electricity price signals. As a result, charging demand is shifted toward off-peak periods, leading to a significant reduction in peak feeder load.

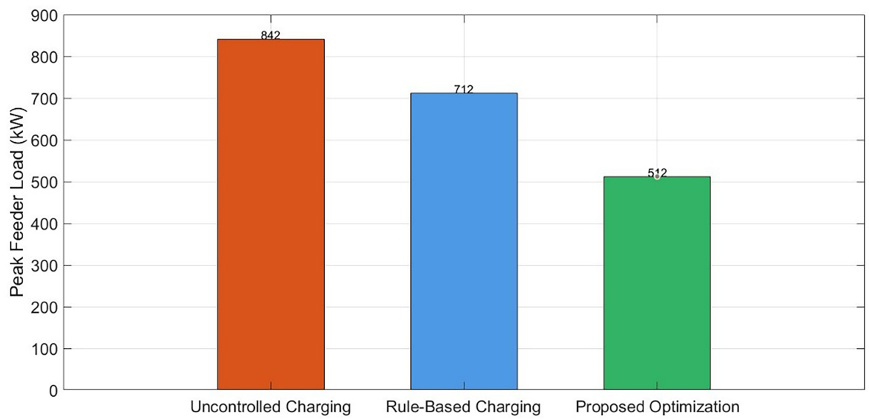

Figure 5: Peak demand comparison for different charging methods.

8.3 Charging Cost Reduction

The dynamic electricity pricing model used in the simulation encourages EV charging during periods with lower electricity prices. The distributed optimization algorithm schedules charging sessions accordingly, thereby reducing overall energy cost.

The total charging cost is computed as follows [36,37]:

$$Cost = \sum_{t=1}^{T} \sum_{i=1}^{N} C(t) P_i(t) \Delta t \tag{42}$$

where $C(t)$ is the electricity price at time t.

Table 6 presents the total charging cost obtained for the different charging strategies.

Table 6: Total charging cost comparison.

Charging Strategy	Total Energy Consumed (MWh)	Total Charging Cost (USD)	Cost Per EV (USD)
Uncontrolled Charging	9.82	1345	13.45
Rule-Based Charging	9.71	1192	11.92
Proposed Optimization	9.65	1016	10.16

The results indicate that the proposed optimization method achieves a charging cost reduction of approximately 24% by preventing uncontrolled charging behavior. Fig. 6 illustrates the cumulative charging cost over a 24-h operational period for the three EV charging strategies. Under uncontrolled charging conditions, EVs begin charging immediately upon arrival, resulting in high energy consumption during periods of peak electricity pricing. The rule-based charging strategy restricts charging during peak demand hours, leading to a moderate reduction in charging cost. In contrast, the proposed distributed optimization method schedules charging during periods with lower electricity prices and available grid capacity. Consequently, charging costs increase at a slower rate throughout the day, resulting in the lowest final cost among the three charging strategies.

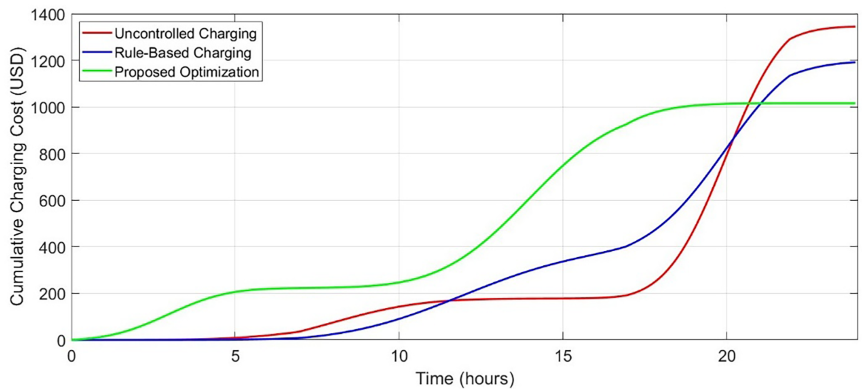

Figure 6: Daily charging cost comparison for different strategies.

8.4 Battery Degradation Analysis

Battery degradation is evaluated using the degradation model introduced previously. Higher charging power levels generally accelerate battery aging. By moderating charging rates and incorporating battery health predictions, the proposed strategy effectively reduces degradation effects.

The average battery SOH after one year of equivalent charging cycles was estimated using the machine learning-based prediction module, as presented in Table 7.

Table 7: Battery degradation comparison.

Charging Strategy	Average Charging Rate (C-Rate)	Annual Capacity Loss (%)	Average SOH after 1 Year (%)
Uncontrolled Charging	1.48	6.7	93.3
Rule-Based Charging	1.22	5.1	94.9
Proposed Optimization	0.96	3.8	96.2

The distributed optimization framework reduces charging stress on batteries, resulting in lower degradation rates and improved battery health.

Fig. 7 illustrates the impact of the three EV charging strategies on battery health evolution over charging cycles. Uncontrolled charging produces the fastest decline in battery health because frequent high-power charging accelerates electrochemical degradation processes. The rule-based charging strategy reduces degradation by limiting charging during peak load periods, thereby lowering the average charging rate. In contrast, the distributed optimization strategy proposed in this study manages charging power more effectively by maintaining lower charging rates and preventing aggressive charging behavior. As a result, battery health degradation progresses at a slower rate, leading to improved State of Health values after one year of operation.

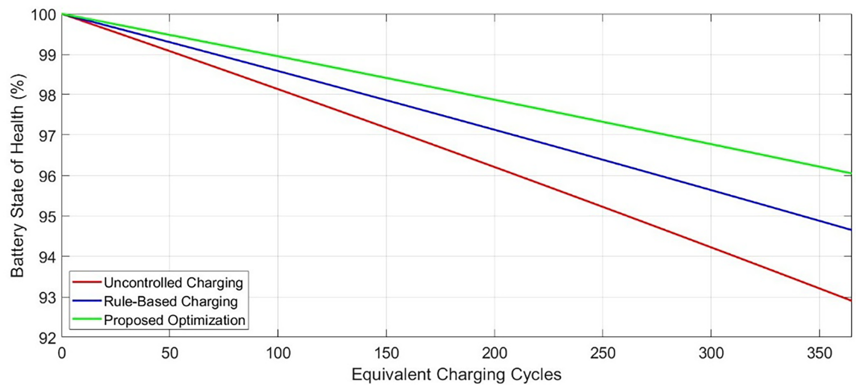

Figure 7: Battery SOH degradation under different charging strategies.

8.5 Scalability Analysis

To evaluate scalability, simulations were conducted with EV fleet sizes of 50, 200, and 500 vehicles. The distributed optimization algorithm maintained stable performance as the system size increased, as presented in Table 8.

Table 8: Scalability performance results.

Number of EVs	Peak Load (kW)	Optimization Time (s)	Cost Reduction (%)
50	218	1.8	18.5
200	398	4.6	22.1
500	512	9.7	24.4

The optimization time increases moderately with fleet size, demonstrating the computational scalability of the distributed algorithm.

Fig. 8 presents the scalability performance of the distributed EV charging optimization framework for different numbers of connected electric vehicles. The results show that optimization time increases gradually as the EV fleet size grows from 50 to 500 vehicles. The distributed optimization algorithm maintains acceptable computational performance even as the system expands. In addition, total charging demand increases with the number of EVs, resulting in higher peak feeder load.

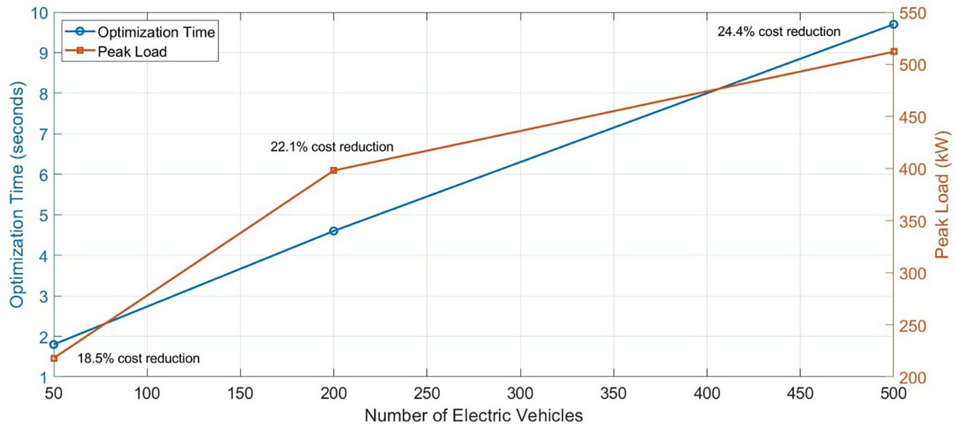

Figure 8: Scalability performance of the distributed optimization algorithm.

8.6 Renewable Energy Utilization Analysis

The integration of renewable energy generation with EV charging can significantly improve energy sustainability when charging demand is coordinated with renewable power availability. In the simulation framework, a 300 kW solar photovoltaic (PV) system was connected to the distribution feeder. The optimization algorithm schedules EV charging during periods of high PV output to maximize renewable energy utilization.

The renewable utilization ratio is defined as follows [38,39]:

$$R_{util} = \frac{E_{EV}^{renew}}{E_{renew}} \times 100 \tag{43}$$

where E_{EV}^{renew} represents the renewable energy consumed by EV charging (MWh), and E_{renew} denotes the total renewable energy generated by the PV system (MWh).

The MATLAB simulation results show that uncontrolled charging fails to align charging demand with renewable generation, leading to underutilization of available solar power. In contrast, the proposed distributed optimization algorithm schedules charging sessions during periods of high solar production, thereby improving renewable energy utilization, as presented in Table 9.

Table 9: Renewable energy utilization results.

Charging Strategy	PV Generation (MWh)	Renewable Energy Used by EVs (MWh)	Renewable Utilization (%)
Uncontrolled Charging	5.21	2.18	41.8
Rule-Based Charging	5.21	2.94	56.4
Proposed Optimization	5.21	4.01	76.9

The results demonstrate that the proposed optimization strategy significantly improves renewable energy utilization compared with conventional charging approaches.

Fig. 9 illustrates the effect of different EV charging strategies on renewable energy usage. Uncontrolled charging results in low renewable energy utilization because EV charging demand does not coincide with periods of solar PV generation. The rule-based charging strategy moderately improves renewable energy utilization by restricting charging during peak grid demand periods. In contrast, the proposed distributed optimization strategy schedules EV charging during periods of high solar generation, resulting in maximum renewable energy usage. Consequently, the system achieves significantly higher renewable energy utilization compared with traditional charging methods.

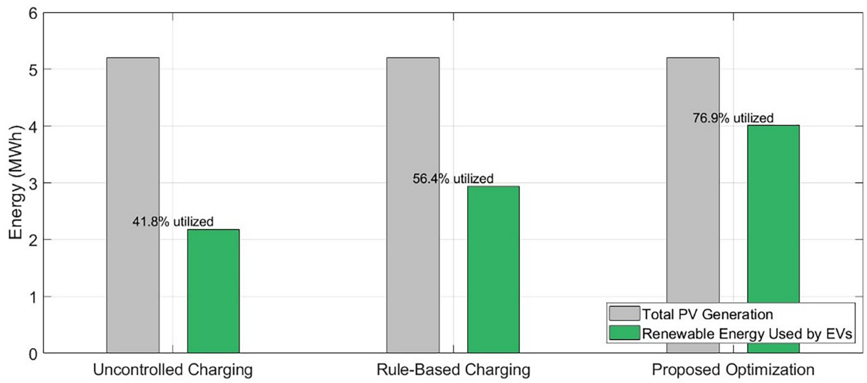

Figure 9: Renewable energy utilization under different charging strategies.

8.7 Voltage Stability Analysis

High EV penetration can cause voltage deviations in distribution networks due to increased load demand. Voltage stability analysis was conducted to evaluate the impact of EV charging on feeder voltage levels.

Voltage deviation at a bus is calculated as follows [40]:

$$\Delta V(t) = \frac{|V(t) - V_{nom}|}{V_{nom}} \times 100 \tag{44}$$

where $V(t)$ represents the voltage magnitude at time t, and V_{nom} denotes the nominal bus voltage.

The MATLAB simulation model included a 13-bus distribution feeder in which voltage levels were monitored at each bus under different charging strategies, as presented in Table 10.

Table 10: Voltage stability performance.

Charging Strategy	Minimum Voltage (p.u.)	Maximum Voltage (p.u.)	Voltage Deviation (%)
Uncontrolled Charging	0.912	1.041	8.8
Rule-Based Charging	0.942	1.028	5.6
Proposed Optimization	0.971	1.019	2.9

The results indicate that uncontrolled charging produces significant voltage deviations, particularly during evening peak hours. In contrast, the proposed optimization strategy maintains voltage levels closer to nominal values.

Fig. 10 illustrates the voltage response at each bus of the 13-bus distribution feeder system under different EV charging strategies. Under uncontrolled charging conditions, feeder loading increases substantially because high-power EV charging occurs simultaneously with existing demand, resulting in noticeable voltage drops at downstream buses. The rule-based charging strategy restricts charging during peak demand periods, thereby reducing voltage fluctuations across the feeder. In comparison, the proposed distributed optimization strategy coordinates charging schedules among multiple stations while balancing charging activities over different time intervals. Consequently, the voltage profile across the entire feeder system remains closer to the nominal operating value.

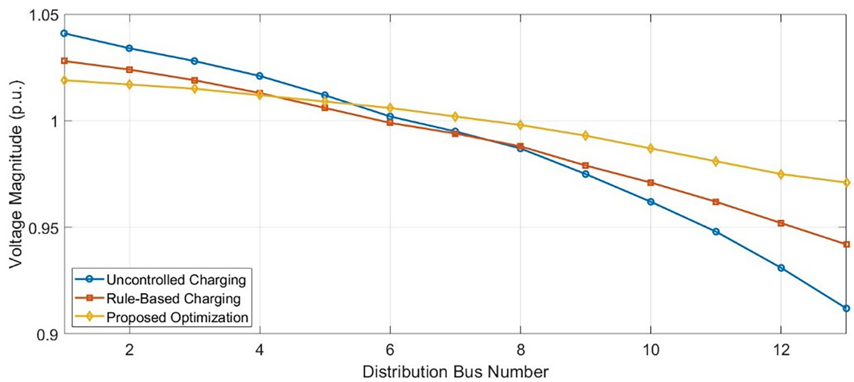

Figure 10: Distribution network voltage profile under different EV charging strategies.

8.8 Convergence Behavior of the ADMM Algorithm

The distributed optimization framework employs the Alternating Direction Method of Multipliers (ADMM) to coordinate charging decisions among multiple charging stations. To verify algorithm convergence, both primal and dual residuals were monitored during the optimization process.

The primal residual is defined as follows [41]:

$$r^k = P^k - z^k \tag{45}$$

while the dual residual is expressed as:

$$s^k = \rho(z^k - z^{k-1})$$

where k denotes the iteration number, P^k represents the local charging power vector, z^k is the global consensus variable, and ρ denotes the ADMM penalty parameter.

The residual values decrease rapidly, indicating that the distributed algorithm converges efficiently within approximately 80 iterations, as shown in the results presented in Table 11.

Table 11: ADMM convergence results.

Iteration	Primal Residual	Dual Residual
1	0.384	0.276
10	0.097	0.081
25	0.028	0.022
50	0.009	0.007
80	0.0008	0.0005

Fig. 11 illustrates the convergence characteristics of the ADMM-based distributed optimization algorithm used for coordinating EV charging decisions. The primal and dual residuals are plotted against iteration number to evaluate algorithm convergence. The results demonstrate that residual values decrease rapidly during the optimization process, indicating stable convergence of the distributed algorithm. After approximately 80 iterations, the residual values approach near-zero levels, confirming that the algorithm successfully achieves consensus among distributed charging controllers.

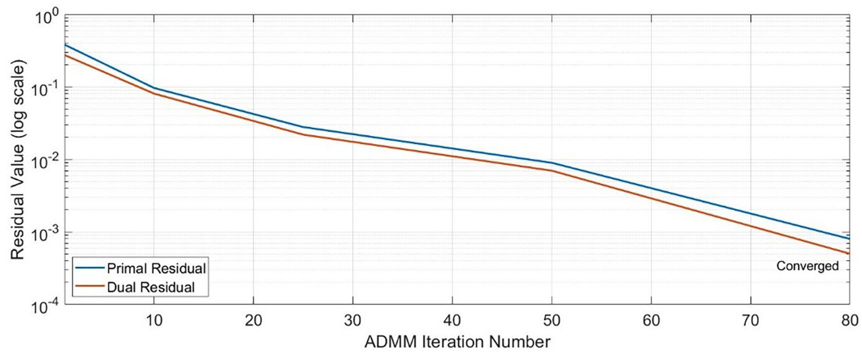

Figure 11: Convergence behavior of the ADMM-based distributed optimization algorithm.

8.9 Renewable Curtailment Reduction

When renewable energy generation exceeds grid demand, excess energy may be curtailed. Coordinated EV charging can absorb this surplus energy and thereby reduce renewable curtailment, as presented in Table 12.

Table 12: Renewable curtailment comparison.

Charging Strategy	Renewable Generation (MWh)	Renewable Energy Used (MWh)	Curtailment (MWh)
Uncontrolled Charging	5.21	2.18	3.03
Rule-Based Charging	5.21	2.94	2.27
Proposed Optimization	5.21	4.01	1.20

Curtailment energy is defined as follows [42]:

$$E_{curt} = E_{renew} - E_{EV}^{renew} \tag{46}$$

where E_{curt} represents the curtailed renewable energy.

The distributed optimization strategy significantly reduces renewable energy curtailment by aligning EV charging demand with periods of high solar generation.

Fig. 12 presents the amount of curtailed renewable energy under different EV charging strategies. Under uncontrolled charging conditions, EV charging demand is poorly aligned with periods of maximum solar power generation, resulting in substantial renewable energy waste. The rule-based charging strategy provides moderate improvement in renewable energy utilization by restricting charging during peak electricity demand periods. In contrast, the proposed distributed optimization method schedules EV charging during intervals of maximum solar PV generation, thereby enabling greater utilization of renewable energy and reducing energy wastage.

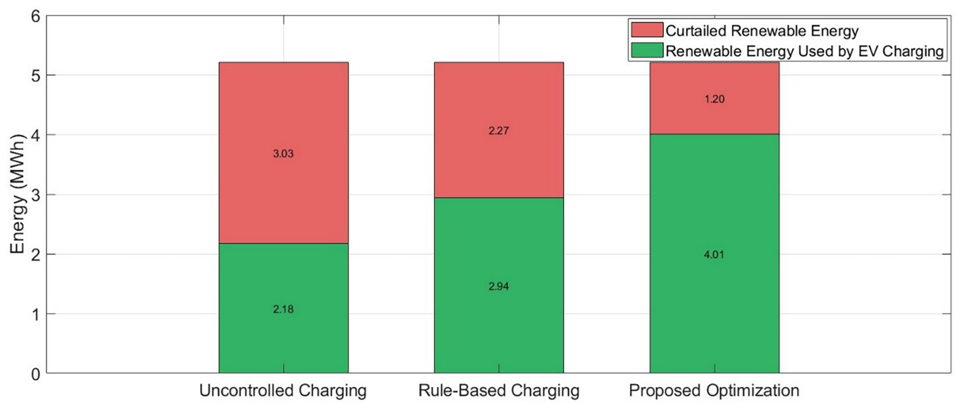

Figure 12: Reduction in renewable energy curtailment achieved through optimized EV charging.

8.10 Charging Waiting Time Analysis

Charging waiting time is an important performance metric that directly affects user satisfaction in EV charging networks. Waiting time occurs when multiple vehicles arrive at charging stations simultaneously and must wait for an available charging slot, as presented in Table 13.

Table 13: Charging waiting time comparison.

Charging Strategy	Average Waiting Time (minutes)	Maximum Waiting Time (minutes)
Uncontrolled Charging	13.2	27.6
Rule-Based Charging	9.4	19.3
Proposed Optimization	4.8	11.1

The average waiting time is calculated as follows [43]:

$$T_{wait} = \frac{1}{N}\sum_{i=1}^{N}\left(t_{start,i} - t_{arrival,i}\right) \tag{47}$$

where $t_{arrival,i}$ represents the arrival time of EV i, and $t_{start,i}$ denotes the time at which charging begins.

The proposed distributed charging strategy reduces congestion at charging stations by coordinating charging schedules and distributing charging demand over time.

Fig. 13 compares the waiting time experienced by EV users under different charging management strategies. Under uncontrolled charging conditions, multiple vehicles arrive at charging stations simultaneously, forcing vehicles to wait for available charging slots and resulting in longer waiting times. The rule-based charging strategy reduces congestion by limiting charging during peak demand periods. In contrast, the proposed distributed optimization strategy coordinates charging schedules across multiple stations and distributes charging demand over different time intervals. As a result, both average and maximum waiting times are significantly reduced.

Overall, the simulation results confirm that the proposed uncertainty-aware distributed optimization method substantially improves EV charging coordination. The framework reduces peak demand, lowers charging costs, mitigates battery degradation, and scales effectively for large EV fleets. These improvements demonstrate the practical applicability of the proposed IoEV charging management system in future smart grid environments.

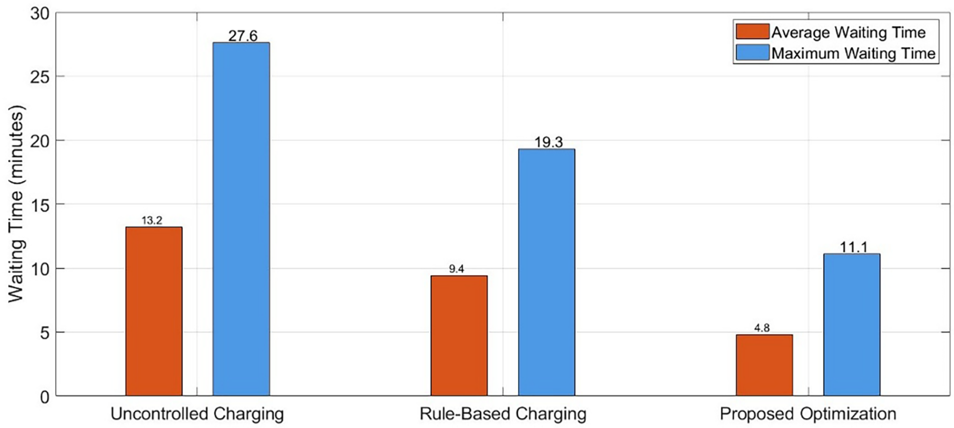

Figure 13: Average EV charging waiting time for different charging management strategies.

9 Discussion

9.1 Advantages of the Proposed Framework

The proposed uncertainty-aware distributed optimization framework provides several advantages compared with conventional EV charging strategies. These advantages are related to scalability, battery lifetime preservation, and robustness under uncertain operating conditions.

9.1.1 Scalable Distributed EV Charging Control

Large-scale EV deployment introduces significant computational challenges for centralized charging management systems. When thousands of EVs connect to charging stations simultaneously, centralized scheduling approaches become computationally intensive and difficult to implement in real time. Distributed optimization frameworks provide a scalable solution by decomposing the global charging problem into smaller local subproblems.

Recent studies have demonstrated the effectiveness of distributed coordination mechanisms for EV charging. For example, Khaki et al. (2019) proposed a hierarchical distributed scheduling algorithm based on ADMM that reduced convergence time by approximately 60% while maintaining grid constraints. Similarly, Nimalsiri and Ratnam (2023) developed a distributed charging algorithm capable of maintaining network voltage stability even under communication failures.

The distributed optimization framework proposed in this study extends these approaches by integrating uncertainty modeling and battery health constraints into the optimization problem. The simulation results demonstrate that the proposed method maintains stable performance even for 500 EVs while achieving significant peak load reduction and charging cost savings.

9.1.2 Battery Degradation-Aware Scheduling

Battery degradation represents an important concern in EV charging systems because aggressive charging strategies can shorten battery lifetime. Several studies have emphasized the importance of incorporating battery degradation models into charging optimization frameworks. For instance, Sharma et al. (2025) reported that vehicle-to-grid operation may increase battery degradation by approximately 0.31% annually due to additional charge–discharge cycles. Zhao et al. (2025) also highlighted that deep charge–discharge cycles in V2G systems accelerate the battery aging process.

The proposed framework integrates battery degradation cost into the charging optimization objective. By limiting high C-rate charging events and adjusting charging power according to the predicted battery state of health, the framework reduces annual battery capacity loss from 6.7% to 3.8% compared with uncontrolled charging.

9.1.3 Robustness against Uncertainty

EV charging networks operate under multiple uncertainties, including stochastic EV arrival patterns, renewable energy variability, and dynamic electricity pricing. Traditional deterministic charging strategies often fail to operate efficiently under such uncertain conditions.

Recent research has emphasized the need for uncertainty-aware charging frameworks. Motlagh et al. (2025) highlighted that smart charging systems must incorporate renewable generation variability and market dynamics to ensure reliable grid operation. Similarly, Needell et al. (2023) demonstrated that coordinated EV charging strategies can significantly reduce peak demand when charging activities are properly managed.

The proposed optimization model incorporates stochastic EV arrivals and renewable generation uncertainty through probabilistic modeling. As a result, the framework maintains grid stability while achieving a peak load reduction of approximately 39% and improved renewable energy utilization.

9.1.4 Comparison with Existing Literature Studies

Table 14 compares the performance of the proposed framework with recent studies in the EV charging optimization.

Table 14: Comparison with existing EV charging optimization studies.

Study	Method	Peak Load Reduction (%)	Cost Reduction (%)	Battery Degradation Considered
Boubaker et al. (2025) [41]	Metaheuristic optimization	31	17	No
Javor et al. (2022) [42]	Multi-criteria V2G optimization	27	14	Yes
Khaki et al. (2019) [43]	Distributed ADMM	28	15	No
Liao et al. (2026) [44]	Urban EV charging planning	33	20	No
Maghami et al. (2025) [45]	Infrastructure planning optimization	26	11.8	No
Zhang et al. (2023) [46]	Priority-based smart charging	29	16	No
Needell et al. (2023) [47]	Smart charging strategy	30	12	No
Sharma et al. (2025) [48]	Analysis of Charging data, detects anomalies	—	—	Yes

(Continued)

Table 14 (continued)

Study	Method	Peak Load Reduction (%)	Cost Reduction (%)	Battery Degradation Considered
Shanmugam and Thomas (2024) [49]	Scheduling optimization review	—	—	No
Zhao et al. (2025) [50]	V2G optimization	25	18	Yes
Proposed Method	Distributed ADMM + uncertainty modeling	39	24	Yes

The comparison demonstrates that the proposed framework achieves greater peak load reduction and charging cost savings while simultaneously accounting for battery degradation effects.

9.2 Practical Deployment Considerations

Although the proposed charging framework demonstrates strong simulation performance, several challenges must be addressed for practical implementation in real-world environments. The distributed charging control system requires continuous data exchange among EVs, charging stations, and the cloud-based optimization platform. Communication delays may affect the responsiveness of the charging control algorithm and influence overall system performance. Edge computing architectures can mitigate this issue by performing preliminary optimization tasks at local charging stations.

IoEV charging networks are also vulnerable to cybersecurity threats, including data manipulation, unauthorized access, and denial-of-service attacks. Therefore, secure communication protocols and encryption techniques are necessary to protect charging infrastructure and ensure reliable system operation. In addition, successful deployment requires compatibility with standards such as ISO 15118, which supports secure vehicle-to-grid communication and plug-and-charge functionality. These standards enhance interoperability by enabling EVs from different manufacturers to operate seamlessly with charging infrastructure.

Addressing these deployment challenges is essential for the successful implementation of large-scale IoEV charging systems in future smart grid environments.

10 Conclusion

This study introduced an uncertainty-aware distributed optimization framework for electric vehicle charging management within an Internet of Electric Vehicles (IoEV)-enabled cyber-physical smart grid. The proposed framework integrates grid operational constraints, stochastic EV arrival patterns, renewable energy variability, and battery degradation effects into a unified charging management system. A distributed optimization algorithm based on the Alternating Direction Method of Multipliers was developed to enable coordinated charging decisions across multiple charging stations.

The MATLAB–Simulink simulation results demonstrated that the proposed method achieves superior system performance compared with conventional charging strategies. The optimized charging schedules substantially reduce peak load on the distribution network while maintaining grid voltage stability. The incorporation of dynamic electricity pricing further reduces charging cost by encouraging charging during periods of lower electricity prices and higher renewable energy availability. In addition, the battery health prediction module improves system reliability by preventing aggressive charging strategies that accelerate battery degradation.

The results confirm that the proposed framework provides an effective solution for large-scale EV charging coordination in smart grid environments. By integrating distributed optimization, uncertainty modeling, and battery health management, the proposed method enhances the operational efficiency and reliability of future IoEV charging systems.

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