

# Collaborative Scheduling Model for the Interaction Between Electric Vehicles and Power Grid in the Internet of Vehicles Environment

Yuhan Guo

Cambridge International Exam Center in Shanghai Experimental School, Shanghai, China

3180197117@qq.com

**Abstract.** The ownership of electric vehicles (EVs) is rising rapidly. Meanwhile, the development of Internet of Vehicles (IoV) technology has established a platform for data interaction and collaborative control between EVs and the power grid. After comprehensively analyzing relevant domestic and international research results, this paper proposes an interaction and joint operation scheduling scheme between EVs and the power grid based on the IoV environment. This scheme takes user satisfaction, power grid operation stability, and system economy as multi-objective optimization directions, and establishes a mathematical model composed of constraints such as State of Charge (SOC) constraints, charging and discharging power constraints, and power grid balance constraints, which is solved by combining distributed optimization and heuristic algorithms. Experimental results show that it can effectively smooth the power grid load curve, improve the user demand response rate, and significantly reduce the system operation cost, thus proving that the IoV has practical value and development potential in Vehicle-to-Grid (V2G) interaction.

**Keywords:** Electric Vehicle (EV), Internet of Vehicles (IoV), Vehicle-to-Grid (V2G), collaborative scheduling, optimization model.

## 1. Introduction

With the continuous development of new energy technologies and intelligent transportation, electric vehicles (EVs) have become an important part of transportation. The concentrated surge in charging demand causes drastic fluctuations in grid load, affecting the stability of the power system. Moreover, EVs, with their energy storage capacity, can interact with the power grid (Vehicle-to-Grid (V2G) interaction), to achieve goals such as peak shaving and valley filling as well as assisting in frequency regulation, thereby providing flexible scheduling resources for the grid[1]. The development of the Internet of Vehicles (IoV) has laid the foundation for the in-depth integration of EVs and power grids. Relying on the IoV, EVs are capable of achieving real-time information exchange, enabling the tracking of vehicle location, charging status and users' travel demands, which provides reliable data support for the power grid. Therefore, establishing a collaborative scheduling model for EV-grid interaction in the IoV environment has become a key research direction in smart grids and intelligent transportation. The objective of this paper is to design a collaborative scheduling model for EV-grid interaction under the IoV environment. By leveraging the coordination of bidirectional information flow and energy flow, the model aims to balance users' charging needs, mitigate impacts on grid operation, improve energy utilization efficiency, and enhance the safe operation level of the power grid.

## 2. Literature Review

### 2.1 Research Status of EV-Grid Interaction

Researches have generally followed an evolutionary path, from disordered charging to ordered charging, and further to bidirectional EV-grid interaction (V2G)/Vehicle-to-Home(V2H)/Vehicle-to-Load (V2L). Early, time-of-use electricity pricing was mainly used to guide load shifting [1]. Later, aggregators were employed for unified coordination, and the objective function evolved from peak shaving and valley filling to multi-objective optimization, including minimizing comprehensive costs,

maximizing the absorption of abandoned wind and solar energy, reducing carbon emissions, and improving user satisfaction. Methodologically, classical models primarily adopt mixed-integer linear/nonlinear programming, robust optimization, and stochastic optimization for solution. In recent years, there has been a growing focus on research related to battery life degradation costs, distribution network line and transformer constraints [2,3]. Furthermore, the use of data-driven approaches and reinforcement learning to address large-scale and highly uncertain scenarios has become increasingly common. Overall, research has shifted from daily static optimization in the past to the integration of real-time closed-loop control and market-oriented interaction at present.

## **2.2 Application of IoV Technology in Energy Scheduling**

The IoV connects vehicles, charging facilities, roads, and power grids through 5G/C-V2X, edge-cloud collaboration, and high-precision positioning, providing a three-dimensional "SOC-Time-Space-Behavior" data foundation for scheduling. Vehicles and charging piles transmit real-time data, such as SOC, location, travel plans, and charging preferences, to the platform via secure communication. The platform formulates rolling load plans through spatiotemporal aggregation analysis and short-term forecasting. Moreover, edge computing gateways at the station/park level perform local optimization and fault isolation, reducing latency and alleviating the pressure of data upload. Combined with renewable energy and energy storage technologies, the IoV enables collaborative integration of EVs, charging piles, stations, grids, and power sources [4]. It leverages digital twins to complete state estimation and sensitivity analysis tasks, and mobilizes flexible market clearing through dynamic electricity pricing, matching transactions, or trading contracts.

## **3. Construction and Methodology of the Collaborative Scheduling Model**

### **3.1 Model Objectives**

The primary goal of establishing a collaborative scheduling model for EV-grid interaction in the IoV environment is to achieve coordination of multiple parts' benefits [1]. From the users' perspective, the core function of EVs is to meet the travel needs of users so the model should ensure that users obtain sufficient battery power within the specified time, avoiding "range anxiety" caused by participating in scheduling. As for the power grid operation, the EV fleet serves as both controllable load and mobile energy storage units. When integrated in an orderly manner, they are able to provide peak shaving and valley filling for the grid, supply reserve capacity, and assist in voltage and frequency regulation. From the perspective of the whole society, the in-depth interaction between EVs and the grid is conducive to the absorption of renewable energy, improving the utilization rate of clean energy and reducing system carbon emissions, which aligns with the dual carbon goals [4]. Reasonable scheduling can achieve the collaborative optimization of energy-transportation-environment. The model objectives are divided into three levels, which are maximizing user satisfaction, ensuring grid stability, and minimizing system operation costs. Weight coefficients are introduced in the process of establishing the mathematical model to balance these different objectives. Ultimately, the model aims to achieve a win-win-win situation for users, the power grid, and society.

### **3.2 Basic Structure of the Model**

In the IoV environment, the collaborative scheduling model can be roughly divided into three layers, including the data layer, the optimization layer, and the control layer. The data layer relies on the IoV platform and charging facilities to collect real-time information related to EV operation, including vehicle location, SOC, remaining mileage, and planned departure time. Grid-side data, such as load curves, electricity price information, and renewable energy generation forecasting, are also integrated here. The data layer provides input for the model, ensuring the real-time performance and accuracy of scheduling decisions. The optimization layer is the core support of the entire model,

which is used to establish a mathematical optimization model based on the collected data, treating EVs as bidirectional energy storage units capable of charging and discharging. By defining objective functions (e.g., maximizing user satisfaction, minimizing system operation costs) and constraints (e.g., SOC constraints) power constraints, and grid balance constraints, a globally optimal charging-discharging plan within a given time period can be generated. Additionally, the layer is required to possess certain predictive capabilities to ensure the predictability of scheduling. For example, it is able to predict users' travel patterns and grid load changes based on historical data. The control layer executes the decisions made by the optimization layer, transmitting scheduling instructions to EVs and charging piles via the IoV communication network to achieve real-time regulation of charging-discharging behavior. When actual results deviate from predictions, the control system needs a feedback mechanism to dynamically adjust the plan. The basic structure of the model embodies a closed-loop operation mode of data perception-optimization decision-execution control, ensuring efficient and reliable interaction between the EV fleet and the power grid.

### 3.3 Mathematical Model

In terms of mathematical modeling, collaborative scheduling models mainly consist of an optimization objective function and multi-dimensional constraint conditions .

Set of vehicles be  $N$  and the set of time be  $T$ . The main variables include charging power  $P_{i,t}^c$ , discharging power  $P_{i,t}^d$ , SOC state  $SOC_{i,t}$ . Variables on the grid side include power purchase power  $P_{grid,t}$ . Comprehensively considering the three objectives of users, the power grid, and the system:

$$\min C = \alpha \sum_{i \in N} \sum_{t \in T} U_{i,t} + \beta \sum_{t \in T} \lambda_t P_{grid,t} + \gamma \sum_{t \in T} |L_t - \bar{L}| \quad (1)$$

The first item represents the user's unmet demand degree, the second item is the power purchase cost, and the third item is the load fluctuation. The coefficients  $\alpha, \beta, \gamma$  are weights.

For constraint conditions:

SOC Constraints:

$$SOC_{i,t+1} = SOC_{i,t} + \eta_c P_{i,t}^c \Delta t - \frac{1}{\eta_d} P_{i,t}^d \Delta t \quad (2)$$

Charging and Discharging Power Constraints:

$$0 \leq P_{i,t}^c \leq P_{max}^c, \quad 0 \leq P_{i,t}^d \leq P_{max}^d \quad (3)$$

Grid Balance Constraints:

$$P_{grid,t} + \sum_{i \in N} (P_{i,t}^c - P_{i,t}^d) = D_t \quad (4)$$

User Demand Constraint: To ensure travel readiness, the state of charge (SOC) of each vehicle before departure must be no less than a preset threshold, guaranteeing that users maintain sufficient battery energy while still participating in grid regulation. Incorporating the objective function and these operational constraints, the model is formulated as a mixed-integer nonlinear programming (MINLP) problem that simultaneously reflects user behavior and grid dynamics. Consistent with the strategy outlined by Jian et al. [6], the formulation aims to minimize load variance across the scheduling horizon while coordinating discrete charging and discharging decisions under nonlinear coupling between energy states and grid balance requirements. This design captures the dual objectives of achieving grid stability and enhancing user satisfaction within an intelligent, data-driven scheduling framework.

### 3.4 Solution Methods

Since the model involves a large number of variables related to vehicles and time periods, it constitutes a large-scale mixed-integer nonlinear optimization problem. In large-scale scenarios, traditional exact algorithms usually exhibit excessively high computational complexity and fail to meet real-time requirements. Therefore, multiple solution strategies are adopted. For distributed optimization methods, vehicles are divided into several groups, each managed by a local scheduler for optimization, and a global scheduling center coordinates the overall arrangement. This approach

effectively reduces the computational load. For heuristic and meta-heuristic methods, algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing (SA) can find high-quality solutions for non-convex problems [7]. The advantages include strong global search capabilities, though tending to get trapped in local optima, which are used in combination with distributed approaches. In recent years, deep reinforcement learning (DRL) has shown strong adaptability in dynamic scheduling. By continuously training intelligent agents in a simulation environment, DRL enables the agents to gradually learn optimal charging and discharging strategies and implement adaptive control for uncertainties.

## 4. Experiments and Results Analysis

### 4.1 Experimental Setup

To evaluate the potential performance of the proposed EV-grid collaborative scheduling model, a simulation-based case study was conducted using a typical urban distribution network system. The baseline data for the experiment were obtained from a representative daily load curve of a regional power grid, following the typical provincial load profiles published by the National Development and Reform Commission[8]. A total of 1,000 vehicles were simulated, distributed across multiple urban areas, including passenger and light commercial vehicles. The battery capacity of the EVs ranged from 30 kWh to 80 kWh, while the maximum charging power was limited to 7–22 kW and the maximum discharging power to 10 kW. Charging and discharging efficiencies were assumed to be 0.90 and 0.92, respectively. The simulation covered a continuous 24-hour period divided into 96 time intervals (15 minutes each). To reflect real-world electricity pricing policies, a time-of-use (TOU) mechanism was applied based on the price ratio range reported by the National Energy Administration of China [9]. The peak, flat, and off-peak electricity prices were set to 1.2, 0.8, and 0.4 CNY/kWh, respectively, consistent with the typical 3:2:1 ratio used in several provincial power systems[10]. The baseline load profile was modeled after a typical summer daily curve, where the maximum grid load occurs between 19:00 and 21:00[8]. To demonstrate the function of the IoV platform, it was assumed that real-time vehicle data—including location, state of charge (SOC), and estimated travel schedules—could be transmitted to the scheduling center, enabling adaptive charging and discharging control. Each vehicle was required to reach an SOC of at least 80% before its next planned trip to ensure travel readiness. The simulation was implemented on a hybrid MATLAB–Python platform using a combination of distributed optimization and heuristic algorithms. Three performance indicators were evaluated: (1) the smoothness of the grid load curve, (2) user demand satisfaction, and (3) overall system operation cost.

### 4.2 Comparative Schemes

To comprehensively verify the advantages of the proposed model, three comparative experiments were designed. Firstly, disordered charging scheme is designed. Under this scheme, no optimization or scheduling was applied to vehicles; vehicle owners charged their cars at any time based on personal needs. This scheme truly reflects the actual situation of EV integration into power grids in some regions currently. However, a critical issue is that charging is concentrated during evening peak hours, leading to a sharp increase in grid load and a further widening of the peak-valley gap. The second is ordered charging scheme, which partially incorporates the concept of optimized scheduling, with the primary goal of peak shaving and valley filling. Vehicles charge their batteries in an organized manner based on time-of-use electricity prices and grid load, but discharging is not considered. While this scheme can partially mitigate load fluctuations, it fails to meet diverse user needs and cannot achieve the goal of reducing system operation costs. Proposed collaborative scheduling model serves as the third scheme, which comprehensively considers real-time information from the IoV, user travel demands, and grid operation constraints. In addition to charging, it incorporates a discharging strategy (V2G). The model enables EVs to act as distributed energy storage devices to participate in grid regulation without affecting users' travel plans. By comparing and analyzing these three schemes, it

can be observed that different scheduling methods affect the power system load curve, user experience, and operation costs, which confirms that the proposed algorithm model exhibits excellent performance and certain practical value.

### 4.3 Simulation Results and Discussion

As for the grid load curve, the disordered charging scheme caused a rapid surge in load during evening peak hours, with the peak-valley difference exceeding 60%, posing a threat to the safe operation of the grid. The ordered charging scheme reduced the peak load to a certain extent but still resulted in concentrated secondary peaks. In contrast, the proposed collaborative scheduling model, which combines charging and discharging, smoothed the overall load curve and controlled the peak-valley difference to approximately 25%, significantly improving the operating status of the grid. As for user satisfaction, in the disordered and ordered charging schemes, some vehicles experienced low SOC due to grid load constraints and charging delays, resulting in an overall satisfaction rate of approximately 80%-88%. Whereas in the collaborative scheduling model, leveraging real-time information exchange via the IoV and a rolling optimization mechanism, the SOC satisfaction rate of vehicles reached over 95% before their scheduled travel, essentially resolving users' range anxiety. The disordered charging scheme incurred the highest system operation cost due to concentrated electricity purchases during peak hours. The ordered charging scheme reduced electricity expenses to some extent by utilizing time-of-use pricing, but the overall savings were limited. The collaborative scheduling model not merely reduced electricity procurement costs by charging during off-peak hours but also enabled profit from electricity arbitrage and peak load reduction by discharging vehicles to supply power back to the grid during peak hours. The simulation results showed that compared with the disordered charging scheme, the total operation cost of the proposed model was reduced by approximately 12%, and by 6% compared with the ordered charging scheme. The simulation results suggest that the proposed model can enhance load stability, improve user satisfaction, and lower operating costs under the given assumptions. However, as these findings are based on simulated data, further real-world testing is required to validate their generalizability.

## 5. Conclusion

This study developed a collaborative scheduling model for the interaction between electric vehicles and the power grid within the Internet of Vehicles (IoV) framework. The model aims to balance user satisfaction, grid stability, and system economy through multi-objective optimization. Simulation-based evaluations indicate that, under the assumed conditions, the proposed model can potentially smooth power load fluctuations, improve user SOC satisfaction, and reduce operation costs compared with uncoordinated or single-direction charging schemes. These results illustrate the model's feasibility and promise in supporting bidirectional EV-grid coordination. Future research will focus on extending the model to account for real-world uncertainties, including renewable energy volatility, user behavior diversity, and large-scale regional coordination. Field data validation and market-oriented transaction mechanisms will also be explored to strengthen the model's practical applicability within intelligent energy systems.

## References

- [1] Jia, H., Ma, Q., Li, Y., Liu, M., & Liu, D. (2023). Integrating electric vehicles to power grids: A review on modeling, regulation, and market operation. *Energies*, 16(17), 6151.
- [2] Rao, S. P., Olusegun, T. S., Ranganathan, P., Kose, U., & Goveas, N. (2025). Vehicle-to-Grid technology: Opportunities, challenges, and future prospects for sustainable transportation. *Journal of Energy Storage*, 110, 114927.
- [3] Sturmberg, B. C., Jones, L., Lucas-Healey, K., Islam, M., & Temby, H. (2021). Niche to normality--an interdisciplinary review of Vehicle-to-Grid. arXiv preprint arXiv:2106.05837.

- [4] Aldhanhani, T., Abraham, A., Hamidouche, W., & Shaaban, M. (2024). Future trends in smart green iov: Vehicle-to-everything in the era of electric vehicles. *IEEE Open Journal of Vehicular Technology*, 5, 278-297.
- [5] Zhang, Y., Chen, X., & Zhang, Y. (2022). Transfer deep reinforcement learning-based large-scale V2G continuous charging coordination with renewable energy sources. *arXiv preprint arXiv:2210.07013*.
- [6] Jian, L., Xu, G., & Chan, C. (2015). Optimal charging strategies of plug-in electric vehicles for minimizing load variance within smart grids. In *Smart Power Systems and Renewable Energy System Integration* (pp. 89–108). Singapore: Springer.
- [7] Gad, A. G. (2022). Particle swarm optimization algorithm and its applications: A systematic review. *Archives of computational methods in engineering*, 29(5).
- [8] National Development and Reform Commission. (2020, December). Typical daily load curves of provincial power grids in China. Retrieved from <https://www.ndrc.gov.cn/xwdt/tzgg/202012/P020201202546044875868.pdf>
- [9] National Energy Administration of China. (2021, August 6). Implementation of time-of-use electricity pricing policies in multiple provinces. Retrieved from [https://www.nea.gov.cn/2021-08/06/c\\_1310111977.htm](https://www.nea.gov.cn/2021-08/06/c_1310111977.htm)
- [10] SolarBe China. (2024, March 11). Peak and valley electricity price difference exceeds 1.3 yuan/kWh in the Pearl River Delta region. Retrieved from <https://cn.solarbe.com/news/20240311/86925.html>