

Review

A Review of Electric Vehicle Integration in Peer-to-Peer Energy Networks

Mohammad Kamran Ikram ^{1,*}, Mehdi Seyedmahmoudian ¹, Gokul Thirunavukkarasu ¹, Saad Mekhilef ¹, Alex Stojcevski ² and Jose Moreira ³

¹ Siemens-Swinburne Energy Transition Hub, Swinburne University of Technology, Melbourne, VIC 3122, Australia

² Curtin University Singapore, Singapore Campus, Singapore 117684, Singapore

³ Siemens, Bayswater, VIC 3153, Australia

* Correspondence: mikram@swin.edu.au

Abstract

The rapid growth of electric vehicle (EV) adoption presents significant challenges for power system stability while creating new opportunities for decentralized energy management. Peer-to-peer (P2P) energy networks have emerged as a promising approach for transforming EVs from passive loads into coordinated grid assets. This paper presents a comprehensive review of EV-P2P integration through a three-layer architectural framework that systematically connects physical infrastructure, market mechanisms, and intelligent control strategies. The Physical Layer reviews how V2X technologies and bidirectional charging enable EVs to operate as flexible storage resources and ancillary service providers. The Transactional Layer reviews on blockchain-based platforms, auction mechanisms, and game-theoretic models for secure energy trading. The Intelligence Layer reviews advanced control strategies, including decentralized optimization methods such as the Alternating Direction Method of Multipliers (ADMM) and Deep Reinforcement Learning. Collectively, the reviewed studies demonstrate that these approaches enable EVs to operate as flexible loads, distributed storage resources, and ancillary service providers, while improving energy trading efficiency, reducing operating costs, and alleviating network congestion under simulated operating conditions. Despite these promising results, a substantial gap remains between simulation-based studies and practical implementation. Future research should prioritize integrated pilot projects to evaluate scalability, interoperability, cybersecurity, and regulatory compliance under realistic operating conditions.

Keywords: peer-to-peer (P2P) energy trading; electric vehicles; vehicle-to-everything (V2X) technologies; blockchain; transactive energy; distributed energy resources (DERs); smart grids; optimization



Academic Editor: Grzegorz Sierpiński

Received: 16 June 2026

Revised: 12 July 2026

Accepted: 14 July 2026

Published: 23 July 2026

Copyright: © 2026 by the authors.

Published by MDPI on behalf of the World Electric Vehicle Association.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The escalating climate crisis, underscored by increasingly stringent global targets such as the Paris Agreement and national Net-Zero commitments, has fundamentally reshaped the global energy landscape [1]. This has propelled an unprecedented acceleration in the deployment of renewable energy resources, driven by dramatic cost reductions, most notably in solar PV module prices, which fell by over 90% between 2010 and 2024 [2]. While Solar Photovoltaic (PV) and Wind Turbines (WT) have emerged as dominant technologies due to their scalability and improving efficiency, their integration into power grids introduces

profound operational complexities. The inherent intermittency and variability of these resources create significant challenges in maintaining the real-time equilibrium between electricity supply and demand, often leading to issues such as overgeneration, the duck curve phenomenon, and grid instability [3].

The challenge of balancing supply and demand is further amplified by the rapid electrification in transportation sector. The proliferation of Electric Vehicles (EVs) introduces substantial, spatially dispersed, and temporally variable new loads onto the grid [4,5]. Unmanaged charging patterns, particularly when clustered during evening peak hours, can lead to localized distribution network overloads, exacerbated peak demand, and elevated system losses [6]. However, EVs also present an unparalleled opportunity to enhance grid stability and flexibility. Their on-board batteries constitute a vast, distributed, mobile energy storage resource that can be leveraged through Vehicle-to-Grid (V2G) technology. This transforms EVs from passive loads into active grid assets capable of providing valuable ancillary services, such as frequency regulation, peak shaving, and spinning reserve [7,8].

Beyond grid-scale services, EVs offer significant local benefits when integrated with distributed energy resources (DERs) like rooftop PV. Strategic charging and discharging cycles through Vehicle-to-Home (V2H) and Vehicle-to-Building (V2B) configurations can significantly reduce household energy costs, provide backup power during grid outages, and increase the self-consumption of locally produced renewable energy [9–11]. Effectively integrating this flexibility requires a move away from the century-old paradigm of centralized, unidirectional power grids toward a more decentralized, participatory electricity ecosystem. In this new landscape, consumers are no longer passive end-users but active prosumers who both consume and produce electricity [9,12].

To facilitate this transition, prosumer energy-sharing models have emerged, categorized primarily into prosumer-to-grid (P2G), peer-to-peer (P2P), and hybrid models. While the P2G model relies on the central grid, the P2P model promotes direct energy trading among prosumers. This approach, often facilitated by technologies such as blockchain, enhances local resilience and fosters market-driven pricing. Industrial interest in P2P energy trading is growing rapidly, with pioneering projects such as the Brooklyn Microgrid in New York [13] and various trials across the UK, Japan, Australia, and the European Union [14–16].

While the potential of EV-P2P integration is widely recognized, the existing literature remains fragmented. Most reviews focus on individual aspects, such as Vehicle-to-Everything (V2X) technologies or blockchain-based energy trading, rather than their interactions. Unlike previous reviews, this paper integrates V2X hardware, blockchain market design, and AI-based control within a unified layered architecture, showing how physical constraints shape market mechanisms and intelligent control strategies. Our analysis also shows that most studies have emerged only within the last few years, highlighting the rapid evolution of this field.

The remainder of this paper is organised as follows: Section 2 discusses the synergy between EVs and P2P networks. Section 3 defines the functional roles of EVs in P2P markets. Section 4 provides a detailed analysis of the models of EV participation in P2P networks. Section 5 synthesizes these findings into a technical roadmap, discussing quantitative performance, implementation gaps, and real-world pilot projects. Finally, Section 6 provides the concluding remarks.

1.1. Methodology and Literature Selection

This review adopts a structured approach to identify and evaluate the existing literature on EV-P2P integration. Relevant studies published from 2010 onwards were collected from three widely used academic databases, namely IEEE Xplore, Scopus, and Web of

Science (WoS). The search strategy utilized boolean operators to combine keywords related to: (i) electric vehicles (EV, V2G, V2H, V2X), (ii) peer-to-peer energy trading (P2P, transactive energy, local energy markets), and (iii) technical frameworks (blockchain, distributed optimization, decentralized control).

The initial search returned approximately 870 publications. After removing duplicate records and non-English studies, the remaining 510 records were screened based on their titles and abstracts to exclude research focused purely on vehicle hardware, battery chemistry, or general grid optimization without a clear EV-P2P integration component. Subsequently, a full-text evaluation was conducted based on the inclusion and exclusion criteria detailed in Table 1.

This filtering process resulted in a curated set of core studies that form the primary basis for the architectural synthesis and quantitative analysis presented in this paper. These are complemented by additional references included throughout the manuscript to provide background information and support the introductory discussion and statistical analysis.

Table 1. Scope and Criteria for Literature Selection.

Criteria	Inclusion Criteria	Exclusion Criteria
Primary Domain	The study must focus on the intersection of EVs and P2P energy trading or sharing.	Studies where either EVs or P2P trading are absent or only mentioned peripherally. Papers on general EV charging without a P2P market are excluded.
Methodological Approach	Focus on studies proposing or analyzing technical architectures, frameworks, or models. This includes optimization, game theory, blockchain protocols, and AI/ML applications.	Purely conceptual or descriptive papers without a technical modeling component. Studies focused exclusively on hardware design or social science aspects without technical simulation.
Key Technologies	Studies involving core enabling technologies: V2X modalities, blockchain/smart contracts, or advanced optimization/control strategies.	Papers that do not engage with the technical implementation details of these core architectures.
Publication Type	Peer-reviewed journal articles and high-impact conference proceedings.	Dissertations, book chapters, editorials, news articles, and non-peer-reviewed grey literature.
Language	Full text published in English.	Papers published in any language other than English.

As shown in Figure 1, research activity in this field has surged since 2020, highlighting a critical inflection point in decentralized energy management. The selected studies are used to deconstruct the EV-P2P ecosystem into three interdependent layers: the Physical Layer (V2X infrastructure), the Transactional Layer (market and blockchain mechanisms), and the Intelligence Layer (optimization and AI-driven control).

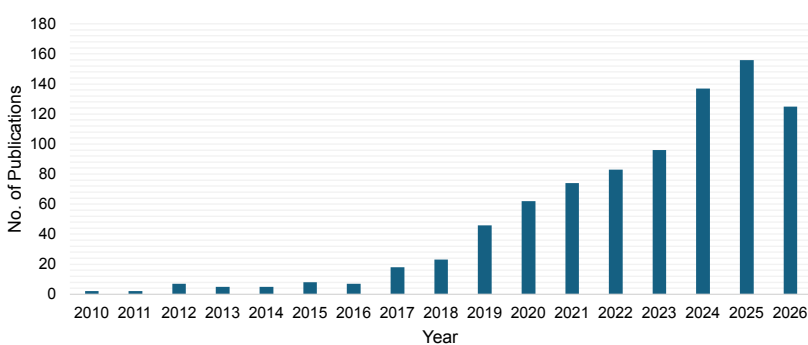


Figure 1. Annual publication trend on EV-P2P integration (Scopus database, accessed June 2026).

1.2. Scope of the Review

To establish the scope of this review, it is necessary to distinguish EV-enabled P2P energy sharing from other closely related paradigms. Although these paradigms employ common technologies, such as bidirectional charging and V2X capabilities, they differ in objectives, participant roles, market structures, and operational principles. Table 2 summarises the major EV integration paradigms and outlines their key characteristics.

Table 2. Comparison of Major EV Integration Paradigms.

Paradigm	Primary Objective	Energy Flow	Trading Mechanism
Behind-the-Meter energy management (V2H/V2B)	Self-consumption and local energy management	EV ↔ Home or Building	No external market participation
Aggregator-based V2G	Grid support and ancillary services	EV Fleet ↔ Utility Grid	Aggregator-coordinated
Local Energy Market (LEM)	Community energy balancing	Multiple local participants	Local market operator
EV-P2P Energy Trading	Direct energy trading between peers	Peer ↔ Peer	Decentralized market
Flexibility Market	Network congestion management and flexibility services	Flexible resources ↔ DSO/TSO	Incentive- or market-based flexibility trading

This review focuses exclusively on EV participation in P2P energy trading networks, where EVs act as autonomous market participants that directly exchange energy with residential prosumers, commercial buildings, and other EVs. Concepts such as V2G, V2H, and V2B are discussed only where they enable or support EV-P2P energy trading. Likewise, local energy markets and flexibility markets are included only when their market designs, optimization methods, or operational principles are directly relevant to EV-P2P systems.

2. Synergies Between EVs and P2P Energy Networks: The Physical Layer

A P2P energy network is a complex socio-technical system composed of several key actors who interact through both physical energy exchange and digital information flows [17]. The conceptual model for this ecosystem, as illustrated in Figure 2, shows these primary actors: Prosumers, who are equipped with DERs like solar PV; traditional Consumers; and mobile energy assets in the form of EVs. All participants remain connected to the main utility grid, which serves as the ultimate source of backup power and a sink for excess energy. The entire ecosystem is coordinated through a digital P2P Platform, a concept explored in numerous community-driven frameworks [18]. This section will deconstruct this physical layer, first by defining the fundamental network architecture and then by providing a detailed review of the critical V2X technologies that enable the EV's active, bidirectional participation in this network, as introduced in foundational V2X studies [19].

2.1. P2P Network Architecture and Key Actors

The conceptual ecosystem shown in Figure 2 comprises a diverse set of actors whose interactions define the P2P energy market. It reflects the P2P and hybrid paradigms summarized in Table 2 and distinguishes them from aggregator-based V2G and behind-the-meter V2H/V2B models, where energy exchange remains centralized or confined to individual premises rather than occurring directly between peers. Central to this model is the prosumer, an entity that can both produce and consume electricity, which may include

residential homes with rooftop solar PV, commercial buildings, or community-owned renewable assets. These prosumers interact with traditional consumers and, most critically for this review, with EV owners, who can act as either consumers (when charging) or producers (when discharging). The research consistently models these heterogeneous agents as the primary participants in local energy transactions, as seen in the work of [20], who designed a P2P market for distributed prosumers and EVs, and [21,22], who modelled trading and grid impacts between commercial fleets and renewable-equipped charging stations.

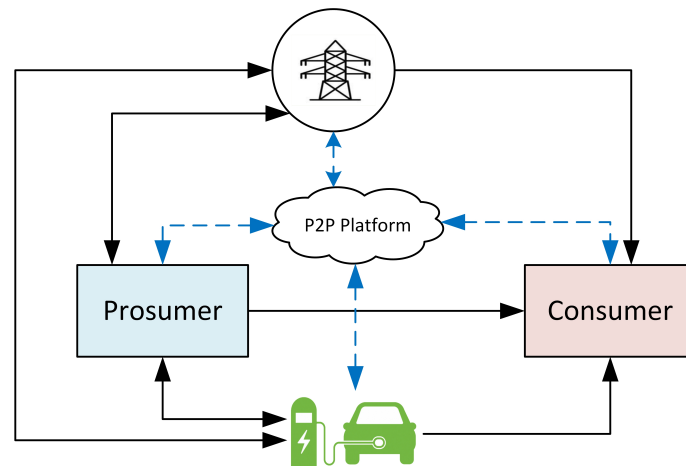


Figure 2. Conceptual model of a P2P energy trading ecosystem. Solid lines represent the physical flow of energy, while dashed lines represent the flow of information and financial data coordinated by the central P2P platform.

Functionally, a P2P energy network can be divided into two main domains: the Physical Domain and the Virtual Domain [23]. The Physical Domain comprises the electrical infrastructure and the flow of energy through V2X-enabled devices, whereas the Virtual Domain provides the digital environment for energy trading, market operation, and system coordination. Existing studies commonly describe P2P energy networks using these two domains, in which the virtual layer manages trading activities while the physical layer enables the actual delivery of electricity through the distribution network or a dedicated microgrid infrastructure [24,25]. Building on this concept, this review further subdivides the Virtual Domain into two analytical layers, namely the Transactional Layer and the Intelligence Layer, resulting in the three-layer framework presented in Section 4.1.

2.2. The Electric Vehicle as a Network Participant

While EV technology has existed since the 19th century [26], its recent integration into smart grids is driven by concerns over fossil fuel depletion and environmental impact, leading to current advancements.

The EVs are broadly classified into four types; Battery Electric Vehicles (BEVs), which rely entirely on electric power stored in batteries and can be charged during EV deceleration and braking [27], and have the highest capacity to impact the grid [28]; Plug-in Hybrid Electric Vehicles (PHEVs), which combine a traditional internal combustion engine (ICE) with an electric motor and battery (usually smaller as compared to BEVs) that can be charged via an external source, therefore have a limited capacity to impact the grid [29]; Hybrid Electric Vehicles (HEVs), primarily use an ICE supplemented by an electric motor, which is charged through regenerative braking and the engine itself; and Fuel-cell electric vehicles (FCEVs), use hydrogen as a fuel. With HEVs and FCEVs, there is no connection with the grid, therefore, they cannot impact the grid.

Because of the multiple benefits of transitioning towards EVs, governments are introducing Zero-Emission Vehicle (ZEV) strategies. Globally, these transitions are accelerated by the European Union's Fit for 55 package [30], China's NEV dual-credit policy [31], and regional incentives in the United States, such as California's ACC II [32]. In Australia, state-level strategies include Queensland's plan to achieve 50% of new passenger vehicle sales as ZEVs by 2030 and 100% by 2036, along with significant rebates and infrastructure investments [33], and Western Australia's initiative to develop Australia's longest EV charging network and provide substantial rebates and grants to support ZEV adoption and infrastructure [34]. Similarly, the Victorian Government has set a target of 50% of all new light vehicle sales to be ZEVs by 2030 [35].

As of mid-2026, the transition toward zero-emission vehicles (ZEVs) has reached a critical stage. Global passenger EV sales are projected to reach approximately 23 million units in 2026, accounting for 27% of all new car sales, as shown in Figure 3 and, annual sales are expected to exceed 35 million units by 2030 [36]. At the same time, renewable electricity generation is expanding to support this growing demand, following the upward trend shown in Figure 4, with total renewable generation projected to surpass 40,000 TWh by 2050 [37].

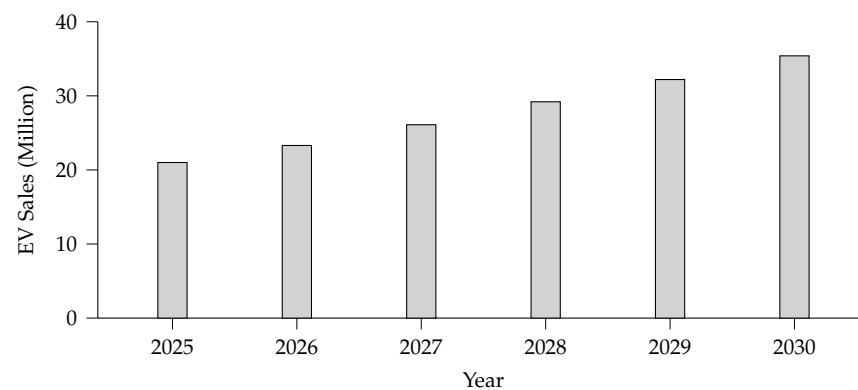


Figure 3. Projected Global Passenger EV Sales (2025–2030) [36].

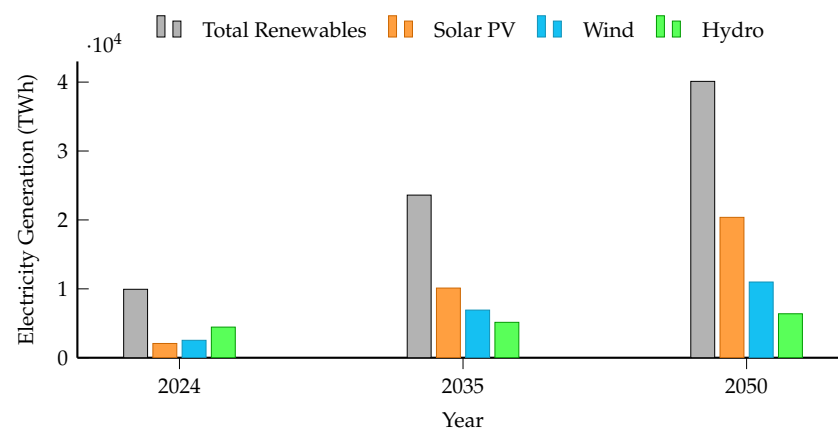


Figure 4. Projected global renewable electricity generation by technology in 2024, 2035, and 2050 [37].

This parallel growth poses a substantial flexibility challenge for future power systems. According to the IEA [37], short-term grid flexibility requirements are expected to increase by a factor of two to seven by 2035. Meanwhile, the global EV fleet is projected to consume more than 2700 TWh of electricity by 2040, representing approximately 6% of global electricity demand (under the Stated Policies Scenario). Leveraging EVs as distributed storage resources through P2P energy networks can help provide the flexibility needed to accommodate higher shares of variable renewable generation.

The integration of EVs into P2P networks has not been a uniform development but rather a dynamic evolution over the last decade. As illustrated in Figure 5, the field has progressed through several distinct phases, each characterized by new technological capabilities and shifting research paradigms. Early concepts in the 2010s focused primarily on centralized, grid-centric models like V2G or G2V, where EVs were treated as controllable loads to support grid stability. The mid-to-late 2010s marked a significant shift towards decentralization, with the emergence of P2P market designs, auction mechanisms, and the first blockchain-based platforms for energy trading. The current era, beginning around 2020, is defined by the integration of artificial intelligence for intelligent optimization and a more holistic view of V2X synergies, where EVs act as dynamic, multi-functional assets within complex energy ecosystems. We will now dig into the specific technologies and models that characterize this evolution.

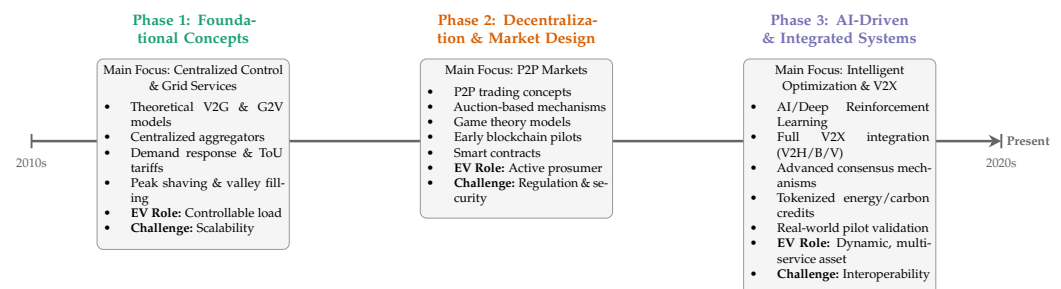


Figure 5. Evolution of EV-P2P Integration Paradigms (2010s–Present). The field has progressed from centralized, grid-focused concepts to decentralized, AI-driven ecosystems where EVs act as dynamic, multi-service assets.

2.3. Bidirectional Charging: The Gateway to Participation

To properly integrate EVs into the power system, a proper charging mechanism should be maintained to allow the bidirectional flow of EV power to the grid and peers [38]. The EV charging methods are broadly of two types: unidirectional and bidirectional. Unidirectional methods usually have uncontrolled or uncoordinated charging, which charges at maximum power without control, leading to peak load and voltage issues [39,40]; delayed charging, which uses pricing to shift charging to off-peak times, potentially causing a second peak [41]; and controlled charging, which adjusts time and power based on network conditions to optimize system use but requires complex control [42].

Bidirectional methods include V2G, where EVs can charge and discharge to the grid, providing grid services but needing bidirectional chargers and communication and active discharging may degrade battery; V2B, where EVs supply power to building loads, reducing costs but offering fewer grid services; and V2H, which supplies power to a single home, supporting local renewables with a simpler setup but limited grid impact. Customer acceptance is the major barrier to implementing all these bidirectional power concepts [43].

2.4. Enabling Technologies: V2X Strategies

The ability of an EV to participate in a P2P market as more than a passive load depends on V2X technologies. V2X is a broad term encompassing the communication protocols and power electronics that enable bidirectional energy flow between an EV battery and external entities. While conventional grid-to-vehicle (G2V) charging only permits energy consumption, V2X enables EVs to function as mobile DER. The different V2X modalities provide a spectrum of capabilities, ranging from simple home backup to complex grid support, with distinct grid impacts, benefits, and challenges, as summarized in Table 3. Figure 6 further classifies V2X technologies according to their primary market functions, ranging from localized P2P energy trading to grid-scale ancillary services.

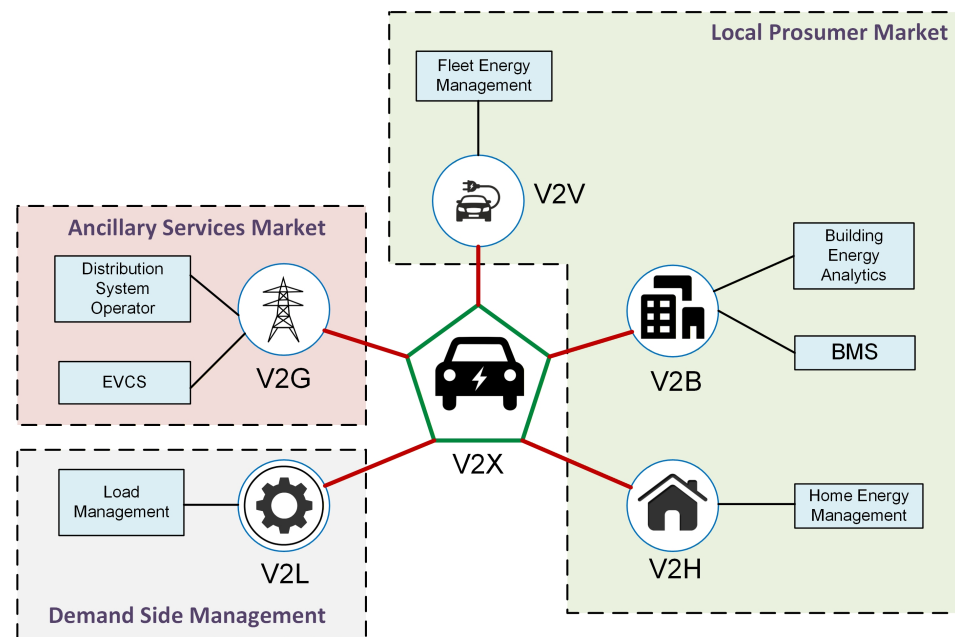


Figure 6. Classification of V2X interaction paradigms based on their primary market objectives. V2V, V2H, and V2B facilitate local P2P energy trading, V2G provides ancillary services to the DSO, and V2L supports demand-side management.

Table 3. Technical Capabilities and Grid Impact of V2X Modalities.

V2X Modality	Primary Function in P2P Networks	Grid Impact	Key Benefit for the System	Critical Challenge	Key Paper(s)
V2G	EV provides energy and ancillary services to the wider distribution network.	High	Enables EVs to act as distributed grid assets for system-wide stability (e.g., frequency regulation).	High infrastructure & communication costs; complex coordination; battery degradation concerns.	[44,45]
V2H	EV powers its owner's home, acting as a behind-the-meter resource.	Low	Increases household self-sufficiency and provides reliable backup power, reducing the home's net load.	Limited system-level impact as it does not directly support peers or provide grid-wide services.	[19,46]
V2B	EV (often from a fleet) powers a commercial building.	Medium	Reduces a building's large peak demand, which can significantly alleviate stress on the local transformer.	High upfront cost for DC chargers; requires complex integration with Building Management System (BMS).	[47]
V2V	EV trades energy directly with another EV.	Localized	Creates hyper-local, mobile energy markets; can alleviate demand at congested charging hubs.	High network and communication complexity; minimal impact on broader grid stability.	[48]
V2L	EV powers standalone appliances (acts as a mobile generator).	Negligible	Provides mobile, off-grid power for remote areas, emergency response, or specific worksites.	Niche use case; does not contribute to the P2P market or grid stability in a meaningful way.	(General V2X)

A technical tension exists between the localized objectives of V2H and V2B and the system-wide objectives of P2P energy trading. While V2H prioritizes household self-sufficiency by reserving battery capacity for the vehicle owner, it can reduce the

aggregate flexibility available to the broader P2P market. Future EV-P2P architectures should therefore incorporate hierarchical flexibility reservation mechanisms capable of evaluating the opportunity cost of allocating EV battery capacity to local backup services versus higher-value applications such as grid support or P2P energy sharing.

2.4.1. V2G: EV as a Grid Asset

V2G is the most extensively studied V2X modality, enabling EVs to both draw power from and inject power into the distribution network. This bidirectional capability allows EVs to function as dispatchable grid assets that can support both local P2P communities and wider electricity markets. Within P2P energy networks, V2G facilitates the provision of ancillary services such as frequency regulation, voltage support, and demand response. For example, ref. [44] proposed a game-theoretic framework that utilizes fleets of V2G-enabled EVs within dynamic demand response programs, while [45] developed a blockchain-based market mechanism for managing V2G transactions.

Despite its significant potential, widespread V2G adoption faces several technical and economic barriers. Key challenges include the high cost of bidirectional DC charging infrastructure and the requirement for secure, reliable communication and control systems. Battery degradation remains the most critical concern, as repeated charge-discharge cycles accelerate capacity fade in lithium-ion batteries, increasing ownership costs and potentially reducing battery lifespan. Consequently, revenues generated through P2P trading and ancillary service participation must be sufficient to offset these degradation costs.

A notable limitation of existing P2P-V2G research is the simplified treatment of battery aging. Many economic models either neglect degradation costs or represent them using linear approximations, which may not accurately capture long-term battery behavior. Future studies should therefore incorporate physics-based degradation models to provide a more realistic assessment of the economic viability and sustainability of V2G participation. As capacity decline is non-linearly dependent on varying cycling conditions, state-of-charge windows, and temperature, factors often overlooked in current P2P energy sharing models [49].

2.4.2. V2H: Enhancing Household Autonomy

V2H represents a more localized, behind-the-meter application of bidirectional charging. In this mode, the EV is defined by its role as a home battery storage system, capable of powering its owner's house directly and isolating from the grid if necessary. V2H offers two primary benefits in a P2P ecosystem. First, it significantly increases a household's energy self-sufficiency, allowing a prosumer to store their excess solar energy generated during the day [50,51] and use it to power their home in the evening, thereby reducing their reliance on either the grid or their peers. Second, it provides a reliable source of backup power during grid outages [52], enhancing household resilience.

The significant financial impact of this capability was quantified by [19], whose simulations showed substantial annual bill savings for households participating in a P2P market combined with V2H dispatch. The optimization model presented in [46], which demonstrated a 23% cost reduction for prosumers using V2H, further highlights its economic benefits. The main limitation of V2H is its low direct impact on the wider P2P market and grid; while it reduces a home's net load, it does not inherently allow for energy sharing with neighbors or provide system-wide grid services.

2.4.3. Emerging and Specialized V2X Modalities

Beyond the primary modalities of V2G and V2H, the literature explores several other V2X technologies that serve more specialized, although equally important, roles within the P2P ecosystem:

- V2B: This can be conceptualized as V2H at a commercial scale. In this mode, a fleet of EVs, typically corporate or employee vehicles, can be used to power a commercial building. Its primary application is in peak shaving to help the building avoid high demand charges from the utility. This capability is highly relevant to the energy management models for smart building clusters, such as the one explored by [47], where a V2B-capable fleet could act as a significant shared energy resource.
- Vehicle-to-Vehicle (V2V): V2V represents the most decentralized form of P2P energy trading, enabling direct energy exchange between EVs without relying on fixed charging infrastructure [53,54]. This capability can facilitate localized energy sharing and help reduce demand at public charging stations during periods of high utilization [55]. However, conventional V2V implementations generally exhibit lower energy transfer efficiency than direct vehicle-to-DC load applications because many existing systems rely on an intermediate AC conversion stage. In these architectures, energy is converted from DC to AC by the supplying vehicle and then back to DC by the receiving vehicle, introducing additional conversion losses [56,57]. Emerging DC-coupled V2V architectures, which employ a common DC bus or dedicated DC charging infrastructure, eliminate the intermediate AC conversion stage and can therefore improve overall energy transfer efficiency while reducing power conversion losses [58].
- Vehicle-to-Load (V2L): This is the simplest form of bidirectional capability, where an EV's battery is used to power standalone appliances or loads via a standard outlet, effectively acting as a mobile generator. While useful for off-grid applications such as emergency response or worksites, its impact on the structured energy trading within P2P networks is negligible, and as such, it is not a primary focus of the market models reviewed in this paper.

While Table 3 classifies V2X modalities according to their technical functions and grid impacts, it does not show how these technologies are integrated with other components in practical energy systems. To address this, Table 4 categorizes studies based on their level of system integration, ranging from single-modality implementations to hybrid frameworks that combine V2X with demand-side management, energy storage, and renewable energy sources. Together, these tables provide complementary perspectives by highlighting both the functional roles of V2X technologies and their integration within broader EV-P2P energy systems.

Having reviewed the various V2X modalities and their integration with complementary technologies such as Demand-Side Management (DSM), Energy Storage Systems, and Renewable Energy Sources, it is evident that EVs are increasingly being positioned as active participants in modern energy systems. These technical advancements, including V2G, V2H, and V2V interactions, provide the operational foundation for decentralized energy trading. Building upon these capabilities, the next stage of research focuses on the market mechanisms that enable energy exchange among participants. Consequently, the following section examines the market models underpinning P2P energy trading, including blockchain-based platforms, auction mechanisms, and decentralized optimization frameworks that support efficient energy trading and grid stability.

Table 4. Comparative Analysis of V2X Modalities in P2P Energy Networks.

Integration Category	Description of Integration	V2X Type	Primary Research Focus/Goal	Key Representative Paper(s)	Remarks
Basic V2X	Studies focusing on the operation of a single V2X modality (e.g., V2G only, or V2H only) without other complex integrations.	V2G, V2H, V2V	To prove the fundamental concept; to design a core market mechanism for that specific modality.	[46] (V2H focus); [48]. (V2V focus)	Foundation stage
V2X with DSM	Combines V2X capabilities with broader DSM strategies, such as smart appliance scheduling or price-based load shifting.	V2G & DSM	To create a holistic home/building energy management system where the EV is one of several flexible resources.	[59,60]	Enhances demand flexibility
V2X with Stationary Energy Storage	Models that co-optimize the operation of EVs (mobile storage) and stationary Battery Energy Storage Systems (BESS).	V2G + BESS	To find the optimal dispatch between mobile and stationary batteries; to enhance community resilience and self-sufficiency.	[19,61]	Mobility vs. Stationarity
V2X with Renewable Energy (RE)	Explicitly models the synergy between V2X and intermittent renewables (e.g., solar PV, wind).	V2G + PV/WT	To use EVs to absorb excess renewable generation, reduce curtailment, and firm renewable output.	[62] (PV-Grid-EV transactions); [63] (managing PV uncertainty)	Improves RE utilization
Fully Integrated/Hybrid Systems	The complex models, integrating V2X with multiple other components (e.g., RE + ES + DSM).	V2X + RE + ES + DSM	To create a comprehensive, system-wide optimization framework for a complete microgrid or local energy community.	[64] (Microgrids + Parking Lot); [47] (Smart Building Clusters); [65] (Fast Charging + Renewables)	Full-stack integration

3. Functional Roles of EVs in P2P Energy Markets

EVs have evolved from passive electricity consumers to active participants in decentralized energy markets, where they simultaneously perform multiple functions as flexible loads, distributed storage resources, and ancillary service providers. Figure 7 illustrates these complementary roles, while Table 5 summarizes their primary functions, market interactions, and associated benefits. Rather than operating independently, these roles create technical and economic synergies that improve renewable energy utilization, reduce operational costs, and enhance distribution network resilience [46,47,66].

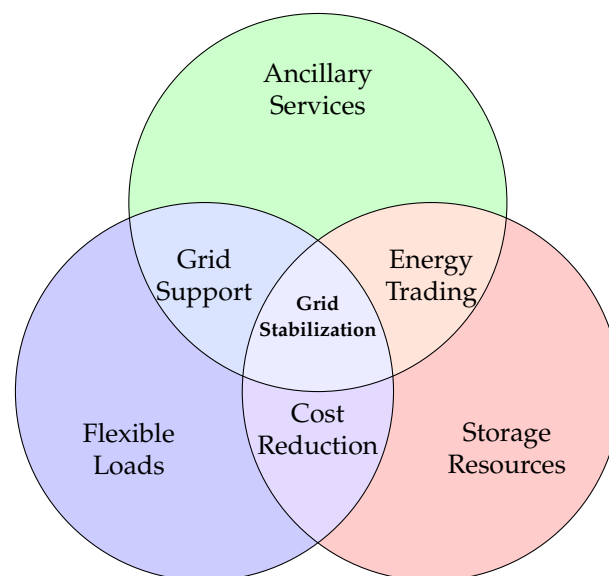
**Figure 7.** Roles of EVs in P2P Energy Networks and their synergies.

Table 5. Functional Roles of EVs in P2P Energy Markets.

Functional Role	Description	Primary Action in P2P Market	Key Benefit	Key Paper(s)
Flexible Load	The EV adjusts its charging schedule according to electricity prices, renewable generation availability, or network conditions.	Purchases energy during low-price periods or when excess local generation is available.	Reduces charging costs and mitigates peak demand.	[46,59]
Storage Resource	The EV battery stores energy obtained from peers or the grid and later discharges it through V2X services.	Trades stored energy and functions as a distributed community energy storage asset.	Enhances self-sufficiency, flexibility, and energy autonomy.	[19,67]
Ancillary Service Provider	The EV supports grid operation by providing services such as voltage regulation, frequency support, and reserve capacity.	Offers flexibility to local markets or responds to aggregator dispatch signals.	Improves grid stability while creating additional revenue streams.	[68,69]

3.1. EVs as Flexible Loads and Storage Resources

Recent studies have extensively investigated the use of EV flexibility to improve decentralized energy management. For example, ref. [59] formulated EV charging as a flexible scheduling problem that adapts to real-time market conditions to improve community-wide energy efficiency. Likewise, ref. [70] demonstrated that coordinated charging can shift electricity demand toward periods of high renewable generation, reducing network loading and improving renewable utilization. Specifically, ref. [22] utilized empirical data from an Australian commercial fleet to demonstrate that hybrid PV-wind integration can postpone peak demand by three hours and reduce overall grid consumption by 7% through optimized charging/discharging cycles.

Within P2P energy markets, this flexibility is commonly achieved through DSM strategies that coordinate charging and discharging while satisfying user mobility requirements [71–74]. Such scheduling approaches reduce peak demand, increase local renewable self-consumption, and enable economically viable participation in decentralized electricity markets [8,75,76].

Beyond flexible demand, EV batteries are increasingly utilized as distributed energy storage resources. Rather than serving only transportation needs, they provide temporary energy storage that facilitates P2P trading and improves local energy balancing. For example, ref. [67] proposed an energy-backed token mechanism that rewards EV owners for providing storage capacity, whereas [19] demonstrated significant reductions in household electricity costs through V2H integration within P2P markets. Similar benefits have been reported using blockchain-enabled charging systems and distributed optimization frameworks, where EVs act as short-term energy buffers that mitigate fluctuations in distributed renewable generation [47,77].

3.2. EVs as Ancillary Service Providers and Coordination Agents

In addition to energy trading, EVs increasingly support power system operation by providing ancillary services and enabling decentralized coordination. Although widespread EV adoption can introduce operational challenges, coordinated charging and discharging enable EV fleets to contribute to voltage regulation, frequency control, and overall grid reliability [66,78]. For example, ref. [48] proposed a blockchain-enabled V2V trading framework that simultaneously facilitates secure energy exchange and supports grid operation, while [68] demonstrated that aggregated EV fleets can effectively provide frequency regulation services comparable to conventional stationary storage.

Recent research has also emphasized the role of EVs as coordination agents within decentralized P2P markets. Auction-based trading strategies [79], reactive power support during fast charging [80], smart building energy management [44], and coordinated charging station control [69,81] collectively demonstrate how coordinated EV operation

improves network performance while reducing charging costs and congestion. These studies highlight that effective coordination is fundamental to realizing the technical and economic benefits of EV-integrated P2P energy systems.

4. Models for EV Participation in P2P Energy Markets

4.1. A Layered Architectural Framework

The participation of EVs in P2P energy networks relies on the coordinated operation of physical infrastructure, market mechanisms, and intelligent decision-making rather than any single technology. To provide a systematic analysis of the literature, this review adopts the layered architectural framework shown in Figure 8. The framework organizes the EV-enabled P2P ecosystem into three interdependent layers, as summarized in Table 6.

Table 6. Hierarchical Three-Layer Architecture for EV-P2P Energy Networks.

Layer	Domain	Core Technologies & Components	Primary Function in the P2P Ecosystem
Physical Layer	Physical	EVs, Battery Systems, Bidirectional Chargers (V2G/V2H/V2B/V2V), Distribution Grid, Smart Meters	Facilitates bidirectional power exchange, enforces hardware and battery operating constraints, and interfaces with the distribution network.
Transactional Layer	Virtual	Blockchain, Smart Contracts, Auction Mechanisms, Game-Theoretic Market Models	Manages P2P energy trading through decentralized pricing, transaction validation, market clearing, and financial settlement.
Intelligence Layer	Virtual	MILP, ADMM, MPC, Deep Reinforcement Learning, Distributionally Robust Optimization (DRO)	Optimizes charging, discharging, and energy trading decisions to improve economic performance, renewable energy utilization, and grid stability.

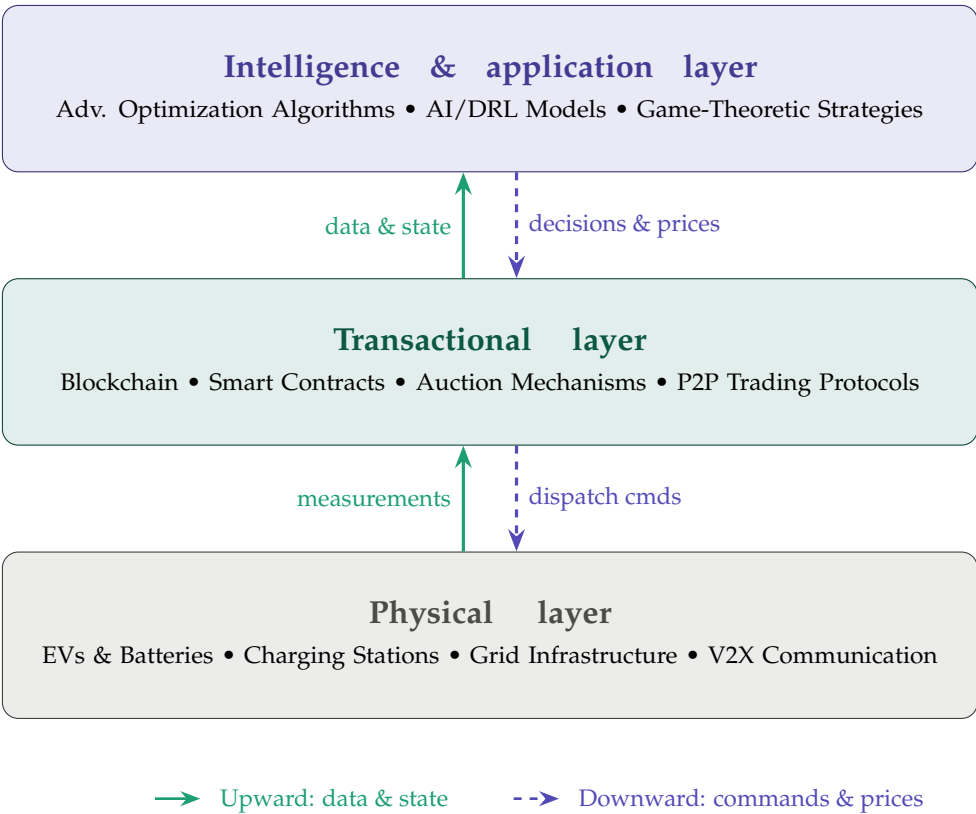


Figure 8. Layered architecture framework for EV-P2P energy trading systems.

The Physical Layer comprises grid infrastructure, V2X technologies, and battery operating constraints. The Transactional Layer encompasses market mechanisms, blockchain platforms, pricing strategies, and trading protocols within the virtual domain. The Intelligence & Application Layer incorporates optimization techniques and intelligent decision-making algorithms for energy management and market coordination. Together, these three layers illustrate how physical energy exchange, market transactions, and intelligent control operate to enable efficient and reliable P2P energy networks.

The Physical Layer was discussed in Section 2. The remainder of this section focuses on the two upper digital layers, namely the Transactional Layer and the Intelligence & Application Layer. This organization provides a consistent basis for comparing existing approaches and evaluating their contributions to the efficiency, scalability, reliability, and intelligence of EV-integrated P2P energy networks.

4.2. The Transactional Layer: Market Mechanisms

While the Physical Layer provides the hardware for energy to flow, the transactional layer provides the fundamental rules and environment that govern how, why, and with whom that energy is traded. This layer is the socio-economic heart of the P2P ecosystem, moving beyond simple physical connections to create a true market. It addresses the critical challenges of establishing trust between unknown peers, discovering fair prices in a dynamic environment, and formalizing the strategic interactions of self-interested participants. At the core of these market designs is the economic objective of maximizing social welfare, which aims to find the optimal allocation of energy that provides the greatest collective benefit to all participants.

The transactional layer is deconstructed into its three foundational pillars as identified in the literature: blockchain-based platforms for establishing decentralized trust, auction and bidding mechanisms for enabling efficient price discovery, and game-theoretic models for analyzing the strategic behavior of market agents. These pillars work in concert to create a robust and viable marketplace for P2P energy exchange, as explored in studies such as [82,83].

4.2.1. Blockchain-Based Platforms

Blockchain technology serves as the foundational trust layer for many decentralized P2P markets, providing a secure, transparent, and immutable ledger for transactions without relying on a central intermediary. Its adoption has been a dominant theme in the literature, evolving from simple conceptual models to highly specialized and integrated platforms. This evolution can be understood through three primary research thrusts: enhancing core performance, increasing economic sophistication, and integrating with external intelligence. As shown in Table 7.

Early conceptual models, such as those by [84,85], were pivotal in establishing the viability of using distributed ledgers for securely processing and logging EV charging transactions. These foundational works proved the principle of a decentralized, tamper-proof record for energy trading. However, they did not address the significant scalability and latency challenges inherent in first-generation blockchains (like Bitcoin's Proof-of-Work), which would be unsuitable for the high-frequency transactions required in real-time energy markets. Recognizing these limitations, a major research thrust has focused on enhancing the performance and efficiency of the underlying distributed ledger technology (DLT). This represents a maturing of the field from a generic one-size-fits-all blockchain approach to application-specific designs. For instance, ref. [48] proposed a custom consensus mechanism (BAC-SDS) specifically for the high-mobility, low-latency demands of V2V networks, while [86] explored Hashgraph as a faster alternative. For stationary charging, ref. [87] ex-

plored Federated Byzantine Agreement (FBA) as a more energy-efficient consensus model for coordinating EV supply equipment. To address data throughput, ref. [88] applied sharding techniques to improve scalability. This focus on the core protocol layer is crucial for making blockchain a viable real-world platform.

Table 7. Critical Evaluation of Key Innovations in Blockchain for EV-P2P Trading.

Paper	Key Challenge Addressed	Proposed Innovation	Critical Bottleneck
[48]	Slow consensus for mobile V2V networks.	A lightweight, application-specific consensus (BAC-SDS) designed for high mobility.	The security of a new consensus protocol is less battle-tested than established ones.
[67]	Market instability from token hoarding.	Economic penalties (demurrage) integrated into the token's smart contract to encourage spending.	Adds economic rules that may slow down the real-time market clearing (ADMM convergence).
[89]	Inability to trade unique assets/contracts.	Use of Non-Fungible Tokens (NFTs) to represent specific energy contracts or EV assets.	High transaction costs and data overhead of NFTs may be impractical for low-value energy trades.
[90]	Computational limit of finding optimal trading strategies.	Integration of Quantum Reinforcement Learning (QRL) for AI-driven decision-making.	Highly theoretical; relies on quantum simulation as practical hardware is not yet commercially viable.
[91]	Disconnect between the market and physical grid control.	Hybridizing blockchain with Model Predictive Control (DMPC) to link the layers.	Assumes perfect, low-latency communication, which is a major challenge in real-world energy systems.

A parallel trend involves increasing the economic sophistication of the on-chain assets. While early models relied on simple, fungible energy tokens, more recent frameworks demonstrate a move towards more complex and functional economic models. A prime example is the energy-backed token market proposed by [67], which introduces a demurrage mechanism to penalize token hoarding and prevent market inflation. Taking this a step further, ref. [89] introduced a novel framework using Non-Fungible Tokens (NFTs) through their TokenGreen concept, allowing unique energy contracts or even the EV assets themselves to be represented and traded on-chain.

Finally, the most significant trend is the integration of blockchain with external intelligence, transforming it from a simple ledger into a platform for smart decision-making. Instead of a standalone solution, blockchain is now increasingly treated as a trust layer upon which advanced control and AI models can operate. This is powerfully demonstrated by the combination of blockchain with Machine Learning for profit optimization [92], and futuristic concepts like Quantum Reinforcement Learning [90].

Many studies, while technologically advanced, rely heavily on simulations [93] or private testnets [94] and do not fully address the challenges of real-world deployment. Key unresolved issues include communication unreliability between EVs and the network, the high computational and financial cost of transactions on public blockchains, and the conspicuous absence of clear regulatory frameworks to govern these decentralized markets. Therefore, while blockchain has been proven effective for security and decentralization in principle, the foremost challenge for future work is to bridge the gap from simulation to scalable, economically viable, and operationally resilient pilot projects.

4.2.2. Auction and Bidding Mechanism

While blockchain provides a secure platform for transactions, it is the auction and bidding mechanism that acts as the economic engine for the P2P market. These mechanisms are the formal rules that govern how prices are discovered and how buyers and sellers are matched, a process critical for achieving the social welfare objective outlined previously.

The literature showcases a progression from standard auction models to more sophisticated designs tailored specifically to the unique challenges of EV energy trading.

A continuous double auction is the most common and intuitive choice, as it allows both buyers (EVs) and sellers (prosumers) to submit bids and offers simultaneously, with a central clearinghouse (often a smart contract) matching them to find a market-clearing price. This approach is fundamental to the models proposed by [45], where it is used to manage demand response, and is a core component of the market designs in several other studies.

However, researchers have identified that a simple auction model may not be sufficient for the complexities of e-mobility. One major theme of innovation is designing auctions for non-traditional scenarios. Recognizing that EV charging can be mobile, ref. [95] designed a novel distributed auction specifically for energy trading between EVs and mobile charging stations. Their mechanism ensures truthfulness and fairness without a central auctioneer, a key innovation for fully decentralized and dynamic markets.

Another critical theme is the integration of non-monetary factors into the auction process to ensure market quality. In a purely price-driven auction, there is a risk of a race to the bottom, where unreliable sellers might win bids but fail to deliver. To counter this, ref. [96] integrated a reputation scheme with a reverse auction. In their model, sellers with a higher reputation score are given an advantage, ensuring that EVs receive reliable service, not just a low price. This aligns economic incentives with operational reliability. A similar focus on quality is seen in [97], who propose a framework based on Quality of Service (QoS) metrics.

The intelligence of the market also depends on the intelligence of its participants. A human cannot be expected to constantly monitor prices and submit optimal bids. Therefore, a significant body of research focuses on the design of sophisticated bidding agents. Studies [98,99] develop automated agents that can act on behalf of EV owners. These agents use predictive models to navigate market uncertainties, deciding on the best times and prices to bid for charging or discharging services [100] also propose a smart bidding strategy that allows prosumers and consumers to interact more effectively. The process through which these mechanisms operate, from bidding to final settlement, is illustrated in the simplified flowchart in Figure 9.

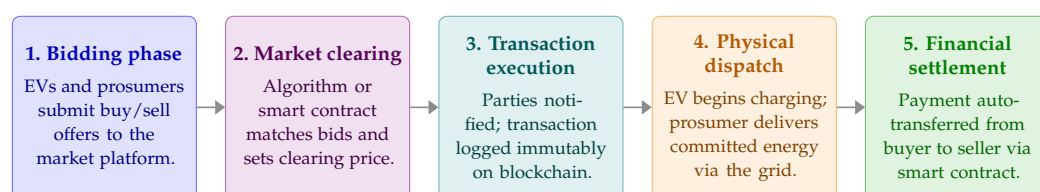


Figure 9. A simplified horizontal flowchart of a typical P2P auction process. The sequence progresses from the initial bidding phase and market clearing to the automated execution, physical dispatch, and final financial settlement, a process often facilitated by smart contracts on a blockchain.

4.2.3. Game-Theoretic Models

While auction mechanisms define the rules for market clearing, they do not inherently capture the strategic decision-making of the market participants themselves. P2P energy networks are complex ecosystems populated by numerous self-interested, autonomous agents, such as EV owners seeking low-cost charging, prosumers aiming to maximize profit from solar generation, and aggregators managing entire fleets. To understand how these agents will behave and to design stable market rules that prevent undesirable outcomes (e.g., market manipulation or instability), the literature widely employs game theory.

In game-theoretic P2P models, each participant i (EV or prosumer) aims to maximize its individual utility function, which can be expressed as

$$U_i(q_i) = \alpha_i \ln(1 + q_i) - \lambda_{\text{P2P}} q_i \quad (1)$$

where q_i is the quantity of energy traded by participant i , α_i denotes the user's preference or comfort coefficient, and λ_{P2P} represents the market-clearing price determined by the P2P trading mechanism. This utility function captures the self-interested behavior of individual participants while enabling the market to converge to a Nash equilibrium, where no participant can improve its utility by unilaterally changing its trading strategy.

Game-theoretic models provide a mathematical framework for analyzing strategic interactions and predicting market equilibrium. The choice of game depends on the specific power dynamic being modeled. A popular approach for modeling hierarchical interactions is the Stackelberg game, which features a leader and one or more followers. This is particularly well-suited for markets with a dominant player, such as a utility, an aggregator, or a distribution system operator. As demonstrated by [101], this model effectively captures the dynamic where an aggregator (the leader) sets a price, and EV owners (the followers) react by optimizing their individual charging strategies in response. Similarly, ref. [102] modeled the complex interaction between the main distribution network and multiple P2P energy hubs as a single-leader, multi-follower game to find a stable operational equilibrium.

For negotiations between peers on a more level playing field, where no single player dominates, different game structures are used. To model direct, bilateral negotiations between groups, ref. [103] utilized a generalized Nash-bargaining model. This cooperative game theory approach is used to derive optimal and provably fair trading contracts between entire aggregations of peers, such as an EV fleet and a coalition of smart homes. In contrast, ref. [104] employed a supermodular game to design a secure trading system that allows for efficient energy exchange both within a local region and between different regions.

These game-theoretic frameworks are rarely used in isolation; they are often integrated with other layers, as shown in Table 8. They provide the intelligence for bidding strategies in auction markets and define the objective functions used in optimization problems. Ultimately, game theory is essential for designing P2P markets that are not only economically efficient but also robust to the strategic, self-interested behavior of their participants, ensuring that the pursuit of individual gain aligns with the overall goal of system-wide stability and social welfare.

Table 8. Analysis of Market Designs and Strategic Models for EV-P2P Trading.

Paper	Market Design Problem Addressed	Proposed Model	Key Insight
[45]	How to set prices and manage demand in a hierarchical V2G environment.	Stackelberg Game & Double Auction	Effectively models the hierarchical power dynamic between a lead service provider and reactive EV owners.
[95]	How to manage efficient and fair trading with non-static, mobile charging stations.	Distributed Auction Game	A novel solution for dynamic, location-based markets that ensures truthfulness without a central auctioneer.
[96]	How to ensure service quality and prevent a race to the bottom in a price-driven auction.	Reverse Auction with a Reputation Scheme	An innovative design that prevents market failure by explicitly rewarding reliable sellers, linking economic incentives to QoS.
[102]	How the main grid should strategically interact with multiple P2P energy hubs.	Single-Leader, Multi-Follower Game	Captures the complex strategic decision-making process between a utility (leader) and multiple P2P markets (followers).

Table 8. Cont.

Paper	Market Design Problem Addressed	Proposed Model	Key Insight
[103]	How groups or coalitions of peers (not just individuals) can find a fair trading agreement.	Nash-Bargaining Solution	A cooperative model that provides a provably fair way to divide the economic surplus for group-based trading.
[99]	How individual EV owners can participate optimally in a volatile and uncertain market.	Intelligent Bidding Agent Design	Focuses on the participant level, creating automated agents to navigate market risks on behalf of users.
[79]	How to create a market for and properly value aging, retired EV batteries.	Double-Sided Auction for Second-Life Batteries	A specific market design that unlocks the value of a key circular economy asset (retired EV batteries).

4.3. The Intelligence Layer: Control Strategies

While the Transactional Layer defines the market rules, the Intelligence Layer provides the operational logic required for market participants to optimize their decisions. This layer comprises the optimization and control algorithms employed by EV owners, aggregators, and system operators to determine charging, discharging, and energy trading strategies under dynamic operating conditions. The primary objectives include minimizing electricity costs, maximizing revenue from P2P energy trading and grid services, and mitigating battery degradation [21,105].

Within the intelligence layer, EV energy management problems are typically solved locally by individual EVs, coordinated through aggregators, or executed by decentralized agents, depending on the underlying market architecture [106]. Despite differences in implementation, most studies formulate EV-P2P energy management as a constrained optimization problem with a broadly consistent mathematical structure [59,64,107]. In particular, the majority of frameworks adopt a cost-minimization objective that accounts for electricity procurement costs, battery degradation, and revenues from P2P energy exchange [64,106].

A general form of the objective function can be expressed as:

$$\min \sum_{t=1}^T \left(C_{grid}(t)(P_{grid}(t) + C_{deg}(t)(E^{cyc}(t) - R_{P2P}(t)(P_{P2P}(t))) \right) \quad (2)$$

where T is the optimization horizon, t is the time step, $C_{grid}(t)$ denotes the cost of electricity imported from the grid at power level $P_{grid}(t)$, $C_{deg}(t)$ represents the battery degradation cost associated with the equivalent cycling energy $E^{cyc}(t)$, and $R_{P2P}(t)$ denotes the revenue obtained from P2P energy transactions involving power $P_{P2P}(t)$.

The optimization is subject to operational constraints, the most fundamental of which is the power balance equation:

$$P_{PV}(t) + P_{WT}(t) + P_{grid}(t) + P_{dis}(t) = P_{load}(t) + P_{ch}(t) + P_{P2P}(t) \quad (3)$$

where $P_{PV}(t)$ and $P_{WT}(t)$ are the power generated by solar PV and wind turbines, $P_{grid}(t)$ is the power exchanged with the utility grid, $P_{dis}(t)$ and $P_{ch}(t)$ are the battery discharging and charging power, and $P_{load}(t)$ represents the local electrical load. $P_{P2P}(t)$ is positive when the EV exports power to the P2P market and negative when it imports energy.

The battery state of charge evolves as:

$$SoC(t+1) = SoC(t) + \left(\eta_{ch} P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}} \right) \frac{\Delta t}{E_{cap}} \quad (4)$$

where η_{ch} and η_{dis} are the charging and discharging efficiencies, respectively, and E_{cap} is the battery energy capacity, and Δt represents the duration of the time step. The state of charge is constrained as:

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \quad (5)$$

to ensure battery longevity and preserve sufficient energy for mobility requirements, typically enforcing a minimum reserve threshold between 20% and 30%.

Charging and discharging power limits are given by:

$$0 \leq P_{ch}(t) \leq P_{ch}^{max}, \quad 0 \leq P_{dis}(t) \leq P_{dis}^{max} \quad (6)$$

while grid exchange and P2P trading power are constrained by converter and network limits:

$$-P_{P2P}^{max} \leq P_{P2P}(t) \leq P_{P2P}^{max}, \quad 0 \leq P_{grid}(t) \leq P_{grid}^{max} \quad (7)$$

Equations (2)–(7) define a generalized EV-P2P optimization framework commonly adopted in the literature. While studies differ in their treatment of uncertainty, market clearing mechanisms, and network constraints, the underlying formulation remains largely consistent. The primary variation lies in the modeling of battery degradation. Many studies adopt simplified linear or convex approximations, which do not fully capture the nonlinear aging behavior associated with high-frequency V2X cycling [49].

This simplification has direct economic implications. The inclusion of C_{deg} reflects the significant levelized cost of storage (LCOS) associated with EV batteries, which are primarily designed for mobility rather than frequent energy arbitrage. Unlike stationary battery energy storage systems, EV batteries experience accelerated degradation under bidirectional cycling, leading to higher effective LCOS and limiting their economic competitiveness in energy trading applications [108,109].

Although the optimization problem remains largely unchanged, the methods used to solve it have evolved considerably. Early studies primarily relied on centralized mathematical programming to obtain globally optimal solutions. As EV participation and market complexity increased, research gradually shifted toward decentralized optimization and, more recently, artificial intelligence-based methods to improve scalability, preserve data privacy, and enable real-time decision-making. Based on this evolution, the optimization strategies reviewed in this paper are classified into centralized, decentralized, and AI-driven approaches. Their characteristics and representative applications are summarized in Table 9.

Table 9. Comparative Analysis of Key Optimization and Control Methodologies.

Methodology	Core Principle/Goal	Key Paper(s)	Key Strength	Critical Limitations
Centralized Optimization (e.g., MILP)	A single controller solves one large optimization problem for all participants.	[110]	Guarantees a mathematically provable, system-wide optimum for the defined community.	Requires a central entity with complete private data from all users; computationally expensive for large systems.
Decentralized Coordination (e.g., ADMM)	The global problem is broken into smaller subproblems solved by individual agents who coordinate.	[64,106]	Agents only share limited information, making it suitable for large networks without compromising user privacy.	The iterative coordination process can be much slower than centralized methods, posing a challenge for real-time applications.

Table 9. Cont.

Methodology	Core Principle/Goal	Key Paper(s)	Key Strength	Critical Limitations
AI/Deep Reinforcement Learning (DRL)	Agents learn optimal strategies through trial-and-error interaction with the market environment.	[59,65]	Can find excellent strategies in complex, dynamic environments without needing an explicit mathematical model.	Can be difficult to interpret or guarantee stability; requires massive amounts of training data/simulations.
Robust Optimization (e.g., DRO)	Finds a solution that performs well even under the worst-case realization of uncertainty.	[69,111]	Ensures the system will not fail even if conditions are much worse than expected.	To protect against the worst case, the solution may sacrifice significant economic efficiency in average or normal conditions.

4.3.1. Centralized and Decentralized Optimization Frameworks

The fundamental architectural choice in designing an EV-P2P control strategy is the degree of centralization. This choice represents a critical trade-off between achieving system-wide optimality and ensuring scalability, privacy, and agent autonomy. Current literature explores both paradigms, with a clear trend moving away from purely centralized models toward more flexible, decentralized frameworks.

Centralized optimization represents the classical control approach, where a single, omniscient entity, such as a microgrid central controller (MGCC) or a community aggregator, collects detailed information from all participants and solves a single, large-scale optimization problem to determine the optimal schedule for everyone. The most common tool for this is Mixed-Integer Linear Programming (MILP), due to its ability to handle both discrete decisions (e.g., on/off state of a generator) and continuous variables (e.g., power output). A clear example is [46], who employed a MILP-based Energy Management System to co-optimize the schedules for an entire community of smart homes with EVs. While this approach can guarantee a truly global optimum for the defined system, its real-world applicability is severely limited. It requires all participants to share private data, such as EV state of charge and personal travel schedules, creating significant privacy concerns [112]. Furthermore, the computational complexity of solving a large-scale MILP problem grows exponentially with the number of participants, rendering the centralized approach intractable for large fleets, and city-scale networks.

To overcome these limitations, decentralized optimization has emerged as the dominant paradigm. Instead of a single central brain, this approach breaks the global problem into smaller, manageable subproblems that are solved locally by each individual agent. These agents then coordinate with each other, typically through a limited message-passing scheme, to converge toward a system-wide optimal solution. This preserves the privacy of each agent and is significantly more scalable for high-density EV environments. Hierarchical frameworks have also gained traction; for instance, ref. [113] developed a two-stage optimization model, while [114] proposed a hierarchical strategy enabling individual EV users to engage directly in transactive markets without aggregators, effectively balancing hardware constraints with travel uncertainty.

The most widely employed technique for achieving this coordination is the Alternating Direction Method of Multipliers (ADMM), which forms the core of many hierarchical and transactive energy frameworks. In this framework, an individual agent n iteratively updates its local decision variables using a proximal operator to reach a global consensus:

$$x_n^{k+1} := \arg \min_{x_n} \left(f_n(x_n) + \frac{\rho}{2} \|x_n - z^k + u_n^k\|^2 \right) \quad (8)$$

where $f_n(x_n)$ is the local objective function, ρ is the penalty parameter, k denotes the iteration index, x_n represents the local decision vector (e.g., charging power), z^k is the global consensus variable, and u_n^k is the dual variable facilitating coordination between the peer and the wider network. In the model proposed in [64], ADMM is used to achieve the equilibrium point for P2P trading between networked microgrids and smart parking lots without a central clearinghouse. Similarly, ref. [106] designed a fully decentralized framework using ADMM that enables coordination between multiple EV aggregators and the distribution system operator. While ADMM and similar distributed methods offer compelling advantages in scalability and privacy, they exhibit slower convergence compared to centralized solvers and can be sensitive to communication delays, presenting a critical challenge for real-time applications.

4.3.2. Intelligent Control Through Reinforcement Learning Paradigms

While deterministic and decentralized optimization models provide robust frameworks for scheduling, they generally depend on accurate system models and point-forecasts. To address the high degree of stochasticity and real-time dynamism inherent in P2P markets, driven by intermittent renewable generation and unpredictable EV user behavior, current research is increasingly adopting model-free approaches, specifically Deep Reinforcement Learning (DRL).

DRL is uniquely suited for decentralized energy management as it allows an agent, such as an individual EV or a home energy management system (HEMS), to learn optimal control policies directly through interaction with the environment without requiring an explicit mathematical model of the entire system. The objective is to derive a policy that maximizes long-term cumulative rewards, a process governed by the foundational Bellman equation. This equation defines the optimal action-value function, $Q^*(s, a)$, representing the maximum expected future reward for taking action a in state s :

$$Q^*(s, a) = \mathbb{E} \left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a \right] \quad (9)$$

In this formulation, $\mathbb{E}$ denotes the expectation operator, s' and a' represent the subsequent state and action, r is the immediate reward (e.g., trading profit or a penalty for grid non-compliance), and $\gamma \in [0, 1]$ is the discount factor. DRL architectures, such as Deep Q-Networks (DQN) and advanced actor-critic models like Proximal Policy Optimization (PPO) [115], utilize deep neural networks to approximate this complex Q^* function. Ref. [115] demonstrates that PPO agents can effectively manage dynamic pricing in VPP environments to balance prosumer fairness with grid stability.

The efficacy of these learning-based paradigms is demonstrated in several recent studies. For instance, ref. [59] developed a DRL-based EMS for a cluster of prosumers with EVs; their multi-agent framework achieved a 19.18% reduction in overall energy costs and improved cluster self-sufficiency by 9.39% while maintaining user comfort constraints. This highlights DRL's capacity to navigate the multi-objective trade-off between economic optimization and end-user requirements.

Further advancing the state-of-the-art, ref. [65] proposed a hybrid framework combining metaheuristic optimization with DRL. In their model, the Dragonfly Algorithm (DFO) performs strategic power allocation, while a DQN agent facilitates fast, adaptive adjustments in response to real-time grid fluctuations. This synergistic approach represents a sophisticated research direction where AI serves as an intelligent layer that enhances the robustness of classical optimization. Furthermore, ref. [116] showed that the Hunter-Prey Optimization Algorithm (HPOA) effectively manages stochastic EV usage, achieving significantly higher revenues in real-time electricity markets than conventional swarm-

based optimization methods. Despite these advantages, the primary limitations of DRL remain high sample complexity and significant computational training requirements, which continue to pose challenges for deployment on low-cost, embedded EV hardware.

4.3.3. Models for Uncertainty and Risk Management

A primary challenge in designing effective P2P energy markets is the pervasive presence of uncertainty. Deterministic optimization models, which assume perfect knowledge of future conditions, are inherently fragile and likely to fail in real-world scenarios. The key sources of uncertainty are twofold: the intermittent nature of renewable energy generation (e.g., fluctuating solar PV output) and the stochastic behavior of EV owners (e.g., unpredictable arrival times, departure times, and initial states of charge). To address this, a significant portion of the literature is dedicated to developing models that can produce reliable and cost-effective schedules despite these uncertainties. These approaches can be broadly categorized into stochastic and robust optimization paradigms:

1. Stochastic optimization is employed when the uncertainty can be characterized by a known or estimated probability distribution. This approach does not seek a single optimal schedule, but rather one that is optimal in an expected sense over a multitude of possible scenarios. A common technique is the use of Monte Carlo methods to generate a large number of scenarios that represent the range of possible outcomes. For instance, ref. [117] explicitly focus on modeling the uncertainty of EV user behavior, using Monte Carlo simulations to create a rich dataset of potential arrival and departure patterns. The energy trading system is then optimized to perform well on average across these scenarios, making it more resilient to real-world variations than a simple deterministic model.
2. In contrast, robust optimization is used when the probability distribution of the uncertain variables is unknown or difficult to trust. Instead of optimizing for an average case, this paradigm seeks a solution that is feasible and performs well even under the worst-case realization of uncertainty within a defined set. While powerful, traditional robust optimization can be overly conservative, leading to high operational costs. To overcome this, many recent studies have turned to Distributionally Robust Optimization (DRO), a more advanced technique that is robust against the worst-case probability distribution from a family of distributions. A leading example is [69,118], who developed a risk-aware coordination framework using DRO and distributionally robust chance constraints. Their model protects EV charging stations from the uncertainties of renewable generation and electricity prices, successfully reducing total operation costs by 26.65% by providing a guaranteed level of performance. Another approach in this domain is the use of Information Gap Decision Theory (IGDT), a non-probabilistic method for decision-making under severe uncertainty, which was applied by [111] to create a risk-averse P2P trading strategy. Beyond probabilistic models, fuzzy-informed optimization has emerged as a powerful tool for handling the inherent imprecision of EV arrival times and load profiles. The framework in [113] demonstrates that fuzzy logic can effectively inform two-stage optimization to mitigate peak demand even under highly uncertain operating conditions.

Ultimately, the choice between these modeling paradigms represents a critical trade-off. Stochastic models can achieve lower costs on average but may perform poorly if the true probability distributions differ from what was assumed. Robust models provide a powerful worst-case guarantee, ensuring system stability, but this security often comes at the price of higher average operational costs. The increasing sophistication of these models demonstrates a clear trend in the field towards creating P2P energy markets that are not just economically efficient, but also fundamentally reliable and resilient.

Table 9 draws these threads together, contrasting centralized, decentralized, AI-driven, and robust approaches side by side. While centralized frameworks offer mathematically provable global optima, the analysis reveals a clear industry pivot toward decentralized coordination (e.g., ADMM) and AI-driven models to address the fundamental challenges of scalability and data privacy. Furthermore, the integration of robust and distributionally robust optimization (DRO) highlights an increasing focus on managing the inherent stochasticity of renewable generation and EV user behavior, albeit at the cost of higher average operational expenses.

5. Discussion and Future Perspectives

5.1. Quantitative Performance

One of the most consistently reported benefits is in economic savings and market efficiency. The primary driver for EV participation in P2P markets is the potential for cost reduction, and the data strongly supports this, Table 10 collects the headline figures across the reviewed studies. Models routinely demonstrate the ability to lower energy costs for prosumers and EV owners by over 20%, as shown by the centralized MILP approach [46] and the DRL-based EMS of [59] (19.18% cost reduction). In some cases, the financial benefits are even more pronounced; for example, the risk-aware coordination framework proposed in [69] reduced total charging station operation costs by 26.65%. The study in [19] provided a tangible, real-world estimate, suggesting annual household bill savings of up to £200. These economic gains are typically achieved by shifting EV charging to low-price periods and enabling prosumers to sell surplus energy at a better price than standard feed-in tariffs. While these simulation results are promising, the high variance in reported savings suggests that performance is highly dependent on local grid constraints and EV penetration levels.

Table 10. Summary of Key Quantitative Performance Metrics Reported in Literature.

Paper	Key Metric Evaluated	Reported Value	Context of the Finding
[65]	Power Mismatch Reduction	35%	Compared to a baseline without the hybrid DFO-DQN optimization in a fast-charging scenario.
[59]	Energy Cost Reduction	19.18%	For a cluster of prosumers using a DRL-based EMS compared to a standard, unoptimized system.
	Self-Sufficiency Ratio (SSR)	9.39% Increase	The DRL-based model improved the local consumption of locally generated energy.
[46]	Prosumer Energy Cost Reduction	Up to 23%	For prosumers utilizing the V2H mode within the P2P system compared to acting as a load only.
	Community Energy Cost Reduction	15%	The overall cost reduction for the entire microgrid community with V2H.
[69]	EVCS Operation Cost Reduction	26.65%	Achieved by the proposed risk-aware DRO coordination framework compared to a non-robust model.
[19]	Annual Household Bill Savings	Up to £200 per year	For households participating in a P2P market with V2H, compared to a standard utility tariff.
[119]	Financial Benefit Increase	21.6%	Overall increase for all participants in the proposed Local Energy Market compared to a Business-as-Usual (BAU) model.
[80]	Network Congestion Reduction	5–10%	Reduction in voltage drops and cable loading, achieved even at a low EV penetration level of <5%.
[67]	Prosumer Welfare Increase	20%	Increase in total welfare specifically from the participation of EVs in the P2P token market.

Table 10. Cont.

Paper	Key Metric Evaluated	Reported Value	Context of the Finding
[120]	EV Net Energy Cost Reduction	70.8%	Achieved for EV owners participating in a P2P market that includes a smart traction system.
[121]	Consumer Cost Reduction	Rs.92.76 (Consumer 1)	The absolute daily cost reduction for consumers participating in the proposed P2P bidding strategy.
	Prosumer Profit Increase	Rs.78.21 (Prosumer 1)	The absolute daily profit increase for prosumers selling energy via the enhanced bidding strategy.

Beyond direct economic savings, these models show a significant positive impact on grid stability and performance. The framework in [65], for instance, demonstrated a 35% reduction in power mismatch in fast-charging scenarios. In terms of direct grid impact, the P2P transaction model in [80] was shown to reduce local network congestion, measured by voltage drops and cable loading, by a notable 5–10%, even with a low EV penetration of less than 5%. Furthermore, EVs are playing an increasingly important role in disaster recovery. Ref. [122] demonstrated that a coordinated P2P-VPP strategy increased load restoration from 55.05% to 94.20% during severe grid outages while significantly reducing economic losses and Energy Not Supplied (ENS).

Finally, the models also demonstrate improvements in energy autonomy and renewable integration. By creating a local market for energy, P2P frameworks encourage the consumption of locally generated renewable energy, thereby increasing the self-sufficiency of the community. The AI-driven model in [59], for example, increased the Self-Sufficiency Ratio (SSR) of the prosumer cluster by 9.39%.

It is critical, however, to interpret these quantitative results with caution. The reported percentage improvements are highly dependent on the specific business-as-usual baseline used in each study, the local tariff structures, and the assumed penetration levels of EVs and renewables. Nevertheless, the consistent and significant magnitude of these reported gains across a wide variety of models, from centralized optimization to decentralized AI, provides powerful, converging evidence that the architectures reviewed in this paper offer substantial and tangible benefits for integrating EVs into future energy systems.

5.2. System Architectures and Technical Trade-Offs

The reviewed studies show that the design of EV-P2P energy systems is shaped by trade-offs rather than a single optimal solution. Figure 5 traced the chronological evolution of these approaches, whereas Figure 10, in contrast, organizes them according to their position along the centralization-decentralization spectrum, highlighting how existing research is distributed across different architectural designs.

The primary tension exists between centralization and decentralization. As illustrated in the quadrant framework (Figure 10), purely centralized optimization models, such as community-level MILP solvers, provide mathematically provable global optima but suffer from poor scalability and significant privacy vulnerabilities due to the required disclosure of user-specific data [64]. Conversely, early-stage purely decentralized models, often based on uncoordinated bidding or Proof-of-Work blockchains, prioritize agent autonomy but frequently incur high communication overhead and lack mechanisms to enforce grid-level constraints. Consequently, the much of the recent research is concentrated in the coordinated decentralization quadrant. Frameworks utilizing ADMM or hierarchical multi-agent architectures [106] represent a pragmatic compromise, preserving peer-level autonomy within a structure that ensures system-wide stability.

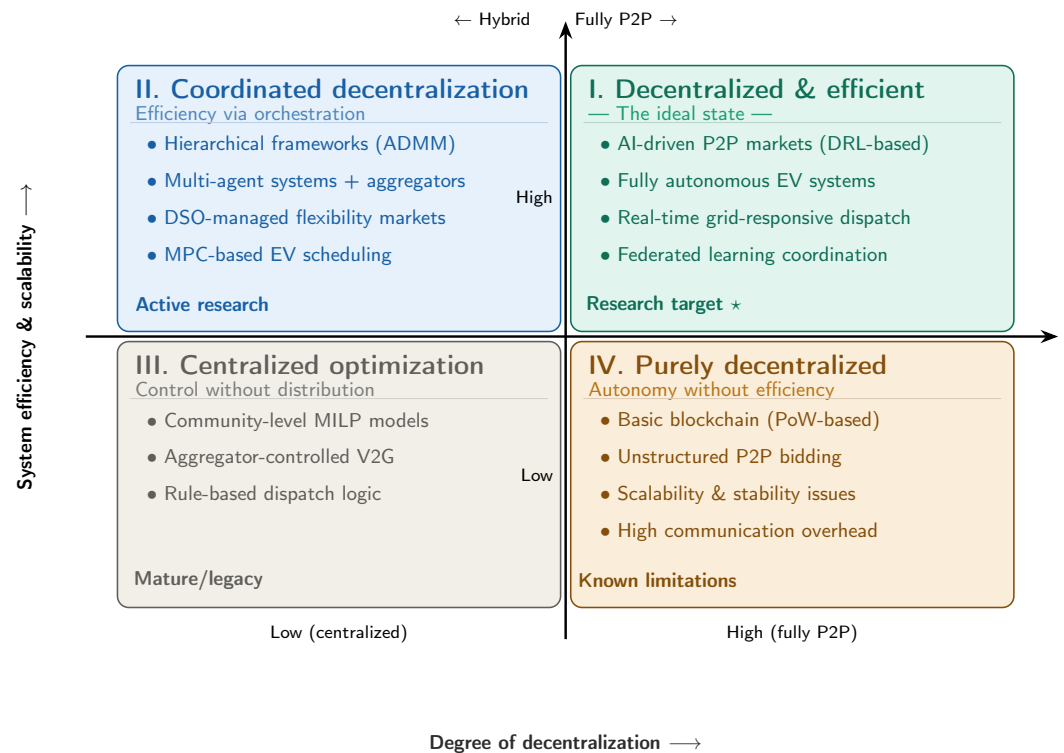


Figure 10. Research landscape of EV-enabled P2P energy trading frameworks.

A secondary critical trade-off concerns model complexity versus practical feasibility. The literature demonstrates an accelerating trend toward sophisticated AI-driven DRL frameworks [59] and nascent concepts such as Quantum Reinforcement Learning [90]. While these paradigms improve decision making under uncertainty and high-dimensional operating conditions, their computational overhead remains a significant barrier to practical deployment. The intensive resources required for training DRL agents and the current reliance on quantum simulators pose substantial challenges for deployment on the low-cost, embedded hardware typically found in EV chargers or home energy gateways.

These developments also highlight the challenge of ensuring physical grid integrity. An economically optimal P2P market is of limited practical value if it results in voltage violations or transformer overloading. Current research is therefore shifting toward explicitly grid-aware designs. Models incorporating Dynamic Operating Envelopes (DOEs) have emerged as an effective approach for assessing and enhancing the hosting capacity of DERs in the Australian grid [123,124]. Their integration into EV-P2P markets represents an important convergence of market design and power systems engineering.

Finally, the architectural shift toward increasingly digitalized and decentralized P2P energy networks introduces new cybersecurity and privacy trade-offs. As decentralized system architectures interconnect large numbers of heterogeneous devices, the attack surface expands beyond the blockchain layer to include IoT communication protocols and other supporting platforms. Although blockchain provides secure and tamper-resistant transaction records, conventional consensus mechanisms often introduce high computational overhead and latency, making them less suitable for real-time EV energy trading. To address this, lightweight alternatives such as Federated Byzantine Agreement (FBA) [87] and Hashgraph [86] have attracted growing interest because they provide faster transaction validation while maintaining network security.

Beyond optimization performance and grid integration, architectural choices also influence the security, privacy, and resilience of EV-P2P energy systems. Protecting user privacy is also an important challenge, as detailed charging and transaction records may

reveal individual travel patterns or energy usage. Differential Privacy (DP) and statistical aggregation [125] have emerged as an effective approach for protecting sensitive information by adding controlled statistical noise during market-clearing processes [126]. In parallel, researchers have proposed intrusion detection and attack-resilient frameworks to strengthen the resilience of decentralized energy trading platforms against cyber threats such as false data injection and Denial-of-Service (DoS) attacks [127,128]. As EV-P2P systems increasingly rely on synchronized communication and measurement infrastructures, specialized detection methods have also been developed to address emerging cyber-physical threats. For example, the VNN-DM (vector neural network-based detection model) has been proposed to detect time synchronization attacks in park-level energy systems, while importance-driven DoS strategies have also been investigated for evaluating the vulnerability of remote state estimation in multi-agent environments [129,130].

5.3. From Theory to Practice: Real-World Pilot Projects

This review reveals a persistent challenge across the EV-P2P research landscape: the gap between theoretical models and practical implementation. Of the studies reviewed, most, particularly those within the Intelligence Layer, validate their frameworks exclusively through simulation.

Simulation studies, including the sophisticated architectures proposed in [59,65], are invaluable for demonstrating theoretical potential and quantifying benefits such as cost reduction and improved grid stability. However, they commonly rely on idealized assumptions, including perfect communication networks, negligible computational constraints, and simplified representations of user behaviour and power system dynamics. Ref. [22] further underscores that the lack of high-resolution empirical data, particularly for week-end driving patterns, remains a major barrier to accurately aligning EV participation with actual community energy demand.

Only a limited number of studies have attempted to address these limitations. The hardware-in-the-loop demonstration in [131] and the data-driven pilot projects reported in [132] represent important steps toward practical validation. Nevertheless, the simulation-to-reality gap remains one of the primary barriers to large-scale deployment of EV-P2P trading systems. Solutions that perform effectively in MATLAB or Python environments may encounter significant challenges when exposed to communication failures, uncertain human behaviour, and the complexities of real distribution networks.

Several pioneering pilot projects have already demonstrated the practical feasibility of decentralized energy trading (Table 11) and provide valuable insights into implementation challenges. These trials demonstrate that the barriers to EV-P2P integration are multi-dimensional. While the Tata Power-DDL and Silicon Valley Power projects proved the technical feasibility of blockchain-based energy and carbon credit trading [133,134], other trials highlighted systemic challenges. For instance, the Brooklyn Microgrid [13] identified significant regulatory and legal hurdles in operating local markets within traditional utility territories, while the Cornwall Local Energy Market [135] revealed that customer engagement and social behavior are as critical as technical optimization. Furthermore, the Share & Charge initiative [136] underscored the urgent need for interoperability standards to allow EVs to roam across different decentralized charging network.

A notable example is the Tata Power-DDL project in Delhi, developed in collaboration with Power Ledger. The project integrated EV charging stations into a blockchain-enabled solar P2P trading platform, demonstrating the feasibility of managing real-time energy transactions across more than 150 sites. Consumers with EVs were able to directly purchase excess solar energy from prosumers, illustrating the potential role of EV infrastructure within urban energy communities [133].

Another significant initiative was conducted by Powerledger and Silicon Valley Power in California. By connecting a 370 kW solar installation with 49 EV charging stations through a blockchain platform, the project enabled tokenized carbon credit trading linked to EV charging activities. The trial demonstrated how P2P platforms can create additional value streams beyond energy trading, including participation in environmental commodity markets [134].

Table 11. Global Pilot Projects and Trials Integrating EVs in P2P Energy Networks.

Project Name	Location	Key Focus Area	Key Learning and Identified Barriers	Ref.
Tata Power-DDL	Delhi, India	Blockchain-enabled Solar & EV P2P	Validated that DLT can handle high-frequency P2P transactions across 150+ sites using real-time smart meter data.	[133]
Silicon Valley Power	California, USA	Tokenized Carbon Credits	Proved that P2P platforms can monetize EV assets via environmental commodities (carbon credits) rather than simple energy arbitrage.	[134]
Brooklyn Microgrid	New York, USA	Community Energy Markets	Highlighted significant legal barriers to behind-the-meter trading within traditional utility franchise territories.	[13]
Chiang Mai University	Thailand	Smart Campus VPP & EV Charging	Successfully integrated EV charging stations into a university-wide Virtual Power Plant using a P2P trading architecture.	[137]
Cornwall Local Energy Market	Cornwall, UK	Grid Flexibility & V2G	Revealed that social behavior and consumer fatigue are as critical as technical optimization in sustaining P2P participation.	[135]
Share & Charge	Germany/Global	Decentralized EV Roaming	Identified the urgent need for standardized communication protocols to allow seamless P2P trading across different charging networks.	[136]

Although limited in scale, these pilot projects provide critical insights that cannot be captured through simulation alone. They highlight practical challenges such as regulatory constraints, customer participation, and integration with existing utility infrastructure. Consequently, lessons learned from these demonstrations will play a vital role in developing robust, scalable, and commercially viable EV-P2P ecosystems. Ultimately, while the theoretical foundations of EV-P2P trading are well established, widespread adoption will depend on proving that these architectures can perform reliably under real-world operating conditions.

5.4. Future Research Directions

While the analysis presented in this paper identifies a field rich with sophisticated models, a significant gap remains between theoretical potential and practical deployment. Future research must pivot from proving algorithmic feasibility to solving multi-dimensional implementation hurdles across the following four priority areas.

5.4.1. Grid-Aware Modeling and Physical Layer Validation

Most existing studies validate P2P energy trading frameworks in simplified computational environments, often relying on linearized power flow models (e.g., refs. [64,106]). While these models provide valuable insights into market behavior, they do not fully capture the nonlinear characteristics of practical distribution networks, particularly three-phase unbalanced systems with high EV penetration [138]. Consequently, there is a growing need for co-simulation frameworks that integrate agent-based market platforms with industry-

standard power system simulators (e.g., PSS/E or OPAL-RT) and communication network emulators. Such frameworks enable P2P algorithms to be evaluated under realistic operating conditions, including voltage unbalance, harmonic distortion, and communication delays. For example, ref. [139] showed that the placement of EV charging stations can significantly influence voltage profiles and power losses in hybrid microgrids, highlighting the importance of evaluating market decisions alongside physical network performance.

Beyond realistic network modeling, Charging-station planning and placement also plays a key role in the effectiveness of P2P energy trading [65]. The location of charging stations influences network loading, available hosting capacity, and access to nearby renewable generation, all of which affect local energy trading opportunities [140]. Charging stations installed at electrically constrained buses may experience limited charging flexibility, reducing the number of feasible energy transactions and the overall efficiency of local P2P markets [139]. While many existing studies optimize charging schedules assuming fixed charging infrastructure, charging-station planning is often treated as a separate problem [141]. Future research should therefore focus on integrated optimization frameworks that jointly consider charging-station placement, charging scheduling, and P2P market design while accounting for both electrical network constraints and market dynamics.

5.4.2. Transparent and Distributed Intelligence Paradigms

The trend toward DRL introduces impressive adaptive capabilities but creates a black box problem; decision-making processes in models such as [59] can be opaque and difficult to verify. For grid operators and regulators to trust decentralized control infrastructure, future research must focus on explainable AI (XAI) for energy markets. Furthermore, to overcome the computational and data-privacy barriers of central training, the next frontier lies in federated and transfer learning, enabling EV fleets to train models collaboratively without exposing raw user data or requiring costly retraining from scratch.

5.4.3. Socio-Economic Dynamics and Behavioral Modeling

Current literature largely assumes that EV owners are rational, economically motivated actors. However, real-world human behavior is driven by a complex mix of convenience, trust, risk aversion, and altruism. While some models have begun using Monte Carlo methods to simulate behavior [117], the field still lacks mature socio-economic frameworks capable of predicting long-term participation patterns. Future research must integrate insights from behavioral economics to design market mechanisms, such as the reputation-based schemes proposed in [96], that are resilient to the inherent unpredictability of human decision-making.

5.4.4. Regulatory Frameworks and Interoperability Standards

The widespread deployment of EV-enabled P2P energy trading remains constrained not only by market regulations but also by the lack of interoperability between charging infrastructure, communication networks, and market platforms [142,143]. Most proposed P2P frameworks assume regulatory support for local energy trading, although such frameworks are still limited in many jurisdictions. Consequently, future research should address regulatory development alongside technical design, enabling engineers, utilities, and policymakers to co-design market rules and operational frameworks.

Interoperability is essential for enabling cross-vendor operation of P2P platforms across different hardware vendors and distribution networks. At the vehicle level, ISO 15118-20 provides standardized communication between EVs and charging stations, supporting features such as Plug & Charge authentication and bidirectional power transfer required for V2G and EV-P2P applications [144]. Communication between charging stations and backend management systems is commonly achieved using the Open Charge

Point Protocol (OCPP 2.0.1), allowing charging infrastructure from different manufacturers to interface with common energy management and trading platforms [145]. At the grid level, standards such as IEEE 2030.5 and OpenADR 2.0b facilitate communication between aggregators and DSOs, enabling demand response, congestion management, and coordinated network operation [146]. In addition, interoperability between Advanced Metering Infrastructure (AMI) and secure market settlement platforms, including blockchain-based solutions, is necessary to ensure trusted energy measurements and transparent financial settlement. Without harmonized communication and interoperability standards, large-scale EV-P2P deployment will remain limited by the complexity of integrating heterogeneous hardware, software, and market platforms [147,148].

6. Conclusions

This review examined the technical and economic evolution of EV integration within P2P energy networks. By organizing the ecosystem into its foundational physical, transactional, and intelligence layers, the literature reveals a clear transition of EVs from a passive load into a flexible grid resource. Through V2X technologies and decentralized market mechanisms, EVs are now positioned to act as critical storage resources and ancillary service providers that enhance grid resilience. The reviewed studies provide strong evidence for the effectiveness of these architectures. Collectively, the reviewed studies indicate that optimized P2P-EV coordination can deliver substantial benefits, including grid congestion relief, enhanced local self-sufficiency, and prosumer cost savings often exceeding 20%. The convergence of secure, blockchain-based market layers with adaptive AI-driven control strategies represents a promising direction toward a fully autonomous and efficient decentralized energy system. Despite this progress, a substantial gap remains between theoretical potential and practical implementation. While the literature is rich in sophisticated optimization models, most of these frameworks rely on idealized simulations that do not fully capture real-world communication latency, human behavior, or non-linear power flows. Closing this simulation-to-reality gap is a major challenge for the next decade of research. Future research should prioritize integrated co-simulation frameworks and physical testbeds to address multidisciplinary hurdles such as cybersecurity, regulatory uncertainty, and technical interoperability. Ultimately, the successful deployment of EV-P2P frameworks in real power systems will be essential for realizing a sustainable, resilient, and participatory energy future.

Author Contributions: Conceptualization, M.K.I. and M.S.; methodology, M.K.I. and G.T.; software validation, M.K.I., M.S. and S.M.; formal analysis, A.S., S.M. and J.M.; investigation, M.S. and S.M.; resources, M.K.I.; data curation, M.K.I.; writing—original draft preparation, M.K.I. and G.T.; writing—review and editing, M.S. and S.M.; visualization, M.S.; supervision, M.S., S.M. and A.S.; project administration, A.S. and J.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable.

Conflicts of Interest: Author Jose Moreira was employed by the company Siemens (Australia). The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. United Nations Framework Convention on Climate Change (UNFCCC). The Paris Agreement. Available online: <https://unfccc.int/process-and-meetings/the-paris-agreement> (accessed on 24 July 2025).
2. IRENA. *Renewable Power Generation Costs in 2024*; International Renewable Energy Agency: Abu Dhabi, United Arab Emirates, 2024.
3. Denholm, P.; O'Connell, M.; Brinkman, G.; Jorgenson, J. *Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart*; Technical Report NREL/TP-6A20-65023; USA DOE Office of Energy Efficiency & Renewable Energy, Contract No. DE-AC36-08GO28308; National Renewable Energy Laboratory (NREL): Golden, CO, USA, 2015. [\[CrossRef\]](#)
4. Zaino, R.; Ahmed, V.; Alhammadi, A.M.; Alghoush, M. Electric vehicle adoption: A comprehensive systematic review of technological, environmental, organizational and policy impacts. *World Electr. Veh. J.* **2024**, *15*, 375. [\[CrossRef\]](#)
5. Pozo-Burgos, E.J.; Alpala, L.O.; Heredia-Campaña, A.L. Electric Mobility Transition, Intelligent Digital Platforms, and Grid-Vehicle Integration Models: A Systematic Review. *World Electr. Veh. J.* **2026**, *17*, 123. [\[CrossRef\]](#)
6. Abdelaal, G.; Gilany, M.I.; Elshahed, M.; Sharaf, H.M.; El'gharably, A. Integration of electric vehicles in home energy management considering urgent charging and battery degradation. *IEEE Access* **2021**, *9*, 47713–47730. [\[CrossRef\]](#)
7. Mojumder, M.R.H.; Ahmed Antara, F.; Hasanuzzaman, M.; Alamri, B.; Alsharef, M. Electric Vehicle-to-Grid (V2G) Technologies: Impact on the Power Grid and Battery. *Sustainability* **2022**, *14*, 13856. [\[CrossRef\]](#)
8. Hannan, M.; Mollik, M.; Al-Shetwi, A.Q.; Rahman, S.; Mansor, M.; Begum, R.; Muttaqi, K.; Dong, Z. Vehicle to grid connected technologies and charging strategies: Operation, control, issues and recommendations. *J. Clean. Prod.* **2022**, *339*, 130587. [\[CrossRef\]](#)
9. Hu, J.; Wu, J.; Ai, X.; Liu, N. Coordinated energy management of prosumers in a distribution system considering network congestion. *IEEE Trans. Smart Grid* **2020**, *12*, 468–478. [\[CrossRef\]](#)
10. Abdalla, M.A.A.; Min, W.; Mohammed, O.A.A. Two-stage energy management strategy of EV and PV integrated smart home to minimize electricity cost and flatten power load profile. *Energies* **2020**, *13*, 6387. [\[CrossRef\]](#)
11. Zafar, B.; Slama, S.A.B. PV-EV integrated home energy management using vehicle-to-home (V2H) technology and household occupant behaviors. *Energy Strategy Rev.* **2022**, *44*, 101001. [\[CrossRef\]](#)
12. Yang, Y.; Wang, S. Resilient residential energy management with vehicle-to-home and photovoltaic uncertainty. *Int. J. Electr. Power Energy Syst.* **2021**, *132*, 107206. [\[CrossRef\]](#)
13. Mengelkamp, E.; Gärtner, J.; Rock, K.; Kessler, S.; Orsini, L.; Weinhardt, C. Designing Microgrid Energy Markets: A Case Study: The Brooklyn Microgrid. *Appl. Energy* **2018**, *210*, 870–880. [\[CrossRef\]](#)
14. Andoni, M.; Robu, V.; Flynn, D.; Abram, S.; Geach, D.; Jenkins, D.; McCallum, P.; Peacock, A. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. *Renew. Sustain. Energy Rev.* **2019**, *100*, 143–174. [\[CrossRef\]](#)
15. Utility Week. EDF Energy to Trial Peer-to-Peer Energy Trading. 2019. Available online: <https://utilityweek.co.uk/edf-energy-trial-peer-peer-energy-trading> (accessed on 12 August 2024).
16. Power Ledger. Power Ledger & Kansai Electric Power Co. to Trial Peer-to-Peer Renewable Energy Trading in Japan. 2020. Available online: <https://powerledger.io/media/powerledger-kansai-electric-power-co-to-trial-peer-to-peer-renewable-energy-trading-in-japan/> (accessed on 12 August 2024).
17. Kobashi, T.; Yoshida, T.; Yamagata, Y.; Naito, K.; Pfenninger, S.; Say, K.; Takeda, Y.; Ahl, A.; Yarime, M.; Hara, K. On the potential of “Photovoltaics + Electric vehicles” for deep decarbonization of Kyoto’s power systems: Techno-economic-social considerations. *Appl. Energy* **2020**, *275*, 115419. [\[CrossRef\]](#)
18. Sai Shibu, N.; Balamurugan, S.; Arjun, D.; Nidhin Mahesh, A. Decentralized power system and future mobility: The use cases of community driven electric vehicle charging infrastructure. In *Proceedings of the 1st ACM International Workshop on Technology Enablers and Innovative Applications for Smart Cities and Communities, TESCA 2019, Co-Located with the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*; Association for Computing Machinery, Inc: New York, NY, USA, 2019; pp. 50–53. [\[CrossRef\]](#)
19. Huty, T.D.; Pena-Bello, A.; Dong, S.; Parra, D.; Rothman, R.; Brown, S. Peer-to-peer electricity trading as an enabler of increased PV and EV ownership. *Energy Convers. Manag.* **2021**, *245*, 114634. [\[CrossRef\]](#)
20. Ma, H.; Xiang, Y.; Sun, W.; Dai, J.; Zhang, S.; Liu, Y.; Liu, J. Optimal Peer-to-Peer Energy Transaction of Distributed Prosumers in High-Penetrated Renewable Distribution Systems. *IEEE Trans. Ind. Appl.* **2024**, *60*, 4622–4632. [\[CrossRef\]](#)
21. Aznavi, S.; Fajri, P.; Shadmand, M.; Khoshkbar-Sadigh, A. Peer-to-Peer Operation Strategy of PV Equipped Office Buildings and Charging Stations Considering Electric Vehicle Energy Pricing. *IEEE Trans. Ind. Appl.* **2020**, *56*, 5848–5857. [\[CrossRef\]](#)
22. Yu, D.; Adhikari, M.P.; Fung, A.S.; Kadir, N.; Mohammadi, F. Integration of Renewable Energy of Solar PV and Wind for the Optimal Charging and Discharging of Plug-in Electric Vehicles. *Sol. Compass* **2026**, *19*, 100166. [\[CrossRef\]](#)
23. Tushar, W.; Nizami, S.; Azim, M.I.; Yuen, C.; Smith, D.B.; Saha, T.; Poor, H.V. Peer-to-Peer Energy Sharing: A Comprehensive Review. *Found. Trends Electr. Energy Syst.* **2023**, *6*, 1–82. [\[CrossRef\]](#)

24. Tushar, W.; Saha, T.K.; Yuen, C.; Morstyn, T.; McCulloch, M.D.; Poor, H.V.; Wood, K.L. A Motivational Game-Theoretic Approach for Peer-to-Peer Energy Trading in the Smart Grid. *Appl. Energy* **2019**, *243*, 10–20. [CrossRef]
25. Tushar, W.; Saha, T.K.; Yuen, C.; Smith, D.; Poor, H.V. Peer-to-Peer Trading in Electricity Networks: An Overview. *IEEE Trans. Smart Grid* **2020**, *11*, 3185–3200. [CrossRef]
26. U.S. Department of Energy. Timeline: History of the Electric Car. 2023. Available online: <https://www.energy.gov/timeline-history-electric-car#:~:text=Around%201832%2C%20Robert%20Anderson%20develops,that%20electric%20cars%20become%20practical> (accessed on 20 June 2024).
27. Ahmadian, A.; Mohammadi-Ivatloo, B.; Elkamel, A. A review on plug-in electric vehicles: Introduction, current status, and load modeling techniques. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 412–425. [CrossRef]
28. Slangen, T.; van Wijk, T.; Ćuk, V.; Cobben, J. The harmonic and supraharmmonic emission of battery electric vehicles in the Netherlands. In *Proceedings of the 2020 International Conference on Smart Energy Systems and Technologies (SEST)*; IEEE: New York, NY, USA, 2020; pp. 1–6.
29. Bhosale, P.; Kumar, R.; Bansal, R. Electric Vehicle Charging Infrastructure, Standards, Types, and Its Impact on Grid: A Review. *Electr. Power Compon. Syst.* **2024**, *53*, 669–693. [CrossRef]
30. Council of the European Union. Fit for 55. 2026. Available online: <https://www.consilium.europa.eu/en/policies/fit-for-55/> (accessed on 15 June 2026).
31. International Energy Agency. Dual Credit System. 2023. Available online: <https://www.iea.org/policies/14779-dual-credit-system> (accessed on 15 June 2026).
32. California Air Resources Board. Advanced Clean Cars Program. 2026. Available online: <https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii> (accessed on 15 June 2026).
33. Queensland Government. Queensland Zero Emission Vehicle Strategy and Action Plan. 2024. Available online: <https://www.publications.qld.gov.au/dataset/zeroemissionvehiclestrategy> (accessed on 21 June 2026).
34. Government of Western Australia. Electric Vehicle (EV) Strategy. 2024. Available online: <https://www.wa.gov.au/service/environment/environment-information-services/electric-vehicle-ev-strategy> (accessed on 21 June 2026).
35. Victoria State Government. Zero Emissions Vehicles Facts. 2024. Available online: <https://www.energy.vic.gov.au/renewable-energy/zero-emission-vehicles> (accessed on 21 June 2026).
36. BloombergNEF. Electric Vehicle Outlook. 2025. Available online: <https://about.bnef.com/insights/clean-transport/electric-vehicle-outlook/> (accessed on 8 July 2026).
37. International Energy Agency. *World Energy Outlook 2025*; Flagship Report; International Energy Agency (IEA): Paris, France, 2025.
38. Nour, M.; Chaves-Ávila, J.P.; Magdy, G.; Sánchez-Miralles, Á. Review of positive and negative impacts of electric vehicles charging on electric power systems. *Energies* **2020**, *13*, 4675. [CrossRef]
39. Shareef, H.; Islam, M.M.; Mohamed, A. A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. *Renew. Sustain. Energy Rev.* **2016**, *64*, 403–420. [CrossRef]
40. Ikram, M.K.; Seyedmahmoudian, M.; Thirunavukkarasu, G.; Mekhilef, S.; Stojcevski, A. Impact of an Optimal SoC-Aware EV Charging Strategy on the Voltage Regulation of Distribution Networks. In *Proceedings of the 2025 IEEE International Conference on Energy Technologies for Future Grids (ETFG)*; IEEE: New York, NY, USA, 2025; pp. 1–6.
41. Shao, S.; Zhang, T.; Pipattanasomporn, M.; Rahman, S. Impact of TOU rates on distribution load shapes in a smart grid with PHEV penetration. In *Proceedings of the IEEE PES T&D 2010*; IEEE: New York, NY, USA, 2010; pp. 1–6.
42. Faddel, S.; Al-Awami, A.T.; Mohammed, O.A. Charge control and operation of electric vehicles in power grids: A review. *Energies* **2018**, *11*, 701. [CrossRef]
43. Habib, S.; Khan, M.M.; Abbas, F.; Tang, H. Assessment of electric vehicles concerning impacts, charging infrastructure with unidirectional and bidirectional chargers, and power flow comparisons. *Int. J. Energy Res.* **2018**, *42*, 3416–3441. [CrossRef]
44. Mansouri, S.; Paredes, Á.; González, J.; Aguado, J. A three-layer game theoretic-based strategy for optimal scheduling of microgrids by leveraging a dynamic demand response program designer to unlock the potential of smart buildings and electric vehicle fleets. *Appl. Energy* **2023**, *347*, 121440. [CrossRef]
45. Aggarwal, S.; Kumar, N. A Consortium Blockchain-Based Energy Trading for Demand Response Management in Vehicle-to-Grid. *IEEE Trans. Veh. Technol.* **2021**, *70*, 9480–9494. [CrossRef]
46. Al-Sorour, A.; Fazeli, M.; Monfared, M.; Fahmy, A.A. Investigation of Electric Vehicles Contributions in an Optimized Peer-to-Peer Energy Trading System. *IEEE Access* **2023**, *11*, 12489–12503. [CrossRef]
47. Shi, M.; Wang, H.; Lyu, C.; Dong, Q.; Li, X.; Jia, Y. An Optimal Regime of Energy Management for Smart Building Clusters With Electric Vehicles. *IEEE Trans. Ind. Inform.* **2024**, *20*, 7619–7629. [CrossRef]
48. Wang, Y.; Zhang, D.; Li, Y.; Jiao, W.; Wang, G.; Zhao, J.; Qiang, Y.; Li, K. Enhancing Power Grid Resilience With Blockchain-Enabled Vehicle-to-Vehicle Energy Trading in Renewable Energy Integration. *IEEE Trans. Ind. Appl.* **2023**, *60*, 2037–2052. [CrossRef]

49. Arif, N.A.; Mekhilef, S.; Seyedmahmoudian, M.; Stojcevski, A. Degradation in Li-ion batteries and capacity decline under different cycling conditions: A comprehensive review. *J. Energy Storage* **2026**, *154*, 121270. [\[CrossRef\]](#)
50. Chen, J.; Zhang, Y.; Li, X.; Sun, B.; Liao, Q.; Tao, Y.; Wang, Z. Strategic integration of vehicle-to-home system with home distributed photovoltaic power generation in Shanghai. *Appl. Energy* **2020**, *263*, 114603. [\[CrossRef\]](#)
51. Etedadi, F.; Danté, A.W.; Kelouwani, S.; Henao, N.; Agbossou, K.; Fournier, M. Distributed coordination of electric vehicles charging station and home energy management systems in residential neighborhood. *Int. J. Electr. Power Energy Syst.* **2025**, *172*, 111142. [\[CrossRef\]](#)
52. Shin, H.; Baldick, R. Plug-in electric vehicle to home (V2H) operation under a grid outage. *IEEE Trans. Smart Grid* **2016**, *8*, 2032–2041.
53. Shurrab, M.; Singh, S.; Otrók, H.; Mizouni, R.; Khadkikar, V.; Zeineldin, H. A stable matching game for v2v energy sharing—a user satisfaction framework. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 7601–7613.
54. Liu, C.; Chau, K.; Wu, D.; Gao, S. Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies. *Proc. IEEE* **2013**, *101*, 2409–2427. [\[CrossRef\]](#)
55. Xu, Y.; Alderete Peralta, A.; Balta-Ozkan, N. Vehicle-to-vehicle energy trading framework: A systematic literature review. *Sustainability* **2024**, *16*, 5020. [\[CrossRef\]](#)
56. Sousa, T.J.; Monteiro, V.; Fernandes, J.A.; Couto, C.; Meléndez, A.A.N.; Afonso, J.L. New perspectives for vehicle-to-vehicle (V2V) power transfer. In *Proceedings of the IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society*; IEEE: New York, NY, USA, 2018; pp. 5183–5188.
57. Medeiros, A.; Canha, L.N.; Garcia, V.J.; de Azevedo, R.M.; dos Santos, R.B. Demand side and flexible energy resource management when operating smart electric vehicle charging stations. In *Advanced Technologies in Electric Vehicles*; Elsevier: Amsterdam, The Netherlands, 2024; pp. 363–384.
58. Wang, Y.; Yuan, L.; Jiao, W.; Qiang, Y.; Zhao, J.; Yang, Q.; Li, K. A Fast and Secured Vehicle-to-Vehicle Energy Trading Based on Blockchain Consensus in the Internet of Electric Vehicles. *IEEE Trans. Veh. Technol.* **2023**, *72*, 7827–7843. [\[CrossRef\]](#)
59. Yavuz, M.; Kivanç, Ö.C. Optimization of a Cluster-Based Energy Management System Using Deep Reinforcement Learning Without Affecting Prosumer Comfort: V2X Technologies and Peer-to-Peer Energy Trading. *IEEE Access* **2024**, *12*, 31551–31575. [\[CrossRef\]](#)
60. Kanakadhurga, D.; Prabakaran, N. Demand response-based peer-to-peer energy trading among the prosumers and consumers. *Energy Rep.* **2021**, *7*, 7825–7834. [\[CrossRef\]](#)
61. Saatloo, A.; Mirzaei, M.; Mohammadi-Ivatloo, B. A Robust Decentralized Peer-to-Peer Energy Trading in Community of Flexible Microgrids. *IEEE Syst. J.* **2023**, *17*, 640–651. [\[CrossRef\]](#)
62. Yao, H.; Xiang, Y.; Gu, C.; Liu, J. Optimal Planning of Distribution Systems and Charging Stations Considering PV-Grid-EV Transactions. *IEEE Trans. Smart Grid* **2024**, *16*, 691–703. [\[CrossRef\]](#)
63. Angaphiwatchawal, P.; Vangkuntod, P.; Teawnarong, A.; Chaitusaney, S. Determination of Regulating Reserve Power in Day-Ahead P2P Energy Market with EV Charging and Discharging for Managing PV System Uncertainty. In *Proceedings of the 2024 21st International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, Khon Kaen, Thailand, 27–30 May 2024; pp. 1–7. ISSN 2837-6471. [\[CrossRef\]](#)
64. Nasiri, N.; Zeynali, S.; Ravadanegh, S.; Kubler, S. Moment-Based Distributionally Robust Peer-to-Peer Transactive Energy Trading Framework Between Networked Microgrids, Smart Parking Lots and Electricity Distribution Network. *IEEE Trans. Smart Grid* **2024**, *15*, 1965–1977. [\[CrossRef\]](#)
65. Chen, J.; Aurangzeb, M.; Iqbal, S.; Shafiullah, M.; Harrison, A. Advancing EV fast charging: Addressing power mismatches through P2P optimization and grid-EV impact analysis using dragonfly algorithm and reinforcement learning. *Appl. Energy* **2025**, *394*, 126157. [\[CrossRef\]](#)
66. Wu, Y.K.; Tan, W.S.; Huang, S.R.; Chiang, Y.S.; Chiu, C.P.; Su, C.L. Impact of generation flexibility on the operating costs of the Taiwan power system under a high penetration of renewable power. *IEEE Trans. Ind. Appl.* **2020**, *56*, 2348–2359. [\[CrossRef\]](#)
67. Alsenani, T.R. The participation of electric vehicles in a peer-to-peer energy-backed token market. *Int. J. Electr. Power Energy Syst.* **2023**, *148*, 109005. [\[CrossRef\]](#)
68. Wang, L.; Kwon, J.; Schulz, N.; Zhou, Z. Evaluation of Aggregated EV Flexibility With TSO-DSO Coordination. *IEEE Trans. Sustain. Energy* **2022**, *13*, 2304–2315. [\[CrossRef\]](#)
69. Chen, X.; Wang, X.; Shahidepour, M. Risk-aware Hierarchical Coordination of Peer-to-Peer Energy Trading for Electric Vehicle Charging Stations in Constrained Power Distribution and Urban Transportation Networks under Uncertainties. *IEEE Trans. Transp. Electrification* **2024**, *10*, 9264–9280. [\[CrossRef\]](#)
70. Kim, B.G.; Ren, S.; Van Der Schaar, M.; Lee, J.W. Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid. *IEEE J. Sel. Areas Commun.* **2013**, *31*, 1219–1234. [\[CrossRef\]](#)
71. Mullan, J.; Harries, D.; Bräunl, T.; Whitely, S. The technical, economic and commercial viability of the vehicle-to-grid concept. *Energy Policy* **2012**, *48*, 394–406. [\[CrossRef\]](#)

72. Fasugba, M.A.; Krein, P.T. Cost benefits and vehicle-to-grid regulation services of unidirectional charging of electric vehicles. In *Proceedings of the 2011 IEEE Energy Conversion Congress and Exposition*; IEEE: New York, NY, USA, 2011; pp. 827–834.
73. Yuan, X.; Liu, X.; Zuo, J. The development of new energy vehicles for a sustainable future: A review. *Renew. Sustain. Energy Rev.* **2015**, *42*, 298–305. [\[CrossRef\]](#)
74. Salman, M.; Arslan, M.; Khan, S.A.; Fahad, S.; Imran, M.; Ullah, S. Demand-side management and managing electric vehicles and their optimal charging locations and scheduling in smart grids. In *Handbook on New Paradigms in Smart Charging for E-Mobility*; Elsevier: Amsterdam, The Netherlands, 2025; pp. 375–403.
75. Barone, G.; Brusco, G.; Menniti, D.; Pinnarelli, A.; Polizzi, G.; Sorrentino, N.; Vizza, P.; Burgio, A. How smart metering and smart charging may help a local energy community in collective self-consumption in presence of electric vehicles. *Energies* **2020**, *13*, 4163. [\[CrossRef\]](#)
76. Rotering, N.; Ilic, M. Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets. *IEEE Trans. Power Syst.* **2010**, *26*, 1021–1029. [\[CrossRef\]](#)
77. Shirley, C.; Sonia, S.E.; Sathya, V.; Manikandan, N.; Vidhyalakshmi, M.; Reddy, C.V.K. Blockchain and deep learning development of smart charging of electric vehicles to meet the demand side management. In *Proceedings of the 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*; IEEE: New York, NY, USA, 2023; pp. 1377–1381.
78. Sun, J.; Tan, S.; Zheng, H.; Qi, G.; Tan, S.; Peng, D.; Guerrero, J.M. A dos attack-resilient grid frequency regulation scheme via adaptive V2G capacity-based integral sliding mode control. *IEEE Trans. Smart Grid* **2022**, *14*, 3046–3057.
79. Zhang, C.; Yang, Y.; Wang, Y.; Qiu, J.; Zhao, J. Auction-based peer-to-peer energy trading considering echelon utilization of retired electric vehicle second-life batteries. *Appl. Energy* **2024**, *358*, 122592. [\[CrossRef\]](#)
80. Haider, S.; Rizvi, R.E.Z.; Walewski, J.; Schegner, P. Investigating peer-to-peer power transactions for reducing EV induced network congestion. *Energy* **2022**, *254*, 124317. [\[CrossRef\]](#)
81. Chen, X.; Wang, X.; Shahidehpour, M.; Affolabi, L.; Lu, Z.; Li, K. Distributed Peer-to-Peer Coordination of Hierarchical Three-Phase Energy Transactions Among Electric Vehicle Charging Stations in Constrained Power Distribution and Urban Transportation Networks. *IEEE Trans. Transp. Electrification* **2023**, *10*, 4407–4420. [\[CrossRef\]](#)
82. Zhang, Z.; Li, R.; Li, F. A Novel Peer-to-Peer Local Electricity Market for Joint Trading of Energy and Uncertainty. *IEEE Trans. Smart Grid* **2020**, *11*, 1205–1215. [\[CrossRef\]](#)
83. Kiltthau, M.; Asman, M.; Karmann, A.; Suriyamoorthy, G.; Beck, J.; Regener, V.; Derksen, C.; Loose, N.; Volkmann, M.; Tripathi, S.; et al. Integrating Peer-to-Peer Energy Trading and Flexibility Market With Self-Sovereign Identity for Decentralized Energy Dispatch and Congestion Management. *IEEE Access* **2023**, *11*, 145395–145420. [\[CrossRef\]](#)
84. Thakur, S.; Hayes, B.; Breslin, G. A unified model of peer to peer energy trade and electric vehicle charging using blockchains. In *Proceedings of the Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER 2018)*, Dubrovnik, Croatia, 12–15 November 2018; p. 77. [\[CrossRef\]](#)
85. Kirpes, B.; Becker, C. Processing electric vehicle charging transactions in a blockchain-based information system. In *Proceedings of the Americas Conference on Information Systems: Digital Disruption AMCIS*; Association for Information Systems: Atlanta, GA, USA, 2018.
86. Bansal, G.; Bhatia, A. A Fast, Secure and Distributed Consensus Mechanism for Energy Trading Among Vehicles using Hashgraph. In *Proceedings of the 2020 International Conference on Information Networking (ICOIN)*; IEEE Computer Society: New York, NY, USA, 2020; Volume 2020, pp. 772–777. [\[CrossRef\]](#)
87. Fattahi, J. A Federated Byzantine Agreement Model to Operate Offline Electric Vehicle Supply Equipment. *IEEE Trans. Smart Grid* **2024**, *15*, 2004–2016. [\[CrossRef\]](#)
88. Wang, B.; Guo, X. Blockchain-enabled transformation: Decentralized planning and secure peer-to-peer trading in local energy networks. *Sustain. Energy Grids Netw.* **2024**, *40*, 101556. [\[CrossRef\]](#)
89. Naik, M.; Singh, A.P.; Pradhan, N.R.; Kumar, N.; Nayak, A.; Guizani, M. TokenGreen: A Versatile NFT Framework for Peer-to-Peer Energy Trading and Asset Ownership of Electric Vehicles. *IEEE Internet Things J.* **2024**, *11*, 13636–13646. [\[CrossRef\]](#)
90. Kumar, M.; Dohare, U.; Kumar, S.; Kumar, N. Blockchain Based Optimized Energy Trading for E-Mobility Using Quantum Reinforcement Learning. *IEEE Trans. Veh. Technol.* **2023**, *72*, 5167–5180. [\[CrossRef\]](#)
91. Sivianes, M.; Zafra-Cabeza, A.; Bordons, C.; IEEE. Blockchain-based peer to peer energy trading using distributed model predictive control. In *Proceedings of the 2022 European Control Conference (ECC)*; University of Sevilla: Sevilla, Spain, 2022; pp. 1832–1837.
92. Said, D. A Decentralized Electricity Trading Framework (DETF) for Connected EVs: A Blockchain and Machine Learning for Profit Margin Optimization. *IEEE Trans. Ind. Inf.* **2021**, *17*, 6594–6602. [\[CrossRef\]](#)
93. Fu, Z.; Dong, P.; Li, S.; Ju, Y.; Liu, H. How blockchain renovate the electric vehicle charging services in the urban area? A case study of Shanghai, China. *J. Clean. Prod.* **2021**, *315*, 128172. [\[CrossRef\]](#)
94. Lasla, N.; Al-Ammari, M.; Abdallah, M.; Younis, M. Blockchain based trading platform for electric vehicle charging in smart cities. *IEEE Open J. Intell. Transp. Syst.* **2020**, *1*, 80–92. [\[CrossRef\]](#)

95. Kim, O.; Le, T.; Shin, M.; Nguyen, V.; Han, Z.; Hong, C. Distributed Auction-Based Incentive Mechanism for Energy Trading Between Electric Vehicles and Mobile Charging Stations. *IEEE Access* **2022**, *10*, 56331–56347. [\[CrossRef\]](#)
96. Debe, M.; Hasan, H.; Salah, K.; Yaqoob, I.; Jayaraman, R. Blockchain-Based Energy Trading in Electric Vehicles Using an Auctioning and Reputation Scheme. *IEEE Access* **2021**, *9*, 165542–165556. [\[CrossRef\]](#)
97. Al-Obaidi, A.; Farag, H. Decentralized Quality of Service Based System for Energy Trading Among Electric Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 6586–6595. [\[CrossRef\]](#)
98. Sagawa, D.; Tanaka, K.; Ishida, F.; Saito, H.; Takenaga, N.; Nakamura, S.; Aoki, N.; Nameki, M.; Saegusa, K. Bidding agents for PV and electric vehicle-owning users in the electricity P2P trading market. *Energies* **2021**, *14*, 8309. [\[CrossRef\]](#)
99. Waseda, F.; Tanaka, K. Bidding Agent for Electric Vehicles in Peer-to-Peer Electricity Trading Market considering uncertainty. In *Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*; Leonowicz, Z., Ed.; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2020. [\[CrossRef\]](#)
100. Kanakadhurga, D.; Prabakaran, N. Peer-to-Peer trading with Demand Response using proposed smart bidding strategy. *Appl. Energy* **2022**, *327*, 120061. [\[CrossRef\]](#)
101. Aggarwal, S.; Kumar, N. PETS: P2P Energy Trading Scheduling Scheme for Electric Vehicles in Smart Grid Systems. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 14361–14374. [\[CrossRef\]](#)
102. Najafi, A.; Pourakbari-Kasmaei, M.; Jasinski, M.; Contreras, J.; Lehtonen, M.; Leonowicz, Z. The role of EV based peer-to-peer transactive energy hubs in distribution network optimization. *Appl. Energy* **2022**, *319*, 119267. [\[CrossRef\]](#)
103. Melendez, K.; Das, T.; Kwon, C. A Nash-bargaining model for trading of electricity between aggregations of peers. *Int. J. Electr. Power Energy Syst.* **2020**, *123*, 106185. [\[CrossRef\]](#)
104. Zhao, K.; Zhang, M.; Lu, R.; Shen, C. A Secure Intra-Regional-Inter-Regional Peer-to-Peer Electricity Trading System for Electric Vehicles. *IEEE Trans. Veh. Technol.* **2022**, *71*, 12576–12587. [\[CrossRef\]](#)
105. Sifakis, N.K.; Kanellos, F.D. Real-Time Multi-Agent Based Power Management of Virtually Integrated Microgrids Comprising Prosumers of Plug-in Electric Vehicles and Renewable Energy Sources. *IEEE Access* **2024**, *12*, 161842–161865. [\[CrossRef\]](#)
106. Yang, J.; Wiedmann, T.; Luo, F.; Yan, G.; Wen, F.; Broadbent, G. A Fully Decentralized Hierarchical Transactive Energy Framework for Charging EVs with Local DERs in Power Distribution Systems. *IEEE Trans. Transp. Electr.* **2022**, *8*, 3041–3055. [\[CrossRef\]](#)
107. Fotopoulou, M.; Rakopoulos, D.; Blanas, O. Day ahead optimal dispatch schedule in a smart grid containing distributed energy resources and electric vehicles. *Sensors* **2021**, *21*, 7295. [\[CrossRef\]](#) [\[PubMed\]](#)
108. Sagaria, S.; van der Kam, M.; Boström, T. Vehicle-to-grid impact on battery degradation and estimation of V2G economic compensation. *Appl. Energy* **2025**, *377*, 124546. [\[CrossRef\]](#)
109. Geng, J.; Hao, H.; Hao, X.; Liu, M.; Dou, H.; Liu, Z.; Zhao, F. Techno-economic comparison of vehicle-to-grid and commercial-scale battery energy storage system: Insights for the technology roadmap of electric vehicle batteries. *World Electr. Veh. J.* **2025**, *16*, 200. [\[CrossRef\]](#)
110. Al-Sorour, A.; Fazeli, M.; Monfared, M.; Fahmy, A.; Searle, J.R.; Lewis, R.P. Enhancing PV Self-Consumption Within an Energy Community Using MILP-Based P2P Trading. *IEEE Access* **2022**, *10*, 93760–93772. [\[CrossRef\]](#)
111. Seyyedeh-Barhagh, S.; Abapour, M.; Mohammadi-Ivatloo, B.; Shafie-khah, M. Risk-based Peer-to-peer Energy Trading with Info-Gap Approach in the Presence of Electric Vehicles. *Sustain. Cities Soc.* **2023**, *99*, 104948. [\[CrossRef\]](#)
112. Masood, S.; Hassan, M.U.; Tsai, P.W.; Zhang, K.; Gao, L.; Dong, M.; Chen, J. APSM: Adaptive privacy budget control in differentially private matching in electric vehicles. *Expert Syst. Appl.* **2025**, *302*, 130453.
113. Ikram, M.K.; Seyedmehmoudian, M.; Thirunavukkarasu, G.S.; Mekhilef, S.; Stojcevski, A. A two-stage fuzzy-informed optimization framework for reduced peak load and hierarchical EV management in smart grids. *J. Energy Storage* **2025**, *136*, 118308. [\[CrossRef\]](#)
114. Islam, M.R.; Rashid, T.S.; Sheikh, M.R.I. Hierarchical Control Strategy for Electric Vehicles: Managing Travel Uncertainty and Engaging EV Owners in Transactive Energy Markets. *Results Eng.* **2025**, *29*, 108897.
115. Boato, B.; Antonelli, N.; Trimboli, M.; Avila, L.; Catuogno, G. Virtual Power Plants for Net-Zero Energy Operation Under Carbon Constraints. *Smart Grids Sustain. Energy* **2026**, *11*, 36. [\[CrossRef\]](#)
116. Yuvaraj, T.; Thirumalai, M.; Savio, F.M.; Bajaj, M.; Blazek, V. Optimized Energy Trading System for Smart Grids: Enhancing Prosumer Profitability through Multiple Trading Mechanisms and Integration of Various Appliances. *E-Prime -Nexus Electr. Electron. Intell. Eng.* **2026**, *17*, 201183. [\[CrossRef\]](#)
117. Hashemipour, N.; Aghaei, J.; Granado, P.; Kavousi-Fard, A.; Niknam, T.; Shafie-Khah, M.; Catalao, J. Uncertainty Modeling for Participation of Electric Vehicles in Collaborative Energy Consumption. *IEEE Trans. Veh. Technol.* **2022**, *71*, 10293–10302. [\[CrossRef\]](#)
118. Wushouerniyazi, N.; Wang, H.; Ding, Y. Coordinated Optimization of Multi-EVCS Participation in P2P Energy Sharing and Joint Frequency Regulation Based on Asymmetric Nash Bargaining. *Energies* **2026**, *19*, 1269. [\[CrossRef\]](#)

119. Ali, L.; Azim, M.; Ojha, N.; Peters, J.; Bhandari, V.; Menon, A.; Green, J.; Muyeen, S. Integrating Forecasting Service and Gen2 Blockchain Into a Local Energy Trading Platform to Promote Sustainability Goals. *IEEE Access* **2024**, *12*, 2941–2964. [CrossRef]
120. El-Zonkoly, A. Double-layer optimal energy management of smart grid incorporating P2P energy trading with smart traction system. *Int. J. Emerg. Electr. Power Syst.* **2023**, *25*, 865–884. [CrossRef]
121. Kanakadhurga, D.; Prabakaran, N. Price-based demand response with renewable energy sources and peer-to-peer trading for residential microgrid with electric vehicle uncertainty. *Comput. Electr. Eng.* **2024**, *119*, 109618. [CrossRef]
122. Rukmani, D.K.; Isac, S. J. Federated AI-Driven Urban Energy Resilience Framework for Smart City Critical Infrastructure Restoration. *Smart Cities* **2026**, *9*, 102. [CrossRef]
123. Brohi, N.A.; Thirunavukkarasu, G.; Seyedmahmoudian, M.; Ahmed, K.; Stojcevski, A.; Mekhilef, S. Advances in hosting capacity assessment and enhancement techniques for distributed energy resources: A review of dynamic operating envelopes in the Australian grid. *Energies* **2025**, *18*, 2922. [CrossRef]
124. Hoque, M.; Khorasany, M.; Azim, M.; Razzaghi, R.; Jalili, M. Dynamic Operating Envelope-Based Local Energy Market for Prosumers with Electric Vehicles. *IEEE Trans. Smart Grid* **2024**, *15*, 1712–1724. [CrossRef]
125. García-Muñoz, F.; Farriol, A.; Eichman, J. Statistical analysis of an energy community's operations in P2P energy trading and flexibility markets. *Sustain. Energy Grids Netw.* **2025**, *43*, 101755. [CrossRef]
126. Masood, S.; Hassan, M.U.; Tsai, P.W.; Chen, J. DLLPM: Dual-layer location privacy matching in V2V energy trading. *J. Syst. Archit.* **2025**, *167*, 103507. [CrossRef]
127. Mohammadi, S.; Eliassen, F.; Zhang, Y.; Jacobsen, H.A. Detecting false data injection attacks in peer to peer energy trading using machine learning. *IEEE Trans. Dependable Secur. Comput.* **2021**, *19*, 3417–3431. [CrossRef]
128. Lin, W.T.; Chen, G.; Zhou, X. Distributed carbon-aware energy trading of virtual power plant under denial of service attacks: A passivity-based neurodynamic approach. *Energy* **2022**, *257*, 124751. [CrossRef]
129. Yang, J.; Shi, F.; Li, Y.; Zhao, Z.; Cui, Q. VNN-DM: A vector neural network-based detection model for time synchronization attacks in park-level energy internet. *Intell. Robot.* **2024**, *4*, 406–421. [CrossRef]
130. Zhao, X.; Liu, G.; Li, L. Importance-driven denial-of-service attack strategy design against remote state estimation in multi-agent intelligent power systems. *Intell. Robot.* **2024**, *4*, 244–255. [CrossRef]
131. Kiltthau, M.; Regener, V.; Zeiselmair, A.; Beck, J.; IEEE. Elicitation and Analysis of Requirements for a Peer-to-Peer Energy Market. In Proceedings of the 2022 IEEE 16th International Conference on Compatibility, Power Electronics, and Power Engineering (CPE-POWERENG), Birmingham, UK, 29 June–1 July 2022. [CrossRef]
132. Gazioglu, I.; Vu Van, T.; Buyuk, A.; Eren, T.; Tuan, L.; Oana, C. Real-Life Demonstration of Blockchain Based Flexibility Trading Between FSPs and DSO. In *Proceedings of the 2023 Asia Meeting on Environment and Electrical Engineering (EEE-AM)*; Leonowicz, Z., Stracqualursi, E., Eds.; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2023. [CrossRef]
133. Power Ledger. Tata Power-DDL Rolls Out Live Peer-to-Peer (P2P) Solar Energy Trading, a First-of-Its-Kind Pilot Project in Delhi. 2021. Available online: <https://powerledger.io/media/tata-power-ddl-rolls-out-live-peer-to-peer-p2p-solar-energy-trading-a-first-of-its-kind-pilot-project-in-delhi/> (accessed on 16 August 2024).
134. Power Ledger. Power Ledger and Silicon Valley Power Trial to Turn Electric Vehicles into Mobile ATMs. 2021. Available online: <https://messari.io/project/power-ledger/research> (accessed on 16 August 2024).
135. Centrica. *The Future of Flexibility: How Local Energy Markets Can Support the UK's Net Zero Energy Challenge*; Technical Report; Centrica: Windsor, UK, 2020.
136. Share & Charge. Share & Charge: Blockchain-Based Peer-to-Peer EV Charging Platform. 2018. Available online: <https://www.delodi.net/sharecharge-en> (accessed on 13 June 2026).
137. Powerledger. BCPG To Install 12 Megawatt Rooftop Solar Power System for Chiang Mai University's Smart City-Clean Energy Project Using Powerledger's P2P Platform. 2018. Available online: <https://www.bcpogggroup.com/en/newsroom/news/240/bcp-g-to-install-12-megawatt-rooftop-solar-power-system-for-chiang-mai-university-s-smart-city-clean-energy-project> (accessed on 13 June 2026).
138. Karmaker, A.K.; Prakash, K.; Siddique, M.N.I.; Hossain, M.A.; Pota, H. Electric vehicle hosting capacity analysis: Challenges and solutions. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113916. [CrossRef]
139. Ikram, M.K.; Seyedmahmoudian, M.; Thirunavukkarasu, G.; Mekhilef, S.; Stojcevski, A. Modeling and Analysis of EV Charging Station Placement Impacts on a Hybrid Microgrid. In *Proceedings of the 2025 IEEE PES 35th Australasian Universities Power Engineering Conference (AUPEC)*; IEEE: New York, NY, USA, 2025; pp. 1–5.
140. Chen, X.; Wang, X.; Lu, Z.; Huang, J.; Huang, Y. Distributed energy trading for electric vehicle charging stations equipped with distributed PV considering transportation network. *Energy Rep.* **2023**, *9*, 819–827. [CrossRef]
141. Aarabi, M.S.; Khanahmadi, M.; Awasthi, A. A literature review on strategic, tactical, and operational perspectives in EV charging station planning and scheduling. *World Electr. Veh. J.* **2025**, *16*, 404. [CrossRef]
142. Wu, Y.; Wu, Y.; Cimen, H.; Vasquez, J.C.; Guerrero, J.M. P2P energy trading: Blockchain-enabled P2P energy society with multi-scale flexibility services. *Energy Rep.* **2022**, *8*, 3614–3628. [CrossRef]

143. Salman, M.; Arslan, M.; Khan, S.A.; Fahad, S.; Imran, M.; Ullah, S. Policies for the future: Promoting electric vehicle deployment. In *Handbook on New Paradigms in Smart Charging for E-Mobility*; Elsevier: Amsterdam, The Netherlands, 2025; pp. 481–507.
144. Tuffner, F. *Electric Vehicle Standards–Grid Service Capabilities: Evaluation of IEEE 2030.13, SAE J3072, ISO 15118-2, ISO 15118-20, OCPP, IEC 61850-7-420, IEEE 2030.5, and OpenADR*; Technical Report PNNL-36214; Pacific Northwest National Laboratory: Richland, WA, USA, 2024.
145. Kirchner, S.R. Ocpp interoperability: A unified future of charging. *World Electr. Veh. J.* **2024**, *15*, 191. [[CrossRef](#)]
146. Adham, M.; Keene, S.; Bass, R.B. Distributed energy resources: A systematic literature review. *Energy Rep.* **2025**, *13*, 1980–1999. [[CrossRef](#)]
147. Mazrae, A.K.; Naderian, H.; Baghaee, H.R.; Sheikh-El-Eslami, M.K.; Karimi, M. Transactive energy and peer-to-peer energy trading based on blockchain: A comprehensive review and a generalized cyber-physical framework. *Energy Strategy Rev.* **2025**, *62*, 101949. [[CrossRef](#)]
148. Chowdhury, A.; Shafin, S.S.; Masum, S.; Kamruzzaman, J.; Dong, S. Secure electric vehicle charging infrastructure in smart cities: A blockchain-based smart contract approach. *Smart Cities* **2025**, *8*, 33. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.