Dual Perspectives: Analysis of the Current State of Research into Vehicle-to-Grid (V2G) Charging Strategies

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Abstract: The large-scale, uncoordinated connection of electric vehicles (EVs) to the grid poses significant challenges to the power system.Vehicle-to-Grid (V2G) technology treats EVs as distributed energy sources via bidirectional energy converters, mitigating grid load fluctuations while facilitating renewable energy integration and enhancing energy utilisation efficiency.Throughout the process, EV users serve as key participants in vehicle-grid interaction technology, while the power grid emerges as the ultimate beneficiary. An irreconcilable conflict of interests exists between these two parties.How to schedule the full participation of EV users in V2G operations, maximising grid benefits without compromising EV user interests, represents both a current research focus and a significant challenge.This review aims to analyse the conflicting interests between grid-side benefits and user-side concerns in V2G charging strategies over the past three years (2022–2025), employing literature review and comparative analysis methodologies. It addresses a research gap in existing reviews by adopting this unique perspective.Summarising the mainstream application of deep learning as an auxiliary function in practical engineering V2G scheduling, with the aim of providing practical reference guidance for engineering decision-makers.The current situation indicates that a ‘renewable energy-electricity-transportation’ coupling system should be established in the future to achieve V2G cluster coordination. This will optimise multiple resources such as wind, solar, hydro, and storage, thereby further enhancing the power grid.Develop intelligent charging and discharging strategies for battery State of Health (SoH) throughout its entire lifecycle, dynamically adjusting depth of discharge, charging power, and service participation types to enhance user satisfaction and incentivise participation in dispatch.

Keywords: Vehicle-to-Grid Interaction; Charging Strategy; Control Strategy; Energy Management

1. Introduction

The global energy transition has propelled electrified transport to become the prevailing trend, with electric vehicles enjoying robust sales worldwide owing to their capacity to achieve decarbonisation[1].EVs, as green modes of transport,Large-scale disorderly charging, particularly during peak electricity consumption periods when charging occurs simultaneously,This will lead to widening disparities between peak and off-peak loads on the grid, causing instability and other issues that severely impact the safe and stable operation of the power system[2].To address this issue, Vehicle-to-Grid (V2G) technology transforms EVs into ‘distributed energy storage units’ via bidirectional converters, establishing a bridge for energy flow between vehicles and the grid. This enables peak shaving and valley filling to stabilise the grid[3].It not only mitigates the intermittency and variability of renewable energy sources but also participates in grid services such as peak shaving and frequency regulation[4].With the rapid increase in electric vehicles, global V2G technology trials are also accelerating, as shown in Figure 1. However, the greatest technical challenge in promoting V2G technology lies in reconciling the conflicting interests between EV users and the electricity grid.The grid operator aims to utilise V2G to achieve peak shaving and valley filling, stabilise frequency, and promote the integration of renewable energy[5].Users are concerned whether the economic returns can offset battery degradation issues, and whether travel and freedom can be guaranteed while participating in V2G scheduling[6].How to scientifically design charging and discharging scheduling strategies to balance the conflicting interests between the grid and users has become a current research hotspot and is also key to achieving V2G commercialisation.

This review aims to analyse and summarise the current state of research within the V2G charging strategy domain from both grid and user perspectives, both domestically and internationally, over the past three years (2022–2025). It examines key research focuses, summarises aspects of interest on both the grid and user sides, outlines mainstream approaches to balancing grid-side and user-side interests, and looks ahead to future research directions. It provides theoretical reference and practical guidance insights for advancing V2G technology from theoretical development towards large-scale application.

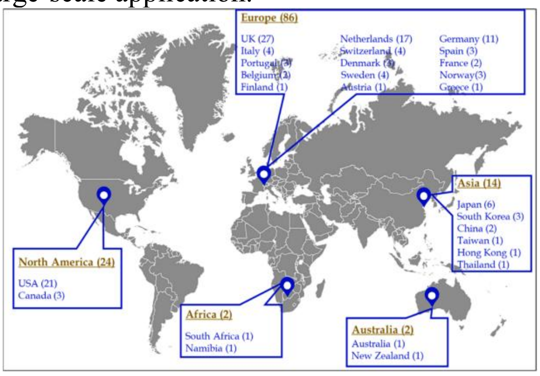

Figure 1. Global V2G Demonstration Project Distribution[30]

2. Literature Review-V2G Charging and Discharging Strategies from a Grid Perspective

EVs, as a dispatchable, secure and efficient form of distributed energy, can fundamentally resolve the operational challenges faced by the grid.From the grid perspective, the key focus areas encompass the following four categories:

2.1 Load Regulation and Peak Shaving

The load curve of conventional power systems exhibits pronounced peak-to-trough variations, and the disorderly charging of a large number of EVs can readily compromise the stability of distribution networks, potentially leading to system collapse.Addressing this issue, Majed et al. designed battery state-of-charge (SOC) charging and discharging strategies tailored to Bangladesh's electricity demand. By optimising EV charging and discharging behaviour under the constraints of meeting minimum user mobility requirements, they compared the performance of genetic algorithm (GA) and particle swarm optimisation (PSO) algorithms to mitigate grid load fluctuations[7].Secchi et al. examined the impact of PV penetration on power grids, proposing a quadratic programming (QP) approach to mathematically model load fluctuation effects. Following simulation, this achieved a reduction in maximum net load variance to 60% under ideal conditions[8].By contrast, Kljajic et al. adopted a practical engineering approach, employing optimal power flow (OPF) to avoid wasting renewable energy while simultaneously achieving indirect load peak shaving[9].Srihari et al. compared the convergence rates of two meta-heuristic algorithms, proposing an improved honey badger algorithm (IHBA) to seek optimal solutions. This approach is optimised with dynamic programming, resolving large-scale EV fleet scheduling problems through a combination of macro- and micro-level strategies[10].Unlike GA, PSO operates slowly but with high stability, whereas IHBA runs faster and is more suitable for ultra-large-scale V2G scheduling.

2.2 Frequency Regulation and Grid Stability

In scenarios where frequency instability compromises grid stability, V2G technology represents a future solution. Through rational charging and discharging scheduling, it enables flexible responses to support the grid.Both Secchi et al. and Kljajic et al. treated node voltages within permissible limits as one of the key constraints throughout their research[8-9].Ouyang et al. conducted direct investigations under grid fault conditions, incorporating voltage source converters (VSCs) and establishing a feasible power model for DC voltage sources. They proposed a strategy based on PCC voltage control to ensure DC overvoltage during EV charging and discharging operations via V2G charging stations during faults, thereby enhancing the robustness of V2G charging/discharging stations against grid disturbances[11].Regarding frequency regulation: The research by Srihari et al. provides a foundation, employing the IHBA algorithm to effectively reduce total harmonic distortion (THD) in grid voltage, thereby improving power quality and enhancing system operational efficiency[10].

2.3 Balancing the Grid Integration of

Renewable Energy Sources

To address the challenges posed by high-penetration grid integration of renewable energy sources, Secchi et al. adopted this as their research context. By employing vehicle-to-grid (V2G) technology to absorb surplus photovoltaic power during midday hours, they optimised the mitigation of curtailed solar generation while simultaneously alleviating fluctuations in net load[8]. Kljajic et al coupled EV charging and discharging behaviour with photovoltaic power generation, seeking an optimal solution through the coordinated optimisation of V2G charging station siting and all-day optimal EV charging and discharging scheduling. Based on European urban low-voltage distribution network data, they employed DIgSILENT PowerFactory simulation modelling to maximise local consumption of photovoltaic power and reduce reliance on external electricity[9].

2.4 Ancillary Services and Reserve Capacity

Srihari et al note that EVs, as adaptable energy storage systems (ESS), play a significant role in ancillary service markets. This assertion defines the commercial prospects of V2G for remunerated services such as continuous frequency regulation, voltage control, and reserve capacity provision to the grid, thereby guiding subsequent research[10]. The smoothed load curve studied by Secchi et al. objectively resembles a single real-time frequency modulation, consistent with the frequency regulation summarised in Section 2.2 above[8].Ouyang et al. conducted research on voltage support during faults, which may also serve as a grid ancillary service[11].

Overall, these studies demonstrate the significant value and potential of V2G charging and discharging technology in optimising grid operations from multiple perspectives.Research methodologies have evolved from single-quantity EV dynamic programming to achieve the most precise scheduling solutions, progressing towards meta-heuristic optimal solutions for large-scale scheduling.The optimisation objective has evolved from solely load levelling to encompass multiple goals, including power quality, economic efficiency, and system stability,Table 1.

Table 1. A Comparative Framework for Grid-Side Research on V2G Charging Strategies

Author(s)	Focus Area	Methodology	Key Outcomes	Challenges
Majed et al [7]	Load regulation, peak shaving and valley filling	SOC Power Range Control Method Combining GA and PSO	Compared to PSO, GA reduced peak load by 43.52% and increased off-peak load by 62.75%.	The issue of insufficient V2G capacity when user participation is not factored in; Ultra-large-scale EV scheduling imposes heightened demands on grid monitoring and cybersecurity.
Secchi et al [8]	Load fluctuations, integration of renewable energy	Quadratic programming (QP) and its implementation in MATLAB using the quadprog solver	Under high EV and PV penetration, reduce net load variance by 60%; improve voltage stability, helping the grid operate within safety standards.	More precise forecasting and real-time control remain challenges for the future; scenarios where PV penetration is excessively high and EV penetration is insufficient have not been considered.
Kljajic et al [9]	Renewable energy integration, voltage stability	Optimal Power Flow (OPF) combined with Mixed-Integer Nonlinear Programming (MINLP)	Reduce power exchange with the upstream grid	Representative data remains insufficient, posing challenges for larger-scale power grids.
Srihari et al [10]	Energy management, load fluctuations, power quality	Improved Honey Badger Algorithm with Dynamic Programming	System efficiency stands at 98.47%, with total harmonic distortion (THD) of the voltage controlled at 3.12%, outperforming algorithms such as WOA.	Focusing solely on optimising the PCC point neglects research into the impact on voltage and power flow distribution across the entire distribution network.
Ouyang et al [11]	Power grid failure, voltage stability	Power Boundary Modelling and PCC Voltage Support Control	The PCC voltage was effectively raised to 0.75 p.u. during the grid failure.	Over-reliance on predictable conditions, coupled with a lack of preparedness for unforeseen contingencies in real-world engineering scenarios.

3. Literature Review-V2 Charging and Discharging Strategy from a User Perspective

Existing research indicates that appropriately incentivised, user-centric charging and discharging strategy design significantly enhances user willingness to participate, thereby promoting the sustainable development of V2G technology. A review of existing literature indicates that research into V2G charging strategies from a user perspective primarily centres on the following five core aspects:

3.1 User Economic Benefits

Considering the use of economic incentives to encourage user participation in V2G scheduling, Lee et al employed a time-of-use (TOU) pricing scheme combined with a dynamic programming (DP) scheduling optimisation algorithm to minimise the charging costs for a single electric vehicle over a 24-hour period. Compared to conventional constant-power charging and discharging methods, the DP algorithm effectively reduced charging costs by approximately 25.2% to 33.7%[13].

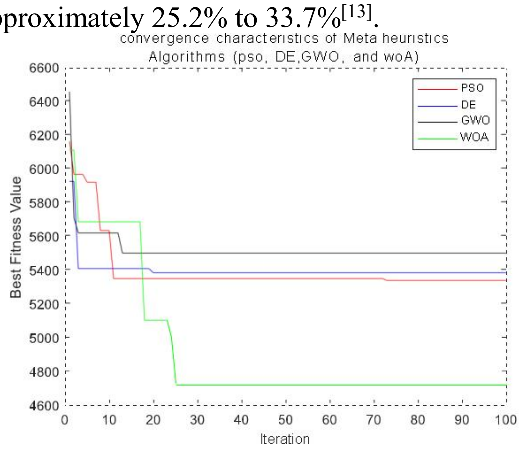

Figure 2. A Comparative Framework for Four Meta-Heuristic Algorithms[14]

Shaheen et al simulated vehicle arrival and departure times under varying electricity price signals, utilising a large-scale car park case study to determine the optimal scheduling plan for each vehicle. The study compared four meta-heuristic algorithms, demonstrating that the Whale Optimisation Algorithm (WOA) achieved the best performance in both convergence speed and cost minimisation[14], Figure 2. The simplification of the battery degradation model constitutes a limitation of the two studies, which lack specific assessments of user benefits.

3.2 Battery Life Cycle

Battery degradation over its lifecycle also impacts user engagement. Consequently, Trivino et al. detailed the effects of excessive discharge in their work, necessitating that algorithms schedule discharges within safe depth-of-discharge limits. Lee et al. established upper and lower SOC constraints for batteries, thereby providing indirect protection[13,16].

Regarding effective battery health management, Zhang et al. proposed an amplitude-based rain gauge counting (MRCC) algorithm that precisely quantifies the equivalent full cycle count (EFCC) within short charge-discharge cycles, while simultaneously addressing challenges in large-scale EV scheduling scenarios[15].Zhao et al established calendar and cycle ageing models for electric trucks and household electric vehicles respectively, validated through data. Based on an economic model coupling time-of-use electricity pricing with battery ageing, they analysed two scenarios: smart single-direction charging and V2G bidirectional charging. By examining the effects of different temperatures, C-rate, and DOD on battery lifespan and net user benefits from V2G participation for both vehicle types. Their findings, combined with those of Zhang et al., collectively establish a foundation for quantifying battery ageing costs[12,15].

3.3 User Travel Protection

The fundamental premise underpinning all strategy research is the imperative to safeguard users' essential daily mobility requirements. The optimisation model incorporates State of Charge (SOC) constraints to ensure that, following participation in the dispatch process, users retain sufficient battery capacity to complete their remaining journey.A study conducted by Lee et al. examined State of Charge (SOC) values before and after scheduling under varying conditions. The results demonstrated that even when charging from 10% to 90% SOC, the DP algorithm optimisation still reduced user charging costs[13].Zhao et al. considered the next day's EV usage scenarios, such as commuting, to set the target state of charge (SOC), thereby ensuring it would not impact the normal operation of EVs the following day[12].

3.4 User Autonomy

Granting users trust and autonomy in decision-making is pivotal in determining their willingness to participate in V2G dispatch over the long term. Compared to centralised, unified dispatch systems, decentralised and distributed architectures enable users to exercise their autonomy.

Trivinoe et al and Shaheen et al both adopted decentralised frameworks, whereby the system delegates decision-making authority to each individual user. Figure 3, In this context, each electric vehicle (EV) constitutes a decision-making unit. Users may autonomously determine charging and discharging behaviour based on their EV's battery capacity, scheduling parameters (such as setting minimum state of charge), and local grid information[14,16].While respecting the user, it also reduces the EV's reliance on the central processing unit, thereby alleviating communication pressure.User personalisation: Zhao et al. incorporated user preference parameters into the model, selecting different scheduling packages based on priorities such as battery life to meet diverse user requirements[12].

3.5 User Behaviour Uncertainty

Throughout the process, the unpredictability of user behaviour constitutes a critical influencing factor. Changes to plans or sudden shifts in behaviour directly impact the benefits users derive from participating in the scheduling process.

Lee et al devised a dynamic programming approach to formulate optimal day-ahead schedules across 24 time slots without accounting for user-specific circumstances. While this method achieves the pinnacle of user benefit, it proves incapable of updating and optimising new scheduling plans in response to actual conditions when unexpected events (such as power outages) occur or users withdraw from the scheduling process[13].Zhang et al, on the contrary, propose a framework for online optimisation of rolling schedules (optimised every 30 minutes): capturing real-time information on EVs connected to the grid, performing high-frequency optimisation, responding to changes in user behaviour (such as early departures), minimising impacts, and compensating for situations where sudden events cannot be promptly updated online[15].

Trivino et al. extended this work by designing a Type-II fuzzy logic autonomous controller to pursue real-time robustness for the system. This approach handles imprecise, fuzzy input information (for instance, if a user selects a 4pm completion time, Type-II will adjust the schedule to finish earlier based on actual conditions). Consequently, the scheduling algorithm exhibits enhanced robustness against errors in estimating user behaviour[16].

Overall, from the perspective of user interests, this encompasses economic benefits, battery life prediction, setting SOC constraints to alleviate range anxiety, decentralising the system while introducing preference settings to respect user choice, and applying new methodologies such as Type-II fuzzy logic to respond promptly to uncertainties, Table 2.

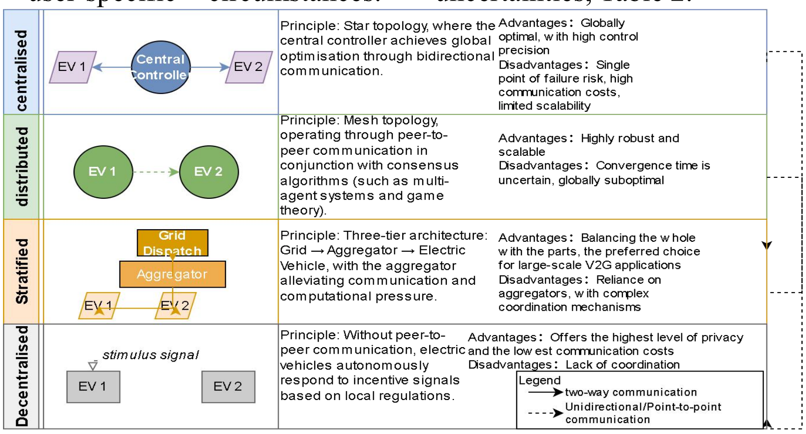

Figure 3. V2G Control Framework: Principles and Distinctions

Table 2. Comparative Framework: User-Side Research on V2G Charging Strategies

Author(s)	Focus Area	Methodology	Key Outcomes	Challenges
Zhao et al [12]	Battery life; Economic benefits; Risks and uncertainties	High-precision battery ageing model coupled with user economic model, Monte Carlo simulation	The preliminary economic benefits of V2G scheduling fall short of battery degradation costs; this provides differentiated strategies for private vehicles and electric vehicle charging.	The model is complex and involves numerous parameters; long-term yield projections are subject to uncertainty.

Lee et al [13]	Economic benefits, battery life	Dynamic Programming (DP) considering the charging efficiency model	Developing a 24-hour optimal scheduling plan: achieving cost reductions of 25.2% to 33.7% compared to conventional charging strategies.	The dispatch plan relies excessively on precise future electricity prices: DP is unsuitable for handling large-scale EV dispatch fleets.
Shaheen et al [14]	Economic benefits, travel security	PSO, DE, WOA, GWO	By comparing four meta-heuristic algorithms, it is demonstrated that WOA delivers optimal performance in terms of cost reduction and convergence when handling large-scale scheduling problems.	Parameter settings influence the results of optimal algorithms.
Zhang et al [15]	Battery life, economic benefits	Coupled Battery Prediction (MRCC) and Economic Model, Employing PSO Optimisation; Online Optimisation	An online quantifiable battery ageing calculation method that reduces battery EFCC by 8.4%	Online optimisation imposes excessive demands on real-time messaging and cannot predict future scenarios; the MRCC methodology's general applicability still requires substantial data validation.
Trivino et al [16]	Travel security, autonomy, risk and uncertainty	Decentralised Type-II Fuzzy Logic Controller	Decentralised architecture safeguards user autonomy; fuzzy time-slot processing accommodates scheduling uncertainties.	Decentralised architecture may lead to local optima.

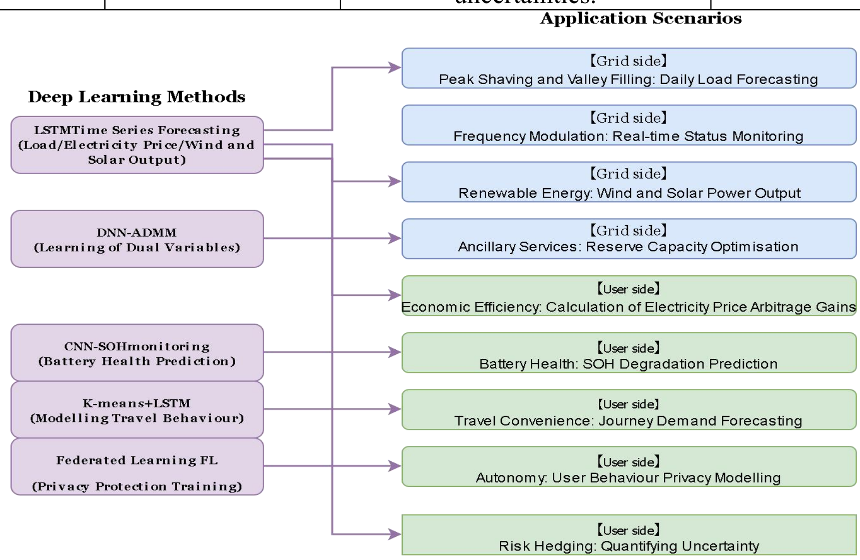

Figure 4. Application of DL in V2G Charging and Discharging Strategies[17-24]

4. Literature Review-Application of DL in V2 Charging and Discharging Strategies

DL possesses capabilities for data learning and recognition. Unlike fuzzy control and stochastic programming, it leverages high-precision data forecasting and dynamic optimisation to demonstrate significant advantages in handling high uncertainty and nonlinear coupling within practical V2G scheduling, Figure 4.

When confronted with uncontrollable factors in reality-load variables-traditional linear statistical models (such as ARIMA) are unable to accurately forecast load.Comi and Elmour compared the total energy fed back into the grid by EV under LSTM and ARIMA predictions. Results indicate that the coefficient of determination (R^2) for LSTM outperformed ARIMA's R^2 (0.46)[17].Ling et al. further investigated the integration with traffic models, employing Pyraformer to forecast V2G load at individual charging stations while simulating users' micro-behaviour during driving. Simulation results demonstrated that Pyraformer outperformed models such as DNN and LSTM in predictive accuracy[19].

In response to the instability of new energy sources, Ghorashi et al incorporated the randomness of renewable energy into the

MTDNN model. By employing a dispatch system to promptly address real-time fluctuations in new energy generation, they ensured stable grid operation when integrating substantial amounts of clean energy and formulated optimal economic dispatch plans. Furthermore, this rapid response capability enables the model to effectively handle real-time ancillary services such as frequency regulation[18].

From the user perspective, DL frequently serves as an auxiliary function to maximise user benefits and achieve high-precision predictions of battery degradation,Wang et al employed a dataset comprising the trajectories of 76,000 private vehicles in Beijing to utilise LSTM for forecasting future charging demand whilst simultaneously arranging scheduling plans. Users may independently schedule arrangements according to their travel plans and requirements[20].Ghimire et al proposed the hybrid deep learning model MoDWT-CRVFL, achieving high-precision forecasting of half-hourly electricity prices in New South Wales, Australia. This demonstrated that MoDWT-CRVFL outperformed models such as LSTM and DNN across multiple evaluation metrics, including forecasting accuracy. Such high-precision electricity price forecasting enables more effective peak-valley arbitrage[23].

High-precision state of charge (SOC) monitoring effectively safeguards battery safety，Cervellieri utilised NASA datasets, the Levenberg-Marquardt algorithm and FFBPN to predict lithium-ion battery state of charge (SOC). Users can ensure each charge-discharge cycle occurs within safe parameters based on these results, while understanding the battery's remaining lifespan enables rational scheduling arrangements[22].Lu et al employed a deep learning framework utilising recurrent neural networks (RNNs) to predict capacity degradation trajectories in lithium batteries under conditions of operational uncertainty. This enables users to dynamically adjust planning based on personalised preferences, incorporating uncertainties inherent in future charging and discharging cycles[21].

In summary, deep learning is essential for predicting uncertainties in real-world scenarios. These studies encompass load forecasting, charging demand, renewable energy output, user battery lifespan, and subsequent planning. By integrating their own requirements with grid responsiveness, users can formulate optimal scheduling plans, Table 3 and Table 4.

Table 3. Grid Applications of DL in V2G Charging Strategies

Author	RL Model	Forecast data	Establish a model	Disadvantages	Applicable scenarios
Antonio and Elsiddig [17]	LSTM	V2G energy transfer	Real-time energy dispatch	relying on historical data	Areas where user behaviour patterns and scale are manageable, such as university campuses and industrial parks.
Ghorashi et al [18]	MTDNN	The Intermittency of Renewable Energy and Electric Vehicles	Economic Scheduling	Low adaptability to operating conditions outside the training set	High-proportion renewable energy source microgrid
Ling et al [19]	Pyraformer	V2G charging and discharging load for a single charging station	Load Forecasting Coupled with Traffic Simulation	Dependence on the authenticity of simulation platforms and data.	Distribution network planning phase and assessment phase

Table 4. User-side Application of DL in V2G Charging Strategies

Author	RL Model	Forecast data	Establish a model	Disadvantages	Applicable scenarios
Wang et al [20]	LSTM	Short-term charging requirements	Timing Prediction Model for Charging Events	Extensive training period	Charging station operators conduct load forecasting
Lu et al [21]	RNN; GRU	Future capacity degradation trajectory of batteries	Battery Degradation Trajectory Prediction Model	High accuracy requirements for future planning of input data	Battery Health Management (BHM) in V2G Dispatch Systems; User-Provided Battery Replacement Cost Estimates
Cervellieri [22]	FFBPN	State of Charge (SOC) of Lithium Batteries	High-Precision Battery State Estimation Model	High standards for data quality	Real-time Status Monitoring During V2G Charging and Discharging Processes

Sujan et al [23]	CNN; RVFL	Half-hourly electricity pricing	MoDWT-CRVFL Hybrid Electricity Price Forecasting Model	Hybrid models feature complex structures and pose challenges for parameter tuning; they demand rigorous preprocessing of input data.	Optimisation of Revenue Decisions for V2G Users Participating in Electricity Market Transactions

5. Literature Review-Balancing Grid Interests and Consumer Interests

The pursuit of load stability on the grid side and the maximisation of benefits on the consumer side present an irreconcilable contradiction in practical engineering.Most studies on grid-side benefits assume unconditional participation of EV users in V2G dispatch without accounting for battery degradation. Similarly, when examining user-side benefits, they focus solely on maximising user gains while disregarding actual grid requirements such as load or frequency.

Effectively balancing the conflicting interests of both parties is key to advancing the commercialisation of V2G technology.

To address the conflict of interests between users and the power grid, this paper reviews five prevalent approaches:

(1)weighted sum:Assign weighting coefficients to different stakeholder groups and integrate them into a single composite function. The multi-objective problem is transformed into a single-objective function to seek the optimal solution.The objective function in Ran et al's study encompassed both user charging costs and grid loss costs, achieving a 9.73% reduction in user costs while mitigating 26.09% of the peak-to-off-peak difference[25].

(2)ε-constraint method:Casals et al employed this methodology to maximise the benefits of V2G for both the grid and users, setting battery life degradation within an acceptable threshold ε. By incorporating real-world driving data analysis, they explored scenarios where mutual interests are optimised within this threshold[26].

(3)Pareto optimal frontier:Unlike the aforementioned two approaches, Pang et al. completely shielded subjective consciousness within their model. They employed the IBBMOPSO algorithm to generate an extensive set of optimal solutions for third parties to select autonomously. Finally, the third parties comprehensively considered the selection rate to choose a satisfactory solution from this set[27].

(4)Master-slave game:Conflicts of interest are transformed into dynamic strategic planning challenges, where multiple stakeholders (in this context, the grid side and the consumer side) seek to maximise their respective interests while identifying a point of equilibrium.Wang et al employed dynamic time-of-use electricity pricing to guide users, devising a framework that simultaneously minimises the grid's peak-to-off-peak load difference while enabling users to minimise their total expenditure based on pricing information. Within this model, the grid holds a dominant position, dynamically adjusting tariffs, while users act as post-decision-making agents in their charging and discharging behaviour[28].

(5)RL:Agents learn optimal strategies through interaction with their environment. Xiao et al designed a “reward function” reflecting both grid stability and user economics, employing trial-and-error to progress from states (time, SOC distribution) to actions (charging/discharging power)[29].

They are not mutually exclusive, but rather each has its own applicable scenarios, and can sometimes be used in combination.For instance, operators may employ weighted averaging during routine operations based on the feasibility of ε-constrained trial projects prior to formal implementation, tailored to varying commercial requirements and models. For large-scale deployment or long-term strategic planning, Pareto frontier analysis may serve as a reference. To address operational uncertainties, reinforcement learning may be utilised to drive real-time adjustments, Table 5

Table 5. Comparative Framework: Balancing Grid-Side Interests with Consumer-Side Interests

Ways	Core concept	Advantages	Disadvantages	Applicable scenarios
weighted sum[25]	Multi-objective transfer target solution	The model is simple.	The weighting coefficients are overly subjective.	Non-open commercial scenarios (such as fleets, transport teams).
ε-constraint method[26]	Select one primary objective, with the others	Capable of identifying a wide	Improperly set constraints may render the problem	Single-objective, clearly defined scenarios;

	becoming constraints.	range of Pareto optimal solutions	unsolvable.	Feasibility analysis prior to project investment
Pareto optimal frontier[27]	Generate a large number of potential optimal solutions for third parties to select from.	Authentic, comprehensive, and objective decision-making data	High computational intensity.	Policy formulation; Technology assessment
Master-slave game[28]	Guide user behaviour through market mechanisms (electricity prices).	Suitable for market mechanisms	Model complexity	Designing a business model for the demand response market
RL[29]	Learning errors through the environment	Highly adaptable, capable of managing dynamic risks and uncertainties,	The design of reward functions presents significant challenges, with performance being heavily dependent upon the design of reward functions.	Real-time microgrid control; Decentralised commercial collaboration; User-specific business models.

6. Summary

This paper conducts an in-depth investigation into grid-side and user-side demands within the field of V2G charging strategies, thereby addressing a research gap in existing literature that has not been approached from this perspective.Furthermore, the application and research findings of deep learning within V2G charging strategies are explored from the perspective of deep learning.This paper explores five methodological approaches to balancing grid-side and consumer-side interests, clarifying the applicable scenarios and scope of each method to provide insights for decision-makers in practical engineering contexts.

Despite demonstrating significant application potential and considerable progress in related research, V2G technology still faces a series of formidable challenges in its journey towards large-scale commercial deployment. These encompass technical, economic, market, and user acceptance hurdles. In response, this paper proposes the following recommendations for future development:

From the user perspective: Intelligent charging and discharging strategies for battery health over its entire lifecycle (State of Health, SoH): Algorithms for precise, online estimation of battery health status (SOH) and remaining useful life (RUL), deeply integrated into V2G optimised scheduling. Exploring how to dynamically adjust depth of discharge, charging power, and service participation types to identify an optimal equilibrium point that maximises the sum of ‘current revenue’ and ‘future residual economic value of the battery’ while ensuring user mobility requirements are met.

From the grid perspective: Collaborative optimisation of V2G clusters with high-proportion renewable energy: Future power systems will be driven by 100% renewable energy. Establishing a ‘renewable energy-electricity-transport’ coupled system enables V2G clusters to synergistically optimise multiple resources including wind, solar, hydro, and storage.

From the perspective of mutual benefit: V2G scheduling strategies for carbon trading. This involves incorporating carbon emission costs/benefits into V2G scheduling models to investigate how optimised V2G scheduling can assist users and aggregators in achieving dual benefits within both electricity and carbon markets, thereby contributing to society's overarching low-carbon objectives.

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