Operations models of electric vehicle loads in power system operations

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Abstract

The increasing penetration of electric vehicles (EVs) presents both challenges and opportunities for modern power systems. While traditionally regarded as flexible loads, EVs are now recognized as potential grid-support assets capable of enhancing system reliability and flexibility. In this paper, we present a comprehensive review of the operational role of EVs in power system operations, focusing on their ability to provide reactive power support, active power regulation, and facilitate the integration of renewable energy (RE). The study examines modeling approaches applied across both transmission and distribution systems, highlighting strategies such as vehicle-to-grid (V2G) control, optimal scheduling, and market-driven coordination. It also discusses the evolving frameworks that enable EVs to participate in ancillary services, voltage regulation, and frequency response. Key challenges, including communication infrastructure, battery degradation, and regulatory limitations, are analyzed. The review concludes by identifying future directions aimed at improving the scalability, efficiency, and reliability of EV-grid integration.

Index Terms

Electric vehicles (EVs); vehicle-to-grid (V2G); power system operation; reactive power support; active power control; renewable energy integration; optimal scheduling; distributed energy resources (DER); transmission systems; distribution networks.

I. Introduction

THE rapid electrification of transportation—driven by global decarbonization efforts and advances in battery technology—has made electric vehicles (EVs) a transformative force in modern power systems. The International Energy Agency (IEA) projects that global EV stock will reach at least 140 million by 2030, with electricity demand exceeding 550 TWh [1]. While this growth adds significant load to the grid, it also creates a valuable opportunity to leverage EVs as controllable distributed energy resources (DERs). With technologies like Vehicle-to-Grid (V2G) and bidirectional charging, EVs can both consume and supply electricity, evolving from passive loads into active grid participants—fundamentally reshaping traditional power system operations.

EVs are particularly well-suited to support grid operations due to their geographic dispersion, flexible charging behavior, and fast response characteristics. Unlike centralized generation units, EVs are embedded within the distribution layer of the grid and often located near demand centers, which enables localized voltage and frequency support. Furthermore, their ability to respond rapidly to control signals allows them to contribute to ancillary services traditionally reserved for large-scale generators. However, to unlock this potential at scale, it is critical to develop robust operational models that address the stochastic nature of EV availability, mobility patterns, and user behavior—while simultaneously satisfying system-level objectives such as reliability, cost-efficiency, and stability.

This paper presents a structured and in-depth review of the operational roles electric vehicles (EVs) play in modern power systems, focusing on three core support services: reactive power compensation, active power regulation, and renewable energy integration. These services leverage the growing deployment of bidirectional chargers, inverter-based V2G interfaces, and advanced scheduling strategies that allow EVs to act as distributed, controllable assets. From a system operations perspective, these functions are deployed differently across distribution and transmission networks, each with distinct modeling requirements and constraints.

In distribution systems, EVs regulate voltage by adjusting reactive power through V2G-enabled chargers. This is supported by decentralized strategies like Distributed Model Predictive Control (DMPC), which allow peer-to-peer voltage coordination without a centralized controller, as proposed by Hu et al[1]. In transmission systems, EVs contribute to frequency regulation, but must also maintain the State of Charge (SOC)required for user mobility. Models such as those developed by Liu et al[2]. balance dispatch signals with SOC targets, ensuring reliable service without compromising user expectations. EVs also enhance the integration of variable renewable energy sources (RES) by acting as mobile storage units. Coordinated optimization frameworks—such as the MILP-based model by Mouli et al [3]enable joint scheduling of EV charging, PV generation, and reserve offerings while minimizing cost and respecting system constraints. Finally, operational models including transactive energy control, distributed scheduling, and auction-based trading are explored, with Zhong et al[4]. introducing a topology-aware V2G auction mechanism that ensures economic fairness and system-aware coordination through ATC(Analytic Target Cascading) and VCG(Vickrey–Clarke–Groves) pricing. Fig 1 demonstrate the EV integration which enables three primary services—reactive power support, active power support, and renewable energy integration—each enhancing grid performance through specific operational functions. Reactive support contributes to voltage regulation and stability; active support aids in peak shaving, valley filling, and frequency regulation; and renewable integration helps mitigate intermittency and balance generation-demand mismatch.

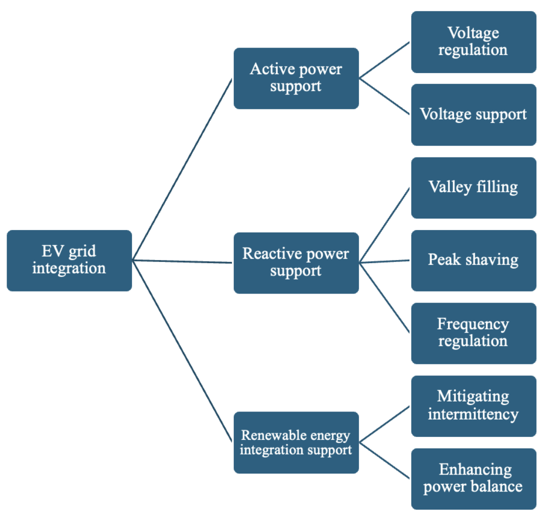

Fig. 1: Classification of electric vehicle (EV) contributions to grid support

The rest of the paper is organized as follows. Section 2 reviews how EVs support the grid through reactive power, active power, and renewable integration. Section 3 examines operational models, including centralized, decentralized, and market-based coordination. Section 4 discusses key challenges like communication latency, battery degradation, and regulation, and outlines future directions for scaling EV-based support. The paper concludes with a summary and reflection on EVs' evolving role in power systems

II. EV INTEGRATION INTO POWER SYSTEM

A. *Reactive power support*

In modern distribution systems, voltage stability is increasingly challenged by high penetrations of **distributed energy resources (DERs)** and flexible loads like electric vehicles (EVs). While reactive power is vital for maintaining voltage levels, conventional devices such as capacitor banks and tap changers are too slow for rapidly changing grid conditions. Centralized control systems offer more adaptability but suffer from scalability and latency issues. The rise of **EVs** with **V2G** capabilities enables dynamic reactive power support via power electronic inverters without disrupting charging. With proper local or distributed control, EVs can contribute to real-time voltage regulation. However, their uncertain availability—driven by user behavior and mobility—requires scalable, robust control frameworks to unlock their full potential.

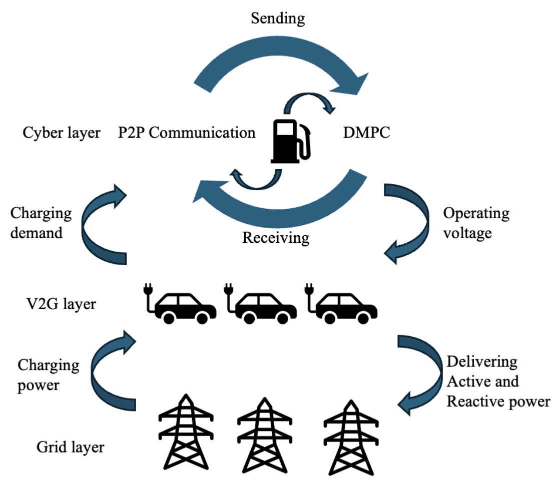

Fig. 2: Framework of Integrating EV Chargers into Voltage Regulation

One approach that addresses these concerns is presented by Hu et al.[1], who develop a Distributed Model Predictive Control (DMPC) framework for real-time voltage regulation using EV chargers in unbalanced distribution networks.The control architecture of this framework is illustrated in Fig. 1. It highlights the interaction between the cyber layer (DMPC and peer-to-peer communication), the V2G layer (bidirectional EV charging), and the grid layer, where active and reactive power are delivered. This layered design supports fully distributed coordination and real-time voltage regulation without relying on centralized supervision. In their design, each EV operates as a local control agent that solves an individual optimization problem to determine its reactive power injection over a future prediction horizon. The local objective is to minimize voltage deviation from nominal values while smoothing control actions across time steps, formulated as:

$$\min J(k) = \sum_{i \in \mathcal{N}_{\text{node}}} \sum_{l=1}^{k^{\text{pre}}} \left[a_i \cdot V_i^p(k+l) - V^{\text{ref}} \right]^2 \tag{1}$$

This objective function is used by each EV charger to minimize voltage deviation across a prediction horizon k^{pre}. Here, $V_i^p(k+l)$ is the predicted voltage at node i at time step $k+l$, and V^{ref} is the target reference voltage. The binary coefficient $a_i \in \{0, 1\}$ allows flexible node participation in the optimization. The control is fully distributed, relying on local voltage data and peer-to-peer communication between EVs. This consensus-based strategy eliminates the need for centralized control and remains effective under communication latency. Simulation on a 37-node feeder confirms the approach enhances voltage flattening and system stability in real time.

While Hu et al.[1] method offers deterministic control with high responsiveness, it assumes a relatively structured environment with predictable EV availability and robust communication. To address these limitations, Valizadeh Haghi and Qu [5] introduce a predictive, uncertainty-aware framework that combines machine learning-based forecasting with distributed stochastic optimization for voltage control. The architecture, as outlined in this paper, consists of two sequential stages: offline modeling and real-time optimization. In the offline phase, historical charging data is used to build kernel-based ensemble forecasts of EV reactive power capacity at each node. These forecasts are then embedded into a distributed sub-gradient optimization routine that adjusts each EV's reactive power output to minimize expected voltage deviation from nominal levels, formulated as:

$$\min_{q_i} \mathbb{E}\left[(V_i - V_{\text{ref}})^2\right] \tag{2}$$

Here, q_i represents the reactive power control input from EV i, and the expectation accounts for the stochastic nature of available capacity and voltage predictions. This structure allows each EV node to act autonomously, relying only on local voltage measurements and predicted capacity. No centralized communication or supervision is required, making the approach highly scalable and resilient to system uncertainty. Simulations conducted on the IEEE 37-node test feeder demonstrate that the method effectively regulates voltages even under high variability in EV availability and renewable energy output.

The two reviewed approaches offer distinct yet complementary strategies for EV-based reactive power support. Hu et al.'s[1] DMPC framework provides precise, real-time voltage regulation through distributed coordination, ideal for structured environments with stable communication. In contrast, Valizadeh Haghi and Qu[5] introduce a robust, prediction-driven model that accounts for EV uncertainty and operates effectively under limited observability. Together, these methods underscore the versatility of EVs as reactive power providers, capable of enhancing grid voltage stability through both deterministic and stochastic control. While reactive power support enhances voltage stability, active power control is equally vital for balancing demand, shaping load profiles, and maintaining frequency. The next section examines how EVs contribute to these services through peak shaving, valley filling, and frequency regulation.

B. Active power support

EVs, with their bidirectional charging and onboard storage, are ideal for grid services like peak shaving, valley filling, and frequency regulation. Their fast response and flexible scheduling help manage fluctuating loads and renewable output. As the grid becomes more decentralized, EVs play a growing role in load balancing and frequency control—while adapting to user preferences and battery limits.

One of the most critical forms of active power support is frequency regulation, which requires fast and flexible resources to correct short-term imbalances between generation and load. Liu et al.[3] propose a dispatch control framework that enables EVs to participate in supplementary frequency regulation (SFR) while considering individual user preferences. The core challenge lies in balancing grid-level frequency correction with state-of-charge (SOC) expectations from EV owners. To address this, the model distributes the Area Control Error (ACE) signal across participating EVs using a decentralized regulation dispatch mechanism. Each EV receives a regulation instruction u_i computed by minimizing the deviation between its actual and expected SOC, while ensuring that the aggregate EV response satisfies the ACE command signal allocated within EV Frequency Regulation Capacity(FRC):

$$\min_{u_i} \sum_{i=1}^{N} \left(\text{SOC}_i^{\text{exp}} - \text{SOC}_i(k)\right)^2 \quad \text{s.t.} \quad \sum_{i=1}^{N} u_i = \text{ACE}(k) \tag{3}$$

Here, u_i is the regulation power allocated to EV i, $\mathrm{SOC}_i^{\mathrm{exp}}$ is the expected state-of-charge set by the user, and $\mathrm{SOC}_i(k)$ is the current SOC at time step k. The dual-objective naturally leads to an optimization problem that minimizes the SOC tracking error while satisfying the ACE constraint, ensuring user satisfaction and grid-level support. A rolling optimization mechanism continuously updates dispatch based on system dynamics and EV availability. Simulation results on an interconnected two-area power system—modeled using real grid data from China—demonstrate that this strategy effectively mitigates frequency deviations while maintaining SOC targets. The EVs were integrated into Area A, where both wind generation and real load profiles were considered. This validates the framework's practicality in real-world SFR applications and confirms that EV fleets can serve as reliable, user-aware frequency regulation assets within large-scale power networks.

These findings demonstrate that EVs are not only capable of supporting system frequency but also of doing so in a user-aware, distributed manner. This sets the stage for exploring their role in managing energy balance through price-responsive strategies and renewable integration.

Beyond frequency regulation, active power support from EVs can also be realized through market-based coordination that enables energy trading and load shaping across distribution networks. While Liu et al. [3] focused on control-based regulation in transmission systems, Zhong et al. [4] present a contrasting strategy tailored for active distribution networks, where EVs participate in local markets under physical grid constraints.

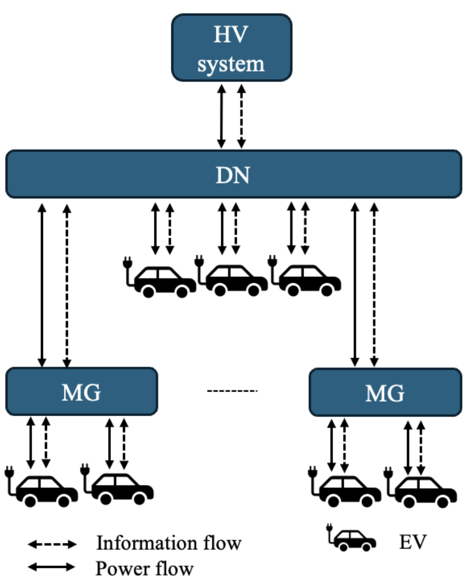

Fig. 3: Topology-aware coordination framework for V2G energy trading

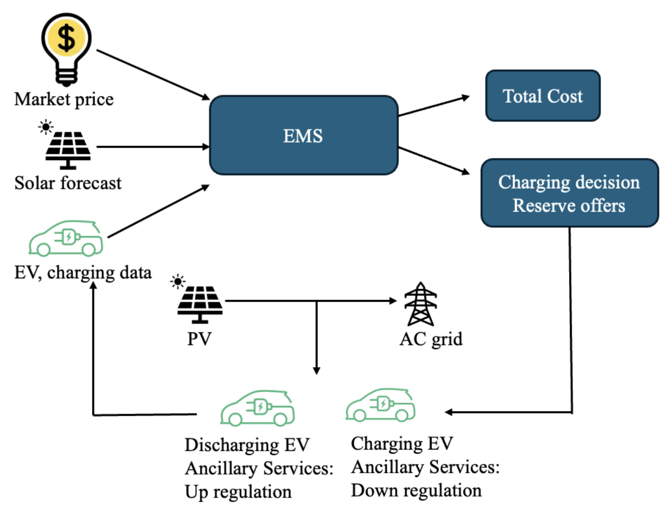

Fig. 4: Simplified architecture of the PV-EV charging and energy management system

The authors propose a topology-aware V2G energy trading framework based on an Analytic Target Cascading (ATC) architecture. Fig. 3 illustrates the hierarchical interaction between the distribution network (DN), microgrids (MGs), and EV aggregators where there is a bidirectional infomation and power flow between the entities . In this model, global objectives—such as minimizing system cost or peak demand—are broken down into local optimization problems, solved independently by EV aggregators or microgrids. A Vickrey–Clarke–Groves (VCG) auction coordinates hierarchical bidding, ensuring strategic participation while maintaining overall system efficiency. A key strength of this framework is its explicit integration of network topology and operational constraints—including voltage limits and line capacities—into the market-clearing process. This results in grid-compliant active power schedules that enable EVs to support **peak shaving, valley filling, and localized balancing** without compromising system security.

Liu et al. and Zhong et al. present complementary models for EV-based active power support—one focused on real-time frequency regulation, the other on market-driven dispatch under network constraints. Together, they show how EVs can adapt across system layers. As renewable penetration rises, their role in supporting grid flexibility becomes even more critical, as explored in the next section.

C. Renewable Energy Integration support

The growing share of renewables like wind and solar introduces variability that complicates balancing supply and demand, maintaining frequency, and ensuring grid stability. EVs with vehicle-to-grid (V2G) capabilities offer a solution by acting as distributed storage and flexible loads—absorbing excess generation, smoothing fluctuations, and supporting services like frequency regulation. This paper reviews strategies leveraging EVs as flexible assets in renewable-rich grids to improve stability and adaptability. In urban areas, PV integration faces two key challenges: misalignment between solar output and demand, and limited local storage. User-driven EV charging patterns can worsen these issues, leading to midday curtailment and evening peak stress.

To address these challenges, Mouli et al.[3] design an integrated energy management system (EMS) for PV-powered EV charging that accounts for solar forecasting, dynamic pricing, and grid support services. As shown in Fig 4., the EMS coordinates real-time decisions between local PV generation, the grid, and EV fleets—optimizing when and how vehicles are charged or discharged based on the charging decision and reserve offer, EV provided ancillary service using up/down regulation. The system operates with the goal of minimizing total operating cost while maximizing PV utilization and reserve market participation. This is formulated as:

$$\min \left(C_{\text{grid}} + C_{\text{V2G}} - R_{\text{reserves}} \right) \tag{4}$$

where C_{grid} is the cost of grid-supplied power, C_{V2G} accounts for discharging-related costs including degradation, and R_{reserves} reflects revenue from reserve provision. This objective ensures the EMS balances local generation, grid interaction, and economic incentives, enabling EVs to act as flexible energy resources in renewable-integrated environments.

Strategy	Net Cost ($)	Max Daily Reduction (%)	V2G	Pricing	PV Forecast	Reserves
IMM/AVG	2.90	–	X	X	X	X
Case 6	-0.91	280.2	X	✓	✓	X
OPT (Full EMS)	-1.53	317.8	✓	✓	✓	✓

TABLE I: Net cost reduction under different smart charging strategies

Simulation results confirm that coordinated PV-EV integration enhances both grid reliability and user economics. Under the optimized strategy, EVs align their charging with solar availability, provide reserve services, and export power through V2G—achieving a **158.6%**cost reduction on average, with daily peaks up to **317.8%**. The net charging cost becomes negative, showing that EVs can earn revenue while supporting the grid. Compared to partial strategies, only the full EMS setup combining solar forecasting, V2G, dynamic pricing, and regulation services delivers these benefits. This validates the role of EVs as active, grid-supporting resources in renewable-integrated power systems.

In high-renewable power systems, frequency control becomes increasingly challenging due to the variability and intermittency of sources like solar PV, wind. Unlike traditional generators, renewables lack inertial response, making the system more sensitive to load-generation imbalances. While Mouli et al.[3] addressed these challenges on the economic and energy management side—optimizing EV charging to absorb PV and offer reserves. Falahati et al.[6] focus on the control and operational stability dimension. Their work explores how real-time EV charging modulation can improve grid frequency response in deregulated environments with high PV penetration.

To achieve this, they propose a fuzzy logic controller that continuously adjusts EV charging rates based on two inputs: grid frequency deviation and state-of-charge (SOC) of the vehicle batteries. Unlike static charging schedules, this dynamic approach enables EVs to act as real-time stabilizing resources, reducing frequency deviation by curtailing or boosting charging in response to grid conditions. Importantly, this is done without affecting user preferences, as SOC constraints are embedded in the control logic.

Area	**Frequency Deviation (Hz) – Max**	**Tie-line Power Deviation – Max**
Area 1 (Dumb Charging)	0.2147	High
Area 1 (Proposed)	0.0623	$\downarrow$ 79%
Area 2 (Proposed)	0.0574	$\downarrow$ 63%
Area 3 (Proposed)	0.0746	$\downarrow$ 68%

TABLE II: Maximum values of frequency and tie-line power deviation

To evaluate the impact of the proposed EV-based control scheme, simulations were conducted on a modified IEEE 39-bus system integrating solar PV and distributed EV fleets across three control areas. The results confirm that dynamically adjusting EV charging based on frequency deviation and SOC significantly enhances grid stability. As shown in Table II, the proposed method reduces maximum frequency deviation in Area 1 from ±0.2147 Hz to 0.0623 Hz, and limits inter-area tie-line power deviations by over 60% across all regions. These reductions demonstrate the ability of EVs to buffer renewable fluctuations in real-time, stabilizing the grid without requiring dispatchable generation or external reserves.

Collectively, these models demonstrate EVs' dual potential in renewable-integrated grids: as real-time stabilizers of grid dynamics and as predictive participants in energy management. [6] show how EVs can actively smooth frequency deviations brought on by RES intermittency, while [3] concentrate on optimizing local PV utilization and market participation. These viewpoints support a key concept: EVs are active grid resources that, when properly synchronized with renewable energy sources, can improve user benefit and system stability.

D. Operational Models for EV Grid Support

As electric vehicles transition from passive consumers to active grid participants, the design of robust, scalable, and economically viable operational models becomes essential. Unlike traditional load models, EV integration must account for charging constraints, user preferences, local network limitations, and evolving market structures. We explores four recent frameworks that operationalize EV coordination through market-based bidding, decentralized optimization, pricing strategies, and secure trading schemes. Each model addresses the dual challenge of maintaining system reliability while enabling flexible EV participation, providing valuable insight into how EVs can be seamlessly embedded within day-ahead planning, real-time scheduling, and distribution-level control architectures.

To enable scalable, user-aware integration of EVs into power system operations, [7]propose a two-stage optimal scheduling framework based on transactive control Fig 5. The model coordinates EV charging through a decentralized price-response mechanism, where aggregators negotiate energy exchanges with both users and the distribution system operator (DSO). Day-ahead scheduling is executed in the first stage, which uses price signals and anticipated demand to identify the best charging windows. The second stage refines those schedules in real time, adjusting for uncertainties in EV availability and local network constraints. Aggregators can dynamically distribute energy while preserving grid stability and user satisfaction.

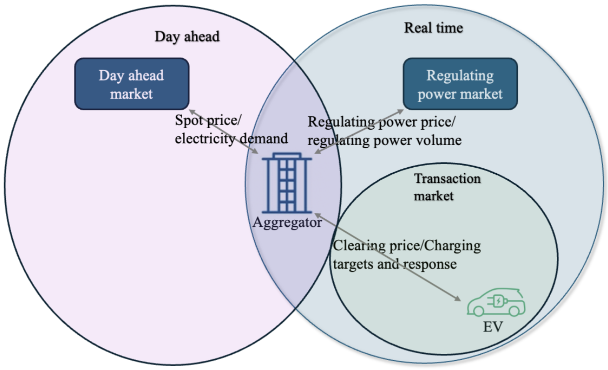

Fig. 5: Distribution of charging costs under varying customer response rates

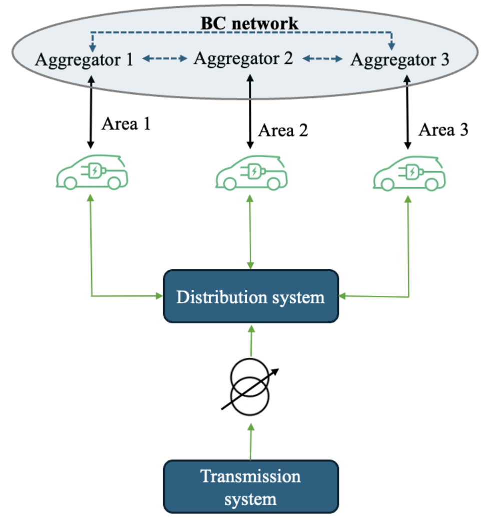

Fig. 6: Hierarchical and zonal coordination architecture for scheduling EVs

At the core of the model is a bilevel optimization problem, where the upper level minimizes overall system cost by adjusting nodal prices, while the lower level represents each EV's response to those prices based on SOC and owner preferences. The interaction is governed by transactive energy principles, ensuring that price formation reflects both local grid limitations and user flexibility.Simulation results confirm the effectiveness of the proposed two-stage transactive control model in achieving coordinated EV integration. Compared to uncontrolled charging, the model significantly improves valley filling, reduces transformer peak loading, and enhances aggregator profitability—demonstrating both grid and economic benefits. They also highlight that higher responsiveness groups leads to lower average charging costs. This demonstrate the model's ability to embed user incentives within grid operations. This reinforces the concept that EVs, when managed through dynamic price-based coordination, can serve as both controllable resources and market-responsive actors.

While transactive energy coordination is effective, real-world deployment must consider hardware limits like the discrete charging levels of commercial EV chargers. Addressing this challenge, [8] propose a grid-aware, two-stage optimization framework that explicitly models discrete charging actions and distribution network capacity constraints to coordinate EV charging in a scalable and reliable manner. In the proposed SOCDC algorithm(Smooth Optimal Coordinated Discrete Charging), stage 1 solves a valley-filling objective while ensuring transformer capacity is not violated. Unlike conventional formulations, this stage uses a binary optimization structure to select feasible charging levels for each EV. Stage 2 then applies a heuristic method to minimize the number of charging on–off transitions, enhancing charging smoothness and device longevity. This two-layer coordination structure enables the model to provide system-level flexibility while preserving local network stability and respecting technical limits on charging infrastructure. Simulation results validate the effectiveness of the SOCDC model in real distribution grid environments. Compared to heuristic-based strategies, SOCDC achieves more uniform load profiles while significantly reducing the frequency of on–off switching events. The model's objective, shown in Equation (5), minimizes control effort by penalizing abrupt changes in charging power:

$$\textbf{SOCDC:} \quad \min_{\mathbf{U}} \; G(\mathbf{U}) = \frac{1}{2}\sum_{n=1}^{N}\sum_{t=0}^{T}(u_{n,t} - u_{n,t+1})^2 \quad \text{s.t. } \mathbf{U} \in \mathcal{U}^* \tag{5}$$

where $u_{n,0} = u_{n,T+1} = 0, \forall n \in \mathbb{N}$. The objective function $G(U)$ represents the total number of on-off switchings/interruptions of all the EVs. This formulation encourages smooth charging behavior while respecting SOC, transformer, and feeder constraints. By addressing the discrete nature of real-world EV chargers and operational limits of the grid, this model offers a realistic and computationally efficient path to integrating EVs as active grid-supportive resources. Building on this, the next framework explores how dynamic pricing strategies can further improve coordination across system operators, aggregators, and end users.

Hierarchical and zonal coordination architecture for scheduling EVs based on the consortium blockchain-enabled framework proposed by Li and Hu [X]. Aggregators (AGs) interact through a BC network to coordinate EV charging/discharging across different zones, interfacing with both distribution and transmission systems.

Recent models have begun integrating pricing mechanisms and market-based optimization into EV coordination to enhance fairness, flexibility, and grid stability. [9] present a dual-layer framework with both centralized and decentralized pricing strategies, balancing aggregator profit, user cost, and grid constraints. The model explores three pricing schemes: a decentralized Stackelberg game (ψ
-IPS), and two centralized mechanisms (BPS and MPS), each solving a multi-objective problem with different trade-offs. The MPS scheme, leveraging a PSO-based algorithm, achieves optimal performance in terms of both transformer loading and charging satisfaction.

Complementing this, [10]propose a secure and scalable two-layer optimization framework based on blockchain and iterative scheduling. Their approach enables a consortium of EV aggregators to participate in a trustless energy trading environment, where bidding and dispatch decisions are coordinated using an improved Krill Herd algorithm. By embedding grid constraints (e.g., power flow, voltage limits) directly into the optimization process, the framework ensures grid-compliant active power support while maintaining user privacy and distributed control. Fig 7. illustrates the hierarchical and zonal architecture used in their scheduling approach, where multiple EV aggregators coordinate across distinct areas through a blockchain-secured network. Simulations on a 30-bus network with 20,000 EVs validate its scalability and performance, particularly under renewable energy integration scenarios.

To better highlight the contrast between these two advanced operational models, Table III provides a comparative overview While both models offer robust solutions to EV scheduling, their underlying architectures and control objectives differ significantly—offering complementary perspectives on the future of intelligent EV-grid coordination.

Grid Constraints	**Optimization Type**	**Strategy Type**	**Scalability**	**Key Result (Comparative)**
Voltage and Transformer	Multi-Objective (PSO)	Centralized + Decentralized	Medium	Outperformed traditional flat pricing by balancing user fairness and grid loading
Power Flow and Voltage	Iterative Metaheuristic (IKHA)	Blockchain-Based Decentralized	High	Provided more scalable, privacy-preserving coordination than aggregator-based pricing models

TABLE III: Comparison of EV Grid Support Strategies

Together, these models underscore the growing sophistication of EV operational frameworks, bridging economic coordination, grid reliability, and user-centric flexibility at both moderate and large deployment scales.

These four frameworks collectively demonstrate the shift toward active, grid-supportive EV coordination through predictive scheduling,pricing signals, and decentralized optimization. From transactive control and discrete-level scheduling to pricing strategies and blockchain-secured bidding, these models address both system-side and user-side requirements. Together, they confirm that operationalizing EVs is not only technically viable but essential for flexible demand response, renewable integration, and the evolution of intelligent power systems.

III. Observation and Future work

The four reviewed operational models collectively highlight the ongoing shift from passive EV usage to active, grid-integrated coordination. Each framework leverages some form of EV aggregation, either through centralized mechanisms (e.g., pricing-based control) or decentralized approaches (e.g., blockchain-enabled systems), to streamline computation and enhance scalability. A common thread among the models is the effort to balance user-centric priorities—such as privacy, cost optimization, and flexible charging—with broader system-level goals like grid stability, congestion management, and voltage compliance. Methodologically, the frameworks employ a range of optimization strategies, from mixed-integer linear programming (MILP) to advanced metaheuristic algorithms like the Krill Herd method, to tackle the non-linear and uncertain nature of EV-grid interactions. Notably, simulation studies across all papers demonstrate strong scalability, with some models successfully handling up to 20,000 EVs, and confirm the feasibility of real-time market participation under coordinated scheduling.

Despite the significant progress demonstrated across these frameworks, several key limitations remain. First, there is a noticeable variation in underlying assumptions — including communication protocols, aggregator hierarchies, and pricing mechanisms — which complicates real-world implementation and interoperability. Additionally, most models focus predominantly on active power scheduling, while the potential of EVs to provide reactive power support and contribute to voltage regulation remains largely underexplored. Among the reviewed works, only one study [10] explicitly incorporates detailed grid constraints, while others adopt simplified distribution models that may overlook critical operational challenges. Furthermore, although renewable energy integration is often considered, most approaches rely on deterministic or overly simplified forecasts, failing to adequately capture the uncertainty and variability inherent in renewable generation.

Based on these observations, several key directions emerge for future research. Models should jointly optimize active and reactive power to enable full-spectrum grid support. Incorporating forecast uncertainty for both renewables and load can improve scheduling robustness. There is a need for lightweight, real-time algorithms responsive to market and grid dynamics. Finally, developing standardized, interoperable protocols—including for blockchain-based coordination—is essential for scalable and practical deployment.

IV. Conclusion

This review has examined four state-of-the-art operational frameworks that enable electric vehicles (EVs) to actively support power system operations through coordinated scheduling, pricing mechanisms, and decentralized control. Across these models, we observe a clear shift toward grid-aware EV integration that balances user preferences with system-level constraints. The use of aggregator-based coordination, optimization-driven scheduling, and innovative communication architectures—such as blockchain—demonstrates the growing maturity of this research area. Despite notable advancements, challenges remain in the areas of reactive power modeling, uncertainty handling, and standardization of decentralized frameworks. Addressing these gaps is critical for scaling EV participation in demand response, enhancing grid flexibility, and supporting renewable energy integration. Future work should focus on unified optimization of active/reactive power, robust scheduling under forecast uncertainty, real-time adaptive control, and the development of standardized protocols to support scalable, secure, and interoperable EV-grid coordination.

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PROJECT PART 1: OPTIMAL POWER FLOW USING GAMS

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 Case-A: Cost Minimizing OPF Solution
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 Bus    P-Optimal      Q-Optimal          Real MC       Reactive MC
             (MW)         (MVAr)          ($/MWh)         ($/MVArh)
   1      400.000          9.053            5.277             0.000
   2      216.982        142.834            5.680             0.000
   3        0.000          0.000            6.104             0.084
   4      181.021        145.241            6.062             0.000
   5        0.000          0.000            6.217             0.170

Real MC      denotes the effect on cost with change in demand at the bus
Reactive MC  denotes the effect on cost with change in reactive demand at the bus
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Fig. 7: OPF results showing optimal active and reactive power dispatch across buses, along with the marginal cost sensitivity to real and reactive power demand at each bus.

1. Using the GAMS code provided, calculated the Y-Bus matrix in polar form.

TABLE IV: Y-bus matrix in per unit (p.u.)

	1	2	3	4	5
1	18.6758	14.6395	4.0905	0	0
2	14.6395	33.3483	4.8871	6.1152	7.8027
3	4.0905	4.8871	30.2953	21.4719	0
4	0	6.1152	21.4719	34.1019	6.6824
5	0	7.8027	0	6.6824	14.4444

TABLE V: Theta matrix values

	1	2	3	4	5
1	5.0247	1.8833	1.8783	0	0
2	1.8833	5.0242	1.8786	1.9138	1.8555
3	1.8783	1.8786	4.9882	1.8314	0
4	0	1.9138	1.8314	4.9868	1.8206
5	0	1.8555	0	1.8206	4.9818

2. Executed the OPF program **minimizing the system cost.**

A. Optimal real and reactive power dispatch for the system

Bus 1 acts as the slack bus, supplying 400 MW to balance the network.Buses 2, and 4 are **generator buses**, supplying the required power, while buses 3 and 5 are **load buses** that consume power.

TABLE VI: Optimal Real and Reactive Power Dispatch at Generator Buses

Bus	Real Power Dispatch (MW)	Reactive Power Dispatch (MVAr)
1	400.00	9.05
2	216.98	142.83
4	181.02	145.24

B. bus voltages and Line Flows

The system's bus voltages and angles are within acceptable limits, with Bus 1 serving as the reference (slack) bus and having a marginal angle of 2.728484E-11 radians. Real, reactive, and complex power flows between buses were analyzed to evaluate system load and inter-bus energy exchange.

TABLE VII: Bus Voltage Magnitudes and Angles(radian)

Bus	Voltage (p.u.)	Voltage Angle (radians)
1	1.0500	0
2	1.0431	-0.1130
3	0.9908	-0.2137
4	1.0205	-0.2074
5	0.9637	-0.2436

TABLE VIII: Real Power Flow Between Buses (ReP in MW)

From / To	1	2	3	4	5
1	0	1.7837	0.9663	0	0
2	-1.7285	0	0.5669	0.6305	1.1778
3	-0.9135	-0.5623	0	-0.3364	0
4	0	-0.6265	0.2547	0	0.3170
5	0	-1.1365	0	-0.3309	0

TABLE IX: Reactive Power Flow Between Buses (ImQ in MVAr)

From / To	1	2	3	4	5
1	0	-0.3931	0.0337	0	0
2	0.5191	0	0.1001	-0.0696	0.3814
3	0.1146	-0.0835	0	-0.6675	0
4	0	0.0769	0.4927	0	0.2965
5	0	-0.2340	0	-0.3116	0

TABLE X: Complex Power Flow Between Buses (S in MVA)

From / To	1	2	3	4	5
1	0	1.8265	0.9669	0	0
2	1.8047	0	0.5757	0.6343	1.2380
3	0.9207	0.5685	0	0.7475	0
4	0	0.6312	0.5546	0	0.4340
5	0	1.1604	0	0.4545	0

C. Total cost, total system losses and the bus-wise Lagrange multipliers

Total cost of generation of electricity: $3453.2982

Total system transmission loss : 0.230033969 *100 (base MVA) pu= 23.003 MW

TABLE XI: Larange multiplier

Bus	Real Power Marginal Cost ($/MWh)	Reactive Power Marginal Cost ($/MVArh)
1	5.2775	0
2	5.6798	0
3	6.1038	0.084
4	6.0623	0
5	6.2167	0.170

The total generation cost of $3453.2982 and transmission loss of 23.003 MW indicate efficient system performance. The bus-wise Lagrange multipliers (marginal costs) quantify the incremental cost of supplying additional real and reactive power. Bus 1 has the lowest real marginal cost ($5.2775/MWh), making it the most economical for additional power injection, while Bus 5 exhibits the highest real ($6.2167/MWh) and reactive ($0.170/MVArh) marginal costs, demonstrating constraints.Reactive marginal costs at Buses 1, 2, and 4 are zero as their generators are able to meet additional reactive demand on its own leading to no additional cost. However, Buses 3 and 5 have non-zero reactive marginal costs as they depend on external support from other buses to meet reactive power demand.As reactive demand increases, the generators will compensate for the losses by increasing their active power output.

PROJECT PART 3: Extension of GAMS Code

Our simulation cases are designed to evaluate the impact of Plug-in Electric Vehicles (PEVs) on bus-level marginal costs, total system cost, and overall system losses. The scenarios are structured as follows:

Case 1: Base case without PEV integration

Case 2: PEVs modeled as additional loads

Case 3: V2G-enabled PEVs supplying both real and reactive power to the grid

Case 4: V2G-enabled PEVs supplying reactive power while consuming real power from the grid

I. Case 1: Base case without PEV integration

In Case 1, the optimal power flow (OPF) model was executed without integrating any Plug-in Electric Vehicles (PEVs). The system operates under conventional conditions. The goal is to minimize the total generation cost. The OPF solution shows the generator dispatch and corresponding marginal costs for both real and reactive power at each bus. As expected, Bus 1, the slack bus, supplies the highest active power (400 MW) to maintain system balance. Buses 2 and 4 also act as generator buses, while Buses 3 and 5 remain as load-only buses.

TABLE XII: Case 1-Base case without PEV integration

Bus	Real Marginal Cost ($/MWh)	Reactive Marginal Cost ($/MVArh)	Total System Cost ($)	Total Real Power Loss (MW)
1	527.75	0		
2	567.98	1.12 E-8		
3	610.38	8.42		
4	606.23	-3.93 E-9		
5	621.67	16.97	3453.30	23.0

The real power marginal cost ranges from $5.28/MWh at Bus 1 to $6.22/MWh at Bus 5. Notably, Buses 3 and 5 show higher reactive marginal costs ($0.084 and $0.170 per MVArh, respectively), indicating their sensitivity to reactive power demand due to limited local support. This highlights areas where reactive power support may be beneficial in future scenarios. The total generation cost was $3453.30, and the total system transmission loss was 23.0 MW.

II. Case 2: PEVs modeled as additional loads

In Case 2, Plug-in Electric Vehicles (PEVs) are integrated into the power system as static loads, consuming both real and reactive power. A total of 28 EVs are connected at Bus 3 and Bus 5 [1]. Each EV is modeled to consume 7 kW (0.007 MW) of real power for charging, and the apparent power capacity of each inverter is set to 8 kVA. This configuration results in a corresponding reactive power demand of 3.87 kVAr (0.00387 MVAr) per EV. The aggregated impact of all EVs is incorporated into the load buses at Bus 3 and Bus 5.

The average charging price for the EV fleet was calculated as 3.9 cents/kWh ($39/MWh), and the discharging price was set at 98% of the charging price[3]. The objective of the OPF model was modified to minimize the combined cost of power generation and EV charging.

TABLE XIII: Case 2 – PEVs Modeled as Additional Loads

Bus	Real Marginal Price ($/MWh)	Reactive Marginal Price ($/MVArh)	EV Charging Cost ($)	Total System Cost ($)	Transmission Loss (MW)
1	527.95	∼0 (EPS)			
2	568.20	9.00e-9			
3	610.65	8.44			
4	606.47	∼0 (EPS)			
5	621.97	17.02	15.29	3,471.03	0.2303

The addition of EVs as static loads increases both the total system cost and transmission loss compared to the base case. The highest reactive marginal cost occurs at Bus 5, indicating increased reactive demand and localized voltage stress due to EV integration.

III. Case 3: V2G-enabled PEVs Supplying Both Real and Reactive Power to the Grid

In Case 3, V2G (Vehicle-to-Grid) functionality is activated, allowing PEVs to supply both real and reactive power back to the grid. The EV fleet connected at Bus 3 and Bus 5 now operates bidirectionally, with Bus 5 contributing -4.541 MW of real power and both buses supplying 0.108 MVAr of reactive power each. The aggregated reactive support amounts to 0.217 MVAr. The EV settings remain consistent with previous cases, while the cost model incorporates the base discharging price (set at 98% of the charging rate) into the overall cost minimization objective.

TABLE XIV: Generator Output and Marginal Costs (Case 3)

Bus	P-Gen (MW)	Q-Gen (MVAr)	Real MC ($/MWh)	Reactive MC ($/MVArh)
1	50.000	0.000	0.000	0.000
2	50.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000
4	50.000	0.000	0.000	0.000
5	0.000	0.000	0.000	0.000

TABLE XV: EV Contribution (Case 3)

Bus	P_EV (MW)	Q_EV (MVAr)	Charging (MW)	Discharging (MW)
3	0.000	0.108	0.000	0.000
5	-4.541	0.108	0.000	-4.541
EV Total Real Power Support (MW)				-4.541
EV Total Reactive Power Support (MVAr)				0.217
Total Generation Cost ($)				623.000
Total Transmission Loss (MW)				48.294

With active V2G support, EVs reduce the generator load and provide voltage support, resulting in a significant drop in total generation cost ($623.00). However, there is a increase in the transmission losses to 48.29 MW, showing a trade-off between cost and efficiency.

VI. Case 4: V2G-enabled PEVs supplying reactive power while consuming real power from the grid

In Case 4, V2G-enabled PEVs are configured to consume real power (charge) while supplying reactive power to the grid. The EVs at Bus 3 and Bus 5 continue to draw their regular charging power while injecting 0.108 MVAr of reactive power each, totaling 0.217 MVAr in support. The cost optimization objective remains the same as in previous cases, minimizing both generation and EV operational costs under this partial support mode.

TABLE XVI: Case4: V2G-enabled PEVs supplying reactive power

Bus	**P-Optimal (MW)**	**Q-Optimal (MVAr)**	**Real MC ($/MWh)**	**Reactive MC ($/MVArh)**
1	400.000	8.995	5.279	0.000
2	217.193	142.818	5.682	0.000
3	0.000	0.000	6.106	0.084
4	181.217	145.144	6.065	0.000
5	0.000	0.000	6.220	0.170
EV Reactive Power Support				
Bus 3 Q_EV Support (MVAr): 0.108				
Bus 5 Q_EV Support (MVAr): 0.108				
Total EV Reactive Power Support (MVAr): 0.217				
Total EV Charging Cost ($): 15.288				

This scenario achieves a balance, EVs assist with reactive power needs while continuing to charge, resulting in moderate system cost ($3,456.71) and low transmission loss (2.29 MW). Reactive marginal costs decrease, indicating improved voltage conditions.

I. VALIDATION

The changing effects of Plug-in Electric Vehicles (PEVs) on power system operations are demonstrated by the simulation in all four scenarios. Both technical and economic metrics exhibit distinct patterns as EV integration moves from passive charging loads to active grid players through V2G functionality.

With a generation cost of $3453.30 and a transmission loss of 23.0 MW, the system sets a benchmark in the base case (Case 1), when EVs are not implemented. Case 2 confirms the additional burden of EV charging by showing a slight increase in system cost and losses once EVs are added as static loads. Because of the increased demand for reactive power, load buses' reactive marginal prices rise, indicating local voltage stress.

Due to the real power injection from EVs, Case 3's full V2G support—where EVs provide both real and reactive power—reduces the generation cost by a significant $623.00. Higher transmission loss (48.29 MW) , indicating a trade-off where losses brought on by reverse power flow are partially compensated by cost savings from EV support.

It is concluded that, Uncoordinated PEV charging (Case 2) increased system cost to $3471.03 and reactive marginal prices up to $17.02/MVArh, highlighting grid stress. In contrast, coordinated V2G operation (Case 3) reduced generation cost to just $623.00, while Case 4 achieved low losses (2.29 MW) with moderate cost ($3456.71) through reactive support alone. These results confirm that with proper coordination and incentives, V2G-enabled PEVs can enhance grid efficiency, reduce costs, and support voltage regulation—benefiting both operators and EV users.