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AI-Driven Vehicle-to-Grid (V2G) in Smart Grids: A Theoretical Study

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Abstract. With the rapid development of renewable energy such as solar and wind power, the matching of supply and demand in the power system faces greater challenges. Electric vehicles (EVs) provide distributed energy storage services such as peak and valley regulation and frequency regulation to the power grid through a two-way vehicle-to-grid (V2G) system, which improves the flexibility and stability of the power grid. This paper proposes a unified framework based on artificial intelligence (AI) that integrates load forecasting, battery health-aware reinforcement learning scheduling, dynamic pricing, and multi-agent collaborative control, aiming to achieve efficient V2G operation in large-scale smart grids. By reviewing relevant literature, this paper analyzes the potential of the framework in improving grid stability, reducing operating costs, promoting the use of renewable energy, and extending battery life, and explores key challenges such as battery degradation, network security, system interoperability, and regulatory complexity. The study points out that the current model is mainly based on theory and simulation, lacking the support of large-scale empirical data. In the future, it is necessary to combine actual operation data and pilot projects to improve battery aging modeling and user behavior differentiation analysis to promote the practical application and optimization of the framework.

Keywords: Deep Learning, Electric Vehicle (EV), Battery Health Management, Demand Response Optimization.

1. Introduction

The accelerating trend toward renewable energy sources includes solar and wind, which significantly increases the variability in power systems and is problematic for matching supply with demand. EVs offer a partial solution too - EVs can serve as distributed energy storage by implementing bidirectional Vehicle-to-Grid (V2G) systems such as peak shaving, frequency regulation, and valley filling instead of using an EV solely for transportation. Integration of EVs replaces Evs transport with grid services for a multi-hour parked state without compromising user convenience. Smart grids serve to implement ICT thoroughly, have automated control improvements, and decentralized coordination of resources - a compatible co-origin to respond to changing electricity levels allowing EPSs to be able to provide appropriate schedule for user needs. ICT typically implements communication standards, such as ISO 15118 to govern secure and trusted

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data for bidirectional power flow, or ISO 15118-20 to communicate the dynamic price with the user when charging [1]. AI replaced the need for solver analysis improvements in quantifying control problems in the energy grid. Using AI in complicated systems such as the energy grid adds complexity, deep learning (DL) and reinforcement learning (RL) improvements in accuracy exhibited anomaly detection, forecasting, and even scheduling in energy systems [2]. More recent studies suggested promising results in employing RL to V2G scheduling successfully, and the simulations produced other optimal outcomes for load variance and cash flow [3,4]. In summary, few works proposed a coherent structure that integrated forecasting, scheduling, control, and pricing parameters relative to battery health and cybersecurity. This study proposes to fill this gap in V2G engineering literature.

This study proposes a broad theoretical framework to build and operate V2G systems at scale in smart grids using artificial intelligence (AI) techniques including machine learning (ML) and reinforcement learning (RL). The framework covers demand forecasting, scheduling with battery health considerations, energy pricing, and multi-agent control methods. The paper reviews the analysis results of the existing literature to highlight performance improvements, long-term sustainability, technical challenges, and policy considerations.

2. AI-driven V2G system architecture and modeling

The system concept is to build an intelligent vehicle-to-grid (V2G) system based on artificial intelligence. It is mainly composed of electric vehicle fleets, aggregators, distribution networks and AI intelligent agents, aiming to achieve centralized coordination of charging/discharging scheduling, load forecasting and dynamic pricing. The system adopts a multi-agent control architecture (see Figure 1), modeling electric vehicle users, aggregators and grid operators as intelligent agents in a cyber-physical environment. Electric vehicles have characteristics such as battery capacity, state of charge (SOC) range and departure deadline, and all charging stations are under the management of the aggregator. The aggregator receives real-time electricity prices, load forecasts and frequency signals from the power grid and transmits this information to the AI agent. The AI agent makes optimization decisions based on this, assists in managing the charging and discharging scheduling of vehicles, and introduces restriction mechanisms in the regulation process to extend battery life.

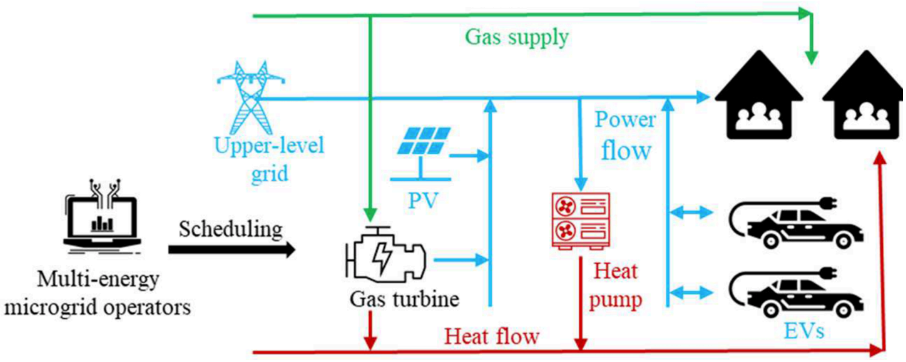

Figure 1. V2G multi-agent control architecture coordinating EVs, aggregators, and grid operators

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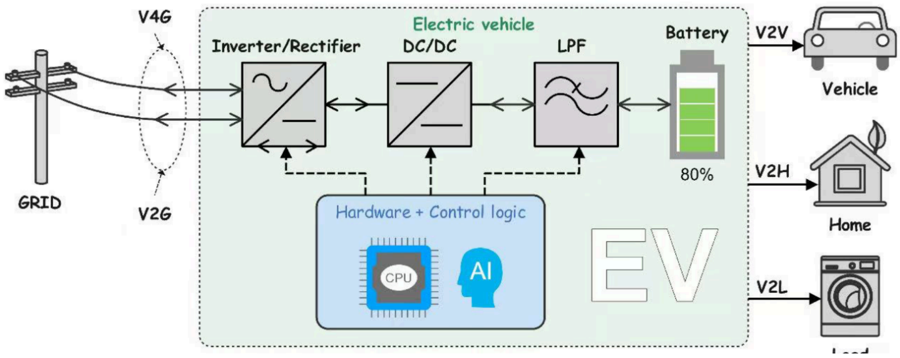

Figure 2. System diagram of AI-driven forecasting and control loops among EV batteries, smart chargers, grid, and edge-AI agents

The AI agents will also be able to communicate dynamically, and securely with one another (Figure 2). Each agent will be specified in the RL formulation, the agent's state (e.g., SOC value, remaining time to depart, anticipated load, price), each agent's possible actions (charging, discharging, or idle), and the reward function for each agent's action. The reward function will represent multiple tasks: savings, load levelling, battery degradation, and keeping the grid stable. The forecasting components will use Deep Learning (DL) algorithms, specifically those using deep neural networks (like Long Short-Term Memory (LSTM) or convolutional neural networks (CNN) to model short-term demand, renewable generated energy, and price movements in order for the agent(s) to make informed decisions. Many papers have shown that DL can represent an improvement in forecasting accuracy against traditional methods [5].

3. AI algorithm integration and scheduling

3.1. Predictive modeling

Accurately forecasting load demand, renewable energy output, and dynamic electricity price trajectories is the cornerstone of any smart energy dispatch framework. High-precision forecasts are critical not only for reducing operational uncertainty but also for improving overall system efficiency and reliability. Martínez-Torres et al. demonstrated that long short-term memory (LSTM) neural networks outperform traditional feed-forward architectures, reducing forecast error rates by 15% to 25%, especially in scenarios with large temporal variations [6]. Based on this insight, the framework integrates multi-source data acquisition mechanisms, including smart meters for real-time energy consumption monitoring, weather APIs for predicting solar and wind energy availability, and historical charging behavior data of electric vehicles (EVs). These diverse data streams form the basis for continuous reinforcement learning (RL) model training and deep reinforcement learning (DRL)-based dispatch strategy development. By incorporating temporal patterns, external factors (such as weather), and user-specific behavioral trends, the system improves its ability to predict demand response events and dynamically optimize charging/discharging decisions.

3.2. Reinforcement learning for V2G scheduling

Sequential decision-making under uncertainty is at the heart of DRL. Notably, DRL techniques, such as Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO), and

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multi-agent RL (MARL) such as Zhang, Chen, and Li's [3] multi-stakeholder hierarchical DRL implementation, reduce the variance of load and enable conservation of State of Charge (SOC)/State of Health (SOH), compared to standard methods of control. Beyond operational efficiency, their reported metrics indicated that their simulations depicted a 97% variance reduction of load and 22% increased use of renewable energy. Recent advancements of safety-aware DLR also employing constrained-based Markov Decision Processes help to further address concerns of battery degradation by including SOH constraints during training and ensuring real-time compliance when making decisions, since obviously battery cells degrade. The experiment results indicate an increase in average SOH of only 3% per year, but it also entails a 10% reduction in Lifecycle Replacement Cost for customers when using an electric vehicle (EV). After all, without compliance for safe electric vehicle behaviors and expectations, EV customers will not be willing to accept the increased risk.

3.3. Dynamic pricing with AI agents

We consider the features of real-time pricing as the model includes them within the agent strategy when forecasting total or scheduled buy/sell tariffs based on grid peak load level usage effects. Part of Escoto et al.'s proposal considered the introduction of a dynamic pricing signal to the speed-sensitive relay in comparison to the responses of the physical controller) or aggregator of the EV behavior, in response to predictable grid behaviour, reflected in the price signal transparently. It also highlighted price- based demand shifting methods could support reductions in peak load by an average 10%, simultaneously improving GHG and social- economic performance outcomes of stakeholders [6,7].

4. Coordination architecture and control strategies

Centralized control, enabled by aggregators, produces globally optimal decisions while scalability and privacy restrictions apply. Alternatively, federated multi-agent structures afford better resilience and privacy but require more sophisticated coordination protocols. For example, in the application environment of Thailand's electric vehicle (EV) charging infrastructure, the multi-agent reinforcement learning (MARL) protocol showed significant advantages over traditional benchmark strategies, not only increasing the occupancy rate of charging stations by about 12%, but also effectively shortening the average waiting time of users, significantly improving the overall service efficiency and user experience. In addition, the edge computing nodes in the smart grid are responsible for processing local real-time data streams, such as key parameters such as frequency, voltage, and temperature, to ensure that the system can achieve rapid response and local decision-making with a response delay of milliseconds or even lower, improving the dynamic adjustment capability and stability of the system. In terms of communication security, the adoption of the international standard ISO 15118-PKI framework and the construction of an AI-based intrusion detection system have become the key to ensuring secure communication between electric vehicles and charging infrastructure. Sharma et al [8]. introduced an anomaly detection model to effectively distinguish between normal and abnormal behaviors, achieving a network security incident detection rate of up to 98.9%, showing the strong potential of AI technology in network security protection. Resilience is not only reflected in the effectiveness of system control, but also emphasizes being ready to respond to various emergencies at any time to ensure the continuous and reliable operation of the system [9]. This is of great significance for ensuring the stability and security of smart grids and electric vehicle charging systems.

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5. Discussion

The effectiveness and feasibility of AI-driven V2G systems have been established through various theoretical simulations and case studies, providing good evidence for their incorporation into future smart grids. The synthesis of results across the literature provides evidence of substantial operational and environmental advantages. For example, systems that employed reinforcement learning (RL) and deep learning methods achieved a reduction of 76% to daily EV charging costs through optimal scheduling and dynamic price forecasting [9]. Load variance at the grid level was reduced by as much as 97%, improving power quality, frequency stability, and mitigating stress on transformers and substations. The capacity to predict and flatten demand curves is especially important in grids with a substantial penetration of intermittent renewable generation (i.e. wind and solar). Additionally, the emissions reductions achieved in the literature ranged from 18% to 22% with the more significant reductions contributing to EV charging and discharging being in line with periods of surplus renewable generation [4]. The impact on battery health in terms of state of health was an improvement of 10% to 15% in SOH life expectancy through intelligent scheduling strategies that included State of Health (SOH) constraints, effectively extending the economic life of EV batteries and delaying replacement costs in the long run. These performance metrics provide evidence of the technical feasibility and real benefits of implementing AI-enabled V2G frameworks if developed using the appropriate hardware and communication standards with collaboration from stakeholders.

Despite these promising outcomes, several critical challenges and limitations remain. First, battery degradation continues to be a primary concern. The V2G operational process includes frequent charging and discharging cycles leading to capacity fade which may discourage EV owners from being participants. For now, AI models must develop a reward function that incorporates SOH-aware constraints that prolong battery health while fulfilling their commitment to the grid [4]. Second, due to the level of connections associated, there is an increased cybersecurity risk within V2G systems. The many interactions between EVs, aggregators, and the grid, with in-the-moment connectivity for thousands of units, increases opportunities for attacks on all parties. While AI-based anomaly detection algorithms have been quite effective so far - e.g., garnered 98% + detection ability [8] - these will not eliminate the risk of zero-day attacks or adversarial attacks. This means specification-based encryption, intrusion detection systems (IDS), and the ability to propagate security patches will remain critical. This said, the scope of V2G will require a coordinated policy and regulatory effort to mitigate the challenges of V2G and fully leverage the opportunities of AI-enhanced V2G systems. Moreover, through e.g., tax incentives, grants for V2G-compatible infrastructure development and smart chargers and bidirectional inverters, governments can play a uniquely impactful role. Compliance with communication protocols such as ISO 15118 would also contribute to improved interoperability throughout the ecosystem. Likewise, developing a licensing regime in which aggregators were legally recognized as intermediaries between EV owners and grid operators would engender a new role that both enhanced oversight/responsibility, and reflected the smart and modernized relationship between these entities. Tariff designs that are dynamic are continuously adapted based on modelling from AI forecasting exercises, meaning more predictable and equitable pricing mechanisms can be developed without sacrificing grid reliability.

Pilot programs in places like the United Kingdom and California have demonstrated the feasibility of V2G integration at scale and the lessons learned can support more significant deployments. These pilot initiatives should ramped up through public-private partnerships to stimulate commercial readiness. On the global stage, authorities such as the Institute of Electrical and Electronics Engineers (IEEE) and the International Electrotechnical Commission (IEC) would need to come together to harmonize jurisdictional standards, notably in cybersecurity certification, transparency in AI algorithms, and data protection across standards. Only by coming together will communities and the coordinated effort of AI-based V2G systems move from the promise of their theoretical potential, to future intelligent sustainable energy systems.

6. Conclusion

In conclusion, this paper creates a unified AI-enabled framework for V2G integration in smart grids. It integrates predictive modelling, battery-aware RL scheduling, dynamic pricing, and multi-agent coordination across an edge-enabled architecture to provide measurable improvements to grid stability, costs, renewable penetration and battery health. Within image schematics, EVs were shown to have coordinated layered relationships with aggregators and distribution grid. While the benefits are clear, there are still significant challenges still, including battery degradation, cybersecurity, interoperability, as well as regulatory complexity. However, this research has certain limitations. Due to the theoretical and simulation-based nature of the study, it lacks extensive empirical validation with real-world V2G operational data. The effectiveness and scalability of the proposed framework under diverse grid conditions and user behaviors remain to be fully tested. For future research, incorporating large-scale real-world datasets and pilot project results will be essential to validate and refine the AI algorithms and system design. More comprehensive modeling of battery aging processes and user heterogeneity can improve scheduling accuracy and user acceptance.

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