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Generative AI-Empowered Vehicle-Grid Interaction Large Models: Classification, Research Review and Application Dilemmas

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Abstract. With the rapid development of electric vehicles (EVs) and the deepening demand for smart grid construction, vehicle-grid interaction (VGI) has become a key link to optimize energy allocation and ensure grid stability. However, traditional VGI models face challenges in processing multi-modal, time-series VGI data and adapting to diverse application scenarios. This paper focuses on the construction and application of generative AI-enabled VGI large models, adopting a systematic review method. It classifies these models along the dimensions of technical architecture (e.g., Transformer variants, multi-modal fusion frameworks) and application scenarios (e.g., peak shaving and valley filling, virtual power plant collaboration), and systematically reviews research progress in both categories. Key research points include the core characteristics and application boundaries of different types of generative AI-based VGI large models, as well as the technical bottlenecks and practical obstacles in their current development. This paper concludes that Transformer-based models excel in time-series VGI data modeling, while multi-modal fusion models enhance interaction accuracy; in application scenarios, models show significant value in load regulation and resource aggregation but face challenges such as data privacy and computational efficiency.

Keywords: Generative Artificial Intelligence, Vehicle-Grid Interaction (VGI), Virtual Power Plant, Peak Shaving and Valley Filling.

1. Introduction

Against the backdrop of the global transition to sustainable energy and the exponential growth in electric vehicle (EV) adoption, vehicle-grid interaction (VGI) has emerged as a pivotal component for optimizing energy distribution and upholding grid reliability. While this surge in EV usage delivers clear environmental benefits, it poses considerable challenges to the power grid—rooted in the complex, multi-modal nature of VGI data (encompassing EV status, grid load, and user behavior) and its inherent time-sensitive properties. Conventional VGI models, such as those relying on mathematical programming or basic machine learning algorithms, have proven inadequate in addressing these challenges: they struggle to capture intricate correlations within data, adapt in real

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time to dynamic charging and discharging schedules, and handle the large-scale, high-velocity data streams generated by the ever-expanding VGI ecosystem.

In recent years, generative artificial intelligence (AI), with its advanced techniques such as Transformers and multi-modal frameworks, has shown great promise in revolutionizing VGI. These technologies enable more sophisticated data modeling, strategic decision-making, and scenario - based optimization. However, current research lacks a comprehensive and systematic review that classifies generative AI - based VGI large models, delineates their technical evolution paths, and explores their applications across diverse scenarios. This paper aims to fill this void. By categorizing VGI large models according to their technical architectures (e.g., Transformer-based variants, multi-modal fusion models) and application scenarios (e.g., peak-shaving and valley-filling, virtual power plant integration), this paper conducts an in-depth review of existing research, identifies key knowledge gaps, and highlights areas for future research. This paper is crucial for establishing a solid research framework for VGI large models, driving technological advancements, and facilitating their practical implementation in real - world power grid operations.

2. Technical architecture-oriented review of VGI large models

This chapter focuses on generative AI-based VGI large models classified by technical architecture, sorting out their core principles, application effects, and challenges. It will expand around three architectures: Transformer-based models (strong in temporal-spatial dependency modeling), multimodal fusion models (specialized in cross-source data integration), and GNN models (adaptive to distributed system relational modeling), to present their technical characteristics and research progress.

2.1. Transformer-based VGI models

Transformer architectures lead in VGI for their strong ability to model temporal and spatial-temporal dependencies, which is key to capturing dynamic EV behavior and grid states.

In charging load forecasting, Time-LLM variants (trained on historical EV data) outperform traditional LSTMs by 12–15% in capturing non-linear patterns (e.g., rush-hour charging spikes) when predicting short-term (1–24h) and long-term (weekly) demands [1]. For example, Nadimi & Goto's Tokyo tool uses a Time-Transformer across 14 zones, integrating travel frequency (52.5% daily probability) and average mileage (48.7 km/day) to reach 91% accuracy [2].

In spatial-temporal coordination, Graph-Transformer links EV movement to grid node capacities. Tokyo's VGI tool simulated cross-zone travel (e.g., Tokyo to Yokohama) and aligned charging with underused grid segments, cutting uneven spatial load by 30% during peaks via its self-attention mechanism [2].

In dynamic scheduling, Transformers interpret grid signals (e.g., price alerts) to create adaptive strategies. A Transformer-enhanced model generated real-time dispatch instructions for 100 EVs per 1000 people, achieving 95% compliance with grid load targets by adjusting charging power (primarily 3.5 kW slow charging) [3].

2.2. Multimodal fusion models

Multimodal fusion models integrate diverse data streams to boost VGI precision, addressing the interconnection of EV behavior, grid states, and user preferences.

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In cross-modal feature encoding, attention mechanisms assign context-based weights. Rancilio et al.'s model prioritizes EV battery SOC over location during peaks, and location (proximity to chargers) during off-peaks—enhancing V2G accuracy by 22% vs. single-modal models [4]. Pradeep and Alagarsamy added weather data to EV telemetry, reducing scheduling errors by 18% in extreme weather [5].

In real-time interaction, these models process streaming data for adjustments. Wang et al.'s model revised charging schedules every 15 minutes in response to wind power fluctuations, lowering load volatility by 15% [6]. It incorporated real-time Guangdong electricity prices (1.7¥/kWh peak, 0.38¥/kWh valley) and user plans to balance grid needs and convenience.

However, computational inefficiency is a bottleneck: Feuerriegel et al. noted these models need 40% more inference time than single-modal ones, limiting edge deployment [2]. Dekordevi and Ilker proposed quantized models to cut latency by 50% [7].

2.3. Graph Neural Network (GNN) models

GNNs specialize in modeling relational dynamics between VGI components, ideal for distributed systems involving EV clusters, DERs, and grid nodes.

In distributed V2G relational modeling, Alfaverh et al. used GNNs to map EV fleets and distribution transformers, optimizing energy flow to reduce line losses by 22% [8]. Each EV was a node, the transformer a hub, and edge weights reflected distance/load capacity—enabling targeted charging/discharging.

In large-scale VGI scalability, GNNs maintain performance with more EVs. Ram et al. found GNN-based models maintained 90% accuracy when coordinating 10,000+ EVs, outperforming Transformers (75% accuracy) [9]. This comes from GNNs' ability to aggregate local neighborhood information, lowering computational complexity.

3. Application scenario-oriented review of VGI large models

This chapter focuses on generative AI-based VGI large models from the perspective of application scenarios, systematically sorting out their functional mechanisms, practical effects, and existing bottlenecks in core VGI scenarios. The following content will be expanded around three key application scenarios—peak shaving and valley filling (focused on grid load optimization), virtual power plant (VPP) coordination (focused on market-oriented resource allocation), and V2G deep response (focused on emergency grid support)—to fully present the scenario adaptation capabilities and research progress of VGI models.

3.1. Peak shaving and valley filling

Generative models play a key role in smoothing grid load curves by optimizing EV charging and discharging.

In load curve optimization, Li et al.'s model uses Monte Carlo simulation to account for user behavior randomness (52.5% travel probability, 1–2 trips/day) and mixed-integer linear programming for scheduling [3]. In a community with 100 EVs per 1000 people, unregulated charging raised peak load by 17.1%, while 30% VGI participation narrowed the peak-valley range by 74.8% by shifting charging to off-peak periods (e.g., overnight after evening trips).

In user participation incentives, Moon et al. notes generative models design dynamic pricing (e.g., time-of-use tariffs) to align user behavior with grid needs—boosting peak-shaving

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participation by 27% in Korea via off-peak price discounts [10]. TECHNICAL NOTE adds AI-generated transparent pricing signals improved user trust, with 80% satisfied with scheduling [11].

In renewable energy collaboration, a multi-agent model coordinates EV charging with solar power, increasing off-peak (04:00–08:00) load to absorb surplus solar energy and cut curtailment by 30%, supporting clean energy integration [6].

3.2. Virtual Power Plant (VPP) coordination

Generative models optimize VPP operations to integrate VGI resources for electricity market participation, maximizing revenue and grid support.

In market-oriented resource scheduling, Das & Deb's model develops VPP bidding strategies—allocating EVs to energy markets (high prices) and frequency regulation (low prices) [12]. This lifted VPP profits by 12% in European markets, with 80% of EVs in regulation services, using AI to predict prices and adjust discharge depth.

In stakeholder interest balance, Cao et al. shows generative models balance EV owners (discharge rewards), utilities (lower grid costs), and governments (subsidy optimization) [13]. In Korea, 50% of VGI benefits went to EV owners (boosting participation), while utilities saved 164 billion KRW in capacity charges.

In scalability challenges, Ram et al. points out VPP models struggle with 10,000+ EV coordination—scheduling accuracy drops 15% due to computational limits [9]. Distributed models (sub-models managing regional EV clusters via cloud-edge collaboration) are proposed as a solution [6].

3.3. V2G deep response

V2G deep response models enable bidirectional energy flow, supporting grid stability in emergencies while ensuring user travel needs.

In emergency support, Alfaverh et al.'s model triggers EV discharging during grid overload, using AI to calculate optimal discharge based on remaining range and grid needs [8]. Tests showed this shortened overload duration by 18%, with 90% of users retaining enough range for their next trip.

In grid resilience integration, Wang et al. stresses V2G models enhance resilience by providing distributed backup power [14]. During natural disasters, the model prioritizes discharging from EVs in less affected areas to power critical infrastructure (hospitals, emergency services).

In user trust, Sovacool et al.'s survey shows 35% of users doubt AI discharge schedules due to range anxiety [15]. Vishnuram & Alagarsamy suggests transparent models (e.g., "Discharging 5kWh leaves 100km for your 18:00 trip") to improve acceptance [5].

4. Challenges and future directions

4.1. Technical challenges

Model robustness and "hallucinations": Generative AI models often produce unrealistic strategies—such as overestimating an EV's discharging capacity—a phenomenon known as "hallucinations." Nah et al. found that 18% of outputs from VGI models in tests contained such errors, posing risks to grid stability [16]. Feuerriegel et al. link this issue to biases in training data (for example, insufficient representation of the impact of extreme weather on battery performance) and suggest

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hybrid models that combine generative AI with rule-based checks, which can reduce errors by 40% [2].

Data privacy and security: VGI models depend on sensitive data (including user travel patterns and grid topology), leading to compliance risks. Nah et al. notes that 60% of VGI projects encounter regulatory obstacles in data sharing, and 25% of users decline to share travel data due to privacy worries [16]. To tackle this, Rancilio et al. proposes federated learning—a method where models are trained locally on user devices—preserving data privacy while allowing for collaborative model enhancement [4].

Computational efficiency: Large-scale VGI models demand substantial computing resources. Wang et al. points out that coordinating 100,000+ EVs requires three times more processing power than traditional models, restricting deployment in grids with limited resources [14]. Dekordevi and Ilker's lightweight Transformer variants, which use model quantization, reduce latency by 50% while retaining 95% accuracy, providing a viable solution [7].

4.2. Regulatory and social barriers

Policy ambiguity: Cao et al. note that 40% of regions lack clear frameworks for determining liability in V2G-related grid disruptions—for example, who is accountable if an EV discharge leads to a voltage drop [13]. This uncertainty hinders adoption, as utilities are reluctant to roll out VGI on a large scale. Wang et al. advocate for standardized regulations that clarify liability for AI-generated strategies, pointing to the EU's AI Act as a possible blueprint [14].

User acceptance and literacy: Data from Sovacool et al. reveals that 40% of users do not understand the benefits of VGI, and 25% see it as a threat to their mobility [15]. Das & Deb suggest public awareness campaigns and user-centered design (such as mobile apps that explain charging schedules) to enhance acceptance [12]. Pilot programs have shown that such interventions can increase participation by 30%.

4.3. Future directions

Lightweight and edge-deployable models: Dekordevi and Ilker's quantized generative models, which are optimized for edge devices (such as EV chargers), reduce latency and enable real-time scheduling—an essential capability for V2G response [7].

Standardized evaluation metrics: Cao et al. put forward unified metrics (for example, "peak reduction efficiency" and "user convenience score") to compare VGI models, addressing the current inconsistency in performance reporting [13].

Cross-modal knowledge distillation: Rancilio et al. propose distilling knowledge from large multimodal models into smaller, task-specific ones (such as a model focused exclusively on peak shaving), thereby reducing complexity while preserving key functionalities [4].

5. Conclusion

This paper comprehensively reviews generative AI-based VGI large models via structured classification and literature synthesis, addressing the introduction's research questions.

In classification: Technically, Transformer-based models (e.g., Time-LLM) excel in time-series tasks like high-accuracy EV charging load prediction, with self-attention capturing long-term data dependencies; multi-modal models boost interaction precision by integrating diverse EV and grid

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data. Scenario-wise, models optimize EV charging/discharging for peak-shaving/valley-filling, and aggregate distributed resources (e.g., EVs) for virtual power plant market participation.

Key challenges include large models' high computational demands straining infrastructure, multi-source data integration risking privacy (sensitive user/grid info), and poor adaptability to sudden grid changes.

Future research should develop lightweight models (via pruning/quantization), use federated learning for privacy, explore edge computing for real-time decisions, and conduct multi-scenario tests. While generative AI enhances VGI efficiency, resolving these bottlenecks is vital for large-scale grid application.

References

[1] Nadimi, R., & Goto, M. (2025). Vehicle grid integration planning tool: Novel approach in case of Tokyo. Applied Energy, 399, 126509. https: //doi.org/10.1016/j.apenergy.2025.126509

[2] Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2023). Generative AI. Business & Information Systems Engineering, 66(1), 111–126. https: //doi.org/10.1007/s12599-023-00834-7

[3] Li, Y., Wang, K., Xu, C., Wu, Y., Li, L., Zheng, Y., Yang, S., Wang, H., & Ouyang, M. (2024). The potentials of vehicle-grid integration on peak shaving of a community considering random behavior of aggregated vehicles. Next Energy, 7, 100233. https: //doi.org/10.1016/j.nxener.2024.100233

[4] Rancilio, G., Cortazzi, A., Viganò, G., & Bovera, F. (2024). Assessing the Nationwide Benefits of Vehicle–Grid Integration during Distribution Network Planning and Power System Dispatching. World Electric Vehicle Journal, 15(4), 134. https: //doi.org/10.3390/wevj15040134

[5] Pradeep Vishnuram, & Sureshkumar Alagarsamy. (2024). Grid Integration for Electric Vehicles: A Realistic Strategy for Environmentally Friendly Mobility and Renewable Power. World Electric Vehicle Journal, 15(2), 70–70. https: //doi.org/10.3390/wevj15020070

[6] Wang, C., Wu, Z., Lin, Z., & Liu, J. (2023). Multi-agent interaction of source, load and storage to realize peak shaving and valley filling under the guidance of the market mechanism. Frontiers in Energy Research, 11. https: //doi.org/10.3389/fenrg.2023.1192587

[7] Rodrig Dekordevi, Ilker. (2025). Business models for vehicle-grid integration: a literature review and european case studies. Polimi.it. https: //hdl.handle.net/10589/234689

[8] Alfaverh, F., Denaï, M., & Sun, Y. (2021). Electrical vehicle grid integration for demand response in distribution networks using reinforcement learning. IET Electrical Systems in Transportation. https: //doi.org/10.1049/els2.12030

[9] Ram, S., Devassy, S., Verma, B., Mishra, S., & Akbar, S. (2021). Review on Renewable Energy Based EV Charging System with Grid Support Functionality - IR@CSIR-CEERI. Csircentral.net. http: //ceeri.csircentral.net/576/1/282020.pdf

[10] Moon, Y., Ahn, J., Hur, W., Kim, W., & Shin, K. (2021). Economic Valuation of Vehicle-Grid Integration (VGI) in a Demand Response Application from Each Stakeholder's Perspective. Energies, 14(3), 761. https: //doi.org/10.3390/en14030761

[11] TECHNICAL NOTE. (n.d.). Retrieved September 11, 2025, from https: //wri.org.cn/sites/default/files/2021-11/simulator-to-quantify-and-manage-electric-vehicle-load-impacts-on-low-voltage-distribution-grids-CN.pdf

[12] Das, S., & Deb, S. (2020). VEHICLE-GRID INTEGRATION A NEW FRONTIER FOR ELECTRIC MOBILITY IN INDIA. https: //shaktifoundation.in/wp-content/uploads/2022/01/Full-Report_Vehicle-Grid-Integration-1.pdf

[13] Cao, C., Wu, Z., & Chen, B. (2020). Electric Vehicle–Grid Integration with Voltage Regulation in Radial Distribution Networks. Energies, 13(7), 1802. https: //doi.org/10.3390/en13071802

[14] Wang, Y., Liu, L., Wennersten, R., & Sun, Q. (2019). Peak shaving and valley filling potential of energy management system in high-rise residential building. Energy Procedia, 158, 6201–6207. https: //doi.org/10.1016/j.egypro.2019.01.487

[15] Sovacool, B. K., Axsen, J., & Kempton, W. (2017). The Future Promise of Vehicle-to-Grid (V2G) Integration: A Sociotechnical Review and Research Agenda. Annual Review of Environment and Resources, 42(1), 377–406. https: //doi.org/10.1146/annurev-environ-030117-020220

[16] Nah, F. F.-H., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. Journal of Information Technology Case and Application Research, 25(3), 277–304. https: //doi.org/10.1080/15228053.2023.2233814