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Bi-directional Optimal Scheduling of Electric Vehicles Based on V2G Technology

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Abstract: *To alleviate the phenomenon of increased electric grid load and expanded fluctuations caused by the surge in electric vehicles (EVs), the author of this thesis proposes a bi-directional optimal scheduling strategy based on Vehicle to Grid (V2G) technology. The plan consists of a model and a reverse model. The goal of the model is to reduce the fluctuation, in electricity grid load with a unique focus on the percentage of decentralized energy, within the entire energy framework.In contrast, the reverse model aims to maximize user benefits, intending to enhance user participation and thereby promote the sustainable development of the strategy. This study utilizes a population genetic algorithm to address the issue and compares it with a multi objective particle swarm optimization algorithm. The findings indicate that the suggested approach not successfully mitigates fluctuations, in electric grid load and minimizes peak to valley variances but also optimizes the gains, for individuals engaging in V2G services.*

Keywords: *Electric Vehicle; Vehicle to Grid; Electric Grid Load; Bi-directional Optimization; Distributed Energy*

1. Introduction

The number of electric vehicles (EVs) is rapidly increasing. Due to the temporal and spatial uncertainty of their charging load, the simultaneous connection of a large number of electric vehicles to the electric grid for charging could cause load shocks to the grid, exacerbating load fluctuations and randomness. Therefore, controlling the charging load of electric vehicles efficiently and suppressing the peak-to-valley load difference have become one of the important challenges facing the electric grid.

At present, in response to the sudden changes in electric grid load caused by the large-scale access of electric vehicles and real-time scheduling issues, scholars worldwide have conducted extensive research on electric vehicle optimization scheduling strategies. In view of the uncertainty of electricity demand on the user side, Wu et al. established the reserve optimization and real-time scheduling model of EV participation, which effectively improved the robustness and economy of aggregators' participation in auxiliary services. Liu et al. established a multi-objective dual-layer charging and discharging real-time scheduling model coordinated between the battery swap station and the electric grid, reducing the peak-to-valley difference through coordinated scheduling. Li et al. adopted a distributed management architecture, formulating scheduling strategies by coordinating the benefits of scheduling centers, agents, and users. Peng et al. considered the optimization strategy of orderly charging and discharging of electric vehicles based on V2G technology. He et al. conducted random simulations of unorganized electric vehicle charging using the Monte Carlo algorithm.

This thesis proposes a bi-directional optimization scheduling model that integrates distributed energy, electric grid supply, and user benefits. The forward model aims to set the charging load and discharging power for each time period, taking into account the proportion of distributed energy supply within the region, with the goal of minimizing the total load variance of the electric grid system. The reverse model, under the conditions of active user participation and adjustability, mainly considers maximizing user benefits. The author uses a multi-population genetic optimization algorithm for an in-depth analysis of the orderly charging model, supplemented by a comparative analysis with the multi-objective particle swarm optimization algorithm, to ultimately determine the optimal power distribution[1-2].

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2. Electric Vehicle Charging and Discharging Strategy Based on Bi-directional Optimization Scheduling Model

2.1 Bi-directional Optimization Model

The bi-directional optimization model considers the benefits of regional users on the basis of using time-of-use electricity pricing strategies to smooth the peak-to-valley load difference. The thesis combines the travel characteristics of residential areas, where the forward regional dispatcher formulates specific electricity usage strategies within the region under the overall electricity strategy. The reverse model, on the other hand, aims to maximize user benefits. The specific model architecture is shown in Figure 1 below.

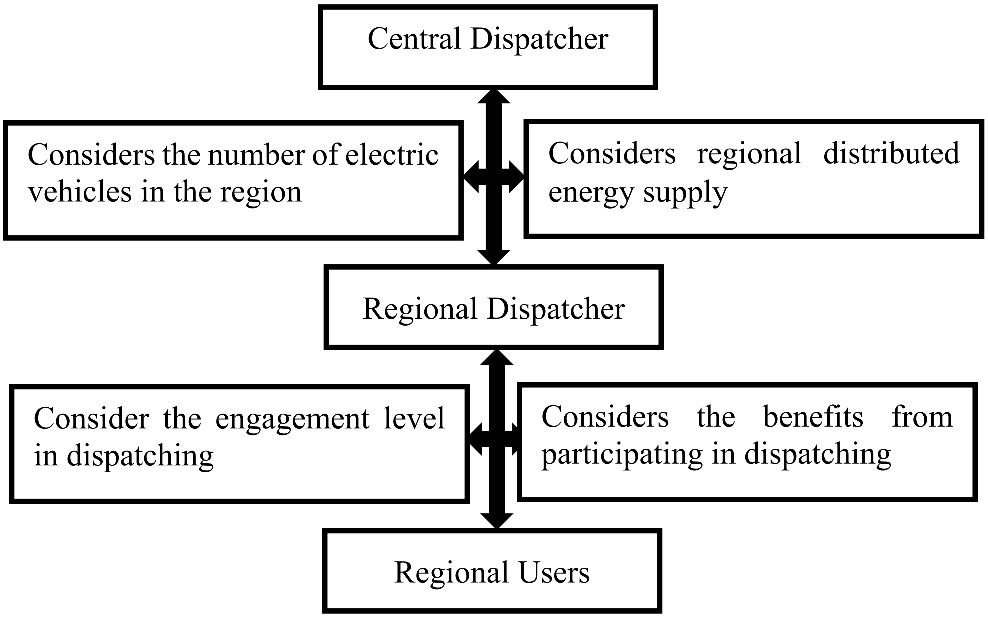

Figure 1: Architecture of the Bi-directional Optimization Model

2.2 Forward Objective Function

The forward objective function is aimed at minimizing the fluctuations of the electric grid.

$$\min F_1 = \sum_{t=1}^{T}\left(P_{else,t} + P_{ev,t} \pm \Delta P_{res,t} - P_{\arg}\right)^2 \tag{1}$$

In the equation, F_1 represents the daily load variance; $P_{else,t}$ represents the non-electric vehicle load at time t; $P_{ev,t}$ represents the electric vehicle load at time t; $P_{res,t}$ represents the distributed energy processing at time t; $P_{\arg}$ represents the daily average electricity load, $P_{\arg} = \frac{1}{T}\sum_{t=1}^{T}\left(P_{else,t} + P_{ev,t} \pm \Delta P_{res,t}\right)$

For the forward objective function, the following constraints are considered:

(1) Charging and discharging power constraints

$$P_{o\max} < P_{ev,t} < P_{i\max} \tag{2}$$

In the equation, $P_{o\max}$ and $P_{i\max}$ respectively represent the maximum values for charging and discharging power.

(2) Distributed energy supply constraints

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$$P_{mres} < \sum_{t=1}^{T} P_{res,t} < P_{Mres} \tag{3}$$

In the equation, P_{mres} and P_{Mres} respectively represent the minimum and maximum values for distributed energy power. $P_{mres} = 0.25$, $P_{Mres} = 0.3,$.

2.3 Reverse Objective Function

The reverse objective function aims at maximizing user benefits.

$$\max F_2 = \left[\sum_{t=T_0}^{T_1} P_{i,t} r_{i,t} s - \sum_{t=T_0}^{T_1} P_{o,t} r_{o,t} s' \right] (T_1 - T_0) \tag{4}$$

In the equation, F_2 represents the user's income; $P_{i,t}$ represents the electric vehicle's charging power at time t; $P_{o,t}$ represents the electric vehicle's discharging power at time t; $r_{i,t}$ represents the electricity price for charging at time t; $r_{o,t}$ represents the electricity price for discharging at time t; s is the charging factor; s' is the discharging factor; T_0 is the start time for electric vehicle charging and discharging; T_1 is the end time for electric vehicle charging and discharging[3-4].

For the reverse objective function, the following constraints are considered:

(1) Charging and discharging constraints

$$\begin{cases} s \times s' = 0 \\ s + s' = 1 \end{cases} \tag{5}$$

The meaning of this equation is that the electric vehicle cannot be in both charging and discharging states at the same time.

(2) Battery capacity constraints

$$0 \le \left(\sum_{t=T_0}^{T_1} P_{i,t} r_{i,t} s - \sum_{t=T_0}^{T_1} P_{o,t} r_{o,t} s' \right) (T_1 - T_0) \le SOC \tag{6}$$

The meaning of this equation is that during the charging and discharging process of the battery, the charge level should be maintained between 0 and full charge.

3. Model Solution Algorithm

The bi-directional optimization model involves complex multi-objective and multi-constraint optimization problems, where different objectives can easily affect each other when reaching the optimum locally. A Pareto frontier is generated, and the optimal solution is obtained using a fuzzy algorithm. By employing the multi-population genetic algorithm (NSGA-II), we use different parameter settings for each population, allowing different populations to evolve in parallel and ultimately selecting the elite populations to obtain the model's optimal solution.

4. Case Analysis

This thesis takes a city's agent as an example. In coordination with the overall scheduling plan of the scheduling center, the agent is responsible for the charging and discharging scheduling within their area. The Monte Carlo algorithm is used to randomly simulate the unorganized load of 500 electric vehicles.

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The response rate of regional electric vehicles to V2G is 80%. A base power of 180 kVA is selected, and the scheduling period is set from 0 to 24 hours, with each hour being a time segment unit, totaling 24 segments. During this period it is expected that the vehicles charging and discharging loads along, with essential loads will stay consistent. This assumption is based on the charging frequency of 10 times, per car owner.The Pareto frontier scatter plot is shown in Figure 2, with the middle point selected as the model's optimal solution, where the load on the electric grid side is 9313.29kW, and the user benefit is 2981.16 yuan. Figure 3 shows the original load and the unorganized charging load curve, and Figure 4 shows the electric vehicle charging and discharging power[5].

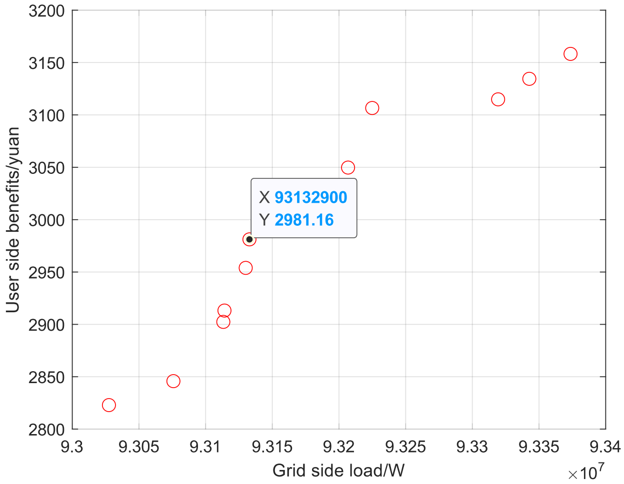

Figure 2: Pareto Frontier of the Objective Function

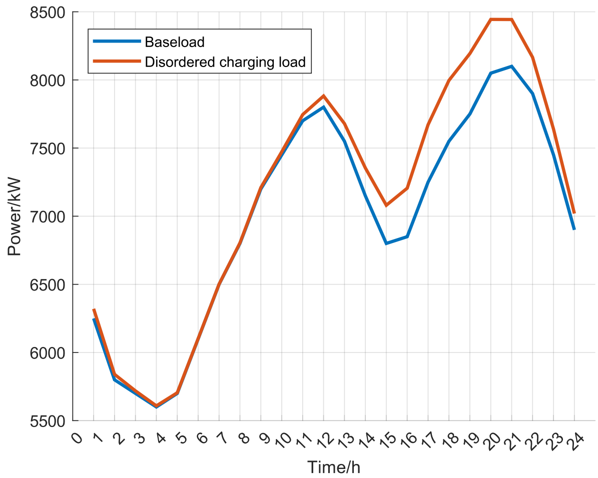

Figure 3: Basic Load and Unorganized Charging Electric Grid Load Curve

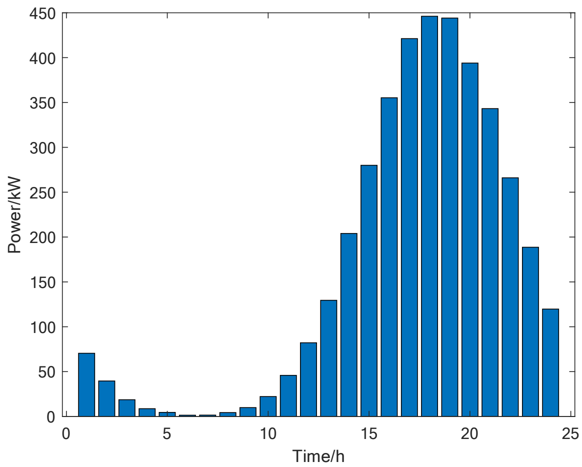

Figure 4: Average Charging and Discharging Power of Electric Vehicles Before Optimization

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To simplify the calculation process, it is assumed that the battery is fully charged after each charging session, and the related parameters of electric vehicles are set as shown in Table 1 below.

Table 1: Electric Vehicle Related Parameters

Parameter	Value
Electric Vehicle Charging Power (kW)	11
Electric Vehicle Discharging Power (kW)	6
Battery Storage Capacity (kWh)	60
Consumption per 100 Km (kWh/100Km)	15

Based on the fluctuation of the unorganized charging load shown in Figure 3, the time-of-use electricity pricing for the V2G strategy is set for different periods as shown in Table 2 below.

Table 2: Time-of-Use Electricity Pricing Settings

Type	Time Period	Charging Price (¥/kWh)	Discharging Price (¥/kWh)
Peak Hours	10:00-14:00	1.2	0.6
	19:00-22:00	1.2	0.6
Normal Hours	08:00-10:00	0.8	0.3
	14:00-19:00	0.8	0.3
	22:00-01:00	0.8	0.3
Off-Peak Hours	01:00-8:00	0.4	0.15

The optimization results are shown in Figures 5 and 6.

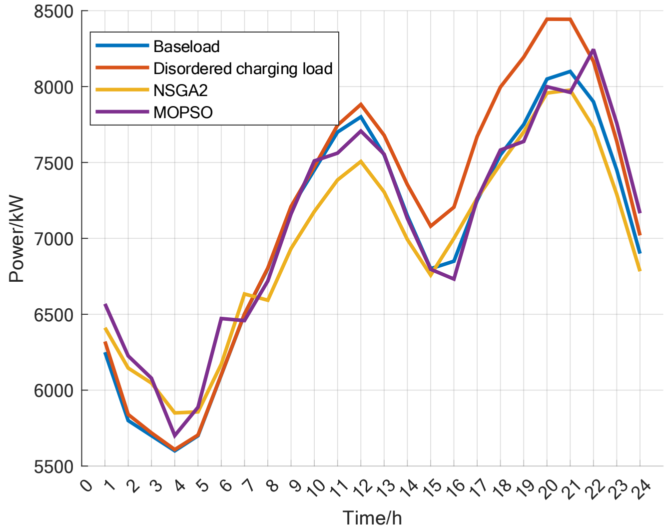

Figure 5: Electric Grid Load Curve Before and After Optimization

The peak base load occurs between 10:00-14:00 and 19:00-22:00, with a peak-to-valley load difference of 420.5 kW. The peak load under unorganized electric vehicle charging further exacerbates load fluctuations, with a peak-to-valley difference reaching 703.8 kW. This thesis utilizes a bi-directional optimization scheduling strategy, calculated using both multi-population genetic algorithms and multi-objective particle swarm optimization algorithms, successfully achieving peak shaving and valley filling. In the genetic algorithm, the peak load occurs between 9:00-13:00 and 19:00-21:00, with a peak-to-valley difference of 317.6 kW, effectively reducing electric grid load fluctuations.

After optimization, user-side benefits reached 3219.48 yuan, with user average monthly benefits increasing by 8% compared to before optimization. This ensures user engagement and indicates that the optimization effect of the model will become more pronounced as the proportion of user response to scheduling increases.

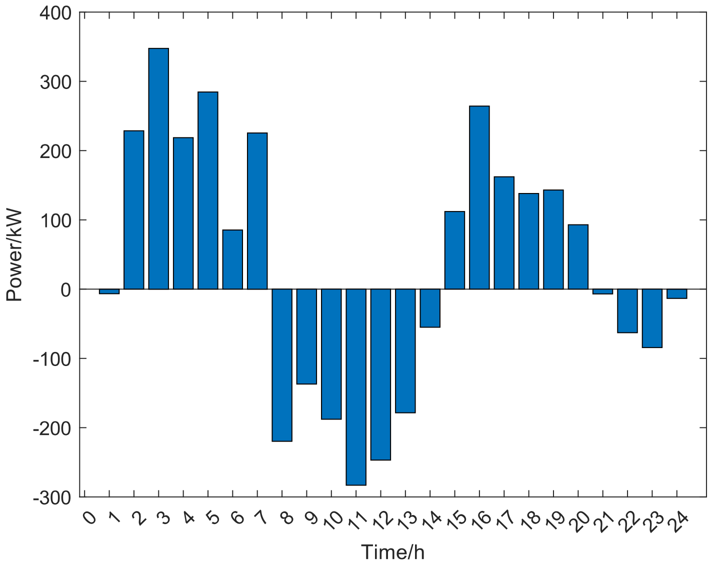

Figure 6: Average Charging and Discharging Power of Electric Vehicles After Optimization

5. Conclusion

This thesis proposes a bi-directional optimization scheduling strategy based on Vehicle-to-Grid (V2G) interaction technology for the region. The forward model aims to minimize the total load variance of the electric grid, considering the proportion of distributed energy in the overall energy structure. Conversely, the reverse model aims to maximize user benefits, intending to enhance user participation and thereby promote the sustainable development of the strategy. The model was analyzed using a multi-population genetic algorithm and compared with a multi-objective particle swarm optimization algorithm. The results show that this model not only effectively smooth electric grid load fluctuations and reduce the peak-to-valley difference but also maximize the economic benefits of regional users based on their V2G response capability. The validity and rationality of the constructed model are proved.

However, the responsiveness of EVs under the V2G strategy proposed in this paper may vary significantly due to differences in economic development levels across regions, leading to discrepancies between the calculated user costs in the model and actual costs. Additionally, the experimental scenarios only consider the usage under normal environmental and social conditions, without taking into account the impact of special climate, environmental, and other factors. Future research will further investigate the specific implementation of scheduling strategies under different regional conditions.

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